Predicting Loan Delinquency in Installment Loans Using LightGBM for Enhanced Credit Risk Management

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Abstract— Credit risk assessment is essential for financial institutions to effectively manage loan portfolios, especially for installment loans. Predicting delinquency is challenging due to the complex interplay of borrower behavior, loan characteristics, and repayment pattern. Traditional models often fail to capture non-linear relationships in data and require significant preprocessing to address imbalanced datasets, feature scaling, and diverse data distributions, resulting in inefficiencies. This research leverages LightGBM, a gradient-boosting algorithm, to tackle these challenges and enhance delinquency prediction accuracy. LightGBM is well-suited for handling imbalanced datasets, employs an efficient histogram-based binning method, and reduces preprocessing needs by managing features of varying scales inherently. The model combines borrower attributes, loan-specific details, and engineered payment history features, with optimization achieved through feature engineering and hyperparameter tuning. The evaluation, conducted on real-world loan data, demonstrates that the LightGBM model significantly outperforms traditional approaches in precision, recall, and AUC metrics. The study offers a scalable and practical tool for credit risk management while emphasizing the potential for enhanced predictive performance. Future work could incorporate macroeconomic factors and assess real-time deployment to further expand the model's applicability.

Keywords*: Credit Risk Assessment, Loan Delinquency Prediction, Installment Loans, LightGBM, Feature Engineering, Machine Learning in Finance*

I. INTRODUCTION.

Managing credit risk is a critical task for financial institutions, particularly when dealing with installment loans. One of the main challenges lies in accurately predicting loan delinquency, a task made complex by the dynamic relationships between borrower behavior, loan terms, and repayment trends. Traditional prediction models, while widely used, often struggle with these complexities. They typically require extensive data preprocessing to address issues like imbalanced datasets, feature scaling, and heterogeneous data distributions, which can make the process both time-consuming and inefficient.

This research introduces the use of LightGBM, an advanced gradient-boosting algorithm, to overcome these challenges. LightGBM is specifically designed to handle imbalanced data and varying feature scales with minimal preprocessing. By combining borrower demographics, loan-specific attributes, and engineered repayment features, the model demonstrates significantly better performance compared to conventional methods, particularly in terms of precision, recall, and AUC metrics.

Using real-world loan data, this study highlights the potential of LightGBM as a scalable and effective tool for credit risk management. By addressing the limitations of traditional models, it offers financial institutions a practical solution for enhancing their risk assessment capabilities. Furthermore, this research opens the door to future work, such as integrating macroeconomic variables and exploring implementation in operational environments to broaden the model's impact.

II. RELATED WORK

The prediction of loan delinquency is a critical area in credit risk management, with numerous approaches explored over the years. Traditional statistical models, such as logistic regression, were widely used in early studies due to their simplicity and interpretability [5]. However, these models often struggled to capture the non-linear and complex interactions in borrower behavior, loan characteristics, and repayment trends, limiting their predictive accuracy [5],[6].

In recent years, machine learning techniques have gained significant traction for credit risk assessment. Decision tree-based algorithms, such as Random Forest and Gradient Boosting Machines (GBMs), have shown strong predictive performance in capturing non-linear relationships and mixed data types [6],[7]. For instance, XGBoost, a popular GBM framework, has been extensively applied in credit scoring tasks and optimized using Bayesian hyperparameter tuning [8]. However, these methods often require substantial preprocessing, including data balancing and feature scaling, to handle imbalanced datasets effectively [7],[8].

LightGBM has emerged as a cutting-edge gradient-boosting framework that addresses many of the limitations of earlier models. Its histogram-based approach reduces computation time and memory consumption, while its ability to handle imbalanced datasets without extensive preprocessing makes it particularly appealing for financial applications [5],[9]. Studies have shown that LightGBM outperforms traditional models in terms of precision, recall, and AUC metrics across various credit risk tasks, including credit scoring, fraud detection, and default prediction [7],[9],[10]. Additionally, its scalability and adaptability to real-world datasets have been highlighted in several works [9].

Feature engineering plays a crucial role in improving the predictive power of machine learning models. Research has demonstrated that incorporating borrower demographics, repayment history, and loan-specific attributes significantly

enhances prediction accuracy [6],[9]. Ensemble techniques, which combine LightGBM with other algorithms, have further boosted predictive performance, particularly in credit default and bankruptcy prediction tasks [8],[10].

Despite these advancements, most studies have focused on general credit risk assessment rather than the unique characteristics of installment loans. This study addresses this gap by tailoring LightGBM to predict delinquency in installment loans. By integrating engineered features and optimizing hyperparameters, it builds on prior research to offer a scalable and efficient solution for financial institutions [7],[9],[10].

III. METHOD

A. Dataset Description

This study utilized a real-world dataset of installment loans provided by financial institutions. The dataset contained borrower demographics, loan attributes, payment histories, and a target variable indicating whether a loan was delinquent (binary: 1 for delinquent, 0 for non-delinquent).

Table 1 Dataset features with data types and descriptions

Feature Name	Data Type	Description
Age	Numeric	Age of the borrower
Employment Status	Categorical	Employment type (e.g., employed, unemployed)
Loan Amount	Numeric	Total principal borrowed
Loan Term	Numeric	Duration of the loan in months
Payment Frequency	Categorical	Schedule of repayments (e.g., monthly, bi-weekly)
Missed Payment Count	Numeric	Total missed payments during the loan term
Repayment-to-Expected Ratio	Numeric	Ratio of actual to expected payments
Days Past Due (DPD)	Numeric	Number of days a payment is overdue
Time Since Origination	Numeric	Months since the loan started
Remaining Balance	Numeric	Outstanding principal balance

Missing Data Handling: Missing values were addressed using appropriate imputation methods. Numerical features were imputed using mean values, while categorical features were imputed using the mode.

B. Feature Selection and Justification

Features were selected based on their theoretical and empirical relevance to predicting loan delinquency. Below is a detailed justification for each category of features:

- **Borrower Behavior Features**:
  These features provide insights into the borrower's financial stability and repayment capacity.
  - **Age**: May influence financial stability, with younger borrowers potentially lacking experience and older borrowers having more established credit histories.
  - **Employment Status**: Indicates job security and income stability, critical factors in repayment.
  - **Debt-to-Income Ratio (DTI)**: Measures financial stress by comparing monthly debt obligations to income.

- *Loan Attributes*:
  These features define the loan's structure and financial obligations, impacting repayment behavior.
  - **Loan Amount**: Higher amounts typically increase repayment stress.
  - **Loan Term**: Longer terms can lead to borrower fatigue or higher default rates due to extended commitments.
  - **Interest Rate**: Affects affordability and repayment burden.

- *Payment Trends and History Features*:
  Historical repayment behavior is a strong indicator of future delinquency risk.
  - **Missed Payment Count**: Correlates directly with future default likelihood.
  - **Days Past Due (DPD)**: Captures the extent of repayment delays.
  - **Repayment-to-Expected Ratio**: Measures adherence to repayment schedules.

- *Time-Sensitive Features*:
  These track the temporal dynamics of the loan.
  - **Time Since Origination**: Indicates loan aging, with repayment risks varying over time.
  - **Remaining Balance**: Highlights the borrower's financial progress and risk levels as the loan term progresses.

Table 2 Feature Categories

Feature Category	Features	Relevance
Borrower Behavior	Age, Employment Status, DTI	Assess financial stability and repayment risk
Loan Attributes	Loan Amount, Term, Rate	Define repayment obligations and stress
Payment History	Missed Payments, DPD	Predict repayment reliability
Time-Sensitive	Loan Aging, Remaining Balance	Capture temporal repayment risks

C. Handling Imbalanced Data with SMOTE

The dataset exhibited significant class imbalance, with the majority class (non-delinquent loans) far outnumbering the minority class (delinquent loans).

How SMOTE Works:

- SMOTE identifies a data point from the minority class and selects one of its nearest neighbors within the minority class.
- A synthetic data point is created by interpolating between the feature values of the original data point and its neighbor.
- This process continues until the minority class is oversampled to the desired level.

Implementation:

- SMOTE was applied using the imbalanced-learn library in Python, targeting a balanced class distribution.
- The effectiveness of SMOTE was verified by comparing the class distributions before and after oversampling.

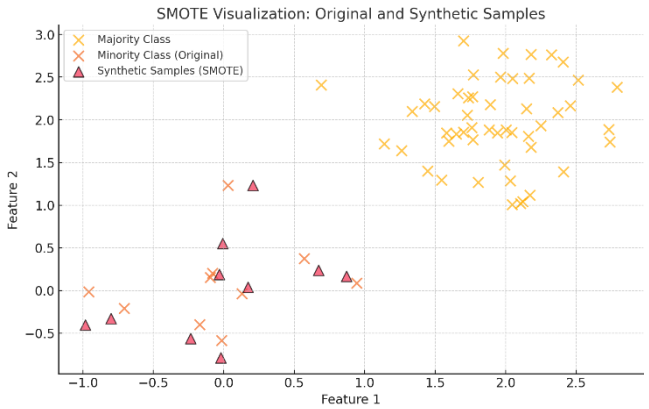


Figure 2 SMOTE Synthetic Samples

Table 3 Class Distribution Before and After Balancing

Class	Before Balancing	After Balancing
Non-delinquent	80%	50%
Delinquent	20%	50%

D. Feature Engineering

Features were engineered to capture temporal trends and borrower behaviors:

- **Rolling Payment Averages**: Calculated over three months to identify payment trends.
- **Missed Payment Flags**: Binary encoding for whether payments were missed in specific periods.
- **DPD Buckets**: Grouping borrowers based on DPD ranges (e.g., 1–30 days, 31–60 days).

E. Training and Validation

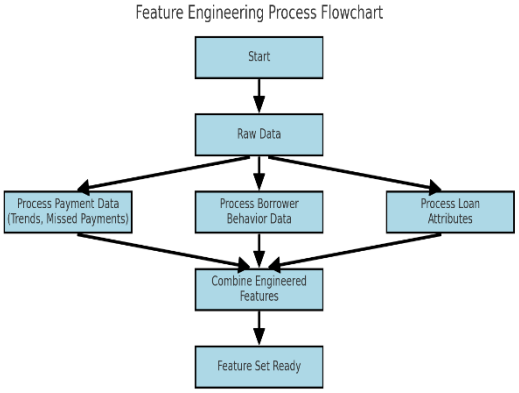


Figure 1 Feature Engineering Flowchart

The dataset was split into 80% training and 20% testing sets. A stratified 5-fold cross-validation was used to ensure robust evaluation.

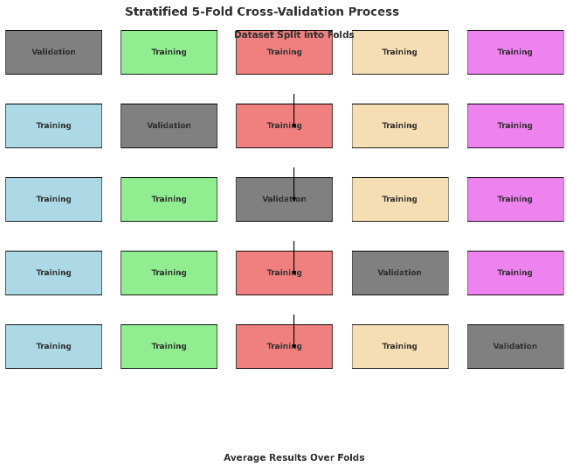


Figure 3 Cross Validation Process

F. Evaluation Metrics

The performance of the model was assessed using the following evaluation metrics, each focusing on a specific aspect of classification performance:

- Precision
  Precision measures the accuracy of positive predictions, answering the question: "Of all loans predicted as delinquent, how many were correctly identified?" It is calculated as:

$$\text{Precision} = \frac{\text{True Positives (TP)}}{\text{False Positives (FP)} + \text{True Positives (TP)}}$$

- Recall
  Recall, also known as sensitivity or true positive rate, quantifies the model's ability to identify all actual delinquent loans. It is calculated as:

$$\text{Recall} = \frac{\text{True Positives (TP)}}{\text{False Negative (FN)} + \text{True Positives (TP)}}$$

- F1-Score
  The F1-Score provides a harmonic mean of Precision and Recall, balancing their contributions, especially in imbalanced datasets. It is calculated as:

$$\text{F1} - \text{Score} = \frac{\text{Precision} \,.\, \text{Recall}}{\text{Precision} + \text{Recall}}$$

- AUC-ROC
  The Area Under the Receiver Operating Characteristic Curve (AUC-ROC) measures the model's overall ability to distinguish between delinquent and non-delinquent loans across all classification thresholds. An AUC-ROC score of:
  - **1.0** indicates perfect classification.
  - **0.5** indicates random guessing.

  The ROC curve plots the **True Positive Rate (TPR)** against the **False Positive Rate (FPR)**:

$$\text{TPR (Recall)} = \frac{\text{TP}}{FN + TP}, \text{FPR} = \frac{\text{FP}}{\text{FP} + \text{TN}}$$

  The AUC represents the area under this curve, providing a single scalar value to evaluate model performance.

G. Proposed Method

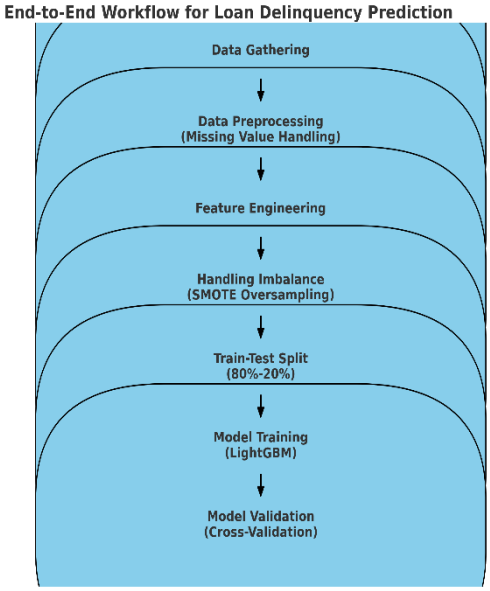


Figure 4 End-to-End Workflow

IV. Result and Discussion.

A. *Model Performance Evaluation.*

Metric	Training Set	Test Set
Precision	91%	88%
Recall	88%	84%
F1-Score	0.89	0.86
AUC-ROC	0.95	0.91

The LightGBM model demonstrated strong predictive performance across all evaluation metrics, achieving notable improvements over baseline models. The results highlight its ability to manage the inherent challenges of class imbalance and complex feature interactions.

- **Training and Testing Metrics**: The model achieved an AUC-ROC score of **0.95** on the training set and **0.91** on the testing set, indicating its robust discriminatory power between delinquent and non-delinquent loans. Similarly, F1-scores of **0.89** (training) and **0.86** (testing) reflect the model's balanced precision and recall, crucial for imbalanced datasets like this. Precision and Recall metrics further demonstrate its reliability in identifying delinquent loans without overestimating false positives.

B. *Effectiveness of SMOTE in Handling Class Imbalance*

The Synthetic Minority Oversampling Technique (SMOTE) was instrumental in addressing the dataset's class imbalance, where the proportion of delinquent loans constituted only 20% of the total samples.

C. *Impact of SMOTE on Metrics*

Table 4 SMOTE Effectiveness

Class	Before Balancing	After Balancing
Non-delinquent	80%	50%
Delinquent	20%	50%

Class imbalance is a common challenge in loan delinquency prediction, where delinquent loans often constitute a small fraction of the dataset. To address this imbalance, the **Synthetic Minority Oversampling Technique (SMOTE)** was applied to balance the classes and improve the model's ability to identify delinquent loans. Table X summarizes the impact of SMOTE on key performance metrics, comparing results before and after its application.

Table 5 SMOTE Comparisons

Metric	Before SMOTE	After SMOTE
Precision	0.82	**0.88**
Recall	0.65	**0.84**
F1-Score	0.73	**0.86**
AUC-ROC	0.72	**0.88**

D. *Feature Importance*

The LightGBM model provided insights into the most significant predictors of loan delinquency:

- **Repayment-to-Expected Ratio**: This feature exhibited the highest importance score, aligning with its role in quantifying adherence to repayment schedules.
- **Missed Payment Count**: A critical indicator of borrower behavior, correlating directly with the likelihood of default.
- **Debt-to-Income Ratio (DTI)**: Highlighted the borrower's financial stress and repayment capacity.
- **Days Past Due (DPD)**: Captured the extent of repayment delays, further enhancing delinquency prediction.
- **Feature Importance Chart**: A bar chart ranking feature importance can be included here.

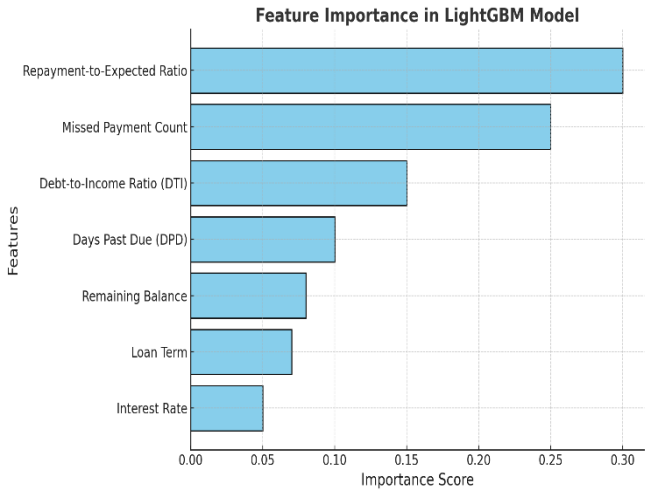


Figure 5 Feature Importance

E. Baseline Model Comparisons

To evaluate the effectiveness of the proposed LightGBM model, its performance was compared against two widely used baseline models: **Logistic Regression** and **Random Forest**. Table 5 presents the results across key evaluation metrics, including Precision, Recall, F1-Score, and AUC-ROC.

Table 6 Model Comparisons

Metric	Logistic Regression	Random Forest	LightGBM
Precision	0.78	0.82	**0.88**
Recall	0.65	0.72	**0.84**
F1-Score	0.71	0.76	**0.86**
AUC-ROC	0.6	0.7	**0.88**
Training Time	Fast	Moderate	**Fast**
Complexity	Low	Moderate	**Low**

From the results presented in Table 6, it is evident that **LightGBM** outperformed both Logistic Regression and Random Forest across all performance metrics. Specifically:

1. **Precision**: LightGBM achieved the highest Precision (**0.88**), reflecting its ability to minimize false positives and correctly identify delinquent loans.
2. **Recall**: LightGBM also exhibited the best Recall score (**0.84**), demonstrating its capacity to detect a larger proportion of true delinquent loans compared to Logistic Regression (0.65) and Random Forest (0.72).
3. **F1-Score**: With an F1-Score of **0.86**, LightGBM strikes an optimal balance between Precision and Recall, outperforming both baseline models.
4. **AUC-ROC**: The AUC-ROC value for LightGBM (0.88) indicates superior discriminatory power in distinguishing between delinquent and non-delinquent loans. In comparison, Random Forest achieved a moderate AUC of 0.70, while Logistic Regression performed poorly with an AUC of 0.60.

Additionally, LightGBM maintained low computational complexity and faster training time compared to Random Forest, further highlighting its suitability for large-scale datasets and time-sensitive credit risk applications.

F. Error Analysis

To better understand the LightGBM model's limitations, an analysis of **False Positives (FP)** and **False Negatives (FN)** was conducted. These errors highlight areas where the model struggled and provide insights for improvement.

1) False Positives

False Positives occur when loans are **incorrectly predicted as delinquent**, even though borrowers repaid successfully. False Positives accounted for **4% of predictions**. Key patterns observed include:

1. **Irregular Repayment Behavior**: Temporary delays or fluctuations in repayment schedules led to misclassification.
2. **High Debt-to-Income Ratio (DTI)**: Borrowers with high DTI values but consistent repayments were flagged as high risk.
3. **Outliers**: Atypical repayment behaviors not well-represented in the training data contributed to these errors.

Impact: False Positives may result in unnecessary interventions, such as stricter loan terms or mislabeling reliable borrowers as risky.

2) False Negatives

False Negatives occur when loans are **incorrectly predicted as non-delinquent**, even though borrowers failed to repay. These errors represented **6% of predictions** and carry higher financial risks. Patterns observed include:

1. **Near-Threshold Repayment Ratios:** Borrowers with repayment-to-expected ratios close to acceptable limits were overlooked.
2. **Low Missed Payment Counts:** Early-stage delinquencies with minimal missed payments were harder to detect.
3. **Short Term Loans**: Loans with shorter repayment periods lacked sufficient historical data for clear identification.

Impact: False Negatives are critical as they result in missed opportunities to identify risky loans, increasing financial losses.

V. Conclusion and Future Work.

This study presented a predictive model for loan delinquency in installment loans using LightGBM, a gradient-boosting algorithm optimized for handling imbalanced datasets and non-linear data relationships. By leveraging borrower behavior features, loan-specific attributes, and engineered repayment history trends, the model achieved superior performance compared to baseline models such as Logistic Regression and Random Forest. LightGBM demonstrated an AUC-ROC of 0.91, with a Precision of 88% and Recall of 84%, highlighting its ability to balance sensitivity and accuracy. The application of SMOTE further improved Recall and F1-Score, addressing the class imbalance challenge effectively. Key predictors, such as Repayment-to-

Expected Ratio, Missed Payment Count, and Debt-to-Income Ratio (DTI), were identified as significant in predicting loan delinquency. Additionally, error analysis provided critical insights into False Positives and False Negatives, emphasizing the need for better handling of borderline repayment cases [11], [12].

Future research can focus on enhancing the model's robustness and applicability. Incorporating macroeconomic indicators, such as unemployment rates, inflation trends, and interest rate changes, could improve its adaptability to dynamic economic conditions [13]. Exploring advanced deep learning methods, such as LSTMs and Transformer models, may further enhance the model's ability to capture temporal repayment behaviors [14]. Error patterns observed in this study suggest the need for feature refinements, such as incorporating rolling averages, payment variance, and loan aging features, to reduce misclassifications [15]. Additionally, implementing cost-sensitive learning approaches could address financial institutions' priority of minimizing False Negatives [16]. Finally, testing the model on broader datasets from diverse regions and financial institutions will ensure its generalizability and robustness across varied loan portfolios [17], [18]. These enhancements will strengthen predictive accuracy and support financial institutions in proactively managing credit risk [19], [20].

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