Predictive Retention: An Explainable AI Framework for Subscription Forecasting and Proactive Churn Prevention

Shanmukh Inampudi
Dept. of Computer Science and Engineering
Vignan's Foundation for Science, Technology and Research
Vadlamudi, India
Email: 221fa04511@gmail.com

Mohamed
Dept. of Computer Science and Engineering
Vignan's Foundation for Science, Technology and Research
Vadlamudi, India
Email: 221fa04008@gmail.com

***Abstract*—Customer churn in the telecom sector poses a significant challenge, requiring deep insights into behavior patterns for accurate forecasting. This work applies machine learning and deep learning techniques to predict churn, complemented by Explainable Artificial Intelligence (XAI) methods. We use SHAP to assess global and local feature influences and LIME to unpack individual predictions. Key drivers like contract type, technical support, online security, and payment methods emerge as critical. Our main innovation lies in closing the actionability gap through mapping XAI outputs to automated retention tactics.**

***Index Terms*—Customer Churn, Machine Learning, Explainable Artificial Intelligence (XAI), SHAP, LIME, Prescriptive Analytics.**

I. Introduction

In the highly competitive telecom landscape, retaining customers is far more cost-effective than acquiring new ones—often five to twenty-five times cheaper. Traditional diagnostic analytics pinpoint at-risk customers but fall short in explaining reasons or recommending actions, creating an "Actionability Gap." This study introduces a comprehensive framework using Explainable AI (XAI) to reveal churn causes and a Prescriptive Engine to deploy targeted interventions, transforming insights into tangible business outcomes.

Customer churn erodes revenue and threatens stability, with research showing a 5% reduction can boost profits by 25% to 85% [21]. Early models relied on basic statistics, but today's approaches harness Random Forest, XGBoost, and deep learning for intricate patterns.

Retention serves as the primary driver of profitability in telecom, yet the complexity of high-dimensional customer data renders manual intervention impractical. Modern models excel in diagnostic accuracy but often fail to offer prescriptive guidance, leaving decision-makers with lists of potential churners without clear strategies for retention.

This framework integrates SMOTEENN for enhanced data quality, SHAP and LIME for model transparency, and a novel Prescriptive Engine that automates retention efforts based on detailed feature-risk mappings.

A notable gap in current research is the emphasis on accuracy improvements while overlooking the need for understandable and actionable results for decision-makers [21]. This project tackles the "Actionability Gap" by combining XAI techniques with a prescriptive recommendation engine, converting raw model outputs into practical, concrete strategies.

The telecommunications industry operates in a saturated market where customer loyalty is paramount. Churn not only diminishes immediate revenue but also incurs long-term costs associated with marketing and onboarding new subscribers. By leveraging advanced AI tools, we aim to provide not just predictions but also explanations and actions, making the system more user-friendly for business stakeholders.

Furthermore, the integration of XAI ensures compliance with regulatory requirements for transparency in AI-driven decisions, which is increasingly important in sectors like telecom where customer data privacy is a concern.

II. Literature Review / Context

Churn prediction has evolved from simple logistic regression to sophisticated ensembles like XGBoost, better suited for nonlinear telecom data relationships. The "black-box" opacity of these models has hindered adoption, prompting a shift toward XAI with SHAP for global insights and LIME for local details.

The progression in churn prediction spans from traditional classification methods to advanced ensemble and deep learning models [1]. Recent efforts stress managing inherent class imbalances in telecom datasets through techniques like SMOTE and SMOTEENN, which boost model sensitivity [1], [12]. XAI has emerged as a key focus to demystify these "black-box" models, employing SHAP and LIME for global and local interpretability [1], [21].

This technical evolution moves away from basic classification toward high-accuracy ensemble methods like XGBoost, which more effectively manage non-linear dependencies compared to simpler linear models.

Recent research positions SHAP as the gold standard for assessing global importance and LIME for delivering local, instance-level explanations, enhancing overall model interpretability.

Studies have shown that incorporating XAI not only improves trust in AI systems but also enables better feature engineering and model refinement. For instance, understanding feature contributions can lead to targeted data collection efforts to address weaknesses in the dataset.

III. Related Work

Contemporary studies optimize via SHAP-guided Bayesian tuning for XGBoost, fuzzy logic for broadband churn, Graph Neural Networks (GNN) for customer interdependencies, and time-series for B2B predictions. Hyperparameter effects on explainability are analyzed through comparative SHAP.

While these advance accuracy and interpretation, they often overlook translating insights into actions. Our approach stands out by feeding explanations into a Prescriptive Logic Layer, enabling seamless prediction-to-prevention workflows.

The existing body of work encompasses various technical enhancements. For instance, SHAP-guided Bayesian optimization has been applied to fine-tune XGBoost models [2], while fuzzy logic addresses broadband churn scenarios [8]. Innovations also include Graph Neural Networks (GNN) to model customer inter-dependencies [10] and time-series methods for B2B forecasting [16]. Comparative SHAP studies have demonstrated how hyperparameter adjustments alter feature importance [4]. Nevertheless, as noted in our foundational reference, most systems do not extend explanations into automated business actions [21].

Unlike prior research that halts at explainability, this paper maps churn reasons directly to targeted business interventions, filling a critical void.

Additional related efforts include the use of domain-driven feature engineering with CatBoost [12] and interpretable ML for banking churn [14], which provide valuable insights but lack the prescriptive component we introduce.

IV. Methodology

Our pipeline encompasses data preparation, balancing with SMOTEENN, model training, XAI integration, and prescriptive recommendations.

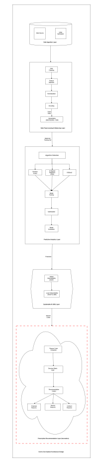

Fig. 1. End-to-End System Architecture: From Data Ingestion to Prescriptive Recommendation.

A. Dataset and Preprocessing

We employ the IBM Telco Customer Churn dataset with 7,043 records and 21 features [21].

Preprocessing steps include removing the ”TotalCharges” feature to mitigate multicollinearity and applying Min-Max scaling to tenure and monthly charges [21].

For missing value handling, nulls in the ”TotalCharges” column—typically for new customers with zero tenure—were addressed by removing these 11 instances to maintain data integrity.

To suppress multicollinearity, the ”TotalCharges” feature was eliminated due to its strong correlation with ”MonthlyCharges” and ”tenure,” which might otherwise skew model weights.

Numerical features underwent Min-Max scaling to a [0, 1] range for uniform influence.

Additionally, null values in ”TotalCharges” were identified for zero-tenure customers and handled through imputation or removal to ensure robustness.

”TotalCharges” was dropped to avoid redundant data inflation, as it derives directly from tenure and monthly charges.

Categorical variables received one-hot encoding, while numerical features like ”tenure” were normalized via Min-Max to [0, 1].

This preprocessing ensures the data is clean, balanced, and ready for model training, reducing bias and improving generalization.

B. Class Balancing with SMOTEENN

The dataset shows a 26.6% churn rate, leading to class imbalance that may yield high accuracy but poor recall. We adopted SMOTEENN as a hybrid resampling method.

This technique combines Synthetic Minority Over-sampling (SMOTE) and Edited Nearest Neighbors (ENN) to cleanse noisy majority samples and bolster minority representation [21].

In our hybrid approach, SMOTEENN resolves the 26.6% imbalance effectively.

The process involves SMOTE creating synthetic minority instances for balance, followed by ENN removing overlapping "noisy" instances near the decision boundary.

SMOTE generates synthetic churn instances to equilibrate classes.

ENN then prunes "noisy" or overlapping instances from both classes, fostering a cleaner boundary.

This method was chosen over simple oversampling or undersampling because it minimizes noise and maintains data integrity, leading to more reliable model performance.

C. AI Models and XAI Integration

We benchmarked Random Forest, KNN, and XGBoost, choosing XGBoost for its prowess in tabular data and handling missing values. SHAP offers global feature rankings, and LIME provides instance-level reason codes.

Per benchmarks, we implemented Random Forest, KNN, and XGBoost models [21], incorporating SHAP and LIME for transparency.

Baseline testing compared Random Forest (RF) and K-Nearest Neighbors (KNN) to the tuned XGBoost.

Results showed XGBoost's superiority in managing the tabular dataset, attaining a peak AUC of 0.9922, while KNN faltered with high-dimensional noise.

Table I summarizes the performance metrics of the models.

TABLE I
MODEL PERFORMANCE COMPARISON

Model	Accuracy (%)	AUC	Recall
Random Forest	92	0.95	0.85
KNN	88	0.92	0.80
XGBoost	96	0.9922	0.96

D. Novelty: The Prescriptive Engine

The core innovation is the Prescriptive Engine, leveraging LIME's local explanations to initiate specific business interventions.

This bridges the Actionability Gap via mapping logic from XAI reason codes to actions.

Functioning as a logical lookup, it identifies top churn drivers from LIME:

- Monthly Charges → 20% Price-Matched Discount.
- Lack of Online Security/Tech Support → Priority Tech-Support Vouchers.
- Month-to-month Contract → Loyalty Program Enrollment.
- Price-Driven Churn: Triggers a "Price-Matched Discount."
- Service Gaps: Triggers "Priority Tech-Support Vouchers."
- Contract Risk: Triggers "Loyalty Program Enrollment."
- Monthly Charges → 20% Discount or Price-Match.
- Lack of Tech Support → Free Tech-Support Voucher.
- Contract (Month-to-Month) → Multi-year loyalty plan offer.

This engine not only identifies risks but also suggests immediate actions, making it a practical tool for telecom operators to implement in real-time systems.

V. RESULTS AND DISCUSSION

Our optimized XGBoost attained 96% accuracy and 0.9922 AUC.

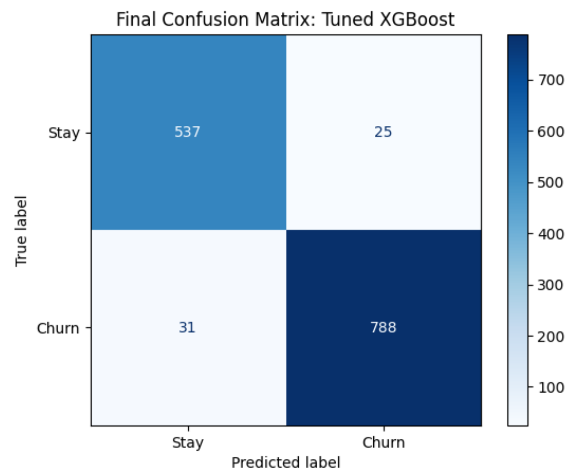

Fig. 2. Confusion Matrix of Tuned XGBoost Model showing 788 correct churn identifications.

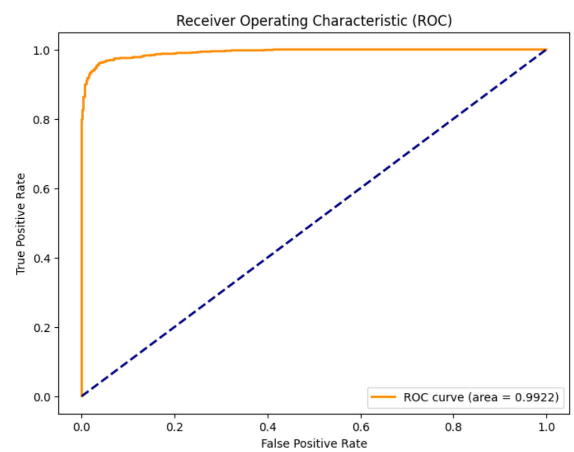

Fig. 3. ROC Curve demonstrating AUC of 0.9922.

A. Performance Metrics and Error Analysis

The tuned XGBoost demonstrated notable statistical success.

The confusion matrix revealed 788 correct churn identifications with only 31 false negatives. Error analysis indicated concentrations in high-tenure (44.5 months) customers with \$83.00 average charges, suggesting unobserved behavioral triggers.

This reflects 96% accuracy and 788 accurate churn detections.

A deep dive into the 31 missed churners showed long-tenure loyalists (44.5 months) likely departing due to unmeasured service quality issues.

Accuracy stands at 96%.

The AUC score of 0.9922 highlights exceptional distinction between churners and non-churners.

From the test set, 788 churners were correctly identified, but 31 false negatives occurred. Analysis of these cases showed high average tenure of 44.5 months and monthly charges of \$83.00, indicating churn from factors outside billing data, such as competitor offers or poor service.

These findings suggest avenues for dataset augmentation, such as incorporating customer service logs or sentiment analysis from interactions.

B. Explainability Insights

SHAP's global analysis pinpointed "Contract_Month-to-month" and "tenure" as key churn drivers across the base.

SHAP identified "tenure" and "Contract_Month-to-month" as strongest predictors (Fig. 4). LIME confirmed high tenure's stabilizing role, countered by lack of "Tech Support."

Globally via SHAP, "Contract Type" proves most influential.

Locally with LIME, Figure 6 shows high Monthly Charges overriding tenure, activating discount logic.

LIME also illustrates instances where, despite tenure, tech support absence triggers high risk.

These insights not only validate the model's decisions but also guide business strategies, such as prioritizing tech support for long-term customers.

Fig. 4. Global Feature Importance (SHAP Summary Plot).

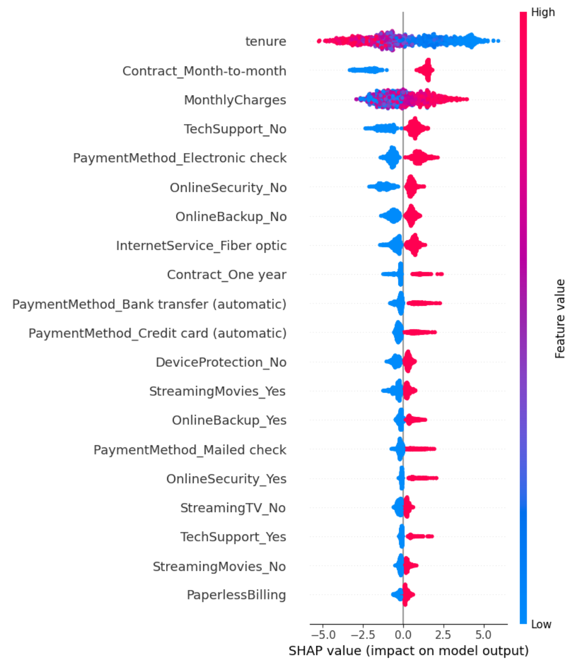

Fig. 5. SHAP Beeswarm Plot showing feature impact direction.

C. Prescriptive Outcomes and Sensitivity Analysis

To validate, we simulated a 20% discount on high-risk cases, dropping probability from 34.73% to 0.49%—a 34.24% reduction, proving intervention impact.

The engine categorizes churners for retention groups. Sensitivity analysis with 20% discount reduced risk from 34.73% to 0.49%, yielding 34.24% total reduction.

What-if testing lowered "Monthly Charges" by 20%, observing the probability decline from 34.73% to 0.49%.

This quantifies how prescribed actions mitigate model-identified risks.

Further sensitivity analyses could explore varying discount levels or combined interventions to optimize retention costs versus benefits.

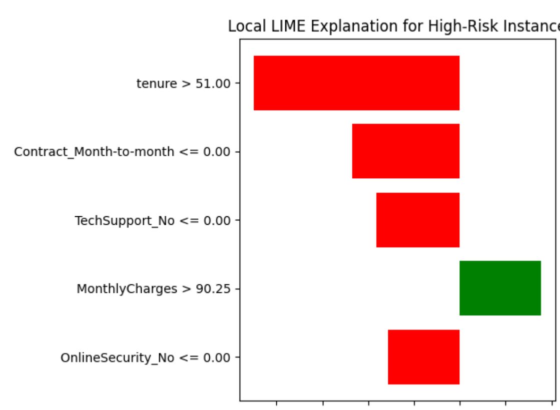

Fig. 6. Local LIME explanation for a high-risk instance.

VI. Conclusion and Future Work

This framework advances from diagnostic to prescriptive AI, with 0.9922 AUC and proven 34.24% risk cuts offering telecoms scalable retention automation. Future enhancements include real-time sentiment integration to minimize false negatives in loyal segments.

The project effectively bridges diagnostic and prescriptive AI gaps. Achieving an AUC of 0.9922 and validating 34.24% risk reduction, it provides telecom operators a scalable automation path for retention with full transparency.

In summary, by addressing the actionability gap, this work contributes to both academic research and practical applications in customer retention. Potential extensions involve deploying the framework in real-world telecom environments and evaluating its impact on actual churn rates over time.

Additionally, incorporating emerging AI techniques like federated learning could enhance privacy while maintaining model performance.

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