

```
In [1]: 1 import pandas as pd
        2 import numpy as np
        3 import matplotlib.pyplot as plt
        4 import seaborn as sns
        5 from sklearn.preprocessing import LabelEncoder
        6 from sklearn.model_selection import train_test_split, cross_val_score
        7 from sklearn.ensemble import RandomForestRegressor, RandomForestClassifier
        8 from sklearn.tree import DecisionTreeClassifier
        9 from sklearn.metrics import accuracy_score, classification_report
       10 from sklearn.model_selection import StratifiedKFold, KFold
       11 from sklearn.metrics import mean_squared_error
```

```
In [2]: 1 # Load the data from the uploaded CSV file
        2 file_path = 'NYPD_Complaint_Data_Current_YTD.csv'
        3 data = pd.read_csv(file_path)
```

In [3]: 1 `print(data.describe)`

```
<bound method NDFrame.describe of
M Cmplnt_To_Dt Cmplnt_To_Tm \
0      736216184 09/30/2016 23:25:00 09/30/2016 23:25:00
1      294332956 09/30/2016 23:16:00 09/30/2016 23:21:00
2      852981427 09/30/2016 23:00:00 09/30/2016 23:05:00
3      369976063 09/30/2016 23:00:00      NaN      NaN
4      117213771 09/30/2016 23:00:00 09/30/2016 23:10:00
...
361735 582350583 01/01/2015 03:50:00 01/01/2016 04:00:00
361736 258046495 01/01/2015 01:25:00 01/01/2016 01:30:00
361737 640212578 01/01/2015 00:30:00 01/01/2016 00:40:00
361738 496500431 06/30/2014 12:00:00 12/29/2015 12:00:00
361739 256379572 12/31/2001 16:00:00 01/01/2016 10:50:00
```

```
RPT_DT KY_CD OFNS_DESC PD_CD \
0      09/30/2016 236 DANGEROUS WEAPONS 782.0
1      09/30/2016 344 ASSAULT 3 & RELATED OFFENSES 101.0
2      09/30/2016 235 DANGEROUS DRUGS 567.0
3      09/30/2016 118 DANGEROUS WEAPONS 793.0
4      09/30/2016 578 HARRASSMENT 2 637.0
...
361735 01/01/2016 105 ROBBERY 399.0
361736 01/01/2016 578 HARRASSMENT 2 638.0
361737 01/01/2016 106 FELONY ASSAULT 109.0
361738 01/01/2016 361 OFF. AGNST PUB ORD SENSBLTY & 639.0
361739 01/01/2016 107 BURGLARY 213.0
```

```
PD_DESC ... ADDR_PCT_CD LOC_OF_OCCUR_DESC \
0 WEAPONS, POSSESSION, ETC ... 42.0 NaN
1 ASSAULT 3 ... 71.0 OPPOSITE OF
2 MARIJUANA, POSSESSION 4 & 5 ... 43.0 INSIDE
3 WEAPONS POSSESSION 3 ... 103.0 NaN
4 HARASSMENT,SUBD 1,CIVILIAN ... 110.0 FRONT OF
...
361735 ROBBERY,COMMERCIAL UNCLASSIFIED ... 30.0 INSIDE
361736 HARASSMENT,SUBD 3,4,5 ... 41.0 NaN
361737 ASSAULT 2,1,UNCLASSIFIED ... 109.0 FRONT OF
361738 AGGRAVATED HARASSMENT 2 ... 50.0 INSIDE
361739 BURGLARY,COMMERCIAL,NIGHT ... 84.0 INSIDE
```

```
PREM_TYP_DESC PARKS_NM HADEVELOPT X_COORD_CD \
0 TRANSIT - NYC SUBWAY NaN NaN 1015308.0
1 STREET NaN NaN 997932.0
2 RESIDENCE - PUBLIC HOUSING NaN CASTLE HILL 1025580.0
3 STREET NaN NaN 1038464.0
4 STREET NaN NaN 1016301.0
...
361735 HOTEL/MOTEL NaN NaN 998372.0
361736 TRANSIT - NYC SUBWAY NaN NaN 1014468.0
361737 BAR/NIGHT CLUB NaN NaN 1030529.0
361738 RESIDENCE - APT. HOUSE NaN NaN 1009735.0
361739 PUBLIC SCHOOL NaN NaN 989682.0
```

```
Y_COORD_CD Latitude Longitude Lat_Lon
0 244373.0 40.837376 -73.887761 (40.837376359, -73.887760929)
1 180172.0 40.661205 -73.950687 (40.661204871, -73.950686652)
2 236918.0 40.816872 -73.850685 (40.816872438, -73.850684927)
```

```
3      192970.0  40.696177 -73.804492 (40.696177006, -73.804492266)
4      209428.0  40.741458 -73.884339 (40.741458245, -73.884339073)
...
361735  240146.0  40.825818 -73.948975 (40.825817778, -73.948974825)
361736  238156.0  40.820315 -73.890825 (40.820315396, -73.890824603)
361737  214093.0  40.754199 -73.832963 (40.754199468, -73.832962523)
361738  261272.0  40.883777 -73.907837 (40.883776851, -73.907836928)
361739  188334.0  40.683617 -73.980416 (40.683616638, -73.980416007)
```

[361740 rows x 24 columns]>

In [4]:

1 data.describe()

Out[4]:

	CMPLNT_NUM	KY_CD	PD_CD	ADDR_PCT_CD	X_COORD_CD	Y_COORD_
count	3.617400e+05	361740.000000	361477.000000	361739.000000	3.558860e+05	355886.0000
mean	5.499403e+08	299.634970	411.857283	63.028830	1.005074e+06	207403.6270
std	2.600874e+08	152.791634	221.006223	34.408404	2.152718e+04	30532.4530
min	1.000097e+08	101.000000	101.000000	1.000000	9.133570e+05	121250.0000
25%	3.241697e+08	118.000000	254.000000	40.000000	9.919450e+05	184359.0000
50%	5.502997e+08	341.000000	357.000000	63.000000	1.004550e+06	206483.0000
75%	7.757034e+08	351.000000	638.000000	94.000000	1.016781e+06	235493.0000
max	9.999994e+08	685.000000	922.000000	123.000000	1.067226e+06	271820.0000

```
In [5]: 1 # Calculate the percentage of missing values in each column
2 missing_data = data.isnull().sum().sort_values(ascending=False)
3 percent_missing = (missing_data / len(data)) * 100
4
5 # Create a DataFrame to view the columns with missing values and their per
6 missing_values_df = pd.DataFrame({'Missing Values': missing_data, 'Percent
7 missing_values_df[missing_values_df['Missing Values'] > 0]
```

Out[5]:

	Missing Values	Percentage
PARKS_NM	357819	98.916072
HADEVELOPT	343044	94.831647
LOC_OF_OCCUR_DESC	73339	20.273954
CMPLNT_TO_DT	62298	17.221761
CMPLNT_TO_TM	62150	17.180848
Lat_Lon	5854	1.618289
Longitude	5854	1.618289
Latitude	5854	1.618289
Y_COORD_CD	5854	1.618289
X_COORD_CD	5854	1.618289
PREM_TYP_DESC	1414	0.390888
PD_CD	263	0.072704
PD_DESC	263	0.072704
OFNS_DESC	38	0.010505
ADDR_PCT_CD	1	0.000276

```
In [6]: 1 # Attempting to remove columns again with direct reference to ensure corre
2 data.drop(['PARKS_NM', 'HADEVELOPT', 'X_COORD_CD', 'Y_COORD_CD', 'Lat_Lon'],
3
4 # Display the current columns to verify the removal
5 data.columns
```

Out[6]: Index(['CMPLNT_NUM', 'CMPLNT_FR_DT', 'CMPLNT_FR_TM', 'CMPLNT_TO_DT',
'CMPLNT_TO_TM', 'RPT_DT', 'KY_CD', 'OFNS_DESC', 'PD_CD', 'PD_DESC',
'CRM_ATPT_CPTD_CD', 'LAW_CAT_CD', 'JURIS_DESC', 'BORO_NM',
'ADDR_PCT_CD', 'LOC_OF_OCCUR_DESC', 'PREM_TYP_DESC', 'Latitude',
'Longitude'],
dtype='object')

```
In [7]: 1 # Remove duplicate rows from the dataset
2 data_cleaned = data.drop_duplicates()
3
4 # Remove rows with any missing values
5 data_cleaned = data_cleaned.dropna()
6
7 # Display the shape of the dataset before and after these operations to sh
8 original_shape = data.shape
9 cleaned_shape = data_cleaned.shape
10 print(original_shape)
11 print(cleaned_shape)
```

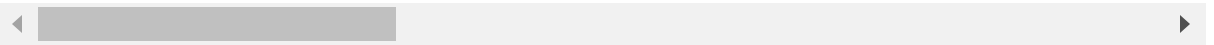
```
(361740, 19)
```

```
(235048, 19)
```

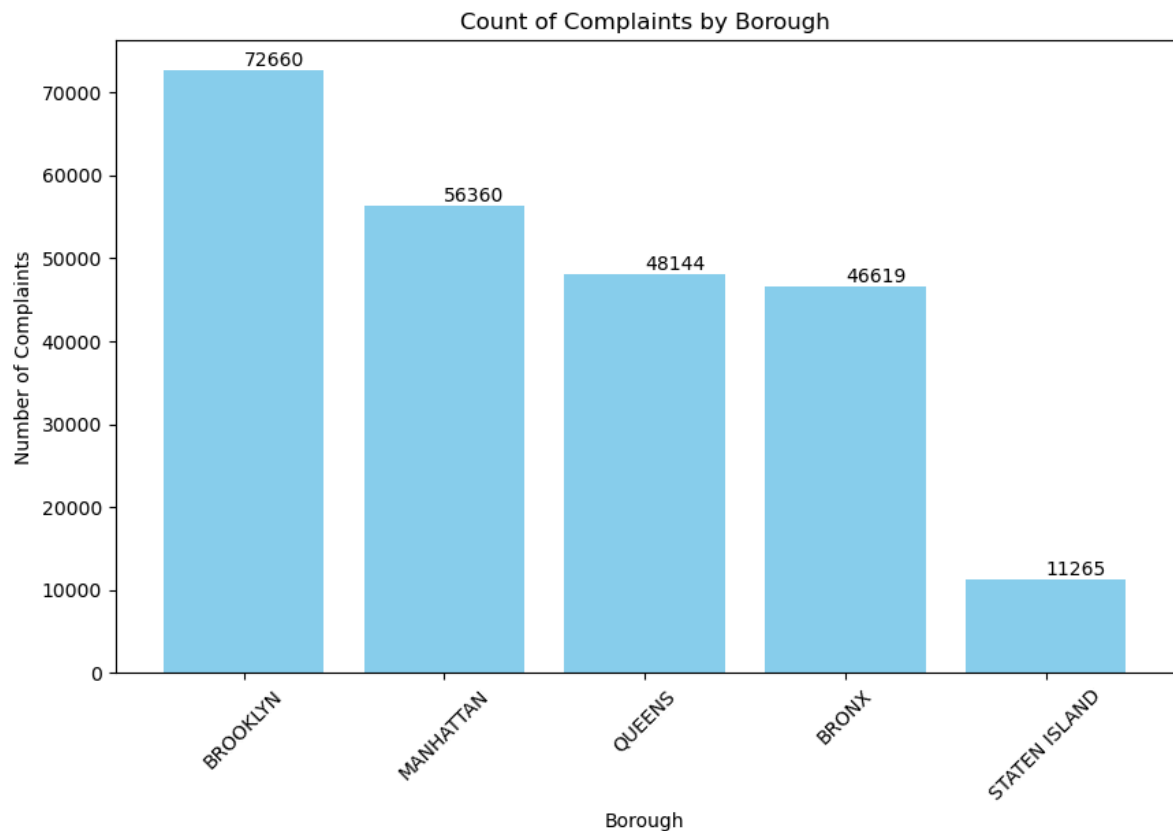
```
In [8]: 1 data_cleaned.head()
```

Out[8]:

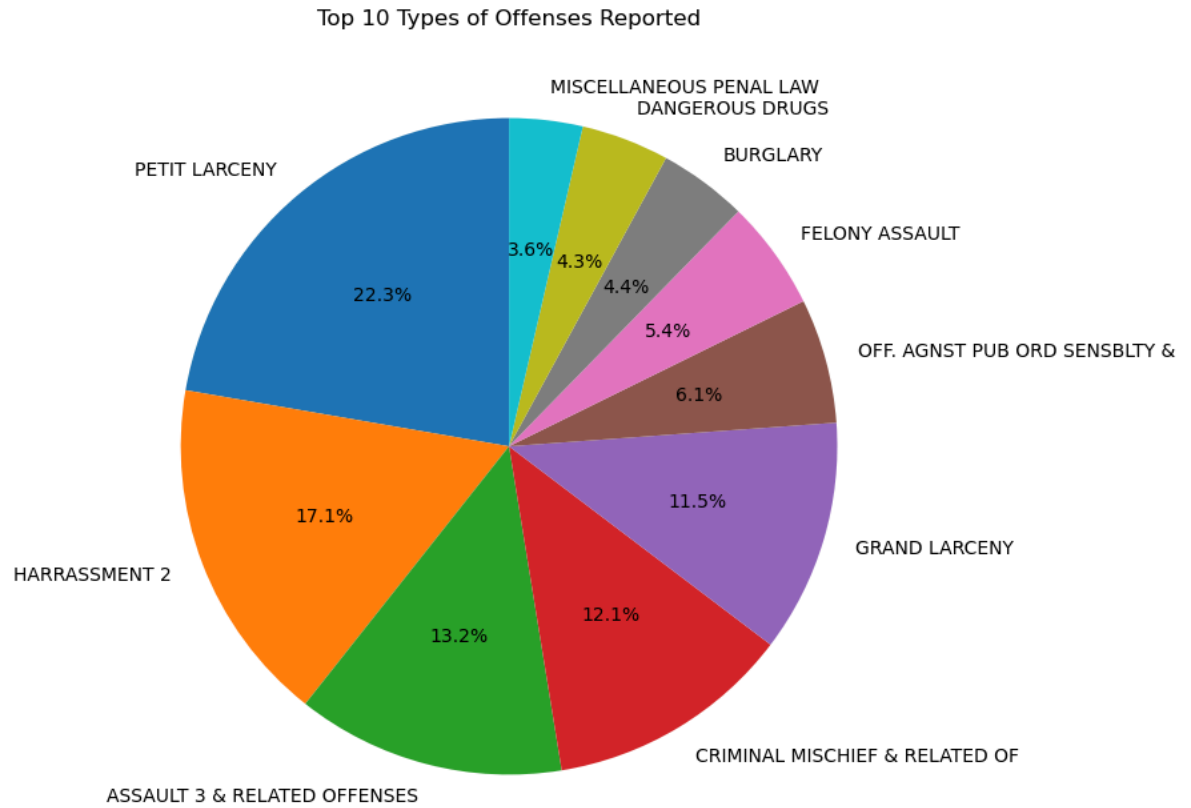
	CMPLNT_NUM	CMPLNT_FR_DT	CMPLNT_FR_TM	CMPLNT_TO_DT	CMPLNT_TO_TM	RPT.
1	294332956	09/30/2016	23:16:00	09/30/2016	23:21:00	09/30/2
2	852981427	09/30/2016	23:00:00	09/30/2016	23:05:00	09/30/2
4	117213771	09/30/2016	23:00:00	09/30/2016	23:10:00	09/30/2
9	589253624	09/30/2016	22:45:00	09/30/2016	22:50:00	09/30/2
10	585217984	09/30/2016	22:45:00	09/30/2016	23:05:00	09/30/2



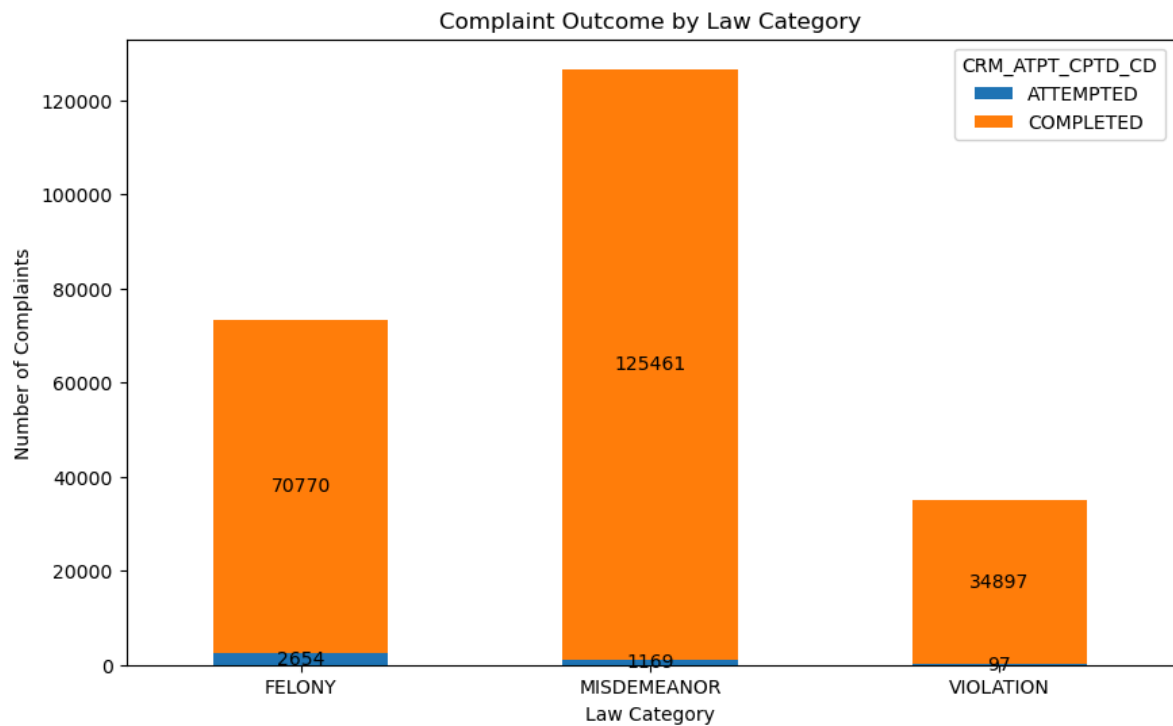
```
In [9]: 1 #Count of Complaints by Borough (established town or City )
2
3 borough_counts = data_cleaned['BORO_NM'].value_counts()
4 plt.figure(figsize=(10, 6))
5 bars = plt.bar(borough_counts.index, borough_counts.values, color='skyblue')
6 plt.title('Count of Complaints by Borough')
7 plt.xlabel('Borough')
8 plt.ylabel('Number of Complaints')
9 plt.xticks(rotation=45)
10 for bar in bars:
11     yval = bar.get_height()
12     plt.text(bar.get_x() + bar.get_width()/2, yval, int(yval), va='bottom')
13 plt.show()
```



```
In [10]: 1 #Types of Offenses
2 offense_counts = data_cleaned['OFNS_DESC'].value_counts().head(10) # Top
3 plt.figure(figsize=(10, 8))
4 patches, texts, autotexts = plt.pie(offense_counts, labels=offense_counts
5 for text in autotexts:
6     text.set_color('black')
7 plt.title('Top 10 Types of Offenses Reported')
8 plt.show()
9
```




```
In [11]: 1 #Complaint Outcome by Law Category
2 outcome_by_category = data_cleaned.groupby(['LAW_CAT_CD', 'CRM_ATPT_CPTD_CD'])
3 bars = outcome_by_category.plot(kind='bar', stacked=True, figsize=(10, 6))
4 plt.title('Complaint Outcome by Law Category')
5 plt.xlabel('Law Category')
6 plt.ylabel('Number of Complaints')
7 plt.xticks(rotation=0)
8 for bar in bars.containers:
9     plt.bar_label(bar, label_type='center')
10 plt.show()
11
```



In [12]:

```

1 # Drop non-numeric and redundant datetime columns
2 data_cleaned.drop(['CMPLNT_FR_DT', 'CMPLNT_FR_TM', 'CMPLNT_TO_DT', 'CMPLNT_TO_TM',
3                    'RPT_DT'], axis=1, inplace=True)
4
5 # Label Encoding for categorical variables
6 label_encoder = LabelEncoder()
7 categorical_columns = ['OFNS_DESC', 'PD_DESC', 'CRM_ATPT_CPTD_CD', 'LAW_CAT_CD',
8                       'BORO_NM', 'LOC_OF_OCCUR_DESC', 'PREM_TYP_DESC']
9 encoding_mappings = {}
10 for column in categorical_columns:
11     # If the column exists in the dataframe and is of type object (categorical)
12     if column in data_cleaned.columns and data_cleaned[column].dtype == 'object':
13         data_cleaned[column] = label_encoder.fit_transform(data_cleaned[column])
14         encoding_mappings[column] = {index: label for index, label in enumerate(label_encoder.classes_)}
15 for column, mapping in encoding_mappings.items():
16     print(f"Encoding for {column}: {mapping}")
17 # Check the datatypes again to confirm all are numeric
18 print(data_cleaned.dtypes)
19
20 # Select features and drop the target variable column for model input
21 X = data_cleaned.drop(['OFNS_DESC', 'CMPLNT_NUM', 'PD_DESC', 'LAW_CAT_CD'], axis=1)
22 y = data_cleaned['OFNS_DESC']
23
24 # Display the first few rows of the prepared data to verify changes
25 print(data_cleaned.head())

```

```

ARREST', 237: 'ROBBERY', 238: 'ROBBERY', 239: 'ROBBERY, CHAIN STORE', 240: 'ROBBERY, PAYROLL', 241: 'ROBBERY, ATM LOCATION', 242: 'ROBBERY, BANK', 243: 'ROBBERY, BAR/RESTAURANT', 244: 'ROBBERY, BEGIN AS SHOPLIFTING', 245: 'ROBBERY, BICYCLE', 246: 'ROBBERY, BODEGA/CONVENIENCE STORE', 247: 'ROBBERY, CAR JACKING', 248: 'ROBBERY, CHECK CASHING BUSINESS', 249: 'ROBBERY, CLOTHING', 250: 'ROBBERY, COMMERCIAL UNCLASSIFIED', 251: 'ROBBERY, DELIVERY PERSON', 252: 'ROBBERY, DOCTOR/DENTIST OFFICE', 253: 'ROBBERY, DWELLING', 254: 'ROBBERY, GAS STATION', 255: 'ROBBERY, HIJACKING', 256: 'ROBBERY, HOME INVASION', 257: 'ROBBERY, LICENSED FOR HIRE VEHICLE', 258: 'ROBBERY, LICENSED MEDALLION CAB', 259: 'ROBBERY, LIQUOR STORE', 260: 'ROBBERY, NECKCHAIN/JEWELRY', 261: 'ROBBERY, ON BUS/ OR BUS DRIVER', 262: 'ROBBERY, OPEN AREA UNCLASSIFIED', 263: 'ROBBERY, PERSONAL ELECTRONIC DEVICE', 264: 'ROBBERY, PHARMACY', 265: 'ROBBERY, POCKETBOOK/CARRIED BAG', 266: 'ROBBERY, PUBLIC PLACE INSIDE', 267: 'ROBBERY, RESIDENTIAL COMMON AREA', 268: 'ROBBERY, UNLICENSED FOR HIRE VEHICLE', 269: 'SALE OF UNAUTHORIZED RECORDING', 270: 'SALE SCHOOL GROUNDS', 271: 'SEXUAL ABUSE 3,2', 272: 'SEXUAL MISCONDUCT, DEVIATE', 273: 'SODOMY 1', 274: 'SODOMY 3', 275: 'SOLICITATION 3,2,1, CRIMINAL', 276: 'SOLICITATION 4, CRIMINAL', 277: 'STOLEN PROP-MOTOR VEHICLE 3RD', 278: 'STOLEN PROPERTY 2,1, POSSESSION', 279: 'STOLEN PROPERTY 2, POSSESSION B', 280: 'STOLEN PROPERTY 3, POSSESSION', 281: 'STOLEN PROPERTY-MOTOR VEH 2ND', 282: 'STRAN

```



```
In [13]: 1 def get_score_DTC(X_train, X_test, y_train, y_test):
2     regressor = DecisionTreeClassifier(max_depth=4)
3     regressor.fit(X_train, y_train)
4     return regressor.score(X_train, y_train)
5
6 def get_score_RFC(X_train, X_test, y_train, y_test):
7     regressor = RandomForestClassifier(max_depth=4)
8     regressor.fit(X_train, y_train)
9     return regressor.score(X_train, y_train)
10 acc_dtc=[]
11 acc_rfc=[]
12
13 dataset = data_cleaned
14 # print(dataset)
15 X = data_cleaned.drop(['OFNS_DESC', 'CMPLNT_NUM', 'PD_DESC', 'LAW_CAT_CD'])
16 y = data_cleaned['OFNS_DESC']
17
18 # Initialize KFold
19 kf = KFold(n_splits=15, shuffle=True, random_state=42)
20
21 # Initialize the models
22 dt = DecisionTreeClassifier(random_state=42)
23 rf = RandomForestClassifier(n_estimators=100, random_state=42)
24
25 # List to store scores
26 dt_scores = []
27 rf_scores = []
28
29 # Perform K-Fold CV
30 for train_index, test_index in kf.split(X):
31     X_train, X_test = X.iloc[train_index], X.iloc[test_index]
32     y_train, y_test = y.iloc[train_index], y.iloc[test_index]
33
34     # Fit Decision Tree
35     dt.fit(X_train, y_train)
36     dt_scores.append(dt.score(X_test, y_test))
37
38     # Fit Random Forest
39     rf.fit(X_train, y_train)
40     rf_scores.append(rf.score(X_test, y_test))
41
42
43 from sklearn.linear_model import LogisticRegression
44 from sklearn.metrics import accuracy_score
45
46 # Initialize the Logistic regression model
47 model = LogisticRegression()
48 model.fit(X_train, y_train)
49 y_pred = model.predict(X_test)
50
51 # Evaluate the model
52 accuracy = accuracy_score(y_test, y_pred)
53 print(f'Accuracy of Logistic regression: {accuracy:.3f}')
54 print("Average Decision Tree accuracy: ", sum(dt_scores) / len(dt_scores))
```

```
55 print("Average Random Forest accuracy: ", sum(rf_scores) / len(rf_scores))
```

Accuracy of Logistic regression: 0.836

Average Decision Tree accuracy: 0.9999149111778747

Average Random Forest accuracy: 0.9987917366622838

C:\Users\harin\anaconda3\anaconda\lib\site-packages\sklearn\linear_model_logistic.py:458: ConvergenceWarning: 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> (<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 (https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression)

```
n_iter_i = _check_optimize_result(
```

In [20]:

```
1 #using regressor model
2 # Initialize the Random Forest Regressor
3 rf_model = RandomForestRegressor()
4
5 # Train the model
6 rf_model.fit(X_train, y_train)
7
8 # Predict on the test set
9 y_pred_rf = rf_model.predict(X_test)
10
11 #we'll look at MSE, RMSE and Accuracy
12 mse = mean_squared_error(y_test, y_pred_rf)
13 rmse = np.sqrt(mse)
14
15 print(f'MSE: {mse:.2f}')
16 print(f'RMSE: {rmse:.2f}')
```

MSE: 0.02

RMSE: 0.13