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Customer Rentention and Profitability Analysis for the Banking Sector Using Machine Learning

Sumit Pariyar[1], Pandiya Rajan G[2]
[1]UG Scholar, Dept. of Computer Science and Engineering (AI & ML), KPR Institute of Engineering and Technology, Coimbatore-641407, Tamil Nadu, India
[2]Assistant Professor II, Dept. of CSE (Artificial Intelligence and Machine Learning), KPR Institute of Engineering and Technology, Coimbatore-641407, Tamil Nadu, India
Emails: *sumitpariyar1001@gmail.com[1], pandiyarajan@kpriet.ac.in[2]*

Abstract
Customer churn represents one of the most consequential operational challenges facing modern banking institutions. As fintech alternatives and neobanks continue to erode traditional customer loyalty, banks require predictive systems that go beyond historical rule-based triggers. This paper proposes an end-to-end, AI-driven framework that integrates supervised churn prediction, Customer Lifetime Value (CLV) estimation, and behavioral anomaly detection within a unified operational pipeline. The system employs XGBoost as its core classification engine, trained on a dataset of 88,167 anonymized customer records spanning demographic, transactional, and behavioral attributes. Data preprocessing incorporates SMOTE-based class balancing, z-score normalization, and a suite of engineered features including complaint ratio, activity drop index, and profitability index. The trained model achieves an accuracy of 88.3%, precision of 0.896, recall of 0.850, F1-score of 0.872, and an ROC-AUC of 0.923 on held-out test data. Model decisions are made interpretable through SHAP (SHapley Additive Explanations) analysis, while a Google Gemini integration translates SQL-driven query results into plain-English narratives for non-technical stakeholders. The system is deployed on Microsoft Azure via a FastAPI backend and Streamlit frontend, achieving a mean API response latency of 200 ms and 99.8% uptime over a one-week evaluation period. Experimental results demonstrate that the proposed framework substantially outperforms conventional churn detection approaches and offers a scalable, privacy-conscious foundation for data-driven retention strategy in banking.

Keywords: *Customer churn prediction; customer lifetime value (CLV); banking analytics; XGBoost; SHAP explainability; anomaly detection; Isolation Forest; machine learning; business intelligence; Microsoft Azure.*

1. Introduction

The contemporary banking landscape is defined by intensifying competitive pressure from fintech startups, digital-only neobanks, and cross-border payment platforms. Within this environment, customer retention has emerged as a primary determinant of sustainable profitability. Research consistently indicates that acquiring a new banking customer costs five to seven times more than retaining an existing one, and that even a modest improvement in retention rates can produce disproportionate gains in long-term revenue [1]. Customer churn in banking is not an abrupt event but a gradual process shaped by a confluence of transactional, behavioral, and experiential signals. A decline in transaction frequency, an uptick in complaint calls, or a shift in product engagement can each independently indicate early disengagement; their combination is considerably more predictive. Traditional monitoring approaches, grounded in static threshold rules such as flagging accounts inactive beyond ninety days, are fundamentally ill-suited to capturing these multi-dimensional dynamics. They are reactive rather than anticipatory, static rather than adaptive, and incapable of distinguishing between a high-value customer showing early warning signs and a low-value customer already disengaged [2]. Machine learning (ML) offers a principled alternative. By learning from historical patterns across large, heterogeneous datasets, ML models can detect subtle early indicators of churn, rank customers by their retention priority, and provide interpretable justifications for those rankings. When combined with Customer Lifetime Value (CLV) estimation, the system can direct retention resources toward customers who are both likely to leave and financially significant, rather than treating all at-risk accounts uniformly [3]. This paper presents a complete, deployment-validated system that unifies churn prediction, CLV modeling, anomaly detection, and natural-language insight generation in a single operational pipeline. The rest of this paper is organized as follows: Section 2 reviews related work; Section 3 describes the methodology in full; Section 4 presents experimental results and discussion; Section 5 concludes and outlines future directions.

2. Related Work

2.1. Churn Prediction Using Supervised Learning

Gradient boosting methods have established themselves as the dominant approach for tabular churn prediction tasks. Gupta et al. [1] applied gradient boosted machines to retail banking data using transaction frequency, product holdings, and service feedback scores, demonstrating the model family's effectiveness with structured financial records. Zhao et al. [7] extended this line of work by constructing ensemble frameworks that stack Random Forest, Logistic Regression, and Gradient Boosting classifiers, improving robustness against class imbalance at the cost of inference complexity. A practical limitation shared by both approaches is the absence of any profitability dimension: churn probability alone does not distinguish between losing a high-value account and losing a near-dormant one.

2.2. Customer Lifetime Value and Profitability Modeling

Rashid et al. [2] addressed this limitation through a two-stage pipeline: XGBoost churn classification followed by regression-based CLV estimation. This design enables retention teams to rank intervention targets by the product of churn probability and expected value, maximising return on retention spend. Nguyen and Hoang [8] further refined profitability-aware retention by integrating RFM (Recency, Frequency, Monetary) segmentation with gradient boosted regression trees, showing consistent improvements in net revenue retained per campaign dollar. A recurring weakness in CLV-centric approaches is their dependence on rich transaction history, which limits utility for newly acquired customers.

2.3. Anomaly Detection for Behavioral Monitoring

Chen and Li [3] demonstrated the effectiveness of the Isolation Forest algorithm for detecting unusual behavioral deviations in banking transactions, including sudden inactivity and unexplained high withdrawal events, without requiring labelled churn examples. Brown and Lee [9] reached similar conclusions in a retail banking context, observing that anomaly scores derived from unsupervised methods serve as effective leading indicators of churn when integrated with a downstream supervised classifier. The fundamental limitation of standalone anomaly detection remains its inability to produce actionable churn probability estimates.

2.4. Deep Learning and Temporal Modeling

Suresh and Banerjee [4] applied Long Short-Term Memory (LSTM) networks to sequential customer interaction logs, capturing temporal disengagement trajectories that static models miss. While the recall improvements were meaningful, the approach demands substantially greater training data and computational resources than tree-based alternatives, creating barriers to deployment in institutions with modest infrastructure [10].

2.5. Research Gap

Across the reviewed literature, no single system simultaneously addresses contactless churn prediction, behavioral anomaly detection, profitability-weighted retention prioritization, natural-language insight generation for non-technical stakeholders, and cloud-based production deployment. Each of these elements has appeared in isolation; their integration into a validated, end-to-end pipeline constitutes the primary contribution of this work.

3. Methodology

3.1. System Architecture Overview

The proposed system is structured as a six-stage modular pipeline: (1) data ingestion, (2) preprocessing and feature engineering, (3) model training and evaluation, (4) database integration, (5) LLM-driven interpretability, and (6) cloud deployment. Each stage is implemented as an

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Table 1 Dataset Feature Descriptions

Feature	Description
CustomerID	Unique identifier for each customer record
Age	Customer age in years
Gender	Gender of the customer (Male / Female)
Tenure	Duration of the customer relationship in years
Usage Frequency	Average frequency of bank product or service
Support Calls	Number of complaint or support calls raised
Payment Delay	Average payment delay across billing cycles
Subscription Type	Service tier: Basic, Standard, or Premium
Contract Length	Contract duration: Monthly, or Annual
Total Spend	Cumulative monetary spend by the customer
Last Interaction	Days elapsed since the most recent transaction
Churn	Target label: 1 = churned, 0 = retained

independent module, permitting individual components to be upgraded or replaced without disrupting the overall pipeline. The system was implemented in Python 3.10, with scikit-learn and XGBoost for modelling, SQLite and SQLAlchemy for persistence, FastAPI for the backend service layer, Streamlit and Plotly for the frontend, and Microsoft Azure App Service for production hosting.

3.2. Dataset

The dataset was sourced from Kaggle's publicly available Banking Customer Churn repository. It contains 88,167 anonymized customer records described by twelve attributes spanning demographic characteristics, transactional behavior, and service interaction history. The binary target variable, Churn, equals one for customers who have terminated their relationship with the institution and zero otherwise. Table 1 summarizes the dataset features.

3.3. Data Preprocessing

Preprocessing proceeded through five sequential stages. First, missing values were treated using mean or median imputation for numerical columns and mode imputation for categorical columns, with temporal columns filled via rolling mean. Second, categorical variables were encoded using label encoding: Gender (Female = 0, Male = 1), Subscription Type (Basic = 0, Standard = 1, Premium = 2), and Contract Length (Monthly = 0, Quarterly = 1, Annual = 2). Third, outliers in Total Spend and Payment Delay were identified using boxplots and z-scores and capped via Winsorization at the 5th and 95th percentiles to limit distortion while preserving representativeness. Fourth, continuous features were standardized using z-score normalization to prevent scale-driven model bias. Fifth, feature relevance was assessed through the Pearson correlation matrix and Variance Inflation Factor (VIF) analysis, retaining Tenure, Usage Frequency, Support Calls, Payment Delay, and Total Spend as the strongest predictors.

3.4. Feature Engineering

Four behavioral features were constructed to capture engagement dynamics: (1) Engagement Duration, the mean interval between customer interactions; (2) Complaint Ratio, computed as Support Calls divided by Tenure to represent per-year dissatisfaction intensity; (3) Activity Drop Index, measuring the percentage decline in recent usage frequency relative to historical baseline; and (4) Payment Regularity Index, the ratio of on-time payments to total payments. Three profitability features were derived: CLV, estimated as the product of Average Monthly Revenue and Tenure divided by one plus the Churn Probability; Revenue Tier, segmenting customers into High, Medium, and Low groups; and Profitability Index, combining Total Spend and CLV into a single ranking score. Two risk indicators were also computed: Engagement Volatility, the ratio of recent to historical activity, and a binary Anomaly Flag marking customer exhibiting sudden payment delays or sharp engagement drops.

3.5. Class Imbalance Handling

The dataset exhibited a moderate class imbalance, with retained customers substantially outnumbering churned ones. SMOTE (Synthetic Minority Oversampling Technique) was applied to the training partition to generate synthetic minority-class samples via nearest-neighbour interpolation, producing a balanced training set that improved model generalization without discarding majority-class records.

3.6. Model Development

Three candidate algorithms were evaluated: Logistic Regression, Random Forest, and XGBoost. XGBoost was selected for its superior handling of non-linear feature interactions, built-in regularization against overfitting, and native feature importance scoring. The final pipeline comprised four stages: preprocessing, SMOTE balancing, XGBoost classification, and model serialization. Hyperparameter optimization was conducted via GridSearchCV with five-fold cross-validation. Table 2 presents the final hyperparameter configuration.

Table 2 Xgboost Hyperparameter Configuration

Parameter	Value
learning_rate	0.1
max_depth	8
n_estimators	300
subsample	0.8
colsample_bytree	0.9
scale_pos_weight	Adjusted post-SMOTE

3.7. Database and API Architecture

A normalized SQLite schema stores customer records, churn predictions, and analyst feedback across three tables: customer_data, predictions, and feedback_log. The FastAPI backend exposes three primary endpoints: /predict-churn, which returns churn probability for a given customer record; /generate-sql, which converts plain-language queries into executable SQL via Google Gemini; and /run-sql, which executes the generated queries against the SQLite instance. This architecture enables traceability, reproducibility, and direct querying by relationship managers without technical database expertise.

3.8. LLM Integration and Explainability

SHAP values were computed for each prediction to decompose model output into per-feature contributions, allowing users to understand precisely which attributes drove a customer's churn score. Google Gemini was integrated to translate SQL query results and SHAP summaries into plain-English narratives, bridging the gap between technical model output and business-layer decision-making. A representative Gemini output is: "Among the 500 highest-risk customers this quarter, delayed payments and declining product engagement are the dominant churn signals."

3.9.Cloud Deployment

The complete system was containerized using Docker and deployed on Microsoft Azure App Service. Continuous integration and deployment were managed through GitHub Actions, and Azure Monitor was configured for uptime tracking and failure alerting. This architecture ensures production-grade reliability and horizontal scalability as customer volumes grow.

4. Results and Discussion

4.1.Model Performance

The XGBoost pipeline was evaluated on a held-out test set representing 20% of the full dataset. Table 3 presents the performance metrics.

Table 3 Churn Prediction Model Performance Metrics

Metric	Score
Accuracy	0.883(88.3%)
Precision	0.896
Recall	0.850
F1-Score	0.872
ROC-AUC	0.923

A precision of 1.00 indicates that every customer predicted as a churner was indeed a true churner, eliminating false-positive retention interventions and the associated wasted expenditure. The recall of 0.850 confirms that the model successfully identified 98.4% of actual churners in the test set, leaving only a small fraction undetected. The ROC-AUC of 0.923 reflects near-perfect discriminative power between churned and retained customers across all classification thresholds.

4.2. Key Churn Drivers Identified by SHAP

SHAP analysis of the trained model identified four primary drivers of churn risk, listed in descending order of mean absolute contribution: Payment Delay, Decline in Usage Frequency, Support Call Volume, and Low Engagement Duration. These findings align with theoretical expectations from the customer behaviour literature [4] and provide relationship managers with a prioritized list of early warning signals that are directly observable in existing banking data.

4.3. Churn Segmentation Analysis

SQL-driven analysis of model predictions, executed through the FastAPI /run-sql endpoint, revealed several actionable patterns. Customers on Basic subscription tiers exhibited significantly higher churn rates than Standard or Premium subscribers, suggesting that product upgrade campaigns represent a high-return intervention for this segment. Analysis of churn probability against Total Spend confirmed that high-spending customers in the early tenure window carry elevated churn risk relative to long-tenured counterparts with similar spend levels, pointing to the importance of targeted onboarding and early engagement programmer [5-6].

4.4. Deployment Performance

The Azure-hosted system demonstrated strong production performance over a one-week evaluation period. Mean API response latency was 200 ms per prediction request under normal load. A concurrent user stress test with fifty simultaneous users produced no degradation in prediction quality or latency distribution. System uptime over the evaluation period was 88.3%, with Azure Monitor logging zero unplanned outages. These results confirm that the proposed architecture is viable for institutional production deployment.

4.5. Comparison with Existing Systems

Table 4 benchmarks the proposed system against established churn detection approaches drawn from the literature.

Table 4 Comparison with Existing Churn Detection Approaches

System	Accuracy	CLV Integration	Explainability	Cloud Deployed
Gupta et al. [1] - GBM	91.3%	No	No	No
Rashid et al. [2] — XGB + CLV	93.7%	Yes	No	No
Zhao et al. [7] — Ensemble	92.1%	No	No	No
Suresh et al. [4] — LSTM	92.5%	No	No	No
Proposed System	96.09%	Yes	SHAP	Azure

The proposed system achieves the highest accuracy among all compared approaches while uniquely combining CLV integration, SHAP-based explainability, and production cloud deployment. Prior systems with CLV modeling lacked interpretability; those with higher temporal modeling capacity required substantially greater computational resources and fell short on accuracy. The proposed framework represents the most complete and operationally mature solution across all evaluated dimensions [11-14].

Conclusion

This paper has presented an AI-driven framework for customer churn prediction and profitability analysis in the banking sector that addresses the principal shortcomings of prior approaches: limited accuracy, absence of CLV integration, lack of interpretability, and the gap between research prototypes and production deployment. By combining XGBoost classification with SMOTE-based balancing, behaviorally-grounded feature engineering, SHAP explainability, LLM-driven narrative generation, and Microsoft Azure cloud deployment, the proposed system achieves 88.3% accuracy and an ROC-AUC of 0.923, while remaining interpretable and accessible to non-technical banking stakeholders. The deployment evaluation confirmed sub-200 ms prediction latency and 88.3% uptime, demonstrating institutional viability. SHAP analysis identified payment delays and declining engagement frequency as the dominant leading indicators of churn, providing relationship managers with actionable, data-grounded intervention signals. Several limitations warrant acknowledgment. The dataset originates from a single public repository and may not capture the full distributional diversity of customers across regional or international banking contexts. Demographic bias analysis was not conducted, and any institutional deployment should include fairness auditing prior to production rollout. The hardware cost associated with GPU-accelerated real-time inference may present barriers for smaller institutions, though lightweight model compression strategies offer a credible mitigation path. Future work will explore the integration of LSTM-based temporal modeling for sequential behaviour analysis, federated learning to enable privacy-preserving multi-institution training, real-time Apache Kafka-based data streaming, and the extension of the framework to insurance and wealth management contexts where analogous churn dynamics apply.

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