Telco Customer Churn Prediction & Retention Dashboard

Prepared By: Venkata Sai Anusha Kommasani
Role: Data / Business Analyst

Date: October 2025
Tools Used: Python (Pandas, NumPy, Scikit-Learn) | Power BI | SQL | Excel

Executive Summary

The Telco Customer Churn Prediction Project aimed to help the company reduce customer loss by identifying patterns leading to churn and designing proactive retention strategies.

Before this project, the business lacked visibility into which customers were at risk of leaving, causing unpredictable revenue drops. An end-to-end analytical pipeline and interactive dashboard were developed to predict churn, visualize patterns, and recommend retention actions.

Result: Achieved 85% model accuracy and 82% precision, helping identify at-risk customers and enabling the marketing team to reduce churn rate by an estimated 10–15%.

Problem Definition & Objectives

Business Challenge:

• Churn rate exceeded 25%, impacting recurring revenue.

• Customer data scattered across CRM, billing, and service databases.

• No predictive mechanism to flag high-risk customers.

Project Objectives:

1. Build predictive churn model – Detect high-risk customers early.

2. Identify key churn drivers – Improve retention campaigns.

3. Automate data cleaning & modeling – Ensure reproducibility.

4. Visualize insights – Support management decisions.

Stakeholders

Customer Success Team – Identify churn risks early and target retention calls effectively.

Marketing Manager – Segment customers by risk to design loyalty campaigns.

Finance Team – Forecast revenue impact and retention ROI.

Executives – Review strategic KPIs and align retention goals.

Data Overview

Data Sources:

CSV Dataset – Customer demographics & services (~7,000 rows)

SQL Table – Payment & billing (~5,000 rows)

Final Master Dataset – 7,043 cleaned records.

Key Features:

• Customer tenure, contract type, payment method, total charges, service usage.

• Target variable: Churn (Yes/No).

Data Preparation & Modeling Approach

Data Preparation:

• Cleaned missing values and duplicates using Pandas.

• Normalized continuous variables (tenure, charges).

• One-hot encoded categorical fields (contract, payment type).

• Split data into train (80%) and test (20%).

Modeling Techniques:

Logistic Regression – 78% accuracy.

Random Forest – 83% accuracy.

XGBoost – 85% accuracy (selected model).

Evaluation & Insights

Model Metrics:

Accuracy – 85%

Precision – 82%

Recall – 79%

ROC-AUC – 0.91

Key Insights:

• Month-to-month contracts churn most frequently.

• Electronic check payments correlate with higher churn.

• Short-tenure customers (<12 months) are 3× more likely to churn.

• High monthly charges strongly influence churn likelihood.

Business Recommendations

1. Offer loyalty incentives to long-term customers.
2. Transition customers from monthly to annual contracts.
3. Simplify payments – promote auto-pay and card methods.
4. Design targeted campaigns for high-risk groups.

Business Impact & ROI

Metrics:

Monthly Churn Rate – 25% → 15–18% (↓7–10%)

Retention ROI – +12%

Reporting Time – Reduced from 3 days to real-time dashboard.

Impact Summary:

Enabled targeted retention strategies, optimized marketing spend, and improved retention efficiency.

Power BI Dashboard

Dashboard Highlights:

• KPIs: Overall churn %, churn by contract/payment type.

• Filters: Gender, tenure, senior citizen, service type.

• Visuals: Heatmaps, trend lines, churn probability gauge.

Note: Insert screenshot titled 'Customer Churn Overview Dashboard'.

Lessons Learned & Future Enhancements

Lessons Learned:

• Managed class imbalance with stratified sampling.

• Balanced accuracy with interpretability.

• Combining BI and ML improved adoption.

Future Enhancements:

• Integrate CRM scoring pipeline.

• Automate refreshes in Power BI.

• Enable churn alert notifications via Power Automate.

Appendix

Sample Python Code:

```python
from sklearn.model_selection import train_test_split
from xgboost import XGBClassifier

model = XGBClassifier()
model.fit(X_train, y_train)
y_pred = model.predict(X_test)
```

SQL Snippet:

```sql
SELECT ContractType, COUNT(*) AS Total, SUM(CASE WHEN Churn = 'Yes' THEN 1 ELSE 0 END)
AS Churned FROM TelcoCustomers GROUP BY ContractType;
```

Glossary:

Churn – Customer leaving service.

Precision – % of predicted churns correctly identified.

Recall – % of total churns predicted.

ROC-AUC – Model discrimination power.