Predicting Customer Churn in a Telecommunications Company

Problem Statemenet

Customer churn is a significant issue in the telecommunications industry. Retaining existing customers is often more cost-effective than acquiring new ones. By analyzing customer data, we can identify patterns and factors that contribute to churn, enabling the company to take proactive measures to retain customers.

1. Import Libraries

In [56]:
```
# Data manipulation and analysis
import pandas as pd
import numpy as np

# Visualization
import matplotlib.pyplot as plt
import seaborn as sns

# Machine Learning
from sklearn.model_selection import train_test_split, GridSearchCV, Stratified
from sklearn.preprocessing import LabelEncoder, StandardScaler
from sklearn.feature_selection import RFECV
from sklearn.metrics import classification_report, confusion_matrix, roc_curve
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier

# Handling imbalanced data
from imblearn.over_sampling import SMOTE

# Suppress warnings
import warnings

warnings.filterwarnings("ignore")
```

2. Load Dataset

In [57]:
```
# Load the dataset
df = pd.read_csv("WA_Fn-UseC_-Telco-Customer-Churn.csv")

# Display first few rows
df.head()
```

Out[57]:

	customerID	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLine
0	7590-VHVEG	Female	0	Yes	No	1	No	No phon servic
1	5575-GNVDE	Male	0	No	No	34	Yes	N
2	3668-QPYBK	Male	0	No	No	2	Yes	N
3	7795-CFOCW	Male	0	No	No	45	No	No phon servic
4	9237-HQITU	Female	0	No	No	2	Yes	N

5 rows × 21 columns

This dataset contains information about a telecom company's customers, including:

- Customer account information (customerID, tenure, contract type, payment method, monthly charges, total charges).
- Demographic information (gender, age range, senior citizen status, partner, dependents).
- Services subscribed (phone service, multiple lines, internet service, online security, online backup, device protection, tech support, streaming TV, streaming movies).
- The target variable is Churn, indicating whether the customer left within the last month.

In [58]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7043 entries, 0 to 7042
Data columns (total 21 columns):
 #   Column            Non-Null Count  Dtype  
---  ------            --------------  -----  
 0   customerID        7043 non-null   object 
 1   gender            7043 non-null   object 
 2   SeniorCitizen     7043 non-null   int64  
 3   Partner           7043 non-null   object 
 4   Dependents        7043 non-null   object 
 5   tenure            7043 non-null   int64  
 6   PhoneService      7043 non-null   object 
 7   MultipleLines     7043 non-null   object 
 8   InternetService   7043 non-null   object 
 9   OnlineSecurity    7043 non-null   object 
 10  OnlineBackup      7043 non-null   object 
 11  DeviceProtection  7043 non-null   object 
 12  TechSupport       7043 non-null   object 
 13  StreamingTV       7043 non-null   object 
 14  StreamingMovies   7043 non-null   object 
 15  Contract          7043 non-null   object 
 16  PaperlessBilling  7043 non-null   object 
 17  PaymentMethod     7043 non-null   object 
 18  MonthlyCharges    7043 non-null   float64
 19  TotalCharges      7043 non-null   object 
 20  Churn             7043 non-null   object 
dtypes: float64(1), int64(2), object(18)
memory usage: 1.1+ MB
```

3. Data Cleaning for EDA

3.1. Convert TotalCharges to Numeric

In [59]:
```python
# Convert 'TotalCharges' to numeric, coerce errors to NaN
df["TotalCharges"] = pd.to_numeric(df["TotalCharges"], errors="coerce")

# Check for missing values in 'TotalCharges'
missing_total_charges = df["TotalCharges"].isnull().sum()
print(f"Total missing values in 'TotalCharges': {missing_total_charges}")
```

```
Total missing values in 'TotalCharges': 11
```

3.2 Handle Missing Values

In [60]:
```python
# Drop rows with missing 'TotalCharges'
df = df.dropna(subset=["TotalCharges"])

# Reset index
df.reset_index(drop=True, inplace=True)
```

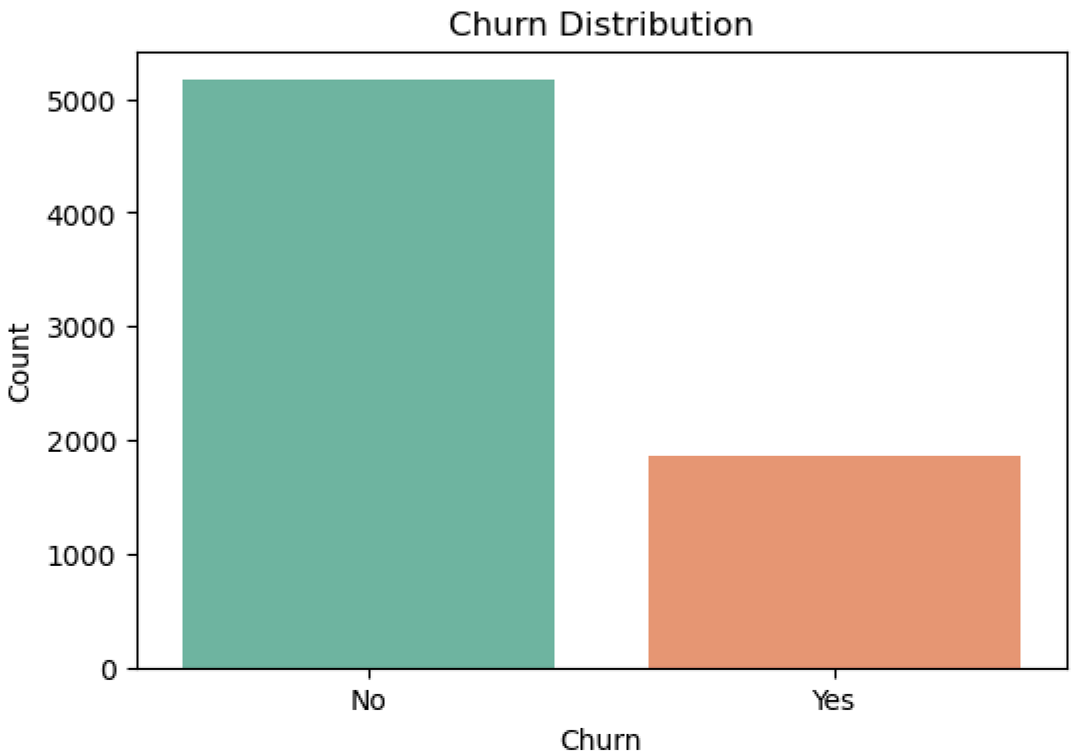
3.3 Remove Unnecessary Columns

In [61]:
```python
# Drop 'customerID' as it's not useful for prediction
df = df.drop(columns=["customerID"])
```

4. Exploratory Data Analysis (EDA)

4.1 Churn Distribution

In [62]:
```
# Count plot for 'Churn'
plt.figure(figsize=(6, 4))
sns.countplot(x="Churn", data=df, palette="Set2")
plt.title("Churn Distribution")
plt.xlabel("Churn")
plt.ylabel("Count")
plt.show()
```



The dataset is imbalanced with more ‘No’ churn instances than ‘Yes’.

4.2 Churn Rate by Contract Type

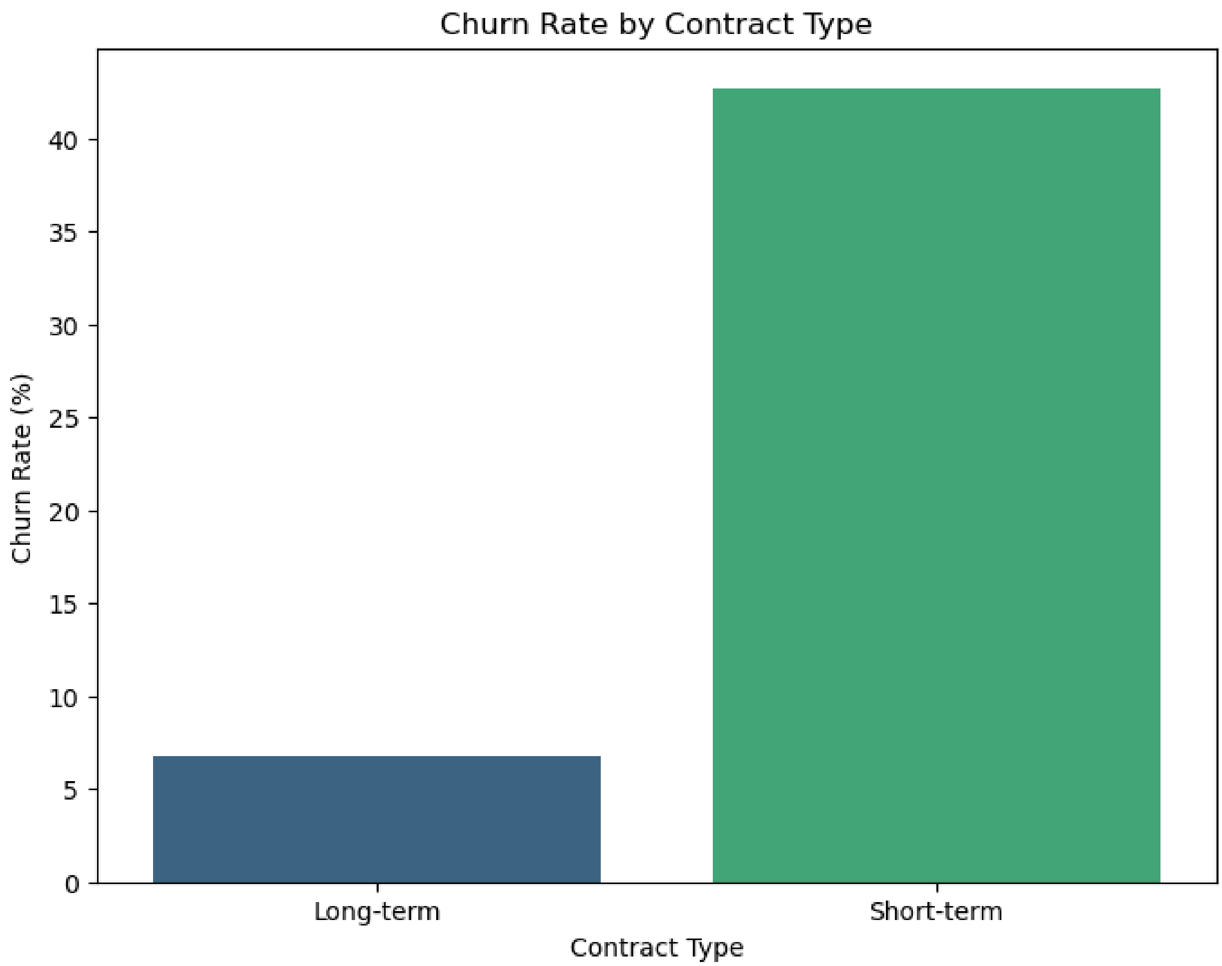
In [63]:
```
# Create 'Contract_Type' variable
df["Contract_Type"] = df["Contract"].apply(
    lambda x: "Short-term" if x == "Month-to-month" else "Long-term"
)
# Map 'Churn' to numeric for calculation
df["Churn_numeric"] = df["Churn"].map({"No": 0, "Yes": 1})

# Calculate churn rate
churn_rate = df.groupby("Contract_Type")["Churn_numeric"].mean().reset_index()
churn_rate["Churn_Rate (%)"] = churn_rate["Churn_numeric"] * 100
churn_rate = churn_rate.drop(columns=["Churn_numeric"])
churn_rate
```

Out[63]:

	Contract_Type	Churn_Rate (%)
0	Long-term	6.778587
1	Short-term	42.709677

In [64]:
```
plt.figure(figsize=(8, 6))
sns.barplot(x="Contract_Type", y="Churn_Rate (%)", data=churn_rate, palette="vi
plt.title("Churn Rate by Contract Type")
plt.xlabel("Contract Type")
plt.ylabel("Churn Rate (%)")
plt.show()
```

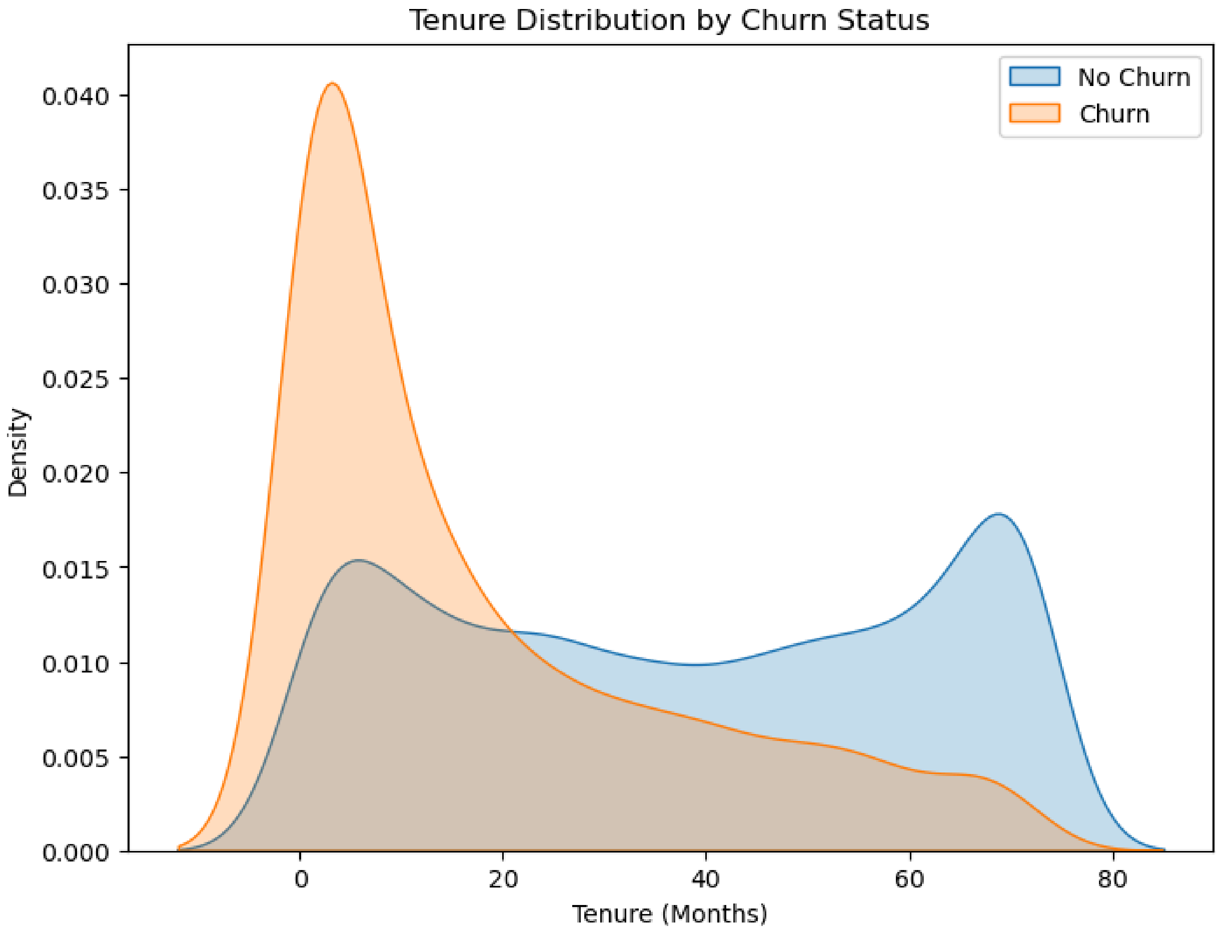


Short-term contracts have a significantly higher churn rate compared to long-term contracts.

4.3 Tenure vs. Churn

In [65]:
```
# Distribution plots for tenure
plt.figure(figsize=(8, 6))
sns.kdeplot(df[df["Churn"] == "No"]["tenure"], label="No Churn", shade=True)
sns.kdeplot(df[df["Churn"] == "Yes"]["tenure"], label="Churn", shade=True)
plt.title("Tenure Distribution by Churn Status")
plt.xlabel("Tenure (Months)")
plt.ylabel("Density")
```

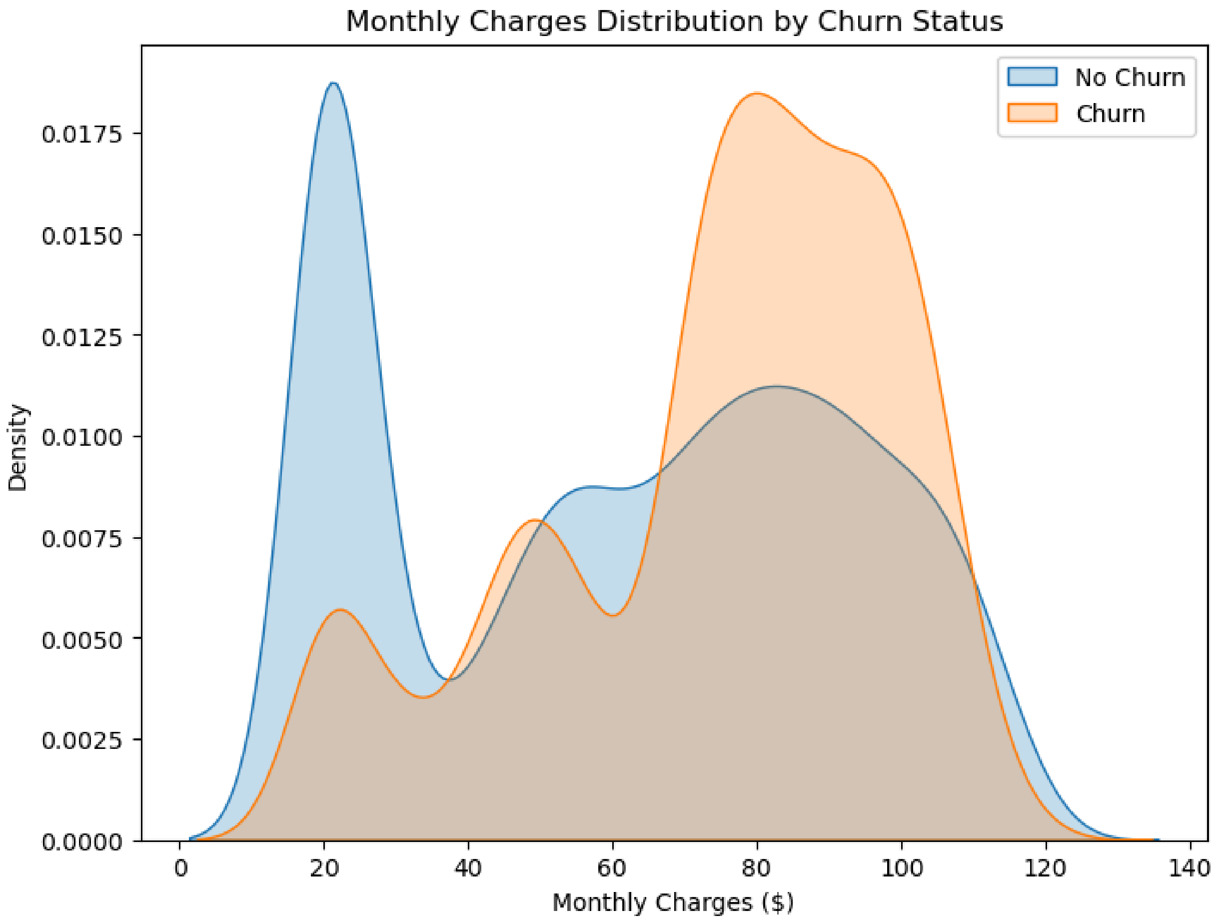
```
plt.legend()
plt.show()
```



Customers with shorter tenure are more likely to churn.

4.4 Monthly Charges vs. Churn

In [67]:
```
# Distribution plots for MonthlyCharges
plt.figure(figsize=(8, 6))
sns.kdeplot(df[df["Churn"] == "No"]["MonthlyCharges"], label="No Churn", shade=
sns.kdeplot(df[df["Churn"] == "Yes"]["MonthlyCharges"], label="Churn", shade=T
plt.title("Monthly Charges Distribution by Churn Status")
plt.xlabel("Monthly Charges ($)")
plt.ylabel("Density")
plt.legend()
plt.show()
```



Customers with higher monthly charges tend to churn more.

5. Data Preprocessing and Encoding

5.1 Encode Binary Variables

In [31]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7032 entries, 0 to 7031
Data columns (total 22 columns):
 #   Column            Non-Null Count  Dtype  
---  ------            --------------  -----  
 0   gender            7032 non-null   object 
 1   SeniorCitizen     7032 non-null   int64  
 2   Partner           7032 non-null   object 
 3   Dependents        7032 non-null   object 
 4   tenure            7032 non-null   int64  
 5   PhoneService      7032 non-null   object 
 6   MultipleLines     7032 non-null   object 
 7   InternetService   7032 non-null   object 
 8   OnlineSecurity    7032 non-null   object 
 9   OnlineBackup      7032 non-null   object 
 10  DeviceProtection  7032 non-null   object 
 11  TechSupport       7032 non-null   object 
 12  StreamingTV       7032 non-null   object 
 13  StreamingMovies   7032 non-null   object 
 14  Contract          7032 non-null   object 
 15  PaperlessBilling  7032 non-null   object 
 16  PaymentMethod     7032 non-null   object 
 17  MonthlyCharges    7032 non-null   float64
 18  TotalCharges      7032 non-null   float64
 19  Churn             7032 non-null   object 
 20  Contract_Type     7032 non-null   object 
 21  Churn_numeric     7032 non-null   int64  
dtypes: float64(2), int64(3), object(17)
memory usage: 1.2+ MB
```

In [32]:

```
# List of binary variables to map
binary_features = ["Partner", "Dependents", "PhoneService", "PaperlessBilling"

# Map 'Yes' to 1 and 'No' to 0
for col in binary_features:
    df[col] = df[col].map({"Yes": 1, "No": 0})
```

In [33]:

```
df.head()
```

Out[33]:

	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines	InternetSe
0	Female	0	1	0	1	0	No phone service	
1	Male	0	0	0	34	1	No	
2	Male	0	0	0	2	1	No	
3	Male	0	0	0	45	0	No phone service	
4	Female	0	0	0	2	1	No	Fiber

5 rows × 22 columns

In [34]:

```
# Map 'Short-term' to 0 and 'Long-term' to 1
df["Contract_Type"] = df["Contract_Type"].map({"Short-term": 0, "Long-term": 1
```

5.2 One-Hot Encode Categorical Variables

In [35]:
```
# Identify categorical variables for one-hot encoding
categorical_vars = [
    "gender",
    "MultipleLines",
    "InternetService",
    "OnlineSecurity",
    "OnlineBackup",
    "DeviceProtection",
    "TechSupport",
    "StreamingTV",
    "StreamingMovies",
    "Contract",
    "PaymentMethod",
]

# Perform one-hot encoding
df_encoded = pd.get_dummies(df, columns=categorical_vars, drop_first=True)
```

In [36]:
```
# Drop 'Contract' variable since we have created Contract_Type, we can drop the
df_encoded = df_encoded.drop(columns=["Contract_Two year", "Contract_One year"
```

In [37]:
```
df_encoded=df_encoded.drop(columns=["Churn_numeric"],axis=1)
```

5.3 Handle Remaining Missing Values

In [38]:
```
df_encoded.head()
```

Out[38]:

	SeniorCitizen	Partner	Dependents	tenure	PhoneService	PaperlessBilling	MonthlyCharges
0	0	1	0	1	0	1	29.85
1	0	0	0	34	1	0	56.95
2	0	0	0	2	1	1	53.85
3	0	0	0	45	0	0	42.30
4	0	0	0	2	1	1	70.70

5 rows × 30 columns

In [39]:
```
# Check for remaining missing values
df_encoded.isnull().sum()
```

Out[39]:
```
SeniorCitizen                            0
Partner                                  0
Dependents                               0
tenure                                   0
PhoneService                             0
PaperlessBilling                         0
MonthlyCharges                           0
TotalCharges                             0
Churn                                    0
Contract_Type                            0
gender_Male                              0
MultipleLines_No phone service           0
MultipleLines_Yes                        0
InternetService_Fiber optic              0
InternetService_No                       0
OnlineSecurity_No internet service       0
OnlineSecurity_Yes                       0
OnlineBackup_No internet service         0
OnlineBackup_Yes                         0
DeviceProtection_No internet service     0
DeviceProtection_Yes                     0
TechSupport_No internet service          0
TechSupport_Yes                          0
StreamingTV_No internet service          0
StreamingTV_Yes                          0
StreamingMovies_No internet service      0
StreamingMovies_Yes                      0
PaymentMethod_Credit card (automatic)    0
PaymentMethod_Electronic check           0
PaymentMethod_Mailed check               0
dtype: int64
```

5.4 Feature Scaling

In [40]:
```python
# List of numerical features
numerical_features = ["tenure", "MonthlyCharges", "TotalCharges"]

# Initialize the scaler
scaler = StandardScaler()

# Scale numerical features
df_encoded[numerical_features] = scaler.fit_transform(df_encoded[numerical_fea
```

6. Machine Learning Modeling

6.1 Define Features and Target

In [41]:
```python
# Define target variable 'Churn'
y = df_encoded["Churn"]

# Define feature set 'X'
X = df_encoded.drop(columns=["Churn"])
```

6.2 Handling Class Imbalance

In [42]:
```
# Check class distribution
y.value_counts(normalize=True)
```

Out[42]:
```
Churn
0    0.734215
1    0.265785
Name: proportion, dtype: float64
```

the dataset is imbalanced. So applyng SMOTE to balance classes

In [43]:
```
# Initialize SMOTE
smote = SMOTE(random_state=42)

# Fit SMOTE to features and target
X_resampled, y_resampled = smote.fit_resample(X, y)

# Check new class distribution
y_resampled.value_counts(normalize=True)
```

Out[43]:
```
Churn
0    0.5
1    0.5
Name: proportion, dtype: float64
```

6.3 Split the Data

In [44]:
```
# Split into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(
    X_resampled, y_resampled, test_size=0.2, random_state=42, stratify=y_resam
)
```

6.4 Feature Selection

Use Recursive Feature Elimination with Cross-Validation (RFECV)

In [45]:
```
# Initialize Logistic Regression model
model = LogisticRegression(max_iter=1000, random_state=42)

# Initialize RFECV
rfecv = RFECV(estimator=model, step=1, cv=StratifiedKFold(5), scoring="accurac

# Fit RFECV
rfecv.fit(X_train, y_train)

# Optimal number of features
print(f"Optimal number of features: {rfecv.n_features_}")

# Selected features
selected_features = X_train.columns[rfecv.support_]
print("Selected features:", list(selected_features))
```

```
Optimal number of features: 25
Selected features: ['Dependents', 'tenure', 'PhoneService', 'MonthlyCharges',
'TotalCharges', 'Contract_Type', 'MultipleLines_No phone service', 'MultipleLi
nes_Yes', 'InternetService_Fiber optic', 'InternetService_No', 'OnlineSecurity
_No internet service', 'OnlineSecurity_Yes', 'OnlineBackup_No internet servic
e', 'OnlineBackup_Yes', 'DeviceProtection_No internet service', 'DeviceProtect
ion_Yes', 'TechSupport_No internet service', 'TechSupport_Yes', 'StreamingTV_N
o internet service', 'StreamingTV_Yes', 'StreamingMovies_No internet service',
'StreamingMovies_Yes', 'PaymentMethod_Credit card (automatic)', 'PaymentMethod
_Electronic check', 'PaymentMethod_Mailed check']
```

6.5 Model Training and Evaluation

6.5.1 Logistic Regression

In [46]:

```
# Create Logistic Regression model with selected features
lr_model = LogisticRegression(max_iter=1000, random_state=42)
lr_model.fit(X_train[selected_features], y_train)

# Predict on test set
y_pred_lr = lr_model.predict(X_test[selected_features])

# Classification report
print("Logistic Regression Classification Report:")
print(classification_report(y_test, y_pred_lr))
```

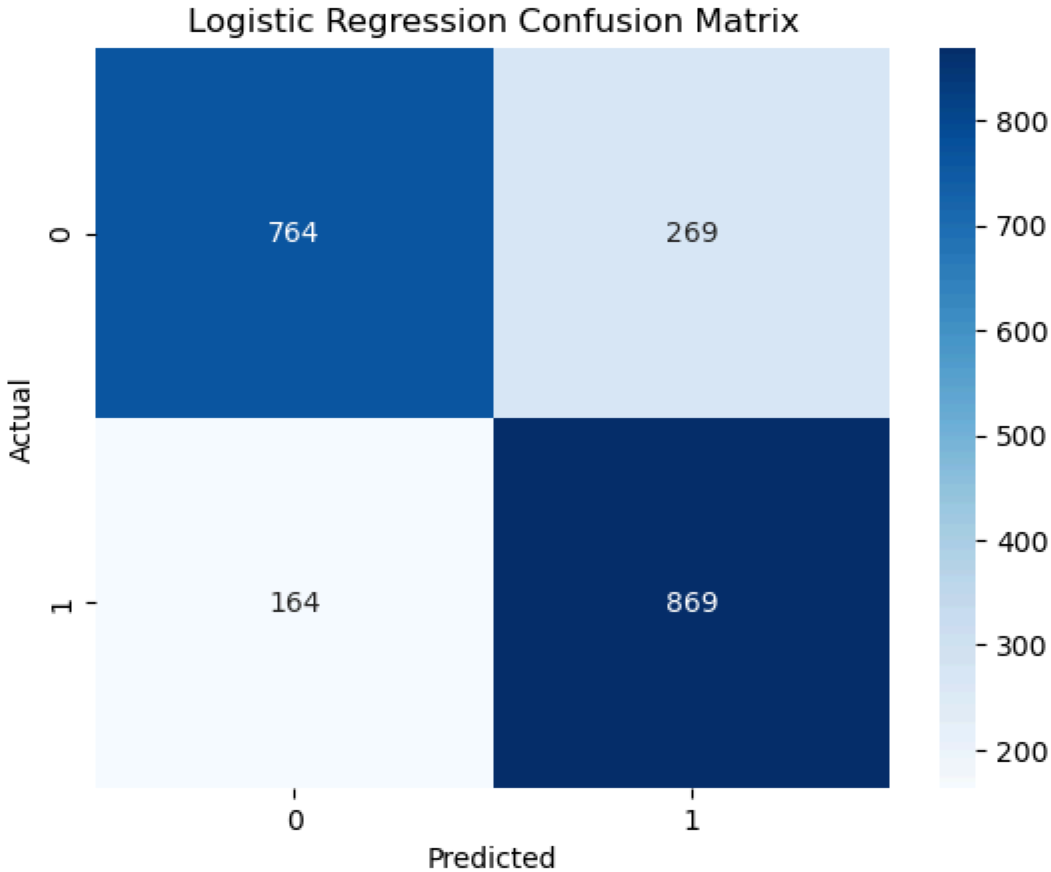
```
Logistic Regression Classification Report:
              precision    recall  f1-score   support

           0       0.82      0.74      0.78      1033
           1       0.76      0.84      0.80      1033

    accuracy                           0.79      2066
   macro avg       0.79      0.79      0.79      2066
weighted avg       0.79      0.79      0.79      2066
```

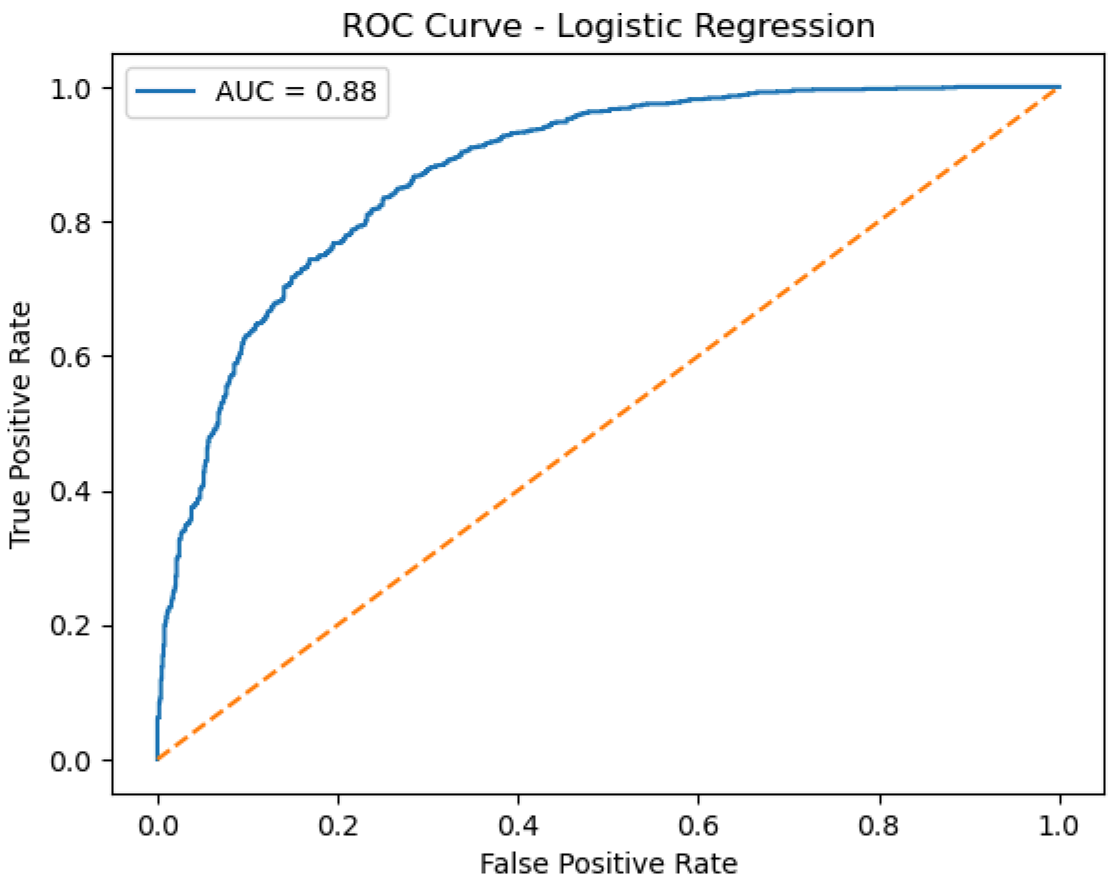
In [47]:

```
# Confusion matrix
cm = confusion_matrix(y_test, y_pred_lr)
sns.heatmap(cm, annot=True, fmt="d", cmap="Blues")
plt.title("Logistic Regression Confusion Matrix")
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.show()
```



In [48]:
```
# ROC Curve
y_pred_proba = lr_model.predict_proba(X_test[selected_features])[:, 1]
fpr, tpr, _ = roc_curve(y_test, y_pred_proba)
auc_score = auc(fpr, tpr)

plt.figure()
plt.plot(fpr, tpr, label=f"AUC = {auc_score:.2f}")
plt.plot([0, 1], [0, 1], linestyle="--")
plt.title("ROC Curve - Logistic Regression")
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.legend()
plt.show()
```



6.5.2 Random Forest Classifier

In [49]:
```
# Define parameter grid
param_grid = {
    "n_estimators": [100, 200],
    "max_depth": [None, 10, 20],
    "min_samples_split": [2, 5],
    "min_samples_leaf": [1, 2],
}

# Initialize Random Forest model
rf = RandomForestClassifier(random_state=42)

# Initialize GridSearchCV
grid_search = GridSearchCV(
    estimator=rf, param_grid=param_grid, cv=5, scoring="accuracy", n_jobs=-1
)

# Fit GridSearchCV
grid_search.fit(X_train[selected_features], y_train)

# Best parameters
print(f"Best Parameters: {grid_search.best_params_}")
```

```
Best Parameters: {'max_depth': None, 'min_samples_leaf': 2, 'min_samples_spli
t': 2, 'n_estimators': 200}
```

In [50]:
```
# Best Random Forest model
best_rf = grid_search.best_estimator_
best_rf.fit(X_train[selected_features], y_train)
```

```
# Predict on test set
y_pred_rf = best_rf.predict(X_test[selected_features])

# Classification report
print("Random Forest Classification Report:")
print(classification_report(y_test, y_pred_rf))
```

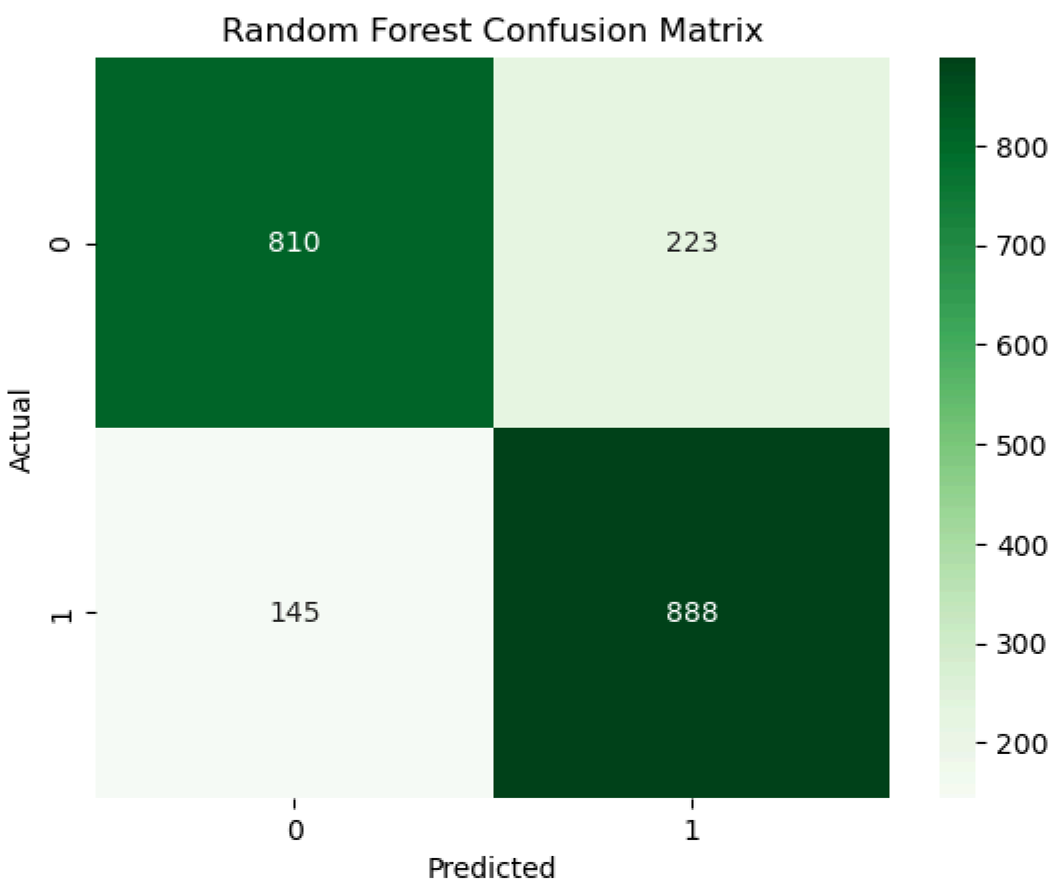
```
Random Forest Classification Report:
              precision    recall  f1-score   support

           0       0.85      0.78      0.81      1033
           1       0.80      0.86      0.83      1033

    accuracy                           0.82      2066
   macro avg       0.82      0.82      0.82      2066
weighted avg       0.82      0.82      0.82      2066
```

In [51]:

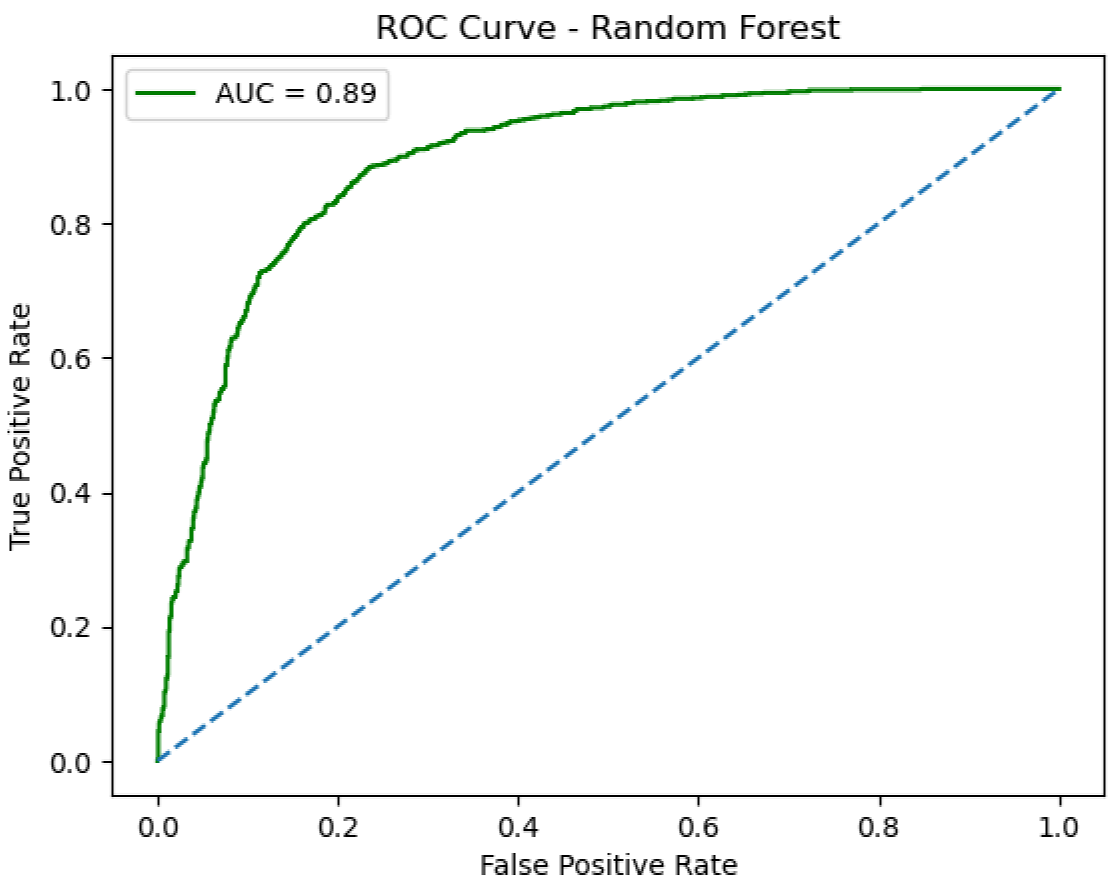
```
# Confusion matrix
cm_rf = confusion_matrix(y_test, y_pred_rf)
sns.heatmap(cm_rf, annot=True, fmt="d", cmap="Greens")
plt.title("Random Forest Confusion Matrix")
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.show()
```



In [52]:

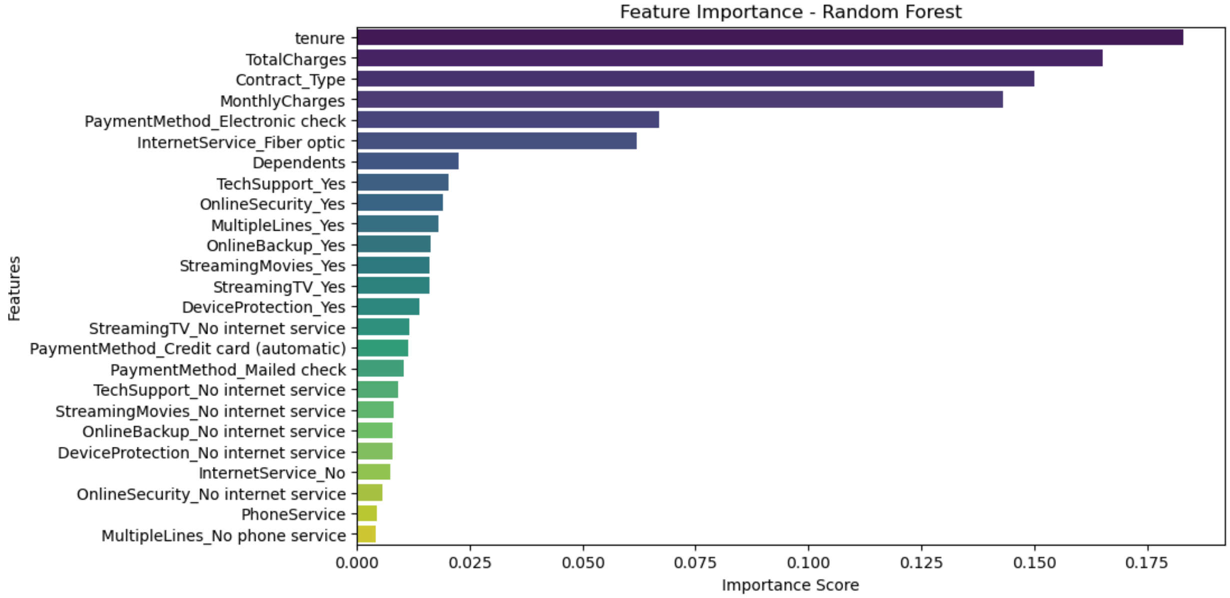
```
# ROC Curve
y_pred_proba_rf = best_rf.predict_proba(X_test[selected_features])[::, 1]
fpr_rf, tpr_rf, _ = roc_curve(y_test, y_pred_proba_rf)
auc_score_rf = auc(fpr_rf, tpr_rf)
```

```
plt.figure()
plt.plot(fpr_rf, tpr_rf, label=f"AUC = {auc_score_rf:.2f}", color="green")
plt.plot([0, 1], [0, 1], linestyle="--")
plt.title("ROC Curve - Random Forest")
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.legend()
plt.show()
```



In [53]:
```
# Feature importance
importances = best_rf.feature_importances_
feature_importance = pd.Series(importances, index=selected_features).sort_valu
    ascending=False
)

plt.figure(figsize=(10, 6))
sns.barplot(x=feature_importance, y=feature_importance.index, palette="viridis"
plt.title("Feature Importance - Random Forest")
plt.xlabel("Importance Score")
plt.ylabel("Features")
plt.show()
```



7. Conclusion

Observation:

- Model performance:
  - Logistic Regression:
    - Accuracy: 0.79
    - AUC: 0.88
  - Random Forest:
    - Accuracy: 0.82
    - AUC: 0.89
  - Both Logistic regression and Random Forest models perform well after handling class imbalance and feature selection.
  - Random Forest typically has higher accuracy and better ability to capture complex patterns.
- key predictors of Churn:
  - Tenure: Lower tenure increases the likelihood of churn.
  - Contract_Type: Short-term contracts are associated with higher churn.
  - MonthlyCharges: Higher charges are linked to increased churn.

Recommendations:

- Customer Retention Strategies:
  - Tenure
    - Implement loyalty programs targeting new customers to increase tenure.
  - Contract
    - Encourage customers to switch to long-term contracts through incentives.
    - Provide discounts for customers who switch to longer-term contracts.

  - Create attractive packages that encourage customers to opt for longer contracts.
- Monthly Chargers
  - Re-evaluate pricing models to ensure competitiveness.