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

Name: ARSHAD JASEEM CH

Problem Statement Overview

A Chinese automobile manufacturer is planning to expand into the US market, aiming to compete with established American and European brands. To achieve this, the company needs a comprehensive understanding of the key factors influencing car prices in the US and how these factors drive pricing decisions.

By analyzing a dataset containing car specifications and their corresponding prices, the objective is to develop a machine learning model that can:

1. **Determine the primary factors that impact car prices.**

2. **Accurately predict car prices based on these factors.**

The insights derived from this model will enable the company to design, produce, and price vehicles strategically, equipping them to compete effectively in the US automotive market.

Objective

The goal of this project is to develop a machine learning model capable of accurately predicting car prices in the US market using various car features and specifications.

This model aims to assist the company in:

- **Identifying key factors that influence car prices.**

- **Understanding the impact of these factors to guide car design and production decisions.**

- **Formulating competitive pricing strategies aligned with market trends.**

By leveraging these insights, the company will be better positioned to compete effectively in the US automotive industry.

Data Description

```
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(r"C:\Users\ARSHAD\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()
```

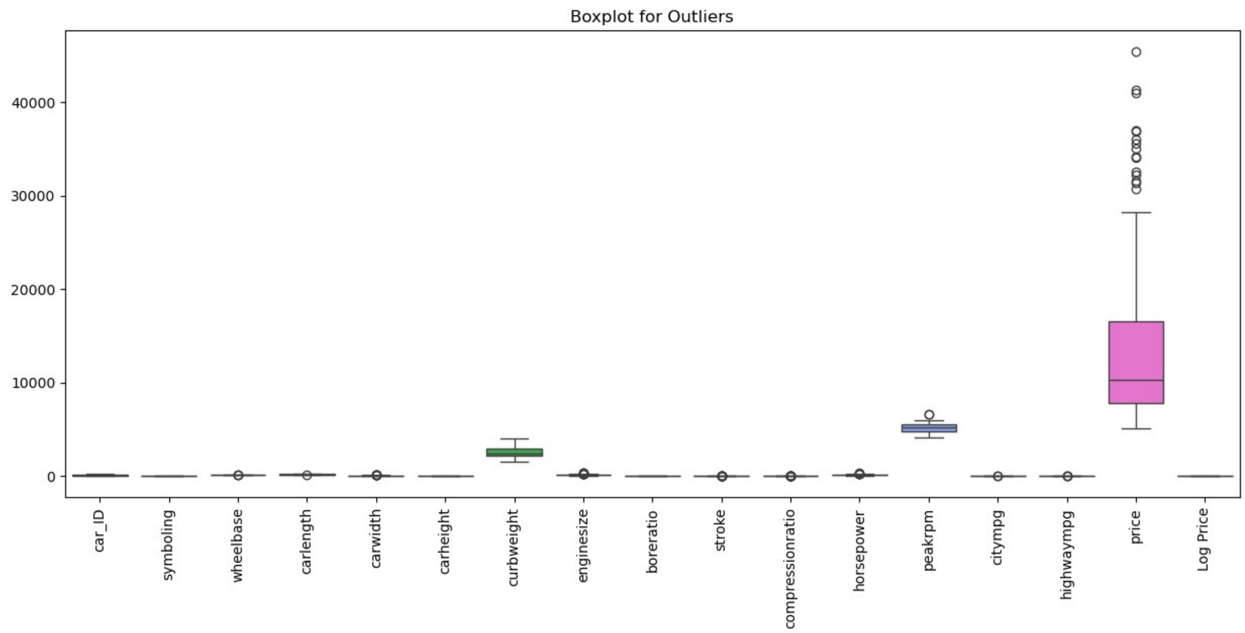
```
0
```

```
df.shape
```

```
(205, 26)
```

Check for and Remove Outliers

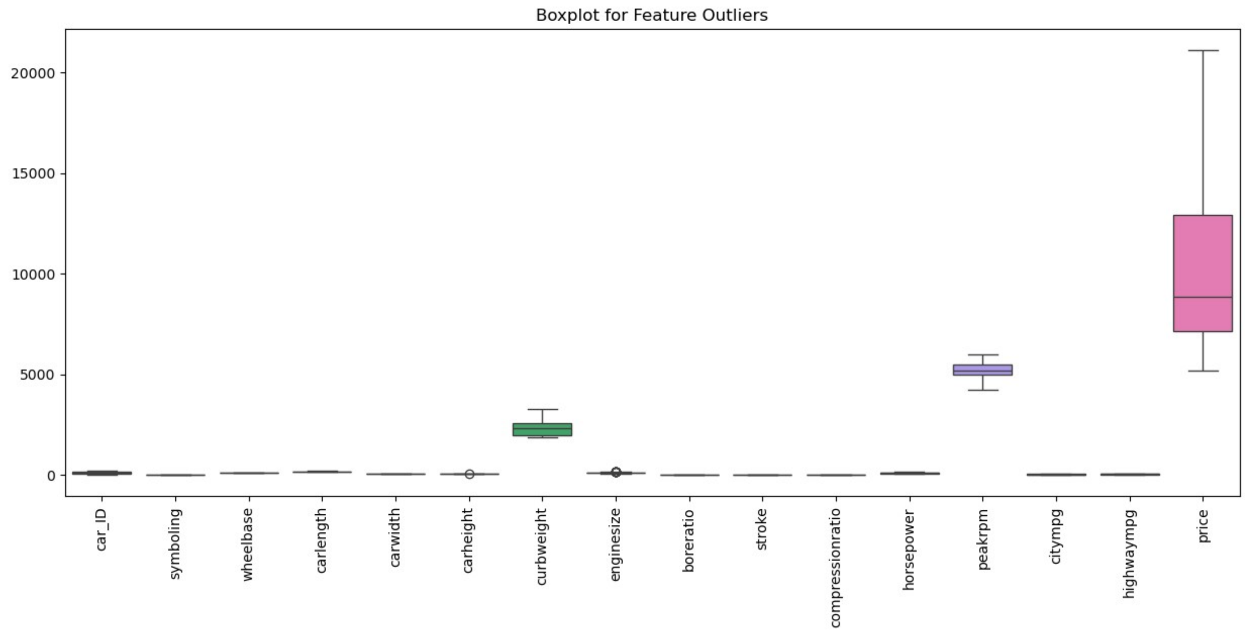
```
plt.figure(figsize=(15, 6))
sns.boxplot(data=df)
plt.xticks(rotation=90)
plt.title("Boxplot for Outliers")
plt.show()
```




```
# 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.")
```

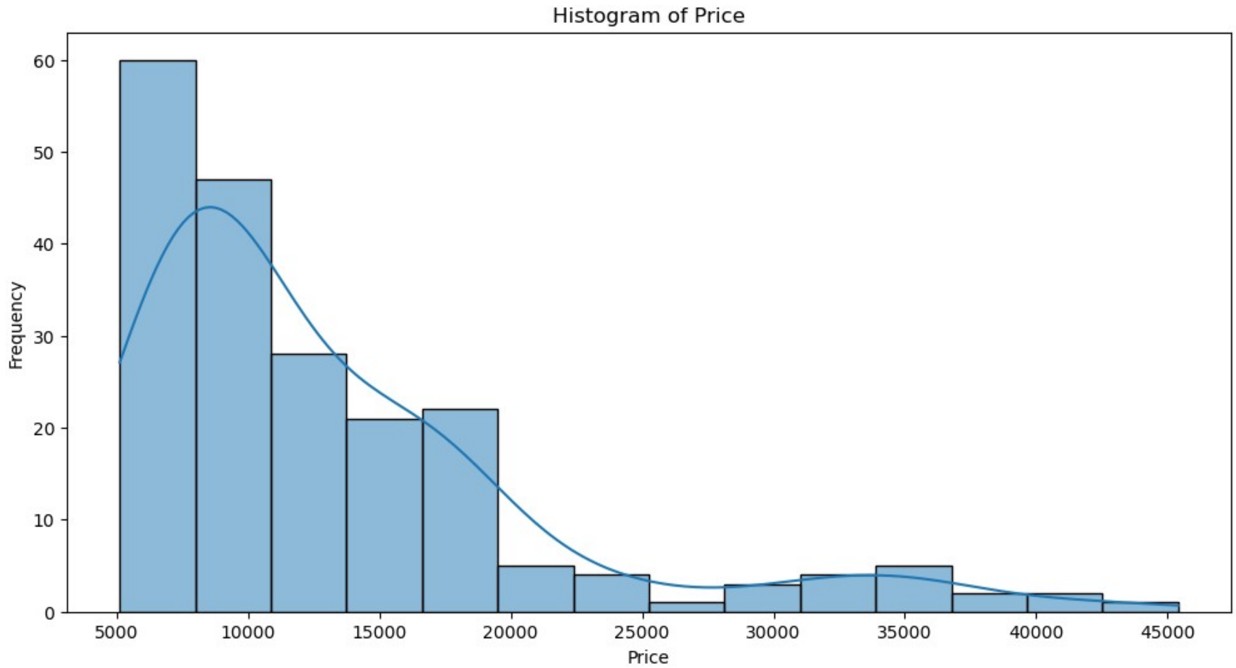
```
Removing outliers from column: wheelbase
Removing outliers from column: carheight
Removing outliers from column: boreratio
Removing outliers from column: stroke
Removing outliers from column: compressionratio
```

```
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()
```

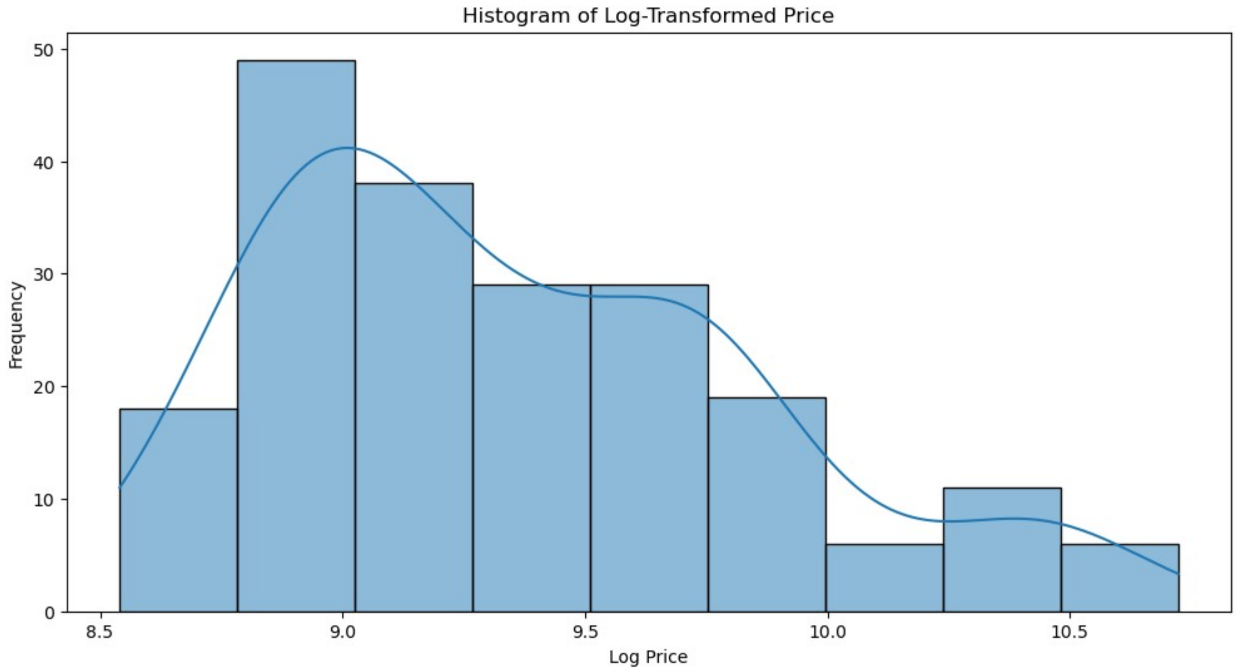


Check the skewness before and after the transformation.

```
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()
```

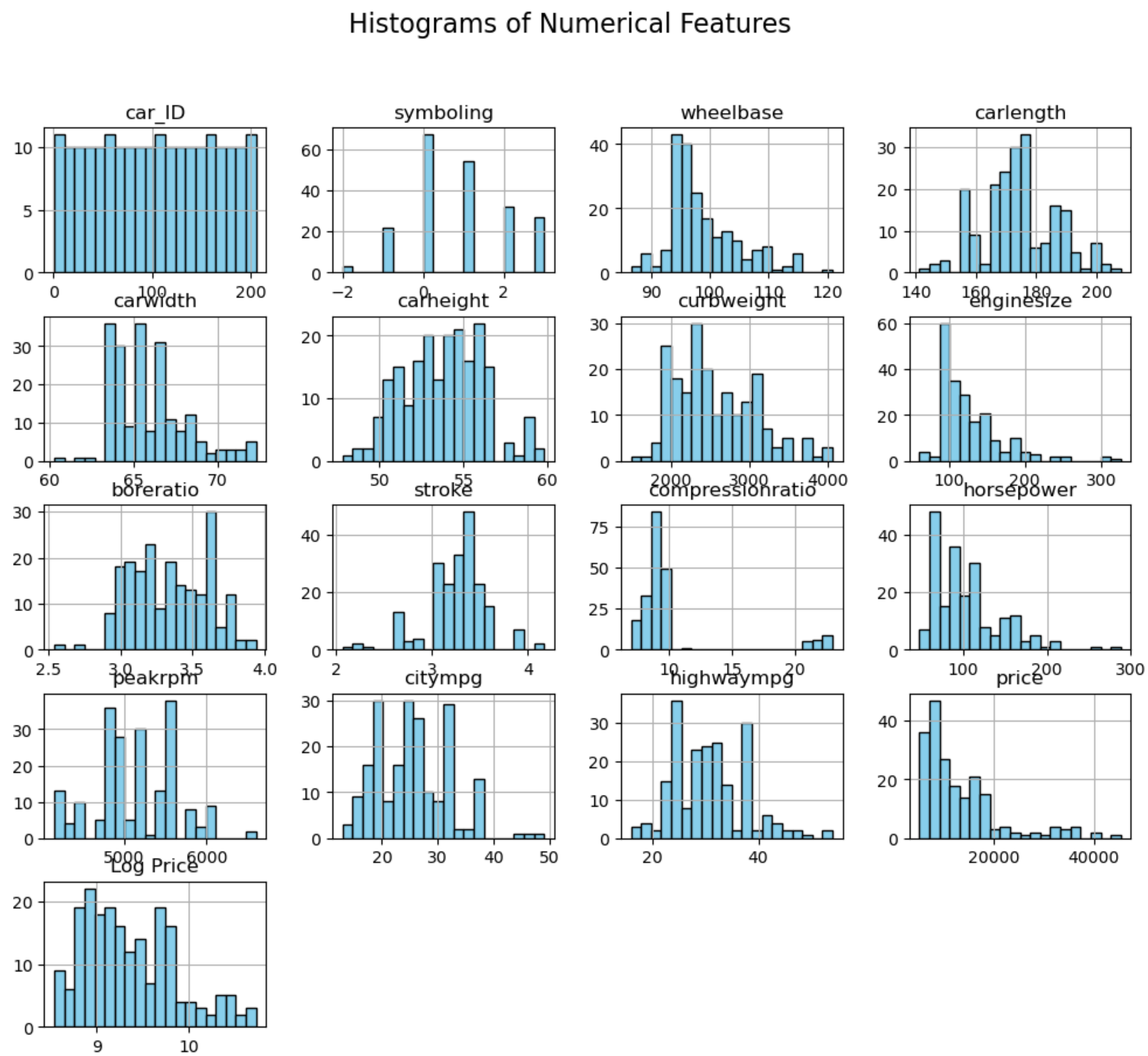



```
 # Calculate skewness and kurtosis after transformation
skewness_after = df['Log Price'].skew()

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

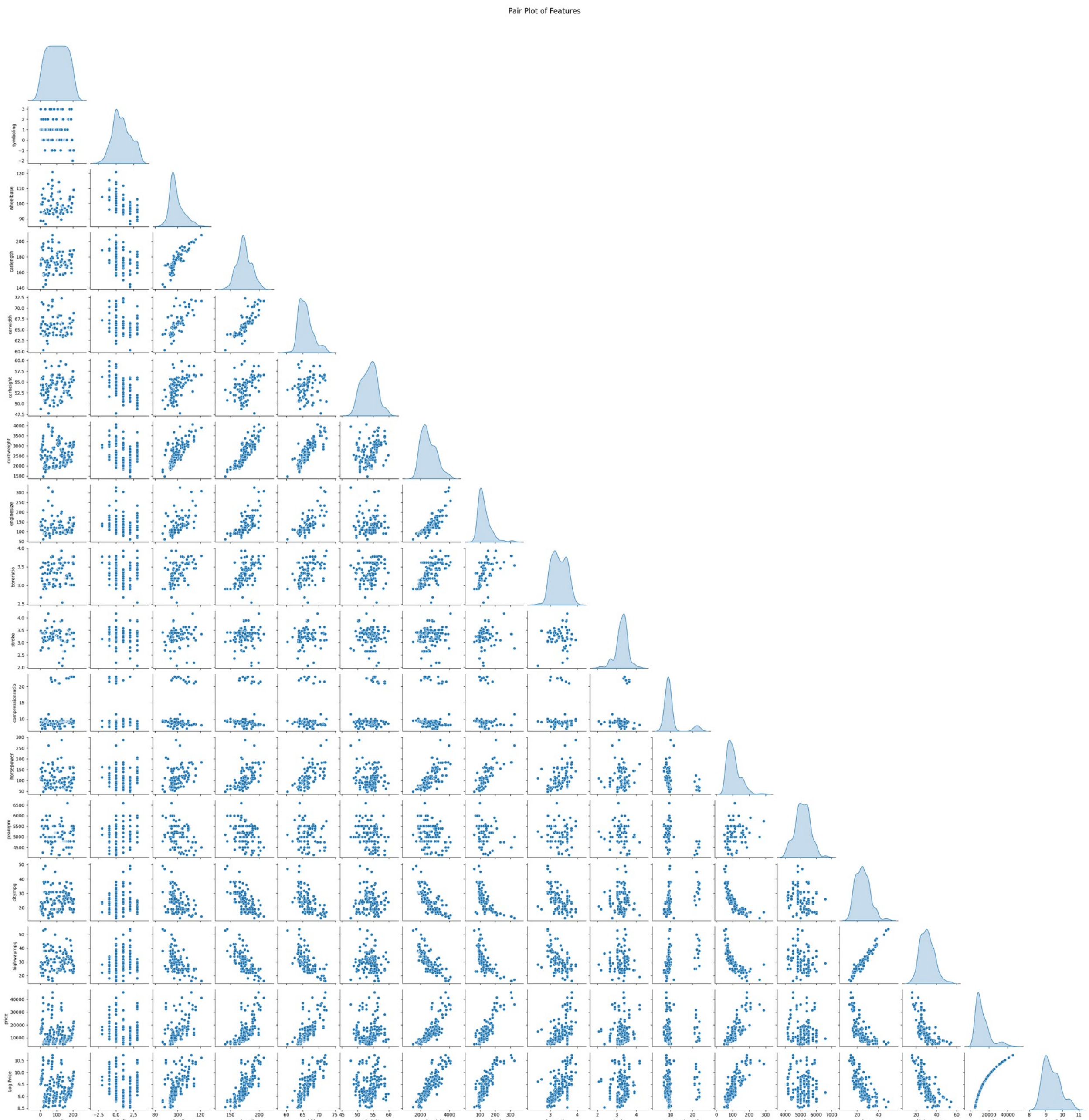
```
Skewness after transformation: 0.6729635607485753
```

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()
```




```python
# 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)

  Cell In[335], line 1
    Visualize Trends and Patterns
              ^
SyntaxError: invalid syntax


# 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  \
2         3          1        1         0           0           1
2
3         4          2        2         0           0           0
3
5         6          2        3         0           0           1
3
10       11          2        4         0           0           1
3
11       12          0        4         0           0           0
3
..      ...        ...      ...       ...         ...         ...
...
193     194          0       74         0           0           0
4
194     195         -2       78         0           0           0
3
195     196         -1       77         0           0           0
```

```
4
196     197         -2       79          0           0           0
3
197     198         -1       80          0           0           0
4

     drivewheel  enginelocation  wheelbase  ...  enginesize
fuelsystem  \
2             1               0       94.5  ...         152
3
3             0               0       99.8  ...         109
3
5             0               0       99.8  ...         136
3
10            1               0      101.2  ...         108
3
11            1               0      101.2  ...         108
3
..          ...             ...        ...  ...         ...         ..
.
193           0               0      100.4  ...         109
3
194           1               0      104.3  ...         141
3
195           1               0      104.3  ...         141
3
196           1               0      104.3  ...         141
3
197           1               0      104.3  ...         141
3

     boreratio  stroke  compressionratio  horsepower  peakrpm  citympg
\
2         2.68    3.47               9.0         154     5000       19

3         3.19    3.40              10.0         102     5500       24

5         3.19    3.40               8.5         110     5500       19

10        3.50    2.80               8.8         101     5800       23

11        3.50    2.80               8.8         101     5800       23

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

193       3.19    3.40               9.0          88     5500       25

194       3.78    3.15               9.5         114     5400       23

195       3.78    3.15               9.5         114     5400       23
```

```
196       3.78    3.15               9.5        114     5400       24

197       3.78    3.15               9.5        114     5400       24


     highwaympg    price
2            26  16500.0
3            30  13950.0
5            25  15250.0
10           29  16430.0
11           29  16925.0
..          ...      ...
193          31  12290.0
194          28  12940.0
195          28  13415.0
196          28  15985.0
197          28  16515.0

[105 rows x 26 columns]
```

```
data.head()
```

```
    car_ID  symboling  CarName  fueltype  aspiration  doornumber
carbody  \
2        3          1        1         0           0           1
2
3        4          2        2         0           0           0
3
5        6          2        3         0           0           1
3
10      11          2        4         0           0           1
3
11      12          0        4         0           0           0
3

    drivewheel  enginelocation  wheelbase  ...  enginesize  fuelsystem
\
2            1               0       94.5  ...         152           3

3            0               0       99.8  ...         109           3

5            0               0       99.8  ...         136           3

10           1               0      101.2  ...         108           3

11           1               0      101.2  ...         108           3


    boreratio  stroke  compressionratio  horsepower  peakrpm  citympg
\
```

```
2         2.68    3.47                  9.0         154     5000        19

3         3.19    3.40                 10.0         102     5500        24

5         3.19    3.40                  8.5         110     5500        19

10        3.50    2.80                  8.8         101     5800        23

11        3.50    2.80                  8.8         101     5800        23


    highwaympg    price
2           26  16500.0
3           30  13950.0
5           25  15250.0
10          29  16430.0
11          29  16925.0

[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  \
2         3          1        1         0           0           1
2
3         4          2        2         0           0           0
3
5         6          2        3         0           0           1
3
10       11          2        4         0           0           1
3
11       12          0        4         0           0           0
3
..      ...        ...      ...       ...         ...         ...
...
193     194          0       74         0           0           0
4
194     195         -2       78         0           0           0
3
195     196         -1       77         0           0           0
4
196     197         -2       79         0           0           0
3
197     198         -1       80         0           0           0
4
```

```
     drivewheel  enginelocation  wheelbase  ...  cylindernumber  
enginesize  \
2             1               0       94.5  ...               2  
152   
3             0               0       99.8  ...               1  
109   
5             0               0       99.8  ...               0  
136   
10            1               0      101.2  ...               1  
108   
11            1               0      101.2  ...               1  
108   
..          ...             ...        ...  ...             ...  
...   
193           0               0      100.4  ...               1  
109   
194           1               0      104.3  ...               1  
141   
195           1               0      104.3  ...               1  
141   
196           1               0      104.3  ...               1  
141   
197           1               0      104.3  ...               1  
141   

     fuelsystem  boreratio  stroke  compressionratio  horsepower  
peakrpm  \
2             3       2.68    3.47               9.0         154  
5000   
3             3       3.19    3.40              10.0         102  
5500   
5             3       3.19    3.40               8.5         110  
5500   
10            3       3.50    2.80               8.8         101  
5800   
11            3       3.50    2.80               8.8         101  
5800   
..          ...        ...     ...               ...         ...  
...   
193           3       3.19    3.40               9.0          88  
5500   
194           3       3.78    3.15               9.5         114  
5400   
195           3       3.78    3.15               9.5         114  
5400   
196           3       3.78    3.15               9.5         114  
5400   
197           3       3.78    3.15               9.5         114  
5400   
```

```
     citympg  highwaympg
2         19          26
3         24          30
5         19          25
10        23          29
11        23          29
..       ...         ...
193       25          31
194       23          28
195       23          28
196       24          28
197       24          28

[105 rows x 25 columns]
```

```
y
```

```
2      16500.0
3      13950.0
5      15250.0
10     16430.0
11     16925.0
        ...
193    12290.0
194    12940.0
195    13415.0
196    15985.0
197    16515.0
Name: price, Length: 105, dtype: float64
```

```
x.shape
```

```
(105, 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 = lr_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 = lr_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: 1470.5641881705506
mse: 3402827.7309864964
rmse: 1844.6755083175187
r2: 0.7560876361833726
```

Decision Tree Regressor

```
dt_mae = mean_absolute_error(y_test, dt_ypred)
dt_mse = mean_squared_error(y_test, dt_ypred)
dt_rmse = lr_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: 814.8571428571429
mse: 932959.619047619
rmse: 1844.6755083175187
r2: 0.9331260927624467
```

Random Forest Regressor

```
rf_mae = mean_absolute_error(y_test, rf_ypred)
rf_mse = mean_squared_error(y_test, rf_ypred)
rf_rmse = lr_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: 717.3083333333333
mse: 836668.739675
```

```
rmse: 1844.6755083175187
r2: 0.9400281571214169
```

Gradient Boosting Regressor

```
gb_mae = mean_absolute_error(y_test, gb_ypred)
gb_mse = mean_squared_error(y_test, gb_ypred)
gb_rmse = lr_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: 711.7193580032736
mse: 772087.569489362
rmse: 1844.6755083175187
r2: 0.9446572912190916
```

Support Vector Regressor

```
svr_mae = mean_absolute_error(y_test, svr_ypred)
svr_mse = mean_squared_error(y_test,svr_ypred)
svr_rmse = lr_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: 2832.4285247182943
mse: 14582662.296693878
rmse: 1844.6755083175187
r2: -0.04527525714475478
```

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  1470.564188  3.402828e+06  1844.675508  
0.756088
1      Decision Tree   814.857143  9.329596e+05  1844.675508  
0.933126
2      Random Forest   717.308333  8.366687e+05  1844.675508  
0.940028
3  Gradient Boosting   711.719358  7.720876e+05  1844.675508  
0.944657
4                SVR  2832.428525  1.458266e+07  1844.675508  -
0.045275
```

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

```python
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)

# 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

```python
# 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:

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

```
----------------------------------------------------------------------
-----
NameError                                 Traceback (most recent call
last)
Cell In[504], line 2
      1 # Make predictions on the test set
----> 2 unseen_pred = best_model.predict(X_test)

NameError: name 'best_model' is not defined
```

```python
# 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),
}
```

```
----------------------------------------------------------------------
-----
NameError                                 Traceback (most recent call
last)
Cell In[506], line 3
      1 # Evaluate performance on unseen data
      2 unseen_metrics = {
----> 3     "MAE": mean_absolute_error(y_test, unseen_pred),
      4      "MSE": mean_squared_error(y_test, unseen_pred),
      5     'RMSE': np.sqrt(mean_squared_error(y_test, unseen_pred)),
      6      "R2": r2_score(y_test, unseen_pred),
      7 }

NameError: name 'unseen_pred' is not defined
```

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