In [81]:
```python
# === 0) Setup
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

from sklearn.model_selection import train_test_split, StratifiedKFold, cross_validate
from sklearn.compose import ColumnTransformer
from sklearn.preprocessing import OneHotEncoder, StandardScaler
from sklearn.metrics import (
    roc_auc_score, average_precision_score, confusion_matrix, classification_report,auc,
    precision_recall_curve, roc_curve, accuracy_score, ConfusionMatrixDisplay
)
from sklearn.tree import DecisionTreeClassifier


from sklearn.pipeline import Pipeline
from sklearn.impute import SimpleImputer
from sklearn.inspection import permutation_importance

from imblearn.pipeline import Pipeline as ImbPipeline
from imblearn.over_sampling import SMOTE

from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
```

In [82]:
```python
#Loading data
df = pd.read_csv('bigml_59c28831336c6604c800002a.csv')

df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3333 entries, 0 to 3332
Data columns (total 21 columns):
 #   Column                  Non-Null Count  Dtype
---  ------                  --------------  -----
 0   state                   3333 non-null   object
 1   account length          3333 non-null   int64
 2   area code               3333 non-null   int64
 3   phone number            3333 non-null   object
 4   international plan      3333 non-null   object
 5   voice mail plan         3333 non-null   object
 6   number vmail messages   3333 non-null   int64
```

```
 7   total day minutes       3333 non-null   float64
 8   total day calls         3333 non-null   int64
 9   total day charge        3333 non-null   float64
 10  total eve minutes       3333 non-null   float64
 11  total eve calls         3333 non-null   int64
 12  total eve charge        3333 non-null   float64
 13  total night minutes     3333 non-null   float64
 14  total night calls       3333 non-null   int64
 15  total night charge      3333 non-null   float64
 16  total intl minutes      3333 non-null   float64
 17  total intl calls        3333 non-null   int64
 18  total intl charge       3333 non-null   float64
 19  customer service calls  3333 non-null   int64
 20  churn                   3333 non-null   bool
dtypes: bool(1), float64(8), int64(8), object(4)
memory usage: 524.2+ KB
```

In [83]:

```python
#checking the distibutions of the data
df['churn'].value_counts()
```

Out[83]:

```
False    2850
True      483
Name: churn, dtype: int64
```

In [84]:

```python
df.corr()
```

Out[84]:

	account length	area code	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
account length	1.000000	-0.012463	-0.004628	0.006216	0.038470	0.006214	-0.006757	0.019260	-0.006745	-0.008955	-0.013176	-0.008960	0.009514	0.02
area code	-0.012463	1.000000	-0.001994	-0.008264	-0.009646	-0.008264	0.003580	-0.011886	0.003607	-0.005825	0.016522	-0.005845	-0.018288	-0.02
number vmail messages	-0.004628	-0.001994	1.000000	0.000778	-0.009548	0.000776	0.017562	-0.005864	0.017578	0.007681	0.007123	0.007663	0.002856	0.01
total day minutes	0.006216	-0.008264	0.000778	1.000000	0.006750	1.000000	0.007043	0.015769	0.007029	0.004323	0.022972	0.004300	-0.010155	0.00
total day calls	0.038470	-0.009646	-0.009548	0.006750	1.000000	0.006753	-0.021451	0.006462	-0.021449	0.022938	-0.019557	0.022927	0.021565	0.00

	account length	area code	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
total day charge	0.006214	-0.008264	0.000776	1.000000	0.006753	1.000000	0.007050	0.015769	0.007036	0.004324	0.022972	0.004301	-0.010157	0.00
total eve minutes	-0.006757	0.003580	0.017562	0.007043	-0.021451	0.007050	1.000000	-0.011430	1.000000	-0.012584	0.007586	-0.012593	-0.011035	0.00
total eve calls	0.019260	-0.011886	-0.005864	0.015769	0.006462	0.015769	-0.011430	1.000000	-0.011423	-0.002093	0.007710	-0.002056	0.008703	0.01
total eve charge	-0.006745	0.003607	0.017578	0.007029	-0.021449	0.007036	1.000000	-0.011423	1.000000	-0.012592	0.007596	-0.012601	-0.011043	0.00
total night minutes	-0.008955	-0.005825	0.007681	0.004323	0.022938	0.004324	-0.012584	-0.002093	-0.012592	1.000000	0.011204	0.999999	-0.015207	-0.01
total night calls	-0.013176	0.016522	0.007123	0.022972	-0.019557	0.022972	0.007586	0.007710	0.007596	0.011204	1.000000	0.011188	-0.013605	0.00
total night charge	-0.008960	-0.005845	0.007663	0.004300	0.022927	0.004301	-0.012593	-0.002056	-0.012601	0.999999	0.011188	1.000000	-0.015214	-0.01
total intl minutes	0.009514	-0.018288	0.002856	-0.010155	0.021565	-0.010157	-0.011035	0.008703	-0.011043	-0.015207	-0.013605	-0.015214	1.000000	0.03
total intl calls	0.020661	-0.024179	0.013957	0.008033	0.004574	0.008032	0.002541	0.017434	0.002541	-0.012353	0.000305	-0.012329	0.032304	1.00
total intl charge	0.009546	-0.018395	0.002884	-0.010092	0.021666	-0.010094	-0.011067	0.008674	-0.011074	-0.015180	-0.013630	-0.015186	0.999993	0.03
customer service calls	-0.003796	0.027572	-0.013263	-0.013423	-0.018942	-0.013427	-0.012985	0.002423	-0.012987	-0.009288	-0.012802	-0.009277	-0.009640	-0.01
churn	0.016541	0.006174	-0.089728	0.205151	0.018459	0.205151	0.092796	0.009233	0.092786	0.035493	0.006141	0.035496	0.068239	-0.05

In [85]:

```
#dropping the columns that are not useful for the model
```

```python
columns_to_drop = [
    "phone number",
    "state",
    "area code",
    "total day charge",
    "total eve charge",
    "total night charge",
    "total intl charge"
]

df = df.drop(columns=columns_to_drop)
```

In [86]:
```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3333 entries, 0 to 3332
Data columns (total 14 columns):
 #   Column                  Non-Null Count  Dtype  
---  ------                  --------------  -----  
 0   account length          3333 non-null   int64  
 1   international plan      3333 non-null   object 
 2   voice mail plan         3333 non-null   object 
 3   number vmail messages   3333 non-null   int64  
 4   total day minutes       3333 non-null   float64
 5   total day calls         3333 non-null   int64  
 6   total eve minutes       3333 non-null   float64
 7   total eve calls         3333 non-null   int64  
 8   total night minutes     3333 non-null   float64
 9   total night calls       3333 non-null   int64  
 10  total intl minutes      3333 non-null   float64
 11  total intl calls        3333 non-null   int64  
 12  customer service calls  3333 non-null   int64  
 13  churn                   3333 non-null   bool   
dtypes: bool(1), float64(4), int64(7), object(2)
memory usage: 341.9+ KB
```

In [87]:
```python
# Converting categorical variables into numerical values
df["international plan"] = df["international plan"].map({"yes":1, "no":0}) # yes stands for churn and No for no churn
df["voice mail plan"] = df["voice mail plan"].map({"yes":1, "no":0}) # yes stands for churn and No for no churn
```

In [88]:
```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3333 entries, 0 to 3332
Data columns (total 14 columns):
```

```
 #   Column                  Non-Null Count  Dtype  
---  ------                  --------------  -----  
 0   account length          3333 non-null   int64  
 1   international plan      3333 non-null   int64  
 2   voice mail plan         3333 non-null   int64  
 3   number vmail messages   3333 non-null   int64  
 4   total day minutes       3333 non-null   float64
 5   total day calls         3333 non-null   int64  
 6   total eve minutes       3333 non-null   float64
 7   total eve calls         3333 non-null   int64  
 8   total night minutes     3333 non-null   float64
 9   total night calls       3333 non-null   int64  
 10  total intl minutes      3333 non-null   float64
 11  total intl calls        3333 non-null   int64  
 12  customer service calls  3333 non-null   int64  
 13  churn                   3333 non-null   bool   
dtypes: bool(1), float64(4), int64(9)
memory usage: 341.9 KB
```

In [89]:
```python
df['churn'] = df['churn'].astype(int)# 1 stands for churn and 0 for no churn
```

In [90]:
```python
# Selecting features and target variable

X = df.drop(columns=['churn'])
y = df['churn']

X
```

Out[90]:

	account length	international plan	voice mail plan	number vmail messages	total day minutes	total day calls	total eve minutes	total eve calls	total night minutes	total night calls	total intl minutes	total intl calls	customer service calls
0	128	0	1	25	265.1	110	197.4	99	244.7	91	10.0	3	1
1	107	0	1	26	161.6	123	195.5	103	254.4	103	13.7	3	1
2	137	0	0	0	243.4	114	121.2	110	162.6	104	12.2	5	0
3	84	1	0	0	299.4	71	61.9	88	196.9	89	6.6	7	2
4	75	1	0	0	166.7	113	148.3	122	186.9	121	10.1	3	3
...	...	...	...	...	...	...	...	...	...	...	...	...	...
3328	192	0	1	36	156.2	77	215.5	126	279.1	83	9.9	6	2
3329	68	0	0	0	231.1	57	153.4	55	191.3	123	9.6	4	3

	account length	international plan	voice mail plan	number vmail messages	total day minutes	total day calls	total eve minutes	total eve calls	total night minutes	total night calls	total intl minutes	total intl calls	customer service calls
3330	28	0	0	0	180.8	109	288.8	58	191.9	91	14.1	6	2
3331	184	1	0	0	213.8	105	159.6	84	139.2	137	5.0	10	2
3332	74	0	1	25	234.4	113	265.9	82	241.4	77	13.7	4	0

3333 rows × 13 columns

In [91]:

```
# splitting the data into training and testing sets

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42, stratify=y)

# Checking the info and size of the training and testing sets
X_test.info()
X_train.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 667 entries, 601 to 1962
Data columns (total 13 columns):
 #   Column                  Non-Null Count  Dtype
---  ------                  --------------  -----
 0   account length          667 non-null    int64
 1   international plan      667 non-null    int64
 2   voice mail plan         667 non-null    int64
 3   number vmail messages   667 non-null    int64
 4   total day minutes       667 non-null    float64
 5   total day calls         667 non-null    int64
 6   total eve minutes       667 non-null    float64
 7   total eve calls         667 non-null    int64
 8   total night minutes     667 non-null    float64
 9   total night calls       667 non-null    int64
 10  total intl minutes      667 non-null    float64
 11  total intl calls        667 non-null    int64
 12  customer service calls  667 non-null    int64
dtypes: float64(4), int64(9)
memory usage: 73.0 KB
<class 'pandas.core.frame.DataFrame'>
Int64Index: 2666 entries, 3286 to 2762
Data columns (total 13 columns):
 #   Column                  Non-Null Count  Dtype
---  ------                  --------------  -----
 0   account length          2666 non-null   int64
```

```
 1   international plan      2666 non-null   int64
 2   voice mail plan         2666 non-null   int64
 3   number vmail messages   2666 non-null   int64
 4   total day minutes       2666 non-null   float64
 5   total day calls         2666 non-null   int64
 6   total eve minutes       2666 non-null   float64
 7   total eve calls         2666 non-null   int64
 8   total night minutes     2666 non-null   float64
 9   total night calls       2666 non-null   int64
 10  total intl minutes      2666 non-null   float64
 11  total intl calls        2666 non-null   int64
 12  customer service calls  2666 non-null   int64
dtypes: float64(4), int64(9)
memory usage: 291.6 KB
```

In [92]:
```
X.describe()
```

Out[92]:

	account length	international plan	voice mail plan	number vmail messages	total day minutes	total day calls	total eve minutes	total eve calls	total night minutes	total night calls	total intl minutes	
count	3333.000000	3333.000000	3333.000000	3333.000000	3333.000000	3333.000000	3333.000000	3333.000000	3333.000000	3333.000000	3333.000000	33.
mean	101.064806	0.096910	0.276628	8.099010	179.775098	100.435644	200.980348	100.114311	200.872037	100.107711	10.237294	
std	39.822106	0.295879	0.447398	13.688365	54.467389	20.069084	50.713844	19.922625	50.573847	19.568609	2.791840	
min	1.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	23.200000	33.000000	0.000000	
25%	74.000000	0.000000	0.000000	0.000000	143.700000	87.000000	166.600000	87.000000	167.000000	87.000000	8.500000	
50%	101.000000	0.000000	0.000000	0.000000	179.400000	101.000000	201.400000	100.000000	201.200000	100.000000	10.300000	
75%	127.000000	0.000000	1.000000	20.000000	216.400000	114.000000	235.300000	114.000000	235.300000	113.000000	12.100000	
max	243.000000	1.000000	1.000000	51.000000	350.800000	165.000000	363.700000	170.000000	395.000000	175.000000	20.000000	

In [93]:
```
# We need to standardize the data before feeding it to the model
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)
```

In [94]:
```
#fit the model and balance the highly imbalanced classes using class_weight parameter
model = LogisticRegression(class_weight="balanced",random_state=42)
```

```
model.fit(X_train_scaled, y_train)
```

Out[94]:

```
LogisticRegression(class_weight='balanced', random_state=42)
```

In [95]:

```
#make predictions
y_pred = model.predict(X_test_scaled)
y_pred_proba = model.predict_proba(X_test_scaled)[:, 1]
print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

           0       0.95      0.76      0.84       570
           1       0.35      0.74      0.47        97

    accuracy                           0.76       667
   macro avg       0.65      0.75      0.66       667
weighted avg       0.86      0.76      0.79       667
```

In [96]:

```
# Evaluate the model using ROC AUC and Average Precision Score
print("Accuracy:", accuracy_score(y_test, y_pred))
print(classification_report(y_test, y_pred))
print("ROC AUC:", roc_auc_score(y_test, y_pred_proba))
```

```
Accuracy: 0.7586206896551724
              precision    recall  f1-score   support

           0       0.95      0.76      0.84       570
           1       0.35      0.74      0.47        97

    accuracy                           0.76       667
   macro avg       0.65      0.75      0.66       667
weighted avg       0.86      0.76      0.79       667

ROC AUC: 0.8151021884608429
```

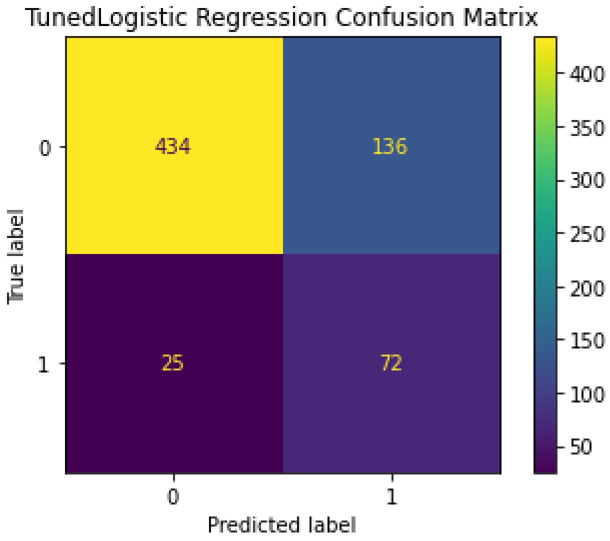
Interpretaion:

The model shows good discrimination ability (ROC AUC 0.815) but struggles with precision for the minority class (class 1). This means it identifies positives well but also produces many false positives.

In [97]:

```
cm = confusion_matrix(y_test, y_pred)

fig, ax = plt.subplots()
```

```python
display = ConfusionMatrixDisplay(confusion_matrix=cm)
display.plot(ax=ax)

ax.set_title("TunedLogistic Regression Confusion Matrix")
plt.show()
```



In [98]:
```python
TP = 72
FP = 136
TN = 434
FN = 25


Precision = TP / (TP + FP)
Recall = TP / (TP + FN)
F1_Score = 2 * (Precision * Recall) / (Precision + Recall)
print(f"Precision: {Precision:.3f}")
print(f"Recall: {Recall:.3f}")
print(f"F1 Score: {F1_Score:.3f}")
```

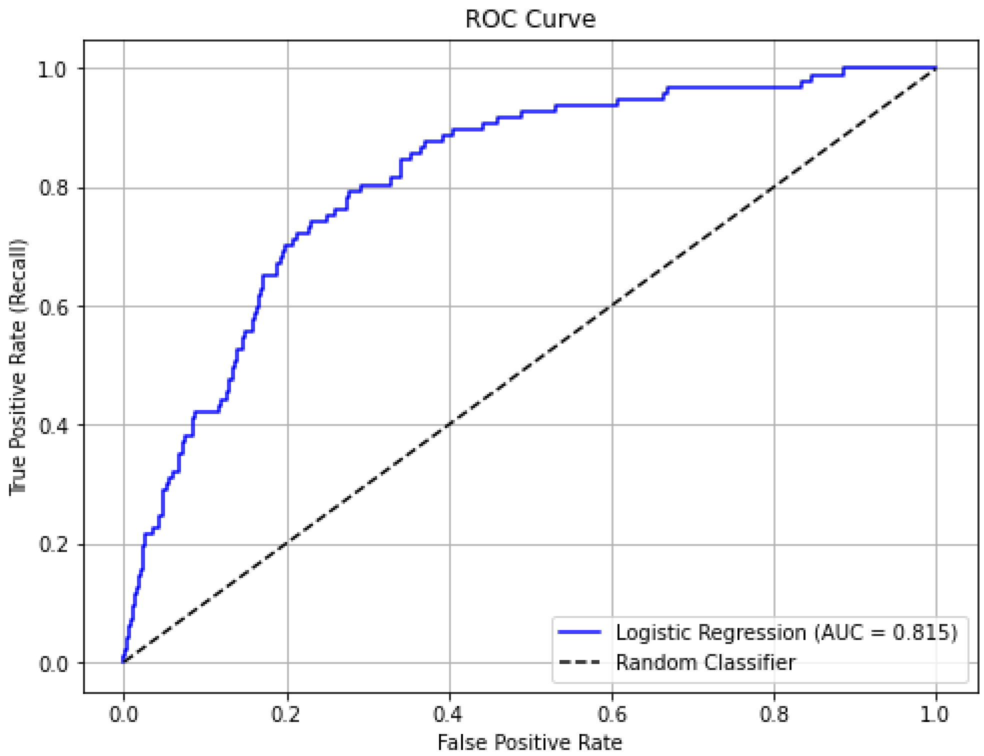
```
Precision: 0.346
Recall: 0.742
F1 Score: 0.472
```

Interpretation:

F1 score is low since the precision score is low and the score of 0.472 , while recall is at 0.742 meaning it correctly identifies 74% of customers who actual churned. Having a low precison means it picks more clients as churned thus the company using its resources to deal with clients who were not churning.

In [99]:
```
roc_auc = roc_auc_score(y_test, y_pred_proba)
print("ROC AUC Score:", roc_auc)


fpr, tpr, thresholds = roc_curve(y_test, y_pred_proba)

plt.figure(figsize=(8,6))
plt.plot(fpr, tpr, label=f'Logistic Regression (AUC = {roc_auc:.3f})', color='blue')
plt.plot([0,1], [0,1], 'k--', label='Random Classifier')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate (Recall)')
plt.title('ROC Curve')
plt.legend(loc='lower right')
plt.grid(True)
plt.show()
```

```
ROC AUC Score: 0.8151021884608429
```



Decision tree

In [100…

```
#instantiate our tree and balancing the imbalanced data
dt = DecisionTreeClassifier(
    max_depth=5,
    min_samples_split=20,
    class_weight="balanced",
    random_state=42
)  # here we are still balancing the data as the data for target has class heavily imbalanced

dt.fit(X_train, y_train)
```

Out[100…

```
DecisionTreeClassifier(class_weight='balanced', max_depth=5,
                       min_samples_split=20, random_state=42)
```

In [101…

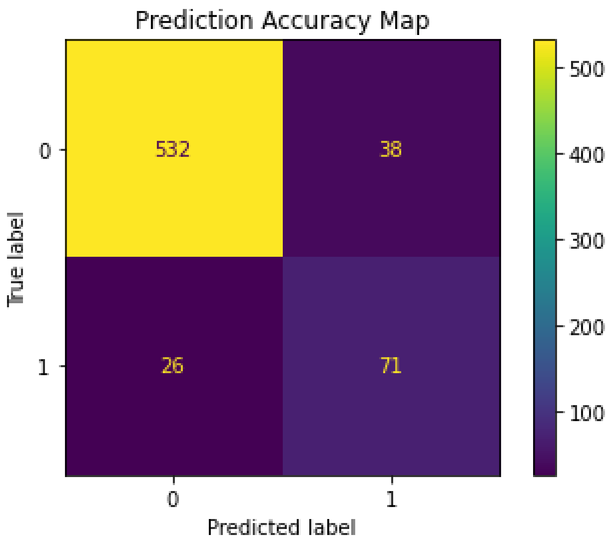
```
#Predict on the test data
y_pred_dt = dt.predict(X_test)
y_prob_dt = dt.predict_proba(X_test)[:, 1]
```

```
#Evaluate the model
print("Classification Report:\n", classification_report(y_test, y_pred_dt))
print("Decision Tree Performance:", accuracy_score(y_test, y_pred_dt))
```

```
Classification Report:
               precision    recall  f1-score   support

           0       0.95      0.93      0.94       570
           1       0.65      0.73      0.69        97

    accuracy                           0.90       667
   macro avg       0.80      0.83      0.82       667
weighted avg       0.91      0.90      0.91       667

Decision Tree Performance: 0.904047976011994
```

In [108…

```
cm = confusion_matrix(y_test, y_pred_dt)

fig, ax = plt.subplots()

display = ConfusionMatrixDisplay(confusion_matrix=cm)
display.plot(ax=ax)

ax.set_title("Prediction Accuracy Map")
plt.show()
```



Interpretation

The weighting did improve recall for churners (0.73), meaning the model is catching more of the clients at risk of leaving.

Precision for churn (0.65) is still relatively low, so the model raises some false alarms — but in churn prediction, false positives are usually less costly than false negatives (better to flag a client who won't leave than miss one who will).

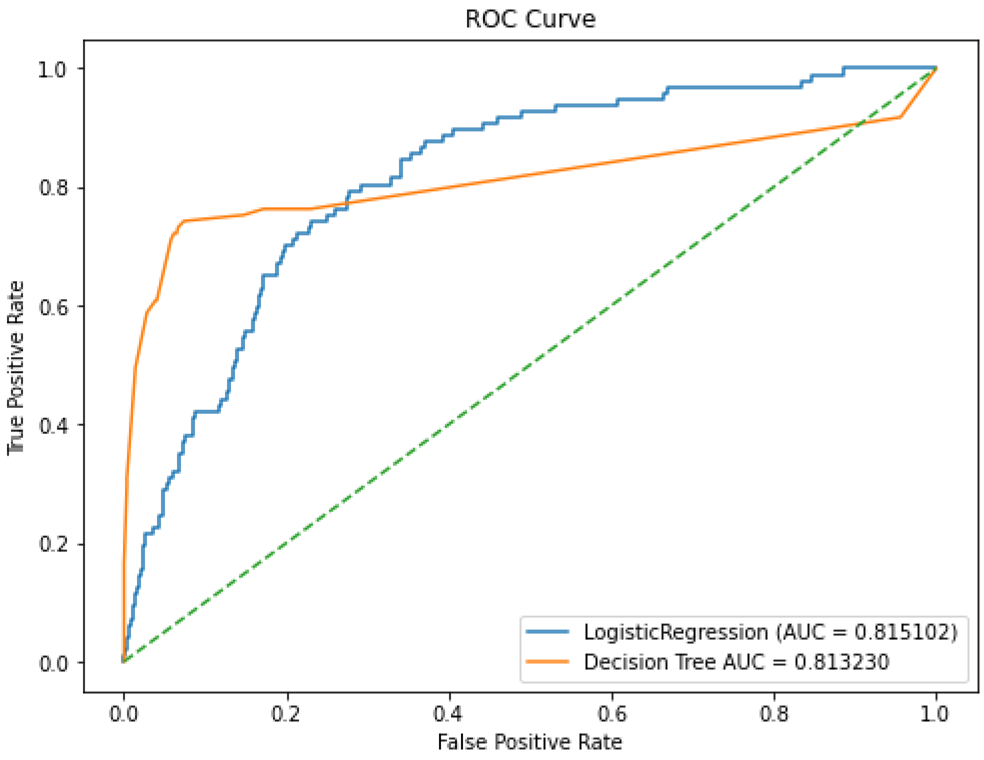
The model is now more balanced: it doesn't just favor the majority class (non-churn), but still struggles to achieve the same precision/recall levels for churn as for non-churn.

In [103…

```
# Compare both models using ROC


lr_fpr, lr_tpr, i = roc_curve(y_test, y_pred_proba)
dt_fpr, dt_tpr, i = roc_curve(y_test, y_prob_dt)

lr_auc = auc(lr_fpr, lr_tpr)
dt_auc = auc(dt_fpr, dt_tpr)
```

In [107…

```
plt.figure(figsize=(8, 6))
plt.plot(lr_fpr, lr_tpr, label=f'LogisticRegression (AUC = {lr_auc:2f})')
plt.plot(dt_fpr, dt_tpr, label=f'Decision Tree AUC = {dt_auc:2f}')
plt.plot([0,1], [0, 1], linestyle='--')

plt.xlabel('False Positive Rate')
plt.title('ROC Curve')
plt.ylabel('True Positive Rate')
plt.legend()
plt.show()
```



Conclusion

Both the logistic regregression and the decision tree model achieved an AUC of 0.81, indicating good discrimination ability.The models can coreectly distinguish between a churned client and a non churned client , 81% of the time thus a can be used to support customer retention strategy.