A new predictive machine-learning approach for detecting creditworthiness of borrowers.

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Abstract—We present in this paper a new approach for predicting creditworthiness of borrowers that we call "Method of splitting the learning set into two region". The aim of this approach consists on the construction of two regions from a learning set, the first called *"Solvency Region"* that contains the feature vectors of the elements that have paid their financial obligations on time and the second one called *"Non-Solvency Region"*, which contains the feature vectors of the elements that have defaulted in paying their debts. Therefore, to predict creditworthiness borrowers, it is sufficient to identify which of the two regions includes his feature vectors; if it doesn't correspond to any region, the credit decision-making requires further analysis. To develop and test our predictive proposed approach, a large set of real and recent credit data obtained from the UCI repository is used, we trained also on a real credit database from a Moroccan bank and the creditworthiness of borrowers are analyzed using two performance measurement indicators such as Classification accuracy and the AUC of the ROC curve as a robustness measurement criteria. The proposed model was compared to three traditional machine-learning algorithms: LR, RBF-NN and the MLP-NN. The experimental results show the improved performance of our proposed predictive method for predicting creditworthiness of borrowers.

Keywords— Creditworthiness, Artificial Intelligence, Credit risk prediction, splitting the learning set into two regions.

I. Introduction

Creditworthiness (CW) is considered as a valuation performed by credit service providers (CSPs) that determines their credibility, behavior and their solvency, i.e. the likelihood that a borrower may default on the payment of their obligations. It is represented as a credit score by financial institutions and banks. The CW of a corporate entity or individual is determined by using different credit scoring models. Hence, a high credit score results in a high creditworthiness, this score is determined on the basis of the wide customer database created generally by banks over the years [1]. It is not possible for all customers to act in the same way in terms of financial performance, therefore, banks need to know their good or bad customers, and they will need a credit scoring (CS) system to do so [2]. Article [3] defines (CS) as the means used to analyze the probability that the applicant will settle or not settle its debts, in order to prevent financial losses.

It is important to collect information from the customers of banking institutions in order to assess credit risk and, simultaneously, to decide whether to lend money to their customers. This process, in turn, can help distinguish good borrowers from bad ones. This means that some borrowers have a clean, good record of accomplishment, so banks can classify them as "good borrowers". Others, who do not have such a good record of accomplishment, may be considered "bad borrowers". It should be noted that such a simple selection process may not ensure correct classification. Therefore, there is an urgent need to develop new accurate automated systems that reduce prediction errors to handle large and complex credit scoring datasets [4]. To deal with this challenge, IT systems have become very popular among scientists and institutions in the last several years.

In recent decades, many scientific researchers have attempted to assess the credit scoring potential of bank customers by using different predictive models [5]. A large number of data mining (DM) and machine learning (ML) techniques have been employed for this purpose, including Neural Networks (NNs), Support Vector Machines (SVM), Decision Trees (DTs), Logistic Regression, and more. Each of these studies examined various data sets to demonstrate the performance of their methodologies. In general, finding a link between lower and higher credit risks is one of the most popular research areas in the field of financial forecasting, consisting of developing and building new predictive systems.

Regarding the main contribution and novelty of this work, we introduce a new method for predicting financial distress related to credit applicants called splitting the learning set into two regions (SLS2Rs); one defective and the other non-defective, characterized by the three following approaches:

- Higher accuracy in predicting bank credit risks;
- Better analyzes of the borrower's classification;
- Greatest improvement of the predictability of existing evaluation methods by minimizing their margin error.

The goal of our proposed method consists on the construction of two regions from a learning set, the first named "Solvency Region" that contains the feature vectors of the elements, which are settled their credits in term and the second one named "Non-Solvency Region", which contains the feature vectors of the elements who failed in the payment of their credits. Therefore, to predict the risk of a customer default, it is enough to know which of the both regions include his feature vectors; if it doesn't correspond to any region, the credit decision making requires so more analysis. To evaluate the performance and to demonstrate the effectiveness of our method, a series of experimental tests and a comparative study are applied. The obtained results suggest that the proposed methodology is very promising in the bank credit risk prediction field and it could be applied to any other CS dataset as well.

II. Creditworthiness banking detection models: A brief review of literature.

In this section, we will review some widely used techniques for predictive credit scoring applied in detecting credit worthiness borrowers in order to create a baseline for the selection of an appropriate tool for developing a banking creditworthiness prediction models, note that this study only reviews the most commonly used techniques as it would be almost impossible to look at all techniques applied in credit scoring. Typically, the existing literature surveys on creditworthiness borrowers prediction or credit scoring models shows that most of these models are either statistical [6] or artificial intelligence (AI) [7] based methods.

A. Statistical models for detection of Creditworthiness.

A credit scoring solution can be built using Metrological statistics models, including; Multiple Discriminant Analysis (MDA)[8], Logistic Regression (LR) [8]-[9], Bayesian approach[10]-[11], Probit analysis[12], Multiple regression and more others. These models have been proven to be quite effective, however, for solving relatively less complex problems in prediction credit risk fields. Some of these techniques are widely applied for prediction and diagnosis in the banking credit risk assessment literature, notably; Multiple Discriminant Analysis and Logistic Regression tools[13]. MDA instrument was initially applied by [14] to analyze the financial distress, bankruptcy and default risks. However, the use of this method has frequently been criticized because of its assumption of the categorical nature of credit data and the fact that the covariance matrices of good and bad credit are unexpected to be equal [15], [16]. In parallel with the MDA approach, LR instrument is becoming a common alternative for making credit-scoring models. Fundamentally, it was emerged as the better technique of choice in anticipating dichotomous outcomes. It has been concluded as one of the most appropriate techniques in the credit risk assessment literature. Authors in article [17] stressed that logistic regression algorithms perform best among all statistical credit risk assessment algorithms. In this context, several studies has shown the effectiveness of the logistic regression approach versus the LDA approach in detection of credit worthiness borrowers. As this model is widely used, a large number of its application have been reported in literature [18].

B. Artificial intelligence models for detection of Creditworthiness.

Against lot of statistical methods and in order to improve prediction performance for detection banking (CW) borrowers, artificial intelligence and soft computing techniques have emerged. In fact, overall the main AI method for prediction (CW) are Artificial Neural Networks (ANNs) [19-20], Support Vector Machines (SVMs) [20]-[21], Fuzzy Logic (Fuzzy) [21], Decision Tree(DT)[22], K-Nearest Neighbor (K-NN)[23], Random Forests algorithms(RFs) [24], Genetic Algorithm [25]-[26], and more others.

AI tools are computer-based techniques of which Artificial Neural Network (ANN or NN) is the most common for bankruptcy prediction simply because it have shown a greater correctness of predictability than any others techniques in (CW) models prediction or credit scoring models, due to its associated memory characteristic and generalization capability, flexibility, robustness, and higher classification accuracy [27]. Many studies arbitrarily employed neural networks algorithms for modelling credit risk compared to others methods of (CW) prediction models [13], [28]. In their study [29], compares Bayesian networks (NB) with Artificial Neural Network (ANNs) algorithm based on back propagation for predicting recovered value in a credit operation. They finds that both the ANN and the NB models provide reliable outcomes, but the ANN is more effective for predicting credit risk with an average score of 82%. Further, Authors in article [30], explore a new practical way based on the Neural Networks that would help the banker to predict the non-payment risk the companies asking for a loan. To evaluate the performance of their technique, they compare it with those of discriminant analysis. The results shows that the neural networks techniques is more accurate in term of predictability. In the same sphere of predicting CW , a research conducted in [31] suggests an ensemble techniques bagging with neural network for creditworthiness assessment. The proposed model showed promising results and outperforms other models for Bosnian commercial bank dataset. Authors demonstrate that the proposed model is empirically proven to be suitable for further use in the assessment of the creditworthiness of applicants. In the same context, Lin et al [32] discussed in their work the application of the classification function and artificial neural networks such as (MLP) and (RBF) in identifying the risk categories of the studied firms. The results showed that the application of the artificial neural network and classification function can effectively support the credit evaluation of applicants. In their study, authors in [33] examined the credit decision using logistic regression and neural network (RBF). The results showed that the logistic regression model was superior to the radial basis function

(RBF) model in terms of overall accuracy rate. However, the radial basis function was better than the identification of likely defaulters. Recently, the work of Yiping. G [34] present a credit risk assessment algorithm based on BP neural network, and the simulation results showed that, compared with the traditional LR algorithm, the proposed model has higher classification accuracy and can effectively reduce investors risk.

III. Development of the Proposed Model.

This model typically requires a quantity of data, which is accumulated by the bank to form a larger learning set to achieve performance gains through predictions; this ensemble can be divided into two different categories. Our learning set includes the bank's credit customers, which can be classified into two groups based on the opinion of the bank's credit administrator: the set of successful customers is the category containing all the cases that managed to repay their credit on time i.e. they are considered as solvency customers; each element of this category is denoted by 0 (Table 1 in blue) and the set of unsuccessful customers is the set of elements that failed to recover their credit i.e., they are considered as non-solvency customers, each element of this set is denoted by 1 (Table 1 in grey).

Table 1. The repartition of the studied categories.

X_1	X_2	$\cdots$	X_s	X_{s+1}	X_{s+2}	$\cdots$	X_N
x_{11}	x_{12}	$\cdots$	X_{1s}	x_{11}	x_{12}	$\cdots$	X_{1N}
x_{21}	x_{22}	$\cdots$	X_{2s}	x_{21}	x_{22}	$\cdots$	X_{2N}
$\vdots$	$\vdots$	$\cdots$	$\vdots$	$\vdots$	$\vdots$	$\cdots$	$\vdots$
x_{P1}	x_{P2}	$\cdots$	X_{ps}	x_{P1}	x_{P2}	$\cdots$	X_{pN}
1	1	…	1	0	0	…	0

Classe1: The group, which contains S Solvency/successful customers, can be represented by the following matrix:

X_1	X_2	$\cdots$	X_s
x_{11}	x_{12}	$\cdots$	X_{1s}
x_{21}	x_{22}	$\cdots$	X_{2s}
$\vdots$	$\vdots$	$\cdots$	$\vdots$
x_{P1}	x_{P2}	$\cdots$	X_{ps}
0	0	…	0

The centroid of this class is:

$$c_0 = \frac{1}{s}\sum_{i=1}^{s} X_i = \frac{1}{s}\sum_{i=1}^{s}\begin{pmatrix} x_{1i} \\ x_{2i} \\ x_{3i} \\ \vdots \\ x_{pi} \end{pmatrix} \tag{1}$$

Classe2: The group that contains $N-s$ non-Solvency / non-successful customers can be also represented by the following matrix:

X_{s+1}	X_{s+2}	$\cdots$	X_N
$x_{1,s+1}$	$x_{1,s+2}$	$\cdots$	X_{1s}
$x_{2,s+1}$	$x_{2,s+2}$	$\cdots$	X_{2s}
$\vdots$	$\vdots$	$\cdots$	$\vdots$
$x_{P,s+1}$	$x_{P,s+2}$	$\cdots$	X_{ps}
1	1	…	1

The centroid of this class is:

$$C_1 = \frac{1}{N-S}\sum_{i=S+1}^{N} X_i = \tfrac{1}{N-S}\sum_{i=1}^{N}\begin{pmatrix} x_{1i} \\ x_{2i} \\ x_{3i} \\ \vdots \\ x_{pi} \end{pmatrix} \tag{2}$$

The worst element among successful customers is the element X_w , which is furthest from the centroid of this class (see Fig.4). Therefore X_w is defined as:

$$d(C_0, X_w) = \max\{d(C_0, X_i), i = 1,\ldots, S\} = r_0 \tag{3}$$

The best element among non-successful customers is the element X_b furthest from the centroid of this class. Therefore X_b is defined as:

$$d(C_1, X_b) = \max\{d(C_1, X_i), i = S+1,\ldots, N\} = r_1 \tag{4}$$

Where $d(Y_1, Y_2)$ is the Euclidean distance defined by:

$$d(Y_1, Y_2) = \sqrt{\sum_{i=1}^{P}(y_{i1} - y_{i2})^2} \tag{5}$$

We constitute the following two regions: the ball with center. C_0 and radius r_0.

$$R_0(C_0, r_0) = \left\{ X \in R^N / d(C_0, X_0) \le r_0 \right\} \tag{6}$$

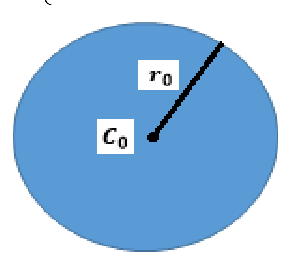


Fig.1. The region $R_0(C_0, r_0)$ with center C_0 and radius r_0.

And the region with center C_1 and radius r_1

$$R_1(C_1, r_1) = \left\{ X \in R^N / d(C_1, X) \le r_1 \right\} \tag{7}$$

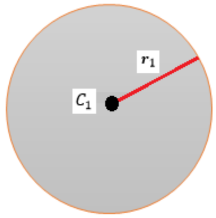


Fig.2. The region $R_1(C_1, r_1)$ with center C_1 and radius r_1.

Important notes:

1) The set of feature vectors $\{X_i, i = 1, \dots, s\}$ of successful customers is completely included in the region $R_0(C_0, r_0)$, i.e.

$$\{X_i, i = 1, \cdots, S\} \subset R_0(C_0, r_0) \quad (8)$$

2) The set of feature vectors $\{X_i, i = s+1, \dots, N\}$ of non-successful customers is completely included in the region $R_1(C_1, r_1)$, i.e.

$$\{X_i, i = S+1, \cdots, N\} \subset R_1(C_1, r_1) \quad (9)$$

Proof:

1) According to equation (6), to show that a vector X belongs to the region $R_0(C_0, r_0)$, it is enough to show that $d(C_0, X) \leq r_1$.

From the equation (3), $d(C_0, X_w)$ is the distance that maximizes the set of distances between C_0 and the feature vectors of successful companies $X_i, i = 1, \dots, s$. It's means that;

$$d(C_0, X_i) \leq d(C_0, X_w) = r_0 \text{ for all i = ,…,S} \quad (10)$$

Therefore, $\{X_i, i = 1, \dots, S\} \subset R_0(C_0, r_0)$

2) In the same procedure of remark 1, according to equation (4), $d(C_1, X_b)$ the distance that maximizes the set of distances between C_1 and the feature vectors of non-successful clients $X_i, i = S+1, \dots, N$. This means that:

$$d(C_1, X_i) \leq d(C_1, X_b) = r_1 \text{ for all } i = S+1, \dots, N \quad (11)$$

Therefore, $\{X_i, i = S+1, \dots, N\} \subset R_1(C_1, r_1)$

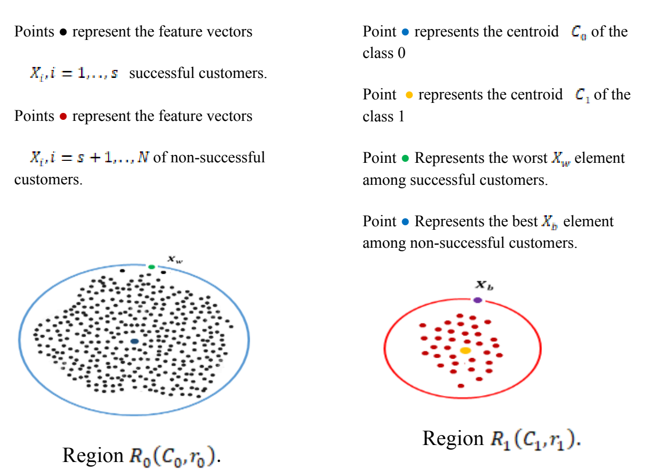
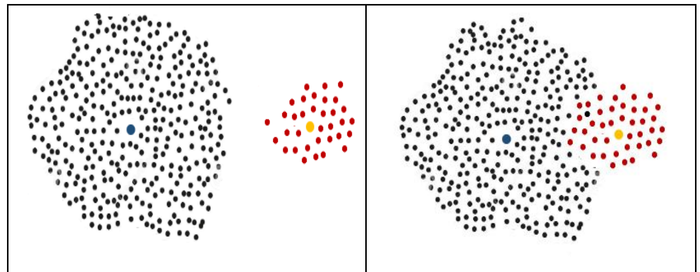


Fig.3. The distribution of the learning set $\{X_i, i = 1, \dots, N\}$ into two b.



(a): separable learning set **(b):** non-separable learning set

Fig.4. Representation of learning sets.

In summation, using the previous important remarks, we deduce the procedure followed in order to predict the bank credit risk of a customer based on a precise learning set accumulated by the bank. We proceed so with the following phases:

Phase of splitting the learning set into two regions:

This phase allows to build two spherical zones by splitting the learning set into two regions $R_1(C_1, r_1)$ and $R_0(C_0, r_0)$ the first contains the risky elements and the second contains the non-risky elements. Depending on the nature of the set under consideration, we follow one of the following two cases :

Case 1: If the learning set, is separable (Fig. 4 (a)), we follow the following steps:

- ***Step 1:*** We calculate the barycentre C_0 of all Successful customers.
- ***Step 2:*** We calculate the C_1 barycentre of all non-Successful customers.
- ***Step 3:*** We determine the worst element X_w among the Successful customers and the radius r_0
- ***Step 4:*** We determine the best X_b element among non-Successful customers and the radius r_1.

Case 2: If the learning set is non-separable (Fig.4 (b)), in this case, to build the two regions we can use the following new optimization problem:

Find X_w and X_b such as:

$$\{d(C_0, X_w) + d(C_1, X_b) = \max\{d(C_0, X_i) + d(C_1, X_j), i = 1, \dots, S; j = S+1, \dots, N\}\}$$

Under constraint $R_0(C_0, r_0) \cap R_1(C_1, r_1) = \phi \quad (12)$

i.e.

Find X_w and X_b such as:

$$\{d(C_0, X_w) + d(C_1, X_b) = \max\{d(C_0, X_i) + d(C_1, X_j), i = 1, \dots, S; j = S+1, \dots, N\}\}$$

Under constraint $d(C_0, X_w) + d(C_1, X_b) \leq d(C_0, C_1) \quad (13)$

Remark: In any case, we can separate the database used into two regions $R_0(C_0, r_0)$ and $R_1(C_1, r_1)$ such as $R_0(C_0, r_0) \cap R_1(C_1, r_1) = \phi$.

Phase of prediction CW / credit risk for new customer:

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Step 1: Feature vector extraction $X = \begin{Bmatrix} x_1 \\ x_2 \\ \vdots \\ x_p \end{Bmatrix}$ of customers.

Step 2: We calculate the distances $d(C_0, X)$ and $d(C_1, X)$.

Step 3: Verify that:

- If $d(C_1, X) \le r_1, X \in R_1(C_1, r_1)$, it means that there is a risk, the customer's application is strongly rejected.
- If $d(C_0, X) \le r_0, X \in R_0(C_0, r_0)$, it means that there is no risk, the customer's application is strongly accepted.
- If $d(C_1, X) \rangle r_1$ and $d(C_0, X) \rangle r_0$, we will compare $d(C_1, X)$ and $d(C_0, X)$, so:
  - If $d(C_1, X) \langle d(C_0, X)$, the credit application is weakly rejected.
  - If $d(C_0, X) \langle d(C_1, X)$, the credit application is weakly accepted.

It should be noted that whether the credit application is rejected or weakly accepted means that the decision is made at the discretion of the bank manager.

IV. Data collection and variable definition.

We describe in this section, bank credit databases on the basis of which we will apply and implement our proposed method (An international and a Moroccan credit database) methods.

A. International bank credit datasets description.

For this work, we use three real credit datasets (obtained from banks in South Germany, Australia, and Taiwan), which are publicly available from the UCI machine learning repository [35]. We chose to use these three credit datasets because they are very frequently used in the field of credit scoring, especially for testing the performance of the classification model, which allows us to use them to test the classification performance of the proposed model and to compare the results with other reference models.

B. Moroccan bank credit datasets description.

The Moroccan dataset is obtained from one of the commercial banks in Morocco. This dataset of customer credit applications is used in the experiments. It is composed of 1000 instances, of which 788 observations (78, 8%) are classified as creditworthy borrowers, while 212 observations (21, 2%) are classified as non-creditworthy borrowers and 14 predictive features. This research uses a dichotomous variable **- Non-Creditworthy -** (Yes = 1, No = 0), as the outcome variable.

The objective of the classification is to predict the non-creditworthiness of borrowers:

Dependent Variable: Creditworthiness borrowers

0 = Creditworthy borrowers.

1= Non-Creditworthy borrowers.

Table 2. Characteristics of Moroccan credit dataset.

Name	Observations	Predictive features	Non-defaulting borrowers	Defaulting borrowers	Number of classes
Morocco credit dataset	1000	A1 – A14	788	212	2

C. Performance metrics / measurement criterion:

To evaluate the effectiveness of the credit prediction model, various performance evaluation criteria can be used, such as classification accuracy, Recall or Sensitivity, Prediction Rate, False Alarm Rate, Specificity, AUC of the ROC curve, F-measure, Kolmogorov-Smirnov test, Gini-Coefficient, and among others. The Criteria for evaluating performance used in this empirical study are Classification Accuracy, the AUC of the ROC curve (Area under the Receiver Operating Characteristic curve) with adding the box plots of predicted pseudo-probabilities as a powerful metric.

- ***The AUC value of the ROC curve:***

The ROC curve (Receiver Operating Characteristic) is a useful tool for evaluating the effectiveness of methods and viewing their capabilities, particularly in the field of credit risk assessment.

- ***The Classification Accuracy rate :***

The classification accuracy is defined as:

$$\text{Accuracy (\%)} = \frac{NCCC}{NCT} \times 100\% \tag{14}$$

Where, NCCC is the Number of correctly classified cases and NCT is the number of cases used in the test.

V. Experiment Results and Analysis.

This section will discuss the implementation methodology of the proposed model using some measurement criteria as presented in (subsection C); in order to evaluate the performance of our proposed model with each compared method by reporting the results of implementing our proposed predictive method on each international and Moroccan datasets. The above section is organized into two sub-sections: the results for the international credit datasets and the results for the Moroccan credit datasets.

A. Experimental tests and comparative study on International banks.

Implementation Process for Comparative Analysis

The performance of our approach based on dividing the training set into risky and non-risky regions is tested on three real-life datasets (South Germany, Australia and Taiwan). These real-life datasets classify credit applicants described by a set of attributes as good or bad credit risks, has been successfully used for credit scoring and rating systems in many previous works. Subsequently, we divide each database into two sets, one for ***the training set*** and the other for the model ***validation set.***

The validation set is also divided into five sub-sets of testing data S1, S2,..., S5. We then provide a comparative study of the performance of our predictive proposed model and other well-known and widely used models in the field of creditworthiness borrower's prediction, such as Logistic Regression (LR), Radial Basis Function Neural Networks (RBF-NN), and Multilayer-Perceptron Neural Networks (MLP-NN) as two robust neural network functions in the area of credit risk prediction.

To measure the predictive ability of each method, we selected the classification accuracy rate as an appropriate and a powerful metric used in predicting creditworthiness of borrowers.

It should be pointed out that, all our numerical experiments are performed in Matlab 2017 on a PC HP, Intel(R) Core(TM) I5-5200U CPU @ 2.20 GHz, 4GB of RAM, O.S w.7.

International credit datasets results

Tables 3, 4 and 5 show the results of predicting borrowers creditworthiness for the three databases. From these results, we can see that our predictive proposed method based on splitting the learning set into two regions outperformed the tested methods for all the five tested sub-datasets.

Table 3. Comparison of the 4 methods of creditworthiness prediction results using South German.

Method	S1	S2	S3	S4	S5
LR	98.71%	93.19%	90.11%	79.12%	75.22%
RBF	99.63%	94.07%	90.77%	81.08%	76.33%
MLP	99.81%	94.43%	91.85%	83.12%	78.42%
Our method	**100%**	**96.84%**	**94.73%**	**91.54%**	**89.11%**

Table 4. Comparison of the 4 methods of creditworthiness prediction results using Australia Credit datasets.

Method	S1	S2	S3	S4	S5
LR	95.60%	90.18%	87.00%	76.01%	69.93%
RBF	96.52%	90.85%	87.66%	79.21%	73.22%
MLP	96.70%	91.32%	88.74%	80.01%	75.31%
Our method	**99.65%**	**98.67%**	**94.62%**	**91.43%**	**89.02%**

Table 5. Comparison of the 4 methods of creditworthiness prediction results using Taiwan Credit datasets.

Method	S1	S2	S3	S4	S5
LR	93.45%	88.36%	81.48%	71.61%	69.89%
RBF	94.63%	91.11%	88.07%	77.12%	70.47%
MLP	95.55%	90.96%	86.61%	80.42%	75.12%
Our method	**99.71%**	**98.72%**	**95.03%**	**90.98%**	**89.44%**

B. Experimental tests and comparative study on Moroccan bank.

Implementation Process for Comparative Analysis

To prove the practicability and the higher performance of our predictive proposed approach of which its consists on splitting of the learning set into two regions, a comparative analysis with some widely and commonly used methods for creditworthiness prediction models such as Artificial Neural Networks, including Multilayer-Perceptron network (MLP), Radial Basis Function (RBF) and Logistic Regression (LR) is performed and presented in this section.

Prediction by RBF neural network model

The RBF classification results by partition and overall are presented in Table 6. As shown, the RBF network correctly classified 578 out of 694 clients in the training sample and 238 out of 306 clients in the test sample. Overall, 83.3% of training cases and 77.8% of test cases were correctly classified.

Table 6. RBF-NN classification.

Sample	Observed	Predicted		
		NO	YES	Correct
Training	NO	529	23	95,8%
	YES	93	49	34,5%
	Overall	89,6%	10,4%	**83,3%**
Testing	NO	220	16	93,2%
	YES	52	18	25,7%
	Overall	88,9%	11,1%	**77,8%**

The box plots of the predicted pseudo-probabilities are displayed in Fig.5. For the dependent variable outcome of customer classification, the chart displays boxplots that categorize the predicted pseudo-probabilities based on whole the data set. The **1st** boxplot, starting from the left, shows the predicted probability of the observed creditworthy customer being in the "Non-defaulting Customer" category. The **2nd** boxplot shows the probability of a creditworthy customer being classified as a "Non-defaulting customer" when it was actually in the "Defaulting customer" category. The **3rd** boxplot shows, for outcomes that observed the "Defaulting Customer" category, the predicted probability of the "Non-defaulting Customer" category. The right boxplot shows the probability of a customer being reported in default when it is actually classified in the correct "Defaulting Customer" category.

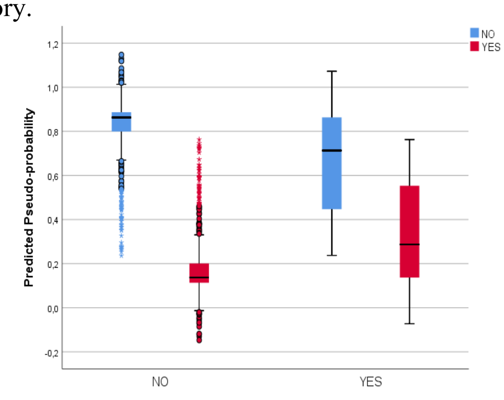

Fig.5. Predicted-by-observed chart for RBF-NN.

The ROC curve of the RBF network prediction method based on the combined training and test samples is presented in Fig.6. As can be seen the method performed better in terms of its ROC curve.

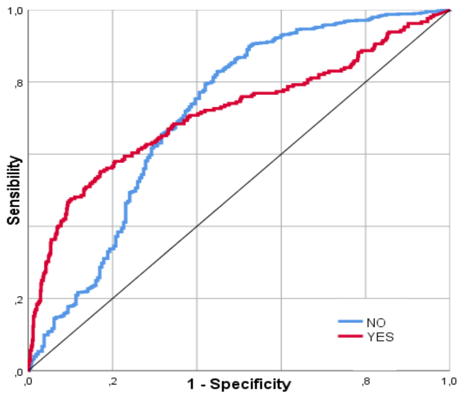

Fig.6. ROC curve for RBF-NN method.

Prediction by MLP neural network model

The classification findings for the MLP-NN model by partition and overall are reported in Table 7. As shown, the MLP network correctly classified 579 out of 694 clients in the training sample and 245 out of 306 clients in the test sample. Overall, 83.4% of training cases and 80.1% of test cases were correctly classified.

Table7: MLP-NN classification

Sample	Observed	Predicted		
		NO	YES	Percent correct
Training	NO	519	33	94,0%
	YES	82	60	42,3%
	Overall %	86,6%	13,4%	**83,4%**
Testing	NO	217	19	91,9%
	YES	42	28	40,0%
	Overall %	84,6%	15,4%	**80,1%**

Fig.7. shows box plots of predicted pseudo-probabilities. For the dependent variable customer classification outcome, the chart displays box plots that classify the predicted pseudo-probabilities based on the whole dataset. The **1st** from the left, boxplot shows the predicted probability of the observed creditworthy customer to be in the **"Non-defaulting** customer" category. The **2nd** boxplot shows, the probability for a creditworthy customer to be classified in **"Non-defaulting customer"** category although he really was in " Defaulting customer" category. The **3rd** boxplot shows, for outcomes that have observed category "Defaulting customer" the predicted probability of **"Non-defaulting customer"** category. The right boxplot shows, the probability a customer is declared defaulted who really be classified in the right category of **" Defaulting customer"**.

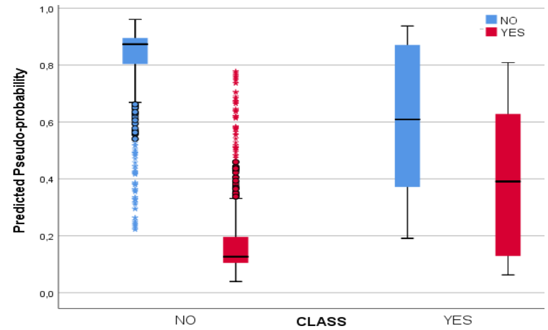

Fig.7. Predicted-by-observed chart for MLP-NN.

The ROC curve of the MLP network predictive model based on both training and test samples together is shown in Fig.8. It can be observed that the model performed better in terms of ROC curve. If a customer in the category " Defaulting customer " and a customer in the category " Non defaulting customer " are randomly selected, there is 0.744 probability that the pseudo-probability predicted by the model for the first customer to be in the " Non defaulting customer " category is greater than the pseudo-probability predicted by the model for the second client to be in the " Non defaulting customer " category.

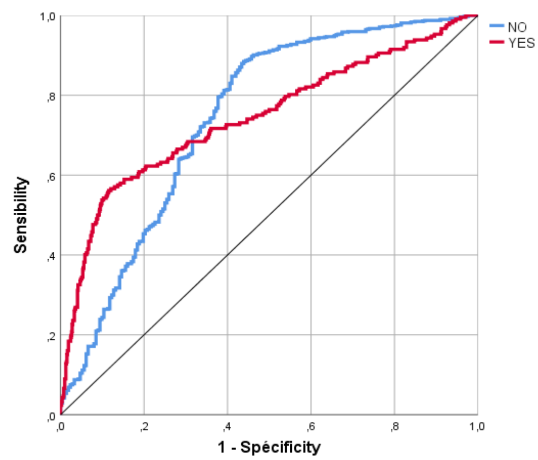

Fig.8. ROC curve for MLP-NN method

Prediction by Regression Logistic model

The current study utilized 694 cases to build the logistic Regression-Scoring model and 306 cases to assess the developed model. The chi-square result testing the significance of the LR model is presented in Table 8. It provides statistical evidence that there is a relationship between the selected variables and the dependent variable. It shows that the chi-square probability (144.989) is less than 0.05. In additional, the classification ability of the LR model is summarized in Table 9. The correct and right predictions are reported in the diagonal cells, while the off-diagonal cells contain the wrong and incorrect predictions. It is noticeable that 87.1% of the non-defaulting clients were classified correctly, 33.3% of the defaulting clients were classified correctly, and overall, the correct classification rate of the LR model was 78% with a threshold of 0.5.

Table 8. Composite tests of model coefficients.

		Chi-square	ddl	Sig.
Step 1	Step	144,989	20	,000
	Block	144,989	20	,000
	Model	144,989	20	,000

Table 9. Logistic Regression classification results.

		Observed			Predicted	
		Training cases			Testing cases	
	No	Yes	% correct	No	Yes	% correct
No	500	74	87,1%	196	40	83,1%
Yes	80	40	33,3%	20	50	71,4%
Overall %			78%			80,4%

Furthermore, the developed method was tested using a testing subset of 306 cases which of (236 No defaulting clients and 70 defaulting clients) that was not used to create the model. The overall classification rate for the testing sample was 80,4%. In fact, the LR credit-scoring model performed better when classifying No-defaulting clients (83,1%) than classifying defaulting clients (71,4%). Similarly, to evaluate the performance of the logistic regression model, we choose the ROC curve of this model based on the combined learning and testing samples illustrated in Fig.10. below. We can observe that the model performed better in terms of the ROC curve.

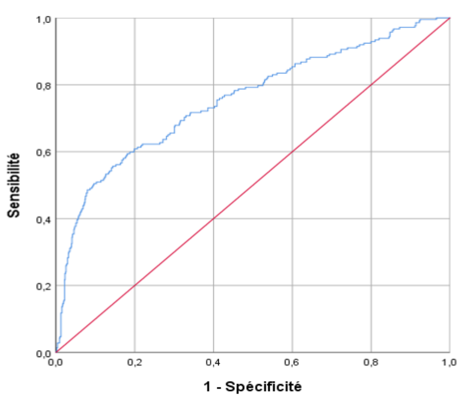

Fig.10. ROC curve for LR model

Prediction by our predictive proposed method

By using, the same learning and testing sample applied in the assessment of the three-credit risk prediction methods on our proposed predictive method, we achieved the following findings:

Table 10. Our predictive proposed method summary.

Training	Cross Entropy Error	286,684
	Incorrect Predictions	16,5%
	Stopping Rule Used	1 consecutive step(s) with no decrease in error
	Training Time	0:00:00,59
Testing	Cross Entropy Error	128,636
	Incorrect Predictions	15,6%

Our predictive proposed method summary, presented in Table 10, contains information about the results of the training and testing sample in which the percentage of incorrect prediction in the training set was 16.5% and for the testing set was only 15.6%, or the least percentage of incorrect prediction of the other methods evaluated. In fact, the small value (= 128.636) of the cross-entropy error in the test sample signals the robustness of our predictive proposed method in predicting creditworthiness of borrowers.

As Table 11 illustrates, our predictive proposed method correctly classified 579 out of 694 clients in the training sample and 261 out of 306 clients in the test sample. Overall, 83.4% of training cases and 85.3% of test cases were correctly classified.

Table 11. Our predictive proposed method classification results.

Sample	Observed	Predicted NO	YES	correct
Training	NO	499	30	94,3%
	YES	85	80	48,5%
	Overall	84,1%	15,9%	**83,4%**
Testing	NO	240	19	92,7%
	YES	26	21	44,7%
	Overall	86,9%	13,1%	**85,3%**

As observed in the ROC plot presented in Fig.11. Our predictive proposed method performed statistically better than other credit risk assessment methods.

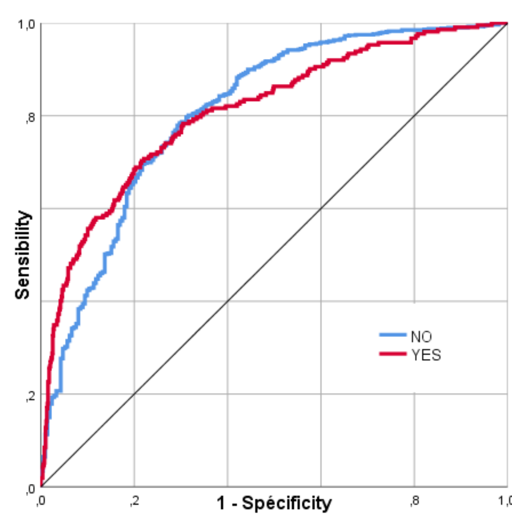

Fig. 11. ROC curve for the predictive proposed method.

Table 12. The summary table of the results of the compared methods.

Methods	Overall accuracy	AUC value
RBF-NN	77,8%	0,712
MLP-NN	80,1%	0,744
LR	80,4%	0,755
proposed method	85,3%	0,809

From the comparison analysis of predictive capability conducted on the four creditworthiness borrowers prediction methods, it is apparent that our proposed predictive method provided better results in terms of predicting creditworthiness as it is illustrated in Table 12. In fact, our predictive proposed method correctly classified 85.3% of the tested cases, which is better than the Radial Basis Function (77.8%), the Multilayer Perceptron (80.1%), and the Logistic Regression method (80.4%). Therefore, our proposed method is more accurate than other credit risk assessment methods. Hence, Fig.12 shows the ROC curves of the classification models tested in this study. One can see that our predictive proposed method achieved better performance in terms of ROC curve (orange curve) compared to the three others methods within our dataset. We conclude that the proposed method obtained the best performance on our Moroccan dataset.

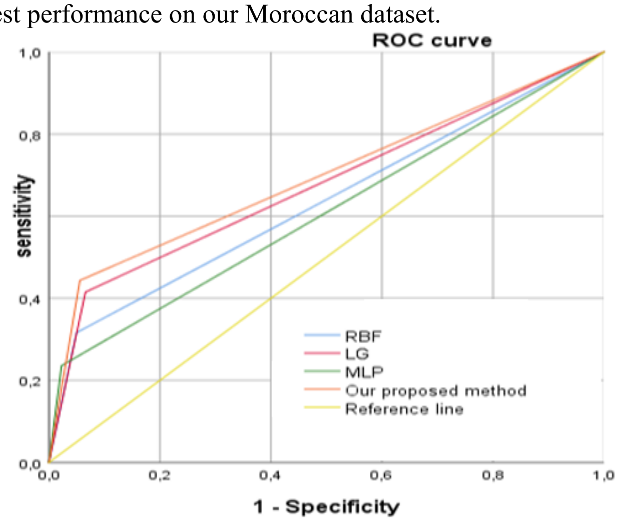

Fig.12. ROC curves obtained by the different compared methods.

VI. Conclusion and Further Research.

To summarize, we proposed a method for predicting creditworthiness of borrowers, which we have called the method of splitting the learning set into two regions, one risky and one not risky. Three contemporary machine-learning methods were compared, to identify the most efficient and best performing model. After giving a description of the using International and Moroccan datasets on the basis of which we have applied our predictive proposed method, each model was compared on the basis of two performance evaluation metrics:

- Classification Accuracy ;
- AUC value of the ROC curve.

As observed in the experimental results, the ROC plot of the proposed method is classifier performed statistically better than other classifiers compared methods which is proven by it AUC value which is equal to 0,809 and an accuracy of 85,3%. Based on the test results, it was concluded that our proposed method based on the splitting the learning set into two regions is the most favorable classification model since it gives the highest accuracy in forecasting and best performance in identification of creditworthiness of borrowers.

In conclusion, Artificial intelligence is a strong tool that can be employed by credit organizations to predict and discover models in credit applicants data, bringing a high degree of rigor. The proposed method can be implemented for a better and more favorable result to determine the creditworthiness of borrowers. The computed prediction can be of immense help to the lenders in determining the repayment capabilities of the borrowers. It is therefore an effective technique to assess financial risks and make appropriate financial decisions whether for conventional banks or Islamic banks (participatory banks) or others.

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