

Digital Transformation of Credit Analysis at LPD Through Machine Learning Implementation

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Abstract: The Village Credit Institution (LPD) is a microfinance institution that plays a vital role in the rural economy in Bali. LPDs provide credit through a manual and subjective analysis process conducted by loan officers. This often hinders the objectivity and consistency of credit analysis. Modernization is a strategic step to address this issue. This study aims to analyze the digital transformation process in the LPD credit analysis system through the implementation of machine learning. Initial analysis indicates that debtors with long tenors, high delinquency rates, and high debt-to-income ratios have a higher risk of default. This pattern serves as the basis for learning a machine learning model using Logistic Regression, Decision Tree, Random Forest, and XGBoost algorithms to classify creditworthiness. The XGBoost algorithm demonstrated the best performance with an accuracy of 93% and an AUC of 0.96. Regarding credit approval, this model was able to identify high-risk potential debtors with significantly better accuracy than conventional methods. By processing thousands of historical data points in a relatively short time, machine learning accelerates decision-making and significantly improves the efficiency and objectivity of credit analysis. This supports the realization of digital transformation in credit analysis at LPDs.

Index Terms: LPD, Digital Transformation, Credit Analysis, Machine Learning, XGBoost Algorithm.

1. Introduction

In addition to being a renowned tourist destination, Bali possesses a unique governance system that distinguishes it from other regions in Indonesia. At the village level, Bali has two types of village governance: official villages and traditional villages. Official villages focus on carrying out government administration and public services, while traditional villages uphold Balinese customs and traditions. These two types of villages can have overlapping territories, so that a region can be part of a traditional village and a separate official village.

To support the economy of its community, each traditional village is permitted to establish a business entity in the form of a financial institution called the Village Credit Institution (LPD). This institution is a microfinance institution that plays a vital role in strengthening the economy of rural communities, particularly in Bali. One type of business is distributing credit to its customers, namely residents of the traditional village concerned [1]. Credit is granted after going through an analysis process that is still carried out manually and relies on subjective assessments by credit officers. This conventional method has several limitations, including a lack of consistency in decision-making, limitations in processing historical data, and an increased potential risk of bad debt due to inaccurate and non-objective evaluations [2]. Credit risk has a positive effect on financial distress, indicating that the higher the level of non-performing loans, the greater the likelihood of a bank experiencing financial distress [3]. This traditional credit risk assessment method also has difficulty

coping with dynamic market changes [4].

Many factors can cause a loan to become problematic [5-7]. Internally, problem loans can arise from errors in credit approval or a lack of monitoring of the debtor's payments. External factors can arise from a lack of debtor compliance or problems in the community's economic conditions, including severe economic instability and increased market risks that can negatively impact people's personal lives [8], resulting in the debtor being unable to pay their loan installments. Among these factors, LPDs can only control those related to internal operations.

As community-based financial institutions, LPDs have unique characteristics. Social relationships and trust (trust-based lending) are important factors in the credit decision-making process. However, reliance on these subjective aspects often hinders the objectivity and consistency of credit analysis. Therefore, modernizing credit assessment systems through digital technology is a strategic step to strengthen institutional sustainability in this era of digital transformation [9, 10].

With the rapid development of information technology, financial institutions are required to undertake digital transformation to adapt to the increasingly competitive business environment. Digitizing the credit analysis process is a strategic step to improve operational efficiency, assessment accuracy, and risk management quality [11]. In this context, machine learning presents itself as a data-driven analytical approach capable of identifying complex patterns from historical data to predict the likelihood of default by potential debtors. By utilizing machine learning algorithms, the credit analysis process can be conducted more quickly, objectively, and measurably [12].

The application of machine learning in credit analysis at LPDs not only reflects technological advancements but also forms part of efforts to strengthen the governance of village financial institutions toward a more modern and sustainable system. This study aims to analyze the digital transformation process in LPD credit analysis systems through the implementation of machine learning and assess its effectiveness in improving the efficiency and accuracy of credit risk assessments. Consequently, the implementation of machine learning is not merely the adoption of new technology but a strategic step toward modernizing credit assessment systems within community-based microfinance institutions.

2. Literature Review

2.1. Village Credit Institutions (LPD) and Their Role in the Local Economy

Village Credit Institutions (LPD) are traditional microfinance institutions operating within traditional villages in Bali [13]. According to Bali Provincial Regulation Number 3 of 2017, LPDs function as financial institutions based on local wisdom. The scope of LPD operations is limited to the specific traditional village; expansion into other areas requires a cooperation contract between the respective traditional villages. Management procedures are regulated in Bali Governor Regulation Number 44 of 2017 and are supplemented by customary regulations in the traditional village concerned. To ensure smooth processes and maintain its sustainability, LPDs apply the principle of prudence in their operations. This is fully regulated in the appendix to the Governor's Regulation. In addition to regulating governance, administration, and reporting, this regulation also regulates credit management in detail [14].

LPDs were established not to maximize profits, but to maintain economic resilience, promote equality and business opportunities, increase purchasing power, and facilitate public payment transactions. To achieve these goals, the LPD operates through three main activities: savings, credit, and investment. The LPD collects funds from the public in the form of various types of savings or deposits. These collected funds are then redistributed, either in the form of various types of loans to the public or investments [15, 16].

2.2. Digital Transformation in the Financial Sector

Digital transformation is a multidimensional concept that reconfigures various aspects of an organization through the application of information technology. The resulting impacts can include changes to business models/processes, organizational structures, or work culture [10]. Digital transformation in the context of financial institutions refers to the process of utilizing digital technology to improve operational efficiency, service quality, and decision-making [17].

In the financial industry, digitalization has resulted in various innovations such as mobile banking, fintech lending, and big data-based credit scoring systems. Microfinance institutions, including LPDs, can benefit significantly from this transformation, particularly in accelerating the credit assessment process, reducing the potential for human error, and expanding access to financing for communities previously excluded from conventional banking systems [18].

Digital transformation also has implications for increased transparency and accountability in the credit decision-making process. Through a data-driven system, every decision can be traced and evaluated based on measurable quantitative indicators [19, 20].

2.3. Machine Learning in Credit Analysis

Machine learning is a branch of artificial intelligence that focuses on the ability of a system to learn from data and make predictions or decisions without explicit programming [21]. In the context of credit analysis, there are three levels of application of machine learning-based models that differ in function and complexity, namely:

- Creditworthiness Classification; this model is used to assess whether a prospective debtor is worthy of receiving credit or not, including assessing the possibility of default. There are various methods that can be applied [22], but the commonly used algorithms are Logistic Regression, Random Forest, XGBoost, or Neural Networks. The

main goal is to reduce the risk of bad credit [23, 24].

- **Credit Limit Estimation:** This involves developing a model to estimate the optimal credit amount after eligibility is determined. The model is developed to estimate the optimal credit amount that can be granted to a debtor. A commonly used approach is a continuous regression model (e.g., Linear Regression, Gradient Boosting Regressor), with the target variable being the historical credit limit of similar customers. This model learns from patterns such as monthly income, debt-to-income ratio (DTO), collateral value, job/business stability, payment history, and the duration of the relationship with the institution. The benefits obtained are determining a loan limit that is proportional to the customer's financial capacity while simultaneously avoiding overexposure or underfinancing [25, 26].
- **Risk-Based Pricing** is a model that adjusts interest rates based on the individual risk profile of the customer. This model predicts the probability of default [27], then relates it to the interest rate that will cover that risk:

$$r = r_f + \text{RiskPremium} \quad (1)$$

where:

- r_f = base interest rate (e.g. market interest rate),
- Risk Premium = a function that links the probability of default (PD) and loss given default (LGD) values.

With this model, the higher the risk of default, the higher the interest rate offered. This aims to balance potential losses. Algorithms used in this model include Gradient Boosting Machines (GBM), Bayesian Regression, and Neural Networks to facilitate risk-based pricing adjustments. The practical impacts include pricing fairness among customers and optimizing institutional profits without increasing systemic risk [28, 29].

Various studies have shown that the application of machine learning can improve the accuracy of credit risk analysis compared to traditional methods based on simple financial scores or ratios [30]. Thus, the application of this technology has great potential to support a more objective and efficient credit assessment system in the LPD environment [31].

2.4. Previous Research

Several previous studies have examined the use of machine learning in the context of credit analysis and microfinance institutions. The implementation of systems using machine learning algorithms such as Random Forest can improve the accuracy and consistency of decisions [32]. Regarding the ability to make predictions, a comparative test was conducted on six machine learning algorithms, namely the Logistic Regression algorithm, K-Nearest Neighbor, Support Vector Machine, Random Forest, Decision Tree, and XGBoost. The experimental results showed that the XGBoost algorithm outperformed the other algorithms, followed by the Random Forest and Decision Tree algorithms [33, 34].

Due to the reliance of traditional credit scoring methods on the experience of financial analysts and the fact that most of the information comes from borrowers, lending institutions currently face significant challenges in predicting credit risk. Therefore, machine learning algorithms have been developed to determine whether borrowers are eligible for loans and committed to repayments [35].

The increasing dynamics and complexity of financial data present significant challenges in assessing the accuracy of credit risk predictions. This is a crucial task in the banking and financial sectors [36]. The potential and limitations of successfully developed artificial intelligence-based credit risk models emphasize the need for a more interpretable model architecture. The system must have a standard validation framework, maintain data privacy, and have clear benchmarks. Ease of setup and alignment with existing policies will contribute significantly to increasing public trust [37].

Research specifically addressing the application of machine learning in the context of LPDs, traditional village-based financial institutions, remains very limited. This limitation opens up opportunities for further research to examine how machine learning technology can be adapted to the unique characteristics of LPDs, including organizational structure, data types, and socio-cultural aspects of village communities.

From the above description, it can be concluded that the application of machine learning in credit analysis is an integral part of the digital transformation of microfinance institutions. With the support of historical data and machine learning algorithms, LPDs can improve efficiency, accuracy, and transparency in the credit analysis process. Furthermore, modernizing the credit assessment system through this technology aligns with efforts to strengthen local wisdom-based financial governance that adapts to the developments of the digital era.

3. Research Methodology

3.1. Research Design

This research uses a quantitative approach with a computational experimental design, aiming to analyze the effectiveness of applying machine learning algorithms in the credit analysis process at Village Credit Institutions (LPD). The main focus of this research is to develop and test a credit risk prediction model based on historical debtor data. A quantitative approach was chosen because it can provide measurable and objective results through numerical analysis of available data.

As previously explained in the background section, this research aims to analyze the digital transformation process in the LPD credit analysis system through the implementation of machine learning and assess its effectiveness in improving the efficiency and accuracy of credit risk assessments. The expected outcome is to provide understanding and confidence to LPDs that implementing machine learning in credit analysis is the right choice. It will also enhance LPDs' image in the eyes of rural communities by demonstrating their capability to adapt to and implement the latest technology in their operational processes. This will undoubtedly eliminate the image of subjectivity in credit proposal assessments.

3.2. Data Sources and Types

The study used secondary data obtained from the LPD and processed in confidential form to protect borrowers' confidentiality. As the data contains sensitive personal financial information, the raw dataset is not publicly disclosed. However, future studies should improve the consistency of documenting the entire data collection process in a more detailed and standardized manner. Institutional governance and protection considerations should be incorporated into the implementation framework. Data obtained from credit transaction archives, including:

- Debtor demographic data, such as age, gender, and employment status.
- Financial data, including loan amount, credit term, payment ratio, and arrears history.
- Final credit status, namely whether the debtor is classified as smooth or in bad debt.

All data used is as is, without any selection, sorting, or processing. The data is taken from the credit distribution process over a specific period of time, and first undergoes a data cleansing process.

To avoid target leakage, the study defined the operational prediction setting as the approval-time credit screening. Only variables available at the time of credit application should be used in the deployable model, such as data on applicants' demographics, income, requested loan amount, proposed loan period, information related to conditions/collateral, and prior borrowing status already recorded before the current application.

Variables that may arise after loan disbursement, including repayment arrears during the loan period, are considered inappropriate for real-time approval prediction as they may contain future information.

In this study, such variables are discussed as retrospective analytical indicators and as a limitation of the existing dataset.

3.3. Research Stages

This research was conducted through several systematic stages as follows:

- a. Data Collection: Data is collected from the LPD credit information system and verified to ensure completeness and consistency. Invalid data or data with missing values will be identified for further processing.
- b. Data Pre-Processing; The data pre-processing stage includes:
 - (1) Data cleaning: Removing or correcting data that is irrelevant, duplicate, or contains input errors.
 - (2) Data transformation: Converting categorical variables into numeric form through label encoding or one-hot encoding techniques.
 - (3) Data normalization: Standardizing the value scale so that each variable has a balanced weight in the model learning process.
 - (4) Dataset Division: The data is split into a training set (80%) and a testing set (20%) for model training and performance evaluation, respectively.
- c. Application of Machine Learning Models: Several machine learning algorithms were used to build credit risk prediction models, including:
 - (1) Logistic Regression, as a baseline model.
 - (2) Decision Tree and Random Forest, to capture non-linear patterns.
 - (3) Gradient Boosting (XGBoost), for more optimal performance on complex datasets.

Each model was trained using the training set and then tested using the testing set to obtain predicted credit status results (smooth or bad).

- d. Model Evaluation; Model performance is evaluated using several statistical metrics commonly used in classification analysis, namely:
 - (1) Accuracy: The proportion of correct predictions to total predictions.
 - (2) Precision: The proportion of creditworthy predictions that are actually correct.
 - (3) Recall (Sensitivity): The model's ability to detect cases of bad credit.
 - (4) F1-Score: Harmonic mean between precision and recall.
 - (5) Area Under the Curve (AUC): A measure of the overall ability of the model to distinguish between two

classes (smooth and default).

The model with the highest metric value will be considered the best model for implementation in the LPD credit analysis system.

The four algorithms, namely Logistic Regression, Decision Tree, Random Forest, and XGBoost, were implemented and compared in this study. However, detailed hyperparameter tuning was not the primary focus of the present work. Therefore, future research should report and optimize model parameters more systematically to improve reproducibility and robustness.

The research results will be analyzed quantitatively, emphasizing the contribution of the best models to improving the efficiency and objectivity of the credit analysis system at LPDs. Furthermore, the discussion will cover the potential integration of the models into LPD management information systems as a step towards sustainable digital transformation.

4. Results and Discussion

4.1. Overview of Research Data

The data used in this study comprises 2,000 credit transaction records from a Village Credit Institution (LPD) in Bali over the past three years. Based on preliminary descriptive analysis, approximately 82% of the total data falls into the current credit category, while the remaining 18% are considered non-performing or high-risk (default). Although the data falls into two categories (smooth and problematic), the entire dataset was utilized in subsequent analyses and calculations. This maintains the reality of the situation and serves as a basis for consideration and assessment of the model's application.

The most influential variables in determining creditworthiness are identified through correlation analysis and data exploration. Some of the main variables include: loan term (tenor), loan amount, history of late payments, percentage of installments to income (Debt-to-Income Ratio) and previous credit history [38].

This analysis shows that borrowers with long tenors, high delinquency rates, and high debt-to-income ratios have a higher risk of default. This pattern forms the basis for the machine learning model used to classify creditworthiness.

4.2. Training Results and Model Evaluation

Four machine learning algorithms were tested to predict credit status, namely Logistic Regression, Decision Tree, Random Forest, and XGBoost. In general, the mathematical equations of the four models used are:

- Logistic Regression

$$P(Y = 1|X) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 X_1 + \dots + \beta_n X_n)}} \quad (2)$$

- Decision Tree

$$f(x) = \begin{cases} c_1: x \in R_1 \\ c_2: x \in R_2 \\ \vdots \\ c_k: x \in R_k \end{cases} \quad (3)$$

- Random Forest

$$f(X) = \frac{1}{M} \sum_{m=1}^M T_m(X) \quad (4)$$

- XGBoost (Extreme Gradient Boosting)

$$\hat{y}^t = \hat{y}^{(t-1)} + f_t(x) \quad (5)$$

The variable X represents the feature vector containing all variables considered in the credit analysis process, while T_m represents the number of trees in the ensemble. The evaluation was conducted using a testing set (20% of the total data) and key performance metrics included accuracy, precision, recall, F1-score, and AUC (Area Under Curve) [39]. A summary of the training and model evaluation results can be seen in Table 1 and Fig. 1.

Overall, the XGBoost model achieved the best performance metrics. This indicates that it is the most accurate model, offering high recall for predicting customer risk levels while maintaining good precision (low false positives). These results are in line with the findings of previous studies [32, 40], which emphasized the superiority of boosting-based algorithms in handling datasets with complex variables. XGBoost is the optimal model because it is able to capture non-linear relationships and interactions between variables more effectively than other models. However, the XGBoost model is sensitive to hyperparameters and requires careful tuning to effectively address class imbalance [41, 42].

Table 1. Summary of the performance of each model

Model	Accuracy	Precision	Recall	F1-Score	AUC
Logistic Regression	0.87	0.84	0.79	0.81	0.89
Decision Tree	0.88	0.85	0.82	0.83	0.90
Random Forest	0.91	0.89	0.86	0.87	0.94
XGBoost	0.93	0.91	0.89	0.90	0.96

The logistic regression model had the lowest performance. However, this model is recognized as being easier to explain and very suitable as a basis for determining regulations [43]. This model is also suitable as a baseline model.

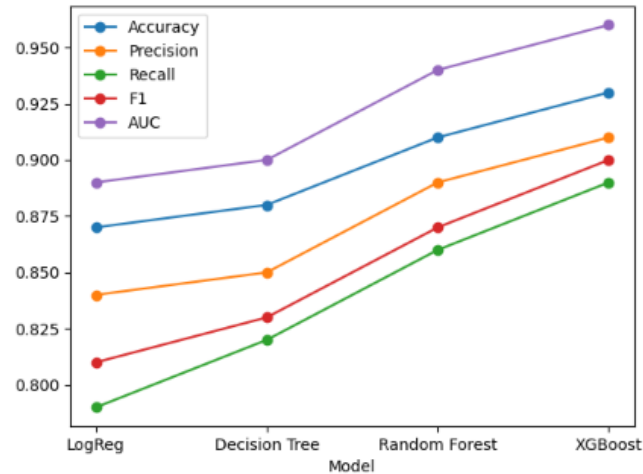


Fig.1. Model performance comparison chart

4.3. Example of Credit Analysis with Dummy Data

a. Simple Dataset

For this credit analysis, fictitious LPD debtor records were used (Table 2), supplemented with key variables typically employed in credit analysis.

Table 2. Example of 10 data on prospective LPD debtors (fictitious)

No	Age	Income (Rp/month)	Loan Amount (Rp)	Length of the Loan (months)	Delinquency History (times)	Debt-to-Income Ratio (%)	Credit Status
1	28	5,000,000	10,000,000	12	0	20	Smooth
2	35	4,500,000	20,000,000	24	1	44	Smooth
3	40	3,000,000	15,000,000	24	2	50	Bad debt
4	31	6,000,000	10,000,000	12	0	17	Smooth
5	45	2,500,000	10,000,000	18	3	60	Bad debt
6	29	4,000,000	8,000,000	10	0	20	Smooth
7	38	3,500,000	12,000,000	24	1	40	Smooth
8	50	3,000,000	15,000,000	30	2	55	Bad debt
9	27	5,500,000	8,000,000	10	0	15	Smooth
10	42	2,800,000	12,000,000	24	2	50	Bad debt

Information:

- The Debt-to-Income Ratio (DTI) shows the percentage of installments relative to monthly income. A high DTI indicates a large debt burden compared to income.
- Credit Status is used as a label for model training (target variable).

Based on this sample debtor data, we illustrate the actual conditions of credit disbursed by LPDs according to

current provisions and policies for assessing credit proposals. The picture obtained from this data will then be used as a reference in determining the assessment benchmarks for the application of the model used.

b. Initial Pattern (Descriptive Analysis)

Based on the data above, it can be observed that:

- (1) Debtors who have a DTI above 45% and arrears ≥ 2 times tend to experience payment default (bad debt).
- (2) Debtors with DTI below 30% are almost all smooth.
- (3) The length of the loan (tenor) factor also has an influence: long tenors (≥ 24 months) appear to increase the risk.

c. Application of a Simple Model (Logistic Regression)

If we use a simple logistic regression model with two dominant variables, X_1 (Debt-to-Income Ratio %) and X_2 (Arrears History), the general model is:

$$PD = \frac{1}{1 + e^{-(\beta_0 + \beta_1 X_1 + \beta_2 X_2)}} \quad (6)$$

From the training results obtained (dummy coefficients):

- $\beta_0 = -5.0$
- $\beta_1 = 0.08$
- $\beta_2 = 0.9$

So, the higher the DTI or the amount of arrears, the greater the chance of default.

d. Decision Making Stage

To determine the creditworthiness threshold, LPD can set it, for example, as presented in Table 3.

Table 3. Creditworthiness threshold

Probability of Default (PD)	Risk Category	Decision
< 0.30	Low	Approve
0.30 – 0.60	Medium	Review / Additional verification required
> 0.60	High	Reject or need additional guarantees

In this way, credit decisions become quantitative, not just the result of an officer's intuition.

e. Example of New Case Prediction with Complete Numerical Scenario

The data used in this case study is presented in Table 4.

Table 4. Customer credit application data (Fictitious)

Name	Monthly Income	Loan Amount	Length of the Loan (months)	Delinquency History (times)	DTI (%)	Guarantee Value	Tenure
I Budi	4,000,000	12,000,000	18	1	45	2,000,000	24

(1) Calculating the probability of non-performing loans (PD) occurring

The PD value is calculated using a simple logistic regression model, taking into account three features: DTI, number of delays, and length of service as an LPD customer (tenure). This calculation uses the coefficient values obtained from the model training results, namely:

- $\beta_0 = -4.8$ (intercept)
- $\beta_{DTI} = 0.07$ (per percent DTI)
- $\beta_{delays} = 0.95$ (per each time of delay)
- $\beta_{tenure} = -0.01$ (per month tenure; long tenure reduces risk)

The formula used [44]:

$$PD = \frac{1}{1+e^{-z}} \quad (7)$$

$$z = \beta_0 + \beta_{DTI} * DTI + \beta_{delays} * numDelays + \beta_{tenure} * tenure \quad (8)$$

$$z = -4.8 + 0.07 \times 45 + 0.95 \times 1 + (-0.01) \times 24 = -0.94$$

$$PD = \frac{1}{1+e^{0.94}} \approx \frac{1}{1+2.56} \approx 0.28$$

This PD value indicates a 28% probability of default for the applicant. This places the applicant in the low-risk category, but approaching the medium category, as the PD value is near the upper limit of the low-risk criteria ($PD < 0.30$).

(2) Estimated Maximum Credit Limit

There are 3 (three) models that can be applied to estimate the maximum credit limit, namely:

- using a simple regression model, with the formula:

$$\begin{aligned} \text{MaxCredit} &= 0.5 \times \text{MonthlyIncome} + 0.01 \times \text{GuaranteeValue} \\ \text{MaxCredit} &= 0.5 \times 4,000,000 + 0.01 \times 2,000,000 = 2,020,000 \end{aligned}$$

- using a combination of business rules model:

$$\begin{aligned} \text{MaxIncome} &= \text{MonthlyIncome} \times \text{IncomeMultiplier} \\ \text{IncomeMultiplier} &= 6 \text{ (adjustable)} \\ \text{MaxIncome} &= 4,000,000 \times 6 = 24,000,000 \\ \text{Next, find the multiplier factor, using the recommended formula:} \\ \text{MultiplierFactor} &= \max(\text{MinMultiplier}, 1 - PD) \text{ and } \text{MinMultiplier} = 0.2, \text{ then } \text{MultiplierFactor} = \\ &= \max(0.2, 1 - 0.28) = 0.72 \end{aligned}$$

By taking this Multiplier Factor into account, the maximum credit limit can be calculated using the formula:

$$\begin{aligned} \text{MaxCredit} &= \min(\text{MaxCreditModel} \times \text{Multiplier}, \text{MaxIncome}) \\ \text{MaxCredit} &= (2,020,000) \times 0.72 = 1,454,400 \end{aligned}$$

- using a conservative income-based approach:

$$\begin{aligned} \text{MaxCredit} &= \text{MonthlyIncome} \times k \times (1 - PD) \\ \text{with } k &= 6 \text{ (policy multiplier), then} \\ \text{MaxCredit} &= 4,000,000 \times 6 \times (1 - 0.28) = 24,000,000 \times 0.72 \\ \text{MaxCredit} &= 17,280,000 \\ \text{Rounded to } &17,250,000 \text{ (to multiples of 250 thousand or 100 thousand).} \\ \text{Based on the results of this calculation, a conservative recommendation can be given for a} \\ \text{maximum credit limit of IDR } &17.25 \text{ million.} \end{aligned}$$

(3) Determination of Interest Rates

In determining the interest rate, the base interest rate is set at 6% per year, the operational markup is set at 3%, and the Loss Given Default (LGD) is set at 40%, representing the estimated loss percentage if the customer defaults. The interest rate limit is set at a minimum of 6% and a maximum of 25%. The formula used is:

- $\text{riskPremium} = (PD \times LGD) / (1 - PD)$
- $\text{InterestRate} = \text{BaseInterestRate} + \text{riskPremium} + \text{operationalMarkup}$

With $PD = 0.28$, we obtain:

$$\text{riskPremium} = \frac{0.28 \times 0.40}{1 - 0.28} = \frac{0.112}{0.72} \approx 0.1556 \text{ (15.56\%)}$$

$$\text{InterestRate} = 0.06 + 0.1556 + 0.03 = 0.2456 \text{ (24.56\%)}$$

InterestRate $\approx$ 24.56% rounded up to 24.5% or 24.75% according to LPD policy.

This calculation shows that the recommended interest rate is quite high because the PD and LGD values produce a fairly large risk premium [45]. To be able to lower the interest rate, LPD can do this with several alternative steps, namely:

- Requesting higher value collateral so that LGD falls, or
- Applying other warranties/additional conditions, or
- Offering shorter loan terms to reduce the Exposure at Default (EAD), which represents the total amount of exposure at the time of default.

(4) The conclusion of this case example is:

- The chance of a problem loan occurring is 28%. This falls into the medium risk category.
- The maximum recommended credit limit is IDR 17,250,000.
- The recommended interest rate is 24.56% per year. This is considered high, and LPDs may consider mitigating measures such as reducing the loan amount, requiring additional collateral, or shortening the loan term.

The proposed creditworthiness thresholds, estimated maximum credit limits, and risk-based pricing illustrations in this section should be interpreted as conceptual examples only. They are included to show how machine learning outputs may be translated into practical credit analysis recommendations in the LPD setting. Nonetheless, these policy rules have not yet been validated using historical portfolio back-testing. Hence, before institutional implementation, further evaluation is needed to assess their effects on approval rate, default rate, profitability, fairness, and policy stability under different economic conditions.

5. Analysis and Discussion

The results show that the application of machine learning significantly improves the efficiency and objectivity of credit analysis at LPDs. The XGBoost model, for example, identifies high-risk potential borrowers with significantly higher accuracy than conventional methods that rely on loan officer intuition.

Furthermore, machine learning models can process thousands of historical data records in a relatively short time, accelerating decision-making. This supports the digital transformation of the LPD credit system, which previously relied heavily on manual evaluation.

Analysis of key variables revealed that factors such as late payment history and the income-to-installment ratio emerged as dominant predictors of credit risk. This information can be used by LPD managers to formulate more measured credit policies, such as setting loan limits based on the debtor's financial capacity.

The application of this machine learning model in the credit analysis system is expected to have several important implications for the digital transformation process at LPDs, including:

- The credit assessment process will be faster and have a lower error rate, thereby increasing LPD operational efficiency.
- Credit decisions are based on data and predictive models rather than solely on officer intuition. The consistent use of a credit reference system plays a significant role in reducing loan default rates [46]. This enhances the objectivity of decisions, thereby fostering customer trust.
- The model can detect high-risk potential borrowers early, thereby reducing the level of non-performing loans. This enhances the accuracy of LPD risk management, which is crucial given that credit risk has a significant negative impact on the stability and profitability of LPDs [47, 48].
- The results of this study can be the basis for the development of a machine learning-based digital credit information system in the LPD environment, which is technologically integrated with the LPD governance system.

In the long term, increased operational efficiency resulting from the implementation of machine learning models in the credit analysis process can help mitigate the negative impact of high credit risk. Integrating risk control mechanisms with operational efficiency will further increase LPD profitability [49]. LPD credit quality and performance sustainability will be maintained through measures to improve the effectiveness of credit risk management [50, 51].

Beyond the technical benefits, the findings of this research also have important social implications. By increasing efficiency and transparency, LPDs can strengthen village communities' trust in local financial institutions and support the sustainability of community-based economies in the digital age.

Although this study reports commonly used classification metrics, namely accuracy, precision, recall, F1-score, and AUC, a practical lending environment requires broader evaluation. Future studies should include ROC and precision-recall curve analysis, calibration assessment such as the Brier score and calibration plots, and cost-sensitive evaluation because the cost of incorrectly approving a high-risk debtor is not equivalent to the cost of rejecting a low-risk debtor. Hence, the current findings should be interpreted as an initial feasibility assessment rather than a complete production-grade validation framework.

Transparency is crucial in credit risk analysis because decision-makers require clear justifications for loan approval or rejection. In this study, important variables were identified through descriptive and correlation analyses. However, future developments should incorporate methods that enhance the explainability of model results.

6. Conclusions and Suggestions

Although the model's results demonstrate excellent performance, several limitations warrant consideration. First, the data used are limited to a single LPD, so generalizing the results to all LPDs in Bali requires caution. Second, the machine learning model requires regular data updates to remain relevant to dynamic economic conditions and debtor behavior. Third, non-technical aspects such as human resource readiness and digital infrastructure at the village level are also determining factors for the successful implementation of this system. Therefore, the success of digital transformation is determined not only by technology but also by organizational readiness and ongoing policy support.

In the context of field implementation, this model can be integrated with the LPD credit information system application to achieve the following:

- Officers only need to input prospective customer data.
- The system automatically calculates and displays the risk level.
- The results can serve as recommendations for credit decisions or as material for credit committee meetings.

Thus, machine learning does not replace human judgment but rather serves as an analytical tool (decision support system) that enhances the accuracy and efficiency of the credit assessment process.

The present study is based on data from one LPD only. Therefore, the findings demonstrate local feasibility rather than common generalizability across all LPDs. In addition, the study did not include temporal validation, such as training on earlier periods and testing on later periods, nor cross-institution validation across multiple LPDs. Future research should address these aspects to evaluate the robustness and transferability of the model under various institutional and economic settings.

All the Declarations and Statements

Author Contributions Statement

I. Gede Made Karma – Conceptualization, Methodology, Project Administration, Supervision, Investigation, Formal Analysis, Writing – Original Draft, Writing – Review & Editing, and Validation.

I. Made Ariana – Formal Analysis, Writing – Original Draft, Writing – Review & Editing, and Validation.

Desak Putu Suciwati – Investigation, Data Curation, and Formal Analysis.

All authors have read and agreed to the published version of the manuscript.

Conflict of Interest Statement

The authors declare no conflict of interest.

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Ethical Declarations

This research uses and analyzes general, non-confidential datasets. Any mention of a person's name is a pseudonym. As the research did not involve direct interaction with human subjects or animals, formal ethical approval and informed consent were not required.

Data Available Statement

This research analyzed publicly available datasets. Some data are shown in this manuscript.

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Declarations of Generative AI in Scholarly Writing

We used AI-based applications such as ChatGPT, SciSpace, and Bohrium to search for the most recent and relevant references on the topics covered.

Abbreviations

The following abbreviations are used in this manuscript:

LPD – Lembaga Perkreditan Desa: Indonesian term for Village Credit Institution.

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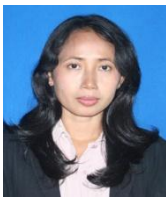


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