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A New Method in Machine Learning Adapted for Credit Risk Prediction of Bank Loans

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Abstract The recent global financial crisis has significantly impacted the financial system, leading to major bank failures and prompting a reevaluation of credit risk management models. Given its critical role in maintaining banking stability, effective credit risk forecasting methods are essential. In light of this, various studies have introduced techniques to analyze, detect, and prevent bank credit defaults. In this paper, we present a new approach for predicting credit risk, known as the "Method of Separating the Learning Set into Two Balls." This method involves partitioning a learning set into two distinct categories: the "Performing Ball," which contains feature vectors of customers with non-defaulting credits, and the "Non-Performing Ball," which includes vectors of customers with defaulting credits. To predict a customer's default risk, it is sufficient to determine which ball their feature vectors belong to. If a customer's vectors do not fall into either category, additional analysis is required for making a credit decision. We evaluated the performance of this method through extensive experimental tests and a comparative analysis. The findings suggest that our approach shows considerable promise for enhancing credit risk prediction in the banking sector.

Keywords Risk Management, Credit Risk Prediction, Artificial neural network, Predictive Modeling, Method of separating the learning set into two balls, Logistic regression.

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1. Introduction

Faced with a rapidly evolving financial landscape and continuous technological advancements, the banking sector has witnessed the emergence of new risks and the exacerbation of existing ones. This evolution complicates risk management for banks, particularly in the realm of credit risk. As financial markets and technologies advance, traditional risk management practices must adapt to address these evolving challenges. The increasing complexity of financial instruments, the proliferation of data, and the heightened speed of transactions contribute to the growing difficulty in accurately assessing and managing credit risk. Consequently, banks are tasked with developing more sophisticated strategies and tools to effectively mitigate these risks and ensure financial stability.

1.1. Credit Risk Prediction and Scoring

Credit risk has become an important topic in the banking field in recent years. It is the most significant risk that banks face. According to Makram et al. [1], credit risk accounts for sixty percent of the overall threat for banks. It is considered a complex multidimensional problem that aims to understand an applicant's behavior and predict risks.

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Therefore, credit risk measurement and management systems have been developed primarily to focus on bank credit scoring problems.
As recognized, credit scoring is a promising tool that aims to distinguish between serious and non-serious bank customers based on their credit history. It is also considered part of the credit evaluation process to reduce the current and expected risk of a customer being a bad credit risk [2]. Furthermore, credit scoring is a decision-making tool for banking credit applications that relies heavily on large amounts of historical customer data, such as age, guarantor, job status, history of previous credit, personal account status, etc. All these variables constitute a feature vector, which depends on the specifics of each applicant, subsequently producing a high dimensionality for the decision process, in another sense, the decision of granting or rejecting the loan is taken from the feature vector of the client, which is formed by various variables.

1.2. A Brief Review of Existing Methods for Predicting Credit Risk

To effectively manage credit risk, many techniques in different domains have been involved in developing models of credit risk prediction [3], such as statistical methods including the linear discriminant analysis [4, 5] and logistic regression approaches [6, 7], those methods have been the most popular used credit scoring techniques due to their accuracy and easy implementation. However, with the evolution of artificial intelligence and machine learning, new novel predictive modeling and classification techniques methods such us artificial neural networks (ANNs), Genetic algorithms (GA), Support vector machines (SVM) and Decision Tree (DT), were been employed for assessing credit risk [8, 13] Despite various advances in credit risk forecasting techniques, credit risk continues to provide a major threat to successful lending and even confronts banks with significant losses that will negatively impact on their financial strength and even their profitability as recently shown by the rise of non-performing loan ratio of Moroccan banks, which has rapidly increased and reached $8,7\%$ in 2018 compared to $6,8\%$ in 2016 [14]. This augmentation is justified by the unwilling of Moroccan financial institutions to use most robust tools in terms of predicting credit risk. Nevertheless, credit managers at Moroccan banks need to develop more effective models to improve the accuracy in term of predicting credit risk.

1.3. Contributions

In this context, and based on the geometric representation in a two-dimensional space and using Principal Component Analysis (PCA) for dimensionality reduction, our paper details the implementation of the ”two balls” method for credit risk prediction. This approach simplifies data visualization by reducing dimensions, enabling the creation of two distinct geometric regions, or ”balls,” through density-based clustering techniques like DBSCAN. These regions effectively separate clients into high-risk (defaulting) and low-risk (non-defaulting) groups. The decision boundaries are determined by calculating the centroids of each cluster and measuring the distance of each data point from these centroids. A client’s feature vector is classified based on whether it falls within the radius of one of these balls; if not, further analysis is required. This method offers a clearer, more intuitive understanding of risk classes, avoiding the complexities of non-linear decision boundaries found in traditional methods. By applying this method to several databases, the results demonstrated a robust separation between the two groups, enhancing classification performance. The implementation, carried out using Python with libraries like scikit-learn for PCA and clustering, ensures transparency and reproducibility. The proposed theoretical model is applicable to all descriptor vectors, regardless of their dimensionality or size. This model is designed to be flexible and adaptable to a wide range of data structures. However, for the purposes of this study, we specifically applied the model to three different databases, each with unique characteristics and varying dimensions of descriptor vectors. By focusing on these three datasets, we were able to thoroughly test and validate the effectiveness of our method in real-world scenarios. These databases allowed us to assess the model’s ability to handle diverse types of data while demonstrating its robustness and generalizability. Despite working with these specific datasets, the theoretical foundation of our model remains broad and can be extended to other datasets or contexts.
We validated the performance of our method through a series of experimental tests and a comprehensive comparative study. The results consistently demonstrated that our approach offers significant potential in the domain of bank credit risk prediction, outperforming traditional methods in terms of accuracy, AUC, F1 score, and recall. This

highlights the robustness and effectiveness of our model, positioning it as a promising tool for more precise and reliable risk assessment in the banking sector.

1.4. Organization

The structure of the paper is as follows: Section 2 provides an overview of methods used in the bank credit risks prediction, Section 3 will details our proposed method, Section 4 and 5, describes the experimental results and relevant discussion. Finally, section 6, provides the conclusion of our research paper.

2. Overview of Methods Used in Credit Risk Prediction

Credit risk prediction is a critical area of research within financial institutions, as accurately assessing a client's probability of default can help mitigate significant financial losses. Over the years, a variety of methodologies have been employed, ranging from traditional statistical models to modern artificial intelligence (AI) and machine learning (ML) approaches. This section provides a comprehensive review of these various credit risk prediction methods, examining their strengths and limitations.

2.1. Traditional Approaches to Credit Risk Prediction: Strengths and Weaknesses

Historically, logistic regression, probit analysis, logit analysis, and linear discriminant analysis (LDA) have been the foundational methods in credit risk modeling due to their simplicity and interpretability. Ohlson's (1980) O-Score model is one of the earliest applications of logistic regression, providing a straightforward way to predict the probability of default by transforming the dependent variable into log-odds [15]. Similarly, probit and logit models offer alternatives for binary classification by assuming different underlying distributions. While these models have been widely adopted, they are limited by their linear assumptions. Singh et al. [16] highlights that logistic and probit models struggle to capture non-linear relationships between borrower characteristics, which are often essential for accurately predicting credit risk. Moreover, these models rely on assumptions such as independent and identically distributed (i.i.d.) observations and homoscedasticity, which do not always hold in real-world datasets, leading to biased estimates and reduced predictive accuracy, particularly when dealing with multicollinearity and heteroscedasticity in financial data.
In contrast, linear discriminant analysis (LDA), as introduced by Altman's Z-Score Model [4], was another popular early method used in credit risk assessment. LDA aims to separate different classes (e.g., default and non-default) by finding linear combinations of features that best discriminate between them. However, LDA assumes that the variables follow a multivariate normal distribution and that the classes share a common covariance matrix, assumptions that are rarely satisfied in modern credit risk datasets. This leads to misclassification errors when the data exhibits non-linear patterns or violates normality, further limiting its applicability in complex financial environments. Barrios et al. [17], pointed out that when these assumptions are violated, LDA becomes unreliable, often failing to accurately classify high-risk borrowers.

2.2. Machine Learning Techniques

Machine learning (ML) techniques have introduced new opportunities to improve predictive accuracy and capture complex patterns in large datasets. Random Forests (RF) and Support Vector Machines (SVM) have been frequently applied in recent years. According to Zhao et al. [20], random forests are particularly effective at reducing overfitting compared to single decision trees. They found that random forests outperformed logistic regression in terms of classification accuracy across various credit risk datasets, with AUC (Area Under the Curve) scores 10% higher on average. However, random forests require more computational resources, and interpretability becomes more challenging as the number of trees increases.
On the other hand, SVMs offer robust performance, especially for datasets with complex boundaries between defaulting and non-defaulting customers. Chen et al. [21], demonstrated that SVMs achieved higher classification precision than random forests in small-to-moderate-sized datasets. However, SVMs require careful tuning of

hyperparameters like the kernel function, which can make them difficult to optimize in practice. Furthermore, Feng et al. [22], noted that while SVMs excelled in precision, they underperformed in recall compared to random forests, suggesting SVMs may miss some at-risk customers.

2.3. Deep Learning Methods

The introduction of Artificial Neural Networks (ANNs) and deep learning approaches has added another layer of complexity and potential to credit risk modeling. Unlike traditional machine learning algorithms, ANNs can learn intricate patterns from large amounts of data. Wang et al. [23], applied a Multilayer Perceptron (MLP) to credit risk data and found that ANNs outperformed logistic regression, random forests, and even XGBoost in highly non-linear environments. The improvement was particularly noticeable when dealing with complex data like transaction histories, where MLP models demonstrated a 10-12% improvement in AUC scores over random forests. However, the complexity of ANNs makes them less interpretable. While logistic regression or even random forests offer some degree of interpretability, ANNs are often considered "black boxes." According to Liu et al. [24], this lack of transparency limits their practical use in the financial sector, where understanding the reasoning behind a model's prediction is essential for decision-making and regulatory compliance.
Recurrent Neural Networks (RNNs), especially Long Short-Term Memory (LSTM) networks, have gained traction in time-series credit risk prediction. Liu et al. [25], applied LSTMs to sequential customer transaction data, demonstrating better recall and precision over traditional methods such as SVMs. LSTMs were able to capture temporal patterns in credit behavior that static models like random forests or logistic regression could not. However, LSTMs, similar to other neural networks, require extensive computational resources and are difficult to interpret.

2.4. Hybrid and Ensemble Approaches

Hybrid and ensemble models, which combine several predictive algorithms, have shown great potential in enhancing credit risk prediction accuracy. Stacking models, which integrate multiple base classifiers like random forests, logistic regression, and XGBoost, were evaluated by Tsai et al. [26]. Their findings showed that stacking produced superior results, with a 15% improvement in AUC scores over standalone random forests and logistic regression models. However, ensemble methods often lack transparency, a common challenge shared with deep learning models. Blending models that combine logistic regression and random forests have shown strong results in terms of interpretability and accuracy. Xu et al. [27], applied this hybrid approach and found that while the predictive accuracy of blending was slightly lower than XGBoost, the interpretability of the results made it more suitable for financial decision-making. Comparing traditional, machine learning, and deep learning methods reveals that while classical models like logistic regression offer transparency and simplicity, they often lag behind modern approaches like random forests, XGBoost, and ANNs in terms of predictive power. Deep learning models, particularly LSTMs and GNNs, have shown the highest potential for credit risk prediction in complex datasets. However, their lack of interpretability and high computational cost limit their practical application. Hybrid models and explainable AI techniques like LIME and SHAP help bridge the gap between accuracy and interpretability, making them valuable in real-world financial applications.

2.5. Comparing Methods and Practical Considerations

The comparison between traditional, machine learning, and deep learning methods reveals that logistic regression offers simplicity and transparency but struggles with non-linear and high-dimensional datasets. Machine learning models, such as random forests and SVMs, provide enhanced predictive power but require greater computational resources and pose interpretability challenges. Deep learning models, particularly ANNs and LSTMs, excel in predictive performance, especially with complex datasets, but their black-box nature limits their practical use in finance. To address the interpretability problem, explainable AI techniques like LIME (Local Interpretable Model-agnostic Explanations) and SHAP (SHapley Additive exPlanations) are increasingly being used. These tools help to explain complex model predictions without sacrificing predictive accuracy. Ribeiro et al. [28], introduced LIME as a tool for generating localized explanations for black-box models, while Lundberg and Lee [29], developed SHAP as a comprehensive method to interpret complex models such as ANNs and random forests. Xu et al. [30], demonstrated that using SHAP in credit risk prediction increased model transparency without compromising performance, making it suitable for use in highly regulated environments. Ultimately, the choice of credit risk prediction model depends on factors such as dataset complexity, regulatory requirements, and the need for model interpretability. While machine learning and deep learning models provide superior performance, their application is limited by their interpretability in real-world financial settings. As a result, traditional models like logistic regression and explainable AI techniques continue to play an important role in ensuring transparency and regulatory compliance in credit risk prediction.

3. Proposed Approach

This model typically requires a substantial amount of data, gathered by the bank to form an extensive training set, which helps enhance prediction accuracy. This dataset is divided into two categories. The first category consists of bank credit holders, classified based on the assessment of the bank's credit manager. Successful customers, who have repaid their loans on time, are included in the first set, with each entry marked as 0 (Table 1, in green). The second category comprises unsuccessful customers, who have defaulted on their loans, and each entry is marked as 1 (Table 1, in grey)
The core idea of the proposed approach is to divide the training set into two spherical regions, each centered on a centroid representing either the performing (low-risk) or non-performing (high-risk) clients. The algorithmic steps to achieve this involve calculating centroids, defining radii, and constructing decision boundaries.

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_{12}	X_{22}	$\cdots$	X_{2N}
$\vdots$	$\vdots$	$\ldots$	$\vdots$	$\vdots$	$\vdots$	$\ldots$	$\vdots$
X_{P1}	X_{P2}	$\cdots$	X_{Ps}	X_{11}	X_{P2}	$\cdots$	X_{PN}
1	1	$\cdots$	1	0	0	$\cdots$	0

Class 1: The group consisting of creditworthy / performing clients 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}
$\vdots$	$\vdots$	$\ldots$	$\vdots$
x_{P1}	x_{P2}	$\cdots$	X_{Ps}
0	0	$\cdots$	0

The centroid of this class is:

$$C_0 = \frac{1}{S}\sum_{i=1}^{S} X_i = \frac{1}{S}\sum_{i=1}^{S} \begin{pmatrix} x_{1i} \\ x_{2i} \\ x_{3i} \\ \vdots \\ x_{pi} \end{pmatrix} \tag{1}$$

Class 2: The group consisting of $N - S$ non-creditworthy / non-performing clients can also be represented by the following matrix:
The barycenter of this class is:

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}
$\vdots$	$\vdots$	$\ldots$	$\vdots$
$x_{P,s+1}$	$x_{P,s+2}$	$\cdots$	x_{Ps}
1	1	$\cdots$	1

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

Identification of Key Elements: To define the boundaries of the regions representing each class, the model identifies two important elements:

- **The Worst-Performing Element** X_W: This is the client from the performing group who is farthest from the centroid C_0. It defines the maximum distance (radius) for performing clients, ensuring all other performing clients fall within this radius.

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

- **The Best-Performing Element** X_b: This is the client from the non-performing group who is farthest from the centroid C_1. This distance defines the boundary for the non-performing clients.

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

The Euclidean distance $\mathbf{d}(\mathbf{C_0}, \mathbf{X})$ between any client's feature vector $\mathbf{X}$ and the centroid $\mathbf{C_0}$ (or $\mathbf{C_1}$) is computed using the formula:

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

This formula helps determine how far a new client's feature vector is from the centroid of performing or non-performing clients. The model then uses this distance to classify new clients.

Two spherical regions are constructed based on the centroids and radii:

- The region with center C_0 and radius r_0

$$R_0(C_0, r_0) = \{X \in \mathbb{R}^N \mid d(C_0, X) \le r_0\} \tag{6}$$

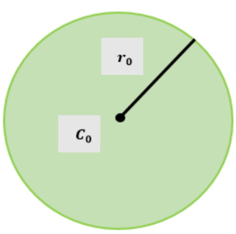

Figure 1. The region $R_0(C_0, r_0)$ with center C_0 and radius r_0.

- The region with center C_1 and radius r_1

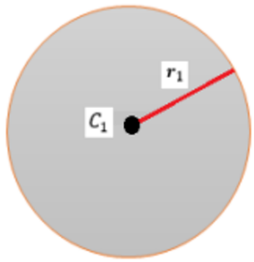

Figure 2. The region $R_1(C_1, r_1)$ with center C_1 and radius r_1.

Important notes

1. The set of feature vectors $\{X_i, i = 1, \ldots, S\}$ for performing clients is entirely contained within the region $R_0(C_0, r_0)$, i.e.

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

2. The set of feature vectors $\{X_i, i = S+1, \ldots, N\}$ for non-performing clients is entirely contained within the region $R_1(C_1, r_1)$, i.e.

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

Proofs:

1. According to Equation 6, to show that a vector X belongs to the region $R_0(C_0, r_0)$, it is sufficient to show that $d(C_0, X) \leq r_1$.
   From Equation 3, $d(C_0, X_w)$ is the distance that maximizes the set of distances between C_0 and the feature vectors of performing clients $X_i, i = 1, \ldots, S$. This means that:
   $$d(C_0, X_i) \leq d(C_0, X_w) = r_0 \quad \text{for all } i = 1, \ldots, S$$
   Therefore, $\{X_i, i = 1, \ldots, S\} \subset R_0(C_0, r_0)$
2. Following the same procedure as in Remark 1, according to Equation 7, $d(C_1, X_b)$ is the distance that maximizes the set of distances between C_1 and the feature vectors of non-performing clients $\{X_i, i = S+1, \ldots, N\}$. This means that:
   $$d(C_1, X_i) \leq d(C_1, X_b) = r_1 \quad \text{for all } i = S+1, \ldots, N \tag{7}$$

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

In summary, using the previous important notes, we deduce the procedure followed to predict a client's bank credit risk based on a precise training set accumulated by the bank. We proceed as follows through the following phases:

Phases of dividing the training set into two regions: This phase involves constructing two spherical regions by dividing the training set into two regions, $R_1(C_1, C_2)$ and $R_0(C_0, r_0)$. The first region contains risky elements, while the second contains non-risky elements. Depending on the nature of the considered set, we follow one of the two cases below:

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

- Step 1: We calculate C_0, the centroid of all performing clients.
- Step 2: We calculate C_1, the centroid of all non-performing clients.
- Step 3: We identify the worst-performing element X_w among the successful clients and determine the corresponding radius r_0.
- Step 4: We identify the best-performing element X_b among the non-successful clients and determine the corresponding radius r_1.

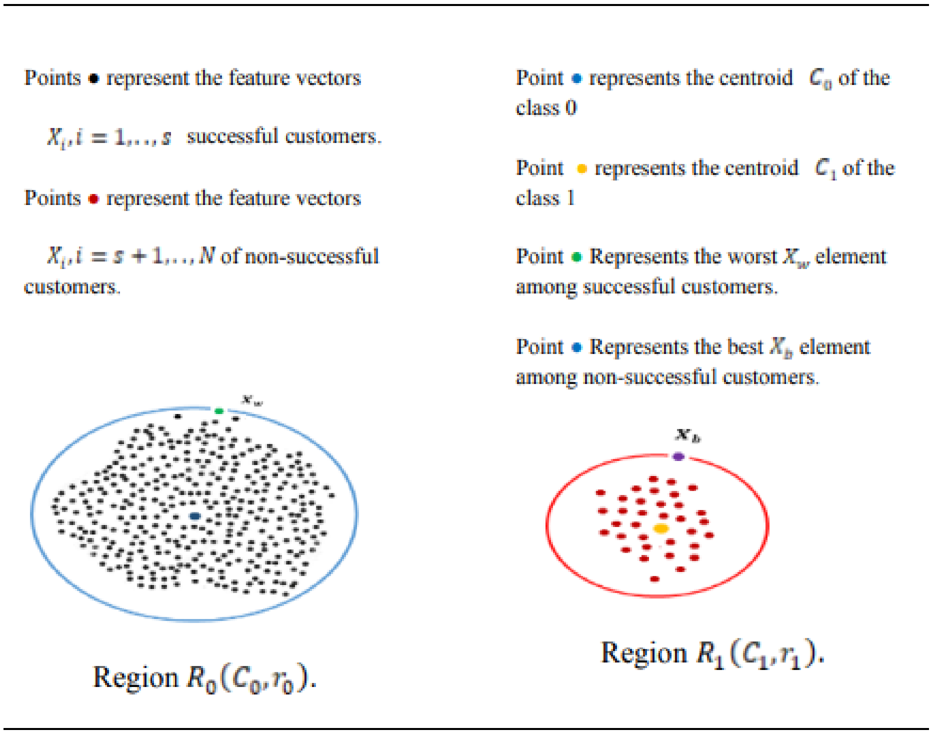

Figure 3. The distribution of the training set $\{X_i, i = 1, \ldots, N\}$ into two regions

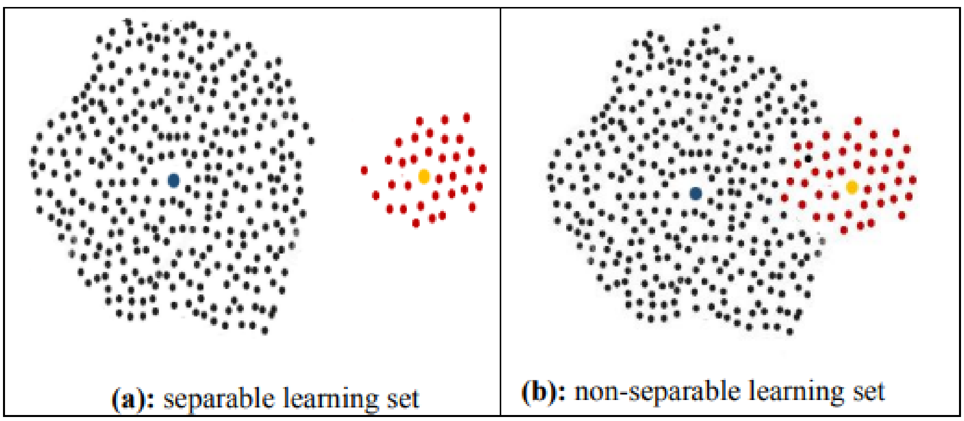

Figure 4. Representation of the training set

Case 2: If the training set is not separable (Fig.4(b)), in this case, to construct the two regions, we can use the following new optimization problem. Find X_w and X_b such that:

$$d(C_0, X_w) + d(C_1, X_b) = \max\{d(C_0, X_i) + d(C_1, X_j) \,|\, i = 1, \ldots, S;\ j = S+1, \ldots, N\} \quad (8)$$

Subject to the constraint: $R_0(C_0, r_0) \cap R_1(C_1, r_1) = \emptyset$
i.e. Find X_w and X_b such that:

$$d(C_0, X_w) + d(C_1, X_b) = \max\{d(C_0, X_i) + d(C_1, X_j) \mid i = 1, \ldots, S;\ j = S+1, \ldots, N\} \tag{9}$$

Subject to the constraint: $d(C_0, X_w) + d(C_1, X_b) \leq d(C_0, C_1)$

Note In all cases, we can divide the database into two regions $R_0(C_0, r_0)$ and $R_1(C_1, C_1)$ such that: $R_0(C_0, r_0) \cap R_1(C_1, C_1) = \emptyset$

Phases for classification a new client:

Once the regions R_0 and R_1 are defined, the model proceeds to classify a new client based on their feature vector X.

- **Phase 1:** Extract feature vectors $X = \{\mathbf{X}_1, \mathbf{X}_2, \mathbf{X}_3, \ldots, \mathbf{X}_P\}$ from the client.
- **Phase 2: Calculate distances:** Compute the Euclidean distances $d(C_0, X)$ et $d(C_1, X)$.
- **Phase 3: Determine Region:**
  - If $d(C_0, X) \leq r_0$, $X \in R_0(C_0, r_0)$, the client falls within R_0, and the loan is accepted. - If $d(C_1, X) \leq r_1$, $X \in R_1(C_1, r_1)$, the client falls within R_1, and the loan is rejected.
- **Inconclusive Cases:** If the client falls outside both regions.
  - Compare the distances $d(C_1, X)$ and $d(C_0, X)$:
    - If $d(C_1, X) < d(C_0, X)$, the credit application is likely to be rejected.
    - If $d(C_0, X) < d(C_1, X)$, the credit application is likely to be accepted.

Bank Manager's Final Decision In borderline cases where the client does not clearly belong to either region, the model provides a recommendation based on the calculated distances, but the final decision is left to the bank manager, who may consider additional factors.

In summary, the proposed approach offers a mathematically rigorous and transparent method for predicting bank loan defaults. It combines concepts from geometry (spherical regions) and statistics (centroid calculations, Euclidean distances) to create a reliable and interpretable model.

4. Application on International Banks

In this section, we implement our credit-risk prediction method using three international bank credit datasets from the UCI Machine Learning Repository [31]. We begin with a detailed description of the feature selection and engineering process, explaining the criteria and methods used to choose and transform relevant variables for the model. Following this, we conduct a thorough evaluation of the model's performance through comparative analysis. This evaluation includes comparisons with other credit-risk prediction methods, using the accuracy as a performance indicator to assess the effectiveness and robustness of our approach.

4.1. Dataset Descriptions

Australian Credit Approval: This dataset comprises 690 records of credit applicants, with each record classified into one of two classes: approved (positive) or not approved (negative). Out of the 690 records, 307 are classified as positive (44.5%) and 383 as negative (55.5%). The dataset includes 15 attributes, categorized into four Boolean, five nominal, and six numerical features, all sourced from the public UCI Machine Learning Repository [31]. These attributes provide a comprehensive view of the applicants' creditworthiness, enabling us to assess the model's predictive accuracy in a real-world context.

Taiwan Credit Card: The Taiwan Credit Card dataset contains 25,000 observations of credit card holders, with each observation representing various financial behaviors and attributes. Among these, 5,529 observations (22.12%) indicate default payments, while 19,471 (77.88%) show no default. The dataset features 23 attributes, including credit amount, gender, education level, marital status, age, past payment history, bill statement amounts, previous

payments, and others, all obtained from the public UCI Machine Learning Repository [31]. This rich dataset allows for an extensive evaluation of our method's performance across a large and diverse set of credit profiles.
German Credit: The German Credit dataset consists of 1,000 cases, each describing individuals' creditworthiness as either good or bad. The dataset is divided into 700 "good" credit cases (70%) and 300 "bad" credit cases (30%). It includes 20 attributes, such as the status of existing checking accounts, credit history, credit amount, age, employment status, and others, all derived from the public UCI Machine Learning Repository [31]. This dataset's synthetic nature and balanced class distribution make it ideal for testing and validating the generalizability of our proposed method.

4.2. Feature Selection and Engineering

4.2.1. Data Preprocessing

Data preprocessing began with cleaning the data to address any issues such as missing values and outliers. For the Australian Credit Approval dataset, missing values in numerical attributes were imputed using the mean, while categorical attributes were filled with the most frequent value. Outliers in numerical attributes were managed using statistical methods such as Z-scores. Similarly, in the Taiwan Credit Card dataset, missing values were handled with median imputation for numerical attributes and mode for categorical attributes. Anomalies in credit amounts and past payments were also addressed. For the German Credit dataset, categorical attributes were converted into numerical variables using techniques like one-hot encoding and label encoding.

4.2.2. Feature selection

Feature scaling was applied to ensure all features contributed equally to the model. This involved standardizing numerical features across all datasets and encoding categorical variables. In addition, we performed correlation analysis to identify and eliminate redundant variables. For instance, in the Australian Credit Approval dataset, strong correlations between credit-related variables and income led to the removal of redundant features. In the Taiwan Credit Card dataset, features with less relevance were discarded based on correlation findings, and for the German Credit dataset, we ensured there was no multicollinearity among features.

4.2.3. Feature engineering

In our feature selection process, correlation analysis played a crucial role in refining the datasets and improving model performance. For the Australian Credit Approval dataset, correlation analysis revealed significant relationships between certain variables, notably between credit features and income levels. These strong correlations indicated redundancy among features, leading us to remove variables that did not provide additional predictive power. By eliminating redundant variables, we aimed to reduce model complexity and enhance its ability to generalize.
In the Taiwan Credit Card dataset, we focused on examining correlations between credit amount and past payment records. This analysis helped us identify and discard variables that were less relevant or redundant. By carefully selecting the most pertinent features, we ensured that the model could more effectively capture the relationships between credit behaviors and default risk.
For the German Credit dataset, we conducted a thorough analysis of correlations among the various attributes to prevent multicollinearity. By addressing multicollinearity, we avoided the issue of highly correlated features that could skew the model's performance and interpretation. This approach ensured that each feature contributed uniquely to the model, improving its robustness and accuracy.

4.3. Results and Comparative Analysis

We evaluated the performance of our proposed approach, which involves separating the learning set into two distinct subsets—one representing risky credit and the other non-risky credit—using three real-life datasets: German Credit, Australian Credit Approval, and Taiwan Credit Card. These datasets, known for their extensive use in credit scoring and evaluation, provided a robust foundation for assessing our method's effectiveness.

Each dataset was split into two parts: a learning set for model training and a validation set. The validation set was further divided into five testing sub-datasets (S1, S2, S3, S4, S5) to ensure thorough evaluation. Our method was compared with three established models in the field of bank credit risk prediction: Logistic Regression (LR), Radial Basis Function Neural Networks (RBF), and Multi-Layer Perceptron Neural Networks (MLP).
To assess predictive performance, we used the classification accuracy as a key metric. Generally, it is defined as the ratio of correctly classified instances to the total number of instances in the test set. This widely used metric measures how well a model distinguishes between different classes. The overall classification accuracy rate is denoted by the symbol η in the following report:

$$\eta = \frac{\text{Correctly classified instances}}{\text{Total number of instances in the test set}} \times 100\%$$

The experimental results were obtained using Python on an HP PC with an Intel(R) Core(TM) i5-5200U CPU @ 2.20 GHz and 4GB of RAM running Windows 7. These results are presented in Tables 2, 3, and 4. These tables illustrate the performance of our method compared to Logistic Regression (LR), Radial Basis Function Neural Networks (RBF), and Multi-Layer Perceptron Neural Networks (MLP) across the five sub-datasets for each dataset. The results demonstrate that our method, based on the separation of the learning set into two distinct balls, consistently outperformed the benchmark models in terms of classification accuracy across all five sub-datasets.

Table 2. Comparison of Credit Risk Prediction Results from Four Methods Using the Germania Dataset

	Testing sets				
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 model	**100%**	**96.84%**	**94.73%**	**91.54%**	**89.11%**

Table 3. Comparison of Credit Risk Prediction Results from Four Methods Using the Australian Dataset

	Testing sets				
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 model	**99.65%**	**98.67%**	**94.62%**	**91.43%**	**89.02%**

Table 4. Comparison of Credit Risk Prediction Results from Four Methods Using the Taiwan Dataset

	Testing sets				
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 model	**99.71%**	**98.72%**	**95.03%**	**90.98%**	**89.44%**

5. Application to Moroccan Banks

In this section, we apply our proposed credit risk prediction method to a dataset from Moroccan banks. This application serves to evaluate the model's performance in a local context, providing insights into how the method can be adapted and optimized for regional financial institutions. By analyzing real-world data from Moroccan banks, we aim to demonstrate the flexibility and robustness of our approach in predicting default risk and supporting credit decision-making in the Moroccan banking sector.

5.1. Dataset description

The dataset is imbalanced, consisting of 788 observations (78.8%) classified as creditworthy customers and 212 observations (21.2%) classified as non-creditworthy customers. The target variable for this classification represents a dichotomous outcome indicating default payment, where:

- 1 = Non-defaulting customer (creditworthy),
- 2 = Defaulting customer (non-creditworthy).

Table 5. Description of the Data Variables Used

Attribute	Description Attribute	Definition of the Vector Attribute
A1	Qualitative	Status of existing checking account
A2	Numerical	Duration in months
A3	Qualitative	Credit history
A4	Qualitative	Purpose
A5	Numerical	Credit amount
A6	Qualitative	Savings account/bonds
A7	Qualitative	Present employment since
A8	Numerical	Instalment rate in percentage of disposable income
A9	Qualitative	Personal status and sex
A10	Qualitative	Other debtors / guarantors
A11	Numerical	Present residence since
A12	Qualitative	Property
A13	Numerical	Age in years
A14	Qualitative	Other installment plans

5.2. Data Preprocessing and Feature Engineering

In our case study, applying the credit risk prediction method to the Moroccan bank dataset required extensive data preprocessing and feature engineering to ensure accurate model performance. These preparatory steps were crucial in handling missing values, eliminating irrelevant features, and enhancing the dataset for more precise prediction. The first step in data preprocessing involved addressing missing values in the dataset, particularly in demographic attributes such as employment status and age. To manage these gaps, we employed mean imputation for continuous numerical variables, such as credit amounts, and mode imputation for categorical variables, such as marital status. Additionally, outliers in certain features, including credit amounts and loan durations, were detected using Z-scores. These outliers were either capped or removed to prevent them from distorting the model's predictions.

Another important aspect of data preparation was converting categorical data into numerical formats. Attributes like customer employment status, education level, and loan purpose were encoded using one-hot encoding, transforming them into binary variables that the machine learning models could interpret effectively. This conversion was essential to ensure that all features contributed equally during the model training process.

Feature engineering played a key role in improving the predictive performance of the model. We conducted correlation analysis to identify and remove redundant variables. For example, a strong correlation was found between credit amount and loan duration, prompting us to remove highly correlated variables to enhance the model's performance and reduce overfitting risks. Additionally, numerical features were standardized to ensure uniform

scaling, particularly important for algorithms like logistic regression and neural networks, which are sensitive to feature magnitudes.
To further improve the model's predictive power, we introduced a new feature: the debt-to-income ratio. This feature was calculated to provide deeper insights into the financial stability of customers, proving to be a valuable addition in differentiating between defaulting and non-defaulting customers.
Through meticulous data preprocessing and the creation of relevant features, we significantly improved the quality of the dataset. This process was essential to maximize the accuracy and robustness of our proposed method in predicting credit risk, demonstrating its superiority over traditional models.

5.3. Model Training and Validation

To perform a thorough comparison between the different credit risk evaluation methods, including our proposed approach, we randomly divided the Moroccan bank dataset into two distinct subsets. The first subset, used for model training, contains 700 cases, representing 70% of the total dataset. This training set was used to build and fine-tune the models, ensuring that they can learn from a representative sample of creditable and non-creditable customers. The second subset, designated for model validation, consists of 300 cases, making up 30% of the data. This validation set was crucial for assessing the predictive performance of the models in real-world scenarios, ensuring that they generalize well to unseen data. By keeping the two subsets disjoint, we avoided data leakage, thereby providing a robust and unbiased evaluation of the models' performance. The breakdown of this division is shown in Table 6 below.

Table 6. Case-processing summary

		Frequency	**%**
Sample	**Training**	700	70%
	Testing	300	30%
Total		1000	100%

5.4. Performance Evaluation

To evaluate the model's predictive performance on the Moroccan banking dataset, we utilized several metrics, including: - **Precision**: It measures the proportion of correctly predicted positive cases out of all cases predicted as positive. It is typically calculated as:

$$\text{Precision} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Positives}}$$

- **F1 Score**: As defined by the harmonic mean of precision and recall, providing a balanced measure of a model's performance. It is particularly useful when dealing with imbalanced datasets, as it accounts for both false positives and false negatives. The F1 score is calculated as:

$$\text{F1 Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

- **Recall**: Also known as sensitivity or true positive rate, measures the proportion of actual positives that are correctly identified by the model. It is crucial for assessing how well the model captures true positive cases, especially in imbalanced datasets. Recall is calculated as:

$$\text{Recall} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}}$$

- **AUC under curve ROC**: It measures the ability of models to distinguish between classes and is particularly useful for imbalanced datasets. The ROC curve itself plots the true positive rate (sensitivity/recall) against the false positive rate (1 - specificity) at different threshold levels.

- Classification Accuracy as a performance metric used in the previous section for international datasets defined by the following formula:

$$\text{Accuracy} = \frac{\text{Number of Correct Predictions}}{\text{Total Number of Predictions}}$$

5.5. *Comparaison Analysis and Discussion*

We present a comparative analysis of our proposed credit risk prediction method against several traditional models, including Logistic Regression (LR) as well as AI models such as Radial Basis Function (RBF) and Multi-Layer Perceptron (MLP). Each model was evaluated using the Moroccan bank dataset to assess its effectiveness in predicting credit risk. The comparison is based on the aforementioned key performance metrics. The results of this analysis for each credit risk prediction method are provided below, with data processed using PYTHON software.

5.5.1. Prediction using LR model

The results obtained for prediction using Logistic Regression (LR) demonstrate that the model is statistically significant, as indicated by Table 7, the chi-square value of 264.041 with 34 degrees of freedom and a significance level of 0.000. These findings reveal that the model's coefficients play an important role in predicting credit risk. The chi-square test suggests that the model with the explanatory variables fits the data well, outperforming a model without predictors.
The low significance level (p ¡ 0.05) for each test (Step, Block, and Model) confirms that every stage of adding variables, as well as the overall model, is significantly related to credit risk prediction. This implies that the variables included in the model have a substantial impact and meaningfully contribute to identifying at-risk customers. In summary, Logistic Regression proves to be an effective and reliable tool for predicting credit risk in this context.

Table 7. Composite tests of model coefficients

		Chi-square	**ddl**	**Sig.**
Step 1		264,041	34	0,000
	Block	264,041	34	0,000
	Model	264,041	34	0,000

After implementing the parameter adjustment method, specifically through class weighting, the results obtained are reflected in Table 8. This adjustment aimed to address the imbalance in the model's performance across different classes. As a result, the precision and recall for Class 1 (Positive) remained stable at 0.79 and 0.84, respectively, indicating that the model continued to effectively identify high-risk customers. However, significant improvements were noted for Class 2 (Negative); precision increased to 0.56 and recall improved to 0.48, reflecting a better balance in predicting non-defaulting customers. The F1-score for Class 2 also rose to 0.52, demonstrating a more equitable trade-off between precision and recall. The overall accuracy of 0.73 and AUC of 0.70 were maintained, showing that the model's general performance remained consistent. This adjustment method effectively enhanced the model's ability to correctly identify non-defaulting customers while preserving its performance for high-risk predictions, as shown by the results in Table 8.

Table 8. LR model Performance Metrics

Metric	**Class 1 (Positive)**	**Class 2 (Negative)**	**Overall**
Precision	0.79	0.56	-
Recall	0.84	0.48	-
F1-score	0.81	0.52	-
Accuracy	-	-	0.73
AUC	-	-	0.70

5.5.2. Prediction using RBF-NN model

The Radial Basis Function Neural Network (RBF-NN) described here comprises three layers: an input layer with 45 units (consisting of 11 factors and 3 standardized covariates), a hidden layer with 4 units optimized to minimize errors, and an output layer with 2 units for classifying clients as ”Defaulting” or ”Non-defaulting,” as illustrated in Figure 5 below. The hidden layer utilizes the Softmax activation function to generate probabilities, while the output layer employs the identity activation function to produce linear values for classification. The model employs the sum of squares as the error function to minimize prediction errors.
The results presented in Table 9 for the Radial Basis Function Neural Network (RBF-NN) indicate that the model exhibits moderate performance in both training and testing phases. During training, the model achieved a Sum of Squares Error (SSE) of 121.218, reflecting a moderate level of error in fitting the training data. The percentage of incorrect predictions was 27.7%, suggesting that nearly a quarter of the predictions were inaccurate, indicating room for improvement in the model’s ability to generalize from the training data. The training time was notably efficient, taking just over 2 seconds, which highlights the model’s quick computational performance.
In the testing phase, the SSE decreased to 56.445, showing that the model performed better on unseen data compared to the training data, indicating a good fit to new data. The percentage of incorrect predictions in testing was 27.1%, very close to the training phase, suggesting that the model generalizes reasonably well but still has a significant proportion of inaccuracies. Overall, while the RBF-NN model demonstrates efficient training and better performance on testing data, the high rate of incorrect predictions points to the need for further optimization and refinement to improve predictive accuracy.

Table 9. Method Summary

Training	Sum of Squares Error	121,218
	Percent Incorrect Predictions	27,7%
	Training time	0:00:02,05
Testing	Sum of Squares Error	56,445
	Percent Incorrect Predictions	27,1%

To improve the performance of the Radial Basis Function Neural Network (RBF-NN) model, we applied a parameter adjustment method known as kernel function optimization. This adjustment aimed to enhance the model’s ability to classify both classes more accurately.
By optimizing the kernel function parameters, such as the spread parameter (which controls the width of the radial basis functions), we achieved the performance metrics shown in Table 10. These results include a precision of 0.77 for Class 1 (Positive) and 0.62 for Class 2 (Negative), a recall of 0.90 for Class 1 and 0.36 for Class 2, and an F1-score of 0.83 for Class 1 and 0.46 for Class 2. The overall accuracy of the model was 0.74, and the AUC was 0.78.
The improved performance metrics reflect a better balance in the model’s ability to predict both positive and negative cases. Although the model’s precision and recall for Class 2 (Negative) are still lower compared to Class 1, the optimization has led to a more robust overall performance. This adjustment underscores the importance of fine-tuning model parameters to enhance predictive accuracy and achieve a more balanced performance across different classes.

Table 10. RBF-NN model Performance Metrics

Metric	**Class 1 (Positive)**	**Class 2 (Negative)**	**Overall**
Precision	0.77	0.62	-
Recall	0.90	0.36	-
F1-score	0.83	0.46	-
Accuracy	-	-	0.74
AUC	-	-	0.78

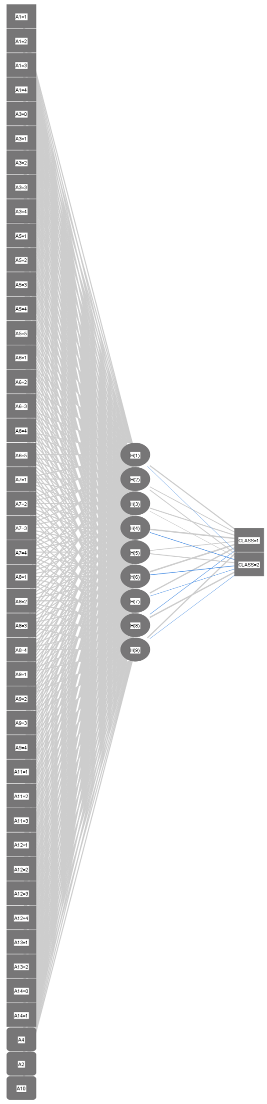

Figure 5. The core architecture of RBF-Neural Network

Figure 6 presents box plots illustrating the predicted pseudo-probabilities associated with the classification of customers. These box plots summarize the distribution of predicted probabilities across the entire dataset, helping to visualize how the model distinguishes between ”Defaulting” and ”Non-defaulting” customers. The first box plot, on the far left, represents the predicted probability for customers correctly classified as ”Non-defaulting.” It reflects the likelihood assigned by the model to creditworthy customers who were indeed placed in the ”Non-defaulting customer” category. The second box plot shows the predicted probability for customers classified as ”Non-defaulting” even though they actually belong to the ”Defaulting customer” group. This highlights cases where the model incorrectly predicts a non-default outcome for customers who should have been classified as defaulters. The third box plot captures the reverse scenario: customers observed as ”Defaulting” but predicted to fall under the ”Non-defaulting” category. This plot indicates the model’s tendency to underpredict default risk for actual defaulters. Finally, the rightmost box plot illustrates the predicted probability for customers correctly classified as

”Defaulting.” This reflects the likelihood that a customer is properly identified as a defaulter, aligning with their actual classification in the ”Defaulting customer” group.
Each box plot provides a detailed view of the distribution of probabilities for different classification outcomes, offering insights into the model's strengths and weaknesses in predicting customer credit risk.

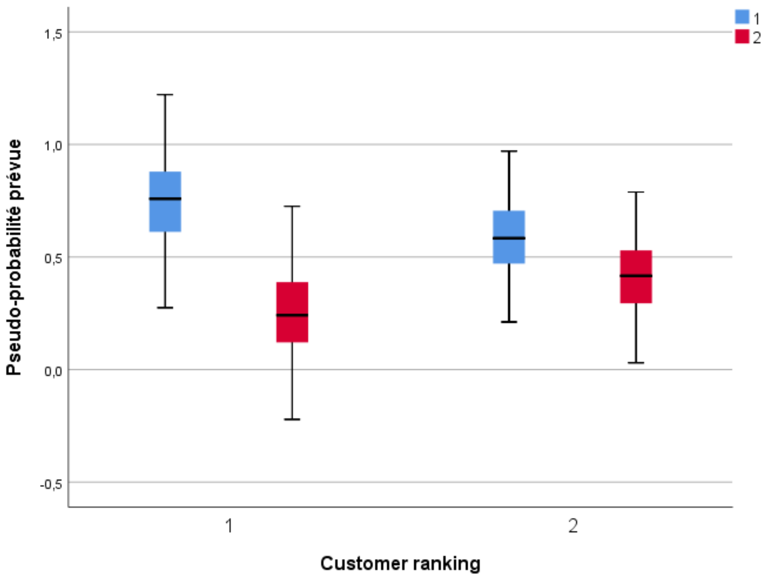

Figure 6. Predicted-by-observed chart of RBF-NN

5.5.3. Prediction using our proposed model

As illustrated in Figure 7, the MLP-NN model designed for credit risk prediction features an input layer with 14 standardized covariates, ensuring uniformity in feature scaling. It includes a single hidden layer with 6 neurons that utilize the tanh activation function to model non-linear relationships within the credit data. The output layer comprises 2 neurons with a softmax activation function, which generates probabilities for binary classification of credit risk (e.g., default vs. non-default). The model employs cross-entropy loss for effective training and optimization. This architecture effectively captures complex patterns and interactions in financial data, making it well-suited for credit risk prediction.
The results of the MLP-NN (Multi-Layer Perceptron Neural Network) method, presented in Table 11, offer insights into its training and testing performance. The MLP-NN model demonstrates reasonable performance, with a low training error and a decent ability to generalize to unseen data. The increase in the percent of incorrect predictions from 23.4% during training to 26.7% during testing suggests that the model does not overfit excessively, although there is some performance degradation when applied to new cases. The use of an early stopping rule played a key role in preventing overfitting, helping maintain a good balance between the training and testing phases. However, the increase in testing error indicates that further improvements could be made through parameter fine-tuning. Adjustments to the model's architecture, such as the number of hidden neurons, or enhanced regularization techniques, could help the model generalize better to unseen data and further reduce the error during testing.
The performance metrics for the MLP-NN (Multi-Layer Perceptron Neural Network), as outlined in Table 12, highlight the model's strengths and areas for improvement in predicting credit risk. For Class 1 (Positive), which represents credit defaults, the model achieves a precision of 0.77, meaning 77% of predicted defaults are correct. The recall of 0.90 shows that 90% of actual defaults are successfully identified, and the F1-score of 0.83 reflects a well-balanced performance between precision and recall for defaulting customers. This demonstrates that the model is highly effective at detecting credit risk, minimizing false negatives.

Table 11. Method summary

Training	Cross Entropy Error	346,757
	Percent Incorrect Predictions	23,4%
	Stopping Rule Used	1 consecutive step(s) with no decrease in error
	Training Time	0:00:00,71
Testing	Cross Entropy Error	150,500
	Percent Incorrect Predictions	26,7%

In contrast, the results for Class 2 (Negative), representing non-defaulting customers, show a more modest performance. With a precision of 0.64, the model correctly identifies 64% of non-defaults, but the recall of 0.40 indicates that it only captures 40% of actual non-defaulting cases. This lower recall affects the F1-score, which stands at 0.49, suggesting the model struggles more with identifying non-defaulting customers, potentially due to class imbalance or difficulties in distinguishing between the two classes.
The model's overall accuracy of 0.75 signifies that 75% of all predictions are correct, reflecting good overall performance. Furthermore, the AUC of 0.80 indicates that the model is effective at distinguishing between defaulting and non-defaulting customers. While the results for Class 1 are strong, the model's performance for Class 2 highlights the need for further fine-tuning, such as addressing class imbalance or adjusting the network's parameters, to improve its ability to generalize better across both classes.

Table 12. MLP-NN Performance Metrics

Metric	**Class 1 (Positive)**	**Class 2 (Negative)**	**Overall**
Precision	0.77	0.64	-
Recall	0.90	0.40	-
F1-score	0.83	0.49	-
Accuracy	-	-	0.75
AUC	-	-	0.80

Figure 8 presents box plots of the predicted pseudo-probabilities for customer classification outcomes. These box plots summarize the predicted probabilities across the entire dataset. The first box plot, on the far left, represents the predicted probability that an observed creditworthy customer is classified correctly as a "Non-defaulting customer." The second box plot displays the probability that a creditworthy customer is incorrectly classified as a "Non-defaulting customer" when they should actually belong to the "Defaulting customer" category. The third box plot shows the predicted probability of customers observed as "Defaulting" but mistakenly classified as "Non-defaulting." Finally, the box plot on the far right illustrates the probability that a customer is correctly classified as a "Defaulting customer," aligning with their actual status.

5.5.4. Prediction using our proposed model

The results of our proposed model, as presented in Table 13 and Table 14, demonstrate the model's effectiveness in predicting credit risk while successfully mitigating overfitting through the use of an early stopping method. During training, the model achieved a Cross Entropy Error of 346.189, with a percent incorrect predictions of 23.2%, indicating that the model learned efficiently from the training data. The early stopping rule, which halted training after 1 consecutive step with no decrease in error, was used to prevent overfitting, ensuring that the model did not continue to learn patterns specific to the training set that might not generalize well to new data. The model completed training in just 0:00:00.51 seconds, highlighting its computational efficiency.
In the testing phase, the Cross Entropy Error dropped to 114.100, and the percent incorrect predictions decreased to 20.3%, showing improved generalization on unseen data. This reduction in error during testing suggests that the early stopping method effectively avoided overfitting and allowed the model to generalize well.

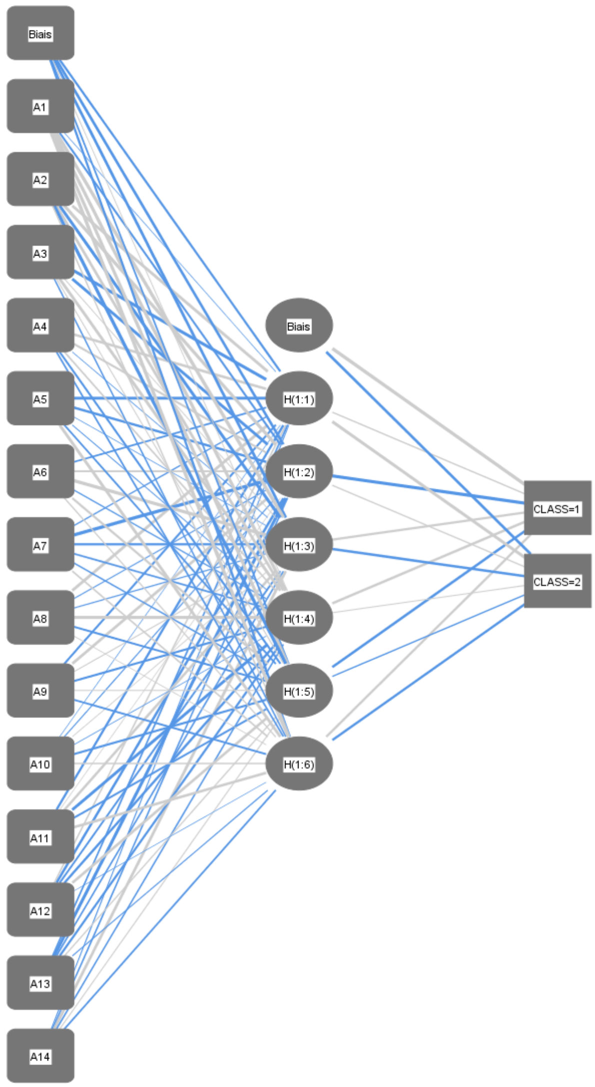

Figure 7. The core architecture of MLP-Neural Network

As for the performance metrics in Table 14, the model exhibits strong results for Class 1 (Positive), with a precision of 0.78 and a recall of 0.92, indicating that the model correctly identifies 78% of predicted defaults and captures 92% of actual defaults. The F1-score of 0.85 reflects a well-balanced performance between precision and recall for defaulting customers. For Class 2 (Negative), the precision and recall are 0.70 and 0.41, respectively, which indicates reasonable performance in identifying non-defaulting customers, though with room for improvement. The F1-score for Class 2 is 0.51, suggesting a moderate balance between precision and recall.
The model's overall accuracy is 0.77, meaning that 77% of all predictions are correct, while the AUC of 0.81 shows a strong ability to distinguish between defaulting and non-defaulting customers. Overall, the use of early stopping

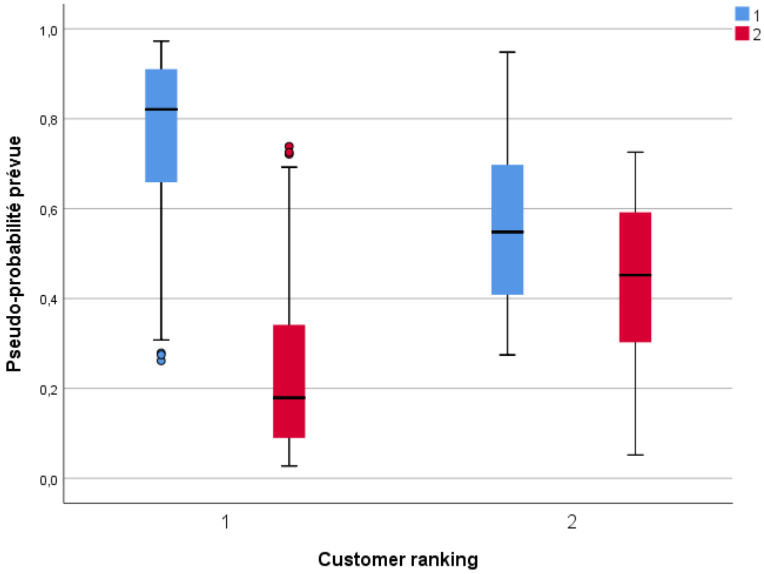

Figure 8. Predicted-by-observed chart of MLP-NN

has helped the model achieve a good balance between learning from the training data and generalizing to new cases, thus preventing overfitting and ensuring reliable predictive performance.

Table 13. Method summary

Training	Cross Entropy Error	346,189
	Percent Incorrect Predictions	23,2%
	Stopping Rule Used	1 consecutive step(s) with no decrease in error
	Training Time	0:00:00,51
Testing	Cross Entropy Error	114,100
	Percent Incorrect Predictions	20,3%

Table 14. Our proposed model Performance Metrics

Metric	Class 1 (Positive)	Class 2 (Negative)	Overall
Precision	0.78	0.70	-
Recall	0.92	0.41	-
F1-score	0.85	0.51	-
Accuracy	-	-	0.77
AUC	-	-	0.81

5.6. Findings and Results

In reviewing the results across the five key performance metrics presented in Table 15 below, our proposed model (MP) demonstrates the strongest overall performance compared to Logistic Regression (LR), Radial Basis Function Neural Network (RBF-NN), and Multi-Layer Perceptron Neural Network (MLP-NN).
For Class 1 (credit defaults), MP has a precision of 0.78, slightly outperforming the other models. The recall for MP is also the highest at 0.92, indicating that it captures a greater portion of true defaults. The combination of these

values results in an F1-score of 0.85, the highest among all models, reflecting a better balance between precision and recall for default prediction.
For Class 2 (non-defaults), MP excels, particularly in precision, with a value of 0.70, outperforming LR (0.56), RBF-NN (0.62), and MLP-NN (0.64). While recall for Class 2 remains relatively low across all models, MP achieves the highest at 0.41, showing a slight improvement in detecting non-defaults. The F1-score for Class 2 follows a similar pattern, with MP leading at 0.51, further demonstrating a more balanced performance for non-default predictions.
In terms of overall accuracy, MP achieves the highest value at 0.77, compared to LR (0.73), RBF-NN (0.74), and MLP-NN (0.75), indicating better predictive capability. The AUC score, which measures the model's ability to distinguish between defaulting and non-defaulting customers, is highest for MP at 0.81, suggesting it offers the best discrimination ability among all models. The ROC curves for all four models, shown in Figures 9, 10, 11, and 12, confirm these findings, with MP having the largest area under the curve.
Thus, Fig. 13 presents the ROC curves of the classification models tested in this study. It is evident that the proposed method (MP), represented by the orange curve, achieved superior performance compared to the other three methods on our dataset. In conclusion, the proposed model consistently outperforms the traditional models across all five metrics, especially in terms of precision, recall, and F1-score for both classes.

Table 15. Summary of performance indicators for the compared credit risk prediction models

Metrics	**LR**	**RBF**	**MLP**	**MP**
Precision				
Class 1	0.79	0.77	0.77	0.78
Class 2	0.56	0.62	0.64	0.70
Recall				
Class 1	0.84	0.90	0.90	0.92
Class 2	0.48	0.36	0.40	0.41
F1-Score				
Class 1	0.81	0.83	0.83	0.85
Class 2	0.52	0.46	0.49	0.51
Accuracy	0.73	0.74	0.75	0.77
AUC	0.70	0.78	0.80	0.81

6. Conclusion

Predicting bank credit default has become a critical task for financial institutions, as they face the challenge of determining whether to extend credit to applicants while managing associated risks. In this paper, we introduced a novel approach for bank credit risk prediction, called the Method of Separating the Learning Set into Two Balls. This method classifies customers into two distinct categories: one representing high-risk customers and the other representing low-risk ones. To validate the superiority and effectiveness of our proposed model, we performed a comparative analysis against several widely used credit risk prediction methods, assessing performance based on key metrics such as accuracy, precision, recall, AUC under ROC curve and F1-score.
Our proposed model is not limited by the dimensionality or size of descriptor vectors, making it highly flexible and adaptable to different types of data structures. For the purposes of this study, we specifically applied the model to three different databases—one from a Moroccan bank and two from international banks—each with its own unique characteristics and dimensions. This diversity in datasets allowed us to thoroughly test and validate the method's effectiveness in real-world scenarios, demonstrating its robustness in handling different types of data. Experimental results across all three datasets proved that our method outperforms other well-known approaches, particularly in terms of accuracy and adaptability to varying credit risk conditions. In addition, the model's ability to generalize

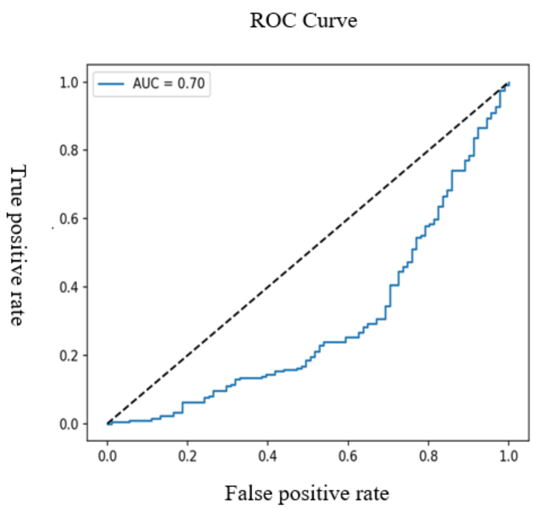

Figure 9. ROC Curve for LR model

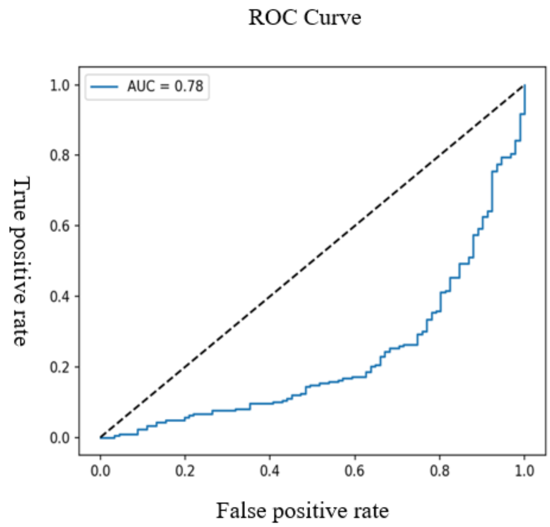

Figure 10. ROC Curve for RBF-NN

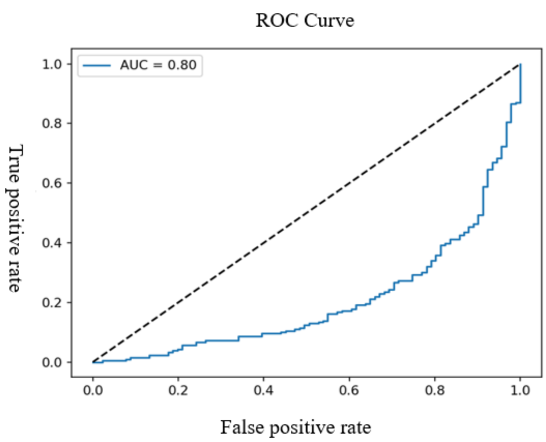

Figure 11. ROC Curve for the MLP-NN model

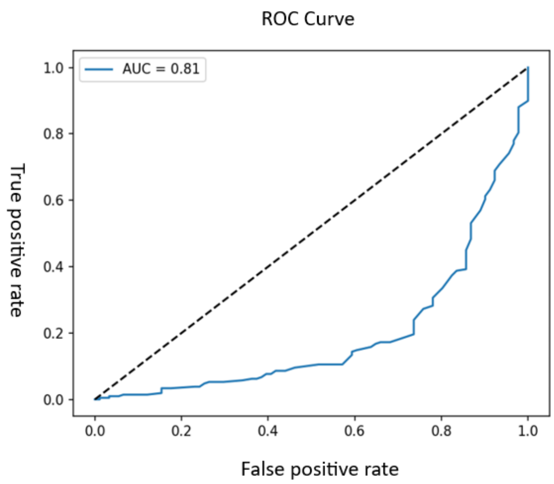

Figure 12. ROC Curve for our proposed model

effectively to new and unseen data highlights its potential for broader application beyond the datasets used in this study.

Despite focusing on these specific datasets, the theoretical foundation of our model remains broad and can be extended to other contexts or datasets. This makes it a versatile tool for financial institutions aiming to improve their credit risk management processes. Furthermore, the results from this research can serve as a valuable reference for credit departments in financial institutions, supporting efforts to mitigate the risks associated with customer defaults and ultimately leading to more informed and strategic credit-granting decisions.

In conclusion, the Method of Separating the Learning Set into Two Balls not only offers enhanced predictive accuracy but also demonstrates a high level of adaptability and generalizability across various datasets. These characteristics make it a promising solution for the evolving needs of modern credit risk management, offering financial institutions a more reliable tool for forecasting potential customer defaults and reducing associated financial risks.

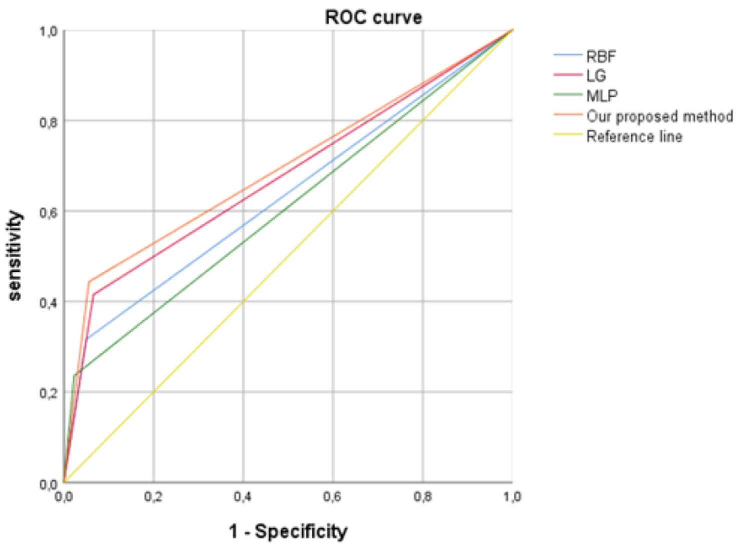

Figure 13. ROC Curves Generated by the Various Comparison Methods

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