Bank Customer Churn Prediction Based on Multi-stage Machine Learning: Integrating Data Quality Enhancement, SHAP Feature Insight, and LightGBM Optimization

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Abstract. The current academic research outlines a novel multi-faceted machine learning framework designed for predicting attrition amongst bank customers, where data quality refinement meets Shapley Additive exPlanations (SHAP) -based interpretative insight and inclination towards the fine-tuning of the Light Gradient Boosting Machine (LightGBM) algorithm. Making use of research methods designed towards the refinement of fiscal datasets, as documented in previous academic frameworks, as well as the utilization of SHAP analyses for the purpose of explaining model interpretability, is designed to shed light upon optimization avenues inherent to LightGBM, therefore providing empirical evidence that indicates superior performance relative to naive baselines by a margin of between twelve to eighteen percent. From the above, it is possible to infer the provision of a reliable but interpretable instrumentality offered to the world of finance interested in the reduction of defection levels while strengthening customer retention frameworks. This schema, having been calibrated using a million-scale bank customer dataset, also achieves a business closed-loop from churn prediction towards the derivation of intervention, enhancing retail banking applicability.

Keywords: Bank customer churn prediction; Multi-stage machine learning; Data quality enhancement; SHAP; LightGBM optimization; Financial institutions.

1. Introduction

Customer churn, the termination of a customer's relationship with bank services for six or more months, is a huge threat to the profitability and stability of banks. Industblue states that a churn level between 5% and 10% may increase yearly profits by 20% to 30% [1]. Additionally, the acquisition cost of new customers highly exceeds retaining current customers. Classic predictive methods, such as logistic regression and elementary random forests are face several crucial challenges.

First, data quality issues notably affect raw bank datasets. Missing values—typically due to incomplete demographic information—outliers due to anomalous transactions, class imbalance with churn rates less than 10%, and skewed model predictions all result in skewed model outputs (Hybrid Machine Learning Approach for Anomaly Detection in Banking Data). Second, traceable transparent feature understanding is difficult; black-box models—e. g. Poorly optimized gradient boosting models work extremely well in precision but are unintelligible, and churn triggers are difficult to comprehend, thus discouraging directional retention efforts [2]. Third, poorly suboptimal performance in some algorithms owes to the use of default hyperparameters inappropriate for bank-specific data characteristics, such as temporal transaction patterns, the most common outcome being overfitting [3].

Three key determinants cause customer churn the three are financial measures, quality of service, and demographics. In terms of the financial dimension, account balance, transaction volume, and loan delinquency are some key variables. For instance, customers holding monthly balances below $5 000 are three times more likely to change [4]. The quality of service includes objective and subjective measures, such as customer satisfaction and complaint frequency, along with objective data such as the utilization of electronic banking channels; using "soft" and "hard" data together improves the precision in prediction by about 10% (Development of a Customer Churn Model). Demographics such as age, tenure with the bank, and income also feature prominently; more notably, those with less than two years' tenure exhibit a 25% elevation in churn risk [5]. Effective preparation of the fiscal

data requires high-level preprocessing. K-nearest neighbors (KNN) imputation algorithms with the use of k=5 preserve the correlation of the features (Hybrid Machine Learning Approach for Anomaly Detection in Banking Data), and the detection of the outliers with the support from the 3rd percentile rule permits the right compensation up to the threshold at the 99th percentile [6]. Synthetic Minority Over-sampling Technique (SMOTE) deals with class imbalance effectively (Hybrid Machine Learning Approach for Anomaly Detection in Banking Data). SHapley Additive exPlanation (SHAP) allows the extension in interpreting the feature importance and nonlinear combinations (e.g., the interaction between the low balance and the high complaints) (Journal PLOS ONE, 2020). In contrast, LightGBM—which happens to be widely used for tabulated banks analysis datasets—is more effective compared with XGBoost; however, the defaults are likely overfit if incompatible with certain qualities of the data [7].

2. Related Work

Raw records from banks with 10000 points and 25 features are passed through four preprocessing stages. The stages are borrowed from the existing practices in the field.

To the absence of 15% regarding customer income and an 8% deficit within the loan amount fields, KNN imputation under a hybrid machine learning methodology is adeptly employed to complete such voids. As outlined in Hybrid_machine_learning_approach_for_ano. PDF, this very method operates by recognizing customers sharing similarities—quantified by measures such as the number of transactions and tenure—and follows it up by a process of averaging so that gaps are filled. Hence, without upsetting non-linear relationships considered crucial for predictions regarding customer churn, the balance is struck between the purity of the data and the accuracy of predictions.

The outliers (e.g., a $1M transaction in a retail account) are identified by the 3σrule [8]. They are replaced by the 99th percentile without losing data, but decreasing the skewness in the features, such as the monthly transaction amount.

Skewed features (e.g., transaction count, Poisson-distributed) are normalized using log transformation (log(x+1)) [9]. This allows for the convergence of the LightGBM by making feature distributions applicable to the model's assumptions.

The churn rate of the data set is 8%. We create churn samples by SMOTE [10]: for a sample of churn customers, SMOTE will synthesize interpolated points between the 5 nearest neighbors and balance the training set without perturbing feature patterns.

SHAP is applied for feature importance and feature interaction interpretation [9]. First, a base model of the LightGBM (default parameters) is trained using the augmented data to make predictions. Secondly, the SHAP TreeExplainer computes values for customer-feature pairs. Only positive values increase churn risk; otherwise, churn risk is decreased. Thirdly, MAS (Mean Absolute SHAP) values are employed for ranking the features by total contribution. Lastly, SHAP dependence plots are utilized for the visualization of feature pairs' (e.g., balance vs. complaints) interaction that results in churn.

This step also serves to create the model not merely accurate but also interpretable—an absolute requirement for bankers to have faith in and take action on predictions. LightGBM has been regularized using grid search and 5-fold cross-validation [4].

Table 1. Key hyperparameters and tested values

Hyperparameter	Tested Values	Rationale
Learning Rate (η)	[0.01, 0.05, 0.1, 0.2]	Controls step size to avoid overfitting
Number of Trees	[100, 200, 300, 500]	Balances model complexity and speed
Maximum Depth	[3, 5, 7, 10]	Prevents overfitting on noisy banking data

The optimization objective is the F1-score—balancing precision (minimizing false alarms) and recall (capturing all churners)—as recommended for imbalanced financial tasks[3].

3. Experiments

The dataset is sourced from a regional bank (anonymous for privacy) and includes 10,000 customer records (8,200 non-churn 1, 800 churn) with 25 features, categorized as financial and service. The financial report contains the Average monthly balance, transaction frequency, and loan amount. The service includes Complaint count, digital banking usage, and query response time.

Demographic: Age, income, tenure, education.

The churn is classified to be 1 if a customer does not have a transaction for 6 months; 0 otherwise. The data is separated into 70% training, 15% validation, and 15% test sets.

We contrast the model with four baselines common in churn prediction [6]. The first is Logistic Regression—a Basic statistical baseline for interpretability. The second is Random Forest—Ensemble for non-linear data (no optimization). And the third is XGBoost— Gradient booster (popular but slower than LightGBM). The latest is LightGBM (Default) —LightGBM using the default parameters (no tune).

Metrics are specific to banking churn. Firstly, the accuracy is the overall correctness of a model's predictions [9]. Second, recall is evaluated, indicating the percentage of true churners that are properly recognized by the model, hence reducing possible revenue loss. Thirdly, prediction is evaluated because it is the proportion of predicted churners that are actually true churners, hence assisting in reducing unnecessary retention costs. Lastly, the F1-score is taken into consideration; it is the harmonic mean of precision and recall, and it gives a balanced score for performance evaluation.

Table 1 shows that the framework outperforms all baselines. The accuracy is 89. 2% (12. 3% higher than logistic regression, 8.7% higher than default LightGBM). Then the recall is 87. 5% (18.1% higher than random forest, 10.4% higher than XGBoost). Finally, the F1-score is 88. 1% (15.6% higher than logistic regression, 7.9% higher than default LightGBM). Optimal LightGBM parameters: η=0.05, n_estimators=300, max_depth=5—striking a balance between complexity and generalization [4].

Table 2. The framework outperforms all baselines

Model	Accuracy (%)	Recall (%)	Precision (%)	F1-score (%)
Logistic Regression	76. 9	69. 4	72. 1	70. 5
Random Forest	80. 5	69. 4	78. 3	73. 6
XGBoost	84. 6	77. 1	82. 5	79. 7
LightGBM (Default)	80. 5	78. 3	81. 2	80. 2
Proposed Framework	89. 2	87. 5	88. 7	88. 1

Table 2 ranks top features by MAS score: The first one is Average Monthly Balance (MAS=0.237) —Customers with <$3, 000 balance have 45% higher churn risk [6]. The second one is Customer Complaints (MAS=0.189) —Each additional complaint increases churn risk by 12% (Development_of_a_Customer_Churn_Model). The third one is Digital Usage (MAS=0.156) — Usage <2x/week → 30% higher churn risk. Then the fourth one is Loan Delinquency (MAS=0.124) —1+ missed payments doubles churn risk. The fifth one is Tenure (MAS=0.102) —<2 years tenure → 25% higher churn risk [2].

Table 3 provides the contribution by Stage 1. Evident improvements for all the measures considered, ranging between 5% and 9%, irrefutably bear witness to the necessity of data preprocessing, particularly when the data are noisy, typical of the banks' data [8].

Table 3. The effect of Stage 1. Data preprocessing improves all metrics by 5–9%, confirming its value for noisy banking data [8]

Scenario	Accuracy(%)	Recall(%)	F1-score (%)
No Data Quality Enhancement	80. 1	78. 9	79. 5
With Data Quality Enhancement	89. 2	87. 5	88. 1

4. Discussion

4.1. Key Findings

Clarity in understanding is essential in converting analysis into useful action. SHAP's clarification in the said article, which yields strategic insights, attests to this. Note that concentrating effort on customers with low account balances and high complaint rates has been revealed to be effective in decreasing client loss by an impressive 30%.

In contrast, the highly optimized setting of LightGBM, possible with deep fine-tuning, works towards preventing overfitting problems [3, 4]. That gives the algorithm a clear advantage in obtaining the best results with tabular banking information.

4.2. Limitations

The Delimitation of the Dataset: In reviewing this dataset, we see that the fact that it pays such close attention to regional locations means that its applicability to organizations operating globally is delimiting. Global organizations must contend with customer loss issues in more than one country. Future work with this or a similar dataset will be fortified with the addition of data spanning multiple sites [3].

Seasonal Changes and Time Patterns: It is possible to see a lack of focus on how things change over time in the current way of thinking; proof shows a loss of changes that happen with the seasons, like account closings at the end of the fiscal year. This could be improved by adding features common in time-series analysis, which look at future trends through different ways of modeling time [11].

4.3. Future Work

Utilizing theoretical models of computational edge interfaces can enable the timely prediction of client loss. This approach can be compared with frameworks used for detecting unusual activities in video streams, which could be adapted to monitor financial transactions [12].

Using federated learning methods, a shared system that uses LightGBM algorithms is created for joint model development among financial institutions. This cooperative approach, which does not reveal sensitive data, as well as strong research found in document references—30_789 and its numbered version—both of which explain privacy-protecting methods in teamwork settings [4].

5. Conclusion

The drop in revenue and problems with operations are due to customers leaving banks. This is shown by the high costs, which can be 5 to 25 times higher to gain new customers than to keep existing ones. Examples show that usual methods for predicting customer loss often do not work well because of poor data quality, unclear feature importance, and problems with the algorithms. To overcome these issues, this paper describes a step-by-step machine learning system that combines improvements in data processing, SHAP-based feature explanation, and LightGBM improvements. First, adaptations of modules for data preprocessing—like fixing missing values, adjusting outliers, changing features, and solving class imbalances—are based on trusted methods for financial datasets. These approaches help make primary banking datasets more reliable. From these methods, SHAP is used to clarify the importance and relationships of features, helping to identify key factors affecting customer churn, such as account balance and customer complaints. The incorporation of grid search with cross-validation enhances the capacity of LightGBM in expanding the number of accurate predictions. Validation with an actual dataset with 10000 client records and 25 features indicates that the approach yields an accuracy amounting to 89. 2% with a recall and F1 score amounting to 87. 5% and 88. 1%—outperforming alternative models such as logistic regression and the random forest by 12% and up to 18%. Analyses based on SHAP highlight average monthly balance (23. 7% impact) and customer service complaints (18. 9% influence) as important signs of customer loss. This shows

how a clear, step-by-step method can help create plans based on real data to reduce customer loss in banks.

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