Predicting customer churn using a telecommunications dataset

- This project is valuable for businesses and involves classification techniques.

1. Importing necessary libraries

In [ ]:
```
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import numpy as np
```

2. Data Exploration

Loading Dataset

In [ ]:
```
df = pd.read_csv("churndata.csv")
df.head()
```

Out[ ]:

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

5 rows × 21 columns

Performing Initial Exploration

In [ ]:
```
df.shape
```

Out[ ]: (7043, 21)

In [ ]:
```
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
```

categorical columns that needs to be converted into numerical

In [ ]:
```
# gender
# partners
# Dependents
# PhoneService
# MultipleLines
# InternetService
# OnlineSecurity
# OnlineBackup
# DeviceProtection
# TechSupport
# StreamingTV
# StreamingMovies
# Contract
# PaperlessBilling
# PaymentMethod
# TotalCharges
# churn
```

In [ ]:
```
df.describe()
```

Out[ ]:

	SeniorCitizen	tenure	MonthlyCharges
count	7043.000000	7043.000000	7043.000000
mean	0.162147	32.371149	64.761692
std	0.368612	24.559481	30.090047
min	0.000000	0.000000	18.250000
25%	0.000000	9.000000	35.500000
50%	0.000000	29.000000	70.350000
75%	0.000000	55.000000	89.850000
max	1.000000	72.000000	118.750000

3. Data Preprocessing

Finding missing values

In [ ]:

```
df.isnull().sum()
```

Out[ ]:

```
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
```

- no null values,that's great

Finding unique values in some columns

In [ ]:

```
# Check the unique values in the 'gender' column
print(df['gender'].unique())
```

```
# Check the unique values in the 'Churn' column
print(df['Churn'].unique())
```

```
['Female' 'Male']
['No' 'Yes']
```

Convert categorical variables into numerical format:

In [ ]:
```
from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()

df['gender'] = le.fit_transform(df['gender'])
df['Partner'] = le.fit_transform(df['Partner'])
df['Dependents'] = le.fit_transform(df['Dependents'])
df['PhoneService'] = le.fit_transform(df['PhoneService'])
df['MultipleLines'] = le.fit_transform(df['MultipleLines'].replace('No phone servic
df['InternetService'] = le.fit_transform(df['InternetService'])
df['OnlineSecurity'] = le.fit_transform(df['OnlineSecurity'].replace('No internet s
df['OnlineBackup'] = le.fit_transform(df['OnlineBackup'].replace('No internet servi
df['DeviceProtection'] = le.fit_transform(df['DeviceProtection'].replace('No intern
df['TechSupport'] = le.fit_transform(df['TechSupport'].replace('No internet service
df['StreamingTV'] = le.fit_transform(df['StreamingTV'].replace('No internet service
df['StreamingMovies'] = le.fit_transform(df['StreamingMovies'].replace('No internet
df['Contract'] = le.fit_transform(df['Contract'])
df['PaperlessBilling'] = le.fit_transform(df['PaperlessBilling'])
df['PaymentMethod'] = le.fit_transform(df['PaymentMethod'])
df['Churn'] = le.fit_transform(df['Churn'])
df['TotalCharges'] = le.fit_transform(df['TotalCharges'])
df['Churn'] = le.fit_transform(df['Churn'])
```

In [ ]:
```
df.head(10)
```

Out[ ]:

	customerID	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	Multipl
0	7590-VHVEG	0	0	1	0	1	0	
1	5575-GNVDE	1	0	0	0	34	1	
2	3668-QPYBK	1	0	0	0	2	1	
3	7795-CFOCW	1	0	0	0	45	0	
4	9237-HQITU	0	0	0	0	2	1	
5	9305-CDSKC	0	0	0	0	8	1	
6	1452-KIOVK	1	0	0	1	22	1	
7	6713-OKOMC	0	0	0	0	10	0	
8	7892-POOKP	0	0	1	0	28	1	
9	6388-TABGU	1	0	0	1	62	1	

10 rows × 21 columns

Feature Selection

In [ ]:

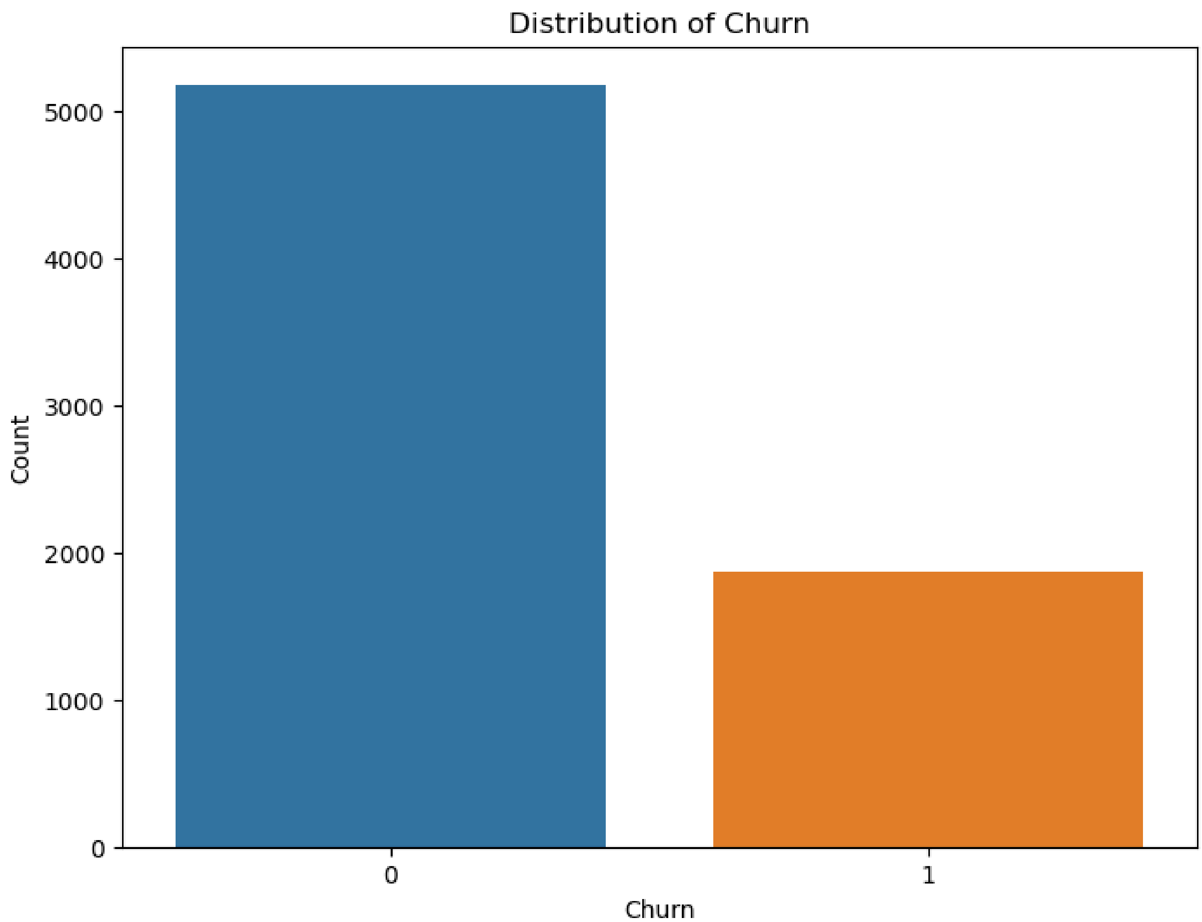
```
X = df.drop(['customerID', 'Churn'], axis=1)
y = df['Churn']
```

4. Visualizing the Relationship of Data Features

distribution of target variable 'Churn'

In [ ]:

```
plt.figure(figsize=(8, 6))
sns.countplot(x='Churn', data=df)
plt.title('Distribution of Churn')
plt.xlabel('Churn')
plt.ylabel('Count')
plt.show()
```



Distribution of Numeric Features

In [ ]:
```
numeric_features = ['tenure', 'MonthlyCharges', 'TotalCharges']
plt.figure(figsize=(14, 4))
for i, feature in enumerate(numeric_features, 1):
    plt.subplot(1, len(numeric_features), i)
    sns.histplot(df[feature], kde=True)
    plt.title(f'Distribution of {feature}')
    plt.xlabel(feature)
plt.tight_layout()
plt.show()
```

```
c:\ProgramData\anaconda3\Lib\site-packages\seaborn\_oldcore.py:1119: FutureWarning:
use_inf_as_na option is deprecated and will be removed in a future version. Convert
inf values to NaN before operating instead.
  with pd.option_context('mode.use_inf_as_na', True):
c:\ProgramData\anaconda3\Lib\site-packages\seaborn\_oldcore.py:1119: FutureWarning:
use_inf_as_na option is deprecated and will be removed in a future version. Convert
inf values to NaN before operating instead.
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use_inf_as_na option is deprecated and will be removed in a future version. Convert
inf values to NaN before operating instead.
  with pd.option_context('mode.use_inf_as_na', True):
```
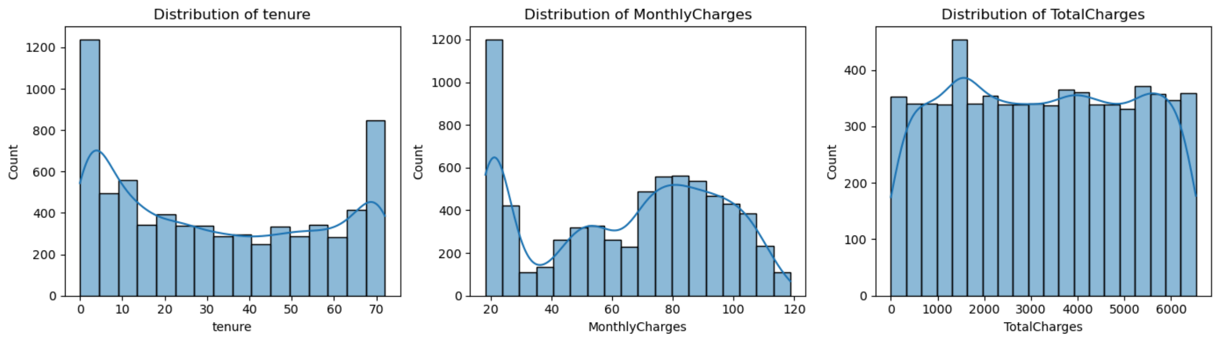
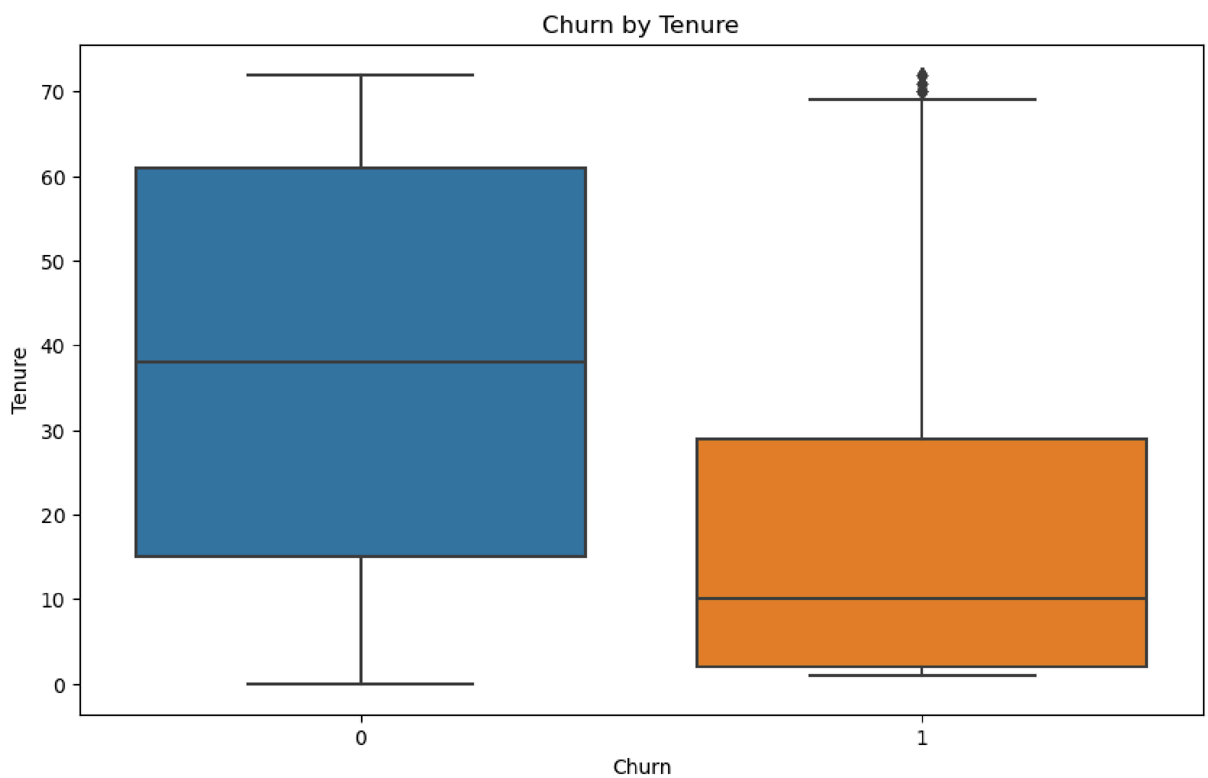



Churn by Tenure

In [ ]:
```
plt.figure(figsize=(10, 6))
sns.boxplot(x='Churn', y='tenure', data=df)
plt.title('Churn by Tenure')
plt.xlabel('Churn')
plt.ylabel('Tenure')
plt.show()
```



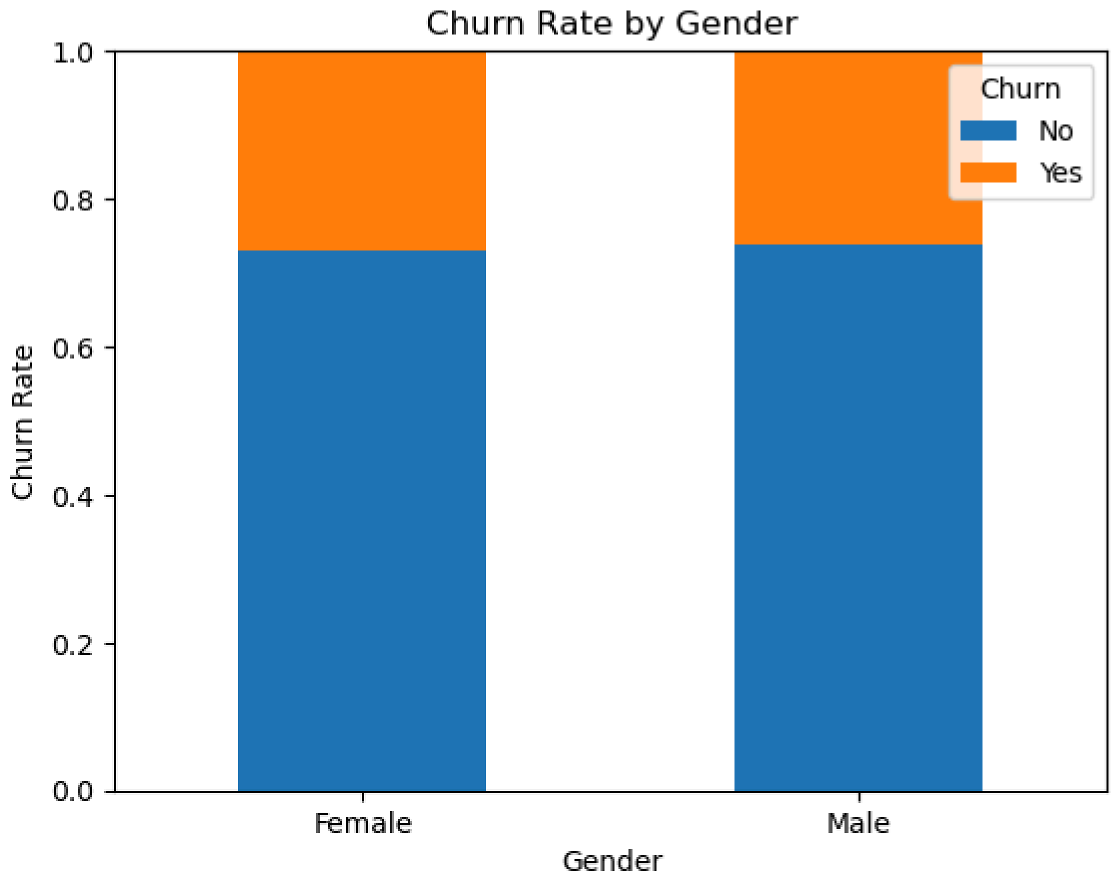
Monthly Charges vs. Total Charges

In [ ]:
```
plt.figure(figsize=(8, 6))
sns.scatterplot(x='MonthlyCharges', y='TotalCharges', hue='Churn', data=df)
plt.title('Monthly Charges vs. Total Charges')
plt.xlabel('Monthly Charges')
plt.ylabel('Total Charges')
plt.show()
```

Churn by Gender

In [ ]:
```python
import seaborn as sns
import matplotlib.pyplot as plt

# Group data by gender and churn status, and calculate churn count
churn_count_by_gender = df.groupby(['gender', 'Churn']).size().unstack()

# Calculate churn rate for each gender
churn_rate_by_gender = churn_count_by_gender.div(churn_count_by_gender.sum(axis=1),

# Map numeric gender values to categorical labels
gender_mapping = {0: 'Female', 1: 'Male'}
churn_rate_by_gender.index = churn_rate_by_gender.index.map(gender_mapping)

# Plot churn rate by gender
plt.figure(figsize=(8, 6))
churn_rate_by_gender.plot(kind='bar', stacked=True)
plt.title('Churn Rate by Gender')
plt.xlabel('Gender')
plt.ylabel('Churn Rate')
plt.xticks(rotation=0)  # Rotate x-axis labels for better readability
plt.legend(title='Churn', loc='upper right', labels=['No', 'Yes'])
plt.ylim(0, 1)  # Set y-axis limit to show churn rate between 0 and 1
plt.show()
```

```
<Figure size 800x600 with 0 Axes>
```



5. Model Training:

Split the data into training and testing sets:

In [ ]:
```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_sta
```

Training Classification Models

In [ ]:
```
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.ensemble import RandomForestClassifier

# Initializing the Models
logistic_model = LogisticRegression()
decision_model = DecisionTreeClassifier()
neighbor_model = KNeighborsClassifier()
rf_model = RandomForestClassifier(n_estimators=100, random_state=42)

# List of additional models
models = {
    'Random Forest': rf_model,
    'Logistic Regression': logistic_model,
    'Decision Tree': decision_model,
```

```
    'K-Neighbors': neighbor_model
}

# Initialize dictionaries to store metrics
accuracy_dict = {}
precision_dict = {}
recall_dict = {}
f1_dict = {}
```

Train and evaluate models

In [ ]:
```
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score

for name, model in models.items():
    model.fit(X_train, y_train)
    y_pred = model.predict(X_test)

    # Compute classification metrics
    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)

    # Store metrics in dictionaries
    accuracy_dict[name] = accuracy
    precision_dict[name] = precision
    recall_dict[name] = recall
    f1_dict[name] = f1

     # Print metrics for each model
    print(f'--- {name} Metrics ---')
    print(f'Accuracy: {accuracy}')
    print(f'Precision: {precision}')
    print(f'Recall: {recall}')
    print(f'F1 Score: {f1}')
    print('-----------------------')
```

```
--- Random Forest Metrics ---
Accuracy: 0.7955997161107168
Precision: 0.660377358490566
Recall: 0.4691689008042895
F1 Score: 0.54858934169279
-----------------------
--- Logistic Regression Metrics ---
Accuracy: 0.8161816891412349
Precision: 0.685064935064935
Recall: 0.5656836461126006
F1 Score: 0.6196769456681351
-----------------------
--- Decision Tree Metrics ---
Accuracy: 0.7224982256919801
Precision: 0.4744318181818182
Recall: 0.4477211796246649
F1 Score: 0.46068965517241384
-----------------------
```

```
c:\ProgramData\anaconda3\Lib\site-packages\sklearn\linear_model\_logistic.py:458: Co
nvergenceWarning: lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
  n_iter_i = _check_optimize_result(
--- K-Neighbors Metrics ---
Accuracy: 0.7572746628814763
Precision: 0.5555555555555556
Recall: 0.4155495978552279
F1 Score: 0.4754601226993865
-----------------------
```

Compare results

In [ ]:

```
print('\n--- Comparison of Model Performance ---')
print('Accuracy:')
for name, accuracy in accuracy_dict.items():
    print(f'{name}: {accuracy}')

print('\nPrecision:')
for name, precision in precision_dict.items():
    print(f'{name}: {precision}')

print('\nRecall:')
for name, recall in recall_dict.items():
    print(f'{name}: {recall}')

print('\nF1 Score:')
for name, f1 in f1_dict.items():
    print(f'{name}: {f1}')
```

```
--- Comparison of Model Performance ---
Accuracy:
Random Forest: 0.7955997161107168
Logistic Regression: 0.8161816891412349
Decision Tree: 0.7310149041873669
K-Neighbors: 0.7572746628814763

Precision:
Random Forest: 0.660377358490566
Logistic Regression: 0.685064935064935
Decision Tree: 0.4915254237288136
K-Neighbors: 0.5555555555555556

Recall:
Random Forest: 0.4691689008042895
Logistic Regression: 0.5656836461126006
Decision Tree: 0.46648793565683644
K-Neighbors: 0.4155495978552279

F1 Score:
Random Forest: 0.54858934169279
Logistic Regression: 0.6196769456681351
Decision Tree: 0.4786795048143054
K-Neighbors: 0.4754601226993865
```