Topic Name: Enhancing Customer Retention in E-Commerce Through Predictive Analytics

Team Number: 10

Team Members:

1. **Mehar Sukthi Buruguru**
2. **Shyamalan Kannan**
3. **Nandan Varma Pericharla**
4. **Rupeshwar Rao**

Project Overview

The goal of this project is to explore how **Predictive Analytics** can be leveraged to **enhance customer retention** in the **e-commerce industry**. We will examine various strategies and technologies that can help businesses better understand customer behavior, predict future actions, and tailor retention strategies accordingly.

Objectives

- Understand the importance of customer retention in e-commerce.
- Identify key predictive analytics techniques and tools.
- Investigate the application of predictive models to forecast customer behavior.

Expected Outcomes

- Improved understanding of customer retention challenges.
- Practical insights for e-commerce companies to enhance customer loyalty.
- Development of a predictive model that can be used to predict churn and recommend retention strategies.

```
# install the required packages
%pip install -r requirements.txt

Requirement already satisfied: pandas in c:\users\raoru\anaconda3\lib\
site-packages (from -r requirements.txt (line 1)) (2.2.2)
Requirement already satisfied: numpy in c:\users\raoru\anaconda3\lib\
site-packages (from -r requirements.txt (line 2)) (1.26.4)
Requirement already satisfied: matplotlib in c:\users\raoru\anaconda3\
lib\site-packages (from -r requirements.txt (line 3)) (3.9.2)
Requirement already satisfied: seaborn in c:\users\raoru\anaconda3\
lib\site-packages (from -r requirements.txt (line 4)) (0.13.2)
Requirement already satisfied: scipy in c:\users\raoru\anaconda3\lib\
site-packages (from -r requirements.txt (line 5)) (1.13.1)
Requirement already satisfied: scikit-learn in c:\users\raoru\
anaconda3\lib\site-packages (from -r requirements.txt (line 6))
```

```
(1.5.1)
Requirement already satisfied: python-dateutil>=2.8.2 in c:\users\
raoru\anaconda3\lib\site-packages (from pandas->-r requirements.txt
(line 1)) (2.9.0.post0)
Requirement already satisfied: pytz>=2020.1 in c:\users\raoru\
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1)) (2024.1)
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(line 3)) (1.2.0)
Requirement already satisfied: cycler>=0.10 in c:\users\raoru\
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(line 3)) (0.11.0)
Requirement already satisfied: fonttools>=4.22.0 in c:\users\raoru\
anaconda3\lib\site-packages (from matplotlib->-r requirements.txt
(line 3)) (4.51.0)
Requirement already satisfied: kiwisolver>=1.3.1 in c:\users\raoru\
anaconda3\lib\site-packages (from matplotlib->-r requirements.txt
(line 3)) (1.4.4)
Requirement already satisfied: packaging>=20.0 in c:\users\raoru\
anaconda3\lib\site-packages (from matplotlib->-r requirements.txt
(line 3)) (24.1)
Requirement already satisfied: pillow>=8 in c:\users\raoru\anaconda3\
lib\site-packages (from matplotlib->-r requirements.txt (line 3))
(10.4.0)
Requirement already satisfied: pyparsing>=2.3.1 in c:\users\raoru\
anaconda3\lib\site-packages (from matplotlib->-r requirements.txt
(line 3)) (3.1.2)
Requirement already satisfied: joblib>=1.2.0 in c:\users\raoru\
anaconda3\lib\site-packages (from scikit-learn->-r requirements.txt
(line 6)) (1.4.2)
Requirement already satisfied: threadpoolctl>=3.1.0 in c:\users\raoru\
anaconda3\lib\site-packages (from scikit-learn->-r requirements.txt
(line 6)) (3.5.0)
Requirement already satisfied: six>=1.5 in c:\users\raoru\anaconda3\
lib\site-packages (from python-dateutil>=2.8.2->pandas->-r
requirements.txt (line 1)) (1.16.0)
Note: you may need to restart the kernel to use updated packages.
```

```python
# 1. Import the required packages
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from scipy.stats import pearsonr
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
```

```python
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import r2_score
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score, roc_auc_score

# 2. Load dataset
file_path = "dataset.csv"
df = pd.read_csv(file_path)

# 3. Drop 'CustomerID' as it is not predictive
if "CustomerID" in df.columns:
    df = df.drop(columns=["CustomerID"])

# 4. Convert specified columns to numeric, setting invalid parsing to
NaN
numeric_columns = [
    "Tenure",
    "WarehouseToHome",
    "HourSpendOnApp",
    "OrderAmountHikeFromlastYear",
    "OrderCount",
    "DaySinceLastOrder",
    "CashbackAmount",
    "CouponUsed",
    "NumberOfDeviceRegistered",
    "NumberOfAddress",
    "SatisfactionScore",
    "Complain",
    "CityTier"
]

for col in numeric_columns:
    if col in df.columns:
        df[col] = pd.to_numeric(df[col], errors='coerce')

# 5. Replace zeros with NaN in selected columns
cols_to_replace_zeros = ["CashbackAmount", "CouponUsed"]
for col in cols_to_replace_zeros:
    if col in df.columns:
        df[col] = df[col].replace(0, np.nan)

# 6. Identify numeric and categorical columns
numeric_cols = df.select_dtypes(include=['number']).columns.tolist()
categorical_cols =
df.select_dtypes(exclude=['number']).columns.tolist()

# 7. Fill missing values
df[numeric_cols] = df[numeric_cols].fillna(df[numeric_cols].median())
for col in categorical_cols:
    df[col] = df[col].fillna(df[col].mode()[0])
```

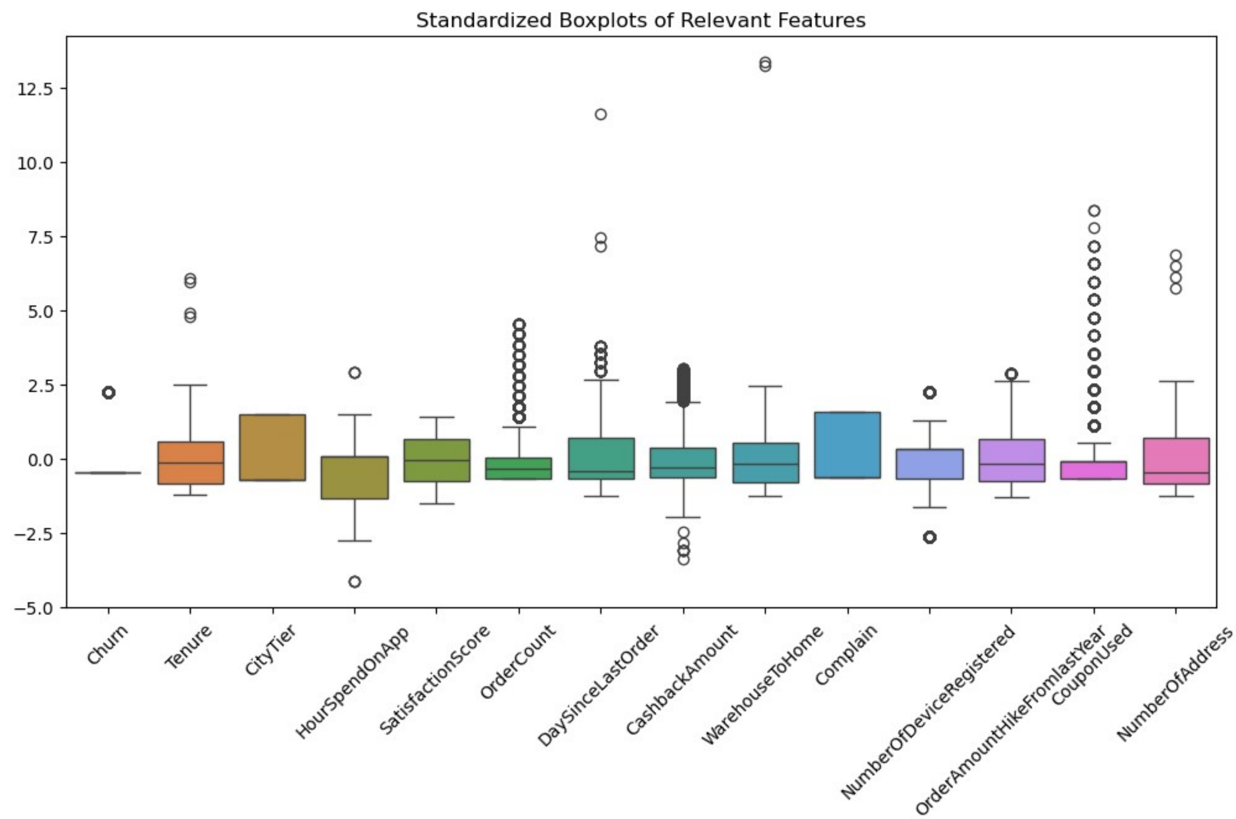
```python
# 8. Drop columns with zero variance (all values the same)
zero_variance_cols = [col for col in numeric_cols if df[col].nunique()
== 1]
df.drop(columns=zero_variance_cols, inplace=True)
print("Dropped zero-variance columns:", zero_variance_cols)
```

```
Dropped zero-variance columns: []
```

```python
# 9. (a) Calculate mean, median, and standard deviation
numeric_cols = df.select_dtypes(include=['number'])
stats = numeric_cols.describe().T
stats["median"] = numeric_cols.median()
print("\nSummary Statistics:")
print(stats)
```

```

Summary Statistics:
                              count        mean        std   min
25%  \
Churn                        5630.0    0.168384   0.374240   0.0
0.0
Tenure                       5630.0   10.134103   8.357951   0.0
3.0
CityTier                     5630.0    1.654707   0.915389   1.0
1.0
WarehouseToHome              5630.0   15.566785   8.345961   5.0
9.0
HourSpendOnApp               5630.0    2.934636   0.705528   0.0
2.0
NumberOfDeviceRegistered     5630.0    3.688988   1.023999   1.0
3.0
SatisfactionScore            5630.0    3.066785   1.380194   1.0
2.0
NumberOfAddress              5630.0    4.214032   2.583586   1.0
2.0
Complain                     5630.0    0.284902   0.451408   0.0
0.0
OrderAmountHikeFromlastYear  5630.0   15.674600   3.591058  11.0
13.0
CouponUsed                   5630.0    2.128242   1.654433   1.0
1.0
OrderCount                   5630.0    2.961812   2.879248   1.0
1.0
DaySinceLastOrder            5630.0    4.459325   3.570626   0.0
2.0
CashbackAmount               5630.0  177.337300  48.967834  12.0
146.0

                              50%    75%    max  median
Churn                         0.0    0.0    1.0     0.0
```

```
Tenure                              9.0    15.0    61.0      9.0
CityTier                            1.0     3.0     3.0      1.0
WarehouseToHome                    14.0    20.0   127.0     14.0
HourSpendOnApp                      3.0     3.0     5.0      3.0
NumberOfDeviceRegistered            4.0     4.0     6.0      4.0
SatisfactionScore                   3.0     4.0     5.0      3.0
NumberOfAddress                     3.0     6.0    22.0      3.0
Complain                            0.0     1.0     1.0      0.0
OrderAmountHikeFromlastYear        15.0    18.0    26.0     15.0
CouponUsed                          2.0     2.0    16.0      2.0
OrderCount                          2.0     3.0    16.0      2.0
DaySinceLastOrder                   3.0     7.0    46.0      3.0
CashbackAmount                    163.0   196.0   325.0    163.0

# 10. Select relevant features for further analysis
selected_features = [
    "Churn", "Tenure", "CityTier", "HourSpendOnApp",
    "SatisfactionScore", "OrderCount", "DaySinceLastOrder",
    "CashbackAmount", "WarehouseToHome", "Complain",
    "NumberOfDeviceRegistered", "OrderAmountHikeFromlastYear",
    "CouponUsed", "NumberOfAddress"
]

selected_features = [col for col in selected_features if col in
df.columns]
df_filtered = df[selected_features]

# 11. Standardize the selected features
scaler = StandardScaler()
df_scaled = pd.DataFrame(scaler.fit_transform(df_filtered),
columns=selected_features)

# 12. (b) Plot the boxplots for standardized features
plt.figure(figsize=(12, 6))
sns.boxplot(data=df_scaled)
plt.xticks(rotation=45)
plt.title("Standardized Boxplots of Relevant Features")
plt.show()
```




```
# 13. (c) Draw pairplots for the standardized features
sns.pairplot(df_scaled)
plt.show()
```

Findings: Columns for Regression, Classification, and Clustering

Regression: We can predict the following column values using regression:

Column	Description
WarehouseToHome	Distance (e.g., kilometers/miles)
HourSpendOnApp	Time spent (e.g., hours)
OrderAmountHikeFromlastYear	Percentage increase (e.g., 15.5%)
CashbackAmount	Monetary value (e.g., $25.30)
Tenure	Duration (e.g., 6.5 months)
DaySinceLastOrder	Continuous measure (e.g., 30.5 days)

Classification: We can perform classification on the below columns:

Column	Description
Churn (target variable)	Predict if a user churns or not
PreferredLoginDevice	Preferred login device of customer
PreferredPaymentMode	Preferred payment method of customer
PreferedOrderCat	Preferred order category of customer in last month
MaritalStatus	Marital status of customer
SatisfactionScore	Satisfactory score of customer on service
NumberOfDeviceRegistered	Number of devices (e.g., 2 devices)
NumberOfAddress	Number of addresses (e.g., 3 addresses)
CouponUsed	Number of coupons used (e.g., 5 coupons)
OrderCount	Number of orders (e.g., 10 orders)
Complain	0 (No) / 1 (Yes)

Clustering: Group using features: All continuous + encoded categorical/discrete columns

Group customers based on Tenure, CityTier, and CashbackAmount.

Key Learnings and Difficulties

What Did We Learn from These Steps?

This assignment emphasized the importance of thorough data cleaning and understanding data distributions.

- Handling missing values required careful consideration of appropriate imputation methods.
- Visualizations revealed challenges in interpreting boxplots with limited data points.
- Difficulties included determining appropriate features for zero replacement and managing overlapping visualizations.
- The exercise highlighted that EDA is a repetitive process and showed how important it is to understand the subject area when cleaning and preparing data.

The columns showing the highest correlation with the target variable (Churn) are:

- Tenure
- OrderCount
- HourSpendOnApp

These columns can be used to build predictive models for customer churn. High correlation indicates that changes in these features are strongly associated with changes in the target variable. For instance, Tenure can help identify long-term customers who are less likely to churn, while Orderount and HourSpendOnApp can provide insights into customer engagement and purchasing behavior.

End of Project_Part_2

Beginning of Project_Part_3

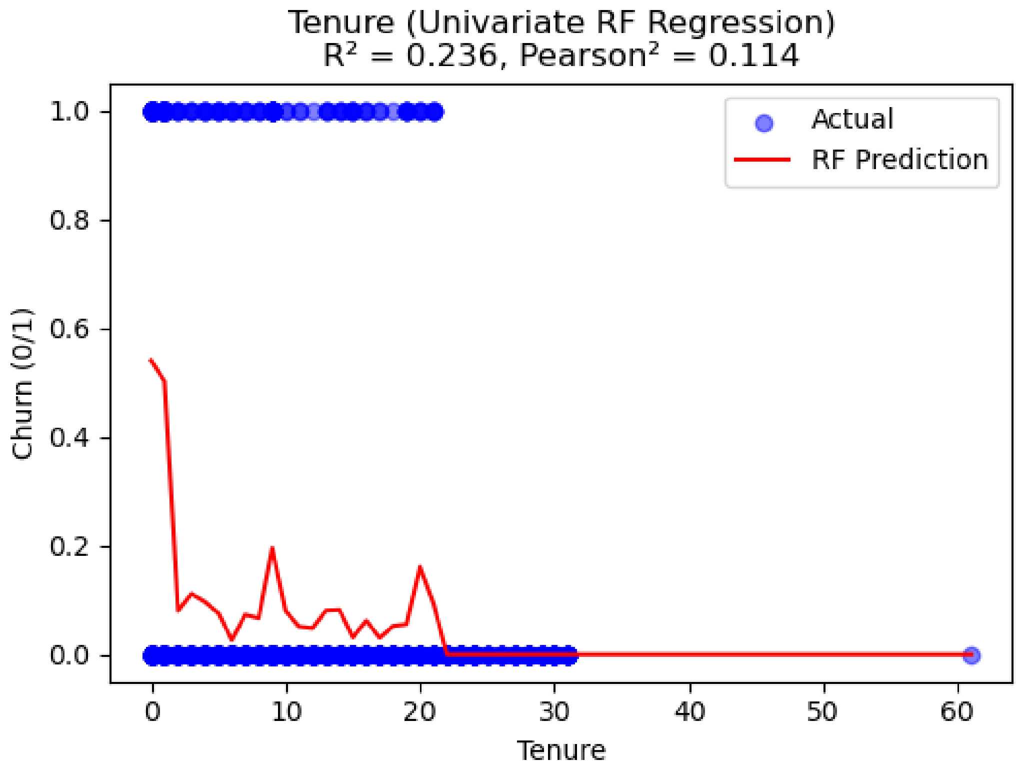
```
#Calculate Pearson's correlation with 'Churn'
correlations = {}
for col in df.select_dtypes(include=['number']).columns:
    if col != "Churn":
        corr, _ = pearsonr(df[col], df["Churn"])
        correlations[col] = corr
        print(f"Pearson correlation between {col} and Churn:
{corr:.3f}")
```

```
Pearson correlation between Tenure and Churn: -0.338
Pearson correlation between CityTier and Churn: 0.085
Pearson correlation between WarehouseToHome and Churn: 0.070
Pearson correlation between HourSpendOnApp and Churn: 0.019
Pearson correlation between NumberOfDeviceRegistered and Churn: 0.108
Pearson correlation between SatisfactionScore and Churn: 0.105
Pearson correlation between NumberOfAddress and Churn: 0.044
Pearson correlation between Complain and Churn: 0.250
Pearson correlation between OrderAmountHikeFromlastYear and Churn: -
0.007
Pearson correlation between CouponUsed and Churn: -0.004
Pearson correlation between OrderCount and Churn: -0.024
Pearson correlation between DaySinceLastOrder and Churn: -0.156
Pearson correlation between CashbackAmount and Churn: -0.156
```

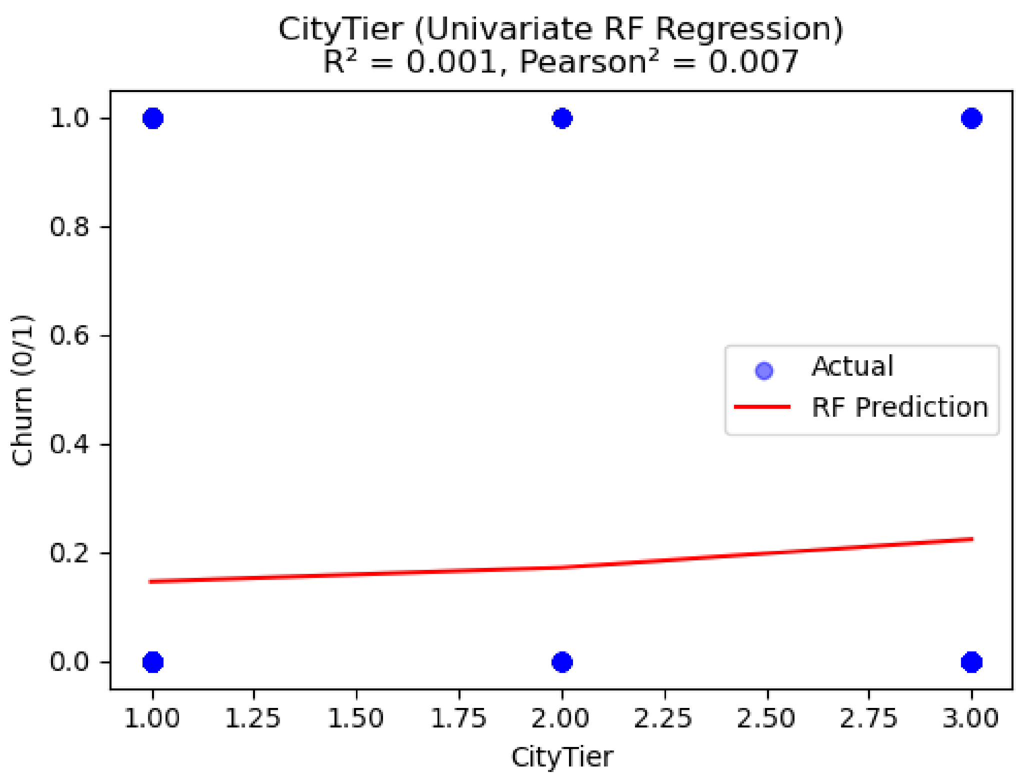
```
# List of numeric features excluding the target variable 'Churn'
numeric_features = [col for col in
df_filtered.select_dtypes(include=['number']).columns if col !=
"Churn"]

print("----- Univariate Random Forest Regression -----")

# Loop through each numeric feature to perform univariate regression
for col in numeric_features:
        # Define the feature (X) and target (y)
        X = df_filtered[[col]]
        y = df_filtered["Churn"]

        # Split the data into training and testing sets
        X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.3, random_state=42)

        # Initialize and fit the RandomForestRegressor model
        rf_reg = RandomForestRegressor(n_estimators=100,
random_state=42)
        rf_reg.fit(X_train, y_train)

        # Predict the target variable for the test set
```

```
        y_pred = rf_reg.predict(X_test)
        r2 = r2_score(y_test, y_pred)  # Calculate the R² score

        # Calculate Pearson correlation and its square
        r, _ = pearsonr(df_filtered[col], df_filtered["Churn"])
        pearson_sq = r ** 2

        # Print the R² and Pearson² scores
        print(f"{col}: Test R² = {r2:.3f}, Pearson² =
{pearson_sq:.3f}")

        # Plot the actual vs predicted values
        plt.figure(figsize=(6, 4))
        plt.scatter(X_test, y_test, color='blue', alpha=0.5,
label="Actual")

        # Sort the indices for plotting the prediction line
        sorted_idx = np.argsort(X_test[col].values.flatten())
        plt.plot(X_test[col].values.flatten()[sorted_idx],
                 y_pred[sorted_idx],
                 color="red",
                 label="RF Prediction")

        # Set plot labels and title
        plt.xlabel(col)
        plt.ylabel("Churn (0/1)")
        plt.title(f"{col} (Univariate RF Regression)\nR² = {r2:.3f},
Pearson² = {pearson_sq:.3f}")
        plt.legend()
        plt.show()
```

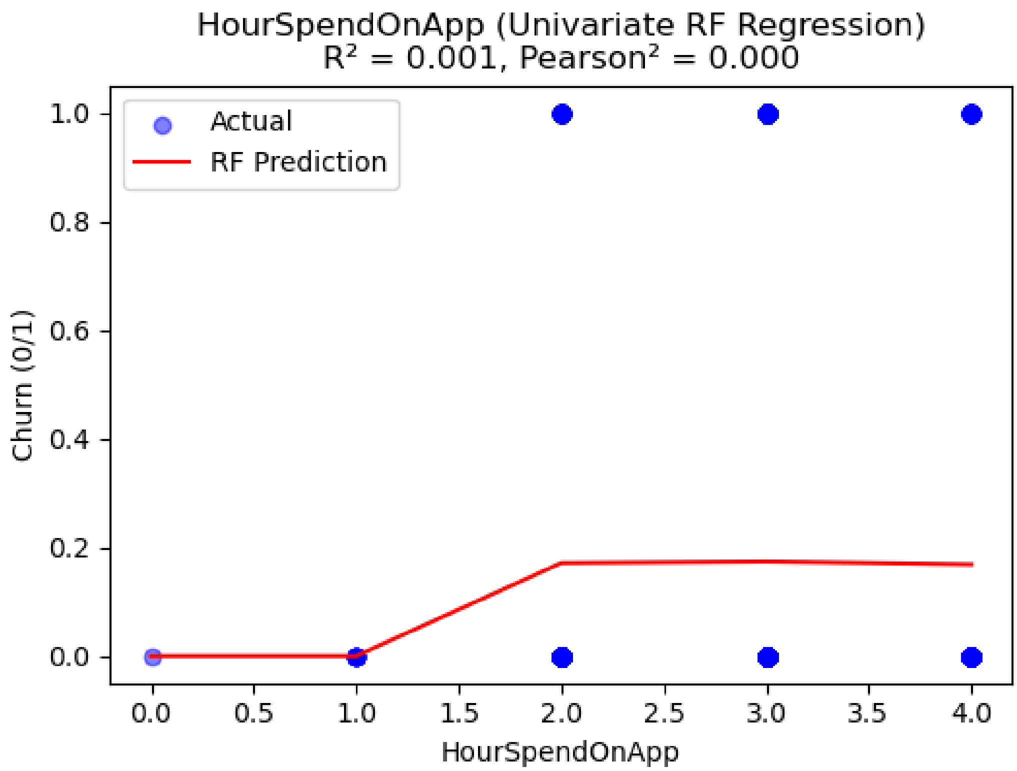
```
----- Univariate Random Forest Regression -----
Tenure: Test R² = 0.236, Pearson² = 0.114
```



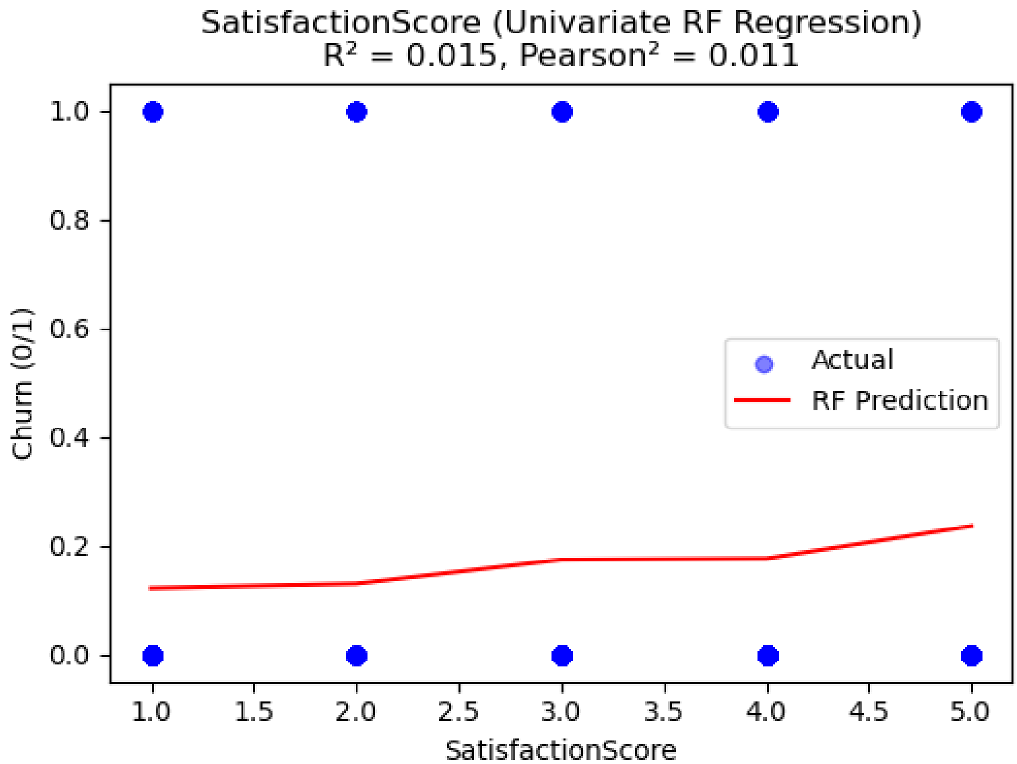

```
CityTier: Test R² = 0.001, Pearson² = 0.007
```



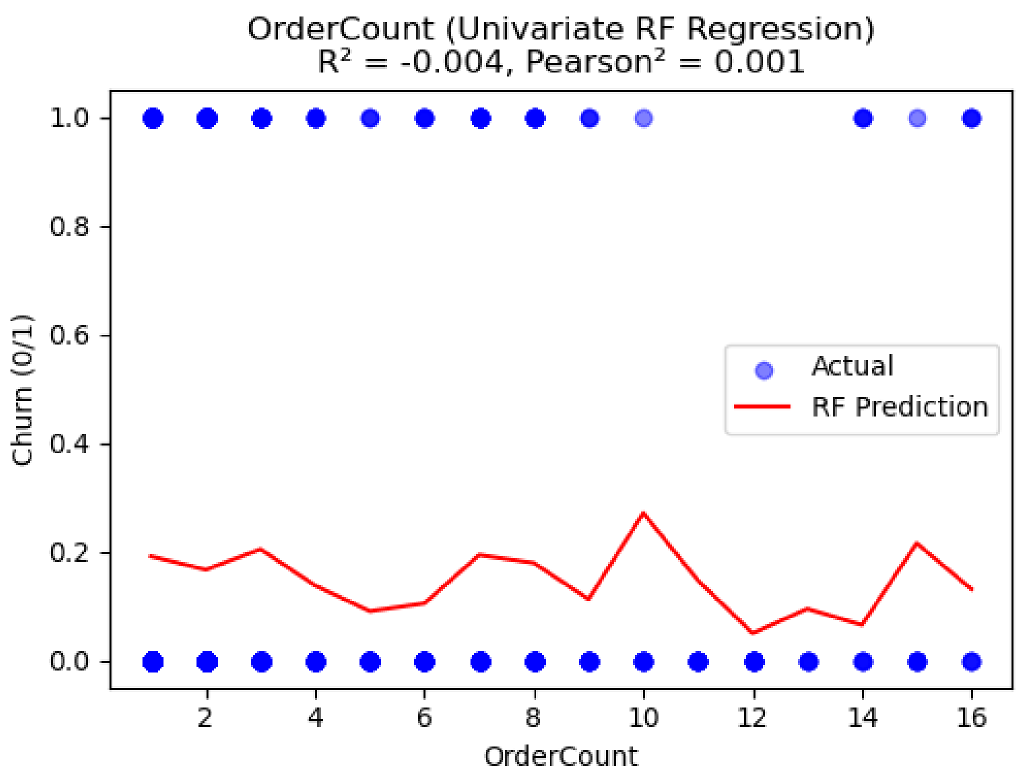
```
HourSpendOnApp: Test R² = 0.001, Pearson² = 0.000
```



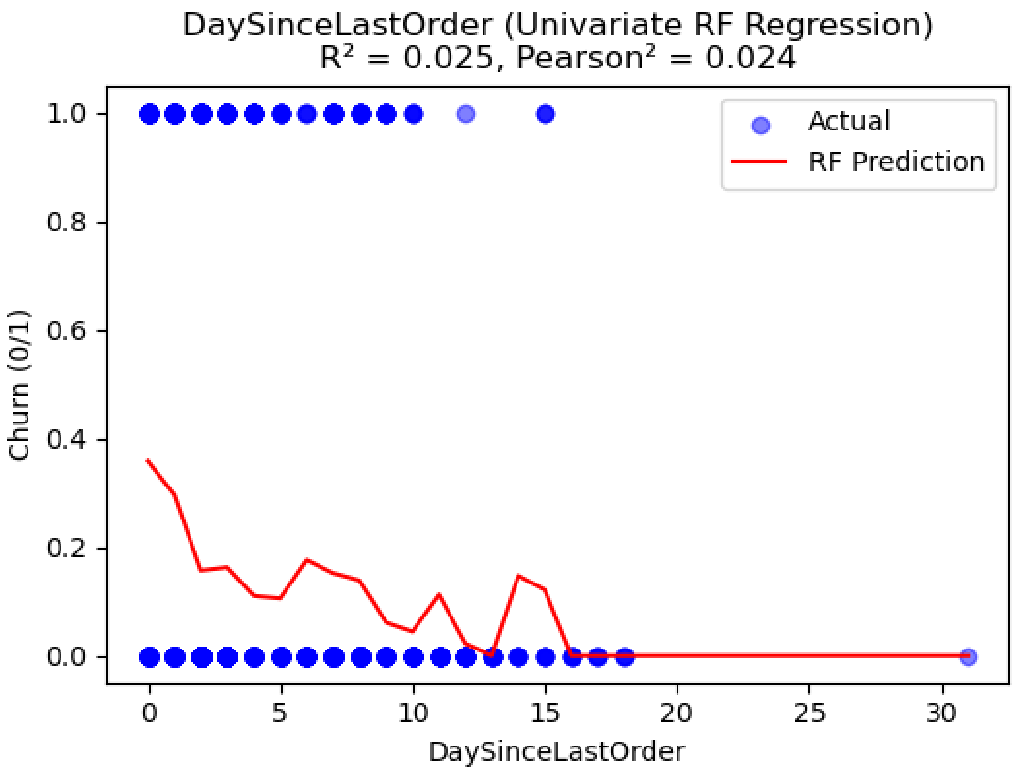

```
SatisfactionScore: Test R² = 0.015, Pearson² = 0.011
```



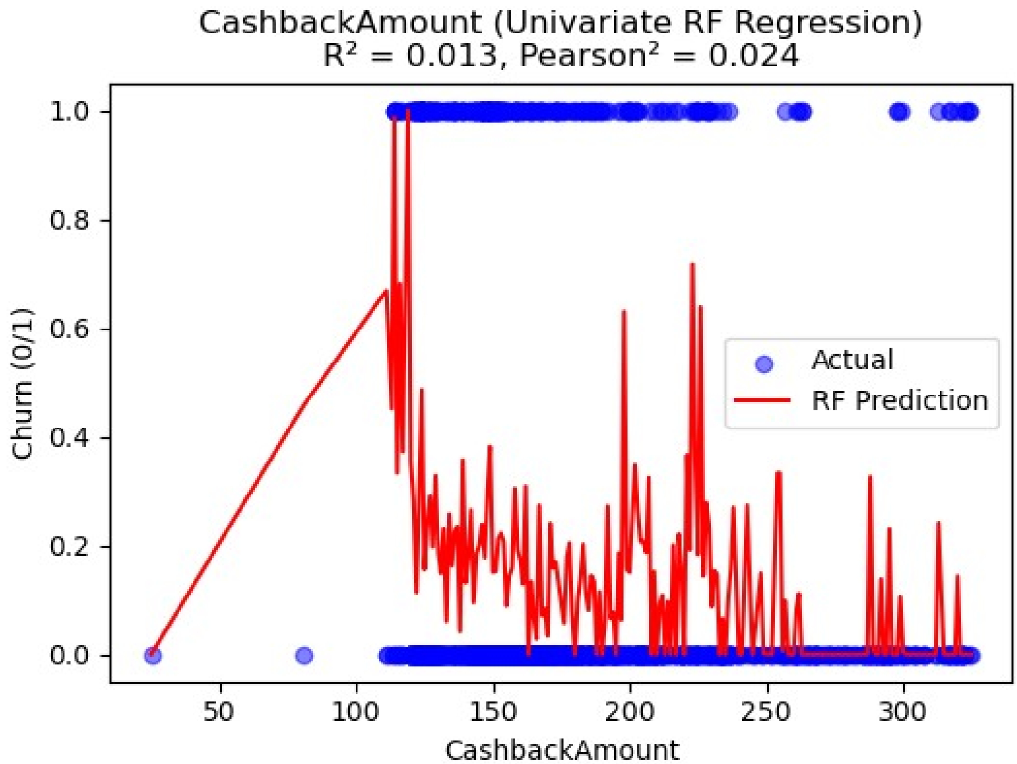

```
OrderCount: Test R² = -0.004, Pearson² = 0.001
```



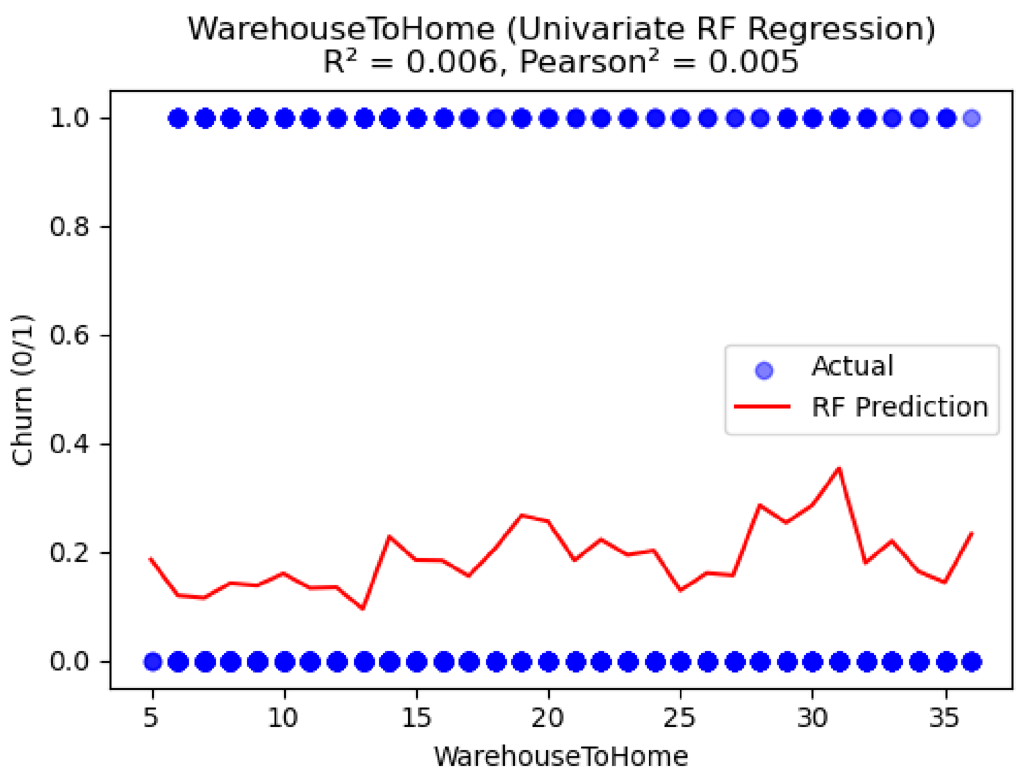
```
DaySinceLastOrder: Test R² = 0.025, Pearson² = 0.024
```



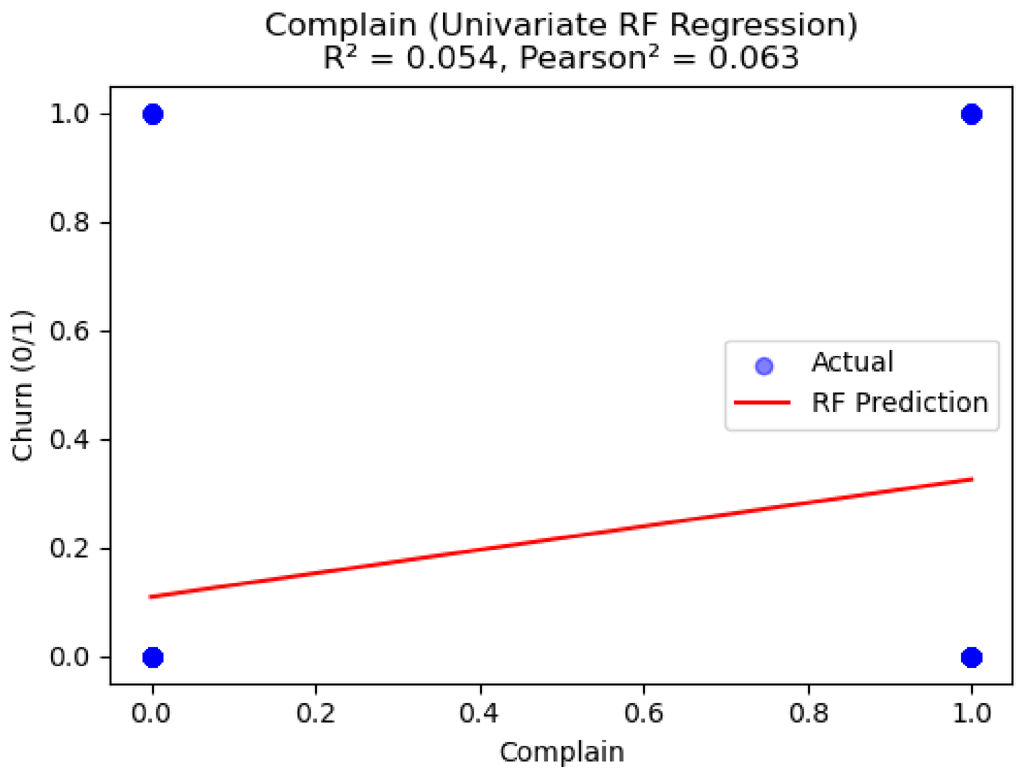

```
CashbackAmount: Test R² = 0.013, Pearson² = 0.024
```



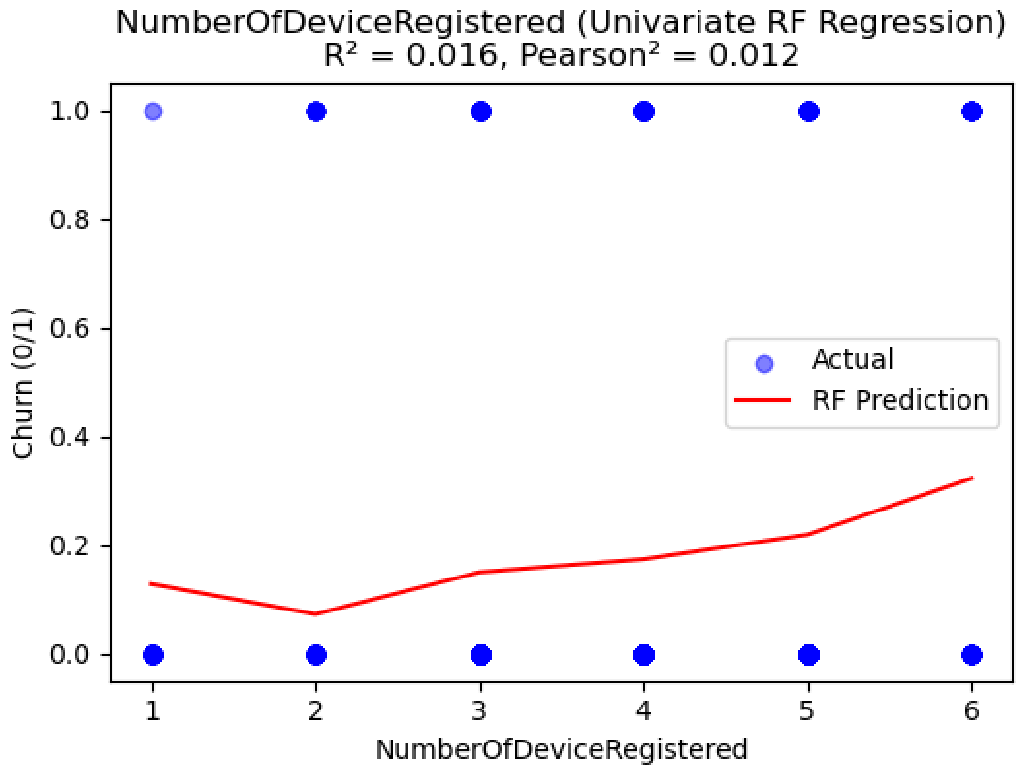

```
WarehouseToHome: Test R² = 0.006, Pearson² = 0.005
```



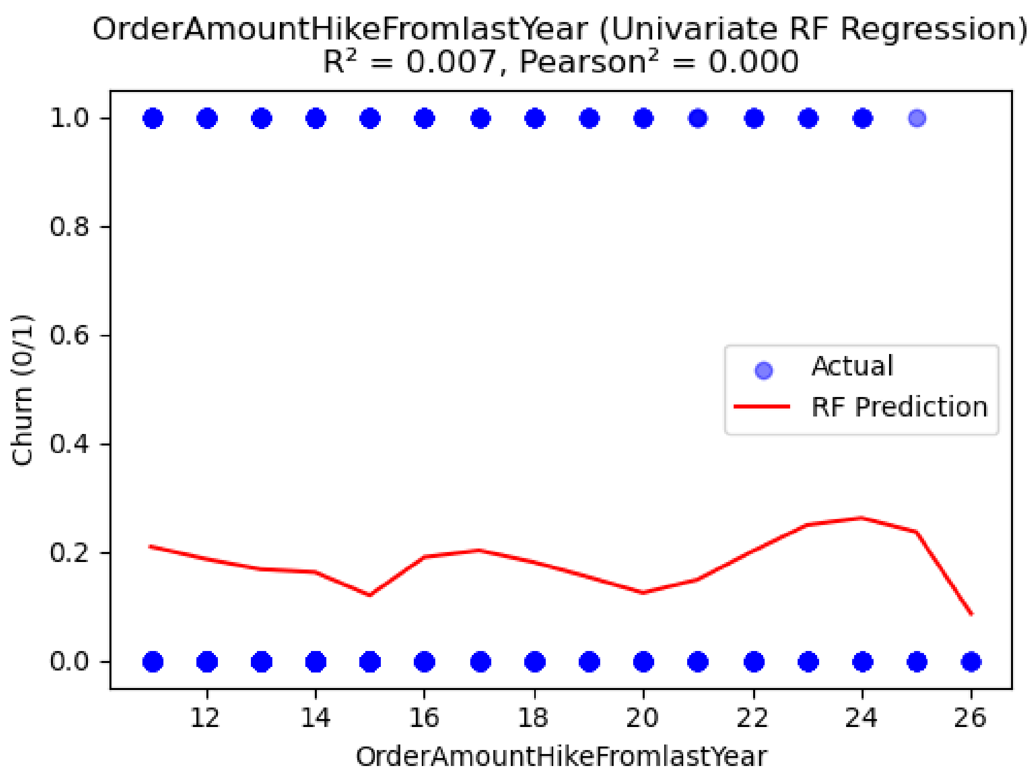
```
Complain: Test R² = 0.054, Pearson² = 0.063
```



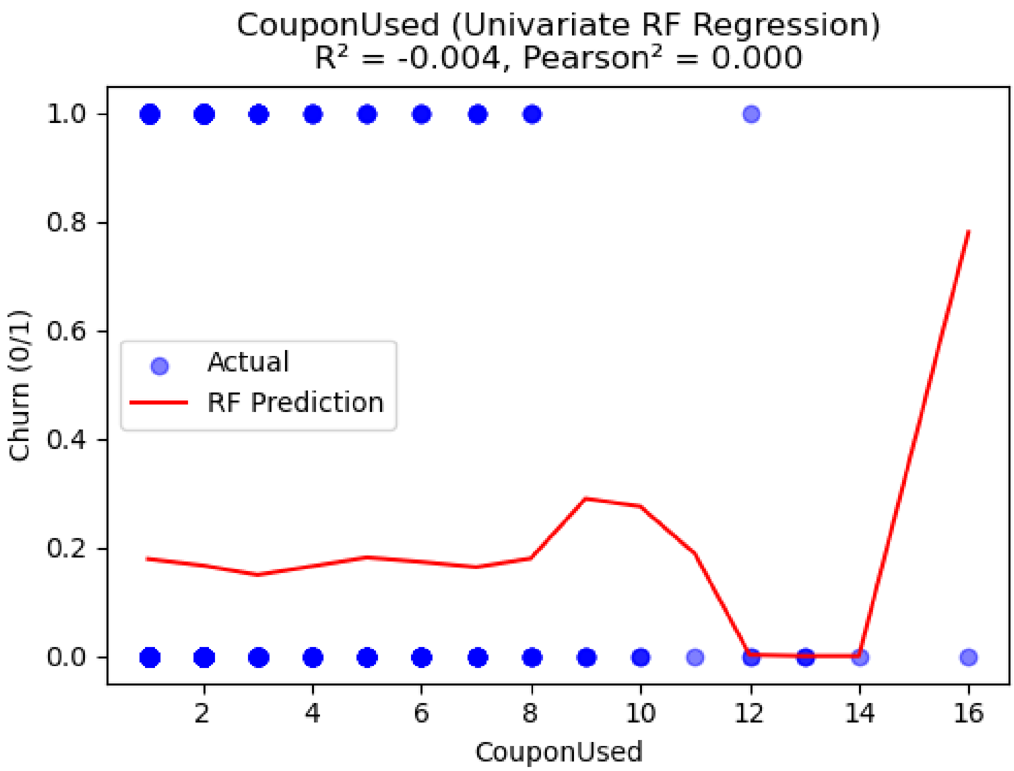

```
NumberOfDeviceRegistered: Test R² = 0.016, Pearson² = 0.012
```



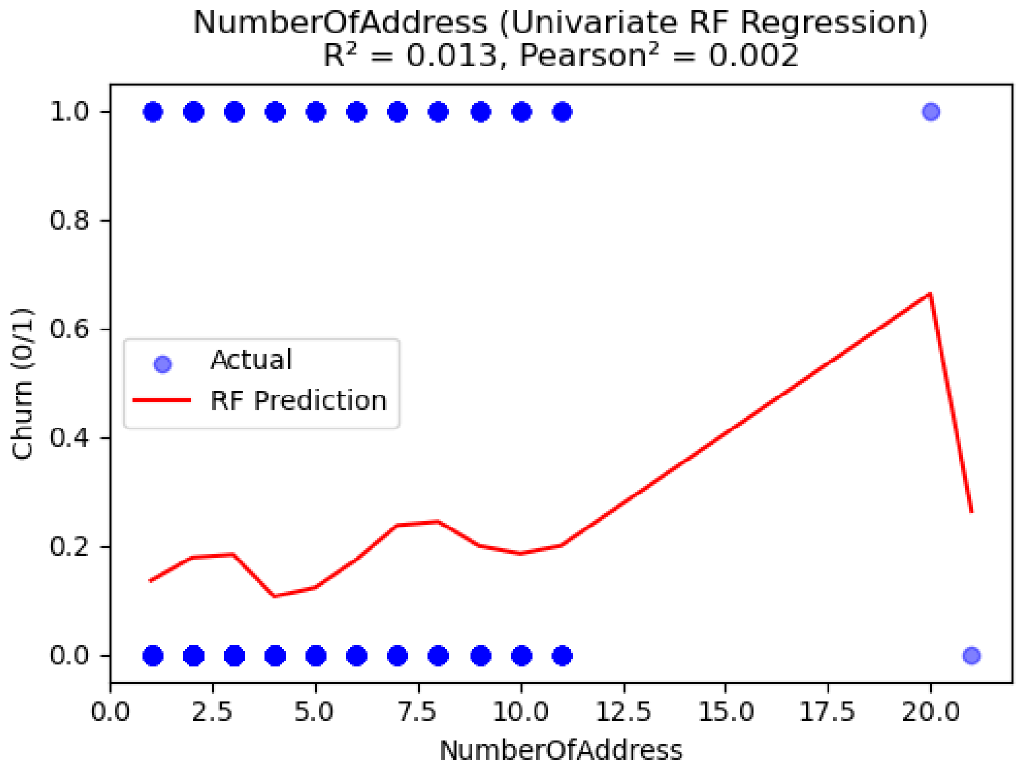

```
OrderAmountHikeFromlastYear: Test R² = 0.007, Pearson² = 0.000
```



```
CouponUsed: Test R² = -0.004, Pearson² = 0.000
```

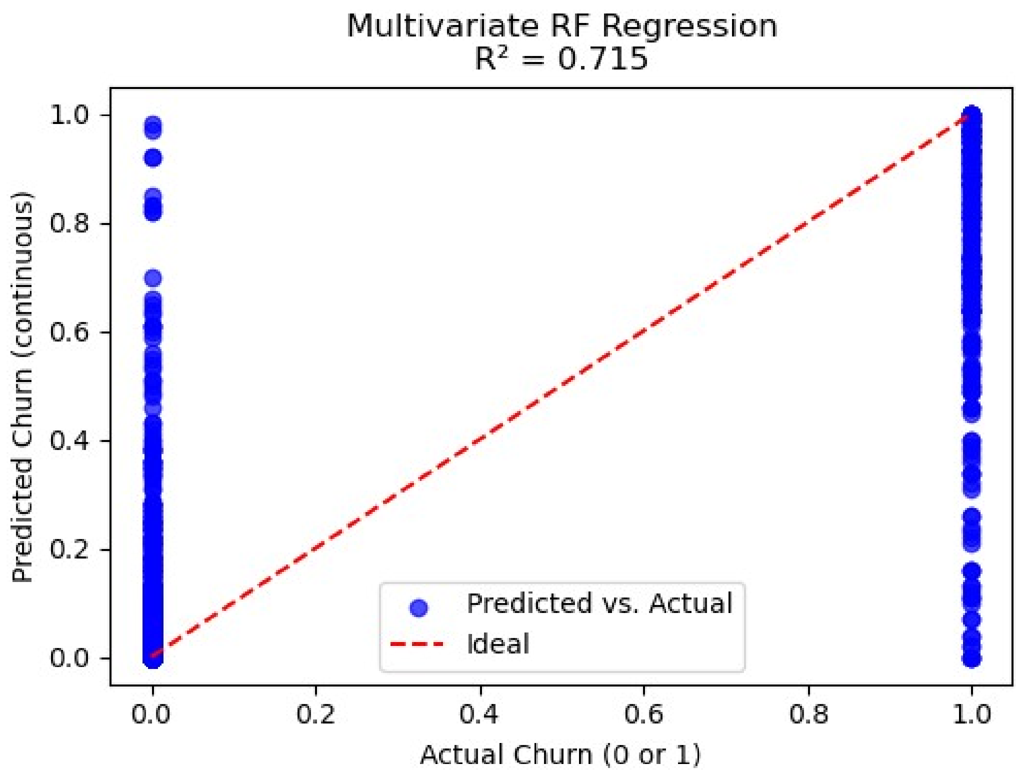



```
NumberOfAddress: Test R² = 0.013, Pearson² = 0.002
```




```
# Define multivariate predictors excluding the target variable 'Churn'
multivariate_predictors = [col for col in df_filtered.columns if col !
= "Churn"]

# Split the data into features (X) and target (y)
X_multi = df_filtered[multivariate_predictors]
y_multi = df_filtered["Churn"]

# Split the data into training and testing sets
X_train_m, X_test_m, y_train_m, y_test_m = train_test_split(X_multi,
y_multi, test_size=0.3, random_state=42)

# Initialize and fit the RandomForestRegressor model
rf_reg_multi = RandomForestRegressor(n_estimators=100,
random_state=42)
rf_reg_multi.fit(X_train_m, y_train_m)

# Predict the target variable for the test set
y_pred_m = rf_reg_multi.predict(X_test_m)

# Calculate the R² score for the model
r2_multi = r2_score(y_test_m, y_pred_m)
print(f"\nMultivariate RF Regression: Test R² = {r2_multi:.3f}")

# Plot the predicted vs actual values
plt.figure(figsize=(6,4))
```

```
plt.scatter(y_test_m, y_pred_m, alpha=0.7, color='blue',
label="Predicted vs. Actual")
plt.xlabel("Actual Churn (0 or 1)")
plt.ylabel("Predicted Churn (continuous)")
plt.title(f"Multivariate RF Regression\nR² = {r2_multi:.3f}")

# Plot the ideal line for reference
plt.plot([0,1], [0,1], color='red', linestyle='--', label="Ideal")
plt.legend()
plt.show()


Multivariate RF Regression: Test R² = 0.715
```




```
# Define features and target variable for classification
X_clf = df_filtered[multivariate_predictors]
y_clf = df_filtered["Churn"]

# Split the data into training and testing sets
X_train_c, X_test_c, y_train_c, y_test_c = train_test_split(X_clf,
y_clf, test_size=0.3, random_state=42)

# Initialize the RandomForestClassifier
rf_clf = RandomForestClassifier(n_estimators=100, random_state=42)
```

```
# Fit the model on the training data
rf_clf.fit(X_train_c, y_train_c)

# Predict the labels for the test data
y_pred_c = rf_clf.predict(X_test_c)

# Predict the probabilities for the test data
y_pred_prob_c = rf_clf.predict_proba(X_test_c)[:, 1]

# Calculate accuracy and ROC AUC score
accuracy = accuracy_score(y_test_c, y_pred_c)
roc_auc = roc_auc_score(y_test_c, y_pred_prob_c)

# Print the results
print(f"Multivariate RF Classification -- Accuracy: {accuracy:.3f},
ROC AUC: {roc_auc:.3f}")
```

```
Multivariate RF Classification -- Accuracy: 0.960, ROC AUC: 0.971
```

Key Learnings from Project Part 3

In Project Part 3, we focused on understanding the correlation between features and the target variable, Churn. We learned that features like Tenure, OrderCount, and HourSpendOnApp have significant correlations with Churn, which can be leveraged to build predictive models.

We also plotted scatterplots for each column to predict churn and found that multiple feature's values help in predicting churn effectively. This multivariate approach provided a more accurate prediction model compared to univariate models. The RandomForestClassifier and RandomForestRegressor were instrumental in achieving high accuracy and R^2 scores.

End of Project_Part_3

Start of Project_Part_4

```
# Import additional required libraries
from sklearn.cluster import AgglomerativeClustering, KMeans,
MiniBatchKMeans, MeanShift, estimate_bandwidth
from sklearn.linear_model import LogisticRegression
from sklearn.neighbors import KNeighborsClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.svm import SVC
from sklearn.naive_bayes import GaussianNB
from sklearn.neural_network import MLPClassifier
from sklearn.decomposition import PCA
from sklearn.metrics import silhouette_score, classification_report
from scipy.cluster.hierarchy import dendrogram, linkage
```

```python
from sklearn.metrics import confusion_matrix

print("\n" + "="*50)
print("CLUSTERING ANALYSIS")
print("="*50)
```

```
==================================================
CLUSTERING ANALYSIS
==================================================
```

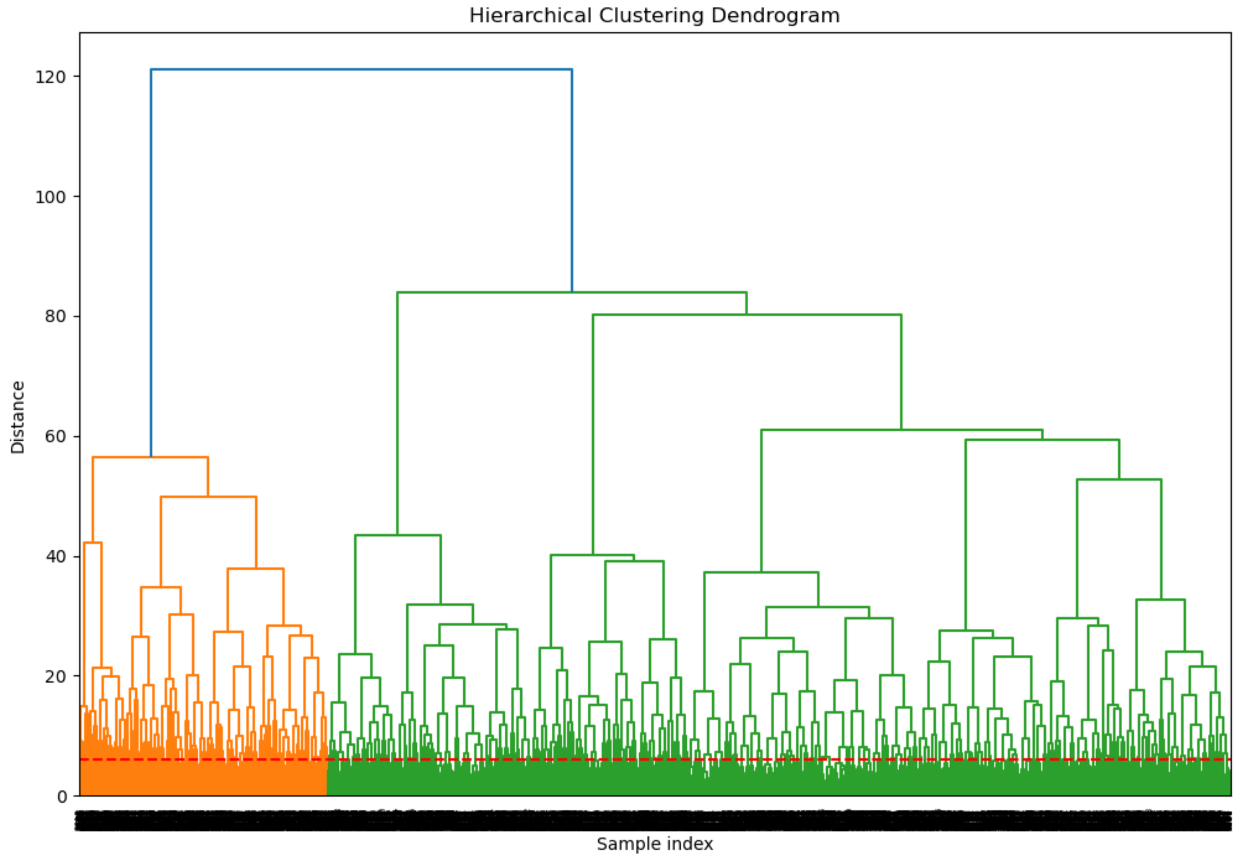
```python
X_cluster = df_filtered.drop(columns=['Churn'])

scaler = StandardScaler()
X_scaled = scaler.fit_transform(X_cluster)

pca = PCA(n_components=2)
X_pca = pca.fit_transform(X_scaled)
print(f"Explained variance by first two PCA components:
{pca.explained_variance_ratio_}")
print(f"Total variance explained:
{sum(pca.explained_variance_ratio_):.2f}")
```

```
Explained variance by first two PCA components: [0.17906357
0.10859986]
Total variance explained: 0.29
```

```python
def evaluate_clustering(X_data, X_pca, model, model_name):
    # Fit the model and predict clusters
    clusters = model.fit_predict(X_data)

    # Determine the number of clusters
    if hasattr(model, 'cluster_centers_'):
        n_clusters = len(model.cluster_centers_)
    else:
        n_clusters = len(np.unique(clusters))

    # Calculate silhouette score if more than one cluster is created
    if n_clusters > 1:
        sil_score = silhouette_score(X_data, clusters)
        print(f"{model_name} Silhouette Score: {sil_score:.3f}")
    else:
        sil_score = np.nan
        print(f"{model_name} created only one cluster, silhouette
score not applicable")

    # Plot the clustering results
    plt.figure(figsize=(12, 5))

    # Scatter plot of the clusters in PCA space
    plt.subplot(1, 2, 1)
```

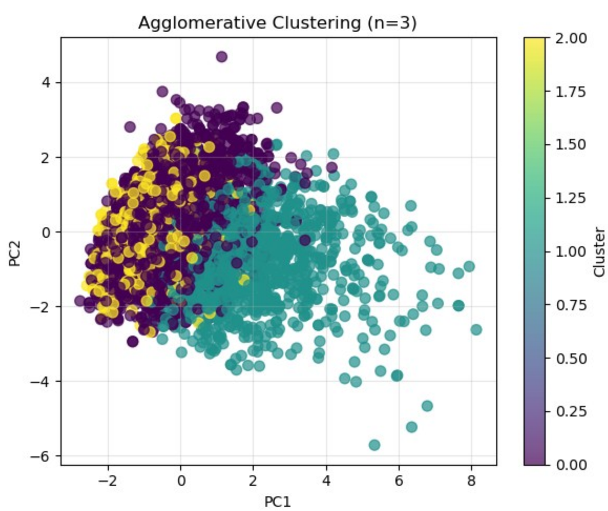
```python
    scatter = plt.scatter(X_pca[:, 0], X_pca[:, 1], c=clusters,
cmap='viridis',
                          alpha=0.7, s=50)
    plt.colorbar(scatter, label='Cluster')
    plt.title(f'{model_name} Clustering (n={n_clusters})')
    plt.xlabel('PC1')
    plt.ylabel('PC2')
    plt.grid(alpha=0.3)

    # Bar plot of average churn rate by cluster
    plt.subplot(1, 2, 2)
    cluster_df = pd.DataFrame({'Cluster': clusters, 'Churn':
df_filtered['Churn']})
    churn_by_cluster = cluster_df.groupby('Cluster')
['Churn'].mean().reset_index()
    sns.barplot(x='Cluster', y='Churn', data=churn_by_cluster)
    plt.title('Average Churn Rate by Cluster')
    plt.xlabel('Cluster')
    plt.ylabel('Churn Rate')
    plt.ylim(0, 1)
    plt.tight_layout()
    plt.show()

    return clusters, sil_score, n_clusters

# 1. Agglomerative Clustering
print("\n1. Agglomerative Clustering")

plt.figure(figsize=(12, 8))
dendrogram_plot = dendrogram(linkage(X_scaled, method='ward'))
plt.title('Hierarchical Clustering Dendrogram')
plt.xlabel('Sample index')
plt.ylabel('Distance')
plt.axhline(y=6, color='r', linestyle='--')
plt.show()
```

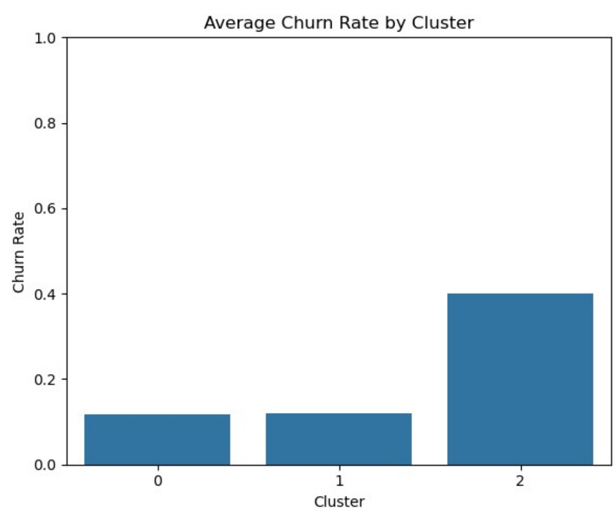
```
1. Agglomerative Clustering
```




```
# Using 3 clusters based on dendrogram
agg_model = AgglomerativeClustering(n_clusters=3)
agg_clusters, agg_silhouette, agg_n_clusters =
evaluate_clustering(X_scaled, X_pca, agg_model, "Agglomerative")
```

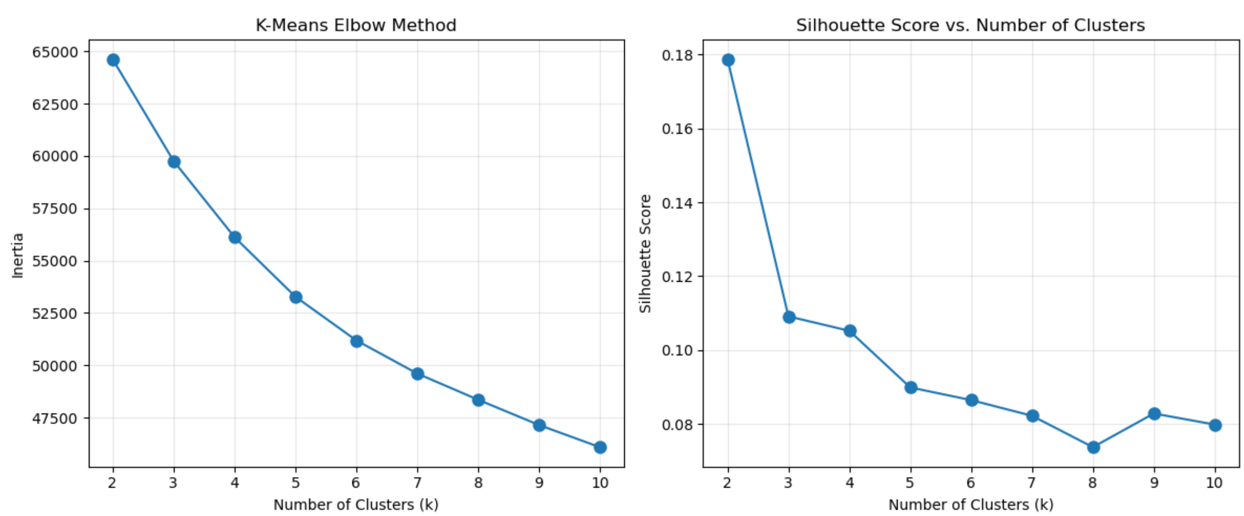
```
Agglomerative Silhouette Score: 0.071
```





```
# 2. K-Means Clustering
print("\n2. K-Means Clustering")

# Initialize lists to store inertia and silhouette scores for
different k values
inertia = []
silhouette_scores = []

# Define the range of k values to evaluate
k_range = range(2, 11)

# Loop over the range of k values
for k in k_range:
    # Initialize and fit the KMeans model
    kmeans = KMeans(n_clusters=k, random_state=42, n_init=10)
    kmeans.fit(X_scaled)

    # Append the inertia (sum of squared distances to the nearest
cluster center)
    inertia.append(kmeans.inertia_)

    # Append the silhouette score (measure of how similar an object is
to its own cluster compared to other clusters)
    silhouette_scores.append(silhouette_score(X_scaled,
kmeans.labels_))

# Plot the inertia values to use the elbow method for determining the
optimal number of clusters
plt.figure(figsize=(12, 5))

# Plot inertia values
plt.subplot(1, 2, 1)
plt.plot(k_range, inertia, 'o-', markersize=8)
plt.title('K-Means Elbow Method')
plt.xlabel('Number of Clusters (k)')
plt.ylabel('Inertia')
plt.grid(alpha=0.3)

# Plot silhouette scores
plt.subplot(1, 2, 2)
plt.plot(k_range, silhouette_scores, 'o-', markersize=8)
plt.title('Silhouette Score vs. Number of Clusters')
plt.xlabel('Number of Clusters (k)')
plt.ylabel('Silhouette Score')
plt.grid(alpha=0.3)

# Adjust layout and show the plots
plt.tight_layout()
plt.show()
```

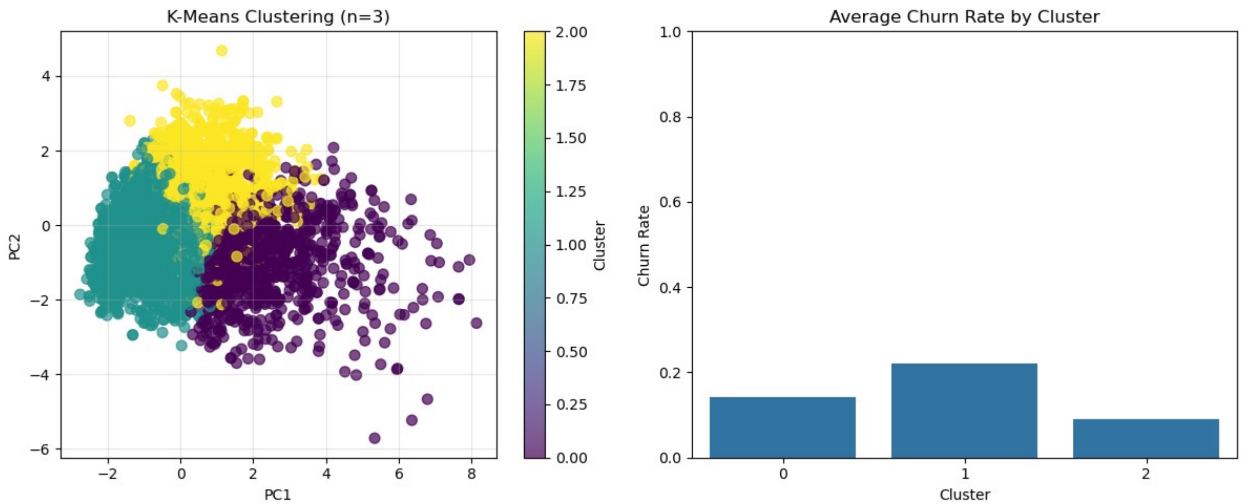
```
2. K-Means Clustering

c:\Users\raoru\anaconda3\Lib\site-packages\joblib\externals\loky\
backend\context.py:136: UserWarning: Could not find the number of
physical cores for the following reason:
[WinError 2] The system cannot find the file specified
Returning the number of logical cores instead. You can silence this
warning by setting LOKY_MAX_CPU_COUNT to the number of cores you want
to use.
  warnings.warn(
  File "c:\Users\raoru\anaconda3\Lib\site-packages\joblib\externals\
loky\backend\context.py", line 257, in _count_physical_cores
    cpu_info = subprocess.run(
               ^^^^^^^^^^^^^^^
  File "c:\Users\raoru\anaconda3\Lib\subprocess.py", line 548, in run
    with Popen(*popenargs, **kwargs) as process:
         ^^^^^^^^^^^^^^^^^^^^^^^^^^^
  File "c:\Users\raoru\anaconda3\Lib\subprocess.py", line 1026, in
__init__
    self._execute_child(args, executable, preexec_fn, close_fds,
  File "c:\Users\raoru\anaconda3\Lib\subprocess.py", line 1538, in
_execute_child
    hp, ht, pid, tid = _winapi.CreateProcess(executable, args,
                       ^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^
```



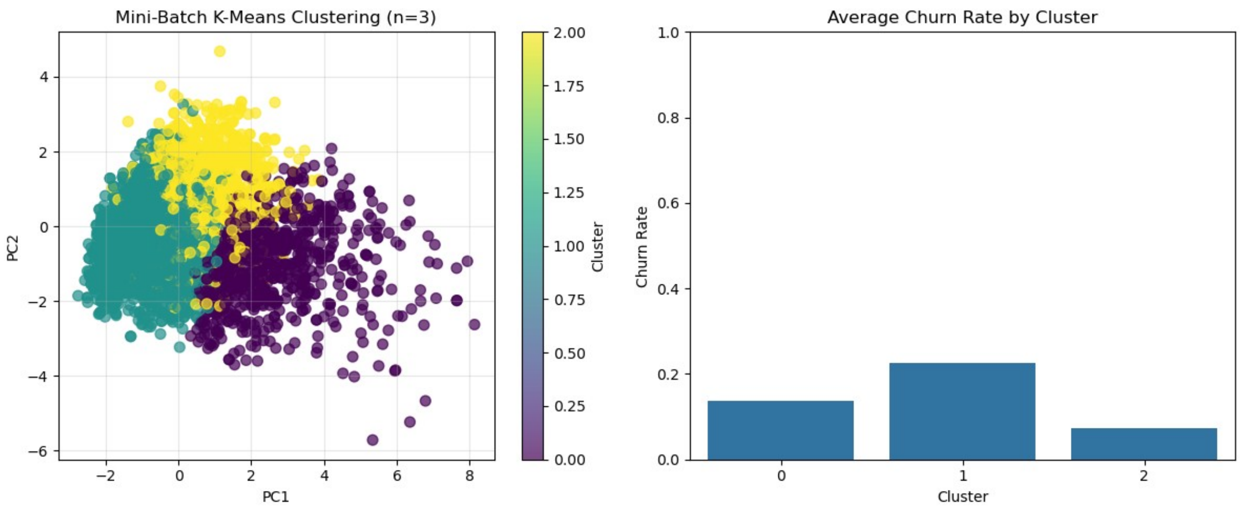

```
optimal_k = 3
kmeans_model = KMeans(n_clusters=optimal_k, random_state=42,
n_init=10)
kmeans_clusters, kmeans_silhouette, kmeans_n_clusters =
evaluate_clustering(X_scaled, X_pca, kmeans_model, "K-Means")

# 3. Mini-Batch K-Means
```

```
print("\n3. Mini-Batch K-Means Clustering")
mbkmeans_model = MiniBatchKMeans(n_clusters=optimal_k,
random_state=42, batch_size=256, n_init=10)
mbkmeans_clusters, mbkmeans_silhouette, mbkmeans_n_clusters =
evaluate_clustering(X_scaled, X_pca, mbkmeans_model, "Mini-Batch K-
Means")
```

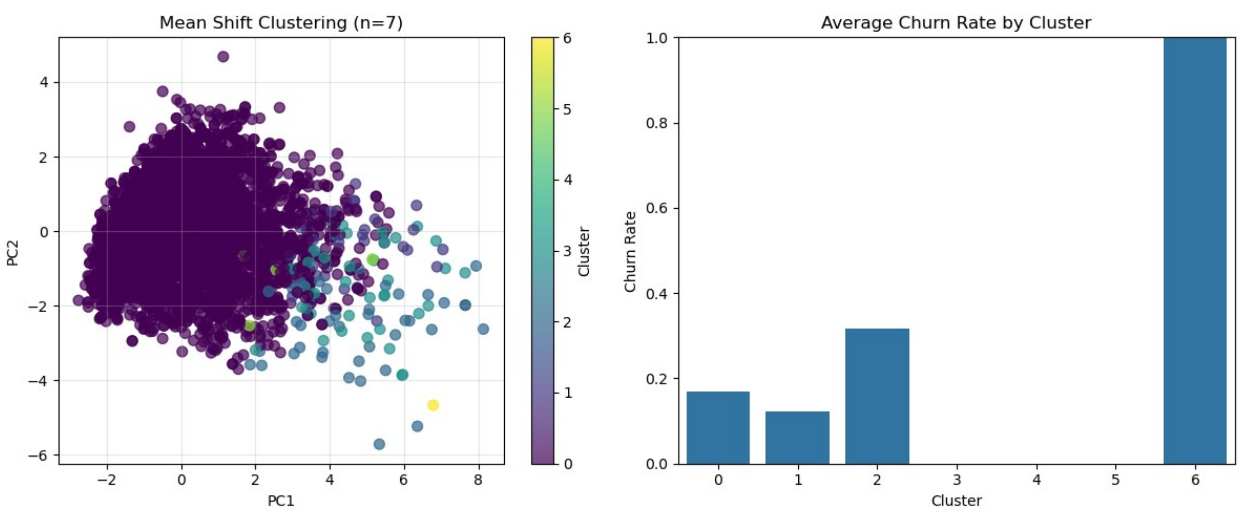
```
K-Means Silhouette Score: 0.109
```




```
3. Mini-Batch K-Means Clustering

c:\Users\raoru\anaconda3\Lib\site-packages\sklearn\cluster\
_kmeans.py:1955: UserWarning: MiniBatchKMeans is known to have a
memory leak on Windows with MKL, when there are less chunks than
available threads. You can prevent it by setting batch_size >= 2048 or
by setting the environment variable OMP_NUM_THREADS=1
  warnings.warn(

Mini-Batch K-Means Silhouette Score: 0.114
```




```python
# 4. Mean Shift Clustering
print("\n4. Mean Shift Clustering")
bandwidth = estimate_bandwidth(X_scaled, quantile=0.2, n_samples=500)
ms_model = MeanShift(bandwidth=bandwidth, bin_seeding=True)
ms_clusters, ms_silhouette, ms_n_clusters =
evaluate_clustering(X_scaled, X_pca, ms_model, "Mean Shift")


4. Mean Shift Clustering
Mean Shift Silhouette Score: 0.299
```




```python
# Compare clustering methods
clustering_results = pd.DataFrame({
    'Method': ['Agglomerative', 'K-Means', 'Mini-Batch K-Means', 'Mean
Shift'],
    'Number of Clusters': [agg_n_clusters, kmeans_n_clusters,
mbkmeans_n_clusters, ms_n_clusters],
```

```
    'Silhouette Score': [agg_silhouette, kmeans_silhouette,
mbkmeans_silhouette, ms_silhouette]
})

print("\nClustering Methods Comparison:")
print(clustering_results.sort_values('Silhouette Score',
ascending=False))
```

```
Clustering Methods Comparison:
              Method  Number of Clusters  Silhouette Score
3         Mean Shift                   7          0.299315
2  Mini-Batch K-Means                   3          0.113925
1            K-Means                   3          0.109128
0      Agglomerative                   3          0.070740
```

```
# Select best clustering method based on silhouette score
best_clustering =
clustering_results.loc[clustering_results['Silhouette
Score'].idxmax()]
print(f"\nBest clustering method: {best_clustering['Method']} with
{best_clustering['Number of Clusters']} clusters")
print(f"Silhouette score: {best_clustering['Silhouette Score']:.3f}")
```

```
Best clustering method: Mean Shift with 7 clusters
Silhouette score: 0.299
```

```
# Add cluster assignments from best method to the original data
if best_clustering['Method'] == 'Agglomerative':
    best_clusters = agg_clusters
elif best_clustering['Method'] == 'K-Means':
    best_clusters = kmeans_clusters
elif best_clustering['Method'] == 'Mini-Batch K-Means':
    best_clusters = mbkmeans_clusters
else:
    best_clusters = ms_clusters

df_filtered = df_filtered.copy()
df_filtered['Cluster'] = best_clusters

cluster_churn = df_filtered.groupby('Cluster')['Churn'].agg(['mean',
'count']).reset_index()
cluster_churn.columns = ['Cluster', 'Churn Rate', 'Count']
print("\nChurn Rate by Cluster:")
print(cluster_churn)

print("\n" + "="*50)
print("CLASSIFICATION ANALYSIS")
print("="*50)
```

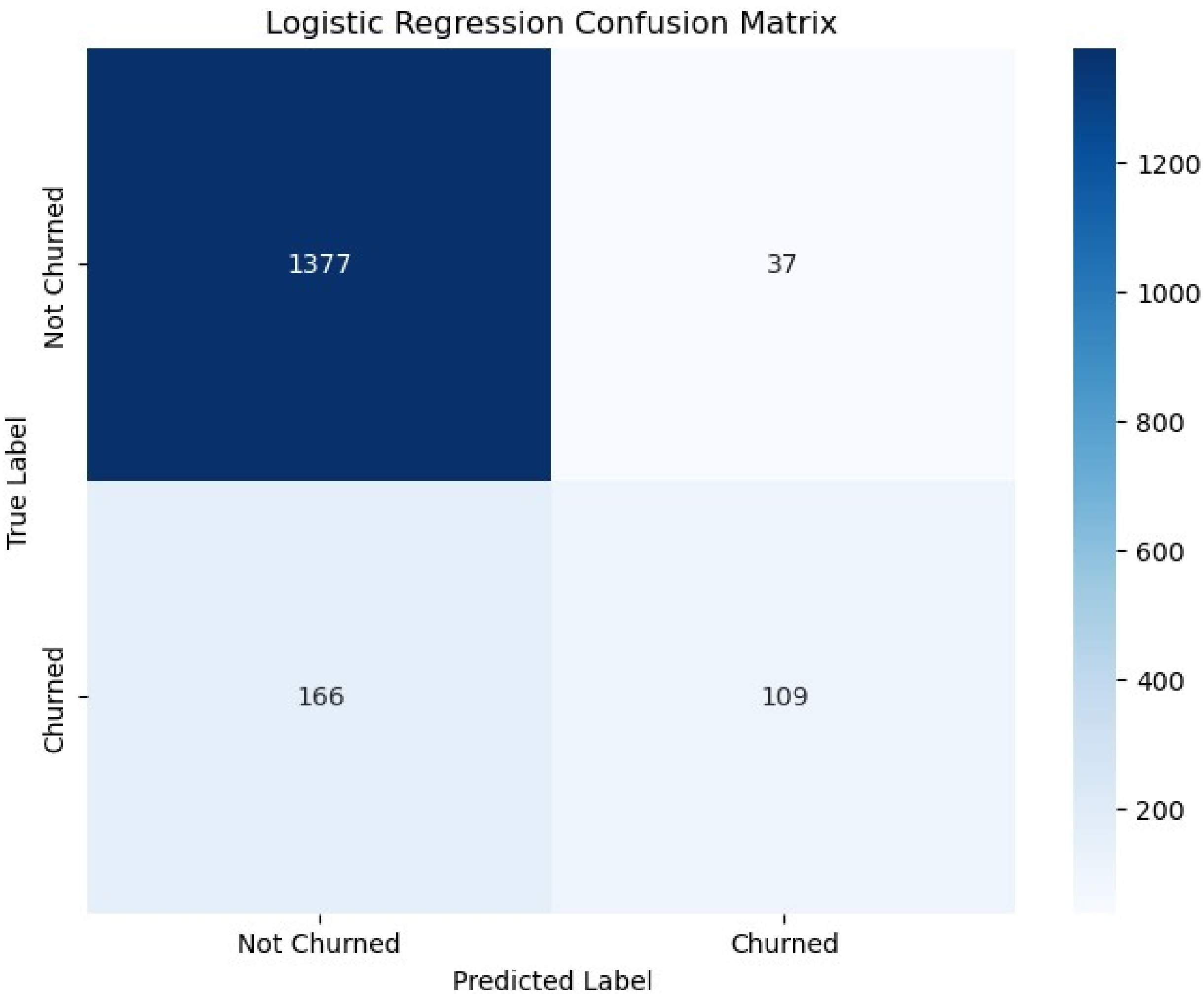
```
Churn Rate by Cluster:
   Cluster  Churn Rate  Count
0        0    0.168937   5505
1        1    0.121212     33
2        2    0.317073     41
3        3    0.000000     42
4        4    0.000000      2
5        5    0.000000      6
6        6    1.000000      1

==================================================
CLASSIFICATION ANALYSIS
==================================================

# Prepare data for classification with and without cluster feature
X_with_cluster = df_filtered.drop(columns=['Churn'])
X_without_cluster = X_with_cluster.drop(columns=['Cluster'])
y = df_filtered['Churn']

# Split the data
X_train_with, X_test_with, y_train, y_test = train_test_split(
    X_with_cluster, y, test_size=0.3, random_state=42)
X_train_without = X_train_with.drop(columns=['Cluster'])
X_test_without = X_test_with.drop(columns=['Cluster'])

# Standardize
scaler_with = StandardScaler()
X_train_with_scaled = scaler_with.fit_transform(X_train_with)
X_test_with_scaled = scaler_with.transform(X_test_with)

scaler_without = StandardScaler()
X_train_without_scaled = scaler_without.fit_transform(X_train_without)
X_test_without_scaled = scaler_without.transform(X_test_without)

def evaluate_classifier(model, X_train, X_test, y_train, y_test,
model_name, with_cluster=True):
    # Fit the model on the training data
    model.fit(X_train, y_train)

    # Predict the labels for the test data
    y_pred = model.predict(X_test)

    # Calculate ROC AUC score if the model supports probability
prediction
    if hasattr(model, "predict_proba"):
        y_pred_prob = model.predict_proba(X_test)[:, 1]
        roc_auc = roc_auc_score(y_test, y_pred_prob)
    else:
        # If the model supports decision function, use it to calculate
```

```
ROC AUC score
        if hasattr(model, "decision_function"):
            y_scores = model.decision_function(X_test)
            roc_auc = roc_auc_score(y_test, y_scores)
        else:
            roc_auc = np.nan

    # Calculate accuracy score
    accuracy = accuracy_score(y_test, y_pred)

    # Generate confusion matrix
    conf_matrix = confusion_matrix(y_test, y_pred)

    # Generate classification report
    class_report = classification_report(y_test, y_pred,
output_dict=True)

    # Print model performance metrics
    print(f"\n{model_name} {'with' if with_cluster else 'without'}
Cluster Feature:")
    print(f"Accuracy: {accuracy:.3f}")
    print(f"ROC AUC: {roc_auc:.3f}")
    print(f"Classification Report:")
    print(classification_report(y_test, y_pred))

    # Plot confusion matrix
    plt.figure(figsize=(8, 6))
    sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues',
                xticklabels=['Not Churned', 'Churned'],
                yticklabels=['Not Churned', 'Churned'])
    plt.title(f'{model_name} Confusion Matrix')
    plt.ylabel('True Label')
    plt.xlabel('Predicted Label')
    plt.show()

    # Plot feature importance if the model supports it
    if hasattr(model, 'feature_importances_'):
        features = X_with_cluster.columns if with_cluster else
X_without_cluster.columns
        importances = pd.DataFrame({
            'Feature': features,
            'Importance': model.feature_importances_
        }).sort_values('Importance', ascending=False)

        plt.figure(figsize=(10, 6))
        sns.barplot(x='Importance', y='Feature',
data=importances.head(10))
        plt.title(f'{model_name} Feature Importance')
        plt.tight_layout()
        plt.show()
```

```python
    # Return model performance metrics
    return {
        'Model': model_name,
        'With Cluster': with_cluster,
        'Accuracy': accuracy,
        'ROC AUC': roc_auc,
        'F1 (Churned)': class_report['1']['f1-score']
    }

# Define classifiers to be used for classification
classifiers = {
    'Logistic Regression': LogisticRegression(max_iter=1000,
random_state=42),
    'K-Nearest Neighbors': KNeighborsClassifier(n_neighbors=5),
    'Decision Tree': DecisionTreeClassifier(random_state=42),
    'Support Vector Machine': SVC(probability=True, random_state=42),
    'Naive Bayes': GaussianNB(),
    'Neural Network': MLPClassifier(hidden_layer_sizes=(100,),
max_iter=1000, random_state=42)
}

# Initialize an empty list to store results
results = []

# Iterate over each classifier
for name, model in classifiers.items():
    # Evaluate the classifier with the cluster feature
    result_with = evaluate_classifier(
        model, X_train_with_scaled, X_test_with_scaled,
        y_train, y_test, name, with_cluster=True
    )
    # Append the result to the results list
    results.append(result_with)

    # Evaluate the classifier without the cluster feature
    result_without = evaluate_classifier(
        model, X_train_without_scaled, X_test_without_scaled,
        y_train, y_test, name, with_cluster=False
    )
    # Append the result to the results list
    results.append(result_without)
```

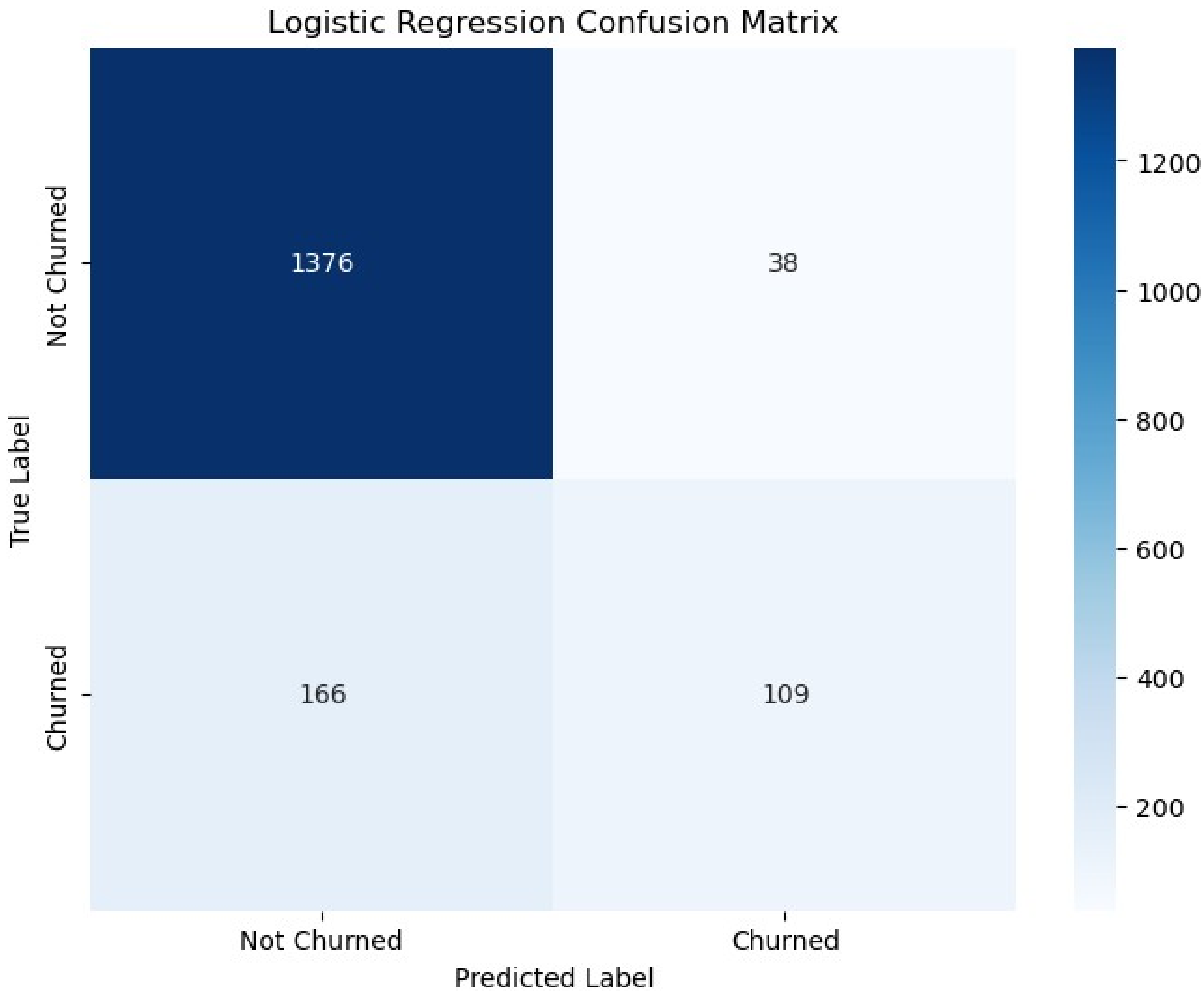
```
Logistic Regression with Cluster Feature:
Accuracy: 0.880
ROC AUC: 0.855
Classification Report:
              precision    recall  f1-score   support
```

```
            0       0.89      0.97      0.93      1414
            1       0.75      0.40      0.52       275

     accuracy                           0.88      1689
    macro avg       0.82      0.69      0.72      1689
 weighted avg       0.87      0.88      0.86      1689
```



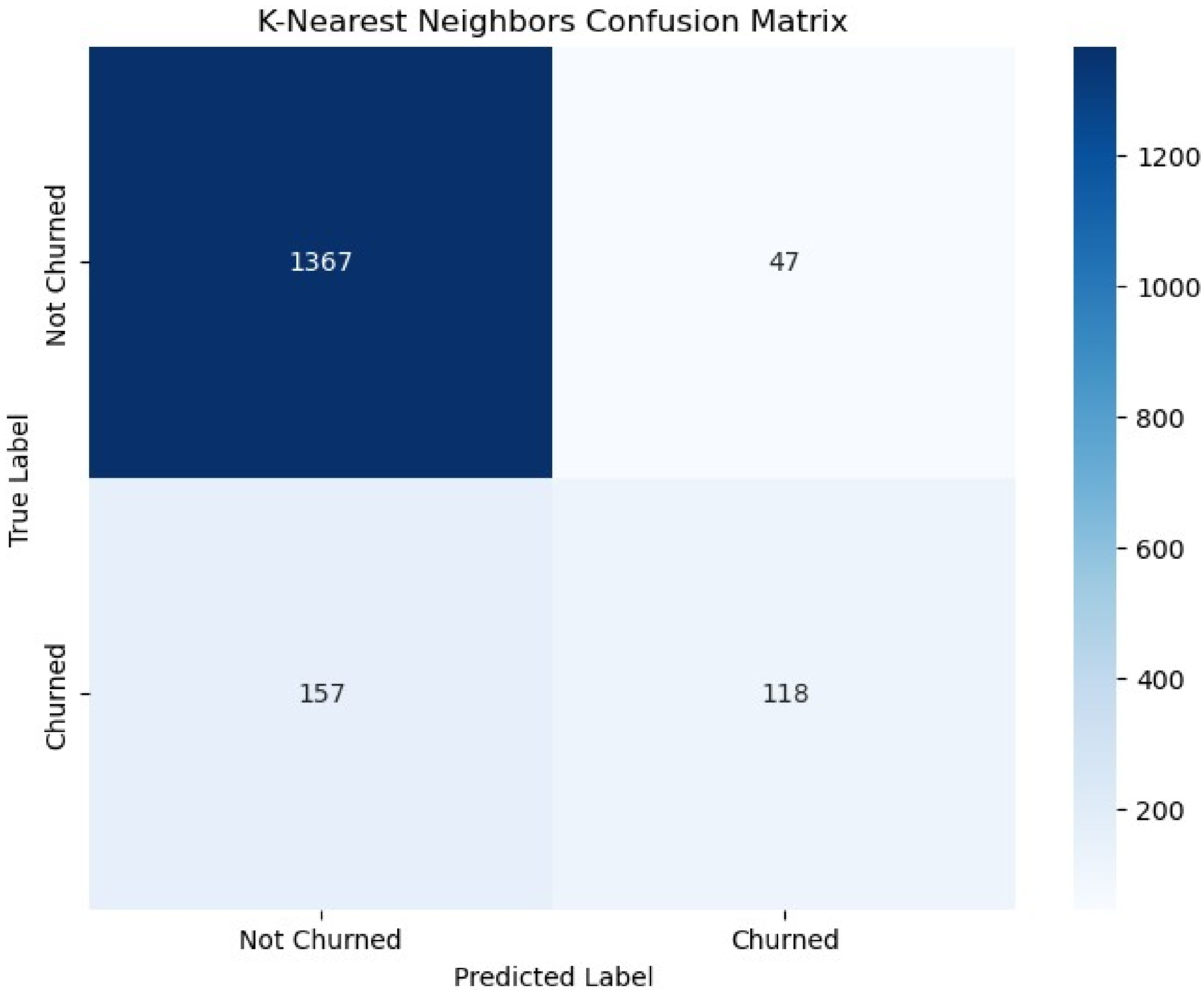

```
Logistic Regression without Cluster Feature:
Accuracy: 0.879
ROC AUC: 0.854
Classification Report:
              precision    recall  f1-score   support

            0       0.89      0.97      0.93      1414
            1       0.74      0.40      0.52       275
```

```
    accuracy                           0.88      1689
   macro avg       0.82      0.68      0.72      1689
weighted avg       0.87      0.88      0.86      1689
```

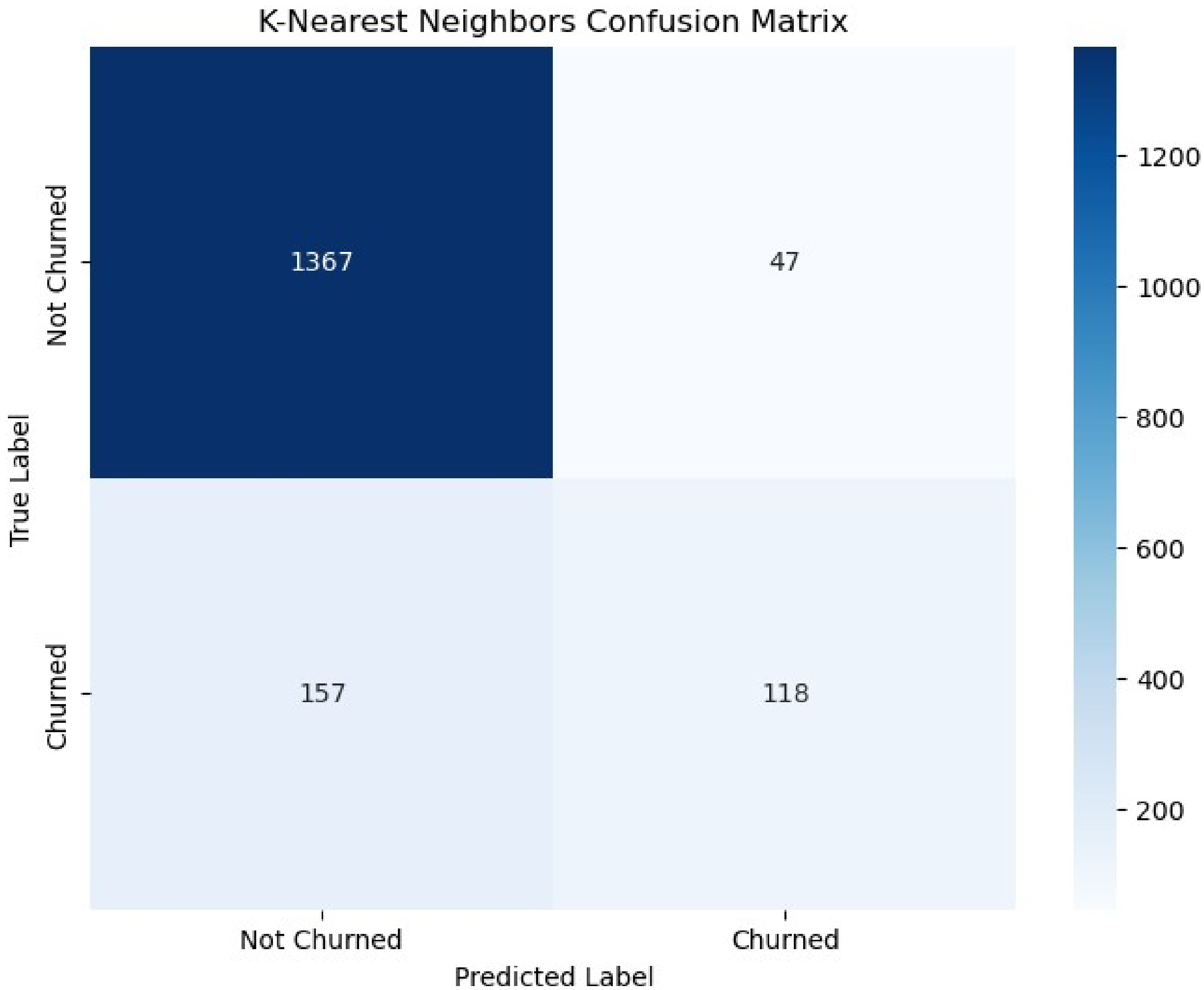



```
K-Nearest Neighbors with Cluster Feature:
Accuracy: 0.879
ROC AUC: 0.889
Classification Report:
              precision    recall  f1-score   support

           0       0.90      0.97      0.93      1414
           1       0.72      0.43      0.54       275

    accuracy                           0.88      1689
   macro avg       0.81      0.70      0.73      1689
```

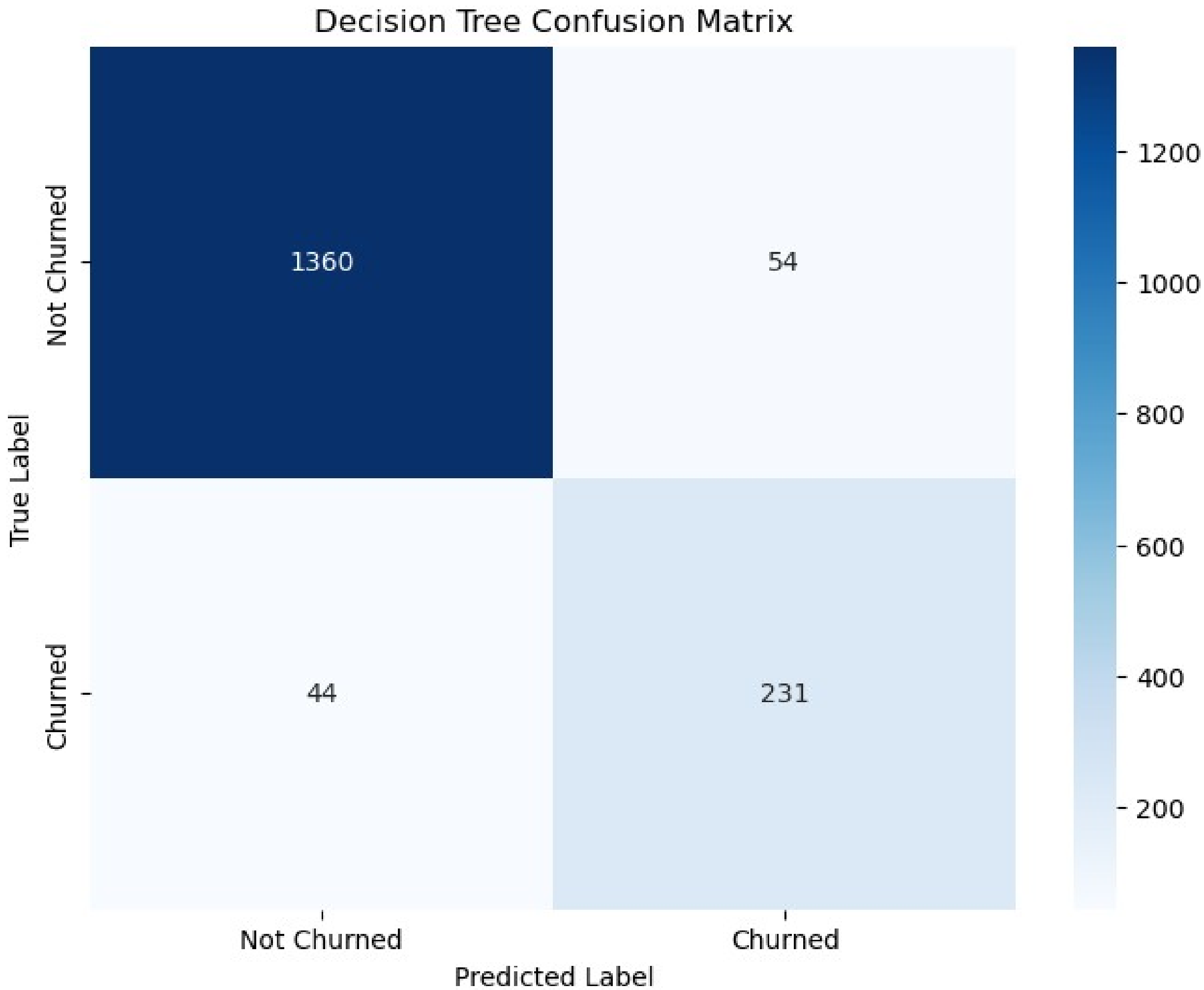
```
weighted avg       0.87      0.88      0.87      1689
```



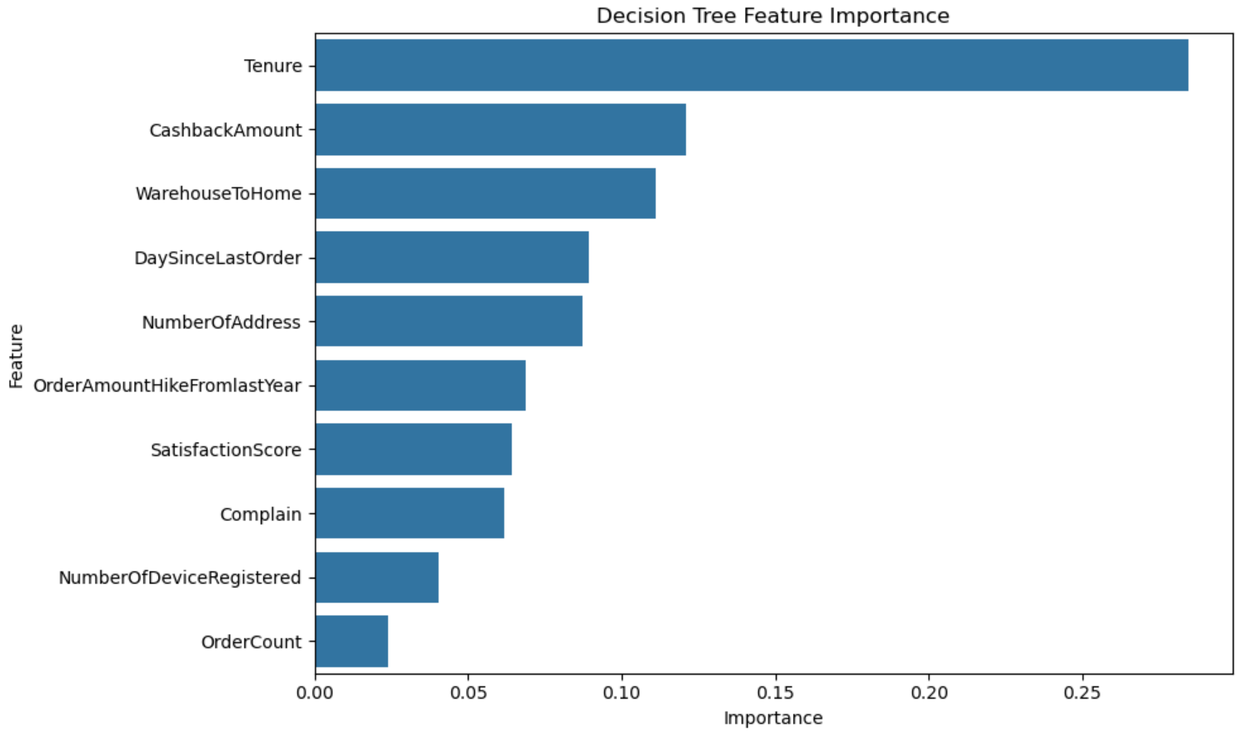

```
K-Nearest Neighbors without Cluster Feature:
Accuracy: 0.879
ROC AUC: 0.889
Classification Report:
              precision    recall  f1-score   support

           0       0.90      0.97      0.93      1414
           1       0.72      0.43      0.54       275

    accuracy                           0.88      1689
   macro avg       0.81      0.70      0.73      1689
weighted avg       0.87      0.88      0.87      1689
```



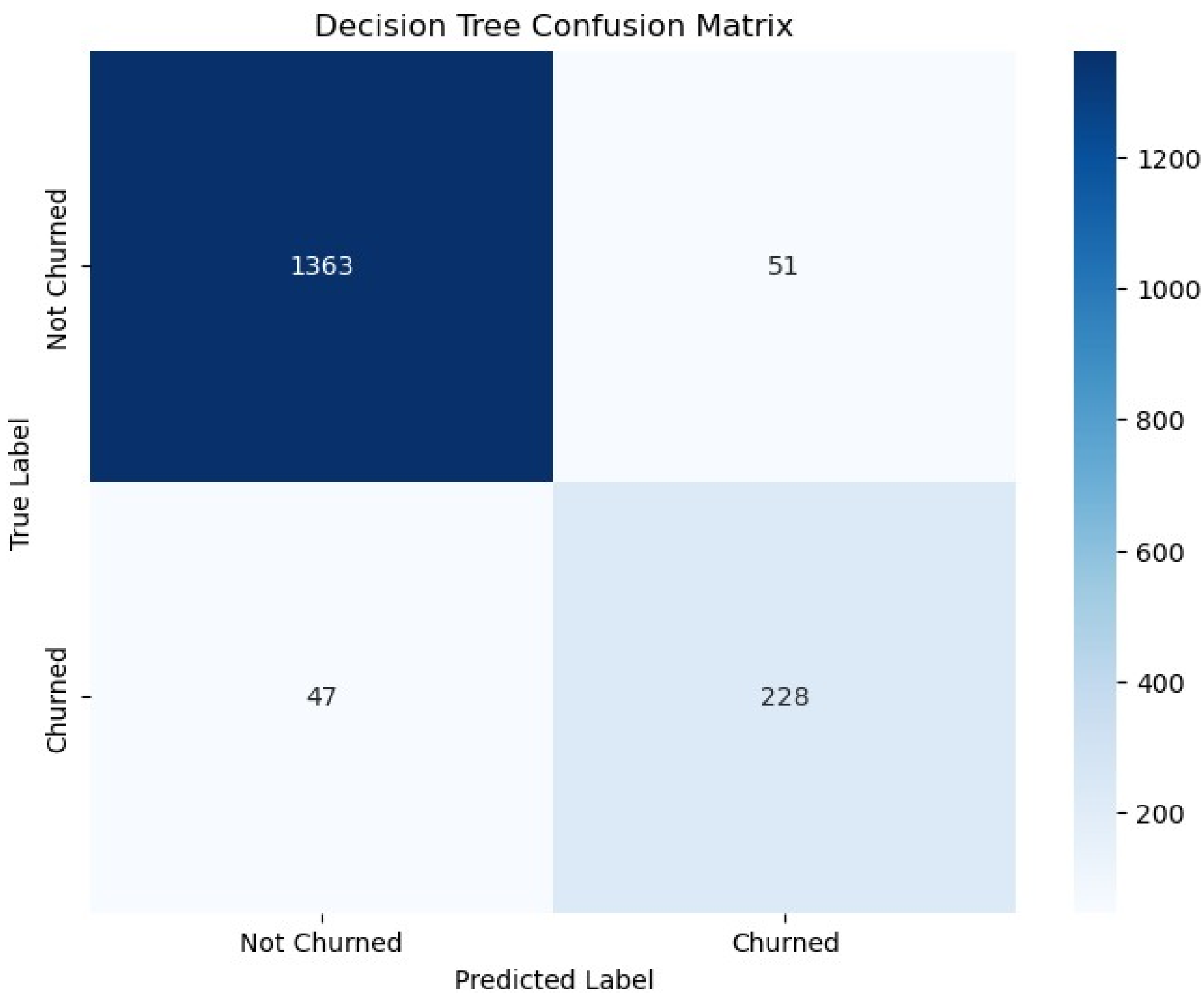

```
Decision Tree with Cluster Feature:
Accuracy: 0.942
ROC AUC: 0.901
Classification Report:
              precision    recall  f1-score   support

           0       0.97      0.96      0.97      1414
           1       0.81      0.84      0.82       275

    accuracy                           0.94      1689
   macro avg       0.89      0.90      0.90      1689
weighted avg       0.94      0.94      0.94      1689
```

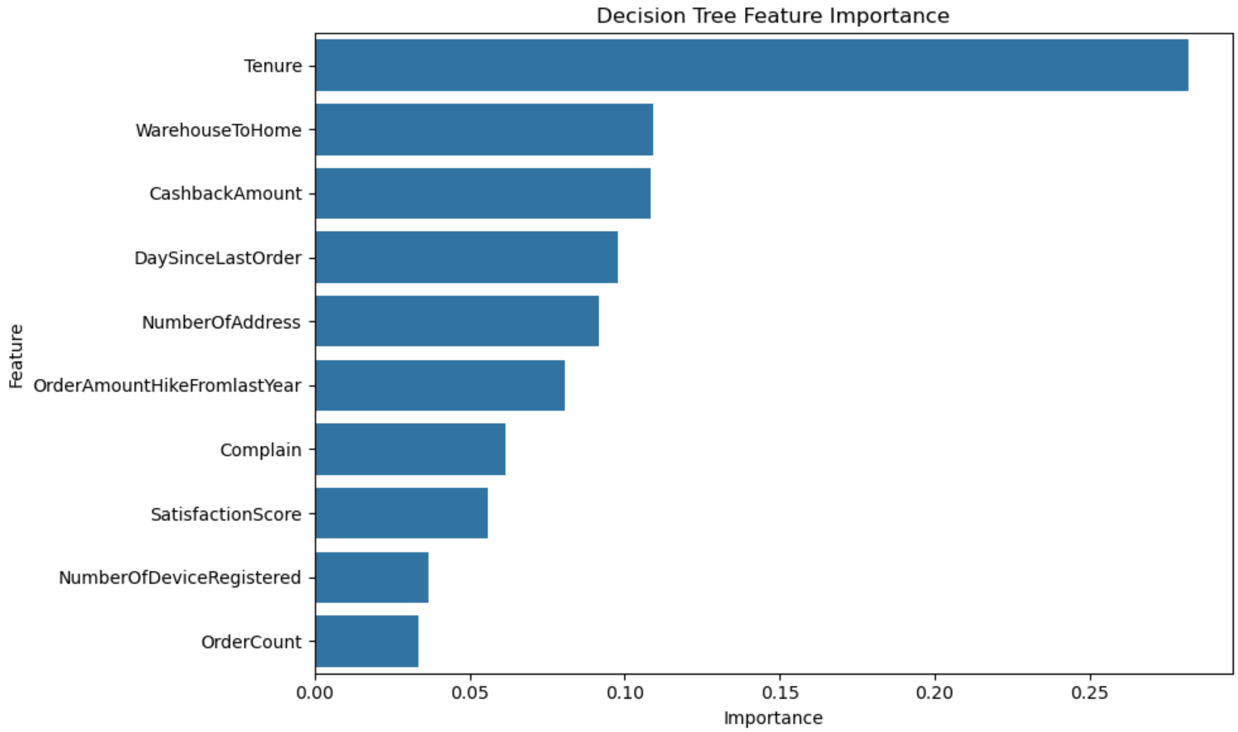


Decision Tree Confusion Matrix
True Label
Not Churned
Churned
Predicted Label
Not Churned
Churned
1360
54
44
231
1200
1000
800
600
400
200

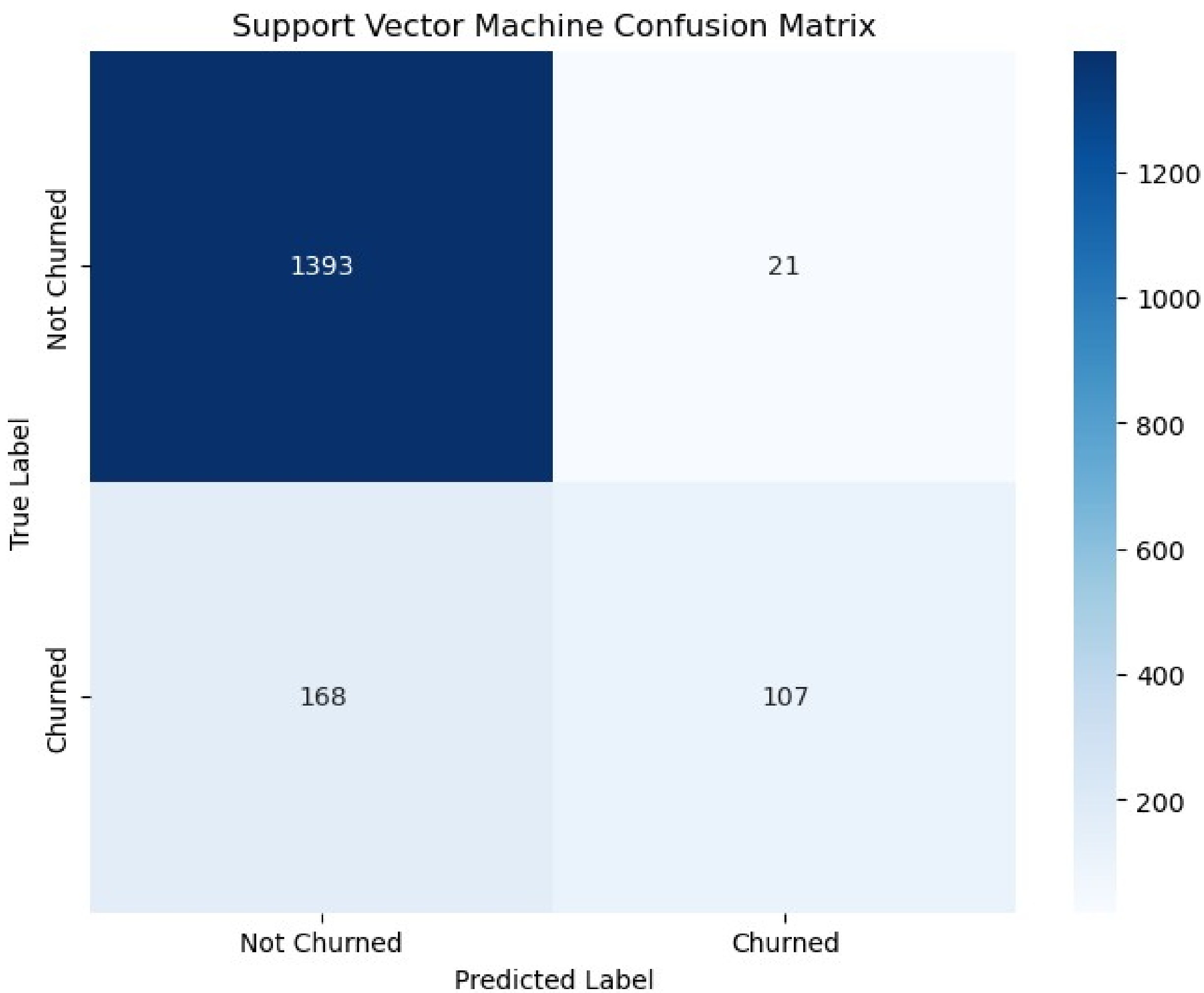



```
Decision Tree without Cluster Feature:
Accuracy: 0.942
ROC AUC: 0.897
Classification Report:
              precision    recall  f1-score   support

           0       0.97      0.96      0.97      1414
           1       0.82      0.83      0.82       275

    accuracy                           0.94      1689
   macro avg       0.89      0.90      0.89      1689
weighted avg       0.94      0.94      0.94      1689
```

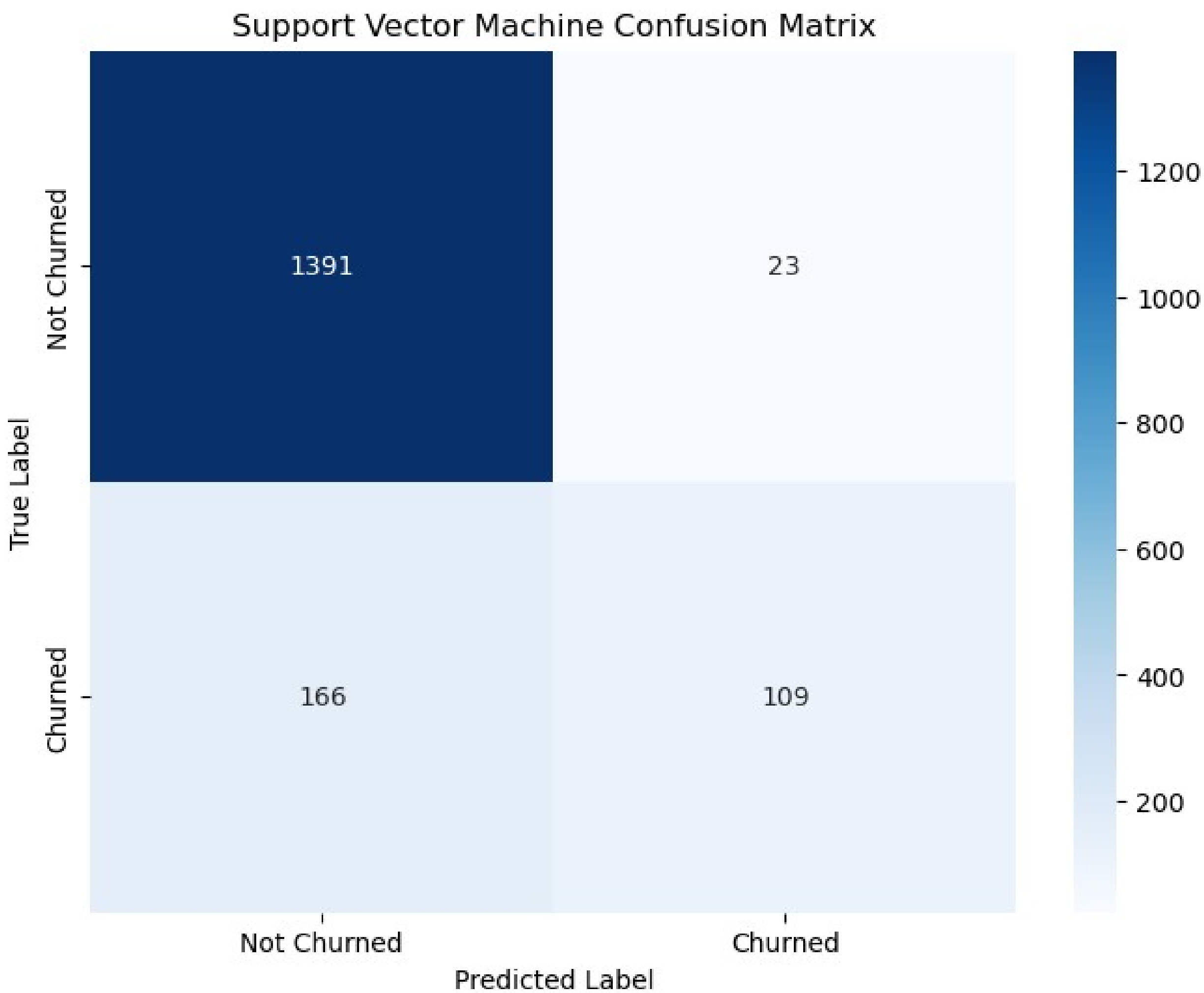

Decision Tree Confusion Matrix
1363
51
47
228
Not Churned
Churned
True Label
Not Churned
Churned
Predicted Label
1200
1000
800
600
400
200



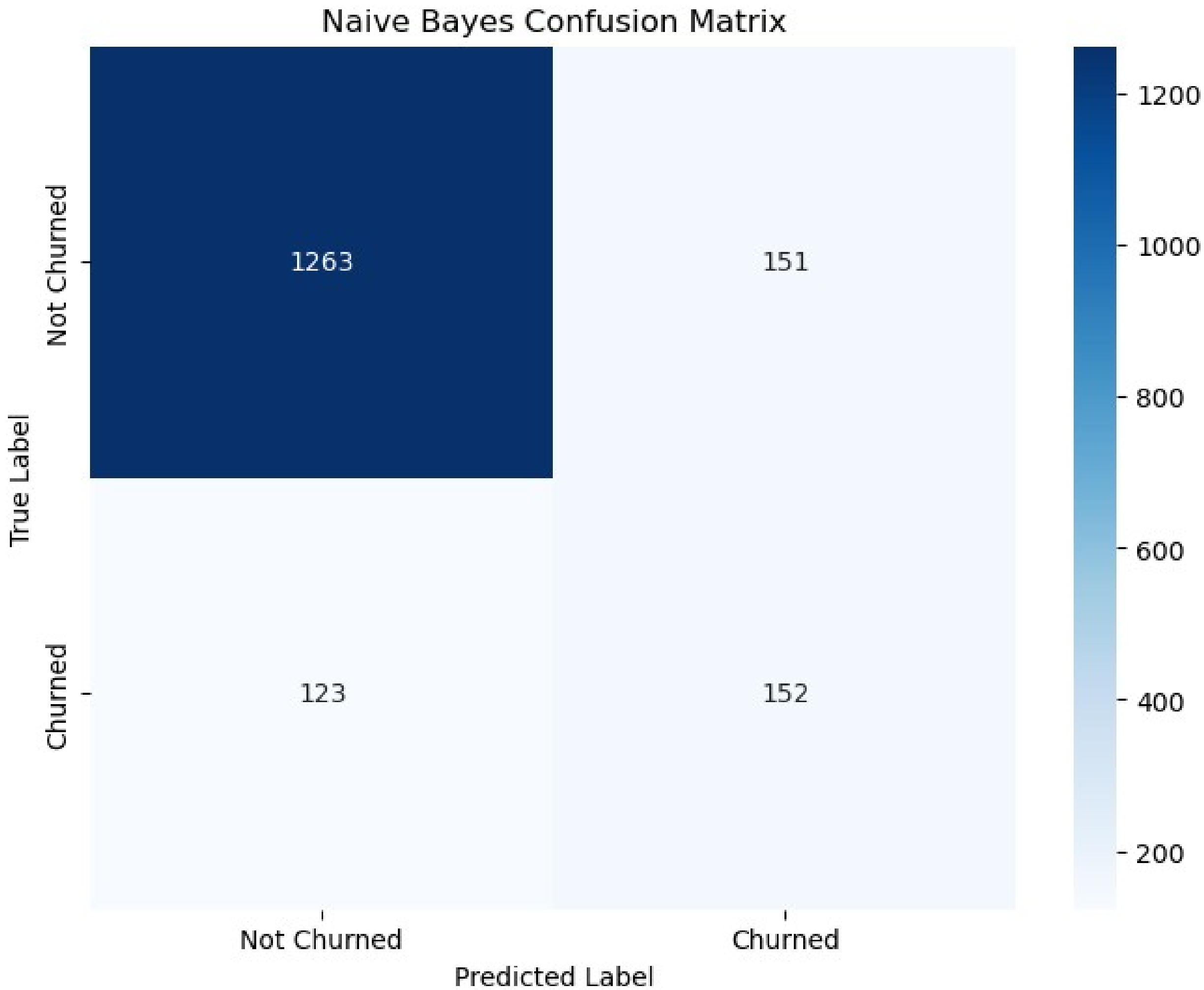

```
Support Vector Machine with Cluster Feature:
Accuracy: 0.888
ROC AUC: 0.896
Classification Report:
              precision    recall  f1-score   support

           0       0.89      0.99      0.94      1414
           1       0.84      0.39      0.53       275

    accuracy                           0.89      1689
   macro avg       0.86      0.69      0.73      1689
weighted avg       0.88      0.89      0.87      1689
```



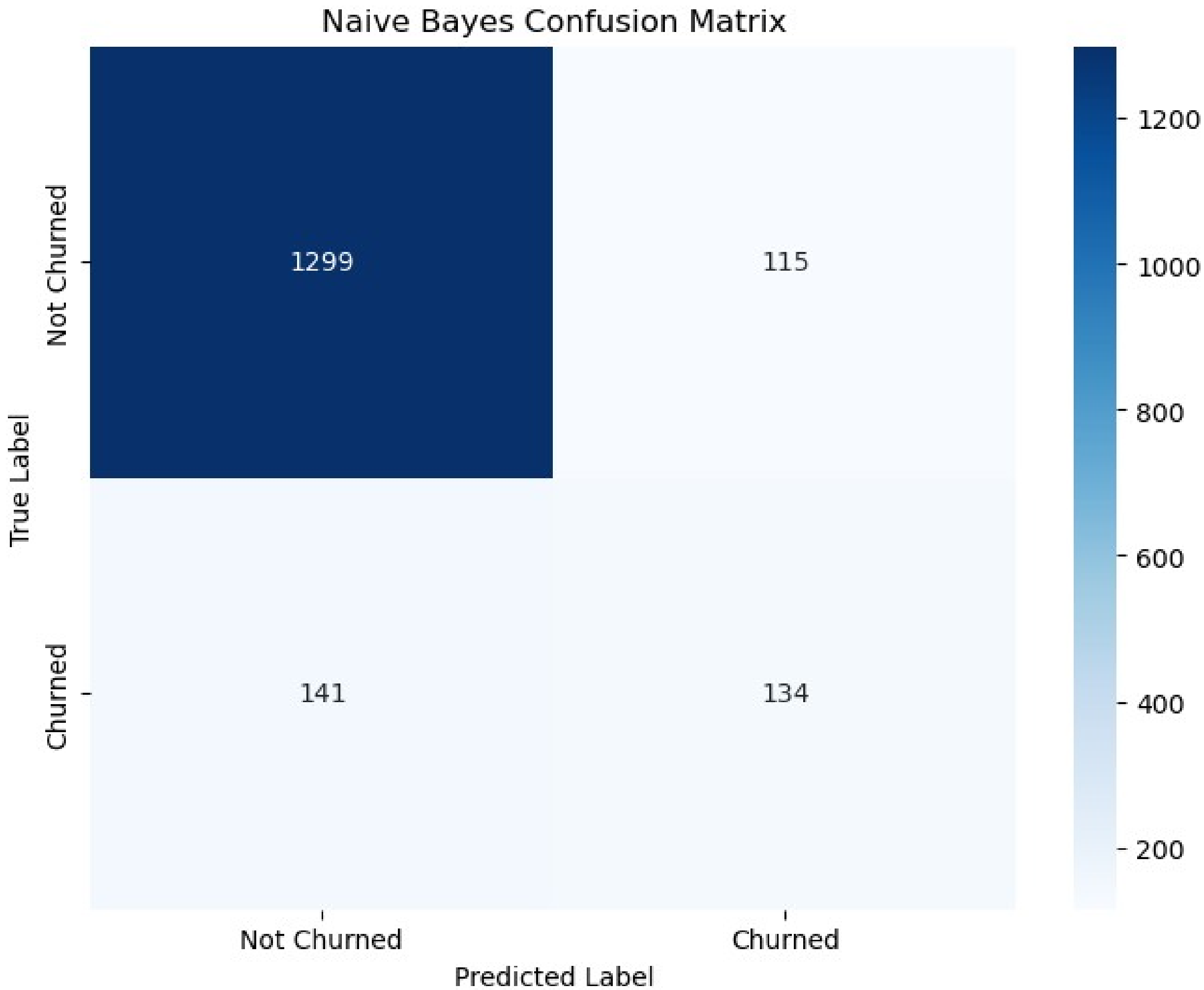

```
Support Vector Machine without Cluster Feature:
Accuracy: 0.888
ROC AUC: 0.897
Classification Report:
              precision    recall  f1-score   support

           0       0.89      0.98      0.94      1414
           1       0.83      0.40      0.54       275

    accuracy                           0.89      1689
   macro avg       0.86      0.69      0.74      1689
weighted avg       0.88      0.89      0.87      1689
```



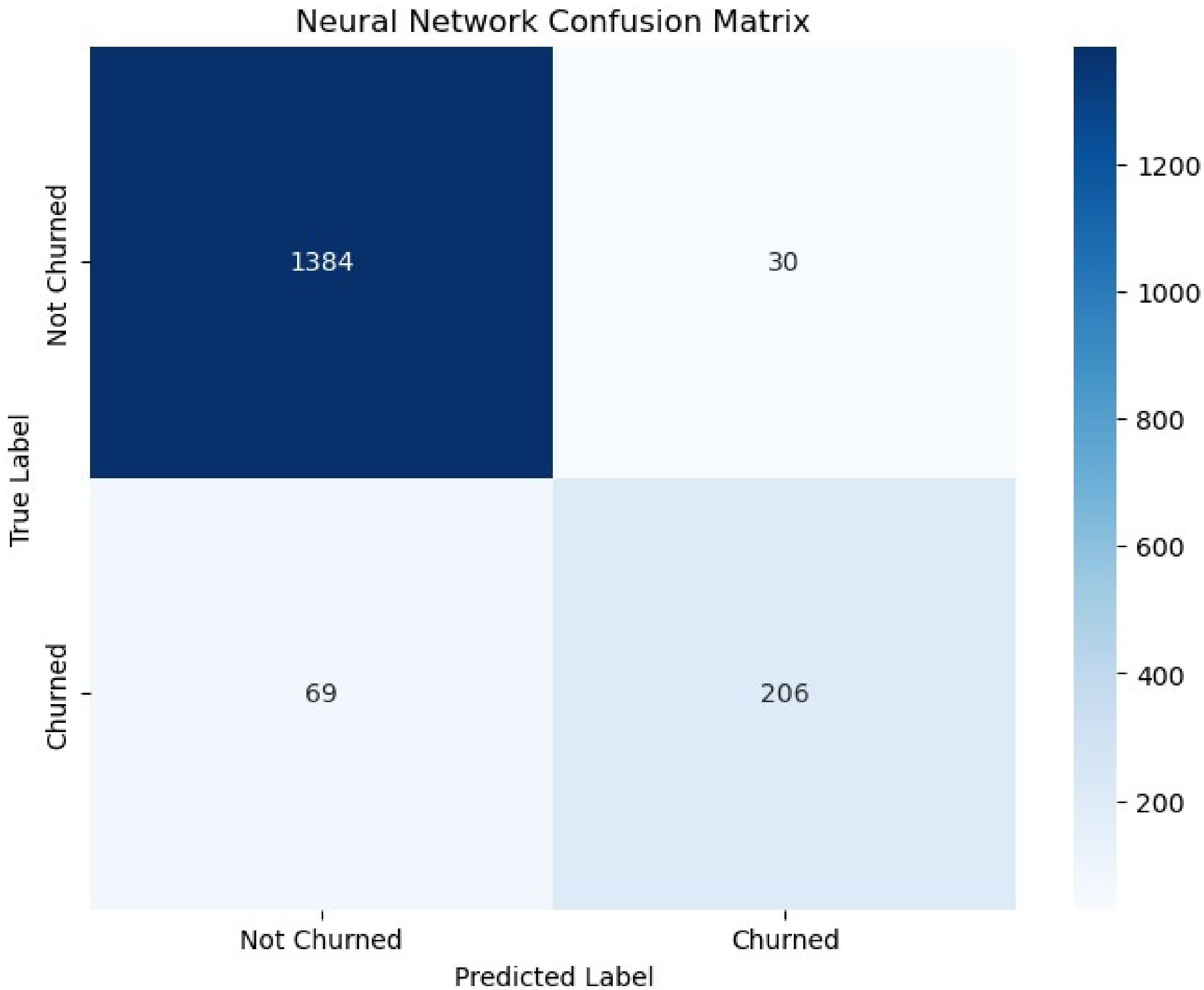

```
Naive Bayes with Cluster Feature:
Accuracy: 0.838
ROC AUC: 0.800
Classification Report:
              precision    recall  f1-score   support

           0       0.91      0.89      0.90      1414
           1       0.50      0.55      0.53       275

    accuracy                           0.84      1689
   macro avg       0.71      0.72      0.71      1689
weighted avg       0.84      0.84      0.84      1689
```



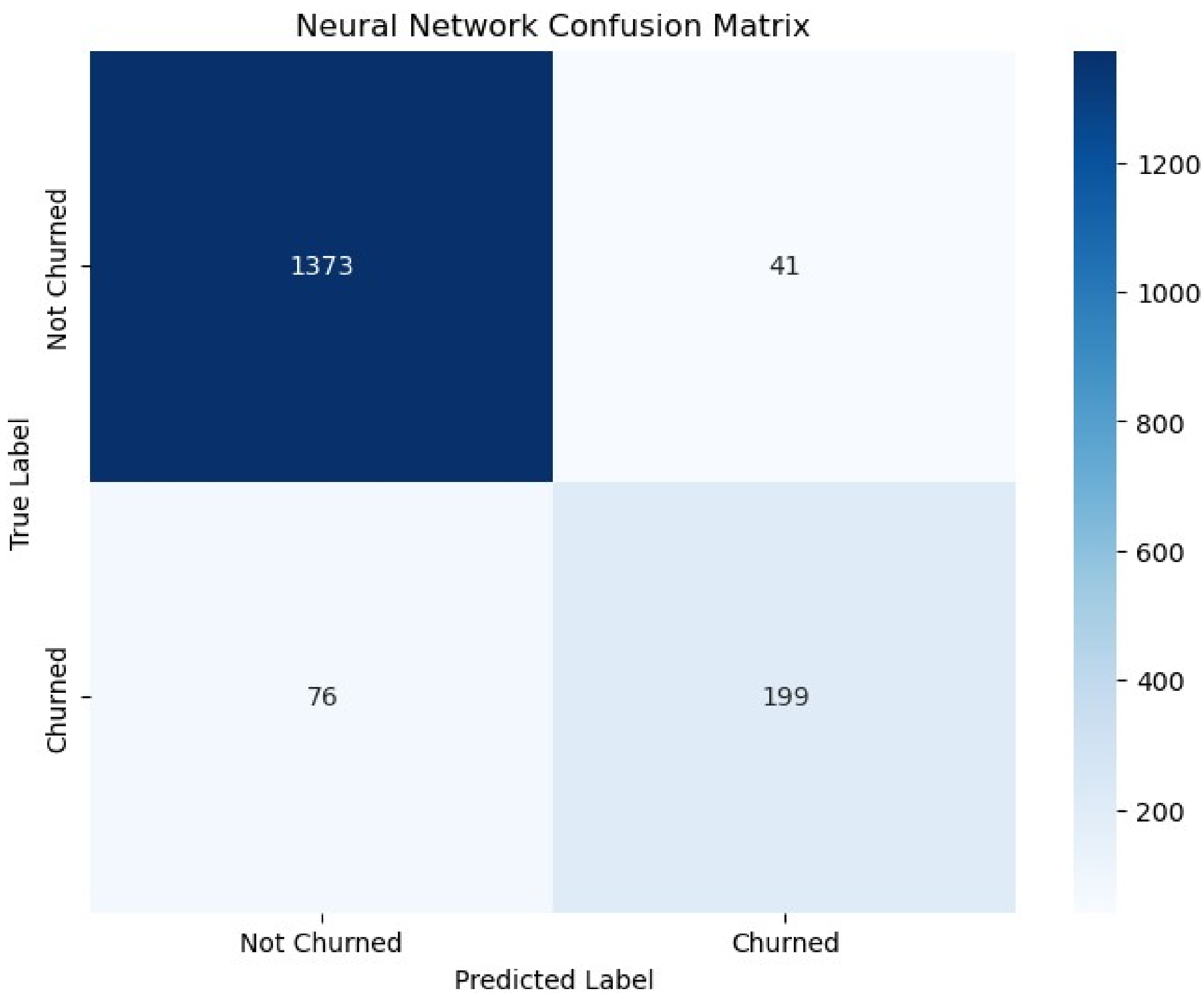

```
Naive Bayes without Cluster Feature:
Accuracy: 0.848
ROC AUC: 0.801
Classification Report:
              precision    recall  f1-score   support

           0       0.90      0.92      0.91      1414
           1       0.54      0.49      0.51       275

    accuracy                           0.85      1689
   macro avg       0.72      0.70      0.71      1689
weighted avg       0.84      0.85      0.85      1689
```




```
Neural Network with Cluster Feature:
Accuracy: 0.941
ROC AUC: 0.971
Classification Report:
              precision    recall  f1-score   support

           0       0.95      0.98      0.97      1414
           1       0.87      0.75      0.81       275

    accuracy                           0.94      1689
   macro avg       0.91      0.86      0.89      1689
weighted avg       0.94      0.94      0.94      1689
```



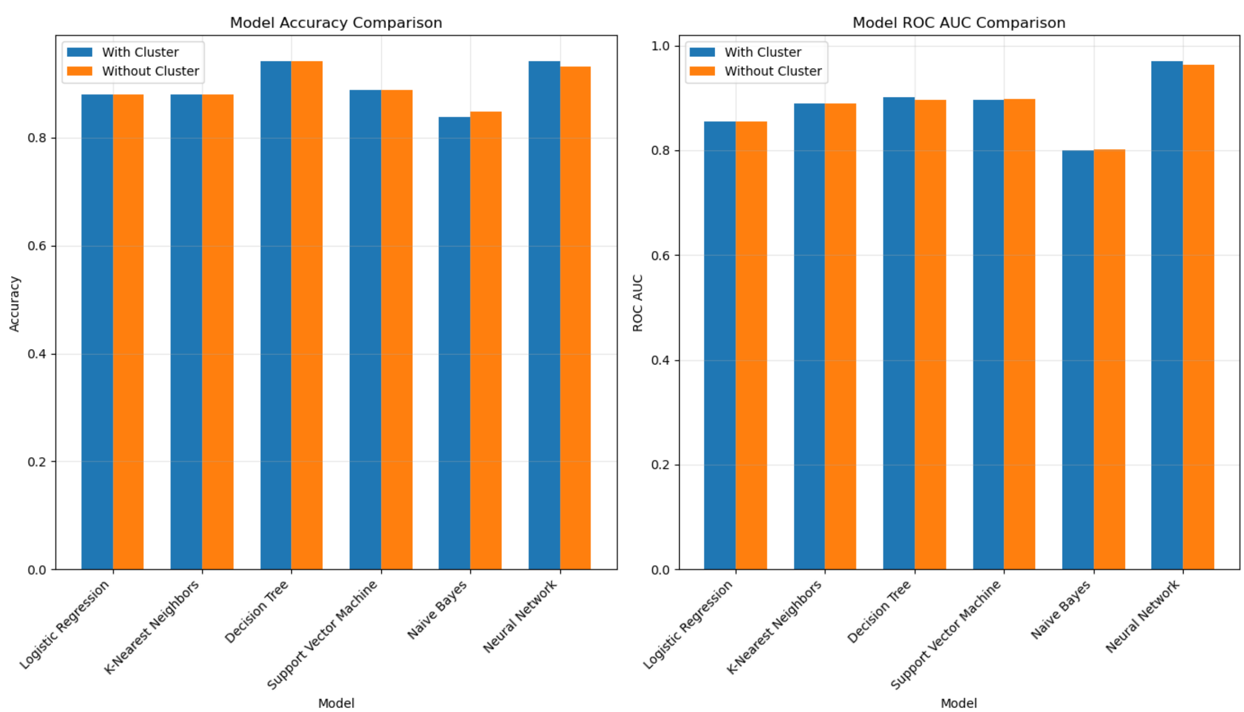

```
Neural Network without Cluster Feature:
Accuracy: 0.931
ROC AUC: 0.963
Classification Report:
              precision    recall  f1-score   support

           0       0.95      0.97      0.96      1414
           1       0.83      0.72      0.77       275

    accuracy                           0.93      1689
   macro avg       0.89      0.85      0.87      1689
weighted avg       0.93      0.93      0.93      1689
```




```
# Compile results
results_df = pd.DataFrame(results)
print("\nAll Classification Results:")
print(results_df.sort_values(['Accuracy', 'ROC AUC'],
ascending=False))

# Identify best model
best_model_row = results_df.loc[results_df['Accuracy'].idxmax()]
print(f"\nBest classification model: {best_model_row['Model']} {'with'
if best_model_row['With Cluster'] else 'without'} cluster feature")
print(f"Accuracy: {best_model_row['Accuracy']:.3f}")
print(f"ROC AUC: {best_model_row['ROC AUC']:.3f}")
print(f"F1 Score for Churned class: {best_model_row['F1
(Churned)']:.3f}")


All Classification Results:
                     Model  With Cluster  Accuracy   ROC AUC  F1
(Churned)
```

```
4             Decision Tree          True  0.941978  0.900905
0.825000
5             Decision Tree         False  0.941978  0.896512
0.823105
10           Neural Network          True  0.941385  0.970693
0.806262
11           Neural Network         False  0.930728  0.963495
0.772816
7   Support Vector Machine         False  0.888099  0.897413
0.535627
6   Support Vector Machine          True  0.888099  0.896423
0.531017
0      Logistic Regression          True  0.879811  0.854785
0.517815
3      K-Nearest Neighbors         False  0.879218  0.888781
0.536364
2      K-Nearest Neighbors          True  0.879218  0.888628
0.536364
1      Logistic Regression         False  0.879218  0.854116
0.516588
9              Naive Bayes         False  0.848431  0.801378
0.511450
8              Naive Bayes          True  0.837774  0.800093
0.525952

Best classification model: Decision Tree with cluster feature
Accuracy: 0.942
ROC AUC: 0.901
F1 Score for Churned class: 0.825

# Plotting the comparison of model accuracies and ROC AUC with and
without cluster feature
plt.figure(figsize=(14, 8))

# Subplot for Accuracy comparison
plt.subplot(1, 2, 1)
model_names = results_df['Model'].unique()
accuracies_with = results_df[results_df['With Cluster'] == True]
['Accuracy'].values
accuracies_without = results_df[results_df['With Cluster'] == False]
['Accuracy'].values

x = np.arange(len(model_names))
width = 0.35

# Bar plot for accuracies with and without cluster feature
plt.bar(x - width/2, accuracies_with, width, label='With Cluster')
plt.bar(x + width/2, accuracies_without, width, label='Without
Cluster')
plt.xlabel('Model')
```

```python
plt.ylabel('Accuracy')
plt.title('Model Accuracy Comparison')
plt.xticks(x, model_names, rotation=45, ha='right')
plt.legend()
plt.grid(alpha=0.3)

# Subplot for ROC AUC comparison
plt.subplot(1, 2, 2)
auc_with = results_df[results_df['With Cluster'] == True]['ROC AUC'].values
auc_without = results_df[results_df['With Cluster'] == False]['ROC AUC'].values

# Bar plot for ROC AUC with and without cluster feature
plt.bar(x - width/2, auc_with, width, label='With Cluster')
plt.bar(x + width/2, auc_without, width, label='Without Cluster')
plt.xlabel('Model')
plt.ylabel('ROC AUC')
plt.title('Model ROC AUC Comparison')
plt.xticks(x, model_names, rotation=45, ha='right')
plt.legend()
plt.grid(alpha=0.3)

# Adjust layout and show plot
plt.tight_layout()
plt.show()
```



```python
# Print the conclusion of the analysis
print("CONCLUSION")
print("="*50)

# Print the best clustering method and its details
print(f"1. Best Clustering Method: {best_clustering['Method']} with
{best_clustering['Number of Clusters']} clusters")

# Print the best classification model and its performance metrics
print(f"2. Best Classification Model: {best_model_row['Model']}
{'with' if best_model_row['With Cluster'] else 'without'} cluster
feature")
print(f"   - Accuracy: {best_model_row['Accuracy']:.3f}")
print(f"   - ROC AUC: {best_model_row['ROC AUC']:.3f}")
print(f"   - F1 Score (Churned): {best_model_row['F1
(Churned)']:.3f}")
```

```
CONCLUSION
==================================================
1. Best Clustering Method: Mean Shift with 7 clusters
2. Best Classification Model: Decision Tree with cluster feature
   - Accuracy: 0.942
   - ROC AUC: 0.901
   - F1 Score (Churned): 0.825
```

Conclusion

Mean Shift clustering identified seven customer segments with a 0.299 silhouette score. Cluster 2 had high churn (31.7%), while Clusters 3-5 had perfect retention. The largest segment (Cluster 0) had 5,505 customers with 16.9% churn.

Adding cluster assignments as features improved model performance. The Decision Tree classifier with cluster features achieved the highest accuracy (94.2%), ROC AUC (0.901), and F1 score (0.825). Neural Networks had the highest ROC AUC (0.971). This combined approach offers valuable insights for targeted retention strategies.

Key Learnings and Outcomes

We clustered the dataset using Agglomerative, K-Means, Mini-Batch K-Means, and Mean-Shift methods. Mean-Shift clustering outperformed others with a silhouette score of 0.299, identifying seven distinct customer segments.

For classification, we used Logistic Regression, K-Nearest Neighbors, Decision Trees, Support Vector Machine, Naive Bayes, and Neural Network. The Decision Tree classifier with cluster features achieved the highest performance with 94.2% accuracy, 0.901 ROC AUC, and 0.825 F1 score. Incorporating cluster features significantly improved classification performance, providing valuable insights for targeted retention strategies.

End of Project_Part_4