CAR PRICE PREDICTION MODEL - MACHINE LEARNING PROJECT

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1. OVERVIEW OF PROBLEM STATEMENT:

By manufacturing cars locally, a Chinese automaker desires to compete with American and European brands and gain a foothold in the US market. Success depends on knowing the variables affecting US auto prices, which are different from those in the Chinese market. In order to determine the factors that have a significant impact on car prices and comprehend how these factors affect pricing, the company has hired a consulting firm to examine a dataset of different cars from the American market. In order to attain competitive pricing, the company's product design and market entry strategy will be guided by this insight.

2. OBJECTIVE:

The objective of this project is to create a regression model that uses a number of independent variables to forecast car prices in the US market. The company will be able to create competitive automobiles and successful business plans with the aid of this model, which will assist in identifying important factors affecting auto prices and explaining how they relate to pricing.

3. DATA DESCRIPTION:

Source: https://drive.google.com/file/d/1FHmYNLs9v0Enc-UExEMpitOFGsWvB2dP/view?usp=drive_link

Car_ID, CarName, fuel type, aspiration, door number, carbody, drivewheel, engine location, wheelbase, carlength, carwidth, carheight, curbweight, engine type, cylinder number, enginesize, fuel system, boreratio, stroke, compression ratio, horsepower, peak rpm, city mpg, highway mpg, and price are among the features.

Importing Libraries

```
# Importing Libraries

import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
```

```
import seaborn as sns

from sklearn.preprocessing import LabelEncoder, OneHotEncoder
from sklearn.feature_selection import VarianceThreshold


from sklearn.preprocessing import StandardScaler, MinMaxScaler

from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import RandomForestRegressor,
GradientBoostingRegressor
from sklearn.svm import SVR
from sklearn.metrics import r2_score, mean_absolute_error,
mean_squared_error

from sklearn.model_selection import GridSearchCV

import joblib
import warnings
warnings.filterwarnings("ignore")
```

4. Importing Data

```
data = pd.read_csv('CarPrice_Assignment.csv')
data
```

```
     car_ID  symboling                   CarName fueltype
aspiration  \
0         1          3        alfa-romero giulia      gas         std

1         2          3       alfa-romero stelvio      gas         std

2         3          1  alfa-romero Quadrifoglio      gas         std

3         4          2               audi 100 ls      gas         std

4         5          2                audi 100ls      gas         std

..      ...        ...                       ...      ...         ...

200     201         -1           volvo 145e (sw)      gas         std

201     202         -1               volvo 144ea      gas       turbo

202     203         -1               volvo 244dl      gas         std

203     204         -1                 volvo 246   diesel       turbo

204     205         -1               volvo 264gl      gas       turbo
```

```
    doornumber      carbody drivewheel enginelocation  wheelbase  ...  \
0          two  convertible        rwd          front       88.6  ...   
1          two  convertible        rwd          front       88.6  ...   
2          two    hatchback        rwd          front       94.5  ...   
3         four        sedan        fwd          front       99.8  ...   
4         four        sedan        4wd          front       99.4  ...   
..         ...          ...        ...            ...        ...  ...   
200       four        sedan        rwd          front      109.1  ...   
201       four        sedan        rwd          front      109.1  ...   
202       four        sedan        rwd          front      109.1  ...   
203       four        sedan        rwd          front      109.1  ...   
204       four        sedan        rwd          front      109.1  ...   

     enginesize  fuelsystem  boreratio  stroke compressionratio  
horsepower  \
0           130        mpfi       3.47    2.68              9.0  
111   
1           130        mpfi       3.47    2.68              9.0  
111   
2           152        mpfi       2.68    3.47              9.0  
154   
3           109        mpfi       3.19    3.40             10.0  
102   
4           136        mpfi       3.19    3.40              8.0  
115   
..          ...         ...        ...     ...              ...  
...   
200         141        mpfi       3.78    3.15              9.5  
114   
201         141        mpfi       3.78    3.15              8.7  
160   
202         173        mpfi       3.58    2.87              8.8  
134   
203         145         idi       3.01    3.40             23.0  
106   
204         141        mpfi       3.78    3.15              9.5  
114   
```

```
     peakrpm citympg  highwaympg    price
0       5000      21          27  13495.0
1       5000      21          27  16500.0
2       5000      19          26  16500.0
3       5500      24          30  13950.0
4       5500      18          22  17450.0
..       ...     ...         ...      ...
200     5400      23          28  16845.0
201     5300      19          25  19045.0
202     5500      18          23  21485.0
203     4800      26          27  22470.0
204     5400      19          25  22625.0

[205 rows x 26 columns]
```

```
df = pd.DataFrame(data)
df.head()
```

```
   car_ID  symboling                   CarName fueltype aspiration
doornumber  \
0       1          3        alfa-romero giulia      gas        std
two
1       2          3       alfa-romero stelvio      gas        std
two
2       3          1  alfa-romero Quadrifoglio      gas        std
two
3       4          2               audi 100 ls      gas        std
four
4       5          2                audi 100ls      gas        std
four

       carbody drivewheel enginelocation  wheelbase  ...
enginesize  \
0  convertible        rwd          front       88.6  ...         130

1  convertible        rwd          front       88.6  ...         130

2    hatchback        rwd          front       94.5  ...         152

3        sedan        fwd          front       99.8  ...         109

4        sedan        4wd          front       99.4  ...         136


   fuelsystem  boreratio  stroke compressionratio horsepower  peakrpm
citympg  \
0        mpfi       3.47    2.68              9.0        111     5000
21
1        mpfi       3.47    2.68              9.0        111     5000
21
```

```
2        mpfi       2.68    3.47                 9.0          154     5000
19
3        mpfi       3.19    3.40                10.0          102     5500
24
4        mpfi       3.19    3.40                 8.0          115     5500
18

   highwaympg    price
0          27  13495.0
1          27  16500.0
2          26  16500.0
3          30  13950.0
4          22  17450.0

[5 rows x 26 columns]
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 205 entries, 0 to 204
Data columns (total 26 columns):
 #   Column            Non-Null Count  Dtype  
---  ------            --------------  -----  
 0   car_ID            205 non-null    int64  
 1   symboling         205 non-null    int64  
 2   CarName           205 non-null    object 
 3   fueltype          205 non-null    object 
 4   aspiration        205 non-null    object 
 5   doornumber        205 non-null    object 
 6   carbody           205 non-null    object 
 7   drivewheel        205 non-null    object 
 8   enginelocation    205 non-null    object 
 9   wheelbase         205 non-null    float64
 10  carlength         205 non-null    float64
 11  carwidth          205 non-null    float64
 12  carheight         205 non-null    float64
 13  curbweight        205 non-null    int64  
 14  enginetype        205 non-null    object 
 15  cylindernumber    205 non-null    object 
 16  enginesize        205 non-null    int64  
 17  fuelsystem        205 non-null    object 
 18  boreratio         205 non-null    float64
 19  stroke            205 non-null    float64
 20  compressionratio  205 non-null    float64
 21  horsepower        205 non-null    int64  
 22  peakrpm           205 non-null    int64  
 23  citympg           205 non-null    int64  
 24  highwaympg        205 non-null    int64  
 25  price             205 non-null    float64
```

```
dtypes: float64(8), int64(8), object(10)
memory usage: 41.8+ KB
```

```
df.dtypes
```

```
car_ID                int64
symboling             int64
CarName              object
fueltype             object
aspiration           object
doornumber           object
carbody              object
drivewheel           object
enginelocation       object
wheelbase           float64
carlength           float64
carwidth            float64
carheight           float64
curbweight            int64
enginetype           object
cylindernumber       object
enginesize            int64
fuelsystem           object
boreratio           float64
stroke              float64
compressionratio    float64
horsepower            int64
peakrpm               int64
citympg               int64
highwaympg            int64
price               float64
dtype: object
```

```
df.describe()
```

```
           car_ID   symboling   wheelbase   carlength    carwidth
carheight  \
count  205.000000  205.000000  205.000000  205.000000  205.000000
205.000000
mean   103.000000    0.834146   98.756585  174.049268   65.907805
53.724878
std     59.322565    1.245307    6.021776   12.337289    2.145204
2.443522
min      1.000000   -2.000000   86.600000  141.100000   60.300000
47.800000
25%     52.000000    0.000000   94.500000  166.300000   64.100000
52.000000
50%    103.000000    1.000000   97.000000  173.200000   65.500000
54.100000
75%    154.000000    2.000000  102.400000  183.100000   66.900000
```

```
55.500000
max    205.000000    3.000000  120.900000  208.100000   72.300000
59.800000

         curbweight  enginesize   boreratio      stroke
compressionratio  \
count   205.000000  205.000000  205.000000  205.000000
205.000000
mean   2555.565854  126.907317    3.329756    3.255415
10.142537
std     520.680204   41.642693    0.270844    0.313597
3.972040
min    1488.000000   61.000000    2.540000    2.070000
7.000000
25%    2145.000000   97.000000    3.150000    3.110000
8.600000
50%    2414.000000  120.000000    3.310000    3.290000
9.000000
75%    2935.000000  141.000000    3.580000    3.410000
9.400000
max    4066.000000  326.000000    3.940000    4.170000
23.000000

       horsepower      peakrpm     citympg  highwaympg         price
count  205.000000   205.000000  205.000000  205.000000    205.000000
mean   104.117073  5125.121951   25.219512   30.751220  13276.710571
std     39.544167   476.985643    6.542142    6.886443   7988.852332
min     48.000000  4150.000000   13.000000   16.000000   5118.000000
25%     70.000000  4800.000000   19.000000   25.000000   7788.000000
50%     95.000000  5200.000000   24.000000   30.000000  10295.000000
75%    116.000000  5500.000000   30.000000   34.000000  16503.000000
max    288.000000  6600.000000   49.000000   54.000000  45400.000000
```

```
df.shape
```

```
(205, 26)
```

```
df.columns
```

```
Index(['car_ID', 'symboling', 'CarName', 'fueltype', 'aspiration',
       'doornumber', 'carbody', 'drivewheel', 'enginelocation',
'wheelbase',
       'carlength', 'carwidth', 'carheight', 'curbweight',
'enginetype',
       'cylindernumber', 'enginesize', 'fuelsystem', 'boreratio',
'stroke',
       'compressionratio', 'horsepower', 'peakrpm', 'citympg',
'highwaympg',
       'price'],
      dtype='object')
```

5.Data preprocessing and Data cleaning

```
# Checking for duplicate
df.duplicated()
```

```
0      False
1      False
2      False
3      False
4      False
       ...  
200    False
201    False
202    False
203    False
204    False
Length: 205, dtype: bool
```

```
df.duplicated().sum()
```

```
0
```

NO DUPLICATES FOUND

```
# Checking for null values
df.isnull()
```

```
     car_ID  symboling  CarName  fueltype  aspiration  doornumber  
carbody  \
0     False      False    False     False       False       False  
False   
1     False      False    False     False       False       False  
False   
2     False      False    False     False       False       False  
False   
3     False      False    False     False       False       False  
False   
4     False      False    False     False       False       False  
False   
..      ...        ...      ...       ...         ...         ...  
...   
200   False      False    False     False       False       False  
False   
201   False      False    False     False       False       False  
False   
202   False      False    False     False       False       False  
False   
203   False      False    False     False       False       False  
False   
204   False      False    False     False       False       False  
```

```
False

     drivewheel  enginelocation  wheelbase  ...  enginesize
fuelsystem  \
0         False           False      False  ...       False
False
1         False           False      False  ...       False
False
2         False           False      False  ...       False
False
3         False           False      False  ...       False
False
4         False           False      False  ...       False
False
..          ...             ...        ...  ...         ...          ..
.
200       False           False      False  ...       False
False
201       False           False      False  ...       False
False
202       False           False      False  ...       False
False
203       False           False      False  ...       False
False
204       False           False      False  ...       False
False

     boreratio  stroke  compressionratio  horsepower  peakrpm  citympg
\
0        False   False             False       False    False    False

1        False   False             False       False    False    False

2        False   False             False       False    False    False

3        False   False             False       False    False    False

4        False   False             False       False    False    False

..         ...     ...               ...         ...      ...      ...

200      False   False             False       False    False    False

201      False   False             False       False    False    False

202      False   False             False       False    False    False

203      False   False             False       False    False    False

204      False   False             False       False    False    False
```

```
     highwaympg  price
0         False  False
1         False  False
2         False  False
3         False  False
4         False  False
..          ...    ...
200       False  False
201       False  False
202       False  False
203       False  False
204       False  False

[205 rows x 26 columns]
```

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

```
car_ID              0
symboling           0
CarName             0
fueltype            0
aspiration          0
doornumber          0
carbody             0
drivewheel          0
enginelocation      0
wheelbase           0
carlength           0
carwidth            0
carheight           0
curbweight          0
enginetype          0
cylindernumber      0
enginesize          0
fuelsystem          0
boreratio           0
stroke              0
compressionratio    0
horsepower          0
peakrpm             0
citympg             0
highwaympg          0
price               0
dtype: int64
```

NO NULL VALUES FOUND

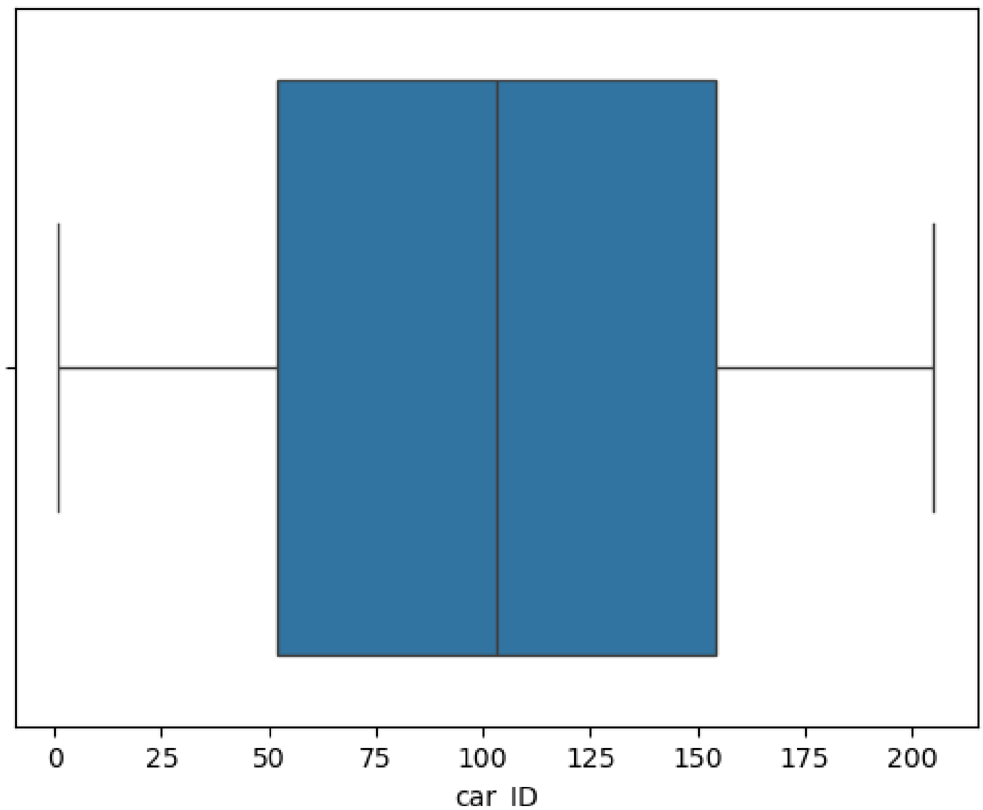
CLASSIFYING COLUMNS

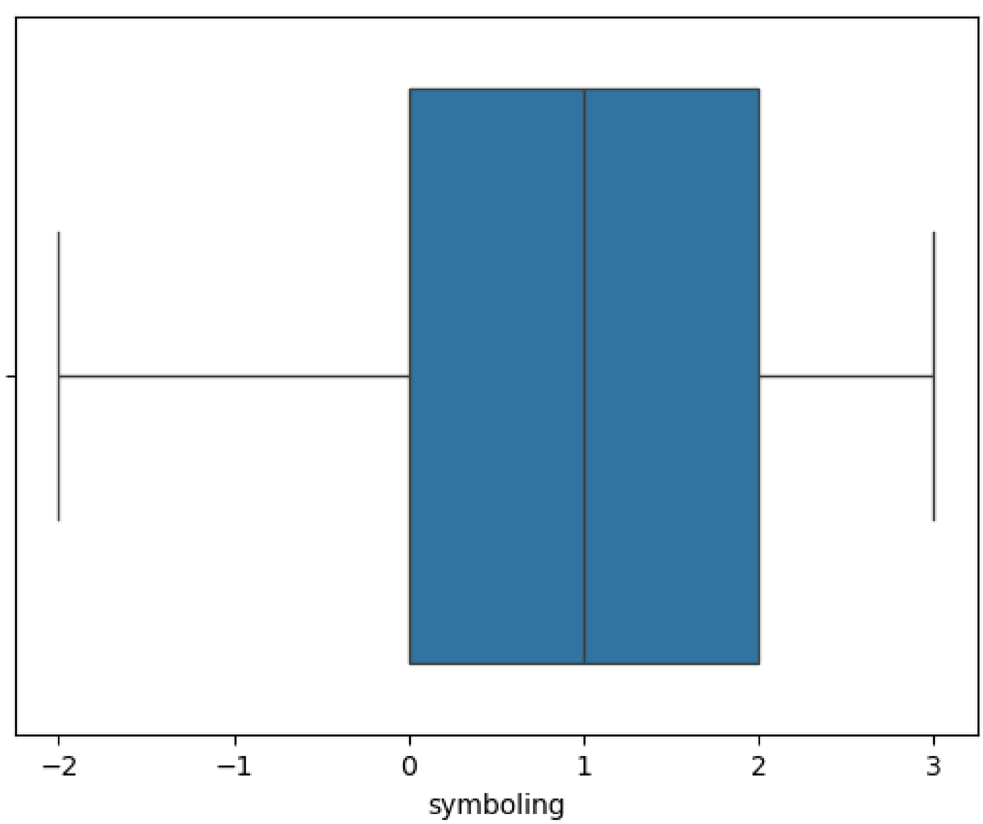
```
numerical_columns = df.select_dtypes(include=['number']).columns
categorical_columns = df.select_dtypes(include=['object']).columns

print("numerical columns: ",numerical_columns)
print("Categorical columns: ",categorical_columns)
```

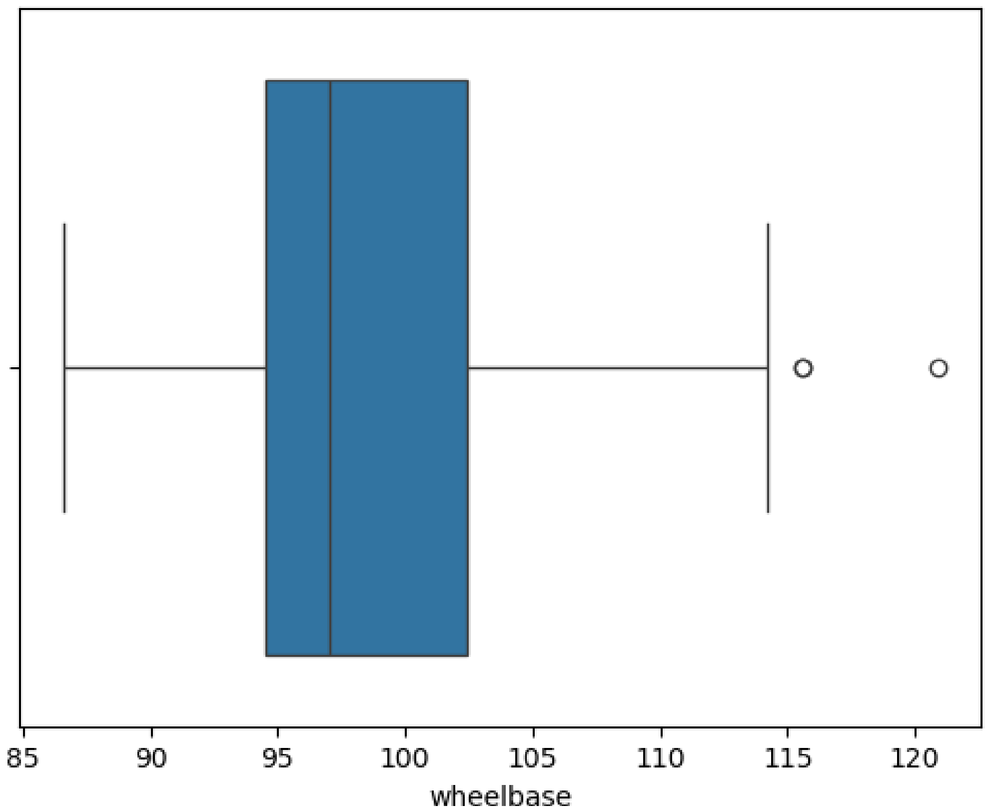
```
numerical columns:  Index(['car_ID', 'symboling', 'wheelbase',
'carlength', 'carwidth',
       'carheight', 'curbweight', 'enginesize', 'boreratio', 'stroke',
       'compressionratio', 'horsepower', 'peakrpm', 'citympg',
'highwaympg',
       'price'],
      dtype='object')
Categorical columns:  Index(['CarName', 'fueltype', 'aspiration',
'doornumber', 'carbody',
       'drivewheel', 'enginelocation', 'enginetype', 'cylindernumber',
       'fuelsystem'],
      dtype='object')
```

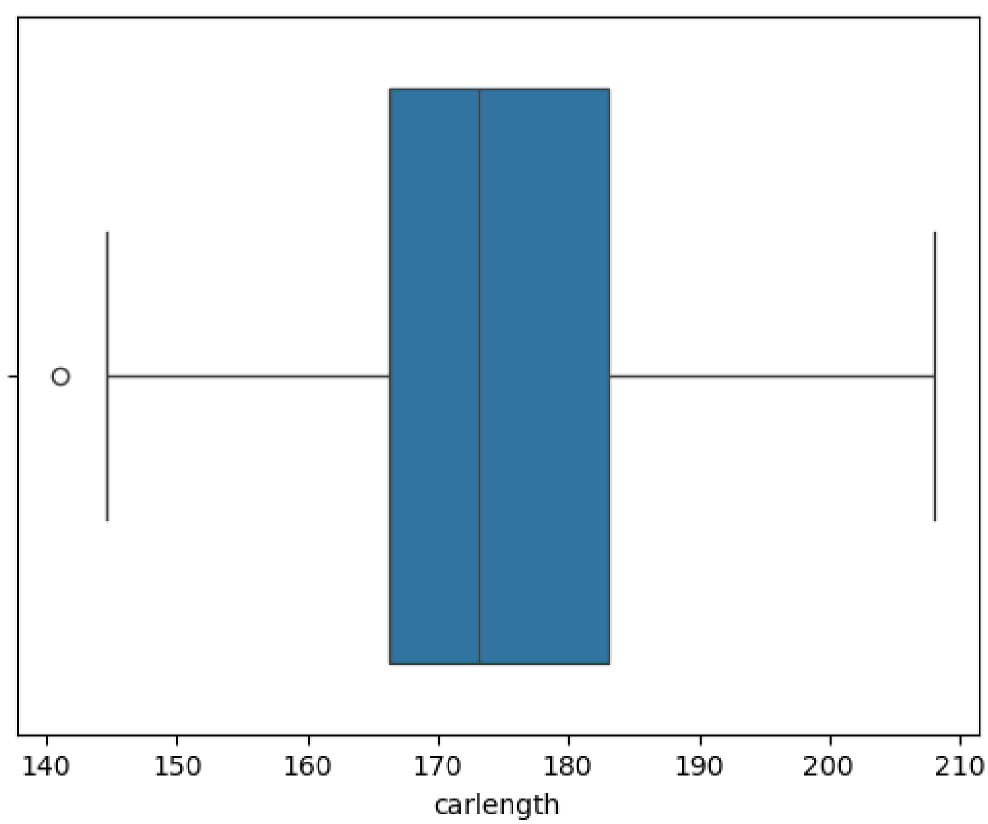
OUTLIER DETECTION

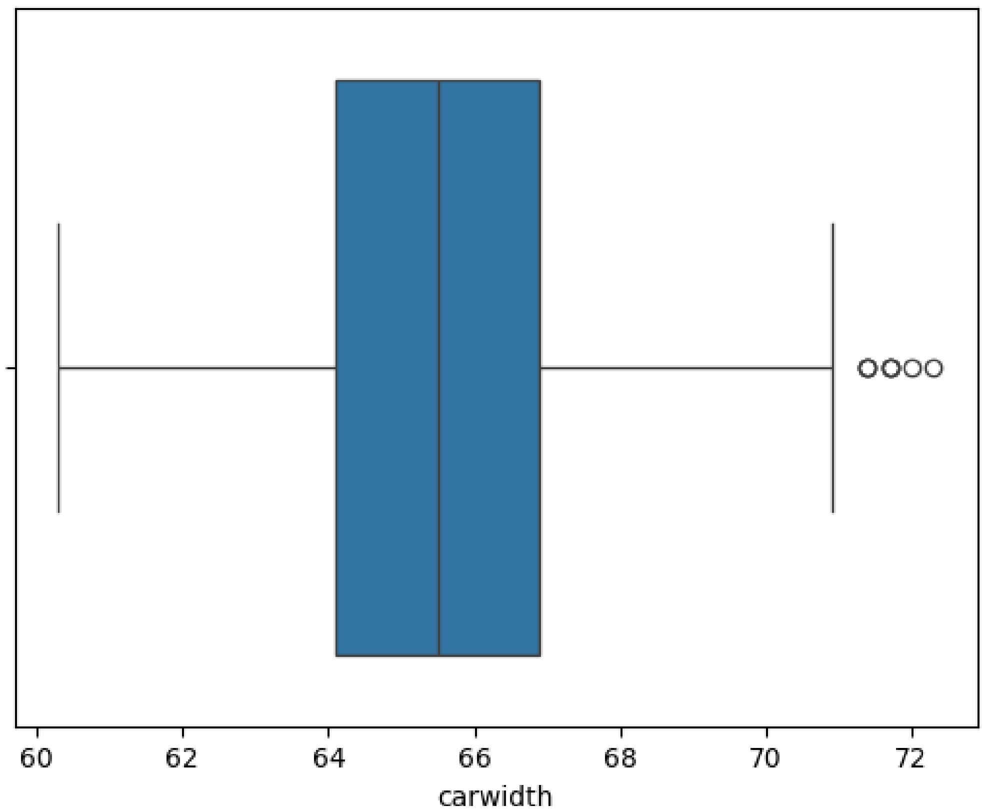
```
# boxplot to identify outliers
for i in df.select_dtypes(include='number').columns:
    sns.boxplot(data=df,x=i)
    plt.show()
```

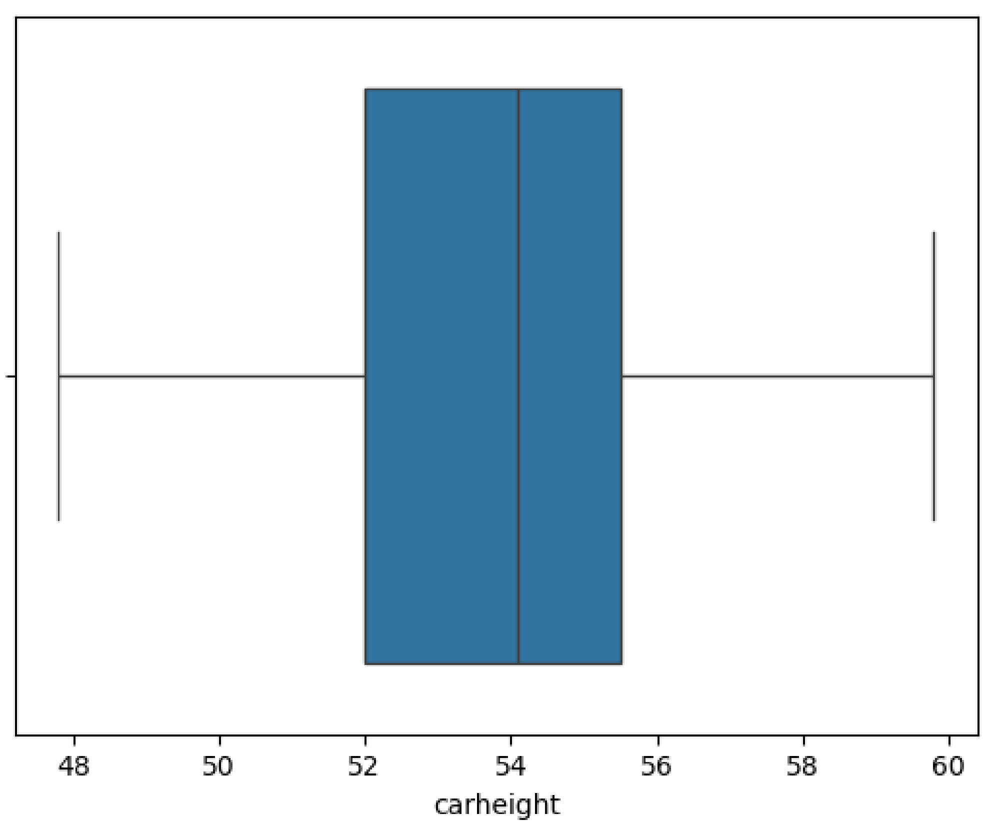

0
25
50
75
100
125
150
175
200
car_ID

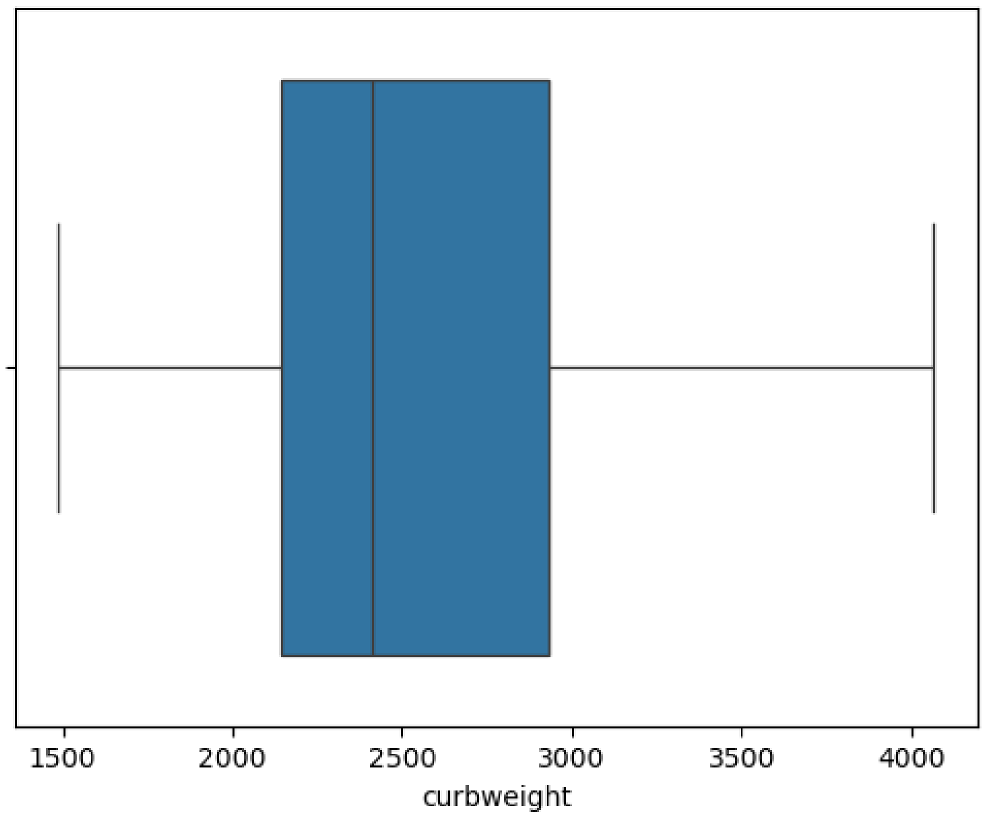

−2
−1
0
1
2
3
symboling

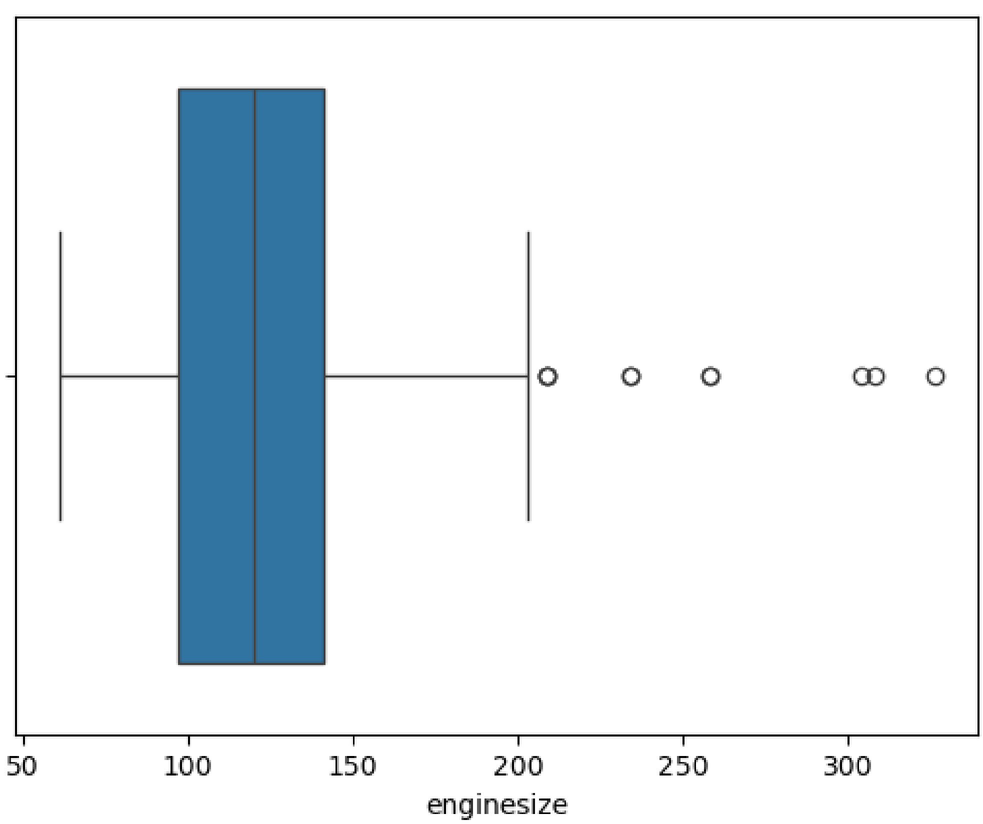

85
90
95
100
105
110
115
120
wheelbase

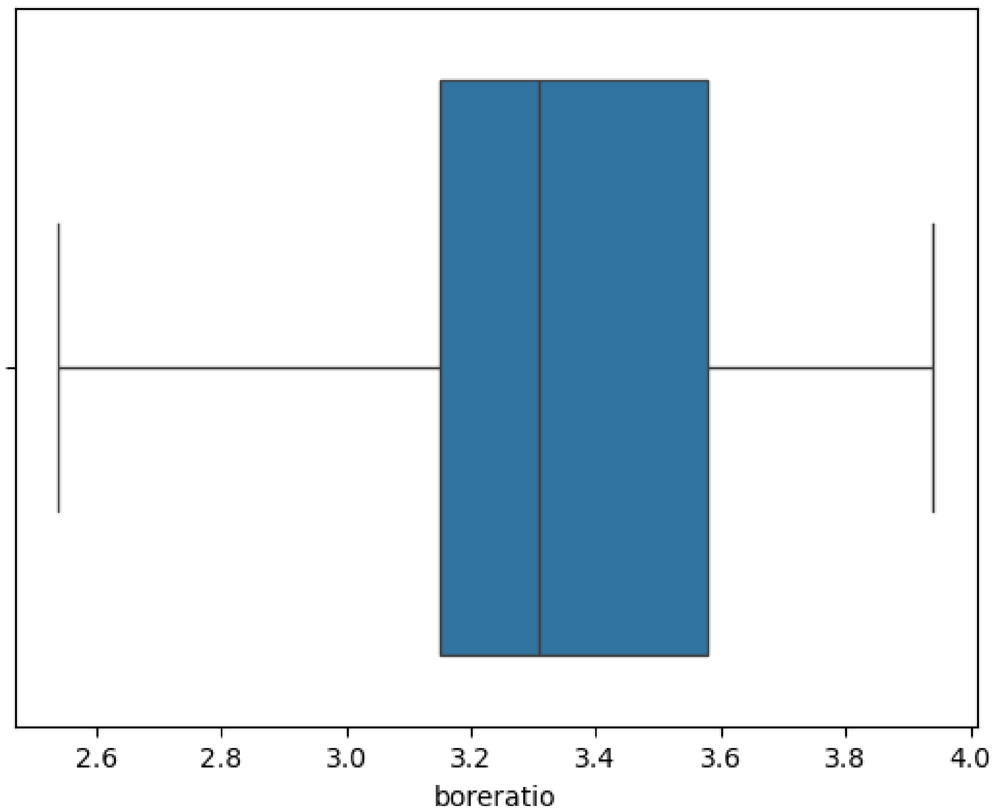

140
150
160
170
180
190
200
210
carlength

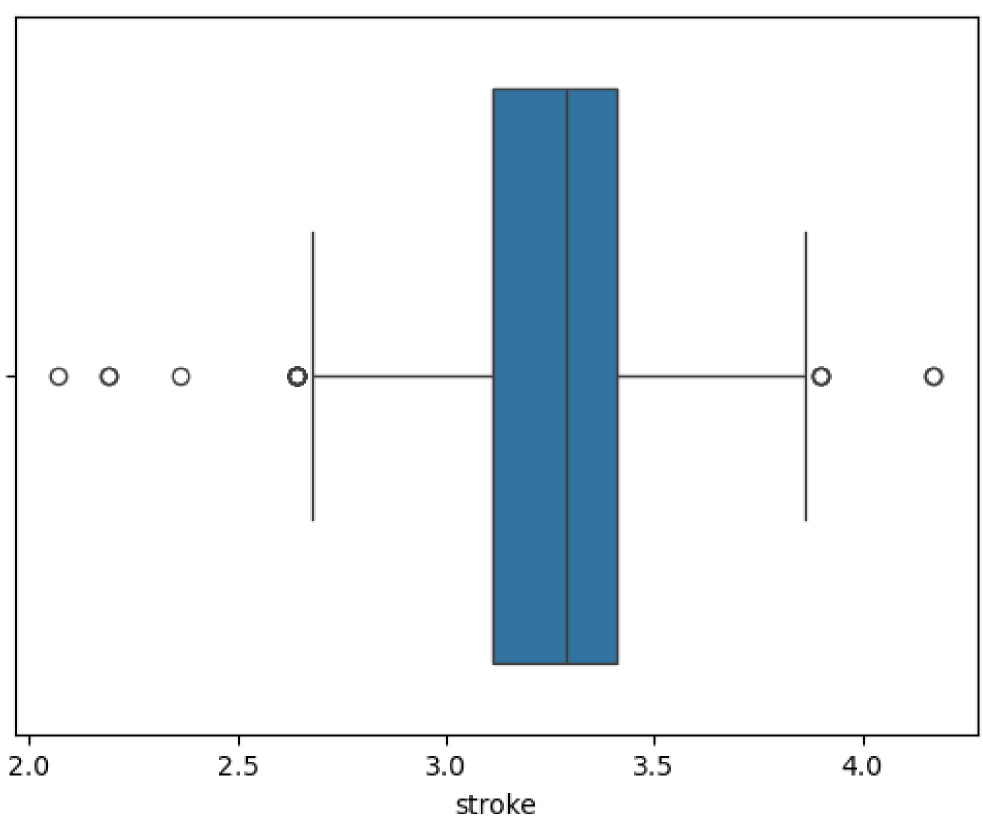

60
62
64
66
68
70
72
carwidth

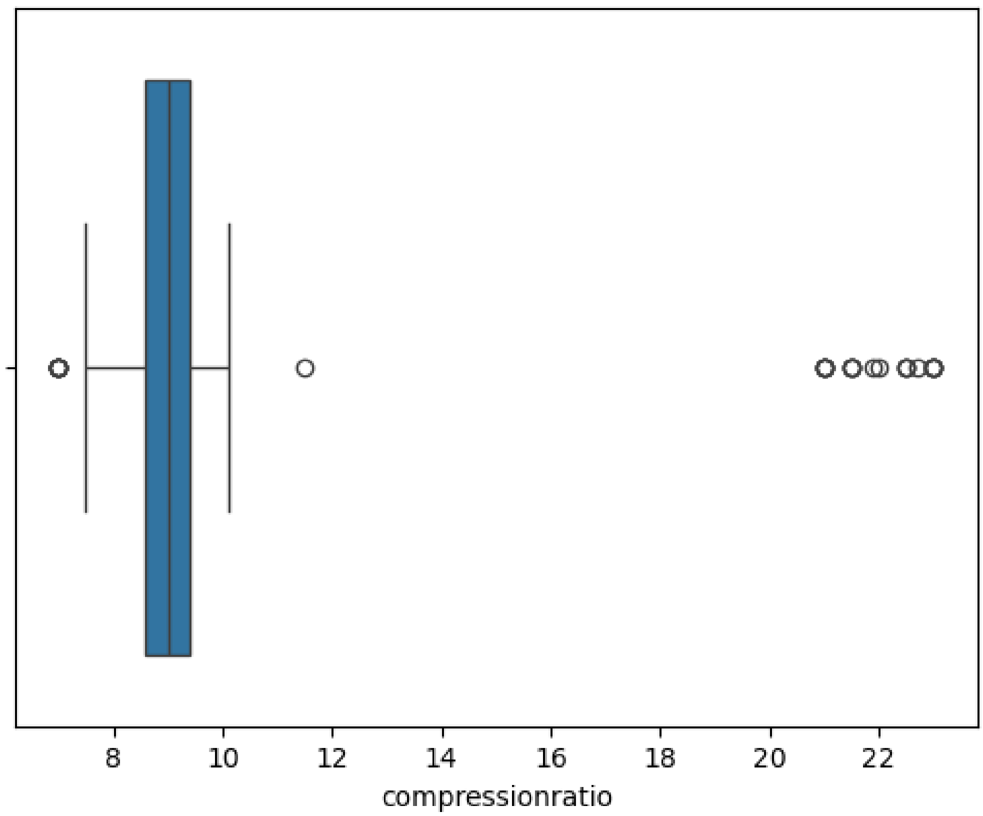

48
50
52
54
56
58
60
carheight

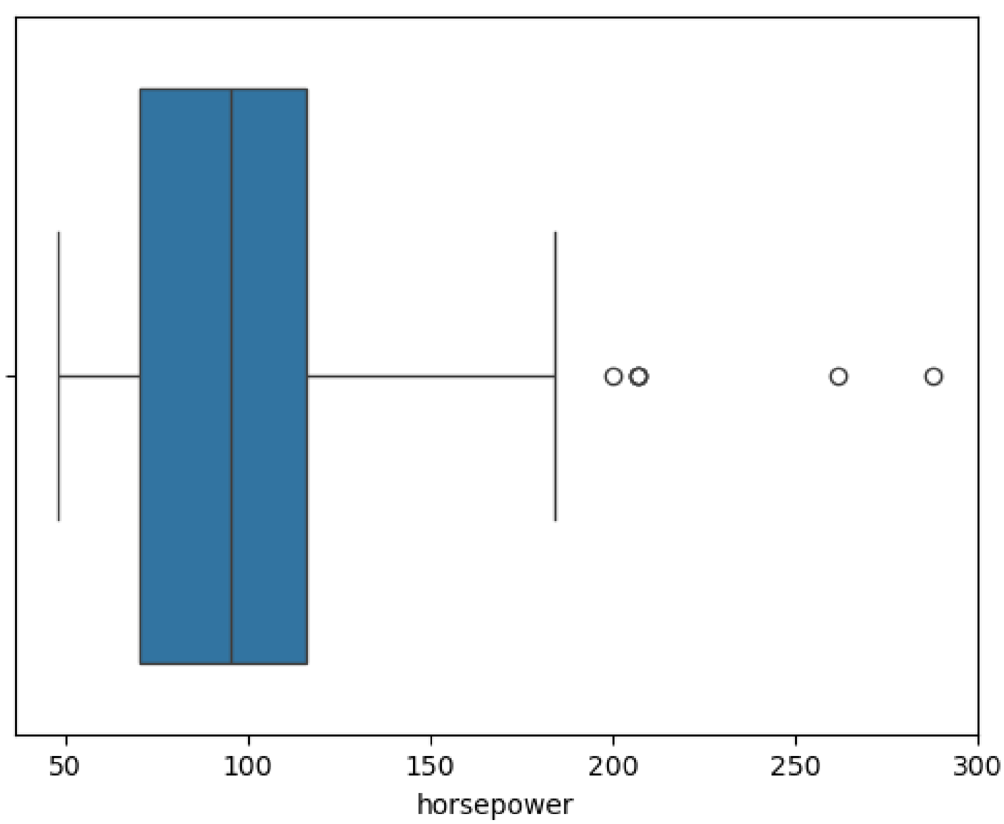

1500
2000
2500
3000
3500
4000
curbweight

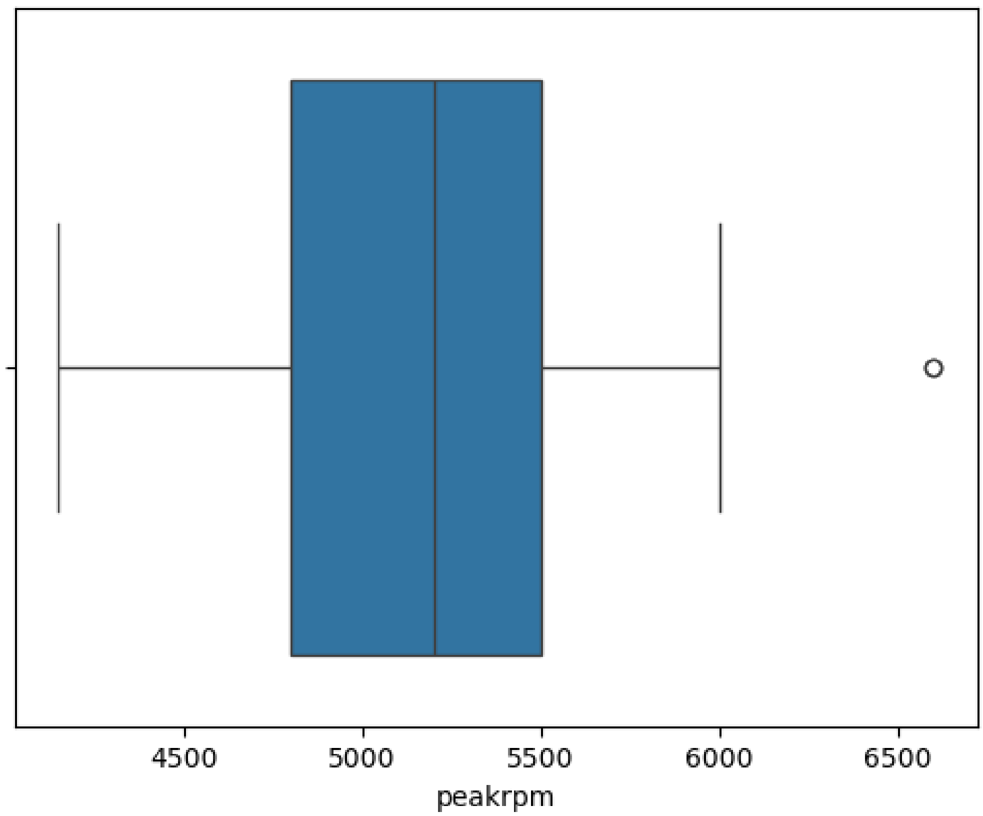

50
100
150
200
250
300
enginesize

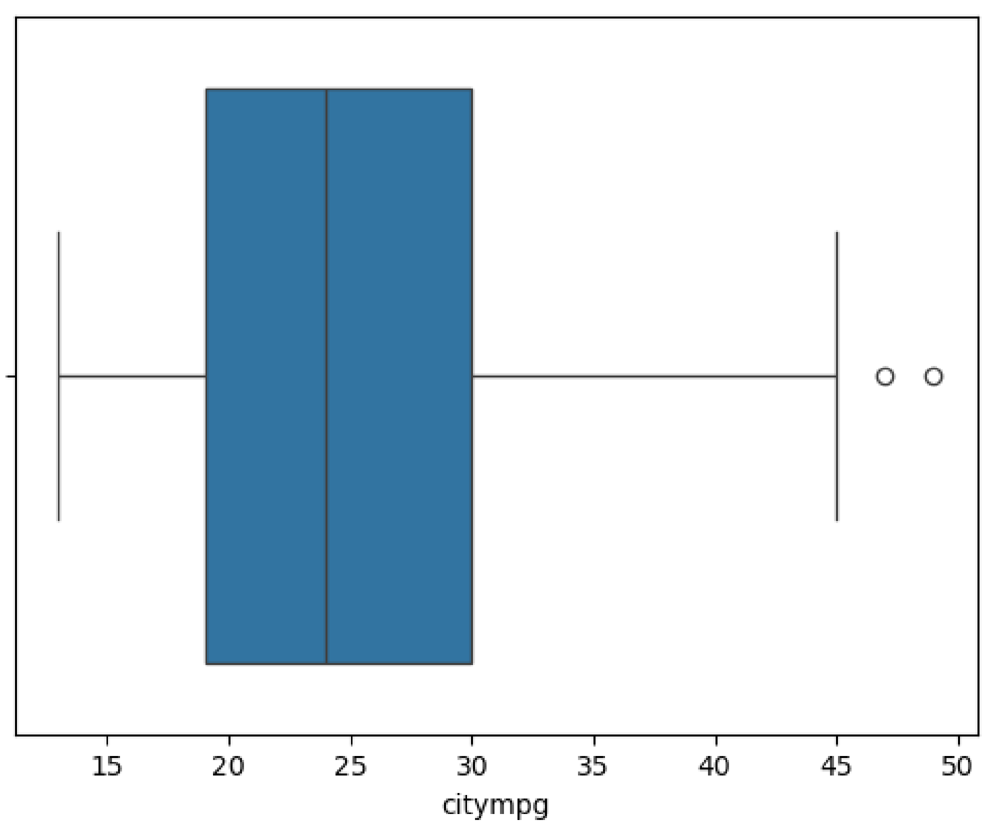

2.6
2.8
3.0
3.2
3.4
3.6
3.8
4.0
boreratio

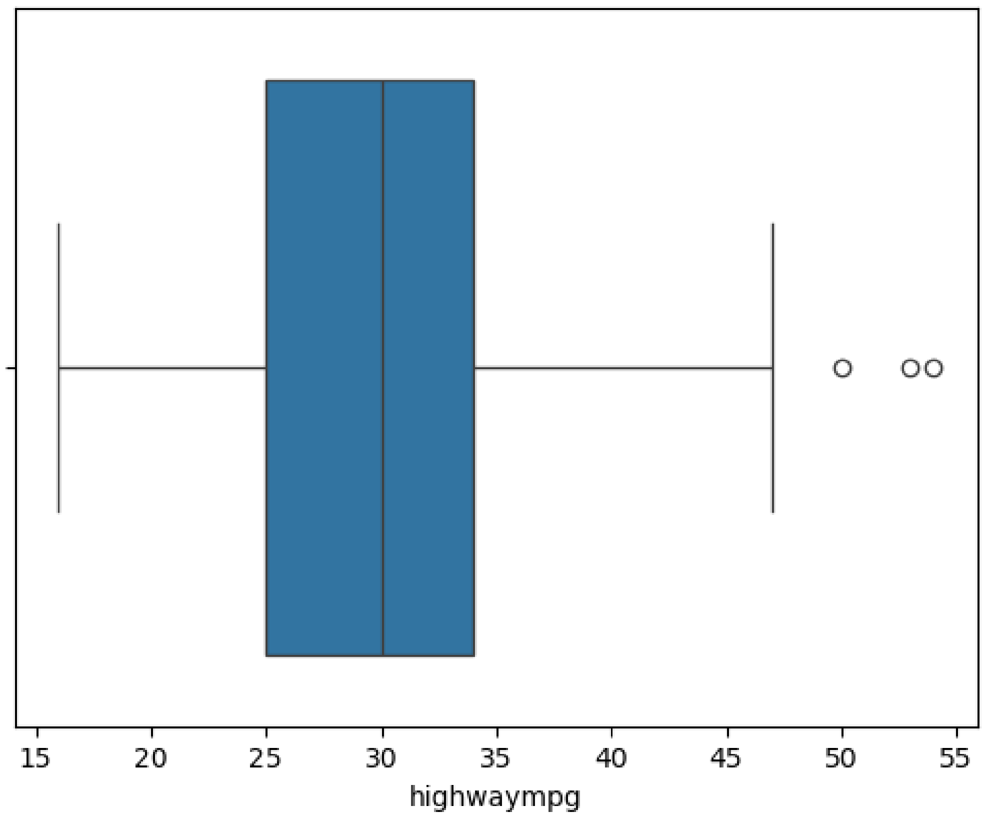

2.0
2.5
3.0
3.5
4.0
stroke

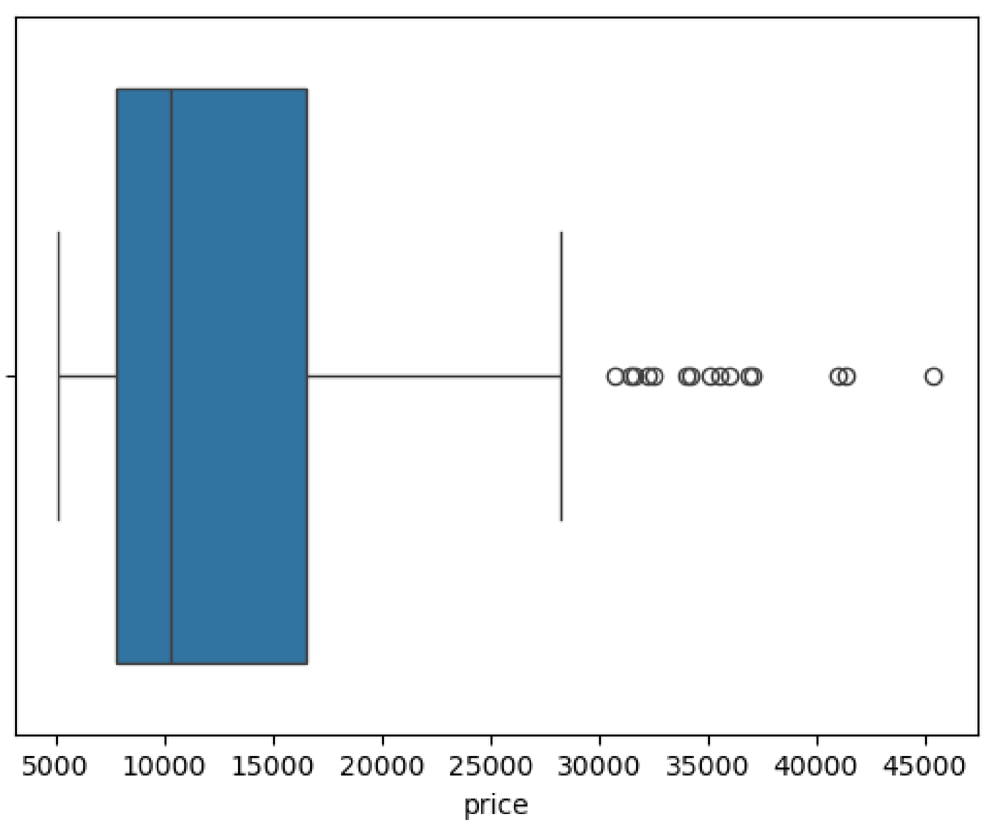

8
10
12
14
16
18
20
22
compressionratio


50
100
150
200
250
300
horsepower


4500
5000
5500
6000
6500
peakrpm

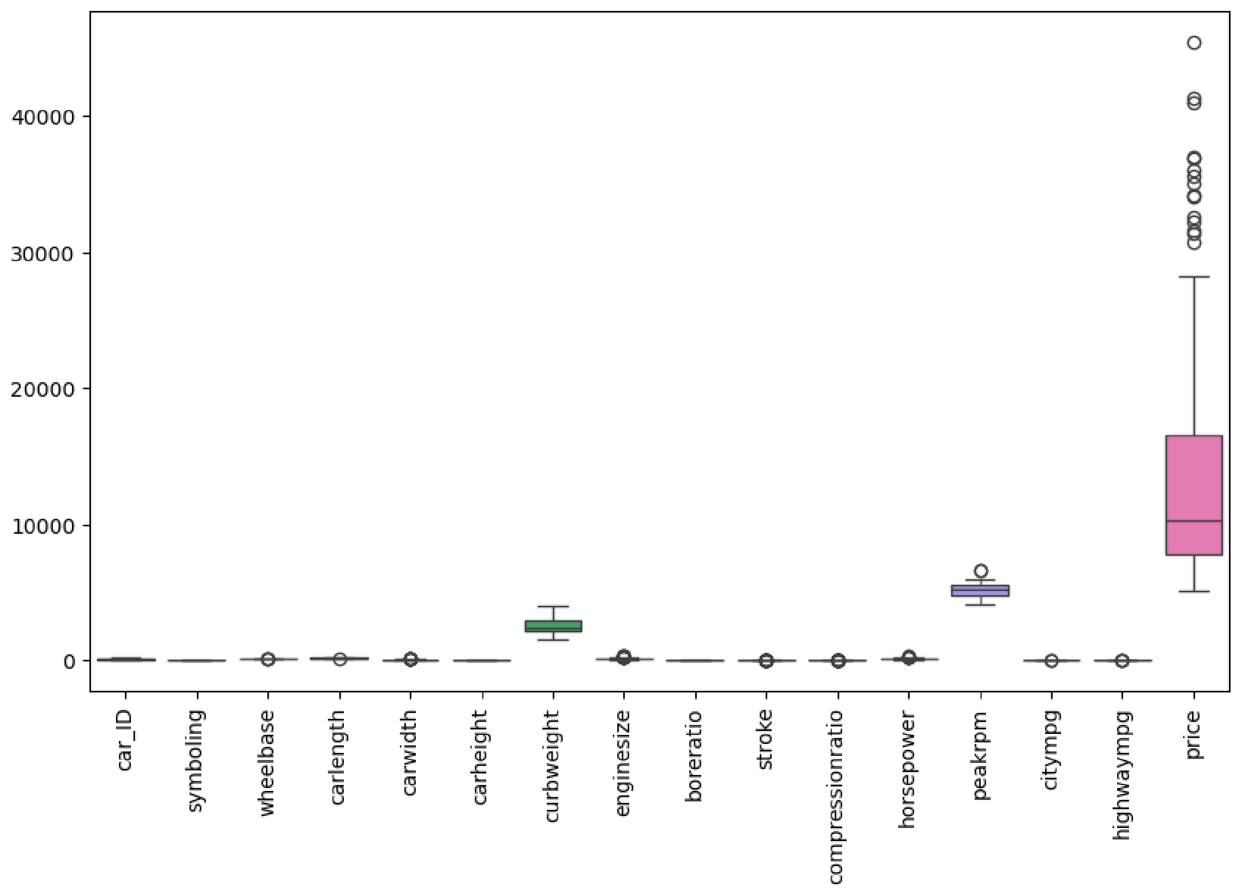

15
20
25
30
35
40
45
50
citympg


15
20
25
30
35
40
45
50
55
highwaympg


5000
10000
15000
20000
25000
30000
35000
40000
45000
price

```
numerical_columns = df.select_dtypes(include=['number']).columns
plt.figure(figsize=(10,6))
sns.boxplot(data = df[numerical_columns])
plt.xticks(rotation=90)
```

```
([0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15],
 [Text(0, 0, 'car_ID'),
  Text(1, 0, 'symboling'),
  Text(2, 0, 'wheelbase'),
  Text(3, 0, 'carlength'),
  Text(4, 0, 'carwidth'),
  Text(5, 0, 'carheight'),
  Text(6, 0, 'curbweight'),
  Text(7, 0, 'enginesize'),
  Text(8, 0, 'boreratio'),
  Text(9, 0, 'stroke'),
  Text(10, 0, 'compressionratio'),
  Text(11, 0, 'horsepower'),
  Text(12, 0, 'peakrpm'),
  Text(13, 0, 'citympg'),
  Text(14, 0, 'highwaympg'),
  Text(15, 0, 'price')])
```



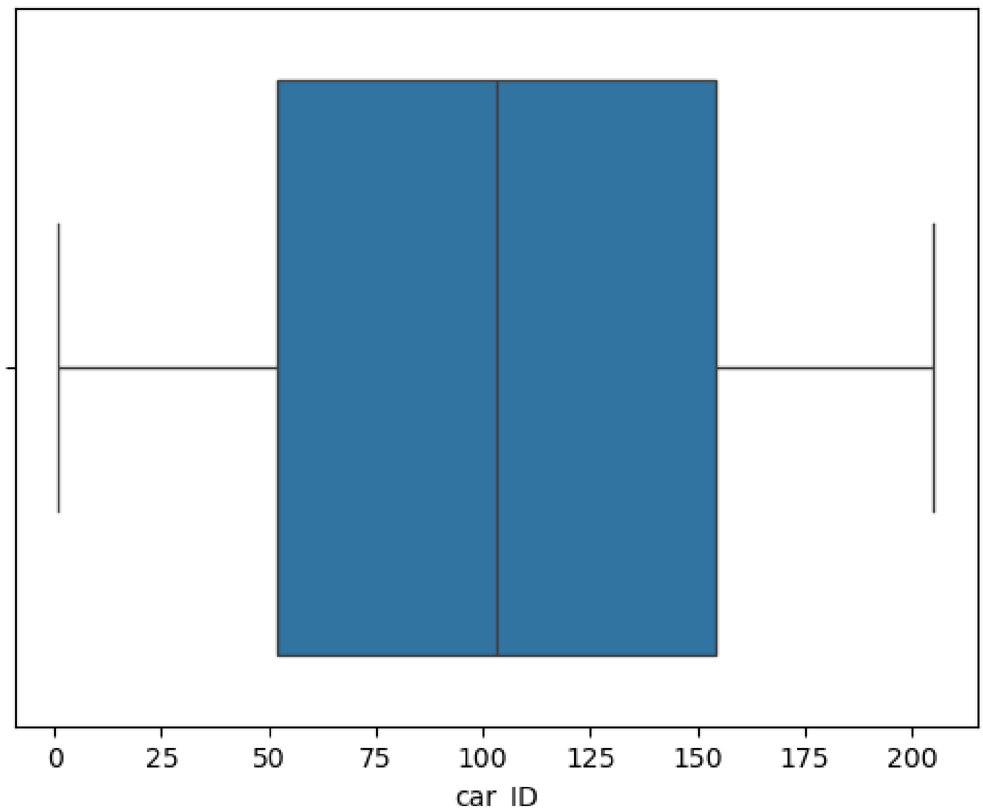
OUTLIERS FOUND

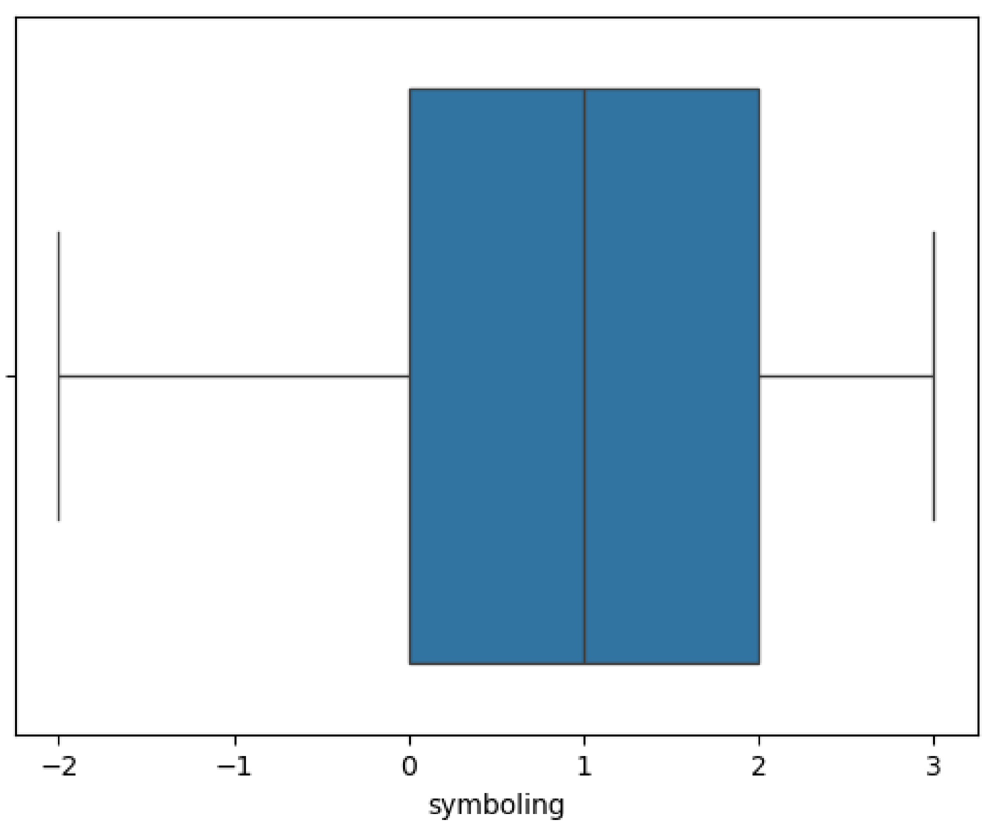
IQR METHOD

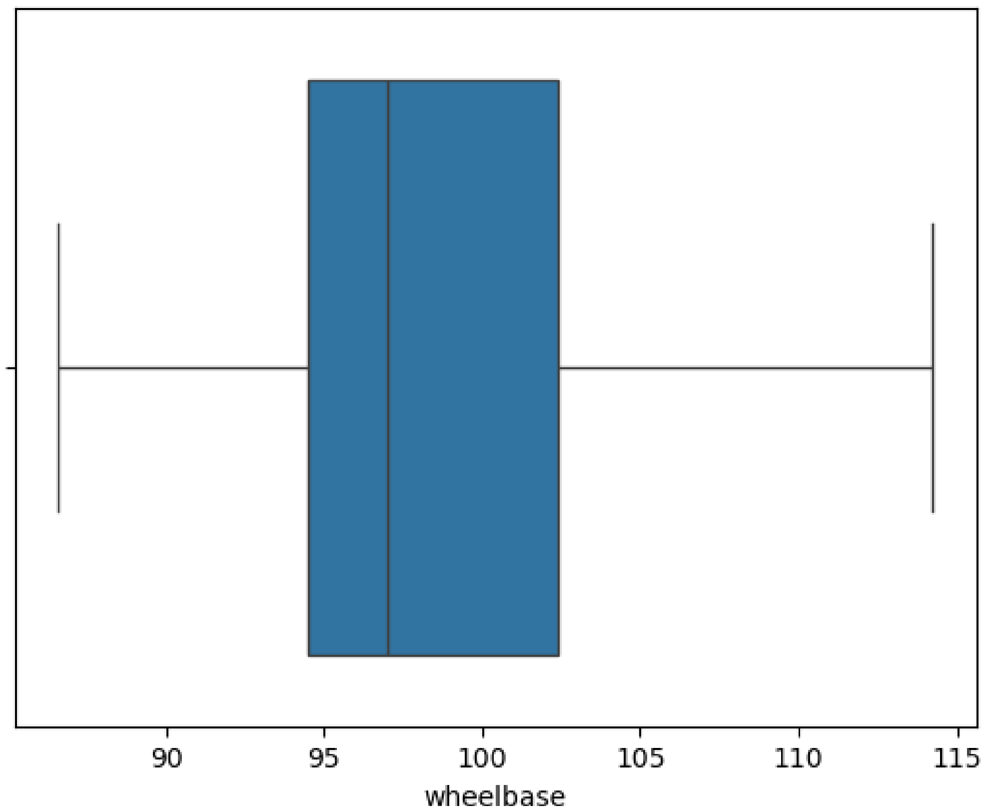
```
# List of features with potential outliers
features = ['wheelbase', 'carlength', 'carwidth', 'enginesize',
'stroke',
            'compressionratio', 'horsepower', 'peakrpm', 'citympg',
'highwaympg', 'price']

# Function to apply IQR method to fix outliers
def fix_outliers_iqr(df, columns):
    for col in columns:
        Q1 = df[col].quantile(0.25)
        Q3 = df[col].quantile(0.75)
        IQR = Q3 - Q1

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

        # Replace outliers with the respective bounds
        df[col] = df[col].apply(lambda x: lower_bound if x <
lower_bound else upper_bound if x > upper_bound else x)

    return df


df = fix_outliers_iqr(df, features)
```

VISUALISING AFTER OUTLIER DETECTION

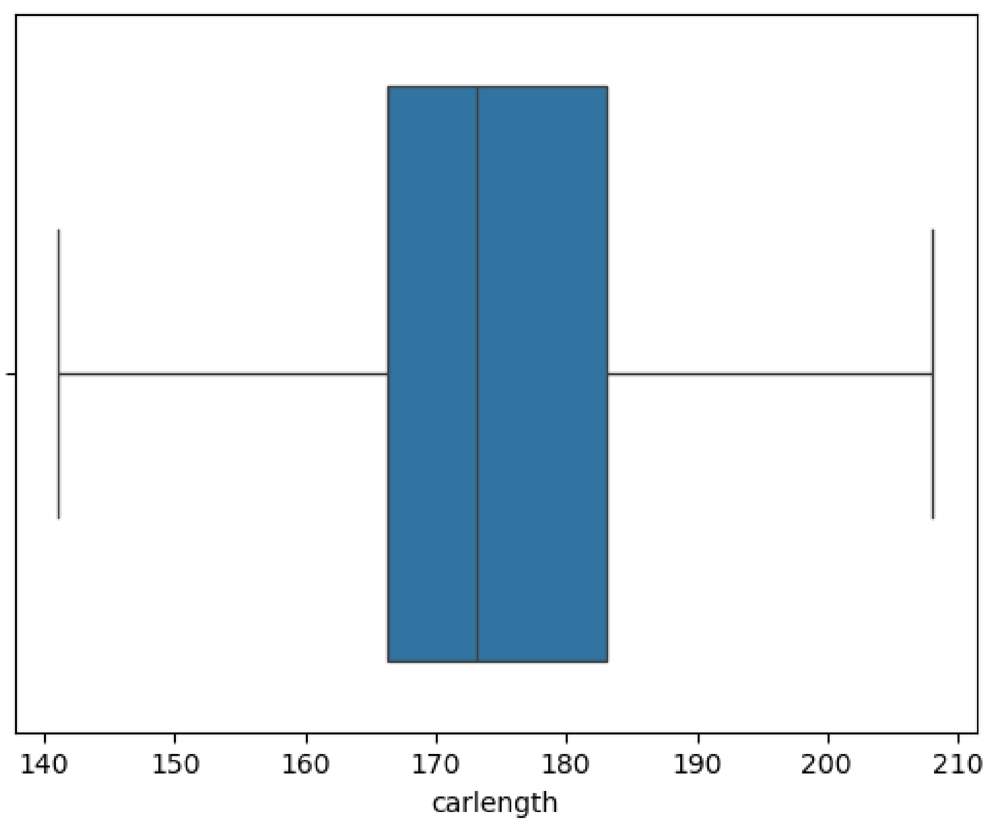
```
# boxplot to identify outliers
for i in df.select_dtypes(include='number').columns:
    sns.boxplot(data=df,x=i)
    plt.show()
```


0
25
50
75
100
125
150
175
200
car_ID

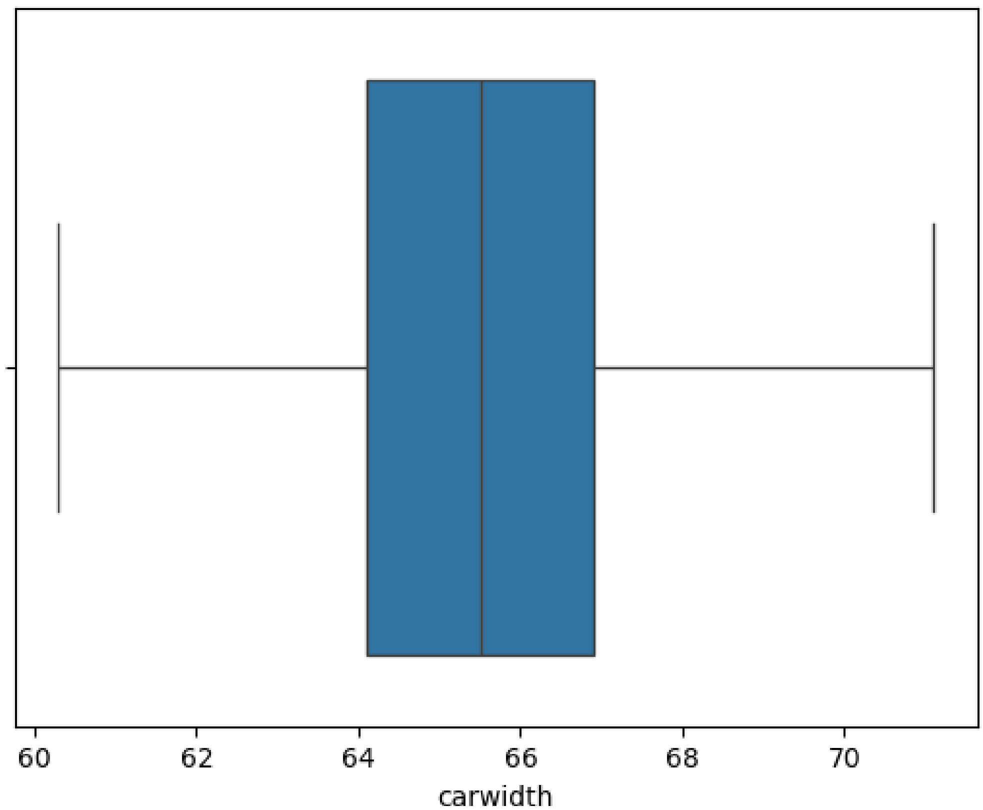

−2
−1
0
1
2
3
symboling

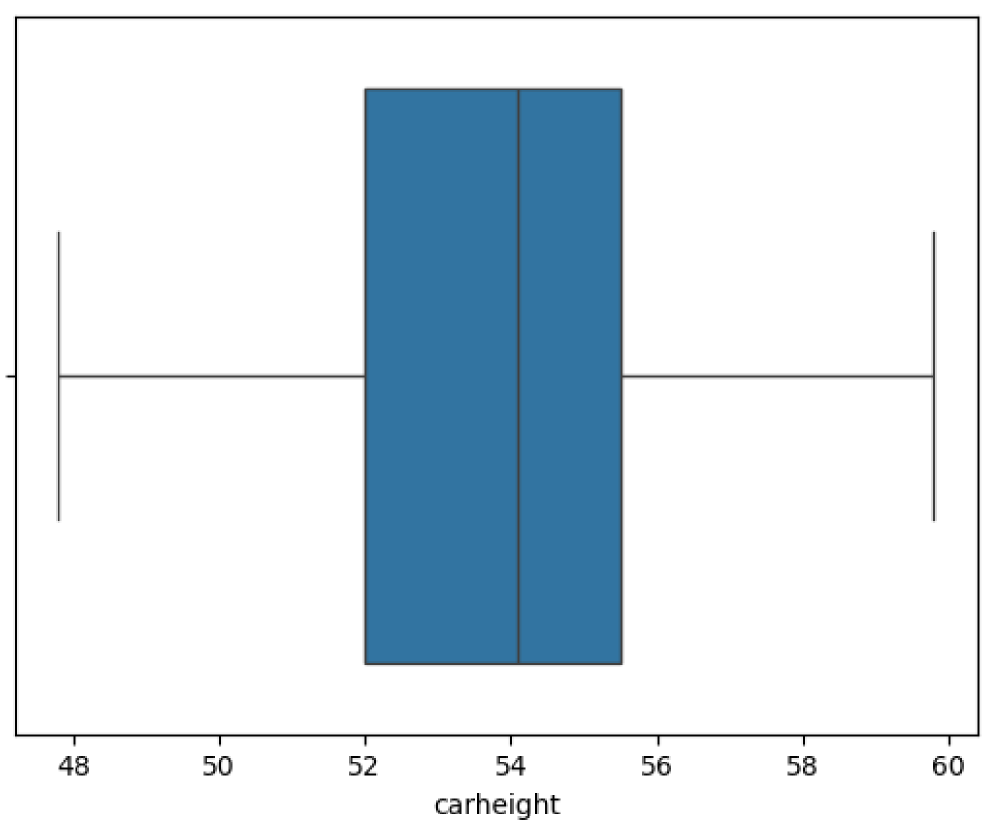


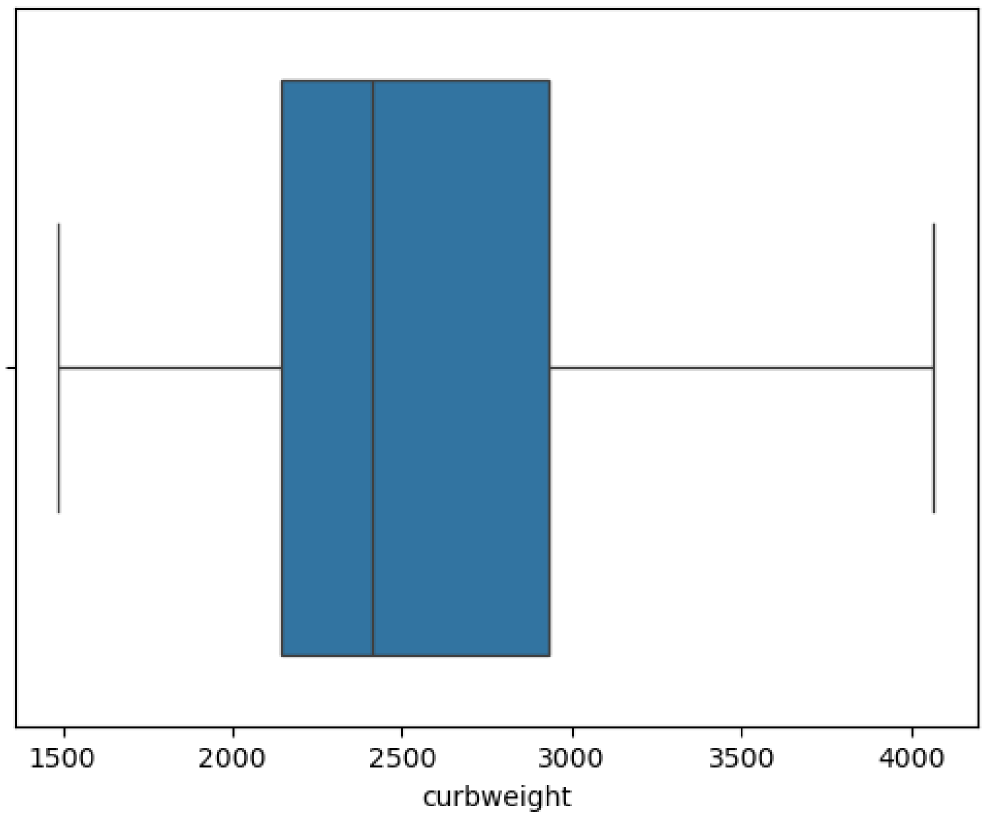
90
95
100
105
110
115
wheelbase

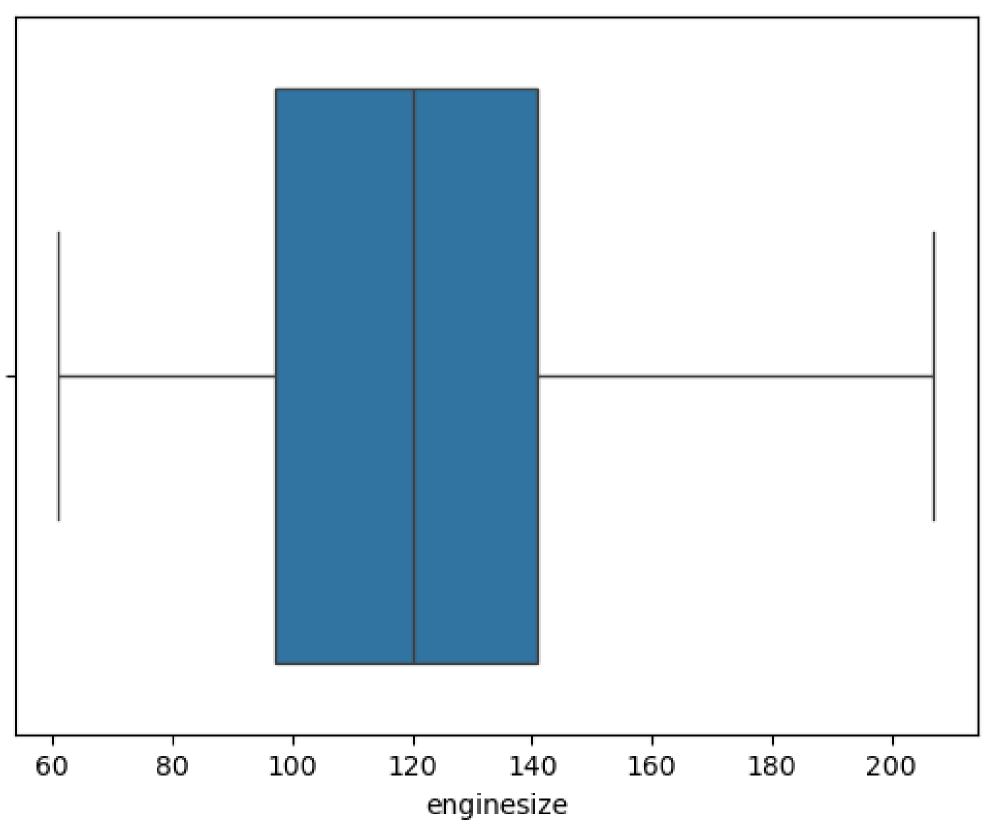


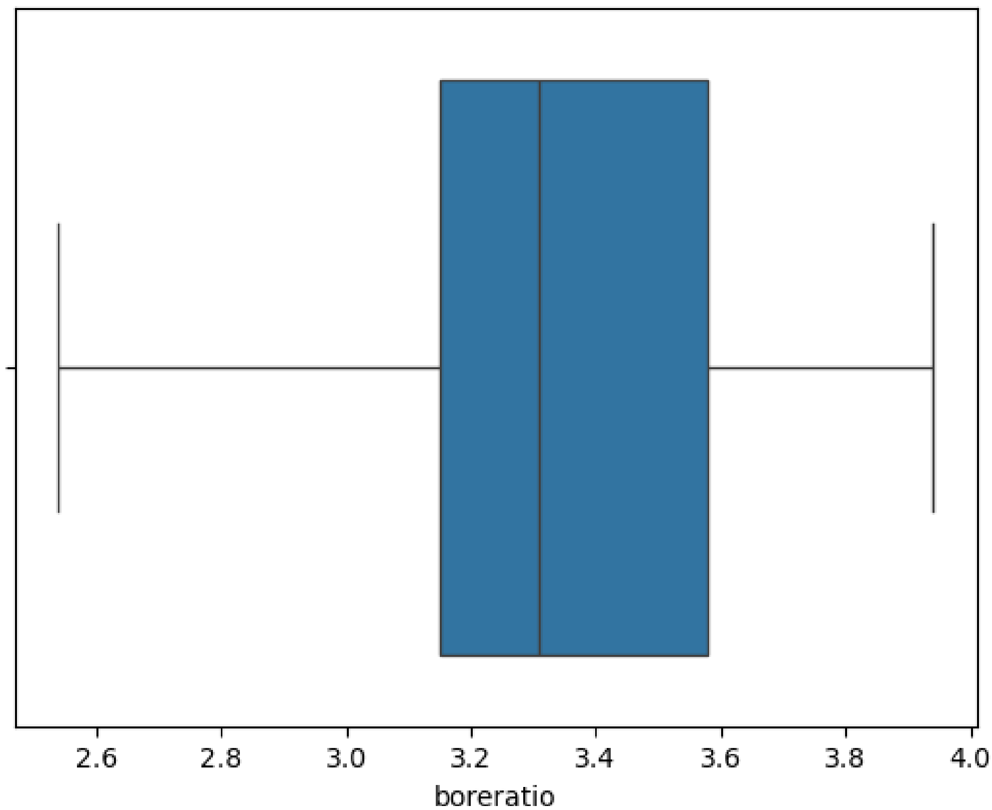
140
150
160
170
180
190
200
210
carlength

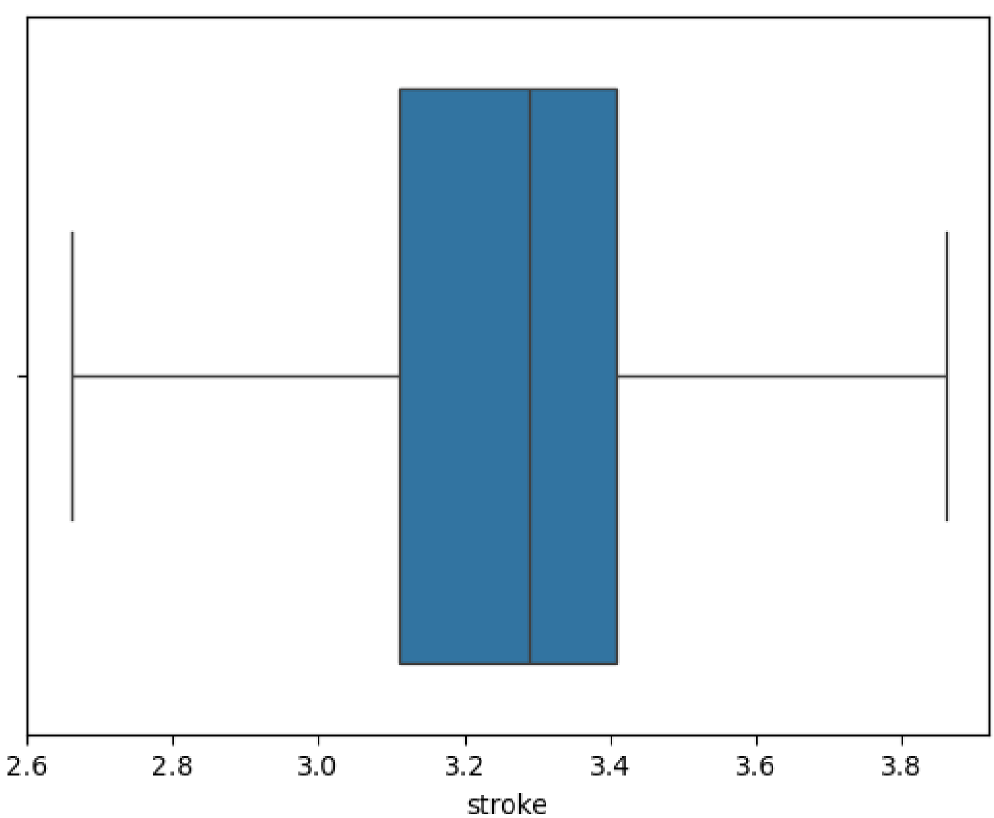

60
62
64
66
68
70
carwidth

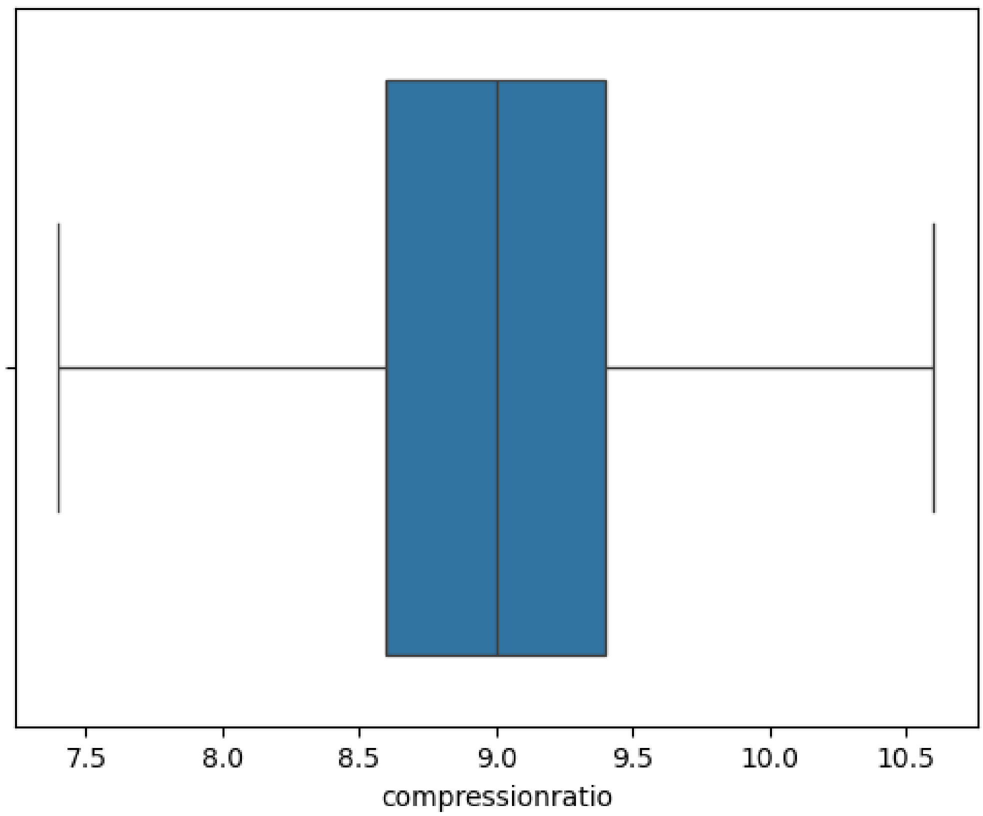

48
50
52
54
56
58
60
carheight


1500
2000
2500
3000
3500
4000
curbweight

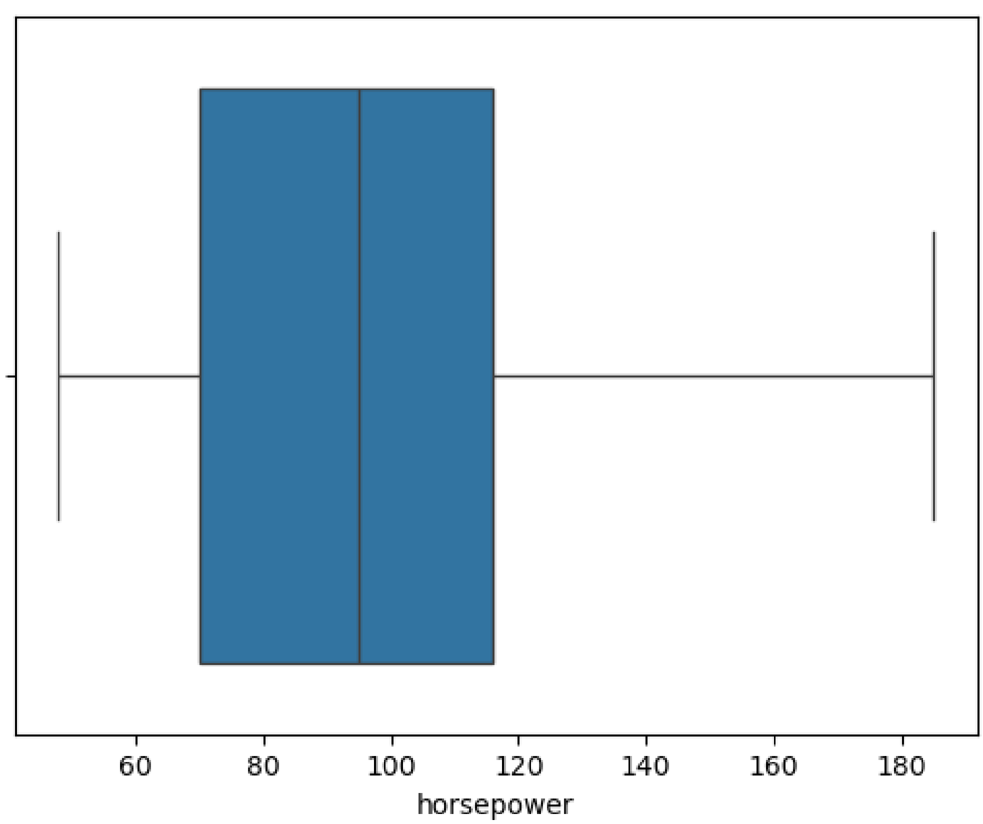

60
80
100
120
140
160
180
200
enginesize


2.6
2.8
3.0
3.2
3.4
3.6
3.8
4.0
boreratio

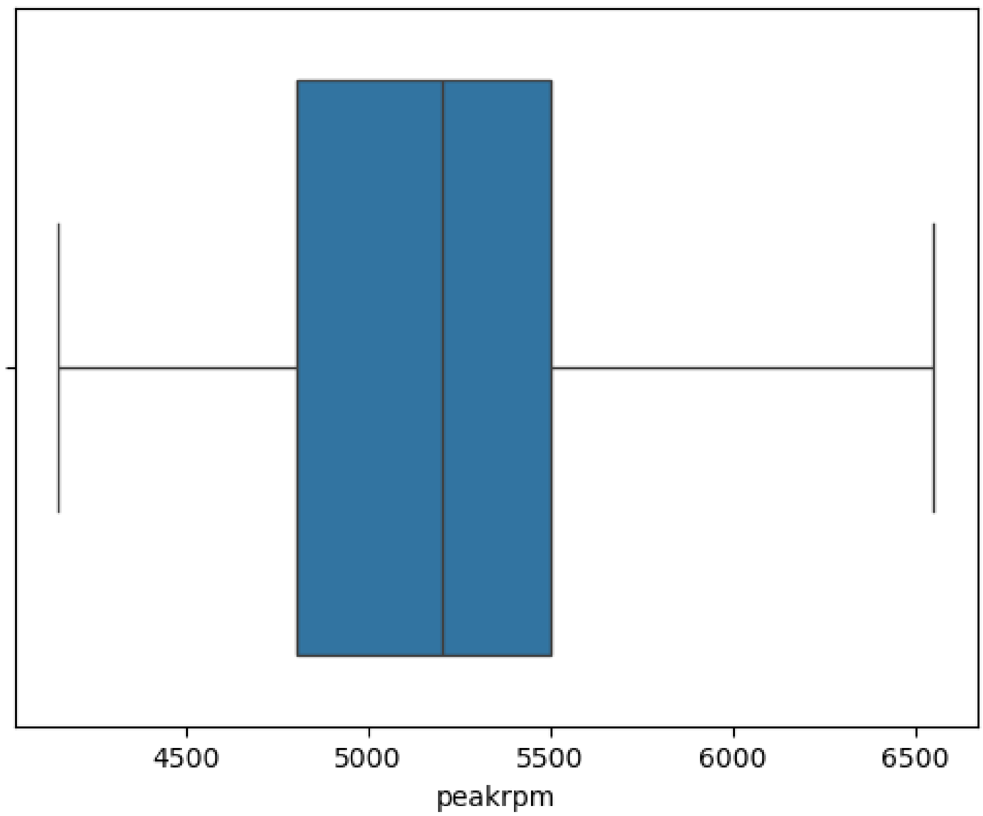

2.6
2.8
3.0
3.2
3.4
3.6
3.8
stroke

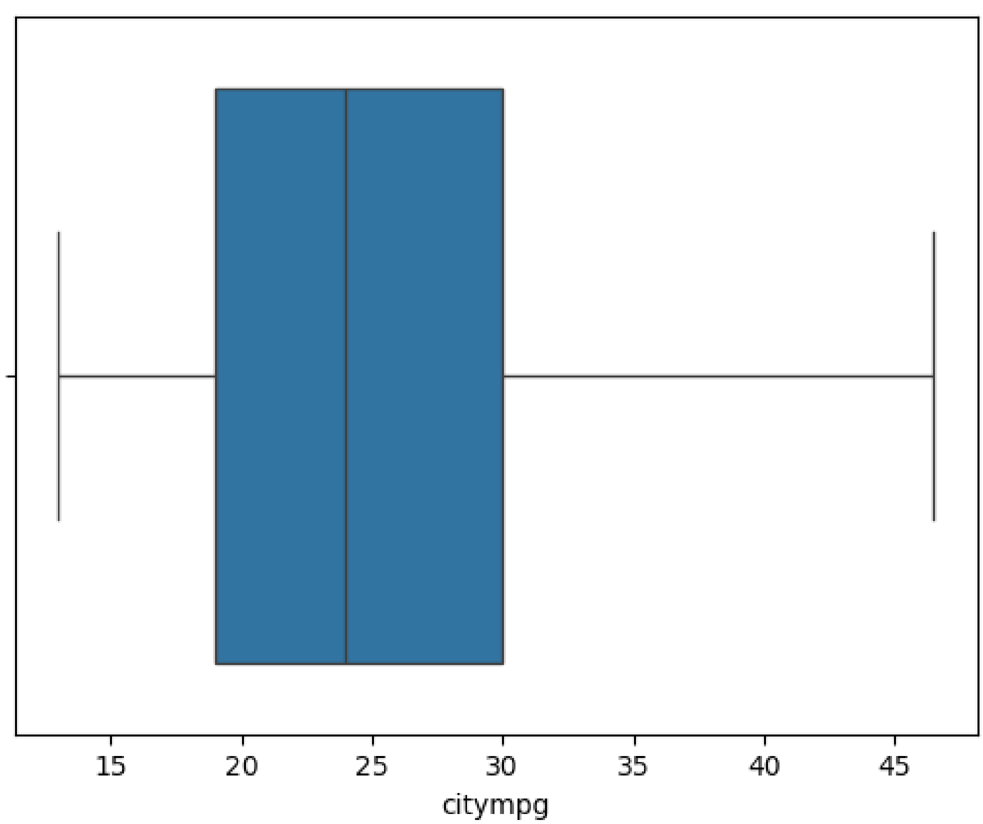


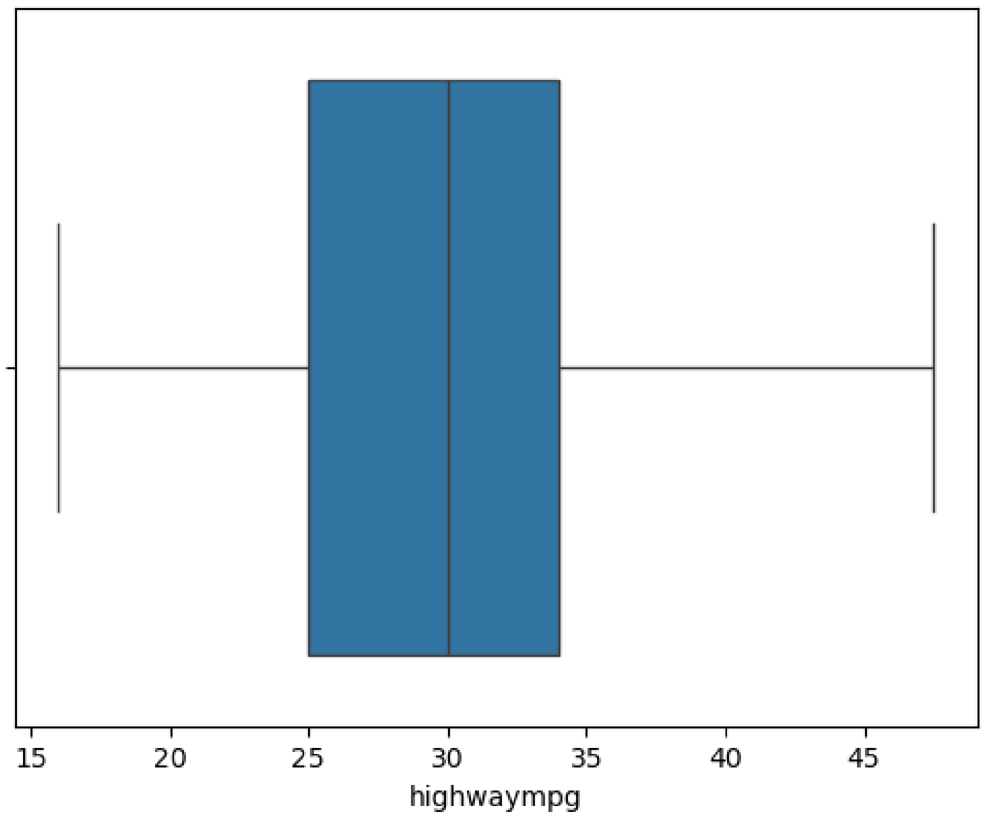
7.5
8.0
8.5
9.0
9.5
10.0
10.5
compressionratio

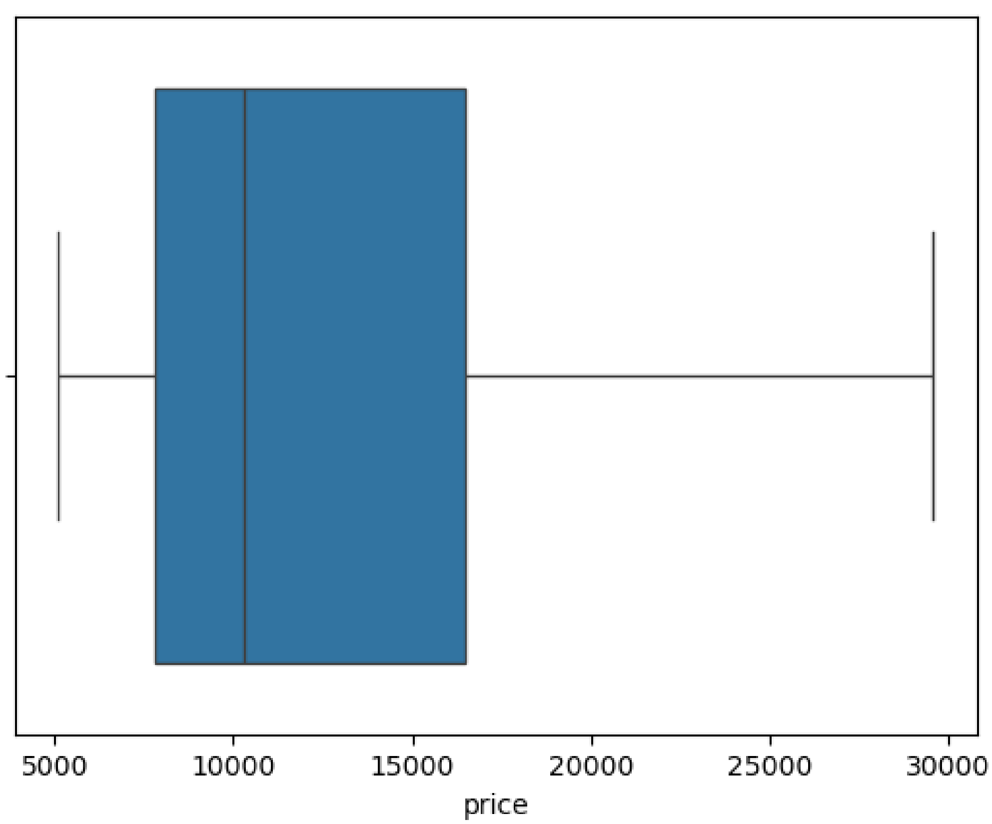


60
80
100
120
140
160
180
horsepower


4500
5000
5500
6000
6500
peakrpm

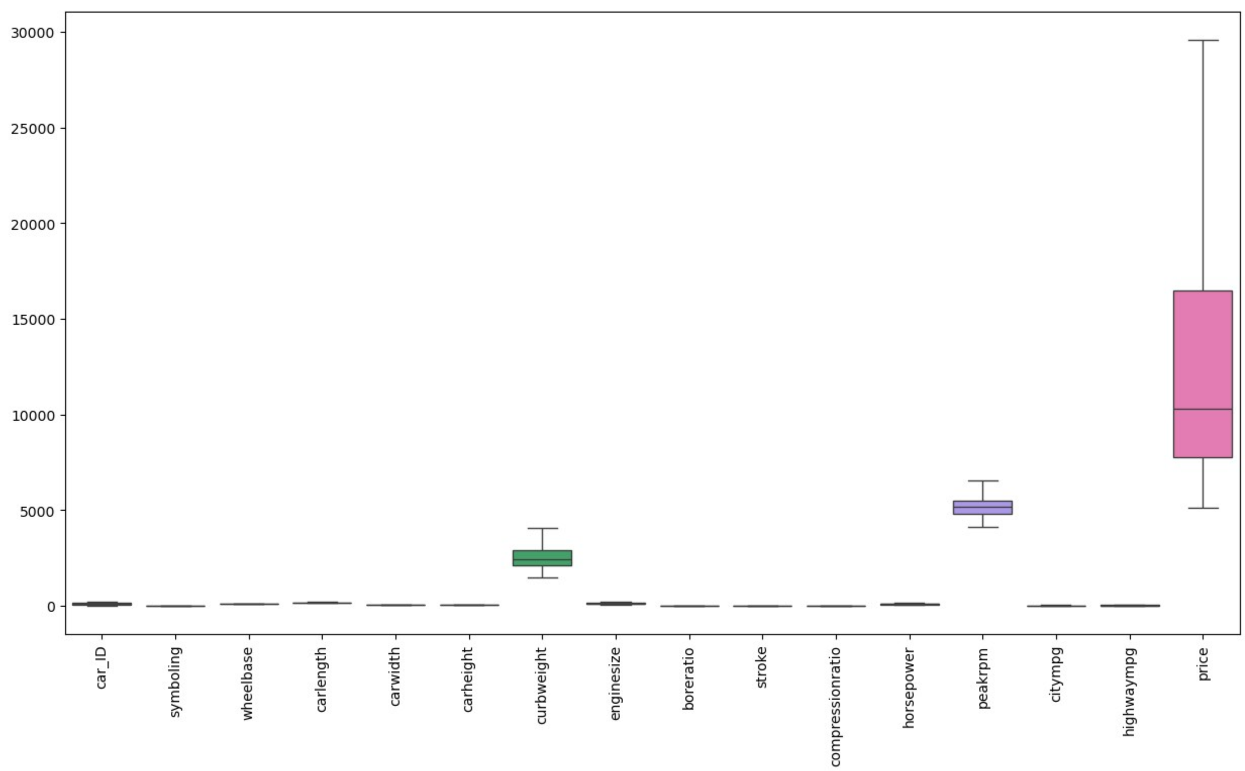

15
20
25
30
35
40
45
citympg


15
20
25
30
35
40
45
highwaympg


5000
10000
15000
20000
25000
30000
price

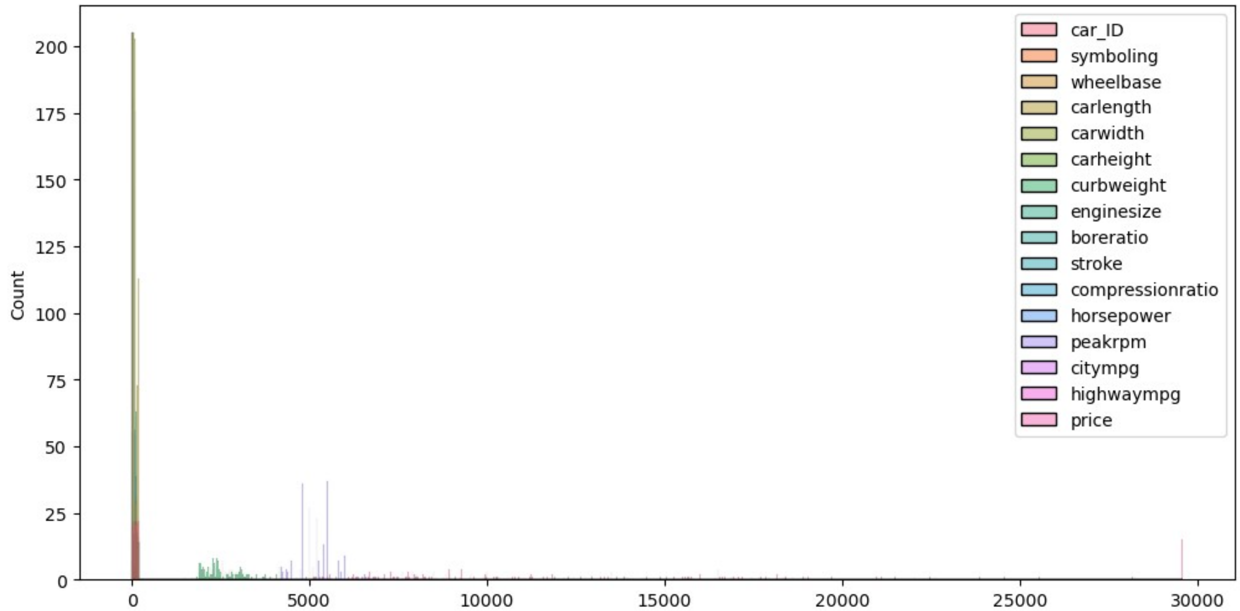
```
numerical_columns = df.select_dtypes(include=['number']).columns
plt.figure(figsize=(15,8))
sns.boxplot(data = df[numerical_columns])
plt.xticks(rotation=90)
```

```
([0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15],
 [Text(0, 0, 'car_ID'),
  Text(1, 0, 'symboling'),
  Text(2, 0, 'wheelbase'),
  Text(3, 0, 'carlength'),
  Text(4, 0, 'carwidth'),
  Text(5, 0, 'carheight'),
  Text(6, 0, 'curbweight'),
  Text(7, 0, 'enginesize'),
  Text(8, 0, 'boreratio'),
  Text(9, 0, 'stroke'),
  Text(10, 0, 'compressionratio'),
  Text(11, 0, 'horsepower'),
  Text(12, 0, 'peakrpm'),
  Text(13, 0, 'citympg'),
  Text(14, 0, 'highwaympg'),
  Text(15, 0, 'price')])
```



CHECKING SKEW

```
# visualising
plt.figure(figsize=(12,6))
sns.histplot(df[numerical_columns])
plt.show()
```

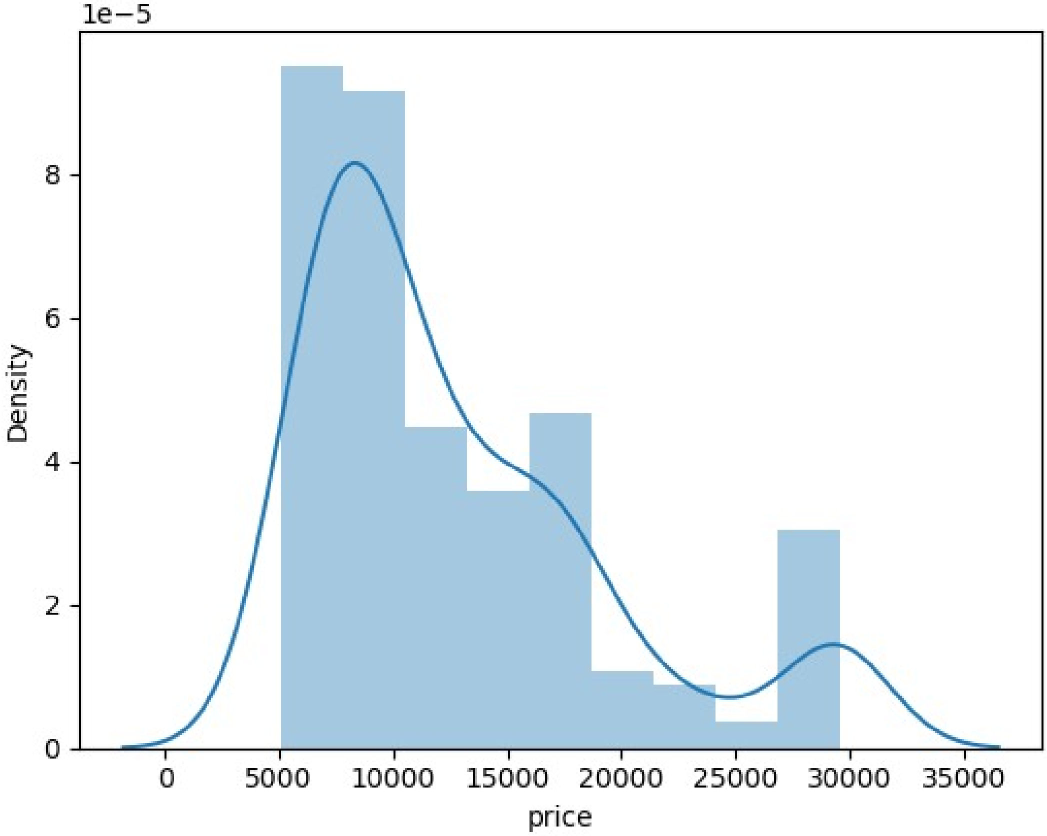



```
df[numerical_columns].skew()
```

```
car_ID              0.000000
symboling           0.211072
wheelbase           0.924916
carlength           0.155954
carwidth            0.776278
carheight           0.063123
curbweight          0.681398
enginesize          0.908453
boreratio           0.020156
stroke             -0.379130
compressionratio    0.035149
horsepower          0.814957
peakrpm             0.049935
citympg             0.604594
highwaympg          0.347441
price               1.222031
dtype: float64
```

```
sns.distplot(df['price'])
```

```
<Axes: xlabel='price', ylabel='Density'>
```



SKEWNESS IS HIGH FOR 'PRICE'

SKEWNESS IS FIXED BY USING LOG TRANSFORMATION

```
df['price'] = np.log(df['price'])
df['wheelbase'] = np.log(df['wheelbase'])
df['carwidth'] = np.log(df['carwidth'])
df['enginesize'] = np.log(df['enginesize'])
df['compressionratio'] = np.log(df['compressionratio'])
df['horsepower'] = np.log(df['horsepower'])

df[numerical_columns].skew()

car_ID              0.000000
symboling           0.211072
wheelbase           0.781960
carlength           0.155954
carwidth            0.696287
carheight           0.063123
curbweight          0.681398
enginesize          0.401418
boreratio           0.020156
stroke             -0.379130
compressionratio   -0.241483
horsepower          0.287093
```

```
peakrpm             0.049935
citympg             0.604594
highwaympg          0.347441
price               0.459254
dtype: float64
```

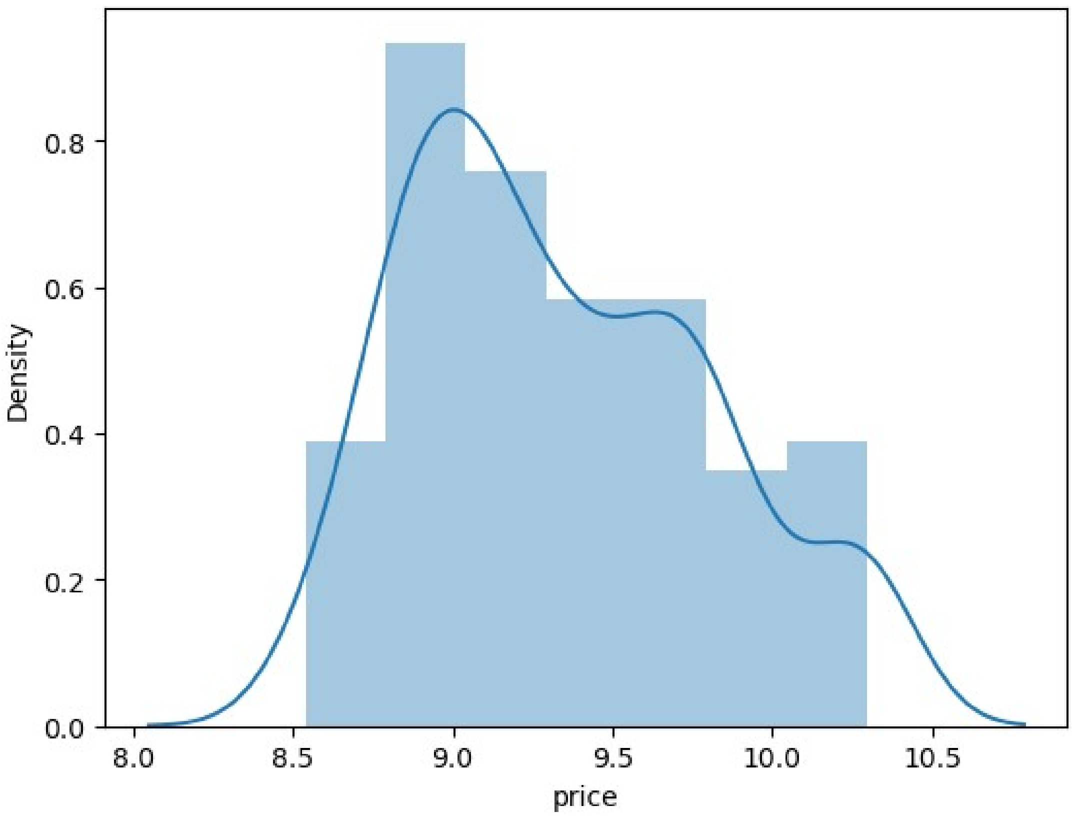
```
df['compressionratio'] = np.sqrt(df['compressionratio'])
df['wheelbase'] = np.sqrt(df['wheelbase'])
```

```
df[numerical_columns].skew()
```

```
car_ID              0.000000
symboling           0.211072
wheelbase           0.766142
carlength           0.155954
carwidth            0.696287
carheight           0.063123
curbweight          0.681398
enginesize          0.401418
boreratio           0.020156
stroke             -0.379130
compressionratio   -0.304199
horsepower          0.287093
peakrpm             0.049935
citympg             0.604594
highwaympg          0.347441
price               0.459254
dtype: float64
```

```
sns.distplot(df['price'])
```

```
<Axes: xlabel='price', ylabel='Density'>
```




```
df[numerical_columns].skew()
```

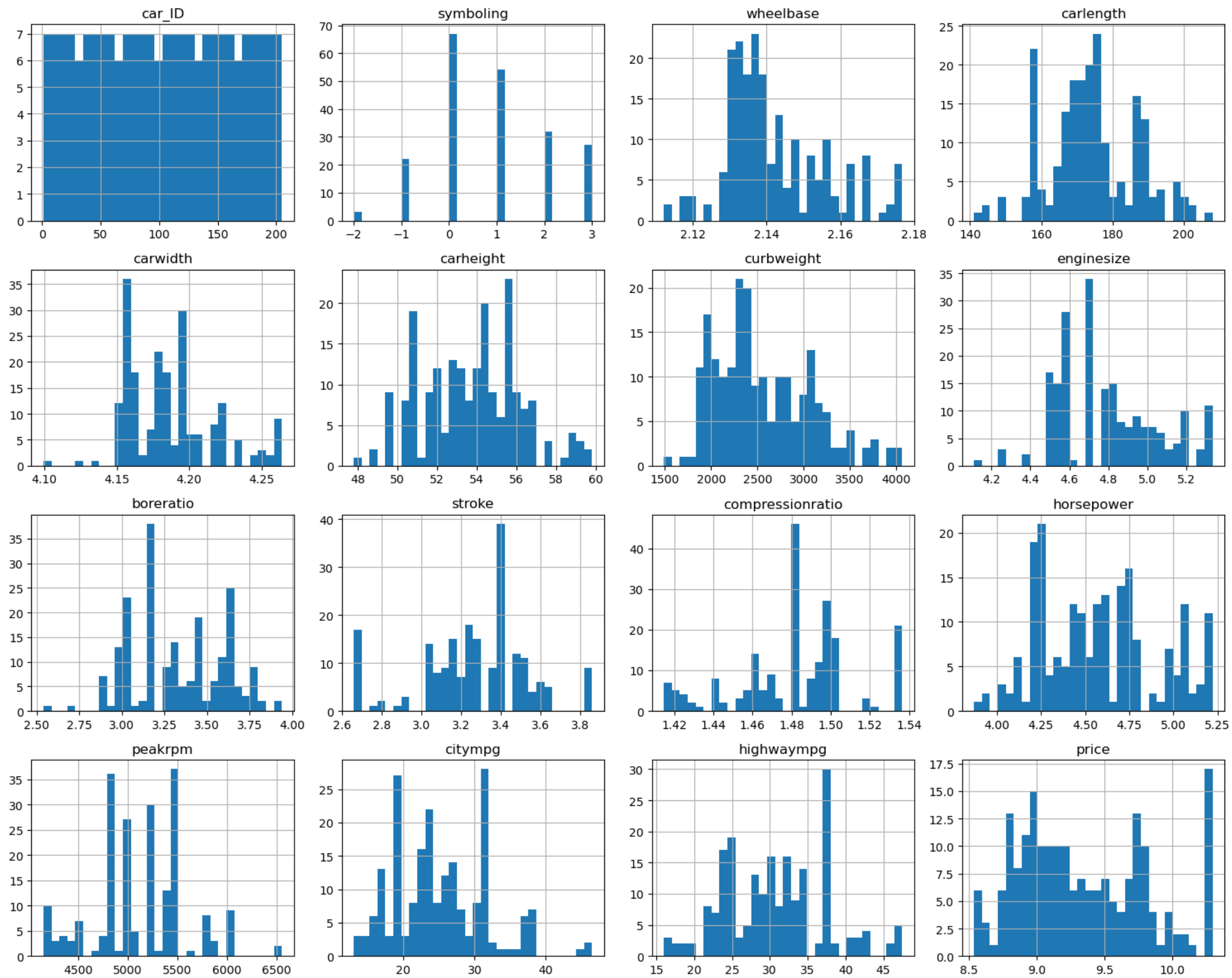
```
car_ID              0.000000
symboling           0.211072
wheelbase           0.766142
carlength           0.155954
carwidth            0.696287
carheight           0.063123
curbweight          0.681398
enginesize          0.401418
boreratio           0.020156
stroke             -0.379130
compressionratio   -0.304199
horsepower          0.287093
peakrpm             0.049935
citympg             0.604594
highwaympg          0.347441
price               0.459254
dtype: float64
```

6. EDA

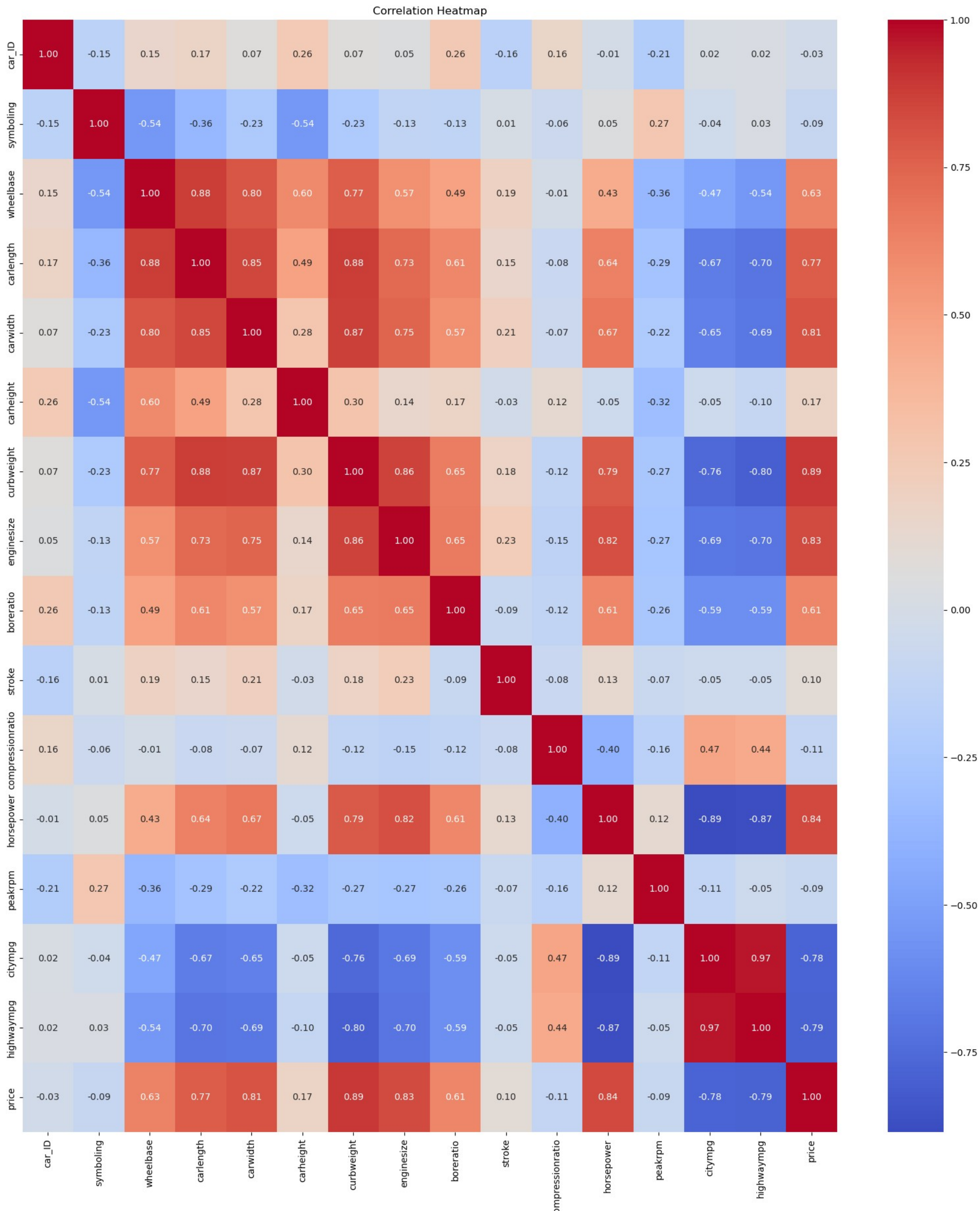
```
df1 = df.copy()
```

```
df1.head()

   car_ID  symboling                   CarName fueltype aspiration 
doornumber  \
0       1          3        alfa-romero giulia      gas        std 
two   
1       2          3       alfa-romero stelvio      gas        std 
two   
2       3          1  alfa-romero Quadrifoglio      gas        std 
two   
3       4          2               audi 100 ls      gas        std 
four   
4       5          2                audi 100ls      gas        std 
four   

       carbody drivewheel enginelocation  wheelbase  ...  
enginesize  \
0  convertible        rwd          front   2.117577  ...    4.867534   

1  convertible        rwd          front   2.117577  ...    4.867534   

2    hatchback        rwd          front   2.132745  ...    5.023881   

3        sedan        fwd          front   2.145500  ...    4.691348   

4        sedan        4wd          front   2.144563  ...    4.912655   


   fuelsystem  boreratio  stroke compressionratio horsepower  peakrpm 
citympg  \
0        mpfi       3.47    2.68         1.482304   4.709530   5000.0 
21.0   
1        mpfi       3.47    2.68         1.482304   4.709530   5000.0 
21.0   
2        mpfi       2.68    3.47         1.482304   5.036953   5000.0 
19.0   
3        mpfi       3.19    3.40         1.517427   4.624973   5500.0 
24.0   
4        mpfi       3.19    3.40         1.442027   4.744932   5500.0 
18.0   

   highwaympg     price  
0        27.0  9.510075  
1        27.0  9.711116  
2        26.0  9.711116  
3        30.0  9.543235  
4        22.0  9.767095  

[5 rows x 26 columns]
```

```python
# Histogram
df1.hist(bins=30, figsize=(15, 12))
plt.tight_layout()
plt.show()
```

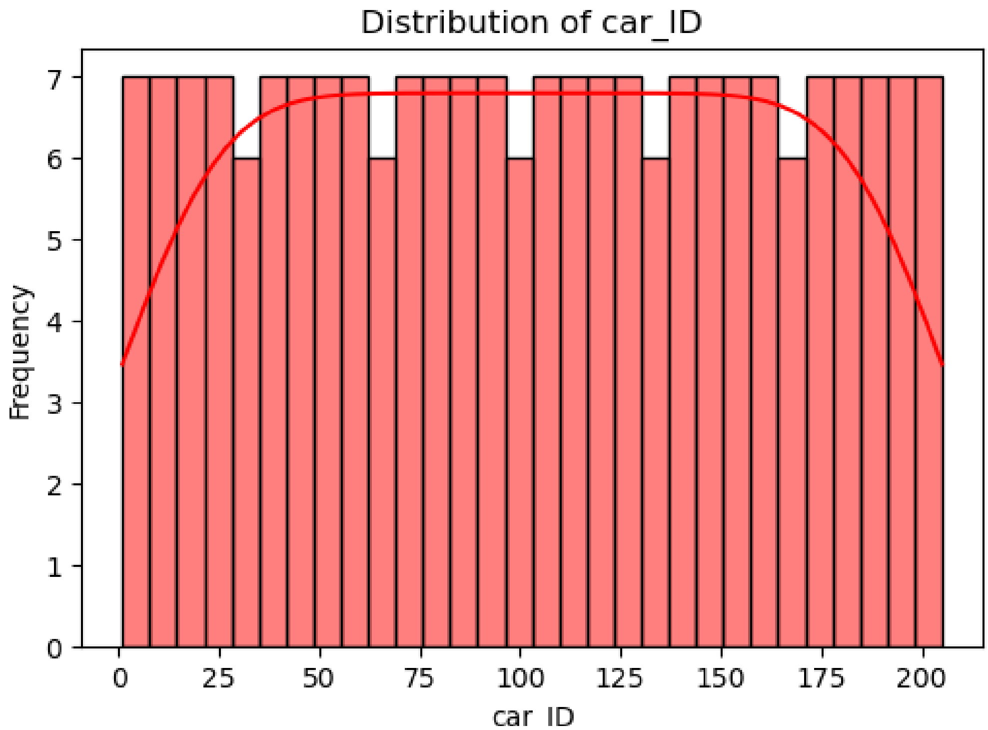


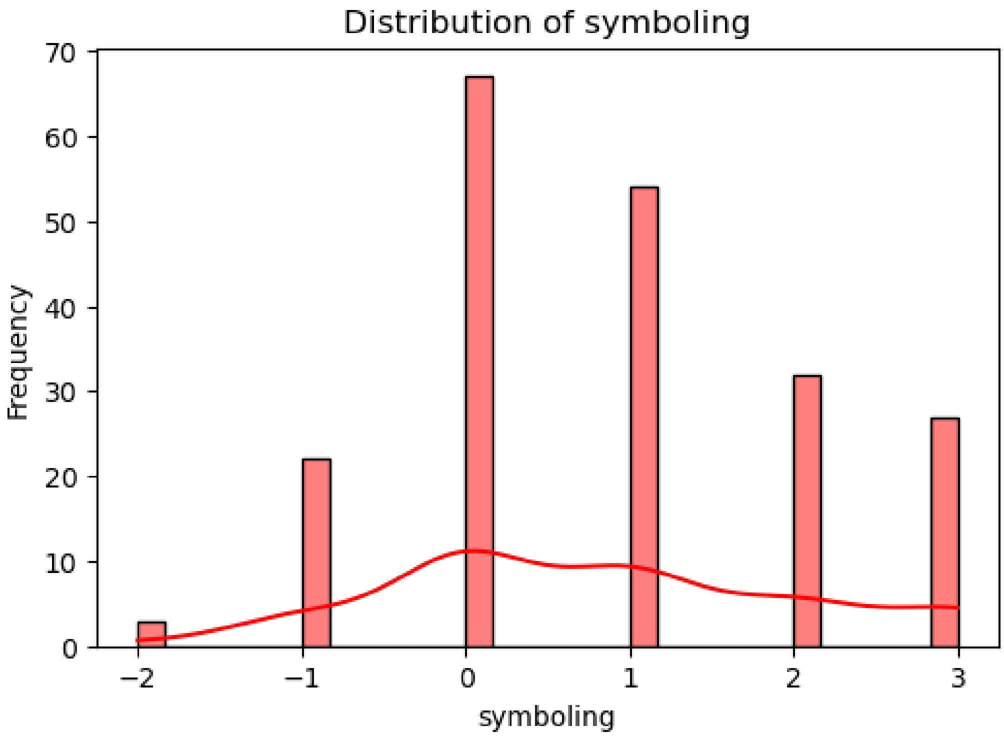

```python
#Compute correlation matrix
corr_matrix = df1[numerical_columns].corr()

# Heatmap
plt.figure(figsize=(20, 22))
sns.heatmap(corr_matrix, annot=True, fmt=".2f", cmap="coolwarm")
plt.title("Correlation Heatmap")
plt.show()
```

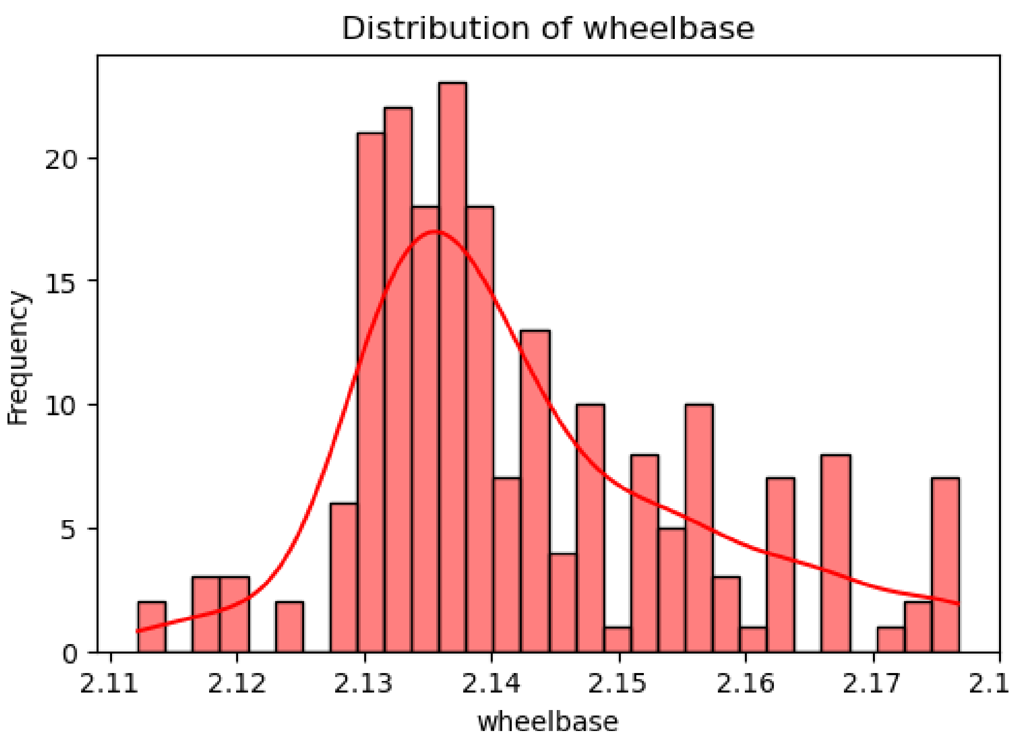


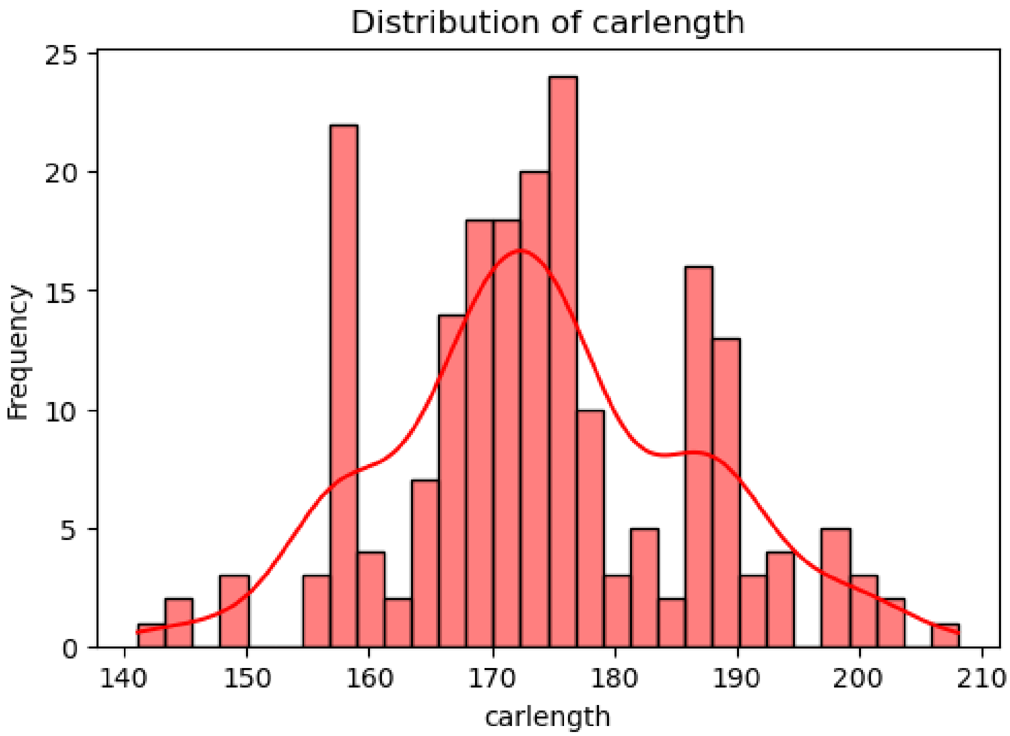

```python
# Plot distribution for numerical column
for feature in numerical_columns:
    plt.figure(figsize=(6, 4))
```

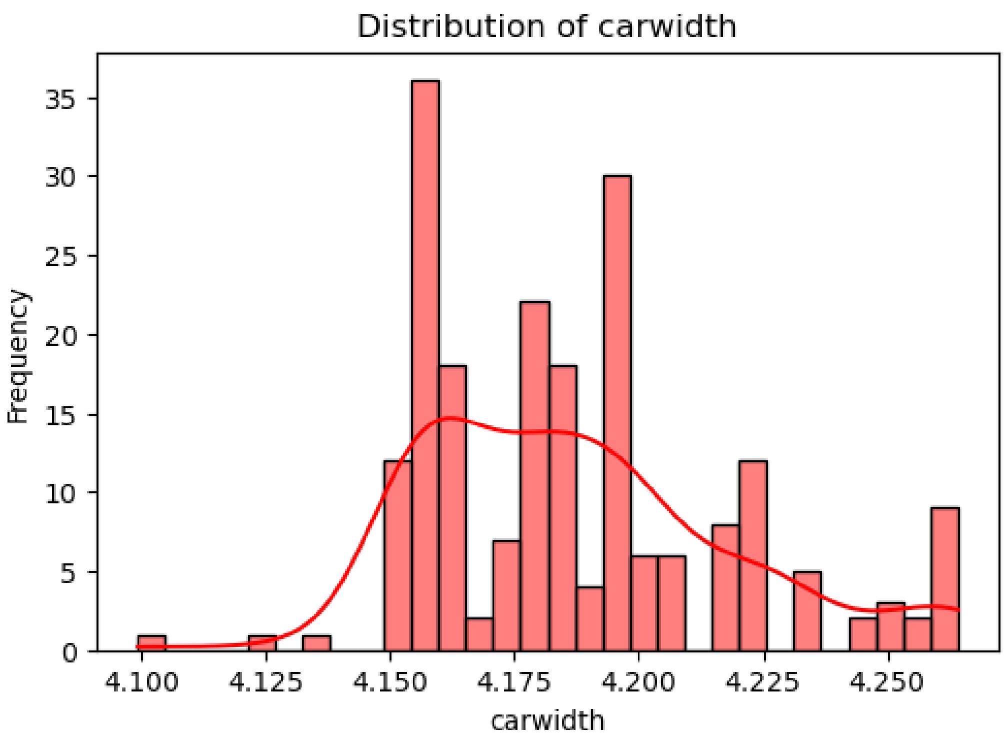
```
    sns.histplot(df1[feature], kde=True, bins=30, color='Red')
    plt.title(f'Distribution of {feature}')
    plt.xlabel(feature)
    plt.ylabel('Frequency')
    plt.show()
```

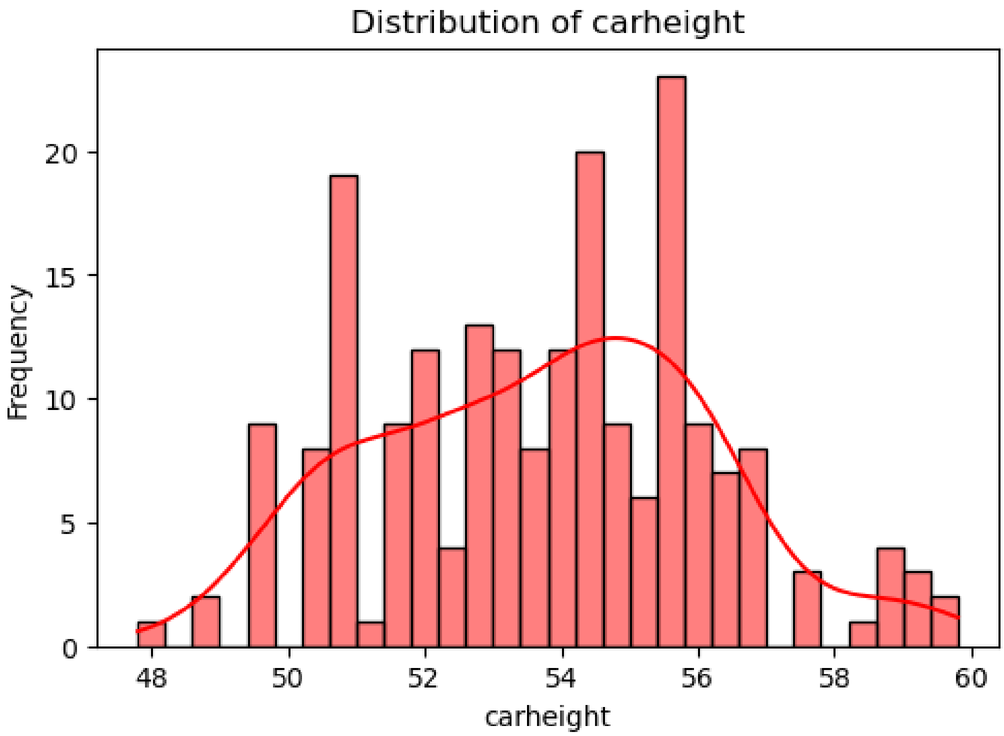


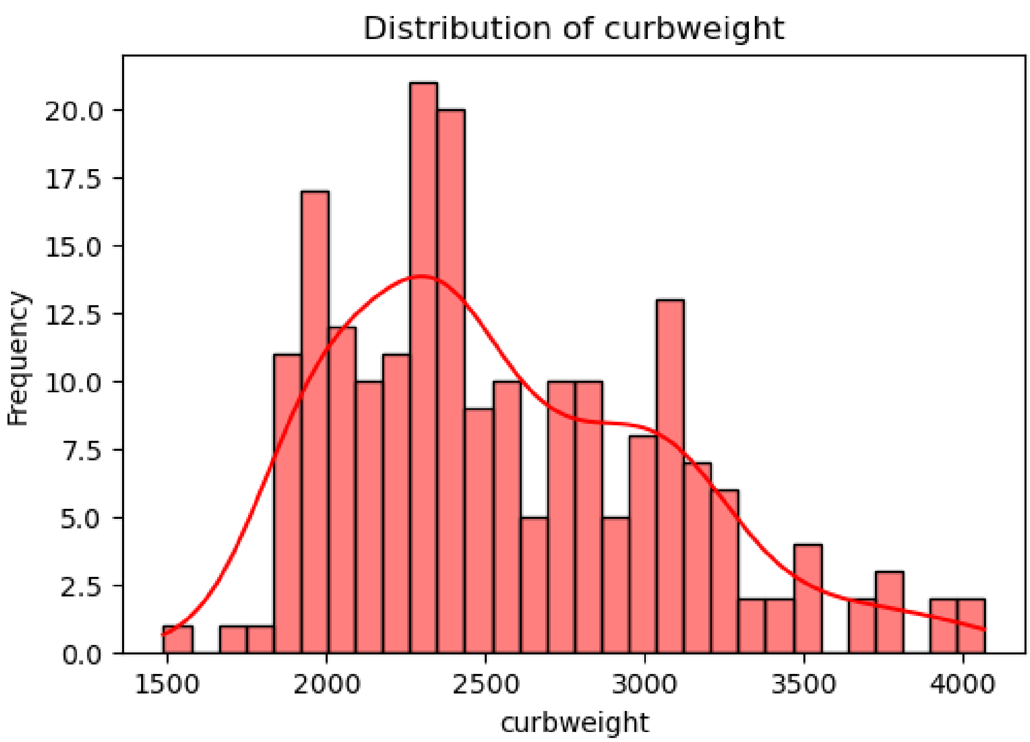

Distribution of symboling
Frequency
symboling
0
10
20
30
40
50
60
70
−2
−1
0
1
2
3

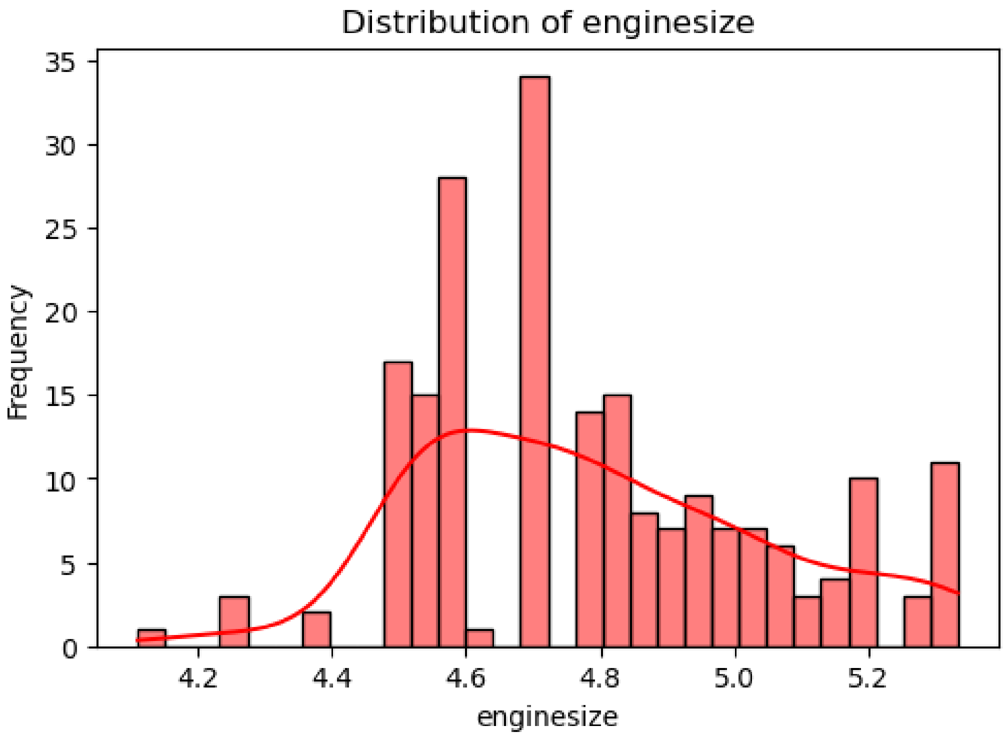

Distribution of wheelbase
Frequency
wheelbase
0
5
10
15
20
2.11
2.12
2.13
2.14
2.15
2.16
2.17
2.18

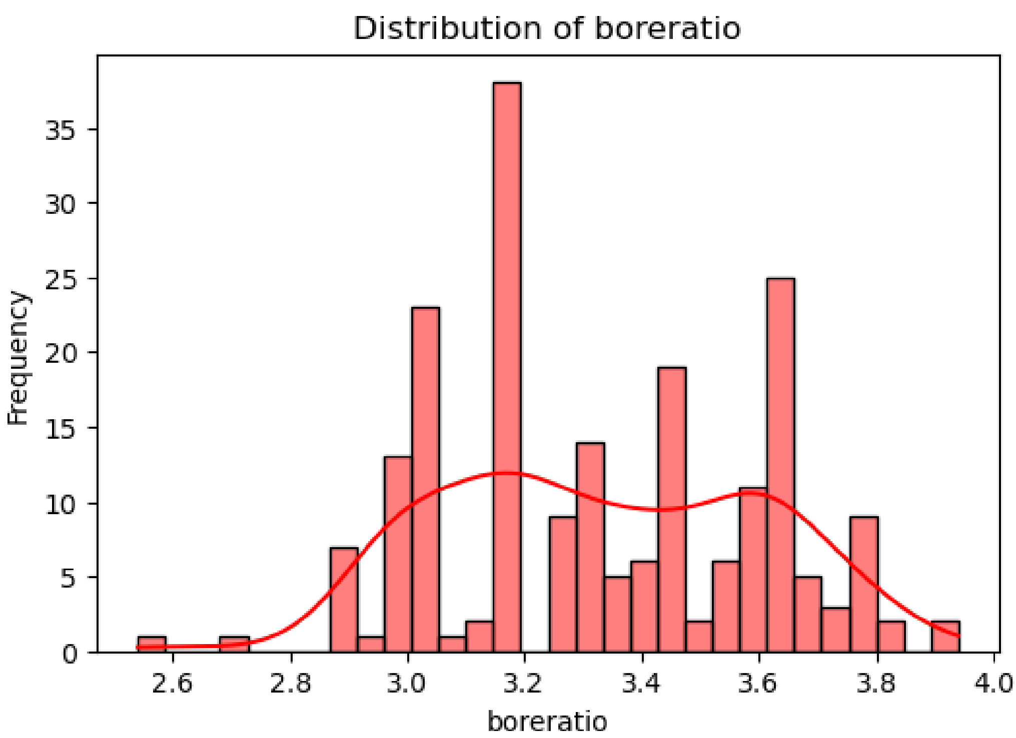

Distribution of carlength
Frequency
carlength
0
5
10
15
20
25
140
150
160
170
180
190
200
210

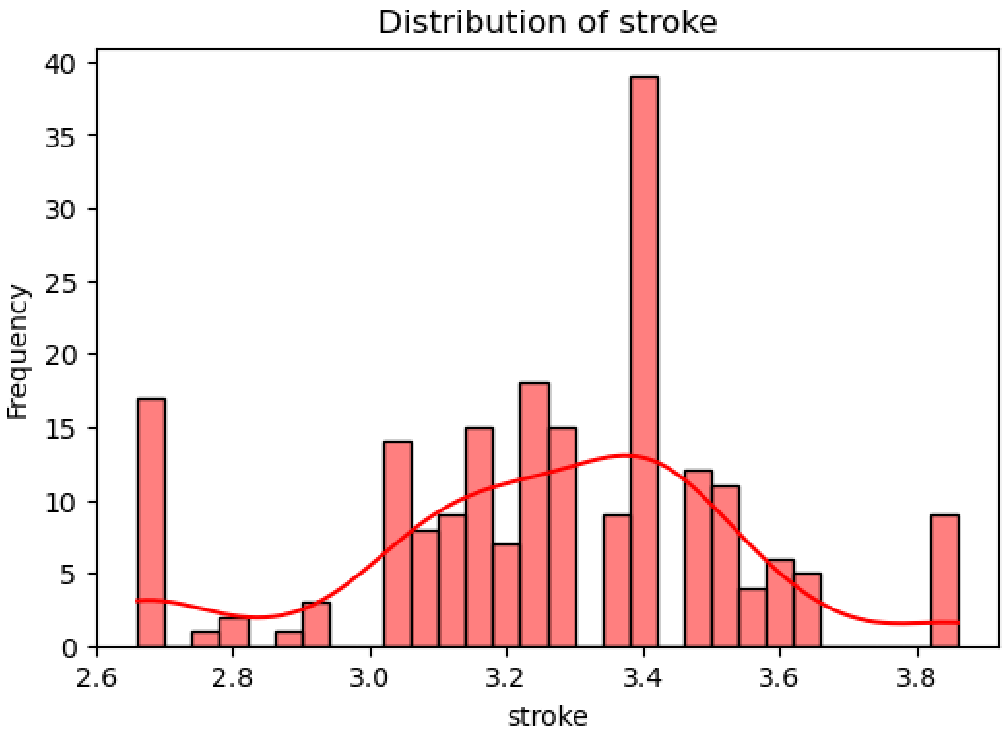

Distribution of carwidth
Frequency
carwidth
0
5
10
15
20
25
30
35
4.100
4.125
4.150
4.175
4.200
4.225
4.250

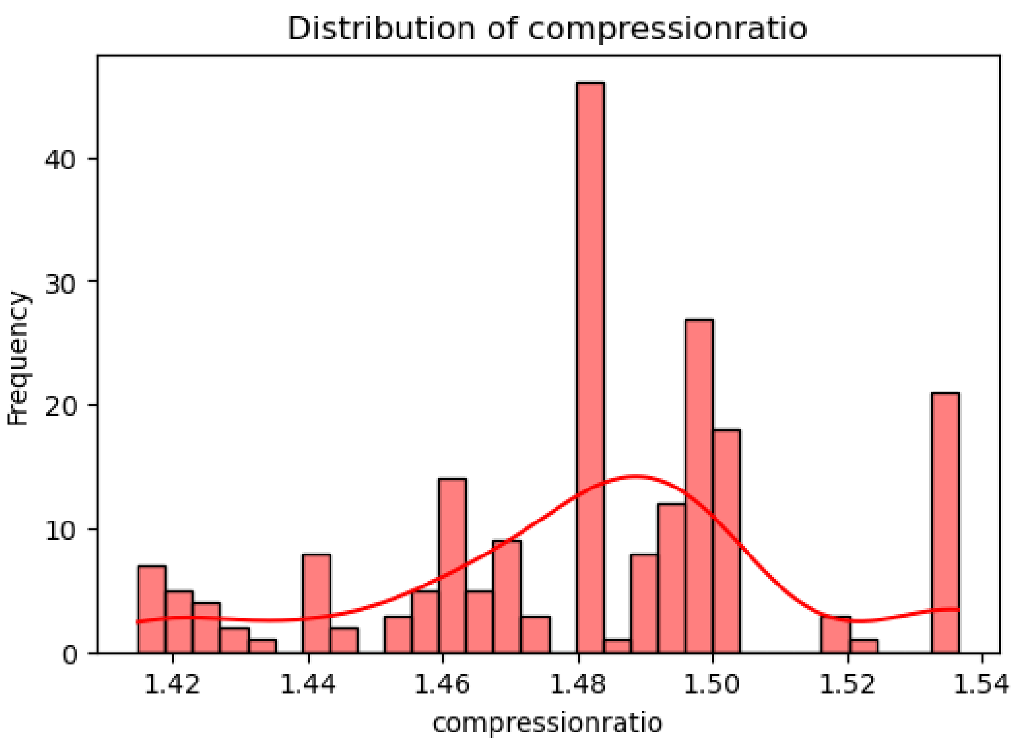

Distribution of carheight
Frequency
0
5
10
15
20
48
50
52
54
56
58
60
carheight

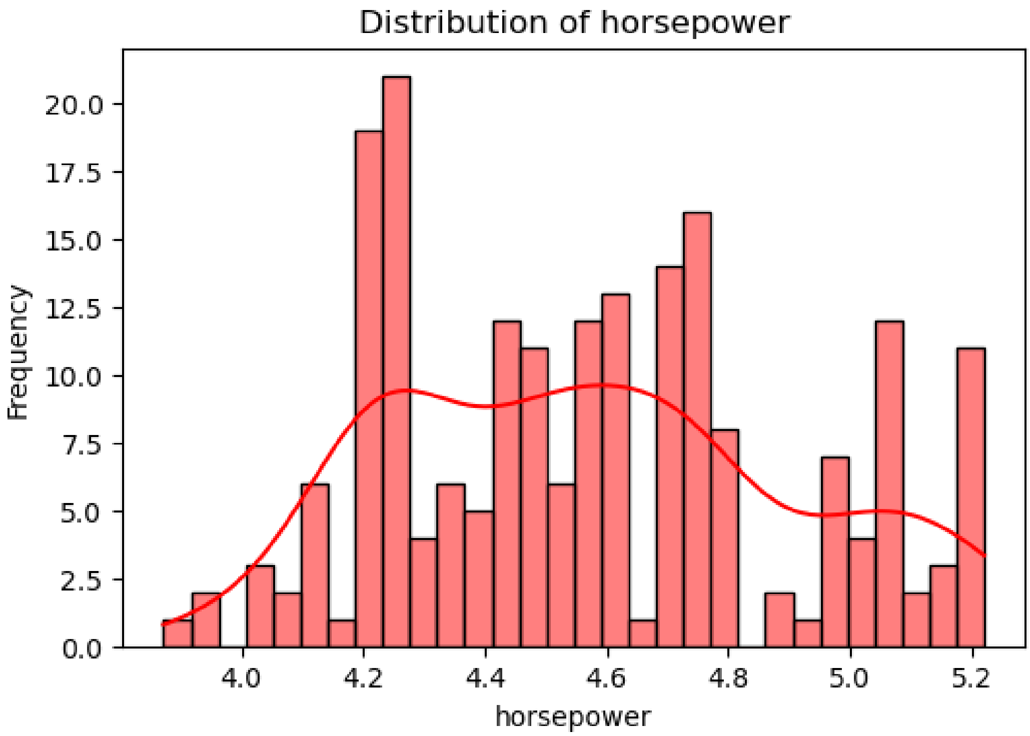

Distribution of curbweight
Frequency
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5
20.0
1500
2000
2500
3000
3500
4000
curbweight

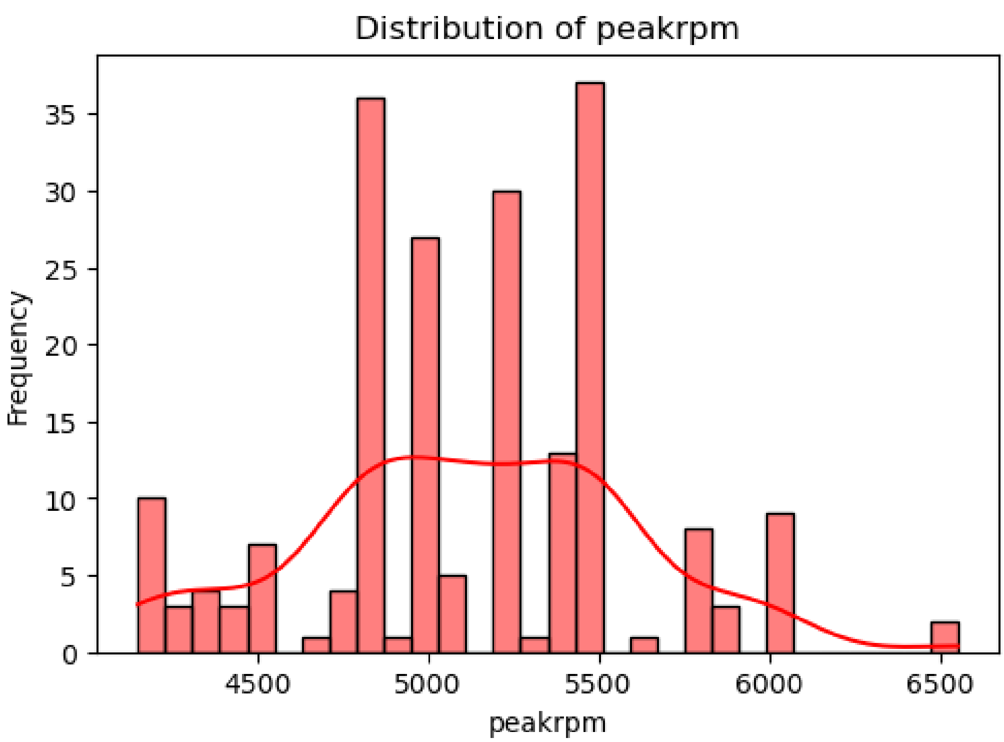

Distribution of enginesize
Frequency
0
5
10
15
20
25
30
35
4.2
4.4
4.6
4.8
5.0
5.2
enginesize

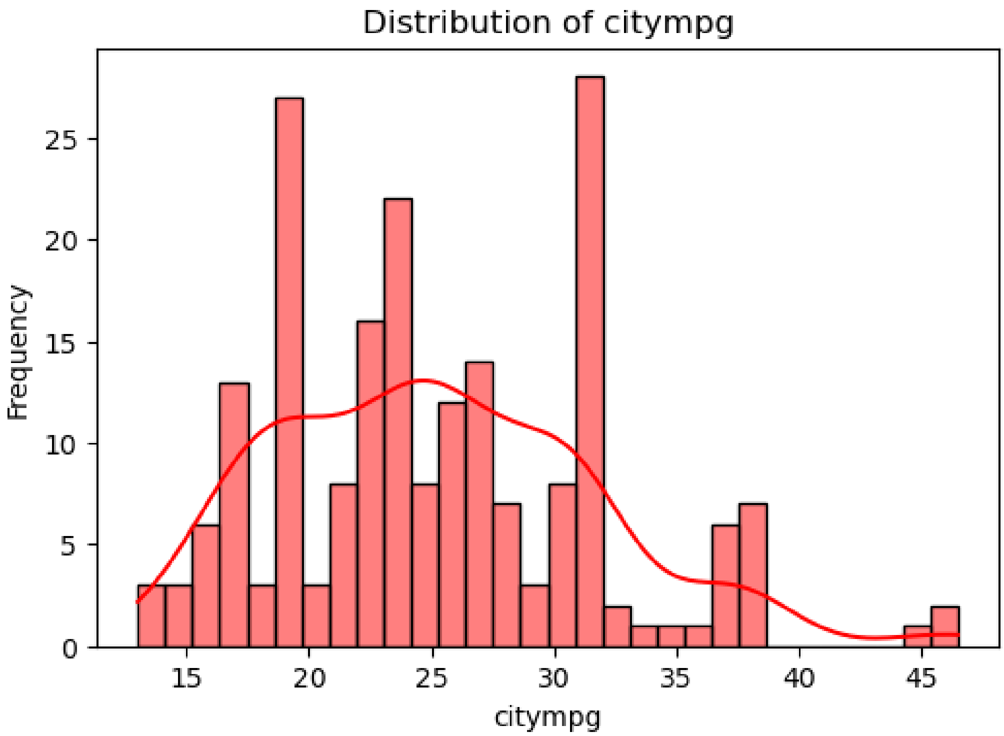

Distribution of boreratio
Frequency
0
5
10
15
20
25
30
35
2.6
2.8
3.0
3.2
3.4
3.6
3.8
4.0
boreratio

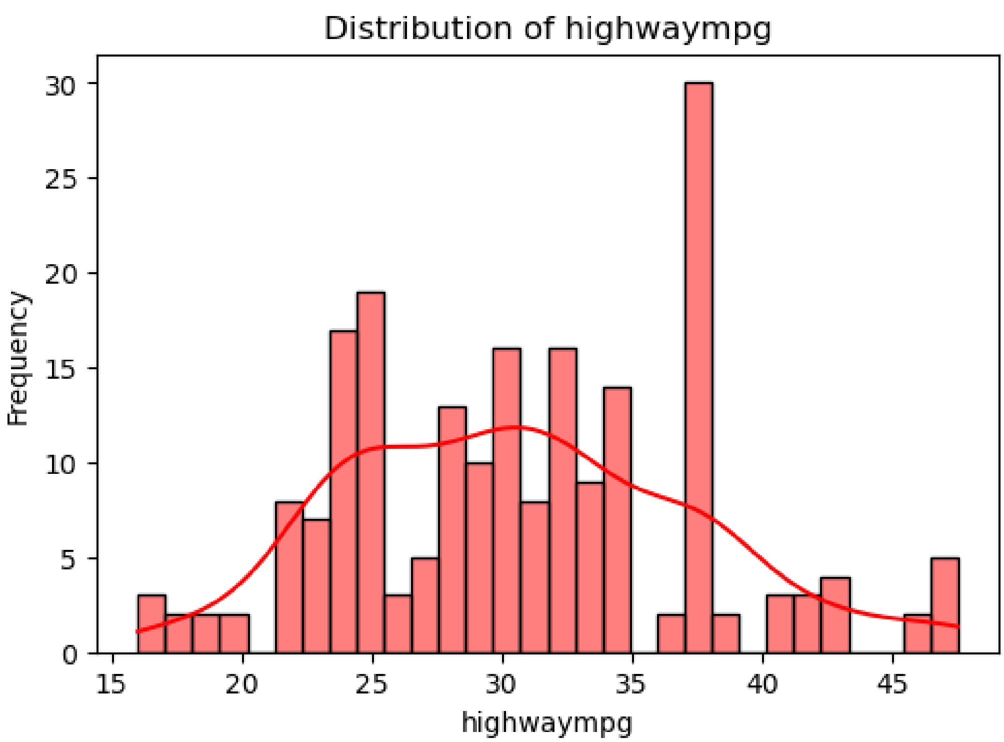

Distribution of stroke
Frequency
0
5
10
15
20
25
30
35
40
2.6
2.8
3.0
3.2
3.4
3.6
3.8
stroke

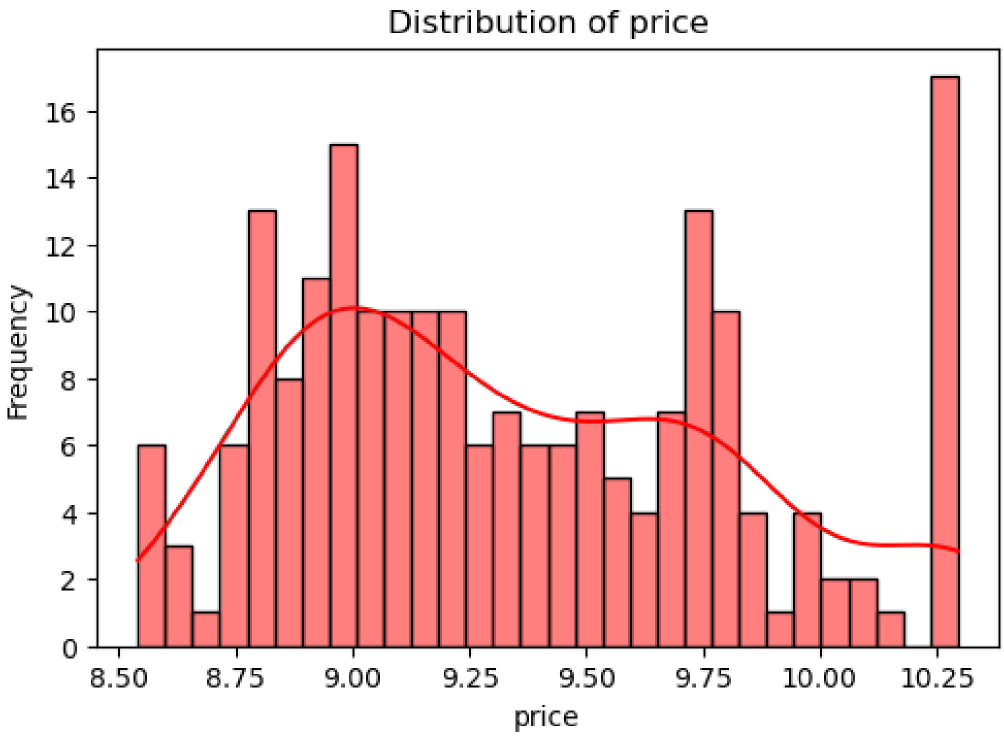

Distribution of compressionratio
Frequency
0
10
20
30
40
1.42
1.44
1.46
1.48
1.50
1.52
1.54
compressionratio


Distribution of horsepower
Frequency
horsepower
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5
20.0
4.0
4.2
4.4
4.6
4.8
5.0
5.2

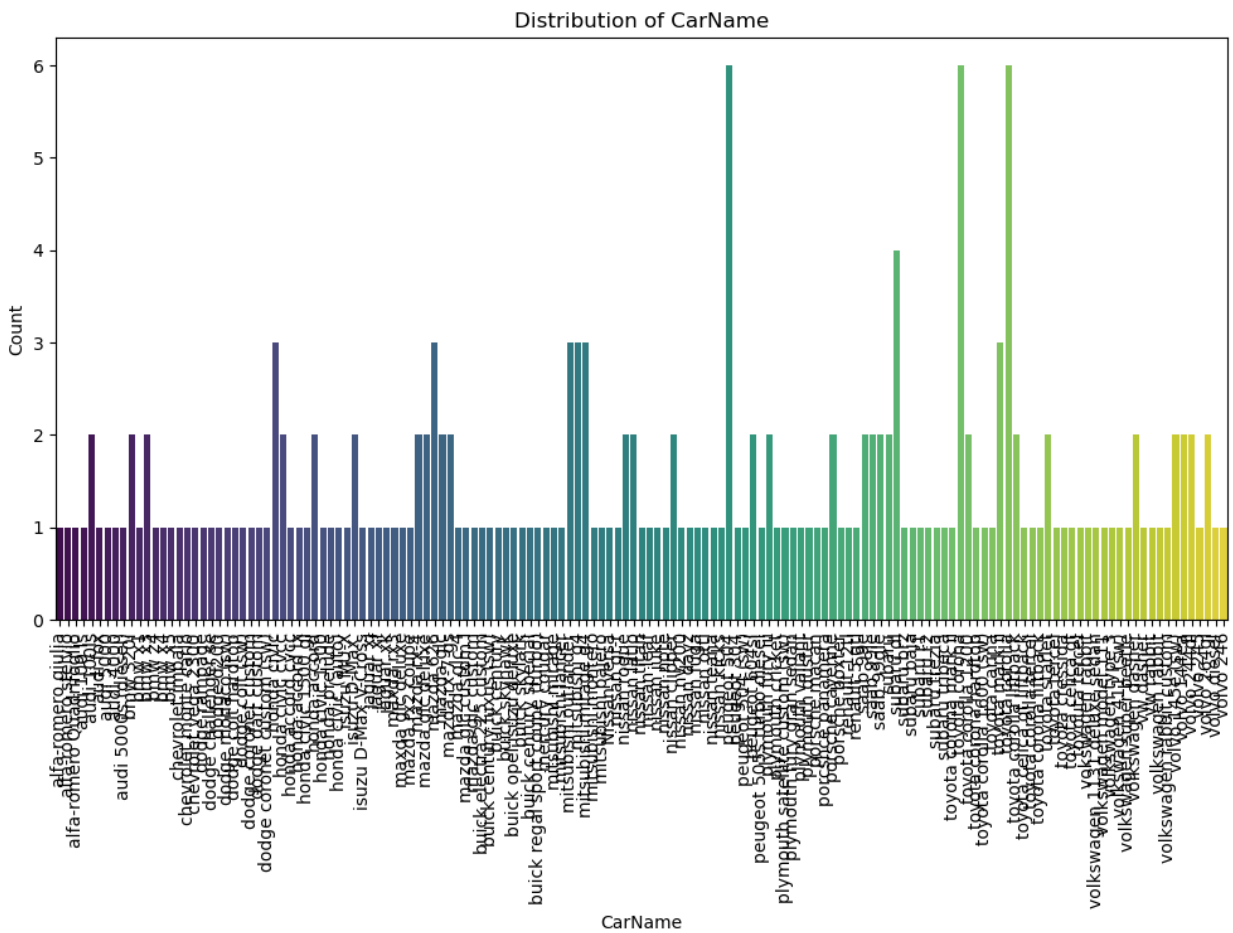

Distribution of peakrpm
Frequency
peakrpm
0
5
10
15
20
25
30
35
4500
5000
5500
6000
6500

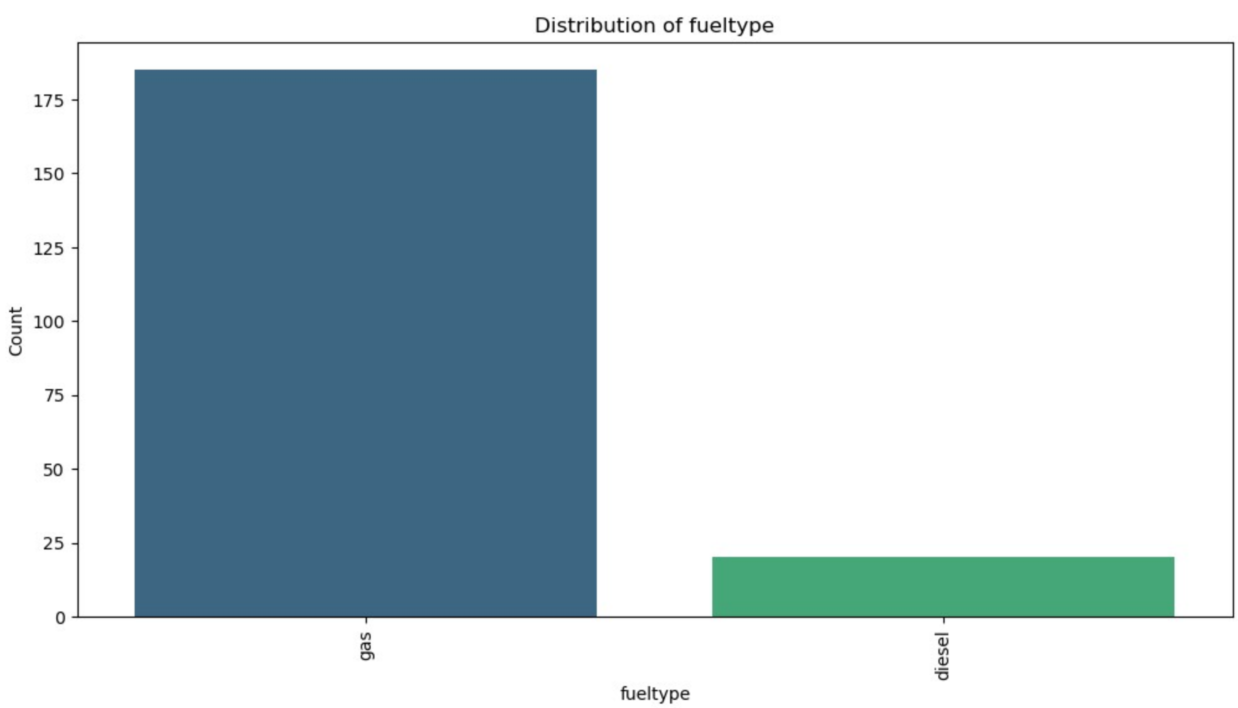

Distribution of citympg
Frequency
0
5
10
15
20
25
15
20
25
30
35
40
45
citympg

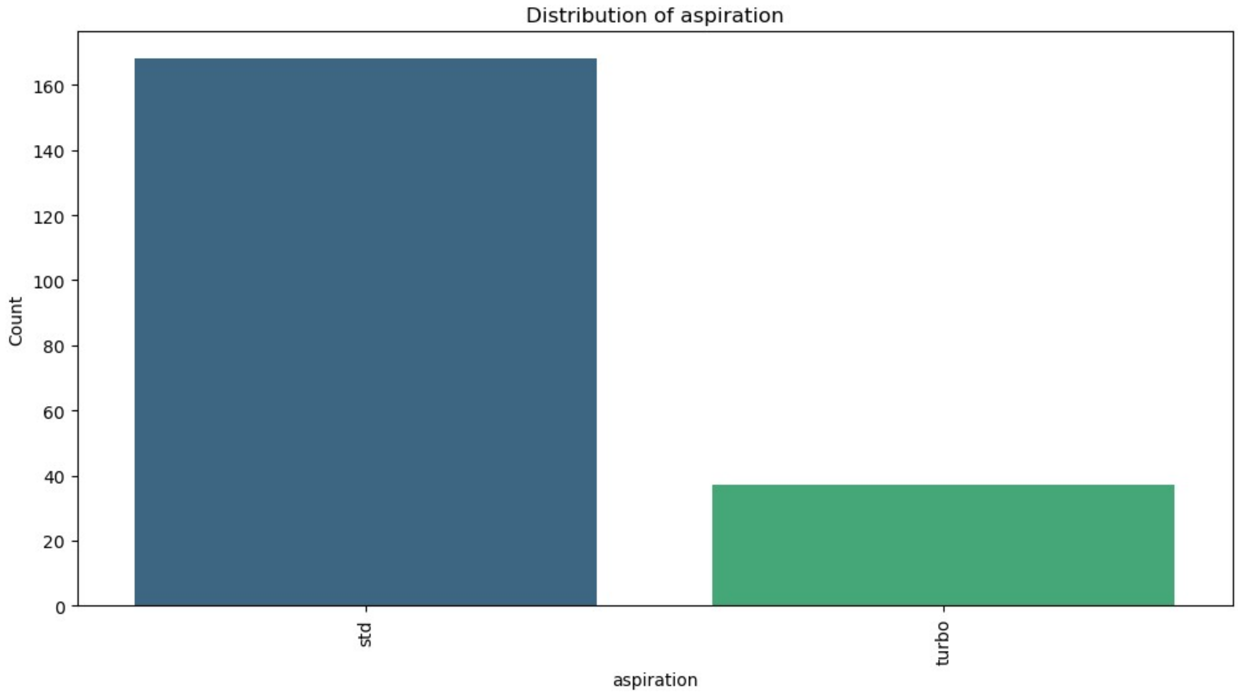

Distribution of highwaympg
Frequency
0
5
10
15
20
25
30
15
20
25
30
35
40
45
highwaympg



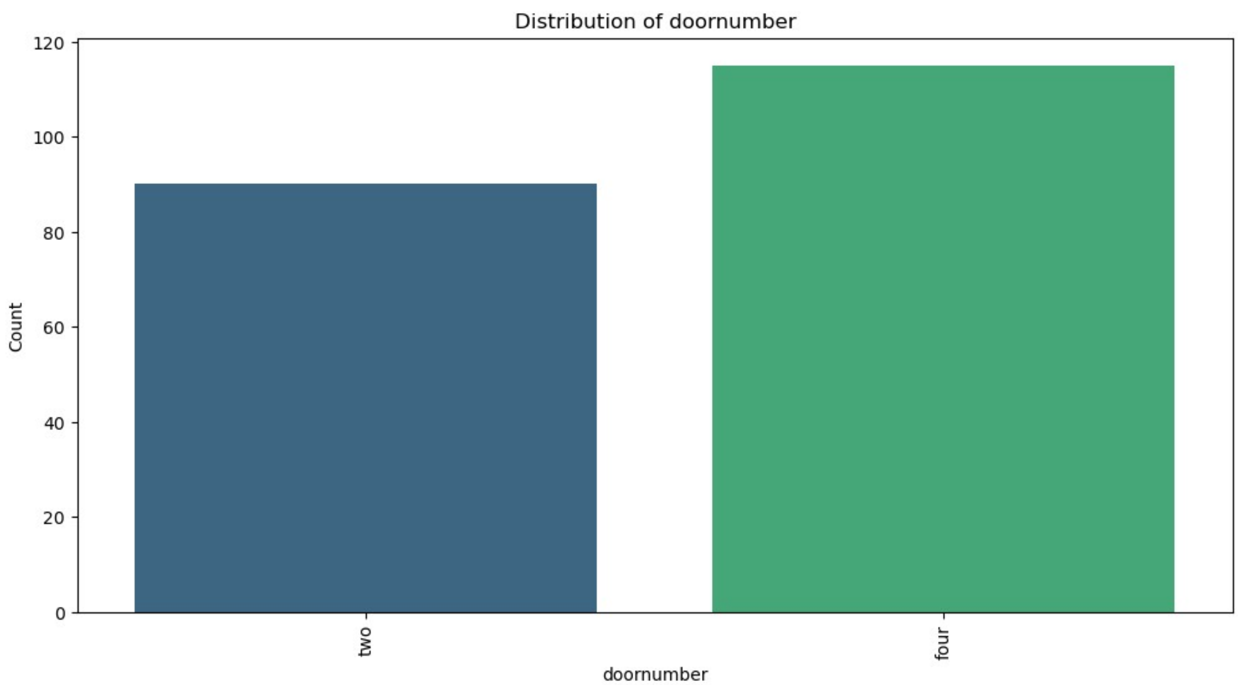

```
categorical_feature = df1.drop(numerical_columns, axis=1)

# Plot bar chart for each categorical feature
for feature in categorical_feature:
    plt.figure(figsize=(12, 6))
    sns.countplot(x=feature, data=df, palette='viridis')
    plt.title(f'Distribution of {feature}')
    plt.xlabel(feature)
    plt.ylabel('Count')
    plt.xticks(rotation=90)
    plt.show()
```


Distribution of CarName
Count
0
1
2
3
4
5
6
CarName

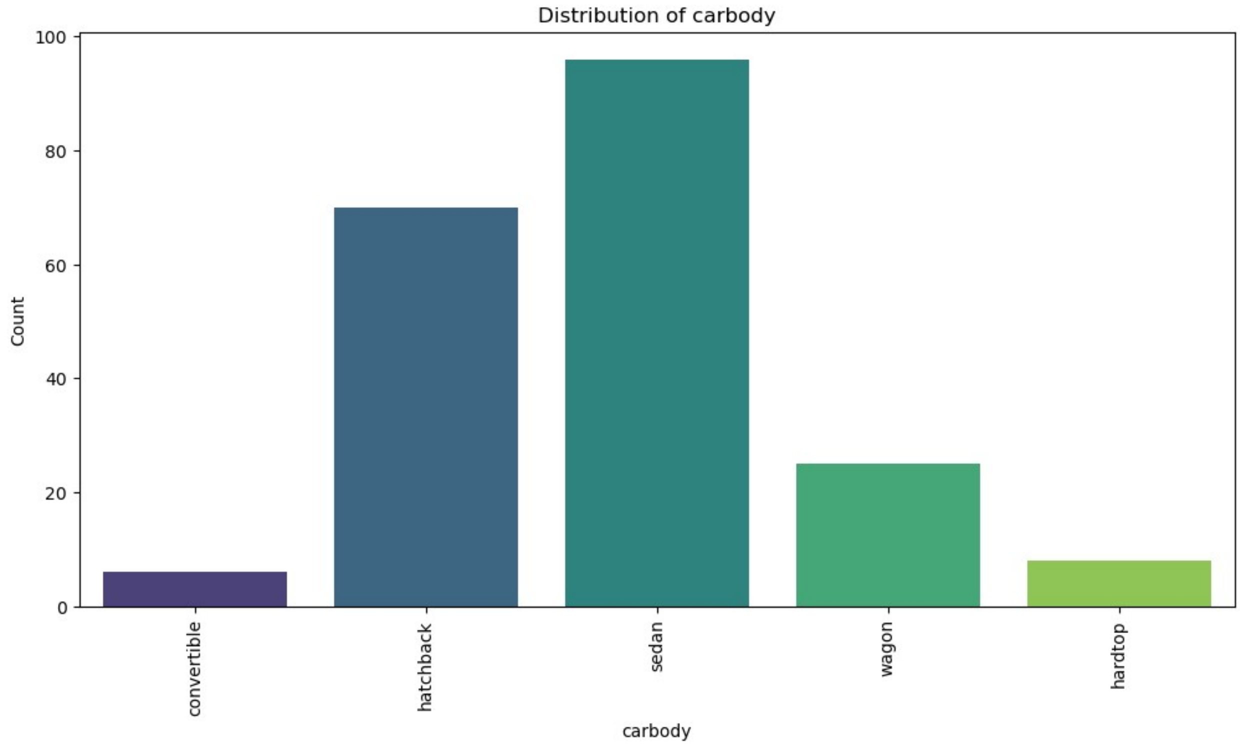

Distribution of fueltype
Count
0
25
50
75
100
125
150
175
gas
diesel
fueltype

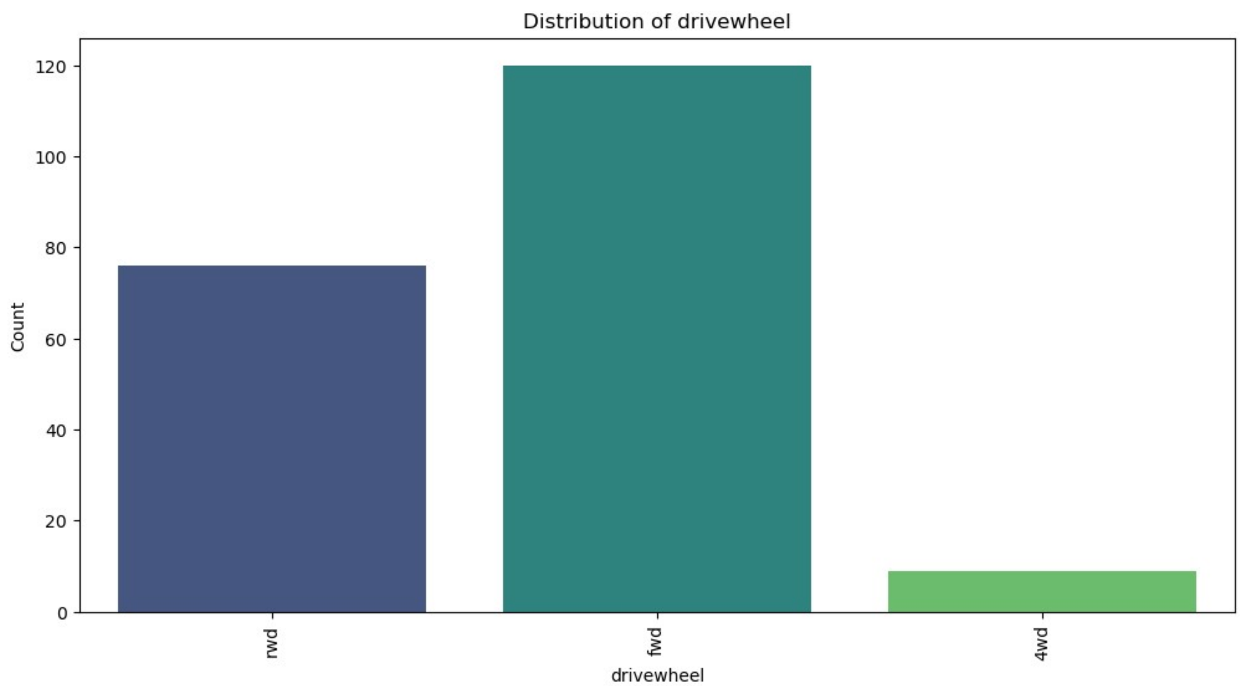


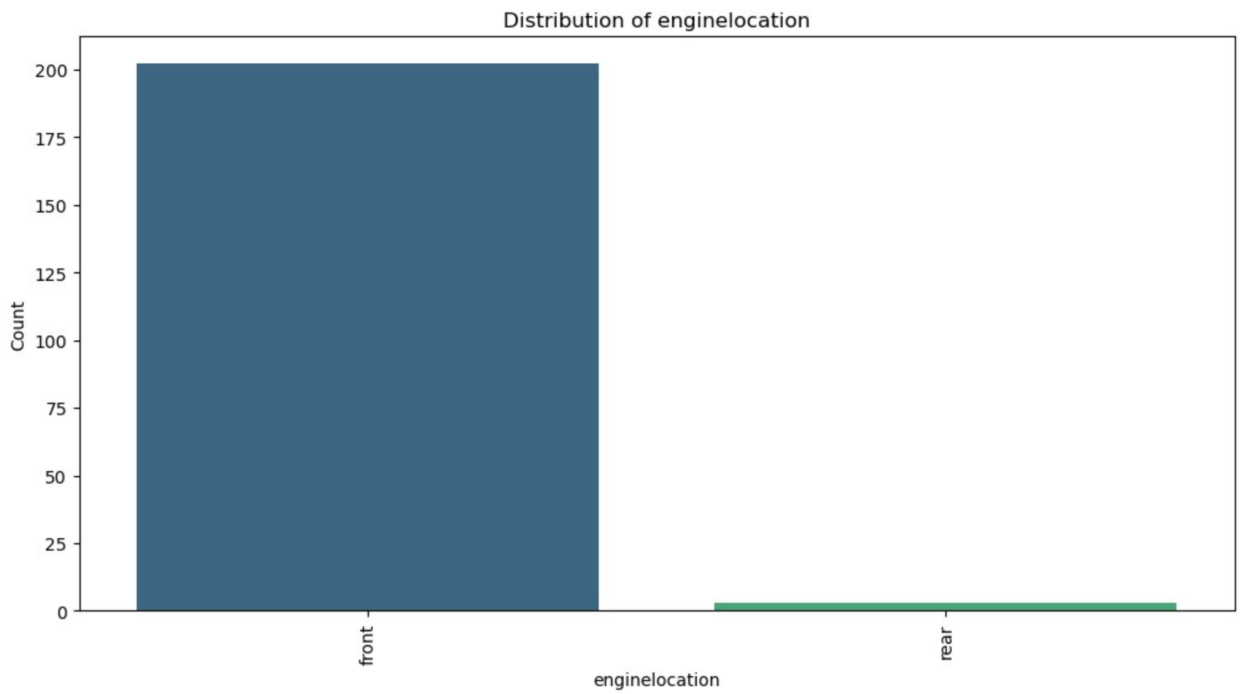
Distribution of aspiration
Count
0
20
40
60
80
100
120
140
160
std
turbo
aspiration

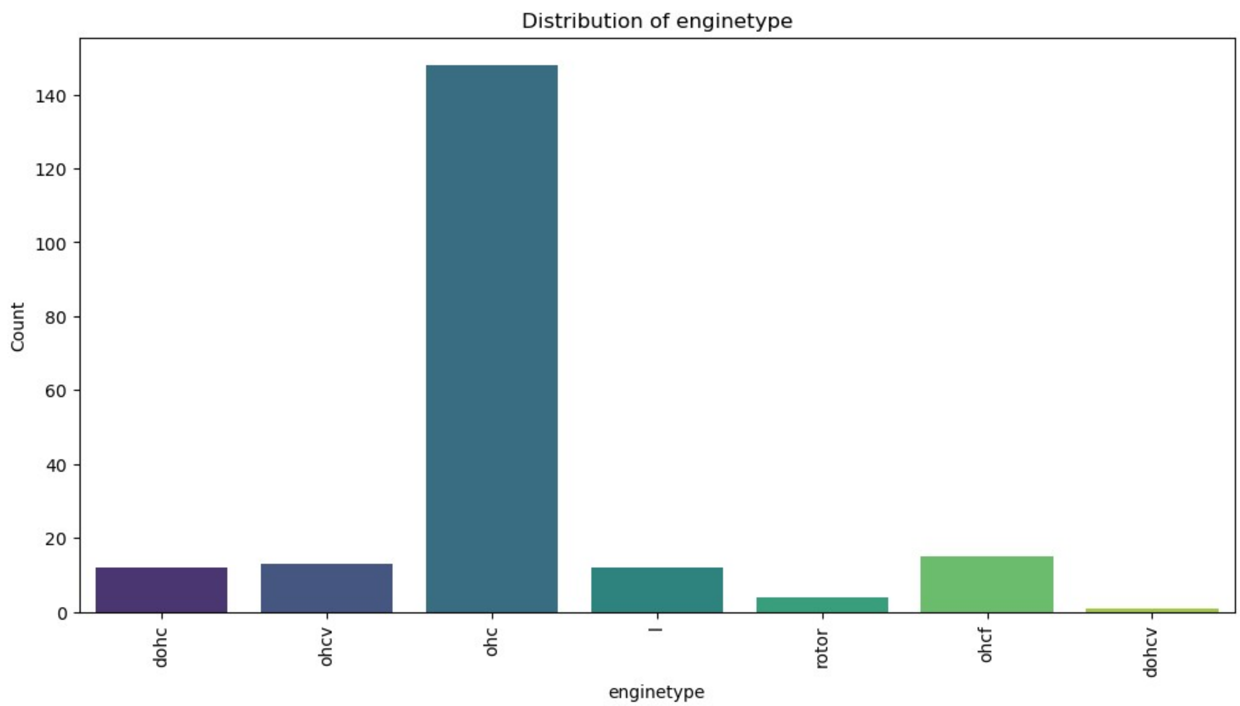


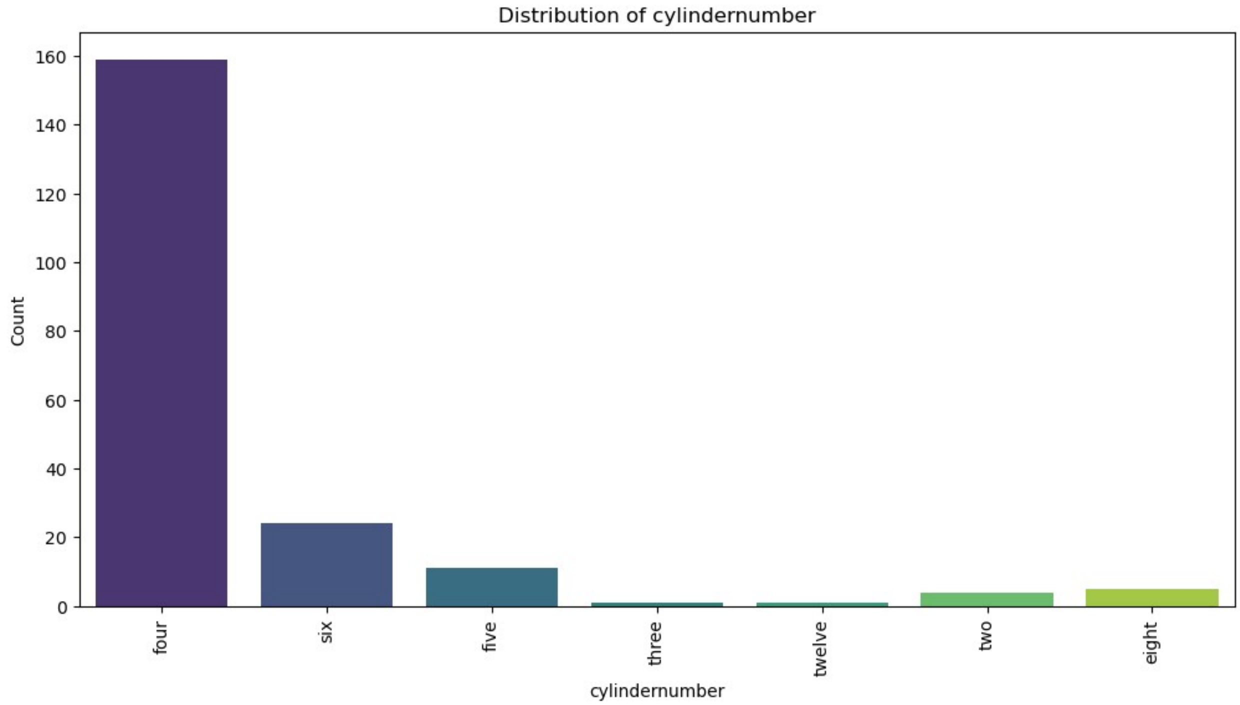
Distribution of doornumber
Count
0
20
40
60
80
100
120
two
four
doornumber

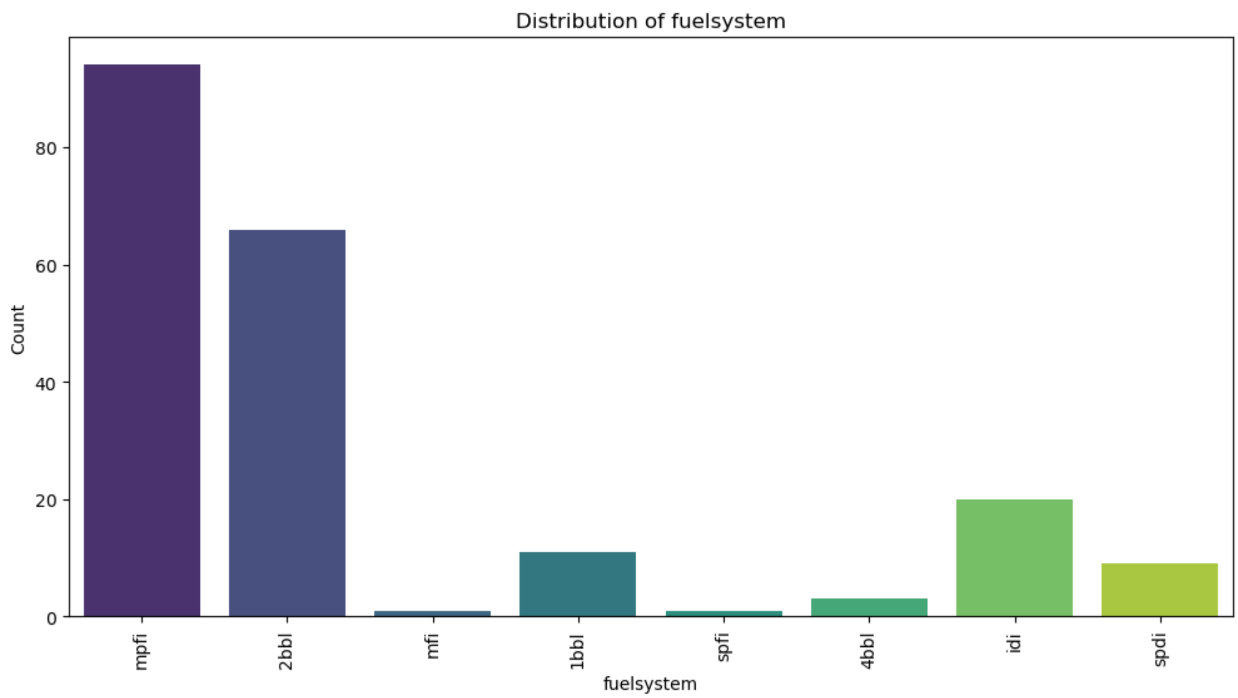

Distribution of carbody
Count
0
20
40
60
80
100
convertible
hatchback
sedan
wagon
hardtop
carbody


Distribution of drivewheel
Count
0
20
40
60
80
100
120
rwd
fwd
4wd
drivewheel


Distribution of enginelocation
Count
200
175
150
125
100
75
50
25
0
front
rear
enginelocation

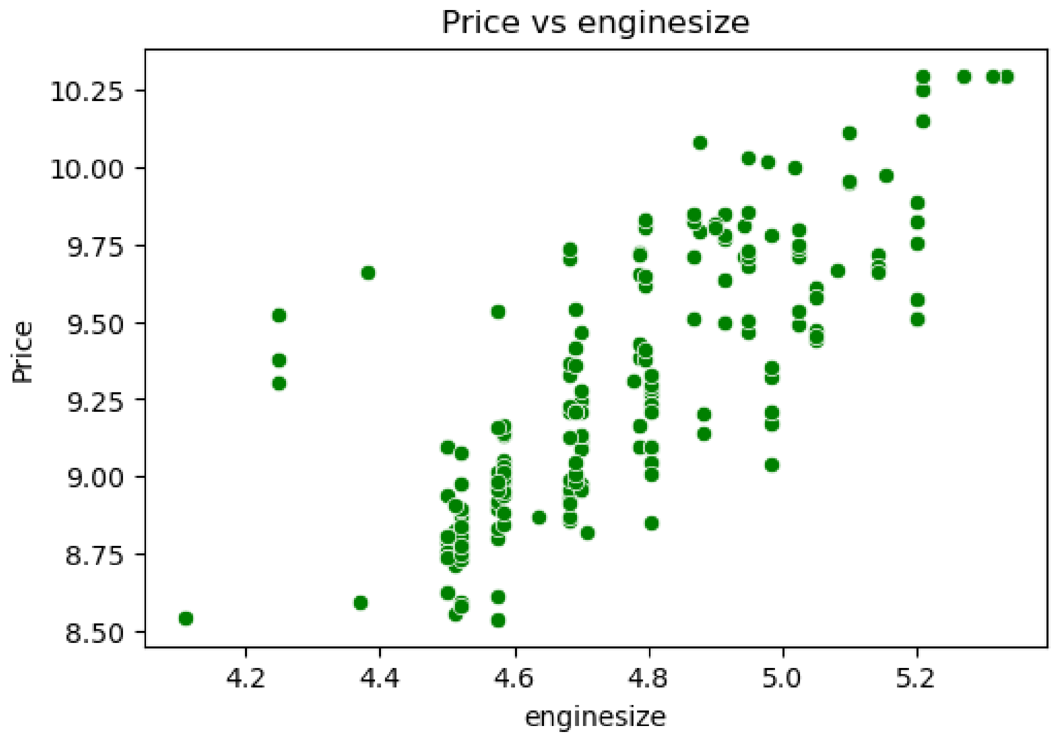

Distribution of enginetype
Count
140
120
100
80
60
40
20
0
dohc
ohcv
ohc
l
rotor
ohcf
dohcv
enginetype

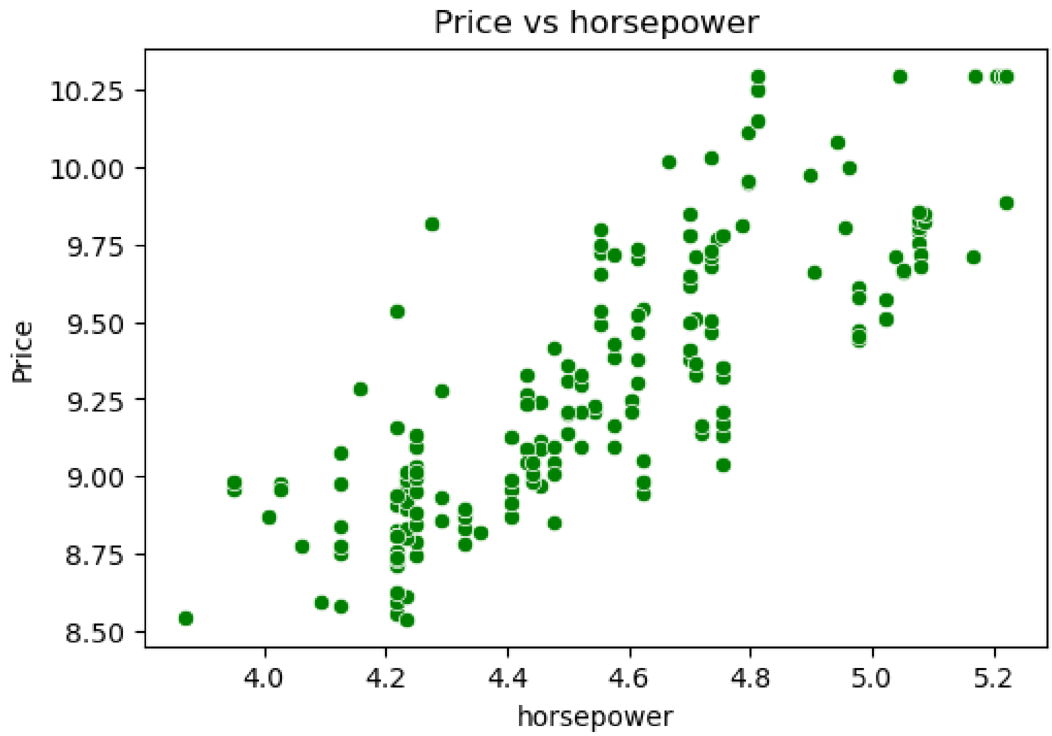


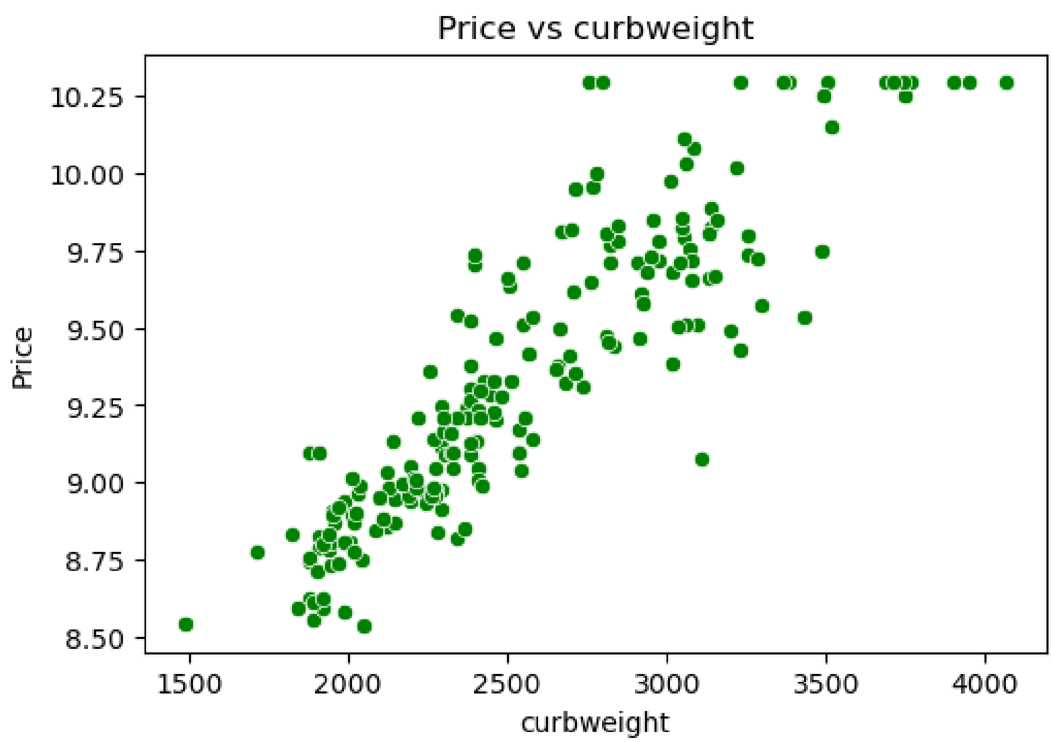


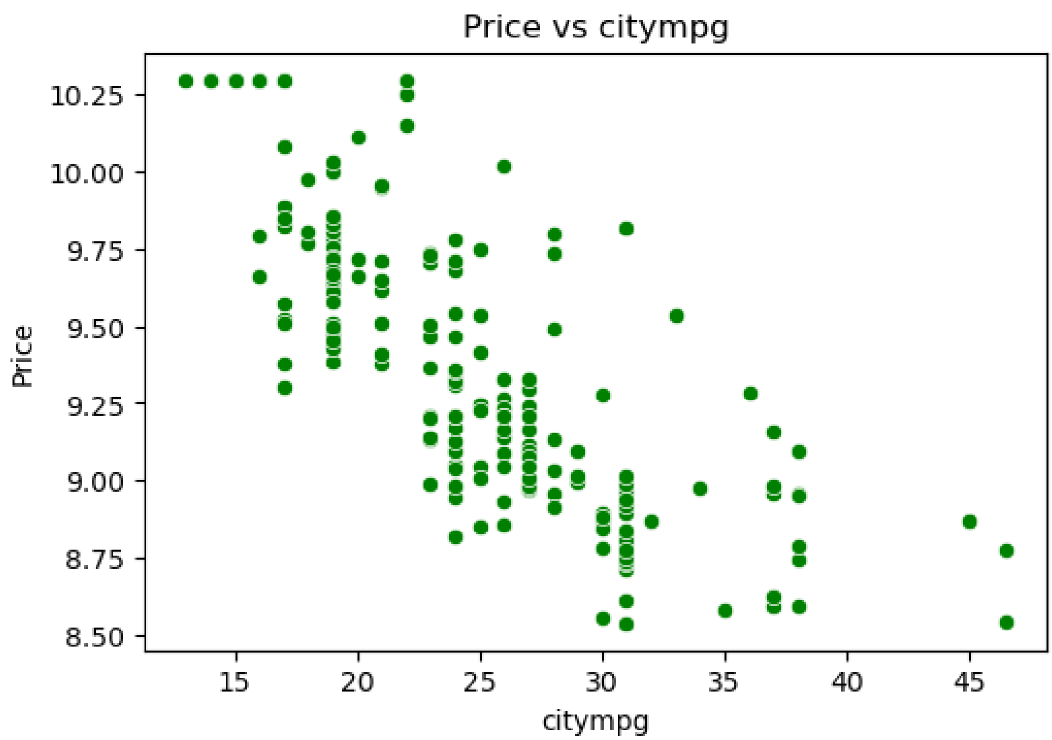

```
# Scatter plots for price vs numerical features
features_to_compare = ['enginesize', 'horsepower', 'curbweight',
'citympg', 'highwaympg']

for feature in features_to_compare:
    plt.figure(figsize=(6, 4))
```

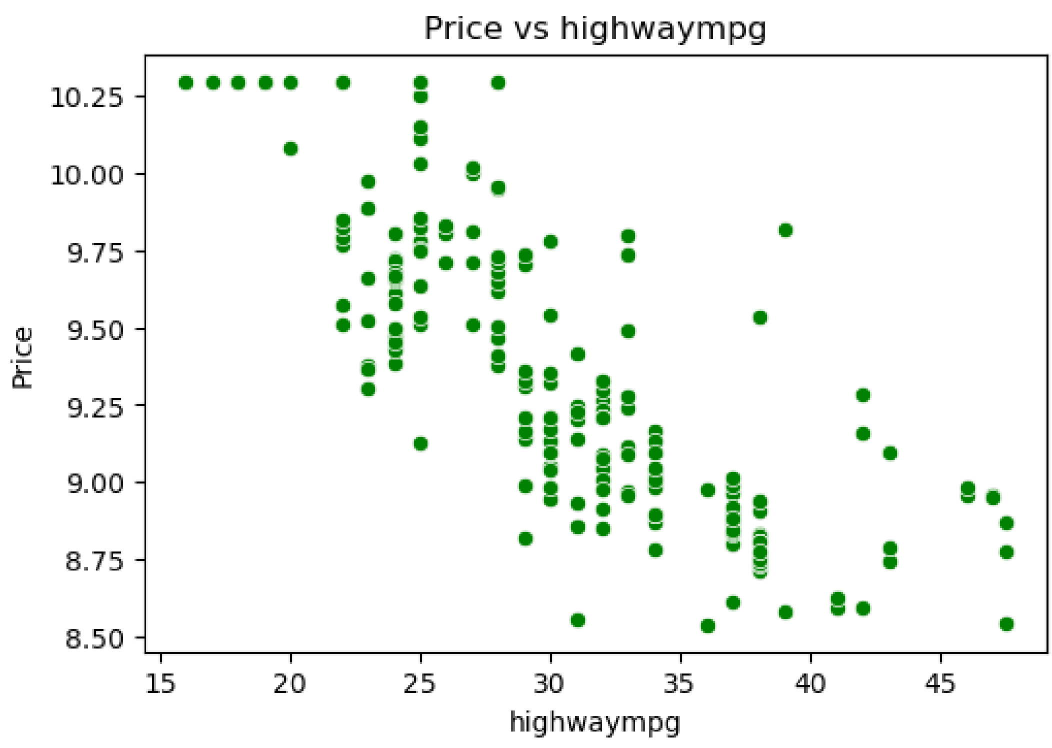
```
    sns.scatterplot(x=df[feature], y=df['price'], color='green')
    plt.title(f'Price vs {feature}')
    plt.xlabel(feature)
    plt.ylabel('Price')
    plt.show()
```




Price vs horsepower
Price
10.25
10.00
9.75
9.50
9.25
9.00
8.75
8.50
4.0
4.2
4.4
4.6
4.8
5.0
5.2
horsepower


Price vs curbweight
Price
10.25
10.00
9.75
9.50
9.25
9.00
8.75
8.50
1500
2000
2500
3000
3500
4000
curbweight





7. FEATURE ENGINEERING

LABEL ENCODING AND ONEHOT ENCODING

```
label_encoder = LabelEncoder()
df_label = df1.copy()
df1.head()
```

```
   car_ID  symboling                   CarName fueltype aspiration 
doornumber  \
0       1          3        alfa-romero giulia      gas        std 
two   
1       2          3       alfa-romero stelvio      gas        std 
two   
2       3          1  alfa-romero Quadrifoglio      gas        std 
two   
3       4          2               audi 100 ls      gas        std 
four   
4       5          2                audi 100ls      gas        std 
four   

       carbody drivewheel enginelocation  wheelbase  ...  
enginesize  \
0  convertible        rwd          front   2.117577  ...    4.867534   

1  convertible        rwd          front   2.117577  ...    4.867534   

2    hatchback        rwd          front   2.132745  ...    5.023881   

3        sedan        fwd          front   2.145500  ...    4.691348   

4        sedan        4wd          front   2.144563  ...    4.912655   


   fuelsystem  boreratio  stroke compressionratio horsepower  peakrpm 
citympg  \
0        mpfi       3.47    2.68         1.482304   4.709530   5000.0 
21.0   
1        mpfi       3.47    2.68         1.482304   4.709530   5000.0 
21.0   
2        mpfi       2.68    3.47         1.482304   5.036953   5000.0 
19.0   
3        mpfi       3.19    3.40         1.517427   4.624973   5500.0 
24.0   
4        mpfi       3.19    3.40         1.442027   4.744932   5500.0 
18.0   

   highwaympg     price  
0        27.0  9.510075  
1        27.0  9.711116  
2        26.0  9.711116  
3        30.0  9.543235  
4        22.0  9.767095  
```

```
[5 rows x 26 columns]

#label Encod
df_label['fueltype'] = label_encoder.fit_transform(df1['fueltype'])
df_label['aspiration'] =
label_encoder.fit_transform(df1['aspiration'])
df_label['doornumber'] =
label_encoder.fit_transform(df1['doornumber'])
df_label['carbody'] = label_encoder.fit_transform(df1['carbody'])
df_label['drivewheel'] =
label_encoder.fit_transform(df1['drivewheel'])
df_label['enginelocation'] =
label_encoder.fit_transform(df1['enginelocation'])
df_label['enginetype'] =
label_encoder.fit_transform(df1['enginetype'])
df_label['cylindernumber'] =
label_encoder.fit_transform(df1['cylindernumber'])
df_label['fuelsystem'] =
label_encoder.fit_transform(df1['fuelsystem'])
df_label.head()

   car_ID  symboling                   CarName  fueltype
aspiration  \
0       1          3        alfa-romero giulia         1           0

1       2          3       alfa-romero stelvio         1           0

2       3          1  alfa-romero Quadrifoglio         1           0

3       4          2               audi 100 ls         1           0

4       5          2                audi 100ls         1           0


   doornumber  carbody  drivewheel  enginelocation  wheelbase  ...  \
0           1        0           2               0   2.117577  ...
1           1        0           2               0   2.117577  ...
2           1        2           2               0   2.132745  ...
3           0        3           1               0   2.145500  ...
4           0        3           0               0   2.144563  ...

   enginesize  fuelsystem  boreratio  stroke  compressionratio
horsepower  \
0    4.867534           5       3.47    2.68          1.482304
4.709530
1    4.867534           5       3.47    2.68          1.482304
4.709530
2    5.023881           5       2.68    3.47          1.482304
5.036953
```

```
3    4.691348           5       3.19    3.40          1.517427
4.624973
4    4.912655           5       3.19    3.40          1.442027
4.744932

   peakrpm  citympg  highwaympg     price
0   5000.0     21.0        27.0  9.510075
1   5000.0     21.0        27.0  9.711116
2   5000.0     19.0        26.0  9.711116
3   5500.0     24.0        30.0  9.543235
4   5500.0     18.0        22.0  9.767095

[5 rows x 26 columns]
```

```
# OneHot encoding

onehot = OneHotEncoder(sparse_output=False)
hot_encod = onehot.fit_transform(df_label[['CarName']])
hot_columns = onehot.get_feature_names_out(['CarName'])

# Creating DataFrame with onehot encoded columns
df_onehot = pd.concat([
    df_label,
    pd.DataFrame(hot_encod, columns=hot_columns)
], axis=1)

df_onehot.head()
```

```
   car_ID  symboling                   CarName  fueltype
aspiration  \
0       1          3        alfa-romero giulia         1           0

1       2          3       alfa-romero stelvio         1           0

2       3          1  alfa-romero Quadrifoglio         1           0

3       4          2               audi 100 ls         1           0

4       5          2                audi 100ls         1           0


   doornumber  carbody  drivewheel  enginelocation  wheelbase  ...  \
0           1        0           2               0   2.117577  ...
1           1        0           2               0   2.117577  ...
2           1        2           2               0   2.132745  ...
3           0        3           1               0   2.145500  ...
4           0        3           0               0   2.144563  ...

   CarName_volkswagen type 3  CarName_volvo 144ea  CarName_volvo 145e
(sw)  \
0                        0.0                  0.0
```

```
0.0
1                          0.0                    0.0
0.0
2                          0.0                    0.0
0.0
3                          0.0                    0.0
0.0
4                          0.0                    0.0
0.0

   CarName_volvo 244dl  CarName_volvo 245  CarName_volvo 246  \
0                  0.0                0.0                0.0
1                  0.0                0.0                0.0
2                  0.0                0.0                0.0
3                  0.0                0.0                0.0
4                  0.0                0.0                0.0

   CarName_volvo 264gl  CarName_volvo diesel  CarName_vw dasher  \
0                  0.0                   0.0                0.0
1                  0.0                   0.0                0.0
2                  0.0                   0.0                0.0
3                  0.0                   0.0                0.0
4                  0.0                   0.0                0.0

   CarName_vw rabbit
0                0.0
1                0.0
2                0.0
3                0.0
4                0.0

[5 rows x 173 columns]
```

```
df_onehot.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 205 entries, 0 to 204
Columns: 173 entries, car_ID to CarName_vw rabbit
dtypes: float64(160), int32(9), int64(3), object(1)
memory usage: 270.0+ KB
```

```
# Dropping categorical values
df_onehot = df_onehot.drop('CarName',axis=1)
```

```
df_onehot.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 205 entries, 0 to 204
Columns: 172 entries, car_ID to CarName_vw rabbit
dtypes: float64(160), int32(9), int64(3)
memory usage: 268.4 KB
```

SETTING Y AS TARGET

```
y = df_onehot['price']
y
x = df_onehot.drop(['price','car_ID'], axis=1)
x
```

```
     symboling  fueltype  aspiration  doornumber  carbody  drivewheel  \
0            3         1           0           1        0           2
1            3         1           0           1        0           2
2            1         1           0           1        2           2
3            2         1           0           0        3           1
4            2         1           0           0        3           0
..         ...       ...         ...         ...      ...         ...
200         -1         1           0           0        3           2
201         -1         1           1           0        3           2
202         -1         1           0           0        3           2
203         -1         0           1           0        3           2
204         -1         1           1           0        3           2

     enginelocation  wheelbase  carlength  carwidth  ...  \
0                 0   2.117577      168.8  4.160444  ...
1                 0   2.117577      168.8  4.160444  ...
2                 0   2.132745      171.2  4.182050  ...
3                 0   2.145500      176.6  4.192680  ...
4                 0   2.144563      176.6  4.195697  ...
..              ...        ...        ...       ...  ...
200               0   2.166164      188.8  4.232656  ...
201               0   2.166164      188.8  4.231204  ...
202               0   2.166164      188.8  4.232656  ...
203               0   2.166164      188.8  4.232656  ...
204               0   2.166164      188.8  4.232656  ...

     CarName_volkswagen type 3  CarName_volvo 144ea  CarName_volvo 145e (sw)  \
0                          0.0                  0.0                      0.0
1                          0.0                  0.0                      0.0
2                          0.0                  0.0
```

```
0.0
3                              0.0                    0.0
0.0
4                              0.0                    0.0
0.0
..                             ...                    ...
...
200                            0.0                    0.0
1.0
201                            0.0                    1.0
0.0
202                            0.0                    0.0
0.0
203                            0.0                    0.0
0.0
204                            0.0                    0.0
0.0

     CarName_volvo 244dl  CarName_volvo 245  CarName_volvo 246  \
0                    0.0                0.0                0.0
1                    0.0                0.0                0.0
2                    0.0                0.0                0.0
3                    0.0                0.0                0.0
4                    0.0                0.0                0.0
..                   ...                ...                ...
200                  0.0                0.0                0.0
201                  0.0                0.0                0.0
202                  1.0                0.0                0.0
203                  0.0                0.0                1.0
204                  0.0                0.0                0.0

     CarName_volvo 264gl  CarName_volvo diesel  CarName_vw dasher  \
0                    0.0                   0.0                0.0
1                    0.0                   0.0                0.0
2                    0.0                   0.0                0.0
3                    0.0                   0.0                0.0
4                    0.0                   0.0                0.0
..                   ...                   ...                ...
200                  0.0                   0.0                0.0
201                  0.0                   0.0                0.0
202                  0.0                   0.0                0.0
203                  0.0                   0.0                0.0
204                  1.0                   0.0                0.0

     CarName_vw rabbit
0                  0.0
1                  0.0
2                  0.0
3                  0.0
4                  0.0
```

```
..                  ...
200                 0.0
201                 0.0
202                 0.0
203                 0.0
204                 0.0

[205 rows x 170 columns]
```

8. FEATURE SELECTION

VARIANCE THRESHOLD

```
var_threshold = VarianceThreshold(threshold=0.5)
x_var = var_threshold.fit_transform(x)
var_selected = x.columns[var_threshold.get_support()].tolist()
print("1.Filter method results: ")
print("\na) Variance threshold")
print(f"Features selected: {len(var_selected)}")
print("Selected Features: ", var_selected[:12],"....")
```

```
1.Filter method results: 

a) Variance threshold
Features selected: 11
Selected Features:  ['symboling', 'carbody', 'carlength', 'carheight', 'curbweight', 'enginetype', 'cylindernumber', 'fuelsystem', 'peakrpm', 'citympg', 'highwaympg'] ....
```

```
var_selected
```

```
['symboling',
 'carbody',
 'carlength',
 'carheight',
 'curbweight',
 'enginetype',
 'cylindernumber',
 'fuelsystem',
 'peakrpm',
 'citympg',
 'highwaympg']
```

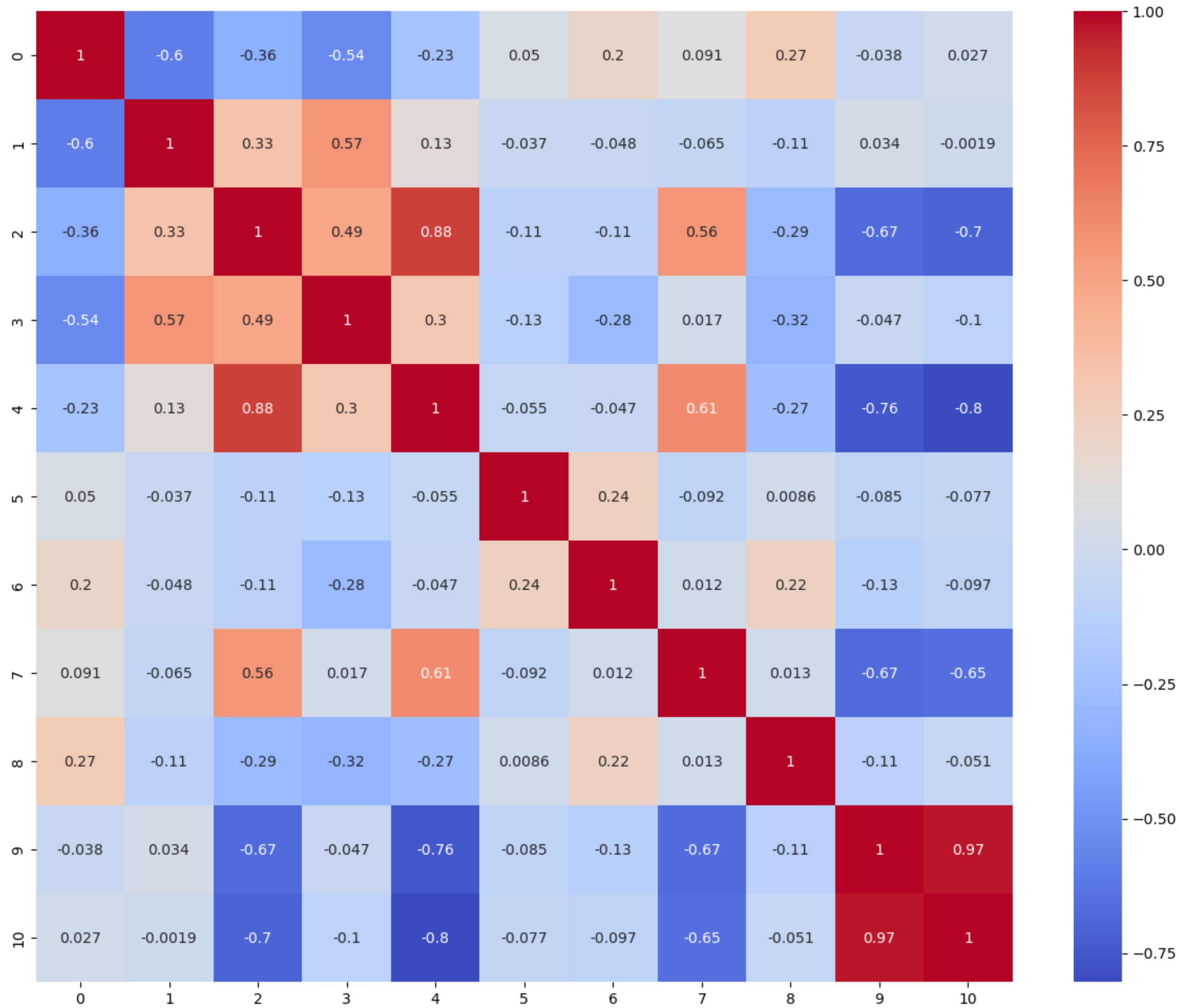
9. FEATURE SCALING

```
standard_scaler = StandardScaler()
minmax_scaler = MinMaxScaler()

# Applying  scaling method
x_standardized = standard_scaler.fit_transform(x_var)
```

```python
# Converting to DataFrame
df_std = pd.DataFrame(x_standardized)
df_std.head()
```

```
          0         1         2         3         4         5         6  \
0  1.743470 -3.050975 -0.426521 -2.020417 -0.014566 -2.865105 -0.147475
1  1.743470 -3.050975 -0.426521 -2.020417 -0.014566 -2.865105 -0.147475
2  0.133509 -0.717207 -0.231513 -0.543527  0.514882  1.886890  1.112210
3  0.938490  0.449677  0.207256  0.235942 -0.420797 -0.013908 -0.147475
4  0.938490  0.449677  0.207256  0.235942  0.516807 -0.013908 -1.407161

          7         8         9        10
0  0.869568 -0.262757 -0.649321 -0.552143
1  0.869568 -0.262757 -0.649321 -0.552143
2  0.869568 -0.262757 -0.958163 -0.702161
3  0.869568  0.791357 -0.186058 -0.102086
4  0.869568  0.791357 -1.112584 -1.302237
```

```python
# Drawing Correlation
correlation = df_std.corr()
plt.figure(figsize=(15, 12))
sns.heatmap(correlation, annot=True, cmap='coolwarm')
plt.show()
```



3. SPLITTING DATA FOR TRAINING AND TESTING

```
X_train, X_test, y_train, y_test = train_test_split(df_std, y,
test_size=0.2, random_state=42)
```

LINEAR REGRESSION

A simple and straightforward model, linear regression shows a linear relationship between one or more independent variables (features) and the dependent variable (target). To determine the best-fitting line, it minimizes the sum of squared residuals. It may perform poorly when relationships are complex or non-linear, even though it works well for datasets with linear trends.

DECISION TREE REGRESSOR

A tree-based model called the Decision Tree Regressor divides the dataset into subsets according to feature values, resulting in a tree structure. While branches denote choices, each leaf represents a prediction. Though it may overfit the data and necessitate pruning or other regularization procedures, it is straightforward and capable of capturing non-linear correlations.

RANDOM FOREST REGRESSOR

To increase prediction accuracy, the Random Forest Regressor is an ensemble learning technique that mixes several decision trees that have been trained on arbitrary subsets of the data and features. Although it improves robustness and decreases overfitting, it could be computationally costly for large datasets.

GRADIANT BOOSTING REGRESSOR

Another ensemble technique called Gradient Boosting Regressor creates consecutive decision trees, each of which fixes the mistakes of the one before it. It provides flexibility through hyperparameter tuning and works incredibly well for intricate, non-linear connections. Nevertheless, it requires a lot of calculation and is susceptible to overfitting if not adjusted appropriately.

SUPPORT VECTOR REGRESSOR (SVR)

SVR finds the hyperplane that best correlates with the data within a tolerance margin by applying the concepts of Support Vector Machines. When used with kernels, it is particularly effective for small-to medium-sized datasets with non-linear connections. Large datasets, however, could be difficult for it to handle, and careful parameter selection is necessary for best results.

11. BUILDING MODELS

```
# Define models
models = {
    "Linear Regression": LinearRegression(),
    "Decision Tree Regressor": DecisionTreeRegressor(random_state=42),
    "Random Forest Regressor": RandomForestRegressor(random_state=42),
    "Gradient Boosting Regressor":
GradientBoostingRegressor(random_state=42),
    "Support Vector Regressor": SVR(kernel='rbf')
}

# Train and evaluate models
results = {}

for name, model in models.items():
    # Train the model
    model.fit(X_train, y_train)

    # Predict on the test set
    y_pred = model.predict(X_test)

    # Calculate metrics
    r2 = r2_score(y_test, y_pred)
```

```
    mae = mean_absolute_error(y_test, y_pred)
    rmse = np.sqrt(mean_squared_error(y_test, y_pred))

    # Store results
    results[name] = {
        "R² Score": r2,
        "MAE": mae,
        "RMSE": rmse
    }
```

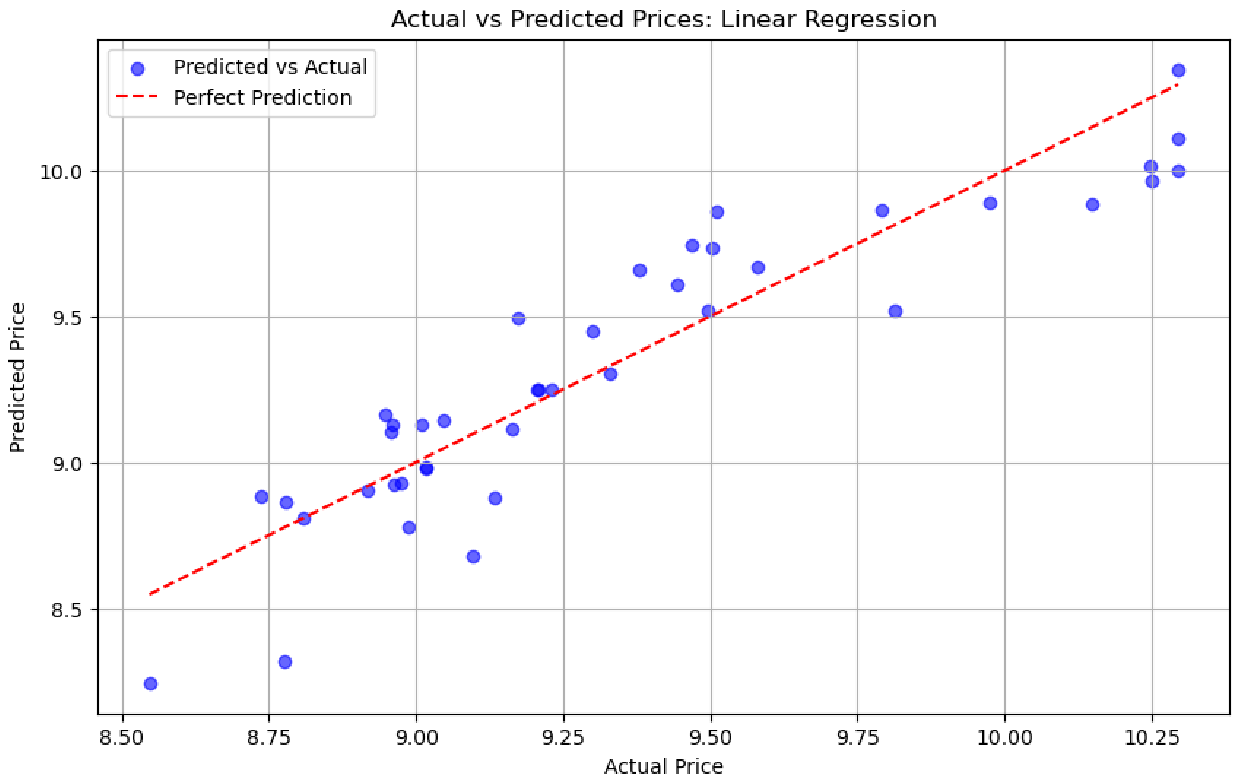
12. MODEL EVALUATION RESULT

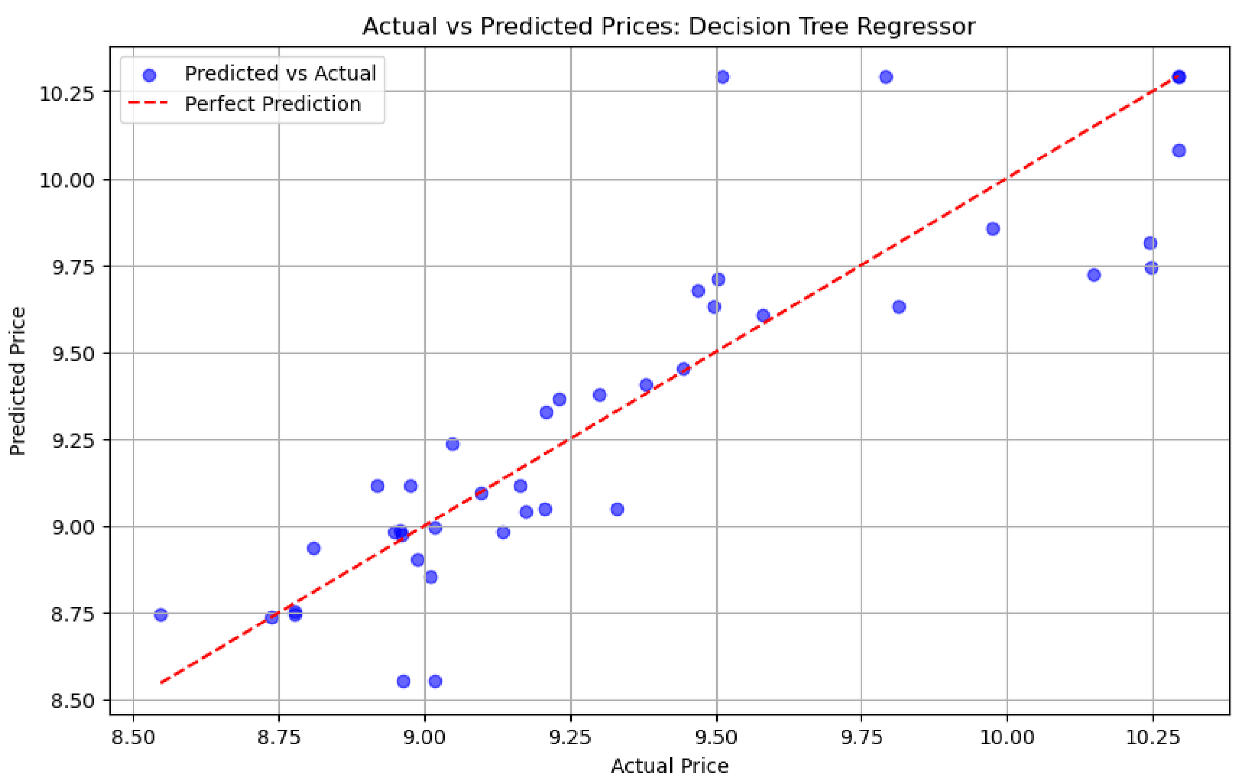
```
# Display results
results_df = pd.DataFrame(results).T
print(results_df)
```

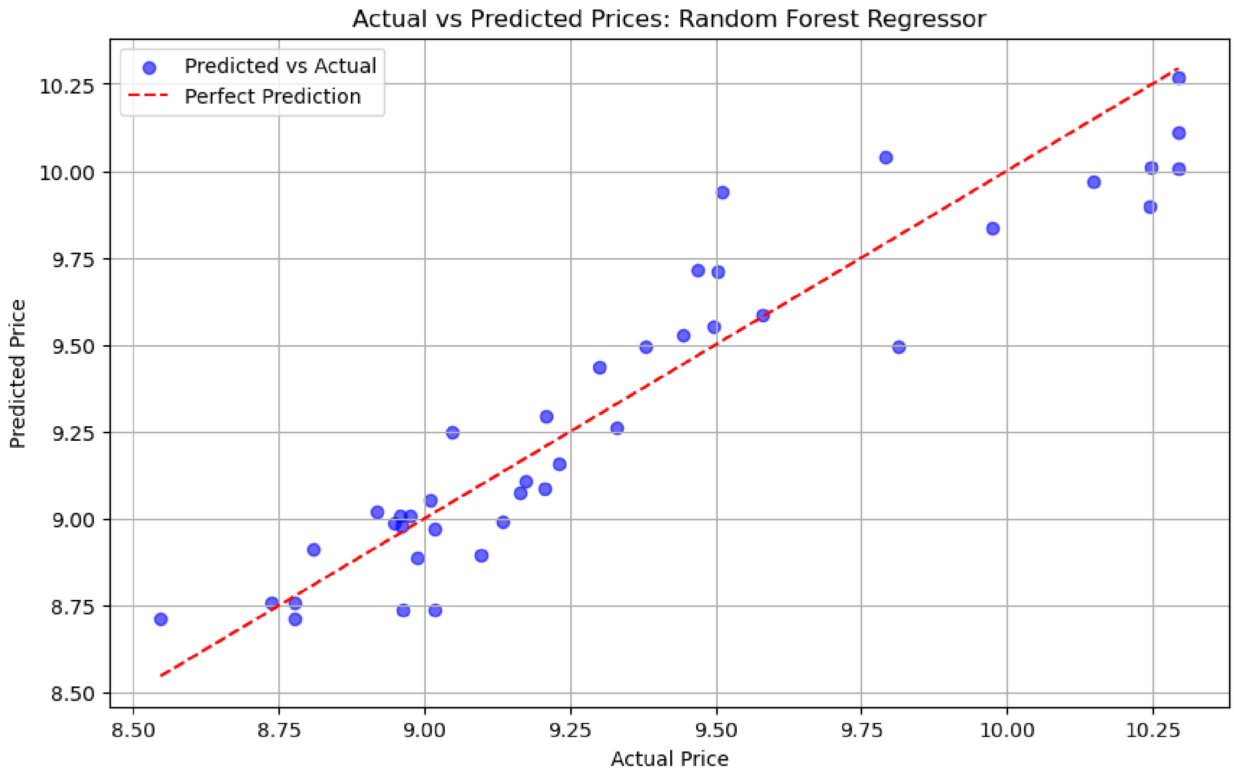
	R² Score	MAE	RMSE
Linear Regression	0.825697	0.161574	0.201772
Decision Tree Regressor	0.744972	0.170912	0.244063
Random Forest Regressor	0.876245	0.136639	0.170016
Gradient Boosting Regressor	0.891191	0.133739	0.159419
Support Vector Regressor	0.790854	0.177862	0.221020

VISUAISATION

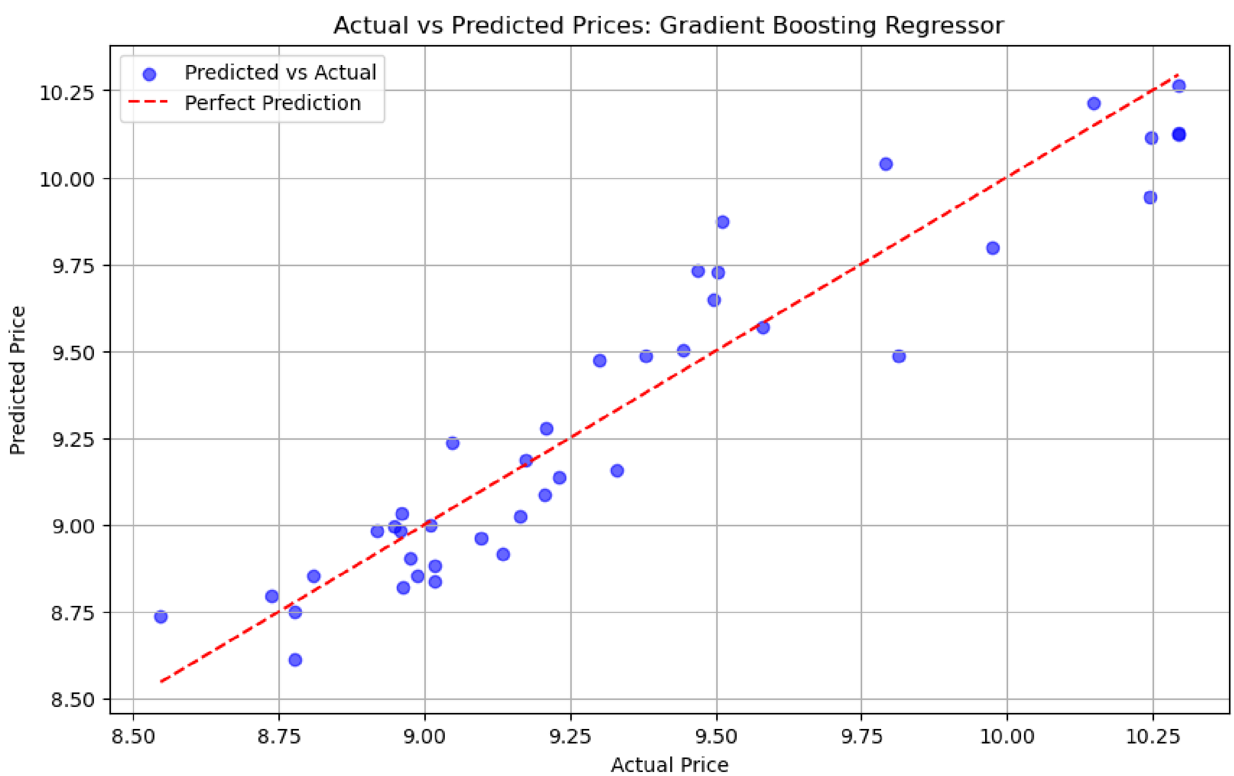
```
# Function to plot actual vs predicted prices
def plot_actual_vs_predicted(y_test, y_pred, model_name):
    plt.figure(figsize=(10, 6))
    plt.scatter(y_test, y_pred, color='blue', alpha=0.6,
label='Predicted vs Actual')
    plt.plot([y_test.min(), y_test.max()], [y_test.min(),
y_test.max()], color='red', linestyle='--', label='Perfect
Prediction')
    plt.title(f'Actual vs Predicted Prices: {model_name}')
    plt.xlabel('Actual Price')
    plt.ylabel('Predicted Price')
    plt.legend()
    plt.grid(True)
    plt.show()

# Iterate through models to plot predictions
for name, model in models.items():
    # Generate predictions for the test set
    y_pred = model.predict(X_test)

    # Call the plotting function
    plot_actual_vs_predicted(y_test, y_pred, name)
```


Actual vs Predicted Prices: Linear Regression
Predicted vs Actual
Perfect Prediction
Predicted Price
Actual Price
8.5
9.0
9.5
10.0
8.50
8.75
9.00
9.25
9.50
9.75
10.00
10.25


Actual vs Predicted Prices: Decision Tree Regressor
Predicted vs Actual
Perfect Prediction
Predicted Price
Actual Price
8.50
8.75
9.00
9.25
9.50
9.75
10.00
10.25
8.50
8.75
9.00
9.25
9.50
9.75
10.00
10.25



Actual vs Predicted Prices: Random Forest Regressor
Predicted vs Actual
Perfect Prediction
Predicted Price
Actual Price
8.50
8.75
9.00
9.25
9.50
9.75
10.00
10.25



Actual vs Predicted Prices: Gradient Boosting Regressor
Predicted vs Actual
Perfect Prediction
Predicted Price
Actual Price
8.50
8.75
9.00
9.25
9.50
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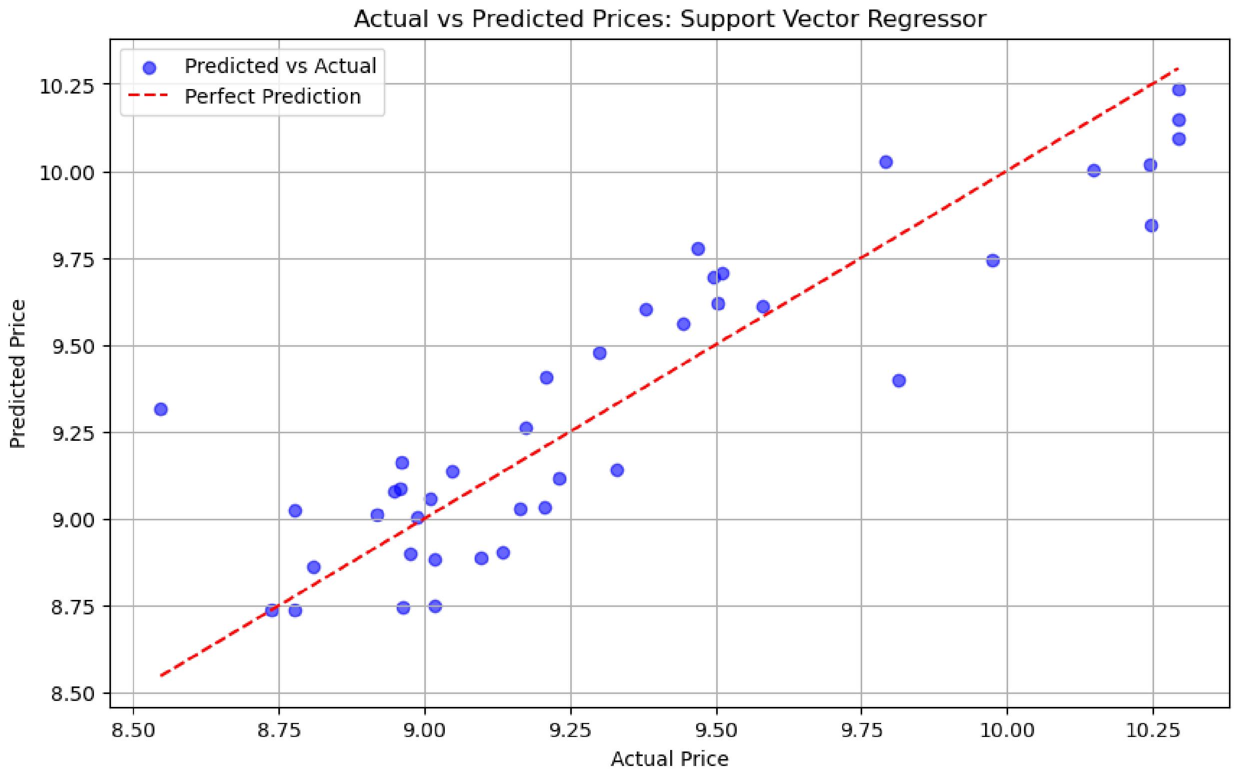
10.00
10.25




```python
# Find the best model based on R² Score
best_model_name = results_df['R² Score'].idxmax()
best_model_metrics = results_df.loc[best_model_name]

print(f"Best Model: {best_model_name}")
print("\nPerformance Metrics:")
print(best_model_metrics)
```

```
Best Model: Gradient Boosting Regressor

Performance Metrics:
R² Score    0.891191
MAE         0.133739
RMSE        0.159419
Name: Gradient Boosting Regressor, dtype: float64
```

```python
# Rank models by R² Score
ranked_models = results_df.sort_values(by='R² Score', ascending=False)
print("Ranked Models by R² Score:")
print(ranked_models)
```

```
Ranked Models by R² Score:
                             R² Score       MAE      RMSE
Gradient Boosting Regressor  0.891191  0.133739  0.159419
Random Forest Regressor      0.876245  0.136639  0.170016
Linear Regression            0.825697  0.161574  0.201772
```

```
Support Vector Regressor     0.790854  0.177862  0.221020
Decision Tree Regressor      0.744972  0.170912  0.244063
```

```python
# Define the model
gbr = GradientBoostingRegressor(random_state=42)

# Define hyperparameters to tune
param_grid = {
    'n_estimators': [100, 200, 300],
    'learning_rate': [0.01, 0.05, 0.1, 0.2],
    'max_depth': [3, 4, 5, 6],
    'min_samples_split': [2, 5, 10],
    'min_samples_leaf': [1, 2, 4],
    'subsample': [0.6, 0.8, 1.0]
}

# Perform Grid Search with Cross Validation
grid_search = GridSearchCV(estimator=gbr, param_grid=param_grid,
                           scoring='r2', cv=5, verbose=2, n_jobs=-1)

# Fit the model
grid_search.fit(X_train, y_train)

# Best parameters and performance
print("Best Parameters:", grid_search.best_params_)
print("Best R² Score:", grid_search.best_score_)
```

```
Fitting 5 folds for each of 1296 candidates, totalling 6480 fits
Best Parameters: {'learning_rate': 0.05, 'max_depth': 6,
'min_samples_leaf': 2, 'min_samples_split': 2, 'n_estimators': 200,
'subsample': 0.6}
Best R² Score: 0.8970872363382394
```

```python
# Use the best estimator for predictions
best_gbr = grid_search.best_estimator_
y_pred = best_gbr.predict(X_test)

# Evaluate on the test set
from sklearn.metrics import r2_score, mean_absolute_error,
mean_squared_error
r2 = r2_score(y_test, y_pred)
mae = mean_absolute_error(y_test, y_pred)
rmse = np.sqrt(mean_squared_error(y_test, y_pred))

print("\nTest Set Performance:")
print(f"R² Score: {r2:.4f}")
print(f"MAE: {mae:.2f}")
print(f"RMSE: {rmse:.2f}")
```

```

Test Set Performance:
```

```
R² Score: 0.9089
MAE: 0.12
RMSE: 0.15
```

SAVIND THE MODEL

```python
# Save the model to a file
joblib.dump(best_gbr, 'car_price_prediction_gb_model.joblib')
print("Model saved as 'car_price_prediction_gb_model.joblib'")
```

```
Model saved as 'car_price_prediction_gb_model.joblib'
```

CONCLUSION

Final Views: The business can benefit from the practical insights into the dynamics of car prices that the Gradient Boosting Regressor model offers Create automobiles that adhere to certain budgetary constraints. Plan your pricing strategy according to the key factors that affect the cost. This project illustrates the usefulness of machine learning in obtaining business insights and shows how to solve regression problems in an organized manner.