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


df = pd.read_csv('/content/CarPrice_Assignment (1).csv')

X = df[['enginesize', 'horsepower', 'citympg', 'highwaympg']] #
Numerical features only
y = df['price']

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

scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

model = LinearRegression()
model.fit(X_train_scaled, y_train)
```

```
LinearRegression()
```

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

print("="*50)
print("MODEL COEFFICIENTS:")
for feature, coef in zip(X.columns, model.coef_):
    print(f"{feature:>12}: {coef:>10.2f}")
print(f"{'Intercept':>12}: {model.intercept_:>10.2f}")

print("\nMODEL PERFORMANCE:")
print(f"{'MSE':>12}: {mean_squared_error(y_test, y_pred):>10.2f}")
print(f"{'RMSE':>12}: {np.sqrt(mean_squared_error(y_test,
y_pred)):>10.2f}")
print(f"{'R-squared':>12}: {r2_score(y_test, y_pred):>10.2f}")
print("="*50)
```

```
==================================================
MODEL COEFFICIENTS:
  enginesize:    4523.40
  horsepower:    1694.22
     citympg:    -392.57
  highwaympg:    -816.36
   Intercept:   13223.41
```

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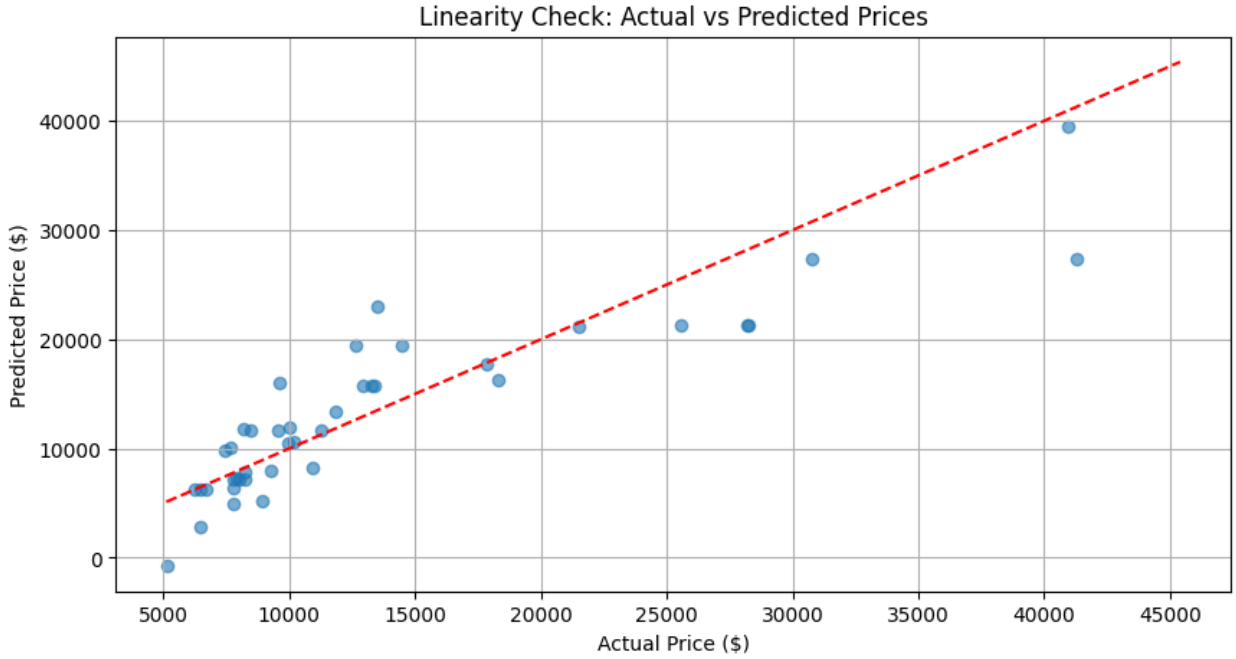
MODEL PERFORMANCE:
         MSE: 16471505.90
        RMSE:    4058.51
   R-squared:       0.79
==================================================


plt.figure(figsize=(10, 5))
plt.scatter(y_test, y_pred, alpha=0.6)
plt.plot([y.min(), y.max()], [y.min(), y.max()], 'r--')
plt.title("Linearity Check: Actual vs Predicted Prices")
plt.xlabel("Actual Price ($)")
plt.ylabel("Predicted Price ($)")
plt.grid(True)
plt.show()
```

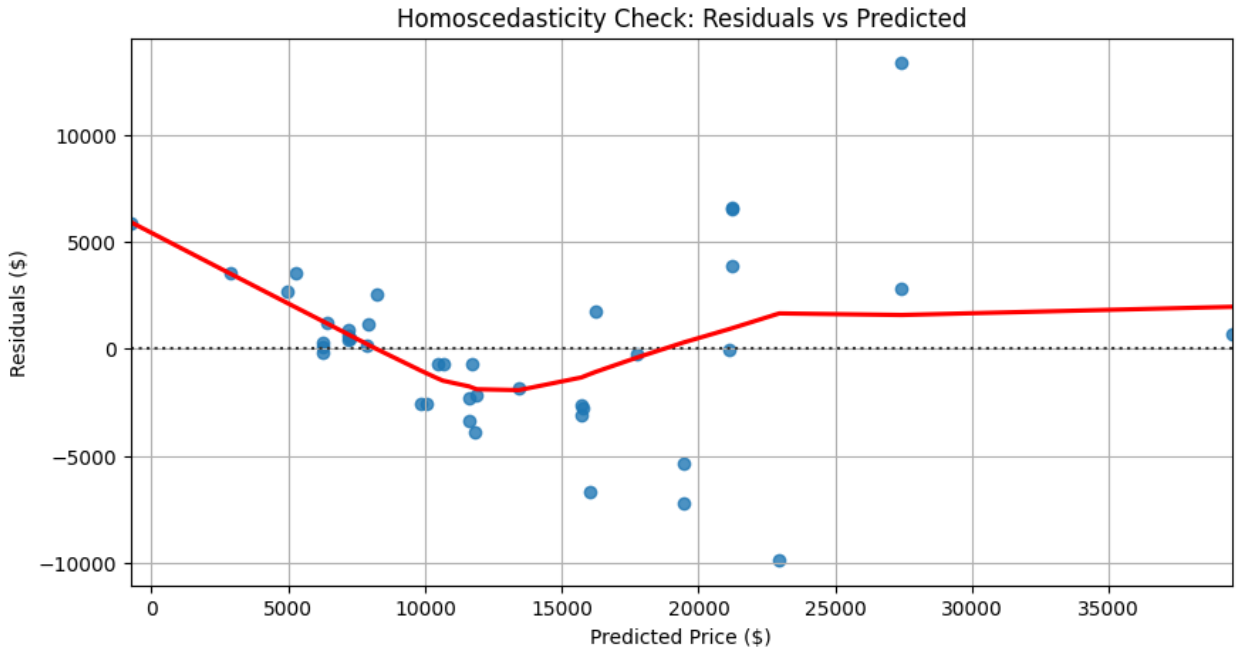



```
# 2. Independence
residuals = y_test - y_pred
dw_test = sm.stats.durbin_watson(residuals)
print(f"\nDurbin-Watson Statistic: {dw_test:.2f}",
      "\n(Values close to 2 indicate no autocorrelation)")

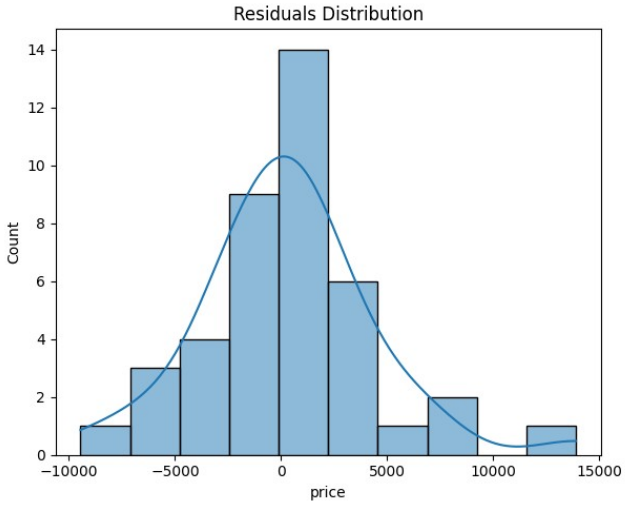

Durbin-Watson Statistic: 2.28
(Values close to 2 indicate no autocorrelation)

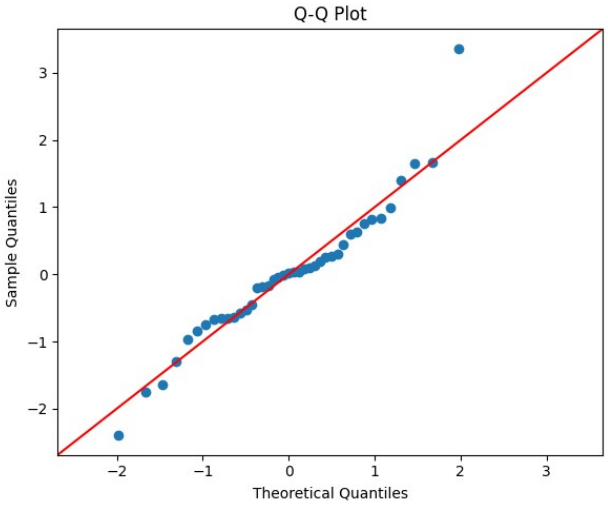
# 3. Homoscedasticity
plt.figure(figsize=(10, 5))
sns.residplot(x=y_pred, y=residuals, lowess=True, line_kws={'color':
```

```
'red'})
plt.title("Homoscedasticity Check: Residuals vs Predicted")
plt.xlabel("Predicted Price ($)")
plt.ylabel("Residuals ($)")
plt.grid(True)
plt.show()
```




```
# 4. Normality of residuals
fig, (ax1, ax2) = plt.subplots(1, 2, figsize=(12, 5))
sns.histplot(residuals, kde=True, ax=ax1)
ax1.set_title("Residuals Distribution")
sm.qqplot(residuals, line='45', fit=True, ax=ax2)
ax2.set_title("Q-Q Plot")
plt.tight_layout()
plt.show()
```


Residuals Distribution
Count
price
0
2
4
6
8
10
12
14
−10000
−5000
0
5000
10000
15000


Q-Q Plot
Sample Quantiles
Theoretical Quantiles
−2
−1
0
1
2
3