MACHINE LEARNING MODULE END PROJECT

A Chinese automobile company aims to enter the U.S. market by establishing a local manufacturing unit, with the goal of competing against established U.S. and European brands. To support this initiative, the company has partnered with an automotive consulting firm to gain insights into the key factors influencing car pricing in the American market, which may differ significantly from the Chinese market. The primary objectives of this project are to identify the variables that significantly impact car prices and to assess how well these variables explain pricing trends. Based on extensive market surveys, the consulting firm has compiled a comprehensive dataset of various car models from across the U.S. market to assist in this analysis.

GOAL

The goal is to develop a model that predicts car prices based on the available independent variables. This model will assist management in understanding how various factors influence pricing, enabling them to adjust car designs, business strategies, and other elements to achieve desired price points. Additionally, the model will serve as a valuable tool for assessing pricing dynamics in new markets.

SOURCE

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

IMPORTING MODULES

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

import warnings
import sys
if not sys.warnoptions:
    warnings.simplefilter("ignore")

from sklearn.preprocessing import StandardScaler, OneHotEncoder, LabelEncoder
from sklearn.compose import ColumnTransformer
from sklearn.model_selection import train_test_split
```

LOADING & PREPROCESSING

1. LOAD THE DATA

In [3]:
```
# LOAD THE DATASET
df = pd.read_csv("CarPrice_Assignment.csv")
df
```

Out[3]:

	car_ID	symboling	CarName	fueltype	aspiration	doornumber	carbody	drivewheel	enginelocation	wheelbase	...
0	1	3	alfa-romero giulia	gas	std	two	convertible	rwd	front	88.6	...
1	2	3	alfa-romero stelvio	gas	std	two	convertible	rwd	front	88.6	...
2	3	1	alfa-romero Quadrifoglio	gas	std	two	hatchback	rwd	front	94.5	...
3	4	2	audi 100 ls	gas	std	four	sedan	fwd	front	99.8	...
4	5	2	audi 100ls	gas	std	four	sedan	4wd	front	99.4	...
...	...	...	...	...	...	...	...	...	...	...	...
200	201	-1	volvo 145e (sw)	gas	std	four	sedan	rwd	front	109.1	...
201	202	-1	volvo 144ea	gas	turbo	four	sedan	rwd	front	109.1	...
202	203	-1	volvo 244dl	gas	std	four	sedan	rwd	front	109.1	...
203	204	-1	volvo 246	diesel	turbo	four	sedan	rwd	front	109.1	...
204	205	-1	volvo 264gl	gas	turbo	four	sedan	rwd	front	109.1	...

205 rows × 26 columns

In [5]:
```
df.shape
```

Out[5]: (205, 26)

2. DISPLAY FIRST & LAST ROWS

In [7]:
```
# DISPLAY FIRST FEW ROWS TO UNDERSTAND THE STRUCTURE OF THE DATA
print(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]
```

In [9]:
```
# DISPLAY LAST FEW ROWS TO UNDERSTAND THE STRUCTURE OF THE DATA
print(df.tail())
```

```
     car_ID  symboling          CarName fueltype aspiration doornumber  \
200     201         -1  volvo 145e (sw)      gas        std       four
201     202         -1      volvo 144ea      gas      turbo       four
202     203         -1      volvo 244dl      gas        std       four
203     204         -1        volvo 246   diesel      turbo       four
204     205         -1      volvo 264gl      gas      turbo       four

    carbody drivewheel enginelocation  wheelbase  ...  enginesize  fuelsystem  \
200   sedan        rwd          front      109.1  ...         141        mpfi
201   sedan        rwd          front      109.1  ...         141        mpfi
202   sedan        rwd          front      109.1  ...         173        mpfi
203   sedan        rwd          front      109.1  ...         145         idi
204   sedan        rwd          front      109.1  ...         141        mpfi

     boreratio  stroke compressionratio horsepower  peakrpm citympg  \
200       3.78    3.15              9.5        114     5400      23
201       3.78    3.15              8.7        160     5300      19
202       3.58    2.87              8.8        134     5500      18
203       3.01    3.40             23.0        106     4800      26
204       3.78    3.15              9.5        114     5400      19

     highwaympg    price
200          28  16845.0
201          25  19045.0
202          23  21485.0
203          27  22470.0
204          25  22625.0

[5 rows x 26 columns]
```

3. FEATURES PROPERTIES OF THE DATASET

In [24]:

```
# DISPLAY FEATURES PROPERTIES OF THE DATASETS
print("Dataset Info:")
df.info()
```

```
Dataset 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
```

4. STATISTICAL SUMMARY OF DATA

In [13]:
```
# DISPLAY STATISTICAL SUMMARY
print("Statistical Summary:")
df.describe()
```

```
Statistical Summary:
```

Out[13]:

	car_ID	symboling	wheelbase	carlength	carwidth	carheight	curbweight	enginesize	boreratio	stroke
count	205.000000	205.000000	205.000000	205.000000	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	2555.565854	126.907317	3.329756	3.255415
std	59.322565	1.245307	6.021776	12.337289	2.145204	2.443522	520.680204	41.642693	0.270844	0.313597
min	1.000000	-2.000000	86.600000	141.100000	60.300000	47.800000	1488.000000	61.000000	2.540000	2.070000
25%	52.000000	0.000000	94.500000	166.300000	64.100000	52.000000	2145.000000	97.000000	3.150000	3.110000
50%	103.000000	1.000000	97.000000	173.200000	65.500000	54.100000	2414.000000	120.000000	3.310000	3.290000
75%	154.000000	2.000000	102.400000	183.100000	66.900000	55.500000	2935.000000	141.000000	3.580000	3.410000
max	205.000000	3.000000	120.900000	208.100000	72.300000	59.800000	4066.000000	326.000000	3.940000	4.170000

5. DISPLAY ALL COLUMN NAMES

In [15]:

```python
# DISPLAY PARTICULAR COLUMN
print("Columns of the dataset:")
df.columns
```

```
Columns of the dataset:
```

Out[15]:

```
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')
```

6. DISPLAY DATATYPES OF ALL COLUMNS

In [17]:

```python
print("Data Types:\n", df.dtypes)
```

```
Data Types:
 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
```

7. NULL / MISSING VALUES IN EACH COLUMN

In [19]:
```
# DISPLAY NULL VALUES IN EACH COLUMN
print("Null values in each column:")
print(df.isnull().sum())
```

```
Null values in each column:
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
```

8. DUPLICATE VALUES

In [21]:
```
# FINDING THE TOTAL NO OF DUPLICATES
df.duplicated().sum()
```

Out[21]:
```
0
```

9. REMOVE IRREGULARITIES IN CAR NAME COLUMN

In [26]:
```
# Checking variable named CarName (now 'carname') which is comprised of two parts -
# the first word is the name of 'car company' and the second is the 'car model'.
df.CarName.head()
```

Out[26]:
```
0           alfa-romero giulia
1          alfa-romero stelvio
2     alfa-romero Quadrifoglio
3                  audi 100 ls
4                   audi 100ls
Name: CarName, dtype: object
```

In [28]:
```
# Retaining only the 'car company' (first half) under a new column 'name' and dropping off the 'carname' column
df['name'] = df['CarName'].apply(lambda x: x.split(' ')[0])
df = df.drop('CarName', axis=1)
df.head()
```

Out[28]:

	car_ID	symboling	fueltype	aspiration	doornumber	carbody	drivewheel	enginelocation	wheelbase	carlength	...	fuel
0	1	3	gas	std	two	convertible	rwd	front	88.6	168.8	...	
1	2	3	gas	std	two	convertible	rwd	front	88.6	168.8	...	
2	3	1	gas	std	two	hatchback	rwd	front	94.5	171.2	...	
3	4	2	gas	std	four	sedan	fwd	front	99.8	176.6	...	
4	5	2	gas	std	four	sedan	4wd	front	99.4	176.6	...	

5 rows × 26 columns

In [30]:
```
# Converting all the entries of 'name' to lower case and checking unique entries of 'name'
df.name = df.name.str.lower()
df.name.unique()
```

Out[30]:
```
array(['alfa-romero', 'audi', 'bmw', 'chevrolet', 'dodge', 'honda',
       'isuzu', 'jaguar', 'maxda', 'mazda', 'buick', 'mercury',
       'mitsubishi', 'nissan', 'peugeot', 'plymouth', 'porsche',
       'porcshce', 'renault', 'saab', 'subaru', 'toyota', 'toyouta',
       'vokswagen', 'volkswagen', 'vw', 'volvo'], dtype=object)
```

In [32]:
```python
# Correcting the irregularities in the names of unique entries of 'companyname'
'''
defining a 'name_rep' function to expedite the process of replacement
'a' is the old value, 'b' is the replaced (corrected) value
'''
def name_rep(df,a,b):
    return df.name.replace(a,b, inplace=True)

name_rep(df,'maxda','mazda')
name_rep(df,'porcshce','porsche')
name_rep(df,'toyouta','toyota')
name_rep(df,'vokswagen','volkswagen')
name_rep(df,'vw','volkswagen')
name_rep(df,'alfa-romero','alfa-romeo')

print(df.name.unique())
print("\nNumber of unique car companies: ",df.name.nunique())
```

```
['alfa-romeo' 'audi' 'bmw' 'chevrolet' 'dodge' 'honda' 'isuzu' 'jaguar'
 'mazda' 'buick' 'mercury' 'mitsubishi' 'nissan' 'peugeot' 'plymouth'
 'porsche' 'renault' 'saab' 'subaru' 'toyota' 'volkswagen' 'volvo']

Number of unique car companies:  22
```

In [34]:
```python
df.head()
```

Out[34]:

	car_ID	symboling	fueltype	aspiration	doornumber	carbody	drivewheel	enginelocation	wheelbase	carlength	...	fuel
0	1	3	gas	std	two	convertible	rwd	front	88.6	168.8	...	
1	2	3	gas	std	two	convertible	rwd	front	88.6	168.8	...	
2	3	1	gas	std	two	hatchback	rwd	front	94.5	171.2	...	
3	4	2	gas	std	four	sedan	fwd	front	99.8	176.6	...	
4	5	2	gas	std	four	sedan	4wd	front	99.4	176.6	...	

5 rows × 26 columns

In [36]:
```
df.shape
```

Out[36]: (205, 26)

10. UNIVARIATE ANALYSIS

In [39]:
```
# Value counts for categorical columns
for col in df.select_dtypes(include='object').columns:
    print(f"Value counts for {col}:\n{df[col].value_counts()}\n")
```

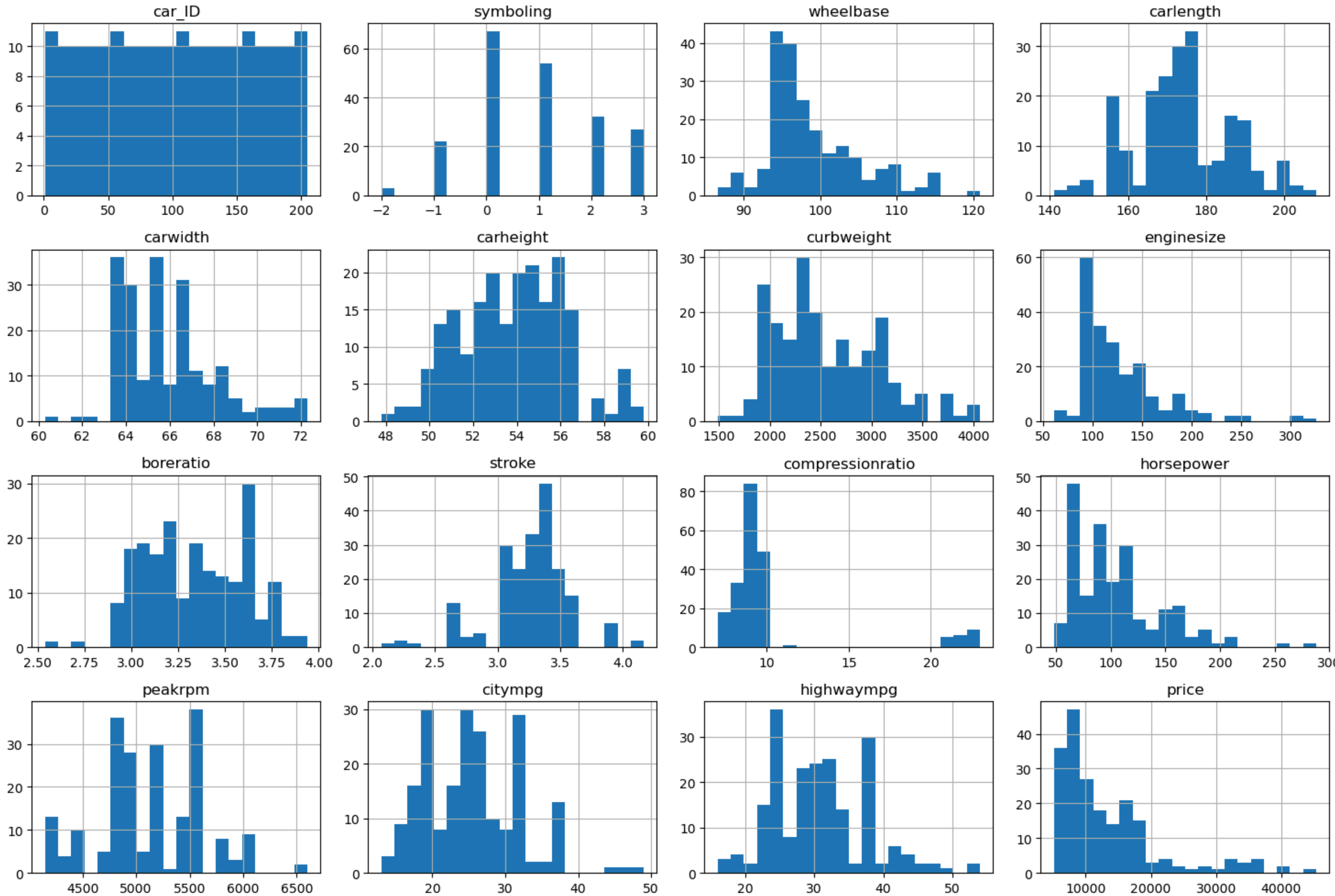
```
Value counts for fueltype:
fueltype
gas       185
diesel     20
Name: count, dtype: int64

Value counts for aspiration:
aspiration
std      168
turbo     37
Name: count, dtype: int64

Value counts for doornumber:
doornumber
four    115
two      90
Name: count, dtype: int64

Value counts for carbody:
carbody
sedan          96
hatchback      70
wagon          25
hardtop         8
convertible     6
Name: count, dtype: int64

Value counts for drivewheel:
drivewheel
fwd    120
rwd     76
4wd      9
Name: count, dtype: int64

Value counts for enginelocation:
enginelocation
front    202
rear       3
Name: count, dtype: int64

Value counts for enginetype:
enginetype
```

```
ohc      148
ohcf      15
ohcv      13
dohc      12
l         12
rotor      4
dohcv      1
Name: count, dtype: int64

Value counts for cylindernumber:
cylindernumber
four      159
six        24
five       11
eight       5
two         4
three       1
twelve      1
Name: count, dtype: int64

Value counts for fuelsystem:
fuelsystem
mpfi    94
2bbl    66
idi     20
1bbl    11
spdi     9
4bbl     3
mfi      1
spfi     1
Name: count, dtype: int64

Value counts for name:
name
toyota        32
nissan        18
mazda         17
mitsubishi    13
honda         13
volkswagen    12
subaru        12
peugeot       11
```

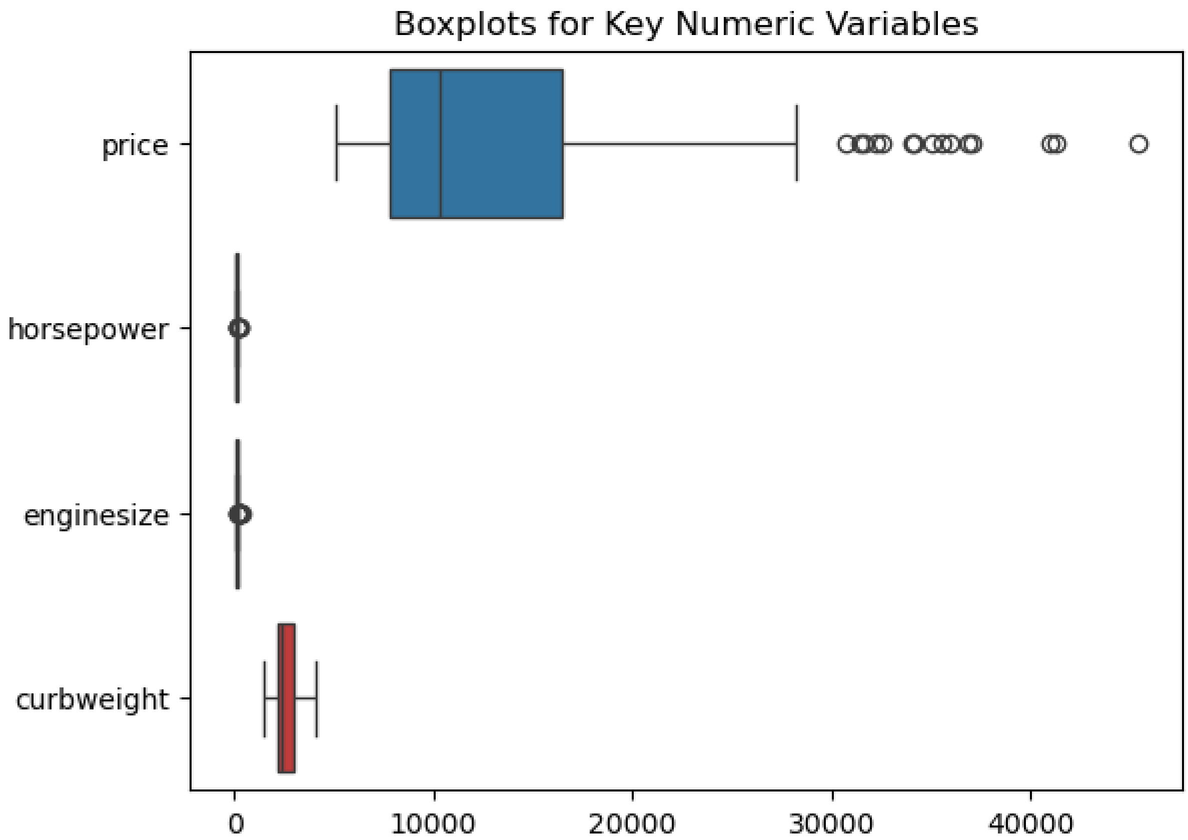
```
volvo          11
dodge           9
buick           8
bmw             8
audi            7
plymouth        7
saab            6
porsche         5
isuzu           4
jaguar          3
chevrolet       3
alfa-romeo      3
renault         2
mercury         1
Name: count, dtype: int64
```

In [42]:

```
# Histograms for numeric features
df.hist(figsize=(15, 10), bins=20)
plt.tight_layout()
plt.show()
```

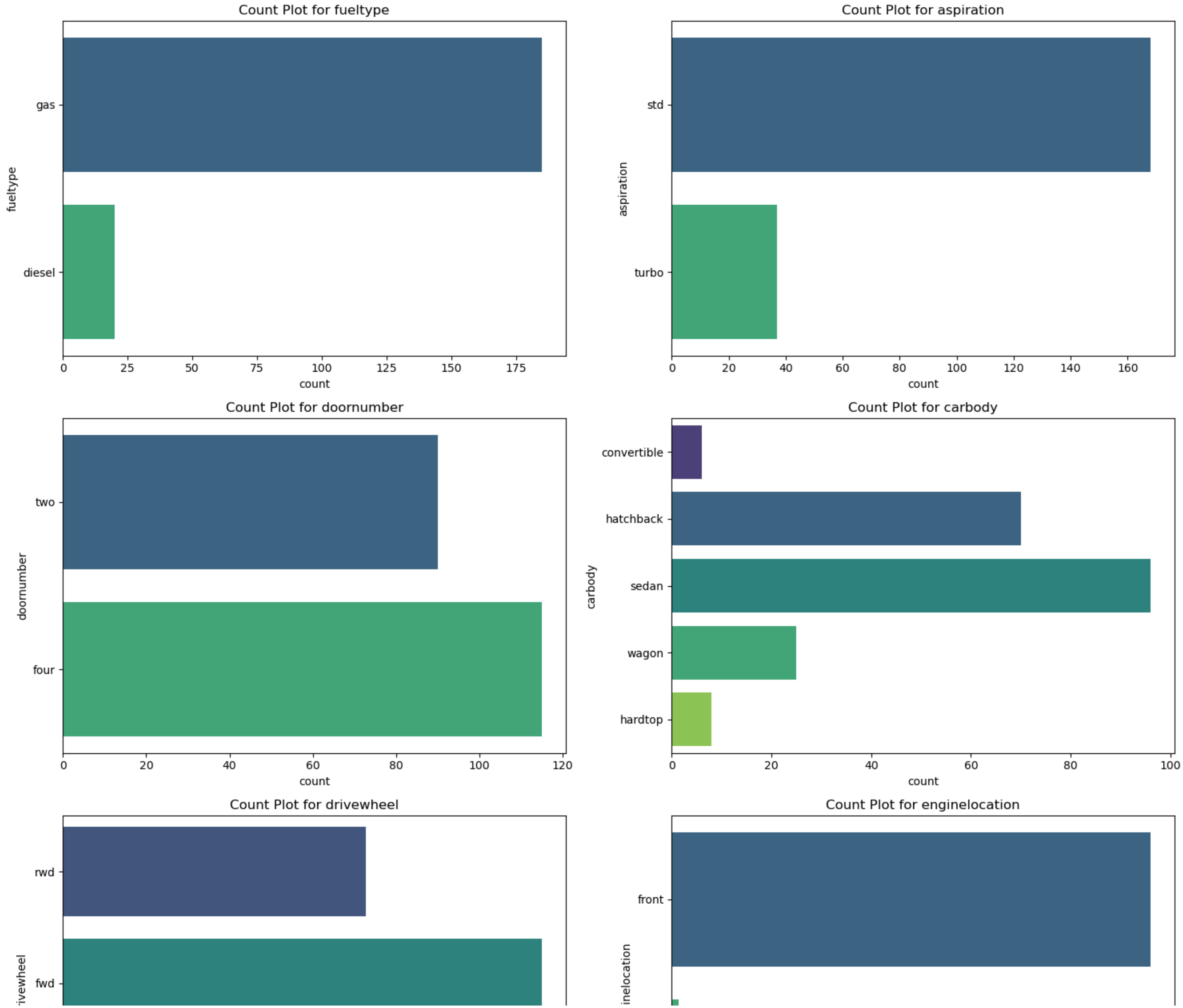


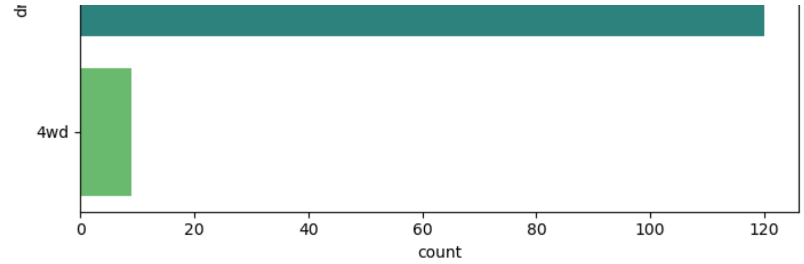
In [44]:
```python
# Boxplots for price and numeric features
sns.boxplot(data=df[['price', 'horsepower', 'enginesize', 'curbweight']], orient='h')
plt.title("Boxplots for Key Numeric Variables")
plt.show()
```

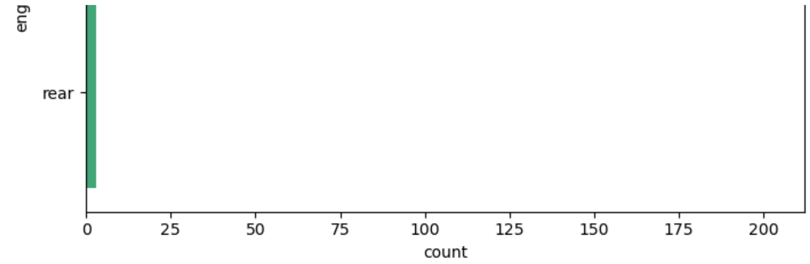


In [46]:
```
# Import necessary libraries
import matplotlib.pyplot as plt
import seaborn as sns

# Create subplots for bar plots of categorical variables
categorical_cols = df.select_dtypes(include='object').columns
n_cols = 2  # Number of columns for the subplot grid
n_rows = (len(categorical_cols) + 1) // n_cols  # Calculate the number of rows needed

fig, axes = plt.subplots(n_rows, n_cols, figsize=(15, 5 * n_rows))
axes = axes.flatten()  # Flatten the 2D axes array into 1D for easier indexing

for i, col in enumerate(categorical_cols):
    sns.countplot(y=col, data=df, palette='viridis', ax=axes[i])
    axes[i].set_title(f"Count Plot for {col}")
```

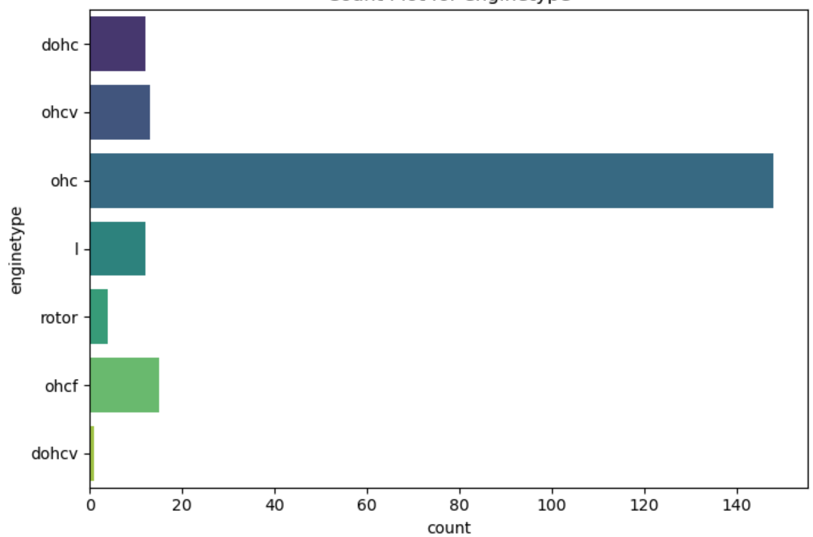
```
# Remove unused subplots
for j in range(len(categorical_cols), len(axes)):
    fig.delaxes(axes[j])

plt.tight_layout()
plt.show()
```


Count Plot for fueltype
fueltype
gas
diesel
0 25 50 75 100 125 150 175
count
Count Plot for aspiration
aspiration
std
turbo
0 20 40 60 80 100 120 140 160
count
Count Plot for doornumber
doornumber
two
four
0 20 40 60 80 100 120
count
Count Plot for carbody
carbody
convertible
hatchback
sedan
wagon
hardtop
0 20 40 60 80 100
count
Count Plot for drivewheel
rivewheel
rwd
fwd
Count Plot for enginelocation
inelocation
front

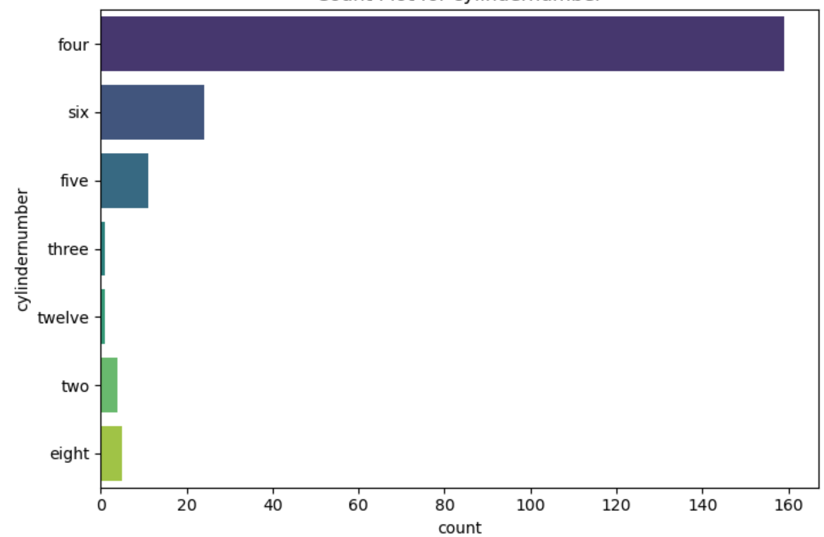




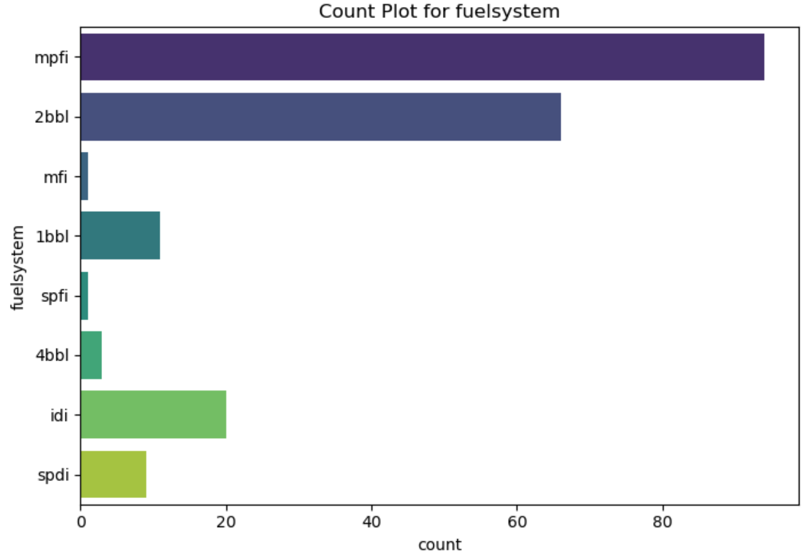
Count Plot for enginetype



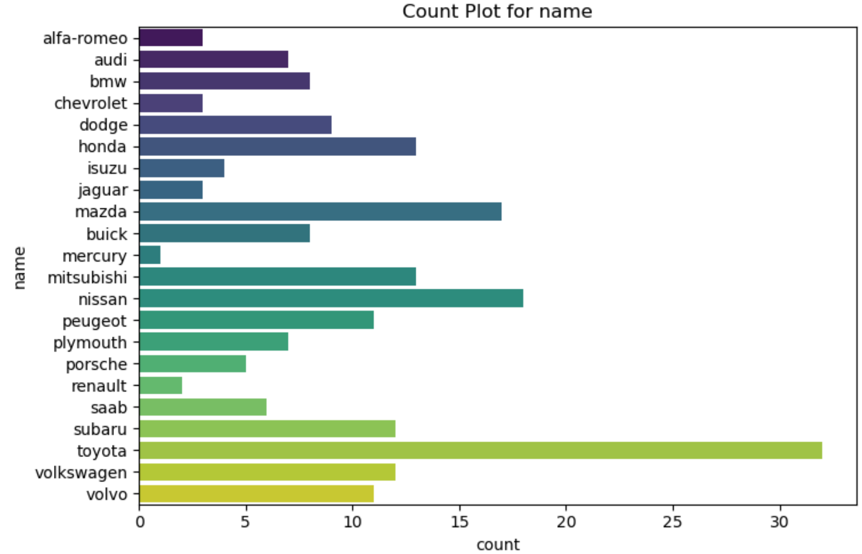
Count Plot for cylindernumber



Count Plot for fuelsystem

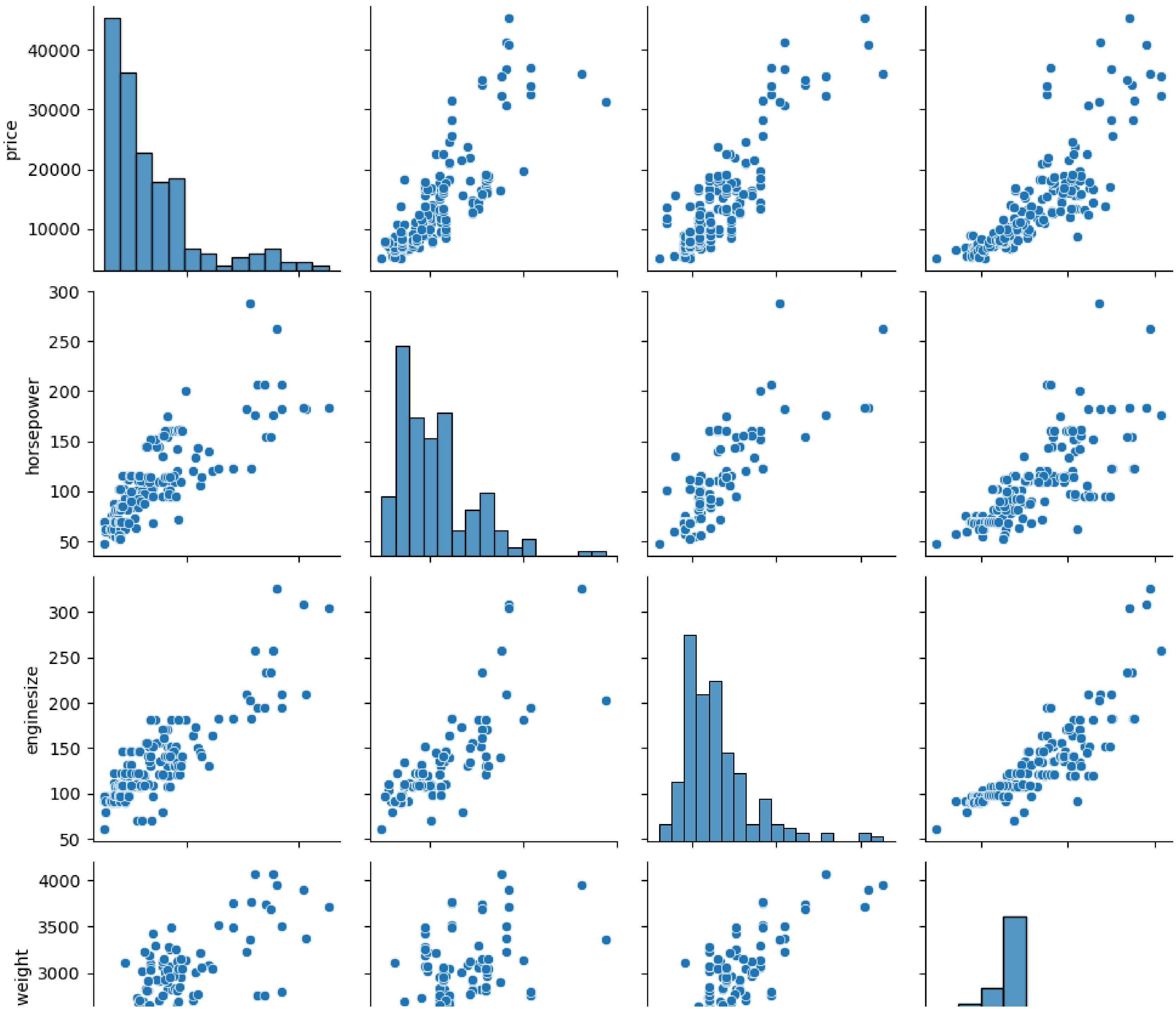


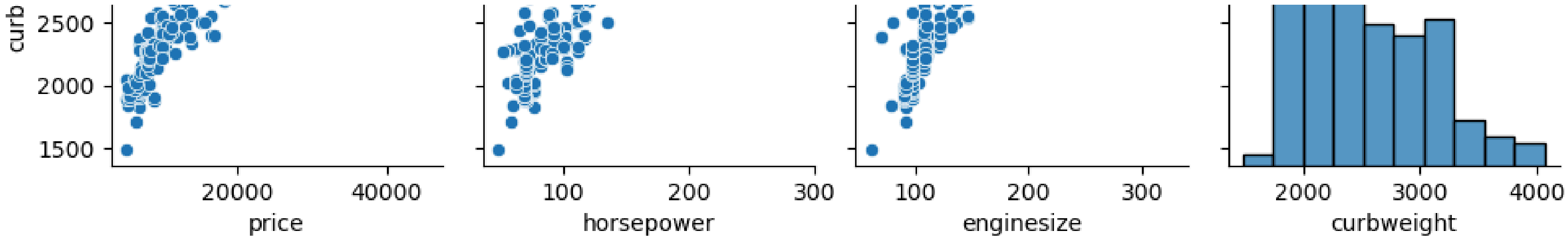
Count Plot for name



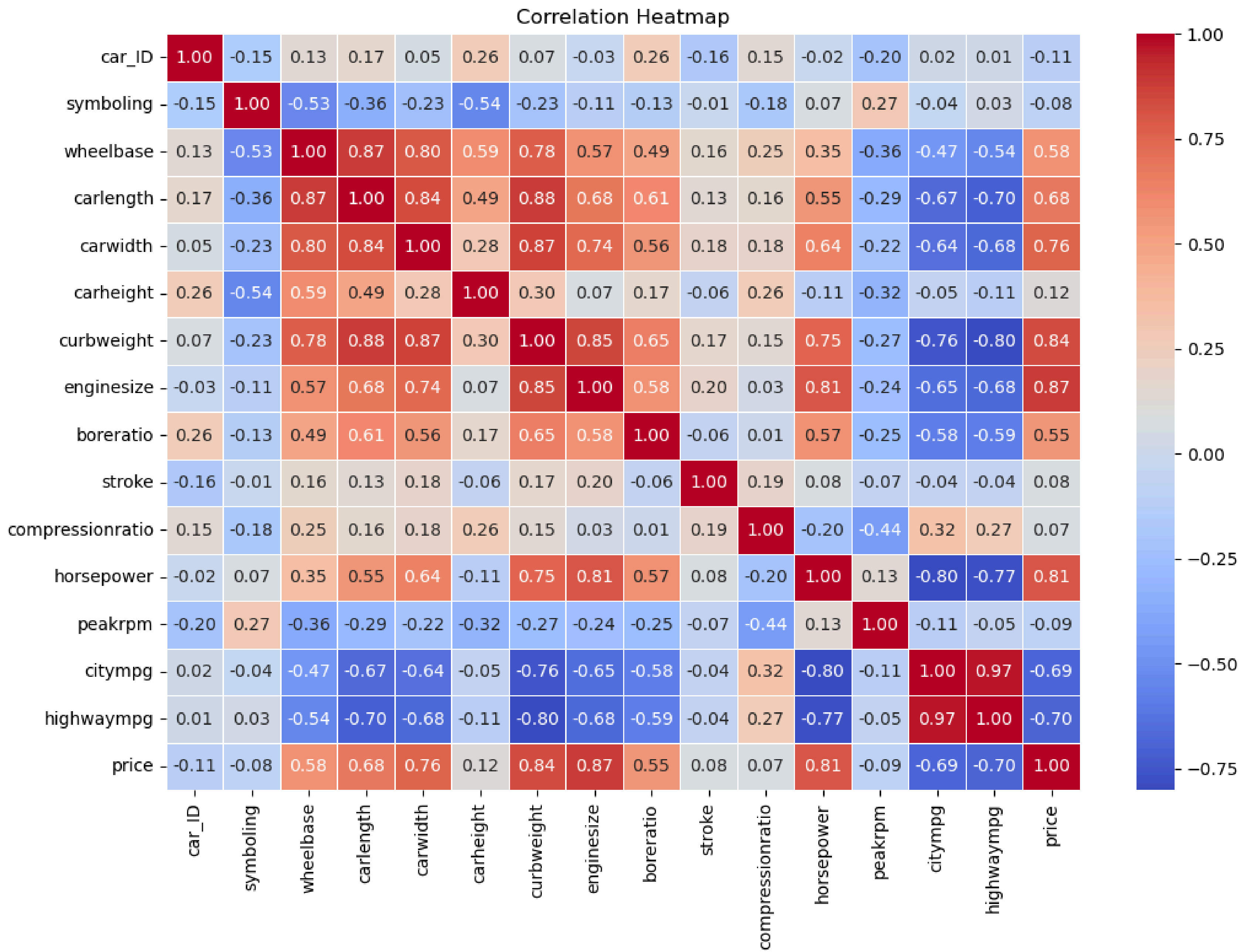
11. BIVARIATE ANALYSIS

In [50]:
```
# 1. Scatter plots for numeric variables
sns.pairplot(df, vars=['price', 'horsepower', 'enginesize', 'curbweight'], kind='scatter')
plt.show()
```


price
horsepower
enginesize
weight
40000
30000
20000
10000
300
250
200
150
100
50
300
250
200
150
100
50
4000
3500
3000

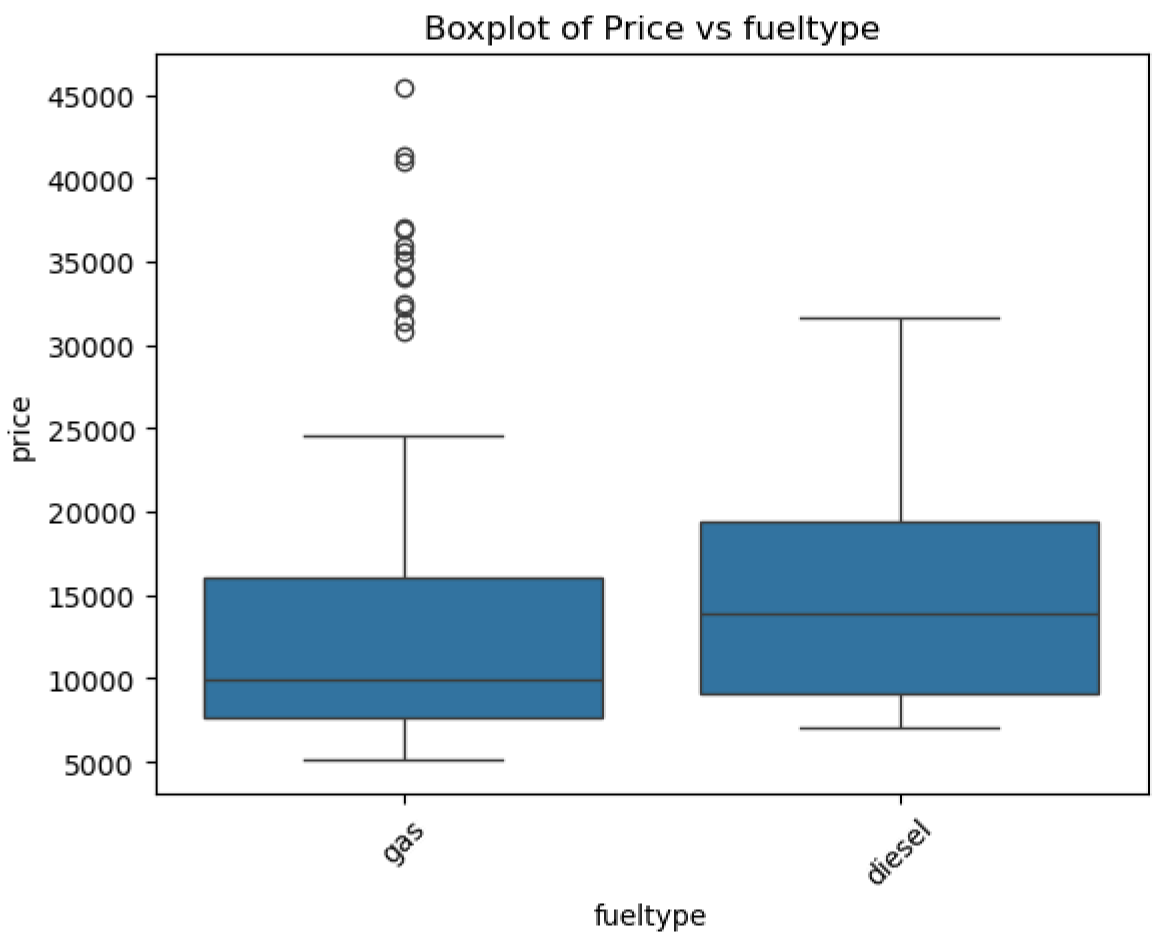


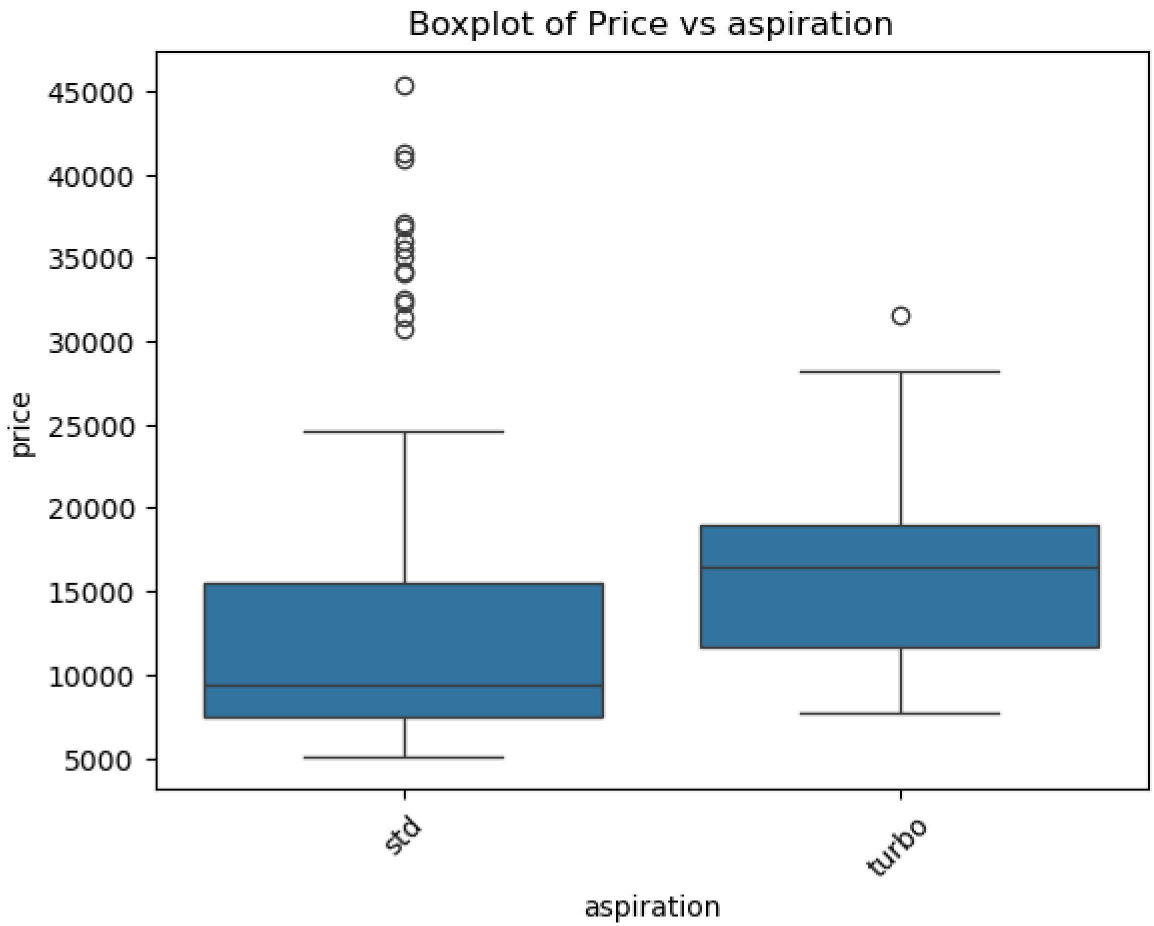
In [52]:
```
# 2. Correlation heatmap for numeric features

# Select only numeric columns for correlation calculation
numeric_df = df.select_dtypes(include=['float64', 'int64'])

# Compute the correlation matrix
correlation = numeric_df.corr()

# Plot the heatmap
plt.figure(figsize=(12, 8))
sns.heatmap(correlation, annot=True, cmap='coolwarm', fmt=".2f", linewidths=0.5)
plt.title("Correlation Heatmap")
plt.show()
```

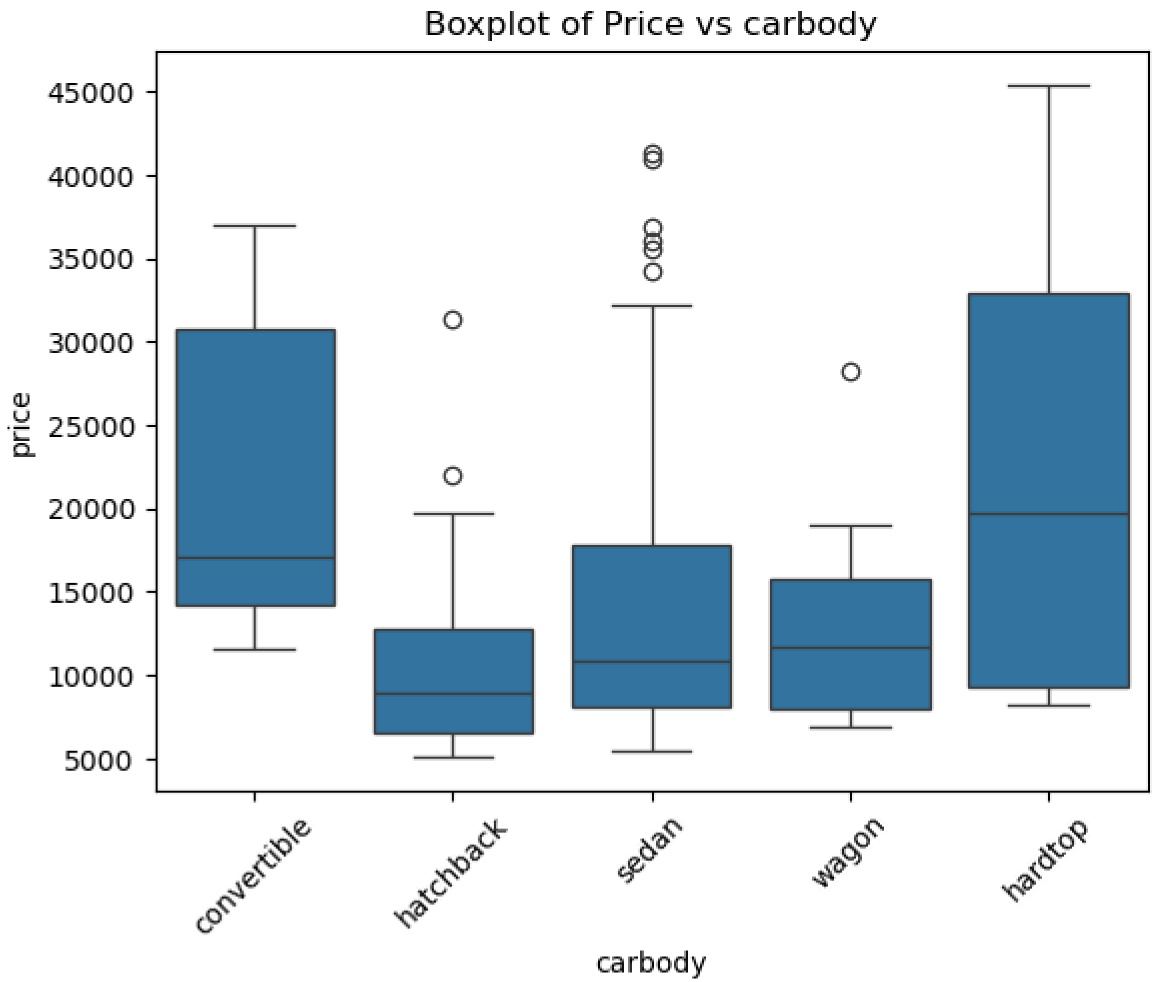


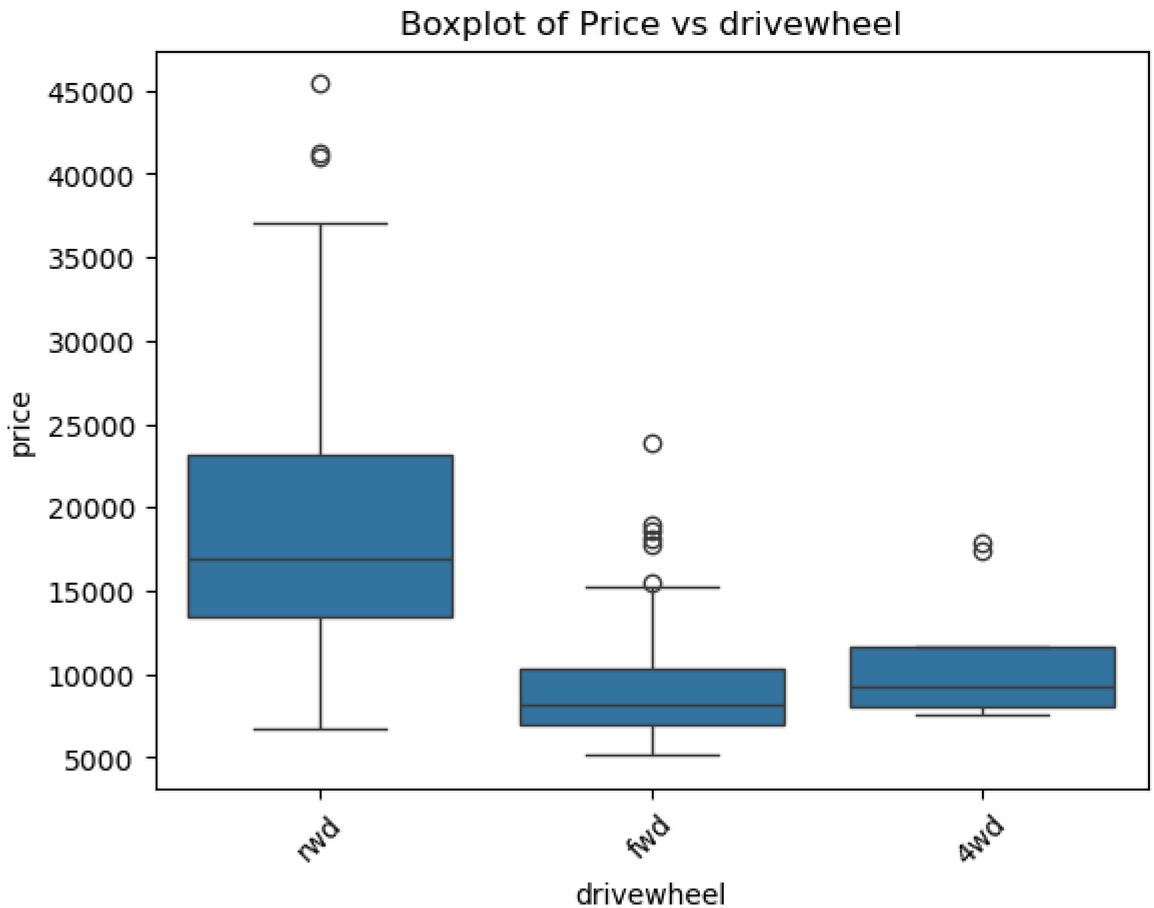
In [54]:
```
# 3. Boxplot of price against categorical variables
for col in ['fueltype', 'aspiration', 'carbody', 'drivewheel']:
```

```
    sns.boxplot(x=col, y='price', data=df)
    plt.title(f"Boxplot of Price vs {col}")
    plt.xticks(rotation=45)
    plt.show()
```

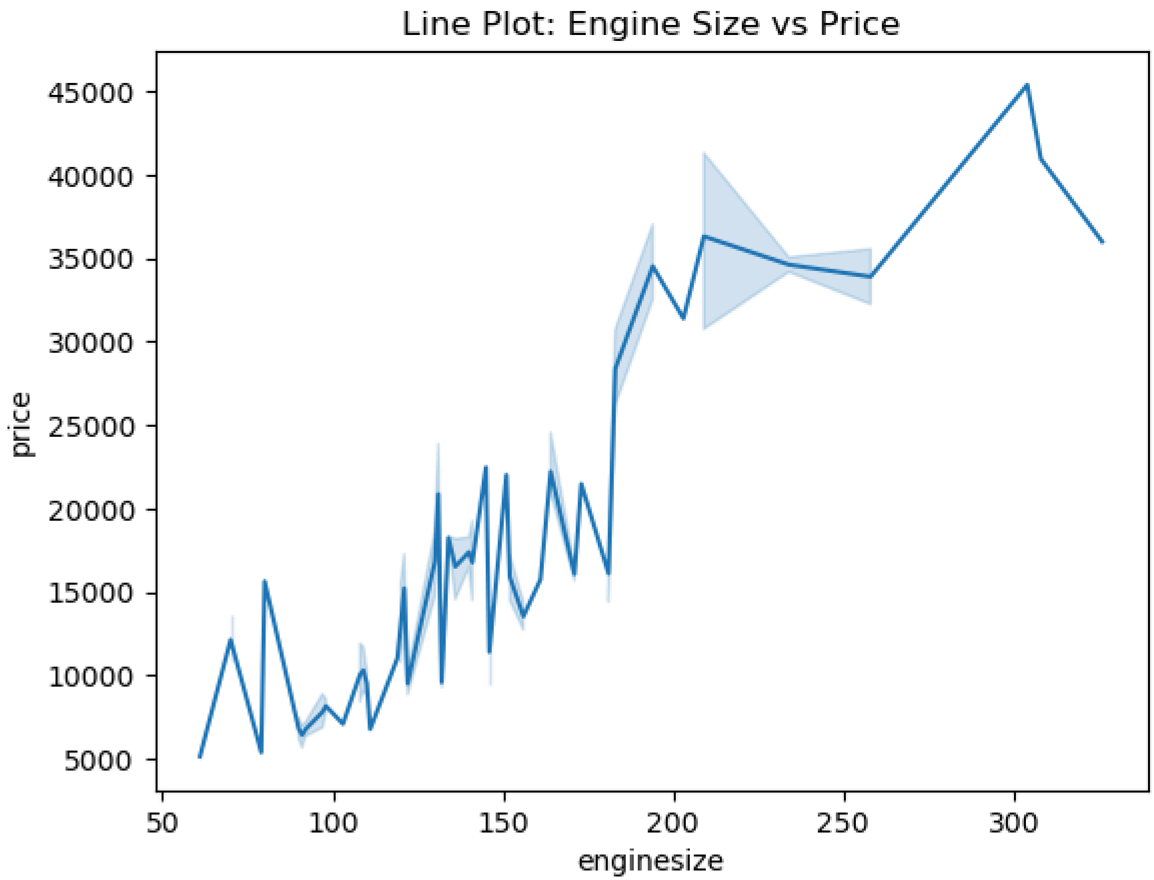



Boxplot of Price vs aspiration
45000
40000
35000
30000
25000
20000
15000
10000
5000
price
std
turbo
aspiration


Boxplot of Price vs carbody
price
45000
40000
35000
30000
25000
20000
15000
10000
5000
convertible
hatchback
sedan
wagon
hardtop
carbody

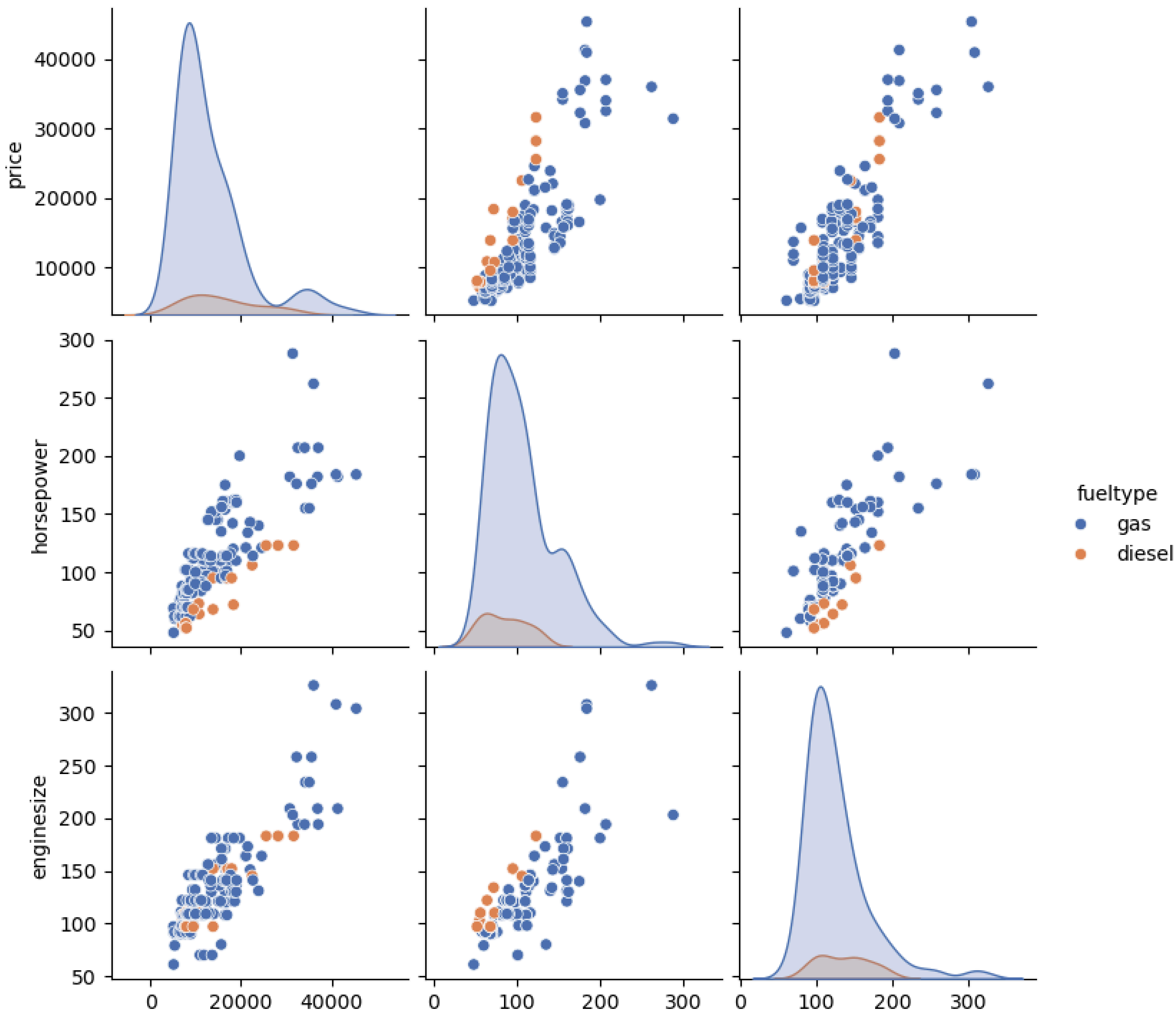


In [56]:
```
# 4. Line plot for engine size and price
sns.lineplot(data=df, x='enginesize', y='price')
plt.title("Line Plot: Engine Size vs Price")
plt.show()
```



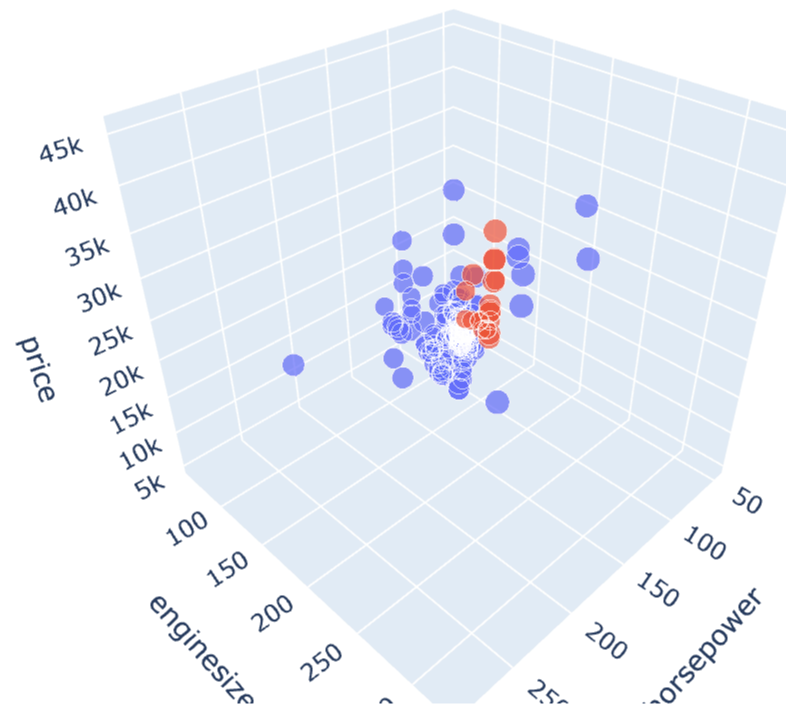
12. MULTIVARIATE ANALYSIS

In [60]:
```
# 1. Pairplot including categorical hue
sns.pairplot(df, vars=['price', 'horsepower', 'enginesize'], hue='fueltype', palette='deep')
plt.show()
```

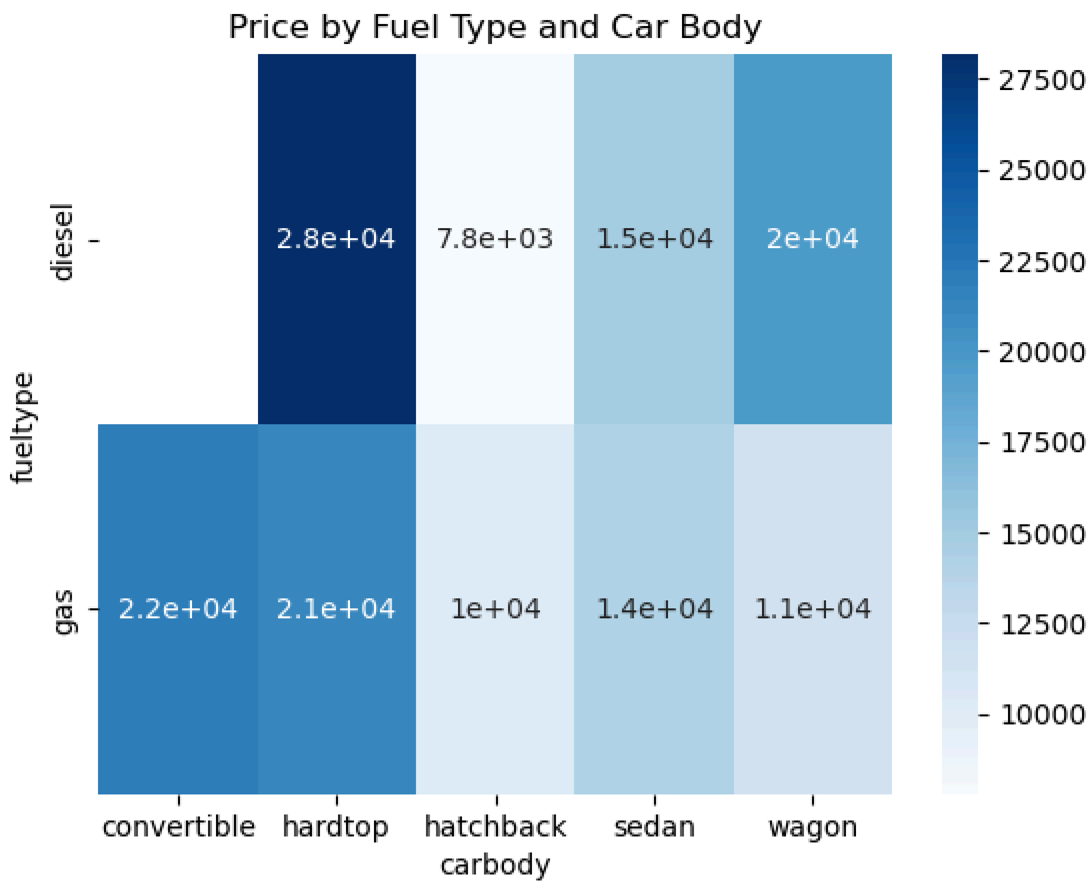

price
horsepower
enginesize
fueltype
gas
diesel

price horsepower enginesize

In [62]:
```
# 2. 3D Scatter plot (requires plotly)
import plotly.express as px
fig = px.scatter_3d(df, x='horsepower', y='enginesize', z='price', color='fueltype', size='curbweight')
fig.show()
```



In [64]:
```
# 3. Heatmap with interactions
pivot_table = pd.pivot_table(df, values='price', index='fueltype', columns='carbody', aggfunc='mean')
sns.heatmap(pivot_table, annot=True, cmap='Blues')
plt.title("Price by Fuel Type and Car Body")
plt.show()
```



DATA CLEANING

1. FEATURE ENCODING

In [69]:
```
binary_cols = ['fueltype', 'aspiration', 'doornumber', 'enginelocation']
df[binary_cols] = df[binary_cols].apply(lambda x: LabelEncoder().fit_transform(x))

# Categorical columns: 'name', 'carbody', 'drivewheel', 'enginetype', 'cylindernumber', 'fuelsystem'
categorical_cols = ['name', 'carbody', 'drivewheel', 'enginetype', 'cylindernumber', 'fuelsystem']

# Using one-hot encoding for categorical variables
df = pd.get_dummies(df, columns=categorical_cols, drop_first=True)
```

2. HANDLING OUTLIERS

In [72]:
```
from scipy.stats import zscore

numeric_cols = df.select_dtypes(include=['int64', 'float64']).columns
z_scores = np.abs(zscore(df[numeric_cols]))
df = df[(z_scores < 3).all(axis=1)]  # Keep rows where z-score < 3
```

3. FEATURE SCALING

In [75]:
```
scaler = StandardScaler()
scaled_columns = numeric_cols.drop('price')  # Exclude the target column ('price') from scaling
df[scaled_columns] = scaler.fit_transform(df[scaled_columns])
```

In [77]:
```
df
```

Out[77]:

	car_ID	symboling	fueltype	aspiration	doornumber	enginelocation	wheelbase	carlength	carwidth	carheight	...	c
0	-1.705395	1.692758	1	0	1	0	-1.777805	-0.399899	-0.851313	-1.980334	...	
1	-1.688383	1.692758	1	0	1	0	-1.777805	-0.399899	-0.851313	-1.980334	...	
2	-1.671371	0.113432	1	0	1	0	-0.706407	-0.190325	-0.136763	-0.520622	...	
3	-1.654360	0.903095	1	0	0	0	0.256036	0.281217	0.220512	0.249782	...	
4	-1.637348	0.903095	1	0	0	0	0.183399	0.281217	0.322591	0.249782	...	
...	...	...	...	...	...	...	...	...	...	...	...	
199	1.679924	-1.465894	1	1	0	0	1.073204	1.346553	0.730906	1.547304	...	
200	1.696936	-1.465894	1	0	0	0	1.944850	1.346553	1.598574	0.736353	...	
201	1.713948	-1.465894	1	1	0	0	1.944850	1.346553	1.547535	0.736353	...	
202	1.730959	-1.465894	1	0	0	0	1.944850	1.346553	1.598574	0.736353	...	
204	1.764983	-1.465894	1	1	0	0	1.944850	1.346553	1.598574	0.736353	...	

181 rows × 66 columns

In [65]:

```
df.columns
```

Out[65]:

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

4. SPLITTING THE DATA INTO TRAINING AND TESTING SET

In [80]:

```
X = df.drop(columns=['price'])  # Features
y = df['price']  # Target variable
```

```python
# 9. Train-test split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Check processed dataset
print("Processed Dataset Shape:", df.shape)
print("Processed Dataset Preview:\n", df.head())
```

```
Processed Dataset Shape: (181, 66)
Processed Dataset Preview:
      car_ID  symboling  fueltype  aspiration  doornumber  enginelocation  \
0 -1.705395   1.692758         1           0           1               0
1 -1.688383   1.692758         1           0           1               0
2 -1.671371   0.113432         1           0           1               0
3 -1.654360   0.903095         1           0           0               0
4 -1.637348   0.903095         1           0           0               0

   wheelbase  carlength  carwidth  carheight  ...  cylindernumber_three  \
0  -1.777805  -0.399899 -0.851313  -1.980334  ...                 False
1  -1.777805  -0.399899 -0.851313  -1.980334  ...                 False
2  -0.706407  -0.190325 -0.136763  -0.520622  ...                 False
3   0.256036   0.281217  0.220512   0.249782  ...                 False
4   0.183399   0.281217  0.322591   0.249782  ...                 False

   cylindernumber_twelve  cylindernumber_two  fuelsystem_2bbl  \
0                  False               False            False
1                  False               False            False
2                  False               False            False
3                  False               False            False
4                  False               False            False

   fuelsystem_4bbl  fuelsystem_idi  fuelsystem_mfi  fuelsystem_mpfi  \
0            False           False           False             True
1            False           False           False             True
2            False           False           False             True
3            False           False           False             True
4            False           False           False             True

   fuelsystem_spdi  fuelsystem_spfi
0            False            False
1            False            False
2            False            False
3            False            False
4            False            False

[5 rows x 66 columns]
```

MODEL IMPLEMENTATION AND EVALUATION

In [82]:
```
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 mean_squared_error, mean_absolute_error, r2_score
import pandas as pd

# Initialize the regression models
models = {
    "Linear Regression": LinearRegression(),
    "Decision Tree Regressor": DecisionTreeRegressor(random_state=42),
    "Random Forest Regressor": RandomForestRegressor(random_state=42, n_jobs=-1),
    "Gradient Boosting Regressor": GradientBoostingRegressor(random_state=42),
    "Support Vector Regressor": SVR(kernel='rbf')
}

# Dictionary to store results
results = {}

# Train and evaluate each model
for name, model in models.items():
    print(f"Training and evaluating {name}...")
    # Train the model
    model.fit(X_train, y_train)
    # Predict on test data
    y_pred = model.predict(X_test)

    # Calculate metrics
    mse = mean_squared_error(y_test, y_pred)
    mae = mean_absolute_error(y_test, y_pred)
    r2 = r2_score(y_test, y_pred)

    # Save results
    results[name] = {"R-squared": r2, "MSE": mse, "MAE": mae}
    print(f"{name} - R-squared: {r2:.3f}, MSE: {mse:.3f}, MAE: {mae:.3f}")
    print("-" * 50)

# Display results in a DataFrame
results_df = pd.DataFrame(results).T  # Transpose for better readability
print("\nComparison of Model Performance:")
```

```python
print(results_df)

# Sort the results by R-squared for better visualization
sorted_results = results_df.sort_values(by="R-squared", ascending=False)
print("\nSorted Results by R-squared:")
print(sorted_results)
```

```
Training and evaluating Linear Regression...
Linear Regression - R-squared: -0.597, MSE: 79979879.040, MAE: 4303.487
--------------------------------------------------
Training and evaluating Decision Tree Regressor...
Decision Tree Regressor - R-squared: 0.862, MSE: 6901322.654, MAE: 1709.306
--------------------------------------------------
Training and evaluating Random Forest Regressor...
Random Forest Regressor - R-squared: 0.930, MSE: 3493466.544, MAE: 1286.072
--------------------------------------------------
Training and evaluating Gradient Boosting Regressor...
Gradient Boosting Regressor - R-squared: 0.930, MSE: 3489361.476, MAE: 1334.132
--------------------------------------------------
Training and evaluating Support Vector Regressor...
Support Vector Regressor - R-squared: -0.055, MSE: 52868726.512, MAE: 4870.108
--------------------------------------------------

Comparison of Model Performance:
                             R-squared           MSE          MAE
Linear Regression            -0.596554  7.997988e+07  4303.487327
Decision Tree Regressor       0.862236  6.901323e+06  1709.306297
Random Forest Regressor       0.930264  3.493467e+06  1286.071703
Gradient Boosting Regressor   0.930346  3.489361e+06  1334.132024
Support Vector Regressor     -0.055363  5.286873e+07  4870.107576

Sorted Results by R-squared:
                             R-squared           MSE          MAE
Gradient Boosting Regressor   0.930346  3.489361e+06  1334.132024
Random Forest Regressor       0.930264  3.493467e+06  1286.071703
Decision Tree Regressor       0.862236  6.901323e+06  1709.306297
Support Vector Regressor     -0.055363  5.286873e+07  4870.107576
Linear Regression            -0.596554  7.997988e+07  4303.487327
```

1. R-squared (Coefficient of Determination):

Interpretation:

R-squared quantifies how well the model explains the variability in the target variable. A higher value, closer to 1, indicates a better fit.

Ranking (Highest to Lowest):

1. **Gradient Boosting Regressor**: 0.9303
2. **Random Forest Regressor**: 0.9303
3. **Decision Tree Regressor**: 0.8622
4. **Support Vector Regressor**: -0.0554 (a negative value indicates a poor fit)
5. **Linear Regression**: -0.5966 (a negative value suggests the model performs worse than predicting the mean of the target variable)

Conclusion:

The **Gradient Boosting Regressor** exhibits the highest R-squared value, demonstrating the best ability to explain the variability in the data.

---

2. Mean Squared Error (MSE):

Interpretation:

MSE represents the average squared difference between the predicted and actual values. Lower MSE values are preferred, indicating better model performance.

Ranking (Lowest to Highest):

1. **Gradient Boosting Regressor**: $3.4894 * 10^6$
2. **Random Forest Regressor**: $3.4935 * 10^6$
3. **Decision Tree Regressor**: $6.9013 * 10^6$
4. **Support Vector Regressor**: $5.2869 * 10^7$
5. **Linear Regression**: $7.9980 * 10^7$

Conclusion:
The **Gradient Boosting Regressor** achieves the lowest MSE, signifying that it produces the smallest squared errors and is the most accurate in terms of prediction.

---

3. Mean Absolute Error (MAE):

Interpretation:
MAE measures the average absolute difference between the predicted and actual values. Lower values indicate better accuracy, with fewer deviations from the true values.

Ranking (Lowest to Highest):

1. **Random Forest Regressor**: 1286.07
2. **Gradient Boosting Regressor**: 1334.13
3. **Decision Tree Regressor**: 1709.31
4. **Linear Regression**: 4303.49
5. **Support Vector Regressor**: 4870.11

Conclusion:
The **Random Forest Regressor** yields the lowest MAE, demonstrating the closest alignment between its predictions and the actual values.

Final Recommendation:

When considering both **R-squared** and **MSE**, the **Gradient Boosting Regressor** stands out as the best model overall. It effectively explains the variance in the data and produces the smallest squared errors.

However, if minimizing absolute errors (MAE) is of paramount importance, the **Random Forest Regressor** slightly edges out Gradient Boosting. Despite this, the differences in performance between the two models are minimal.

Given its balanced performance across multiple metrics, **Gradient Boosting Regressor** is recommended as the optimal model for predicting car prices.

FEATURE IMPORTANCE ANALYSIS

In [84]:
```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

# Calculate correlation of price with each feature
correlation_with_price = df.corr()["price"].sort_values(ascending=False)
correlation_table = correlation_with_price.to_frame(name="Correlation with Price")

# Filter the table to display only positive correlation values
positive_correlation_table = correlation_table[correlation_table["Correlation with Price"] > 0]

# Display the filtered table
print("Features with Positive Correlation with Price:")
display(positive_correlation_table)
```

```
Features with Positive Correlation with Price:
```

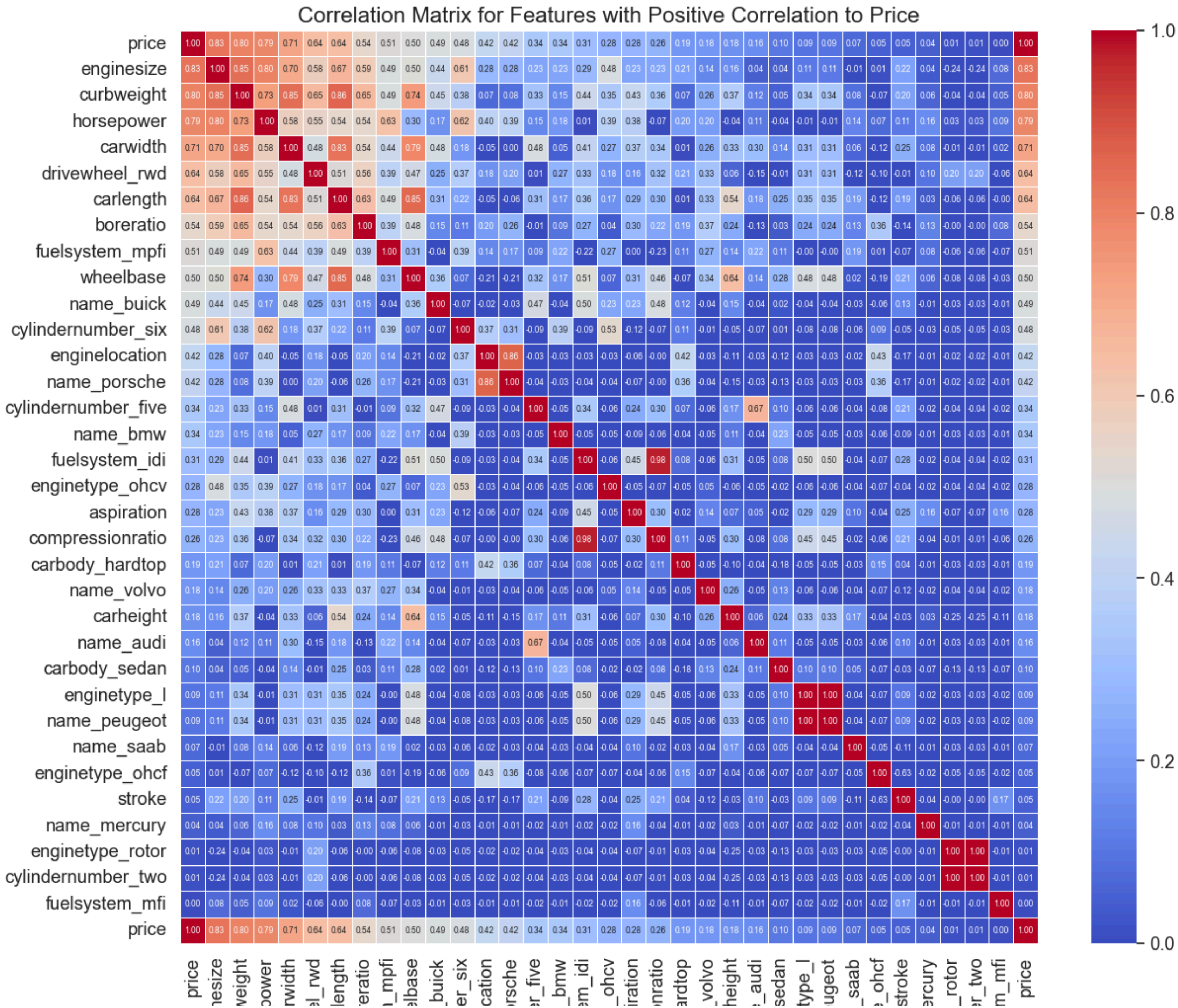
	Correlation with Price
price	1.000000
enginesize	0.830473
curbweight	0.802365
horsepower	0.792024
carwidth	0.711771
drivewheel_rwd	0.638593
carlength	0.638258
boreratio	0.536939
fuelsystem_mpfi	0.509319
wheelbase	0.499827
name_buick	0.491968
cylindernumber_six	0.484293
enginelocation	0.423143
name_porsche	0.420193
cylindernumber_five	0.342106
name_bmw	0.338747
fuelsystem_idi	0.305847
enginetype_ohcv	0.280770
aspiration	0.279749
compressionratio	0.263098
carbody_hardtop	0.188320
name_volvo	0.181358

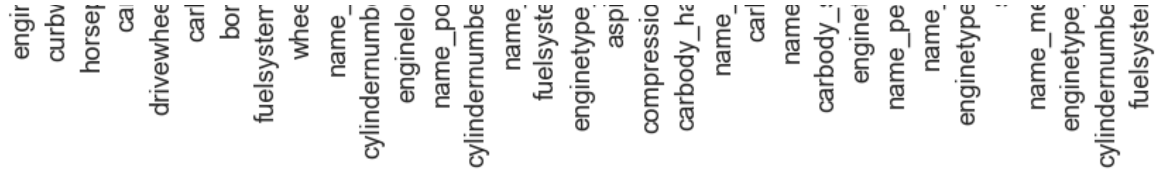
	Correlation with Price
carheight	0.175122
name_audi	0.157468
carbody_sedan	0.103060
enginetype_l	0.094218
name_peugeot	0.094218
name_saab	0.067297
enginetype_ohcf	0.052134
stroke	0.051856
name_mercury	0.043512
enginetype_rotor	0.010037
cylindernumber_two	0.010037
fuelsystem_mfi	0.004357

In [86]:

```
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt

# Filter the correlation table for positive correlation values
positive_correlations = correlation_table[correlation_table["Correlation with Price"] > 0]

# Extract the feature names with positive correlation
positive_features = positive_correlations.index.tolist()

# Create a subset of the dataframe with only positive correlation features and price
positive_correlation_matrix = df[positive_features + ["price"]].corr()

# Adjust the font scale and create the heatmap
sns.set(font_scale=1.2)  # Adjust font scale for better readability
plt.figure(figsize=(14, 12))  # Adjust the figure size for larger boxes
sns.heatmap(
    positive_correlation_matrix,
```

```
    annot=True,
    fmt=".2f",  # Format the annotations to 2 decimal places
    annot_kws={"size": 6},  # Adjust the size of annotation text
    cmap="coolwarm",
    linewidths=0.5,
    vmin=0,  # Minimum correlation value (only positive correlations are shown)
)
plt.title("Correlation Matrix for Features with Positive Correlation to Price", fontsize=16)
plt.show()
```


Correlation Matrix for Features with Positive Correlation to Price
price
enginesize
curbweight
horsepower
carwidth
drivewheel_rwd
carlength
boreratio
fuelsystem_mpfi
wheelbase
name_buick
cylindernumber_six
enginelocation
name_porsche
cylindernumber_five
name_bmw
fuelsystem_idi
enginetype_ohcv
aspiration
compressionratio
carbody_hardtop
name_volvo
carheight
name_audi
carbody_sedan
enginetype_l
name_peugeot
name_saab
enginetype_ohcf
stroke
name_mercury
enginetype_rotor
cylindernumber_two
fuelsystem_mfi
price
1.0
0.8
0.6
0.4
0.2
0.0



To identify the key features most strongly correlated with car price, we typically categorize correlation values based on the following thresholds:

- **Strong correlation**: Absolute correlation value ≥ 0.7
- **Moderate correlation**: Absolute correlation value between 0.5 and 0.7
- **Weak correlation**: Absolute correlation value < 0.5

Based on these criteria, the features exhibiting a **strong correlation** (correlation coefficient ≥ 0.7) with car price are as follows:

1. **Engine Size**: 0.8305
2. **Curb Weight**: 0.8024
3. **Horsepower**: 0.7920
4. **Car Width**: 0.7118

These features demonstrate the highest levels of correlation with car price and are likely to be significant predictors in the model.

HYPER PARAMETER TUNING

In [89]:
```python
from sklearn.model_selection import GridSearchCV
from sklearn.ensemble import RandomForestRegressor, GradientBoostingRegressor
from sklearn.tree import DecisionTreeRegressor
from sklearn.svm import SVR
from sklearn.linear_model import LinearRegression
from sklearn.metrics import r2_score, mean_squared_error, mean_absolute_error

# Define parameter grids for each model
param_grid_rf = {
    'n_estimators': [100, 200, 300],
    'max_depth': [10, 20, 30],
    'min_samples_split': [2, 5, 10],
    'min_samples_leaf': [1, 2, 4]
}

param_grid_gb = {
    'n_estimators': [100, 200, 300],
    'learning_rate': [0.01, 0.1, 0.2],
    'max_depth': [3, 5, 7],
    'subsample': [0.8, 1.0]
}

param_grid_dt = {
    'max_depth': [10, 20, 30],
    'min_samples_split': [2, 5, 10],
    'min_samples_leaf': [1, 2, 4]
}

param_grid_svr = {
    'C': [0.1, 1, 10],
    'kernel': ['linear', 'rbf', 'poly'],
    'epsilon': [0.1, 0.2, 0.5],
    'gamma': ['scale', 'auto']
}

# Linear Regression has no hyperparameters to tune in this case
```

```
param_grid_lr = {}

# Initialize models
models = {
    "Random Forest": (RandomForestRegressor(random_state=42), param_grid_rf),
    "Gradient Boosting": (GradientBoostingRegressor(random_state=42), param_grid_gb),
    "Decision Tree": (DecisionTreeRegressor(random_state=42), param_grid_dt),
    "Support Vector Regressor": (SVR(), param_grid_svr),
    "Linear Regression": (LinearRegression(), param_grid_lr)
}

# Perform GridSearchCV and evaluate performance
best_estimators = {}
for model_name, (model, param_grid) in models.items():
    print(f"Performing GridSearchCV for {model_name}...")

    if param_grid:  # Skip GridSearchCV for models with no hyperparameters to tune
        grid_search = GridSearchCV(model, param_grid, cv=3, scoring='r2', n_jobs=-1)
        grid_search.fit(X_train, y_train)
        best_model = grid_search.best_estimator_
        print(f"Best parameters for {model_name}: {grid_search.best_params_}")
    else:
        model.fit(X_train, y_train)  # Train model directly for Linear Regression
        best_model = model

    # Store the best estimator
    best_estimators[model_name] = best_model

    # Evaluate performance on the test set
    y_pred = best_model.predict(X_test)
    r2 = r2_score(y_test, y_pred)
    mse = mean_squared_error(y_test, y_pred)
    mae = mean_absolute_error(y_test, y_pred)
    print(f"{model_name} Performance after Hyperparameter Tuning:")
    print(f"R-squared: {r2:.4f}")
    print(f"Mean Squared Error: {mse:.4f}")
    print(f"Mean Absolute Error: {mae:.4f}")
    print("-" * 50)
```

```
Performing GridSearchCV for Random Forest...
Best parameters for Random Forest: {'max_depth': 10, 'min_samples_leaf': 1, 'min_samples_split': 2, 'n_estimators': 1
00}
Random Forest Performance after Hyperparameter Tuning:
R-squared: 0.9282
Mean Squared Error: 3595887.4571
Mean Absolute Error: 1295.1399
--------------------------------------------------
Performing GridSearchCV for Gradient Boosting...
Best parameters for Gradient Boosting: {'learning_rate': 0.1, 'max_depth': 5, 'n_estimators': 100, 'subsample': 0.8}
Gradient Boosting Performance after Hyperparameter Tuning:
R-squared: 0.9094
Mean Squared Error: 4538433.5470
Mean Absolute Error: 1451.8173
--------------------------------------------------
Performing GridSearchCV for Decision Tree...
Best parameters for Decision Tree: {'max_depth': 10, 'min_samples_leaf': 1, 'min_samples_split': 5}
Decision Tree Performance after Hyperparameter Tuning:
R-squared: 0.8518
Mean Squared Error: 7426333.2763
Mean Absolute Error: 1689.4226
--------------------------------------------------
Performing GridSearchCV for Support Vector Regressor...
Best parameters for Support Vector Regressor: {'C': 10, 'epsilon': 0.5, 'gamma': 'scale', 'kernel': 'linear'}
Support Vector Regressor Performance after Hyperparameter Tuning:
R-squared: 0.6652
Mean Squared Error: 16772056.3722
Mean Absolute Error: 2135.2316
--------------------------------------------------
Performing GridSearchCV for Linear Regression...
Linear Regression Performance after Hyperparameter Tuning:
R-squared: -0.5966
Mean Squared Error: 79979879.0405
Mean Absolute Error: 4303.4873
--------------------------------------------------
```

Model Performance Evaluation: Tuning Results

1. Gradient Boosting Regressor

Before Tuning:

- **R-squared**: 0.9303
- **MSE**: 3.489361 * 10^6
- **MAE**: 1334.1320

After Tuning:

- **R-squared**: 0.9094 (↓)
- **MSE**: 4.538433 * 10^6 (↑)
- **MAE**: 1451.8173 (↑)

Observation: The model performance **decreased** after tuning. There was a slight drop in the R-squared value, indicating a marginally worse fit. Additionally, both MSE and MAE increased, suggesting that the tuning led to a deterioration in prediction accuracy, potentially due to overfitting or suboptimal hyperparameters.

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2. Random Forest Regressor

Before Tuning:

- **R-squared**: 0.9303

- **MSE**: 3.493467 * 10^6
- **MAE**: 1286.0717

After Tuning:

- **R-squared**: 0.9282 (↓)
- **MSE**: 3.595887 * 10^6 (↑)
- **MAE**: 1295.1399 (↑)

Observation: The performance of the Random Forest Regressor **slightly decreased** after tuning. Although the changes are minor, both the R-squared and MAE showed a slight decline, while MSE increased. These results indicate that the model's ability to predict accurately marginally worsened, possibly due to the model becoming slightly overfitted during tuning.

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3. Decision Tree Regressor

Before Tuning:

- **R-squared**: 0.8622
- **MSE**: 6.901323 * 10^6
- **MAE**: 1709.3063

After Tuning:

- **R-squared**: 0.8518 (↓)
- **MSE**: 7.426333 * 10^6 (↑)
- **MAE**: 1689.4226 (↓)

Observation: The Decision Tree Regressor also exhibited **a slight decrease in performance** post-tuning. While the R-squared dropped, the MSE increased, and MAE showed a small improvement. This indicates that tuning had a minor effect on the model, with some improvement in terms of error measurement, though the overall model fit worsened slightly.

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4. Support Vector Regressor (SVR)

Before Tuning:

- **R-squared**: -0.0554
- **MSE**: 5.286873 * 10^7
- **MAE**: 4870.1076

After Tuning:

- **R-squared**: 0.6652 (↑)
- **MSE**: 1.677206 * 10^7 (↓)
- **MAE**: 2135.2316 (↓)

Observation: The **Support Vector Regressor showed significant improvement** after tuning. The R-squared increased substantially, turning positive and rising dramatically, indicating a much better fit to the data. Additionally, both MSE and MAE decreased considerably, confirming that the tuning enhanced the model's predictive performance significantly, making it much more competitive.

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5. Linear Regression

Before Tuning:

- **R-squared**: -0.5966
- **MSE**: 7.997988 * 10^7
- **MAE**: 4303.4873

After Tuning:

- **R-squared**: -0.5966 (no change)
- **MSE**: 7.997988 * 10^7 (no change)

- **MAE**: 4303.4873 (no change)

Observation: The **Linear Regression model did not experience any change** post-tuning, as hyperparameter tuning is generally not applicable to this model. The model's performance remained unchanged, with no improvement or degradation observed.

Conclusion:

The Support Vector Regressor (SVR) demonstrated the most substantial improvement after tuning. The model's R-squared increased significantly, turning positive, while both MSE and MAE showed marked reductions, making SVR a much more viable option for predicting car prices after tuning.

In contrast, the performance of both **Gradient Boosting** and **Random Forest** models slightly declined after tuning. This could indicate that the hyperparameter tuning resulted in a slight overfitting of the model or that the parameter combinations were not optimal.

The **Decision Tree Regressor** also showed a marginal decrease in performance, although MAE improved slightly, suggesting that the model's error metrics were somewhat optimized post-tuning.

Lastly, **Linear Regression** did not exhibit any change in performance, as no tuning was applied to this model.

In summary, **SVR** emerged as the most improved model, although it still did not outperform Gradient Boosting or Random Forest in terms of R-squared. Nonetheless, the significant improvement in its performance after tuning makes it a more competitive model in the regression task for car prices.

In [ ]:

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