Final Project Data Science

Customer Churn Prediction : Identifying At-Risk Customers

Introduction

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Finance student with a strong interest in data analytics and business insights, equipped with hands-on experience in predictive modeling and data visualization

Education

Finance, BINUS University – Semester 5

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Overview Project

Customer Churn Prediction : Identifying At-Risk Customers

This project focuses on predicting customer churn using historical demographic, behavioral, and service usage data. The goal is to understand what factors drive customers to leave and to build a predictive model that identifies high-risk customers before they churn. The project combines data analysis and machine learning to provide both actionable business insights and a deployable churn detection system.

Project Objectives

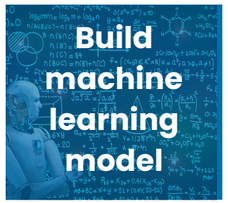
1

Predict customer churn accurately by leveraging demographic, service usage, and behavioral features to proactively identify customers at risk of leaving

2

Uncover the most influential churn factors, providing actionable insights that help the business implement more targeted and effective retention strategies

3



Build and optimize a machine learning model that is both interpretable and efficient, using a simplified set of top predictive features, ensuring it can be easily deployed into real-time systems or operational workflows

Goal

The goal of this project is to proactively reduce customer churn and improve retention by leveraging machine learning to identify customers who are most likely to leave. By analyzing historical data on demographics, service usage, billing patterns, and satisfaction scores, the project aims to build a predictive model that flags high-risk customers before they churn

Tools

Streamlit

Project Background

Project Overview

This project focuses on **predicting customer churn** in a telecommunications company using historical data on customer demographics, service usage, contract types, and satisfaction. The aim is to **build a reliable machine learning model** that can accurately identify high-risk customers before they leave

Why This Project Matters ?

Customer churn poses a serious challenge to subscription-based businesses like telecom providers. Retaining existing customers is significantly more cost-effective than acquiring new ones. By understanding **who is likely to churn and why**, the business can proactively implement retention strategies, reduce revenue loss, and improve long-term customer lifetime value (CLTV)

Expected Outcomes

Early Detection of High-Risk Customers Accurately predict customers most likely to churn in the near future using behavior and service usage patterns

Insight into Key Churn Drivers Uncover the most impactful features influencing churn (e.g., contract type, satisfaction score, internet type)

Deployable and Lightweight Model Deliver a simplified model using top features — optimized for real-time use and seamless integration into operational systems

Data-Driven Retention Strategies Provide actionable insights for marketing and customer service teams to design targeted offers, campaigns, or service improvements

Beneficiaries

1

Marketing & Retention Teams :
to design personalized outreach to at-risk customers

2

Customer Success & Operations :
to monitor churn risk in real time and improve satisfaction

3

Business Strategy Team :
to align churn insights with revenue planning and resource allocation

Problem Statement

Problem Statement

1 *Difficult to Identify Who Will Churn*

It is unclear which customers are at risk of churning just by looking at raw customer data, there is no systematic way to predict churn based on their behavior and profile

2 *Need for a Data-Driven Churn Prediction Model*

A machine learning model is needed to predict churn likelihood using historical, behavioral, and demographic data

3 *No Predictive System for Early Detection*

Currently, there is no data-driven mechanism to proactively identify customers who are at risk of churning

Objectives

Predict customer churn accurately by leveraging demographic, service usage, and behavioral features to proactively identify customers at risk of leaving

Uncover the most influential churn factors, providing actionable insights that help the business implement more targeted and effective retention strategies

Build and optimize a machine learning model that is both interpretable and efficient, using a simplified set of top predictive features, ensuring it can be easily deployed into real-time systems or operational workflows

The success of this project will be measured using the following metrics :

Recall (Sensitivity)	ROC-AUC Score	F1-score	Business Insight
Measures how well the model identifies actual churners, minimizing false negatives is critical in a business context	Evaluates the model's overall ability to distinguish between churners and non-churners	Balances precision and recall, ensuring robust performance across both metrics	The interpretability of the model, including feature importance and churn segmentation should provide actionable insights for strategies

Data Understanding & Preprocessing

Kaggle

Why Do Customers Leave? Can You Spot the Churners?

Dive into Customer Behavior: Can You Predict Who Stays or Goes?

k kaggle.com

https://www.kaggle.com/datasets/hassanelfattmi/why-do-customers-leave-can-you-spot-the-churners

The dataset contains data from Telco customers in California, including demographics, service details, satisfaction scores, and churn status, intended for analyzing customer behavior and predicting churn

7043
Number of Records

53
Number of Variables

20 numerical

33 categorical

Target Variable (churn_value)

0 = tidak churn	1 = churn

No duplicate rows were found in the dataset

Missing Values

Note : All other columns have 0 missing values

Categorical Column	Missing
churn_reason	5174
offer	3877
internet_type	1526

Filled with "*Unknown*"

Data Transformation

numerical features

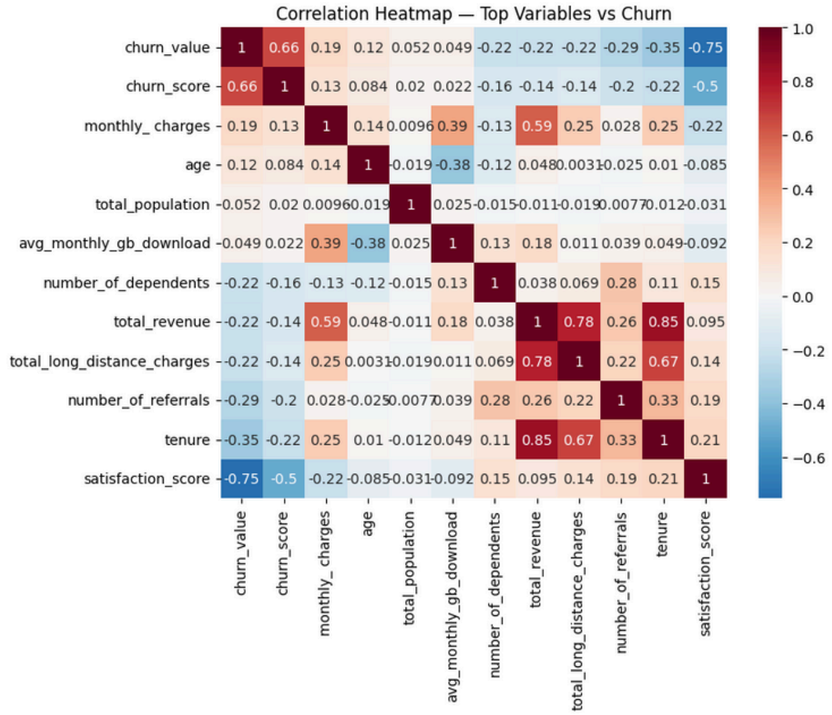
Standard Scaler — Ensures all numeric values are on the same scale (mean = 0, std = 1), improving model convergence and performance

categorical features

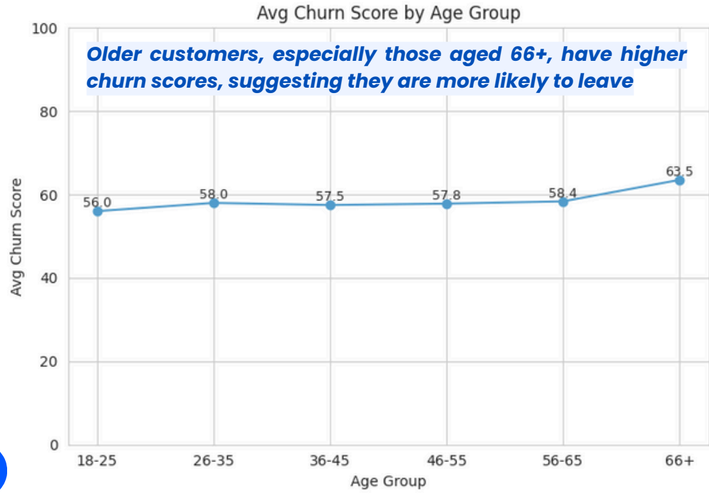
One-Hot Encoding — Converts categories into binary columns so that machine learning models can interpret them numerically without implying any ordinal relationship

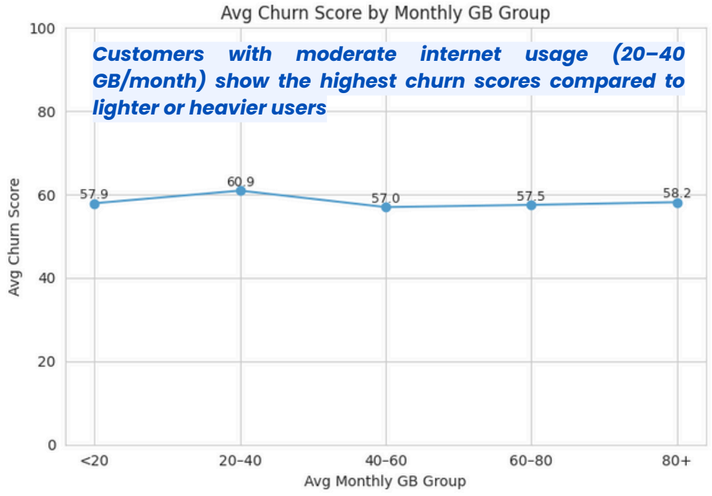
Explanatory Data Analysis

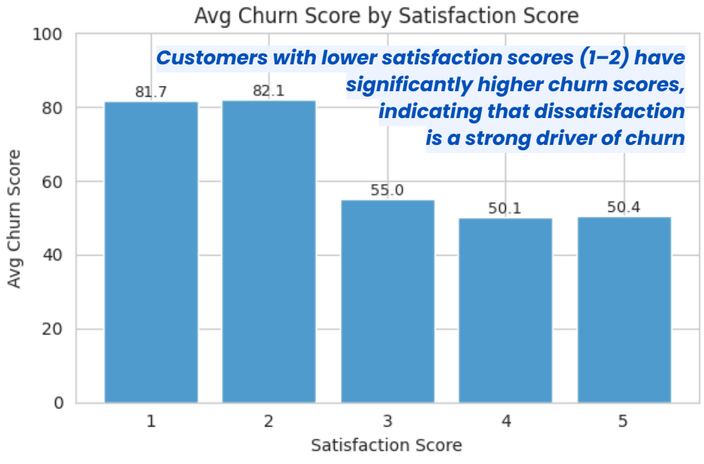
Satisfaction score shows the strongest negative correlation with churn, indicating that more satisfied customers are significantly less likely to churn. Additionally, customers with longer tenure and those who have referred others tend to be more loyal

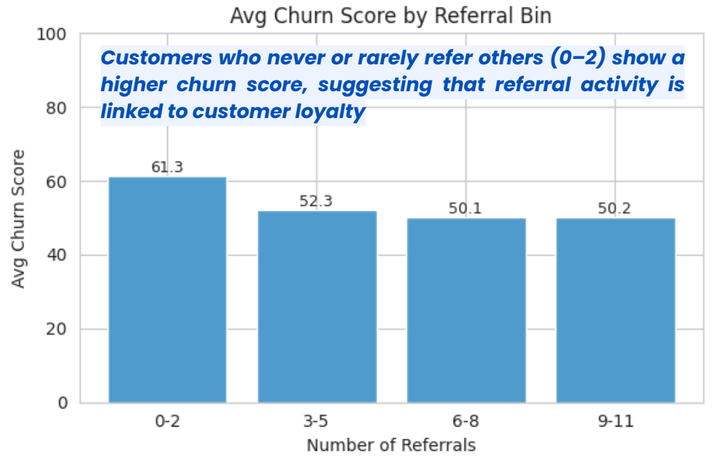


Other factors like number of dependents, total revenue, and long-distance charges also show slight negative correlations. On the other hand, variables like age and monthly charges have very weak influence on churn likelihood.

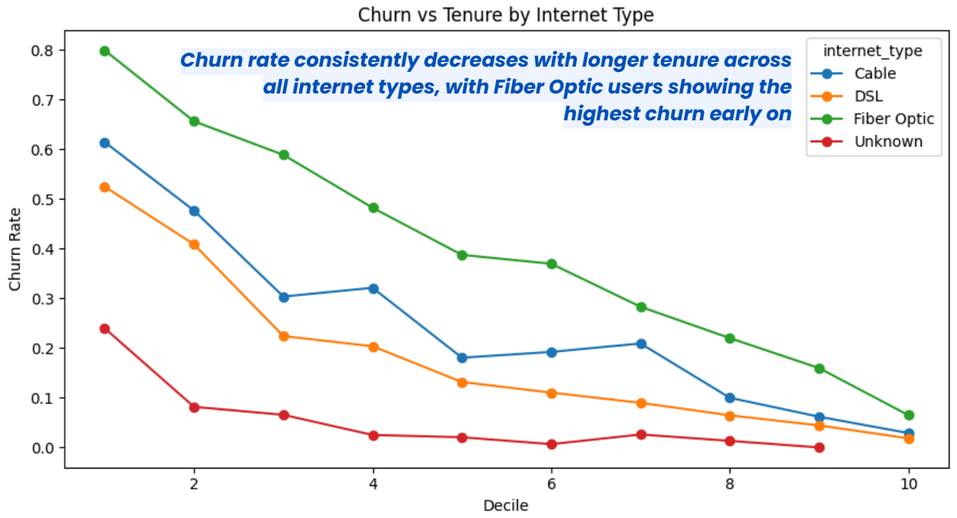


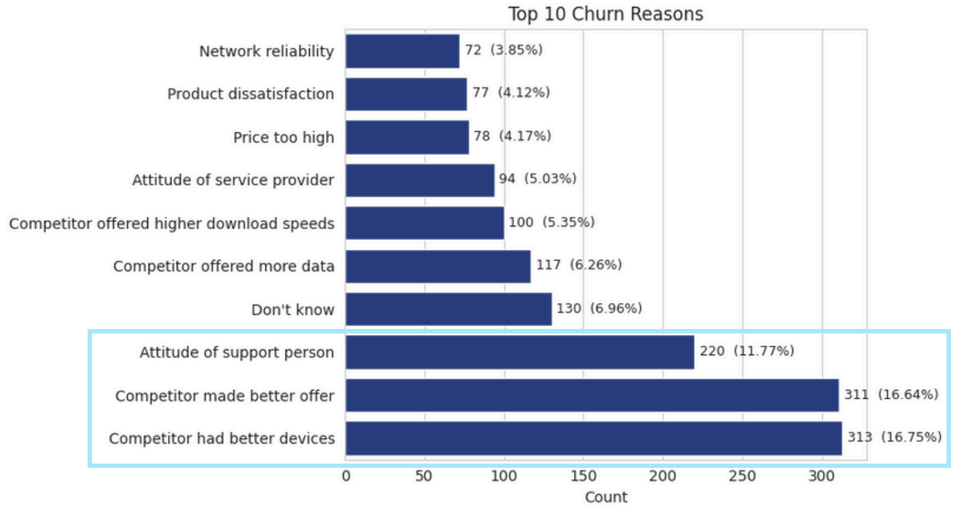


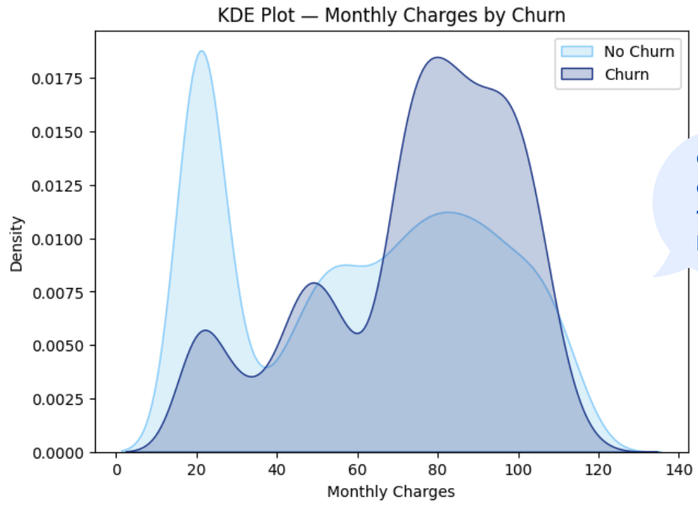




Explanatory Data Analysis

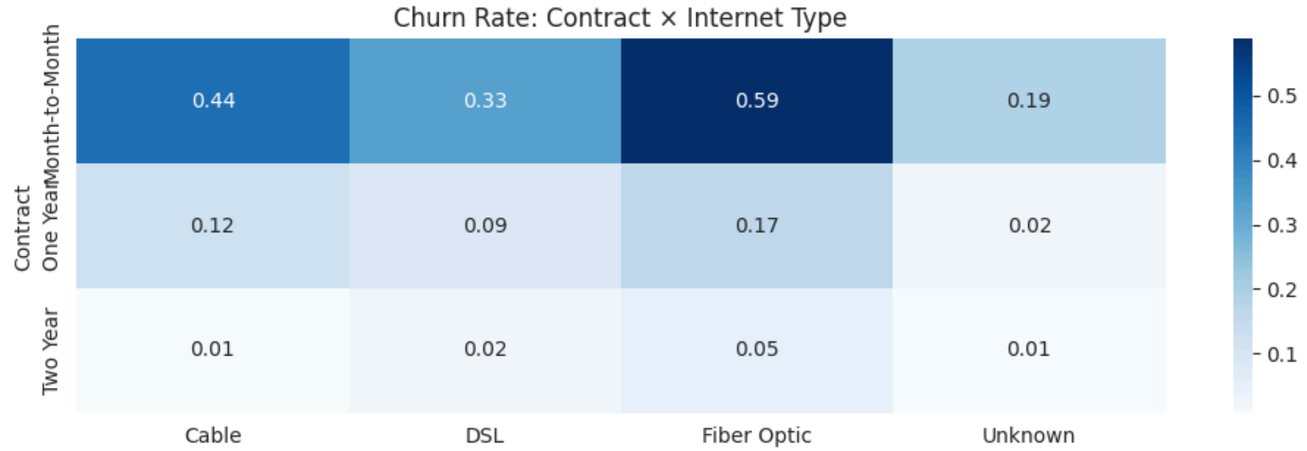






Customers who churn tend to have higher monthly charges, while those who stay are concentrated in the lower monthly charge range, suggesting that higher costs may contribute to churn

Estimated Monthly Revenue Lost due to Churn : 139,130.85



Customers on month-to-month contracts, especially those using fiber optic internet, have the highest churn rates, while those on one or two year contracts show significantly lower churn across all internet types

Machine Learning

Data Leakage

1. churn_value
2. churn_score
3. churn_label
4. customer_status
5. churn_category
6. churn_reason
7. customer_id

Train Test Split

80% training data	20% test data

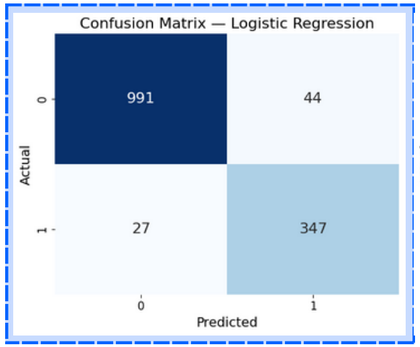
Model Training

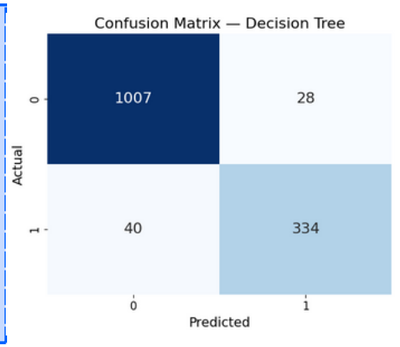
Trained classifiers include :

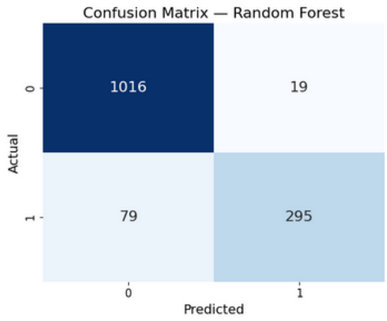
- Logistic Regression
- Decision Tree
- Random Forest
- XGBoost

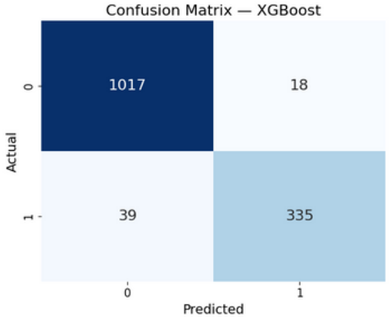
Model Evaluation (Evaluated using standard classification metrics)

Model	Accuracy	Precision	Recall	F1	ROC_AUC
Logistic Regression	0.949610	0.887468	0.927807	0.907190	0.990713
XGBoost	0.959546	0.949008	0.895722	0.921596	0.990700
Random Forest	0.930447	0.939490	0.788770	0.857558	0.973495
Decision Tree	0.951739	0.922652	0.893048	0.907609	0.932997









Chose **Logistic Regression** because it achieved the **highest recall** (92.78%), meaning it successfully detected the most actual churners among all models

Machine Learning (Final Model for Deployment)

Final Model for Deployment

To ensure the model is production-ready and efficient for real-time use, we simplified it using only the ***Top-10 most important features***

Top-10 important features

city ***satisfaction_score*** ***online_security*** ***dependents*** ***referred_a_friend*** ***number_of_referrals*** ***senior_citizen*** ***monthly_ charges*** ***contract*** ***offer***

*Coefficients from Logistic Regression were aggregated by original feature name (after one-hot encoding), and the Top-10 most impactful features were selected based on their absolute coefficient values.

Refit Model Using Top-10 Features

- Simpler pipeline is built using only the Top-10 most important features
- Re-trained Logistic Regression using only selected numerical and categorical features
- Re-evaluated on the same test set

Logistic Regression (Top-10 Variables)

Accuracy	Precision	Recall	F1	ROC_AUC
0.950319	0.874384	0.949197	0.910256	0.991397

Optimation Logistic Regression (Top-10 Variables)

Before Tuning

Cross-Validation [Stratified K-Fold] > **CV ROC-AUC: 0.9925**

*Even without tuning, performance was already strong & stable

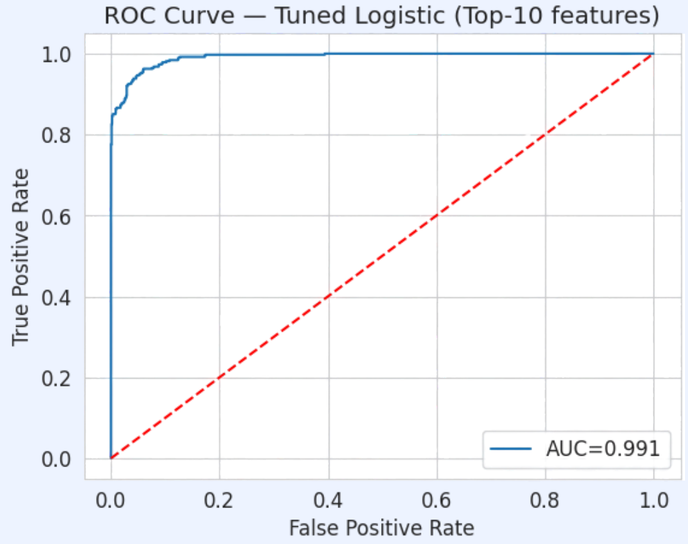
After Tuning

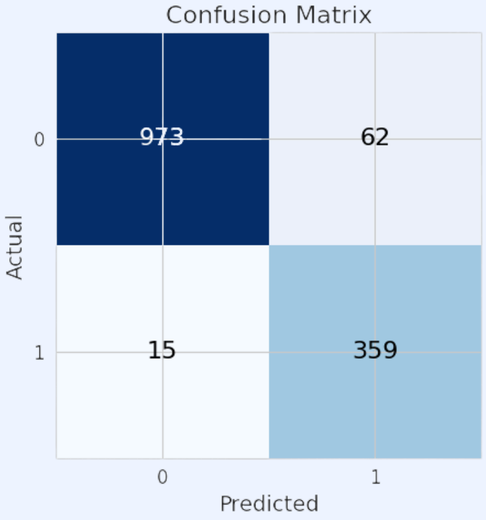
Hyperparameter Tuning [GridSearchCV] > **CV ROC-AUC: 0.9927**

*Slight performance boost after tuning

Test Metrics

Accuracy	Precision	Recall	F1	ROC_AUC
0.945351	0.852731	0.959893	0.903144	0.991477





Conclusion & Recommendation

Conclusion :

- The churn prediction project successfully uncovered key patterns in customer behavior that correlate with churn. The exploratory analysis showed that customers with low satisfaction, shorter tenure, and no referral activity are more prone to leaving. Additionally, higher monthly charges and month-to-month contracts, especially with fiber optic internet, were linked with higher churn rates
- Using logistic regression as the final model, chosen for its high recall score (92.78%) and interpretability, the model was able to reliably detect most churners. The model was then optimized and simplified using only the top 10 most influential features, making it suitable for business deployment and real-time monitoring

Streamlit : http://bit.ly/4fZkswq

Implement Targeted Retention Programs

To reduce churn effectively, retention strategies should be tailored based on the characteristics and reasons of customers most at risk. Based on churn pattern analysis and dominant churn reasons, here's a breakdown of targeted actions :

Prioritize Short-Term Contract Customers

- Offer exclusive discounts or cashback to convert them to 1- or 2-year contracts
- Provide contract extension bundles with added value (e.g. extra data, free premium support)

Address Low Satisfaction Segments

- Trigger automatic service follow-ups or apology credits for customers with low scores
- Route them to a retention specialist or VIP support line to recover the relationship

Respond to Common Churn Reasons

- Launch "Win-Back Offers" targeting customers citing competitor deals (e.g., limited-time upgrades)
- Invest in agent retraining and track churn correlation by support ticket
- Offer temporary data boosts or network optimization callbacks for speed-related complaints

Personalize Campaigns Based on Usage & Referral Data

- Build segmented campaigns offering personalized promos for low-engagement users
- Encourage referrals with double-sided incentives (e.g. "Refer & Save")

Conclusion & Recommendation

Operationalize the Predictive Churn Model

To transform the churn prediction model from analysis into business impact, it should be embedded into operational workflows. Below are the three most actionable and strategic steps for deployment :

Integrate Churn Scores into CRM and Internal Dashboards

Having churn risk scores directly visible in CRM or customer success tools enables teams to respond faster and more precisely

How to implement

- Connect the trained churn model to data pipeline (weekly or monthly scoring)
- Add churn risk scores as a field in CRM (e.g., Salesforce, HubSpot, Zoho)
- Use visual indicators like colored tags (e.g., red = high risk) to help agents identify at-risk customers at a glance

Launch Trigger-Based Retention Campaigns

Churn prevention must be timely. Automation ensures high-risk customers receive personalized intervention before it's too late

How to implement

- Set up threshold rules (e.g., churn probability > 80%)
- Connect to your marketing tools to run A/B tests and optimize results
- Trigger automated actions like sending personalized offers, assigning follow-ups, or scheduling calls

Monitor, Evaluate, and Retrain the Model Regularly

Customer behavior and market conditions change. Without ongoing monitoring, model performance can degrade over time

How to implement

- Track key performance metrics (e.g., recall, F1, AUC) using dashboards
- Gather feedback from users (e.g., “Was this alert helpful?”)
- Retrain the model every 3–6 months with the latest data and fine-tune the thresholds if needed

Thank you!

Felicia Angjaya