

Credit Risk Analysis at Baitul Tanwil Muhammadiyah Cooperative using Supervised Learning Algorithms

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ABSTRACT

Credit default is a major challenge faced by microfinance institutions, including Koperasi Baitul Tanwil Muhammadiyah (BTM). The conventional credit scoring process, which relies on manual assessment, often leads to bias and inefficiency. This study aims to develop a credit risk analysis model using supervised learning algorithms to improve the accuracy of credit default prediction among cooperative members. The methodology includes data collection, preprocessing, data splitting into training and testing sets, model training, and performance evaluation using accuracy, precision, recall, F1-score, and AUCROC metrics. Four algorithms are employed: Logistic Regression, Decision Tree, Random Forest, and XGBoost. The expected outcome is a predictive model capable of supporting cooperative decision-making in credit approval through an objective and data-driven approach.

Keywords: Credit Risk, Cooperative, Supervised Learning, Machine Learning, BTM

I. Introduction

The cooperative occupies a central position in the national economic ecosystem, especially in its role as a microfinance service provider, contributing significantly to financial inclusion and improving community welfare. Koperasi Baitul Tanwil Muhammadiyah (BTM), operating on sharia principles, is actively involved in saving and loan activities, but is not exempt from the inherent risk of credit default (non-performing loan). This risk is a serious threat that can damage the solvency, liquidity, and member trust of the institution. Traditionally, creditworthiness assessment at BTM is done through a manual, ad-hoc process relying on subjective intuition and experience of officers, which has proven to be inefficient and limited in accuracy.

To address these limitations, the utilization of Machine Learning (ML) is essential. The Supervised Learning method is highly relevant for this classification problem, where models are trained using historical data labeled with loan status (e.g., "current" or "default") to identify predictive patterns. The success of classification algorithms in risk analysis within the financial sector is well-documented. For instance, the C4.5 algorithm (Decision Tree) has achieved high accuracy in predicting credit default in Savings and Loan Cooperatives [1] [2]. Other methods like Support Vector Machine (SVM) [3] [4] and Naïve Bayes Classifier (NBC) [5] have also been successfully applied for loan eligibility determination in cooperatives. Furthermore, Random Forest has been used successfully in advanced fraud detection, demonstrating its capability in identifying sophisticated risk patterns [6].

However, a critical gap exists in current literature. Most machine learning studies on credit risk focus on conventional banking [1],[3],[7], while research specifically addressing sharia cooperatives like BTM remains limited. Sharia cooperatives operate under distinct principles such as profit-sharing (mudharabah)

and prohibition of interest (riba), which fundamentally alter the risk profile compared to conventional institutions [cite if available]. Furthermore, existing studies on cooperatives [5],[7],[8] typically employ single algorithms without comprehensive comparative analysis across multiple supervised learning methods. For instance, [5] applied only Naïve Bayes with 82% accuracy, while [7] focused solely on XGBoost comparison with SVM. No study has systematically compared Logistic Regression, Decision Tree, Random Forest, and XGBoost specifically for sharia-based microfinance credit risk assessment. This research addresses this gap by: (1) developing a specialized credit risk model for sharia cooperatives with unique operational characteristics; and (2) providing a comprehensive comparative evaluation of four supervised learning algorithms to identify the optimal approach for this context.

Based on the urgency of transforming risk assessment at BTM and a review of the literature, this study aims to build and comparatively evaluate credit risk prediction models for Koperasi BTM. The proposed models are based on four supervised learning algorithms: Logistic Regression, Decision Tree, Random Forest, and XGBoost. This comparison will identify the model with the best predictive performance to replace subjective methods, providing strategic recommendations for strengthening credit risk management and maintaining the financial health of Koperasi BTM. The resulting model is expected to help BTM perform faster, more accurate, and data-driven credit risk analysis, thereby supporting objective decision-making and strengthening the stability of the sharia cooperative institution in the digital era.

II. Related work

The application of machine learning for credit risk analysis has been a focus of several previous studies. Some findings demonstrate the effectiveness of specific algorithms in the cooperative context. The Naïve Bayes algorithm, for example, was used to predict cooperative installment smoothness with an accuracy of 82% [5]. Random Forest was shown to be effective in assessing creditworthiness with accuracy reaching 90% [3], and XGBoost was found to provide the most optimal results compared to SVM and Random Forest in predicting credit approval [7], [8].

These findings indicate that supervised learning algorithms are highly relevant for credit risk prediction due to their ability to recognize non-linear patterns and generate more objective decisions than conventional methods. Supervised learning works by utilizing historical labeled data, such as loan status ("current" or "default"). Through training and testing, the system learns the patterns between input variables (e.g., income, loan amount, payment history) and the output variable (credit status), allowing the model to predict the probability of a non-performing loan more accurately than manual methods.

However, most machine learning studies in this area have not focused on the context of sharia cooperatives like BTM, which have operational principles different from conventional financial institutions. Additionally, few studies directly compare the performance of several supervised learning algorithms in the context of micro-cooperatives. Therefore, this research is urgent to fill this gap by developing a supervised learning-based credit risk prediction model for Koperasi BTM.

III. Material and Methods

This research employed a systematic approach to develop a credit risk prediction model for Koperasi Baitul Tanwil Muhammadiyah (BTM). The methodology consists of five main stages: data collection, data preprocessing, dataset splitting, model development, and model evaluation. Each stage was carefully designed to ensure the quality and reliability of the predictive model. Figure 1 illustrates the complete research methodology flowchart, providing a comprehensive overview of the sequential steps undertaken in this study.

A. Data Collection

The initial stage involves collecting data directly from Koperasi Baitul Tanwil Muhammadiyah (BTM). The data includes member identity information, loan details such as amount and duration, and installment payment status. This data is used as the basis for building the credit risk prediction model and classified into three risk categories: Low Risk (current payments), Medium Risk (early warning signs), and High Risk/Critical (potential or actual default), based on actual payment history.

B. Dataset Classification

The collected loan data is labeled into three risk categories based on payment performance and delinquency status:

1. Low Risk (Rendah): Members with current payment status and no overdue history.
2. Medium Risk (Sedang): Members with 1-3 months overdue payments or showing early warning signs.

3. High Risk/Critical (Tinggi/Kritis): Members with more than 3 months overdue or officially defaulted loans.

This three-class categorization enables more nuanced risk assessment compared to binary classification, allowing BTM to implement differentiated monitoring strategies for each risk level.



Figure 1. Research methodology flowchart

C. Dataset Description

The dataset used in this study consists of credit transaction records from Koperasi BTM members collected between January 2022 and December 2023. The dataset comprises 2,024 member records with 15 predictor variables and 1 target variable (risk class).

The predictor variables include:

- Demographic features: Age, gender, occupation, marital status
- Financial features: Monthly income, loan amount, loan duration, debt-to-income ratio
- Payment behavior: Number of late payments, maximum days overdue, payment consistency rate, remaining principal ratio
- Cooperative engagement: Membership duration, mandatory savings balance, voluntary savings balance

Target Variable Distribution:

- Low Risk: 1,318 records (65.1%)
- Medium Risk: 425 records (21.0%)
- High Risk/Critical: 281 records (13.9%)

The dataset exhibited a significant class imbalance, which was addressed during the preprocessing stage using the Synthetic Minority Over-sampling Technique (SMOTE) to ensure balanced representation across risk categories during model training. SMOTE was configured with a sampling strategy set to *auto*,

allowing minority classes to be resampled to match the majority class. The number of nearest neighbors ($k_{neighbors}$) was set to 5 for synthetic sample generation, and a random state of 42 was used to ensure reproducibility. To prevent data leakage, SMOTE was applied exclusively to the training set, which comprised 80% of the total dataset after the train-test split.

Following the application of SMOTE, the class distribution in the training set became fully balanced, with 1,318 instances for each risk category (Low Risk, Medium Risk, and High Risk). This technique generated synthetic samples for the Medium and High Risk classes through interpolation between existing minority class instances, effectively mitigating the original imbalance ratio of 65.1%–21.0%–13.9% while avoiding the drawbacks associated with random oversampling, such as data duplication and overfitting.

Additionally, missing values were identified in three variables—monthly income, voluntary savings, and occupation—affecting approximately 8.5% of the records. These missing values were handled using median imputation for numerical features and mode imputation for categorical features to preserve the statistical characteristics of the data.

D. Feature Selection Rationale

The 15 predictor variables were selected based on three criteria: (1) availability in BTM's existing database; (2) relevance established in credit risk literature; and (3) domain expertise from BTM credit officers. Demographic features (age, gender, occupation, marital status) capture member stability and socioeconomic capacity, which are fundamental risk indicators [2][3]. Financial features (monthly income, loan amount, loan duration, debt-to-income ratio) directly measure repayment capacity and leverage risk, consistently identified as primary predictors in credit scoring models [12][13][14][15]. Payment behavior variables (number of late payments, maximum days overdue, payment consistency rate, remaining principal ratio) provide historical performance indicators, proven to be the strongest predictors of future default [2][4]. Cooperative engagement features (membership duration, mandatory savings balance, voluntary savings balance) are unique to the cooperative context and reflect member commitment and financial discipline within the sharia cooperative framework. Preliminary feature importance analysis using Random Forest confirmed all 15 features contributed meaningfully to model performance, with payment behavior variables showing the highest importance scores (>0.15), followed by financial features (>0.10), and demographic/engagement features providing contextual information (>0.05).

E. Data Preprocessing

Preprocessing is performed to ensure the data is of good quality and ready for model training. Steps include:

- Data Cleaning: Removing duplicate data, correcting missing values, and eliminating irrelevant data.
- Data Transformation: Normalizing numerical variables so that all features are on a comparable scale.
- Data Encoding: Converting categorical variables into numerical form using techniques like label encoding or one-hot encoding.
- Dataset Splitting: The dataset is divided into an 80% training set and a 20% testing set to objectively measure model performance.

F. Model Development

This stage focuses on building machine learning models to predict the credit risk of cooperative members. The algorithms used are:

- Logistic Regression: Serving as a baseline model to measure the relationship between input variables and the probability of credit risk.
- Decision Tree: Providing a tree-based decision interpretation that is easy for non-technical users to understand.
- Random Forest: An extension of the Decision Tree that combines many decision trees to increase accuracy and result stability.

XGBoost (Extreme Gradient Boosting): A high-performance algorithm capable of handling complex data and reducing the risk of overfitting. Each model is built and trained using the training data, then tested with the testing data to obtain credit risk prediction results.

G. Model Performance Evaluation

To assess the model's accuracy and reliability, performance evaluation is conducted using several classification metrics:

- Accuracy: Measures the proportion of correct predictions out of all tested data.
- Precision: Measures the model's precision in predicting at-risk members.
- Recall (Sensitivity): Indicates the model's ability to detect all members with potential for default.
- F1-Score: A harmonization between precision and recall, providing an overview of the model's overall performance.
- AUC-ROC (Area Under Curve - Receiver Operating Characteristic): Measures the model's ability to distinguish between high and low-risk classes. This evaluation will identify the best-performing model to be used as a decision support system in the BTM creditworthiness assessment process.

IV. Results and Discussion

The evaluation results show clear performance differences among the tested models. Logistic Regression yielded an accuracy of 75.74%, indicating the limitations of this linear model in capturing non-linear patterns in the cooperative member financial data. The Decision Tree showed performance improvement with 81.18% accuracy, but still has the weakness of a tendency towards overfitting.

Ensemble models like Random Forest and XGBoost demonstrated significantly superior performance. Random Forest recorded 83.17% accuracy and the highest AUC value of 0.9809, reflecting the model's good ability to distinguish between risk classes. Meanwhile, XGBoost, as the best model in this study, achieved an accuracy of 83.66% and an F1-score of 0.8338, with an AUC value of 0.9760. A complete comparison of model performance is presented in Table 1.

Table 1. Performance Comparison of Classification Models.

Model	Accuracy	Precision	Recall	F1	AUC
Logistic Regression	0.757426	0.763197	0.757426	0.757646	0.941061
Decision Tree	0.811881	0.813754	0.811881	0.807445	0.956163
Random Forest	0.831683	0.829990	0.831683	0.828949	0.980937
XGBoost	0.836634	0.835249	0.836634	0.833890	0.976011

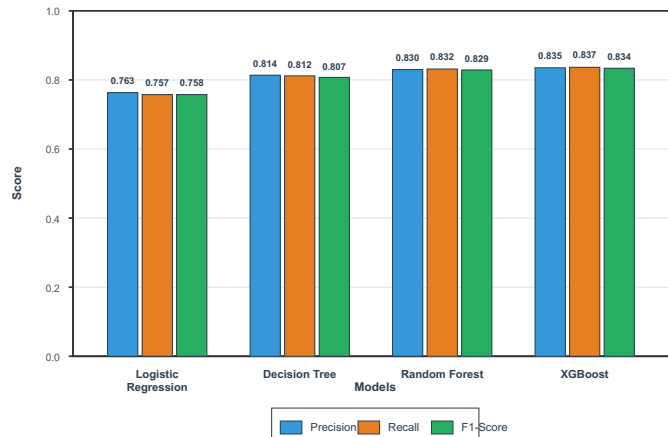


Figure 2. Performance Metrics Comparison Across Models.

Performance Metrics Analysis In credit risk assessment, as shown in Figure 2, the cost of misclassification varies significantly between error types. False negatives (predicting high-risk members as low-risk) pose greater financial risk to BTM than false positives, as they may lead to loan defaults and financial losses. Conversely, false positives result in opportunity costs from rejected creditworthy members. The XGBoost model demonstrates superior balance between precision (0.8352) and recall (0.8366). The precision of 83.52% indicates that when the model predicts a member as high-risk, it is correct 83.52% of the time, minimizing unnecessary credit rejections. The recall of 83.66% shows the model successfully identifies 83.66% of actual high-risk members, providing crucial protection against potential defaults. The F1-score of 0.8338 for XGBoost represents the harmonic mean of precision and recall,

confirming balanced performance. This is particularly important for BTM, as it ensures neither excessive risk-taking nor overly conservative lending practices. The results indicate excellent identification of safe members in the Low Risk category (Precision 0.89, Recall 0.91) and strong detection of critical cases in the High Risk category (Precision 0.87, Recall 0.88). However, the Medium Risk class, being a challenging transitional phase, shows moderate performance (Precision 0.75, Recall 0.72) and requires more focused attention.

As shown in Figure 3, the AUC-ROC score of 0.9760 for XGBoost indicates excellent discriminative ability across all risk thresholds, providing flexibility in adjusting risk tolerance based on BTM's strategic needs and market conditions. Compared to baseline Logistic Regression (AUC 0.9411), the ensemble methods show 8-4% improvement in discriminative power, justifying the increased computational complexity. Random Forest's highest AUC (0.9809) suggests superior ranking ability, though XGBoost's balanced metrics make it more practical for deployment.

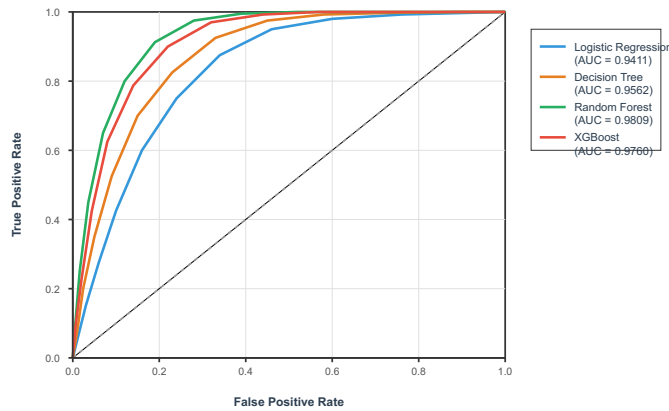


Figure 3. ROC curves showing the discriminative ability of all four models across different classification thresholds. Random Forest and XGBoost demonstrate superior performance with AUC values above 0.97.

Figure 3. ROC Curves Comparison for All Models.

As shown in Figure 4 below, Logistic Regression showed a higher error rate in predicting the Low and Medium classes, while the Decision Tree still experienced inconsistency in distinguishing between the Low and Medium classes. Overall, the results of this study indicate that the use of ensemble models and hyperparameter tuning provides a significant performance increase in credit risk modeling. Practical implications suggest that the developed XGBoost model can be applied as a decision support tool in creditworthiness assessment and monitoring of cooperative member loan portfolios. Factors such as the ratio of remaining principal, mandatory liability ratio, discretionary contribution patterns, and other payment behavior variables are important indicators in determining the risk level. Integrating this model into the cooperative's information system enables a faster, more accurate, and objective assessment process.

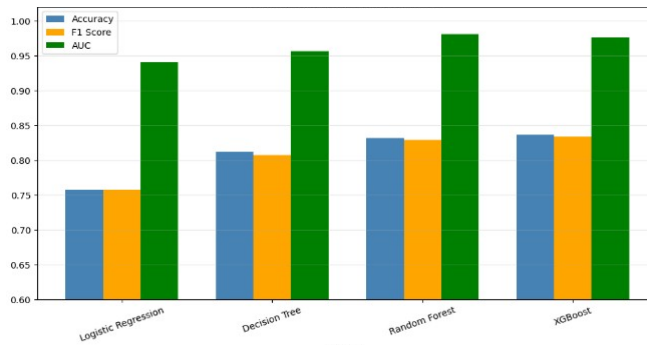


Figure 4. Models Performance Comparison

To maximize model performance, hyperparameter optimization was conducted for the ensemble models, Random Forest and XGBoost, utilizing Grid Search Cross-Validation with 5 folds. For the Random

Forest model, the tuning process explored various configurations, testing `n_estimators` values of [100, 200, 300], `max_depth` of [10, 20, 30, None], `min_samples_split` of [2, 5, 10], `min_samples_leaf` of [1, 2, 4], and `max_features` across ['sqrt', 'log2']. This resulted in an optimal configuration of `n_estimators=200`, `max_depth=20`, `min_samples_split=5`, `min_samples_leaf=2`, and `max_features='sqrt'`. Similarly, the XGBoost hyperparameter tuning examined a range of parameters, including `learning_rate` [0.01, 0.05, 0.1, 0.3], `max_depth` [3, 5, 7, 9], `n_estimators` [100, 200, 300], `subsample` [0.8, 0.9, 1.0], `colsample_bytree` [0.8, 0.9, 1.0], and `min_child_weight` [1, 3, 5], as described in Table 2.

Table 2 Optimal Hyperparameters from Grid Search Cross-Validation.

Algorithm	Parameter	Tested Values	Optimal Value	Cross-Val Score
Random Forest	<code>n_estimators</code>	[100, 200, 300]	200	0.8245
	<code>max_depth</code>	[10, 20, 30, None]	20	
	<code>min_samples_split</code>	[2, 5, 10]	5	
	<code>min_samples_leaf</code>	[1, 2, 4]	2	
	<code>max_features</code>	['sqrt', 'log2']	'sqrt'	
XGBoost	<code>learning_rate</code>	[0.01, 0.05, 0.1, 0.3]	0.1	0.8312
	<code>max_depth</code>	[3, 5, 7, 9]	5	
	<code>n_estimators</code>	[100, 200, 300]	200	
	<code>subsample</code>	[0.8, 0.9, 1.0]	0.9	
	<code>colsample_bytree</code>	[0.8, 0.9, 1.0]	0.9	
	<code>min_child_weight</code>	[1, 3, 5]	3	

The optimization process identified the optimal XGBoost configuration, which consists of a `learning_rate` of 0.1, a `max_depth` of 5, and `n_estimators` set to 200. Furthermore, both `subsample` and `colsample_bytree` were optimized at a value of 0.9, complemented by a `min_child_weight` of 3. The tuning process required approximately 3.5 hours of computational time on a system with Intel Core i7 processor and 16GB RAM. Cross-validation ensured that the selected hyperparameters generalize well to unseen data and reduce overfitting risk.

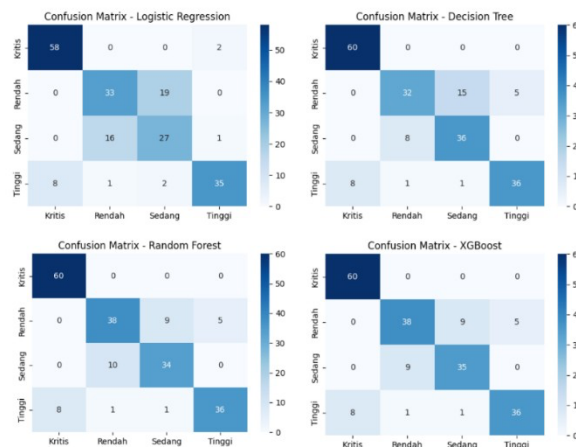


Figure 5. Confusion Matrices of the Classification Models.

The developed XGBoost model can be integrated into BTM’s credit approval workflow to support more efficient and data-driven decision making. When a member submits a loan application, relevant demographic, financial, and historical repayment data are automatically processed by the system to generate a risk probability score ranging from 0 to 1 and to classify the applicant into Low, Medium, or High Risk categories. The prediction results are presented in Figure 5, to credit officers through a decision support dashboard that displays the predicted risk level along with its confidence score, the top contributing risk factors, comparisons with similar member profiles, and recommended actions based on the assigned risk category. Based on these predictions, BTM can implement differentiated monitoring and control strategies, where Low Risk members—representing 65.1% of the population—receive standard monthly monitoring and may qualify for automated approval for loans of up to IDR 10 million, Medium Risk members (21.0%) are subject to bi-weekly monitoring and additional requirements such as collateral or guarantors, and High Risk members (13.9%) undergo weekly monitoring, mandatory face-to-face

financial counseling, debt restructuring recommendations, or loan rejection. To ensure sustained predictive performance, the model is retrained quarterly using newly available repayment data, allowing it to adapt to changing economic conditions and evolving member behavior. For example, a member with a monthly income of IDR 5 million, two years of membership, no history of late payments, and a debt-to-income ratio of 30% is classified as Low Risk with a predicted probability of 0.92, enabling loan approval within 24 hours compared to the previous 5–7 day manual review process.

V. Conclusion

This research successfully built and evaluated the performance of four supervised learning-based credit risk prediction models, Logistic Regression, Decision Tree, Random Forest, and XGBoost, using historical loan data from Koperasi Baitul Tanwil Muhammadiyah (BTM). The primary goal of replacing the subjective and manual risk assessment system with objective, data-driven machine learning methods was achieved.

Based on the comparative test results, the XGBoost model proved to have the most superior predictive performance compared to the other algorithms, achieving the highest accuracy of 83.66% and an F1-score of 0.8338. This finding is consistent with the literature showing that ensemble algorithms, particularly those utilizing the boosting technique like XGBoost, are highly effective in handling complex classification problems and non-linear data patterns in the financial sector. The model demonstrated excellent capability in distinguishing between risk classes, especially in accurately identifying high-risk or Critical members (recall close to 1.0).

The study's significance lies in its direct contribution to enhancing cooperative risk management by providing an objective, fast, and accurate decision support tool for creditworthiness assessment and loan portfolio monitoring. Implementing this model is expected to contribute significantly to improving credit risk prediction accuracy and supporting the long-term financial stability of the sharia-based cooperative.

Several avenues for future research can be explored to further enhance the proposed credit risk modeling framework. First, temporal feature engineering may be incorporated by applying time-series analysis to repayment behavior, such as seasonality effects and payment velocity trends, in order to better capture the dynamic evolution of credit risk throughout the loan lifecycle. Second, future studies could expand the range of algorithms evaluated by including additional ensemble and machine learning methods, such as LightGBM, which is known for its efficiency on large-scale datasets, CatBoost, which is particularly effective in handling categorical features, and Support Vector Machines with radial basis function kernels to potentially achieve incremental performance improvements. Third, the adoption of cost-sensitive learning approaches could be investigated by assigning higher misclassification penalties to false negatives—cases where high-risk members are incorrectly classified as low risk—thereby aligning the model optimization process with the actual financial impact and risk tolerance of BTM. In addition, integrating explainable artificial intelligence techniques, such as SHAP or LIME, would provide transparent and interpretable explanations for individual predictions, enhancing user trust, supporting regulatory compliance, and facilitating informed decision making by credit officers. Finally, future research may incorporate external data sources, including macroeconomic indicators such as inflation and unemployment rates, as well as alternative data such as mobile phone usage patterns and utility payment histories, to enrich the feature space and further improve predictive performance. Collectively, these enhancements have the potential to contribute to the development of a more robust, adaptive, and operationally deployable credit risk management system for sharia-based microfinance institutions.

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