ChurnGuard: An AI-Powered Customer Churn Prediction System for Telecom Industry Using Machine Learning

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Abstract — Customer churn prediction is a critical business intelligence challenge in the telecom industry, where retaining existing customers is significantly more cost-effective than acquiring new ones. This paper presents ChurnGuard, an end-to-end machine learning system designed to identify at-risk telecom customers before they cancel their subscriptions. Using the IBM Telco Customer Churn dataset comprising 7,043 records and 21 features, we implement and compare two supervised learning models: Logistic Regression as an interpretable baseline and Random Forest as the primary classifier. The proposed system covers the complete data science lifecycle including data ingestion, exploratory data analysis (EDA), preprocessing, model training, evaluation using appropriate metrics for imbalanced datasets, feature importance extraction, risk tier segmentation, and deployment as an interactive Streamlit web application. The Random Forest classifier achieved a ROC-AUC of 87% and a Recall of 62%, outperforming Logistic Regression across all key metrics. The system segments customers into High, Medium, and Low churn-risk tiers and provides actionable retention recommendations. A business ROI analysis demonstrates a potential net saving of $100,000 per month through model-driven retention campaigns.

Keywords: Customer Churn Prediction, Random Forest, Logistic Regression, Telecom Analytics, Machine Learning, Streamlit, Risk Segmentation, ROC-AUC, Class Imbalance, Business Intelligence

I. Introduction

Customer churn, defined as the phenomenon where a customer discontinues their relationship with a service provider, represents one of the most significant challenges facing the global telecommunications industry. Research consistently demonstrates that acquiring a new customer costs five to seven times more than retaining an existing one [1]. With average annual churn rates ranging from 20% to 40% in competitive telecom markets, companies stand to lose millions in revenue without effective early-warning systems.

Traditional approaches to churn management are predominantly reactive — businesses only recognize lost customers after cancellation has occurred, by which point any retention intervention is impossible. The emergence of machine learning offers a transformative alternative: predictive models capable of identifying at-risk customers weeks or months before they churn, enabling proactive retention strategies with measurable financial impact.

This paper presents ChurnGuard, a complete end-to-end machine learning pipeline and web application that addresses this challenge. The system ingests real telecom customer data, performs comprehensive exploratory analysis, trains and evaluates multiple classification models, segments customers by risk level, and deploys predictions through an interactive browser-based interface accessible to non-technical business stakeholders. The key contributions of this work are:

- An end-to-end reproducible ML pipeline for telecom churn prediction built entirely in Python.
- A rigorous comparison of Logistic Regression and Random Forest classifiers using metrics appropriate for imbalanced datasets.
- A three-tier customer risk segmentation system (High, Medium, Low) enabling proportional retention resource allocation.
- A fully deployed Streamlit web application — ChurnGuard — providing real-time churn scoring with actionable business recommendations.
- A quantified business ROI analysis demonstrating the financial value of model-driven retention over baseline approaches.

II. Literature Survey

Verbeke et al. [1] proposed a profit-driven framework for churn modeling and demonstrated that cost-sensitive classifiers significantly outperform accuracy-based models on telecom churn datasets, establishing the importance of business-oriented evaluation metrics such as Recall and F1-Score over simple accuracy.

Nie et al. [2] conducted a comprehensive survey of twelve machine learning algorithms applied to customer churn prediction and concluded that ensemble methods, particularly Random Forest and Gradient Boosting, consistently outperform single classifiers on imbalanced datasets — a finding that directly motivates our model selection.

Breiman [3] introduced the Random Forest algorithm and demonstrated its robustness to noise and overfitting through ensembling, along with its reliable feature importance extraction capabilities — both properties central to the ChurnGuard system.

Mozer et al. [4] established Logistic Regression as a strong interpretable baseline for churn prediction in the wireless telecommunications domain, highlighting its utility for business-facing explainability — supporting its inclusion as our comparative baseline model.

Sharma and Panigrahi [5] compared neural network approaches against classical machine learning on telecom churn, finding that classical models including Random Forest and Logistic Regression outperformed deep learning approaches on small-to-medium structured datasets of the scale used in this work.

III. Proposed System

ChurnGuard is structured as a six-module pipeline that transforms raw customer data into actionable business

intelligence through a deployed web interface. Figure 1 illustrates the complete system architecture.

Raw Data → EDA → Preprocessing → Model Training → Evaluation → Deployment

Fig. 1: ChurnGuard System Architecture Pipeline

A. Module 1: Data Ingestion

The data ingestion module loads the IBM Telco Customer Churn dataset using the pandas library. Initial validation confirms 7,043 rows and 21 feature columns. Shape checks, data type verification, and sample row inspection are performed to ensure data integrity before downstream processing.

B. Module 2: Exploratory Data Analysis

EDA is performed prior to preprocessing to understand the data in its raw state. This module generates churn distribution charts revealing a 26.5% baseline churn rate, boxplots comparing tenure distributions across churn classes, bar charts for categorical features including contract type and payment method, and a correlation heatmap identifying key numerical relationships. Key findings include: month-to-month contract customers churn at 45% versus 3% for two-year contracts; customers without tech support churn at nearly double the rate; and high monthly charges combined with short tenure represent the highest-risk combination.

C. Module 3: Data Preprocessing

The preprocessing module applies six sequential transformations: (1) TotalCharges column conversion from object to numeric, with whitespace entries replaced by NaN and subsequently dropped; (2) CustomerID column removal as it carries no predictive signal; (3) binary column label encoding converting Yes/No values to 1/0; (4) one-hot encoding of multi-category features including InternetService, Contract, and PaymentMethod; (5) StandardScaler normalization applied to continuous numeric columns (tenure, MonthlyCharges, TotalCharges); and (6) stratified 80/20 train-test split preserving class distribution.

D. Module 4: Model Training

Two classifiers are trained and serialized. Logistic Regression serves as an interpretable linear baseline, providing coefficient-based feature weights and well-calibrated probability outputs. Random Forest, configured with 100 estimators and max_depth=10, serves as the primary model, leveraging ensemble learning to capture non-linear relationships and interactions between features. Both models are persisted as .pkl files using joblib for deployment reuse without retraining.

E. Module 5: Evaluation

Both models are evaluated on the held-out test set using metrics appropriate for the class-imbalanced nature of the dataset. Accuracy is reported but not used as the primary criterion. Recall — the proportion of actual churners correctly identified — is treated as the primary business metric, as false negatives (missed churners) carry greater cost than false positives. Confusion matrices, classification reports, and ROC curves are generated for both models.

F. Module 6: Insight Extraction and Deployment

The final module extracts Random Forest feature importances to identify the top churn drivers, segments all customers into High (>60%), Medium (30-60%), and Low (<30%) risk tiers based on predicted churn probability, performs ROI quantification, and launches the ChurnGuard Streamlit web application enabling real-time prediction for non-technical business users.

IV. Dataset Description

The IBM Telco Customer Churn dataset, publicly available via Kaggle [6], contains records of 7,043 telecom customers from a fictional California-based telecommunications company. Each record includes 21 features spanning four categories: demographic attributes (gender, SeniorCitizen, Partner, Dependents), subscribed services (PhoneService, MultipleLines, InternetService, OnlineSecurity, OnlineBackup, DeviceProtection, TechSupport, StreamingTV, StreamingMovies), account information (tenure, Contract, PaperlessBilling, PaymentMethod), and billing details (MonthlyCharges, TotalCharges). The binary target variable Churn indicates whether the customer left within the last month. The dataset exhibits a class imbalance of approximately 73.5% non-churners to 26.5% churners, necessitating the use of Recall-oriented evaluation rather than raw accuracy.

V. Results and Discussion

Table I presents the comparative performance of both models evaluated on the 20% held-out test set of 1,409 samples.

Metric	Logistic Regression	Random Forest	Improvement	Winner
Accuracy	~80%	~82%	+2%	Random Forest
Precision	~65%	~70%	+5%	Random Forest
Recall	~55%	~62%	+7%	Random Forest
F1-Score	~60%	~65%	+5%	Random Forest
ROC-AUC	~84%	~87%	+3%	Random Forest

Table I: Model Performance Comparison

The Random Forest classifier outperformed Logistic Regression across all five-evaluation metrics. Most significantly, it achieved a 7-percentage point improvement in Recall — identifying 62% of actual churners compared to Logistic Regression's 55%. This is the most critical metric for this application, as each missed churner represents a preventable revenue loss. The ROC-AUC of 87% indicates that the model correctly ranks a randomly selected churner above a randomly selected non-churner 87% of the time, demonstrating strong discriminative capability.

Feature importance analysis revealed the top five churn predictors: (1) Contract type — month-to-month

customers exhibit 45% churn versus 3% for two-year contracts; (2) Tenure — customers within their first 12 months churn at significantly higher rates; (3) Monthly Charges — charges exceeding $65/month correlate strongly with churn; (4) Internet Service type — fiber optic users churn disproportionately; and (5) Tech Support — absence of tech support nearly doubles churn probability.

VI. Business Impact and ROI Analysis

To quantify the practical value of the ChurnGuard system, a conservative ROI analysis was performed under the following assumptions: 1,000 high-risk customers identified per month; average customer lifetime value (CLV) of $500; retention campaign cost of $50 per customer; and a 30% retention success rate among contacted customers.

Under these parameters, monthly revenue saved equals 1,000 × 30% × $500 = $150,000. Total campaign cost equals 1,000 × $50 = $50,000. Net monthly ROI therefore equals $100,000, representing a 200% return on retention investment. This analysis conservatively excludes secondary benefits including improved customer lifetime value from enhanced service experiences and reduced acquisition costs from improved net promoter scores among retained customers.

VII. Conclusion and Future Work

This paper presented ChurnGuard, a complete end-to-end machine learning system for proactive telecom customer churn prediction. The system successfully implements a six-module pipeline from raw data ingestion to deployed web application. The Random Forest classifier achieved strong performance with 87% ROC-AUC and 62% Recall, outperforming the Logistic Regression baseline on all metrics. Customer risk segmentation and actionable retention recommendations add direct business value beyond raw prediction. The deployed ChurnGuard Streamlit application demonstrates that machine learning models can be effectively packaged for use by non-technical business stakeholders.

Future work will address four key enhancements: (1) application of SMOTE oversampling to handle the 26.5% class imbalance and improve Recall further; (2) integration of gradient boosting models including XGBoost and LightGBM for performance benchmarking; (3) implementation of SHAP-based explainability to provide individual prediction explanations within the web application; and (4) connection to a live customer database for automated batch prediction and real-time scoring pipelines.

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