Forecasting the financial distress of industrial companies: analysis through the technique of neural networks and SVMs

Mohamed Sofien Nouri[1*], Younes Boujelbene[2*]

[1] Ph.D. in Economic Sciences, FSEG of Sfax, University of Sfax, Tunisia
[2] Professor in Economic Sciences, FSEG of Sfax, University of Sfax, Tunisia

Corresponding Author
[*] *medsofiennouri@gmail.com*
[*] *younes.boujelbene@gamil.com*

Abstract: This research focuses on the detection of potential business failures using artificial intelligence methods such as neural techniques and SVMs.

The failure prediction model will be an efficient tool for all the actors of the company to detect any potential difficulty. This decision support tool will be built on the basis of a set of financial variables from the literature that reflect the complexity of the default phenomenon. Finally, this research aims to contribute to all decision-makers, internal or external to the company. Indeed, it is a question of proposing a clear vision of the forecasting techniques and of showing the quality of forecasting of the non-parametric techniques as regards the forecasting of the failure of companies.

In this context, our research aims at explore a new practical approach based on neural networks and neural networks and SVMs to prevent the failure of firms, in a first step, and failure, in a first step, and to judge on the degree of accuracy the degree of accuracy of the models produced by these two techniques, in a second step. To reach this objective, the prediction quality of the model resulting from the neural network technique is compared to that of the SVM technique.

Keywords: Forecasting, business failure, neural network, SVM, non-parametric method.

1. Introduction

The business environment has been characterized by intense voting in recent years. As a result, there have been significant changes that have disrupted the international economy and forced businesses to make great efforts to adapt and survive. This environment has been characterized in recent years by complexity due to the accelerated development of technological innovation (computing, electronics, etc.) and by the uncertainties linked to the globalization of economic activities. The industrial sector is a country's engine of growth. One of the main reasons for the failure of industrial enterprises in Tunisia was the inability to maintain the necessary competitiveness and to prevent the risk of potential difficulties.

Faced with this complexity, these uncertainties and these changes in the environment, companies are likely to be affected by difficulties from their birth until their death. Those who prepare for it usually get away with it without major damage, but those who don't realize it soon enough or don't take the necessary measures in time risk being eliminated from the market. Indeed, the early detection of the failure is of crucial importance, because it allows taking preventive measures in due time preventive actions of restructuring or reorganization in order to eliminate or at least reduce the risk of failure of the company.

The prediction of company bankruptcy has been the subject of a considerable number of research works since the 1930s, attempting to highlight the various determinants that can affect the existence of firms and thus proposing a range of methods and statistical approaches for business leaders and financial analysts to guard against the risk of bankruptcy. Since the 1990s, neural networks initially used in the physical sciences have entered the management sciences as new forecasting techniques. As a result, business failure prediction models incorporate advances in artificial intelligence. The object of our work is situated in this perspective. It aims to show the contribution of neural networks and SVMs in terms of predicting business failure.

2. Literature Review

Financial distress has serious consequences for the company and its environment which has attracted the attention of economists, practitioners and researchers for several years and has justified the use of econometric and technical methods to create a model allowing the early detection of failing companies in order to limit its consequences and take the necessary measures in a timely manner. The prediction of financial distress is an area of investigation that dates back to the 1930s with the study of [1], since then there have been several generations of models allowing the early detection of a failure. Although there has not been a great change in the methodology used or the variables chosen, it is the evolution of statistical tools that has made this area of study still a hot topic.

Predicting the financial distress of a company can be approached as a classification problem, which is generally composed of two categories: healthy and bankrupt. Two methods have marked the history of this type of forecasting model methods, parametric methods and non-parametric methods.

Parametric statistical classification methods establish a functional relationship between the explanatory variables and the variable being explained. Since the 1960s, a wide variety of methods have appeared in the literature with the aim of modeling the risk of failure, one of the best known being discriminant analysis. Indeed, the unidimensional approach of [2] was among the first works aiming at separating healthy firms from failing firms through the study of financial ratios; Beaver's objective was to classify firms based on the most discriminating ratio. A critical threshold was determined in order to separate the group of healthy firms from the group of failing firms. The Beaver method thus provides a simple and effective indicator.

On the other hand, the lack of robustness due to the uniqueness of the ratio used explains the rarity of the use of this method thereafter. Numerous studies were subsequently carried out, such as multivariate discriminant analysis, which allows for a richer explanation of the company's situation. This technique leads to the construction of a score function, which is the linear combination of a number of ratios.

Since the 90s, artificial intelligence has entered the economic and financial sciences as a new forecasting technique. The importance of detecting financial distress has attracted the attention of researchers in recent years in order to limit the serious consequences caused by this condition ([3], [4], [5], [6]).

Several statistical tools with artificial intelligence are used, but there are three methods that have been successful in this field: neural networks, decision trees and support vector machines (SVM).

The most popular method, used since the 1990s, is neural networks [7]. Several network architectures have been applied in the area of financial distress prediction (e.g., neural multilayer perceptron [8], back-propagation neural networks [9], and probabilistic neural networks [10]. The convolution neural network method is one of the first machine learning methods used to predict bankruptcy, and thus serves as a benchmark for others for other methods used later.

The SVM method has enjoyed considerable success in the field of financial distress prediction since the late 2000s [11]. This method has been characterized as the least sensitive technique to unbalanced data. Similarly, this method has been qualified by its robustness and accuracy quality in terms of bankruptcy [12]. Several research works have investigated the accuracy of SVM methods in terms of prediction ([13], [14], [15], [16], [17], [18]).

3. Methodology

A. Data collection

Our database consists of 160 healthy and failing industrial firms for the years 2019 and 2020. Financial ratios derived from accounting data on the financial statements of these firms constitute our database (see Table I).

The choice of these ratios is based on the literature review and the degree of their relevance for financial analysis: liquidity, profitability and financial structure ratios. The selection of financial variables capable of analyzing the situation of firms is an important step in the development of a failure prediction model. According to the teaching of financial analysis, the economic or financial profitability of the firm, the structure of its balance sheet and its capacity to be solvent are the elements most correlated with the risk of bankruptcy.

Brezigar and Masten describe that the selection of financial variables capable of analyzing the situation of firms is an important step in the development of a failure prediction model [19]. Consistent with the teaching of financial analysis, the firm's economic or financial profitability, balance sheet structure, and repayment capacity are the most correlated with default.

Table I: List of variables used in this research (financial ratios)

	Variables	**Measurement of variables**
Profitability		
R01	Financial profitability	Net income/Net equity
R02	Economic profitability	Operating income/Total assets
R03	Operating profitability	Operating income/Operating assets
R04	Return on Investment	Earnings before interest, taxes, depreciation and amortization/ Assets-Liabilities
R05	Gross Profit Margin	Gross Profit/Total Sales
Rotation and Management		
R06	Asset turnover	Sales/ Total assets
R07	Turnover of fixed assets	Sales/Net fixed assets
R08	Inventory turnover	Sales/Inventories
R09	Days Sales Outstanding	Net Accounts Receivable/Daily Net Sales
R10	Profitability rate	Net income /Sales
R11	Growth rate of turnover	Sales n - Sales n-1
Debt ratios		
R12	Financial dependence	Long- and medium-term debt/Permanent equity
R13	Repayment capacity	Long and medium term/Cash-flow net debt
R14	Financial burden	Financial expenses/Gross operating surplus
Liquidity		
R15	General liquidity	*Current assets/Current liabilities*
R16	Reduced liquidity	*Current assets-stocks/Current liabilities*
R17	Immediate liquidity	*Cash/Current liabilities*
R18	Liquidity of assets	*Current assets /Total assets*
Financing and Structure		
R19	Financial autonomy	Equity / Total Balance Sheet
R20	Financial Independence	Equity /Financial and bank debt
R21	Coverage of financial expenses	Cash-flow /Financial expenses
R22	Debt repayment capacity	Cash-flow /Long-term debt
R23	General solvency	Current assets /Short term debt
R24	Equity ratio	Shareholders' equity/Total liabilities
R25	Fixed Assets Ratio	Net Fixed Assets /Total Assets

B. Construction of training and test samples

A learning sample with known rankings was used to model the different techniques used and to learn the ranking rules using the characteristics of the failed firms. It is necessary to study the reliability of the generalization of these rules in order to apply them. For this reason, we used a second independent sample called a test.

Random sampling was performed on the dependent variable "bankruptcy". We selected about 70% of the data for learning and 30% for testing our risk assessment model.

C. Choice of the technique

i. Artificial neural network

ANNs are widely used because of their generalization capability. ANN is a non-parametric technique inspired by biological neural systems. The multilayer perceptron is widely used in practice and generates performances especially in classification problems. The architecture of this network consists of an input layer, one or more hidden layers and an output layer. Each of these layers is made up of several neurons whose role is to process the input information and generate an output value that is transmitted to the neurons of the next layer. The learning phase at the level of this network allows determining all the synaptic weights wi that minimize the error function. The widely used algorithm for learning the multilayer perceptron to deal with classification problems is the back-propagation gradient algorithm. Indeed, the error computed from the output layer is back propagated through the network, and the weights are modified until the error is minimized.

The implemented model is a multilayer gradient backpropagation perceptron comprising an input layer, an output layer and one or more hidden layers connected by neurons to be optimized.

At the level of this process, there is no theoretical basis to determine in advance the number of hidden layers and neurons needed to obtain a performing model. It is therefore necessary to implement a procedure for designing a numerical model that allows the number of layers to be varied as well as the neurons that are linked. The neurons are interconnected and each one constitutes a processing element that receives and transfers data using synaptic weights wi. The weighted sum of the inputs is transformed with a non-linear activation function (sigmoid): $F(x) = \frac{1}{1+e^{-x}}$

The majority of studies have shown the performance of ANNs in terms of accuracy and robustness compared to traditional statistical forecasting methods

ii. Support-vector machine

The SVM technique is a machine learning method that has gained a lot of momentum in classification topics over the last decade [20].

This technique is based on the principle of maximizing a separation margin by creating a hyperplane separating the data into two classes. The generalization and optimization capabilities of SVMs are very efficient even with non-linear data. This technique requires fundamental choices such as the type of kernel to use and the appropriate parameters of this

kernel. The notion of the maximum margin between the two groups and the separating hyperplane search procedure only solves discrimination problems for linearly separable data. To face the data linearity problem, the kernel trick is to reconsider the discrimination problem in a higher dimensional space, possibly of infinite dimension, and to build a linear classifier in this space.
The kernel functions K can be defined as (xi,xj) = U(xi).U(xj) . They compute the dot product of projections of the input data into a higher dimensional space.
The kernel function used in SVM is based on the mathematical principle known as Mercer's theorem [21]. Based on this principle, the kernel function is the result of the scalar products of the input vectors in a larger space. K-functions satisfying these rules are called kernel functions.
Parameter C is called regularization parameter used to penalize classification error. This value represents the evaluation between empirical error and generalization error. In order to determine the most efficient parameter C, we have to try several values and measure the generalization error. Thus, the choice of parameters is made on the basis of the lowest generalization error.

D. Performance Measures

The performance of the model is measured by its discriminating power and its ability to estimate the probability of failure. Several measures are proposed to assess the predictive performance of the model.
Chen [22] admits that predictive performance is measured by the overall accuracy ability of the model i.e., by measuring the percentage of correctly classified cases. In addition, the study of business failure generally reports Type I errors and Type II errors. Abedini et al [23] describe that the Type II error shows a percentage of failing firms that are classified as healthy by the model, while the Type II error shows the percentage of healthy firms classified as failing by the model. The Type I error is more serious than the Type II error and can be costly in a wrong decision.
We note that :
Type 1 error: represents the really failing firms, assessed by the model as healthy.
Type 2 error: represents the really healthy firms, assessed by the model as failing.
Each assignment error weakens the performance of the model. The aim is to minimize this type of error caused by the erroneous classification of companies.
We note that the confusion matrix allows us to determine the percentage of firms that are well classified for a given classification threshold. In some cases, we find ourselves with a sample with very unbalanced classes (for example, more healthy firms than failing firms), so the confusion matrix can provide an erroneous picture of the model's predictive capacity. In addition, the confusion matrix directly presents the class to which a firm is assigned for a given threshold, so in order to compare two classifiers, the same threshold must be set for both cases in order to decide. As a result, it can be seen that there is a loss of information because the comparison leads to a certain result, either one performs better than the other or both perform the same.
In order to face this problem, the Receiver Operating Characteristic (ROC) curve resulting in the graphical representation of all the confusion matrices for the different thresholds seems to

be the efficient tool. In this case, the comparison of two classifiers presents a type of result that is sometimes better and sometimes less efficient. The ROC curve then compensates for the problem of loss of information and it will be well adapted to our case.
The general idea behind the ROC curve is to measure the performance of the model for all possible classification thresholds.
The ROC curve is a graphical presentation of the performance of two-class classifiers. This curve has been used successfully in different fields and more precisely in machine learning [24] and in the analysis of the performance of algorithms [25].
In terms of company classification, this curve relates the proportion of healthy companies classified as such (healthy company is assigned to the group of healthy companies) to the proportion of poorly classified failing companies (failing company is assigned to the group of healthy companies) when the score threshold is varied.
The proportion of healthy firms ranked well, also called sensitivity and denoted Se, is defined as the percentage of healthy firms correctly identified while the proportion of failing firms ranked well, also called specificity and denoted Sp, is defined as failing firms correctly identified.
The classification rule consists in assigning, for a given classification threshold t, a company with a score $s > t$, to class 1, and to class 0 if $s < t$.
The ROC curve allows to define the threshold value by representing the sensitivity Se on the ordinate as a function of (1- Sp) on the abscissa. If we note by class 0 the healthy firms that are well classified and by class 1 the failing firms that are well classified, the ROC curve is then presented in a plane where the vertical axis noted corresponds to the proportion of firms in class 0 that are well classified. The horizontal axis corresponds to the proportion of individuals in class 1 who are poorly classified.

Given these definitions, the expressions for Se and Sp are as follows:

$$\mathbf{Sp} = \frac{\textit{rate of well classified failing companies}}{\textit{rate of well classified failing companies+rate of misclassification of failing companies}} \quad \textbf{and}$$

$$\mathbf{Se} = \frac{\textit{rate of good ranking of healthy companies}}{\textit{rate of good ranking of healthy companies+misclassification rate of healthy companies}}$$

4. Case study and conclusions

A. Case Study

The case study of this research consists of a set of financial data related to Tunisian industrial companies. All the data used for this study were collected from accountants and auditors over the period 2019 and 2020.
From the available list, 300 companies were selected. Each company is represented by the dependent variable "company status" which informs about its situation. The "firm status" is a binary variable that takes two values: 1 for healthy firms and 1 for defaulting borrowers. Of the 300 firms, 200 firms are classified as healthy (Class 1), and 100 firms are classified

as having business and financial difficulties and are at risk of being eliminated from the market. The latter are classified as defaulters (Class 0). In this study 25 financial ratios are supposed to influence the state of the company and reflect its situation. (See Table I).

B. Failure modeling process using the neural method

The neural network parameterization procedure corresponds to a method for calculating optimal weights. The commonly applied algorithm for this purpose is the back propagation algorithm, which can be used for supervised learning.

In forward propagation, each neuron in the input layer receives an external signal, processes it and sends it to the neurons in the hidden layer. The global input, which each hidden neuron receives, is then given by the weighted sum of all inputs.

Multi Layer Perceptron (MLP) networks are applied in this study in combination with the error guardian back-propagation learning method called "Back-Propagation". This technique requires the user to perform multiple trials in order to identify the optimal neural architecture that improves the predictive power of the model in identifying business conditions.

The training data of the neural network thus includes the 14 ratios initially considered the most significant; these ratios form the neurons of the input layer. The desired output is formed of binary values: 1 for healthy companies and 0 for failing companies (output layer), this output forms the neuron of the output layer.

The transfer function chosen is the logistic sigmoid (exponential) one since the variable to be explained is binary. And finally, we retained the mean square error (MSE) as a performance function to judge the predictive quality of the model.

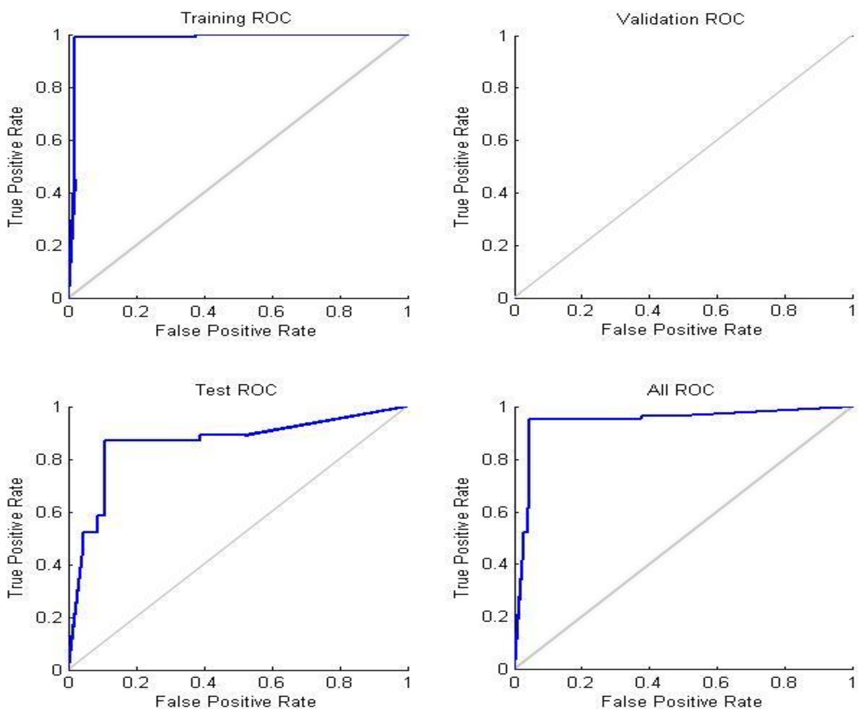

Figure 1: ROC curve obtained by RNA

It is possible to characterize the ROC curve numerically by calculating the area under the curve. This is the Area Under Curve (AUC) criterion. It measures the probability of placing a healthy company ahead of a failing one. Thus, in the case of perfect discrimination, AUC = 1, healthy firms are sure to be placed ahead of failing firms. On the contrary, if AUC = 0.5, the classifier assigns scores at random, so there is as much chance of assigning a healthy firm in front of a failing one as the opposite. The reference situation corresponds to the situation at which the ROC curve merges with the first bisector, our classifier must do.
The area under the ROC curve measures the discrimination quality of the model and reflects the probability that a healthy firm has a higher score than a failing firm, the latter being drawn at random. The area under the ROC curve of neural networks is equal to 0.82644.
The AUC value is equal to 0.98223 for the training sample and 0.73682 for the test sample. Our model has a good discriminating power, i.e. it is 83.644% likely that a state is correctly classified by the test over the range of possible threshold values.

C. *Failure Modeling process using the SVM method*

The SVM method is used in various domains and especially to solve classification problems. It is therefore a technique endowed with artificial intelligence based both on the assumption of linearity in a multidimensional space and on the theory of optimization. The basic principle of the SVM technique is to reduce the discrimination problem to a larger space and search for an optimal hyperplane (separating hyperplane). This technique constructs two hyperplanes parallel to each side of the separating hyperplane, to compute the margin. The hyperplane with the largest distance to the landmarks of the two classes of data, indicates a good separation, since in general the larger margin realizes the lower generalization error of the classifier.
The determination of the separating surfaces is achieved by inserting a kernel function into the scalar product, which implicitly induces a nonlinear transformation of the data into a higher-dimensional intermediate space. The performance of the SVM technique in classification can be defined in terms of a search for a set of optimal parameters. In this context, we try to determine in the following an efficient kernel function, a regularization parameter C that minimizes the misclassification error and an appropriate combination of kernel function parameters.
The good optimization of the parameters of the different kernels allows to improve the performance of the SVM in terms of classification. The parameterization is done using the tune.svm function in R. This function allows to test several values of the parameter C by estimating the prediction performance. We used the radial-based kernel function due to its versatility, good overall performance, and small number of parameters (Bhattacharyya et al., 2011).
The application of the radial-based SVM method on the selected sample of variables allowed us to have a good performance. The error rate is less than 0.2.

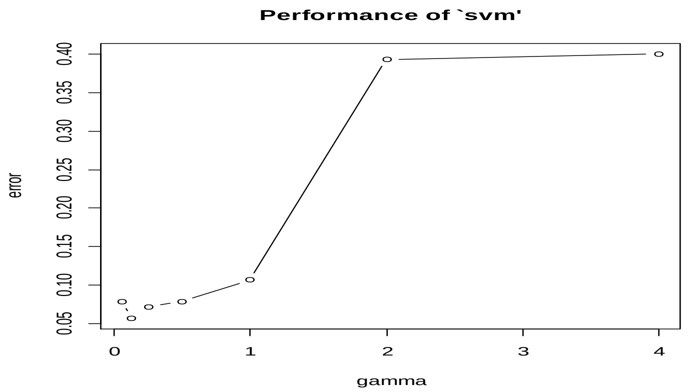

Figure 2: Performance of SVM

Table II: the ranking rates obtained by SVM

	Apprentissage	**Test**
Taux de bon classement	94,07%	89, 46%
Sensibility	0,9546	0,9136
Specificity	0,9269	0,8756
Error type I	0,0731	0,1244
Error type II	0,0454	0.0864
Precision	0,9364	0,8793
F-measure	0,9598	0,8821

This table shows that the overall good ranking rate obtained by the model is 89.46%. The rate of good classification of healthy companies is 91.36%, while that of failing companies is 87.56%. The type I error (classifying a failing company as healthy), amounts to 12.44%while that of type II is 8.64%.

D. Discussion des résultats de cette recherche

The application of neural networks and SVM techniques to two samples of healthy and failing firms allowed us to obtain relevant prediction models as shown in the table below.

Table III: The rate of good ranking obtained by the models

	ANN	**SVM**
Rate of correct classification	83.64%	89.64%

The explanation of these results is actually related to statistical rather than economic causes, since non-parametric techniques do not require restrictive assumptions as is the case with the parametric technique. In this respect, we found that there is a difference in terms of predictive quality between the neural network technique and the SVM technique. Indeed, SVMs offer a better predictive quality than neural networks.

In The majority of cases, the main problem pertaining to the bankruptcy prediction domain is to determine the variables that have a significant influence on the probability of failure. As a result, the accuracy quality of the models in terms of prediction is improved by selecting the most significant financial variables that can reflect the firm's situation in an accurate way. To distinguish solvent firms from non-creditworthy firms, Huang and Wang [26] identified the key financial ratios and their corresponding financial factors that offer the best discriminating power. They concluded that cash flow, profitability, solvency, and financial factors are among the most useful financial ratios that can effectively differentiate between solvent and non-solvent firms.

In our case, the relevant forecast rates obtained using both techniques relate to the performance of the latter in the decision support domain on the one hand and on the other hand, to the right choice of financial ratios.

5. Conclusion and Limitations

This paper aims to explore a new practical approach based on neural network and SVM techniques to prevent the failure of firms, in a first step, and to judge their performance in terms of predictive capacity of a potential bankruptcy. This research is motivated by the inadequacies of parametric methods in terms of forecasting. To achieve this objective, the forecasting quality of the model resulting from the neural network technique is compared to that of SVMs. The performance of both techniques in terms of prediction was found with a slight superiority of SVMs over neural networks.

Using the ANN technique the predictive capacity of the model amounts to 83, 64% which is lower than the rates acquired by the SVM method amounting to 89.64%.

The practical contributions of our research are at two levels:

- Managers, investors and bankers have a description of the informational practices in terms of default indicators. This allows them to make a comparative diagnosis of their own failure indicator systems. Thus, the decision-maker finds a contribution in our work, giving him the possibility to take into account the whole set of indicators in the prediction of failure and the reduction of uncertainty.

- The improvement of the understanding of the use of non-parametric techniques in the prediction of the failure of companies.

Any research work that is meant to be scientific has its limits and some future avenues of research. We list them briefly:

* Limitations

Among the limitations of our study, we can mention the size of the sample, the unavailability of data over a fairly large horizon that exceeds two years.

*Future research avenues

In order to obtain more relevant results, our research could be extended to identify two different failure profiles relative to the large firm compared to the SME: This would allow enlightening comparisons between small and large firms and identify differentiated failure profiles.

References

[1] Fitzpatrick P.I. «A comparison of the successful industrial enterprises with those of failed companies», The Accountants Publishing Company(1932)

[2] Beaver W., "Financial ratios as predictors of failure, Empirical Research in Accounting: Selected studies", Journal of Accounting Research, 6, 165-182

[3] Kumar, PR, Ravi, V., "Bankruptcy prediction in banks and firms via statistical and intelligent techniques". European Journal of Operational Research, 2007, vol. 180, issue 1, 1-28.

[4] Lin, Y. W. Hu and Tsai C. , "Machine Learning in Financial Crisis Prediction: A Survey" Applications and Reviews, vol. 42, no. 4, pp. 421-436, July 2012

[5] Sun, J., Li, H., Huang, Q.-H., He, K.-Y., "Predicting financial distress and corporate failure: A review from the state-of-the-art definitions, modeling, sampling, and featuring approaches". Knowledge-Based Systems Volume 57, February 2014, Pages 41-56

[6] Alaka, H.A., Oyedele, L.O., Owolabi, H.A., Kumar, V., Ajayi, S.O., Akinade, O.O., Bilal, M., 2018. « Systematic review of bankruptcy prediction models: towards a framework for tool selection". Expert Syst. Appl. 94, 164–184

[7] West, D. (2000), « Modèles de notation de crédit des réseaux neuronaux », Computers and Operations Research, Vol. 27 n° 11/12, p. 1131-1152.

[8] Iturriaga, F.L., et Sanz, I.P., "Bankruptcy visualization and prediction using neural networks: A study of U.S. commercial banks". Expert Systems with Applications.2015. 42(6)

[9] Lee, S., Choi, W.S., 2013. A multi-industry bankruptcy prediction model using back-propagation neural network and multivariate discriminant analysis. Expert Syst. Appl. 40, 2941–2946

[10] Yajnik M., Moons., Kurose J. & Towsley D. "Measurement and modeling of the temporal dependence in packet loss". In Proccedings of IEEE INFOCOM 1999, p. 345–352

[11] Lin, Y. W. Hu and Tsai C. , "Machine Learning in Financial Crisis Prediction: A Survey," in IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews), vol. 42, no. 4, pp. 421-436, July 2012

[12] Young Kim S.Y , Upneja A (2021). "Majority voting ensemble with a decision trees for business failure prediction during economic downturns". Journal of Innovation & Knowledge, Volume 6, Issue 2, April–June 2021, Pages 112-123.

[13] Chaudhuri, A., De, K.,. « Fuzzy support vector machine for bankruptcy prediction ». Appl. Soft Comput. (2011) , 2472–2486

[14] Wang, G., Ma, J.,. « A hybrid ensemble approach for enterprise credit risk assessment based on Support Vector Machine". Expert Syst. Appl. (2012), 39, 5325–5331.

[15] Khemakhem S.et Boujelbene Y.,“Support vector machines for credit risk assessment with imbalanced datasets”. Int. J. Data Min. Model. Manag. .(2018) , 10(2): 171-187

[16] Li, X., Wang, F., Chen, X.,. “Support vector machine ensemble based on Choquet integral for financial distress prediction”. International Journal of Pattern Recognition and Artificial Intelligence.(2015), Vol. 29, No. 04

[17] Martín-Torres, S., Carvelo, A., Casado, A., Rodríguez, L.,. “Authentication of the geographical origin and the botanical variety of avocados using liquid chromatography fingerprinting and deep learning methods”.Chemometrics and Intelligent Laboratory Systems. Volume 199, 15 April 2020, 103960

[18]Shen, F., Liu, Y., Wang, R, Zhou, W., (2020), “A dynamic financial distress forecast model with multiple forecast results under unbalanced data environment ”, Knowledge-Based Systems, Volume 192.

[19] Brezigar and Masten(2012), “CART-based selection of bankruptcy predictors for the logit model”., Expert Systems with Applications 39(11), 10153–10159

[20] Cristianini, N. et Taylor, JS (2000), An Introduction to Support Vector Machines and Other Kernel-Based Learning Methods, University Press, Cambridge.

[21] Mercer, J. (1909), “Functions of positive and negative type and their connection with the theory of integral equations”, Philosophical Transactions of the Royal Society, Vol. 83 No. 559, pp. 441-458.

[22] Chen, M.Y. (2011), Predicting Corporate Financial Distress Based on Integration of Decision Tree Classification and Logistic Regression. Expert Systems with Applications, 38, 11261-11272.

[23] Abedini, M., Ahmadzadeh, F. and Noorossana, R. (2016), “Customer credit scoring using a hybrid data mining approach”, Kybernetes, Vol. 45 No. 10, pp. 1576-1588

[24] Spackman K.A. Signal detection theory: Valuable tools for evaluating inductive learning. In Proc. 6th Int. Workshop on Machine Learning, 1989, pp. 160–163.

[25] David J. Hand(2009), Measuring classifier performance: a coherent alternative to the area under the ROC curve, Machine Learning volume 77, pages103–123 (2009).

[26] Huang, J. and Wang, H. (2017), “A data analytics framework for key financial factors”, Journal of Modelling in Management, Vol. 12 No. 2