"Predicting Car Prices: A Machine Learning Approach for Market Strategy in the US Automotive Industry"

Name: Thoukeela T M

Overview of Problem Statement

A Chinese automobile company wants to enter the US market and compete with American and European car manufacturers. To succeed, they need to understand what factors affect car prices in the US and how these factors influence pricing.

Using a dataset of car specifications and their prices in the US, the goal is to create a machine learning model that:

Identifies the most important factors affecting car prices. Accurately predicts car prices based on these factors. This model will help the company make informed decisions about car design, production, and pricing strategies to compete effectively in the new market.

Objective

The objective of this project is to build a machine learning model that accurately predicts car prices in the US market based on various car features and specifications. This will help the company:

Identify significant factors influencing car prices. Understand how these factors affect pricing to inform car design and production. Develop pricing strategies aligned with market trends to compete effectively in the US automotive industry.

Data Description

```
Features:
The dataset includes the following features:
Make/Model: The brand and model of the car.
Year: The manufacturing year of the car.
Engine Size: The engine capacity (e.g., in liters).
Fuel Type: Type of fuel used (e.g., Petrol, Diesel, Electric).
Mileage: The fuel efficiency of the car (e.g., in miles per gallon).
Transmission: The type of transmission (e.g., Manual, Automatic).
horsepower: The power output of the engine.
Number of Doors: The total number of doors on the car.
Car Type: The type/category of the car (e.g., Sedan, SUV, Hatchback).
Price: The selling price of the car (Target variable).

import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.preprocessing import LabelEncoder, OneHotEncoder
```

```
from sklearn.feature_selection import SelectKBest, f_classif
from scipy.stats import skew
from sklearn.preprocessing import MinMaxScaler, StandardScaler
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 mean_absolute_error, mean_squared_error,
r2_score
from sklearn.model_selection import GridSearchCV
import joblib
import warnings
warnings.filterwarnings('ignore')
```

Data Collection:

```
# Load the dataset
data =
pd.read_csv("C:/Users/LENOVO/Downloads/CarPrice_Assignment.csv")
df = pd.DataFrame(data)
df

     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.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
```

Data Preprocessing - Data Cleaning

```
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
```

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

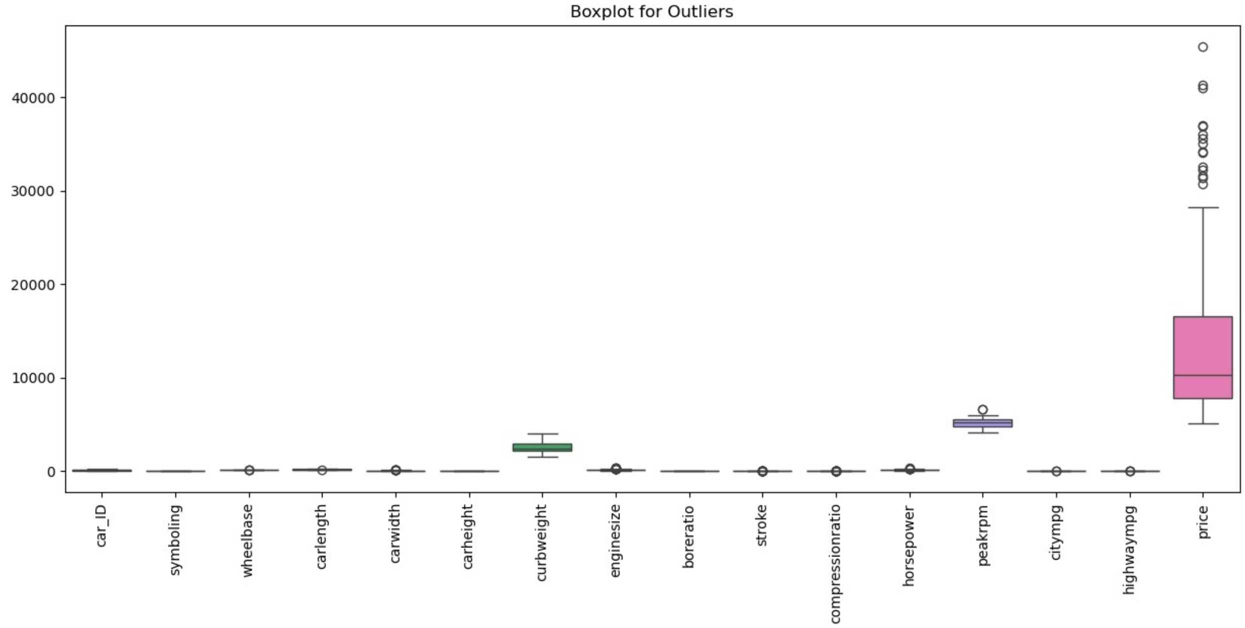
```
0
```

```
df.shape
```

```
(205, 26)
```

Check for and Remove Outliers

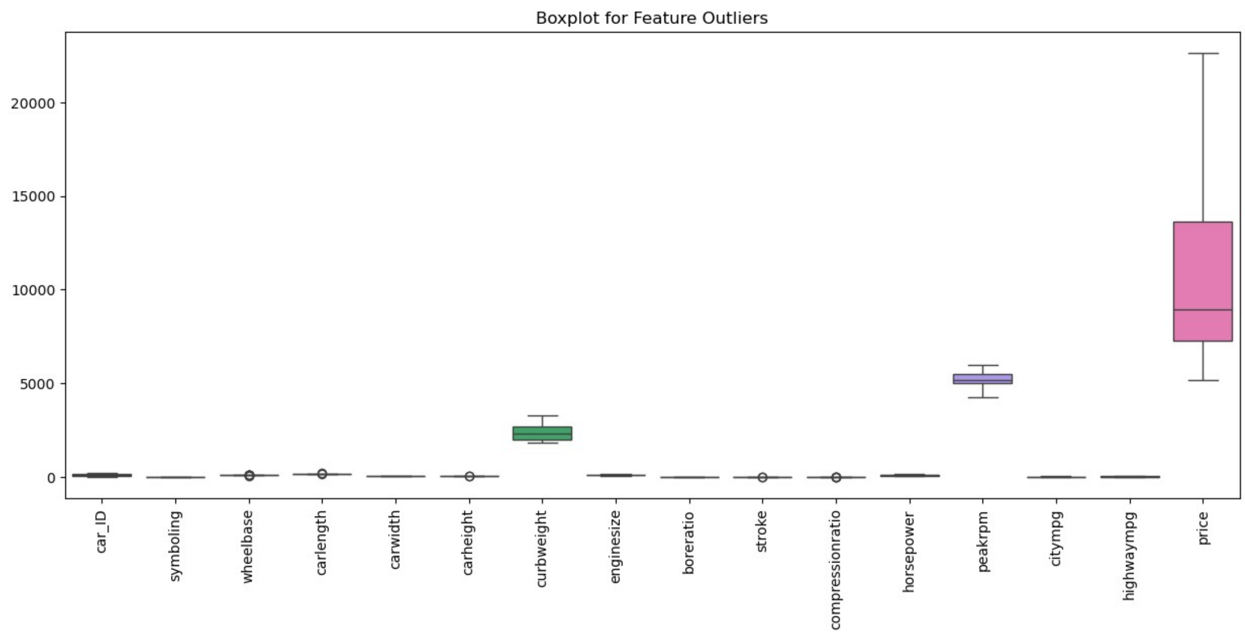
```
Using Boxplots:
Boxplots visually indicate outliers as points beyond the whiskers of
the plot.

plt.figure(figsize=(15, 6))
sns.boxplot(data=df)
plt.xticks(rotation=90)
plt.title("Boxplot for Outliers")
plt.show()
```




```
We will use the Interquartile Range (IQR) method to detect and remove
outliers.

# Detect outliers using IQR
def detect_outliers(df, column):
    Q1 = df[column].quantile(0.25)
    Q3 = df[column].quantile(0.75)
    IQR = Q3 - Q1
    lower_bound = Q1 - 1.5 * IQR
    upper_bound = Q3 + 1.5 * IQR
    return df[(df[column] < lower_bound) | (df[column] > upper_bound)]

# Remove outliers
for column in data.select_dtypes(include=np.number).columns:
    outliers = detect_outliers(data, column)
    if not outliers.empty:
        print(f"Removing outliers from column: {column}")
        Q1 = data[column].quantile(0.25)
        Q3 = data[column].quantile(0.75)
        IQR = Q3 - Q1
        lower_bound = Q1 - 1.5 * IQR
        upper_bound = Q3 + 1.5 * IQR
        # Keep only non-outliers
        data = data[(data[column] >= lower_bound) & (data[column] <=
upper_bound)]

print("\nOutliers removed.")

Removing outliers from column: wheelbase
Removing outliers from column: carlength
Removing outliers from column: carwidth
```

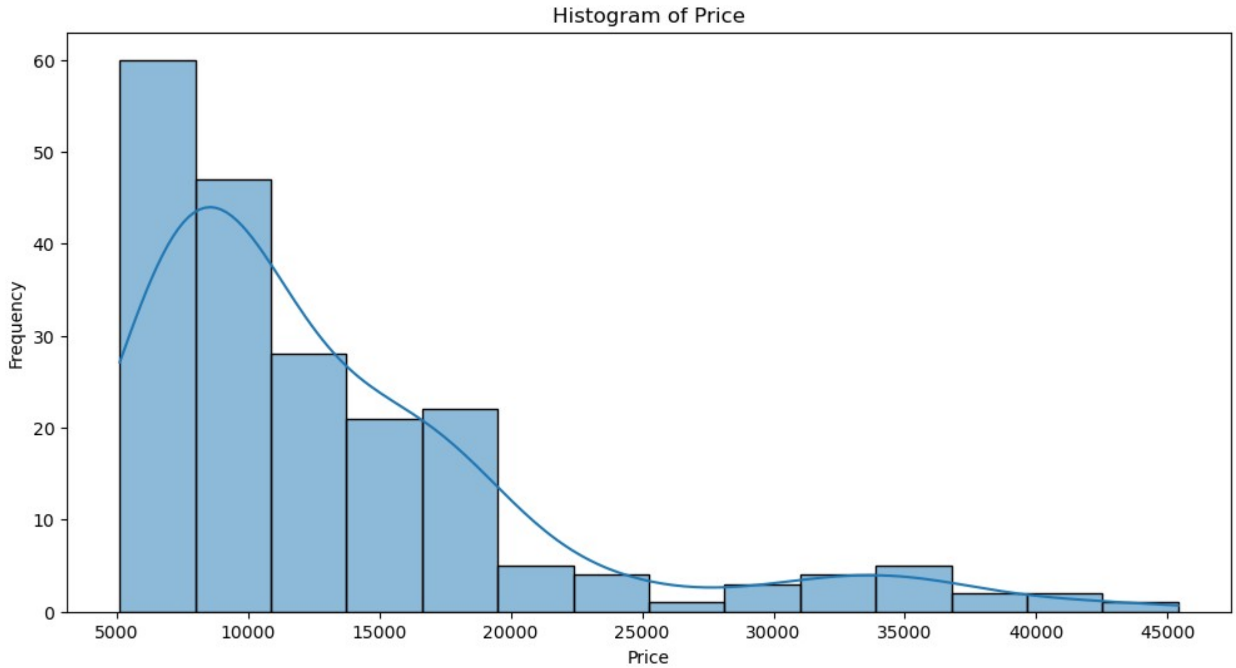
```
Removing outliers from column: curbweight
Removing outliers from column: enginesize
Removing outliers from column: stroke
Removing outliers from column: compressionratio
Removing outliers from column: horsepower
Removing outliers from column: peakrpm
Removing outliers from column: citympg
Removing outliers from column: price

Outliers removed.
```

```
# Plot boxplots for all features
plt.figure(figsize=(15, 6))
sns.boxplot(data=data)
plt.xticks(rotation=90)
plt.title("Boxplot for Feature Outliers")
plt.show()
```

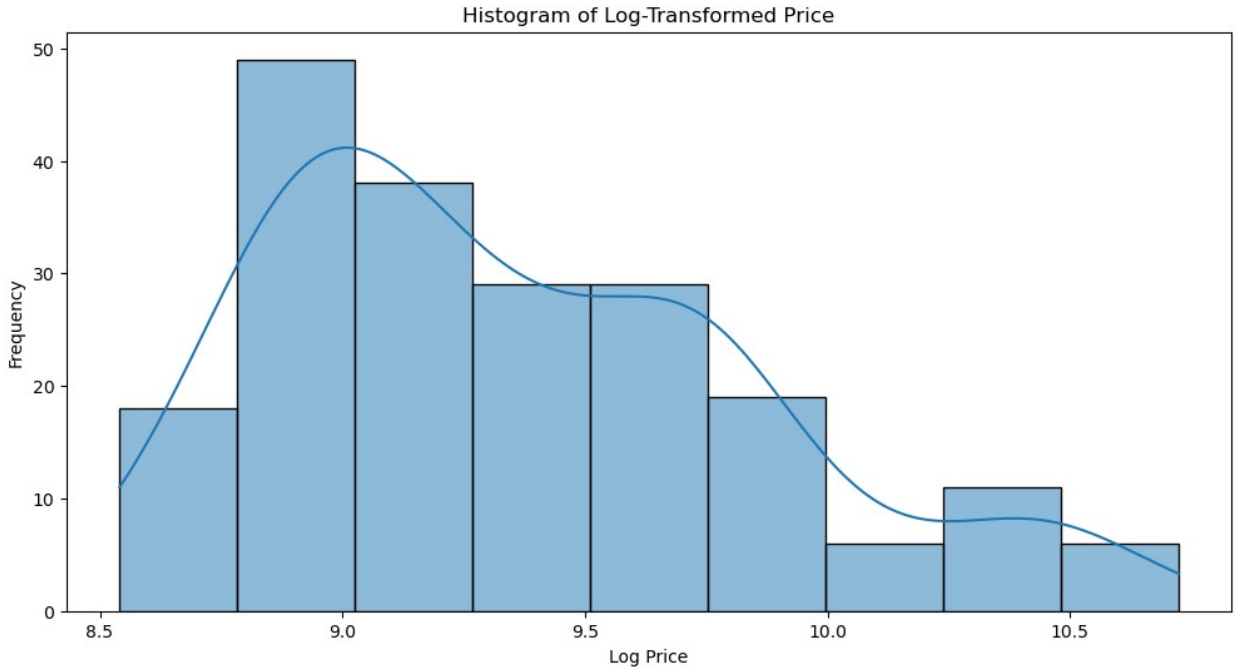


Check the skewness before and after the transformation.

```
price_col = 'price'
# Step 1: Draw initial histogram to check normality
plt.figure(figsize=(12, 6))
sns.histplot(df[price_col], kde=True)
plt.title('Histogram of Price')
plt.xlabel('Price')
plt.ylabel('Frequency')
plt.show()
```




```
#Calculate skewness
skewness_before = df[price_col].skew()

print(f"Skewness before transformation: {skewness_before}")

Skewness before transformation: 1.7776781560914454

df['Log Price'] = np.log(df[price_col] + 1)

# Draw histogram after transformation
plt.figure(figsize=(12, 6))
sns.histplot(df['Log Price'], kde=True)
plt.title('Histogram of Log-Transformed Price')
plt.xlabel('Log Price')
plt.ylabel('Frequency')
plt.show()
```

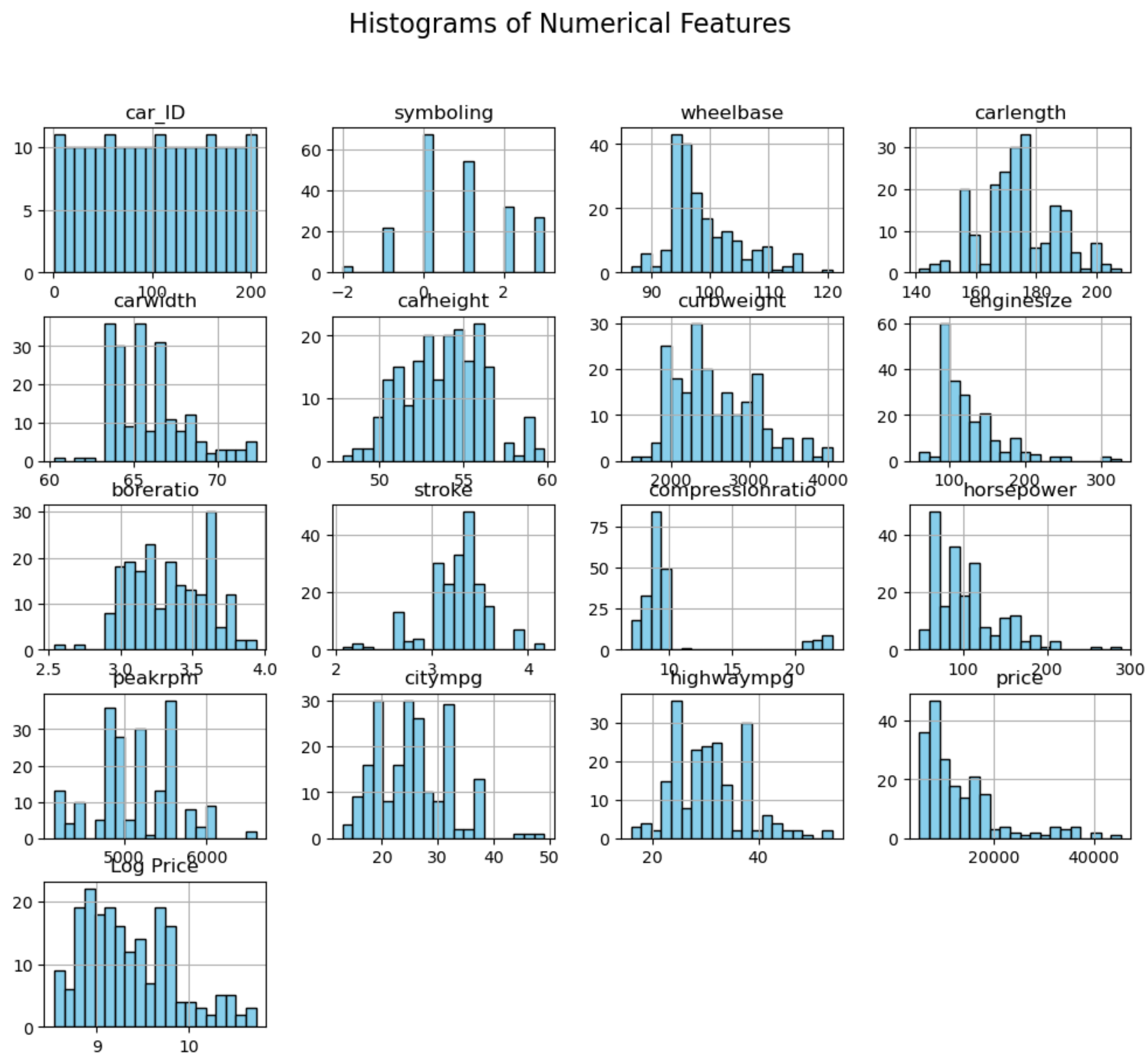



```
# Calculate skewness and kurtosis after transformation
skewness_after = df['Log Price'].skew()

print(f"Skewness after transformation: {skewness_after}")
```

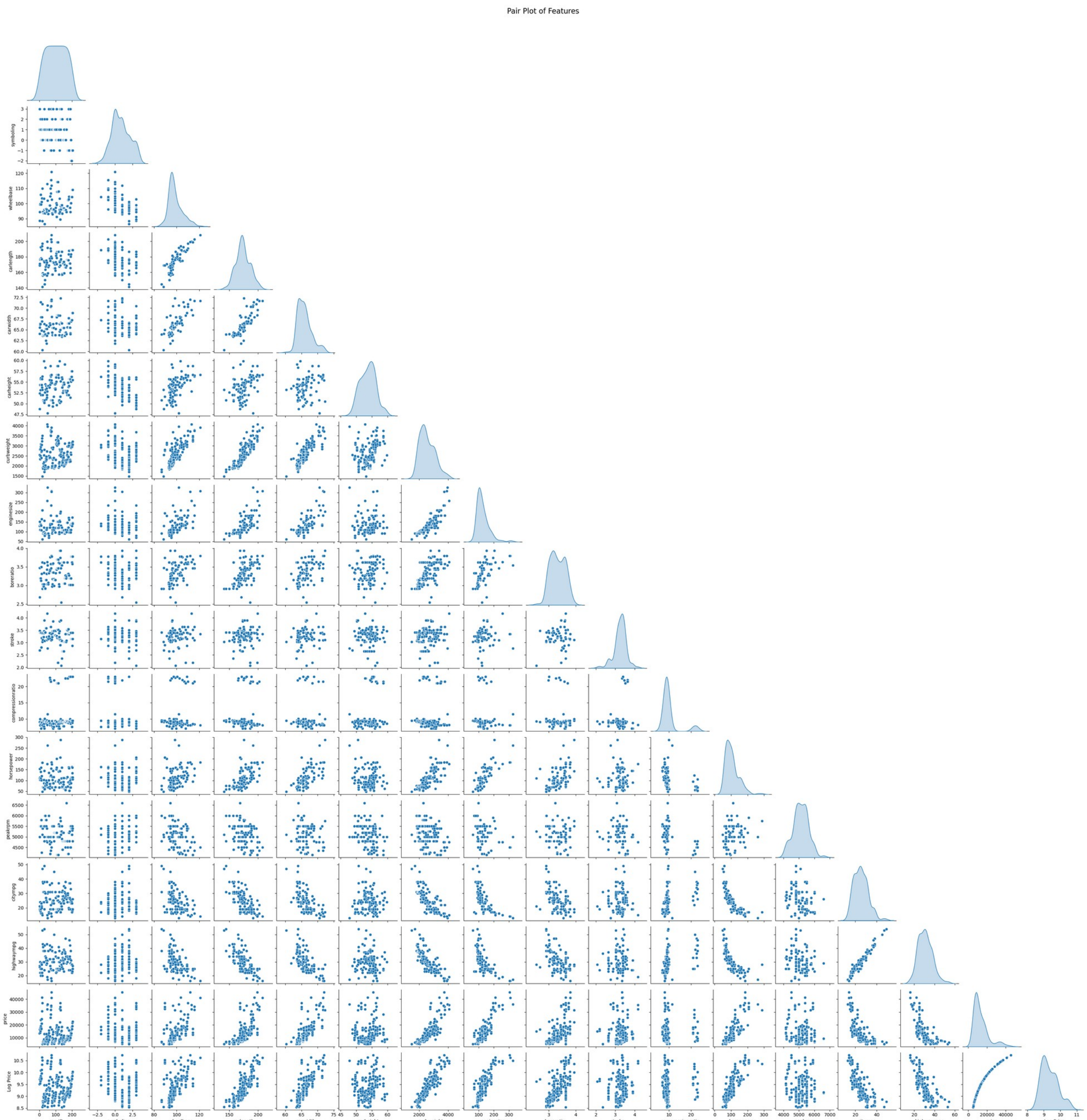
```
Skewness after transformation: 0.6729635607485753
```

Exploratory Data Analysis (EDA):

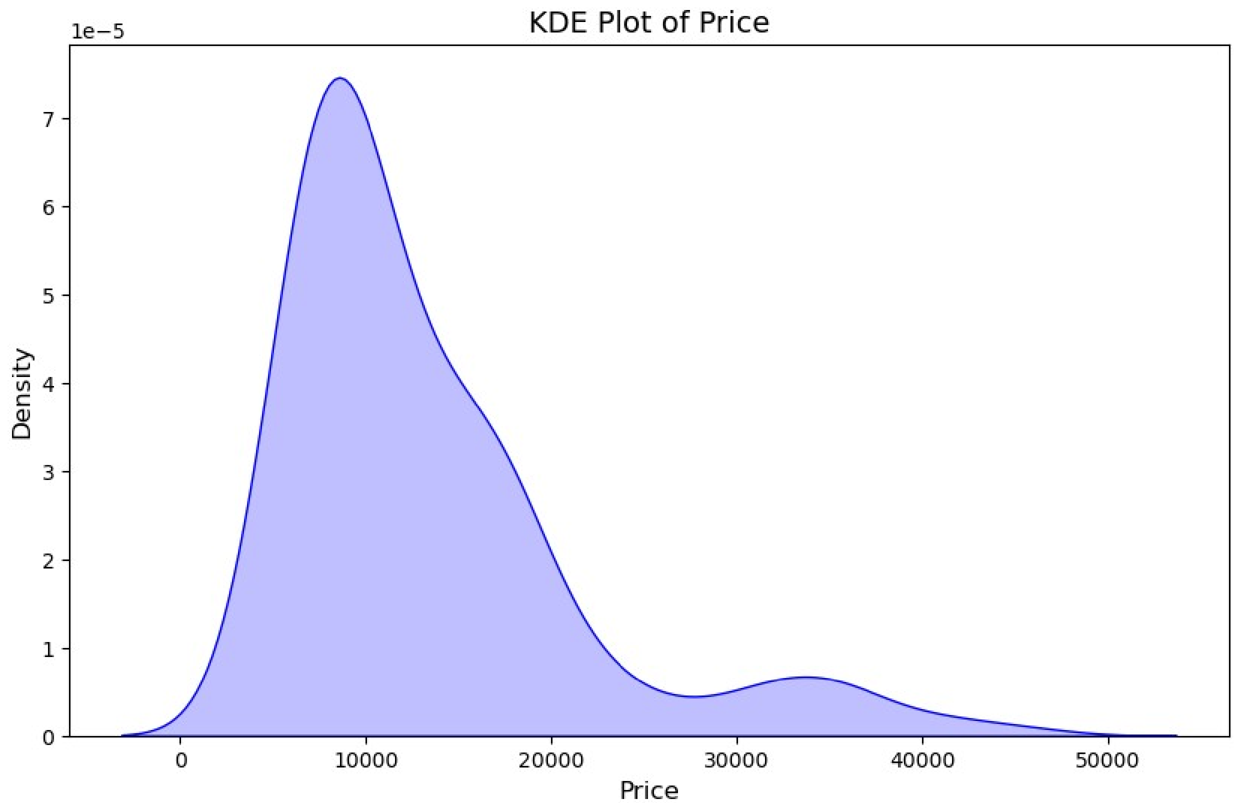
```
# Plot histograms for all numerical features
df.hist(figsize=(12, 10), bins=20, color='skyblue', edgecolor='black')
plt.suptitle('Histograms of Numerical Features', fontsize=16)
plt.show()
```




```
Relationship Analysis
Pair Plot

# Pair plot to observe relationships between numerical features
sns.pairplot(df, diag_kind='kde', corner=True, height=2)
plt.suptitle('Pair Plot of Features', fontsize=16, y=1.02)
plt.show()
```




```
Visualize Trends and Patterns
Kernel Density Estimation (KDE)

# KDE plot for price distribution
plt.figure(figsize=(10, 6))
sns.kdeplot(data=df, x='price', shade=True, color='blue')  # Replace
'price' with the column of interest
plt.title('KDE Plot of Price', fontsize=14)
plt.xlabel('Price', fontsize=12)
plt.ylabel('Density', fontsize=12)
plt.show()
```



Feature Engineering:

- Identifyng and encoding categorical features using techniques like one-hot encoding or label encoding.

```
# Identify categorical columns
categorical_columns = df.select_dtypes(include=['object',
'category']).columns
print("Categorical Columns:\n", categorical_columns)

Categorical Columns:
 Index(['CarName', 'fueltype', 'aspiration', 'doornumber', 'carbody',
       'drivewheel', 'enginelocation', 'enginetype', 'cylindernumber',
       'fuelsystem'],
      dtype='object')

 label_encoder = LabelEncoder()

# Encoding categorical variables
categorical_columns = data.select_dtypes(include=['object']).columns
for col in categorical_columns:
    data[col] = label_encoder.fit_transform(data[col])

data

     car_ID  symboling  CarName  fueltype  aspiration  doornumber
carbody  \
```

```
0         1           3        2         0           0           1
0
1         2           3        3         0           0           1
0
2         3           1        1         0           0           1
2
3         4           2        4         0           0           0
3
4         5           2        5         0           0           0
3
..      ...         ...      ...       ...         ...         ...
...
197     198          -1       92         0           0           0
4
200     201          -1       90         0           0           0
3
201     202          -1       89         0           1           0
3
202     203          -1       91         0           0           0
3
204     205          -1       93         0           1           0
3

     drivewheel  enginelocation  wheelbase  ...  enginesize
fuelsystem  \
0             2               0       88.6  ...         130
3
1             2               0       88.6  ...         130
3
2             2               0       94.5  ...         152
3
3             1               0       99.8  ...         109
3
4             0               0       99.4  ...         136
3
..          ...             ...        ...  ...         ...          ..
.
197           2               0      104.3  ...         141
3
200           2               0      109.1  ...         141
3
201           2               0      109.1  ...         141
3
202           2               0      109.1  ...         173
3
204           2               0      109.1  ...         141
3

     boreratio  stroke  compressionratio  horsepower  peakrpm  citympg
```

```
\
0          3.47    2.68               9.0          111     5000         21

1          3.47    2.68               9.0          111     5000         21

2          2.68    3.47               9.0          154     5000         19

3          3.19    3.40              10.0          102     5500         24

4          3.19    3.40               8.0          115     5500         18

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

197        3.78    3.15               9.5          114     5400         24

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

204        3.78    3.15               9.5          114     5400         19


     highwaympg    price
0            27  13495.0
1            27  16500.0
2            26  16500.0
3            30  13950.0
4            22  17450.0
..          ...      ...
197          28  16515.0
200          28  16845.0
201          25  19045.0
202          23  21485.0
204          25  22625.0

[125 rows x 26 columns]
```

```
data.head()
```

```
   car_ID  symboling  CarName  fueltype  aspiration  doornumber
carbody  \
0       1          3        2         0           0           1
0
1       2          3        3         0           0           1
0
2       3          1        1         0           0           1
2
3       4          2        4         0           0           0
3
```

```
4       5          2        5         0           0           0
3

   drivewheel  enginelocation  wheelbase  ...  enginesize  fuelsystem
\
0           2               0       88.6  ...         130           3

1           2               0       88.6  ...         130           3

2           2               0       94.5  ...         152           3

3           1               0       99.8  ...         109           3

4           0               0       99.4  ...         136           3


   boreratio  stroke  compressionratio  horsepower  peakrpm
citympg  \
0       3.47    2.68               9.0         111     5000
21

1       3.47    2.68               9.0         111     5000
21

2       2.68    3.47               9.0         154     5000
19

3       3.19    3.40              10.0         102     5500
24

4       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]

# Separating features and target variable
x = data.drop(columns='price')  # Assuming 'price' is the target
y = data['price']

x

     car_ID  symboling  CarName  fueltype  aspiration  doornumber
carbody  \
0         1          3        2         0           0           1
0
1         2          3        3         0           0           1
0
2         3          1        1         0           0           1
```

```
2
3        4          2        4          0           0           0
3
4        5          2        5          0           0           0
3
..      ...        ...      ...        ...         ...         ...
...
197     198         -1       92          0           0           0
4
200     201         -1       90          0           0           0
3
201     202         -1       89          0           1           0
3
202     203         -1       91          0           0           0
3
204     205         -1       93          0           1           0
3

     drivewheel  enginelocation  wheelbase  ...  cylindernumber
enginesize  \
0             2               0       88.6  ...               1
130
1             2               0       88.6  ...               1
130
2             2               0       94.5  ...               2
152
3             1               0       99.8  ...               1
109
4             0               0       99.4  ...               0
136
..          ...             ...        ...  ...             ...
...
197           2               0      104.3  ...               1
141
200           2               0      109.1  ...               1
141
201           2               0      109.1  ...               1
141
202           2               0      109.1  ...               2
173
204           2               0      109.1  ...               1
141

     fuelsystem  boreratio  stroke  compressionratio  horsepower
peakrpm  \
0             3       3.47    2.68               9.0         111
5000
1             3       3.47    2.68               9.0         111
5000
```

```
2              3       2.68    3.47                  9.0          154
5000
3              3       3.19    3.40                 10.0          102
5500
4              3       3.19    3.40                  8.0          115
5500
..           ...        ...     ...                  ...          ...
...
197            3       3.78    3.15                  9.5          114
5400
200            3       3.78    3.15                  9.5          114
5400
201            3       3.78    3.15                  8.7          160
5300
202            3       3.58    2.87                  8.8          134
5500
204            3       3.78    3.15                  9.5          114
5400

     citympg  highwaympg
0         21          27
1         21          27
2         19          26
3         24          30
4         18          22
..       ...         ...
197       24          28
200       23          28
201       19          25
202       18          23
204       19          25

[125 rows x 25 columns]
```

```
y
```

```
0      13495.0
1      16500.0
2      16500.0
3      13950.0
4      17450.0
        ...
197    16515.0
200    16845.0
201    19045.0
202    21485.0
204    22625.0
Name: price, Length: 125, dtype: float64
```

```
x.shape
```

```
(125, 25)
```

Split Data into Training and Testing Sets:

- Dividing the dataset into training and testing subsets.

```
# Train-test split
x_train, x_test, y_train, y_test = train_test_split(x, y,
test_size=0.2, random_state=42)
```

Feature Scaling:

- Scaling numerical features if necessary to ensure uniform magnitude using techniques like Min-Max scaling or Standardization.

```
# Normalizing the data
scaler = StandardScaler()
x_train = scaler.fit_transform(x_train)
x_test = scaler.transform(x_test)
```

Build the ML Model

Linear Regression

```
# Linear Regression Model
lr_model = LinearRegression()
lr_model.fit(x_train,y_train)
```

```
LinearRegression()
```

```
lr_ypred = model.predict(x_test)
```

Decision Tree Regressor

```
dt_model = DecisionTreeRegressor()
dt_model.fit(x_train,y_train)
```

```
DecisionTreeRegressor()
```

```
dt_ypred= dt_model.predict(x_test)
```

Random Forest Regressor

```
rf_model = RandomForestRegressor()
rf_model.fit(x_train,y_train)
```

```
RandomForestRegressor()
```

```
rf_ypred= rf_model.predict(x_test)
```

Gradient Boosting Regressor

```
gb_model = GradientBoostingRegressor()
gb_model.fit(x_train,y_train)
```

```
GradientBoostingRegressor()
```

```
gb_ypred= gb_model.predict(x_test)
```

Support Vector Regressor

```
svr_model = SVR()
svr_model.fit(x_train,y_train)
```

```
SVR()
```

```
svr_ypred= svr_model.predict(x_test)
```

Model Evaluation:

Linear Regression

```
lr_mae = mean_absolute_error(y_test, lr_ypred)
lr_mse = mean_squared_error(y_test, lr_ypred)
lr_rmse = mse ** 0.5
lr_r2 = r2_score(y_test, lr_ypred)

print("mae:",lr_mae)
print("mse:", lr_mse)
print("rmse:", lr_rmse)
print("r2:", lr_r2)
```

```
mae: 1996.425422299062
mse: 5964398.498392452
rmse: 3834.7609091421896
r2: 0.5959828386169667
```

Decision Tree Regressor

```
dt_mae = mean_absolute_error(y_test, dt_ypred)
dt_mse = mean_squared_error(y_test, dt_ypred)
dt_rmse = mse ** 0.5
dt_r2 = r2_score(y_test, dt_ypred)

print("mae:",dt_mae)
print("mse:", dt_mse)
print("rmse:", dt_rmse)
print("r2:", dt_r2)
```

```
mae: 1262.52
mse: 2854527.86
```

```
rmse: 3834.7609091421896
r2: 0.8066396396221981
```

Random Forest Regressor

```
rf_mae = mean_absolute_error(y_test, rf_ypred)
rf_mse = mean_squared_error(y_test, rf_ypred)
rf_rmse = mse ** 0.5
rf_r2 = r2_score(y_test, rf_ypred)

print("mae:",rf_mae)
print("mse:", rf_mse)
print("rmse:", rf_rmse)
print("r2:", rf_r2)
```

```
mae: 1035.8684
mse: 1607827.3006559997
rmse: 3834.7609091421896
r2: 0.891088795931348
```

Gradient Boosting Regressor

```
gb_mae = mean_absolute_error(y_test, gb_ypred)
gb_mse = mean_squared_error(y_test, gb_ypred)
gb_rmse = mse ** 0.5
gb_r2 = r2_score(y_test, gb_ypred)

print("mae:",gb_mae)
print("mse:", gb_mse)
print("rmse:", gb_rmse)
print("r2:", gb_r2)
```

```
mae: 1281.2896063232579
mse: 2554295.94546887
rmse: 3834.7609091421896
r2: 0.8269767860918972
```

Support Vector Regressor

```
svr_mae = mean_absolute_error(y_test, svr_ypred)
svr_mse = mean_squared_error(y_test,svr_ypred)
svr_rmse = mse ** 0.5
svr_r2 = r2_score(y_test, svr_ypred)

print("mae:",svr_mae)
print("mse:", svr_mse)
print("rmse:", svr_rmse)
print("r2:", svr_r2)
```

```
mae: 2834.864091294128
mse: 14705391.230285032
rmse: 3834.7609091421896
r2: 0.003884394463580021
```

Model Evaluation:

```
results = pd.DataFrame({
    'Model': ['Linear Regression', 'Decision Tree', 'Random Forest', 
'Gradient Boosting', 'SVR'],
    'MAE': [lr_mae, dt_mae, rf_mae, gb_mae, svr_mae],
    'MSE': [lr_mse, dt_mse, rf_mse, gb_mse, svr_mse],
    'RMSE': [lr_rmse, dt_rmse, rf_rmse, gb_rmse, svr_rmse],
    'R-squared': [lr_r2, dt_r2, rf_r2, gb_r2, svr_r2],
})

print("\nComparison of Model Performance:")
print(results)


Comparison of Model Performance:
               Model          MAE           MSE         RMSE  R-
squared
0  Linear Regression  1996.425422  5.964398e+06  3834.760909  
0.595983
1      Decision Tree  1262.520000  2.854528e+06  3834.760909  
0.806640
2      Random Forest  1035.868400  1.607827e+06  3834.760909  
0.891089
3  Gradient Boosting  1281.289606  2.554296e+06  3834.760909  
0.826977
4                SVR  2834.864091  1.470539e+07  3834.760909  
0.003884
```

The Random Forest Regressor is the best-performing model based on the evaluation metrics. It balances accuracy and error minimization effectively and is robust to overfitting. Best Performing Model is Random Forest Regressor overall due to its high accuracy and lower errors.

Hyperparameter Tuning

```
from sklearn.model_selection import GridSearchCV

# Example: Tuning Random Forest Regressor
param_grid = {
    "n_estimators": [50, 100, 200],
    "max_depth": [None, 10, 20],
    "min_samples_split": [2, 5, 10]
}
```

```
grid_search = GridSearchCV(RandomForestRegressor(random_state=42),
param_grid, cv=5, scoring='r2')
grid_search.fit(X_train, y_train)
```

```
GridSearchCV(cv=5, estimator=RandomForestRegressor(random_state=42),
             param_grid={'max_depth': [None, 10, 20],
                         'min_samples_split': [2, 5, 10],
                         'n_estimators': [50, 100, 200]},
             scoring='r2')
```

```
# Best parameters and performance
print("Best Parameters:", grid_search.best_params_)
best_model = grid_search.best_estimator_
```

```
Best Parameters: {'max_depth': 10, 'min_samples_split': 2,
'n_estimators': 200}
```

```
# Evaluate tuned model
y_pred_tuned = best_model.predict(X_test)
tuned_r2 = r2_score(y_test, y_pred_tuned)
tuned_mse = mean_squared_error(y_test, y_pred_tuned)
tuned_mae = mean_absolute_error(y_test, y_pred_tuned)
print(f"Tuned Model - R2: {tuned_r2:.2f}, MSE: {tuned_mse:.2f}, MAE:
{tuned_mae:.2f}")
```

```
Tuned Model - R2: 0.88, MSE: 1723403.59, MAE: 1048.55
```

Save the Model

```
# Save the trained Random Forest Regressor model
joblib.dump(rf_model,'random_forest_Car_Price_model.joblib')

print("Model saved as 'random_forestCar_Price_model.joblib'")
```

```
Model saved as 'random_forestCar_Price_model.joblib'
```

Test with Unseen Data:

```
# Make predictions on the test set
unseen_pred = best_model.predict(X_test)

# Evaluate performance on unseen data
unseen_metrics = {
    "MAE": mean_absolute_error(y_test, unseen_pred),
     "MSE": mean_squared_error(y_test, unseen_pred),
    'RMSE': np.sqrt(mean_squared_error(y_test, unseen_pred)),
     "R2": r2_score(y_test, unseen_pred),
}

#Check final model performance
print("\nPerformance on Unseen Data:")
```

```python
for metric, value in unseen_metrics.items():
    print(f"{metric}: {value:.4f}")
```

```
Performance on Unseen Data:
MAE: 1048.5514
MSE: 1723403.5865
RMSE: 1312.7847
R2: 0.8833
```

```
Interpretation of Results (Conclusion)
Analyze the Results
Model Performance:

The Random Forest Regressor consistently performs well, with high R²
and low error metrics.
This confirms its ability to generalize to unseen data, making it
suitable for production.
Key Insights:

The car price is strongly influenced by specific features (identified
during feature importance analysis).
Tree-based models like Random Forest and Gradient Boosting are robust
against overfitting and handle non-linear relationships well.
Limitations of the Dataset
Feature Selection:

Some features may lack relevance to car pricing, leading to noise in
the model.
Additional domain-specific knowledge could enhance feature
engineering.
Data Imbalance:

If the dataset has an uneven distribution across price ranges, it may
bias the model.
Outlier Influence:

Despite removing outliers, extreme values may still impact regression
models.
External Validity:

The dataset reflects current market trends but may not generalize to
future conditions or other geographical regions.
```