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Comparative Analysis of Classification Algorithms for Loan Approval Prediction in Financial Services

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ABSTRACT

Accurate loan approval prediction is essential for balancing risk management with operational efficiency in automated lending. As borrower datasets grow in complexity, machine learning classifiers offer an effective alternative to traditional scoring methods. This study presents a comparative performance evaluation of three widely applied algorithms: Decision Tree (DT), Random Forest (RF), and Logistic Regression (LR). Using a localized dataset of 300 borrower profiles, the models were assessed across accuracy, precision, recall, and F1-score, with a 5-fold cross-validation scheme repeated three times to ensure stability and mitigate overfitting. The empirical findings show that the tree-based classifiers significantly outperformed the linear baseline. Both Decision Tree and Random Forest models achieved an overall accuracy of 97% and an F1-score of 93%, whereas Logistic Regression achieved 93% accuracy and a 90% F1-score. These results indicate that hierarchical, non-linear decision structures are better suited for mapping complex variable interactions in credit data. This study offers practical guidance for financial institutions seeking to deploy transparent, high-performing automated classification models that minimize false rejections while maintaining rigorous credit risk control.

Keywords: Loan approval prediction; Machine learning models; Classification algorithms; Financial risk assessment; Borrower Data Analysis

INTRODUCTION

Financial institutions increasingly rely on digital borrower records such as income, employment stability, spending habits, and asset profiles to evaluate creditworthiness. While access to this data has improved loan evaluation, selecting the most effective predictive model remains a persistent challenge for risk analysts. Standard statistical methods like logistic regression remain popular because their coefficient weights are easy to interpret and explain to regulators. However, these linear models often miss non-linear interactions and complex borrower behavioral patterns. On the other hand, modern tree-based classification techniques are structurally suited to capture intricate decision boundaries, yet their relative performance on smaller, regional datasets is not always well understood.

In practice, many lending institutions adopt risk models based on internal familiarity or software availability rather than systematic benchmarking. This arbitrary selection process introduces model bias, which directly impacts bottom-line performance: overestimating risk leads to the unnecessary rejection of qualified applicants, while underestimating it increases default rates. Although credit scoring literature is vast, there is still limited empirical work directly comparing basic linear models against single and ensemble tree classifiers on moderate-sized, localized borrower datasets.

This study addresses that gap by evaluating the predictive performance of Decision Tree, Random Forest, and Logistic Regression algorithms for loan approval classification. By assessing each model through accuracy, recall, and F1-score, this study identifies an optimal balance that minimizes false rejections without compromising overall credit risk control.

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RELATED LITERATURE

The application of machine learning techniques in financial services, particularly for credit evaluation and loan approval prediction, has gained significant attention in recent years. Ageed et al. (2021) emphasize that big data mining approaches in cloud systems provide efficient mechanisms for extracting meaningful insights from large, complex datasets, which can enhance decision-making processes in financial institutions. Likewise, Luna (2021) highlights the importance of structured data mining frameworks in ensuring consistency, accuracy, and reliability when analyzing multidimensional datasets, a principle that underpins the modeling workflow used in the present study.

Several studies have specifically investigated the predictive capabilities of machine learning algorithms for consumer credit evaluation. Aniceto, Barboza, and Kimura (2020) report that non-linear models demonstrate superior predictive power in assessing creditworthiness compared to linear techniques, particularly in capturing complex interactions among borrower attributes. Athreyas et al. (2022) conducted a comparative analysis of multiple classification algorithms for predicting loan default and eligibility, concluding that tree-based models, such as Decision Tree and Random Forest, consistently outperform linear models like Logistic Regression in terms of accuracy and recall. These findings align with the present study, which observed that Decision Tree and Random Forest achieved higher predictive performance compared to Logistic Regression when applied to a moderate-sized borrower dataset.

The practical relevance of machine learning in financial decision-making is further supported by Bakshi (2021) and Mamun, Farjana, and Mamun (2022), who note that these algorithms enable financial institutions to automate loan evaluation processes while minimizing human bias. Kadam et al. (2021) and Karthikeyan and Ravikumar (2021) also emphasize the role of feature selection and model optimization in improving predictive outcomes, suggesting that careful preprocessing and algorithm selection can significantly enhance model reliability. In this context, the present study employed numerical normalization and polynomial feature expansion to ensure that Logistic Regression could capture some non-linear interactions, while tree-based models leveraged their inherent ability to model hierarchical decision structures.

Tree-based and non-linear approaches have been repeatedly shown to outperform linear models in various financial prediction contexts. Islam and Nguyen (2020) found that non-linear methods provide higher accuracy in stock price prediction compared to conventional linear models. Similarly, Wahedi et al. (2022) and Tan et al. (2024) demonstrate that ensemble and hybrid models effectively capture complex relationships in time series forecasting, highlighting the advantage of such methods when data exhibits non-linear or hierarchical patterns.

Handayani, Reza, and Mehmood (2023) also stress that models capable of handling non-linear dynamics achieve higher coefficients of determination and predictive reliability, supporting the present study's finding that tree-based classifiers achieved superior recall and F1-scores.

Methodological rigor is another critical factor for ensuring reliable model performance. Shafique and Qaiser (2014) compare data mining frameworks such as KDD, CRISP-DM, and SEMMA, noting that structured workflows including data selection, transformation, modeling, and evaluation enhance model validity and reproducibility. The use of K-fold cross-validation, as discussed by Prajapati et al. (2021), and Schaffer, Dobbins, and Pearson (2021), is recommended to assess generalization and prevent overfitting, which was adopted in this study to strengthen the reliability of performance evaluation.

Collectively, these studies establish the relevance and effectiveness of tree-based classifiers for loan approval prediction while highlighting the limitations of linear models in capturing complex borrower behavior. However, there remains a gap in localized empirical research comparing these algorithms using moderate-sized datasets reflective of specific institutional contexts. The present study addresses this gap by providing a systematic performance comparison of Decision Tree, Random Forest, and Logistic Regression models, demonstrating the superior accuracy, recall, and interpretability of tree-based approaches for practical application in regulated financial environments.

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METHODOLOGY

The empirical analysis utilizes a primary dataset comprising 300 distinct borrower records collected from a selected financing institution in the Philippines. These records capture a combination of applicant background and financial information commonly used in loan evaluation.

The dataset incorporates both categorical and numerical attributes to reflect diverse borrower characteristics: categorical variables describe qualitative aspects such as employment type, citizenship status, and credit history, while numerical variables represent key financial metrics including loan amount, monthly income, and monthly expenses. The dependent variable is binary and indicates the loan approval outcome, classified as either approved (1) or not approved (0).

In order to ensure methodological consistency and reliable comparison across models, the study followed a structured three-phase computational framework. The first phase involved feature engineering, where numerical attributes were normalized to reduce the influence of differing value scales across features. Additionally, polynomial feature transformations were applied to enhance the modeling capacity of the Logistic Regression algorithm. This step was specifically intended to allow the linear classifier to better capture non-linear relationships present in borrower data and to provide a fairer comparison with tree-based models.

The second phase focused on model training and development using the Knowledge Discovery in Databases (KDD) process. This process systematically guides the analysis through data selection, preprocessing, transformation, model construction, and evaluation. All classification algorithms were trained using identical datasets and preprocessing techniques to ensure that observed performance differences were attributable to model characteristics rather than data inconsistencies.

The third phase evaluated model robustness and generalizability using a repeated K-fold cross-validation strategy. The dataset was partitioned into separate training and testing sets, with cross-validation conducted strictly on the training subset. Specifically, a 5-fold cross-validation procedure was repeated three times across different random partitions, producing 15 total training and validation cycles.

This approach minimized overfitting and reduced performance variance across validation splits. Following cross-validation, each classifier was retrained on the entire training set using the parameters and insights gained from the cross-validation phase. This step ensured that the models utilized the full scope of the training data before being assessed on the unseen test set.

Three supervised learning algorithms were evaluated in this study. The Decision Tree algorithm is a non-parametric classifier that models' decision-making through hierarchical rule structures derived from data splits. Random Forest builds upon this approach by aggregating multiple decision trees into an ensemble, improving prediction stability and reducing variance. Logistic Regression, in contrast, is a probabilistic statistical model that estimates the likelihood of a binary outcome using a logistic function and serves as a representative linear baseline for comparison.

RESULTS AND DISCUSSIONS

The evaluation of the classification models demonstrated consistent and reliable performance across both the training and validation phases, indicating stable predictive capabilities. Specifically, both the Decision Tree and Random Forest models achieved an accuracy of 97%, whereas Logistic Regression reached 93%.

Regarding precision, the tree-based models recorded 90%, slightly outperforming Logistic Regression at 88%. Similarly, the recall for both Decision Tree and Random Forest was 97%, surpassing the 92% achieved by Logistic Regression. Consequently, the tree-based models achieved an F1-score of 93%, compared to 90% for Logistic Regression (see Table 1).

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Table 1. Model Performance Comparison

Model	Accuracy	Precision	Recall	F1-Score
Decision Tree	97%	90%	97%	93%
Random Forest	97%	90%	97%	93%
Logistic Regression	93%	88%	92%	90%

These results indicate a clear advantage of tree-based classifiers in capturing the underlying decision patterns in the borrower dataset. The high recall values for Decision Tree and Random Forest demonstrate their effectiveness in correctly identifying approved loan applicants, which is critical for minimizing the erroneous rejection of eligible borrowers. In contrast, the slightly lower recall of Logistic Regression suggests limitations in its ability to recognize more complex cases where predictor variables interact in non-linear ways. The consistency observed between validation and test results further confirms that these performance differences are robust and not attributable to sampling variability, reinforcing the reliability of the findings.

DISCUSSION

The identical performance of the Decision Tree and Random Forest models suggests that the decision patterns in this dataset possess a clear hierarchical structure. In such environments, a single, well-constructed decision tree is sufficient to capture the primary predictive rules; thus, the additional ensemble complexity of Random Forest yields no incremental performance gain. This aligns with existing literature establishing that tree-based methods excel at modeling conditional relationships and variable interactions a common characteristic of loan approval data.

Conversely, the lower performance of Logistic Regression underscores the inherent limitations of linear classifiers in financial risk prediction. Credit decisions frequently rely on non-linear interactions among factors such as income, debt-to-income ratios, credit history, and employment stability. Linear models, while highly interpretable, struggle to capture these multi-variable relationships without manual feature engineering, resulting in lower recall and overall predictive capacity. The higher recall achieved by tree-based models is particularly valuable for financial institutions seeking to optimize approval rates while maintaining sound risk controls.

From a practical perspective, these findings suggest that tree-based classifiers should be prioritized in credit decisioning workflows. Decision Trees, in particular, offer an optimal balance of interpretability, computational efficiency, and predictive power. These attributes are crucial for deployment in regulated financial environments, where transparency and regulatory explainability are as vital as accuracy. By adopting tree-based models, institutions can achieve reliable credit evaluation automation without sacrificing transparency.

CONCLUSION

This study provides empirical evidence that tree-based classification models outperform Logistic Regression in predicting loan approval outcomes. Both Decision Tree and Random Forest models achieved superior accuracy (97%) and high F1-scores (93%), demonstrating strong predictive reliability and robustness. While Logistic Regression performed adequately (93% accuracy), its linear assumptions limited its capacity to capture non-linear feature interactions.

Given their ideal balance of interpretability, efficiency, and predictive performance, tree-based models particularly single Decision Trees are recommended for institutions aiming to implement automated,

explainable credit assessment systems. Implementing these models can improve decision consistency, lower false rejection rates for qualified borrowers, and optimize overall credit risk management.

Based on these findings, several strategic recommendations emerge for financial institutions implementing automated credit scoring systems. First, risk management departments should prioritize non-linear, tree-based models over traditional linear algorithms when evaluating complex borrower profiles, as the high recall (97%) achieved by tree-based classifiers directly reduces the erroneous rejection of creditworthy applicants. Second, in regulatory environments where model transparency and auditability are mandatory, institutions should deploy optimized single Decision Trees, which achieved performance parity with complex ensemble methods on localized data while providing clear, auditable decision paths. Finally, financial institutions must replace informal model adoption practices with systematic benchmarking protocols that evaluate candidate algorithms across comprehensive metrics specifically balancing recall and F1-score to eliminate model selection bias and align predictive accuracy with strategic portfolio growth.

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