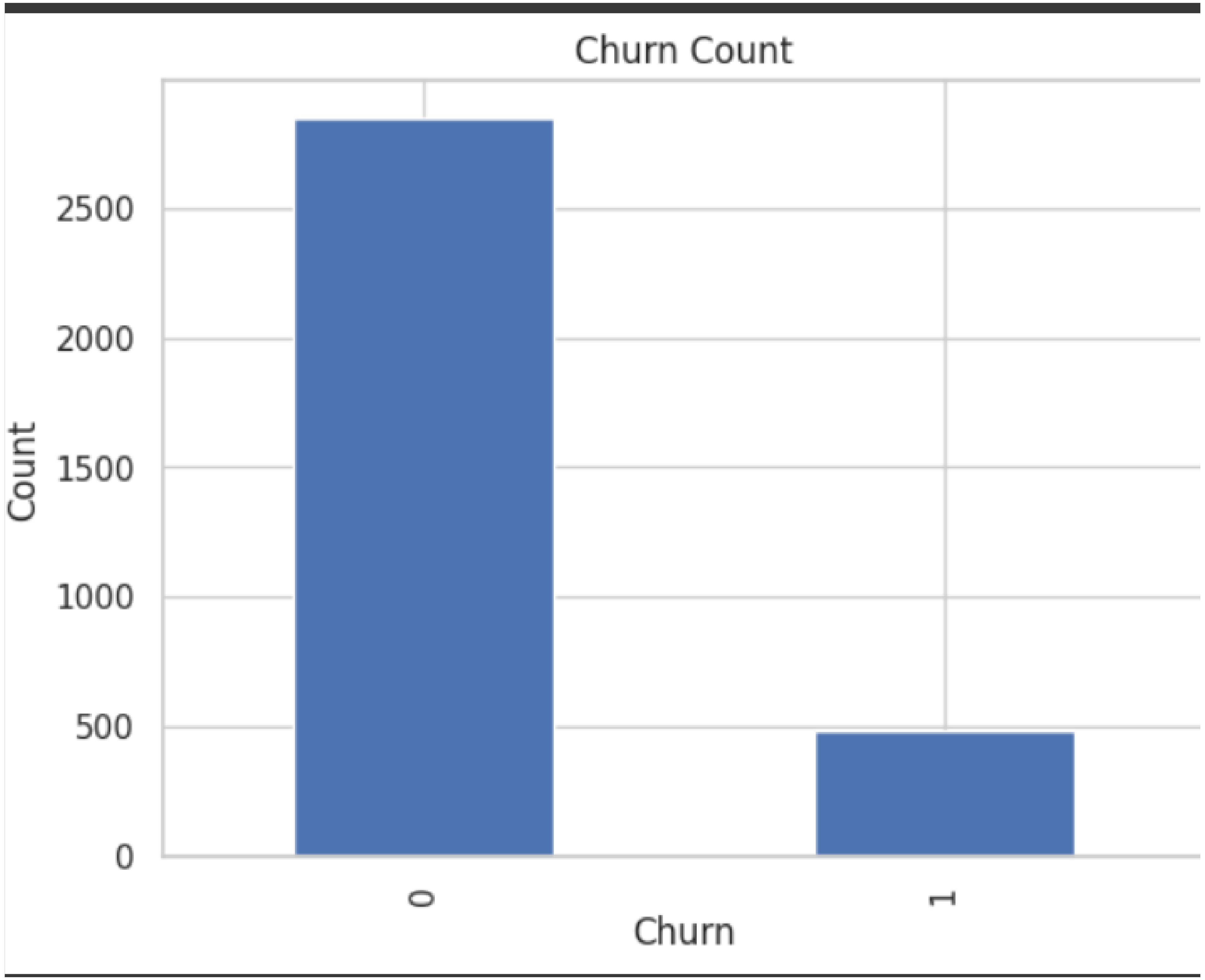
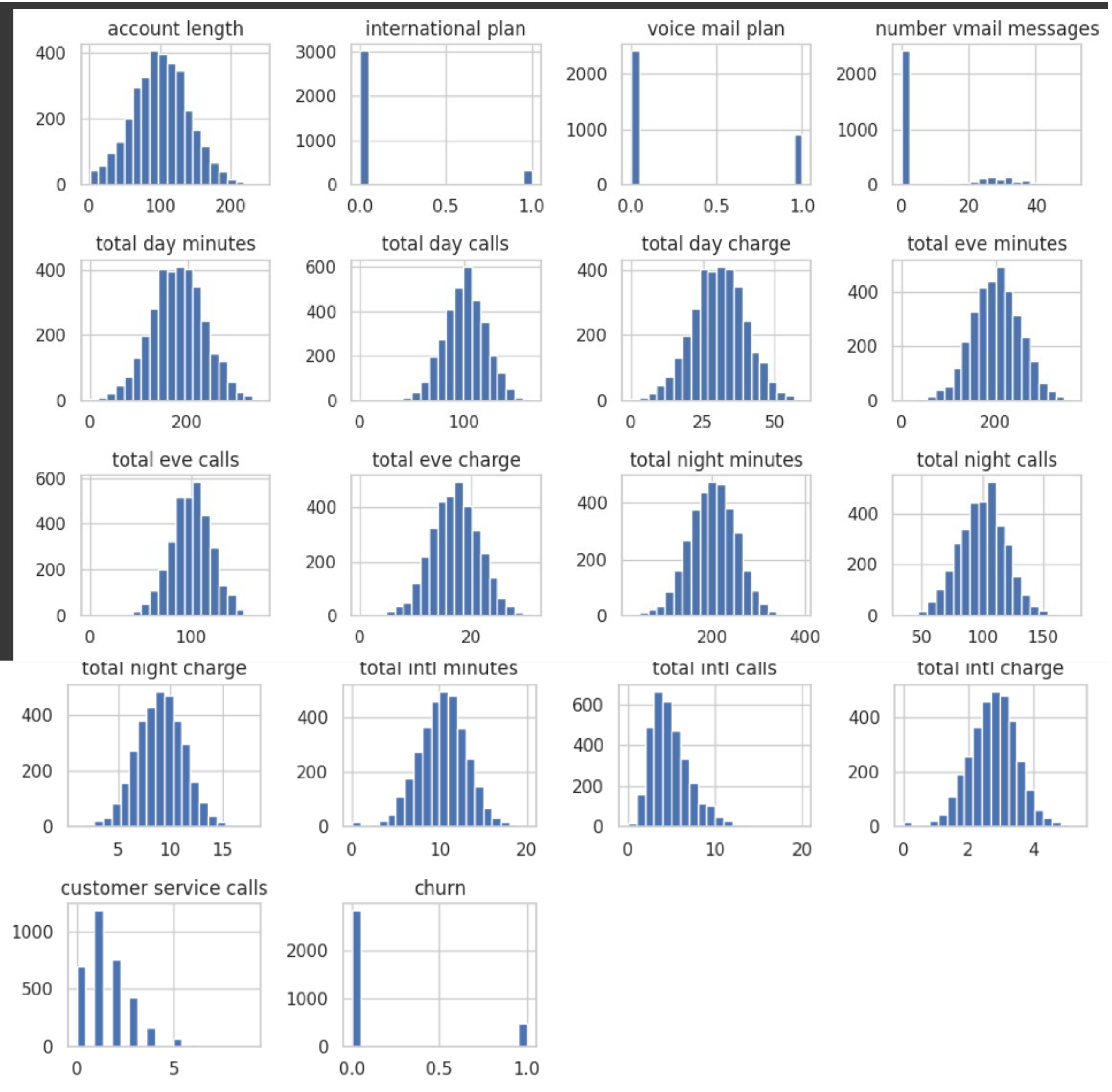
BUSINESS

PROJECT

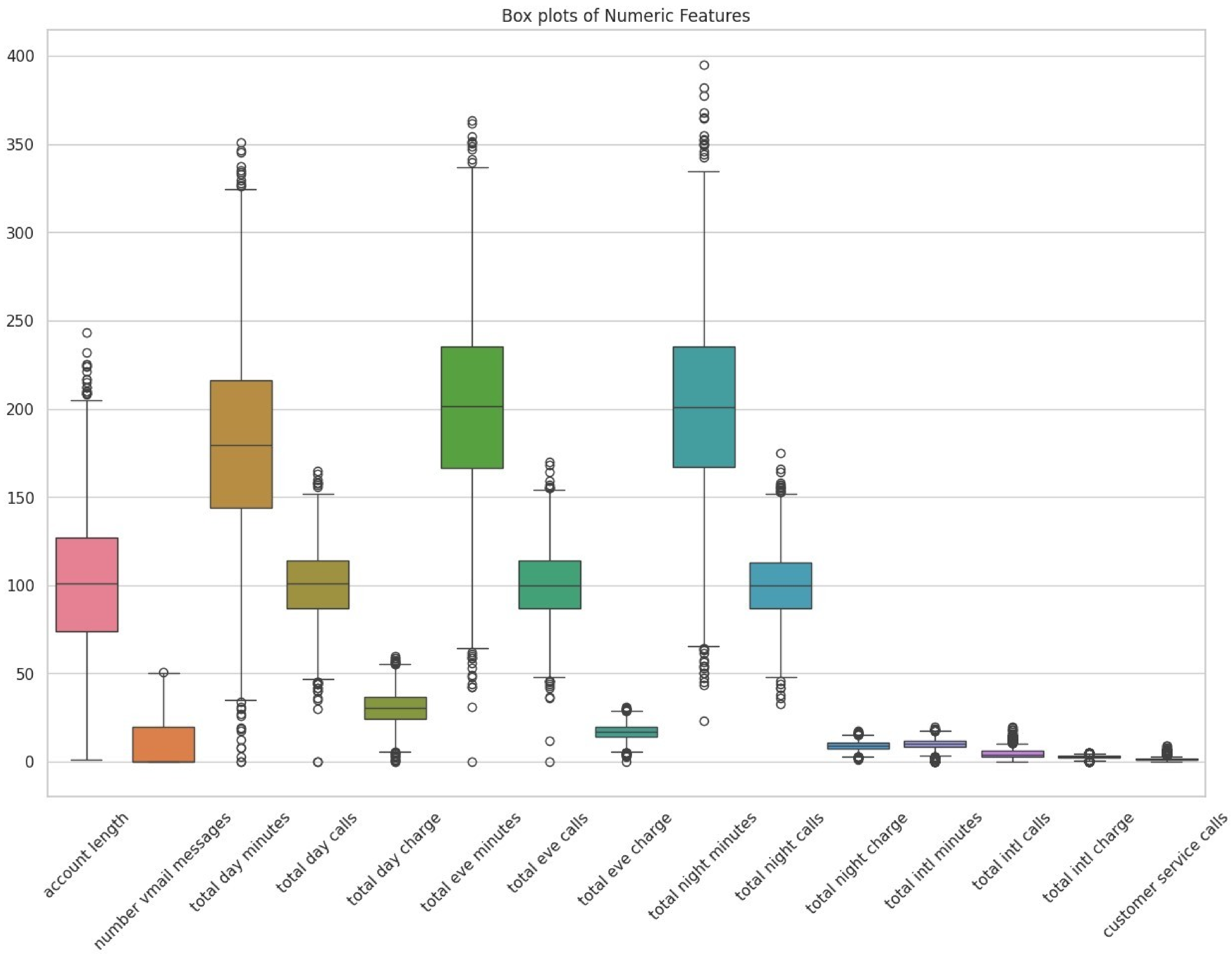
AFTER ANALYSIS WE ALSO BUILD A PREDICTOR MODEL TO ASSIST IN FUTURE PREDICTIONS

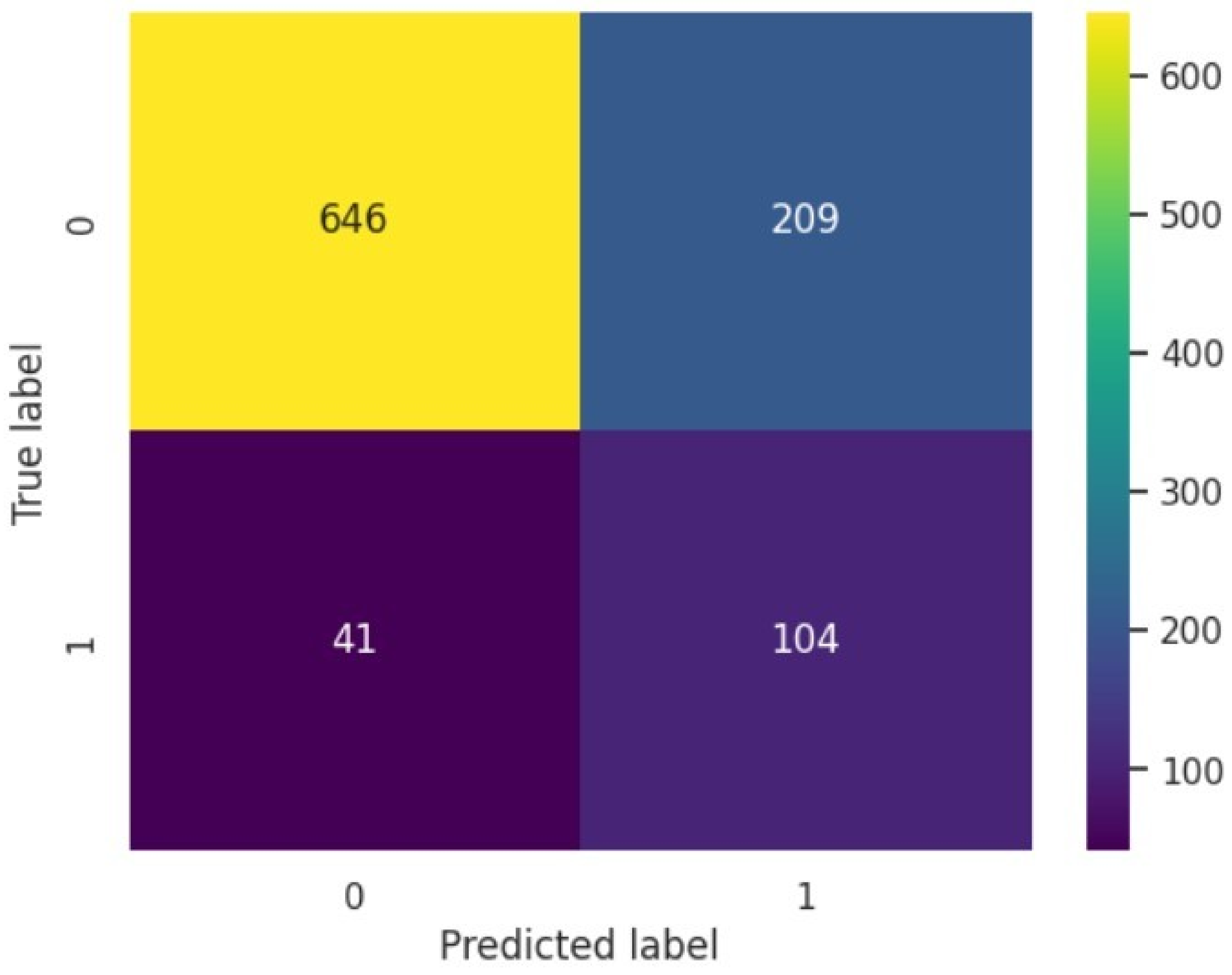


Churn is our target variable. From our graph we have an imbalance with our data.



As seen, most of our variables are normally distributed.

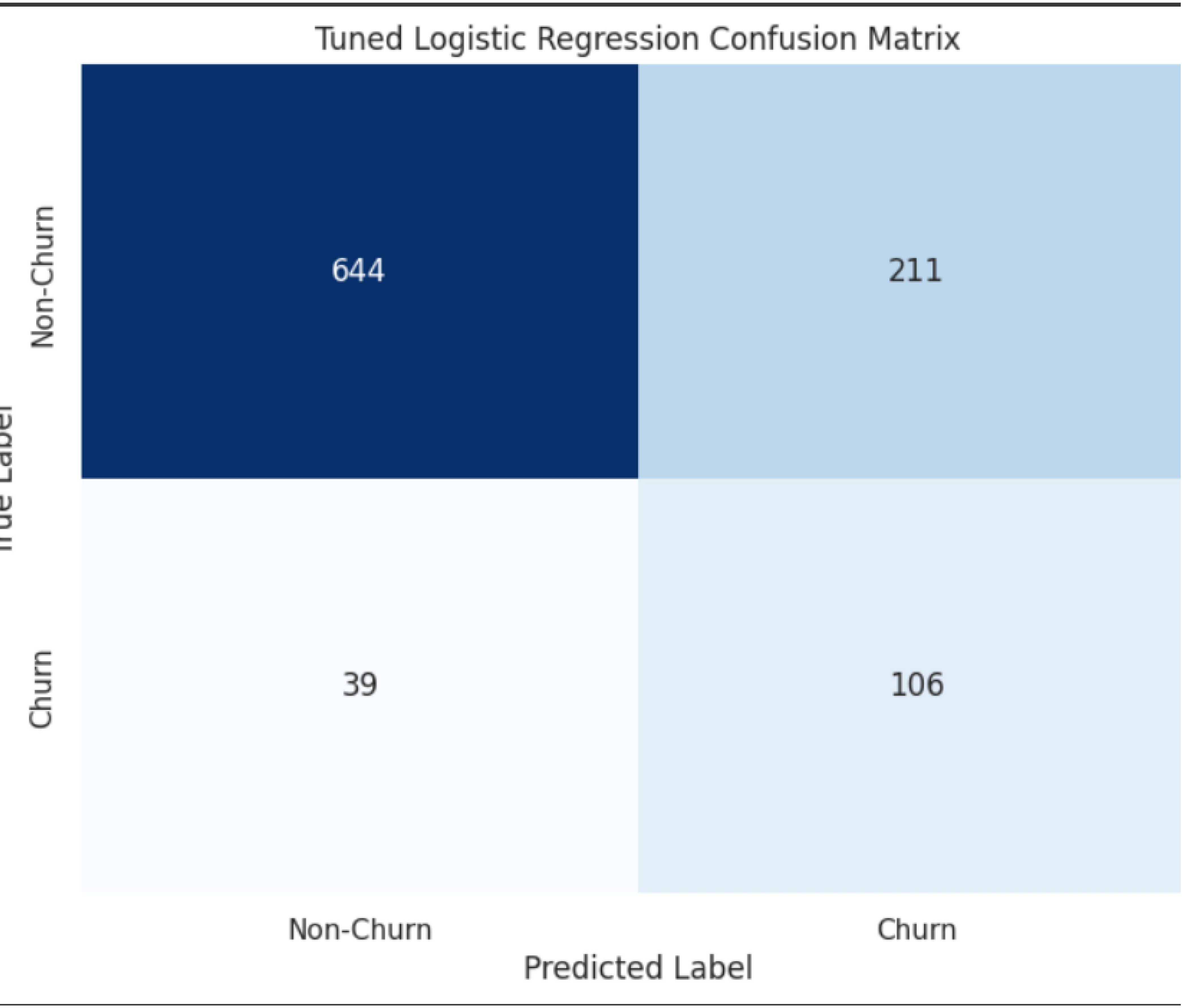

Box plots of Numeric Features
400
350
300
250
200
150
100
50
0
account length
number vmail messages
total day minutes
total day calls
total day charge
total eve minutes
total eve calls
total eve charge
total night minutes
total night calls
total night charge
total intl minutes
total intl calls
total intl charge
customer service calls



Baseline logistic model

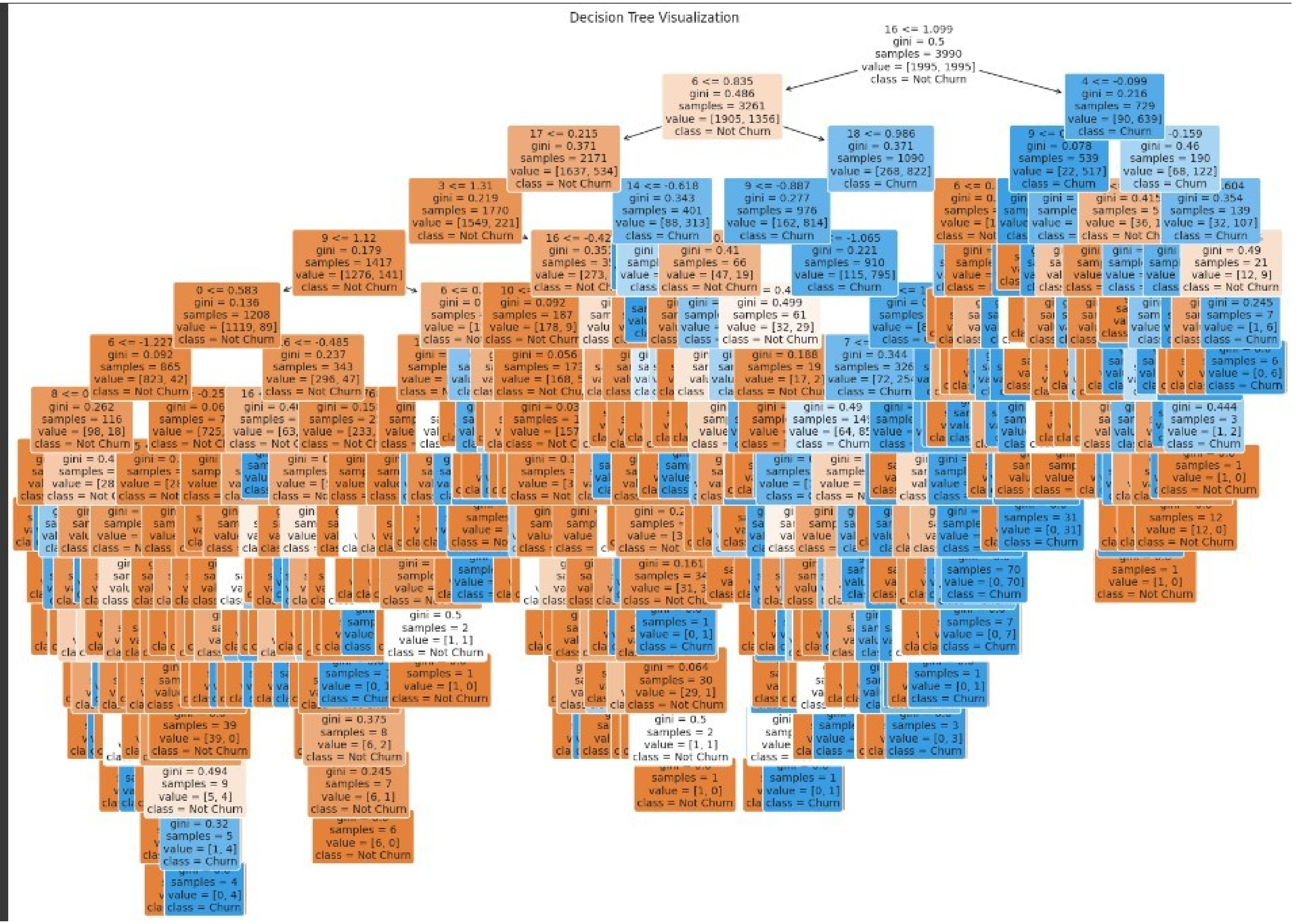
Imbalance Issue: The model struggles with predicting the minority class
1) is quite low at 0.33, indicating a high number of f

Recall for Churn: The recall for churn (0.72) is relatively good, meaning t
identifying actual churn cases, though it comes at the cost of ma
For class 0 (non-churn): 0.94, indicating that when the model predicts n
time.
For class 1 (churn): 0.33, indicating lower precision, so when the model
the time. Accuracy Score:
0.75: The model correctly classified 75% of the instances. While thi
imbalanced nature of the dataset means that accuracy alone might no
performance.



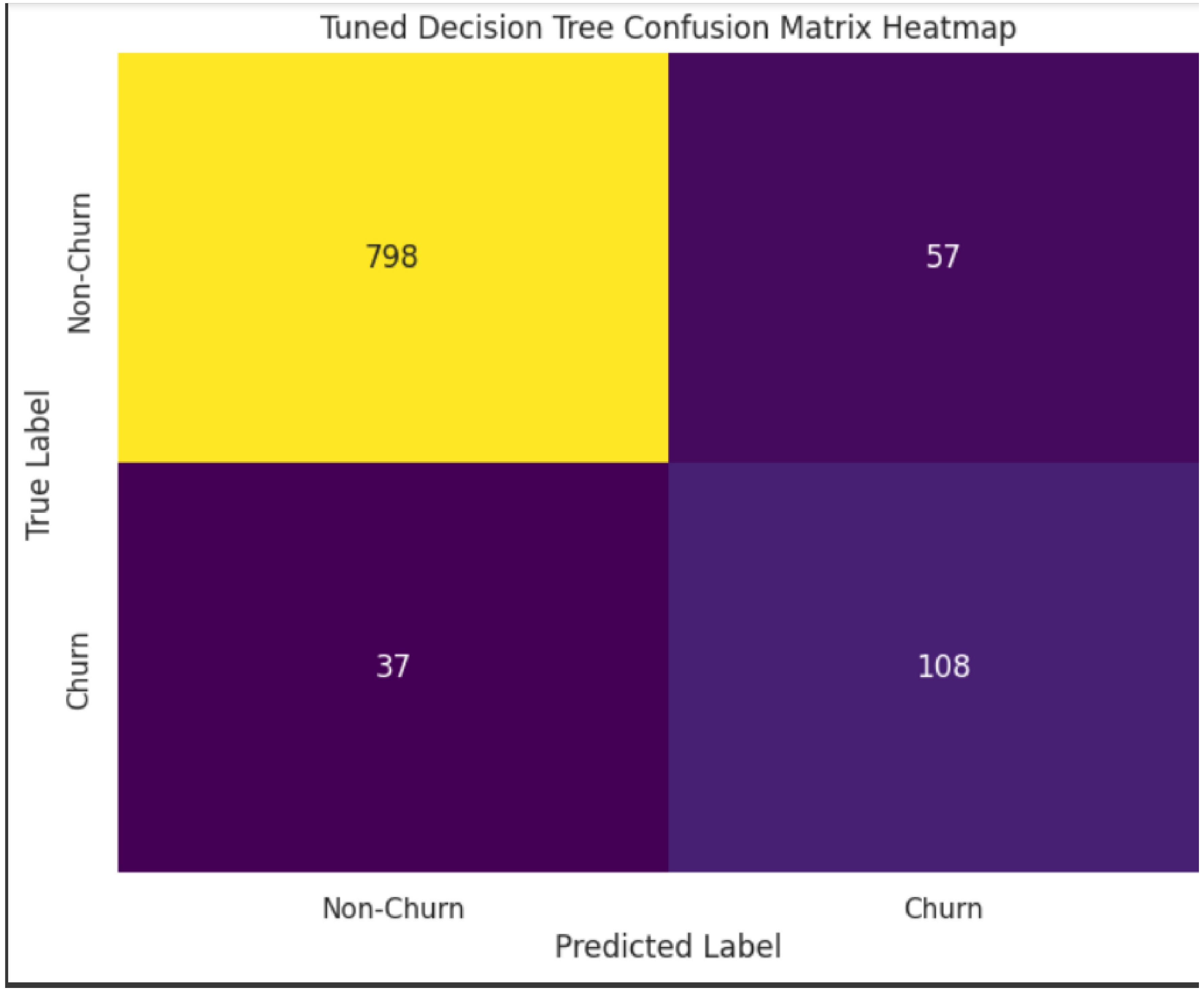
Tuned Logistic Regression Confusion Matrix
Non-Churn
Churn
644
211
39
106
Non-Churn
Churn
Predicted Label

Significant Improvement:



Higher Accuracy:

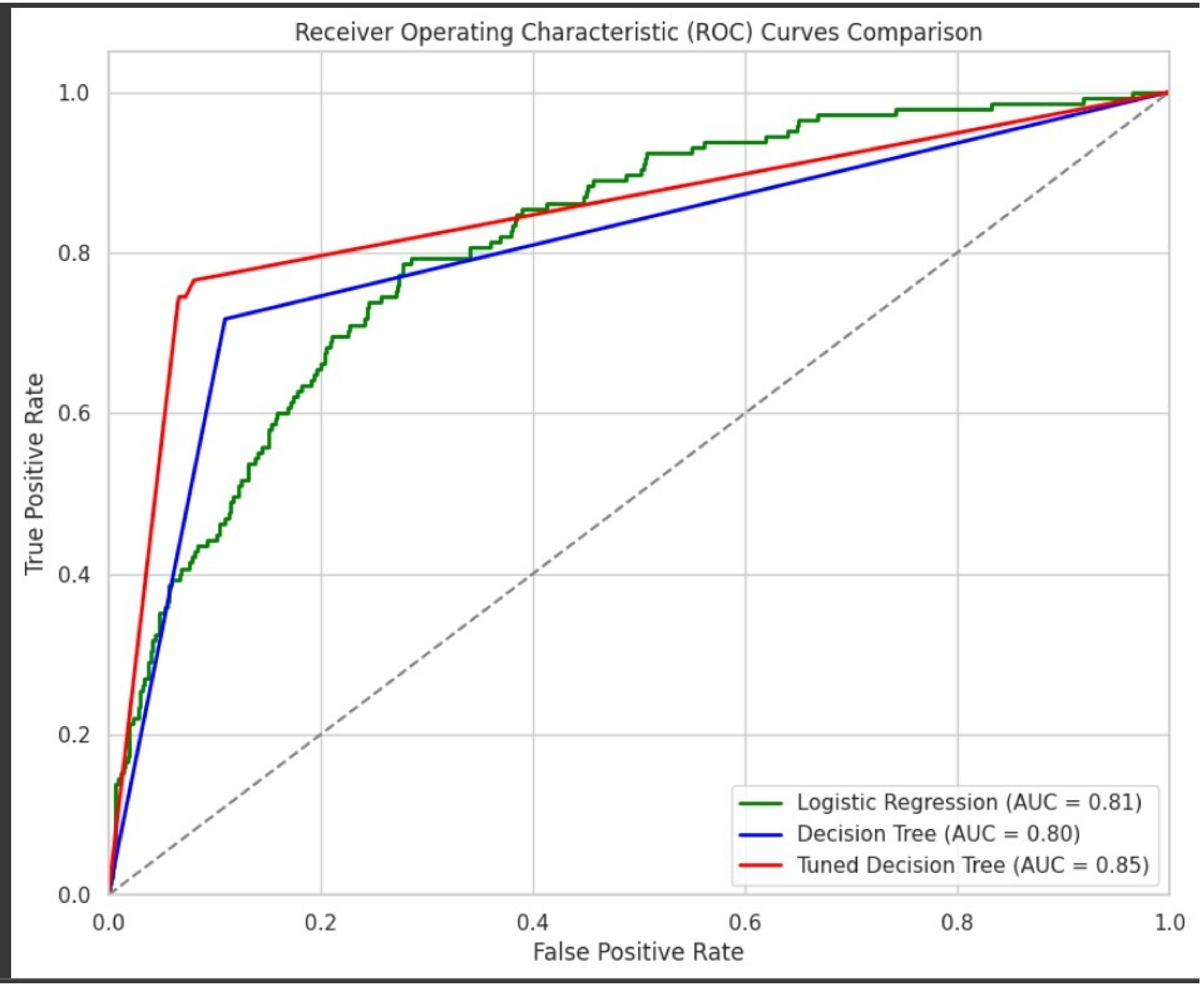
Better Handling of Imbalance:



Improved Accuracy:

Balanced Performance:

Effective Tuning:



model comparisons

Tuned Decision Tree: This model has th
best performance among the three mo
left corner, which signifie

Logistic Regression: With an AUC of 0.8
Decision Tree but not as well a

Decision Tree: This model has the low

indicating it has the least effective c

RECOMMENDATIONS

The predictive model we developed can accurately forecast customer churn based on various customer attributes and behaviors. By leveraging this model, Telecom can:

Target At-Risk Customers: Identify customers at high risk of churn and take proactive steps to retain them, such as offering personalized incentives or improving customer service.

Optimize Marketing Strategies: Focus marketing efforts on features and services that reduce churn, based on the insights gained from feature importance.

Enhance Customer Experience: Understand common factors leading to churn and address underlying issues, such as billing disputes, service dissatisfaction, or lack of engagement.

The predictive model not only answers the business question but also provides a practical tool for reducing customer churn, thereby minimizing revenue loss and improving customer loyalty.