In [1]:
```
import pandas as pd
import numpy as np
from xgboost import XGBRegressor
from sklearn.preprocessing import StandardScaler, LabelEncoder
from sklearn.model_selection import train_test_split, RandomizedSearchCV, GridSearc
from sklearn.metrics import r2_score, mean_absolute_error, mean_squared_error
import matplotlib.pyplot as plt
import seaborn as sns
import time
```

In [2]:
```
# Read the dataset
file_path = r"D:\CV things\ML projects\audi.csv"
df = pd.read_csv(file_path)
print(df.shape)
df
```

```
(10668, 9)
```

Out[2]:

	model	year	price	transmission	mileage	fuelType	tax	mpg	engineSize
0	A1	2017	12500	Manual	15735	Petrol	150	55.4	1.4
1	A6	2016	16500	Automatic	36203	Diesel	20	64.2	2.0
2	A1	2016	11000	Manual	29946	Petrol	30	55.4	1.4
3	A4	2017	16800	Automatic	25952	Diesel	145	67.3	2.0
4	A3	2019	17300	Manual	1998	Petrol	145	49.6	1.0
...	...	...	...	...	...	...	...	...	...
10663	A3	2020	16999	Manual	4018	Petrol	145	49.6	1.0
10664	A3	2020	16999	Manual	1978	Petrol	150	49.6	1.0
10665	A3	2020	17199	Manual	609	Petrol	150	49.6	1.0
10666	Q3	2017	19499	Automatic	8646	Petrol	150	47.9	1.4
10667	Q3	2016	15999	Manual	11855	Petrol	150	47.9	1.4

10668 rows × 9 columns

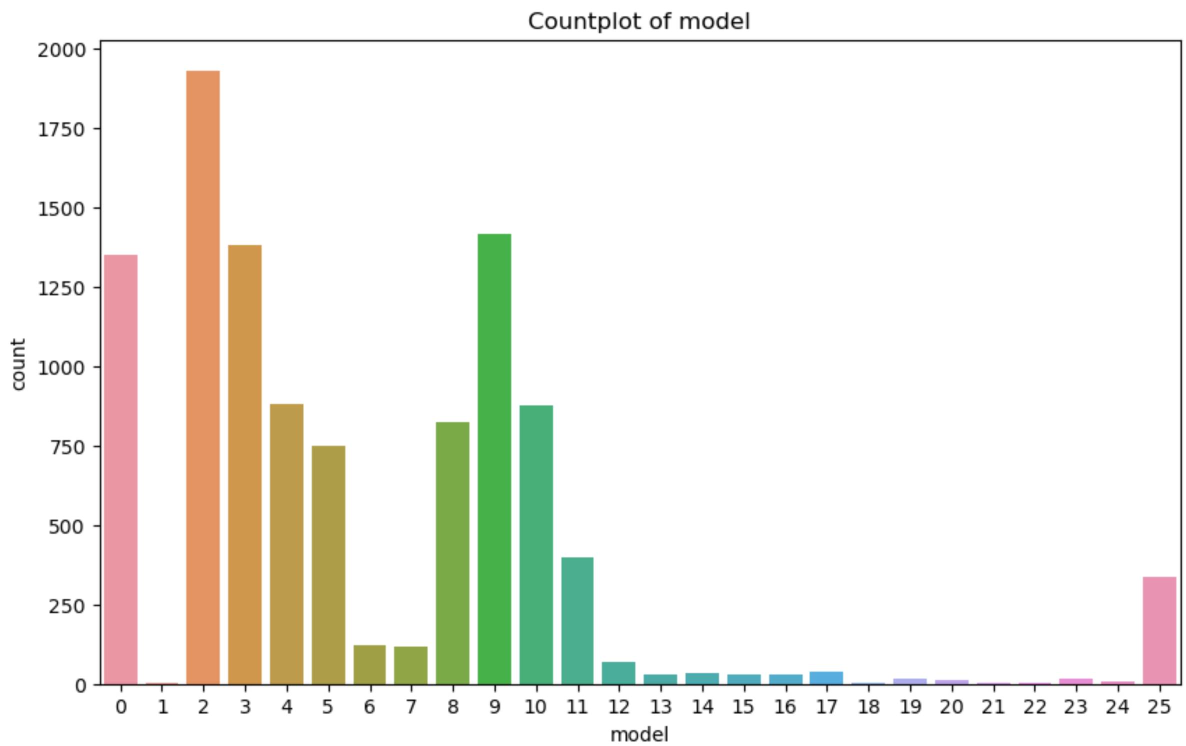
In [3]:
```
# Label Encoding for categorical features
categorical_features = ['model', 'transmission', 'fuelType']
le = LabelEncoder()
df[categorical_features] = df[categorical_features].apply(lambda col: le.fit_transf
df.head()
```

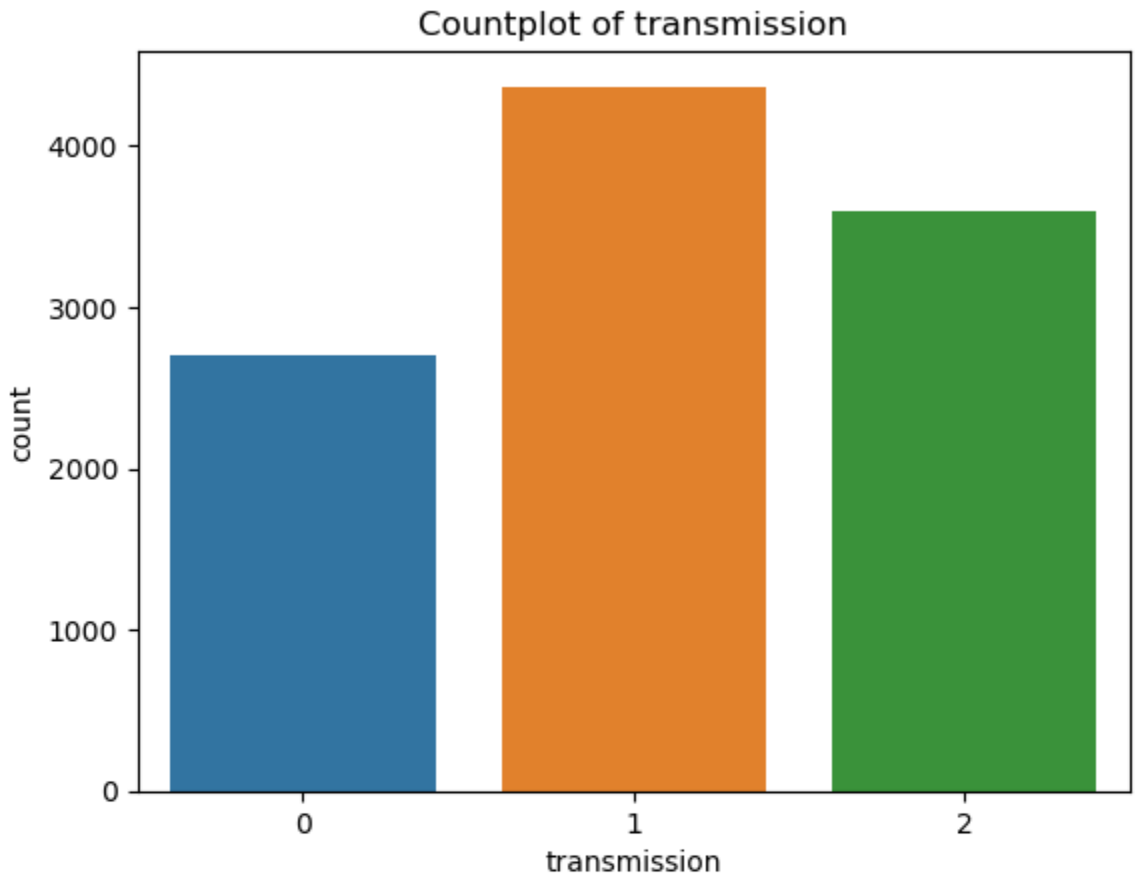
Out[3]:

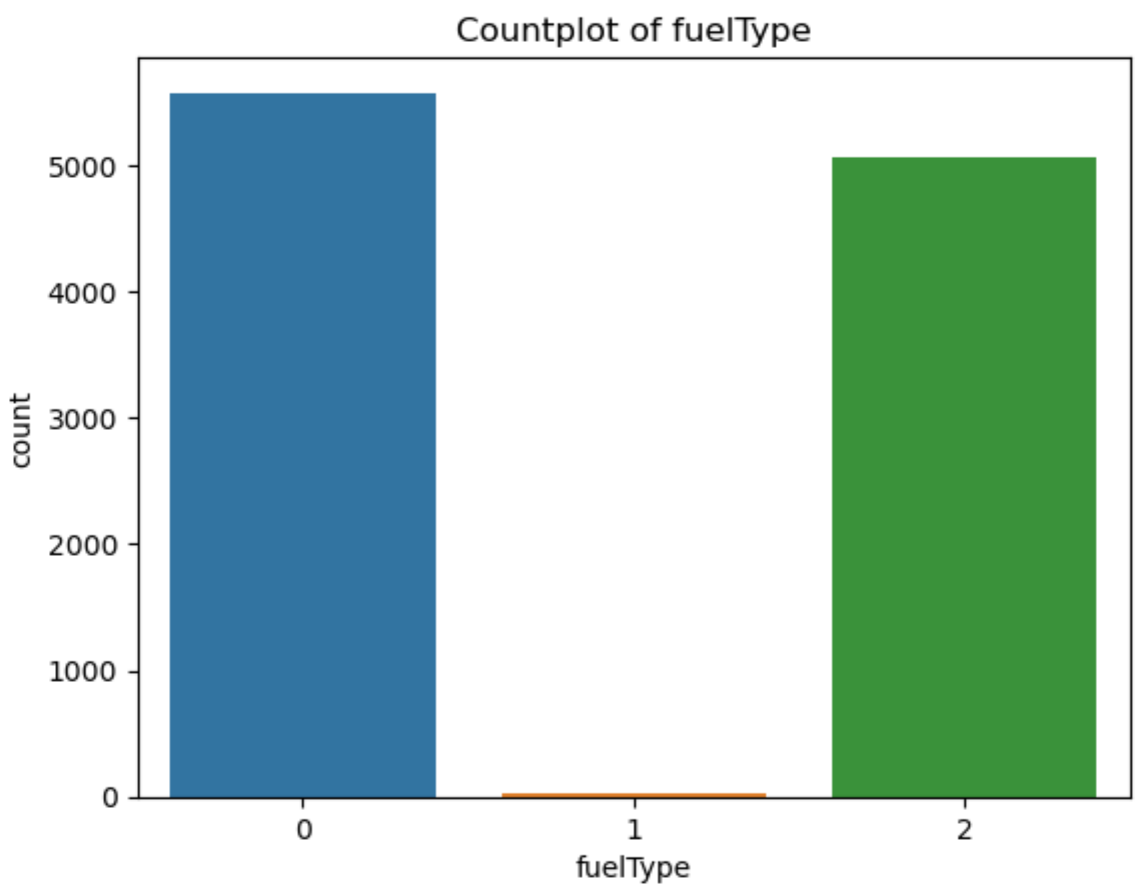
	model	year	price	transmission	mileage	fuelType	tax	mpg	engineSize
0	0	2017	12500	1	15735	2	150	55.4	1.4
1	5	2016	16500	0	36203	0	20	64.2	2.0
2	0	2016	11000	1	29946	2	30	55.4	1.4
3	3	2017	16800	0	25952	0	145	67.3	2.0
4	2	2019	17300	1	1998	2	145	49.6	1.0

In [4]:

```
# Countplot for categorical variables
plt.figure(figsize=(10, 6))
for col in categorical_features:
    sns.countplot(data=df, x=col)
    plt.title(f'Countplot of {col}')
    plt.show()
```




Countplot of transmission
4000
3000
2000
1000
0
count
0
1
2
transmission


Countplot of fuelType
5000
4000
3000
2000
1000
0
count
0
1
2
fuelType

In [5]:
```
# Preprocessing
X = df.drop('price', axis=1)
y = df['price']

# Train-test split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_sta
```

In [6]:
```
# R2 Score before Feature Engineering
xgb = XGBRegressor()

xgb.fit(X_train, y_train)
y_pred = xgb.predict(X_test)
r2_base = r2_score(y_test, y_pred)
print(f"R2 Score before feature engineering: {r2_base}")
```

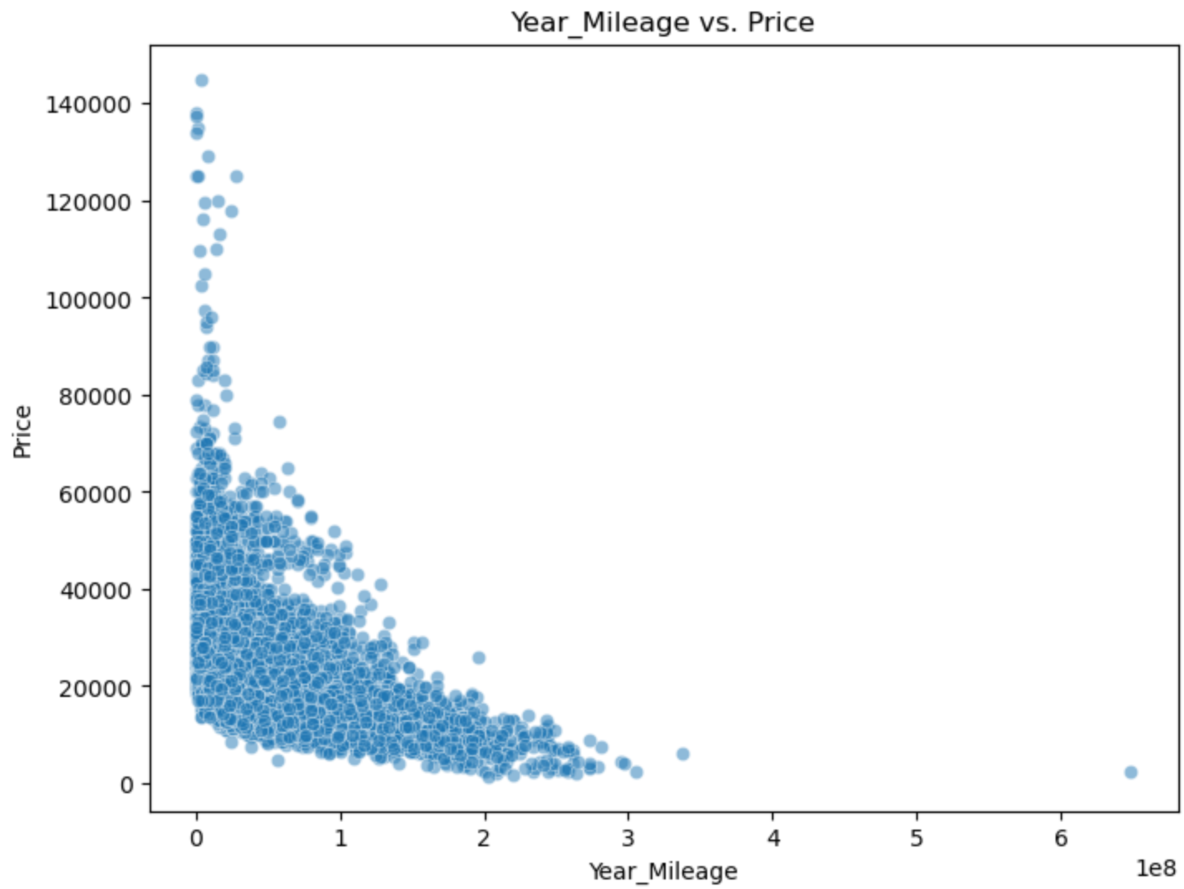
```
R2 Score before feature engineering: 0.9624305988307729
```

In [7]:
```
# Feature Engineering - Creating a new feature 'Year_Mileage'
df['Year_Mileage'] = df['year'] * df['mileage']
df.head()
```

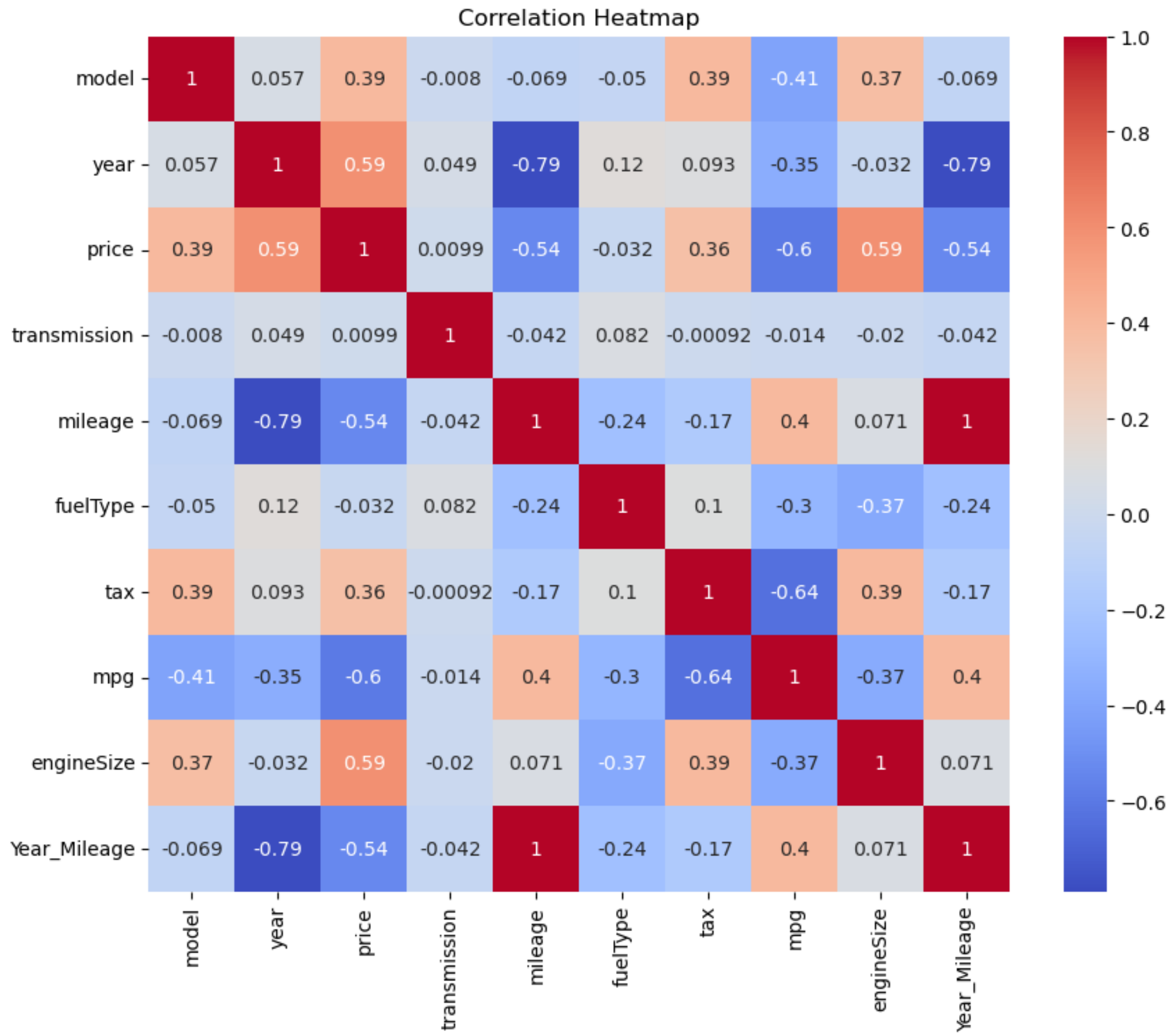
Out[7]:

	model	year	price	transmission	mileage	fuelType	tax	mpg	engineSize	Year_Mileage
0	0	2017	12500	1	15735	2	150	55.4	1.4	31737495
1	5	2016	16500	0	36203	0	20	64.2	2.0	72985248
2	0	2016	11000	1	29946	2	30	55.4	1.4	60371136
3	3	2017	16800	0	25952	0	145	67.3	2.0	52345184
4	2	2019	17300	1	1998	2	145	49.6	1.0	4033962

In [8]:
```
# Scatterplot showing Year_Mileage vs. Price after feature engineering
plt.figure(figsize=(8, 6))
sns.scatterplot(data=df, x='Year_Mileage', y='price', alpha=0.5, palette='viridis')
plt.title('Year_Mileage vs. Price')
plt.xlabel('Year_Mileage')
plt.ylabel('Price')
plt.show()
```



In [9]:
```
# Correlation heatmap
plt.figure(figsize=(10, 8))
sns.heatmap(df.corr(), annot=True, cmap='coolwarm')
plt.title('Correlation Heatmap')
plt.show()
```

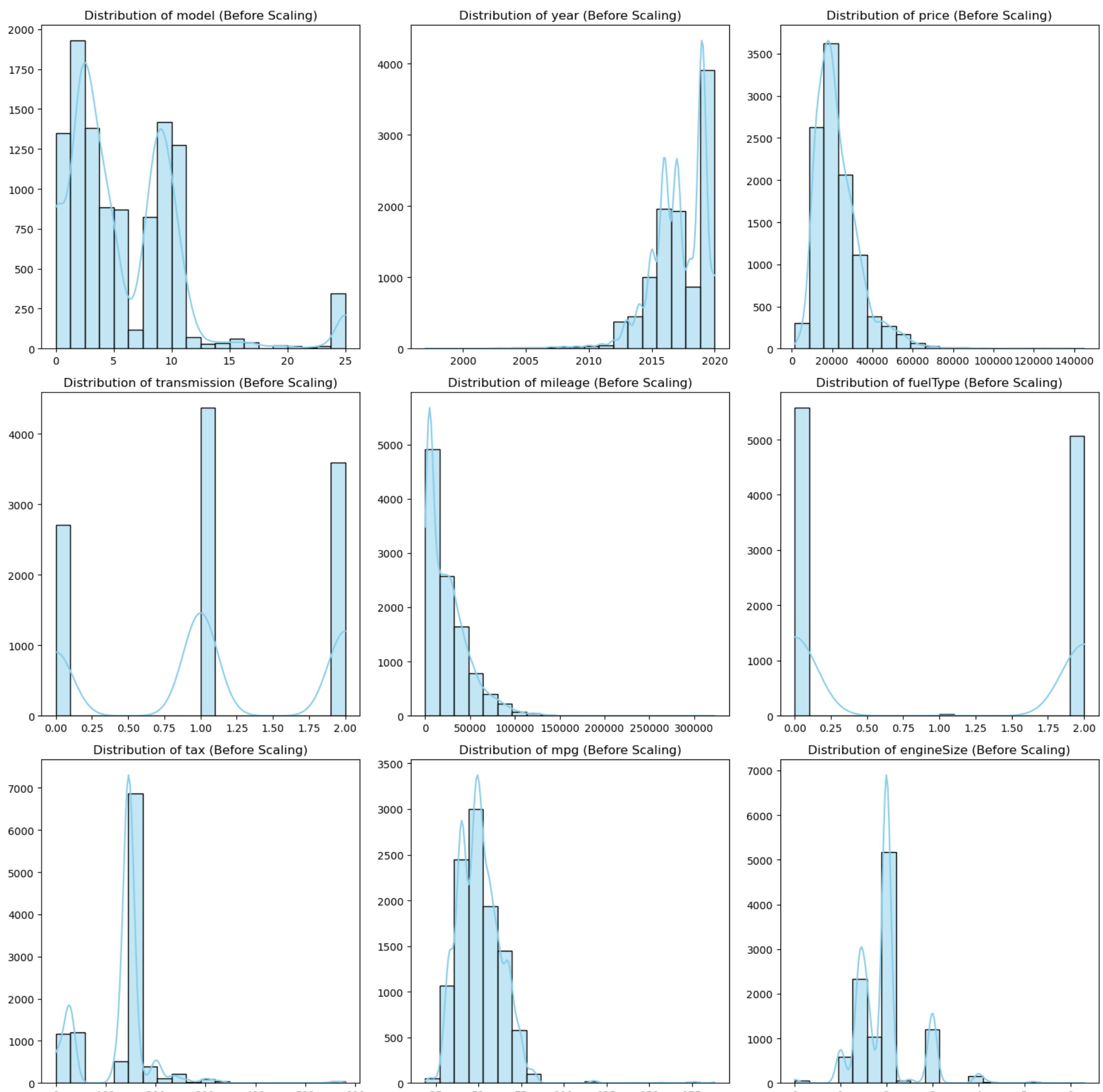


In [10]:

```
# Preprocessing
X = df.drop('price', axis=1)
y = df['price']

# Train-test split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_sta

# R2 Score after Feature Engineering
xgb = XGBRegressor()
xgb.fit(X_train, y_train)
y_pred = xgb.predict(X_test)
r2_base = r2_score(y_test, y_pred)

print(f"R2 Score after feature engineering: {r2_base}")
```

```
R2 Score after feature engineering: 0.9613934545410823
```

In [11]:
```python
# Get numerical columns and set the ones to display
numerical_columns = df.select_dtypes(include='number').columns.tolist()
num_cols_to_display = 9
num_cols = numerical_columns[:num_cols_to_display]

# Visualize distributions before scaling for each numerical feature separately
plt.figure(figsize=(15, 15))

for i, col in enumerate(num_cols):
    plt.subplot(3, 3, i+1)
    sns.histplot(df[col], bins=20, kde=True, color='skyblue')
    plt.title(f"Distribution of {col} (Before Scaling)")
    plt.xlabel('')
    plt.ylabel('')

plt.tight_layout()
plt.show()
```

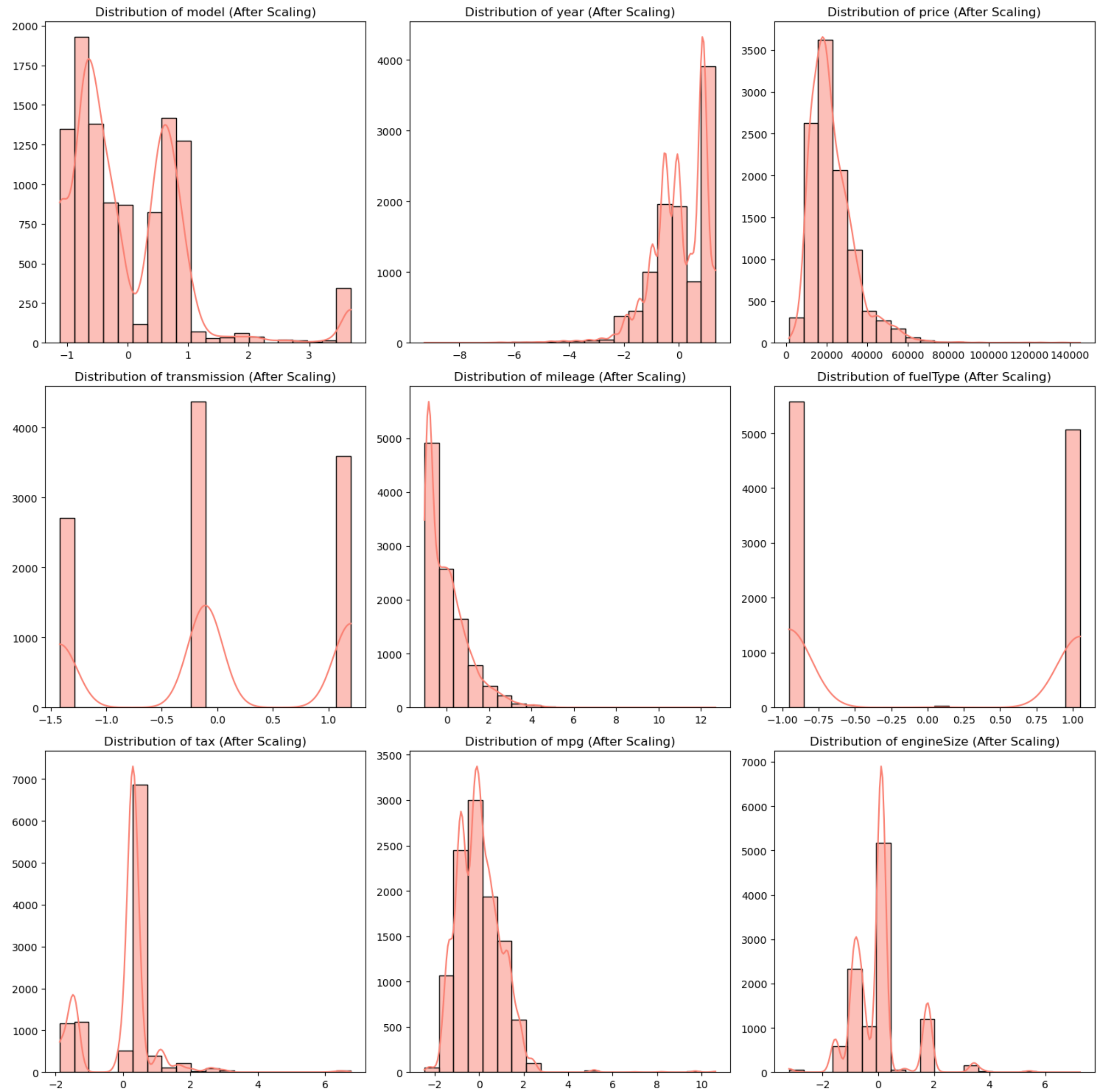


In [12]:
```python
# Assuming df contains your dataset and numerical_columns are the columns you want
scaler = StandardScaler()
X_scaled = scaler.fit_transform(df[numerical_columns])

# Create a DataFrame for scaled features
X_scaled_df = pd.DataFrame(X_scaled, columns=numerical_columns)
X_scaled_df['price'] = df['price']  # Include the target variable if needed

X = X_scaled_df.drop('price', axis=1)
y = X_scaled_df['price']

X_scaled_df.head()
```

Out[12]:

	model	year	price	transmission	mileage	fuelType	tax	mpg	engineSize
0	-1.123544	-0.046450	12500	-0.108347	-0.386836	1.050783	0.357147	0.357550	-0.880218
1	-0.160831	-0.507834	16500	-1.417348	0.483989	-0.954181	-1.578323	1.037130	0.114925
2	-1.123544	-0.507834	11000	-0.108347	0.217781	1.050783	-1.429440	0.357550	-0.880218
3	-0.545916	-0.046450	16800	-1.417348	0.047853	-0.954181	0.282706	1.276528	0.114925
4	-0.738459	0.876318	17300	-0.108347	-0.971285	1.050783	0.282706	-0.090355	-1.543647

In [13]:
```python
# Visualize distributions after scaling for each numerical feature separately
plt.figure(figsize=(15, 15))

for i, col in enumerate(num_cols):
    plt.subplot(3, 3, i+1)
    sns.histplot(X_scaled_df[col], bins=20, kde=True, color='salmon')  # Adjust col
    plt.title(f"Distribution of {col} (After Scaling)")
    plt.xlabel('')
    plt.ylabel('')

plt.tight_layout()
plt.show()
```



In [14]:
```
# Assuming you've performed the train-test split previously
X_train_scaled, X_test_scaled, y_train_scaled, y_test_scaled = train_test_split(X,
```

In [15]:
```
# R2 Score after scaling
scaled_xgb = XGBRegressor()
scaled_xgb.fit(X_train_scaled, y_train_scaled)
y_pred_scaled = scaled_xgb.predict(X_test_scaled)
r2_scaled = r2_score(y_test_scaled, y_pred_scaled)
print(f"R2 Score after scaling: {r2_scaled}")
```

```
R2 Score after scaling: 0.9613934545410823
```

In [16]:
```
# Hyperparameter tuning
param_dist = {
    'n_estimators': range(100, 300),
    'learning_rate': [0.01, 0.1, 0.2, 0.3],
    'max_depth': range(3, 8)
}

# Initialize XGBoost regressor and RandomizedSearchCV
xgb = XGBRegressor()

# RandomizedSearchCV
start_time_random = time.time()

random_search = RandomizedSearchCV(estimator=xgb, param_distributions=param_dist, n

# Perform RandomizedSearchCV on the scaled training data
random_search.fit(X_train_scaled, y_train_scaled)

# Get the best estimator
best_xgb_random = random_search.best_estimator_

end_time_random = time.time()
random_search_time = end_time_random - start_time_random

# Predictions using the best model
y_pred_random = best_xgb_random.predict(X_test_scaled)
```

In [17]:
```
# Print mean scores and standard deviations for different hyperparameter combinatio
cv_results = random_search.cv_results_
for mean_score, std_score, params in zip(
    cv_results["mean_test_score"],
    cv_results["std_test_score"],
    cv_results["params"]
):
    print(f"Mean R2: {mean_score:.4f}, Std: {std_score:.4f} for {params}")
```

```
Mean R2: 0.8895, Std: 0.0035 for {'n_estimators': 151, 'max_depth': 7, 'learning_ra
te': 0.01}
Mean R2: 0.9585, Std: 0.0036 for {'n_estimators': 294, 'max_depth': 6, 'learning_ra
te': 0.3}
Mean R2: 0.8792, Std: 0.0027 for {'n_estimators': 228, 'max_depth': 3, 'learning_ra
te': 0.01}
Mean R2: 0.9394, Std: 0.0018 for {'n_estimators': 237, 'max_depth': 7, 'learning_ra
te': 0.01}
Mean R2: 0.9610, Std: 0.0044 for {'n_estimators': 166, 'max_depth': 4, 'learning_ra
te': 0.3}
Mean R2: 0.9591, Std: 0.0036 for {'n_estimators': 228, 'max_depth': 6, 'learning_ra
te': 0.3}
Mean R2: 0.9617, Std: 0.0028 for {'n_estimators': 124, 'max_depth': 6, 'learning_ra
te': 0.1}
Mean R2: 0.8467, Std: 0.0033 for {'n_estimators': 152, 'max_depth': 4, 'learning_ra
te': 0.01}
Mean R2: 0.9542, Std: 0.0023 for {'n_estimators': 114, 'max_depth': 4, 'learning_ra
te': 0.1}
Mean R2: 0.9599, Std: 0.0021 for {'n_estimators': 231, 'max_depth': 4, 'learning_ra
te': 0.1}
Mean R2: 0.9002, Std: 0.0019 for {'n_estimators': 210, 'max_depth': 4, 'learning_ra
te': 0.01}
Mean R2: 0.9297, Std: 0.0019 for {'n_estimators': 208, 'max_depth': 7, 'learning_ra
te': 0.01}
Mean R2: 0.9606, Std: 0.0033 for {'n_estimators': 176, 'max_depth': 4, 'learning_ra
te': 0.2}
Mean R2: 0.8640, Std: 0.0030 for {'n_estimators': 204, 'max_depth': 3, 'learning_ra
te': 0.01}
Mean R2: 0.9539, Std: 0.0022 for {'n_estimators': 213, 'max_depth': 3, 'learning_ra
te': 0.1}
Mean R2: 0.9620, Std: 0.0024 for {'n_estimators': 208, 'max_depth': 5, 'learning_ra
te': 0.1}
Mean R2: 0.9608, Std: 0.0032 for {'n_estimators': 165, 'max_depth': 5, 'learning_ra
te': 0.3}
Mean R2: 0.9573, Std: 0.0023 for {'n_estimators': 163, 'max_depth': 4, 'learning_ra
te': 0.1}
Mean R2: 0.9610, Std: 0.0034 for {'n_estimators': 204, 'max_depth': 4, 'learning_ra
te': 0.2}
Mean R2: 0.9619, Std: 0.0030 for {'n_estimators': 263, 'max_depth': 6, 'learning_ra
te': 0.2}
```

In [18]:

```
# Evaluate the model
r2_random = r2_score(y_test_scaled, y_pred_random)
mae = mean_absolute_error(y_test_scaled, y_pred_random)
mse = mean_squared_error(y_test_scaled, y_pred_random)
rmse = np.sqrt(mse)

print("Best XGBoost Model Parameters:", random_search.best_params_)
```

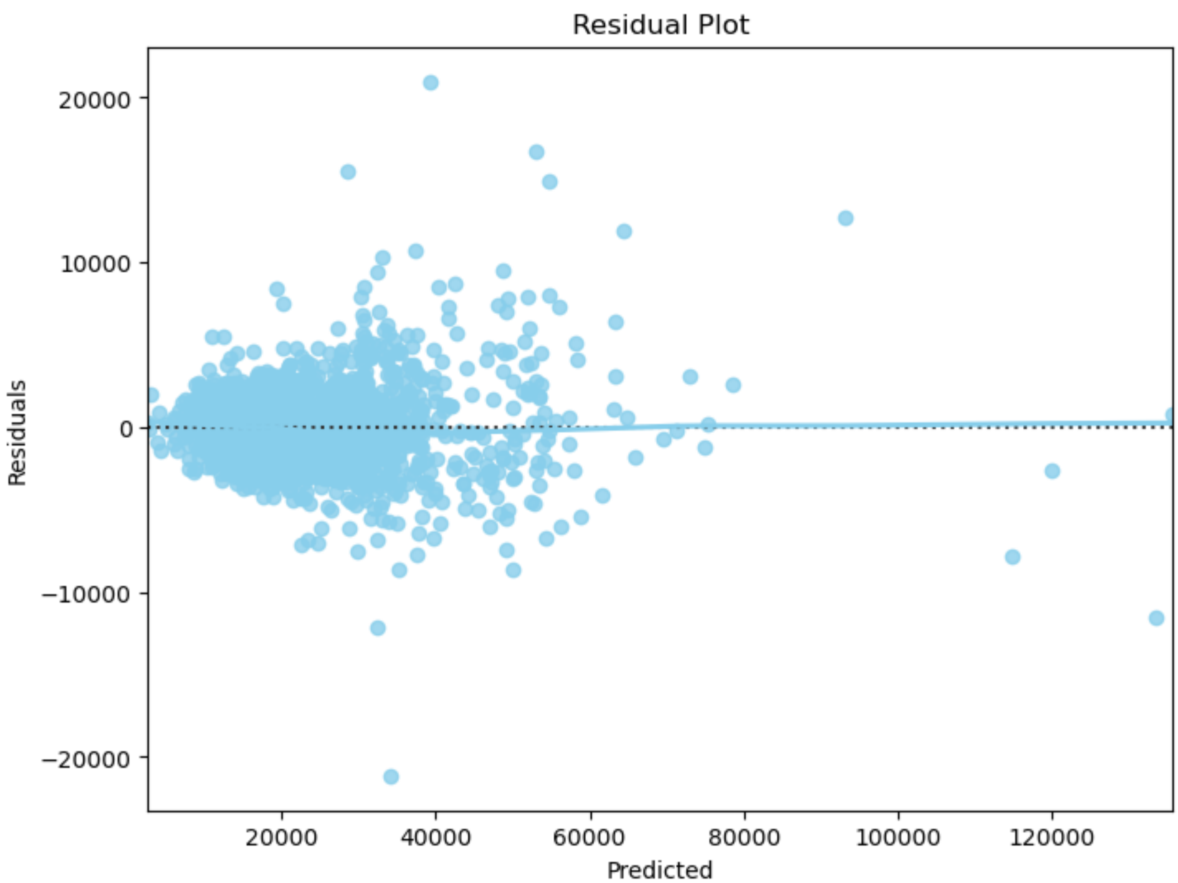
```
Best XGBoost Model Parameters: {'n_estimators': 208, 'max_depth': 5, 'learning_rate
': 0.1}
```

In [19]:

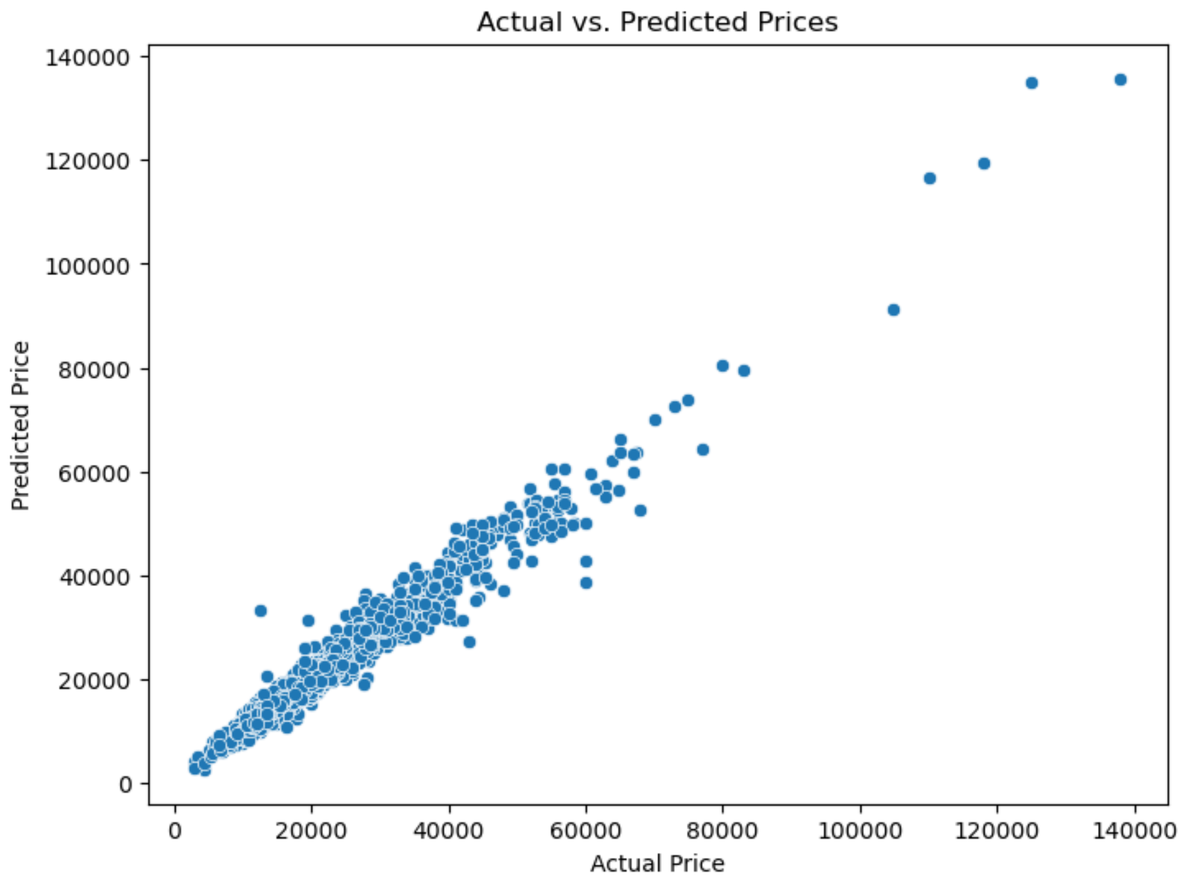
```
print(f"R2 Score after RandomizedSearchCV: {r2_random}")

print(f"MAE: {mae}")
print(f"MSE: {mse}")
print(f"RMSE: {rmse}")
```

```
R2 Score after RandomizedSearchCV: 0.9609913901632462
MAE: 1554.2503148430178
MSE: 5369702.057036524
RMSE: 2317.2617584201666
```

In [20]:
```python
# Residual plot
residuals = y_test_scaled - y_pred_random
plt.figure(figsize=(8, 6))
sns.residplot(x=y_pred_scaled, y=residuals, lowess=True, color='skyblue')
plt.title('Residual Plot')
plt.xlabel('Predicted')
plt.ylabel('Residuals')
plt.show()
```



In [21]:
```python
# Scatterplot for actual vs. predicted prices
plt.figure(figsize=(8, 6))
sns.scatterplot(x=y_test_scaled, y=y_pred_random)
plt.title('Actual vs. Predicted Prices')
plt.xlabel('Actual Price')
plt.ylabel('Predicted Price')
plt.show()
```



In [22]:

```
# Define the parameter grid for GridSearchCV
param_grid = {
    'n_estimators': [100, 150, 200, 250, 300],
    'learning_rate': [0.01, 0.1, 0.2, 0.3],
    'max_depth': [3, 4, 5, 6, 7]
}

# Initialize XGBoost regressor
xgb = XGBRegressor()

# GridSearchCV
start_time_grid = time.time()

# Initialize GridSearchCV
grid_search = GridSearchCV(estimator=xgb, param_grid=param_grid, cv=5, scoring='r2'

# Perform GridSearchCV on the scaled training data
grid_search.fit(X_train_scaled, y_train_scaled)

end_time_grid = time.time()
grid_search_time = end_time_grid - start_time_grid

# Get the best estimator
best_xgb_grid = grid_search.best_estimator_

# Predictions using the best model from GridSearchCV
y_pred_grid = best_xgb_grid.predict(X_test_scaled)
```

In [23]:
```
# Print mean scores and standard deviations for different hyperparameter combinatio
cv_results = grid_search.cv_results_
for mean_score, std_score, params in zip(
    cv_results["mean_test_score"],
    cv_results["std_test_score"],
    cv_results["params"]
):
    print(f"Mean R2: {mean_score:.4f}, Std: {std_score:.4f} for {params}")
```

```
Mean R2: 0.6913, Std: 0.0096 for {'learning_rate': 0.01, 'max_depth': 3, 'n_estimat
ors': 100}
Mean R2: 0.8061, Std: 0.0051 for {'learning_rate': 0.01, 'max_depth': 3, 'n_estimat
ors': 150}
Mean R2: 0.8609, Std: 0.0031 for {'learning_rate': 0.01, 'max_depth': 3, 'n_estimat
ors': 200}
Mean R2: 0.8900, Std: 0.0025 for {'learning_rate': 0.01, 'max_depth': 3, 'n_estimat
ors': 250}
Mean R2: 0.9077, Std: 0.0025 for {'learning_rate': 0.01, 'max_depth': 3, 'n_estimat
ors': 300}
Mean R2: 0.7381, Std: 0.0053 for {'learning_rate': 0.01, 'max_depth': 4, 'n_estimat
ors': 100}
Mean R2: 0.8439, Std: 0.0035 for {'learning_rate': 0.01, 'max_depth': 4, 'n_estimat
ors': 150}
Mean R2: 0.8939, Std: 0.0019 for {'learning_rate': 0.01, 'max_depth': 4, 'n_estimat
ors': 200}
Mean R2: 0.9181, Std: 0.0017 for {'learning_rate': 0.01, 'max_depth': 4, 'n_estimat
ors': 250}
Mean R2: 0.9304, Std: 0.0018 for {'learning_rate': 0.01, 'max_depth': 4, 'n_estimat
ors': 300}
Mean R2: 0.7700, Std: 0.0045 for {'learning_rate': 0.01, 'max_depth': 5, 'n_estimat
ors': 100}
Mean R2: 0.8673, Std: 0.0028 for {'learning_rate': 0.01, 'max_depth': 5, 'n_estimat
ors': 150}
Mean R2: 0.9114, Std: 0.0025 for {'learning_rate': 0.01, 'max_depth': 5, 'n_estimat
ors': 200}
Mean R2: 0.9316, Std: 0.0028 for {'learning_rate': 0.01, 'max_depth': 5, 'n_estimat
ors': 250}
Mean R2: 0.9413, Std: 0.0030 for {'learning_rate': 0.01, 'max_depth': 5, 'n_estimat
ors': 300}
Mean R2: 0.7878, Std: 0.0069 for {'learning_rate': 0.01, 'max_depth': 6, 'n_estimat
ors': 100}
Mean R2: 0.8813, Std: 0.0038 for {'learning_rate': 0.01, 'max_depth': 6, 'n_estimat
ors': 150}
Mean R2: 0.9208, Std: 0.0022 for {'learning_rate': 0.01, 'max_depth': 6, 'n_estimat
ors': 200}
Mean R2: 0.9393, Std: 0.0020 for {'learning_rate': 0.01, 'max_depth': 6, 'n_estimat
ors': 250}
Mean R2: 0.9482, Std: 0.0022 for {'learning_rate': 0.01, 'max_depth': 6, 'n_estimat
ors': 300}
Mean R2: 0.7973, Std: 0.0068 for {'learning_rate': 0.01, 'max_depth': 7, 'n_estimat
ors': 100}
Mean R2: 0.8884, Std: 0.0036 for {'learning_rate': 0.01, 'max_depth': 7, 'n_estimat
ors': 150}
Mean R2: 0.9261, Std: 0.0020 for {'learning_rate': 0.01, 'max_depth': 7, 'n_estimat
ors': 200}
Mean R2: 0.9424, Std: 0.0018 for {'learning_rate': 0.01, 'max_depth': 7, 'n_estimat
ors': 250}
Mean R2: 0.9502, Std: 0.0025 for {'learning_rate': 0.01, 'max_depth': 7, 'n_estimat
ors': 300}
Mean R2: 0.9439, Std: 0.0020 for {'learning_rate': 0.1, 'max_depth': 3, 'n_estimato
rs': 100}
Mean R2: 0.9498, Std: 0.0021 for {'learning_rate': 0.1, 'max_depth': 3, 'n_estimato
rs': 150}
Mean R2: 0.9533, Std: 0.0021 for {'learning_rate': 0.1, 'max_depth': 3, 'n_estimato
rs': 200}
Mean R2: 0.9552, Std: 0.0022 for {'learning_rate': 0.1, 'max_depth': 3, 'n_estimato
rs': 250}
Mean R2: 0.9569, Std: 0.0022 for {'learning_rate': 0.1, 'max_depth': 3, 'n_estimato
```

```
rs': 300}
Mean R2: 0.9530, Std: 0.0024 for {'learning_rate': 0.1, 'max_depth': 4, 'n_estimato
rs': 100}
Mean R2: 0.9566, Std: 0.0024 for {'learning_rate': 0.1, 'max_depth': 4, 'n_estimato
rs': 150}
Mean R2: 0.9590, Std: 0.0022 for {'learning_rate': 0.1, 'max_depth': 4, 'n_estimato
rs': 200}
Mean R2: 0.9605, Std: 0.0022 for {'learning_rate': 0.1, 'max_depth': 4, 'n_estimato
rs': 250}
Mean R2: 0.9615, Std: 0.0023 for {'learning_rate': 0.1, 'max_depth': 4, 'n_estimato
rs': 300}
Mean R2: 0.9582, Std: 0.0029 for {'learning_rate': 0.1, 'max_depth': 5, 'n_estimato
rs': 100}
Mean R2: 0.9603, Std: 0.0026 for {'learning_rate': 0.1, 'max_depth': 5, 'n_estimato
rs': 150}
Mean R2: 0.9618, Std: 0.0024 for {'learning_rate': 0.1, 'max_depth': 5, 'n_estimato
rs': 200}
Mean R2: 0.9626, Std: 0.0024 for {'learning_rate': 0.1, 'max_depth': 5, 'n_estimato
rs': 250}
Mean R2: 0.9630, Std: 0.0022 for {'learning_rate': 0.1, 'max_depth': 5, 'n_estimato
rs': 300}
Mean R2: 0.9608, Std: 0.0028 for {'learning_rate': 0.1, 'max_depth': 6, 'n_estimato
rs': 100}
Mean R2: 0.9621, Std: 0.0028 for {'learning_rate': 0.1, 'max_depth': 6, 'n_estimato
rs': 150}
Mean R2: 0.9628, Std: 0.0027 for {'learning_rate': 0.1, 'max_depth': 6, 'n_estimato
rs': 200}
Mean R2: 0.9630, Std: 0.0026 for {'learning_rate': 0.1, 'max_depth': 6, 'n_estimato
rs': 250}
Mean R2: 0.9630, Std: 0.0026 for {'learning_rate': 0.1, 'max_depth': 6, 'n_estimato
rs': 300}
Mean R2: 0.9601, Std: 0.0028 for {'learning_rate': 0.1, 'max_depth': 7, 'n_estimato
rs': 100}
Mean R2: 0.9608, Std: 0.0030 for {'learning_rate': 0.1, 'max_depth': 7, 'n_estimato
rs': 150}
Mean R2: 0.9610, Std: 0.0030 for {'learning_rate': 0.1, 'max_depth': 7, 'n_estimato
rs': 200}
Mean R2: 0.9607, Std: 0.0030 for {'learning_rate': 0.1, 'max_depth': 7, 'n_estimato
rs': 250}
Mean R2: 0.9604, Std: 0.0031 for {'learning_rate': 0.1, 'max_depth': 7, 'n_estimato
rs': 300}
Mean R2: 0.9519, Std: 0.0032 for {'learning_rate': 0.2, 'max_depth': 3, 'n_estimato
rs': 100}
Mean R2: 0.9554, Std: 0.0032 for {'learning_rate': 0.2, 'max_depth': 3, 'n_estimato
rs': 150}
Mean R2: 0.9573, Std: 0.0034 for {'learning_rate': 0.2, 'max_depth': 3, 'n_estimato
rs': 200}
Mean R2: 0.9586, Std: 0.0035 for {'learning_rate': 0.2, 'max_depth': 3, 'n_estimato
rs': 250}
Mean R2: 0.9596, Std: 0.0036 for {'learning_rate': 0.2, 'max_depth': 3, 'n_estimato
rs': 300}
Mean R2: 0.9575, Std: 0.0033 for {'learning_rate': 0.2, 'max_depth': 4, 'n_estimato
rs': 100}
Mean R2: 0.9598, Std: 0.0032 for {'learning_rate': 0.2, 'max_depth': 4, 'n_estimato
rs': 150}
Mean R2: 0.9609, Std: 0.0035 for {'learning_rate': 0.2, 'max_depth': 4, 'n_estimato
rs': 200}
Mean R2: 0.9617, Std: 0.0033 for {'learning_rate': 0.2, 'max_depth': 4, 'n_estimato
rs': 250}
```

```
Mean R2: 0.9620, Std: 0.0032 for {'learning_rate': 0.2, 'max_depth': 4, 'n_estimato
rs': 300}
Mean R2: 0.9608, Std: 0.0027 for {'learning_rate': 0.2, 'max_depth': 5, 'n_estimato
rs': 100}
Mean R2: 0.9619, Std: 0.0027 for {'learning_rate': 0.2, 'max_depth': 5, 'n_estimato
rs': 150}
Mean R2: 0.9623, Std: 0.0025 for {'learning_rate': 0.2, 'max_depth': 5, 'n_estimato
rs': 200}
Mean R2: 0.9624, Std: 0.0025 for {'learning_rate': 0.2, 'max_depth': 5, 'n_estimato
rs': 250}
Mean R2: 0.9622, Std: 0.0026 for {'learning_rate': 0.2, 'max_depth': 5, 'n_estimato
rs': 300}
Mean R2: 0.9623, Std: 0.0030 for {'learning_rate': 0.2, 'max_depth': 6, 'n_estimato
rs': 100}
Mean R2: 0.9626, Std: 0.0030 for {'learning_rate': 0.2, 'max_depth': 6, 'n_estimato
rs': 150}
Mean R2: 0.9623, Std: 0.0030 for {'learning_rate': 0.2, 'max_depth': 6, 'n_estimato
rs': 200}
Mean R2: 0.9619, Std: 0.0030 for {'learning_rate': 0.2, 'max_depth': 6, 'n_estimato
rs': 250}
Mean R2: 0.9616, Std: 0.0031 for {'learning_rate': 0.2, 'max_depth': 6, 'n_estimato
rs': 300}
Mean R2: 0.9600, Std: 0.0038 for {'learning_rate': 0.2, 'max_depth': 7, 'n_estimato
rs': 100}
Mean R2: 0.9596, Std: 0.0039 for {'learning_rate': 0.2, 'max_depth': 7, 'n_estimato
rs': 150}
Mean R2: 0.9592, Std: 0.0039 for {'learning_rate': 0.2, 'max_depth': 7, 'n_estimato
rs': 200}
Mean R2: 0.9586, Std: 0.0041 for {'learning_rate': 0.2, 'max_depth': 7, 'n_estimato
rs': 250}
Mean R2: 0.9581, Std: 0.0042 for {'learning_rate': 0.2, 'max_depth': 7, 'n_estimato
rs': 300}
Mean R2: 0.9548, Std: 0.0026 for {'learning_rate': 0.3, 'max_depth': 3, 'n_estimato
rs': 100}
Mean R2: 0.9581, Std: 0.0025 for {'learning_rate': 0.3, 'max_depth': 3, 'n_estimato
rs': 150}
Mean R2: 0.9597, Std: 0.0025 for {'learning_rate': 0.3, 'max_depth': 3, 'n_estimato
rs': 200}
Mean R2: 0.9604, Std: 0.0028 for {'learning_rate': 0.3, 'max_depth': 3, 'n_estimato
rs': 250}
Mean R2: 0.9610, Std: 0.0027 for {'learning_rate': 0.3, 'max_depth': 3, 'n_estimato
rs': 300}
Mean R2: 0.9592, Std: 0.0043 for {'learning_rate': 0.3, 'max_depth': 4, 'n_estimato
rs': 100}
Mean R2: 0.9607, Std: 0.0045 for {'learning_rate': 0.3, 'max_depth': 4, 'n_estimato
rs': 150}
Mean R2: 0.9612, Std: 0.0046 for {'learning_rate': 0.3, 'max_depth': 4, 'n_estimato
rs': 200}
Mean R2: 0.9615, Std: 0.0046 for {'learning_rate': 0.3, 'max_depth': 4, 'n_estimato
rs': 250}
Mean R2: 0.9615, Std: 0.0045 for {'learning_rate': 0.3, 'max_depth': 4, 'n_estimato
rs': 300}
Mean R2: 0.9603, Std: 0.0035 for {'learning_rate': 0.3, 'max_depth': 5, 'n_estimato
rs': 100}
Mean R2: 0.9608, Std: 0.0031 for {'learning_rate': 0.3, 'max_depth': 5, 'n_estimato
rs': 150}
Mean R2: 0.9606, Std: 0.0030 for {'learning_rate': 0.3, 'max_depth': 5, 'n_estimato
rs': 200}
Mean R2: 0.9604, Std: 0.0030 for {'learning_rate': 0.3, 'max_depth': 5, 'n_estimato
```

```
rs': 250}
Mean R2: 0.9601, Std: 0.0030 for {'learning_rate': 0.3, 'max_depth': 5, 'n_estimato
rs': 300}
Mean R2: 0.9603, Std: 0.0036 for {'learning_rate': 0.3, 'max_depth': 6, 'n_estimato
rs': 100}
Mean R2: 0.9600, Std: 0.0033 for {'learning_rate': 0.3, 'max_depth': 6, 'n_estimato
rs': 150}
Mean R2: 0.9594, Std: 0.0035 for {'learning_rate': 0.3, 'max_depth': 6, 'n_estimato
rs': 200}
Mean R2: 0.9589, Std: 0.0036 for {'learning_rate': 0.3, 'max_depth': 6, 'n_estimato
rs': 250}
Mean R2: 0.9584, Std: 0.0036 for {'learning_rate': 0.3, 'max_depth': 6, 'n_estimato
rs': 300}
Mean R2: 0.9582, Std: 0.0042 for {'learning_rate': 0.3, 'max_depth': 7, 'n_estimato
rs': 100}
Mean R2: 0.9573, Std: 0.0043 for {'learning_rate': 0.3, 'max_depth': 7, 'n_estimato
rs': 150}
Mean R2: 0.9565, Std: 0.0044 for {'learning_rate': 0.3, 'max_depth': 7, 'n_estimato
rs': 200}
Mean R2: 0.9560, Std: 0.0044 for {'learning_rate': 0.3, 'max_depth': 7, 'n_estimato
rs': 250}
Mean R2: 0.9555, Std: 0.0045 for {'learning_rate': 0.3, 'max_depth': 7, 'n_estimato
rs': 300}
```

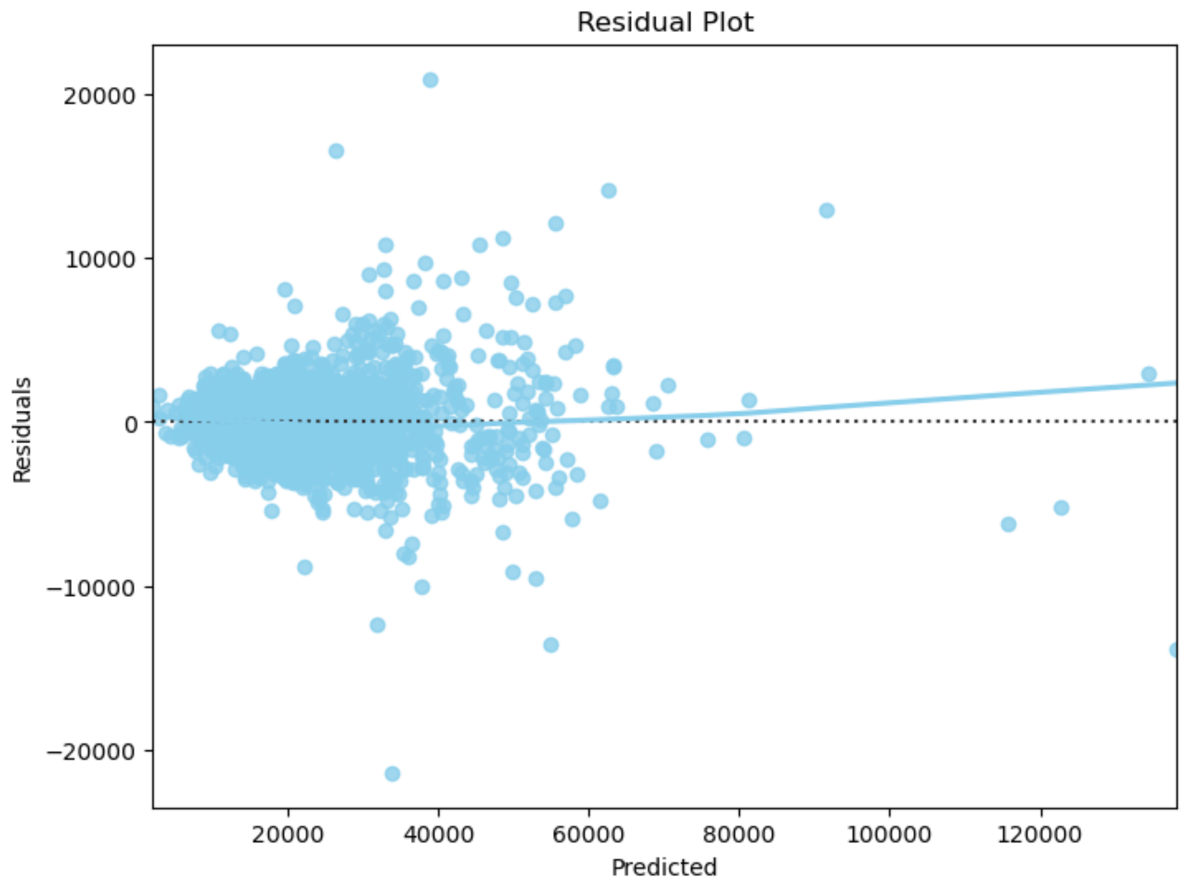
In [24]:

```
# Evaluate the model
r2_grid = r2_score(y_test_scaled, y_pred_grid)

print("Best XGBoost Model Parameters (GridSearchCV):", grid_search.best_params_)
print(f"R2 Score after GridSearchCV: {r2_grid}")
```

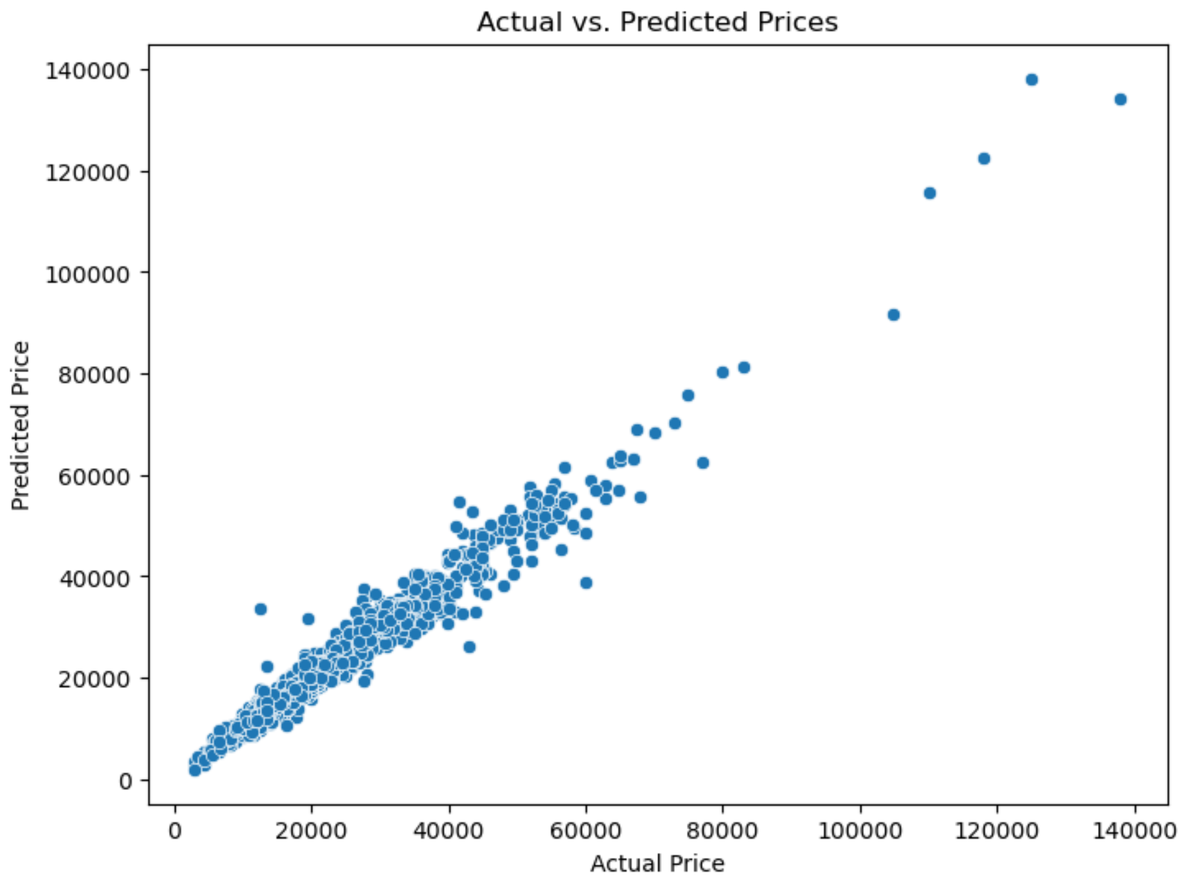
```
Best XGBoost Model Parameters (GridSearchCV): {'learning_rate': 0.1, 'max_depth': 6
, 'n_estimators': 300}
R2 Score after GridSearchCV: 0.963084519548073
```

In [25]:

```
# Residual plot
residuals = y_test_scaled - y_pred_grid
plt.figure(figsize=(8, 6))
sns.residplot(x=y_pred_grid, y=residuals, lowess=True, color='skyblue')
plt.title('Residual Plot')
plt.xlabel('Predicted')
plt.ylabel('Residuals')
plt.show()
```



In [26]:
```
# Scatterplot for actual vs. predicted prices
plt.figure(figsize=(8, 6))
sns.scatterplot(x=y_test_scaled, y=y_pred_grid)
plt.title('Actual vs. Predicted Prices')
plt.xlabel('Actual Price')
plt.ylabel('Predicted Price')
plt.show()
```

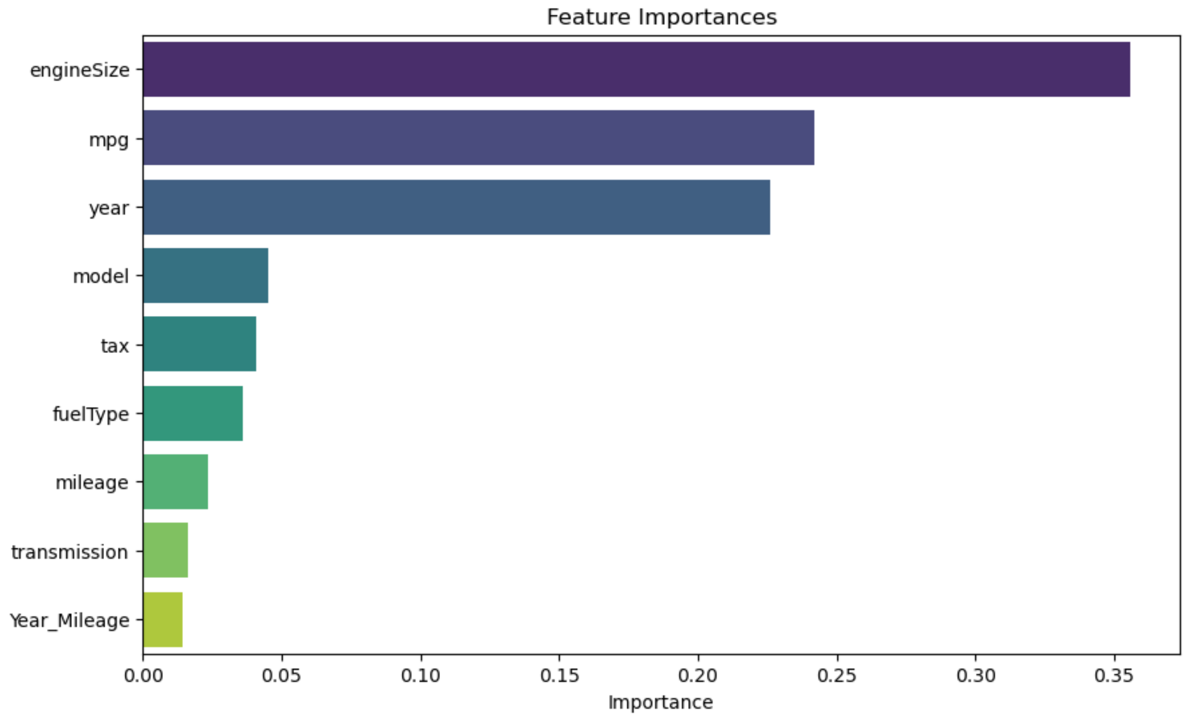


In [27]:
```
print(f"RandomizedSearchCV took {random_search_time} seconds.")
print(f"GridSearchCV took {grid_search_time} seconds.")
```

```
RandomizedSearchCV took 10.409626483917236 seconds.
GridSearchCV took 53.03264260292053 seconds.
```

In [28]:
```
# Display feature importance for the best model in decreasing order and different c
plt.figure(figsize=(10, 6))
feat_importances = pd.Series(best_xgb_grid.feature_importances_, index=X.columns)
feat_importances = feat_importances.sort_values(ascending=False)  # Sort in decreas
sns.barplot(x=feat_importances.values, y=feat_importances.index, palette='viridis')
plt.title('Feature Importances')
plt.xlabel('Importance')
```

Out[28]:
```
Text(0.5, 0, 'Importance')
```



In [29]:
```
# Select the top 5 features based on importance
top_features = feat_importances.index[:5]

# Extract only the top 5 features from the original dataset
X_top5 = X[top_features]

# Train-test split with the selected features
X_train_top5, X_test_top5, y_train_top5, y_test_top5 = train_test_split(X_top5, y,

# Initialize XGBoost regressor
xgb_top5 = XGBRegressor()

# Fit the model using the top 5 features
xgb_top5.fit(X_train_top5, y_train_top5)

# Make predictions
y_pred_top5 = xgb_top5.predict(X_test_top5)

# Evaluate the model with the top 5 features
r2_top5 = r2_score(y_test_top5, y_pred_top5)

print(f"R2 Score with the top 5 features: {r2_top5}")
```

```
R2 Score with the top 5 features: 0.9569746615504151
```