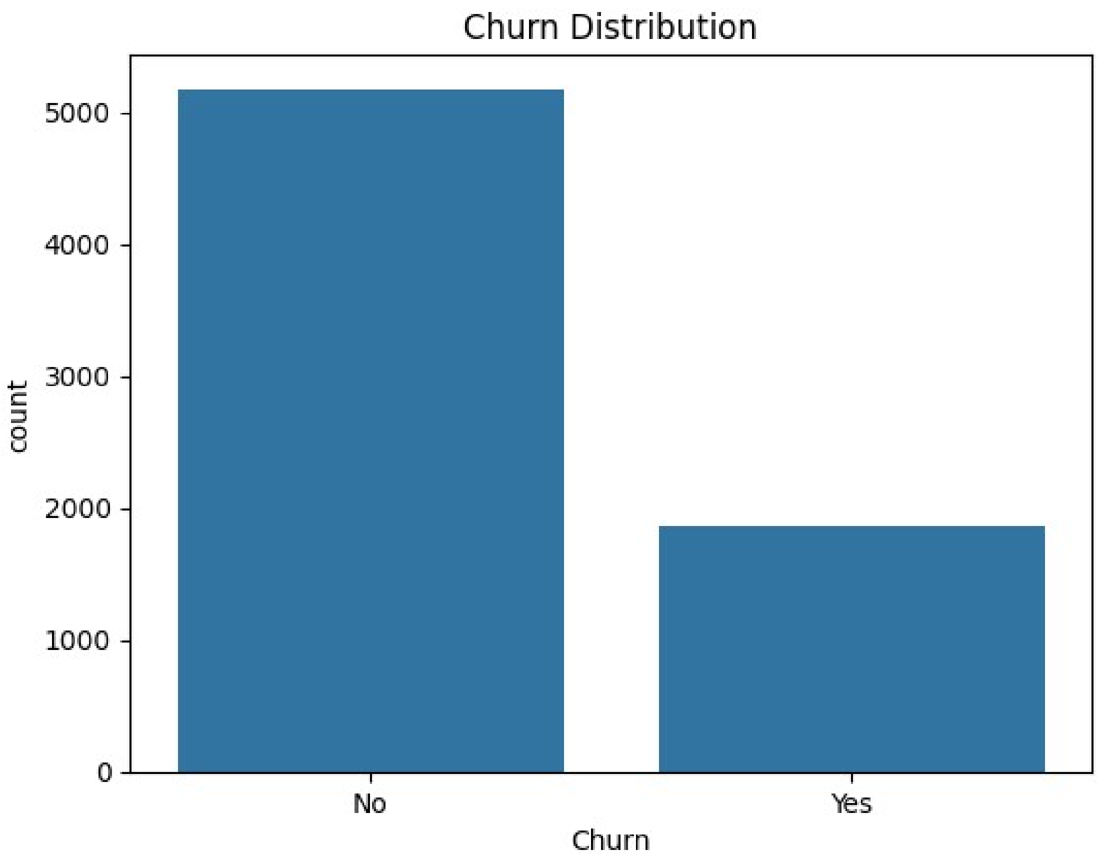
```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder
from sklearn.linear_model import LogisticRegression
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import accuracy_score, precision_score,
recall_score, f1_score, classification_report, confusion_matrix

# Load the dataset
data = pd.read_csv('Customer_data.csv')

# Display the first few rows of the dataset
data.head()
```

{"type":"dataframe","variable_name":"data"}

```python
# Get basic information about the dataset
data.info()

# Summary statistics for numerical features
data.describe()

# Visualize the distribution of target variable (Churn)
sns.countplot(x='Churn', data=data)
plt.title("Churn Distribution")
plt.show()
```

```
<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      7032 non-null   float64
 20  Churn             7043 non-null   object
dtypes: float64(2), int64(2), object(17)
memory usage: 1.1+ MB
```




```
# Check for missing values
data.isnull().sum()
```

```
customerID          0
gender              0
SeniorCitizen       0
Partner             0
Dependents          0
tenure              0
PhoneService        0
MultipleLines       0
InternetService     0
OnlineSecurity      0
```

```
OnlineBackup         0
DeviceProtection     0
TechSupport          0
StreamingTV          0
StreamingMovies      0
Contract             0
PaperlessBilling     0
PaymentMethod        0
MonthlyCharges       0
TotalCharges        11
Churn                0
dtype: int64
```

```python
# Drop rows with missing values in the dataset directly
data.dropna(inplace=True)

# Check for missing values
data.isnull().sum()
```

```
customerID          0
gender              0
SeniorCitizen       0
Partner             0
Dependents          0
tenure              0
PhoneService        0
MultipleLines       0
InternetService     0
OnlineSecurity      0
OnlineBackup        0
DeviceProtection    0
TechSupport         0
StreamingTV         0
StreamingMovies     0
Contract            0
PaperlessBilling    0
PaymentMethod       0
MonthlyCharges      0
TotalCharges        0
Churn               0
dtype: int64
```

```python
features = ['tenure', 'Contract', 'MonthlyCharges', 'TotalCharges',
'PaymentMethod',
    'PaperlessBilling', 'Dependents', 'Partner', 'SeniorCitizen',
    'InternetService', 'OnlineSecurity', 'OnlineBackup',
'DeviceProtection',
    'TechSupport', 'StreamingTV', 'StreamingMovies', 'PhoneService',
'Churn']
```

```
# Keep only the most relevant features
data = data[features]

data.head()
```


{"summary":"{\n \"name\": \"data\",\n \"rows\": 7032,\n \"fields\": [\n   {\n   \"column\": \"tenure\",\n   \"properties\": {\n   \"dtype\": \"number\",\n   \"std\": 24,\n   \"min\": 1,\n   \"max\": 72,\n   \"num_unique_values\": 72,\n   \"samples\": [\n   8,\n   53,\n   12\n   ],\n   \"semantic_type\": \"\",\n   \"description\": \"\"\n   }\n   },\n   {\n   \"column\": \"Contract\",\n   \"properties\": {\n   \"dtype\": \"category\",\n   \"num_unique_values\": 3,\n   \"samples\": [\n   \"Month-to-month\",\n   \"One year\",\n   \"Two year\"\n   ],\n   \"semantic_type\": \"\",\n   \"description\": \"\"\n   }\n   },\n   {\n   \"column\": \"MonthlyCharges\",\n   \"properties\": {\n   \"dtype\": \"number\",\n   \"std\": 30.08597388404983,\n   \"min\": 18.25,\n   \"max\": 118.75,\n   \"num_unique_values\": 1584,\n   \"samples\": [\n   102.85,\n   20.05,\n   36.85\n   ],\n   \"semantic_type\": \"\",\n   \"description\": \"\"\n   }\n   },\n   {\n   \"column\": \"TotalCharges\",\n   \"properties\": {\n   \"dtype\": \"number\",\n   \"std\": 2266.7713618831453,\n   \"min\": 18.8,\n   \"max\": 8684.8,\n   \"num_unique_values\": 6530,\n   \"samples\": [\n   5594.0,\n   6840.95,\n   6148.45\n   ],\n   \"semantic_type\": \"\",\n   \"description\": \"\"\n   }\n   },\n   {\n   \"column\": \"PaymentMethod\",\n   \"properties\": {\n   \"dtype\": \"category\",\n   \"num_unique_values\": 4,\n   \"samples\": [\n   \"Mailed check\",\n   \"Credit card (automatic)\",\n   \"Electronic check\"\n   ],\n   \"semantic_type\": \"\",\n   \"description\": \"\"\n   }\n   },\n   {\n   \"column\": \"PaperlessBilling\",\n   \"properties\": {\n   \"dtype\": \"category\",\n   \"num_unique_values\": 2,\n   \"samples\": [\n   \"No\",\n   \"Yes\"\n   ],\n   \"semantic_type\": \"\",\n   \"description\": \"\"\n   }\n   },\n   {\n   \"column\": \"Dependents\",\n   \"properties\": {\n   \"dtype\": \"category\",\n   \"num_unique_values\": 2,\n   \"samples\": [\n   \"Yes\",\n   \"No\"\n   ],\n   \"semantic_type\": \"\",\n   \"description\": \"\"\n   }\n   },\n   {\n   \"column\": \"Partner\",\n   \"properties\": {\n   \"dtype\": \"category\",\n   \"num_unique_values\": 2,\n   \"samples\": [\n   \"No\",\n   \"Yes\"\n   ],\n   \"semantic_type\": \"\",\n   \"description\": \"\"\n   }\n   },\n   {\n   \"column\": \"SeniorCitizen\",\n   \"properties\": {\n   \"dtype\": \"number\",\n   \"std\": 0,\n   \"min\": 0,\n   \"max\": 1,\n

```
\"num_unique_values\": 2,\n        \"samples\": [\n          1,\n
0\n        ],\n        \"semantic_type\": \"\",\n
\"description\": \"\"\n      }\n    },\n    {\n      \"column\":
\"InternetService\",\n      \"properties\": {\n        \"dtype\":
\"category\",\n        \"num_unique_values\": 3,\n        \"samples\":
[\n          \"DSL\",\n          \"Fiber optic\"\n        ],\n
\"semantic_type\": \"\",\n        \"description\": \"\"\n      }\
n    },\n    {\n      \"column\": \"OnlineSecurity\",\n
\"properties\": {\n        \"dtype\": \"category\",\n
\"num_unique_values\": 3,\n        \"samples\": [\n          \"No\",\n
\"Yes\"\n        ],\n        \"semantic_type\": \"\",\n
\"description\": \"\"\n      }\n    },\n    {\n      \"column\":
\"OnlineBackup\",\n      \"properties\": {\n        \"dtype\":
\"category\",\n        \"num_unique_values\": 3,\n        \"samples\":
[\n          \"Yes\",\n          \"No\"\n        ],\n
\"semantic_type\": \"\",\n        \"description\": \"\"\n      }\
n    },\n    {\n      \"column\": \"DeviceProtection\",\n
\"properties\": {\n        \"dtype\": \"category\",\n
\"num_unique_values\": 3,\n        \"samples\": [\n          \"No\",\n
\"Yes\"\n        ],\n        \"semantic_type\": \"\",\n
\"description\": \"\"\n      }\n    },\n    {\n      \"column\":
\"TechSupport\",\n      \"properties\": {\n        \"dtype\":
\"category\",\n        \"num_unique_values\": 3,\n        \"samples\":
[\n          \"No\",\n          \"Yes\"\n        ],\n
\"semantic_type\": \"\",\n        \"description\": \"\"\n      }\
n    },\n    {\n      \"column\": \"StreamingTV\",\n
\"properties\": {\n        \"dtype\": \"category\",\n
\"num_unique_values\": 3,\n        \"samples\": [\n          \"No\",\n
\"Yes\"\n        ],\n        \"semantic_type\": \"\",\n
\"description\": \"\"\n      }\n    },\n    {\n      \"column\":
\"StreamingMovies\",\n      \"properties\": {\n        \"dtype\":
\"category\",\n        \"num_unique_values\": 3,\n        \"samples\":
[\n          \"No\",\n          \"Yes\"\n        ],\n
\"semantic_type\": \"\",\n        \"description\": \"\"\n      }\
n    },\n    {\n      \"column\": \"PhoneService\",\n
\"properties\": {\n        \"dtype\": \"category\",\n
\"num_unique_values\": 2,\n        \"samples\": [\n          \"Yes\",\
n          \"No\"\n        ],\n        \"semantic_type\": \"\",\n
\"description\": \"\"\n      }\n    },\n    {\n      \"column\":
\"Churn\",\n      \"properties\": {\n        \"dtype\": \"category\",\
n        \"num_unique_values\": 2,\n        \"samples\": [\n
\"Yes\",\n          \"No\"\n        ],\n        \"semantic_type\":
\"\",\n        \"description\": \"\"\n      }\n    }\n  ]\
n}","type":"dataframe","variable_name":"data"}

# Initialize LabelEncoder
label_encoder = LabelEncoder()

# Apply label encoding to categorical columns
data['Contract'] = label_encoder.fit_transform(data['Contract'])  #
```

```
Month-to-month=0, One year=1, Two year=2
data['PaymentMethod'] =
label_encoder.fit_transform(data['PaymentMethod'])  # Electronic
check=0, Mailed check=1, etc.
data['PaperlessBilling'] =
label_encoder.fit_transform(data['PaperlessBilling'])  # No=0, Yes=1
data['Dependents'] = label_encoder.fit_transform(data['Dependents'])
# No=0, Yes=1
data['Partner'] = label_encoder.fit_transform(data['Partner'])  #
No=0, Yes=1
data['InternetService'] =
label_encoder.fit_transform(data['InternetService'])  # DSL=0, Fiber
optic=1, No=2
data['OnlineSecurity'] =
label_encoder.fit_transform(data['OnlineSecurity'])  # No=0, Yes=1
data['OnlineBackup'] =
label_encoder.fit_transform(data['OnlineBackup'])  # No=0, Yes=1
data['DeviceProtection'] =
label_encoder.fit_transform(data['DeviceProtection'])  # No=0, Yes=1
data['TechSupport'] = label_encoder.fit_transform(data['TechSupport'])
# No=0, Yes=1
data['StreamingTV'] = label_encoder.fit_transform(data['StreamingTV'])
# No=0, Yes=1
data['StreamingMovies'] =
label_encoder.fit_transform(data['StreamingMovies'])  # No=0, Yes=1
data['PhoneService'] =
label_encoder.fit_transform(data['PhoneService'])  # No=0, Yes=1

# For the target column "Churn"
data['Churn'] = label_encoder.fit_transform(data['Churn'])  # No=0,
Yes=1

data.head()
```


```
{"summary":"{\n  \"name\": \"data\",\n  \"rows\": 7032,\n  \"fields\":
[\n    {\n      \"column\": \"tenure\",\n      \"properties\": {\n
\"dtype\": \"number\",\n        \"std\": 24,\n        \"min\": 1,\n
\"max\": 72,\n        \"num_unique_values\": 72,\n        \"samples\":
[\n          8,\n          53,\n          12\n        ],\n
\"semantic_type\": \"\",\n        \"description\": \"\"\n      }\
n    },\n    {\n      \"column\": \"Contract\",\n      \"properties\":
{\n        \"dtype\": \"number\",\n        \"std\": 0,\n
\"min\": 0,\n        \"max\": 2,\n        \"num_unique_values\": 3,\n
\"samples\": [\n          0,\n          1,\n          2\n        ],\n
\"semantic_type\": \"\",\n        \"description\": \"\"\n      }\
n    },\n    {\n      \"column\": \"MonthlyCharges\",\n
\"properties\": {\n        \"dtype\": \"number\",\n        \"std\":
30.08597388404983,\n        \"min\": 18.25,\n        \"max\": 118.75,\
n        \"num_unique_values\": 1584,\n        \"samples\": [\n
102.85,\n          20.05,\n          36.85\n        ],\n
```

```
\"semantic_type\": \"\",\n        \"description\": \"\"\n      }\
n    },\n    {\n      \"column\": \"TotalCharges\",\n
\"properties\": {\n        \"dtype\": \"number\",\n        \"std\":
2266.7713618831453,\n        \"min\": 18.8,\n        \"max\": 8684.8,\
n        \"num_unique_values\": 6530,\n        \"samples\": [\n
5594.0,\n          6840.95,\n          6148.45\n        ],\n
\"semantic_type\": \"\",\n        \"description\": \"\"\n      }\
n    },\n    {\n      \"column\": \"PaymentMethod\",\n
\"properties\": {\n        \"dtype\": \"number\",\n        \"std\":
1,\n        \"min\": 0,\n        \"max\": 3,\n
\"num_unique_values\": 4,\n        \"samples\": [\n          3,\n
1,\n          2\n        ],\n        \"semantic_type\": \"\",\n
\"description\": \"\"\n      }\n    },\n    {\n      \"column\":
\"PaperlessBilling\",\n      \"properties\": {\n        \"dtype\":
\"number\",\n        \"std\": 0,\n        \"min\": 0,\n
\"max\": 1,\n        \"num_unique_values\": 2,\n        \"samples\":
[\n          0,\n          1\n        ],\n        \"semantic_type\":
\"\",\n        \"description\": \"\"\n      }\n    },\n    {\n
\"column\": \"Dependents\",\n      \"properties\": {\n
\"dtype\": \"number\",\n        \"std\": 0,\n        \"min\": 0,\n
\"max\": 1,\n        \"num_unique_values\": 2,\n        \"samples\":
[\n          1,\n          0\n        ],\n        \"semantic_type\":
\"\",\n        \"description\": \"\"\n      }\n    },\n    {\n
\"column\": \"Partner\",\n      \"properties\": {\n        \"dtype\":
\"number\",\n        \"std\": 0,\n        \"min\": 0,\n
\"max\": 1,\n        \"num_unique_values\": 2,\n        \"samples\":
[\n          0,\n          1\n        ],\n        \"semantic_type\":
\"\",\n        \"description\": \"\"\n      }\n    },\n    {\n
\"column\": \"SeniorCitizen\",\n      \"properties\": {\n
\"dtype\": \"number\",\n        \"std\": 0,\n        \"min\": 0,\n
\"max\": 1,\n        \"num_unique_values\": 2,\n        \"samples\":
[\n          1,\n          0\n        ],\n        \"semantic_type\":
\"\",\n        \"description\": \"\"\n      }\n    },\n    {\n
\"column\": \"InternetService\",\n      \"properties\": {\n
\"dtype\": \"number\",\n        \"std\": 0,\n        \"min\": 0,\n
\"max\": 2,\n        \"num_unique_values\": 3,\n        \"samples\":
[\n          0,\n          1\n        ],\n        \"semantic_type\":
\"\",\n        \"description\": \"\"\n      }\n    },\n    {\n
\"column\": \"OnlineSecurity\",\n      \"properties\": {\n
\"dtype\": \"number\",\n        \"std\": 0,\n        \"min\": 0,\n
\"max\": 2,\n        \"num_unique_values\": 3,\n        \"samples\":
[\n          0,\n          2\n        ],\n        \"semantic_type\":
\"\",\n        \"description\": \"\"\n      }\n    },\n    {\n
\"column\": \"OnlineBackup\",\n      \"properties\": {\n
\"dtype\": \"number\",\n        \"std\": 0,\n        \"min\": 0,\n
\"max\": 2,\n        \"num_unique_values\": 3,\n        \"samples\":
[\n          2,\n          0\n        ],\n        \"semantic_type\":
\"\",\n        \"description\": \"\"\n      }\n    },\n    {\n
\"column\": \"DeviceProtection\",\n      \"properties\": {\n
```

```
\"dtype\": \"number\",\n        \"std\": 0,\n        \"min\": 0,\n
\"max\": 2,\n        \"num_unique_values\": 3,\n        \"samples\":
[\n          0,\n          2\n        ],\n        \"semantic_type\":
\"\",\n        \"description\": \"\"\n      }\n    },\n    {\n
\"column\": \"TechSupport\",\n      \"properties\": {\n
\"dtype\": \"number\",\n        \"std\": 0,\n        \"min\": 0,\n
\"max\": 2,\n        \"num_unique_values\": 3,\n        \"samples\":
[\n          0,\n          2\n        ],\n        \"semantic_type\":
\"\",\n        \"description\": \"\"\n      }\n    },\n    {\n
\"column\": \"StreamingTV\",\n      \"properties\": {\n
\"dtype\": \"number\",\n        \"std\": 0,\n        \"min\": 0,\n
\"max\": 2,\n        \"num_unique_values\": 3,\n        \"samples\":
[\n          0,\n          2\n        ],\n        \"semantic_type\":
\"\",\n        \"description\": \"\"\n      }\n    },\n    {\n
\"column\": \"StreamingMovies\",\n      \"properties\": {\n
\"dtype\": \"number\",\n        \"std\": 0,\n        \"min\": 0,\n
\"max\": 2,\n        \"num_unique_values\": 3,\n        \"samples\":
[\n          0,\n          2\n        ],\n        \"semantic_type\":
\"\",\n        \"description\": \"\"\n      }\n    },\n    {\n
\"column\": \"PhoneService\",\n      \"properties\": {\n
\"dtype\": \"number\",\n        \"std\": 0,\n        \"min\": 0,\n
\"max\": 1,\n        \"num_unique_values\": 2,\n        \"samples\":
[\n          1,\n          0\n        ],\n        \"semantic_type\":
\"\",\n        \"description\": \"\"\n      }\n    },\n    {\n
\"column\": \"Churn\",\n      \"properties\": {\n        \"dtype\":
\"number\",\n        \"std\": 0,\n        \"min\": 0,\n
\"max\": 1,\n        \"num_unique_values\": 2,\n        \"samples\":
[\n          1,\n          0\n        ],\n        \"semantic_type\":
\"\",\n        \"description\": \"\"\n      }\n    }\n  ]\
n}","type":"dataframe","variable_name":"data"}
```

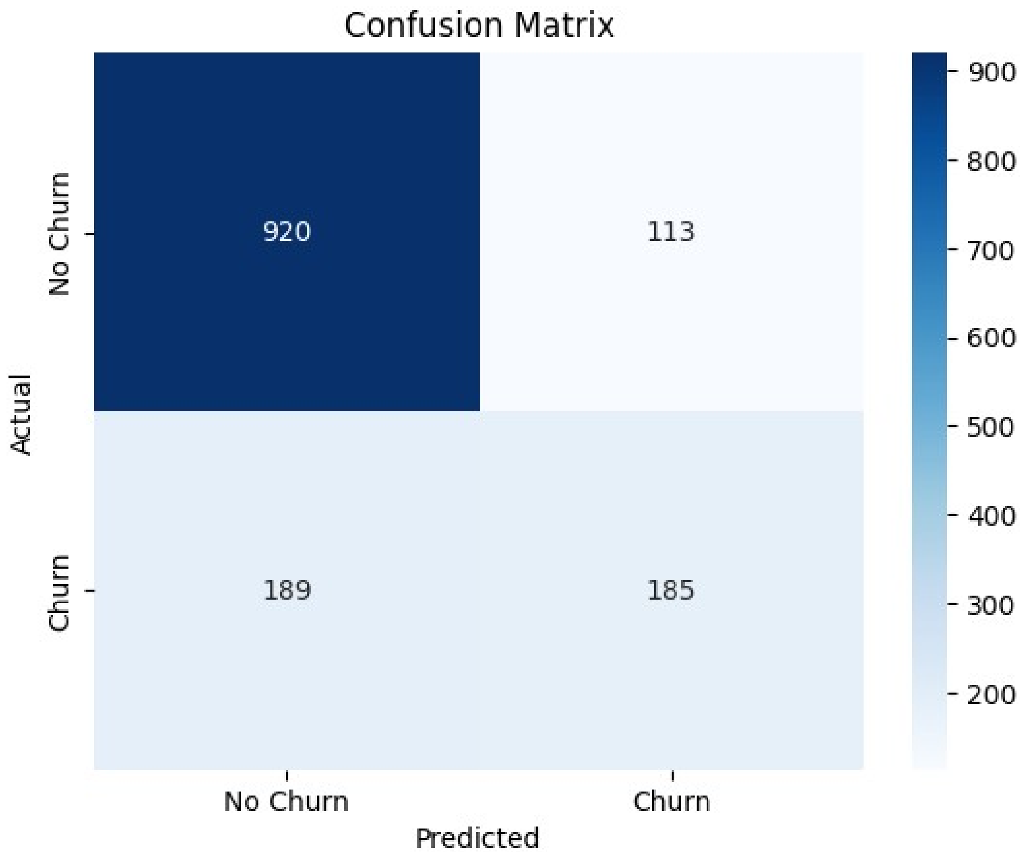

```python
# Prepare features (X) and target (y)
X = data.drop(['Churn'], axis=1)  # Drop 'Churn' columns
y = data['Churn']  # Target variable
# Split the data into training and testing sets (80% train, 20% test)
X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.2, random_state=42)
X.shape
```

```
(7032, 17)
```

```python
# Scale the numeric features (important for Logistic Regression)
scaler = StandardScaler()

# Apply scaling to the features
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

# Initialize the Logistic Regression model
log_reg_model = LogisticRegression(random_state=42)
```

```python
# Train the model on the scaled training data
log_reg_model.fit(X_train_scaled, y_train)

# Make predictions on the test data
y_pred = log_reg_model.predict(X_test_scaled)

# Evaluate the model
accuracy = accuracy_score(y_test, y_pred)
precision = precision_score(y_test, y_pred)
recall = recall_score(y_test, y_pred)
f1 = f1_score(y_test, y_pred)

print(f'Accuracy: {accuracy:.2f}')
print(f'Precision: {precision:.2f}')
print(f'Recall: {recall:.2f}')
print(f'F1 Score: {f1:.2f}')

# Print the classification report
print('\nClassification Report:')
print(classification_report(y_test, y_pred))

# Plot the confusion matrix
conf_matrix = confusion_matrix(y_test, y_pred)
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues',
xticklabels=['No Churn', 'Churn'], yticklabels=['No Churn', 'Churn'])
plt.title('Confusion Matrix')
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.show()
```

```
Accuracy: 0.79
Precision: 0.62
Recall: 0.49
F1 Score: 0.55

Classification Report:
              precision    recall  f1-score   support

           0       0.83      0.89      0.86      1033
           1       0.62      0.49      0.55       374

    accuracy                           0.79      1407
   macro avg       0.73      0.69      0.70      1407
weighted avg       0.77      0.79      0.78      1407
```




```
def predict_churn(log_reg_model, scaler, label_encoder):
    # Collect user input based on the relevant features
    tenure = int(input("Enter tenure (Number of months with the
company): "))

    contract = input("Enter contract type (Month-to-month/One year/Two
year): ")
    contract = 0 if contract.lower() == "month-to-month" else (1 if
contract.lower() == "one year" else 2)

    monthly_charges = float(input("Enter monthly charges (USD): "))
    total_charges = float(input("Enter total charges (USD): "))

    payment_method = input("Enter payment method (Electronic
check/Mailed check/Bank transfer): ")
    payment_method = 0 if payment_method.lower() == "electronic check"
else (1 if payment_method.lower() == "mailed check" else 2)

    paperless_billing = input("Do you use paperless billing? (Yes/No):
")
    paperless_billing = 1 if paperless_billing.lower() == "yes" else 0

    dependents = input("Do you have dependents? (Yes/No): ")
```

```
    dependents = 1 if dependents.lower() == "yes" else 0

    partner = input("Do you have a partner? (Yes/No): ")
    partner = 1 if partner.lower() == "yes" else 0

    senior_citizen = int(input("Enter senior citizen status (0: No, 1: 
Yes): "))

    internet_service = input("Enter internet service (DSL/Fiber 
optic/No): ")
    internet_service = 0 if internet_service.lower() == "dsl" else (1 
if internet_service.lower() == "fiber optic" else 2)

    online_security = input("Do you have online security? (Yes/No): ")
    online_security = 1 if online_security.lower() == "yes" else 0

    online_backup = input("Do you have online backup? (Yes/No): ")
    online_backup = 1 if online_backup.lower() == "yes" else 0

    device_protection = input("Do you have device protection? 
(Yes/No): ")
    device_protection = 1 if device_protection.lower() == "yes" else 0

    tech_support = input("Do you have tech support? (Yes/No): ")
    tech_support = 1 if tech_support.lower() == "yes" else 0

    streaming_tv = input("Do you have streaming TV? (Yes/No): ")
    streaming_tv = 1 if streaming_tv.lower() == "yes" else 0

    streaming_movies = input("Do you have streaming movies? (Yes/No): 
")
    streaming_movies = 1 if streaming_movies.lower() == "yes" else 0

    phone_service = input("Do you have phone service? (Yes/No): ")
    phone_service = 1 if phone_service.lower() == "yes" else 0

   # Create a DataFrame with user input for prediction
    user_data = pd.DataFrame([[tenure, contract, monthly_charges, 
total_charges, payment_method, paperless_billing,
                               dependents, partner, senior_citizen, 
internet_service, online_security,
                               online_backup, device_protection, 
tech_support, streaming_tv, streaming_movies,
                               phone_service]],
                             columns=X.columns)


    # Apply scaling to the user input using the same scaler
    user_data_scaled = scaler.transform(user_data)

    # Predict churn
```

```python
    prediction = log_reg_model.predict(user_data_scaled)

    # Output the prediction
    if prediction == 0:
        print("\n\t\tThe customer is predicted to stay (No churn).")
    else:
        print("\n\t\tThe customer is predicted to churn (Yes).")

# Example usage:
# Assuming that the log_reg_model, scaler, and label_encoders have
been trained and initialized
predict_churn(log_reg_model, scaler, label_encoder)
```

```
Enter tenure (Number of months with the company): 12
Enter contract type (Month-to-month/One year/Two year): One year
Enter monthly charges (USD): 45.60
Enter total charges (USD): 540.00
Enter payment method (Electronic check/Mailed check/Bank transfer):
Electronic check
Do you use paperless billing? (Yes/No): Yes
Do you have dependents? (Yes/No): No
Do you have a partner? (Yes/No): Yes
Enter senior citizen status (0: No, 1: Yes): 0
Enter internet service (DSL/Fiber optic/No): Fiber optic
Do you have online security? (Yes/No): Yes
Do you have online backup? (Yes/No): No
Do you have device protection? (Yes/No): Yes
Do you have tech support? (Yes/No): Yes
Do you have streaming TV? (Yes/No): Yes
Do you have streaming movies? (Yes/No): No
Do you have phone service? (Yes/No): Yes

		The customer is predicted to stay (No churn).
```