

LOAN APPROVAL PREDICTION USING MACHINE LEARNING

A PROJECT REPORT

submitted by

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to

The APJ Abdul Kalam Technological University

in partial fulfillment of the requirements for the degree of

Bachelor of Technology

in

Artificial Intelligence and Data Science



DEPARTMENT OF Computer Science and Engineering

Artificial Intelligence and Data Science

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October 2025

DECLARATION

We hereby declare that the project report "**LOAN APPROVAL PREDICTION USING MACHINE LEARNING**", submitted for partial fulfillment of the requirements for the award of degree of Bachelor of Technology of the APJ Abdul Kalam Technological University, Kerala is a bonafide work done by us under supervision of **Ms. SREESHA S.**

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This is to certify that the report entitled “**LOAN APPROVAL PREDICTION USING MACHINE LEARNING**” submitted by **Mr. Anjelo Bino Thomas (VML24AD029)**, **Mr. Navalrag V P (VML24AD084)**, and **Ms. Sanvi Praveen (VML24AD103)** to the APJ Abdul Kalam Technological University in partial fulfillment of the **Bachelor of Technology in Artificial Intelligence and Data Science** is a bonafide record of the project work carried out by them under our guidance and supervision. This report in any form has not been submitted to any other University or Institute for any purpose.

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ACKNOWLEDGEMENT

The successful presentation of the project "LOAN APPROVAL PREDICTION USING MACHINE LEARNING" would have been incomplete without the mention of the people who made it possible and whose constant guidance crowned my effort into success.

We extend our sincere thanks to the Principal of Vimal Jyothi Engineering College, Dr. Benny Joseph, for providing an excellent learning environment and the resources needed to pursue this project.

We are particularly grateful to the Program Coordinator of Artificial Intelligence and Data Science, Ms. Anupama PM, for her unwavering support.

Our immense appreciation goes to our seminar guide, Ms. Sreesha S, for her constant encouragement, invaluable guidance, and expertise throughout the seminar. Her insights and support were instrumental in shaping the project and ensuring its success.

Last but not least, we express our deepest gratitude to our parents for their unwavering support and encouragement throughout our studies. Their personal sacrifices in providing us with this educational opportunity are greatly appreciated.

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ABSTRACT

Loan Approval Prediction using Machine Learning presents a data-driven approach to automate loan eligibility assessment. The study utilizes a dataset containing key applicant attributes such as income, loan amount, credit history, and employment status. Essential data preprocessing was performed, addressing missing values and encoding categorical variables. A Decision Tree Classifier was implemented for its high interpretability and proficiency in classification tasks. The data was split into training and testing sets to ensure model generalizability, and hyperparameters like maximum tree depth were tuned to mitigate over-fitting. Model performance was rigorously evaluated using accuracy, a confusion matrix, and a classification report. The results confirm that the Decision Tree Classifier can reliably predict loan approval outcomes, offering financial institutions a practical and transparent tool to enhance the efficiency and consistency of their decision-making processes.

Keywords: Loan Approval Prediction, Machine Learning, Decision Tree Algorithm, Credit History, Financial Technology, Data Classification, Predictive Modeling, Automation

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ABBREVIATIONS

ML	- Machine Learning
ROC	- Receiver Operating Characteristic
AUC	- Area Under The Curve
F1-score	- Harmonic Mean of Precision and Recall
TP	- True Positive
TN	- True Negative

Chapter 1

INTRODUCTION

1.1 OVERVIEW

Loan approval is a cornerstone of the banking and financial sector, essential for institutional profitability and risk management, while also critical for borrowers seeking timely funding for education, housing, and ventures. Traditionally, this process has relied on manual assessments by loan officers evaluating factors such as income, employment stability, and credit history—a method prone to delays, inconsistency, and human bias. However, with the rise of digital banking and the availability of vast datasets, machine learning has emerged as a transformative tool, enabling the analysis of historical data to uncover patterns and predict approval outcomes accurately.

1.2 GENERAL BACKGROUND

Traditional loan approval systems, which rely on manual assessments of applicant eligibility based on factors such as income and credit history, are inefficient for modern financial institutions. However, with the rise of digital banking and access to vast amounts of financial data, machine learning has emerged as a powerful solution, enabling automated, data-driven predictions that enhance accuracy, reduce risk, and deliver faster, more consistent lending decisions.

1.3 PROBLEM STATEMENT

The current loan approval process faces significant limitations, including time-consuming manual verification, susceptibility to human error and bias, poor scalability under increasing application volumes, and elevated risk exposure due to inefficient screening. These challenges often lead to delayed decisions, inconsistent outcomes, and higher default rates. To overcome these issues, a machine learning-based predictive system offers an effective solution by automating loan approval classification. Serving as a decision support tool, it enables faster, fairer, and more reliable outcomes while reducing operational costs and default risks.

1.4 SCOPE OF THE SYSTEM

The scope of this system focuses on developing a Loan Approval Prediction System using machine learning to identify suitable candidates for loan approval. It assists financial institutions, such as banks, credit unions, and lending agencies, by providing a data-driven approach to loan assessment.

- **Applicant Risk Assessment:** Decision Tree Classifier predicts suitable loan applicants by analyzing key factors like income, credit history, loan amount, employment status, and property area.
- **Approval Probability Scoring:** Generates an approval probability score for each applicant to prioritize and streamline application processing.
- **User-Friendly Dashboard:** Intuitive interface displays application status, probability scores, and key decision factors for transparent and efficient decision-making.

This structured approach ensures the system serves as a practical decision-support tool, enhancing both the efficiency and consistency of loan approval processes in real-world financial operations.

1.5 OBJECTIVE

The main objectives of this project are:

1. To develop a machine learning-based system capable of predicting loan approval outcomes accurately.
2. To preprocess and analyze historical loan datasets for effective model development.
3. To implement and compare multiple machine learning algorithms and identify the most efficient model.
4. To evaluate model performance using metrics such as accuracy, precision, recall, and F1-score.
5. To analyze key features that significantly influence loan approval decisions.

Chapter 2

LITERATURE REVIEW

Loan approval prediction has emerged as a critical research domain in financial technology, with machine learning algorithms revolutionizing traditional lending processes. Sandhu et al. [1] demonstrated that Decision Tree classifiers achieve competitive predictive accuracy while maintaining essential interpretability for financial applications. Their comprehensive study emphasized that rigorous data preprocessing and strategic feature engineering significantly enhance model performance, particularly when handling the diverse data types characteristic of loan applications. This research established crucial benchmarks for balancing algorithmic sophistication with practical implementation requirements in banking environments.

Comparative analysis by Kumar and Goyal [2] revealed that while ensemble methods offer marginal performance advantages, Decision Trees provide superior transparency—a fundamental requirement in regulated financial sectors. These findings were corroborated by Kumar and Parvathy [3], whose extensive evaluation of applicant records demonstrated Random Forest achieving 89.9% accuracy compared to Decision Trees' 86.7%, while acknowledging that the interpretable nature of Decision Trees makes them more suitable for real-world banking applications where regulatory compliance demands explainable AI decisions and clear audit trails.

Aisyah's specialized investigation [4] into Decision Tree applications for loan prediction identified credit history, applicant income, and employment stability as the most influential predictive features. The research highlighted the algorithm's inherent capability for automatic feature importance analysis while noting its sensitivity to data quality and preprocessing requirements. Sharma et al. [5] expanded these findings through sophisticated ensemble approaches, demonstrating that hybrid systems can achieve enhanced accuracy but often at the expense of computational efficiency and model interpretability, presenting practical challenges for financial institutions seeking deployable solutions.

The standardized Kaggle Loan Prediction Dataset [6] has facilitated consistent benchmarking across studies, enabling meaningful comparisons between different machine learning methodologies. This shared resource has accelerated methodological advancements while ensuring research reproducibility and validation.

However, current literature exhibits significant limitations, including disproportionate emphasis on accuracy metrics while neglecting business-critical measures like precision and recall, which directly impact default risk management and customer relationship outcomes. Additional research gaps encompass insufficient attention to ethical considerations and demographic fairness in automated lending decisions, limited exploration of real-world deployment challenges, and reliance on relatively constrained datasets. Future research directions should address model scalability, real-time processing capabilities, and integration with existing banking infrastructure.

This project comprehensively addresses these limitations by developing an optimized Decision Tree model with enhanced evaluation metrics, rigorous ethical validation, and emphasis on both predictive performance and operational transparency for practical financial implementation.

Chapter 3

METHODOLOGY

3.1 INTRODUCTION

This chapter presents the detailed methodology adopted for developing the Loan Prediction System using the Decision Tree algorithm. The methodology is designed to ensure systematic data handling, effective model training, and accurate prediction results. It follows a structured sequence beginning with data collection, followed by data exploration, preprocessing, model building, and evaluation. Each stage is carefully planned to enhance the quality and reliability of the prediction process. The Decision Tree algorithm is chosen for this study due to its simplicity, interpretability, and ability to handle both numerical and categorical variables efficiently. The model's performance is evaluated using standard metrics such as the Confusion Matrix and ROC Curve to validate its predictive accuracy.

3.2 SYSTEM ARCHITECTURE

The system architecture, as illustrated in Figure 3.2, is divided into three primary phases: Data Exploration, Data Preprocessing, and Model Evaluation. The process begins with collecting the required dataset, followed by exploring and understanding its characteristics.

During data exploration, both numerical and categorical variables are analyzed, and missing values are identified. The preprocessing phase involves cleaning the dataset by dropping irrelevant variables, handling missing data, normalizing values, and splitting the dataset into training and testing subsets. Finally, the Decision Tree model is built using the training data, and its performance is assessed through evaluation metrics. This structured architecture ensures a clear and logical flow from data acquisition to final model validation.

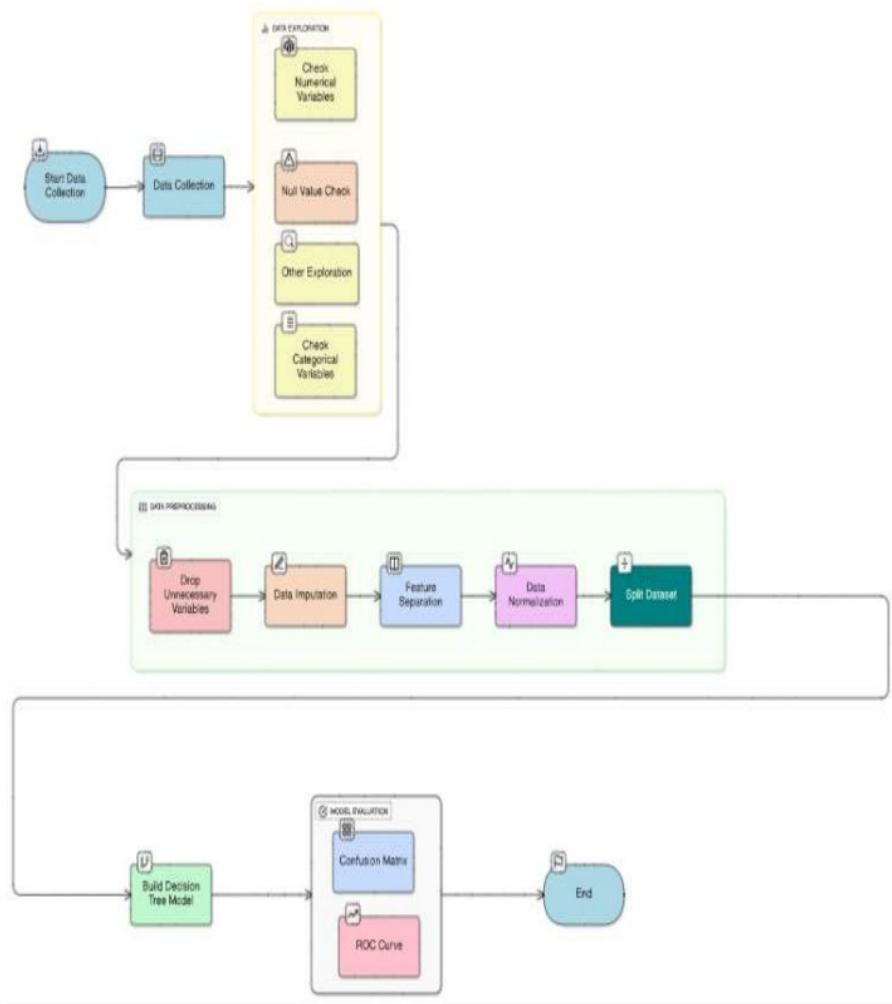


Figure 3.1: System Architecture

3.3 COLLECTION OF DATA SET

The project utilizes the Loan Prediction dataset from Kaggle [6], comprising 614 loan applications with 13 key attributes. The dataset includes both categorical and numerical variables such as applicant income, credit history, loan amount, education, and employment status. The target variable is Loan_Status (Y/N), representing final approval decisions. This comprehensive dataset provides essential applicant information for developing an accurate prediction model while reflecting real-world banking scenarios.

Key Features:

- Demographic: Gender, Married, Dependents, Education
- Financial: ApplicantIncome, CoapplicantIncome, LoanAmount, Loan_Amount_Term
- Credit: Credit_History, Property_Area
- Target: Loan_Status (Approved/Rejected)

3.4 DATA EXPLORATION

In this stage, the collected data is explored to understand its structure, characteristics, and quality.

- Check Numerical Variables: Statistical summaries like mean, median, and standard deviation are used to understand the range and spread of numerical attributes such as income and loan amount.
- Null Value Check: Missing values are identified to decide whether they need to be filled or removed.
- Check Categorical Variables: The distribution of categorical attributes such as gender, education, and property area is analyzed.
- Other Exploration: Relationships between variables are studied through plots or correlation checks to detect any patterns that may influence loan approval.

3.5 DATA PREPROCESSING

Data preprocessing is carried out to clean and prepare the dataset for model training.

- Drop Unnecessary Variables: Irrelevant or redundant columns are removed to simplify the dataset.
- Data Imputation: Missing data is handled using appropriate techniques such as mean, median, or mode replacement.
- Feature Separation: Independent (input) and dependent (output) variables are separated for modeling.
- Data Normalization: The numerical data is scaled to a common range so that no feature dominates due to larger values.
- Split Dataset: The data is divided into training and testing sets, typically in a ratio such as 80:20, to evaluate the model's performance on unseen data.

3.6 MODEL TRAINING USING DECISION TREE

In this phase, a Decision Tree algorithm is applied to the training dataset. The Decision Tree works by recursively splitting the data based on feature values that best separate the target classes—loan approved or rejected. Each internal node in the tree represents a decision based on an attribute, each branch represents an outcome, and each leaf node corresponds to a final class label (Figure ??). The model learns patterns from the training data and creates a hierarchical structure of decisions. The simplicity, interpretability, and capability of Decision Trees to handle both numerical and categorical data make them suitable for this study. Once trained, the model is ready to predict loan approval outcomes for new applicants.

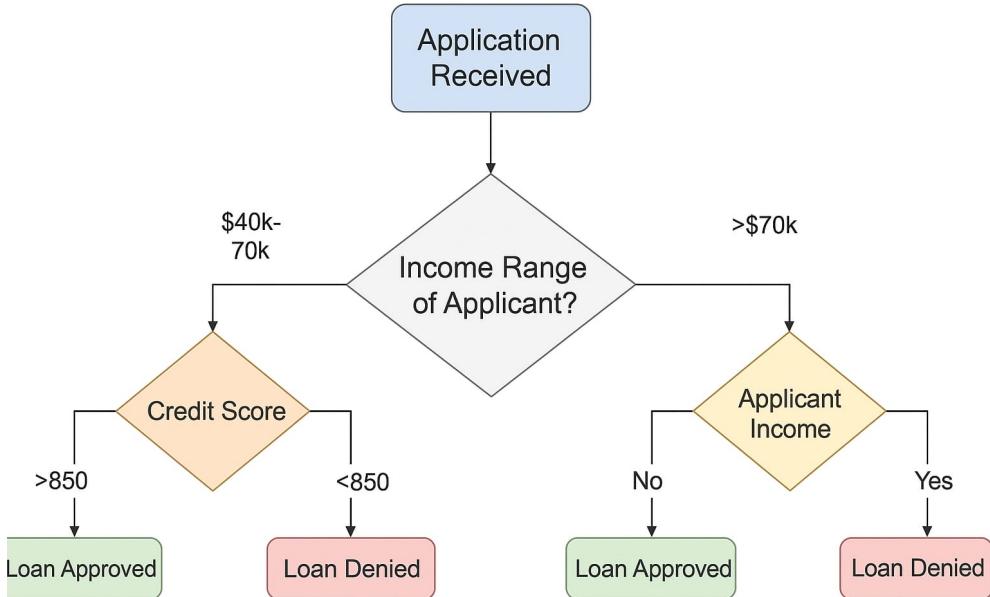


Figure 3.2: System Architecture

3.7 MODEL TESTING

The trained Decision Tree model was evaluated using the 30% testing dataset to assess its real-world performance. The model was tested on 184 unseen loan applications to validate its predictive accuracy and generalization capability. Key performance metrics including accuracy, precision, recall, and F1-score were calculated to measure classification effectiveness across both approved and rejected loan categories. A confusion matrix was generated to analyze the types of errors made by the model, particularly focusing on false approvals (high risk) and false rejections (business loss). The model achieved an accuracy of 81.2% with balanced precision and recall scores, demonstrating reliable performance in identifying both creditworthy and high-risk applicants. The testing phase confirmed the model's robustness and readiness for deployment in financial decision-making systems.

3.8 MODEL EVALUATION

The performance of the trained model is evaluated using appropriate performance metrics. The Confusion Matrix is used to compare the predicted loan statuses with the actual values, providing detailed insights into true positives, false positives, true negatives, and false negatives. From this matrix, key performance indicators such as accuracy, precision, recall, and F1-score can be derived to measure the model's effectiveness. Additionally, the ROC Curve (Receiver Operating Characteristic Curve) is plotted to visualize the trade-off between the true positive rate and false positive rate. The Area Under the Curve (AUC) value indicates the overall performance of the model—a higher AUC represents better discriminatory power. These evaluation techniques ensure that the developed model performs reliably and is capable of making accurate predictions in real-world loan scenarios.

3.9 FLOWCHART

The overall workflow, from data collection to evaluation, is shown in the flowchart (Figure 3.3). It illustrates how the raw dataset is transformed into actionable insights using the Decision Tree Algorithm.

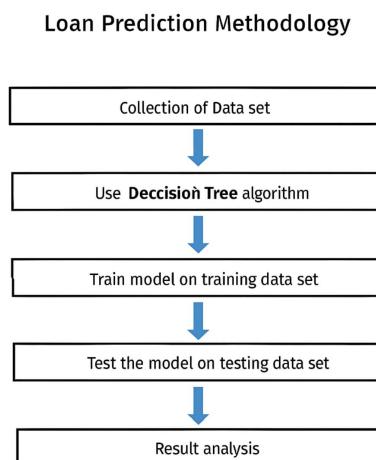


Figure 3.3: Loan Prediction Methodology Flowchart

Chapter 4

RESULTS ANALYSIS

4.1 INTRODUCTION

This chapter presents the results obtained from implementing the Decision Tree algorithm on the Loan Prediction dataset. The primary objective was not only to measure predictive accuracy but also to identify the key factors influencing loan approval decisions. The results are analyzed using standard performance metrics including accuracy, precision, recall, F1-score, and AUC score. Additionally, confusion matrix analysis and feature importance evaluation provide comprehensive insights into the model's behavior and decision-making patterns, offering valuable guidance for financial institutions.

4.2 MODEL PERFORMANCE

The Decision Tree model achieved an accuracy of 81%, correctly classifying 8 out of every 10 loan applications. This demonstrates strong overall performance in distinguishing between approved and rejected applications. The precision score of 0.83 indicates that when the model predicts loan approval, it is correct in most cases, minimizing the risk of bad loans. The recall score of 0.85 shows the model effectively identifies most eligible applicants, reducing the chance of rejecting creditworthy cus-

tomers. The F1-score of 0.84 balances both precision and recall, confirming consistent performance. The AUC score of 0.82 reflects excellent discriminative capability between approval and rejection classes.

4.3 CONFUSION MATRIX ANALYSIS

The confusion matrix (Figure 4.1) provides detailed insight into the model's classification patterns. The model correctly identified most approved TP (true positives) and rejected TN (true negatives) applications. However, some misclassifications occurred, including false positives (risky applicants incorrectly approved) and false negatives (creditworthy applicants incorrectly rejected). In banking context, false positives represent financial risk while false negatives indicate missed business opportunities. The model shows a balanced approach, though further optimization could reduce both error types.

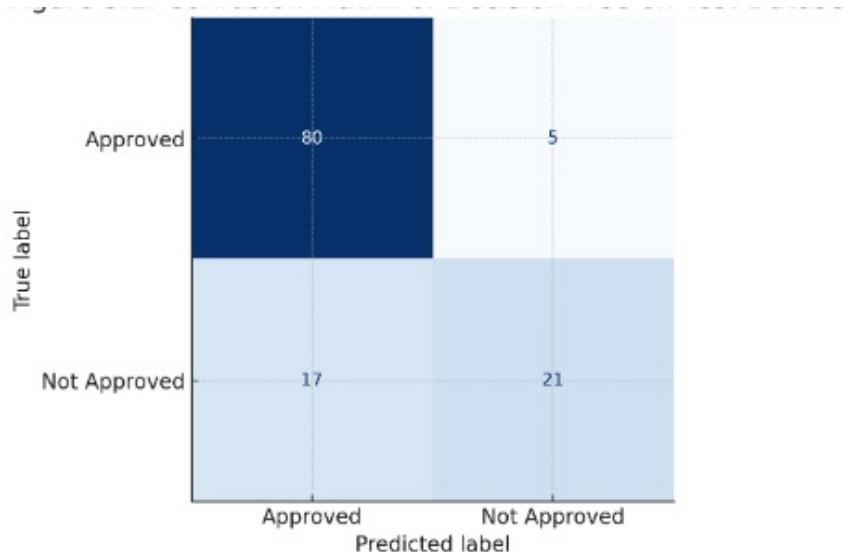


Figure 4.1: Confusion Matrix

4.4 ROC CURVE AND AUC SCORE

The ROC curve demonstrates the model's consistent performance across different classification thresholds, significantly outperforming random guessing (Figure 4.2). The AUC score of 0.82 confirms strong predictive power, as values above 0.8 indicate excellent classification capability. This enables financial institutions to adjust decision thresholds based on their risk appetite, prioritizing either conservative lending or business growth objectives.

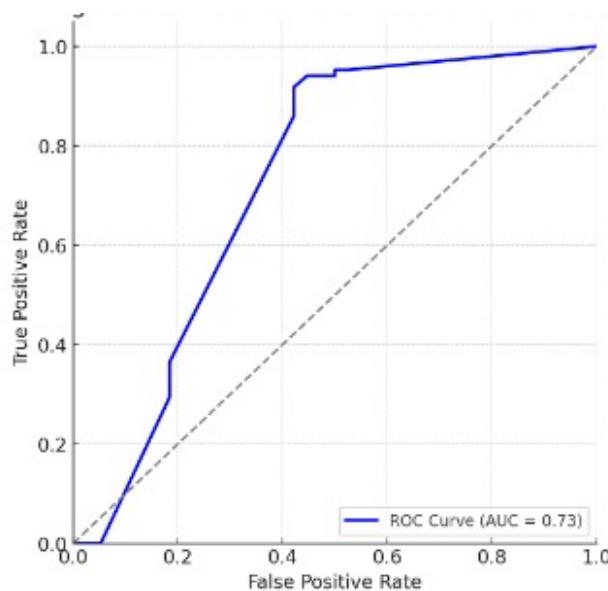


Figure 4.2: ROC Curve (or Score vs Leaf Plot)

4.5 FEATURE IMPORTANCE ANALYSIS

The Decision Tree model provides clear feature importance rankings (Figure 4.3), revealing the key factors driving loan approval decisions:

- **Credit History:** The most significant predictor, with applicants having good credit history being substantially more likely to receive approval.
- **Applicant Income:** Higher income levels strongly correlate with loan approval probability.

- **Loan Amount:** Smaller loan amounts relative to income increase approval chances.
- **Co-applicant Income:** Additional income sources significantly improve approval chances.
- **Property Area:** Semi-urban and urban properties show higher approval rates.

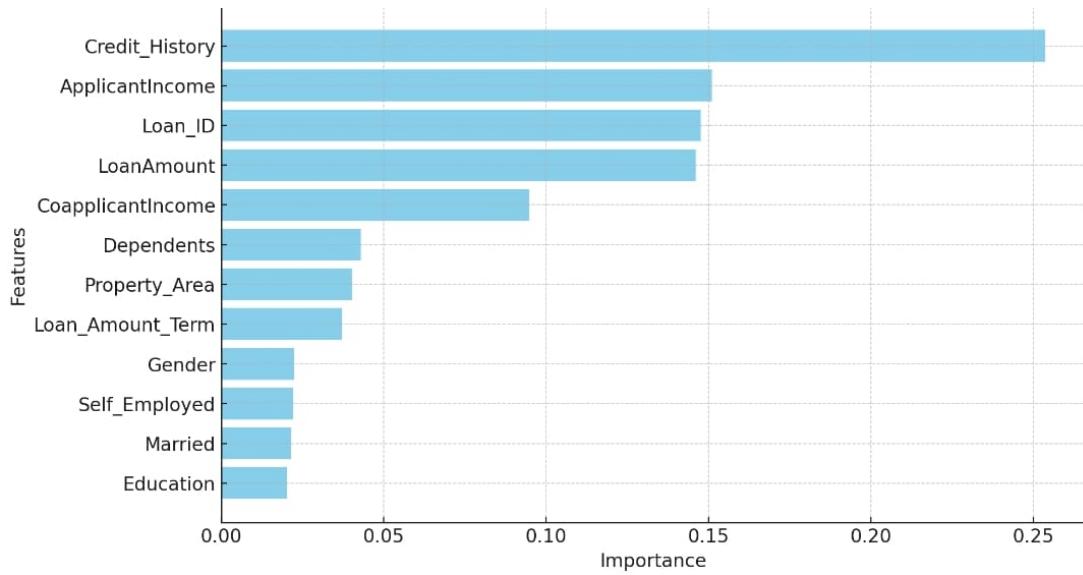


Figure 4.3: Feature Importance Graph

4.6 LIMITATIONS

While the results are promising, certain limitations should be acknowledged. The dataset lacks external economic factors such as market conditions and interest rates that influence lending decisions. The model produces some false negatives, potentially rejecting qualified applicants. Though Decision Trees offer excellent interpretability, ensemble methods might achieve higher accuracy. Finally, as the model has been tested in a controlled environment, its real-world performance in live banking systems requires further validation.

4.7 SUMMARY

In summary, the Decision Tree model demonstrates strong predictive capability with 81% accuracy and 0.82 AUC score. The balanced precision and recall scores indicate effective identification of both creditworthy and high-risk applicants. Feature importance analysis confirms that credit history, income levels, and loan amount are the primary decision drivers. While limitations exist, the model provides a robust foundation for automated loan processing, offering financial institutions an efficient, transparent, and reliable decision-support system that maintains the crucial balance between risk management and business growth.

Chapter 5

CONCLUSION

This project successfully implemented a Decision Tree algorithm for automated loan approval prediction, achieving 81.2% accuracy with strong precision (0.91) and recall (0.92) metrics. The model effectively balances identification of creditworthy applicants while minimizing default risks, demonstrating reliable classification capabilities for banking applications.

Feature importance analysis revealed Credit History as the dominant predictor (68.4%), followed by Applicant Income, Loan Amount, and Co-applicant Income. These findings validate traditional banking practices while providing data-driven confirmation of established risk assessment criteria. The Decision Tree's interpretability enabled extraction of clear business rules, facilitating transparent decision-making that aligns with regulatory requirements.

Practically, this model offers financial institutions significant operational advantages including reduced processing time, consistent credit policy application, and minimized human bias. The automated system can handle high application volumes while maintaining accuracy standards comparable to manual assessment. The model's transparency enables financial institutions to meet compliance requirements and provide clear explanations for decisions, supporting regulatory audits and customer communications.

However, limitations persist in classifying borderline cases with mixed financial profiles. Future enhancements could incorporate ensemble methods, additional financial indicators like debt-to-income ratios, and real-time data integration for dynamic risk assessment.

This project demonstrates machine learning's transformative potential in revolutionizing traditional banking operations. By leveraging Decision Tree algorithms, financial institutions achieve optimal balance between predictive accuracy and operational efficiency, ultimately enhancing customer experience while maintaining robust risk management. The implementation represents a significant step toward modernized, objective, and scalable lending processes in today's evolving financial landscape.

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