

CO2 emission by vehicles

CO2 emissions from vehicles are a significant contributor to global warming and climate change. The widespread use of internal combustion engine (ICE) vehicles powered by gasoline and diesel fuels has led to substantial CO2 emissions, affecting air quality and public health. Various factors, including driving habits, fuel type, and vehicle efficiency, influence the emission of high amounts of CO2. Understanding these factors is crucial to developing effective strategies to mitigate the impact of vehicle emissions on the environment and climate.

Objective

The objective of this project is to analyze the factors influencing high CO2 emissions from vehicles, develop predictive models to assess and identify vehicles emitting high amounts of CO2 and propose strategies for mitigating these emissions. This aims to contribute towards addressing global warming and climate change by promoting more sustainable transportation practices.

There are a few abbreviations that have been used to describe the features.

Model

4WD/4X4 = Four-wheel drive, AWD = All-wheel drive, FFV = Flexible-fuel vehicle, SWB = Short wheelbase, LWB = Long wheelbase, EWB = Extended wheelbase

Transmission

A = Automatic, AM = Automated manual, AS = Automatic with select shift, AV = Continuously variable, M = Manual, 3 - 10 = Number of gears

Fuel type

X = Regular gasoline, Z = Premium gasoline, D = Diesel, E = Ethanol (E85), N = Natural gas,

Fuel Consumption

City and highway fuel consumption ratings are shown in liters per 100 kilometers (L/100 km) - the combined rating (55% city, 45% highway) is shown in L/100 km and in miles per gallon (mpg)

CO2 Emissions

The tailpipe emissions of carbon dioxide (in grams per kilometer) for combined city and highway driving

Importing the necessary libraries

```
In [ ]: import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.preprocessing import LabelEncoder, MinMaxScaler
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression, Lasso, Ridge
from sklearn.svm import SVR
from sklearn.ensemble import RandomForestRegressor
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import GradientBoostingRegressor
from xgboost import XGBRegressor
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score
from sklearn.model_selection import GridSearchCV, RandomizedSearchCV
```

```
In [ ]: df=pd.read_csv('/content/drive/MyDrive/Dataset/CO2_Emissions_Canada[1].csv')
```

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

```
Out[ ]:
```

| | Make | Model | Vehicle Class | Engine Size(L) | Cylinders | Transmission | Fuel Type | Fuel Consumption City (L/100 km) | Fuel Consumption Hwy (L/100 km) |
|---|-------|------------|---------------|----------------|-----------|--------------|-----------|----------------------------------|---------------------------------|
| 0 | ACURA | ILX | COMPACT | 2.0 | 4 | AS5 | Z | 9.9 | 6.7 |
| 1 | ACURA | ILX | COMPACT | 2.4 | 4 | M6 | Z | 11.2 | 7.7 |
| 2 | ACURA | ILX HYBRID | COMPACT | 1.5 | 4 | AV7 | Z | 6.0 | 5.8 |
| 3 | ACURA | MDX 4WD | SUV - SMALL | 3.5 | 6 | AS6 | Z | 12.7 | 9.1 |
| 4 | ACURA | RDX AWD | SUV - SMALL | 3.5 | 6 | AS6 | Z | 12.1 | 8.7 |

EDA

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

Out[]:

| | Engine Size(L) | Cylinders | Fuel Consumption City (L/100 km) | Fuel Consumption Hwy (L/100 km) | Fuel Consumption Comb (L/100 km) | Fuel Consumption Comb (mpg) | Emissio |
|--------------|-------------------|-------------|---|--|---|-----------------------------------|---------|
| count | 7385.000000 | 7385.000000 | 7385.000000 | 7385.000000 | 7385.000000 | 7385.000000 | 73 |
| mean | 3.160068 | 5.615030 | 12.556534 | 9.041706 | 10.975071 | 27.481652 | 2 |
| std | 1.354170 | 1.828307 | 3.500274 | 2.224456 | 2.892506 | 7.231879 | |
| min | 0.900000 | 3.000000 | 4.200000 | 4.000000 | 4.100000 | 11.000000 | |
| 25% | 2.000000 | 4.000000 | 10.100000 | 7.500000 | 8.900000 | 22.000000 | 2 |
| 50% | 3.000000 | 6.000000 | 12.100000 | 8.700000 | 10.600000 | 27.000000 | 2 |
| 75% | 3.700000 | 6.000000 | 14.600000 | 10.200000 | 12.600000 | 32.000000 | 2 |
| max | 8.400000 | 16.000000 | 30.600000 | 20.600000 | 26.100000 | 69.000000 | 5 |

In []: `df.shape`

Out[]: (7385, 12)

Checking for missing values

In []: `df.isna().sum()`

Out[]:

| | |
|----------------------------------|---|
| 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 | |

Checking for duplicates

In []: `df.duplicated().sum()`

Out[]: 1103

In []: `df.drop_duplicates(inplace=True)`
`df`

Out[]:

| | Make | Model | Vehicle Class | Engine Size(L) | Cylinders | Transmission | Fuel Type | Fuel Consumption City (L/100 km) | Consump Hwy (L |
|------|-------|-------------|----------------|----------------|-----------|--------------|-----------|----------------------------------|----------------|
| 0 | ACURA | ILX | COMPACT | 2.0 | 4 | AS5 | Z | 9.9 | |
| 1 | ACURA | ILX | COMPACT | 2.4 | 4 | M6 | Z | 11.2 | |
| 2 | ACURA | ILX HYBRID | COMPACT | 1.5 | 4 | AV7 | Z | 6.0 | |
| 3 | ACURA | MDX 4WD | SUV - SMALL | 3.5 | 6 | AS6 | Z | 12.7 | |
| 4 | ACURA | RDX AWD | SUV - SMALL | 3.5 | 6 | AS6 | Z | 12.1 | |
| ... | ... | ... | ... | ... | ... | ... | ... | ... | |
| 7380 | VOLVO | XC40 T5 AWD | SUV - SMALL | 2.0 | 4 | AS8 | Z | 10.7 | |
| 7381 | VOLVO | XC60 T5 AWD | SUV - SMALL | 2.0 | 4 | AS8 | Z | 11.2 | |
| 7382 | VOLVO | XC60 T6 AWD | SUV - SMALL | 2.0 | 4 | AS8 | Z | 11.7 | |
| 7383 | VOLVO | XC90 T5 AWD | SUV - STANDARD | 2.0 | 4 | AS8 | Z | 11.2 | |
| 7384 | VOLVO | XC90 T6 AWD | SUV - STANDARD | 2.0 | 4 | AS8 | Z | 12.2 | |

6282 rows × 12 columns

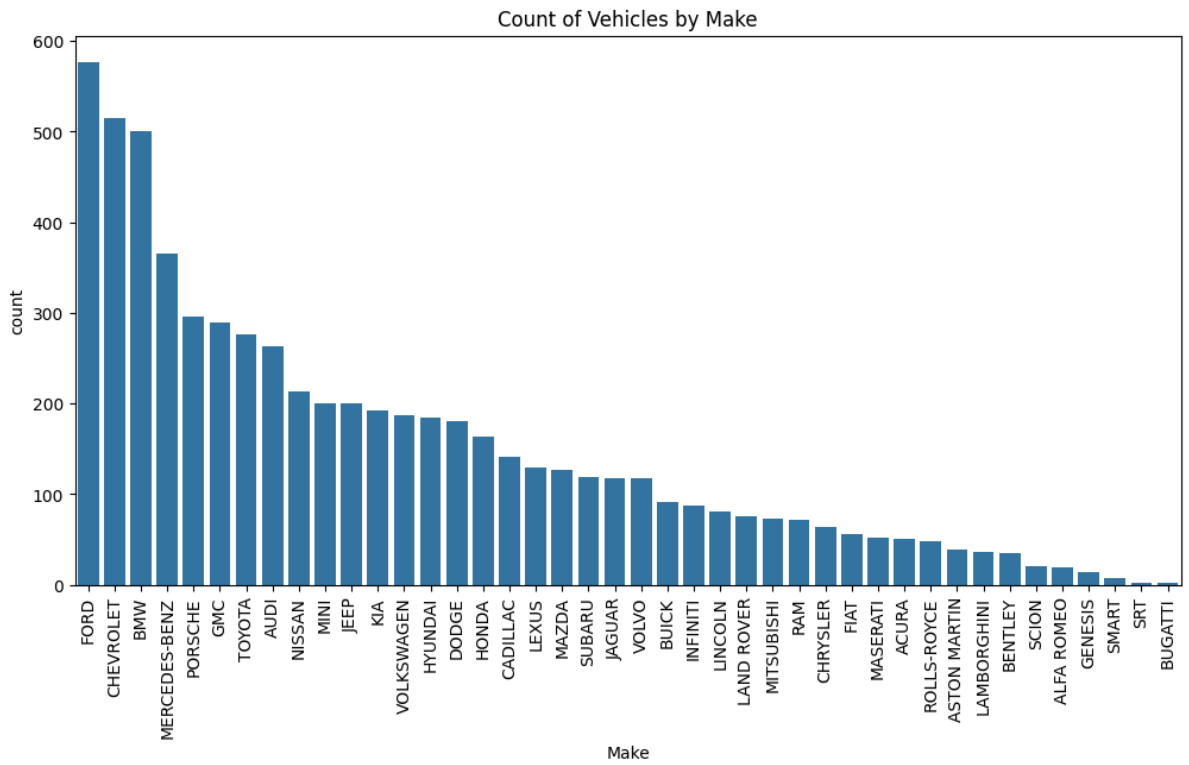
In []: `df.duplicated().sum()`

Out[]: 0

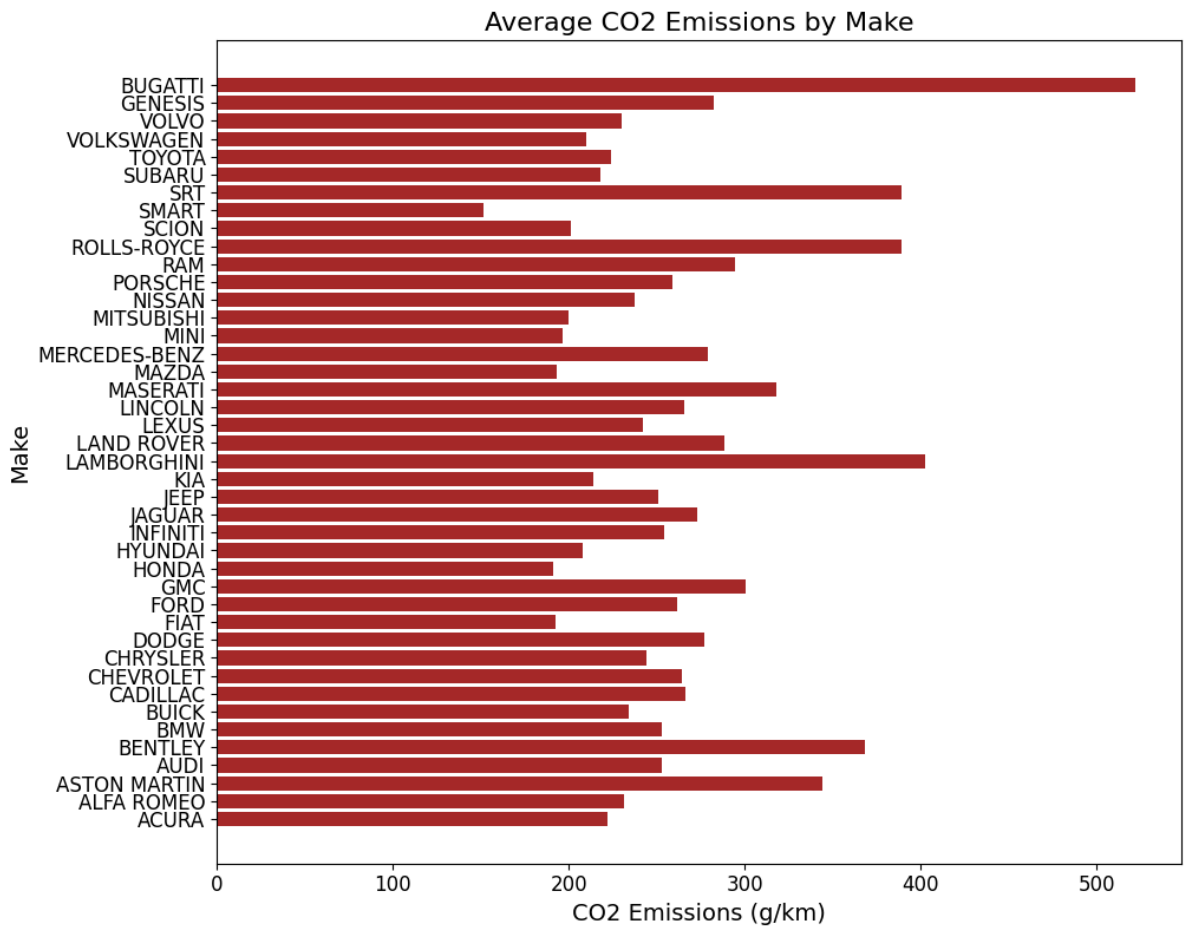
In []: `# df['Make'].value_counts()`

Univariate,Bivariate and multivariate analysis

In []: `plt.figure(figsize=(12, 6))
sns.countplot(data=df, x='Make', order=df['Make'].value_counts().index)
plt.title('Count of Vehicles by Make')
plt.xticks(rotation=90)
plt.show()`



```
In [ ]: make=df['Make'].unique()
co2_means=[]
for i in make:
    co2_mean=df[df['Make']==i]['CO2 Emissions(g/km)'].mean()
    co2_means.append(co2_mean)
plt.figure(figsize=(10, 8))
plt.barh(make, co2_means, color='brown')
plt.title('Average CO2 Emissions by Make', fontsize=16)
plt.xlabel('CO2 Emissions (g/km)', fontsize=14)
plt.ylabel('Make', fontsize=14)
plt.tight_layout()
plt.xticks(fontsize=12)
plt.yticks(fontsize=12)
plt.show()
```



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

```
Out[ ]: Model
F-150 FFV          32
F-150 FFV 4X4      31
MUSTANG            27
FOCUS FFV          24
F-150 4X4          20
..
LS 500             1
LS 500h            1
NX 300 AWD F SPORT 1
RX 350 L AWD       1
XC40 T4 AWD        1
Name: count, Length: 2053, dtype: int64
```

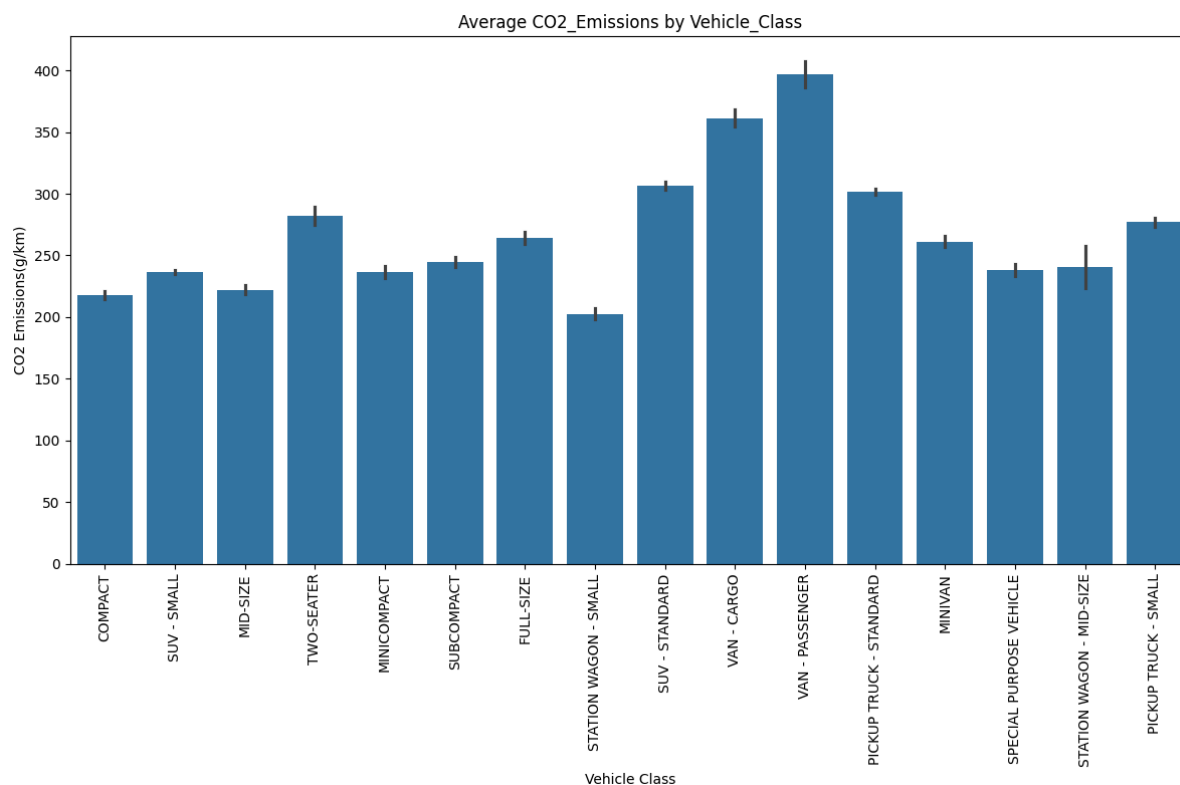
```
In [ ]: df['Vehicle Class'].value_counts()
```

```
Out[ ]: Vehicle Class
SUV - SMALL                1006
MID-SIZE                   983
COMPACT                    903
SUV - STANDARD             613
SUBCOMPACT                 533
FULL-SIZE                  508
PICKUP TRUCK - STANDARD    475
TWO-SEATER                 381
MINICOMPACT                274
STATION WAGON - SMALL      214
PICKUP TRUCK - SMALL       133
VAN - PASSENGER            66
SPECIAL PURPOSE VEHICLE    65
MINIVAN                    61
STATION WAGON - MID-SIZE   45
VAN - CARGO                 22
Name: count, dtype: int64
```

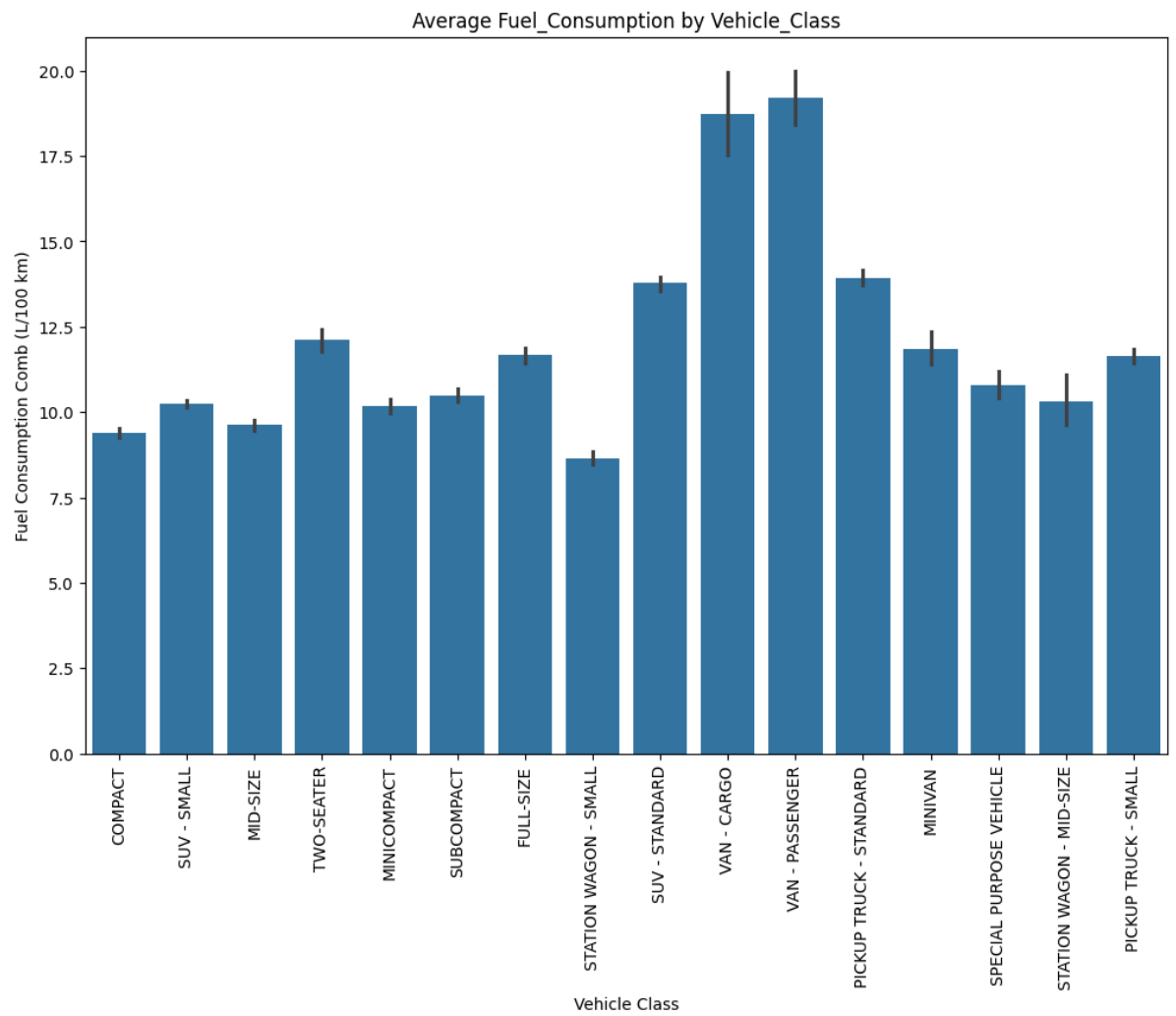
```
In [ ]: df['Vehicle Class'].unique()
```

```
Out[ ]: array(['COMPACT', 'SUV - SMALL', 'MID-SIZE', 'TWO-SEATER', 'MINICOMPACT',
        'SUBCOMPACT', 'FULL-SIZE', 'STATION WAGON - SMALL',
        'SUV - STANDARD', 'VAN - CARGO', 'VAN - PASSENGER',
        'PICKUP TRUCK - STANDARD', 'MINIVAN', 'SPECIAL PURPOSE VEHICLE',
        'STATION WAGON - MID-SIZE', 'PICKUP TRUCK - SMALL'], dtype=object)
```

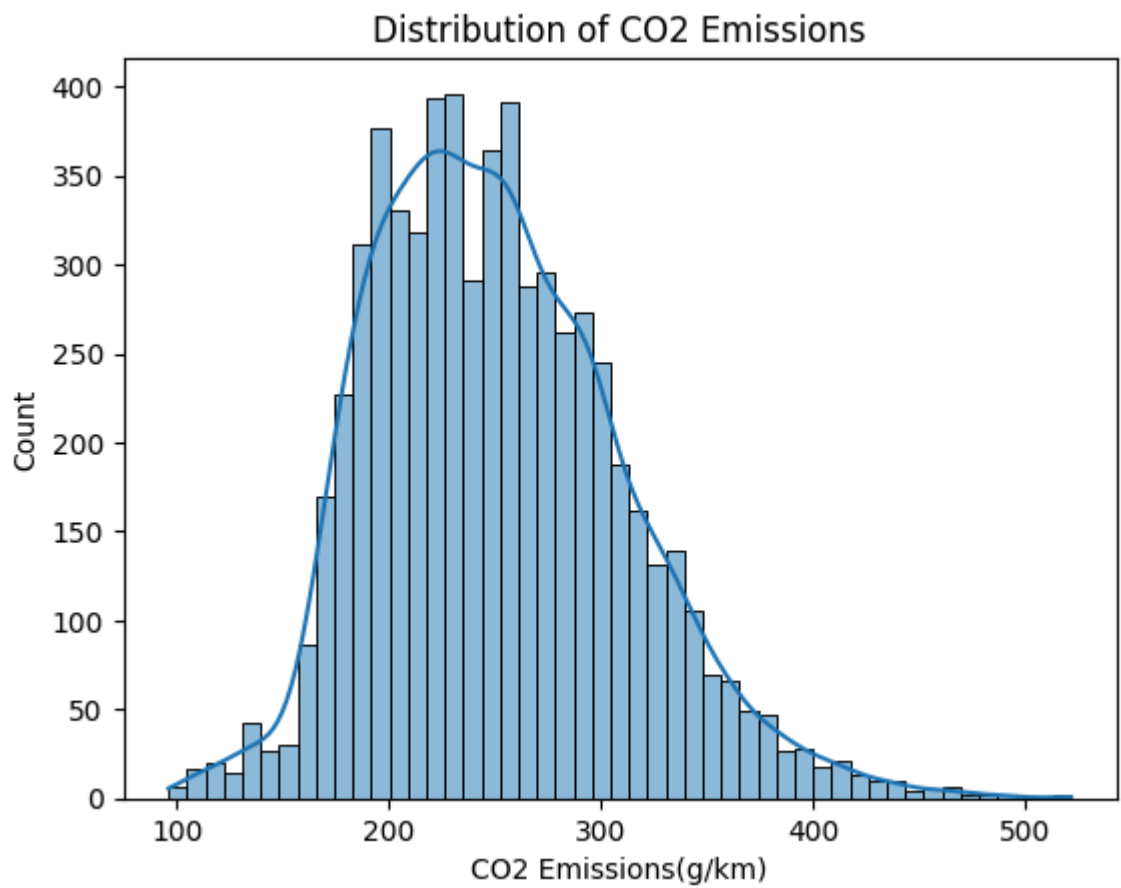
```
In [ ]: plt.figure(figsize=(12,8))
sns.barplot(data=df, x='Vehicle Class', y='CO2 Emissions(g/km)')
plt.title('Average CO2_Emissions by Vehicle_Class')
plt.xticks(rotation=90)
plt.tight_layout()
plt.show()
```



```
In [ ]: plt.figure(figsize=(12, 8))
sns.barplot(data=df, x='Vehicle Class', y='Fuel Consumption Comb (L/100 km)')
plt.title('Average Fuel_Consumption by Vehicle_Class')
plt.xticks(rotation=90)
plt.show()
```

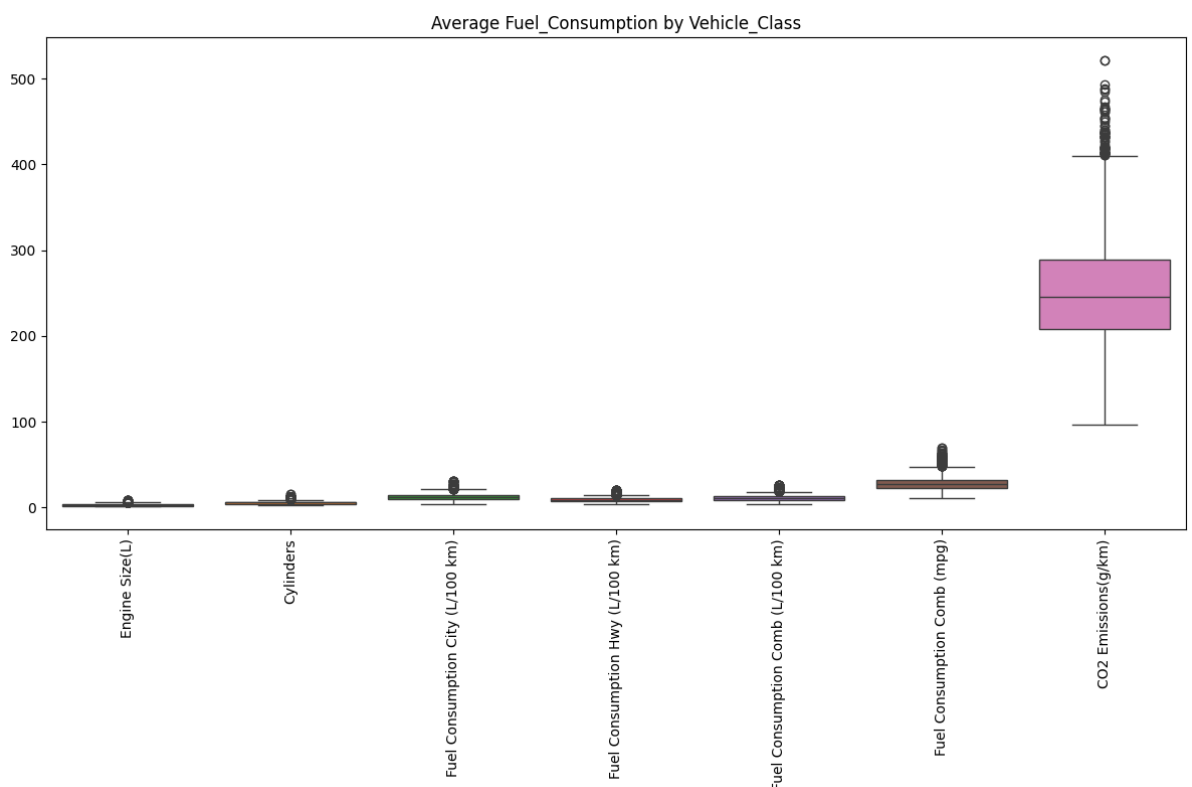


```
In [ ]: sns.histplot(data=df, x='CO2 Emissions(g/km)', kde=True)
plt.title('Distribution of CO2 Emissions')
plt.show()
```

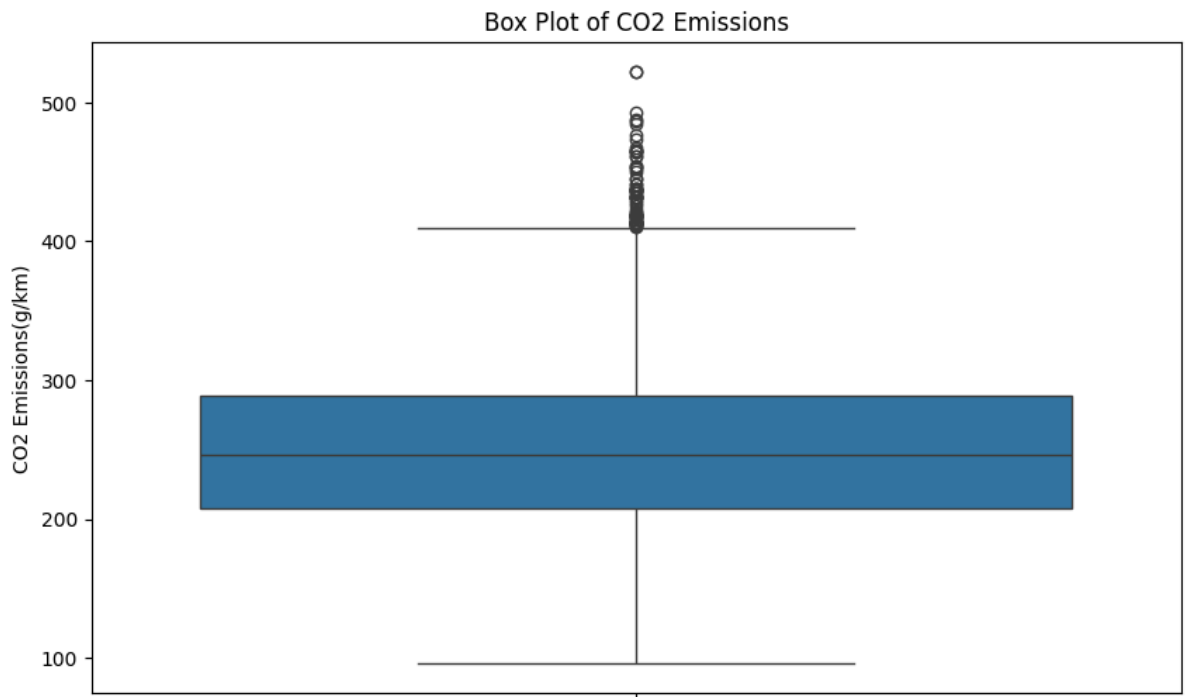



Detection of Outliers

```
In [ ]: plt.figure(figsize=(12, 8))
sns.boxplot(data=df)
plt.title('Average Fuel_Consumption by Vehicle_Class')
plt.xticks(rotation=90)
plt.tight_layout()
plt.show()
```



```
In [ ]: plt.figure(figsize=(10, 6))
sns.boxplot(y=df['CO2 Emissions(g/km)'])
plt.title('Box Plot of CO2 Emissions')
plt.show()
```



```
In [ ]: Q1 = df['CO2 Emissions(g/km)'].quantile(0.25)
Q3 = df['CO2 Emissions(g/km)'].quantile(0.75)
IQR = Q3 - Q1

lower_bound = Q1 - 1.5 * IQR
upper_bound = Q3 + 1.5 * IQR

# outliers=df[(df['CO2 Emissions(g/km)']<lower_bound) | (df['CO2 Emissions(g/km)']>
# outliers
```

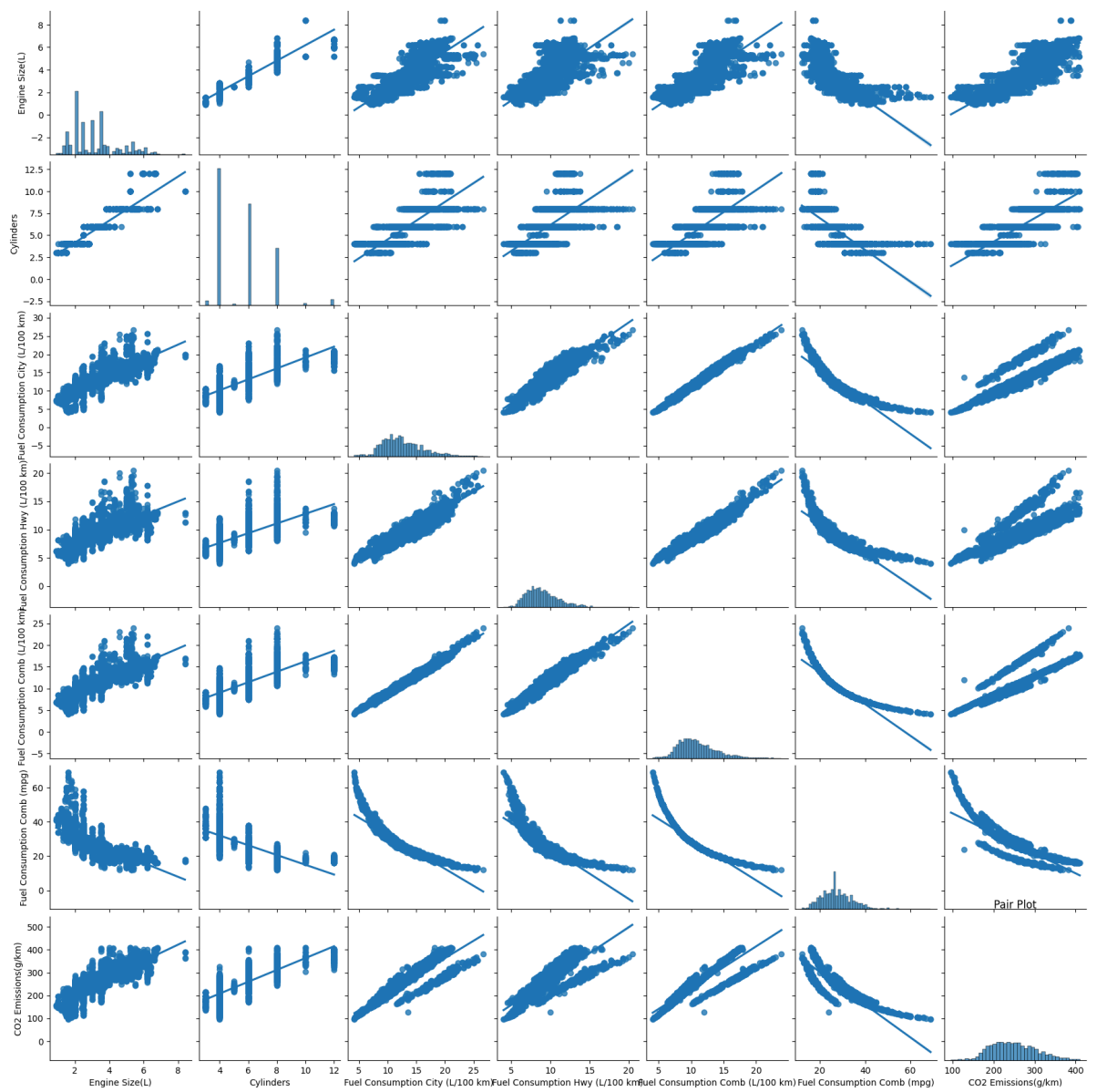
```
In [ ]: df= df[(df['CO2 Emissions(g/km)'] >= lower_bound) & (df['CO2 Emissions(g/km)'] <= u
df
```

Out[]:

| | Make | Model | Vehicle Class | Engine Size(L) | Cylinders | Transmission | Fuel Type | Fuel Consumption City (L/100 km) | Consump Hwy (L/100 km) |
|------|-------|-------------|----------------|----------------|-----------|--------------|-----------|----------------------------------|------------------------|
| 0 | ACURA | ILX | COMPACT | 2.0 | 4 | AS5 | Z | 9.9 | |
| 1 | ACURA | ILX | COMPACT | 2.4 | 4 | M6 | Z | 11.2 | |
| 2 | ACURA | ILX HYBRID | COMPACT | 1.5 | 4 | AV7 | Z | 6.0 | |
| 3 | ACURA | MDX 4WD | SUV - SMALL | 3.5 | 6 | AS6 | Z | 12.7 | |
| 4 | ACURA | RDX AWD | SUV - SMALL | 3.5 | 6 | AS6 | Z | 12.1 | |
| ... | ... | ... | ... | ... | ... | ... | ... | ... | ... |
| 7380 | VOLVO | XC40 T5 AWD | SUV - SMALL | 2.0 | 4 | AS8 | Z | 10.7 | |
| 7381 | VOLVO | XC60 T5 AWD | SUV - SMALL | 2.0 | 4 | AS8 | Z | 11.2 | |
| 7382 | VOLVO | XC60 T6 AWD | SUV - SMALL | 2.0 | 4 | AS8 | Z | 11.7 | |
| 7383 | VOLVO | XC90 T5 AWD | SUV - STANDARD | 2.0 | 4 | AS8 | Z | 11.2 | |
| 7384 | VOLVO | XC90 T6 AWD | SUV - STANDARD | 2.0 | 4 | AS8 | Z | 12.2 | |

6208 rows × 12 columns

```
In [ ]: sns.pairplot(df,kind='reg')
plt.title('Pair Plot', y=1.02)
plt.show()
```



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

```
Out[ ]: Transmission
AS6      1138
AS8      1052
M6        773
A6        648
A8        376
AM7       365
AS7       276
A9        263
AV        241
M5        168
AS10      151
AM6       107
AV7        92
AV6        89
A5         77
M7         77
AS9        65
A4         60
AM8        45
A7         41
AV8        34
A10        28
AS5        26
AV10        9
AM5         4
AS4         2
AM9         1
Name: count, dtype: int64
```

```
In [ ]: df['Transmission'].unique()
```

```
Out[ ]: array(['AS5', 'M6', 'AV7', 'AS6', 'AM6', 'A6', 'AM7', 'AV8', 'AS8', 'A7',
        'A8', 'M7', 'A4', 'M5', 'AV', 'A5', 'AS7', 'A9', 'AS9', 'AV6',
        'AS4', 'AM5', 'AM8', 'AM9', 'AS10', 'A10', 'AV10'], dtype=object)
```

```
In [ ]: def categorize_transmission(transmission):
        if transmission in ['AV7', 'AV6', 'AV8', 'AV', 'AV10', 'AM5', 'AM6', 'AM7', 'AM8', 'AM9']:
            return 'Automated Manual'
        if transmission in ['AS6', 'AS8', 'AS9', 'AS10', 'AS4', 'AS7', 'AS5']:
            return 'Automatic'
        if transmission in ['A5', 'A6', 'A7', 'A8', 'A9', 'A10', 'A4', 'M6', 'M7', 'M5']:
            return 'Manual'
        # else:
        #     return 'Unknown'
df['Transmission_Category'] = df['Transmission'].apply(categorize_transmission)
```

<ipython-input-26-9849cac08ab3>:10: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
df['Transmission_Category'] = df['Transmission'].apply(categorize_transmission)

```
In [ ]: def categorize_vehicle_class(vehicle_class):
        suvs=['SUV - SMALL', 'SUV - STANDARD']
        cars=['MID-SIZE', 'COMPACT', 'SUBCOMPACT', 'FULL-SIZE', 'TWO-SEATER', 'MINICOMPACT']
        trucks=['PICKUP TRUCK - STANDARD', 'PICKUP TRUCK - SMALL']
        others=['VAN - PASSENGER', 'SPECIAL PURPOSE VEHICLE', 'MINIVAN', 'VAN - CARGO']

        if vehicle_class in suvs:
            return 'SUVs'
        elif vehicle_class in cars:
```

```

        return 'Cars'
    elif vehicle_class in trucks:
        return 'Trucks'
    else:
        return 'Others'
df['Vehicle Class Category'] = df['Vehicle Class'].apply(categorize_vehicle_class)

```

<ipython-input-27-5c31f26e50a7>:15: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy

```

df['Vehicle Class Category'] = df['Vehicle Class'].apply(categorize_vehicle_class)

```

In []: df

Out[]:

| | Make | Model | Vehicle Class | Engine Size(L) | Cylinders | Transmission | Fuel Type | Fuel Consumption City (L/100 km) | Consump Hwy (L |
|------|-------|-------------|----------------|----------------|-----------|--------------|-----------|----------------------------------|----------------|
| 0 | ACURA | ILX | COMPACT | 2.0 | 4 | AS5 | Z | 9.9 | |
| 1 | ACURA | ILX | COMPACT | 2.4 | 4 | M6 | Z | 11.2 | |
| 2 | ACURA | ILX HYBRID | COMPACT | 1.5 | 4 | AV7 | Z | 6.0 | |
| 3 | ACURA | MDX 4WD | SUV - SMALL | 3.5 | 6 | AS6 | Z | 12.7 | |
| 4 | ACURA | RDX AWD | SUV - SMALL | 3.5 | 6 | AS6 | Z | 12.1 | |
| ... | ... | ... | ... | ... | ... | ... | ... | ... | |
| 7380 | VOLVO | XC40 T5 AWD | SUV - SMALL | 2.0 | 4 | AS8 | Z | 10.7 | |
| 7381 | VOLVO | XC60 T5 AWD | SUV - SMALL | 2.0 | 4 | AS8 | Z | 11.2 | |
| 7382 | VOLVO | XC60 T6 AWD | SUV - SMALL | 2.0 | 4 | AS8 | Z | 11.7 | |
| 7383 | VOLVO | XC90 T5 AWD | SUV - STANDARD | 2.0 | 4 | AS8 | Z | 11.2 | |
| 7384 | VOLVO | XC90 T6 AWD | SUV - STANDARD | 2.0 | 4 | AS8 | Z | 12.2 | |

6208 rows × 14 columns

In []: df['Vehicle Class Category'].value_counts()

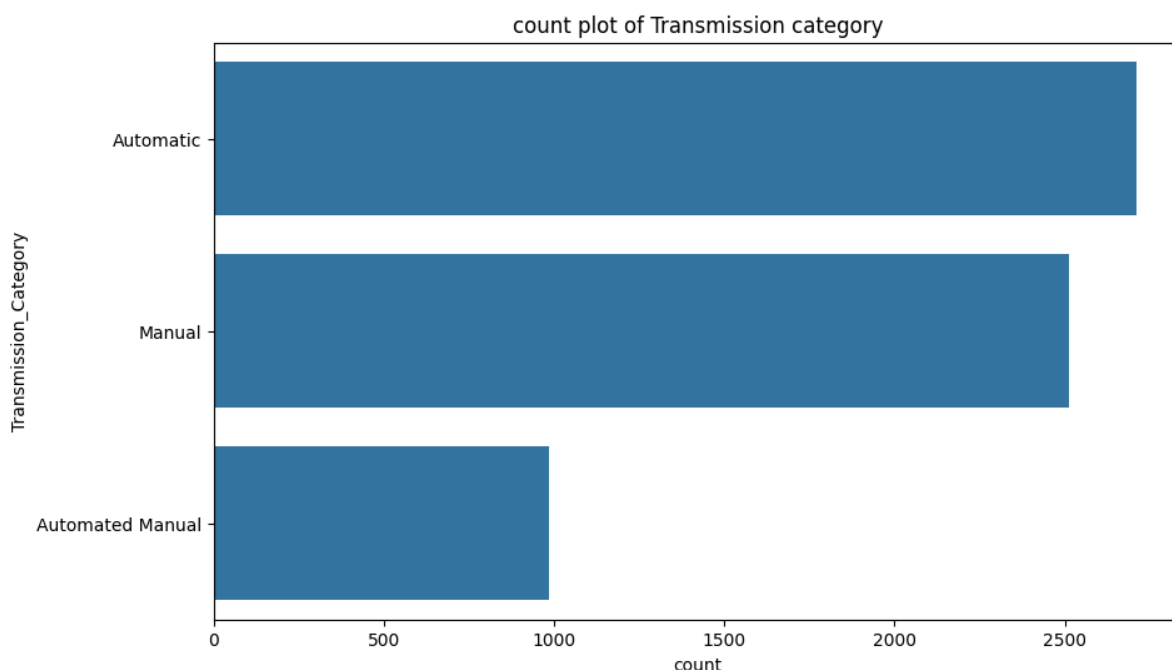
```
Out[ ]: Vehicle Class Category
Cars      3817
SUVs      1608
Trucks     607
Others     176
Name: count, dtype: int64
```

```
In [ ]: df['Transmission_Category'].value_counts()
```

```
Out[ ]: Transmission_Category
Automatic      2710
Manual         2511
Automated Manual    987
Name: count, dtype: int64
```

```
In [ ]: plt.figure(figsize=(10,6))
sns.countplot(df.Transmission_Category)
plt.title(label='count plot of Transmission category')
```

```
Out[ ]: Text(0.5, 1.0, 'count plot of Transmission category')
```



```
In [ ]: le_transmission = LabelEncoder()
df['Transmission_Category']=le_transmission.fit_transform(df['Transmission_Category'])
le_vehicle_class = LabelEncoder()
df['Vehicle Class Category']=le_vehicle_class.fit_transform(df['Vehicle Class Category'])
```

<ipython-input-32-027448899426>:2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
df['Transmission_Category']=le_transmission.fit_transform(df['Transmission_Category'])

<ipython-input-32-027448899426>:4: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
df['Vehicle Class Category']=le_vehicle_class.fit_transform(df['Vehicle Class Category']);df

Out[]:

| | Make | Model | Vehicle Class | Engine Size(L) | Cylinders | Transmission | Fuel Type | Fuel Consumption City (L/100 km) | Consump Hwy (L |
|------|-------|-------------|----------------|----------------|-----------|--------------|-----------|----------------------------------|----------------|
| 0 | ACURA | ILX | COMPACT | 2.0 | 4 | AS5 | Z | 9.9 | |
| 1 | ACURA | ILX | COMPACT | 2.4 | 4 | M6 | Z | 11.2 | |
| 2 | ACURA | ILX HYBRID | COMPACT | 1.5 | 4 | AV7 | Z | 6.0 | |
| 3 | ACURA | MDX 4WD | SUV - SMALL | 3.5 | 6 | AS6 | Z | 12.7 | |
| 4 | ACURA | RDX AWD | SUV - SMALL | 3.5 | 6 | AS6 | Z | 12.1 | |
| ... | ... | ... | ... | ... | ... | ... | ... | ... | |
| 7380 | VOLVO | XC40 T5 AWD | SUV - SMALL | 2.0 | 4 | AS8 | Z | 10.7 | |
| 7381 | VOLVO | XC60 T5 AWD | SUV - SMALL | 2.0 | 4 | AS8 | Z | 11.2 | |
| 7382 | VOLVO | XC60 T6 AWD | SUV - SMALL | 2.0 | 4 | AS8 | Z | 11.7 | |
| 7383 | VOLVO | XC90 T5 AWD | SUV - STANDARD | 2.0 | 4 | AS8 | Z | 11.2 | |
| 7384 | VOLVO | XC90 T6 AWD | SUV - STANDARD | 2.0 | 4 | AS8 | Z | 12.2 | |

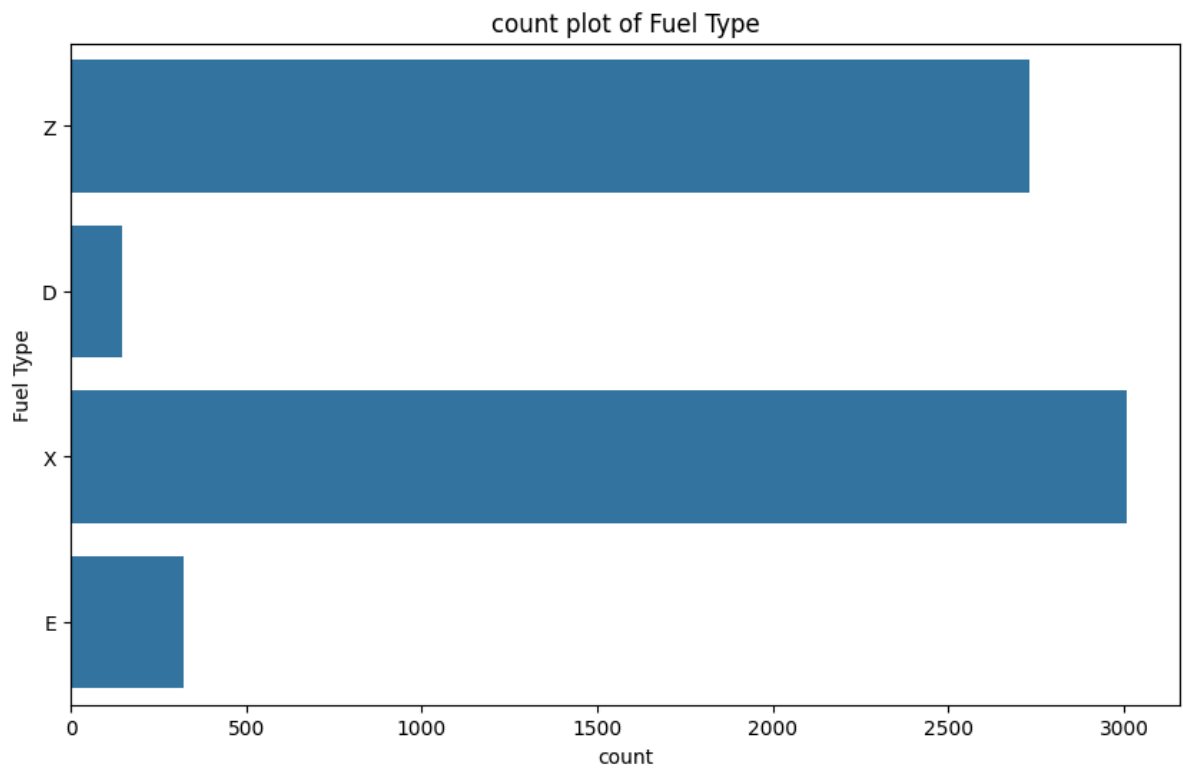
6208 rows × 14 columns

```
In [ ]: df['Fuel Type'].value_counts()
df= df[df['Fuel Type']!='N']
```

```
In [ ]: plt.figure(figsize=(10,6))
sns.countplot(df['Fuel Type'])
plt.title(label='count plot of Fuel Type')
```

```
Out[ ]: Text(0.5, 1.0, 'count plot of Fuel Type')
```





```
In [ ]: onehot_res=pd.get_dummies(df['Fuel Type'],dtype='int',drop_first=True)
onehot_res.columns = ['ethanol','regular gasoline','premium gasoline']
onehot_res
```

```
Out[ ]:
```

| | ethanol | regular gasoline | premium gasoline |
|------|---------|------------------|------------------|
| 0 | 0 | 0 | 1 |
| 1 | 0 | 0 | 1 |
| 2 | 0 | 0 | 1 |
| 3 | 0 | 0 | 1 |
| 4 | 0 | 0 | 1 |
| ... | ... | ... | ... |
| 7380 | 0 | 0 | 1 |
| 7381 | 0 | 0 | 1 |
| 7382 | 0 | 0 | 1 |
| 7383 | 0 | 0 | 1 |
| 7384 | 0 | 0 | 1 |

6207 rows × 3 columns

```
In [ ]: pd.concat([df,onehot_res],axis=1)
df=df.join(onehot_res)
```

```
In [ ]: df.columns
```

```
Out[ ]: 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)',
        'Transmission_Category', 'Vehicle Class Category', 'ethanol',
        'regular gasoline', 'premium gasoline'],
        dtype='object')
```

```
In [ ]: df
```

```
Out[ ]:
```

| | Make | Model | Vehicle Class | Engine Size(L) | Cylinders | Transmission | Fuel Type | Fuel Consumption City (L/100 km) | Fuel Consumption Hwy (L/100 km) |
|------|-------|-------------|----------------|----------------|-----------|--------------|-----------|----------------------------------|---------------------------------|
| 0 | ACURA | ILX | COMPACT | 2.0 | 4 | AS5 | Z | 9.9 | |
| 1 | ACURA | ILX | COMPACT | 2.4 | 4 | M6 | Z | 11.2 | |
| 2 | ACURA | ILX HYBRID | COMPACT | 1.5 | 4 | AV7 | Z | 6.0 | |
| 3 | ACURA | MDX 4WD | SUV - SMALL | 3.5 | 6 | AS6 | Z | 12.7 | |
| 4 | ACURA | RDX AWD | SUV - SMALL | 3.5 | 6 | AS6 | Z | 12.1 | |
| ... | ... | ... | ... | ... | ... | ... | ... | ... | ... |
| 7380 | VOLVO | XC40 T5 AWD | SUV - SMALL | 2.0 | 4 | AS8 | Z | 10.7 | |
| 7381 | VOLVO | XC60 T5 AWD | SUV - SMALL | 2.0 | 4 | AS8 | Z | 11.2 | |
| 7382 | VOLVO | XC60 T6 AWD | SUV - SMALL | 2.0 | 4 | AS8 | Z | 11.7 | |
| 7383 | VOLVO | XC90 T5 AWD | SUV - STANDARD | 2.0 | 4 | AS8 | Z | 11.2 | |
| 7384 | VOLVO | XC90 T6 AWD | SUV - STANDARD | 2.0 | 4 | AS8 | Z | 12.2 | |

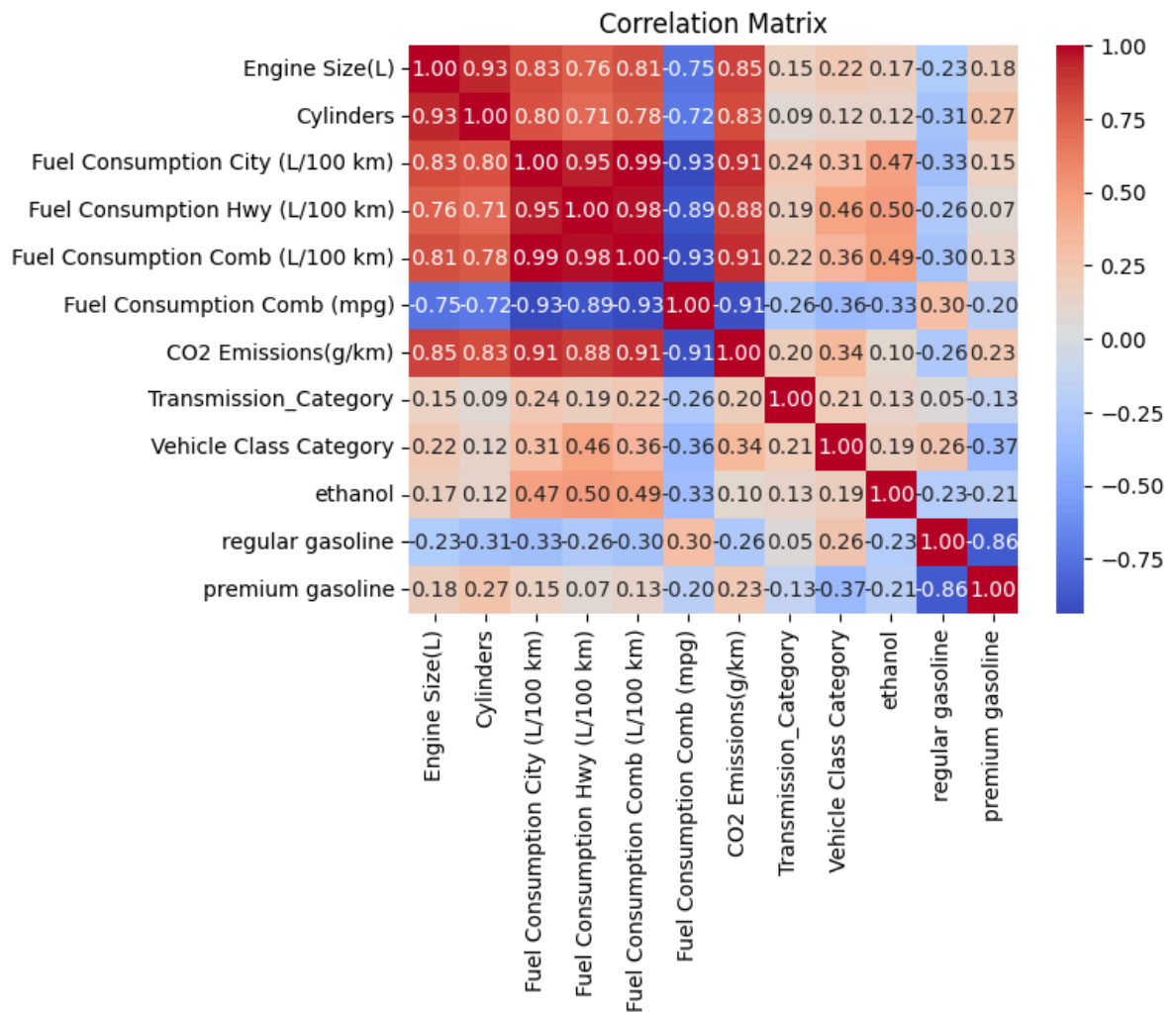
6207 rows × 17 columns



```
In [ ]: df.drop(columns=['Make', 'Model', 'Vehicle Class', 'Transmission', 'Fuel Type'], inplace=True)
```

```
In [ ]: cor=df.corr()
sns.heatmap(cor,annot=True, cmap='coolwarm', fmt=".2f")
plt.title('Correlation Matrix')
```

```
Out[ ]: Text(0.5, 1.0, 'Correlation Matrix')
```



In []: df

Out[]:

| | Engine Size(L) | Cylinders | Fuel Consumption City (L/100 km) | Fuel Consumption Hwy (L/100 km) | Fuel Consumption Comb (L/100 km) | Fuel Consumption Comb (mpg) | CO Emissions(g/km) |
|------|----------------|-----------|----------------------------------|---------------------------------|----------------------------------|-----------------------------|--------------------|
| 0 | 2.0 | 4 | 9.9 | 6.7 | 8.5 | 33 | 19 |
| 1 | 2.4 | 4 | 11.2 | 7.7 | 9.6 | 29 | 22 |
| 2 | 1.5 | 4 | 6.0 | 5.8 | 5.9 | 48 | 13 |
| 3 | 3.5 | 6 | 12.7 | 9.1 | 11.1 | 25 | 25 |
| 4 | 3.5 | 6 | 12.1 | 8.7 | 10.6 | 27 | 24 |
| ... | ... | ... | ... | ... | ... | ... | ... |
| 7380 | 2.0 | 4 | 10.7 | 7.7 | 9.4 | 30 | 21 |
| 7381 | 2.0 | 4 | 11.2 | 8.3 | 9.9 | 29 | 23 |
| 7382 | 2.0 | 4 | 11.7 | 8.6 | 10.3 | 27 | 24 |
| 7383 | 2.0 | 4 | 11.2 | 8.3 | 9.9 | 29 | 23 |
| 7384 | 2.0 | 4 | 12.2 | 8.7 | 10.7 | 26 | 24 |

6207 rows × 12 columns

```
In [ ]: x=df.drop(columns=['CO2 Emissions(g/km)'])
        y= df['CO2 Emissions(g/km)']
```

Training and Testing

```
In [ ]: x_train,x_test,y_train,y_test=train_test_split(x, y, test_size=0.3, random_state=42)
```

```
In [ ]: minmax=MinMaxScaler()
        x_train_scaled=minmax.fit_transform(x_train)
        x_test_scaled=minmax.transform(x_test)
```

```
In [ ]: model=LinearRegression()
        model.fit(x_train_scaled, y_train)
        y_pred=model.predict(x_test_scaled)
        y_pred_train=model.predict(x_train_scaled)
```

```
In [ ]: mae = mean_absolute_error(y_train, y_pred_train)
        mse = mean_squared_error(y_train, y_pred_train)
        rmse = np.sqrt(mse)
        r_squared = r2_score(y_train, y_pred_train)

        print("Mean Absolute Error (MAE):", mae)
        print("Mean Squared Error (MSE):", mse)
        print("Root Mean Squared Error (RMSE):", rmse)
        print("R-squared:", r_squared)
```

Mean Absolute Error (MAE): 2.932416155449537
Mean Squared Error (MSE): 21.688716360117162
Root Mean Squared Error (RMSE): 4.657114595982921
R-squared: 0.9930518798158267

```
In [ ]: mae = mean_absolute_error(y_test, y_pred)
        mse = mean_squared_error(y_test, y_pred)
        rmse = np.sqrt(mse)
        r_squared = r2_score(y_test, y_pred)

        print("Mean Absolute Error (MAE):", mae)
        print("Mean Squared Error (MSE):", mse)
        print("Root Mean Squared Error (RMSE):", rmse)
        print("R-squared:", r_squared)
```

Mean Absolute Error (MAE): 3.0488703440899885
Mean Squared Error (MSE): 24.536631118416263
Root Mean Squared Error (RMSE): 4.95344638796225
R-squared: 0.9921897554352468

```
In [ ]: lasso_model = Lasso(alpha=0.01)
        lasso_model.fit(x_train_scaled, y_train)
```

```
Out[ ]: ▼      Lasso
        Lasso(alpha=0.01)
```

```
In [ ]: y_pred_lasso_train = lasso_model.predict(x_train_scaled)
        y_pred_lasso_test = lasso_model.predict(x_test_scaled)
```

```
In [ ]: lasso_train_rmse =np.sqrt(mean_squared_error(y_train, y_pred_lasso_train, squared=False))
        lasso_test_rmse = np.sqrt(mean_squared_error(y_test, y_pred_lasso_test, squared=False))
        lasso_train_r2 = r2_score(y_train, y_pred_lasso_train)
        lasso_test_r2 = r2_score(y_test, y_pred_lasso_test)
        lasso_train_MAE = mean_absolute_error(y_train, y_pred_lasso_train)
```

```
lasso_test_MAE = mean_absolute_error(y_test, y_pred_lasso_test)
lasso_train_MSE = mean_squared_error(y_train, y_pred_lasso_train)
lasso_test_MSE = mean_squared_error(y_test, y_pred_lasso_test)
```

```
In [ ]: print(f'Lasso Regression - Training RMSE: {lasso_train_rmse}, Testing RMSE: {lasso_test_rmse}')
print(f'Lasso Regression - Training R2: {lasso_train_r2}, Testing R2: {lasso_test_r2}')
print(f'Lasso Regression - Training MAE: {lasso_train_MAE}, Testing MAE: {lasso_test_MAE}')
print(f'Lasso Regression - Training MSE: {lasso_train_MSE}, Testing MSE: {lasso_test_MSE}')
```

```
Lasso Regression - Training RMSE: 2.162139589845112, Testing RMSE: 2.229810550204147
Lasso Regression - Training R2: 0.9929988660198148, Testing R2: 0.9921309634351295
Lasso Regression - Training MAE: 2.9574269432226044, Testing MAE: 3.0761790908508257
Lasso Regression - Training MSE: 21.854200139095703, Testing MSE: 24.721331816023202
```

Hyper parameter tuning

```
In [ ]: alpha_values = [0.01, 0.1, 1.0, 10.0, 100.0]
lasso = Lasso()
grid_params = {
    'alpha': alpha_values,
}
grid_search = GridSearchCV(lasso, param_grid=grid_params, cv=5, scoring='neg_mean_squared_error')
grid_search.fit(x, y)
best_alpha = grid_search.best_params_['alpha']
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/linear_model/_coordinate_descent.py:631: ConvergenceWarning: Objective did not converge. You might want to increase the number of iterations, check the scale of the features or consider increasing regularisation. Duality gap: 1.683e+03, tolerance: 1.509e+03
    model = cd_fast.enet_coordinate_descent(
```

```
In [ ]: best_alpha
```

```
Out[ ]: 0.01
```

```
In [ ]: mlr=LinearRegression()
rf=RandomForestRegressor()
svr=SVR()
dt=DecisionTreeRegressor()
xgb=XGBRegressor()
gb=GradientBoostingRegressor()
lasso=Lasso(alpha=0.01)
```

```
In [ ]: model_names = ['Multiple Linear Regression', 'RandomForest', 'Support Vector Regression']
train_scores = []
mae_values = []
mse_values = []
rmse_values = []
r_squared_values = []
```

```
In [ ]: models=[mlr, rf, svr, dt, xgb, gb, lasso]
for model in models:
    model.fit(x_train_scaled, y_train)
    train_predictions = model.predict(x_train_scaled)
    train_score = r2_score(y_train, train_predictions)
    y_pred=model.predict(x_test_scaled)
    mae = mean_absolute_error(y_test, y_pred)
    mse = mean_squared_error(y_test, y_pred)
    rmse = np.sqrt(mse)
```

```

r_squared = r2_score(y_test, y_pred)

train_scores.append(train_score)
mae_values.append(mae)
mse_values.append(mse)
rmse_values.append(rmse)
r_squared_values.append(r_squared)

```

```

In [ ]: metrics_df = pd.DataFrame({
    'Model': model_names,
    'Train R2 Score': train_scores,
    'MAE': mae_values,
    'MSE': mse_values,
    'RMSE': rmse_values,
    'R-squared': r_squared_values
})
print(metrics_df)

```

| | Model | Train R2 Score | MAE | MSE \ |
|---|----------------------------|----------------|----------|------------|
| 0 | Multiple Linear Regression | 0.993052 | 3.048870 | 24.536631 |
| 1 | RandomForest | 0.999060 | 2.223861 | 14.383373 |
| 2 | Support Vector Regressor | 0.956425 | 7.571255 | 138.186436 |
| 3 | DecisionTree | 0.999622 | 2.293122 | 20.930668 |
| 4 | XGBoost | 0.999049 | 2.104387 | 11.106306 |
| 5 | GradientBoosting | 0.996143 | 2.742368 | 16.865813 |
| 6 | Lasso | 0.992999 | 3.076179 | 24.721332 |

| | RMSE | R-squared |
|---|-----------|-----------|
| 0 | 4.953446 | 0.992190 |
| 1 | 3.792542 | 0.995422 |
| 2 | 11.755273 | 0.956014 |
| 3 | 4.575005 | 0.993338 |
| 4 | 3.332613 | 0.996465 |
| 5 | 4.106801 | 0.994631 |
| 6 | 4.972055 | 0.992131 |

```

In [ ]: rf=RandomForestRegressor(n_estimators=300,max_features='auto',max_depth=50,random_s
rf.fit(x_train_scaled,y_train)
y_pred_rf=rf.predict(x_test_scaled)
print('mae', mean_absolute_error(y_test, y_pred))
print('mse', mean_squared_error(y_test, y_pred))
print('rmse',np.sqrt(mse))
print('r_squared',r2_score(y_test, y_pred))

```

/usr/local/lib/python3.10/dist-packages/sklearn/ensemble/_forest.py:413: FutureWarning: `max_features='auto'` has been deprecated in 1.1 and will be removed in 1.3. To keep the past behaviour, explicitly set `max_features=1.0` or remove this parameter as it is also the default value for RandomForestRegressors and ExtraTreesRegressors.

```

warn(
mae 3.0761790908508257
mse 24.721331816023202
rmse 4.972055089801721
r_squared 0.9921309634351295

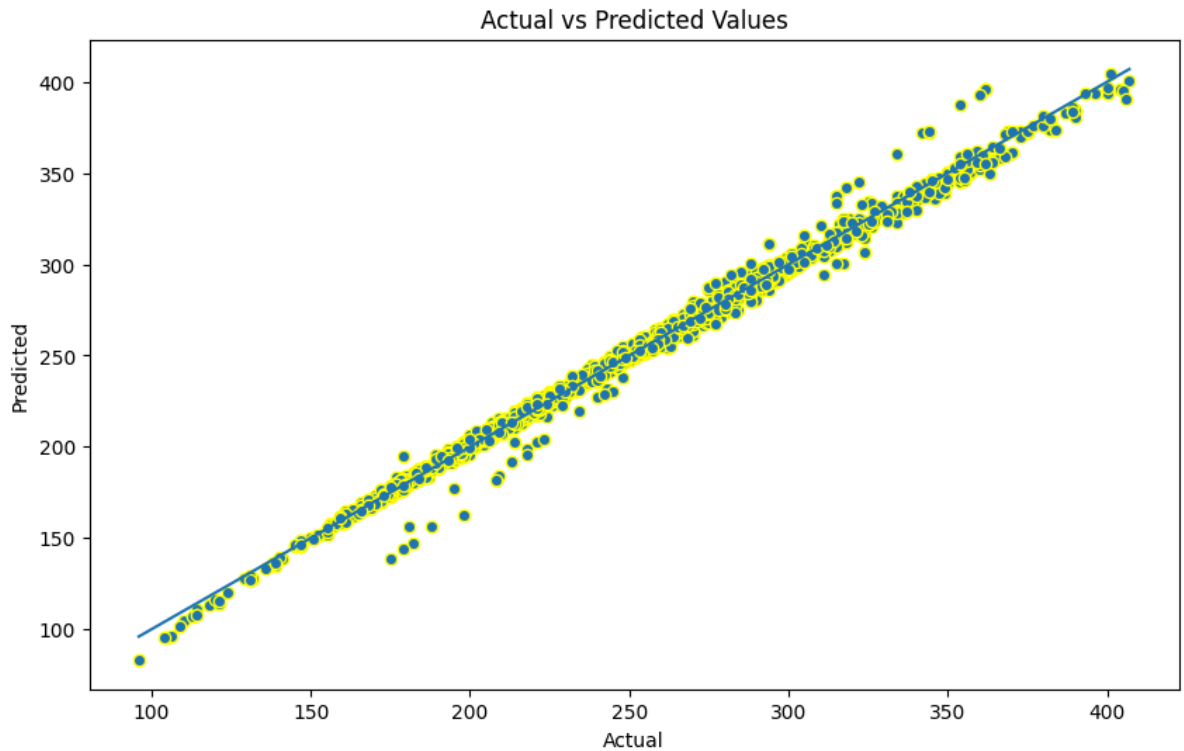
```

Plot actual vs. predicted values

```

In [ ]: plt.figure(figsize=(10, 6))
plt.scatter(y_test, y_pred,edgecolors=(1,1,0))
plt.plot([min(y_test), max(y_test)], [min(y_test), max(y_test)])
plt.xlabel('Actual')
plt.ylabel('Predicted')
plt.title('Actual vs Predicted Values')
plt.show()

```



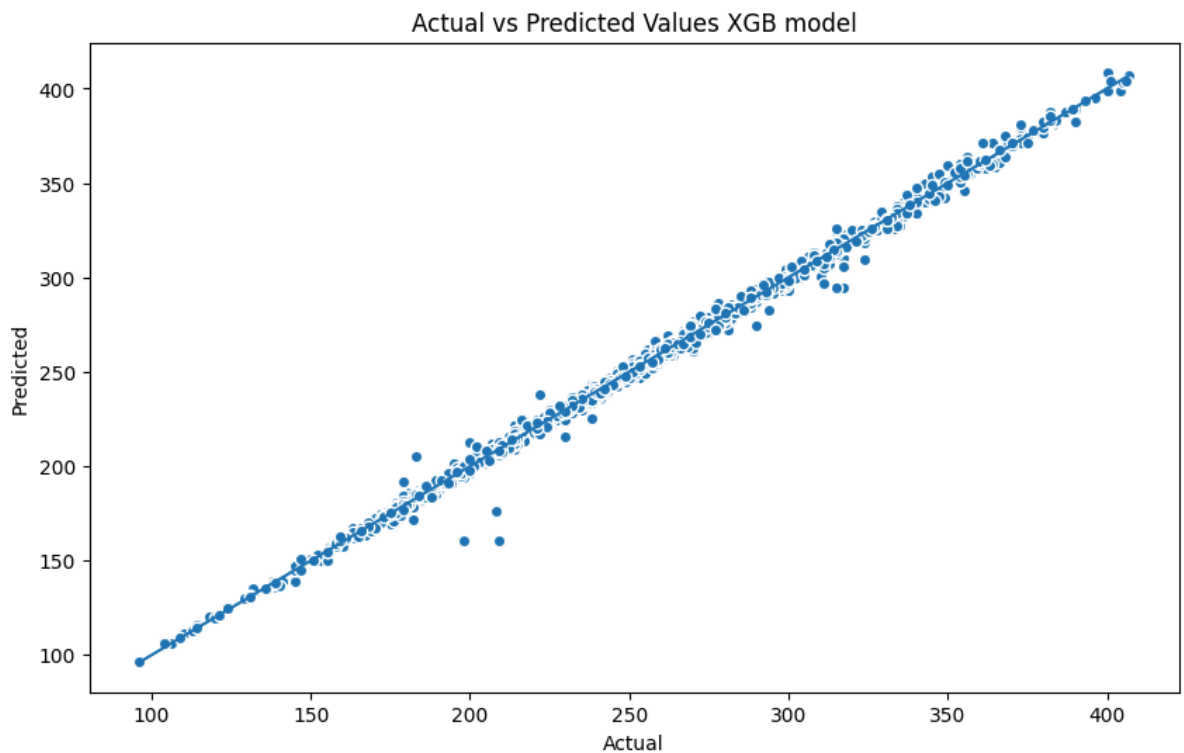
Best Model

```
In [ ]: xgb=XGBRegressor()  
xgb.fit(x_train_scaled,y_train)  
y_pred_xgb=xgb.predict(x_test_scaled)  
print('Mean Absolute Error:', mean_absolute_error(y_test, y_pred_xgb))  
print('Mean Squared Error:', mean_squared_error(y_test, y_pred_xgb))  
print('Root Mean Square Error:', np.sqrt(mse))  
print('R2_squared:', r2_score(y_test, y_pred_xgb))
```

```
Mean Absolute Error: 2.1043865676855313  
Mean Squared Error: 11.106306404307675  
Root Mean Square Error: 4.972055089801721  
R2_squared: 0.9964647563550962
```

Actual Vs Predicted of XGB

```
In [ ]: plt.figure(figsize=(10, 6))  
plt.scatter(y_test, y_pred_xgb, edgecolors=(1,1,1))  
plt.plot([min(y_test), max(y_test)], [min(y_test), max(y_test)])  
plt.xlabel('Actual')  
plt.ylabel('Predicted')  
plt.title('Actual vs Predicted Values XGB model')  
plt.show()
```



XGB is the best model

Deployment

```
In [ ]: needed_files={'Minmax':minmax,'model':xgb,'Label_Encoder_Transmission': le_transmis
        'Label_Encoder_Vehicle_Class': le_vehicle_class,'dataframe':df}
import pickle
file=open('file.pkl','wb')
pickle.dump(needed_files,file)
```

```
In [ ]: file1=open('file.pkl','rb')
res=pickle.load(file1)
res['model']
```

```
Out [ ]: XGBRegressor
XGBRegressor(base_score=None, booster=None, callbacks=None,
             colsample_bylevel=None, colsample_bynode=None,
             colsample_bytree=None, device=None, early_stopping_rounds=
None,
             enable_categorical=False, eval_metric=None, feature_types=
None,
             gamma=None, grow_policy=None, importance_type=None,
             interaction_constraints=None, learning_rate=None, max_bin=
None,
             max_cat_threshold=None, max_cat_to_onehot=None,
             max delta step=None, max depth=None, max leaves=None,
```

```
In [ ]: import pandas
import numpy as np
import sklearn
import pickle
import streamlit as st
file1=open(r"C:\Users\Nanz\Downloads\file (7).pkl",'rb')
dict1=pickle.load(file1)
# print(dict1)
```



```

le_transmission_cat=dict1['Label_Encoder_Transmission']
le_vehicle_cat=dict1['Label_Encoder_Vehicle_Class']
model=dict1['model']
minmax= dict1['Minmax']
st.title('CO2 emission by vehicles')
st.header('Deployed model')
Engine=st.slider('Engine capacity in Litres',min_value=0.8,max_value=10.0,step=0.1)
Cylinders=st.selectbox('Enter the number of cylinders:',options=range(2,21))
fuel_cons_city=st.slider('Fuel Consumption in city:',min_value=3.0,max_value=35.0,step=0.1)
fuel_cons_hwy=st.slider('Fuel Consumption in Highway:',min_value=3.0,max_value=35.0,step=0.1)
fuel_cons_comb=st.slider('Fuel Consumption in Combined:',min_value=3.0,max_value=35.0,step=0.1)
fuel_cons_comb_mpg=st.slider('Fuel Consumption in Combined in mpg:',min_value=3.0,max_value=35.0,step=0.1)
transmission=st.selectbox('Transmission category',['Automated Manual','Automatic','Manual','Semi Automatic'])
Vehicle_cat=st.selectbox('Vehicle class category',['SUVs','Cars','Trucks','Others'])
st.subheader('Fuel Type Categorization')
st.write('Note: Choose any one of the fuel type listed below..If your fuel type is ethanol = st.selectbox('Ethanol',[0,1])
regular_gasoline = st.selectbox('Regular Gasoline',[0,1])
premium_gasoline = st.selectbox('Premium Gasoline',[0,1])

def prediction(engine_size,cylinders,fuel_consumption_city,fuel_consumption_hwy,fuel_consumption_comb,fuel_consumption_comb_mpg,transmission_cat,vehicle_cat,regular_gasoline,premium_gasoline):
    features = np.array([engine_size, cylinders, fuel_consumption_city, fuel_consumption_hwy, fuel_consumption_comb, fuel_consumption_comb_mpg, transmission_cat, vehicle_cat, regular_gasoline, premium_gasoline]).reshape(1, -1)
    scaled_features = minmax.transform(features)
    return model.predict(scaled_features)[0]

def categorize_co2_level(co2_emission):
    if co2_emission < 150:
        return 'Low'
    elif 150 <= co2_emission <= 300:
        return 'Medium'
    else:
        return 'High'

if st.button('Predict CO2 Emission'):
    result = prediction(Engine, Cylinders, fuel_cons_city, fuel_cons_hwy, fuel_cons_comb, fuel_cons_comb_mpg, transmission, Vehicle_cat, regular_gasoline, premium_gasoline)
    co2_level = categorize_co2_level(result)
    st.write(f'The predicted CO2 emission of the vehicle is: {result:.2f}')
    st.write(f'The CO2 emission level is: {co2_level}')

```

In [14]: !jupyter nbconvert --to pdf '/content/drive/MyDrive/Colab Notebooks/Copy of CO2_emission_by_vehicles.ipynb'

```

[NbConvertApp] Converting notebook /content/drive/MyDrive/Colab Notebooks/Copy of CO2_emission_by_vehicles.ipynb to pdf
[NbConvertApp] Writing 2245877 bytes to /content/drive/MyDrive/Colab Notebooks/Copy of CO2_emission_by_vehicles.pdf

```

In []: