In [1]:
```
import numpy as np
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestRegressor, GradientBoostingRegressor
from sklearn.metrics import mean_squared_error,mean_absolute_error,r2_score
from sklearn.preprocessing import StandardScaler,LabelEncoder
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.linear_model import LinearRegression
from sklearn.tree import DecisionTreeRegressor
from sklearn.svm import SVR
from sklearn.feature_selection import SelectKBest,f_regression,RFE
```

In [2]:
```
Data = pd.read_csv('CarPrice_Assignment.csv')
```

In [3]:
```
df = pd.DataFrame(Data)
```

In [4]:
```
df.head(2)
```

Out[4]:

	car_ID	symboling	CarName	fueltype	aspiration	doornumber	carbody	drivewheel
0	1	3	alfa-romero giulia	gas	std	two	convertible	rwd
1	2	3	alfa-romero stelvio	gas	std	two	convertible	rwd

2 rows × 26 columns

In [5]:
```
df.describe()
```

Out[5]:

	car_ID	symboling	wheelbase	carlength	carwidth	carheight	curbweight
count	205.000000	205.000000	205.000000	205.000000	205.000000	205.000000	205.00000C
mean	103.000000	0.834146	98.756585	174.049268	65.907805	53.724878	2555.56585
std	59.322565	1.245307	6.021776	12.337289	2.145204	2.443522	520.68020
min	1.000000	-2.000000	86.600000	141.100000	60.300000	47.800000	1488.00000
25%	52.000000	0.000000	94.500000	166.300000	64.100000	52.000000	2145.00000
50%	103.000000	1.000000	97.000000	173.200000	65.500000	54.100000	2414.00000
75%	154.000000	2.000000	102.400000	183.100000	66.900000	55.500000	2935.00000
max	205.000000	3.000000	120.900000	208.100000	72.300000	59.800000	4066.00000

In [6]:
```
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
```

In [7]:
```
df.isnull().sum()
```

Out[7]:
```
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
```

In [8]:
```
df.duplicated().sum()
```

Out[8]:
```
0
```

In [9]:
```
import warnings
warnings.filterwarnings('ignore')
```

In [10]:
```
num_df = df.select_dtypes(include=['int64', 'float64'])

skewness = num_df.skew()
kurtosis = num_df.kurt()
```

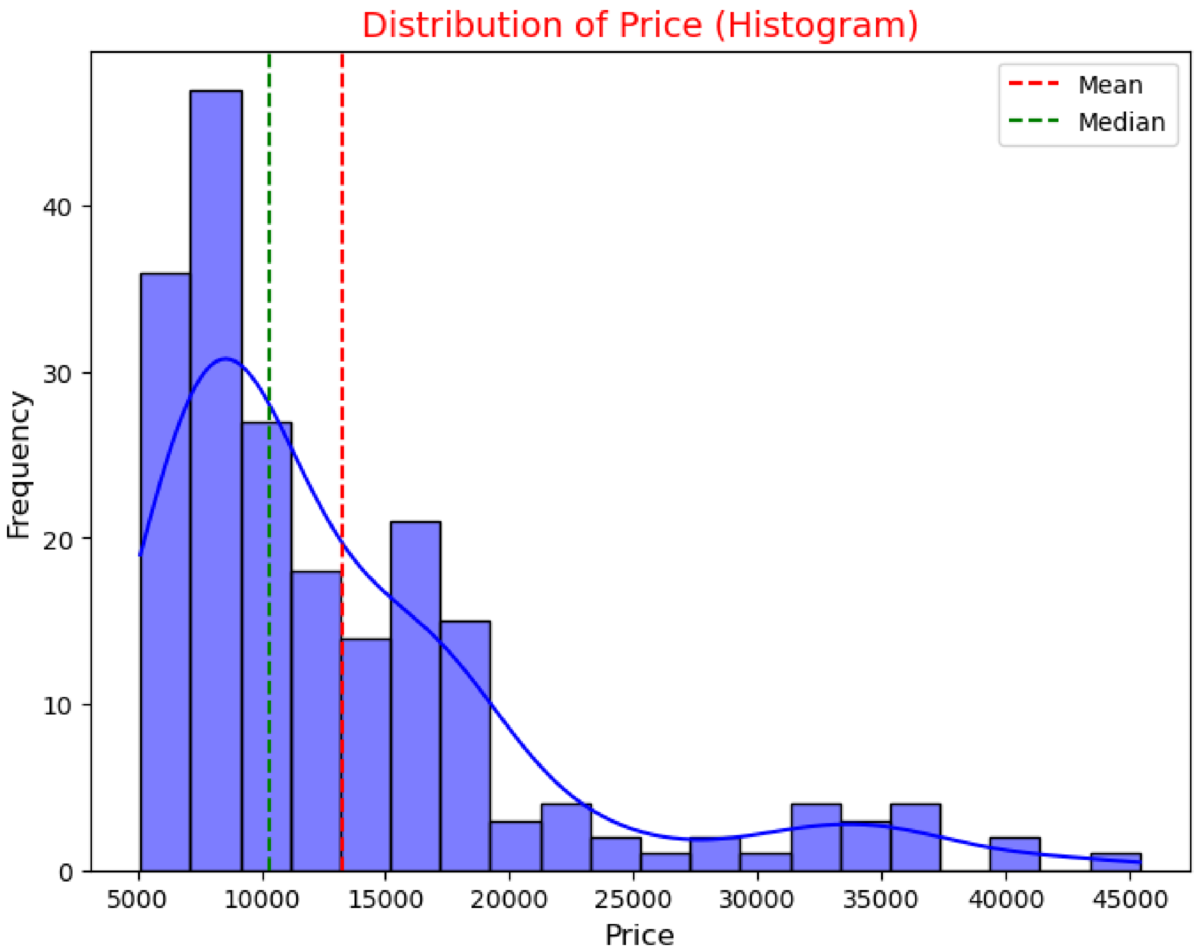
In [11]:
```
skewness
```

Out[11]:
```
car_ID              0.000000
symboling           0.211072
wheelbase           1.050214
carlength           0.155954
carwidth            0.904003
carheight           0.063123
curbweight          0.681398
enginesize          1.947655
boreratio           0.020156
stroke             -0.689705
compressionratio    2.610862
horsepower          1.405310
peakrpm             0.075159
citympg             0.663704
highwaympg          0.539997
price               1.777678
dtype: float64
```

In [12]:
```
kurtosis
```

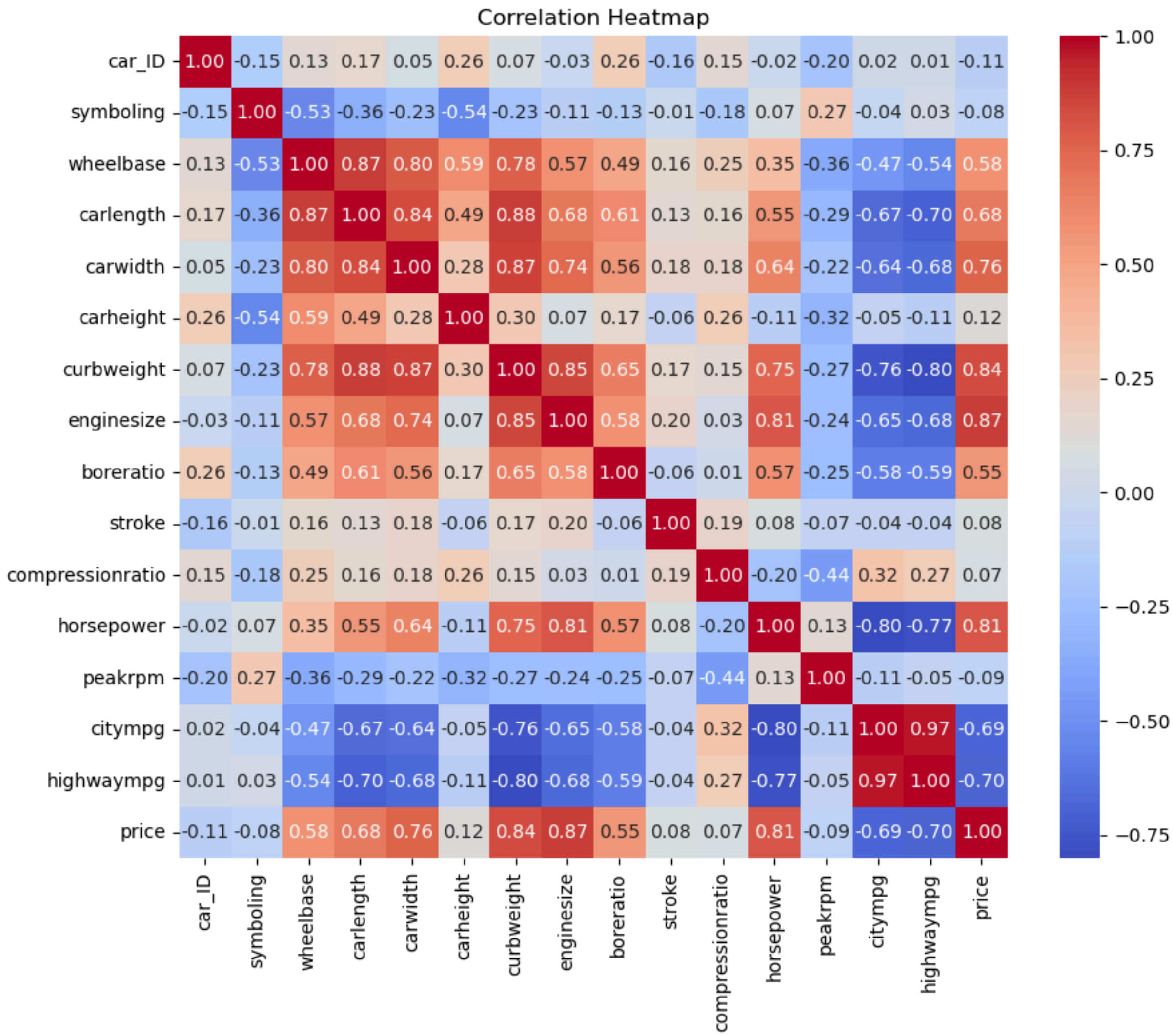
Out[12]:
```
car_ID             -1.200000
symboling          -0.676271
wheelbase           1.017039
carlength          -0.082895
carwidth            0.702764
carheight          -0.443812
curbweight         -0.042854
enginesize          5.305682
boreratio          -0.785042
stroke              2.174396
compressionratio    5.233054
horsepower          2.684006
peakrpm             0.086756
citympg             0.578648
highwaympg          0.440070
price               3.051648
dtype: float64
```

In [13]:
```
plt.figure(figsize=(8, 6))
sns.histplot(df['price'], kde=True, bins=20, color='blue')
plt.title('Distribution of Price (Histogram)', fontsize=14,color='red')
plt.axvline(df['price'].mean(), color='red', linestyle='--', label='Mean')
plt.axvline(df['price'].median(), color='green', linestyle='--', label='Median')
plt.xlabel('Price', fontsize=12)
plt.ylabel('Frequency', fontsize=12)
plt.legend(fontsize=10)
plt.show()
```

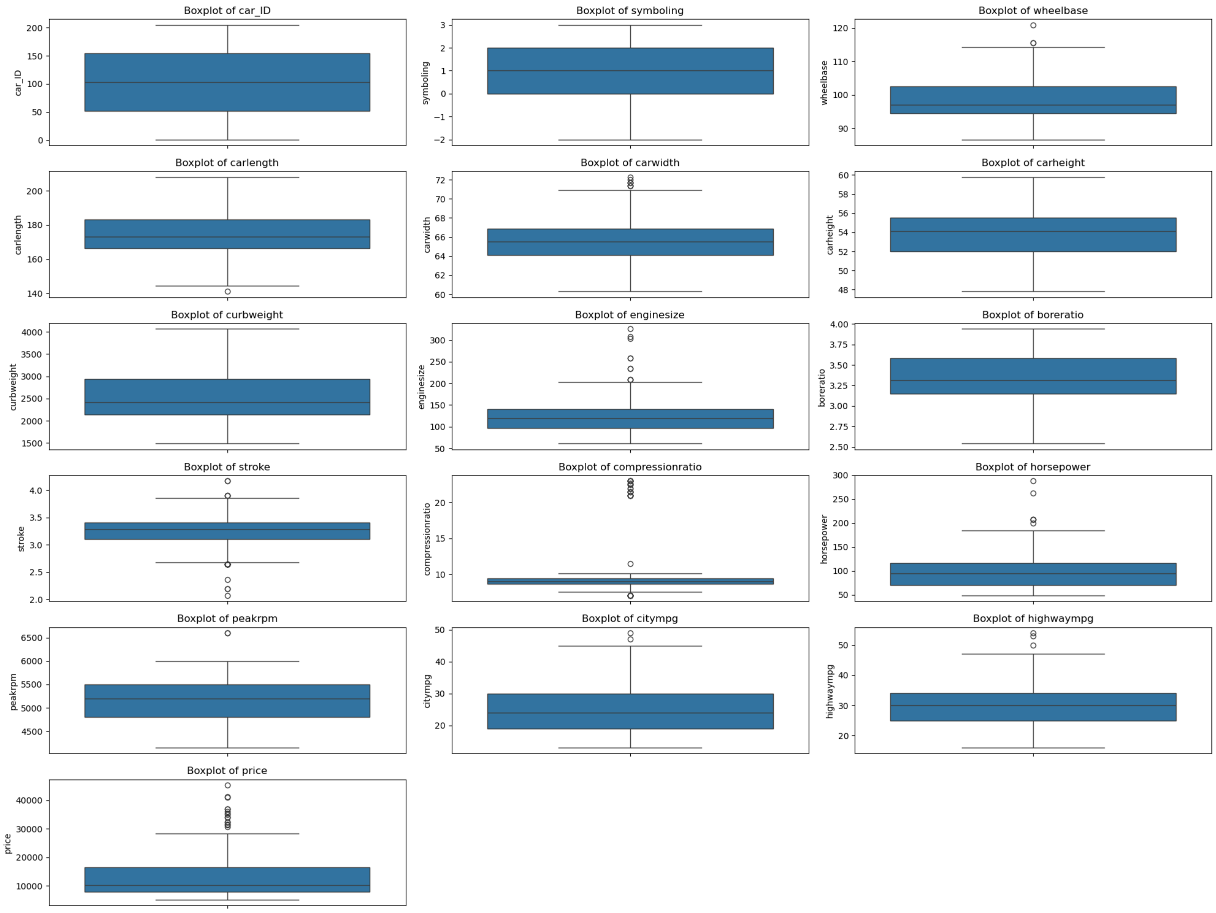


In [26]:
```
correlation_matrix = num_df.corr()

plt.figure(figsize=(10, 8))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', fmt=".2f")
plt.title("Correlation Heatmap")
plt.show()
```

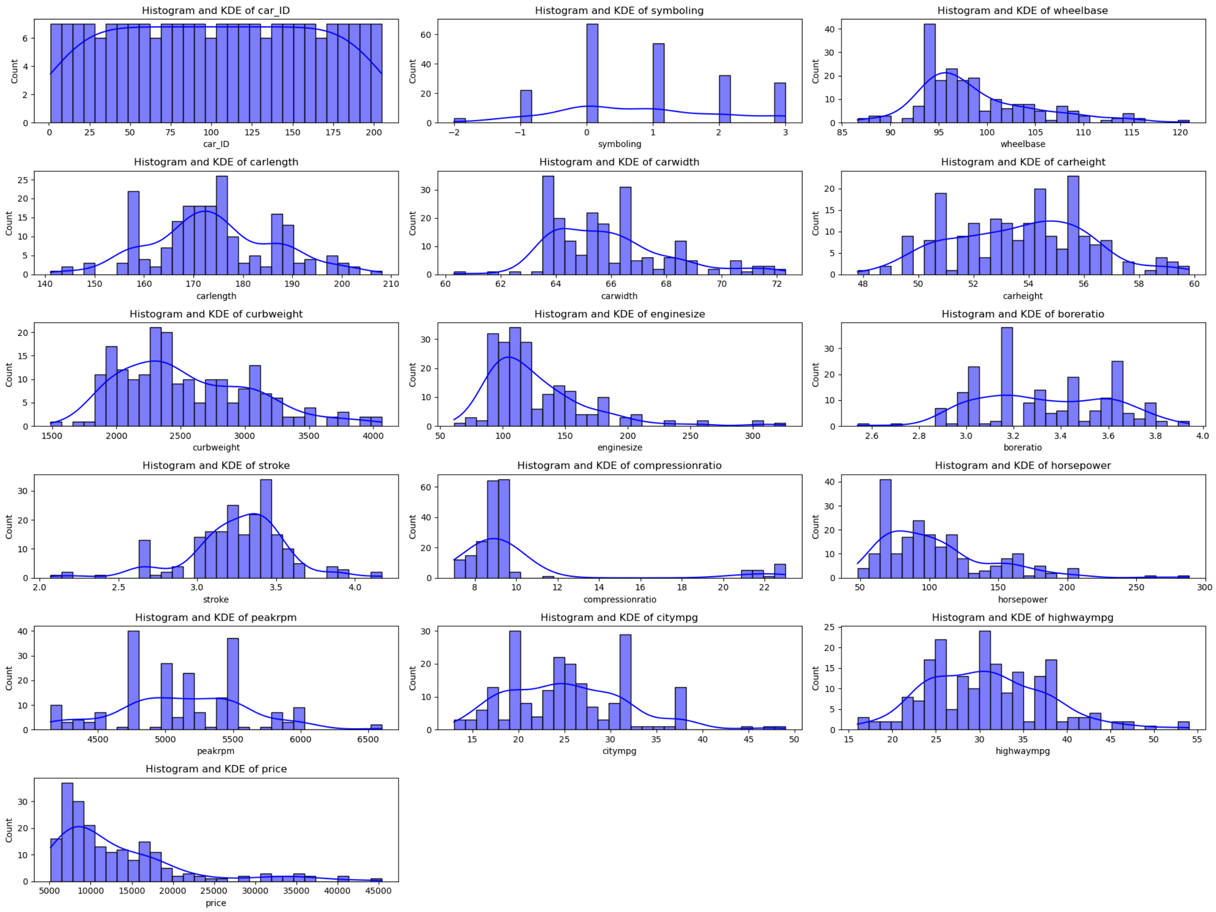


In [28]:
```
# Select only numerical columns
numerical_columns = df.select_dtypes(include=['float64', 'int64']).columns
# Set up the plot size
plt.figure(figsize=(20, 15))
# Loop through each numerical column and draw a boxplot
for i, column in enumerate(numerical_columns, 1):
 plt.subplot(len(numerical_columns) // 3 + 1, 3, i)
 sns.boxplot(data=df, y=column)
 plt.title(f"Boxplot of {column}")
 plt.tight_layout()
plt.show()
```



In [29]:

```
# Select only numerical columns
numerical_columns = df.select_dtypes(include=['float64', 'int64']).columns
# Set up the plot size
plt.figure(figsize=(20, 15))
# Loop through each numerical column and draw a histogram with KDE
for i, column in enumerate(numerical_columns, 1):
 plt.subplot(len(numerical_columns) // 3 + 1, 3, i)
 sns.histplot(data=df, x=column, kde=True, color='blue', bins=30)
 plt.title(f"Histogram and KDE of {column}")
 plt.tight_layout()
plt.show()
```



In [31]:
```
df.head(10)
```

Out[31]:

	car_ID	symboling	CarName	fueltype	aspiration	doornumber	carbody	drivewhe
0	1	3	alfa-romero giulia	gas	std	two	convertible	rv
1	2	3	alfa-romero stelvio	gas	std	two	convertible	rv
2	3	1	alfa-romero Quadrifoglio	gas	std	two	hatchback	rv
3	4	2	audi 100 ls	gas	std	four	sedan	fv
4	5	2	audi 100ls	gas	std	four	sedan	4v
5	6	2	audi fox	gas	std	two	sedan	fv
6	7	1	audi 100ls	gas	std	four	sedan	fv
7	8	1	audi 5000	gas	std	four	wagon	fv
8	9	1	audi 4000	gas	turbo	four	sedan	fv
9	10	0	audi 5000s (diesel)	gas	turbo	two	hatchback	4v

10 rows × 26 columns

In [32]:

```
# Identify numerical columns
numerical_columns = df.select_dtypes(include=['int64', 'float64']).columns
# Detect outliers using IQR for each column
for col in numerical_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

 # Count outliers
 outliers = df[(df[col] < lower_bound) | (df[col] > upper_bound)]
 print(f"Column: {col}, Outliers: {len(outliers)}")
```

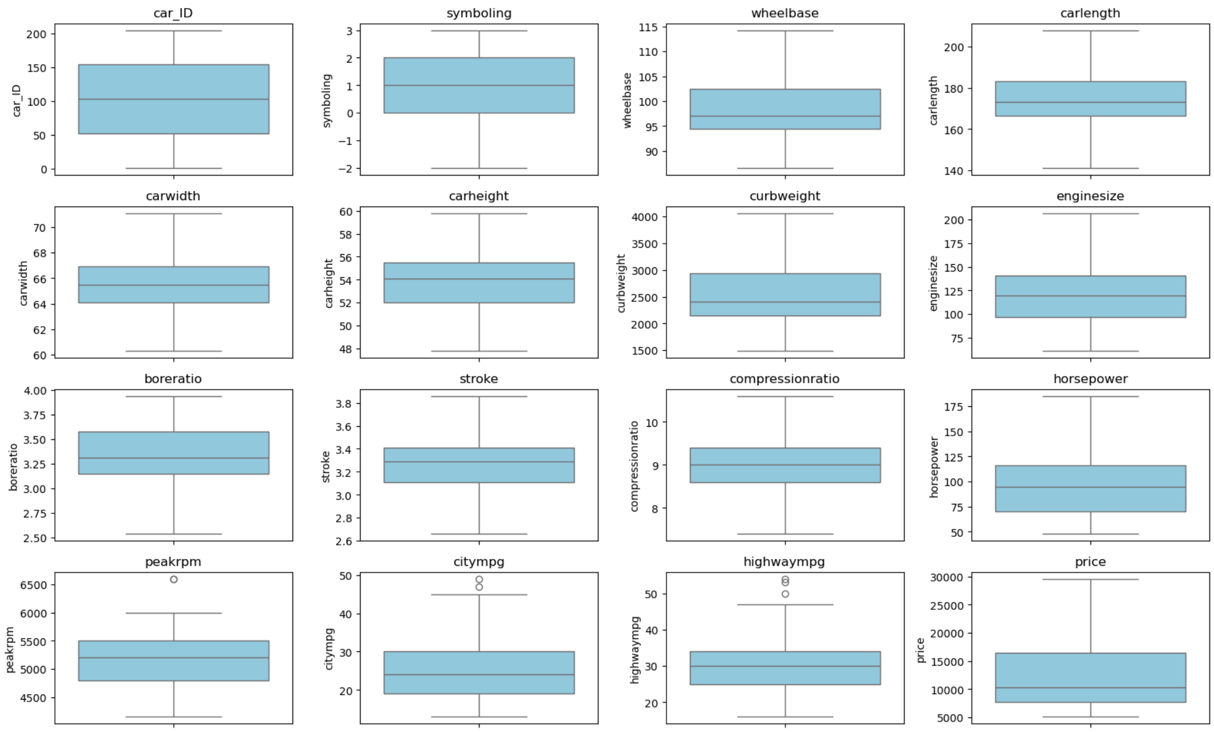
```
Column: car_ID, Outliers: 0
Column: symboling, Outliers: 0
Column: wheelbase, Outliers: 3
Column: carlength, Outliers: 1
Column: carwidth, Outliers: 8
Column: carheight, Outliers: 0
Column: curbweight, Outliers: 0
Column: enginesize, Outliers: 10
Column: boreratio, Outliers: 0
Column: stroke, Outliers: 20
Column: compressionratio, Outliers: 28
Column: horsepower, Outliers: 6
Column: peakrpm, Outliers: 2
Column: citympg, Outliers: 2
Column: highwaympg, Outliers: 3
Column: price, Outliers: 15
```

In [33]:

```python
# Create a cleaned dataset
df_cleaned = df.copy()
# List of columns to check for outliers
columns_with_outliers = ['wheelbase', 'carlength', 'carwidth', 'enginesize', 'strok
# Capping outliers
for column in columns_with_outliers:
 Q1 = df_cleaned[column].quantile(0.25)
 Q3 = df_cleaned[column].quantile(0.75)
 IQR = Q3 - Q1
 lower_bound = Q1 - 1.5 * IQR
 upper_bound = Q3 + 1.5 * IQR
 # Cap the outliers
 df_cleaned[column] = df_cleaned[column].apply(lambda x: lower_bound if x < lower_b
```

In [36]:

```python
# Set up the figure size
plt.figure(figsize=(16, 12))
# Create boxplots for all numeric columns in df_cleaned
for i, column in enumerate(df_cleaned.select_dtypes(include='number').columns, 1):
 plt.subplot(5, 4, i) # Create a grid of subplots (adjust rows/cols as needed)
 sns.boxplot(y=df_cleaned[column], color='skyblue')
 plt.title(column)
# Adjust layout to avoid overlap
plt.tight_layout()
plt.show()
```



In [ ]:
```
# Encoding
```

In [37]:
```
# Creating a new dataframe df_cleaned based on the original df
df_cleaned = df.copy()
# Label encoding for the 'symboling' column (ordinal data)
label_encoder = LabelEncoder()
df_cleaned['symboling'] = label_encoder.fit_transform(df_cleaned['symboling'])
# One-Hot Encoding for categorical columns (nominal data)
df_cleaned = pd.get_dummies(df_cleaned, columns=['fueltype', 'aspiration', 'doornum
 'carbody', 'drivewheel', 'enginelocation','wheelbase','carlength','carwidth','carh
 'enginetype', 'cylindernumber', 'enginesize','fuelsystem','boreratio','stroke','co

# Check the first few rows to confirm the encoding
df_cleaned.head()
```

Out[37]:

	car_ID	symboling	CarName	curbweight	price	fueltype_diesel	fueltype_gas	aspi
0	1	5	alfa-romero giulia	2548	13495.0	False	True	
1	2	5	alfa-romero stelvio	2548	16500.0	False	True	
2	3	3	alfa-romero Quadrifoglio	2823	16500.0	False	True	
3	4	4	audi 100 ls	2337	13950.0	False	True	
4	5	4	audi 100ls	2824	17450.0	False	True	

5 rows × 556 columns

In [76]:
```
numeric_columns = df_cleaned.select_dtypes(include=['int64', 'float64']).columns.to
numeric_columns.remove('price')
scaler = StandardScaler()
df_cleaned[numeric_columns] = scaler.fit_transform(df_cleaned[numeric_columns])
X = df_cleaned.drop(columns = ['price'])
y = df_cleaned['price']
```

In [78]:
```
# Split into train and test sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_sta
```

In [80]:
```
# Separate features (X) and target variable (y)
X = df_cleaned.drop(columns=['price']) # Features (all columns except 'price')
y = df_cleaned['price'] # Target variable ('price')
```

In [82]:
```
selector = SelectKBest(score_func=f_regression,k=20)
x_new = selector.fit_transform(X,y)
```

In [84]:
```
Selected_features = X.columns[selector.get_support()]
feature_score = pd.DataFrame({'features':X.columns,'score':selector.scores_}).sort_
```

In [86]:
```
print("Selected Features:", Selected_features)
print("\nFeature Scores:")
print(feature_score)
```

```
Selected Features: Index(['curbweight', 'drivewheel_fwd', 'drivewheel_rwd', 'enginet
ype_ohc',
       'enginetype_ohcv', 'cylindernumber_eight', 'cylindernumber_four',
       'cylindernumber_six', 'enginesize_209', 'fuelsystem_2bbl',
       'fuelsystem_mpfi', 'boreratio_3.8', 'compressionratio_8.0',
       'horsepower_182', 'horsepower_184', 'peakrpm_4750', 'citympg_14',
       'citympg_16', 'highwaympg_16', 'highwaympg_25'],
      dtype='object')

Feature Scores:
                  features       score
2               curbweight  468.594431
249    cylindernumber_four  192.612277
16          drivewheel_rwd  140.059236
15          drivewheel_fwd  115.353549
303        fuelsystem_mpfi   74.082624
..                     ...         ...
382   compressionratio_7.5    0.000788
127        carlength_181.7    0.000774
443         horsepower_111    0.000100
227          carheight_55.7    0.000036
222          carheight_55.1    0.000006

[554 rows x 2 columns]
```

In [88]:
```
X_selected = X[Selected_features]
X_train_selected, X_test_selected, y_train, y_test = train_test_split(X_selected, y
```

In [90]:
```
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train_selected)
```

```
X_test_scaled = scaler.fit_transform(X_test_selected)
```

In [92]:
```
# Initialize models
models={"Linear Regression":LinearRegression(),
 "Decision Tree Regressor":DecisionTreeRegressor(),
"Random Forest Regressor":RandomForestRegressor(),
"Gradient Boosting Regressor":GradientBoostingRegressor(),
"Support Vector Regressor":SVR()}
```

In [94]:
```
print("Training set shape (features):", X_train_scaled.shape)
print("Test set shape (features):", X_test_scaled.shape)
print("Training set shape (target):", y_train.shape)
print("Test set shape (target):", y_test.shape)
```

```
Training set shape (features): (164, 20)
Test set shape (features): (41, 20)
Training set shape (target): (164,)
Test set shape (target): (41,)
```

In [98]:
```
# MODEL EVALUATION
results={}       # use to store evaluation result

for model_name, model in models.items():
    # fit the model
    model.fit(X_train_scaled,y_train)
    # make the prediction
    y_pred = model.predict(X_test_scaled)
    # Evaluate the model
    mse = mean_squared_error(y_test,y_pred)
    mae = mean_absolute_error(y_test,y_pred)
    r2 = r2_score(y_test,y_pred)
    rmse = np.sqrt(mean_squared_error(y_test,y_pred))
    # Store the results
    results[model_name] = {"MSE": mse, "MAE":mae,"RMSE":rmse,"R²": r2,}
```

In [100…
```
# Convert results to DataFrame for better visualization
results_df = pd.DataFrame(results).T
print(results_df)
```

```
                                      MSE          MAE         RMSE        R²
Linear Regression            9.542248e+06  2009.757898  3089.052863  0.879126
Decision Tree Regressor      1.518954e+07  2558.709341  3897.375512  0.807591
Random Forest Regressor      1.705659e+07  2498.787541  4129.962554  0.783941
Gradient Boosting Regressor  2.123520e+07  2517.967415  4608.166600  0.731009
Support Vector Regressor     8.670856e+07  5695.907738  9311.743165 -0.098355
```

In [102…
```
# Finding Best model
```

In [104…
```
best_model_name = max(results, key=lambda x: results[x]['R²'])
best_model = models[best_model_name]
print(f"The best model is: {best_model_name}")
```

```
The best model is: Linear Regression
```

In [106…
```
# Feature selection
```

In [112…

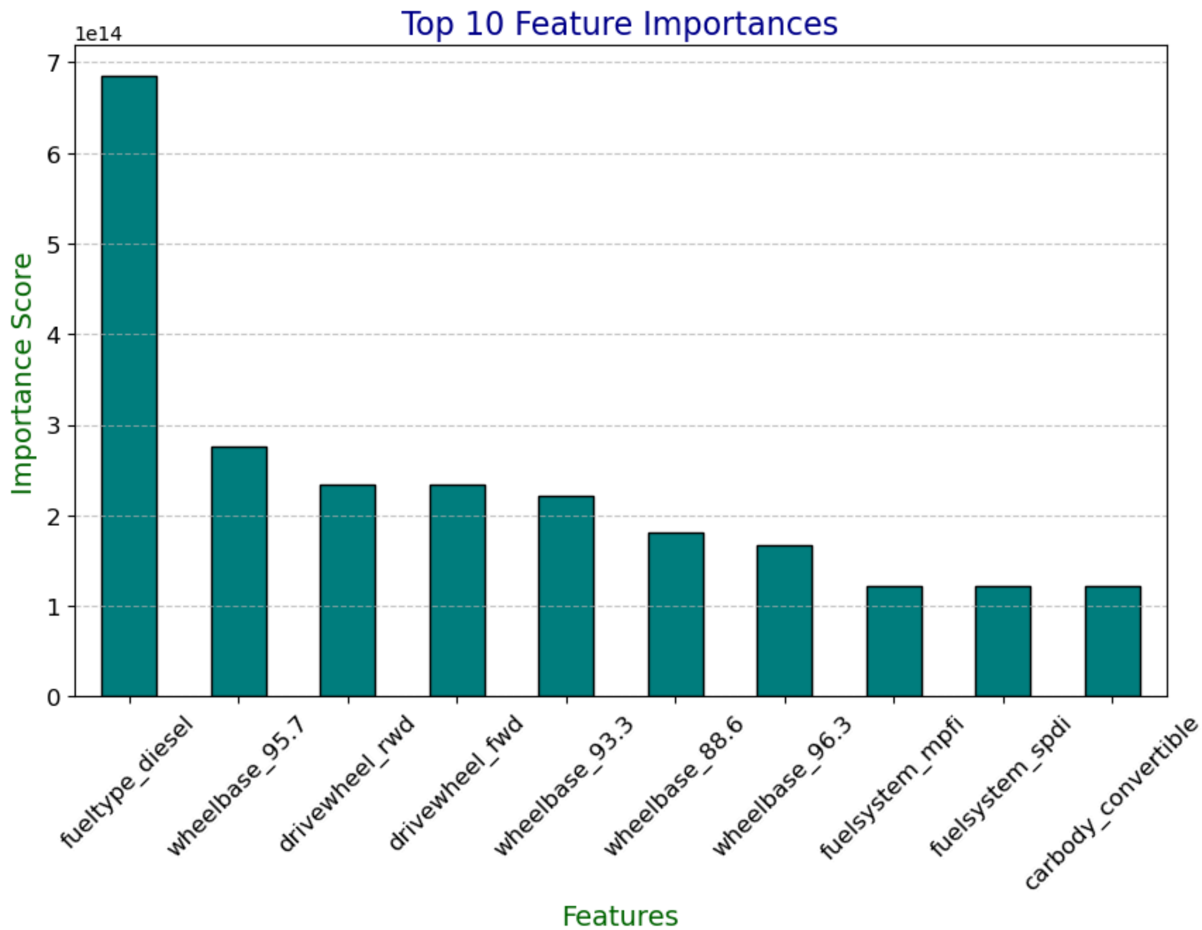
```
# Extract coefficients as feature importances
feature_importances = pd.Series(best_model.coef_, index=X.columns).sort_values(asce

# Display feature importances
print("Feature Importances (from coefficients):\n", feature_importances)
```

```
Feature Importances (from coefficients):
 fueltype_diesel     6.842782e+14
wheelbase_95.7      2.751550e+14
drivewheel_rwd      2.345453e+14
drivewheel_fwd      2.345453e+14
wheelbase_93.3      2.211978e+14
                        ...
wheelbase_102.0    -4.578681e+14
doornumber_two     -1.114616e+15
doornumber_four    -1.114616e+15
aspiration_turbo   -1.118583e+15
aspiration_std     -1.118583e+15
Length: 554, dtype: float64
```

In [116…

```
plt.figure(figsize=(10, 6))
feature_importances.head(10).plot(kind='bar', color='teal', edgecolor='black')
plt.title('Top 10 Feature Importances', fontsize=16, color='darkblue')
plt.xlabel('Features', fontsize=14, color='darkgreen')
plt.ylabel('Importance Score', fontsize=14, color='darkgreen')
plt.xticks(fontsize=12, rotation=45, color='black')
plt.yticks(fontsize=12, color='black')
plt.grid(axis='y', linestyle='--', alpha=0.7)
plt.show()
```


Top 10 Feature Importances
1e14
Importance Score
Features
fueltype_diesel
wheelbase_95.7
drivewheel_rwd
drivewheel_fwd
wheelbase_93.3
wheelbase_88.6
wheelbase_96.3
fuelsystem_mpfi
fuelsystem_spdi
carbody_convertible

In [ ]: