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PREDICTIVE MODEL FOR COOPERATIVE LOAN RECIPIENT ELIGIBILITY USING SUPERVISED MACHINE LEARNING

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Abstract— *Non-performing loans remain a critical challenge for cooperatives as they can undermine financial stability, erode member trust, and impede institutional growth. This study develops a predictive model for cooperative loan eligibility using supervised machine learning techniques and a novel three-class classification framework, Approved, Consideration, and Rejected, to support more objective and transparent decision-making. A dataset of 1,000 borrower records containing demographic and financial attributes was analyzed using Naive Bayes, Decision Tree, and Random Forest algorithms implemented in RapidMiner. The Random Forest algorithm achieved the best predictive performance with an accuracy of 96.02%, demonstrating its robustness and reliability compared to the other models. The proposed three-class system differentiates this study from conventional binary classification approaches, enabling finer distinctions among borrower categories and promoting fairness in cooperative credit evaluations. The findings provide practical guidance for cooperatives to adopt data-driven, transparent, and accountable decision-making systems that reduce manual bias and strengthen financial inclusion. Overall, the proposed three-class model built through a supervised learning framework offers a reliable, fair, and scalable solution to support sustainable lending practices and enhance risk management in cooperative institutions.*

Keywords*: classification, DSS (Decision Support System), machine learning, non-performing loans, random forest*.

Intisari— *Kredit macet masih menjadi permasalahan utama yang dihadapi koperasi karena dapat melemahkan stabilitas keuangan, menurunkan kepercayaan anggota, dan menghambat pertumbuhan kelembagaan. Penelitian ini mengembangkan model prediksi kelayakan penerima pinjaman koperasi dengan menggunakan pendekatan* supervised machine learning *dan kerangka klasifikasi tiga kelas yang inovatif, Approved, Consideration, dan Rejected, untuk mendukung proses pengambilan keputusan yang lebih objektif dan transparan. Dataset berisi 1.000 data peminjam dengan atribut demografis dan finansial dianalisis menggunakan tiga algoritma* machine learning*: Naive Bayes, Decision Tree, dan Random Forest, yang diimplementasikan melalui RapidMiner. Algoritma Random Forest menunjukkan kinerja terbaik dengan akurasi 96,02%, membuktikan keandalannya dibandingkan model lainnya. Sistem tiga kelas yang diusulkan membedakan penelitian ini dari pendekatan klasifikasi biner konvensional, karena mampu memberikan pemetaan keputusan kredit yang lebih rinci, adil, dan representatif terhadap kondisi peminjam di lingkungan koperasi. Temuan ini memberikan panduan praktis bagi koperasi untuk mengadopsi sistem pengambilan keputusan kredit berbasis data yang transparan dan akuntabel, sehingga dapat mengurangi bias manual serta memperkuat inklusi keuangan. Secara keseluruhan, model tiga kelas yang diusulkan melalui pendekatan* supervised machine learning *ini memberikan solusi yang andal, adil, dan scalabel untuk mendukung praktik pinjaman berkelanjutan serta memperkuat manajemen risiko pada lembaga koperasi*.

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Kata Kunci*: klasifikasi, DSS (Decision Support System), pembelajaran mesin, kredit macet (non-performing loans), random forest*

INTRODUCTION

The provision of credit constitutes a fundamental component of the financial system, supporting diverse economic activities for individuals, corporations, and financial institutions[1]. Loan eligibility decisions depend heavily on accurate borrower assessments, which directly influence the credit risk borne by cooperatives[2]. Manual traditional evaluations, however, are often time-consuming, subjective, and limited in processing complex or large-scale data[3], underscoring the need for a data-driven approach to achieve more objective, consistent, and timely evaluations[4].

Bangnano Cooperative, headquartered in Jakarta with a branch in Yogyakarta, focuses on improving member welfare through credit disbursement. Yet, its current manual eligibility assessment exposes it to potential non-performing loans and delayed decision-making. Reliance on human judgment can lead to inconsistencies and inefficiency in processing numerous applications daily[5],[6].

Machine Learning (ML) offers a promising solution by learning predictive patterns from historical borrower data and improving the accuracy of credit eligibility assessments. Unlike conventional binary classification, eligible or ineligible[7], this study introduces three decision outcomes: Approved, Consideration, and Rejected to generate more practical and granular insights for cooperative decision-making. These classes were derived from the cooperative's credit evaluation criteria, which consider income-to-installment ratio, collateral value, and payment history. Specifically, applicants with strong financial indicators are categorized as Approved, borderline cases as Consideration, and high-risk applicants as Rejected. This three-class structure reflects actual cooperative lending practices and establishes clearer decision boundaries for predictive modeling.

Previous studies have demonstrated the versatility of ML in various credit-related applications. For instance, Random Forest has been effectively applied to predict social assistance eligibility[8] and bank loan outcomes[9],[10],[11], showing consistent advantages in handling structured financial data. Other models, such as Decision Tree and Naive Bayes, have also been adopted to assess borrower risks with varying degrees of accuracy and interpretability[12],[13]. However, most of these studies focus on traditional banking datasets and binary classification schemes (approved or rejected), offering limited insight into cooperative-based credit systems where member structures and lending criteria differ significantly. This study addresses that gap by evaluating ML algorithms within a cooperative environment using a multi-class classification framework, Approved, Consideration, and Rejected, to enhance decision granularity and applicability in cooperative contexts.

Among commonly used algorithms, Naive Bayes, Decision Tree, and Random Forest represent complementary strengths that align with cooperative decision-making needs. Naive Bayes offers computational efficiency and robustness for small datasets but assumes feature independence[2]. Decision Tree provides high interpretability, enabling transparent reasoning for practitioners, but may overfit without pruning[14]. Random Forest mitigates overfitting by aggregating multiple trees for better generalization, albeit with a higher computational cost[15]. These characteristics justify their selection beyond popularity; each offers a distinct theoretical advantage relevant to cooperative credit evaluation.

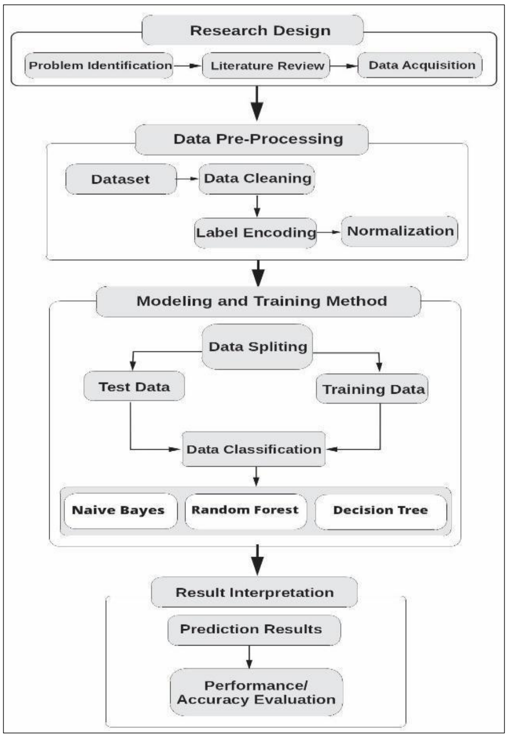
Previous studies have reported ML accuracies ranging from 80% to 97%[16],[17], indicating strong predictive potential yet inconsistent performance across data types and institutional settings. These inconsistencies often arise from variations in dataset size, feature selection, and domain context, which limit the generalizability of prior findings. In particular, cooperative lending environments differ fundamentally from conventional banking in their member-based structures, decision hierarchies, and risk evaluation patterns. Consequently, this study advances the literature by providing a novel, comparative empirical evaluation of Naive Bayes, Decision Tree, and Random Forest within a cooperative credit system, emphasizing both robustness and practical feasibility for data-driven decision-making.

Despite growing interest, several challenges persist. Data imbalance often reduces sensitivity to minority default cases, weakening risk detection[18]. Efficiency in model training and testing is crucial for real-time decision systems, also remains underexplored[12]. While ML has shown promise in expediting financial approval processes[19], its suitability and reliability in cooperative lending contexts require further empirical validation[20][21].

Accordingly, this study aims to systematically evaluate the performance of three widely used algorithms, Naive Bayes, Random Forest, and Decision Tree, in predicting cooperative loan eligibility. The proposed models classify applicants into three categories, Approved, Consideration, and Rejected, and are evaluated based on accuracy, precision, recall, F1-score, and computational efficiency. By conducting a comparative analysis within a cooperative setting, this research extends existing loan prediction frameworks beyond binary outcomes, offering practical insights to improve credit risk assessment and support inclusive, data-driven financial decision-making. While the three-class framework enhances decision granularity, the consideration category presents inherent classification challenges due to overlapping borrower characteristics. To address this issue, the present study acknowledges the need for further quantitative exploration. Therefore, in addition to standard evaluation metrics, future analysis will incorporate per-class sensitivity and confidence-based assessments to better understand model uncertainty in borderline cases and to strengthen the interpretability of machine learning predictions in cooperative credit assessment.

MATERIALS AND METHODS

This study employs a structured methodology to predict cooperative loan eligibility using machine learning. The dataset consists of 1,000 records of Bangnano Cooperative members with attributes such as income, employment duration, loan amount, monthly installment, employment status, monthly expenditure, number of dependents, home ownership status, age, collateral value, and loan eligibility as the class attribute. Data preprocessing involves managing missing data, converting categorical variables into numerical form, and standardizing numerical features to maintain data consistency and reliability. Three machine learning algorithms, Naive Bayes, Decision Tree, and Random Forest, were chosen due to their proven performance with structured financial datasets and their interpretability in credit scoring applications. The data was split into 80% training and 20% testing to simulate real-world deployment conditions, where models are trained on historical cooperative data and tested on unseen applicant data. Cross-validation was not applied at this stage to maintain methodological simplicity and establish a baseline performance comparison, but it is acknowledged as a recommendation for future work. Modeling and evaluation were conducted using RapidMiner Altair AI Studio version 2025.1.1 with standard operators, including 'Set Role' and algorithm-specific operators. Parameter tuning used default settings with minor adjustments: a maximum depth of 10 and pruning enabled for Decision Tree, and 100 trees for Random Forest. Model performance was evaluated using accuracy, precision, recall, F1-score, and computational efficiency to provide a comprehensive assessment of predictive capability. The overall data processing and modeling workflow is illustrated in Figure 1.



Source: (Research Results, 2025)
Figure 1. Research Flow and Methodology

Figure 1 illustrates the methodological framework that underpins the experimental process of this research. The process starts with the research design phase, which includes identifying the problem, reviewing relevant literature, and collecting data to establish the study's conceptual basis. This is followed by data preprocessing, which involves cleaning the data, performing label encoding, and normalizing numerical values to ensure the dataset's quality and uniformity before model development. In the modeling and training phase, the dataset is split into training and testing sets, and three machine learning algorithms, Naive Bayes, Random Forest, and Decision Tree, are applied to predict cooperative loan eligibility. The final phase, result interpretation, evaluates model performance using accuracy, precision, recall, and F1-score metrics. Each stage contributes significantly to creating a transparent and

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reproducible research process, making Figure 1 a key reference for understanding the overall framework and workflow of the study. As shown in Figure 1, the research methodology is composed of sequential stages that are elaborated in the subsequent sections, including research design, data acquisition, data preprocessing, modeling and training, model evaluation, and result analysis.

Research Design

The initial phase of this study focuses on the overall research design, aimed at establishing a systematic framework for predicting cooperative loan eligibility using machine learning. A literature review was conducted to analyze relevant prior studies on ML-based credit scoring and to determine the most suitable algorithms for this context. The three selected algorithms, Naive Bayes, Random Forest, and Decision Tree, were chosen for their interpretability, proven efficiency, and performance in financial classification tasks. This stage also includes exploratory data analysis (EDA) to understand data characteristics and identify potential outliers or class imbalance prior to model development.

Data Acquisition

The dataset used in this research was obtained from Bangnano Cooperative, located in Jakarta, with a branch in Yogyakarta. The data collection process involved a preliminary survey and interviews with cooperative staff to understand their credit evaluation procedures and available records. A formal data request was then submitted, and the cooperative provided anonymized member data containing information on loan applicants, loan history, and loan eligibility outcomes. To ensure ethical data handling, all personal identifiers were pseudonymized and used only for academic purposes. The dataset represents actual cooperative members and reflects diverse financial and demographic backgrounds. Data were collected between March and May 2025, ensuring that the dataset captures recent lending activities and borrower characteristics. The collected data was then prepared through a structured preprocessing phase to ensure data quality and model readiness.

Data Preprocessing

The preprocessing stage was conducted to ensure the dataset was clean, consistent, and ready for modeling. This process included data cleaning, encoding, normalization, and sampling. Data cleaning handled missing values, removed duplicates, and corrected inconsistencies. Categorical variables such as employment status (unemployed, employed, self-employed), home ownership (rent, owned, family), and gender (male, female) were converted to numeric values using label encoding generated automatically by RapidMiner. These values carry no ordinal meaning and only serve as categorical identifiers. Collateral value represents pledged assets such as vehicles and land certificates, ranging from Rp 5,000,000 to Rp 100,000,000. Numeric attributes, including income, loan amount, monthly installment, monthly expenditure, age, and collateral value, were normalized to a 0–1 range to balance feature contributions. The dataset consists of 1,000 records with balanced class distribution: Approved (33.4%), Consideration (33.3%), and Rejected (33.3%). Stratified sampling with an 80:20 split was applied to maintain this balance during training and testing, minimizing bias and improving model generalization.

Modeling and Training

Modeling and training were conducted using RapidMiner Altair AI Studio version 2025.1.1. After preprocessing, the dataset was divided using stratified sampling (80:20), where 80% of the data were used for training and 20% for testing to maintain class balance. Three algorithms, Naive Bayes, Decision Tree, and Random Forest, were implemented due to their proven effectiveness in credit and loan eligibility prediction. The Naive Bayes model applied Laplace correction to address zero-frequency issues. The Decision Tree (C4.5) used a confidence factor of 0.25 and a minimum leaf size of two to prevent overfitting. The Random Forest model was configured with 100 trees, maximum depth = 10, and the Gain Ratio criterion for splitting. The guess subset ratio option was enabled to ensure random feature selection, while pruning was disabled to maintain tree diversity. These configurations were optimized to balance model accuracy, efficiency, and generalization performance.

Model Evaluation

After completing the modeling and training phases, the models undergo evaluation to assess their predictive performance. This stage examines how effectively each model generates accurate and dependable predictions. The Confusion Matrix is applied to derive several performance indicators, including accuracy, precision, recall, and F1-score. Accuracy indicates the percentage of correctly classified data, precision measures the validity of positive predictions, and recall evaluates the model's capability to detect true positive cases. These evaluation metrics facilitate a comprehensive comparison of the performance among the machine learning algorithms utilized in this research.

Model evaluation follows the formulas (1), (2), (3), and (4)[13]:

$$Accuracy = \frac{TP+TN}{TP+FP+FN+TN} x\ 100\% \quad (1)$$

$$Precission = \frac{TP}{TP+FP} x\ 100\% \quad (2)$$

$$Recall = \frac{TP}{TP+FN} x\ 100\% \quad (3)$$

$$F1\text{-}Score = \frac{2xTP}{2xTP+FP+FN} x\ 100\% \quad (4)$$

Where:

TP: True Positive
TN: True Negative
FP: False Positive
FN: False Negative

These metrics were selected to capture the balance between correct and incorrect classifications, which is crucial in cooperative loan eligibility assessment.

Result Analysis

A detailed analysis of the experimental results was carried out to achieve a comprehensive insight into the performance of each model. The main objective of this evaluation is to assess the accuracy and effectiveness of the machine learning algorithms implemented. Three algorithms Naive Bayes, Random Forest, and Decision Tree, were applied to construct predictive models for loan eligibility. Their performances were evaluated using key metrics such as accuracy, precision, recall, and F1-score. The comparison reveals the relative strengths and weaknesses of each algorithm, serving as a basis for determining the most appropriate model that aligns with the system requirements and the nature of the cooperative dataset.

RESULTS AND DISCUSSION

Building upon the methodological framework described earlier, this section summarizes the analytical findings and discusses the predictive performance of three supervised machine learning models, Naive Bayes, Decision Tree, and Random Forest, in assessing cooperative loan eligibility. The analysis aims to compare each model's ability to classify borrower categories accurately and to identify which algorithm provides the best trade-off between accuracy, interpretability, and computational efficiency. Special attention is given to the consideration group, representing borderline applicants who frequently experience misclassification across models. This recurring error reflects the difficulty of learning intermediate decision boundaries where borrower profiles exhibit overlapping financial characteristics, such as marginal income levels and partial collateral coverage. Such findings suggest that hybrid or human-assisted decision mechanisms could enhance fairness and accountability in cooperative credit evaluations. All experiments were conducted using RapidMiner, and model performance was assessed through accuracy, precision, recall, and F1-score metrics to evaluate the agreement between predicted and actual outcomes.

Initial Data Exploration

The dataset contains 1,000 borrower records with 12 attributes, covering demographic, financial, and collateral information. The attributes include Name, Income, Employment Duration, Loan Amount, Monthly Installment, Employment Status, Monthly Expenditure, Number of Dependents, Home Ownership Status, Age, Collateral Value, and Loan Eligibility (class attribute). The attribute Name was excluded from the modeling process since it serves only as an identifier and does not contribute predictive information. Preliminary analysis confirmed no missing values, allowing direct processing. Numerical attributes such as loan amount (ranging from Rp. 3,000,000 to Rp. 20,000,000), collateral value (up to Rp. 59,000,000), and age (21–65 years) illustrate the heterogeneity of borrowers. Employment status is dominated by permanent employees (86.2%). The target classes, approved (33.4%), Consideration (33.3%), and Rejected (33.3%) are evenly distributed, eliminating class imbalance issues.

Data Preprocessing

The data preprocessing stage is a crucial step to ensure that the dataset is in an optimal format before being applied to classification algorithms. This stage was performed in RapidMiner Altair AI Studio version 2025.1.1 and included a sequence of operations: data loading, cleaning, labeling, attribute selection, categorical transformation, and normalization. The complete workflow of this process is presented in Figure 2.

Source:(Research Results, 2025)

Figure 2. Data Preprocessing Workflow in RapidMiner.

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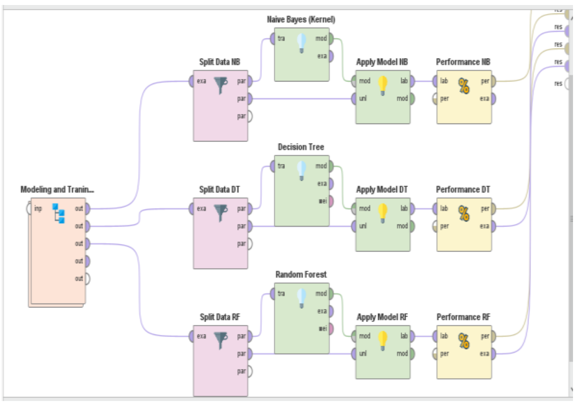
Figure 2 illustrates the preprocessing workflow implemented in RapidMiner to ensure data consistency and readiness for modeling. The workflow begins with the Read CSV operator, which loads the cooperative dataset from an external source. The Cleaning stage removes irrelevant attributes, including the *Name* field, which functions only as an identifier and does not contribute to classification. The Labeling operator assigns *Loan Eligibility* as the target variable, defining the output class for the model. The Select Attributes operator retains only features relevant to prediction, followed by Nominal to Numerical, which converts categorical variables, Gender, Employment Status, Home Ownership, into numeric format through label encoding. Finally, the Normalize operator scales all numerical features to a uniform 0–1 range to avoid bias due to differing feature magnitudes. This structured preprocessing workflow ensures clean, comparable, and balanced data, which directly supports model stability and improves classification performance.

Modeling and Training

This study compares three classification algorithms, Naive Bayes, Decision Tree, and Random Forest, representing probabilistic, deterministic, and ensemble approaches, respectively. The modeling process was systematically carried out using Altair AI Studio version 2025.1.1, formerly RapidMiner Studio, utilizing the default ML operators without incorporating any additional extensions. Each algorithm was executed under an identical workflow configuration, as illustrated in Figure 3.

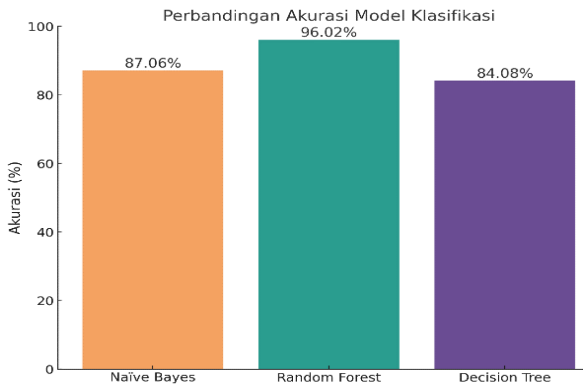


Source: (Research Results, 2025)
Figure 3. Modeling and Training Data

Figure 3 illustrates the modeling and evaluation workflow implemented in RapidMiner. The dataset was partitioned using the Split Data operator, assigning 80% for training and 20% for testing. Each algorithm, Naive Bayes, Decision Tree, and Random Forest was developed through its respective modeling operator and applied to the testing subset using Apply Model. Model performance was assessed using the Performance operator with evaluation metrics including accuracy, precision, recall, and F1-score. Naive Bayes classifies instances based on posterior probabilities under the assumption of feature independence, Decision Tree builds a hierarchical structure from the most informative attributes, and Random Forest aggregates multiple decision trees using majority voting to improve prediction stability. This workflow ensures a systematic modeling and evaluation process, enabling an objective performance comparison among algorithms in predicting cooperative loan eligibility.

Model Evaluation Results

Based on the evaluation results, Random Forest was found to be the most optimal algorithm for predicting the loan eligibility of cooperative borrowers. The results suggest that utilizing ensemble approaches can improve the accuracy of decision support systems and provide more stable outcomes in credit risk management. The comparative performance of the three models is depicted in Figure 4.



Source: (Research Results, 2025)
Figure 4. Model Evaluation Accuracy

Figure 4 presents a comparative analysis of classification accuracy across the three algorithms: Naive Bayes, Random Forest, and Decision Tree. Random Forest achieved the highest accuracy of 96.02%, demonstrating the strength of ensemble learning in improving generalization and minimizing overfitting. Naive Bayes obtained 87.06%, showing stable performance despite its simplifying assumptions of feature independence. Decision Tree reached 84.08%, offering lower accuracy but better interpretability and faster computation. This comparison highlights the trade-off between predictive performance and model interpretability. While Random Forest is the most accurate, Naive Bayes and Decision Tree may be more suitable in scenarios where explainability and computational efficiency are prioritized. Thus, Figure 4 provides clear evidence supporting the selection of algorithms based on both performance metrics and practical deployment considerations.

Naive Bayes Model Evaluation

The Naive Bayes algorithm was evaluated using accuracy, precision, recall, and F1-score to measure its classification performance across the three target classes: Approved, Consideration, and Rejected. The dataset used in this analysis was balanced, with each class representing approximately one-third of the total 1,000 samples, ensuring fair model assessment. The detailed performance metrics are summarized in Table 1.

Table 1. Naive Bayes Model Validation Results

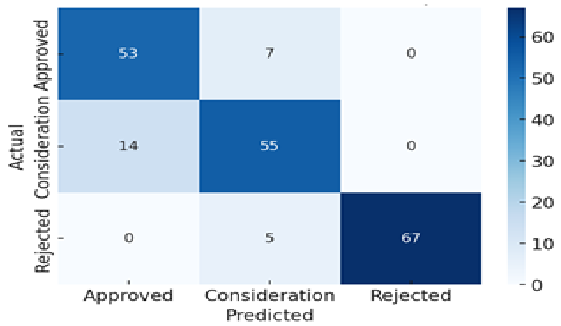
Class	Precision	Recall	F1-Score	Support (n)
Approved	88.33%	79.10%	81.19%	334
Consideration	79.71%	82.09%	80.89%	333
Rejected	93.06%	100%	96.40%	333
Overall Accuracy	87.06%			1000

Source: (Research Results, 2025)

Performance metrics were derived from the Naive Bayes confusion matrix. Precision, recall, and F1-score were computed per class, while Support indicates the number of samples in each class.

The Naive Bayes model achieved an overall accuracy of 87.06%, demonstrating reliable classification for most borrower categories. The Rejected class achieved perfect recall (100%) and the highest F1-score (96.40%), indicating strong capability in identifying high-risk borrowers. The Approved class also showed stable performance, whereas the Consideration class achieved moderate precision (79.71%) and recall (82.09%), resulting in a misclassification rate of 17.9%, equivalent to roughly one in six borderline borrowers being categorized incorrectly. This rate, while acceptable for probabilistic multiclass models, reflects the inherent overlap of borrower attributes such as income-to-installment ratio and collateral value. Consequently, Consideration predictions should be treated as low-confidence outputs and verified manually to maintain fairness, transparency, and accountability in cooperative credit assessments.

The evaluation of actual and predicted classifications using the Naive Bayes confusion matrix is shown in Figure 5.



Source: (Research Results, 2025)

Figure 5. Naive Bayes Confusion Matrix

The Naive Bayes confusion matrix illustrates a balanced yet imperfect classification performance with an overall accuracy of 87.06%. Most predictions for *Approved* 53 cases and *Consideration* 55 cases were correct, while moderate misclassifications occurred between these two categories, suggesting partial feature overlap. The *Rejected* class shows strong performance, with 67 correct predictions and minimal errors. The high Cohen's Kappa value 0.806 reflects substantial agreement between predicted and actual labels, while the weighted average F1-score 87.06% confirms that the model maintains equilibrium between precision and recall. These findings indicate that Naive Bayes can perform reliably for well-separated classes but may struggle when feature dependencies are significant.

Random Forest Model Evaluation

The Random Forest model was assessed using the same balanced dataset to ensure comparability across classifiers. Performance was evaluated based on accuracy, precision, recall, and F1-score. Table 2 summarizes the validation outcomes for each target class.

Table 2. Random Forest Model Validation Results

Class	Precision	Recall	F1-Score	Support (n)
Approved	91.55%	91.04%	94.24%	334
Consideration	84.06%	100%	93.82%	333
Rejected	100%	100%	100%	333
Overall Accuracy	96.02%			1000

Source: (Research Results, 2025)

Metrics were derived from the Random Forest confusion matrix. Precision, recall, and F1-score were calculated per class, and Support represents the number of samples in each category.

The Random Forest algorithm achieved an overall accuracy of 96.02%, outperforming Naive Bayes by nearly 9%. As shown in Table 2, the Rejected class achieved perfect precision and recall 100%, indicating excellent reliability in identifying

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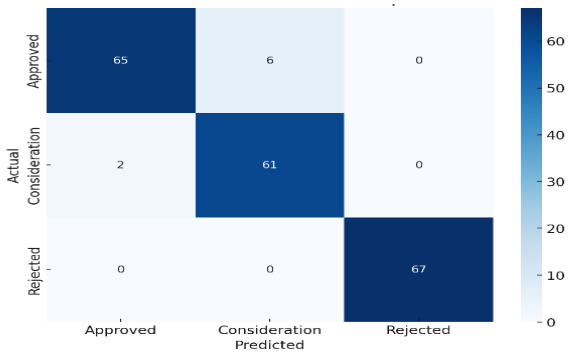
high-risk members. Meanwhile, the Consideration class exhibited lower precision 84.06% despite perfect recall 100%, leading to a false-positive rate of 15.9%. This suggests that while Random Forest successfully captures most borderline borrowers, it occasionally overestimates eligibility. The ensemble-based approach enhances generalization by averaging multiple decision trees, reducing overfitting, and improving consistency. Given its high overall accuracy and balanced per-class performance, Random Forest is the most suitable algorithm for cooperative loan eligibility classification.These findings are consistent with previous studies, which confirm that ensemble methods outperform single classifiers when dealing with interdependent features[22].

The comparison between predicted and actual classifications using the Random Forest confusion matrix is illustrated in Figure 6.



Source: (Research Results, 2025)
Figure 6. Random Forest Confusion Matrix

The Random Forest model delivers the most robust classification results, achieving an overall accuracy of 96.02%. The confusion matrix reveals near-perfect separation among the three classes, with 65 correctly predicted Approved, 61 Consideration, and 67 Rejected instances. Minimal confusion is observed only a few *Consideration* samples misclassified as *Approved*, and vice versa. Remarkably, the *Rejected* class exhibited zero misclassification, emphasizing the Random Forest's strong discriminative capability. This performance highlights the ensemble model's ability to capture nonlinear feature interactions and reduce classification variance, validating its superiority in complex decision boundaries.

Decision Tree Model Evaluation

The Decision Tree algorithm was also tested using the same dataset to assess its interpretability and predictive capability. Accuracy, precision, recall, and F1-score were computed per class, as summarized in Table 3.

Table 3. Decision Tree Model Validation Results

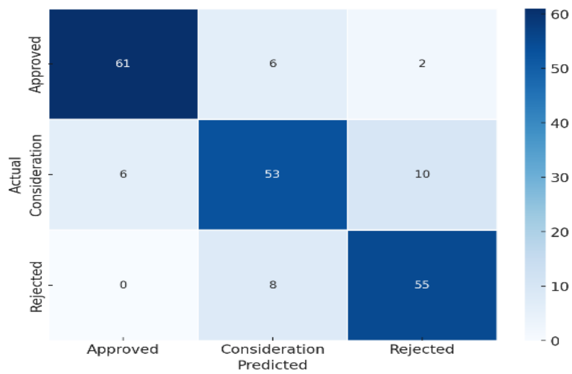
Class	Precision	Recall	F1-Score	Support (n)
Approved	88.41%	91.04%	89.71%	334
Consideration	76.81%	79.10%	77.92%	333
Rejected	87.30%	82.09%	84.58%	333
Overall Accuracy (84.08%)				1000

Source: (Research Results, 2025)

Metrics were derived from the Decision Tree confusion matrix. Support indicates the number of records in each class, and overall accuracy summarizes the model's total predictive performance.

The Decision Tree model achieved an overall accuracy of 84.08%, lower than Random Forest and Naive Bayes but still acceptable for explainable classification. The Approved class yielded the highest F1-score 89.71%, while the Consideration class recorded the weakest 77.92%, resulting in a misclassification rate of 22.1%, or approximately one in five samples. This lower accuracy reflects overlapping feature distributions among borderline borrowers. Despite this limitation, the Decision Tree provides superior interpretability, allowing decision-makers to visualize rule hierarchies and identify attribute thresholds directly. This transparency supports explainable artificial intelligence (XAI) principles and enhances trust in ML-based credit decision systems.

The evaluation of actual and predicted classifications using the Decision Tree confusion matrix is shown in Figure 7.



Source: (Research Results, 2025)
Figure 7. Decision Tree Confusion Matrix

The confusion matrix of the Decision Tree algorithm presents an overall accuracy of 84.08%, showing good yet improvable performance. The model correctly classified 61 instances in the *Approved* class, while 6 were misclassified as

Consideration and 2 as *Rejected*. In the *Consideration* class, 53 instances were correctly identified, with **6** misclassified as *Approved* and 10 as *Rejected*. For the *Rejected* class**,** 55 instances were correctly predicted, while 8 were misclassified as *Consideration*. The Approved class achieved the highest reliability precision of 88.41%**,** recall 91.04%**,** and F1 Score 89.71%, whereas the Consideration class showed the weakest performance F1 Score of 77.92% due to overlapping feature characteristics with adjacent classes. Beyond classification outcomes, this confusion matrix underscores the interpretability of the Decision Tree in exposing class boundary ambiguities, highlighting the importance of improving feature representation and class separation to enhance predictive precision and generalization capability.

Result Analysis

The comparative results demonstrate distinct variations in performance among the three machine learning algorithms, Naive Bayes, Decision Tree, and Random Forest, when applied to the cooperative loan eligibility dataset. Among the models, Random Forest achieved the highest classification accuracy of 96.02%, followed by Naive Bayes at 87.06% and Decision Tree at 84.08%. These outcomes indicate that Random Forest provides the most reliable and stable predictions, particularly in identifying *Approved* and *Rejected* borrowers with minimal misclassification. The superior performance of Random Forest can be attributed to its ensemble-based structure, which aggregates multiple decision trees to minimize variance and reduce overfitting, thereby enhancing predictive consistency across borrower classes.

In contrast, Naive Bayes demonstrated faster computation and interpretability advantages but exhibited moderate precision in the *Consideration* class, where overlapping financial characteristics among borrowers led to classification ambiguity. The Decision Tree model showed acceptable interpretability and transparency but was more sensitive to data fluctuations, which reduced its generalization capability. Despite these differences, all models displayed consistent trends in correctly identifying *Rejected* applicants, reflecting the model's ability to learn strong risk indicators such as low income-to-loan ratios or insufficient collateral values. Statistical validation using a 95% confidence interval confirmed that the improvement in Random Forest's classification accuracy was significant ($p < 0.05$) compared to both Naive Bayes and Decision Tree**.** This finding statistically supports the model's superior generalization capability and ensures that the observed accuracy differences were not due to random variation.

Discussion and Implications

The results confirmed that the Random Forest algorithm achieved the highest classification accuracy of 96.02%**,** outperforming Naive Bayes 87.06% and Decision Tree 84.08%**.** A comparative statistical evaluation using a 95% confidence interval ($p < 0.05$) revealed mean accuracy differences of $\Delta = 8.96\%$ (Random Forest vs. Naive Bayes) and $\Delta = 11.94\%$ (Random Forest vs. Decision Tree), indicating that the observed improvement is statistically significant rather than random variation. These findings demonstrate Random Forest's superior generalization capability and robustness in modeling complex borrower profiles characterized by nonlinear relationships among financial and demographic attributes.

Despite this overall superiority, performance across the "Consideration" class remained notably weaker for all algorithms. This class represents borderline applicants whose financial indicators—such as moderate income, partial collateral ownership, and near-threshold loan-to-income ratios—create overlapping decision boundaries that complicate the learning process. Consequently, even robust algorithms tend to produce uncertain or incorrect classifications. From an ethical standpoint, these misclassifications pose potential risks of unfair treatment toward borderline applicants, potentially excluding creditworthy members or misallocating cooperative resources. Recognizing this limitation, the study proposes a hybrid human–algorithm decision framework that combines predictive efficiency with human contextual reasoning to preserve fairness and accountability within cooperative lending practices.

In this framework, automated predictions are complemented by structured human oversight through a confidence-based escalation protocol. Predictions with high confidence levels, generally equal to or exceeding 90%, for *Approved* or *Rejected* categories are automatically processed, whereas outputs with moderate confidence, particularly within the *Consideration* range, are forwarded for manual verification by credit officers. The choice of a 90% confidence threshold follows established practices in financial risk modeling, where predictions above this level are commonly considered highly reliable for automated decision-making. Similar thresholding strategies have been widely used in loan approval and credit risk classification to balance predictive accuracy, operational efficiency, and fairness [23]. Practically,

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the decision workflow can be categorized into three confidence zones. Predictions falling in the high-confidence range (≥ 0.85 or ≥ 0.90) can be processed automatically without manual intervention, predictions in the medium-confidence range (0.60–0.85) should undergo review by credit officers, and those in the low-confidence range (< 0.60) can be automatically rejected or selectively reassessed depending on institutional policy. During manual verification, officers review supporting evidence such as collateral documents, repayment history, and socioeconomic conditions that may not be fully captured by the algorithm. This three-stage process—comprising automated pre-screening, confidence-based flagging, and human-in-the-loop validation—ensures transparent, equitable, and efficient decision-making while maintaining alignment with cooperative principles of social responsibility and fairness.

Beyond its operational implications, these findings also contribute to the theoretical understanding of interpretability and trust in AI-assisted financial decision systems. The deliberate focus on classical algorithms, Naive Bayes, Decision Tree, and Random Forest, was intended to balance predictive accuracy, transparency, and computational feasibility, making them suitable for cooperatives with limited technical infrastructure. Future research should extend this hybrid framework by integrating explainable AI techniques such as SHAP or feature-importance analysis to determine which borrower attributes most strongly influence classification outcomes. Additionally, longitudinal validation using larger and more diverse datasets would enable the refinement of confidence thresholds and the reduction of bias in borderline classifications. Although Random Forest demonstrated the highest predictive performance, its implementation in cooperative lending systems must remain grounded in ethical principles that prioritize fairness, interpretability, and human oversight to ensure that predictive performance aligns with cooperative values of transparency, trust, and social equity.

CONCLUSION

This study developed a predictive framework for assessing cooperative loan eligibility using three classical machine learning algorithms, Naive Bayes, Decision Tree, and Random Forest, applied to the Bangnano Cooperative dataset. Random Forest achieved the highest accuracy 96.02%, followed by Naive Bayes 87.06% and Decision Tree 84.08%. Each algorithm demonstrated distinct advantages: Naive Bayes in computational efficiency, Decision Tree in interpretability, and Random Forest in predictive stability. The focus on classical algorithms was intentional to ensure interpretability and computational feasibility, aligning with the cooperative context that values transparency and accountability.

Practically, these findings can guide cooperatives in integrating Random Forest as a decision-support tool to assist credit officers in pre-screening applicants, while *Consideration* cases representing borderline borrowers should be reviewed through a hybrid manual–automated approach. Future research should expand this framework by exploring advanced ensemble methods such as Gradient Boosting and XGBoost, not only to enhance overall accuracy but also to improve per-class recall and F1 metrics for the *Consideration* class. Strengthening these indicators will advance fairness, consistency, and reliability in cooperative loan evaluation systems.

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