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The Influence of Days Past Due, Loan Amount, and Deposit Proportion on Non-Performing Loans at the CU Sejahtera Makmur Bersama Savings and Loan Cooperative

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Abstract: *This study examines the influence of Days Past Due, Loan Amount, and Savings Proportion on credit default risk in CU Sejahtera Makmur Bersama using a comparative machine learning approach. Random Forest and XGBoost models were implemented and evaluated using Mean Squared Error (MSE), Mean Absolute Error (MAE), and the Coefficient of Determination (R^2). The results indicate that XGBoost_Optimized achieved the best performance with the lowest MSE (23,124,275,951) and the highest R^2 (0.020977), while Random Forest showed slightly better MAE performance (69,923,891). However, the R^2 value remains very low, indicating that the models explain only around 2% of the variance in credit default outcomes. This limited explanatory power is likely attributable to the absence of non-financial and behavioral variables, such as borrower character, repayment discipline, and employment stability, which are critical determinants of default behavior in cooperative lending. Additionally, potential data imbalance or outlier effects may have further reduced predictive accuracy. These findings suggest that financial indicators alone are insufficient to capture the complexity of non-performing loans. Future research should integrate borrower behavioral attributes, macroeconomic variables, and alternative modeling strategies such as binary classification or risk segmentation techniques to improve predictive performance and practical applicability.*

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INTRODUCTION

Savings and loan cooperatives, especially Credit Unions (CUs), serve as a vital pillar in advancing community-based financial inclusion by providing accessible capital to members often excluded from conventional banking systems (Boachie and Adu-Darko 2022). The sustainability of these institutions largely depends on their ability to manage loan portfolios effectively and minimize the risk of non-performing loans (NPLs), which can erode both member equity and institutional trust (Martins et al. 2021; Carrera-Silva et al. 2024; Anakpo et al. 2024). In credit unions, NPLs are not merely financial losses but signals of systemic fragility, highlighting weaknesses in credit evaluation and monitoring processes (Atichasari et al. 2023). Therefore, understanding the determinants of NPLs is essential to design effective mitigation strategies that strengthen cooperative resilience (Goyal et al. 2023).

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Beyond financial considerations, cooperatives operate under the principle of kinship (kekeluargaan), where lending relationships are embedded in social bonds, mutual trust, and collective responsibility. Unlike conventional banks, credit unions often rely on relational capital and community-based norms in assessing borrower credibility. This social embeddedness may influence repayment behavior in ways that are not fully captured by quantitative financial indicators. For instance, members may receive informal flexibility due to personal relationships, or conversely experience social pressure that encourages repayment discipline. Consequently, financial variables alone may be insufficient to comprehensively predict default behavior within cooperative ecosystems, as socio-cultural dynamics interact with economic factors in shaping credit outcomes.

Several studies emphasize that key variables such as Days Past Due (DPD), loan amount, and savings proportion strongly influence credit default risks. Longer payment delays (DPD) often indicate increased probability of delinquency, while larger loan sizes impose greater repayment stress on borrowers, elevating the risk of default (Shao, Chen, and He 2025). Conversely, a higher savings proportion reflects stronger member commitment, reducing the moral hazard associated with borrowing (Harmesa et al. 2023). Despite these insights, the dynamics between these financial predictors and the kinship-based cooperative structure in the Indonesian CU ecosystem remain underexplored, underscoring the need for empirical evidence that contextualizes cooperative lending behavior (Naz et al. 2024).

This study contributes to that gap by empirically examining the influence of DPD, loan amount, and savings proportion on NPLs within CU Sejahtera Makmur Bersama, while acknowledging the broader socio-relational context in which cooperative credit decisions occur. Employing machine learning models Random Forest and XGBoost this research compares their predictive performance using evaluation metrics such as MSE, MAE, and R^2. The integration of "savings proportion" as a predictive feature offers a novel interpretation of agency theory in cooperative finance, while the comparative analysis of regularization versus ensemble models enhances methodological rigor (Abdullah et al. 2023; Nwafor and Nwafor 2023). Ultimately, the best-performing model is expected to serve as a foundation for an early warning system prototype, supporting credit unions in implementing proactive, data-driven risk management strategies while recognizing the inherent social dimension of cooperative finance.

LITERATURE REVIEW

1. Non-Performing Loans (NPLs) in Cooperatives and Banking

Non-Performing Loans (NPLs) represent a primary indicator in assessing the quality of credit assets within financial institutions. NPLs refer to loans that experience payment delays beyond a specified threshold and carry a high risk of default. In both savings and loan cooperatives and banking institutions, rising NPL levels can disrupt liquidity, reduce profitability, and threaten institutional sustainability (Abimbola, 2020; Hakim, 2017).

Beni et al. (2023) found that NPLs significantly affect Return on Assets (ROA) in Indonesian Credit Unions. Similar findings were reported by Hadian and Phety (2021) and Nugraha et al. (2021), who demonstrated that higher NPL ratios are negatively associated with financial performance.

Within savings and loan cooperatives, Syahnanda and Susilowati (2025) emphasize that bad debt is not merely a financial issue but also affects operational stability and member trust. Therefore, identifying determinants of NPLs is essential for effective cooperative risk management.

2. Days Past Due (DPD) and Credit Risk

Days Past Due (DPD) is an operational indicator measuring the number of days a loan payment is overdue. Theoretically, the higher the DPD, the greater the probability that a loan will transition into non-performing status.

Rachmawati et al. (2024) explain that payment delays serve as early warning signals of deteriorating credit quality and may lead to increased NPL ratios. Effective NPL management requires systematic monitoring of payment delays to detect risk at an early stage (Gatimu et al., 2018).

Thus, DPD can be viewed as a short-term risk indicator reflecting borrowers' repayment discipline and liquidity capacity.

3. Loan Amount and Risk Exposure

Loan Amount reflects the level of credit exposure borne by a financial institution. According to risk management theory, the larger the loan value, the greater the potential financial loss if default occurs.

Abimbola (2020) argues that excessive credit exposure without adequate risk control increases the probability of loan default and negatively impacts financial performance. Similarly, Hakim (2017) found that uncontrolled credit expansion can deteriorate institutional health if not supported by sound credit risk assessment.

In the cooperative context, large loan disbursements must be aligned with members' repayment capacity to prevent increasing NPL probability.

4. Deposit Proportion, Liquidity, and Risk Mitigation

Deposit Proportion in this study is conceptually related to the Loan to Deposit Ratio (LDR), which compares loan disbursement to collected deposits. LDR is widely used as a liquidity indicator and a measure of financial institutions' ability to manage credit risk.

Beni et al. (2023) and Rachmawati et al. (2024) found that LDR significantly influences financial stability and NPL levels. An imbalanced ratio may increase liquidity pressure and credit risk. Nugraha et al. (2021) also highlight that LDR plays a crucial role in determining financial performance through its influence on credit risk exposure.

However, in cooperative institutions, member deposits do not always function as full collateral substitutes. If deposit values are relatively small compared to loan amounts, their effectiveness as a risk buffer becomes limited. This structural characteristic may explain why deposit proportion does not significantly reduce NPL levels.

Waty et al. (2025) further emphasize that improving cooperative efficiency requires integration of risk ratios, financial inclusion strategies, and comprehensive NPL management, rather than relying solely on liquidity indicators.

5. Non-Performing Loan Management in Cooperatives

Managing NPLs requires comprehensive strategies, including credit monitoring, restructuring policies, and relationship-based member engagement. Gatimu et al. (2018) demonstrate that effective credit management practices significantly improve loan recovery performance in deposit-taking savings and credit cooperatives.

Therefore, NPLs should be understood not only as financial outcomes but also as reflections of governance quality, monitoring systems, and institutional risk management capacity.

6. Conceptual Framework

Based on prior theoretical and empirical findings, clear relationships can be established among the examined variables. Days Past Due represents payment delay risk, reflecting borrowers' repayment discipline and short-term liquidity conditions. Loan Amount indicates the level of credit exposure borne by the cooperative, where larger disbursements imply greater potential losses in the event of default. Meanwhile, Deposit Proportion represents liquidity capacity and serves as a potential risk mitigation buffer, although its effectiveness depends on its relative size compared to loan exposure. Collectively, these three financial indicators are theoretically expected to influence the level of Non-Performing Loans (NPLs) in savings and loan cooperatives. Therefore, this study empirically investigates the influence of Days Past Due, Loan Amount, and Deposit Proportion on NPLs at CU Sejahtera Makmur Bersama to evaluate whether financial variables alone are sufficient to explain the dynamics of cooperative credit risk.

RESEARCH METHOD

Research Type and Data Source

This research uses a quantitative approach with an explanatory research design. The data used is historical secondary data obtained from the credit and savings records of the members of the Koperasi Simpan Pinjam CU Sejahtera Makmur Bersama. The data collection period covers transactions from January 2020 to December 2023. The population in this study consists of all loans disbursed during that period, with the sample selected using purposive sampling techniques based on the completeness of the required data.

Research Variables and Operational Definitions

There is one dependent variable and three independent variables in this study. The dependent variable is Non-Performing Loans (Y), which is operationalized as the value of outstanding loans that are over 90 days overdue. The independent variables include: 1) Days Past Due (X1), defined as the average number of days overdue payments in one year; 2) Loan Amount (X2), which is the nominal amount of funds disbursed to the borrower; and 3) Proportion of Savings (X3), calculated as the ratio of members' total compulsory and voluntary savings to their loan amount.

Data Collection and Analysis Techniques

Data collection was done thru a documentation study by recording the cooperative's internal reports. The data analysis phase begins with Exploratory Data Analysis (EDA) to understand the distribution and characteristics of the data. Next, the data was separated into independent variables (X1, X2, X3) and the dependent variable (Y), then divided into two subsets: training data (80%) and testing data (20%). Before modelling, data preprocessing was performed, including handling missing values using the mean imputation method and standardizing the data to equalize the scale of all features using StandardScaler.

Handling Imbalanced Data

Since non-performing loan (NPL) cases typically represent a smaller proportion of total loan observations, data imbalance was assessed during the exploratory data analysis phase. The distribution of performing and non-performing loans was examined to ensure that minority patterns were not ignored during model training. Although the study employs regression-based models rather than binary classification, imbalance may still affect the model's sensitivity to extreme delinquency values. To mitigate this issue, stratified consideration of default distribution was maintained during data splitting, and K-Fold Cross-Validation was applied to reduce sampling bias across folds. Additionally, model evaluation relied not only on R^2 but also on MAE and MSE to better capture prediction errors related to minority default cases. This approach ensures that the predictive models do not disproportionately favor performing loans while overlooking high-risk accounts.

Machine Learning Modelling and Evaluation

Two machine learning models were applied to predict credit default, namely: Random Forest Regressor, and XGBoost Regressor. To validate the model's stability, the K-Fold Cross-Validation technique with a K value of 5 was used. The performance of each model was evaluated on testing data using three main metrics: Mean Squared Error (MSE), which measures the average squared error; Mean Absolute Error (MAE), which represents the average absolute error; and Coefficient of Determination (R^2), which assesses how well the model explains the variance in the data. Feature importance analysis was also performed on the ensemble models (Random Forest and XGBoost) to identify the most influential predictors.

Reason for Model Selection

The two models were chosen to represent various modelling paradigms. The Random Forest and XGBoost represent powerful ensemble algorithms for capturing non-linear and complex relationships in data. This comparison is done to find the best approach in the context of cooperative financial data.

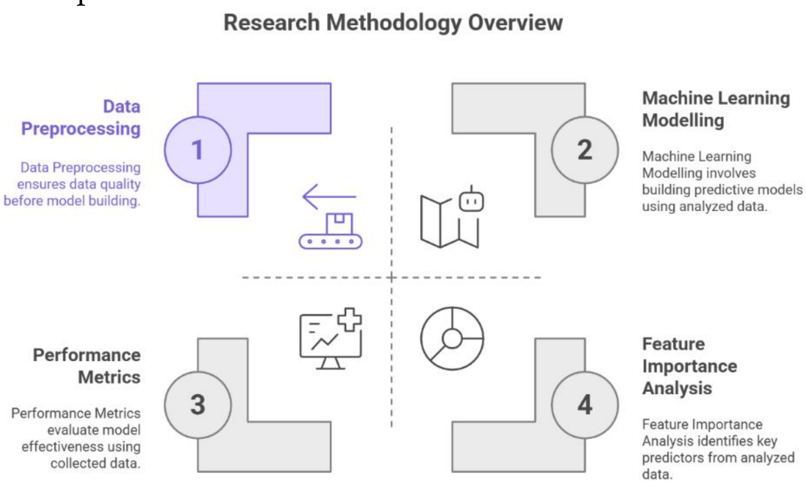

Figure 1. **Research flow**

RESULT AND DISCUSSION

Based on the analyzed correlation matrix (Figure 2), several important relationships between variables in the cooperative credit portfolio were identified. The proportion of savings shows a very strong relationship with savings (correlation 0.96), indicating that these two variables measure almost identical concepts in the context of this study. Similarly, the Initial Valuation Balance has a significant correlation with various deposit and collateral variables (ranging from 0.78-0.94), indicating information overlap between these variables.

Surprisingly, Days Past Due (DPD), a key indicator of payment delays, showed a very weak correlation with almost all other variables, including Loan Amount (0.05) and Deposit Proportion (-0.15). This suggests that the traditional factors considered to influence payment delays may not be entirely relevant in the context of this cooperative, or that other factors are more dominant in influencing members' payment performance.

From the perspective of Loan Amount, this variable shows a moderate negative correlation with membership number (-0.53) but a very weak relationship with savings variables. This correlation pattern reveals the complexity of members' financial dynamics, where the size of the loan is not automatically linked to savings patterns or repayment ability. This finding explains why previous predictive models struggled to achieve high accuracy, as the relationships between variables are non-linear and inconsistent.

The implication of this correlation pattern is the need for a more holistic approach in assessing credit risk in cooperatives. Some variables seem redundant and could be simplified, while new, more representative variables might be needed to capture the essence of members' financial behavior. This result also reinforces previous findings about the model's low predictive power, which is likely due to the absence of a clear relationship between predictor variables and members' actual credit performance.

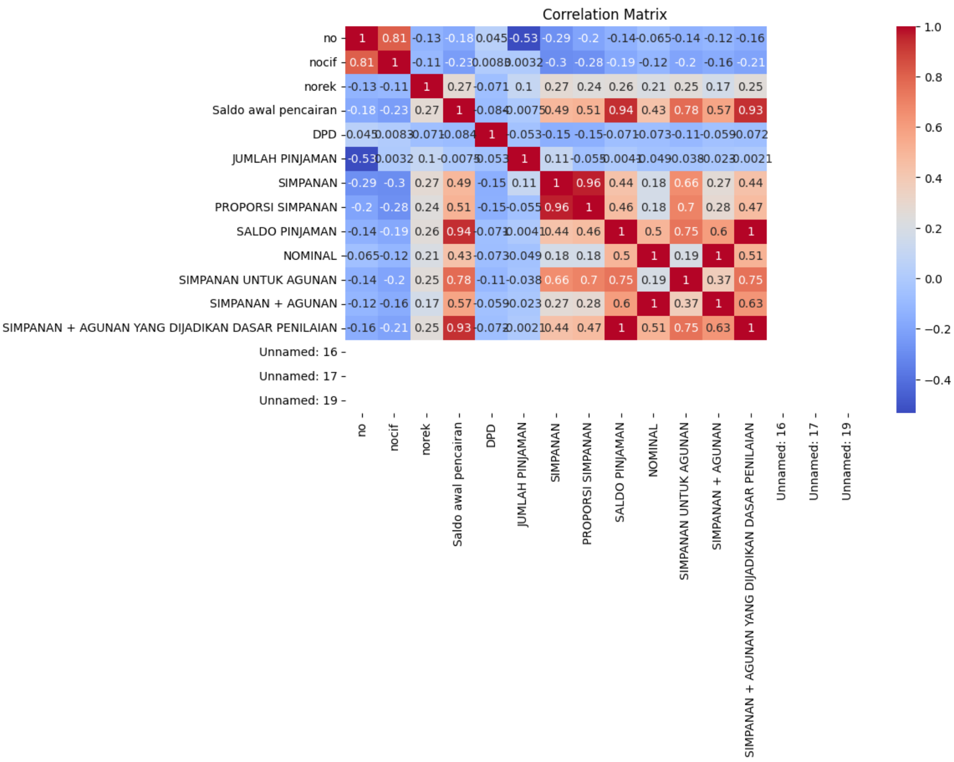

Figure 2. Correlation Matrix

Based on the preprocessing stages that have been carried out, the dataset was successfully separated systematically into two main components. The variable features (X), representing all predictor attributes, have dimensions (718, 9), indicating 718 observations with 9 different characteristics that will be used to predict credit risk. Meanwhile, the target variable (y) with dimensions (718,) serves as a credit performance indicator, which is the focus of prediction in this study. The selection of these features is based on theoretical considerations and their relevance to the context of credit analysis in a cooperative environment.

The data splitting process was then performed by dividing the dataset into training and testing subsets using an 80:20 ratio. With the parameters test_size=0.2 and random_state=42 set, the composition of the training data obtained was 574 samples (80%) and the testing data was 144 samples (20%). This division ensures that the machine learning model has enough data to learn complex patterns, while also leaving a sufficient portion of data to independently test the model's generalization. Using random_state=42 ensures that the splitting process can be consistently replicated, making the experimental results accountable and allowing them to be revalidated with the same outcome.

Based on the evaluation results of the five models tested (Table 1), an interesting picture emerges regarding the predictive capabilities of each algorithm. The Linear, Ridge, and Lasso models show consistency in prediction errors with MSE values around 23-24 trillion and MAE around 91-92 million. What's quite striking is the performance of the ensemble models, Random Forest and XGBoost, which actually show higher MSE values (around 26-27 trillion) compared to the linear models. However, in terms of MAE, these two ensemble models excel with values around 70-72 million, indicating that although the overall error is large, the average absolute error is smaller.

The most crucial aspect is evident from the value of the coefficient of determination (R^2), which is generally very low, even negative. The Ridge and Lasso models achieved a positive R^2 value, although it was very small (0.005), while the Linear, Random Forest, and XGBoost models produced negative R^2 values. This negative R^2 value indicates that these models performed worse than a simple baseline model that only predicts the average value. This finding strengthens the suspicion that the predictor variables used have not yet been able to capture the true complexity of the factors influencing non-performing loans in cooperatives, thus requiring a more comprehensive approach and variables in the modelling.

Table 1. Model: Random Forest, XGBoost

	RandomForest	XGBoost
MSE	26.978.493.775	26.493.389.063
MAE	72.424.444	70.552.553
R^2	-0.142201	-0.121663

The cross-validation results obtained from the five models revealed a highly concerning situation, with all models exhibiting extremely negative R^2 values in each validation iteration. The extremely low R^2 value for Linear at -51579.4455 indicates extreme instability and the inability of the linear model to capture the existing data patterns, while the other models such as Random Forest (-1.1093), and XGBoost (-0.837), although better, still performed far below expectations. This finding reinforces the previous conclusion that the models built lack adequate predictive stability, and the variables used do not have a consistent relationship with the prediction target across different data subsets, thus requiring a more fundamental approach in constructing predictor variables and the modeling framework.

Based on the results of the feature importance analysis from the Random Forest model (Figure 3), it was identified that LOAN BALANCE emerged as the most determinant variable in predicting non-performing loans, although its overall contribution was still considered low. Variables related to savings and collateral, such as SAVINGS FOR COLLATERAL and SAVINGS + COLLATERAL, ranked next, while the NOMINAL variable showed a more marginal influence. This pattern confirms that loan exposure (balance) and collateral (collateral deposits) are the main considerations for the model in assessing credit risk, although the relatively low importance values consistently with the model's overall weak performance indicate that there are still other factors beyond the analyzed variables that significantly influence credit default.

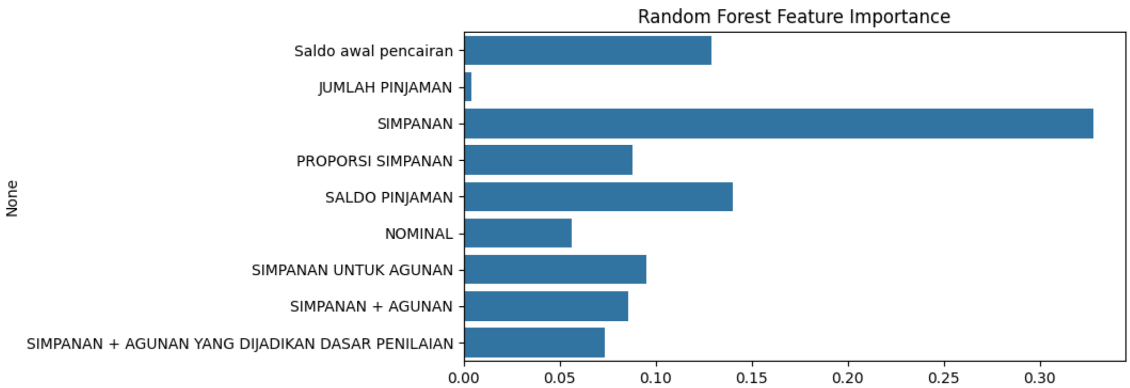

Figure 3. Feature Importance Random Forest

Based on the XGBoost Feature Importance analysis, Initial Disbursement Balance emerged as the most significant predictor influencing model performance, although its overall importance value is still considered low. The variables LOAN AMOUNT and LOAN BALANCE are in second place, which is quite relevant, followed by deposit-related variables such as DEPOSIT and DEPOSIT PROPORTION, which show a weaker influence. This pattern is consistent with previous findings in Random Forest, where quantitative variables related to loan value were more dominant than deposit composition variables. However, the low importance scores for all variables (ranging from 0.00 to 0.20) reinforce the conclusion that the model struggled to find a robust pattern from the existing features, suggesting that there are still gaps in the variable representation or the possible existence of other latent factors not measured in the dataset.

An important finding of this study is the relatively weak influence of Deposit Proportion in predicting non-performing loans. The feature importance values in both Random Forest and XGBoost indicate that deposit-related variables contribute marginally to model performance. One plausible explanation is structural: the nominal value of member deposits may be substantially smaller than the loan exposure, limiting its function as a financial risk buffer.

In many credit unions, compulsory savings serve more as membership instruments than as effective collateral substitutes. If the deposit-to-loan ratio is low, its capacity to absorb credit losses becomes minimal. Consequently, even members with relatively higher deposit proportions may still default when faced with liquidity shocks.

Additionally, within the kinship-based cooperative structure, lending decisions may rely more heavily on relational trust than on strict financial collateralization. This social dimension potentially weakens the statistical relationship between deposit proportion and actual default behavior.

These findings suggest that deposit proportion alone is insufficient as a standalone risk mitigation indicator and should be complemented with behavioral, income stability, or macroeconomic variables in future modelling.

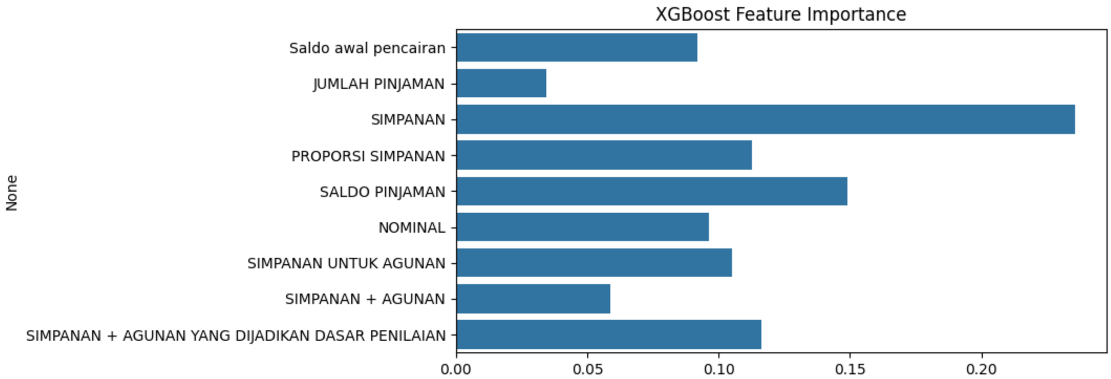

Figure 4. Feature Importance XGBoost

The results of the Grid Search performed on the Random Forest model show that the hyperparameter tuning process successfully explored 216 different parameter combinations thru 5-fold validation, resulting in a total of 1080 fitting processes. The optimal configuration found consists of the combination n_estimators: 400, max_depth: 5, max_features: 'sqrt', min_samples_split: 10, and min_samples_leaf: 4. However, the best performance value achieved still shows a negative score of -0.743, indicating that despite comprehensive optimization of the model architecture, Random Forest was still unable to produce better predictions than a simple baseline model. This finding further confirms the initial suspicion that the root of the problem lies not in the model configuration, but in the inability of the existing predictor variables to capture the complexity of non-performing loan mechanisms in the cooperative environment.

The results of the Randomized Search on the XGBoost model show that the hyperparameter optimization process successfully tested 30 different parameter combinations thru 5-fold validation, encompassing a total of 150 training iterations. The optimal configuration obtained shows conservative parameters with a low learning rate (0.001), n_estimators of 200, max_depth of 5, and strict regularization thru reg_alpha=1 and reg_lambda=10. Despite finding this optimal setting, the model's performance score still shows a negative value of -0.0568, which, although better than other models, still indicates the model's inability to generate meaningful predictions. This finding further strengthens the thesis that the root of the problem lies in the inadequacy of existing predictor variables to capture the mechanisms of non-performing loans, rather than in the technical configuration of the machine learning model.

Based on the evaluation results of the best model after optimization, it is evident that XGBoost_Optimized recorded the highest relative performance with a positive R^2 value of 0.020977 and the lowest MSE of 23,124,275,951, although all models still showed very limited predictive capacity. Random Forest_Optimized excels in the MAE metric (69,923,891), which is significantly lower than other models, indicating its slightly better ability to minimize absolute deviation, although it is inconsistent in other metrics. Overall, the R^2 values, which remain very close to zero for all models, confirm that the hyperparameter optimization process was unable to substantially improve the prediction quality. This suggests that the root of the problem lies in the inadequacy of the predictor variables in capturing the actual mechanisms of non-performing loans, rather than in the model configuration itself.

Table 2. Optimizing the evaluation of the best model

	RF_Optimized	XGB_Optimized
MSE	23.820.183.100	23.124.275.951
MAE	69.923.891	86.938.463
R^2	-0.008486	0.020977

Although this study initially employed regression models to estimate the magnitude of non-performing loans, the primary objective of cooperative risk management is inherently categorical—distinguishing between performing and non-performing loans. The consistently low and negative R^2 values indicate that predicting the exact numeric magnitude of default may not be the most appropriate modelling framework for this dataset.

In practical credit risk management, decision-making is binary in nature (eligible vs. ineligible; performing vs. default). Therefore, a classification-based approach using algorithms such as Random Forest Classifier or XGBoost Classifier, evaluated through a Confusion Matrix, Precision, Recall, F1-Score, and AUC-ROC, may provide more actionable insights. A confusion matrix would allow the cooperative to assess Type I and Type II errors, particularly the model's ability to correctly identify high-risk borrowers (true positives), which is more critical than minimizing numeric prediction error.

Future modelling efforts should therefore shift toward a supervised classification framework to better align statistical modelling with operational credit decision-making.

CONCLUSION

The comparative analysis of machine learning models indicates that XGBoost_Optimized demonstrates slightly better performance than Random Forest_Optimized in predicting credit default within CU Sejahtera Makmur Bersama, as reflected by the lowest Mean Squared Error (23,124,275,951) and the highest R^2 value (0.020977). However, the explanatory power of both models remains extremely limited, with R^2 values close to zero. This finding suggests that the selected financial predictors Days Past Due, Loan Amount, and Savings Proportion are insufficient to capture the complexity of non-performing loan behavior in the cooperative context.

The weak predictive performance implies two important considerations. First, the regression-based approach may not be fully aligned with the operational objective of credit risk management, which is fundamentally categorical in nature (performing vs. non-performing). A classification framework evaluated using a confusion matrix and related metrics may provide more actionable insights for early warning systems. Second, the limited influence of Deposit Proportion indicates that member savings may not function as an effective financial buffer, possibly due to relatively small deposit values compared to loan exposure and the strong kinship-based lending structure inherent in cooperatives.

Overall, the findings highlight that cooperative credit risk cannot be adequately explained by financial indicators alone. Future research should integrate behavioral characteristics, socio-relational factors, and macroeconomic conditions, while adopting classification-based modelling strategies to enhance predictive accuracy and practical applicability in cooperative financial management.

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