Linear Regression

About Dataset

Car Price Prediction Dataset Description:

This dataset contains 10,000 entries created for the purpose of predicting car prices. Each row represents information about a car and its price. The descriptions of the columns are as follows:

Columns Descriptions:

Brand: Specifies the brand of the car (e.g., Toyota, BMW, Ford).
Example values: "Toyota", "BMW", "Mercedes".

Model: Specifies the model of the car (e.g., Corolla, Focus, X5).
Example values: "Corolla", "Focus", "X5".

Year: The production year of the car. Newer years typically indicate higher prices.
Example values: 2005, 2018, 2023.

Engine_Size: Specifies the engine size in liters (L). Larger engines generally correlate with higher prices.
Example values: 1.6, 2.0, 3.5.

Fuel_Type: indicates the type of fuel used by the car:
Petrol: Cars running on gasoline.
Diesel: Cars running on diesel fuel.
Hybrid: Cars that use both fuel and electricity.
Electric: Fully electric cars.

Transmission: The type of transmission in the car:
Manual: Manual transmission.
Automatic: Automatic transmission.
Semi-Automatic: Semi-automatic transmission.

Mileage: The total distance the car has traveled, measured in kilometers. Lower mileage generally indicates a higher price.
Example values: 15,000, 75,000, 230,000.

Doors: The number of doors in the car. Commonly 2, 3, 4, or 5 doors.
Example values: 2, 3, 4, 5.

Owner_Count: The number of previous owners of the car. Fewer owners generally indicate a higher price. Example values: 1, 2, 3, 4.

Price:The estimated selling price of the car. It is calculated based on several factors such as production year, engine size, mileage, fuel type, and transmission.
Example values: 5,000, 15,000, 30,000.

Import Required Libraries

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import OneHotEncoder, StandardScaler
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_absolute_error, mean_squared_error,
r2_score
```

Load the Dataset

```
data = pd.read_csv("car_price_dataset.csv")
```

Data Information

```
data.head()

        Brand   Model  Year  Engine_Size Fuel_Type    Transmission
Mileage  \
0         Kia     Rio  2020          4.2    Diesel          Manual
289944
1   Chevrolet  Malibu  2012          2.0    Hybrid       Automatic
5356
2    Mercedes     GLA  2020          4.2    Diesel       Automatic
231440
3        Audi      Q5  2023          2.0  Electric          Manual
160971
4  Volkswagen    Golf  2003          2.6    Hybrid  Semi-Automatic
286618

   Doors  Owner_Count  Price
0      3            5   8501
1      2            3  12092
2      4            2  11171
3      2            1  11780
4      3            3   2867

data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 10 columns):
 #   Column        Non-Null Count  Dtype  
---  ------        --------------  -----  
 0   Brand         10000 non-null  object 
 1   Model         10000 non-null  object 
 2   Year          10000 non-null  int64  
 3   Engine_Size   10000 non-null  float64
 4   Fuel_Type     10000 non-null  object 
 5   Transmission  10000 non-null  object 
 6   Mileage       10000 non-null  int64  
 7   Doors         10000 non-null  int64  
 8   Owner_Count   10000 non-null  int64  
 9   Price         10000 non-null  int64  
dtypes: float64(1), int64(5), object(4)
memory usage: 781.4+ KB
```

Data Preprocessing

```
data.isnull().sum()
```

```
Brand           0
Model           0
Year            0
Engine_Size     0
Fuel_Type       0
Transmission    0
Mileage         0
Doors           0
Owner_Count     0
Price           0
dtype: int64
```

Encoding Categorical Variables

Since columns like Brand, Model, Fuel_Type, and Transmission are categorical, we convert them using One-Hot Encoding.

```
categorical_features = ['Brand', 'Model', 'Fuel_Type', 'Transmission']
data = pd.get_dummies(data, columns=categorical_features, drop_first=True)
```

Splitting Features and Target

```python
X = data.drop(columns=['Price'])  # Features
y = data['Price']  # Target variable
```

Scaling Numerical Features

```python
scaler = StandardScaler()
X[['Year', 'Engine_Size', 'Mileage', 'Doors', 'Owner_Count']] = 
scaler.fit_transform(
    X[['Year', 'Engine_Size', 'Mileage', 'Doors', 'Owner_Count']]
)
```

Train-Test Split

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

Train the Linear Regression Model

```python
model = LinearRegression()
model.fit(X_train, y_train)
```

```
LinearRegression()
```

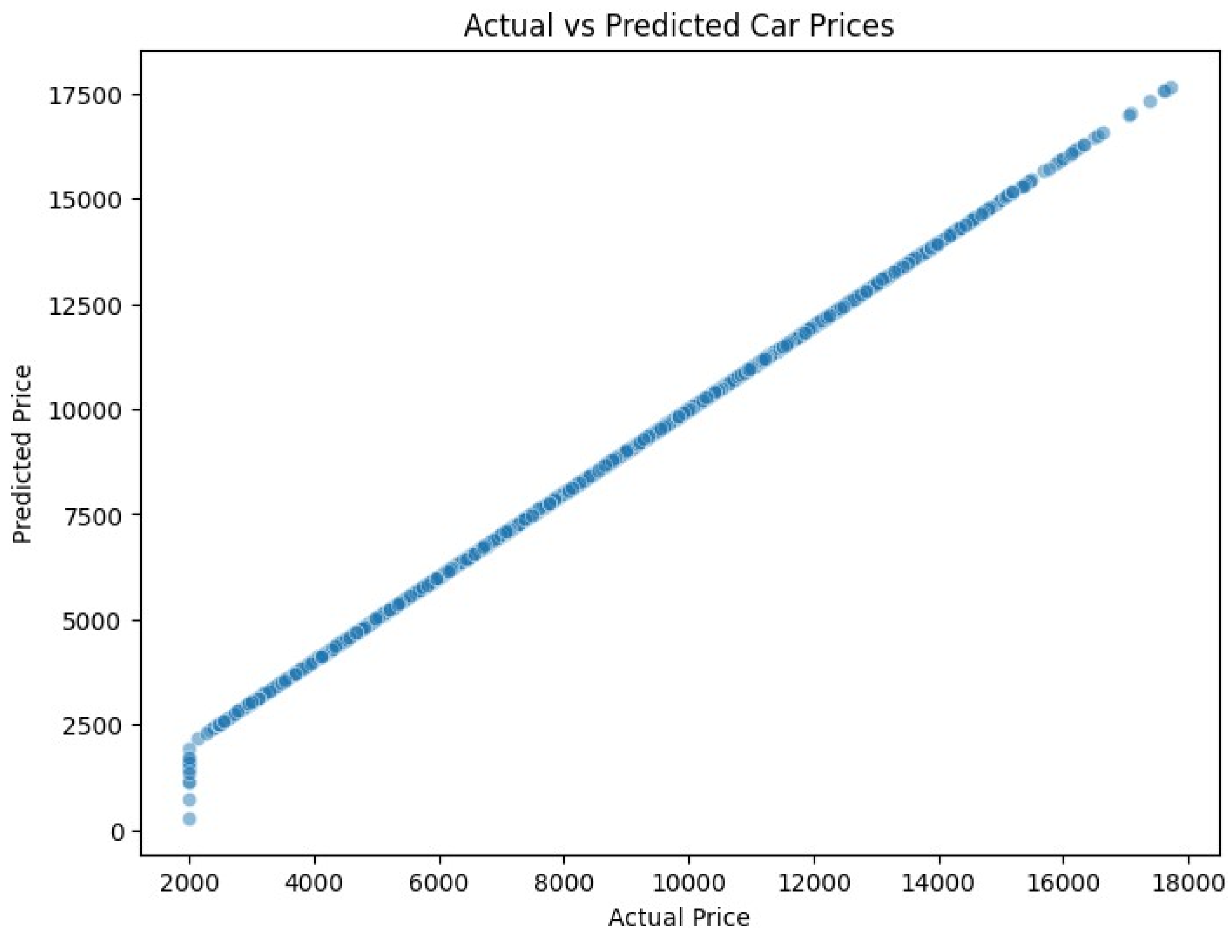
Model Evaluation

```python
y_pred = model.predict(X_test)

# Evaluation Metrics
mae = mean_absolute_error(y_test, y_pred)
mse = mean_squared_error(y_test, y_pred)
rmse = np.sqrt(mse)
r2 = r2_score(y_test, y_pred)

print(f"Mean Absolute Error (MAE): {mae:.2f}")
print(f"Mean Squared Error (MSE): {mse:.2f}")
print(f"Root Mean Squared Error (RMSE): {rmse:.2f}")
print(f"R-squared Score (R²): {r2:.4f}")
```

```
Mean Absolute Error (MAE): 20.00
Mean Squared Error (MSE): 4213.92
Root Mean Squared Error (RMSE): 64.91
R-squared Score (R²): 0.9995
```

Visualizing Predictions

```
plt.figure(figsize=(8,6))
sns.scatterplot(x=y_test, y=y_pred, alpha=0.5)
plt.xlabel("Actual Price")
plt.ylabel("Predicted Price")
plt.title("Actual vs Predicted Car Prices")
plt.show()
```



Conclusion of Car Price Prediction Model

The Linear Regression model performs exceptionally well, with an R^2 score of 0.9995, meaning it explains 99.95% of the variance in car prices. The low MAE (20.00) and RMSE (64.91) indicate accurate predictions. However, the high R^2 suggests potential overfitting, so further validation and testing on unseen data are recommended.

```
```