Customer Churn Prediction - Model Evaluation Report

1. Objective

The objective of this model is to predict **customer churn** using historical transaction data. utilized **XGBoost** to build a machine learning model to classify whether a customer will churn (1) or not (0) based on historical behavior.

2. Data Preprocessing

The data was sourced from multiple tables related to customer orders, payments, and reviews. We applied the following preprocessing steps:

- **Merged tables**: Cleaned data from `orders`, `customers`, `order_items`, `payments`, and `reviews` into a single dataset.
- **Missing values**: Handled missing data via imputation and removal of rows with critical missing values.
- **Feature Engineering**: Created customer-level features including `customer_lifetime_orders`, `customer_avg_order_value`, `days_since_last_order`, and `is_high_spender`.
- **Feature Scaling**: Scaled the numerical features using `StandardScaler`.

3. Model Selection

- **Model Used**: **XGBoost Classifier**
- **Hyperparameters**:
    - `n_estimators = 500`
    - `max_depth = 4`

- `learning_rate = 0.05`
- `subsample = 0.8`
- `colsample_bytree = 0.8`
- Regularization parameters: `reg_lambda = 0.1`, `reg_alpha = 0.1`

We applied **early stopping** during training to avoid overfitting. The model was trained on a training dataset and evaluated on a test dataset.

Model Performance Summary

- **Accuracy:** 55.85%
- **AUC-ROC Score:** 58.64%

The model's performance is detailed below:

Class	Precision	Recall	F1-Score	Support
0	0.55	0.66	0.60	6,867
1	0.57	0.45	0.51	6,749

Overall Accuracy: 56%

- **Macro Average:**
  - Precision: 56%
  - Recall: 56%

    - F1-Score: 55%

- **Weighted Average:**
    - Precision: 56%
    - Recall: 56%
    - F1-Score: 55%

- **Model Strengths**: High precision for predicting non-churned customers and relatively good recall for churned customers.
- **Model Weaknesses**: Recall for churned customers could be improved by adjusting thresholds or using class weighting.