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FINANCIAL RISK ASSESSMENT IN SAVINGS AND CREDIT COOPERATIVES IN ECUADOR: MACHINE LEARNING MODELS

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ABSTRACT

This paper examines financial risk in credit unions in the European Union, as well as their crucial role in contributing to financial inclusion, especially among the rural population. These organizations face challenges, including regulation, liquidity, solvency, and delinquency. To address these challenges, machine learning models are recommended as they can handle large data sets and have predictive potential for financial risk. The article draws on the cooperatives' financial and economic criteria, using logistic regression, Random Forest, and Gradient Boosting tools, and analyzes indicators of delinquency, profitability, and solvency. The results indicated that the tree model offers better risk assessment quality, but practical challenges persist in its implementation, ranging from a lack of infrastructure to a fear of change. The report states that machine learning can enable the cooperative sector to become sustainable through better risk management and informed financial actions.

KEYWORDS: Financial risk, Credit unions, Machine learning, Risk management, Predictive models

1. INTRODUCTION

Credit unions are an essential foundation for financial inclusion in Ecuador, especially in the countryside and among poor and vulnerable populations who have limited access to formal financial services. The International Co-operative Alliance (2025) It also states that these organizations are indispensable to promoting economic development by assisting small entrepreneurs and rural communities. But they are characterised by being unsustainable (they risk unviability) and also not resilient (they become more or less the target of ill-prepared financial risk management, leading to a shortage of cash and economic capital).

In Ecuador, the absence of a homogeneous regulatory body for cooperatives leaves a significant gap between large and small enterprises. The smaller ones, as long as they are not effectively controlled by the

Superintendence of Popular and Solidarity Economy (SEPS) and the Software Fund, are more likely to be affected by economic and criminal crises (Moreta, 2024). With this mix of risks has come the adoption of a new way to minimize exposure and stay financially secure.

In such a case, technical innovation, particularly predictive models powered by machine learning, represents a new way of approaching financial risk. In this way, large volumes of data can be analyzed and conclusions can be drawn that are not recognizable with standard methods. According to Guerrero et al. (2024), AI can revolutionize banks' decision-making. Cooperative financial risk has macroeconomic, mesoeconomic, and microeconomic aspects. At the macroeconomic level, international economic volatility, as well as variations in commodity prices and government policies, impact the very stability of the sector (Oñate et al., 2022). At the mesoeconomic level, there are large differences between cooperatives in terms of standard capacity and access to technology, leading to different performance in risk management (Haro and Poaquiza, 2022).

At the microeconomic level, financial risk is closely related to the socioeconomic profile of the members of the cooperative. Factors that lead to delinquency among microcredit members include informal work, unemployment, and low incomes (INEC, 2023). In addition, many small cooperatives have inadequate scoring systems; as a consequence, the problem of high-risk loans is generated (Cárdenas, 2023). Based on these issues, we suggest that both supervised and unsupervised machine learning models can be employed to reduce financial risk. These applications evaluate economic indicators, historical data, or macroeconomic variables to generate accurate estimates, thus facilitating more informed and less uncertain decision-making (Zambrano, 2016). However, there are obstacles to the effective use of these tools. et al., 2024). They are difficult to overcome, requiring the transfer of systems and frequent training of personnel.

The ultimate purpose of this research is to show how the good use of Machine Learning models can help increase efficiency in the financial risk management of cooperatives in Ecuador. The findings of this study are intended to add not only academic value, but also to be used as pragmatic tools for the development of the sustainability and stability of the country's cooperatives.

Methodology

Study Design

The study applies the quantitative and predictive model, taking as a reference the cross-section of January 2025 of savings and credit cooperatives in Ecuador. Both a non-experimental and correlational design is used and the relationship between different financial indicators and the risk of delinquency is analyzed, which is measured by an index with a value of 1 (high risk) when the percentage of delinquency is greater than 9% (the national average) or 0 otherwise. This is consistent with previous literature on credit risk modeling (Altman, 1968; Ohlson, 1980).

Data Source and Variables

The data were extracted from the financial bulletin for the month of January 2025. The variables included in the analysis are defined and justified as follows:

Table 1. Table of variables

Variable	Definition	Justification and Studies
SOLVENCY (%)	Relationship between equity and total assets.	This ratio reveals whether the cooperative can sustain its losses and meet its obligations. Altman (1968) incorporated the proportion of capital into its Z-Score model; Ohlson (1980) it also made solvency a key determinant in the prediction of bankruptcies; Beaver (1966) He emphasized the need to maintain capital reserves for the stability of the financial position.
ROA (%)	Return on assets, calculated as net income divided by total assets.	The ROA assesses the efficiency of the use of resources in the process of generating profits. It was part of the early model for predicting bankruptcies by Altman (1968), predicting financial difficulties by Beaver (1966) and was also a significant variable in the credit risk analysis of Zmijewski (1984).

SWR (%)	Return on equity, which shows the return generated on the capital invested.	A good ROE indicates that the company is creating shareholder value by generating profits from its shareholders' investments. This ratio, combined by Altman (1968) and Ohlson (1980) to measure stability and Berger y Bouwman (2013) stating that a low ROE is associated with a higher financial risk of the lending institution.
CARTERA_VENCER (%)	Proportion of the portfolio due (non-performing loans) over the total credit portfolio.	This series is a fundamental basis for identifying deterioration in credit quality. Hamid y Yunus (2017) they applied it to assess credit risk; Dionne (2004) he used it to forecast credit losses; The reports of the Basel Committee (2011) They suggest following the evolution of the non-performing loan portfolio to anticipate risks.
FINANCIAL INTERMEDIATION (%)	Relationship between deposits and placements, which indicates the efficiency in the financial intermediation of the cooperative.	An optimal level of intermediation indicates that deposits are converted into loans in the most efficient way. Spajić (2002) he indicated the relevance of intermediation for the stability of the financial system; Molyneux and Thornton (1992) demonstrated their influence on the composition of funding adopted; Berger and Bouwman (2013) considered it a milestone in managing the risk of financial institutions.
FINANCIAL EFFICIENCY (%)	Relationship between operating expenses and income, an indicator of efficiency in the operational management of the cooperative.	Increased Productivity The mother of all benefits of operational efficiency is the cost reduction that leads to increased profits. More efficient companies are less likely to fail (Molyneux and Thornton, 1992); they are dominant in competitiveness; Berger and Bouwman (2013) incorporate it to detect operational weaknesses in their models.
FINANCIAL MARGIN (%)	The difference between revenues and financial costs, expressed as a percentage of revenues.	The higher the margin, the better the pocket for future profitability and strength. Spajić (2002) Molyneux and Sealey (1992) recognized it as a measure of stability in the financial sector in relation to the quality of management, in recent times, the results obtained confirm that its value is useful for customers, if as a measure of credit risk (Berger and Bouwman, 2013).
MOROS_ACT (%)	NPL ratio on assets, which relates the non-performing loan portfolio to the total assets.	This ratio reflects the effect of the poor situation of the portfolio on the liquidity and strength of the company. Agarwal et al. (2012) used it to forecast credit losses; Ohlson (1980) incorporated it into his model for predicting bankruptcy; and the Basel Committee (2010) advocates using it to assess asset quality.
CARTERA_PATR (%)	Ratio between non-performing loans and equity, which shows the exposure of equity capital to credit risk.	A high proportion of the industry average implies that a substantial proportion of equity is locked in unprofitable advances. The Basel Committee (2010) based itself on this to point out systemic risk; Agarwal et al. (2012) included it in their models to analyze financial resilience, considering it as a fundamental indicator to measure credit quality (Jiménez, Saurina & Valderrama, 2012).
LIQUIDITY (%)	Ratio of liquid assets to current liabilities, which measures the ability to cover short-term obligations.	Responsiveness to contingencies: This is critical and for this, liquidity is important. It was considered in Ohlson (1980) in predictive models; in Altman (1968), it was considered essential when assessing financial stability; and in Beaver (1966), it was used as a predictor of bankruptcies, indicating that there is a relationship between bankruptcy risk management and cash risk management.

Source: Own elaboration, 2025.

Analytical Procedure
Data Preprocessing:
Transformation of continuous variables using logarithms (e.g., *MARGEN_FINANCIERO*, *TOTAL_ACTIVOS*, and *CARTERA_CREDITO*) to stabilize variance and improve interpretation.

Standardization of variables using StandardScaler to homogenize the measurement scale.

Data Division:
The data are divided into training (80%) and test (20%) sets by stratified random partitioning to maintain the proportion of classes in the dependent variable.

Predictive Models:
Classification models based on Machine Learning are implemented, including Logistic Regression, Random Forest and Gradient Boosting. Hyperparameters are optimized using GridSearchCV and performance is evaluated using accuracy metrics, recall, F1-score, and confusion matrices.

Evaluation of Variables:
Permutation Importance and SHAP-based techniques are used to identify and validate the importance of each variable in predicting risk, allowing the model to be refined and redundant or uninformative variables to be discarded.

Interpretation of Results:
The coefficients of the Logistic Regression model are interpreted in terms of Odds Ratios and are complemented with the analysis of marginal effects to evaluate the variation in the probability of default in the face of changes in each variable. Tree-based models (Random Forest and Gradient Boosting) are used to extract the relative importance of variables, facilitating decision-making for financial risk management.

Results

Logistic Regression

The logistic regression model was adjusted using the following independent variables, since after a trial-and-error analysis, they were the variables that came closest to significance:

- CARTERA_VENCER
- FINANCIAL INTERMEDIATION
- FINANCIAL EFFICIENCY
- FINANCIAL MARGIN
- MOROS_ACT

The analysis carried out with the *statsmodels* package revealed the coefficients, p-values and marginal effects:

Table 2. Paquete statsmodels

```
Optimization terminated successfully.
         Current function value: 0.409993
         Iterations 9
                           Logit Regression Results
==============================================================================
Dep. Variable:          DEPENDIENTE   No. Observations:                  193
Model:                        Logit   Df Residuals:                      187
Method:                         MLE   Df Model:                            5
Date:              Tue, 25 Mar 2025   Pseudo R-squ.:                  0.3841
Time:                      12:14:36   Log-Likelihood:                -79.129
converged:                     True   LL-Null:                       -128.48
Covariance Type:          nonrobust   LLR p-value:                 9.892e-20
==================================================================================
                     coef    std err          z      P>|z|      [0.025      0.975]
----------------------------------------------------------------------------------
const             -3.3763      1.680     -2.009      0.044      -6.669      -0.083
CARTERA_VENCER    14.8033     10.569      1.401      0.161      -5.911      35.518
INTERMEDIACION    -0.6207      0.741     -0.837      0.402      -2.074       0.832
EFICIENCIA       -34.3020     12.418     -2.762      0.006     -58.640      -9.964
MARGEN          -298.7809    177.069     -1.687      0.092    -645.831      48.269
MOROS_ACT        112.2691     20.090      5.588      0.000      72.894     151.644
==================================================================================
        Logit Marginal Effects
=====================================
Dep. Variable:          DEPENDIENTE
Method:                        dydx
At:                         overall
==================================================================================
                    dy/dx    std err          z      P>|z|      [0.025      0.975]
----------------------------------------------------------------------------------
CARTERA_VENCER     1.9582      1.371      1.428      0.153      -0.729       4.646
INTERMEDIACION    -0.0821      0.098     -0.842      0.400      -0.273       0.109
EFICIENCIA        -4.5374      1.521     -2.983      0.003      -7.519      -1.556
MARGEN           -39.5226     22.862     -1.729      0.084     -84.332       5.286
MOROS_ACT         14.8509      1.752      8.476      0.000      11.417      18.285
----------------------------------------------------------------------------------
```

The MOROS_ACT variable showed a significant positive coefficient ($p < 0.001$), indicating that an increase in the credit-to-asset ratio increases the probability of classifying the cooperative as at risk (1). FINANCIAL EFFICIENCY presented a significant negative coefficient ($p < 0.01$), which indicates that there was a negative effect associated with the probability of risk. But all the other variables, although with low coefficients, have participated in the model as a whole.

Tree-Based Models
a) Random Forest
Random Forest's model with GridSearchCV was 72.9% accurate in the test set. The confounding matrix (see Fig. 1) indicates that the model adequately classifies both at-risk and non-at-risk cooperatives, with a slight asymmetry in class 1 detection.

Table 3. Random Forest

Variable	Importance
MOROS_ACT	0.221
CARTERA_PATR	0.146
ROE	0.135
LENGTH	0.108
FINANCIAL EFFICIENCY	0.075
FINANCIAL INTERMEDIATION	0.072
CARTERA_VENCER	0.066
FINANCIAL MARGIN	0.063
SOLVENCY	0.059
LIQUIDITY	0.053

b) Gradient Boosting
The performance of the Gradient Boosting model was reported with an accuracy of 70.8%. Using hyperparameter optimization, a model was enabled with the parameters learning_rate = 0.2, n_estimators = 200, and max_depth = 3.

Table 4. Gradient Boosting

Variable	Importance
MOROS_ACT	0.369
ROE	0.184
FINANCIAL INTERMEDIATION	0.099
LENGTH	0.075
CARTERA_PATR	0.067
SOLVENCY	0.057
LIQUIDITY	0.049
CARTERA_VENCER	0.038
FINANCIAL MARGIN	0.033
FINANCIAL EFFICIENCY	0.029

Comparison of models and discussion of results
Three predictive methods to predict financial risk in SACCOs were reviewed: logistic regression, random forest and gradient impulse. The dependent variable took the value of 1 if the delinquency rate was higher than 9% and 0 otherwise. The independent variables were SOLVENCY, ROA, ROE, CARTERA_VENCER, FINANCIAL INTERMEDIATION, FINANCIAL EFFICIENCY, FINANCIAL MARGIN, MOROS_ACT, CARTERA_PATR and LIQUIDITY.

Logistic Regression Results:
The logistics model had an accuracy of 64.5%. Although we can interpret the coefficients directly as odds ratios and also estimate marginal effects (which is very important to understand how the probability of risk changes

with changes in each predictor (Altman, 1968; Ohlson, 1980)), the performance of these types of models was not at the level of, for example, the tree-based prediction model. This is in line with research indicating that logistic regression may underestimate the nonlinear relationships and complex interaction effects that appear in financial data (Beaver, 1966; Zmijewski, 1984).

Random Forest and Gradient Boosting results:

Random Forest's model achieved an accuracy of 72.9%, while Gradient Boosting obtained 70.8%. Both models, by effectively capturing complex interactions and nonlinear relationships between variables, offered substantial improvements in risk classification. In particular, measures of variable importance revealed that indicators such as MOROS_ACT and ROE are determinants in predicting risk, which is in line with studies by Agarwal et al. (2012) and recommendations by the Basel Committee (2010).

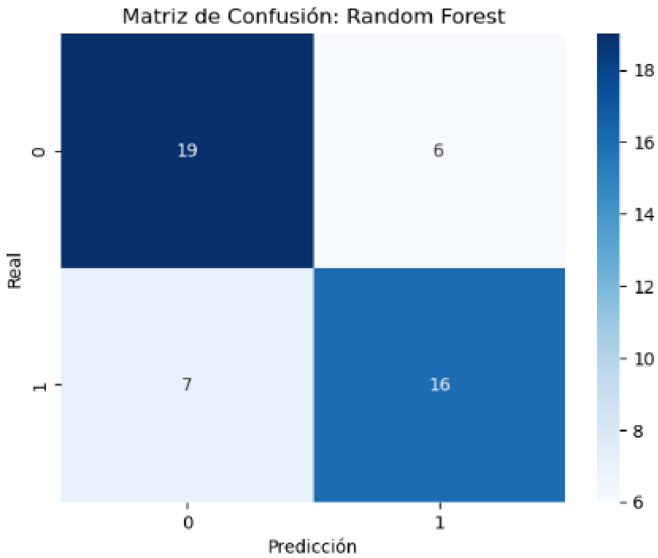
Comparative Discussion

Logistic regression offers features such as an explanatory model that is commonly used in financial risk analysis (Altman, 1968; Ohlson, 1980). However, this model is considered to be less effective when there are nonlinear relationships. In contrast, tree-based methods, such as Random Forest and Gradient Augmentation, have shown better classification performance, due to their ability to learn complex interactions without prespecified functional forms (Breiman, 2001; Friedman, 2001).

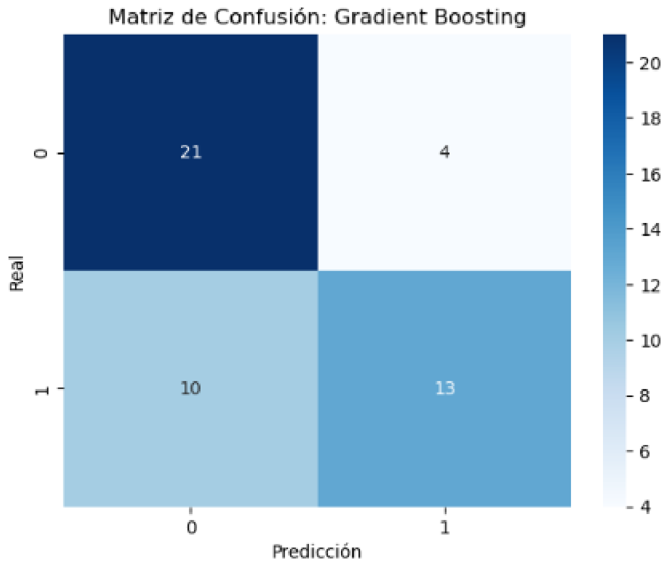
The better performance of the Random Forest in this research shows us that the use of interaction and correlation capacity (intrinsically present in the forest model) helps to evidence financial risk in cooperatives. However, the logistic model remains key to understanding the impact of each variable and, therefore, on managerial decision-making and correctional policies (Berger & Bouwman, 2013).

Appendices- In the original Spanish language

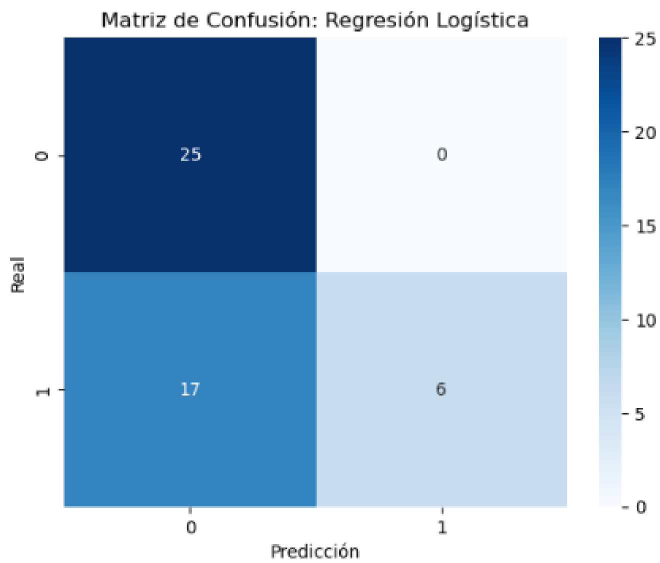
```
Accuracy: 0.7291666666666666
Reporte de Clasificación:
              precision    recall  f1-score   support

           0       0.73      0.76      0.75        25
           1       0.73      0.70      0.71        23

    accuracy                           0.73        48
   macro avg       0.73      0.73      0.73        48
weighted avg       0.73      0.73      0.73        48
```



```
Accuracy: 0.7083333333333334
Reporte de Clasificación:
              precision    recall  f1-score   support

           0       0.68      0.84      0.75        25
           1       0.76      0.57      0.65        23

    accuracy                           0.71        48
   macro avg       0.72      0.70      0.70        48
weighted avg       0.72      0.71      0.70        48
```




```
Accuracy: 0.6458333333333334
Reporte de Clasificación:
              precision    recall  f1-score   support

           0       0.60      1.00      0.75        25
           1       1.00      0.26      0.41        23

    accuracy                           0.65        48
   macro avg       0.80      0.63      0.58        48
weighted avg       0.79      0.65      0.59        48
```



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