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Financial Predictors and Non-Performing Loans at CU Sejahtera Makmur Bersama: A Machine Learning Assessment

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Abstract

Credit unions expand access to member-based finance, yet credit deterioration can undermine institutional resilience. This study assesses the limited predictive value of conventional financial indicators for non-performing loans (NPLs) at CU Sejahtera Makmur Bersama using historical cooperative records for 2020–2023. The submitted analysis contains 718 observations, an 80:20 training–test split, and comparisons involving linear benchmarks, Random Forest, and XGBoost regression. The best reported optimized XGBoost result has $R^2 = 0.020977$, whereas optimized Random Forest has $R^2 = -0.008486$; thus XGBoost is only relatively better among the tested models, and neither result supports operational deployment. The study also identifies unresolved issues concerning the nine-feature model specification, the timing of Days Past Due, and the internal consistency of error metrics. Its contribution lies in showing the limits of financial-only screening and framing a more responsible cooperative-credit assessment that adds repayment behavior, borrower characteristics, collateral quality, and governance. Islamic cooperative-finance principles provide a comparative ethical lens, not a claim that the studied credit union operates under Sharia contracts.

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INTRODUCTION

Member-owned credit unions improve financial participation by pooling savings and extending loans to members who may have limited access to formal banking. Their social purpose, however, depends on prudent lending, reliable repayment, and the protection of members' deposits. A persistent accumulation of non-performing loans (NPLs) threatens liquidity, member confidence, and cooperative continuity. Studies of savings groups and

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credit unions connect inclusion to institutional resilience, while research on NPLs demonstrates the importance of both borrower-level and institutional conditions (Boachie & Adu-Darko, 2022; Anakpo et al., 2024; Carrera-Silva et al., 2024; Atichasari et al., 2023).

Credit deterioration is multidimensional. Loan amounts and outstanding balances describe financial exposure; member savings may reflect available buffers or commitment; and repayment arrears are an observable manifestation of financial distress. Nevertheless, variables that are readily available from accounting systems do not necessarily identify why a member becomes unable or unwilling to repay. Macroeconomic pressures, repayment history, household income shocks, credit terms, collateral liquidity, and monitoring practices may add information unavailable in a purely financial snapshot (Goyal et al., 2023; Naz et al., 2024; Xu et al., 2024).

Machine-learning approaches can capture nonlinear patterns, but predictive value cannot be assumed merely because an ensemble algorithm is used. Prior research demonstrates that credit-scoring performance depends strongly on information quality, validation design, and the definition of the outcome (Khandani et al., 2010; Lessmann et al., 2015; Abdullah et al., 2023; Nwafor & Nwafor, 2023; Bitetto et al., 2024). Recent research also shows the relevance of nontraditional borrower information and the importance of explaining model-based credit decisions (Gambacorta et al., 2024; Černevičienė & Kabašinskas, 2024). These lessons are especially relevant to small cooperative datasets, where limited sample sizes and incomplete borrower records constrain generalization.

The present study revisits the reported modelling exercise at CU Sejahtera Makmur Bersama using records from January 2020 to December 2023. Instead of treating small differences between Random Forest and XGBoost as proof of reliable forecasting, this paper asks what can legitimately be learned from their weak out-of-sample performance. It also distinguishes a continuous overdue-loan amount from a binary probability of default, because those outcomes require different models, interpretation, and evaluation metrics.

The paper makes three contributions. First, it offers an institution-specific assessment of the limits of accounting-oriented indicators for modelling problematic loan balances. Second, it identifies modelling-design questions—particularly predictor definition, temporal ordering, and potential target leakage—that must be resolved before any early-warning claim. Third, it connects responsible cooperative lending with a comparative Islamic-finance perspective emphasizing fairness, transparent contracts, due diligence, and risk governance. The studied institution is a conventional credit union; no Sharia compliance is inferred. The central research questions concern (1) the relative performance of the tested regression models, (2) the adequacy of recorded financial predictors, and (3) the implications for responsible lending and future data collection.

LITERATURE REVIEW AND THEORETICAL FRAMEWORK

Cooperative Lending, Information Asymmetry, and Credit Risk

Cooperatives have a dual objective: meeting members' financing needs while safeguarding a jointly funded loan portfolio. A prospective borrower typically knows more about personal income volatility, repayment priorities, and business conditions than the lender. This information asymmetry can weaken selection and monitoring, particularly if lending decisions depend on a narrow set of administrative variables. Credit-union

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sustainability literature highlights the links among governance, portfolio performance, and member participation (Martins et al., 2021; Anakpo et al., 2024). Therefore, exposure variables and savings measures are useful descriptions of a loan relationship but should not be mistaken for complete measures of repayment capacity or willingness.

Loan Exposure, Savings Commitment, and Borrower Behavior

Loan amount and outstanding balance describe the scale of possible losses, although a large loan is not itself evidence of weak borrower quality. Savings balances and the savings-to-loan ratio may proxy liquidity buffers, membership engagement, or collateral arrangements. Their meaning depends on whether savings are freely withdrawable, pledged, or mechanically linked to loan size. Days Past Due (DPD) is more directly associated with arrears, but its causal and predictive interpretation requires care: a DPD value measured after the assessment date can contain information about an outcome it is supposed to predict. These conceptual distinctions explain why a financial indicator can be associated with existing delinquency without necessarily improving an advance forecast (Kaufman et al., 2012; Naz et al., 2024).

Machine-learning Credit Scoring and Validation

Random Forest averages predictions over decision trees, whereas XGBoost combines sequentially trained trees to address residual prediction errors and regularization (Breiman, 2001; Chen & Guestrin, 2016). Both can model complex interactions but remain sensitive to outcome definition, feature availability, sample design, and validation leakage. Benchmark research shows that algorithm rankings can change with the evaluation criterion and that performance should be judged against simple baselines and intended decisions rather than against another complex model alone (Lessmann et al., 2015). For continuous overdue balances, regression diagnostics such as MAE, MSE, and R^2 are applicable. For an explicitly binary default label, classification metrics such as precision, recall, ROC-AUC, PR-AUC, and calibration are more appropriate. These are distinct tasks and cannot be treated as interchangeable.

Islamic Financial Inclusion as a Comparative Ethical Perspective

Although CU Sejahtera Makmur Bersama is not presented as an Islamic cooperative, its social objectives can be discussed alongside principles relevant to Islamic cooperative finance. Islamic financial-services governance emphasizes prudent risk management, transparent dealings, stakeholder protection, and the responsibility to avoid unjust financing outcomes (Islamic Financial Services Board [IFSB], 2015). In Sharia-compliant cooperatives, the applicable financing contract and allocation of risk must additionally be assessed; risk sharing cannot be presumed for every Islamic contract. This comparative perspective supports proportionate member screening, fair treatment of financially vulnerable borrowers, responsible arrears management, and human review of any algorithmic flag. Research on Islamic microbanking has also identified borrower screening, loan monitoring, enforcement, and branch leadership as interconnected aspects of bad-debt management (Nugroho et al., 2018). It is an ethical and conceptual comparison, not empirical evidence of Sharia-compliant operations at the investigated credit union.

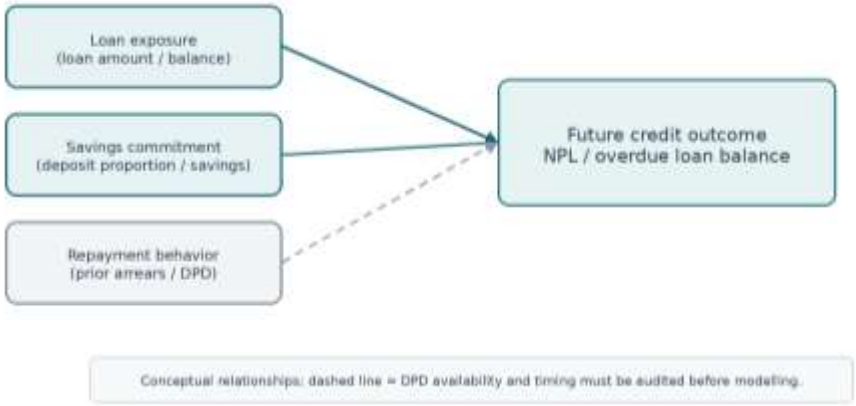
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Conceptual Framework

The conceptual model distinguishes exposure, financial commitment, and prior repayment behavior as potentially complementary sources of information about future problematic loans. Borrower characteristics, economic conditions, collateral quality, and institutional governance may influence the same outcome, but these domains were not measured in the submitted model. Figure 1 depicts hypothesized relationships rather than confirmed causal effects. The dashed DPD pathway specifically signals the need to verify that historical arrears are recorded before the outcome window.

Figure 1. Conceptual Framework



METHODS

Research Design, Setting, and Data Structure

The study uses a quantitative, retrospective case-study design based on cooperative savings and loan administrative records covering January 2020–December 2023. The original report describes purposive inclusion of records with the required information and a final analytical matrix of 718 rows. It does not establish whether each row represents a unique loan, member, loan-period, or transaction; consequently, this revision refers to "observations" rather than assuming one independent borrower per record. The authors must verify the record identifier, the number of unique members and loans, the observation date, missingness, exclusions, and repeat-member structure against the raw dataset before final publication.

Outcome, Predictor Variables, and Feature Mapping

The dependent variable was originally defined as the monetary value of outstanding loans with payments more than 90 days overdue. This is a continuous amount and therefore supports a regression-oriented analysis, not a direct estimate of the likelihood of delinquency. A binary NPL indicator, if desired, must be constructed separately at a specified observation date and prediction horizon. The original variable description names DPD, loan amount, and savings proportion, whereas the reported training matrix has nine features and the feature-importance plots identify nine financial fields. Table 1 makes that difference explicit.

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Table 1. Variables and Reported Analytical Fields

Item	Original Definition or Display	Interpretation / Audit Requirement
Target y	Outstanding loan amount >90 days overdue	Continuous overdue amount; currency, valuation date and zero handling must be checked.
DPD	Average days of overdue payment in one year	Reported in methods and correlation analysis; absent from the displayed nine-feature importance lists. Verify timing and inclusion.
Loan Amount	Amount originally disbursed (jumlah pinjaman)	Exposure indicator; specify whether original principal or current lending amount.
Deposit Proportion	Compulsory + voluntary savings / loan amount	Ratio; verify denominator, pledge status, and measurement date.
Additional displayed fields	Initial disbursement balance; savings; loan balance; nominal; savings for collateral; savings + collateral; savings + collateral used as valuation basis	Nine charted predictors in total when combined with loan amount and deposit proportion; map each to the exact dataset field and calculation.

The model plots list these nine features: initial disbursement balance; loan amount; savings; savings proportion; loan balance; nominal; savings for collateral; savings plus collateral; and savings plus collateral used as the valuation basis. DPD is discussed in the correlation matrix but does not appear among those nine displayed predictors. Accordingly, the existing output does not demonstrate that DPD was included in the fitted Random Forest or XGBoost models. A feature dictionary, code audit, and consistent revised title/variable statement are required before attributing the model's performance to DPD.

Preprocessing and Data Partitions

The original workflow reports exploratory data analysis, mean imputation for missing numerical values, StandardScaler standardization, and a random 80:20 partition using test_size = 0.2 and random_state = 42. The resulting training and testing counts are 574 and 144 observations, respectively. The source does not establish whether imputation and standardization were fitted only to training data or to the entire dataset before the split. This is a material reproducibility limitation. In a corrected analysis, the data should first be partitioned; any imputer, scaler, and feature-selection transformation should then be fitted exclusively within the training fold using a leakage-safe pipeline (Kaufman et al., 2012).

Potential Leakage, Dependence, and Prediction Timing

Because the target is defined using >90-day arrears, DPD should be allowed as a prospective predictor only when its value is observed at an earlier, documented decision time and the NPL outcome is measured during a later, nonoverlapping interval. Contemporaneous or outcome-derived DPD would represent target leakage rather than genuine advance warning. Likewise, loan balance and collateral-related fields may encode the accounting consequences of arrears if measured after the outcome date. If multiple observations belong to the same member or loan, a random record-level split can also put highly related records into both train and test sets. Prospective re-estimation should therefore adopt a time-based holdout, borrower/loan-group separation where applicable,

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and an explicit forecast horizon. No leakage-free re-estimation is claimed here because raw records, timestamps, and scripts were not supplied.

Model Comparison, Cross-validation, and Tuning

The narrative in the submitted results refers to five algorithms—ordinary linear regression, Ridge, Lasso, Random Forest Regressor, and XGBoost Regressor—although numerical tables are supplied only for the two tree ensembles. Five-fold cross-validation was reported. Random Forest grid search evaluated 216 parameter combinations across five folds (1,080 fits), and XGBoost randomized search considered 30 combinations across five folds (150 fits). The reported optimized Random Forest settings were n_estimators = 400, max_depth = 5, max_features = "sqrt", min_samples_split = 10, and min_samples_leaf = 4. The reported optimized XGBoost settings included learning_rate = 0.001, n_estimators = 200, max_depth = 5, reg_alpha = 1, and reg_lambda = 10. The full search spaces, scoring rule, shuffle options, random seeds for all searches, and any handling of repeated members are not documented and require confirmation.

Evaluation and Comparison Benchmark

Test performance was described using mean squared error (MSE), mean absolute error (MAE), and the coefficient of determination (R^2), with lower MSE/MAE and higher R^2 indicating better fit. The reference mean-prediction benchmark is implicit in the definition of test-set R^2: scores at or below zero indicate little or no advantage over a mean-based benchmark under the relevant evaluation definition. However, no independently fitted and reported dummy-regressor experiment is available from the submitted material. A final study should report that baseline explicitly, with currency units, test-set target distribution, MAE, RMSE, and uncertainty intervals. Classification performance is not reported because the fitted task was a monetary regression rather than a verified binary NPL classifier.

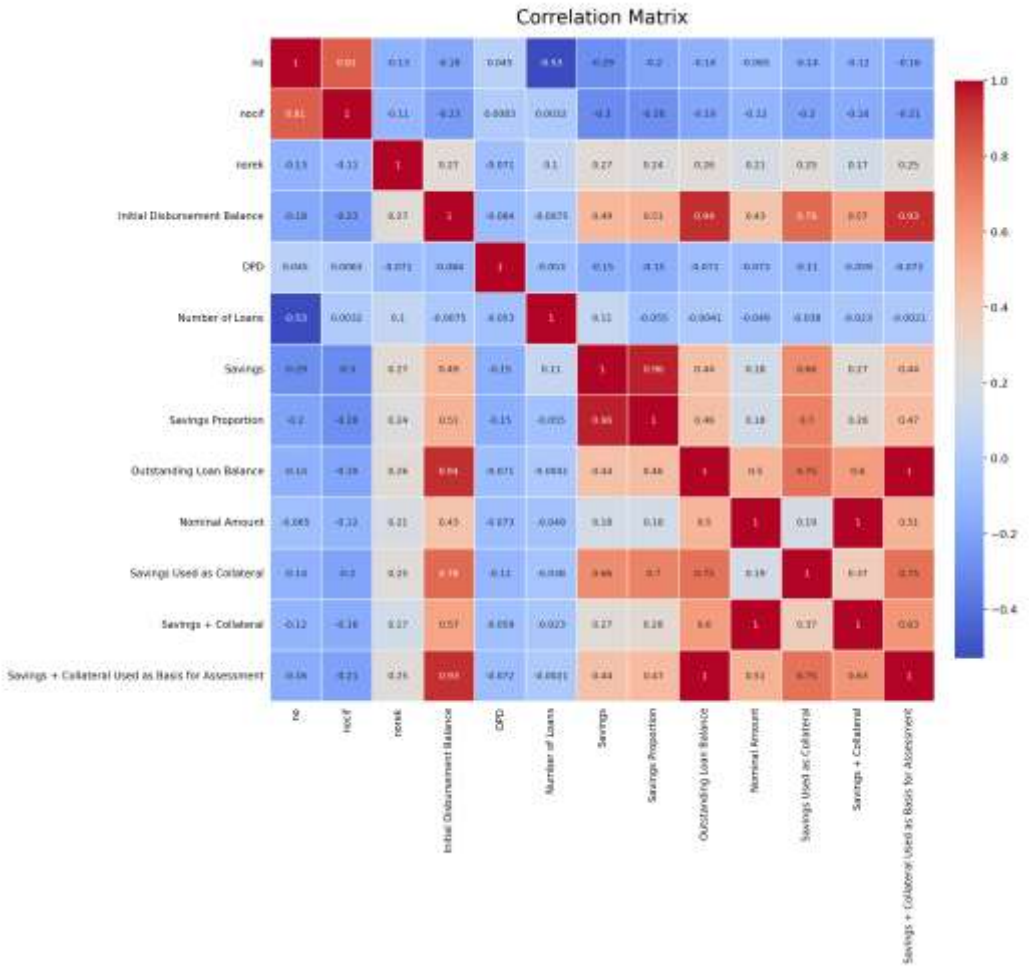
RESULTS AND DISCUSSION

Descriptive Relationships and Data Completeness

The original correlation matrix (Figure 2) indicates a high relationship between savings proportion and savings (reported r = 0.96), and positive correlations between initial valuation balance and several deposit/collateral fields (approximately 0.78–0.94). Such patterns may indicate overlapping financial constructs; they do not independently establish causal effects or additional predictive information. The original correlation graphic shows weak DPD associations with loan amount (approximately r = −0.053) and savings proportion (r = −0.15), although the original narrative describes the former as +0.05. Because these coefficients compare pairs of predictors rather than demonstrating correlations with the prediction target, they cannot substantiate a causal or predictive claim concerning NPLs.

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Figure 2. Correlation Matrix



Holdout Regression Results

Table 2 reproduces the two ensemble comparisons in the submitted manuscript without inferring unreported sample details. The original, untuned models had negative R^2 values: −0.142201 for Random Forest and −0.121663 for XGBoost. Following the reported optimization, XGBoost produced a positive but near-zero R^2 of 0.020977, compared with −0.008486 for Random Forest. Thus XGBoost was relatively better on R^2 among the two optimized models, while neither model demonstrated sufficiently strong explanatory power for operational loan approval or early-warning decisions.

Table 2. Reported Holdout Scores for Ensemble Models

Model	MSE (Reported)	MAE (Reported)	R^2 (Reported)
Random Forest	26,978,493,775	72,424,444	−0.142201
XGBoost	26,493,389,063	70,552,553	−0.121663
Random Forest, optimized	23,820,183,100	69,923,891	−0.008486
XGBoost, optimized	23,124,275,951	86,938,463	0.020977

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A critical arithmetic check remains unresolved: for errors measured on the same observations in the same units, MSE must be at least the square of MAE. The reported monetary-scale MAEs, when squared, greatly exceed the corresponding listed MSEs. Hence the original MSE and MAE columns cannot simultaneously represent conventional untransformed regression metrics for the same target and test predictions. The exact preprocessing/transformations, numeric separators, target unit, inverse transformation, and metric code need to be audited. Until they are reconciled, individual error magnitudes should not be interpreted economically or used to validate deployment. The R^2 comparisons are presented as source-reported, not independently reproduced.

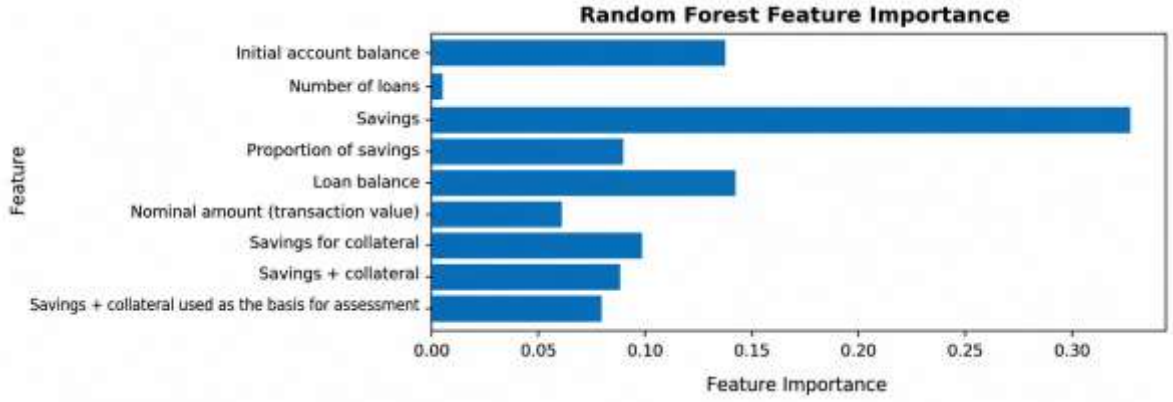
Cross-validation and Tuning Stability

The narrative reports extremely negative cross-validation R^2 for the linear baseline (approximately −51,579.4455), together with less extreme but still negative scores for Random Forest (−1.1093) and XGBoost (−0.837). It further reports a grid-search score of −0.743 for the optimized Random Forest and a randomized-search score of −0.0568 for optimized XGBoost. However, individual fold scores, the exact scoring function, target transformations, and validation grouping were not provided. These figures are therefore descriptive of the submitted record rather than a verified assessment of stability. Large variation between folds would be consistent with unstable estimation, but its precise cause cannot be assigned without inspecting the dataset and code.

Feature Importance and Substantive Interpretation

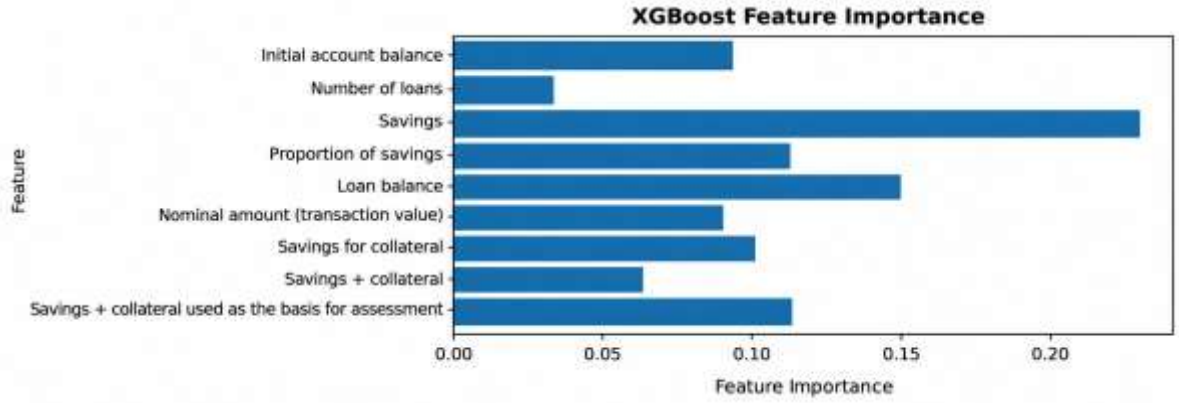
The originally supplied importance graphics identify savings ("SIMPANAN") as the highest-scoring variable in both ensemble plots. Loan balance is also prominent, especially in XGBoost, whereas other variables contribute smaller algorithm-dependent shares. The source narrative instead described loan balance or initial disbursement balance as dominant; this revision follows the graphics rather than that inconsistent prose. Importance scores are relative summaries within a model and should not be read as causal effects or as proof that a predictor is reliable out of sample. Correlated savings and collateral fields can redistribute importance across alternative variables, making single-feature rankings particularly unstable.

Figure 3. Random Forest Feature Importance



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Figure 4. XGBoost Feature Importance



Implications for Cooperative Finance and Islamic Ethical Principles

The substantive result is not that a complex algorithm has solved default prediction, but that a narrow, largely balance-sheet-oriented dataset has not yielded useful predictive separation. Portfolio monitoring should combine accounting fields with verified past-payment trajectories, income and employment volatility, loan age and terms, borrower financial capability, actual collateral quality, and internal governance or collection practices. Broader economic context may explain cohort-level changes in repayment capacity (Goyal et al., 2023; Xu et al., 2024). Any future decision aid should use a meaningful baseline, transparent error analysis, periodic monitoring, and human review rather than replacing cooperative credit officers.

From an Islamic-finance comparative perspective, prudence, contractual transparency, equitable treatment, and member protection offer criteria for responsible model governance. These principles are relevant to the cooperative's inclusion mission but do not establish that the CU uses Sharia contracts. Evidence from Islamic microfinance institutions during the COVID-19 pandemic indicates that non-performing financing weakened the examined relationships between murabahah and ijarah financing and return on assets (Lisa et al., 2023). This evidence concerns Islamic microfinance institutions, not the conventional credit union investigated here. Any attempt to transfer the present analysis to an Islamic savings-and-financing cooperative would additionally require identifying the actual contract types, Sharia oversight and applicable risk-allocation rules (IFSB, 2015). Since predictive performance is weak and reporting inconsistencies remain, automated rejection or pricing of members based on the submitted models would be premature and potentially unfair.

Study Limitations and Future Research

Several limitations define the scope of inference. First, the records describe only one cooperative and a limited observation count, restricting external validity. Second, the unit of observation and member-level dependence have not been verified. Third, the displayed nine-feature set differs from the three named predictors, and historical DPD timing is not established. Fourth, preprocessing order, model search settings, and reported MSE/MAE values require a reproducibility audit. Fifth, the dataset lacks confirmed behavioral, demographic, macroeconomic, detailed repayment-history, collateral-quality, and

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governance variables. These limitations prevent causal claims and make the present regression outputs unsuitable for immediate operational decision-making.

Future work should first construct a timestamped loan-level panel; specify a fixed prediction date and forward outcome window; check loan/member identifiers and data quality; and distinguish the continuous overdue amount from a binary 90-day default event. Experiments should compare transparent baseline regressors or logistic classifiers with the same leak-free time-based validation, fit preprocessing within training folds, report appropriate performance and calibration measures, and examine fairness for vulnerable members. Collecting borrower behavior, repayment trajectories, collateral verification, income shocks, and cooperative governance information would directly test whether richer information addresses the weak predictability documented here (Alvi et al., 2024). Explainability can be considered only after the model reaches a defensible validation standard (Černevičienė & Kabašinskas, 2024).

CONCLUSION

The reported comparison at CU Sejahtera Makmur Bersama shows that optimized XGBoost was only relatively better than optimized Random Forest on R^2 (0.020977 versus −0.008486). These near-zero values indicate that the examined financial data do not adequately capture variation in overdue loan amounts. The results do not justify deployment of either model as a stand-alone credit approval or early-warning tool. Interpretation is further constrained by the unresolved nine-versus-three predictor discrepancy, potential DPD target leakage, and incompatible reported MSE/MAE scales. The study therefore contributes a cautionary case: meaningful cooperative credit-risk analytics require reliable observation timing and richer borrower, repayment, collateral, economic, and governance data, together with transparent validation. These requirements also complement ethical commitments to fairness, prudence, and member protection found in Islamic cooperative-finance discussions.

REFERENCES

Abdullah, M., Chowdhury, M. A. F., Uddin, A., & Moudud-Ul-Huq, S. (2023). Forecasting nonperforming loans using machine learning. Journal of Forecasting, 42(7), 1664–1689. https://doi.org/10.1002/for.2977

Alvi, J., Arif, I., & Nizam, K. (2024). Advancing financial resilience: A systematic review of default prediction models and future directions in credit risk management. Heliyon, 10(21), e39770. https://doi.org/10.1016/j.heliyon.2024.e39770

Anakpo, G., Mishi, S., Tshabalala, N., & Mushonga, F. B. (2024). Sustainability of credit union: A systematic review of measurement and determinants. Journal of African Business, 25(3), 509–530. https://doi.org/10.1080/15228916.2023.2185423

Atichasari, A. S., Ratnasari, A., Kulsum, U., Kahpi, H. S., Wulandari, S. S., & Marfu, A. (2023). Examining non-performing loans on corporate financial sustainability: Evidence from Indonesia. Sustainable Futures, 6, 100137. https://doi.org/10.1016/j.sftr.2023.100137

e-ISSN: 3047-4167
p-ISSN: 3089-6061

Bitetto, A., Cerchiello, P., Filomeni, S., Tanda, A., & Tarantino, B. (2024). Can we trust machine learning to predict the credit risk of small businesses? Review of Quantitative Finance and Accounting, 63, 925–954. https://doi.org/10.1007/s11156-024-01278-0

Boachie, C., & Adu-Darko, E. A. (2022). Ghana: Susu, village savings and loans, credit union, rotating savings system. In Transforming Africa: How Savings Groups Foster Financial Inclusion, Resilience and Economic Development. Emerald Publishing. https://doi.org/10.1108/978-1-80262-053-520221011

Breiman, L. (2001). Random forests. Machine Learning, 45, 5–32. https://doi.org/10.1023/A:1010933404324

Carrera-Silva, K., Rodríguez Ulcuango, O. M., Abdo-Peralta, P., Castelo Salazar, Á. G., Samaniego Erazo, C. A., & Haro Ávalos, D. (2024). Beyond the financial horizon: A critical review of social responsibility in Latin American credit unions. Sustainability, 16(18), 7908. https://doi.org/10.3390/su16187908

Chen, T., & Guestrin, C. (2016). XGBoost: A scalable tree boosting system. Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, 785–794. https://doi.org/10.1145/2939672.2939785

Černevičienė, J., & Kabašinskas, A. (2024). Explainable artificial intelligence (XAI) in finance: A systematic literature review. Artificial Intelligence Review, 57, 216. https://doi.org/10.1007/s10462-024-10854-8

Gambacorta, L., Huang, Y., Qiu, H., & Wang, J. (2024). How do machine learning and non-traditional data affect credit scoring? New evidence from a Chinese fintech firm. Journal of Financial Stability, 73, 101284. https://doi.org/10.1016/j.jfs.2024.101284

Goyal, S., Singhal, N., Mishra, N., & Verma, S. K. (2023). The impact of macroeconomic and institutional environment on NPL of developing and developed countries. Future Business Journal, 9, 45. https://doi.org/10.1186/s43093-023-00216-1

Islamic Financial Services Board. (2015). Core Principles for Islamic Finance Regulation (Banking Segment) (IFSB-17). https://www.ifsb.org/

Kaufman, S., Rosset, S., Perlich, C., & Stitelman, O. (2012). Leakage in data mining: Formulation, detection, and avoidance. ACM Transactions on Knowledge Discovery from Data, 6(4), Article 15. https://doi.org/10.1145/2382577.2382579

Khandani, A. E., Kim, A. J., & Lo, A. W. (2010). Consumer credit-risk models via machine-learning algorithms. Journal of Banking & Finance, 34(11), 2767–2787. https://doi.org/10.1016/j.jbankfin.2010.06.001

Lessmann, S., Baesens, B., Seow, H.-V., & Thomas, L. C. (2015). Benchmarking state-of-the-art classification algorithms for credit scoring: An update of research. European Journal of Operational Research, 247(1), 124–136. https://doi.org/10.1016/j.ejor.2015.05.030

e-ISSN: 3047-4167
p-ISSN: 3089-6061

Lisa, O., Nugroho, L., Orban, I., Utami, W., & Nugraha, E. (2023). The performance of Islamic microfinance institutions in the COVID-19 pandemic: Is asset quality important? Sosyoekonomi, 31(58), 145–160. https://doi.org/10.17233/sosyoekonomi.2023.04.07

Martins, P., Pinheiro de Lima, E., Bortoluzzi, S. C., & Gouvea da Costa, S. E. (2021). Performance assessment of the operations strategy of credit unions. International Journal of Productivity and Performance Management, 72(1), 109–136. https://doi.org/10.1108/IJPPM-10-2020-0521

Naz, F., Lutfullah, T., Pervaiz, S., & Ahmad, M. I. (2024). Factors influencing loan delinquency in microfinance institutions: A literature review. In Microfinance: Interventions in Challenging Contexts (pp. 75–90). Springer. https://doi.org/10.1007/978-981-97-5388-8_5

Nugroho, L., Villaroel, W., & Utami, W. (2018). The challenges of bad debt monitoring practices in Islamic micro banking. European Journal of Islamic Finance, (11). https://doi.org/10.13135/2421-2172/2758

Nwafor, C. N., & Nwafor, O. Z. (2023). Determinants of non-performing loans: An explainable ensemble and deep neural network approach. Finance Research Letters, 56, 104084. https://doi.org/10.1016/j.frl.2023.104084

Xu, Q., Liu, C., Luo, J., & Liu, F. (2024). Using machine learning to investigate the determinants of loan default in P2P lending: Are there differences between before and during COVID-19? Pacific-Basin Finance Journal, 102550. https://doi.org/10.1016/j.pacfin.2024.102550