Data Preprocessing

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn import metrics
from sklearn.metrics import mean_absolute_error, mean_squared_error,
r2_score



# !pip install sklearn


df = pd.read_csv('co2.csv')
df.head()
```

```
    Make       Model Vehicle Class  Engine Size(L)  Cylinders
Transmission  \
0  ACURA         ILX       COMPACT             2.0          4
AS5
1  ACURA         ILX       COMPACT             2.4          4
M6
2  ACURA  ILX HYBRID       COMPACT             1.5          4
AV7
3  ACURA     MDX 4WD   SUV - SMALL             3.5          6
AS6
4  ACURA     RDX AWD   SUV - SMALL             3.5          6
AS6

  Fuel Type  Fuel Consumption City (L/100 km)  \
0         Z                               9.9
1         Z                              11.2
2         Z                               6.0
3         Z                              12.7
4         Z                              12.1

   Fuel Consumption Hwy (L/100 km)  Fuel Consumption Comb (L/100
km)  \
0                              6.7                                  8.5

1                              7.7                                  9.6

2                              5.8                                  5.9

3                              9.1                                 11.1
```

```
4                              8.7                                10.6


   Fuel Consumption Comb (mpg)  CO2 Emissions(g/km)
0                           33                  196
1                           29                  221
2                           48                  136
3                           25                  255
4                           27                  244
```

```
df.head()
```

```
    Make       Model Vehicle Class  Engine Size(L)  Cylinders
Transmission  \
0  ACURA         ILX       COMPACT             2.0          4
AS5
1  ACURA         ILX       COMPACT             2.4          4
M6
2  ACURA  ILX HYBRID       COMPACT             1.5          4
AV7
3  ACURA     MDX 4WD   SUV - SMALL             3.5          6
AS6
4  ACURA     RDX AWD   SUV - SMALL             3.5          6
AS6

  Fuel Type  Fuel Consumption City (L/100 km)  \
0         Z                               9.9
1         Z                              11.2
2         Z                               6.0
3         Z                              12.7
4         Z                              12.1

   Fuel Consumption Hwy (L/100 km)  Fuel Consumption Comb (L/100
km)  \
0                              6.7                                 8.5

1                              7.7                                 9.6

2                              5.8                                 5.9

3                              9.1                                11.1

4                              8.7                                10.6


   Fuel Consumption Comb (mpg)  CO2 Emissions(g/km)
0                           33                  196
1                           29                  221
2                           48                  136
3                           25                  255
4                           27                  244
```

```
df.shape
```

```
(7385, 12)
```

```
len(df)
```

```
7385
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7385 entries, 0 to 7384
Data columns (total 12 columns):
 #   Column                            Non-Null Count  Dtype  
---  ------                            --------------  -----  
 0   Make                              7385 non-null   object 
 1   Model                             7385 non-null   object 
 2   Vehicle Class                     7385 non-null   object 
 3   Engine Size(L)                    7385 non-null   float64
 4   Cylinders                         7385 non-null   int64  
 5   Transmission                      7385 non-null   object 
 6   Fuel Type                         7385 non-null   object 
 7   Fuel Consumption City (L/100 km)  7385 non-null   float64
 8   Fuel Consumption Hwy (L/100 km)   7385 non-null   float64
 9   Fuel Consumption Comb (L/100 km)  7385 non-null   float64
 10  Fuel Consumption Comb (mpg)       7385 non-null   int64  
 11  CO2 Emissions(g/km)               7385 non-null   int64  
dtypes: float64(4), int64(3), object(5)
memory usage: 692.5+ KB
```

```
df.isna().sum()
```

```
Make                                0
Model                               0
Vehicle Class                       0
Engine Size(L)                      0
Cylinders                           0
Transmission                        0
Fuel Type                           0
Fuel Consumption City (L/100 km)    0
Fuel Consumption Hwy (L/100 km)     0
Fuel Consumption Comb (L/100 km)    0
Fuel Consumption Comb (mpg)         0
CO2 Emissions(g/km)                 0
dtype: int64
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7385 entries, 0 to 7384
Data columns (total 12 columns):
 #   Column                            Non-Null Count  Dtype  
---  ------                            --------------  -----  
 0   Make                              7385 non-null   object 
 1   Model                             7385 non-null   object 
 2   Vehicle Class                     7385 non-null   object 
 3   Engine Size(L)                    7385 non-null   float64
 4   Cylinders                         7385 non-null   int64  
 5   Transmission                      7385 non-null   object 
 6   Fuel Type                         7385 non-null   object 
 7   Fuel Consumption City (L/100 km)  7385 non-null   float64
 8   Fuel Consumption Hwy (L/100 km)   7385 non-null   float64
 9   Fuel Consumption Comb (L/100 km)  7385 non-null   float64
 10  Fuel Consumption Comb (mpg)       7385 non-null   int64  
 11  CO2 Emissions(g/km)               7385 non-null   int64  
dtypes: float64(4), int64(3), object(5)
memory usage: 692.5+ KB
```

```
df['Make'].value_counts()
```

```
Make
FORD             628
CHEVROLET        588
BMW              527
MERCEDES-BENZ    419
PORSCHE          376
TOYOTA           330
GMC              328
AUDI             286
NISSAN           259
JEEP             251
DODGE            246
KIA              231
HONDA            214
HYUNDAI          210
MINI             204
VOLKSWAGEN       197
MAZDA            180
LEXUS            178
JAGUAR           160
CADILLAC         158
SUBARU           140
VOLVO            124
INFINITI         108
BUICK            103
RAM               97
LINCOLN           96
MITSUBISHI        95
```

```
CHRYSLER           88
LAND ROVER         85
FIAT               73
ACURA              72
MASERATI           61
ROLLS-ROYCE        50
ASTON MARTIN       47
BENTLEY            46
LAMBORGHINI        41
ALFA ROMEO         30
GENESIS            25
SCION              22
SMART               7
BUGATTI             3
SRT                 2
Name: count, dtype: int64
```

```
df[df['Make'] == 'SMART'][['Make' , 'Fuel Type']]
```

```
       Make Fuel Type
943   SMART         Z
944   SMART         Z
2072  SMART         Z
2073  SMART         Z
3189  SMART         Z
3190  SMART         Z
4255  SMART         Z
```

```
df.columns
```

```
Index(['Make', 'Model', 'Vehicle Class', 'Engine Size(L)',
'Cylinders',
       'Transmission', 'Fuel Type', 'Fuel Consumption City (L/100
km)',
       'Fuel Consumption Hwy (L/100 km)', 'Fuel Consumption Comb
(L/100 km)',
       'Fuel Consumption Comb (mpg)', 'CO2 Emissions(g/km)'],
      dtype='object')
```

```
df['Make'].value_counts()
```

```
Make
FORD              628
CHEVROLET         588
BMW               527
MERCEDES-BENZ     419
PORSCHE           376
```

```
TOYOTA            330
GMC               328
AUDI              286
NISSAN            259
JEEP              251
DODGE             246
KIA               231
HONDA             214
HYUNDAI           210
MINI              204
VOLKSWAGEN        197
MAZDA             180
LEXUS             178
JAGUAR            160
CADILLAC          158
SUBARU            140
VOLVO             124
INFINITI          108
BUICK             103
RAM                97
LINCOLN            96
MITSUBISHI         95
CHRYSLER           88
LAND ROVER         85
FIAT               73
ACURA              72
MASERATI           61
ROLLS-ROYCE        50
ASTON MARTIN       47
BENTLEY            46
LAMBORGHINI        41
ALFA ROMEO         30
GENESIS            25
SCION              22
SMART               7
BUGATTI             3
SRT                 2
Name: count, dtype: int64
```

```python
from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()
df["Make"] = le.fit_transform(df["Make"])
df["Make"].value_counts()
```

```
Make
13    628
9     588
5     527
28    419
32    376
```

```
39    330
15    328
3     286
31    259
20    251
11    246
21    231
16    214
17    210
29    204
40    197
27    180
24    178
19    160
8     158
38    140
41    124
18    108
7     103
33     97
25     96
30     95
10     88
23     85
12     73
0      72
26     61
34     50
2      47
4      46
22     41
1      30
14     25
35     22
36      7
6       3
37      2
Name: count, dtype: int64
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7385 entries, 0 to 7384
Data columns (total 12 columns):
 #   Column                            Non-Null Count  Dtype
---  ------                            --------------  -----
 0   Make                              7385 non-null   int64
 1   Model                             7385 non-null   object
 2   Vehicle Class                     7385 non-null   object
 3   Engine Size(L)                    7385 non-null   float64
```

```
 4   Cylinders                         7385 non-null   int64
 5   Transmission                      7385 non-null   object
 6   Fuel Type                         7385 non-null   object
 7   Fuel Consumption City (L/100 km)  7385 non-null   float64
 8   Fuel Consumption Hwy (L/100 km)   7385 non-null   float64
 9   Fuel Consumption Comb (L/100 km)  7385 non-null   float64
 10  Fuel Consumption Comb (mpg)       7385 non-null   int64
 11  CO2 Emissions(g/km)               7385 non-null   int64
dtypes: float64(4), int64(4), object(4)
memory usage: 692.5+ KB
```

```
df['Model'].value_counts()
```

```
Model
F-150 FFV                32
F-150 FFV 4X4            32
MUSTANG                  27
FOCUS FFV                24
SONIC                    20
                         ..
Camry TRD                 1
Cullinan Black Badge      1
1500 4X4 EcoDiesel        1
1500 EcoDiesel            1
Sentra SR                 1
Name: count, Length: 2053, dtype: int64
```

```
df.drop('Model' , axis =1,  inplace=True)
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7385 entries, 0 to 7384
Data columns (total 11 columns):
 #   Column                            Non-Null Count  Dtype
---  ------                            --------------  -----
 0   Make                              7385 non-null   int64
 1   Vehicle Class                     7385 non-null   object
 2   Engine Size(L)                    7385 non-null   float64
 3   Cylinders                         7385 non-null   int64
 4   Transmission                      7385 non-null   object
 5   Fuel Type                         7385 non-null   object
 6   Fuel Consumption City (L/100 km)  7385 non-null   float64
 7   Fuel Consumption Hwy (L/100 km)   7385 non-null   float64
 8   Fuel Consumption Comb (L/100 km)  7385 non-null   float64
 9   Fuel Consumption Comb (mpg)       7385 non-null   int64
 10  CO2 Emissions(g/km)               7385 non-null   int64
dtypes: float64(4), int64(4), object(3)
memory usage: 634.8+ KB
```

```
df['Vehicle Class'].value_counts()
```

```
Vehicle Class
SUV - SMALL                 1217
MID-SIZE                    1133
COMPACT                     1022
SUV - STANDARD               735
FULL-SIZE                    639
SUBCOMPACT                   606
PICKUP TRUCK - STANDARD      538
TWO-SEATER                   460
MINICOMPACT                  326
STATION WAGON - SMALL        252
PICKUP TRUCK - SMALL         159
MINIVAN                       80
SPECIAL PURPOSE VEHICLE       77
VAN - PASSENGER               66
STATION WAGON - MID-SIZE      53
VAN - CARGO                   22
Name: count, dtype: int64
```

```
df["Vehicle Class"] = le.fit_transform(df["Vehicle Class"])
df["Vehicle Class"].value_counts()
```

```
Vehicle Class
11    1217
2     1133
0     1022
12     735
1      639
10     606
6      538
13     460
3      326
9      252
5      159
4       80
7       77
15      66
8       53
14      22
Name: count, dtype: int64
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7385 entries, 0 to 7384
Data columns (total 11 columns):
 #   Column                                  Non-Null Count  Dtype
---  ------                                  --------------  -----
 0   Make                                    7385 non-null   int64
 1   Vehicle Class                           7385 non-null   int64
```

```
 2   Engine Size(L)                    7385 non-null   float64
 3   Cylinders                         7385 non-null   int64
 4   Transmission                      7385 non-null   object
 5   Fuel Type                         7385 non-null   object
 6   Fuel Consumption City (L/100 km)  7385 non-null   float64
 7   Fuel Consumption Hwy (L/100 km)   7385 non-null   float64
 8   Fuel Consumption Comb (L/100 km)  7385 non-null   float64
 9   Fuel Consumption Comb (mpg)       7385 non-null   int64
 10  CO2 Emissions(g/km)               7385 non-null   int64
dtypes: float64(4), int64(5), object(2)
memory usage: 634.8+ KB
```

```
df['Transmission'].value_counts()
```

```
Transmission
AS6     1324
AS8     1211
M6       901
A6       789
A8       490
AM7      445
A9       339
AS7      319
AV       295
M5       193
AS10     168
AM6      132
AV7      118
AV6      113
M7        91
A5        84
AS9       77
A4        65
AM8       62
A7        53
AV8       39
A10       31
AS5       26
AV10      11
AM5        4
AM9        3
AS4        2
Name: count, dtype: int64
```

```
df["Transmission"] = le.fit_transform(df["Transmission"])
df["Transmission"].value_counts()
```

```
Transmission
15    1324
17    1211
```

```
25      901
3       789
5       490
9       445
6       339
16      319
19      295
24      193
12      168
8       132
22      118
21      113
26       91
2        84
18       77
1        65
10       62
4        53
23       39
0        31
14       26
20       11
7         4
11        3
13        2
Name: count, dtype: int64
```

```
df['Transmission'].value_counts()
```

```
Transmission
15    1324
17    1211
25     901
3      789
5      490
9      445
6      339
16     319
19     295
24     193
12     168
8      132
22     118
21     113
26      91
2       84
18      77
1       65
10      62
4       53
```

```
23      39
0       31
14      26
20      11
7        4
11       3
13       2
Name: count, dtype: int64
```

```python
df['Fuel Type'].value_counts()
```

```
Fuel Type
X    3637
Z    3202
E     370
D     175
N       1
Name: count, dtype: int64
```

```python
df["Fuel Type"] = le.fit_transform(df["Fuel Type"])
df["Fuel Type"].value_counts()
```

```
Fuel Type
3    3637
4    3202
1     370
0     175
2       1
Name: count, dtype: int64
```

```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7385 entries, 0 to 7384
Data columns (total 11 columns):
 #   Column                            Non-Null Count  Dtype  
---  ------                            --------------  -----  
 0   Make                              7385 non-null   int64  
 1   Vehicle Class                     7385 non-null   int64  
 2   Engine Size(L)                    7385 non-null   float64
 3   Cylinders                         7385 non-null   int64  
 4   Transmission                      7385 non-null   int64  
 5   Fuel Type                         7385 non-null   int64  
 6   Fuel Consumption City (L/100 km)  7385 non-null   float64
 7   Fuel Consumption Hwy (L/100 km)   7385 non-null   float64
 8   Fuel Consumption Comb (L/100 km)  7385 non-null   float64
 9   Fuel Consumption Comb (mpg)       7385 non-null   int64  
 10  CO2 Emissions(g/km)               7385 non-null   int64  
dtypes: float64(4), int64(7)
memory usage: 634.8 KB
```

```
# df = df.drop(['Make', 'Model','Vehicle Class','Transmission'],
axis=1)
# df.shape

df["Fuel Type"].value_counts()
```

```
Fuel Type
3    3637
4    3202
1     370
0     175
2       1
Name: count, dtype: int64
```

```
from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()
df["Fuel Type"] = le.fit_transform(df["Fuel Type"])
df["Fuel Type"].value_counts()
```

```
Fuel Type
3    3637
4    3202
1     370
0     175
2       1
Name: count, dtype: int64
```

Correlation

```
correlation = df.corr()
correlation
```

```
                                      Make  Vehicle Class  Engine
Size(L)  \
Make                              1.000000      -0.029558        -
0.146199
Vehicle Class                    -0.029558       1.000000
0.142704
Engine Size(L)                   -0.146199       0.142704
1.000000
Cylinders                        -0.162065       0.105978
0.927653
Transmission                      0.181923      -0.156562        -
0.322389
Fuel Type                         0.045368      -0.033560
0.058296
Fuel Consumption City (L/100 km) -0.197389       0.240941
```

```
0.831379
Fuel Consumption Hwy (L/100 km)  -0.126010       0.329828
0.761526
Fuel Consumption Comb (L/100 km) -0.175238       0.274388
0.817060
Fuel Consumption Comb (mpg)       0.182649      -0.277606        -
0.757854
CO2 Emissions(g/km)              -0.151955       0.286468
0.851145

                                  Cylinders  Transmission  Fuel
Type  \
Make                              -0.162065      0.181923   0.045368

Vehicle Class                      0.105978     -0.156562  -0.033560

Engine Size(L)                     0.927653     -0.322389   0.058296

Cylinders                          1.000000     -0.270011   0.125175

Transmission                      -0.270011      1.000000   0.212872

Fuel Type                          0.125175      0.212872   1.000000

Fuel Consumption City (L/100 km)   0.800702     -0.345839  -0.075605

Fuel Consumption Hwy (L/100 km)    0.715252     -0.355371  -0.129812

Fuel Consumption Comb (L/100 km)   0.780534     -0.353609  -0.095539

Fuel Consumption Comb (mpg)       -0.719321      0.331213  -0.016880

CO2 Emissions(g/km)                0.832644     -0.316660   0.100306


                                  Fuel Consumption City (L/100 km)  \
Make                                                     -0.197389
Vehicle Class                                             0.240941
Engine Size(L)                                            0.831379
Cylinders                                                 0.800702
Transmission                                             -0.345839
Fuel Type                                                -0.075605
Fuel Consumption City (L/100 km)                          1.000000
Fuel Consumption Hwy (L/100 km)                           0.948180
Fuel Consumption Comb (L/100 km)                          0.993810
Fuel Consumption Comb (mpg)                              -0.927059
CO2 Emissions(g/km)                                       0.919592

                                  Fuel Consumption Hwy (L/100 km)  \
Make                                                    -0.126010
Vehicle Class                                            0.329828
```

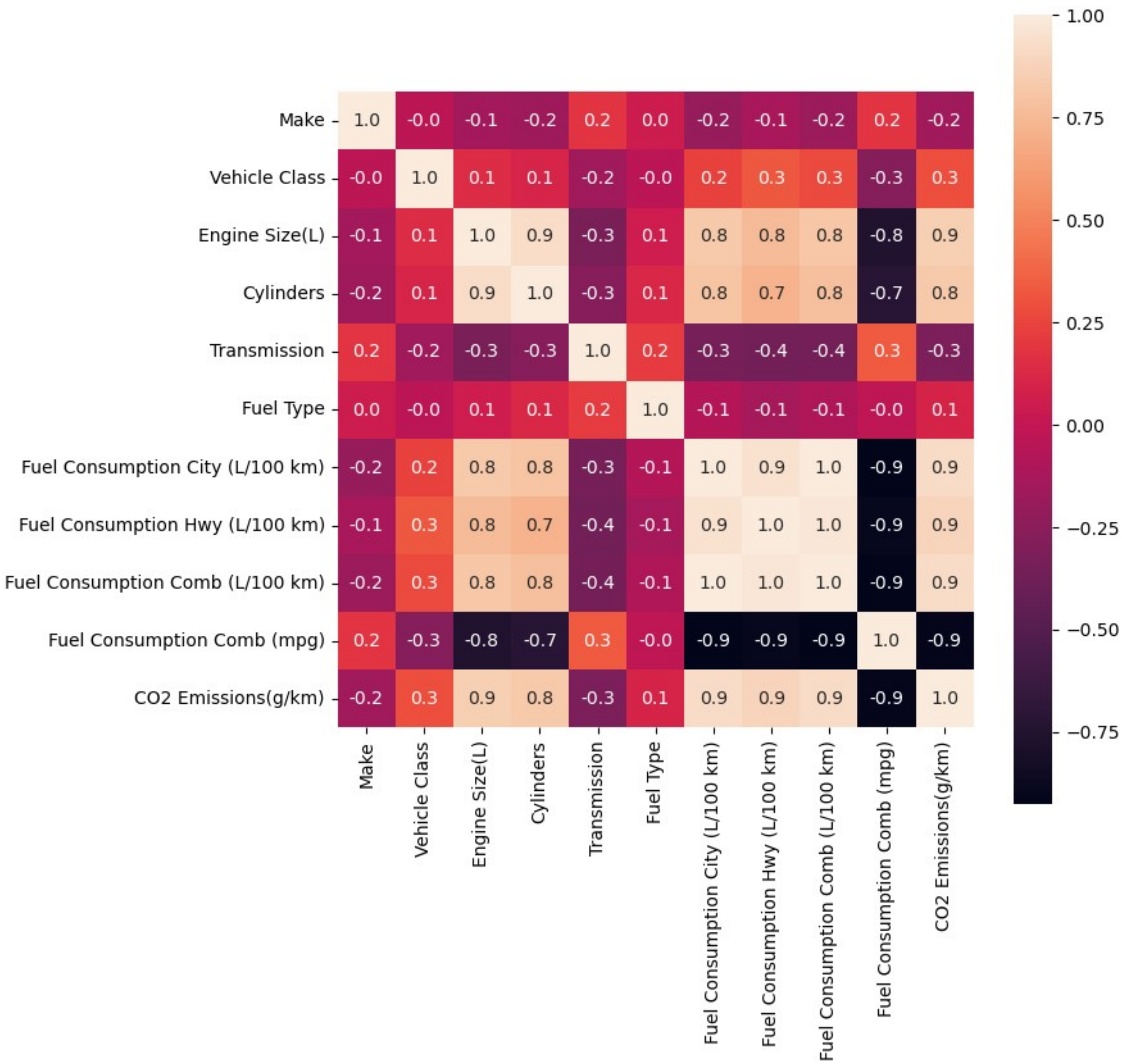
```
Engine Size(L)                                                 0.761526
Cylinders                                                      0.715252
Transmission                                                  -0.355371
Fuel Type                                                     -0.129812
Fuel Consumption City (L/100 km)                               0.948180
Fuel Consumption Hwy (L/100 km)                                1.000000
Fuel Consumption Comb (L/100 km)                               0.977299
Fuel Consumption Comb (mpg)                                   -0.890638
CO2 Emissions(g/km)                                            0.883536

                                  Fuel Consumption Comb (L/100 km)  \
Make                                                     -0.175238
Vehicle Class                                             0.274388
Engine Size(L)                                            0.817060
Cylinders                                                 0.780534
Transmission                                             -0.353609
Fuel Type                                                -0.095539
Fuel Consumption City (L/100 km)                          0.993810
Fuel Consumption Hwy (L/100 km)                           0.977299
Fuel Consumption Comb (L/100 km)                          1.000000
Fuel Consumption Comb (mpg)                              -0.925576
CO2 Emissions(g/km)                                       0.918052

                                  Fuel Consumption Comb (mpg)  \
Make                                                 0.182649
Vehicle Class                                       -0.277606
Engine Size(L)                                      -0.757854
Cylinders                                           -0.719321
Transmission                                         0.331213
Fuel Type                                           -0.016880
Fuel Consumption City (L/100 km)                    -0.927059
Fuel Consumption Hwy (L/100 km)                     -0.890638
Fuel Consumption Comb (L/100 km)                    -0.925576
Fuel Consumption Comb (mpg)                          1.000000
CO2 Emissions(g/km)                                 -0.907426

                                  CO2 Emissions(g/km)
Make                                        -0.151955
Vehicle Class                                0.286468
Engine Size(L)                               0.851145
Cylinders                                    0.832644
Transmission                                -0.316660
Fuel Type                                    0.100306
Fuel Consumption City (L/100 km)             0.919592
Fuel Consumption Hwy (L/100 km)              0.883536
Fuel Consumption Comb (L/100 km)             0.918052
Fuel Consumption Comb (mpg)                 -0.907426
CO2 Emissions(g/km)                          1.000000
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7385 entries, 0 to 7384
Data columns (total 11 columns):
 #   Column                             Non-Null Count  Dtype  
---  ------                             --------------  -----  
 0   Make                               7385 non-null   int64  
 1   Vehicle Class                      7385 non-null   int64  
 2   Engine Size(L)                     7385 non-null   float64
 3   Cylinders                          7385 non-null   int64  
 4   Transmission                       7385 non-null   int64  
 5   Fuel Type                          7385 non-null   int64  
 6   Fuel Consumption City (L/100 km)   7385 non-null   float64
 7   Fuel Consumption Hwy (L/100 km)    7385 non-null   float64
 8   Fuel Consumption Comb (L/100 km)   7385 non-null   float64
 9   Fuel Consumption Comb (mpg)        7385 non-null   int64  
 10  CO2 Emissions(g/km)                7385 non-null   int64  
dtypes: float64(4), int64(7)
memory usage: 634.8 KB
```

```python
# constructing a heatmap to nderstand the correlation
plt.figure(figsize=(8,8))
sns.heatmap(correlation, square=True, fmt='.1f', annot=True)
```

```
<Axes: >
```



DATA SPLITING

```
X = df.drop('CO2 Emissions(g/km)', axis=1)
Y = df['CO2 Emissions(g/km)']

X.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7385 entries, 0 to 7384
Data columns (total 10 columns):
 #   Column                             Non-Null Count  Dtype
---  ------                             --------------  -----
 0   Make                               7385 non-null   int64
```

```
 1   Vehicle Class                       7385 non-null   int64
 2   Engine Size(L)                      7385 non-null   float64
 3   Cylinders                           7385 non-null   int64
 4   Transmission                        7385 non-null   int64
 5   Fuel Type                           7385 non-null   int64
 6   Fuel Consumption City (L/100 km)    7385 non-null   float64
 7   Fuel Consumption Hwy (L/100 km)     7385 non-null   float64
 8   Fuel Consumption Comb (L/100 km)    7385 non-null   float64
 9   Fuel Consumption Comb (mpg)         7385 non-null   int64
dtypes: float64(4), int64(6)
memory usage: 577.1 KB
```

```
Y.info()
```

```
<class 'pandas.core.series.Series'>
RangeIndex: 7385 entries, 0 to 7384
Series name: CO2 Emissions(g/km)
Non-Null Count  Dtype
--------------  -----
7385 non-null   int64
dtypes: int64(1)
memory usage: 57.8 KB
```

```
from sklearn.model_selection  import train_test_split
X_TRAIN , X_TEST , Y_TRAIN, Y_TEST = train_test_split(X,Y, test_size =
0.25, random_state=25)
print("Size of Train X =  " , len(X_TRAIN))
print("Size of Train Y =  " , len(Y_TRAIN))
print("Size of Test X =  " , len(X_TEST))
print("Size of Test Y =  " , len(Y_TEST))
```

```
Size of Train X =   5538
Size of Train Y =   5538
Size of Test X =   1847
Size of Test Y =   1847
```

LINEAR REGRESSION

```
from sklearn.linear_model import LinearRegression
model= LinearRegression()
model.fit(X_TRAIN, Y_TRAIN)
```

```
LinearRegression()
```

Prediction on Train Data

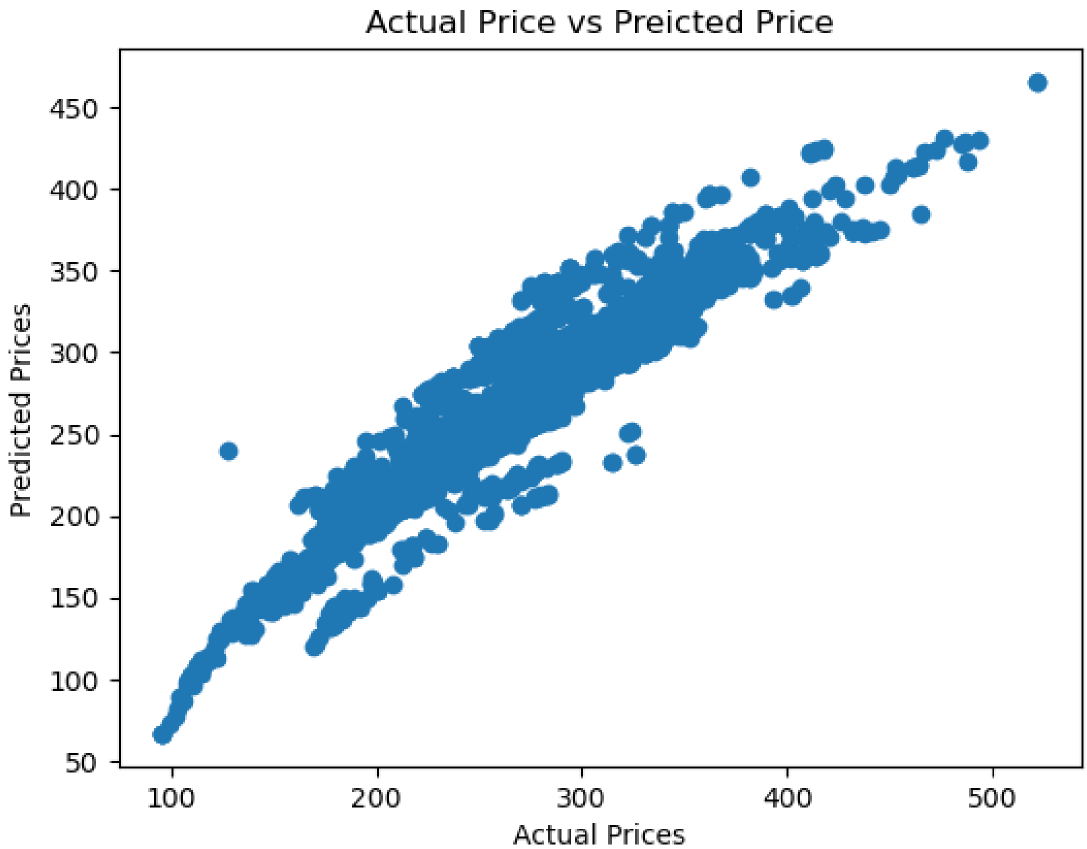
```
# accuracy for prediction on training data
training_data_prediction = model.predict(X_TRAIN)
print(training_data_prediction)
```

```
[280.013408   315.84268011 144.72620894 ... 294.17432435 236.5539138
 198.74325804]
```

```
# R squared error
score_1 = metrics.r2_score(Y_TRAIN, training_data_prediction)

# Mean Absolute Error
score_2 = metrics.mean_absolute_error(Y_TRAIN,
training_data_prediction)

print("R squared : ", score_1)
print('Mean Absolute Error : ', score_2)
```

```
R squared :  0.9153849568066784
Mean Absolute Error :  11.17147303195528
```

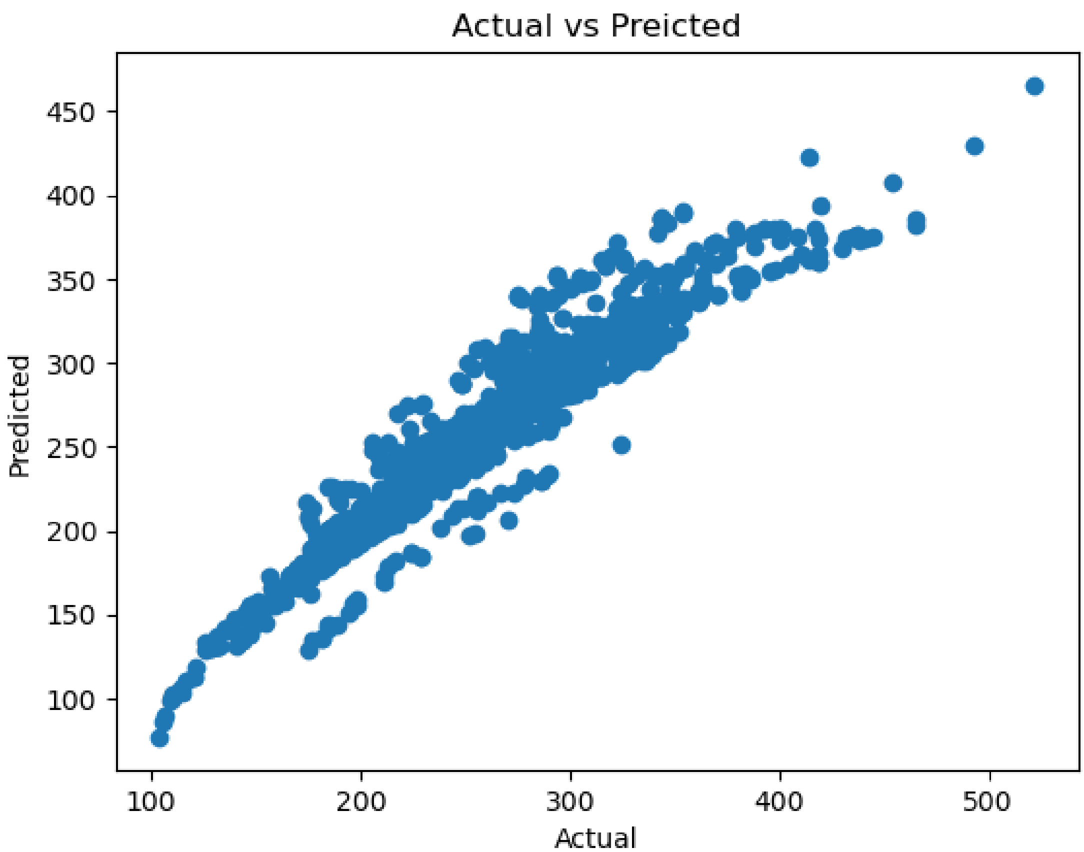
```
plt.scatter(Y_TRAIN, training_data_prediction)
plt.xlabel("Actual Prices")
plt.ylabel("Predicted Prices")
plt.title("Actual Price vs Preicted Price")
plt.show()
```



Prediction on Test Data

```
y_pred = model.predict(X_TEST)
y_pred
print(y_pred)

[233.2941932  283.77211363 242.956709   ... 237.3456667  191.57369611
 174.13609452]

# R squared Score
score_1 = metrics.r2_score(Y_TEST, y_pred)

# Mean Absolute Error
score_2 = metrics.mean_absolute_error(Y_TEST, y_pred)

print("R squared Score : ", score_1)
print('Mean Absolute Error : ', score_2)

R squared Score :  0.9173989134759174
Mean Absolute Error :  11.044093610214464

plt.scatter(Y_TEST, y_pred)
plt.xlabel("Actual")
```

```
plt.ylabel("Predicted")
plt.title("Actual vs Preicted")
plt.show()
```



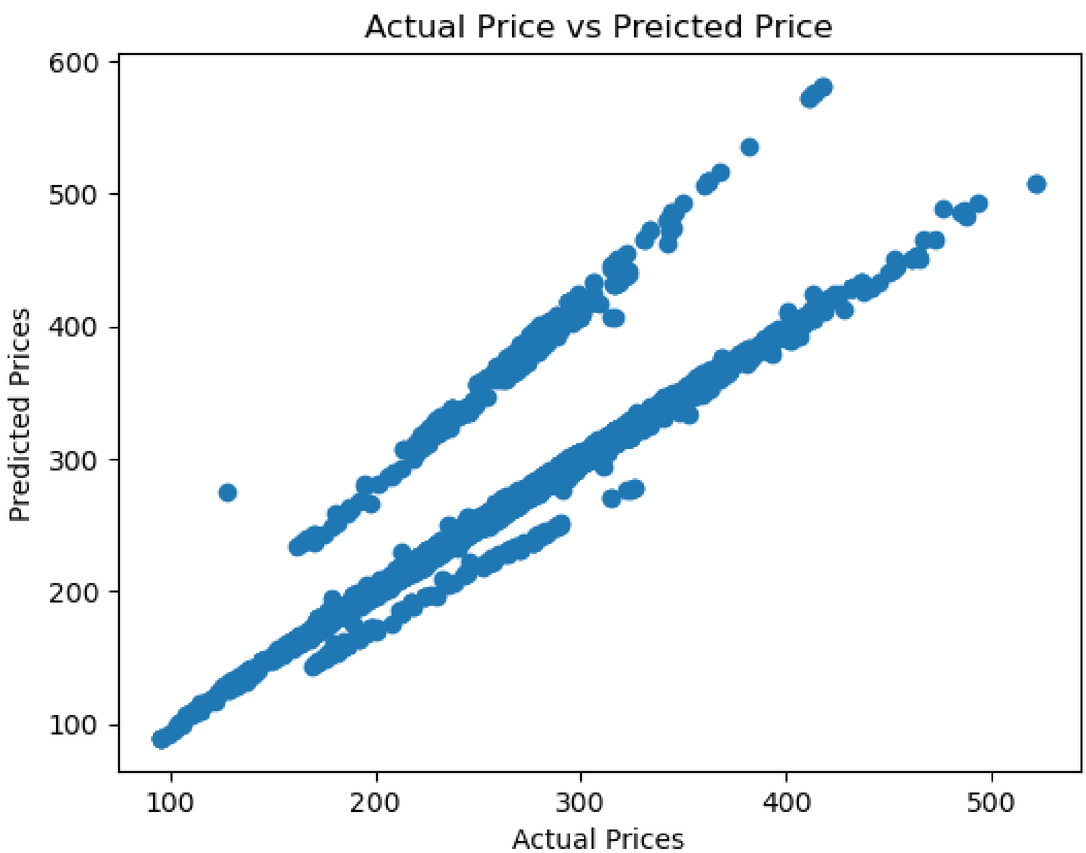
SVM REGRESSION

```
from sklearn.svm import SVR
svr = SVR(kernel='linear')

svr.fit(X_TRAIN, Y_TRAIN)

SVR(kernel='linear')
```

Prediction on Train Data

```
# accuracy for prediction on training data
training_data_prediction = svr.predict(X_TRAIN)
print(training_data_prediction)
```

```
[279.58450148 319.15835613 150.61361469 ... 290.65433483 279.41839813
 193.94021626]

# R squared error
score_1 = metrics.r2_score(Y_TRAIN, training_data_prediction)

# Mean Absolute Error
score_2 = metrics.mean_absolute_error(Y_TRAIN,
training_data_prediction)

print("R squared : ", score_1)
print('Mean Absolute Error : ', score_2)

R squared :  0.812235212106675
Mean Absolute Error :  8.393098579369461

plt.scatter(Y_TRAIN, training_data_prediction)
plt.xlabel("Actual Prices")
plt.ylabel("Predicted Prices")
plt.title("Actual Price vs Preicted Price")
plt.show()
```



Prediction on Test Data

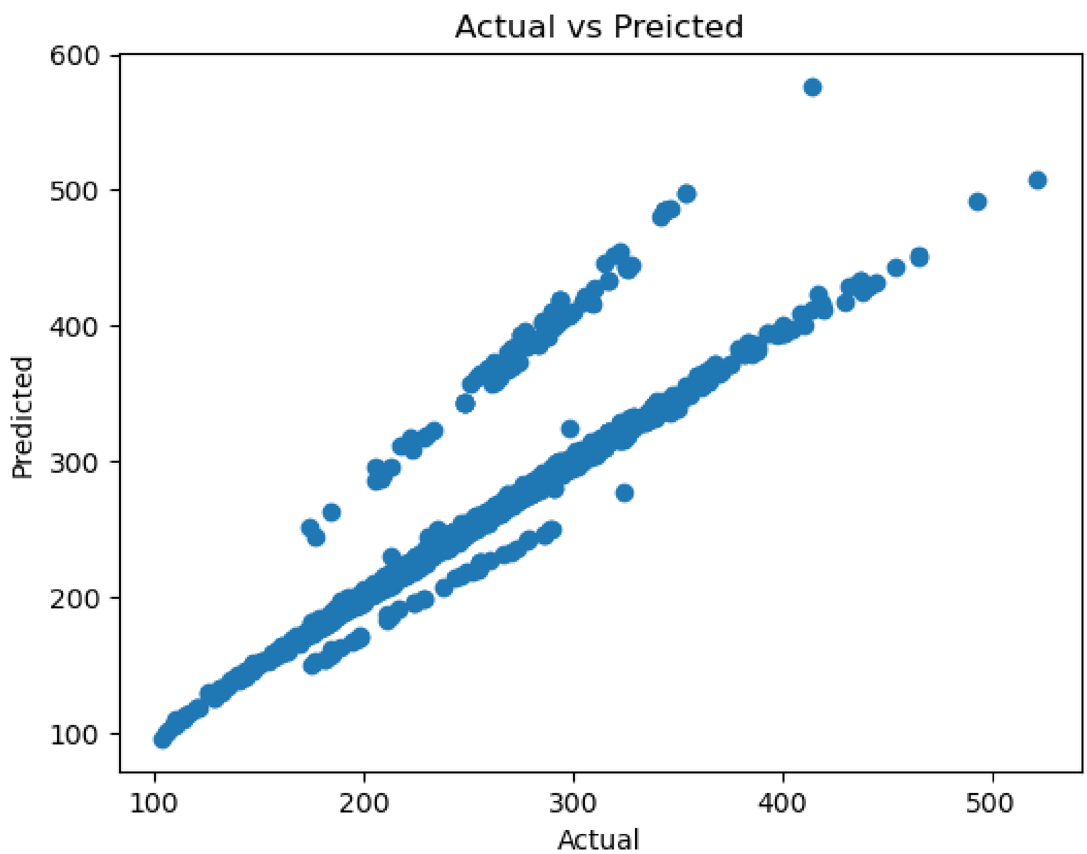
```
y_pred = svr.predict(X_TEST)
y_pred
print(y_pred)
```

```
[241.93941487 283.5429716  238.16100842 ... 233.67655131 185.32175089
 174.78062399]
```

```
# R squared Score
score_1 = metrics.r2_score(Y_TEST, y_pred)

# Mean Absolute Error
score_2 = metrics.mean_absolute_error(Y_TEST, y_pred)

print("R squared Score : ", score_1)
print('Mean Absolute Error : ', score_2)
```

```
R squared Score :  0.819230911133283
Mean Absolute Error :  8.066009439876659
```

```
plt.scatter(Y_TEST, y_pred)
plt.xlabel("Actual")
plt.ylabel("Predicted")
plt.title("Actual vs Preicted")
plt.show()
```



REGRESSION DECISION TREE

```
# import the regressor
from sklearn.tree import DecisionTreeRegressor

# create a regressor object
regressor = DecisionTreeRegressor(random_state = 25)

# fit the regressor with X and Y data
regressor.fit(X_TRAIN, Y_TRAIN)

DecisionTreeRegressor(random_state=25)
```

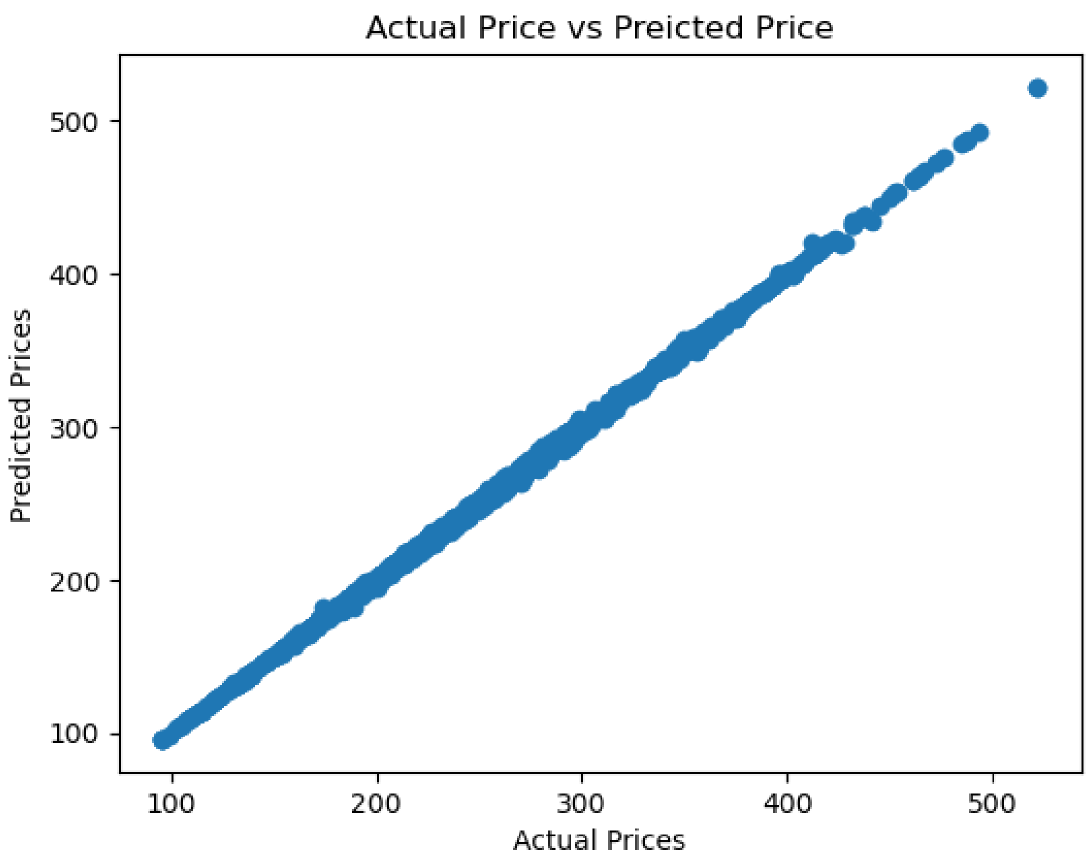
Prediction on Train Data

```
# accuracy for prediction on training data
training_data_prediction = regressor.predict(X_TRAIN)
print(training_data_prediction)

[279.         321.         150.66666667 ... 290.         195.
 195.        ]
```

```
# R squared error
score_1 = metrics.r2_score(Y_TRAIN, training_data_prediction)

# Mean Absolute Error
score_2 = metrics.mean_absolute_error(Y_TRAIN,
training_data_prediction)

print("R squared : ", score_1)
print('Mean Absolute Error : ', score_2)
```

```
R squared :  0.9996932983241511
Mean Absolute Error :  0.37144834820891154
```

```
plt.scatter(Y_TRAIN, training_data_prediction)
plt.xlabel("Actual Prices")
plt.ylabel("Predicted Prices")
plt.title("Actual Price vs Preicted Price")
plt.show()
```



Prediction on Test Data

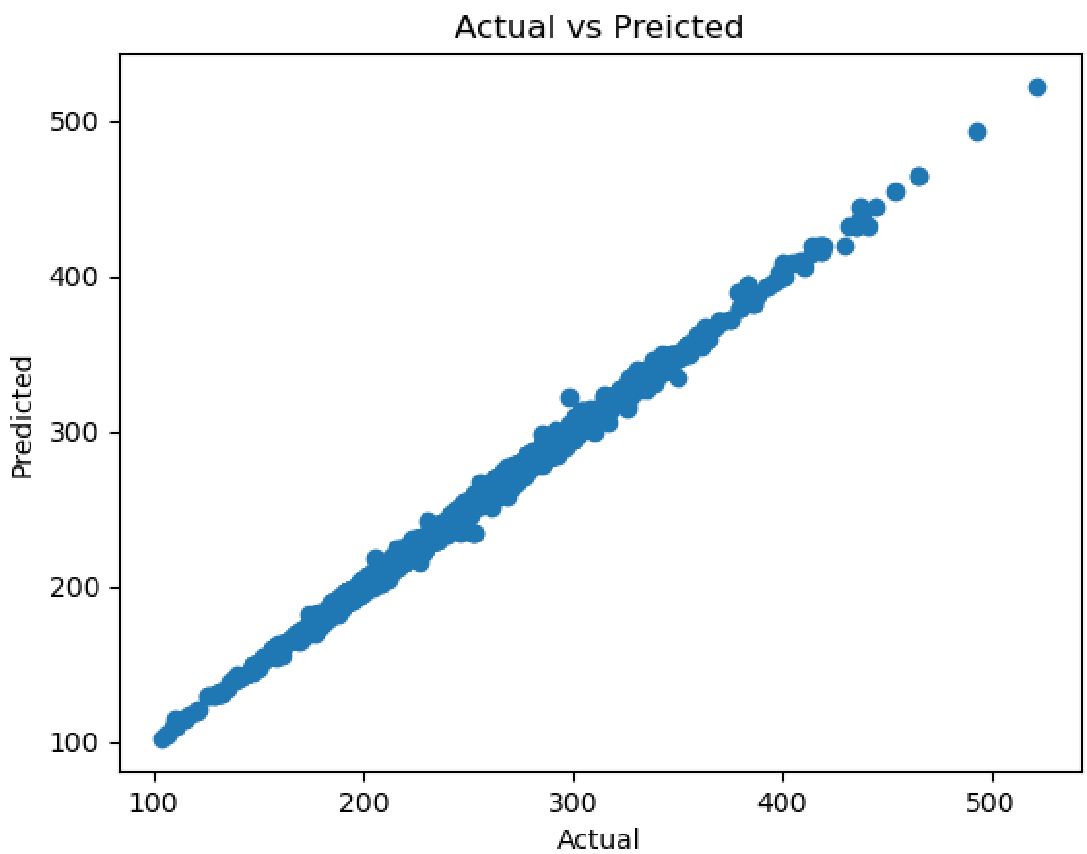
```
y_pred = regressor.predict(X_TEST)
y_pred
print(y_pred)
```

```
[244.  285.  238.  ... 233.  186.  172.5]
```

```
# R squared Score
score_1 = metrics.r2_score(Y_TEST, y_pred)

# Mean Absolute Error
score_2 = metrics.mean_absolute_error(Y_TEST, y_pred)

print("R squared Score : ", score_1)
print('Mean Absolute Error : ', score_2)
```

```
R squared Score :  0.9975867297567413
Mean Absolute Error :  1.6402377085105833
```

```
plt.scatter(Y_TEST, y_pred)
plt.xlabel("Actual")
plt.ylabel("Predicted")
plt.title("Actual vs Preicted")
plt.show()
```



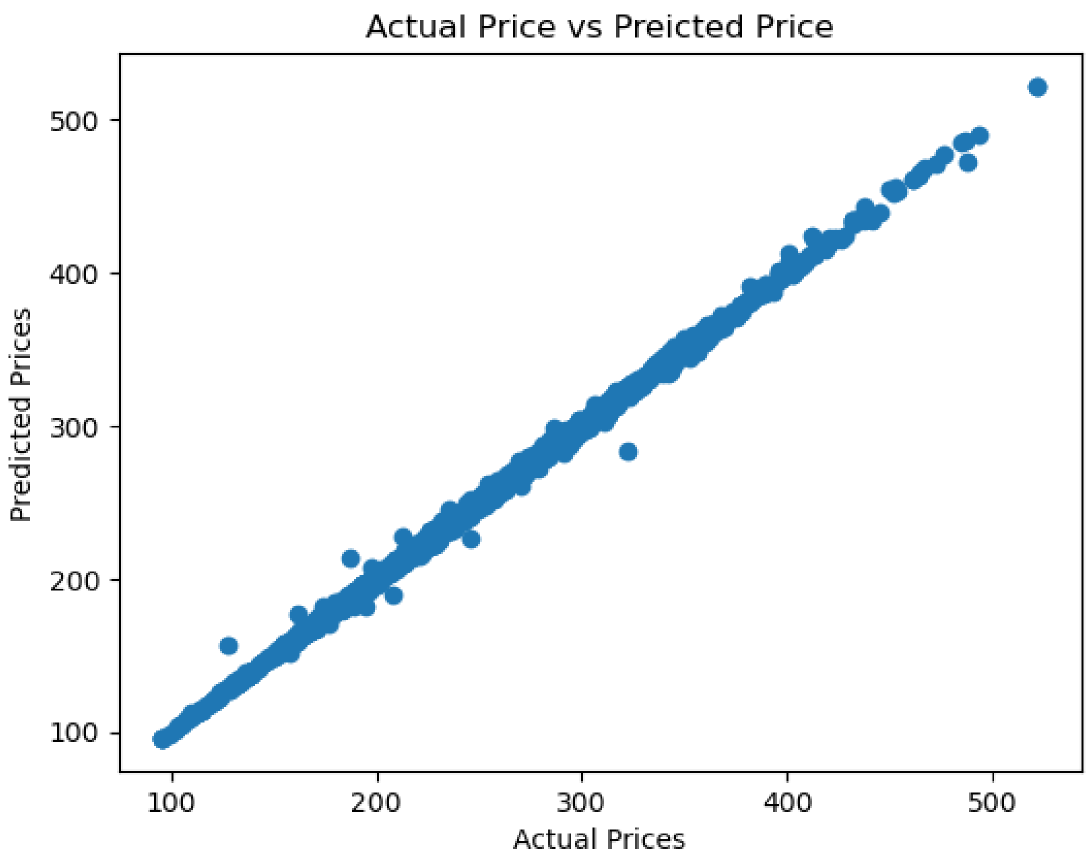
RANDOM FOREST

```
from sklearn.ensemble import RandomForestRegressor

regressor = RandomForestRegressor(n_estimators=5, random_state=25)

# fit the regressor with X and Y data
regressor.fit(X_TRAIN, Y_TRAIN)

RandomForestRegressor(n_estimators=5, random_state=25)
```

Prediction on Training Data

```
# accuracy for prediction on training data
training_data_prediction = regressor.predict(X_TRAIN)
print(training_data_prediction)
```

```
[278.2         321.          151.65333333 ... 290.          182.4
 195.        ]

# R squared error
score_1 = metrics.r2_score(Y_TRAIN, training_data_prediction)

# Mean Absolute Error
score_2 = metrics.mean_absolute_error(Y_TRAIN,
training_data_prediction)

print("R squared error : ", score_1)
print('Mean Absolute Error : ', score_2)

R squared error :  0.9991172692628274
Mean Absolute Error :  0.8785836894937649

plt.scatter(Y_TRAIN, training_data_prediction)
plt.xlabel("Actual Prices")
plt.ylabel("Predicted Prices")
plt.title("Actual Price vs Preicted Price")
plt.show()
```



Prediction on Test Data

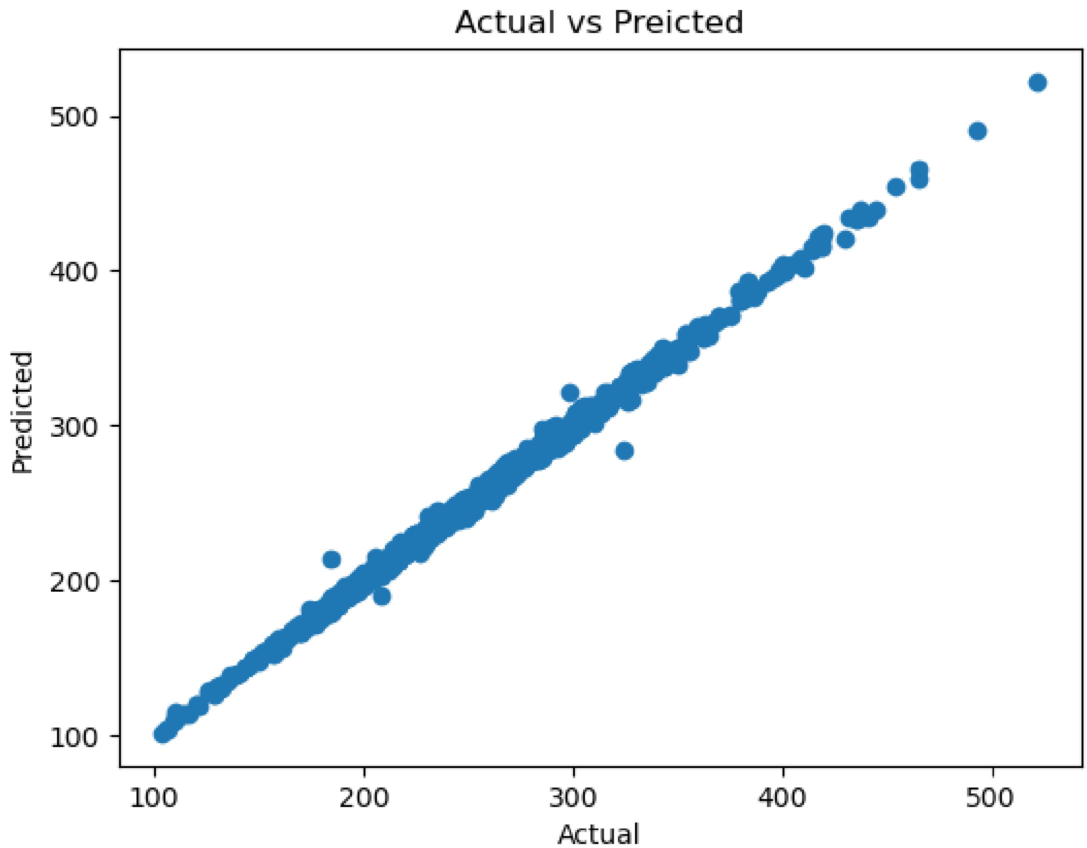
```
y_pred = regressor.predict(X_TEST)
y_pred
```

```
array([244.        , 285.        , 238.        , ..., 232.4       ,
       186.        , 174.06666667])
```

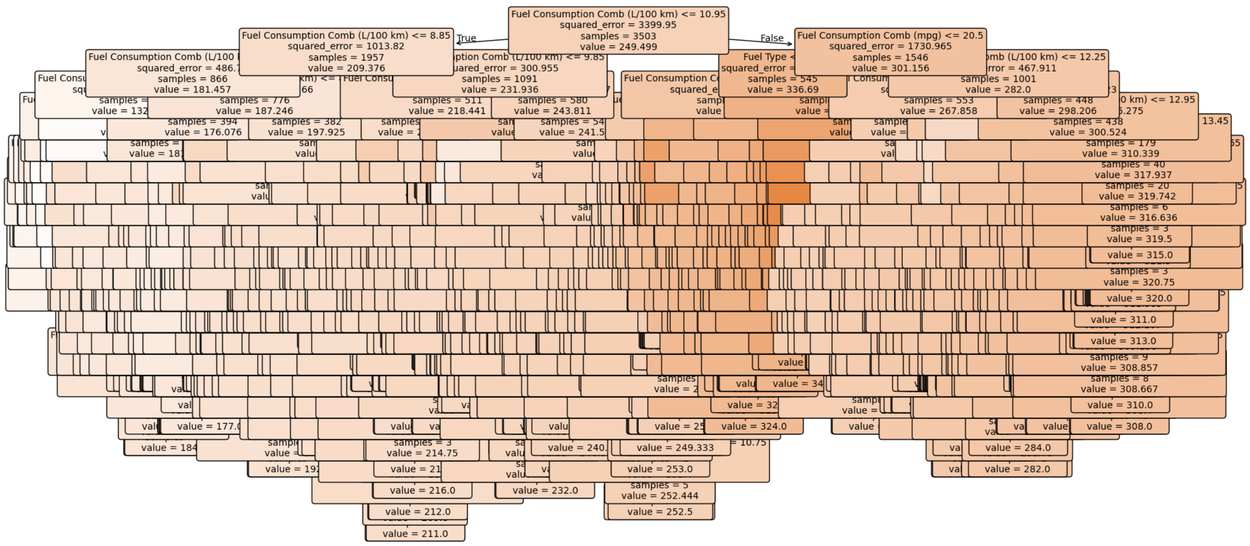
```
# R squared Score
score_1 = metrics.r2_score(Y_TEST, y_pred)

# Mean Absolute Error
score_2 = metrics.mean_absolute_error(Y_TEST, y_pred)

print("R squared Score : ", score_1)
print('Mean Absolute Error : ', score_2)
```

```
R squared Score :  0.9975115254335551
Mean Absolute Error :  1.818620193498374
```

```
plt.scatter(Y_TEST, y_pred)
plt.xlabel("Actual")
plt.ylabel("Predicted")
plt.title("Actual vs Preicted")
plt.show()
```




```python
from sklearn.tree import plot_tree
import matplotlib.pyplot as plt

# Assuming regressor is your trained Random Forest model
# Pick one tree from the forest, e.g., the first tree (index 0)
tree_to_plot = regressor.estimators_[0]

# Plot the decision tree
plt.figure(figsize=(20, 10))
plot_tree(tree_to_plot, feature_names=df.columns.tolist(),
filled=True, rounded=True, fontsize=10)
plt.title("Decision Tree from Random Forest")
plt.show()
```



xgboost

```
import xgboost as xgb
```

```
---------------------------------------------------------------------------
ModuleNotFoundError                       Traceback (most recent call last)
Cell In[114], line 1
----> 1 import xgboost as xgb

ModuleNotFoundError: No module named 'xgboost'
```

```
xgb_model = xgb.XGBRegressor(objective='reg:squarederror',  # Specify the objective for regression
                             n_estimators=100,
                             learning_rate=0.1,
                             max_depth=3,
                             random_state=42)

# Train the model
xgb_model.fit(X_TRAIN, Y_TRAIN)
```

```
---------------------------------------------------------------------------
NameError                                 Traceback (most recent call last)
Cell In[115], line 1
----> 1 xgb_model = xgb.XGBRegressor(objective='reg:squarederror',  # Specify the objective for regression
      2                              n_estimators=100,
      3                              learning_rate=0.1,
```

```
      4                                  max_depth=3,
      5                                  random_state=42)
      7 # Train the model
      8 xgb_model.fit(X_TRAIN, Y_TRAIN)

NameError: name 'xgb' is not defined
```