Data-Driven Approach in Determining Problem Credit Management Strategies in the Small & Medium Enterprises Banking Sector

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Submitted:
November 22, 2025

Revised:
December 28, 2025

Accepted:
January 29, 2026

Published Online:
January 31, 2026

ABSTRACT

The increase in non-performing loans in the SME sector represents a major challenge for the banking industry, as it directly affects financial stability and profitability. Conventional credit risk assessment approaches are considered insufficient in detecting potential defaults at an early stage. This study aims to apply a data-driven approach to determine effective strategies for managing non-performing loans in the SME banking sector. The research utilizes historical SME credit data from Bank X Regional 11 and applies a Random Forest machine learning algorithm to predict credit collection. The analyzed variables include payment behavior, credit structure, and the financial condition of debtors. The results indicate that the last payment date is the most influential variable in predicting credit risk, followed by loan tenor, loan realization timing, interest rate, and savings balance. The Random Forest model demonstrates high accuracy and stability in credit risk classification. Based on these findings, non-performing loan management strategies are formulated using the G-STIC framework integrated with the 3-C approach (Character, Capacity, Capital), emphasizing early warning systems, credit structure adjustments, and debtor-based risk control. This study provides practical insights for banks in enhancing objectives and sustainable SME credit risk management.

***Keywords**: Data-Driven Approach, Non-Performing Loans, SMEs, Random Forest, Risk Management.*

INTRODUCTION

The banking sector plays a vital role in national economic development through its function as a financial intermediary, mobilizing public funds and channeling them to productive sectors, particularly Small and Medium Enterprises (SMEs). SMEs significantly contribute to employment, value creation, and economic resilience (Algan, 2019; Enaifoghe, 2023). Therefore, sustainable SME financing is essential not only for banking business growth but also for financial system stability and broader economic development (Chibueze, 2021). However, SMEs carry relatively higher credit risk due to their sensitivity to economic fluctuations, limited financial records, and dependence on market conditions. This risk is reflected in the Non-Performing Loan (NPL) ratio, a key measure of credit quality and bank performance (Brik, 2024). Elevated NPL ratios can reduce profitability, increase provisioning, and threaten banking stability. To maintain prudential standards, the Financial Services Authority (*Otoritas Jasa Keuangan*/OJK) sets a gross NPL threshold of 5%, beyond which banks may face regulatory and operational consequences.

Empirical data highlight the relevance of this issue. The Indonesian banking sector maintained an NPL ratio below the regulatory threshold during the 2020–2024 period,

JIMKES
Jurnal Ilmiah Manajemen Kesatuan
Vol. 14 No. 1, 2026
pp. 1389-1402
IBI Kesatuan
ISSN 2337 – 7860
E-ISSN 2721 – 169X
DOI: 10.37641/jimkes.v14i1.4906

although temporary spikes were observed during the COVID-19 pandemic due to economic contraction, reduced consumer purchasing power, and pressure on business operations. Post-pandemic recovery from 2022 to 2024 saw a gradual improvement in NPL levels, driven by increasing domestic demand and proactive credit restructuring policies by banks and regulators (Dimri, 2023). While these aggregate trends suggest resilience, they do not capture the heterogeneous conditions across different bank segments and regions, particularly within the SME sector, where credit risk dynamics remain concerning.

Internal data from Bank X Regional 11 reveals a stark illustration of this challenge. The SME segment's NPL ratio increased significantly from 6.10% in June 2024 to 8.19% in July 2025, surpassing the regulatory threshold and exceeding the levels observed in the micro and consumer credit segments. This trend indicates structural weaknesses in credit risk management, rather than short-term cyclical fluctuations (Siraj et al., 2024). The declining NPL coverage ratio during 2023–2024 further emphasizes a reduced protective buffer against potential credit losses, highlighting the urgency of targeted interventions in this segment. According to Bank Indonesia Regulation Number 15/2/PBI/2023, banks with a net NPL ratio above 5% may be subject to intensive supervisory measures, reinforcing the regulatory importance of addressing SME credit risk proactively.

Traditional credit risk management approaches, which are reactive and rely on post-default evaluations, are inadequate to address SME credit challenges. Advances in machine learning enable banks to adopt predictive, data-driven models that detect risk patterns before loans become non-performing (Gafsi, 2025). Research by Nkambule et al. (2024) shows that machine learning models can improve NPL prediction accuracy by over 90% compared to conventional statistical methods. Algorithms such as Decision Tree, Random Forest, and K-Nearest Neighbor (KNN) are effective in handling complex data, offering interpretability, stability, and flexibility in identifying non-linear risk patterns.

Recent studies corroborate the effectiveness of these methods in practical banking contexts. Wulandari (2019) reported 81% prediction accuracy using the Decision Tree C4.5 algorithm, while Pratama and Nugroho (2024) found that Random Forest improved predictive accuracy to 85%. International studies by Kuyoro et al. (2022) suggest that Random Forest consistently achieves accuracy rates exceeding 90% for credit risk classification. These findings highlight that integrating machine learning into credit risk management is not only technically feasible but strategically relevant, enabling banks to make data-informed decisions that optimize risk-return trade-offs and comply with regulatory standards.

Despite the potential of machine learning, a clear research gap exists: most predictive models focus solely on technical accuracy without linking the results to actionable banking strategies. This study addresses this gap by combining predictive analytics with strategic frameworks, including the G-STIC and the 3C approach (Character, Capacity, Capital), ensuring that model outputs are interpretable and actionable for managerial decision-making. By focusing specifically on SME Bank X Regional 11, this study aims to identify the key borrower characteristics that drive NPLs, evaluate the predictive performance of Decision Tree, Random Forest, and KNN algorithms, and propose strategies to integrate predictive insights into practical risk management policies.

LITERATURE REVIEW

Determinants of Non-Performing Loans in Indonesian Banks

Non-Performing Loans (NPLs) are a key indicator of banking asset quality and overall financial system stability. The World Bank (2020) defines NPLs as loans with principal or interest payments overdue by more than 90 days, or loans assessed as having a high probability of default, a definition widely adopted as an international supervisory standard. Fanesha et al. (2021) and the Financial Services Authority (2024) emphasize the strategic importance of the NPL ratio, as it reflects banks' credit risk exposure and poses potential systemic risks when elevated. From a risk management perspective, NPLs represent the outcome of weaknesses in credit screening, monitoring, and portfolio management.

Empirical evidence indicates that rising NPLs have significant economic implications. The International Monetary Fund (2021) notes that increasing NPLs reduces bank profitability, constrains liquidity, and limits new lending, thereby weakening the banking intermediation function and economic growth. Furthermore, Berger and DeYoung (2020) document a bidirectional relationship between NPLs and bank efficiency, where poor credit quality both reflects and exacerbates operational inefficiencies. These findings underline that NPL management is a core component of risk governance and financial sector sustainability. Utami (2021) finds that loan tenure has a significant effect on bad credit, indicating that longer or mismatched repayment periods can raise default risk. Similarly, Atieno et al. (2025) demonstrate that credit terms significantly influence non-performing loans in commercial banks, emphasizing that poorly designed loan tenures contribute to higher NPL levels. Empirical studies show that credit ceiling limits on the maximum credit extended significantly influence NPL levels. Poorly calibrated or weakly enforced ceilings lead banks to overextend credit beyond borrowers' capacity, raising default risk and NPL ratios (Louzis et al., 2012). Similarly, credit expansion without adequate risk controls is a key driver of NPL accumulation, highlighting that effective credit ceilings are crucial for banking stability (Anastasiou et al., 2019).

Credit Risk and Non-Performing Loans in Indonesian SMEs

Small and Medium Enterprises (SMEs) play a strategic role in both the global and national economies. The OECD (2021) states that SMEs are the backbone of the global economy due to their significant contribution to Gross Domestic Product (GDP), job creation, and innovation. In Indonesia, the Ministry of Cooperatives and SMEs (2022) noted that MSMEs contribute more than 60% of the national GDP and absorb over 97% of the workforce. However, SMEs are also known as the credit segment most vulnerable to default risk. The World Bank (2020) highlighted a large financing gap in the SME sector, where many businesses struggle to access formal credit due to limited collateral, poor financial reporting quality, and high cash flow volatility. This situation increases the likelihood of non-performing loans.

Research by Nugroho et al. (2021) shows that SME loans statistically have a higher NPL risk than corporate loans. This risk stems from SMEs' dependence on short-term market demand, weak business diversification, and limited managerial capabilities. The European Banking Authority (2024) also confirms that SME NPL ratios tend to increase during periods of macroeconomic stress, such as rising interest rates and slowing global demand. In the Indonesian context, the Financial Services Authority (2024) emphasized that although the national gross NPL is relatively controlled, the contribution of MSME loans to total NPL remains significant. Therefore, credit risk management in the SME sector is a strategic issue that requires a more adaptive and data-driven approach. Several studies indicate that individual-level credit behavior variables, such as outstanding debt balance and payment history, have a significant impact on default probability. Bhandary and Ghosh (2025) show that historical credit information, including loan balance and repayment patterns, enhances default prediction in credit classification models. Similarly, Muñoz et al. (2023) identify repayment history as a key predictor of creditworthiness, significantly improving model performance and confirming the critical role of payment history in assessing default risk.

Machine Learning for Predicting SME Non-Performing Loans in Indonesia

Traditional approaches to credit analysis, such as financial statement-based assessments and the 3Cs (Character, Capacity, and Capital) principle, have long been used as the basis for credit decision-making. Markov (2022) stated that traditional credit analysis using financial statements and the 3Cs (Character, Capacity, and Capital) framework has long been the basis for assessing MSME creditworthiness. Utami and Rahman (2021) argued that financial statement-based analysis is static and often fails to capture dynamic debtor behavior. Campbell et al. (2019) added that character assessments are subjective and dependent on analyst interpretation, potentially introducing bias. Ayyagari et al. (2023) emphasized that excessive reliance on collateral limits access to financing for productive SMEs lacking sufficient assets. Therefore, a predictive approach integrating financial and non-financial data is needed for early credit risk detection.

Machine Learning (ML), a subset of AI, enables data-driven predictions and has become essential in banking credit risk management (Alpaydın, 2020). Supervised learning, which uses labeled historical data, is most relevant for NPL prediction (James et al., 2021). ML models can improve credit risk prediction accuracy by up to 20% over traditional methods, with decision tree-based algorithms like Random Forest and Gradient Boosting excelling at capturing non-linear relationships in SME default prediction (Hossain et al., 2025; Agboola, 2025). Distance-weighted KNN further enhances classification on large credit datasets (Amer et al., 2025). The G-STIC framework aligns strategic objectives with operational tactics and performance control, while successful credit risk strategies require adaptive control responding to economic changes (Kotler et al., 2021; Chernev, 2022; Johnson et al., 2023). Given that SME NPLs are influenced by debtor factors, macroeconomic conditions, and bank risk management quality, integrating ML-based predictive methods with frameworks like G-STIC enables accurate, adaptive, and sustainable credit risk management.

RESEARCH METHODS

This study employs a quantitative approach with a descriptive-analytical design, aiming to analyze historical credit data of SME Bank X customers and develop a predictive model for Non-Performing Loan (NPL) risk. Quantitative methods are particularly suitable for analyzing numerical data and supporting objective decision-making processes (Creswell & Creswell, 2017). The research focuses on SME Bank X customers with active credit facilities, utilizing secondary data obtained from the bank's internal systems. The data covers historical customer credit records, which are considered reliable and highly relevant to the research objectives (Hair et al., 2019).

The study examines credit collectibility as the dependent variable, serving as an indicator of NPLs, while the independent variables include credit term, credit ceiling, debit balance, payment history, savings balance, and interest rate level. To ensure a balanced representation of credit performance, stratified sampling based on credit collectibility status is applied. This method is particularly recommended for handling imbalanced financial datasets, as it maintains proportionality between current and non-performing loans.

Data analysis begins with descriptive techniques to outline the characteristics of customer credit data, followed by Exploratory Data Analysis (EDA) to detect patterns, outliers, and data distribution. Correlation analysis is also conducted to identify relationships among variables and assess potential multicollinearity. For predictive modeling, the study employs decision tree and random forest algorithms, selected for their ability to handle non-linear data and their interpretability in the context of credit risk assessment. The dataset is split into 70% training and 30% testing sets, with 5-fold cross-validation applied to enhance model generalization. Model performance is evaluated using a confusion matrix, with metrics including accuracy, precision, recall, F1-Score, and Area Under the Receiver Operating Characteristic Curve (AUC-ROC), focusing specifically on the model's ability to detect risky credit at an early stage.

The overall research process is guided by the Cross-Industry Standard Process for Data Mining (CRISP-DM) framework, which encompasses business understanding, data understanding, data preparation, modeling, evaluation, and deployment. By adhering to this structured framework, the study ensures that the methodology is systematic, reproducible, and aligned with the strategic objectives of the bank (Wirth & Hipp, 2021). This approach not only facilitates robust predictive modeling but also provides actionable insights for enhancing SME credit risk management.

RESULTS

Bank X, a national financial institution focused on SME financing, faces increasing credit risk due to the sector's vulnerability to economic fluctuations, limited capital, and heterogeneous managerial capacity. Although the national SME NPL ratio remains below the regulatory threshold of 5%, Bank X Regional 11 experienced a significant increase in SME NPLs from 6.10% in June 2024 to 8.19% in July 2025, exceeding both regulatory limits and the bank's risk appetite (Financial Services Authority, 2024).

This deterioration has led to higher Allowance for Impairment Losses (*Cadangan Kerugian Penurunan Nilai*/CKPN), reduced profitability, and potential pressure on capital adequacy and reputation, indicating weaknesses in credit underwriting and post-disbursement monitoring. To address this issue, this study develops a machine learning–based Early Warning System (EWS) for SME credit risk. Model performance is evaluated based on improved identification of high-risk debtors, enhanced credit decision quality, and the targeted reduction of the SME NPL ratio to ≤5% within a 12–18 month horizon. The proposed framework applies Decision Tree, Random Forest, and K-Nearest Neighbor algorithms, integrated with the G-STIC framework and the 3-C approach (Character, Capacity, and Condition) as the basis of Bank X's risk management policy.

The analysis used historical credit data from SME Bank X Regional 11 covering June 2024–July 2025. The initial dataset comprised 36,000 observations, from which 2,762 observations were selected using stratified sampling for modeling. The dataset includes 10 attributes: one target variable (KOL_ADK1) and nine predictor variables representing customer credit, financial, and liquidity characteristics.

Initial analysis identified a class imbalance, with current loans accounting for 94.8% and non-performing loans for 5.2%, indicating the need for imbalance handling during data preparation to avoid model bias. Data preparation involved data cleaning, structural validation, missing value treatment, and class imbalance management, resulting in a final dataset of 2,762 observations. Missing values occurred only in the SAVINGS variable and were addressed through zero imputation, as they indicate the absence of an active savings balance. The post-imputation descriptive statistics are presented in Table 1.

Table 1. Descriptive Statistics of Research Variables

Collectibility	Type	Missing	Minimum	Maximum	Average / Values
KOL_ADK1	Binominal	0	0	1	Values: 0 (2620), 1 (2620)
RATE	Real	0	0.018	0.163	Average: 0.088
JK_WKT (BLN)	Integer	0	6	369	Average: 59.257
PLAFON	Real	0	10100000	787500000	Average: 469004827.386
BAKI_DEBET	Real	0	0	7874497827	Average: 390984597.215
REALIZATION DATE	Polynominal	0	31-10-2024 (1)	26-12-2022 (67)	Values as displayed
DUE_DATE	Polynominal	0	31-12-2027 (1)	30-07-2026 (86)	Values as displayed
LAST_PAYMENT_DATE	Polynominal	0	30-03-2025 (1)	31-07-2025 (492)	Values as displayed
SAVINGS	Real	0	0	21000000000	Average: 11630078.728
TABUNGAN	Integer	0	0	7073774203	Average: 17341679.661

The descriptive statistics in Table 1 provide an overview of the characteristics of the credit dataset used in this study. The target variable (KOL_ADK1) shows a balanced distribution in the modeling sample, indicating that stratified sampling was effective in preserving class representation. The predictor variables exhibit substantial variation across interest rates, loan tenures, credit limits, outstanding balances, payment amounts, and savings balances, reflecting heterogeneous financial conditions among SME borrowers. The date variables realization_date, due_date, and last_payment_date show consistent temporal ranges and were therefore retained as informative features to capture repayment behavior and credit maturity patterns. Following descriptive analysis, the dataset was divided using a stratified 90:10 train–test split. To mitigate class imbalance in the training data, the SMOTE technique was applied, ensuring a balanced class distribution and enabling the models to learn credit risk patterns more effectively.

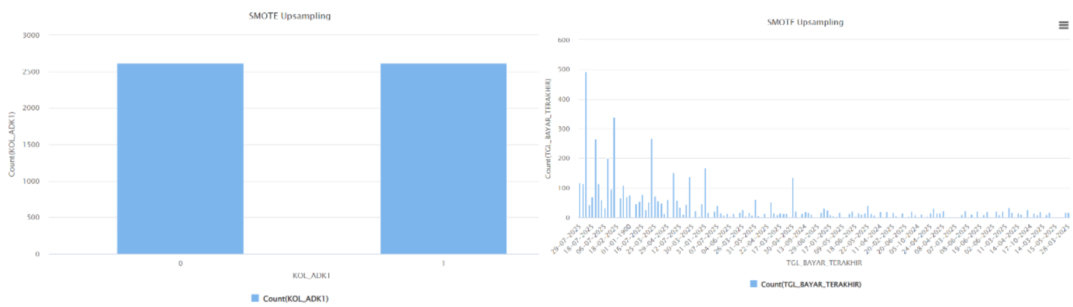
The descriptive statistical results of the main attributes are shown in Table 2, which shows that financial variables such as ceiling, debit balance, payment amount, and savings have a very wide distribution with a high standard deviation, reflecting the heterogeneity of the risk profile of SME customers.

Table 2. Descriptive Statistics of Credit Attributes

Attribute	Count	Mean	STD	Min	Max
KOL_ADK =Collectibility	5240	-	-	0/1	0/1
LAST_PAYMENT_DATE =Last Payment Date	5240	-	-	07-31-2024	07-25-2025
JK_WKT (BLN) =Time Period in Months	5240	59.24	35.462	6	369
REALIZATION DATE =Credit Realization Date	5240	-	-	10-31-2024	05-04-2024
BALANCED DEBIT = Outstanding Loan	5240	390421978.816	512823748.915	0	7874497827
DUE_DATE =Due Date	5240	-	-	12-31-2027	03-25-2026
CEILING =Credit limit	5240	468845470.702	524611292.947	101000000	7875000000
JMLH_BYR = Payment Amount	5240	11630260.925	65947774.233	0	2100000000
SAVINGS = Saving Balance	5240	14200360.233	122619474.059	0	7073774203
RATE =Flower	5240	0.088	0.030	0.018	0.163

Table 2 shows that the SME credit portfolio is highly heterogeneous. Credit term (JK_WKT) averages 59.24 months with a wide range, indicating varied loan durations. Outstanding loan (BALANCED DEBIT) and Credit limit (CEILING) show large variability, reflecting differences in loan amounts. Payment amount (JMLH_BYR) and Savings balance (SAVINGS) also vary greatly, highlighting diverse debtor liquidity and repayment behavior. Interest rate (RATE) ranges from 1.8% to 16.3%, showing variation based on credit risk and loan characteristics. These results emphasize the need for predictive models and early warning systems to effectively manage NPL risk.

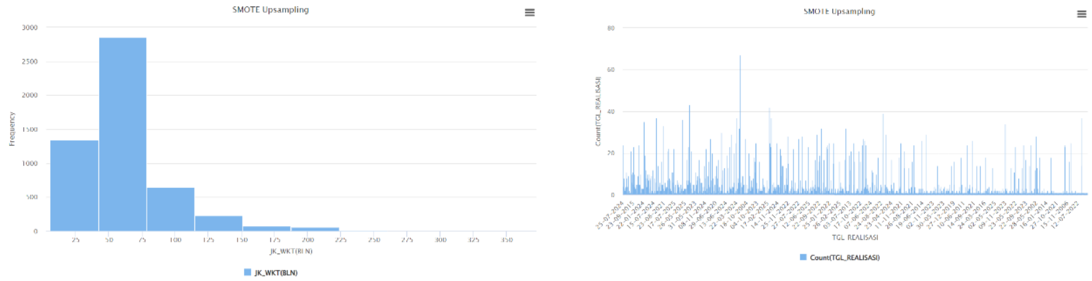
To strengthen the understanding of data patterns, visualization was performed using RapidMiner after applying SMOTE, which is shown in Figure 2.



(a) (b)

Figure 1. (a) Collectibility Distribution (b) Last Payment Date

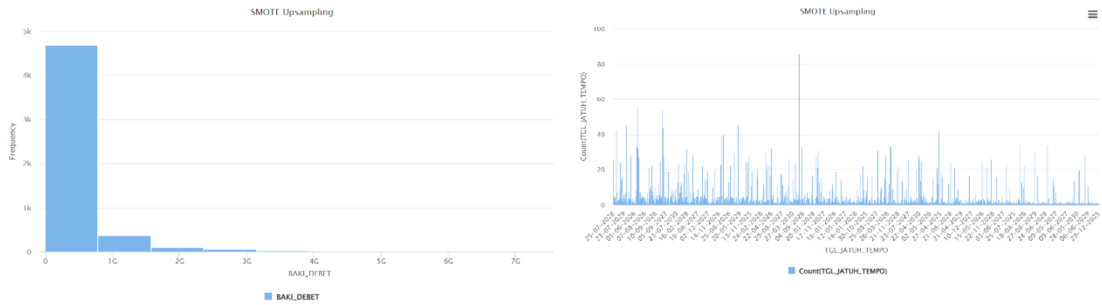
Figure 1 presents the results of the SMOTE upsampling process. Figure 1(a) shows the collectibility distribution (kol_adk1), indicating that the two classes are evenly balanced after upsampling, which helps reduce model bias toward the majority class. Meanwhile, Figure 1(b) illustrates the distribution of the last payment date, highlighting repayment activity concentrated on specific dates and reflecting observable payment behavior patterns over time.



(a) (b)

Figure 2. (a) Credit Terms (b) Realization Dates Reflect Variations in Credit Age.

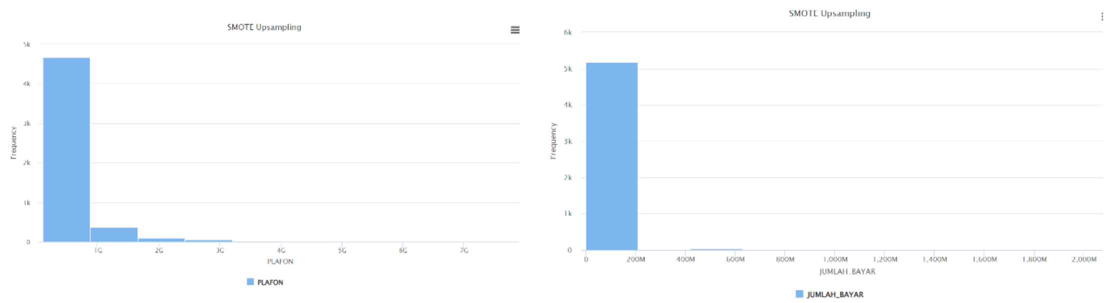
Figure 2 illustrates the characteristics of credit tenure and realization timing after the smote upsampling process. Figure 2(a) shows the distribution of credit terms (jk_wkt_bln), indicating substantial variation in loan maturity, with a higher concentration of loans in shorter to medium tenures and fewer observations at longer terms. Figure 2(b) presents the distribution of realization dates, reflecting fluctuations in credit disbursement activity over time and capturing temporal patterns in loan origination behavior.



(a) (b)

Figure 3. (a) Debit Balance (b) Maturity Dates

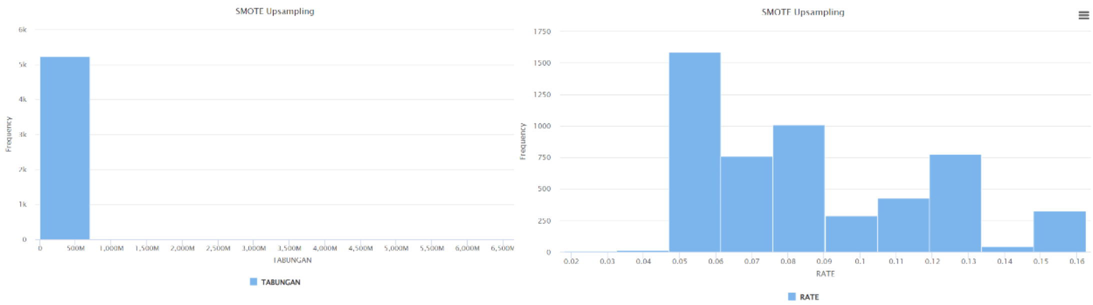
Figure 3 presents the distribution of (a) debit balances and (b) maturity dates after SMOTE upsampling. The debit balance distribution is highly right-skewed, with most observations concentrated at lower balance values and only a few accounts exhibiting high debit amounts. Meanwhile, the maturity date distribution shows varying frequencies across time periods, with several noticeable peaks, indicating uneven concentrations of accounts maturing at specific intervals.



(a) (b)

Figure 4. (a) Credit Ceiling (b) Payment Amounts

Figure 4 shows that the majority of MSME loans have a credit ceiling in the lowest range (0–1C), with approximately 40 occurrences, while higher credit limits are much less frequent, with very few loans exceeding 2C. Similarly, payment amounts are concentrated in the lower bracket (0–200M), decreasing sharply as the amounts increase, with minimal activity beyond 400M. These patterns indicate that the upsampled SME data is heavily skewed toward smaller loan values and lower repayment obligations, suggesting that most SMEs operate with limited credit facilities and modest payment capacities.



(a) (b)

Figure 5. (a) Savings Distribution (b) Interest Rate

Figure 5 shows that MSME savings are heavily concentrated in the lowest range (0–500M), with approximately 50 occurrences, and drop sharply for higher brackets, with virtually no activity beyond 1,500M, indicating that most MSMEs maintain minimal savings balances. The interest rate distribution is more varied, with the highest frequency around 0.04–0.05 (about 1,500 occurrences), followed by notable concentrations at 0.07–0.08 (around 1,000 occurrences) and 0.11–0.12 (approximately 750 occurrences), suggesting multiple common interest rate tiers in MSME lending, generally ranging from 2% to 16%. Together, these patterns reflect the financial constraints of MSMEs with limited savings and the varied interest rate structures they face in the upsampled SMOTE data. The unit of analysis in this project is one active SME credit facility per customer. The independent variables are measured during the observation period (t), while the target variable (KOL_ADK1) is determined during the evaluation period (t + Δ). This approach ensures no information leakage and makes the model a prospective, rather than a reactive, early warning system.

Credit risk modeling for Bank X Region 11 was conducted using a machine learning classification approach with KOL_ADK1 as the target variable (0 = current credit, 1 = non-performing loan) and predictors including rate, credit ceiling, term, outstanding debit, payment amount, savings, and payment dates. Three algorithms were tested: Decision Tree, Random Forest, and K-Nearest Neighbors (KNN), following stages of data import, missing value handling, binomial transformation, normalization, class balancing with SMOTE, a 90:10 train-test split, and evaluation using confusion matrices and classification metrics. The Decision Tree achieved 96.18% accuracy and 96.95% recall for NPLs, while Random Forest showed the best performance with 97.52% accuracy, 98.07% precision, 96.95% NPL recall, and an AUC of 0.994, demonstrating strong stability and non-linear handling. KNN performed lower, with 92.75% accuracy and 87.40% NPL recall, and was more sensitive to noise and data scale. Spearman rank correlation analysis identified the most influential variables for non-performing loans as Last Payment Date (ρ = +0.423), Time Period (ρ = +0.111), Realization Date (ρ = +0.059), Rate (ρ = −0.044), and Savings (ρ = −0.029).

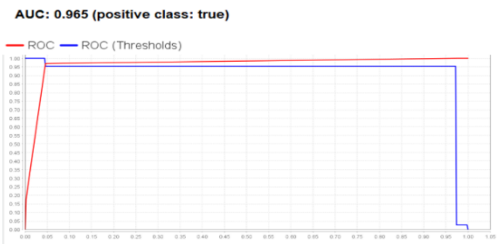
Model performance evaluation was conducted to determine the optimal classification algorithm in predicting the credit risk of Bank X Region 11 customers. The assessment was not only based on the overall accuracy level, but also considered the model's ability to detect NPL as a positive class, which has the highest risk cost implications for the bank. The three algorithms evaluated in this study include Decision Tree, Random Forest, and

KNN. The evaluation was conducted using accuracy, precision, recall, F1-score, and Area Under Curve (AUC) metrics. A summary of the evaluation results is presented in Table 3.

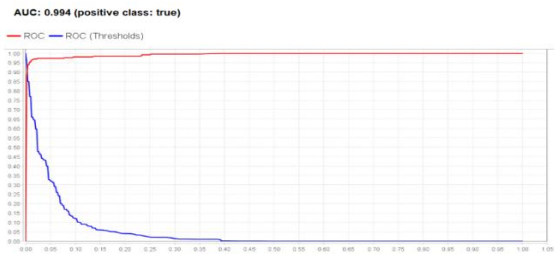
Table 3. Comparison of Classification Algorithm Models

Model	Accuracy	Precision	Recall	F1-Score	AUC
Decision Tree	96.18%	95.49%	96.95%	96.21%	0.965
Random Forest	97.52%	98.07%	96.95%	97.50%	0.994
KNN	92.75%	97.86%	87.40%	92.34%	0.962

Based on Table 3, random forest demonstrated the best performance with an accuracy rate of 97.52%, an F1-score of 97.50%, and the highest AUC value of 0.994. These achievements indicate that Random Forest has very strong class discrimination capabilities and an optimal balance between precision and recall compared to the other two algorithms.



(a)



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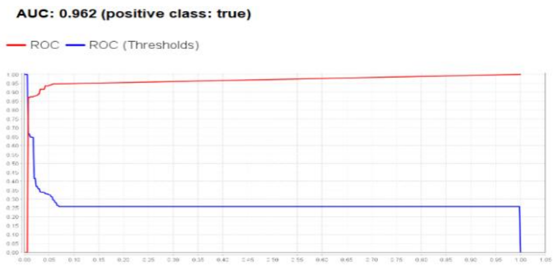

(c)

Figure 6. (a) Decision Tree, (b) Random Forest, (c) KNN

Figure 6 presents the Receiver Operating Characteristic (ROC) curves, which visually support the quantitative evaluation of the models. The Decision Tree shows a curve close to the upper left corner with an AUC of 0.965, indicating consistent and reliable classification performance. Random Forest exhibits the ROC curve nearest to the upper left corner, with a sharp increase in true positive rate at low false positive rates, reflecting its superior ability to distinguish current and non-performing loans across thresholds. KNN, while achieving a high AUC of 0.962, displays a steeper curve, suggesting greater sensitivity to threshold changes. Random Forest demonstrates the highest stability and consistency in performance among the three models.

In the context of credit risk management, NPL recall is the most crucial metric because it directly relates to the model's ability to detect non-performing debtors. False negative errors (non-performing loans predicted as current) carry a much greater risk cost than false positives. The evaluation results show that Random Forest and Decision Tree have the same high NPL recall value (96.95%), but Random Forest excels in terms of precision and aggregate stability. The combination of high precision and strong recall makes Random Forest highly suitable for application as an Early Warning System (EWS) for credit risk, as it is able to detect a large proportion of problem debtors while reducing the risk of excessive false alarms.

Based on both quantitative and visual evaluations, Random Forest emerges as the best algorithm for credit risk classification at Bank X Region 11. It demonstrates the highest accuracy and stability, with a relatively low risk of false negatives, and effectively captures non-linear relationships between credit variables. These strengths make Random Forest highly suitable for data-driven decision-making, supporting efforts to reduce NPL levels and enhance the quality of SME credit portfolios. Consequently, it is recommended as the primary model for developing a decision support and early warning system, serving not only as an analytical tool but also as a strategic instrument for sustainable credit risk management.

DISCUSSION

The findings of this study indicate that the risk of Non-Performing Loans (NPLs) in the SME segment of Bank X Regional 11 is influenced by a combination of payment behavior, credit structure, and the financial condition of debtors. Among the variables analyzed, the last payment date emerged as the most dominant indicator for detecting potential NPLs, confirming that historical payment patterns play a stronger role than nominal credit characteristics alone (Bhandary & Ghosh, 2025). Loan tenure and the timing of credit disbursement also contribute to default risk when misaligned with the debtor's cash flow capacity and revenue cycles, consistent with findings by Rishabh (2024) and Battaglia et al. (2024), who emphasize the importance of flexible loan terms and timing in reducing default probability. Additionally, interest rate levels and savings balances reinforce the analysis that debtors' liquidity and cost of financing indirectly affect the sustainability of loan repayment (Ayyagari et al., 2023).

The implementation of a Random Forest-based collectibility prediction model demonstrated high accuracy and stability in classifying NPL risk, supporting prior research that highlights the superiority of Random Forest in handling non-linear and imbalanced credit datasets (Pratama & Nugroho, 2024). This model's predictive performance allows for more objective and systematic risk assessment, reducing reliance on subjective judgment in traditional credit evaluations (Utami & Rahman, 2021; Markov, 2022). Furthermore, by integrating this data-driven approach with the G-STIC strategic framework and the 3-C principles Character, Capacity, and Condition, the bank can enhance its ability to proactively manage SME credit risk while maintaining strategic alignment between operational tactics and organizational goals (Kotler et al., 2021; Chernev, 2022).

The practical implications of this study are substantial for Bank X's management. Utilizing payment behavior and financial characteristics as core indicators enables the development of a more effective EWS for SME credit risk. Such a system allows the bank to take proactive mitigation measures, including adjusting loan tenors, designing repayment schedules, implementing risk-based pricing, and selectively offering restructuring programs to cooperative debtors. In addition, the Random Forest model improves the consistency and objectivity of risk assessments, supporting sustainable portfolio management by identifying high-risk borrowers with a lower likelihood of false negatives. This proactive and data-informed strategy enhances the bank's capacity to maintain NPL levels within its risk appetite and contributes to long-term financial stability.

This study confirms that integrating machine learning with traditional risk management frameworks provides a robust approach to SME credit supervision. By combining predictive analytics with strategic governance and behavioral data, Bank X can strengthen its credit risk management practices, mitigate potential losses, and optimize portfolio quality. The findings underscore the value of adopting advanced analytics for operational decision-making in banking, particularly in sectors with heterogeneous borrowers and varying financial resilience. The study also highlights the need for continuous monitoring, regular data updates, and integration of additional macroeconomic and sector-specific variables to further enhance the model's predictive accuracy and generalizability.

CONCLUSION

Based on the research and analysis, it can be concluded that the risk of NPLs in the SME segment of Bank X Regional 11 is influenced not only by credit amounts but also by payment behavior, the suitability of the credit structure, and the financial resilience of debtors. Variables such as last payment date, credit term, realization time, interest rate, and savings balance have proven relevant in predicting potential NPLs. The implementation of a machine learning-based collectibility prediction system using the Random Forest algorithm enhances the accuracy of risk assessments and supports the development of an early detection system for non-performing loans. By integrating the G-STIC framework and the 3-C approach, the study provides a strong empirical basis for Bank X to gradually reduce its NPL ratio and maintain credit risk within established limits.

The findings carry significant practical implications for the bank's management in strengthening SME credit risk strategies. Using payment history as a key early warning indicator allows proactive mitigation measures, such as adjusting tenors, arranging payment schedules, implementing risk-based pricing, and selectively providing restructuring to cooperative debtors. Additionally, a Random Forest-based prediction system improves the consistency and objectivity of risk assessments while reducing reliance on subjective judgment in lending decisions. From a policy perspective, the results highlight the importance of combining behavioral and financial data within a structured risk management framework to ensure the long-term sustainability of SME loan portfolios.

This study has several limitations. The data is restricted to a single region, so findings may not represent the entire banking network. The observation period is relatively short, limiting insights into long-term risk dynamics. Moreover, non-financial factors such as sector-specific conditions and macroeconomic variables were not explicitly included in the model. Future research should consider cross-regional data, longer time horizons, and additional macro and sectoral indicators to enhance the generalizability and robustness of SME credit risk prediction models.

Acknowledgement

The author expresses his appreciation and gratitude to the management of Bank X Regional 11 and all parties who provided data and information support during the implementation of this research. He also expresses his gratitude to all parties who contributed directly and indirectly to the successful completion of this research.

FUNDING STATEMENT: This research did not receive any specific grant from funding agencies in the public, commercial, or not - for - profit sectors.

CONFLICTS OF INTEREST: The author declares no conflict of interest.

DECLARATION OF GENERATIVE AI STATEMENT: During the preparation of this work, the author(s) used ChatGPT, Grammarly, and Turnitin in order to assist with language refinement, grammar checking, and originality verification. After using this tool/service, the author(s) reviewed and edited the content as needed and take full responsibility for the content of the publication.

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