Telco Customer Churn Prediction: Final Model Development and Analysis

1. Executive Summary

This report details the development and optimization of a predictive model to identify customers at high risk of churning (leaving the company). Due to the high cost of customer acquisition, the primary business objective was maximizing **Recall**—correctly identifying the largest possible percentage of actual churners—while maintaining high overall model quality.

The final model, a **Tuned XGBoost Classifier**, achieved a Recall of **80%** with a strong Precision of **58%** at the optimal F1-Score threshold. This configuration means the model is highly effective at saving customers (catching 8 out of 10 at-risk customers) while providing a reliable list for the Retention Team.

Final Model Metric	Score (Churn Class)
ROC AUC	**0.853**
Recall	**0.80**
Precision	**0.58**
F1-Score	**0.67**

2. Exploratory Data Analysis (EDA): Key Churn Drivers

Initial data analysis revealed significant structural imbalance and several strong correlations with churn:

- **Class Imbalance:** The dataset exhibits a significant imbalance, with approximately **73% Non-Churn** and **27% Churn**. This finding necessitated the prioritization of Recall and F1-Score over simple Accuracy.
- **Contract Type (Highest Influence):** Customers on a **Month-to-month** contract represent the vast majority of churners. Customers on 1-year and 2-year contracts are highly stable.
- **Tenure:** Churn is heavily concentrated among **new customers** (low tenure). The probability of churn drops significantly after the first 12 months.
- **Services:** Customers utilizing **Fiber Optic** internet service and those with **higher Monthly Charges** showed a significantly elevated churn rate, suggesting potential issues with service quality or pricing sensitivity at the high-end tier.
- **Demographics: Senior Citizens** and customers who are **single** (no Partner) or **without Dependents** exhibited higher churn rates, indicating they are less "locked-in" to the service.

3. Model Development and Evaluation Strategy

3.1. Evaluation Metrics

Given the cost disparity (losing a customer is more costly than sending an unnecessary retention email), model evaluation focused on:

- **Recall (True Positive Rate):** The most critical metric, reflecting the percentage of actual churners correctly identified.
- **Precision (Positive Predictive Value):** The percentage of predicted churners who actually churn (measures false alarms).
- **ROC AUC:** Measures the overall discriminatory power of the model, independent of the classification threshold.

3.2. Baseline Model Performance

Initial modeling confirmed that ensemble methods would be necessary to achieve the target performance.

Model	Accuracy	Precision	Recall	F1-Score	ROC AUC
Logistic Regression	0.81	0.65	0.50	0.56	0.84
Random Forest	0.80	0.62	0.51	0.56	0.83
LightGBM (Baseline)	0.76	0.55	0.82	0.66	0.78

- **Observation:** Boosting models (like the baseline LightGBM) immediately delivered the highest **Recall** ($\mathbf{0.82}$) due to their ability to handle class imbalance, confirming the strategic path forward.

4. Final Model Selection and Optimization

4.1. Boosting Model Tuning

The project focused on hyperparameter tuning and class balancing for the XGBoost and LightGBM models, which are ideally suited for this non-linear classification task.

- **XGBoost Final Hyperparameters:** Tuning using Grid Search led to the selection of robust parameters, including `learning_rate: 0.1`, `max_depth: 5`, and `n_estimators: 100`.

4.2. Threshold Optimization

The final step involved adjusting the prediction threshold to find the optimal operating point for the business, moving from the default 0.5.

Optimization Point	Threshold	Recall	Precision	F1-Score	Business Focus
Prior Setting	≈ 0.4	0.83	0.55	0.66	Maximum Retention
Best F1 Setting	**0.5503**	**0.80**	**0.58**	**0.67**	Balanced Cost-Effectiveness

The **Best F1 Threshold of 0.5503** was chosen as it slightly improved the overall F1-Score while maintaining an exceptionally high Recall of 0.80.

4.3. Final Performance Metrics

The final XGBoost model, evaluated at the optimized threshold, provides a high-confidence list for the retention team:

Metric	Non-Churn (Class 0)	Churn (Class 1)
Precision	0.91	$\mathbf{0.58}$
Recall	0.77	$\mathbf{0.80}$
F1-Score	0.83	$\mathbf{0.67}$

Confusion Matrix:

- True Negatives (Non-Churners Correctly Identified): 588
- False Positives (Loyal Customers Flagged as Churn): 173
- False Negatives (Churners Missed): 60
- True Positives (Churners Correctly Identified): **236**

5. Conclusion and Recommendations

The final XGBoost model is highly successful, achieving the key business objective of maximizing customer retention (Recall $= 0.80$).

Recommendation for Deployment:

1. **Deploy the XGBoost model using a classification threshold of 0.55.**
2. **Targeted Campaigns:** Use the model's feature importance scores (which will favor `Contract_Month-to-month`, `Tenure`, and `InternetService_Fiber Optic`) to design customized retention offers for the high-risk segment.
3. **Monitor False Positives:** The 173 False Positives (customers who would have stayed but received an offer) represent the cost of the retention program. This number should be tracked against the saved revenue from the 236 True Positives.