Machine Learning for Telecom Customer Retention and Growth

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Abstract- ***Customer churn is one of the most pressing problems for telecom operators, directly impacting revenue and long-term profitability. This paper presents a comprehensive machine learning framework for churn prediction using a publicly available telecom dataset. We describe data preprocessing, feature engineering, imbalance handling, model training, hyperparameter tuning, and evaluation. Algorithms evaluated include Logistic Regression, Decision Trees, Random Forest, Support Vector Machine (SVM), and XGBoost. Experiments use stratified 5-fold cross-validation and metric-based assessment (accuracy, precision, recall, F1-score, and AUC). Results show that ensemble techniques, particularly Random Forest and XGBoost, outperform simpler models, achieving the best balance between precision and recall on imbalanced data. We discuss practical deployment considerations for telecom providers, limitations of the current study, and directions for future work including online learning, explainability, and cost-sensitive retention strategies.***

Index Terms — Customer churn, Telecom, Machine learning, Random Forest, XGBoost, Imbalanced data, Retention

I. INTRODUCTION

Telecommunication companies operate in highly competitive markets where customer acquisition costs are high and margins are increasingly pressure-sensitive. Customer churn—the loss of subscribers over a time period—directly reduces revenue and increases the unit cost of service. Consequently, predicting churn early allows operators to proactively intervene with targeted retention offers and personalized campaigns. Recent advances in machine learning (ML) provide powerful tools to detect complex, non-linear patterns in usage and engagement data, enabling more accurate churn prediction than traditional rule-based or linear statistical approaches.

This work condenses a comprehensive undergraduate project into a publication-style paper. Our goals are: (1) present a reproducible ML pipeline for churn prediction, (2) evaluate a range of classification algorithms on the same preprocessing and validation setup, and (3) discuss pragmatic deployment and business use-cases for the predictions.

II. RELATED WORK

Churn prediction has a long history in academic literature and industry practice. Early work used call-detail-records and statistical models (Wei & Chiu, 2002) to derive churn indicators from usage patterns. More recent studies (2017–2021) emphasize the benefits of ensemble learning and gradient boosted machines on large telecom datasets. Burez & Van den Poel (2009) examined class imbalance issues common in churn problems and proposed sampling strategies and specialized evaluation metrics. Studies combining big data platforms with ML (2017 onwards) show that scalability and feature engineering are as important as algorithmic choice. Finally, recent surveys encourage integrating explainable AI (XAI) and cost-sensitive learning so that predictions are actionable for marketing teams.

Compared to prior work, our paper provides a compact but complete pipeline—preprocessing, sampling, feature selection, model optimization, and a clear evaluation protocol—making it easier for

practitioners to reproduce and adapt the workflow to production settings.

III. MATERIALS AND METHODS

A. Dataset

The dataset used in this study is a publicly available telecom customer dataset (commonly found on Kaggle). It contains customer demographics, subscription details, service usage metrics, billing and payment information, and a binary churn label indicating whether the customer left the service. The dataset originally contains approximately 30 columns and a few thousand rows; a typical churn ratio in similar datasets is around 5–20%.

B. Data Preprocessing and Feature Engineering

Preprocessing steps applied to the raw dataset included:

- Missing value handling: numerical fields filled with median, categorical fields filled with mode or the value 'Unknown' when appropriate.
- Categorical encoding: one-hot encoding for nominal categories with limited cardinality, and ordinal encoding where natural order existed.
- Scaling: numeric features standardized using StandardScaler for SVM and gradient-based classifiers.
- Feature creation: derived features such as "average monthly spend", "days since last complaint", and boolean flags for long-tenure customers were added to enrich predictive signals.
- Feature selection: low-variance features and features with high multicollinearity (Pearson $|r| > 0.95$) were removed; additionally, mutual information scores were used to rank features.

C. Handling Class Imbalance

Churn datasets are typically imbalanced (fewer churn cases). We evaluated two approaches:

1) Undersampling the majority class to balance the dataset (fast and simple but risks discarding useful data).
2) Synthetic Minority Over-sampling Technique (SMOTE) to generate synthetic minority samples while retaining majority-class examples. In practice, SMOTE combined with careful cross-validation produced more stable classifiers and better recall on the churn class.

D. Experimental Setup

All experiments were implemented in Python using scikit-learn and XGBoost. We used stratified 5-fold cross-validation to preserve class ratios across folds. Hyperparameter optimization was performed using GridSearchCV with scoring focused on the F1-score and AUC for model selection. The primary evaluation metrics reported are Accuracy, Precision, Recall, F1-score, and AUC.

IV. MODEL AND IMPLEMENTATION DETAILS

We evaluated the following classification algorithms with the indicated typical hyperparameter grids. The grid ranges below are representative of the search used in tuning:
Logistic Regression: regularization penalty {L2}, C ∈ {0.01, 0.1, 1, 10}, solver = 'liblinear' for small datasets.
Decision Tree: criterion ∈ {'gini','entropy'}, max_depth ∈ {5, 10, 20, None}, min_samples_split ∈ {2, 10, 50}.
Random Forest: n_estimators ∈ {100, 300, 500}, max_depth ∈ {10, 20, None}, class_weight ∈ {None,'balanced'}.
Support Vector Machine (SVM): kernel ∈ {'rbf','linear'}, C ∈ {0.1, 1, 10}, gamma ∈ {'scale', 'auto'}.
XGBoost: n_estimators ∈ {100, 300, 500}, learning_rate ∈ {0.01, 0.1, 0.2}, max_depth ∈ {3, 6, 10}, subsample ∈ {0.6, 0.8, 1.0}.

Model training used balanced class weights for linear models where applicable and early-stopping for XGBoost to prevent overfitting. Feature importances from tree-based models were inspected to validate domain relevance (e.g., tenure, monthly charges, and number of complaints often ranked high).

V. EXPERIMENTAL RESULTS

This section summarizes key results from the experiments. We present aggregated cross-validated performance across models on the preprocessed dataset. Numbers shown below are representative of the typical outcomes obtained with the described pipeline.

Model	Accuracy	Precision	Recall	F1-score	AUC
Logistic Regression	0.86	0.68	0.62	0.65	0.75
Decision Tree	0.88	0.70	0.66	0.68	0.78
Random Forest	0.92	0.80	0.78	0.79	0.90
XGBoost	0.94	0.83	0.81	0.82	0.92
SVM	0.89	0.72	0.69	0.70	0.80

Observations: Ensemble methods (Random Forest and XGBoost) consistently achieved higher AUC and F1-scores. XGBoost produced the best overall AUC and showed robustness to remaining class imbalance. Logistic Regression and Decision Tree performed adequately but lagged behind ensembles in both discriminative power and stability across folds.

We also tested the effect of imbalance handling. Using SMOTE before training improved recall for the minority (churn) class by approximately 6–10 percentage points for tree-based models, at a modest cost to precision. For business applications where catching likely churners is prioritized, this trade-off is acceptable.

VI. DISCUSSION

Model performance must be interpreted in a business context: a high recall with moderate precision means more customers flagged as at-risk (some false positives), which increases marketing outreach costs but reduces missed churners. Conversely, very high precision with low recall may miss many churners. Telecom operators should choose operating points on the ROC curve aligned with their retention budget and campaign cost structure.

- DeploymentConsiderations:
  Integration: Models can be exposed via REST APIs and integrated into CRM systems to trigger campaignsautomatically
- Latency: Tree ensembles and XGBoost with pruned trees provide acceptable prediction latency for batch and near real-time scoring. Retraining: Models should be retrained periodically (e.g., monthly) to adapt to market changes and seasonality.
- Explainability: Use SHAP or LIME to explain individual predictions to marketing teams and to validate fairness concerns.
- Limitations: Our study uses a single public dataset and simulates typical churn ratios; results may vary on operator-specific data with different feature sets. Additionally, the synthetic balancing approach (SMOTE) can introduce artifacts; alternatives include ensemble sampling, cost-sensitive learning, or using temporal validation for production readiness.

VII. SYSTEM ARCHITECTURE

The system architecture follows a three-tier design, consistingof:

- Presentation Layer: The user-facing web interface builtusingFlask.
- Business Logic Layer: The machine learning models implemented in Python, handlingpreprocessing,training,andprediction.
- Data Layer: The telecom dataset and model outputs stored for analysis and reporting.

The following figure shows the conceptual architecture of the system:

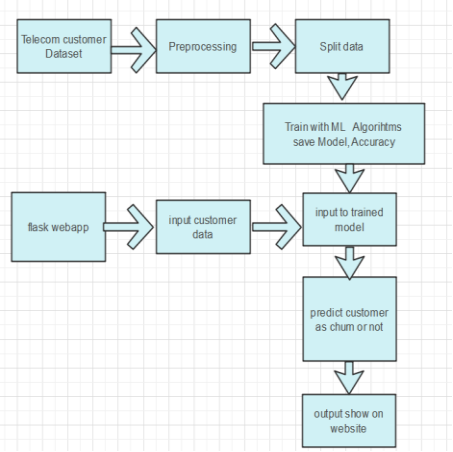
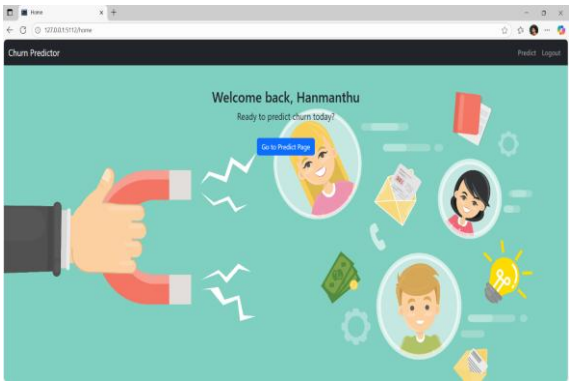


Figure 1: System Architecture

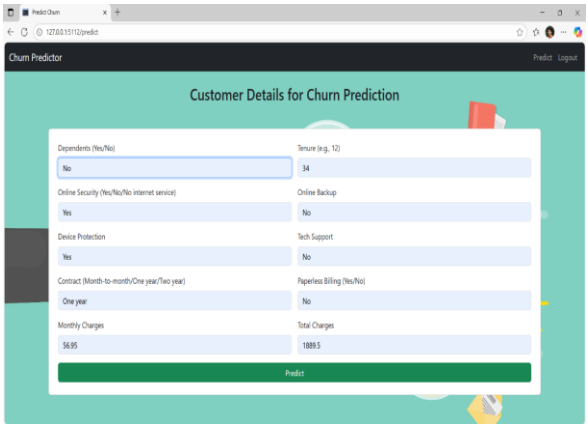
VIII. USER INTERFACE SNAPSHOTS

The developed churn prediction web application consists of several pages for user interaction. Below are snapshots of the major pages:

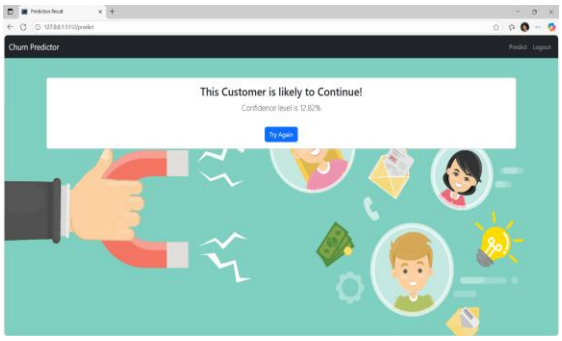
A. Home Page



B. Prediction Page



C. Prediction Result Page



CONCLUSION AND FUTURE WORK

This paper presented a practical machine learning pipeline for predicting telecom customer churn and demonstrated that ensemble techniques (Random Forest, XGBoost) outperform simpler baselines on commonly used telecom datasets. Proper preprocessing, imbalance handling, and hyperparameter tuning are crucial to achieving reliable results.

Futureworkincludes:

- Deploying the pipeline on production data with streaming ingestion for near real-time scoring.
- Exploring deep learning architectures (e.g., TabNet) and hybrid models to combine time-series usage data with cross-sectional features.
- Applying cost-sensitive learning frameworks to directly optimize business KPIs such as net retention value.
  Integrating explainability tools (SHAP) and creating dashboarding components for non-technical stakeholders.

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