

Customer Churn Analyzer

Overview - A machine learning-based analyzer that predicts customer churn using service usage, billing, and interaction data to support proactive retention strategies.

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Problem Statement & Business Impact

- ❖ Problem: Identify customers likely to cancel subscription.
- ❖ Business Impact:
- ❖ Preventing churn is more cost-effective than acquiring new users.
- ❖ Retention strategies improve revenue & customer loyalty.

Dataset Overview

- 1002 rows, 10 columns
- ❖ Key Features:
 - Contract, SupportCalls, MonthlyBill, PaymentMethod
 - Billing Issues, DataUsageGB, TenureMonths, AutoPay
 - Target: Churn (Yes/No)

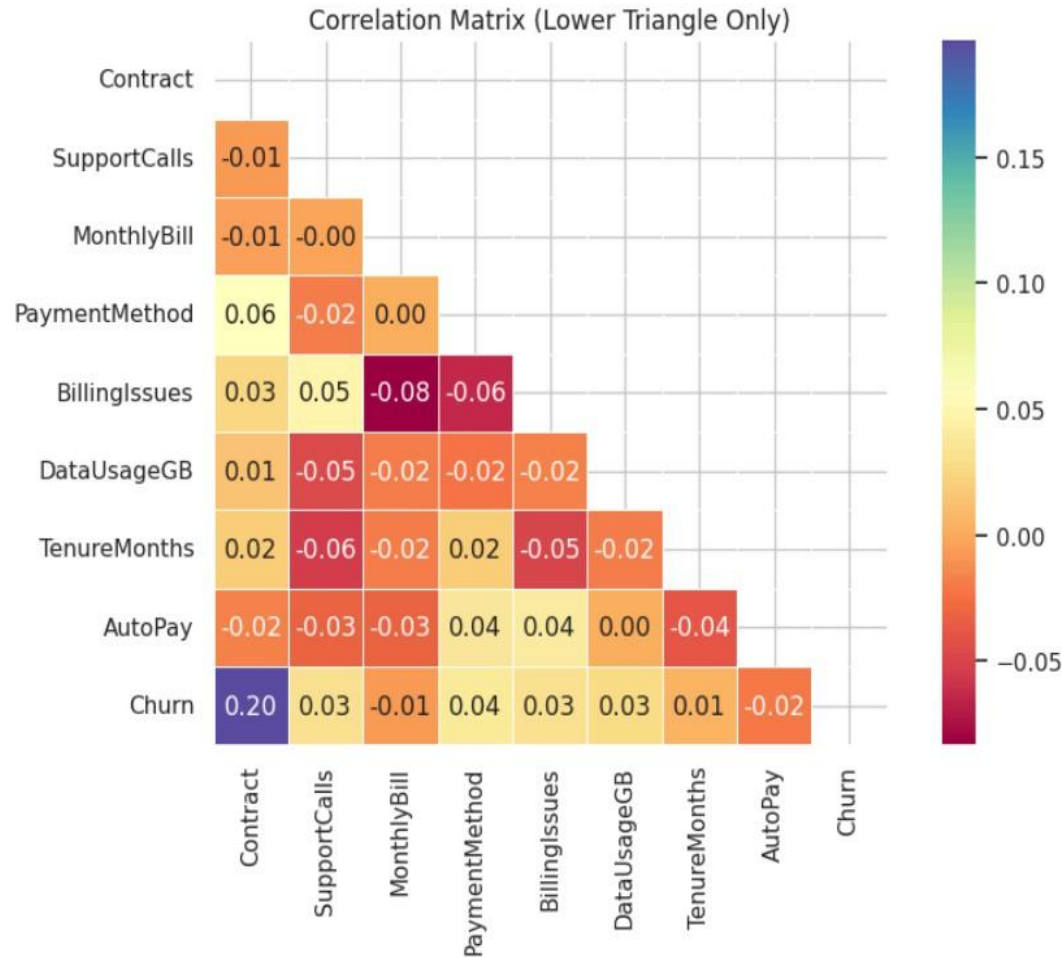
```
↕ CustomerID Contract SupportCalls MonthlyBill PaymentMethod BillingIssues \
0 C001 Monthly 5 120.00 CreditCard 1
1 C002 Annual 1 80.00 UPI 0
2 C003 Monthly 5 74.12 CreditCard 1
3 C004 Annual 1 46.44 UPI 0
4 C005 Monthly 4 105.61 DebitCard 0

DataUsageGB TenureMonths AutoPay Churn
0 60.00 6 0 Yes
1 95.00 24 1 No
2 105.81 36 1 Yes
3 74.44 21 0 No
4 105.19 16 1 Yes
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1002 entries, 0 to 1001
Data columns (total 10 columns):
# Column Non-Null Count Dtype
---
0 CustomerID 1002 non-null object
1 Contract 1002 non-null object
2 SupportCalls 1002 non-null int64
3 MonthlyBill 1002 non-null float64
4 PaymentMethod 1002 non-null object
5 BillingIssues 1002 non-null int64
6 DataUsageGB 1002 non-null float64
7 TenureMonths 1002 non-null int64
8 AutoPay 1002 non-null int64
9 Churn 1002 non-null object
dtypes: float64(2), int64(4), object(4)
memory usage: 78.4+ KB
None
Churn
No 528
Yes 474
Name: count, dtype: int64
```

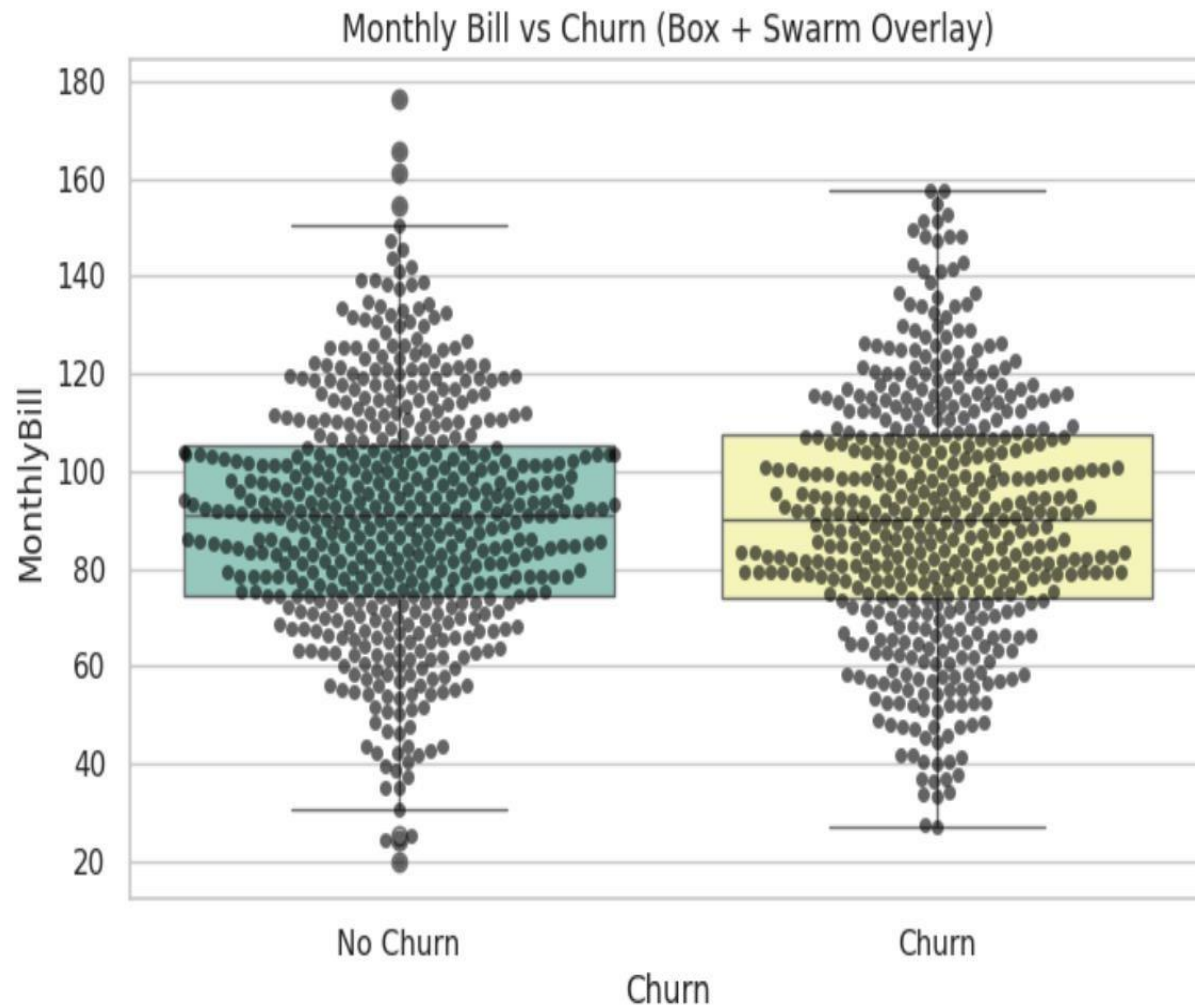
EDA - Correlation Heatmap

9/8/25, 12:26 PM

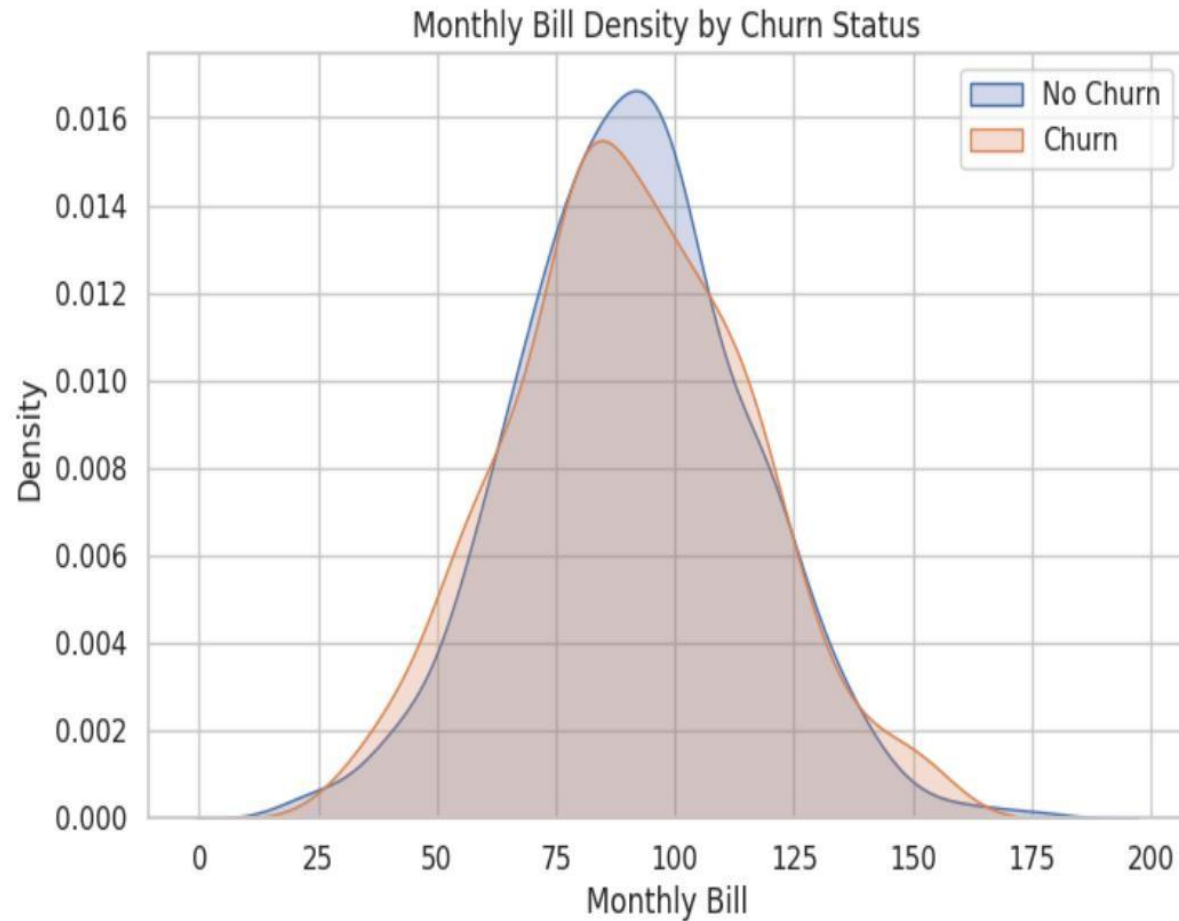
Customer Churn Analyzer.ipynb - Colab



EDA - Monthly Bill vs Churn

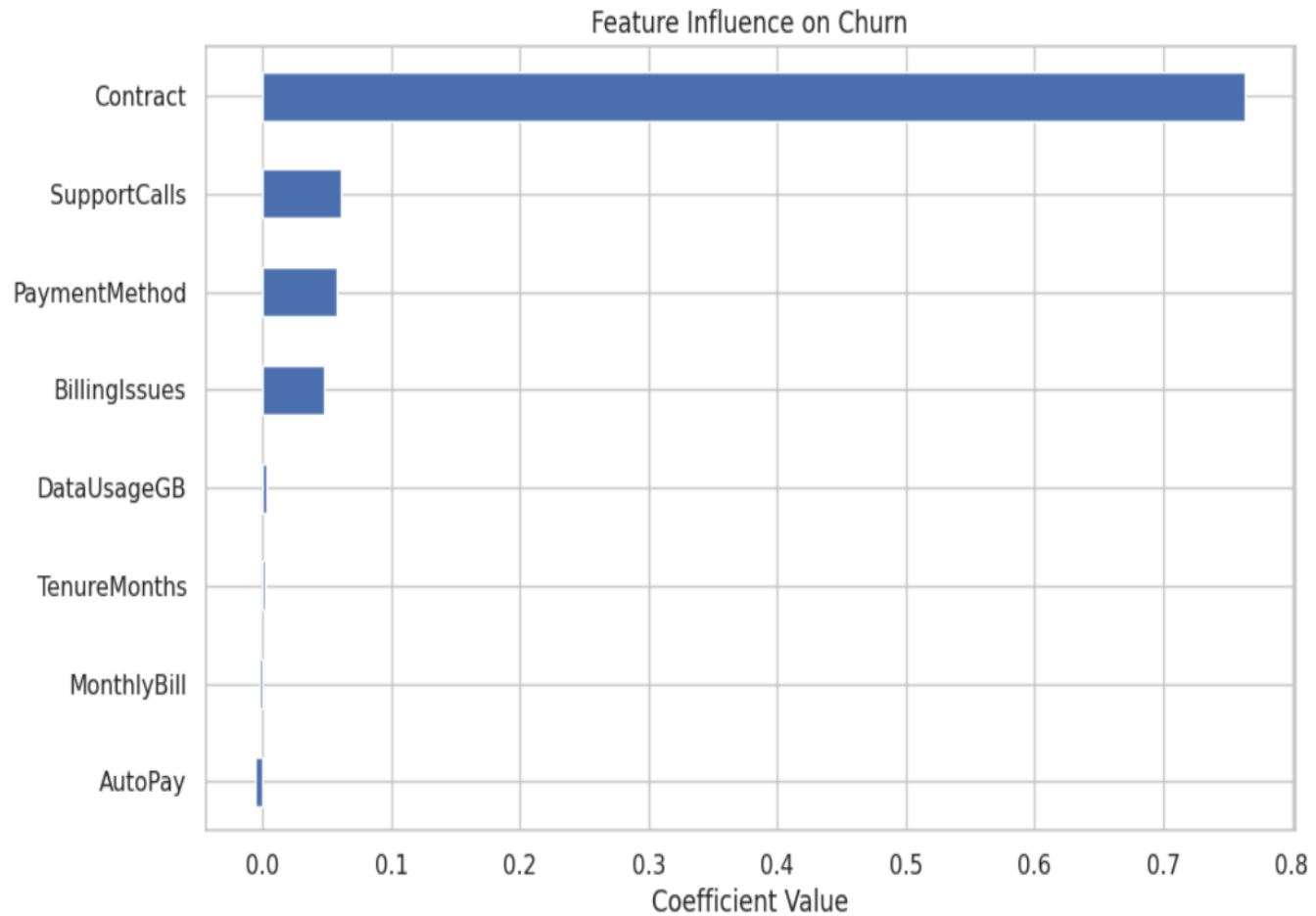


EDA - Monthly Bill Density by Churn



Avg Monthly Bill (Churned): ₹90.37
Avg Monthly Bill (Retained): ₹90.71

Feature Importance



Model Evaluation

- Confusion Matrix:
- $\begin{bmatrix} 89 & 69 \\ 69 & 74 \end{bmatrix}$
-

Performance:

- Accuracy: 54%
- F1 Score: 0.52
- Precision/Recall ~0.52-0.56

```
➡ Confusion Matrix:  
[[89 69]  
 [69 74]]
```

Classification Report:

	precision	recall	f1-score	support
0	0.56	0.56	0.56	158
1	0.52	0.52	0.52	143
accuracy			0.54	301
macro avg	0.54	0.54	0.54	301
weighted avg	0.54	0.54	0.54	301

F1 Score: 0.5174825174825175

Prediction Example

❖ Input:

- Contract: Monthly, Support Calls: 4, Monthly Bill: 110, Payment Method: Credit Card,
- Billing Issues: 0, Data Usage GB: 85, Tenure Months: 12, Auto Pay: Yes
- Prediction: Churn = **Yes**

Conclusion & Future Work

- Logistic Regression baseline achieved ~54% accuracy (F1 = 0.52)
- ❖ Future Improvements:
 - Try Decision Trees, Random Forest, XGBoost
 - Hyperparameter tuning
 - Feature engineering
 - Handle class imbalance



THANK YOU!