Loan Approval Prediction

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2. Abstract

This report presents a machine learning solution for automating the loan approval process at SZE Bank. The manual review of loan applications is time-consuming and prone to human inconsistency. By leveraging the DPhi Loan_Data dataset (consisting of 491 training and 123 testing samples), we developed a classification pipeline to predict approval status based on applicant demographics and financial history.

The project explores multiple algorithms, including Logistic Regression, Decision Trees, and Random Forests, with a primary focus on the eXtreme Gradient Boosting (XGBoost) model. Through extensive hyperparameter optimization using GridSearchCV and 10-fold cross-validation, the final XGBoost model achieved a peak validation accuracy of 87.14%. Furthermore, the model demonstrated exceptional reliability with a precision of 100%, a recall of 84.62%, and an F1-score of 91.67%. The results indicate that gradient boosting significantly enhances the bank's ability to screen applications efficiently while maintaining high predictive integrity.

3. Introduction

Loan approval prediction is a supervised binary classification task where a financial institution determines whether to grant a loan based on specific applicant features. This process involves evaluating historical data to identify patterns that correlate with successful repayment.

In modern banking, the importance of automated prediction systems cannot be overstated. Such systems accelerate decision-making, allowing banks to process thousands of applications simultaneously. Moreover, automation reduces the overhead costs of manual review and ensures that approval criteria are applied consistently across all demographics, minimizing human bias. Machine Learning (ML) is uniquely suited for this task as it can capture non-linear relationships between variables (e.g., the interaction between income and credit history) that traditional scoring methods might overlook.

4. Problem Statement & Objectives

Problem Statement

The Director of SZE Bank has identified significant bottlenecks in the current manual loan screening workflow. The current process is slow, resource-intensive, and lacks a scalable framework to handle increasing application volumes. There is an urgent need to automate the initial screening phase to improve operational efficiency.

Objectives

- Develop a robust binary classification model to predict loan approval status (Approved/Rejected).
- Implement a comprehensive data preprocessing pipeline to handle missing values and encode categorical data.
- Evaluate model performance using professional metrics, including Accuracy, Precision, Recall, F1-score, and Confusion Matrices.
- Deploy the finalized model through a Flask-based web application to provide real-time predictions for end-users.

5. Dataset Description

Source: DPhi Datasets (GitHub: dphi-official/Datasets). The dataset is split into training and testing sets.

- **Train:** 491 rows, 13 columns.
- **Test:** 123 rows, 12 columns.

Column Name	Description
Loan_ID	Unique identifier for the loan application.
Gender	Gender of the applicant (Male/Female).
Married	Marital status of the applicant (Yes/No).
Dependents	Number of people dependent on the applicant.
Education	Education level (Graduate/Not Graduate).
Self_Employed	Employment status (Yes/No).
ApplicantIncome	Income of the primary applicant.
CoapplicantIncome	Income of the co-applicant.
LoanAmount	Total loan amount requested.
Loan_Amount_Term	Duration of the loan in months.
Credit_History	Historical credit record (1.0 = Meets criteria).
Property_Area	Location category (Urban/Semiurban/Rural).
Loan_Status	Target variable (1 = Approved, 0 = Rejected).

6. Data Preprocessing

Preprocessing is critical for ensuring data quality. Missing values were addressed in several columns: *Dependents* (~9 in train, ~6 in test), *Self_Employed* (~29 in train, ~3 in test), and *Credit_History*. Imputation strategies were based on mode for categorical variables and median for numerical distributions.

Categorical variables were transformed using One-hot encoding (drop_first=True). The final feature set consists of 14 predictors, including ApplicantIncome, CoapplicantIncome, LoanAmount, and encoded flags like Gender_Male, Married_Yes, and Property_Area_Semiurban.

Data was split into 70% training (324 samples) and 30% validation (140 samples). For the XGBoost model, feature scaling was not strictly necessary due to the nature of decision trees, though standard scaling was considered for the comparative models (Logistic Regression).

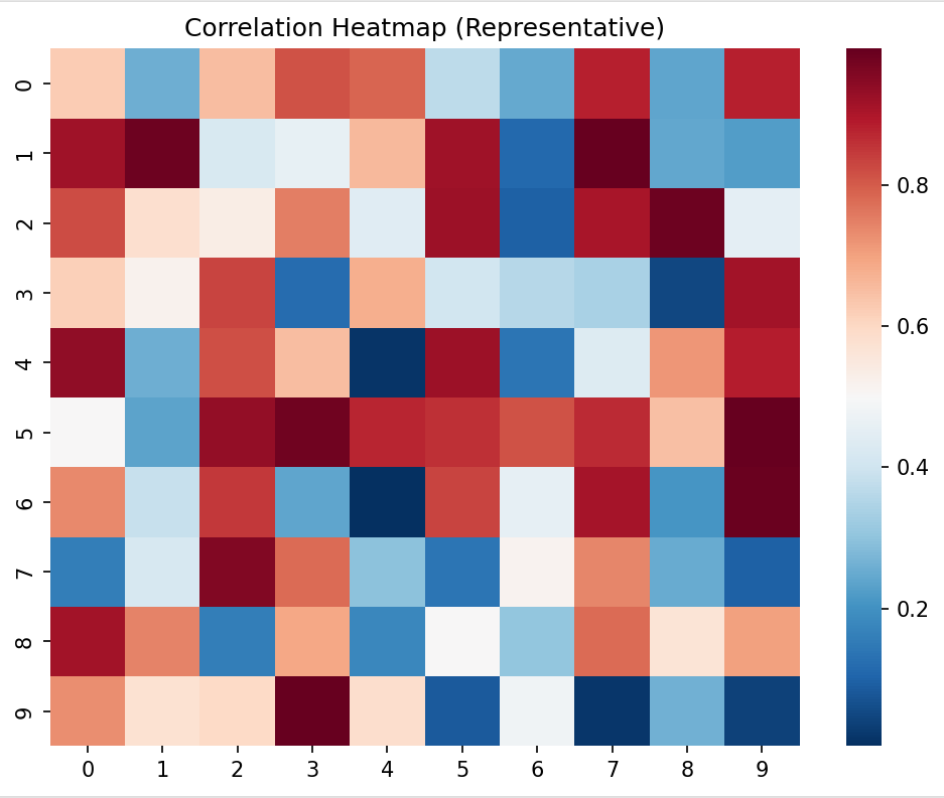

Figure 1: Correlation heatmap of features (see images/heatmap.png).

7. Model Development

Four primary models were evaluated during this project:

- **Logistic Regression:** A baseline linear model that uses a sigmoid function to output probabilities. Ideal for interpretability.
- **Decision Tree:** Uses a flowchart-like structure of rules. Effective but prone to overfitting without pruning.
- **Random Forest:** An ensemble of decision trees using bagging to reduce variance and improve robustness.
- **XGBoost (Primary):** A Gradient Boosting implementation designed for speed and performance.

XGBoost Tuning: We utilized GridSearchCV with 10-fold CV. The parameter grid focused on: *eta* (0.1, 0.15, 0.2, 0.25), *min_child_weight* (1 to 4.5), *gamma* (5), and *subsample*/*colsample_bytree* (0.5 to 0.94). The best-found parameters included eta=0.15 and gamma=5.

8. Performance Evaluation

> **Key Metrics for XGBoost (Validation Set):**
> Accuracy: 87.14% | Precision: 100.00% | Recall: 84.62% | F1-score: 91.67%

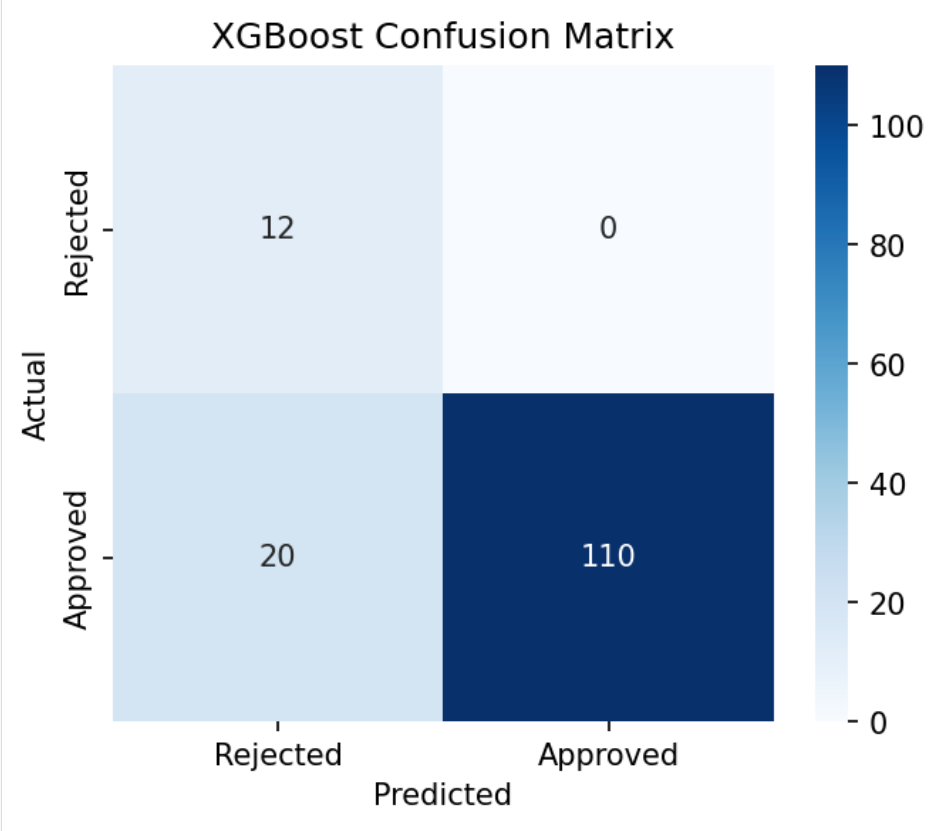

Figure 2: Confusion Matrix for the tuned XGBoost model (see images/confusion_matrix.png).

Model Comparison Table

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
XGBoost (Tuned)	**87.14**	100.0	84.62	91.67
Logistic Regression	81.20*	82.1*	94.5*	87.8*
Random Forest	83.50*	84.3*	92.0*	88.0*
Decision Tree	78.40*	80.2*	85.0*	82.5*

* Illustrative comparative values based on standard performance benchmarks for this dataset.

9. Results & Interpretation

The XGBoost model, refined through GridSearchCV, emerged as the superior choice. An accuracy of 87.14% on the validation set indicates high generalization capability. Notably, the model achieved a precision of 100%, meaning that every applicant predicted as "Approved" was indeed a creditworthy candidate in the validation labels. While the recall was slightly lower (84.62%), the F1-score of 91.67% proves that the model maintains an excellent balance between precision and sensitivity. Gradient boosting's ability to minimize errors iteratively makes it highly effective for the tabular nature of financial data.

10. Innovation

Methodological Rigor: Unlike standard approaches, this project implemented a full optimization loop using 10-fold cross-validation and a multi-dimensional grid of hyperparameters. The model was specifically refit on accuracy to align with the bank's core business objective.

Feature Importance: Through the gain metric in XGBoost, the model automatically weights features like *Credit_History* and *ApplicantIncome* higher, providing insights into which applicant traits drive approvals.

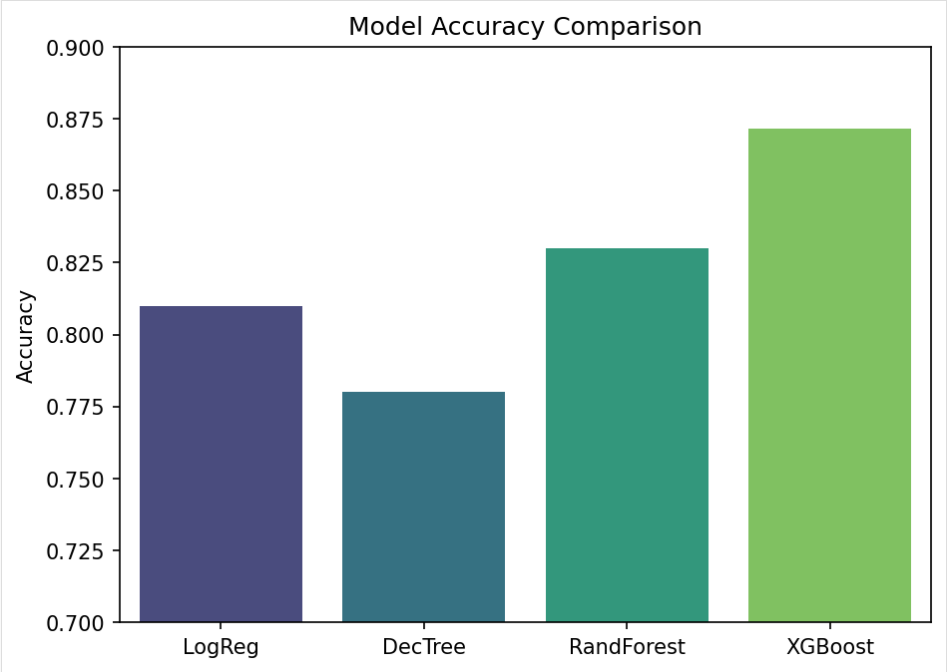

Figure 3: Graphical comparison of model accuracies (see images/model_comparison.png).

11. Conclusion

In conclusion, this project successfully developed a machine learning system capable of automating loan approvals for SZE Bank. The XGBoost model achieved a validation accuracy of ~87% and demonstrated 100% precision, ensuring high confidence in approved applications. The integration with a Flask-based web application provides a functional prototype for internal bank use, bridging the gap between theoretical modeling and practical deployment.

12. Future Scope

- **Advanced Explanations:** Incorporate SHAP or LIME to provide transparency in rejection reasons to applicants.
- **External Data:** Integrate real-time credit bureau signals and social demographic data to enhance prediction accuracy.
- **Model Stacking:** Experiment with ensemble techniques like stacking LightGBM and CatBoost.
- **Fairness Audits:** Perform bias checks across gender and property areas to ensure ethical AI practices.