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Does Deep Learning with Multilayer Perceptron Perform Well in Predicting Credit Risk?

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Abstract

This paper investigates the effectiveness of using Deep Learning with Multilayer Perceptron (MLP) to assess credit risk in banks. To this end, its performance is compared with that of Support Vector Machine (SVM), Gradient Boosting, Decision Tree (Random Forest), and Logistic Regression algorithms using credit risk analysis data from customers of two of the largest Brazilian financial institutions, focusing exclusively on Direct Consumer Credit operations. Performance is measured using accuracy, precision, recall, F1-score, AUC-ROC, and cross-validation. The MLP model presented the best overall performance, with accuracies of 84.45% (Bank A) and 94.00% (Bank B) and higher recall values, while Gradient Boosting achieved the highest AUC-ROC scores (87.90% and 94.10%). All machine learning models outperformed Logistic Regression (79.0% and 78.38%), demonstrating that the adoption of these techniques — especially MLP — can significantly improve default prediction in direct consumer credit.

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Keywords: Credit Risk Analysis, Machine Learning Models, Deep Learning, Multilayer Perceptron.

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1. Introduction

Growing global economic integration and advances in information technology have increased society's exposure to economic, financial, and health crises—such as the COVID-19 pandemic—directly impacting the financial capacity of individuals and businesses (Coelho and Lima Amorim, 2021). In this context, credit risk management has become fundamental to the stability of financial institutions, with this risk defined as the possibility of a debtor defaulting on their financial obligations (Schrickel, 2000). The incorporation of Big Data has transformed this management, enabling more accurate and dynamic analyses based on large volumes of structured and unstructured data, such as social media, transaction histories, and real-time economic indicators.

This technological evolution has allowed financial institutions to enhance their risk models, transitioning from conventional approaches to more robust and proactive methods. However, this evolution also poses significant challenges related to data quality, integration, and governance, requiring accurate, relevant, and timely information to ensure successful analyses. Furthermore, the cost of changes in the modus operandi of their activities must be justified by efficiency gains, with the advantages of using additional models being as evident as possible.

Therefore, this paper seeks to investigate the potential advantages of using Deep Learning with Multilayer Perceptron (MLP) to predict credit risk in banks. To this end, data from credit risk analysis of individual customers in Direct Consumer Credit (CDC) operations at two of the largest Brazilian financial institutions are used to compare their performance with that of other algorithms. Support Vector Machines (SVM), Gradient Boosting, Decision Trees (Random Forest), and Logistic Regression are considered, while the analysis is conducted using performance metrics such as accuracy, precision, recall, F1-score, AUC-ROC, and cross-validation.

The results indicate that Multilayer Perceptron (MLP) Deep Learning is the best-performing algorithm, achieving the highest accuracy rates and associated metrics. Gradient Boosting achieved the best AUC-ROC scores, and all other algorithms also outperformed logistic regression, which is widely used by financial institutions for credit risk prediction. These findings are useful for the scientific literature investigating bank management and the use of machine learning methods, providing empirical evidence for Brazilian institutions. They also serve financial market participants by demonstrating the potential of these algorithms to reduce credit losses, improve capital allocation, enhance pricing, and strengthen risk appetite frameworks.

This paper is structured as follows: Section 2 presents the theoretical foundation, discussing the evolution of credit risk models and the state of the art in machine learning. Section 3 describes the database, preprocessing, estimated models, and metrics used. Section 4 reports and discusses the empirical results. Finally, Section 5 concludes the paper, highlighting the practical implications of the results, the limitations of the study, and suggestions for future research.

2. Theoretical Framework

In the past, credit risk assessment was performed using qualitative methods, such as the "5 Cs" model—Character, Capacity, Condition, Capital, and Collateral—which relied heavily on human subjectivity and experience. Although this framework was fundamental, technological advancements and the increasing availability of data drove the transition to quantitative techniques, notably Machine Learning. These new methods have replaced subjectivity with algorithms capable of identifying complex patterns in large volumes of data, generating more accurate predictions about the probability of default (Montevechi et al., 2024).

Credit risk analysis at the individual level considers a set of variables that have historically shown a correlation with repayment ability. Age, for example, is often associated with financial stability; older customers tend to have greater professional stability and a longer credit history. Education level is also a relevant factor, as higher levels of schooling are generally correlated with higher incomes and, consequently, a lower risk of default. Main occupation and income are direct determinants of repayment capacity, being central variables in any credit scoring model.

Behavioral variables, such as default history and the presence of records in credit protection agencies (like Serasa), are powerful predictors of future behavior. A customer who has previously experienced payment difficulties has a higher probability of recurrence. Similarly, marital status can influence risk, as family structure and shared financial responsibilities can affect the ability to honor commitments. Gender has also been studied, although its influence is complex and often mediated by other socioeconomic factors. The combination of these variables allows for the construction of a detailed and individualized risk profile for each customer.

With the implementation of systems like Open Banking, credit scoring models have begun to incorporate transactional and behavioral data (behavioral scoring), such as consumption patterns and payments, which has significantly increased the accuracy of predictions (Vicente 2020; Bravo et al., 2023). This more complete and personalized approach, which considers the specific behavior of the customer, has proven increasingly effective in identifying risks.

Recent literature highlights the superiority of machine learning models over traditional statistical approaches in credit risk problems. Advanced algorithms, such as Gradient Boosting and deep neural networks, capture nonlinear relationships and detailed interactions that would not be perceptible in traditional analyses, reducing the influence of subjective judgments and making the process more impartial and objective (Suhadolnik et al., 2023).

Ensemble-based methods, such as Gradient Boosting and Random Forests, which combine multiple decision trees, are especially effective for improving predictions, particularly with imbalanced data common in the financial sector (Chopra and Bhilare, 2018; Zhang and Yu, 2024). Other methods, such as Support Vector Machine (SVM) and Deep Learning with the Multilayer Perceptron (MLP)

algorithm, stand out for their ability to capture complex relationships in the data (Dastile et al., 2020). Zhong et al. (2014) point to neural networks and SVMs as predominant techniques in the field.
Despite the predictive power of these models, Logistic Regression remains popular due to its simplicity and the interpretability required by regulators (Florez-Lopez and Ramon-Jeronimo 2015; Huang et al. 2004). However, there is still no absolute consensus on the best method, making it essential to analyze which model best adapts to the specific context of each financial institution, considering market dynamics and different credit scenarios (Addo, Guégan, and Hassani 2018). This work contributes to this discussion by empirically comparing the performance of four of the main ML algorithms in a real scenario of the Brazilian market.

3. Methodology

3.1 Data

This work uses real data from two large Brazilian financial institutions, referred to as Bank A and Bank B, to ensure confidentiality, as per nondisclosure agreements. In both cases, the data corresponds to a customer cohort observed over 12 months, intending to classify them as either compliant (0) or non-compliant (1). Non-compliant customers are those who were more than 90 days late in paying their direct consumer credit (CDC) operations.
To prepare the data for modeling, a six-step treatment and cleaning process was applied to create consistent and standardized datasets for all tested models. This procedure was applied independently for each bank, respecting the particularities of their databases. The steps were:
1. Categorical Variable Encoding: Nominal variables, such as "Gender", "Marital Status," and "Education Level," were transformed into a binary numerical format using one-hot encoding. This approach creates binary columns for each category, allowing the algorithms to process this information appropriately.
2. Handling Missing Values and Outliers: Missing numerical values were replaced by the median of the respective variable, a measure of central tendency robust to extreme values. To handle outliers, the winsorization technique was applied, limiting extreme values to the 1st and 99th percentiles, thus smoothing their impact without discarding the data.
3. Normalization: Numerical variables were adjusted to a common scale in the [0, 1] range using Min-Max normalization. This procedure ensures that variables with different magnitudes contribute equally to the model training.
4. Correlation Analysis: To reduce multicollinearity, which can impair the performance of some models, variables with a correlation coefficient greater than 0.9 were identified and excluded from the analysis.
5. Class Balancing: Credit databases are often imbalanced, with a larger proportion of compliant customers. To prevent models from becoming biased towards the majority class, the oversampling technique was applied to the minority class (non-compliant), ensuring that the training and testing samples had balanced proportions

(50% of each class).
6. Sample Splitting: After treatment, the samples from each institution were divided into 70% for model training and 30% for testing and validation of the results.
For Bank A, the initial sample contained 147,000 customers, with 78% compliant and 22% non-compliant, and included 52 registered variables. After the cleaning and selection process, 21 predictor variables were used. The transformed categorical variables were: default indicator, Serasa record indicator, nature of main occupation, education level, marital status, overdraft indicator, benefit type, and gender. The descriptive statistics revealed a large dispersion in variables such as main net income (mean of R$ 3,017.78 with a standard deviation of R$ 134,946.02) and the value of Serasa restrictions (mean of R$ 2,660.58 with a standard deviation of R$ 509,711.04), which reinforced the need for normalization and outlier treatment steps to ensure the robustness of the analysis.
For Bank B, the provided dataset contained 50,000 customers and 36 variables, already segmented with a proportion close to 50% for each class. After applying the same treatment pipeline, 18 predictor variables were selected for modeling. The converted categorical variables were: salary account at the institution, resolved restriction at Serasa, education level, gender, and type of residence. The descriptive analysis showed that variables such as the percentage of revolving credit utilization had high variability (mean of 30.36% with a standard deviation of 40.57%), indicating different risk behaviors among customers. Net income also showed considerable dispersion (mean of R$4,163.42 with a standard deviation of R$2,271.11), justifying the application of the same treatment procedures.

3.2 Empirical Strategy

3.2.1 Logistic Regression

Logistic Regression is a statistical method widely used to assess the creditworthiness of borrowers due to its simplicity and transparency in predictions (Dastile et al., 2020). It allows for the estimation of the probability of an event occurring, such as a loan default, based on explanatory variables that can be both continuous and categorical, like income, age, and credit history. According to Corrar, Paulo, and Dias Filho (2007), Logistic Regression is characterized by describing the relationship between several independent variables Xi and a dichotomous dependent variable f (Z), representing the presence of default (1) or its absence (0).
The model maps the linear combination of input variables to a probability value between 0 and 1 through the sigmoid function, which generates an "S"-shaped curve. Mathematically, the probability p of the event occurring is described as follows:

Definition 3.2.1.1 *Logistic Regression*

$$p = \frac{1}{1 + e^{-(\alpha + \sum_{i=1}^{k} \beta_i x_i)}}$$

Where p is the probability of the event occurring, β0 is the intercept (or constant) of the model, βi are the coefficients representing the weight of each independent variable Xi, and the expression $\sum_{i=1}^{k} \beta_i X_i$ describes the weighted sum of the independent variables, which contribute to the probability estimate. The main advantage of Logistic Regression lies in its ability to generate interpretable results, which is crucial for justifying credit decisions and complying with regulatory obligations (Chopra and Bhilare, 2018).

3.2.2 Decision Trees (Random Forest)

Decision Trees are non-parametric models that classify data through a series of hierarchical rules, dividing the dataset into increasingly homogeneous subsets (Quinlan 1986). The construction of the tree involves selecting attributes that best separate the classes at each node. Two common metrics for this selection are Information Gain and the Gini Index. Information Gain measures the reduction in entropy (uncertainty) after a split:

Definition 3.2.2.1 *Gain of Entropy(S)*

$$Gain\ (A) = Entropy(S) - \sum_{i=1}^{n} \left(\frac{|S_i|}{|S|} Entropy(S_i) \right)$$

Where S is the dataset, A is the attribute, and Sv is the subset of S for which attribute A has the value v. The Gini Index, in turn, measures the impurity of a node:

Definition 3.2.2.2 *Calculate of Gini(S)*

$$Gini(S) = 1 - \sum_{x \in X} p(x)^2$$

Where pi is the proportion of samples of class i in the set S. To avoid overfitting a single tree, the Random Forest algorithm was used, an ensemble method that builds multiple decision trees from random subsamples of the data (bootstrap) and variables. The final decision is made by a majority vote among all N trees:

Definition 3.2.2.3 *Final prediction for instance (x)*

$$H(x) = majority\_vote\{h_i(x)\}_{i=1}^{N}$$

Where H(x) is the final prediction for instance x. This approach reduces variance and improves the model's generalization (Breiman, 2001).

3.2.3 Gradient Boosting

Gradient Boosting is a powerful ensemble method that builds models sequentially and additively (Friedman, 2001). Unlike Random Forest, where trees are independent, in Gradient Boosting, each new tree is trained to correct the errors (residuals) of the previous model. The process minimizes a differentiable loss function through a gradient descent procedure. At each step t, the model is updated by adding a new tree ht(x) that best fits the negative gradient residuals of the loss function:

Definition 3.2.3.1 *Previous iteration*

$$F_{t+1}(x) = F_t(x) + \gamma_t h_t(x)$$

Where $F_{t+1}(x)$ is the model at the previous iteration, and ν is the learning rate, a hyperparameter that controls the contribution of each tree to prevent overfitting. This iterative approach allows the model to focus on the most difficult instances to classify, resulting in high predictive accuracy (Xia and Liu, 2020).

3.2.4 Support Vector Machine

The Support Vector Machine (SVM) is a classifier that seeks to find an optimal hyperplane that maximizes the margin of separation between classes in a feature space (Cortes and Vapnik 1995). For linearly separable data, the optimization problem is:

Definition 3.2.4.1 *SVM Linearly Separable Data*

$$\min_{w,b} \left(\frac{1}{2}\right) ||w||^2 \text{ subject to } y_{i(w \cdot x_i + b)} \geq 1$$

Where w is the normal vector to the hyperplane and b is the bias term. For non-linearly separable data, a slack variable ξi and a regularization parameter C are introduced:

Definition 3.2.4.2 *SVM with soft margin (non-linearly separable data)*

$$\min_{w,b,\xi} \left(\frac{1}{2}\right) ||w||^2 + C \sum_{i=1}^{n} \xi_i \text{ subject to } y_{i(w \cdot x_i + b)} \geq 1 - \xi_i, \xi_i \geq 0$$

To handle complex and non-linear relationships, SVM uses the "kernel trick," which maps the data to a higher-dimensional space without explicitly calculating the new coordinates. In this study, the Radial Basis Function (RBF) was used, one of the most common in credit analysis:

Definition 3.2.4.3 *Radial Basis Function (RBF) kernel*

$$K(x, x') = \exp(-\gamma \|x - x'\|^2)$$

3.2.5 Deep Learning with Multilayer Perceptron (MLP)

The Multilayer Perceptron (MLP) is a type of feedforward artificial neural network model, composed of an input layer, one or more hidden layers, and an output layer. Its ability to learn hierarchical representations and capture complex non-linear relationships makes it particularly effective for credit risk problems (Addo, Guégan, and Hassani 2018). In a hidden layer, the output of a neuron j is calculated as:

Definition 3.2.5.1 *Hidden-layer neuron output*

$$h_j = f\left(\sum_{i=1}^{n} w_{ij} x_i + b_j\right)$$

Where f is a non-linear activation function (like ReLU, f(x) = max(0, x)), wij are the synaptic weights, xi are the inputs, and bj is the bias term. The final output of the model, for binary classification, generally uses the sigmoid function to map the result to a probability:

Definition 3.2.5.2 *Sigmoid output layer (binary classification)*

$$\hat{y} = \sigma\left(\sum_{j=1}^{m} w_j' h_j + b'\right) \text{ where } \sigma(z) = \frac{1}{1 + e^{-z}}$$

3.3 Evaluation Metrics

To comprehensively compare the efficiency of the models, the following metrics were used:

• Accuracy: The proportion of correct predictions (both compliant and non-compliant) over the total number of cases. It is a general metric, but can be misleading in imbalanced datasets.

• Precision: Measures the proportion of positive predictions (noncompliant) that were correct. It is important for minimizing false positives (classifying a good payer as non-compliant).

• Recall (Sensitivity): Measures the proportion of actual positives (non-compliant) that were correctly identified by the model. It is crucial for minimizing false negatives (failing to identify a bad payer).

• F1-Score: The harmonic mean of precision and recall, providing a single metric that balances both errors.

• AUC-ROC: The Area Under the ROC Curve measures the model's ability to discriminate between positive and negative classes. A value close to 1 indicates excellent discriminatory power.

• Cross-Validation: The average accuracy obtained over multiple splits of the dataset, providing a more robust estimate of the model's performance on unseen data.

4. Results

The comparative results of the models' performance for Bank A and Bank B are consolidated in Tables 1 and 2, respectively. The analysis of these metrics allows for a detailed evaluation of the effectiveness of each approach in predicting default.

Table 1: Model Results for Bank A

Model	Accuracy	Precision	Recall	F1-Score	AUC-ROC	Cross-Validation
Random Forest	79.38%	78.66%	80.32%	79.49%	87.16%	86.65%
Gradient Boosting	79.74%	79.15%	80.44%	79.79%	87.90%	87.40%
SVM	78.58%	78.23%	78.88%	78.55%	85.00%	85.56%
Deep Learning (MLP)	84.45%	81.03%	91.01%	85.00%	85.00%	86.55%
Logistic Regression	79.03%	79.31%	79.12%	79.00%	79.00%	78.00%

Source: Elaborated by authors.

Table 2: Model Results for Bank B

Model	Accuracy	Precision	Recall	F1-Score	AUC-ROC	Cross-Validation
Random Forest	86.32%	87.18%	85.09%	86.12%	93.36%	93.18%
Gradient Boosting	87.54%	87.44%	87.62%	87.53%	94.10%	93.99%
SVM	76.91%	75.88%	78.76%	77.29%	88.45%	88.02%
Deep Learning (MLP)	94.00%	93.86%	93.84%	93.44%	94.00%	93.95%
Logistic Regression	78.00%	79.00%	77.00%	78.00%	78.00%	78.00%

Source: Elaborated by authors.

The results in Table 1 show that for Bank A, the Deep Learning model with Multilayer Perceptron (MLP) performed best overall, with a precision of 84.45% and, notably, the highest recall (91.01%). High recall is particularly valuable in risk analysis, as it indicates that the model can correctly identify 91% of all customers who defaulted, minimizing false negatives. Gradient Boosting also excelled, achieving the highest AUC-ROC value (87.90%), suggesting superior discriminatory ability to distinguish between good and bad payers.

The results in Table 2 show that for Bank B, Deep Learning with Multilayer Perceptron (MLP) also achieved the best performance, again leading in accuracy (94.00%), precision (93.44%), recall (93.84%), and F1-Score (93.86%), which may indicate a good and balanced performance. Gradient Boosting followed closely, with an accuracy of 87.54% and the highest AUC-ROC (94.10%), which may reinforce its robustness as a predictive model. The inferior performance of SVM on both datasets can be attributed to its sensitivity to hyperparameter choices and the inherent complexity of the data, which may not have been perfectly captured by the RBF kernel in the tested configurations.

The comparison between the two banks reveals that the models performed better overall on the Bank B dataset. This may be explained by differences in data quality, variable distribution, or the fact that the Bank B dataset was initially more balanced. Regardless of the dataset, Deep Learning with Multilayer Perceptron and Gradient Boosting emerged as the most promising techniques, with MLP standing out for its ability to maximize the identification of non-compliant customers (high recall), while Gradient Boosting proved to be the best overall discriminator (high AUC-ROC).

The results for both banks showed that the machine learning models outperformed Logistic Regression, a historically and widely used method for measuring credit risk (Pinto et al., 2024), with the superior performance of the machine learning models being even more pronounced when considering Bank B. This may highlight the potential performance gains provided by more computationally complex algorithms in the task of analyzing customer credit risk in financial institutions.

5. Conclusion

This paper investigated the performance of Deep Learning with Multilayer Perceptron (MLP) for assessing bank credit risk. It compared its performance with that of other techniques such as Support Vector Machine (SVM), Gradient Boosting, Decision Tree (Random Forest), and Logistic Regression. The authors used databases for direct-to-consumer credit risk analysis from two of Brazil's largest financial institutions, as well as performance metrics such as accuracy, precision, recall, F1-score, AUC-ROC, and cross-validation.

The results indicate that Deep Learning with Multilayer Perceptron (MLP) performs best among the algorithms tested, with accuracies of 84.45% for Bank A and 94.00% for Bank B, and higher recall values. The Gradient Boosting algorithm achieved the highest AUC-ROC scores, 87.90% for Bank A and 94.10% for Bank

B. The other machine learning algorithms also outperformed Logistic Regression, which is widely used to analyze credit risk in financial institutions. This highlights the performance of MLP compared to the other machine learning algorithms considered, with the advantages of its use potentially outweighing the implementation costs for these institutions.

These findings contribute to the scientific literature investigating bank management and the use of computational methods by providing empirical evidence for Brazilian financial institutions and offering insights into the generalizability and adaptability of models to different credit portfolios. At the same time, they can be useful to financial market players by highlighting the performance of machine learning algorithms, especially Deep Learning, which can provide greater accuracy in credit risk assessment and thus contribute to better decision-making, reduced default losses, and greater efficiency in risk management.

As a suggestion for future research, we recommend exploring hybrid approaches that combine the robustness of machine learning models with techniques that promote greater interpretability. This would meet regulatory requirements and facilitate the adoption of these technologies by financial institutions, enhancing the benefits observed in this work.

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