

# Customer Churn Prediction in the Telecom Industry

## ▶ PRESENTED BY:

- ▶ Vidhi Shukla
- ▶ Unni Krishnan
- ▶ Vamshi Krishna Vallabhaneni

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# Introduction



Problem Statement:



Customer churn is a critical challenge in the telecom industry. Predicting churn helps businesses retain high-value customers.



Objective:



Build a machine learning model to predict churn and provide insights to reduce churn rates.

# Data Understanding



**Dataset:**



**The dataset contains customer data with metrics like ARPU, data usage, and recharge history.**



**Sample features include:**

1. Total Recharge Amount
2. Data Usage
3. Call Usage
4. Recharge Counts
5. Customer Last month Recharge.
6. Total Monthly Charges
7. VBC(Volume based count)
8. Average Revenue per User & Total Data Usage

# Exploratory Data Analysis (EDA)

## Churn Distribution & Recharge Amount Distribution



**Churn Distribution:**



**Show the distribution of  
churners vs non-churners.**



**Key Insights:**

1. High ARPU customers tend to churn less.
2. Higher recharge drop correlates with churn.

# Feature Engineering



**High-Value Customer Filter:**  
**Filtered customers based on recharge amount.**



## **Derived Features:**

1. Recharge Drop
2. Call Drop
3. Data Usage Drop



**These features help in identifying customer churn patterns.**

Like: High Value Customers

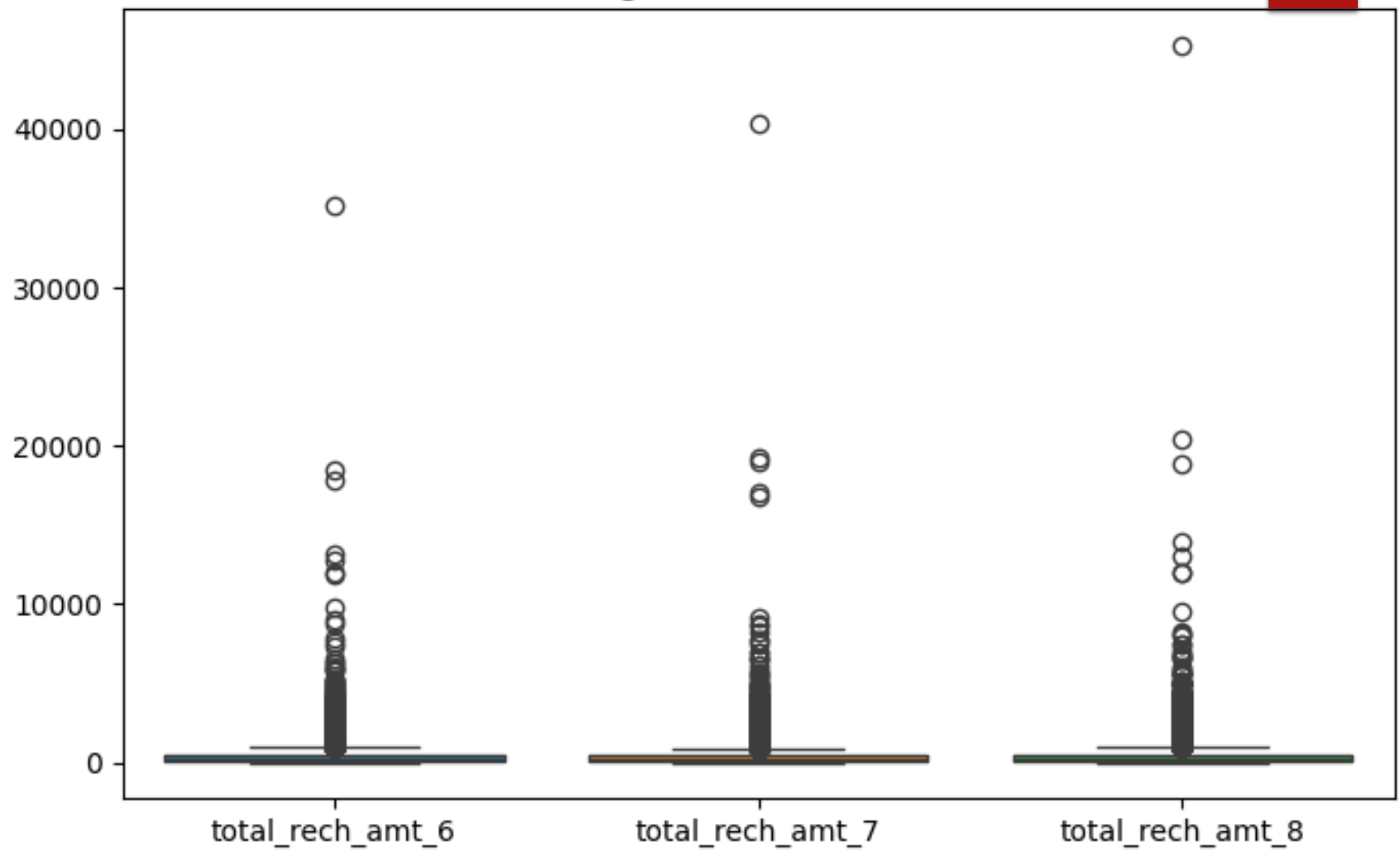
New Features :

Recharge Drop

Call Drop

Data usage Drop

Recharge Amount Distribution



# Modeling Process



## Models Used:

1. Logistic Regression
2. Random Forest
3. XGBoost



**Train-Test Split: 80-20**



**Handling Imbalance:  
Applied SMOTE to balance  
the data.**

## Evaluating Logistic Regression Model

Model Performance:

	precision	recall	f1-score	support
0	0.97	0.90	0.94	5484
1	0.41	0.73	0.52	519
accuracy			0.89	6003
macro avg	0.69	0.81	0.73	6003
weighted avg	0.92	0.89	0.90	6003

ROC-AUC Score: 0.8895785813766866

Confusion Matrix:

```
[[4940  544]
 [ 141  378]]
```



## Evaluating Random Forest Model

Model Performance:

	precision	recall	f1-score	support
0	0.97	0.97	0.97	5484
1	0.63	0.63	0.63	519
accuracy			0.94	6003
macro avg	0.80	0.80	0.80	6003
weighted avg	0.94	0.94	0.94	6003

ROC-AUC Score: 0.9322082878340072

Confusion Matrix:

```
[[5293  191]
 [ 190  329]]
```

## Evaluating Random Forest Model

Model Performance:

	precision	recall	f1-score	support
0	0.97	0.97	0.97	5484
1	0.63	0.63	0.63	519
accuracy			0.94	6003
macro avg	0.80	0.80	0.80	6003
weighted avg	0.94	0.94	0.94	6003

ROC-AUC Score: 0.9322082878340072

Confusion Matrix:

```
[[5293  191]
 [ 190  329]]
```

# Model Evaluation

- ▶ Metrics Evaluated:
  - ▶ 1. Accuracy
  - ▶ 2. Precision
  - ▶ 3. Recall
  - ▶ 4. F1-Score
- ▶ Random Forest Model performed the best with the highest ROC-AUC score.



Best Parameters for Random Forest: {'max\_depth': 30, 'min\_samples\_split': 2, 'n\_estimators': 200}

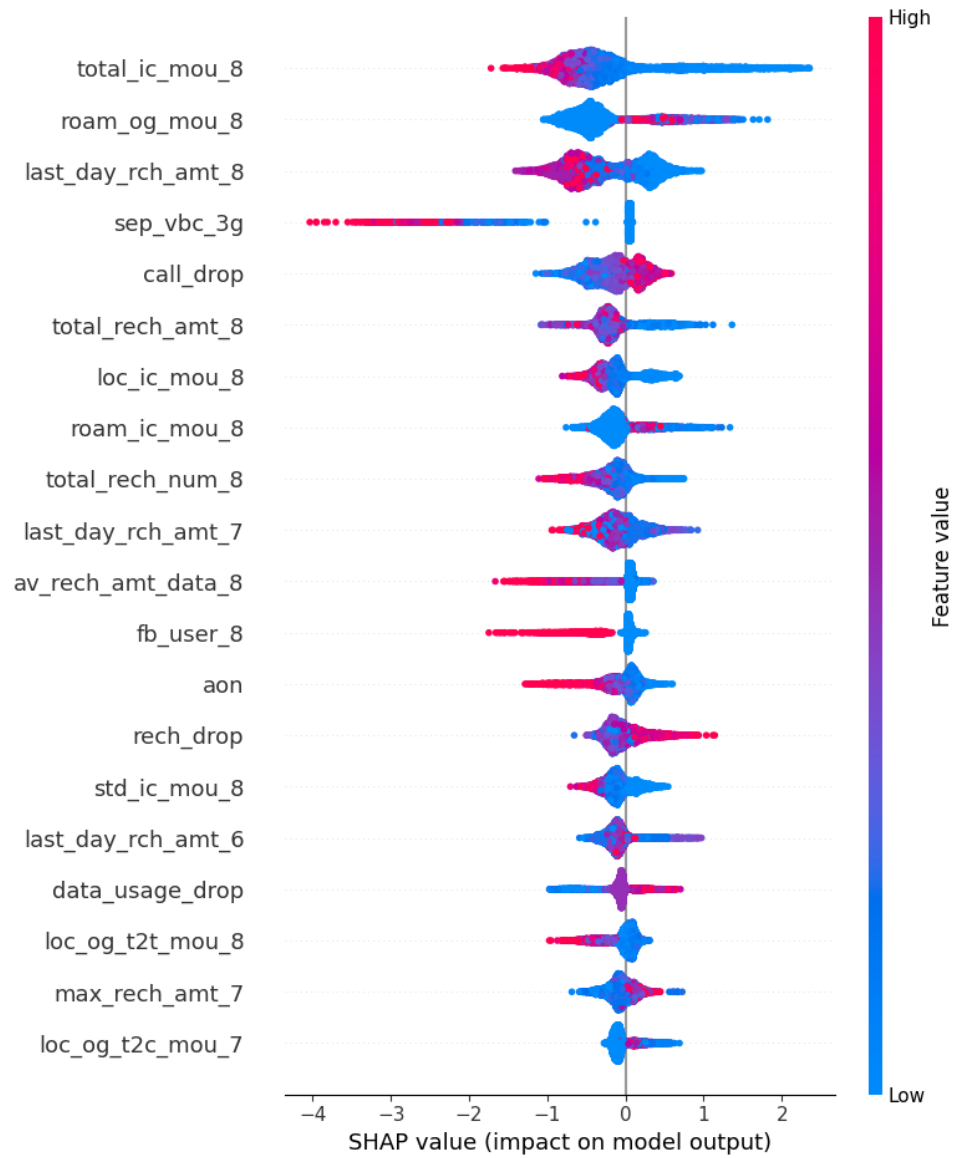
Final Model Performance:

	precision	recall	f1-score	support
0	0.97	0.96	0.96	5484
1	0.62	0.63	0.63	519
accuracy			0.94	6003
macro avg	0.79	0.80	0.80	6003
weighted avg	0.94	0.94	0.94	6003

ROC-AUC Score: 0.9327339016708617

Confusion Matrix:

```
[[5285  199]
 [ 191  328]]
```



# Feature Importance & Recommendations



## Key Features Impacting Churn:

1. Recharge Drop
2. Data Usage Drop
3. AON (Age on Network)



## Business Recommendations:

1. Focus on high-value customers with declining data and recharge usage.
2. Implement targeted retention campaigns.



# Conclusion

## ► Conclusion:

The model successfully predicts customer churn with key indicators such as recharge drop and data usage decline. Implementing retention strategies based on these insights can reduce churn.

