Machine Learning project

In [46]:
```python
import pandas as pd
import numpy as np
import warnings
warnings.filterwarnings('ignore')
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.preprocessing import StandardScaler, LabelEncoder
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 r2_score, mean_squared_error, mean_absolute_error
import matplotlib.pyplot as plt
import seaborn as sns
```

In [7]:
```python
# 1. Loading and Preprocessing
df = pd.read_csv("CarPrice_Assignment.csv")
```

In [9]:
```python
df.info
```

Out[9]:
```
<bound method DataFrame.info of      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]>
```

In [11]:
```python
df.head
```

Out[11]:
```
<bound method NDFrame.head of      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
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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]>
```

In [13]:
```python
df.tail
```

Out[13]:
```
<bound method NDFrame.tail of      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]>
```

In [19]:
```python
df.shape
```

Out[19]:
```
(205, 26)
```

In [35]:
```python
missing_values = df.isnull().sum()
print(missing_values)
```

```
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
```

Data Cleaning and Preprocessing

In [48]:
```python
# Handle missing values (if any)
for col in df.select_dtypes(include=np.number).columns:
    df[col].fillna(df[col].mean(), inplace=True) # Or median, or dropna, etc.
```

In [95]:
```python
# One-Hot Encode CATEGORICAL features FIRST
categorical_cols = df.select_dtypes(exclude=np.number).columns
df = pd.get_dummies(df, columns=categorical_cols, drop_first=True)  # Key change!

# Feature Scaling for NUMERICAL features SECOND
numerical_cols = df.select_dtypes(include=np.number).columns
scaler = StandardScaler()
df[numerical_cols] = scaler.fit_transform(df[numerical_cols])
```

In [97]:
```python
# Convert categorical features to numerical using Label Encoding or One-Hot Encoding
categorical_cols = df.select_dtypes(exclude=np.number).columns
for col in categorical_cols:
    le = LabelEncoder()
    df[col] = le.fit_transform(df[col])  # Or use pd.get_dummies for One-Hot Encoding
```

In [99]:
```python
# Feature Scaling for numerical features (important for SVR and Gradient Boosting)
numerical_cols = df.select_dtypes(include=np.number).columns
scaler = StandardScaler()
df[numerical_cols] = scaler.fit_transform(df[numerical_cols])
```

In [101…
```python
# Define features (X) and target (y)
X = df.drop('price', axis=1)  # Assuming 'price' is the target variable
y = df['price']
```

In [103…
```python
# Split data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)  # Adjust test size as needed
```

In [111…
```python
# 2. Model Implementation
models = {
    "Linear Regression": LinearRegression(),
    "Decision Tree": DecisionTreeRegressor(random_state=42),
    "Random Forest": RandomForestRegressor(random_state=42),
    "Gradient Boosting": GradientBoostingRegressor(random_state=42),
    "Support Vector Regression": SVR()
}

results = {}
for name, model in models.items():
    model.fit(X_train, y_train)
    y_pred = model.predict(X_test)
    r2 = r2_score(y_test, y_pred)
    mse = mean_squared_error(y_test, y_pred)
    mae = mean_absolute_error(y_test, y_pred)
    results[name] = {'r2': r2, 'mse': mse, 'mae': mae}
```

In [113…
```python
# 3. Model Evaluation
print("Model Evaluation:")
for name, metrics in results.items():
    print(f"{name}:")
    for metric, value in metrics.items():
        print(f"  {metric}: {value}")
    print("-" * 20)
```

```
Model Evaluation:
Linear Regression:
  r2: -3.187310081900956e+25
  mse: 3.961853985753371e+25
  mae: 3080938811689.398
--------------------
Decision Tree:
  r2: 0.8686457713142739
  mse: 0.16327444179943937
  mae: 0.25369065521628487
--------------------
Random Forest:
  r2: 0.9533052290306544
  mse: 0.05804200398613472
  mae: 0.17418542528735687
--------------------
Gradient Boosting:
  r2: 0.9326100142072609
  mse: 0.08376633491950379
  mae: 0.2067109922891758
--------------------
Support Vector Regression:
  r2: 0.4011703465773214
  mse: 0.7443504360218921
  mae: 0.5519018324004277
--------------------
```

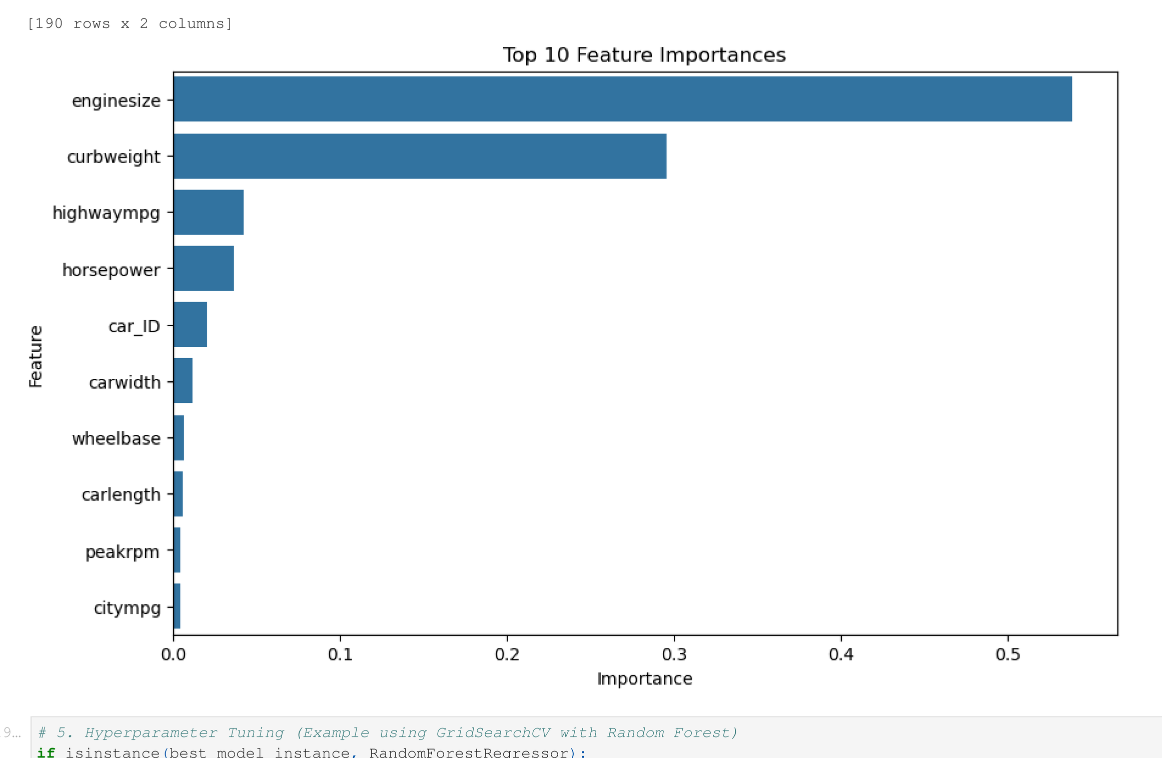
In [115…
```python
# Identify the best performing model (example - based on highest R-squared)
best_model = max(results, key=lambda k: results[k]['r2'])
print(f"Best Performing Model: {best_model}")
```

```
Best Performing Model: Random Forest
```

In [117…
```python
# 4. Feature Importance Analysis (Example using Random Forest - adapt for other models)
best_model_instance = models[best_model] # Get the instance of the best model.
if isinstance(best_model_instance, RandomForestRegressor): # Check if it is a random forest
    feature_importances = best_model_instance.feature_importances_
    feature_importance_df = pd.DataFrame({'Feature': X.columns, 'Importance': feature_importances})
    feature_importance_df = feature_importance_df.sort_values(by='Importance', ascending=False)
    print("\nFeature Importance (Random Forest):")
    print(feature_importance_df)
    plt.figure(figsize=(10, 6))
    sns.barplot(x='Importance', y='Feature', data=feature_importance_df.head(10)) # Plot top 10
    plt.title('Top 10 Feature Importances')
    plt.show() # Display the plot
elif hasattr(best_model_instance, 'coef_'):  # Check for linear models
    feature_importance_df = pd.DataFrame({'Feature': X.columns, 'Importance': best_model_instance.coef_})
    feature_importance_df = feature_importance_df.sort_values(by='Importance', ascending=False)
    print("\nFeature Importance (Linear Model):")
    print(feature_importance_df)
    plt.figure(figsize=(10, 6))
    sns.barplot(x='Importance', y='Feature', data=feature_importance_df.head(10).abs()) # Plot top 10, absolute values for linear models
    plt.title('Top 10 Feature Importances (Absolute Values)')
    plt.show()
else:
    print("\nFeature importance analysis not directly available for the best model.")
```

```
Feature Importance (Random Forest):
                            Feature  Importance
7                        enginesize    0.538823
6                        curbweight    0.295807
14                       highwaympg    0.042438
11                       horsepower    0.036676
0                            car_ID    0.020347
..                              ...         ...
71         CarName_mazda glc custom l    0.000000
131  CarName_toyota corolla 1600 (sw)    0.000000
60        CarName_isuzu D-Max V-Cross    0.000000
148         CarName_volkswagen rabbit    0.000000
119               CarName_subaru baja    0.000000

[190 rows x 2 columns]
```



In [119…
```python
# 5. Hyperparameter Tuning (Example using GridSearchCV with Random Forest)
if isinstance(best_model_instance, RandomForestRegressor):
    param_grid = {  # Example parameter grid - adjust based on the model
        '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=3, scoring='r2', n_jobs=-1)
    grid_search.fit(X_train, y_train)

    best_rf_model = grid_search.best_estimator_
    y_pred_tuned = best_rf_model.predict(X_test)
    r2_tuned = r2_score(y_test, y_pred_tuned)
    print(f"\nHyperparameter Tuned Random Forest R-squared: {r2_tuned}")
    print(f"Best parameters: {grid_search.best_params_}")

    # Compare performance after tuning
    print(f"Original Random Forest R-squared: {results['Random Forest']['r2']}")
elif isinstance(best_model_instance, GradientBoostingRegressor): # Example for GradientBoosting
    param_grid = {
        'n_estimators': [50, 100, 200],
        'learning_rate': [0.01, 0.1, 0.5],
        'max_depth': [3, 5, 7]
    }
    grid_search = GridSearchCV(GradientBoostingRegressor(random_state=42), param_grid, cv=3, scoring='r2', n_jobs=-1)
    grid_search.fit(X_train, y_train)
    best_gb_model = grid_search.best_estimator_
    y_pred_tuned = best_gb_model.predict(X_test)
    r2_tuned = r2_score(y_test, y_pred_tuned)
    print(f"\nHyperparameter Tuned Gradient Boosting R-squared: {r2_tuned}")
    print(f"Best parameters: {grid_search.best_params_}")
    print(f"Original Gradient Boosting R-squared: {results['Gradient Boosting']['r2']}")

else:
    print(f"Hyperparameter tuning not implemented for {best_model}")
```

```
Hyperparameter Tuned Random Forest R-squared: 0.9426605298224078
Best parameters: {'max_depth': 10, 'min_samples_split': 10, 'n_estimators': 200}
Original Random Forest R-squared: 0.9533052290306544
```

In [ ]: