used-carspdfFinal

December 12, 2023

[ ]:
```
# Data Manipulation
import numpy as np
import pandas as pd
import warnings
# Visualization
import matplotlib.pyplot as plt
import seaborn as sns
from datetime import datetime
from sklearn.tree import export_graphviz
import pydot
#Train Test Split
from sklearn.model_selection import train_test_split

#Scaling
from sklearn.preprocessing import StandardScaler

#Models
import optuna
import xgboost as xgb
from sklearn.dummy import DummyRegressor
from skopt import BayesSearchCV
from sklearn.ensemble import RandomForestRegressor
from xgboost import XGBRegressor
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LinearRegression
from sklearn.svm import SVR
from sklearn.neighbors import KNeighborsRegressor
from sklearn.tree import DecisionTreeRegressor
from sklearn.model_selection import GridSearchCV

#Deep Neural Networks:
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Activation
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.callbacks import EarlyStopping

#Evaluation
```

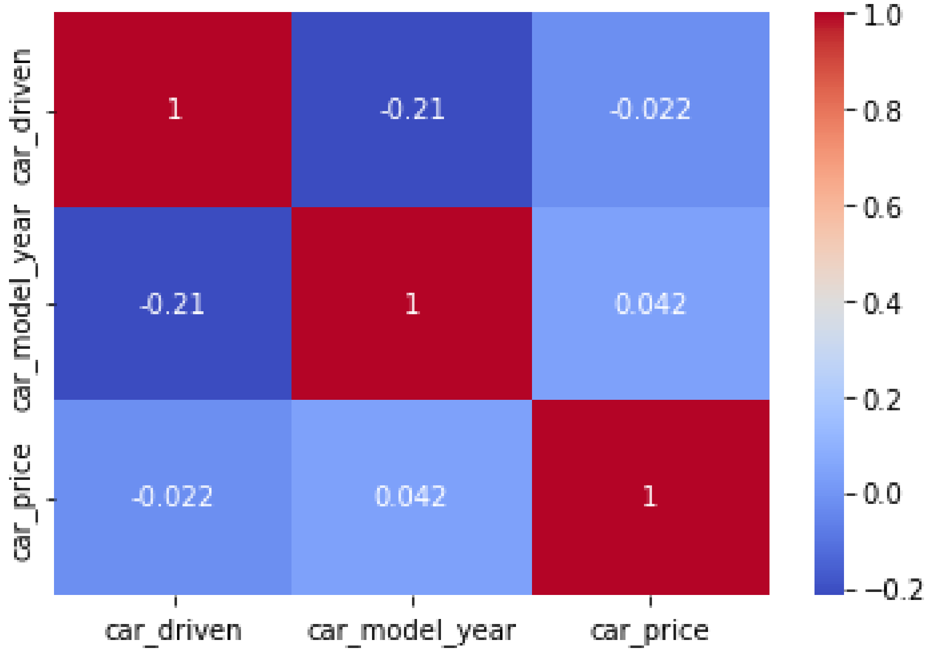
```python
from sklearn.model_selection import cross_val_score
from sklearn.metrics import classification_report
from sklearn.metrics import mean_absolute_error
from sklearn.metrics import mean_squared_error
from sklearn.metrics import r2_score
from sklearn.metrics import explained_variance_score

cars = pd.read_csv(r'C:\Users\rocke\Downloads\used_cars\used_car_cleaned.csv', delimiter=',')
cars2 = pd.read_csv(r'C:\Users\rocke\Downloads\used_cars\archive (2)\UsedCarsSA_Clean_EN.csv', delimiter=',')
warnings.filterwarnings("ignore")


# print(cars.head())
# print(cars2.head())

# CLEANING CODE

cars2 = cars2.drop(['Origin', 'Color', 'Options', 'Engine_Size', 'Fuel_Type', 'Region', 'Negotiable'], axis=1)
cars2 = cars2.rename(columns={'Make': 'car_brand', 'Type': 'car_model', 'Year': 'car_model_year', 'Gear_Type': 'car_transmission', 'Mileage': 'car_driven', 'Price': 'car_price'})
cars2 = cars2[cars.columns]
cars2 = cars2[cars2['car_price'] != 0]
cars = pd.concat([cars, cars2], ignore_index=True)
print(cars)
cars.to_csv("used_car_data.csv")
# Calculate correlations for selected columns
correlation_columns = ['car_driven', 'car_model_year', 'car_price']
correlation_matrix = cars[correlation_columns].corr()

# Create a heatmap to visualize the correlation matrix
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm')
plt.show()
sns.pairplot(data=cars,hue='car_transmission')
plt.show()

# price distribution

plt.figure(figsize=(15,8))

plt.subplot(1,2,1)
plt.title('Price Distribution Plot')
sns.histplot(cars['car_price'])
plt.ticklabel_format(useOffset=False, style='plain', axis=('x'))
```

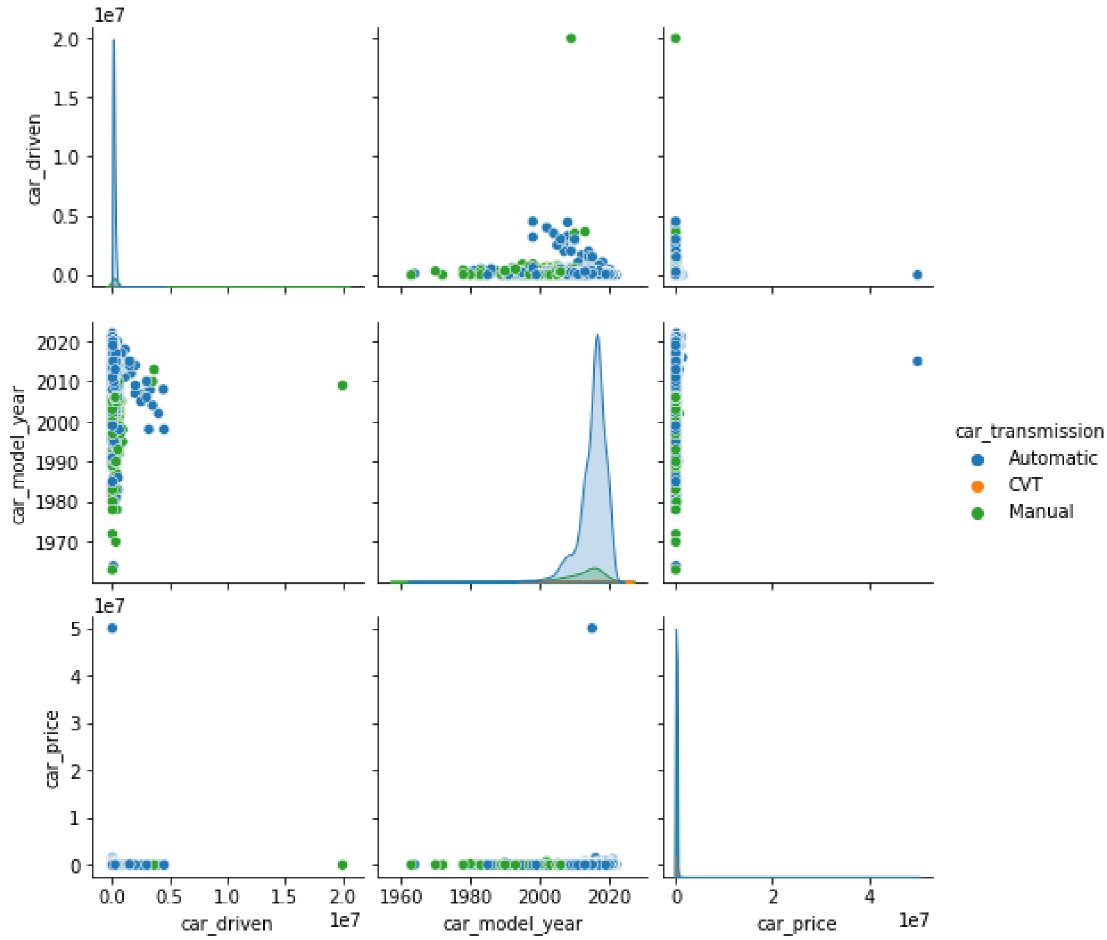
```
plt.subplot(1,2,2)
plt.title('Price Spread')
sns.boxplot(y=cars['car_price'])
plt.ticklabel_format(useOffset=False, style='plain', axis=('y'))

plt.show()

#price outliers
expensive = cars.loc[cars['car_price'] > 200000]
cars = cars[cars['car_price'] <= 200000]
cars = cars[cars['car_price'] >= 5000]

plt.figure(figsize=(15,8))

plt.subplot(1,2,1)
plt.title('Price Distribution Plot')
sns.histplot(cars['car_price'])
plt.ticklabel_format(useOffset=False, style='plain', axis=('x'))

plt.subplot(1,2,2)
plt.title('Price Spread')
sns.boxplot(y=cars['car_price'])
plt.ticklabel_format(useOffset=False, style='plain', axis=('y'))

plt.show()

# Create a box plot to visualize the distribution of car prices by transmission␣
↪type
sns.boxplot(x='car_transmission', y='car_price', data=cars)
plt.show()

plt.figure(figsize=(15,8))

plt.subplot(1,2,1)
plt.title('Year Distribution Plot')
sns.histplot(car['car_model_year'])
plt.ticklabel_format(useOffset=False, style='plain', axis=('x'))

plt.subplot(1,2,2)
plt.title('Year Spread')
sns.boxplot(y=car['car_model_year'])
plt.ticklabel_format(useOffset=False, style='plain', axis=('y'))

plt.show()

# Create a bar plot to visualize the average car price by car brand
```

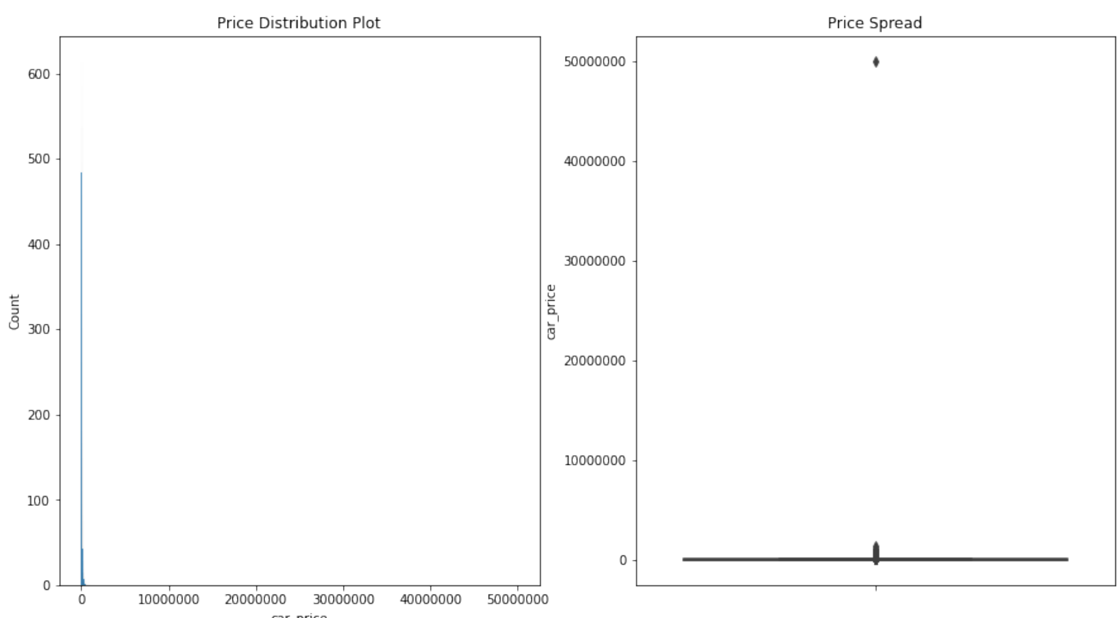
```python
brandPrice = cars.groupby(['car_brand'])['car_price'].mean().reset_index()
sns.barplot(x='car_brand', y='car_price', data=brandPrice)
plt.xticks(rotation=90)
plt.show()



# milage outliers

plt.subplot(1,2,1)
plt.title('Mileage Distribution Plot')
sns.histplot(cars['car_driven'])
plt.ticklabel_format(useOffset=False, style='plain', axis=('x'))

plt.subplot(1,2,2)
plt.title('Mileage Spread')
sns.boxplot(y=cars['car_driven'])
plt.ticklabel_format(useOffset=False, style='plain', axis=('y'))

plt.show()

print(cars.loc[cars['car_driven'] > 500000])
cars = cars[cars['car_driven'] <= 500000]
print(cars[cars['car_transmission'] == 118008.5011120378])
sns.boxplot(y='car_driven', x='car_transmission',data=cars)
plt.show()


cars = cars[cars['car_model_year'] >= 2000]
print(cars.dtypes)

plt.figure(figsize=(15,8))

plt.subplot(1,2,1)
plt.title('Mileage Distribution Plot')
sns.histplot(cars['car_driven'])
plt.ticklabel_format(useOffset=False, style='plain', axis=('x'))

plt.subplot(1,2,2)
plt.title('Mileage Spread')
sns.boxplot(y=cars['car_driven'])
plt.ticklabel_format(useOffset=False, style='plain', axis=('y'))

plt.show()


# encoded categorical variables and feature choosing
```

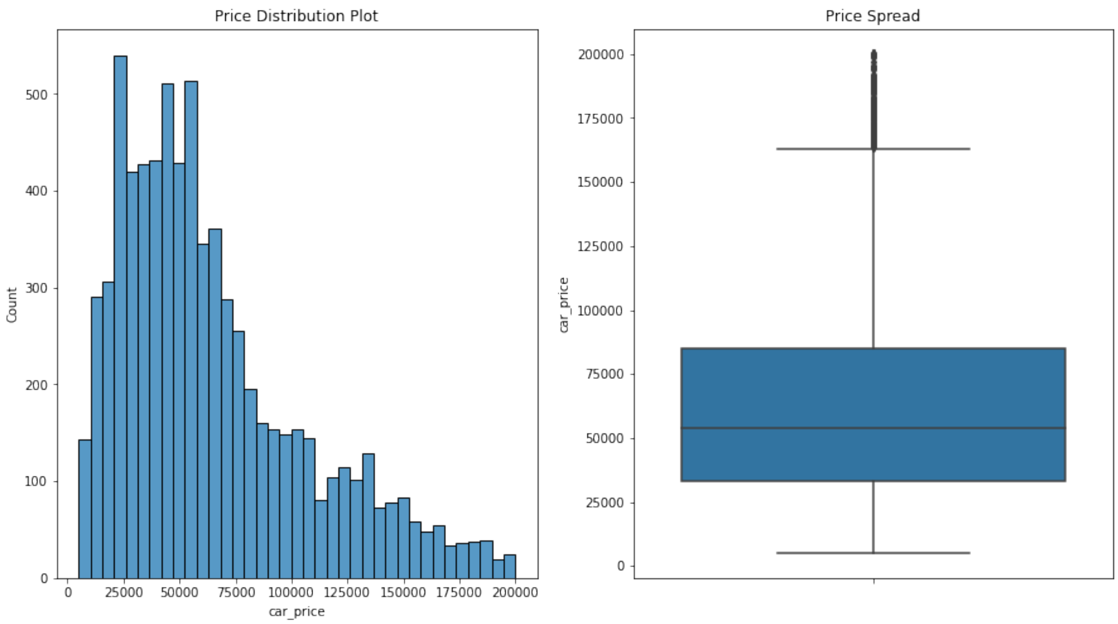
```python
cars_encoded = pd.get_dummies(cars, columns=['car_brand', 'car_model',
 ↪'car_transmission'])

# Split the data into features (X) and target (y)
X = cars_encoded.drop('car_price', axis=1)
y = cars_encoded['car_price']

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3,
 ↪random_state = 42)
```

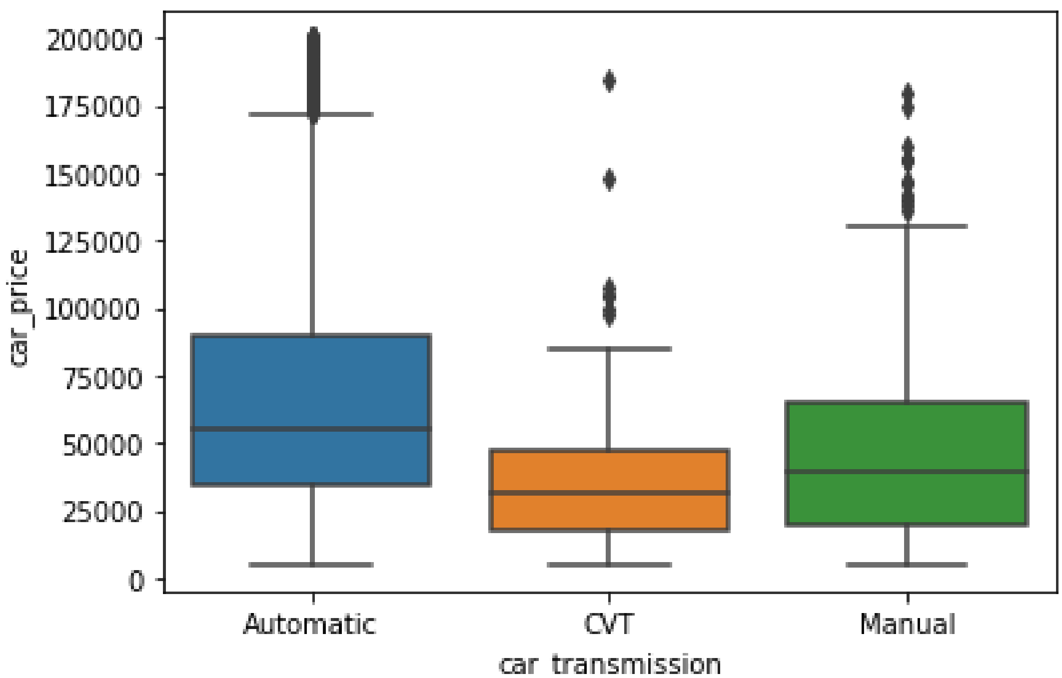
```
       car_brand    car_model  car_driven car_transmission  car_model_year  \
0        Hyundai       Tucson     83491.0        Automatic            2018
1      Chevrolet  Trailblazer    222000.0        Automatic            2009
2          Great         Wall         0.0        Automatic            2022
3           Ford       Fusion    178000.0        Automatic            2012
4     Mitsubishi      Attrage     10500.0        Automatic            2020
…            …            …          …                …              …
7790         Kia      Sorento    257000.0           Manual            2006
7791        Audi           A6     77000.0        Automatic            2015
7792   Chevrolet       Camaro    150000.0        Automatic            2010
7793      Nissan       Altima     18500.0        Automatic            2011
7794    Cadillac        Other    256000.0        Automatic            2013

      car_price
0       64000.0
1       20000.0
2      135000.0
3       23000.0
4       32000.0
…          …
7790    15000.0
7791    75000.0
7792    53000.0
7793    22000.0
7794    40000.0

[7795 rows x 6 columns]
```


car_driven
car_model_year
car_price
1
-0.21
-0.022
-0.21
1
0.042
-0.022
0.042
1
car_driven
car_model_year
car_price
1.0
0.8
0.6
0.4
0.2
0.0
−0.2


1e7
car_driven
car_model_year
car_price
car_transmission
Automatic
CVT
Manual

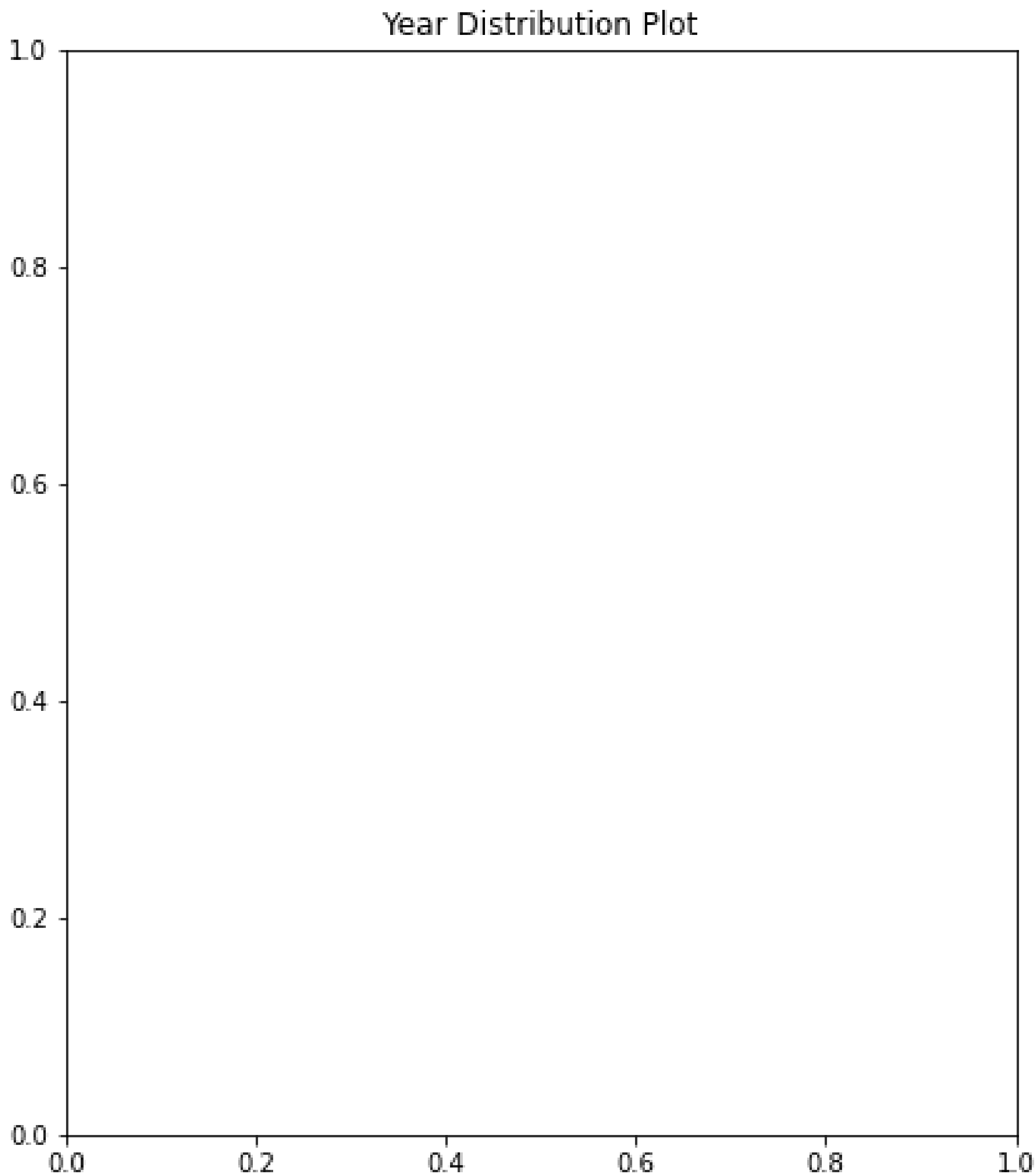

Price Distribution Plot
Count
car_price
Price Spread
car_price






```
---------------------------------------------------------------------------
NameError                                 Traceback (most recent call last)
```

```
Input In [2], in <module>
    114 plt.subplot(1,2,1)
    115 plt.title('Year Distribution Plot')
--> 116 sns.histplot(car['car_model_year'])
    117 plt.ticklabel_format(useOffset=False, style='plain', axis=('x'))
    119 plt.subplot(1,2,2)

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



[ ]:
```
print('Random Forest Regression')
# Generate a baseline using DummyRegressor
dummy_model = DummyRegressor(strategy='mean')
dummy_model.fit(X_train, y_train)

# Predict using the baseline model
y_pred_baseline = dummy_model.predict(X_test)

# Evaluate the baseline model
mae_baseline = mean_absolute_error(y_test, y_pred_baseline)
print(f'Baseline Mean Absolute Error: {mae_baseline}')
mse_baseline = mean_squared_error(y_test, y_pred_baseline)
print(f'Baseline Mean Squared Error: {mse_baseline}')
print(f'Baseline Root Mean Squared Error: {mse_baseline**0.5}')

print("Hyperparameter Optimization Step")
def objective(trial):
    params = {
        'n_estimators': trial.suggest_int('n_estimators', 100, 1000),
        'max_depth': trial.suggest_int('max_depth', 1, 150),
        'min_samples_split': trial.suggest_int('min_samples_split', 2, 30),
        'min_samples_leaf': trial.suggest_int('min_samples_leaf', 1, 10),
        'max_features': trial.suggest_categorical('max_features', ['sqrt',␣
↪'log2', None])
    }
    rf_model = RandomForestRegressor(random_state=42, **params)
    rf_model.fit(X_train, y_train)
    y_pred = rf_model.predict(X_test)
    return mean_squared_error(y_test, y_pred)

study = optuna.create_study(direction='minimize')
study.optimize(objective, n_trials=100)

rf_best_params = study.best_params
print(f'Best Hyperparameters: {rf_best_params}')
# rf_best_params = {'n_estimators': 869, 'max_depth': 133, 'min_samples_split':␣
↪7, 'min_samples_leaf': 1, 'max_features': 'sqrt'}

# Use the best model for predictions
best_rf_model = RandomForestRegressor(random_state=42, **rf_best_params)
best_rf_model.fit(X_train, y_train)
feature_importance = best_rf_model.feature_importances_

# Get the feature names
feature_names = X_train.columns

# Create a DataFrame for feature importance
```

```
feature_importance_df = pd.DataFrame({
    'Feature': feature_names,
    'Importance': feature_importance
})

# Sort the DataFrame by importance in descending order
feature_importance_df = feature_importance_df.sort_values(by='Importance',␣
 ↪ascending=False)

# Display the feature importance DataFrame
print("Feature Importance:")
print(feature_importance_df.head(10))


y_pred = best_rf_model.predict(X_test)
y_pred_rf = y_pred
errors = abs(y_pred - y_test)
print('Mean Absolute Error:', round(np.mean(errors), 2))
mape = 100 * (errors / y_test)
# Calculate and display accuracy
accuracy = 100 - np.mean(mape)

# Evaluate the model
mse = mean_squared_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)
feature_importance = best_rf_model.feature_importances_

# print(f'Feature Importance: {feature_importance}')
print(f'Mean Squared Error: {mse}')
print(f'Root Mean Squared Error: {mse**0.5}')
print(f'R-squared: {r2}')
print('Accuracy:', round(accuracy, 2), '%.')
```

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[ ]:
```
print("Linear Regression")
X2 = cars.drop(['car_price', 'car_transmission', 'car_model', 'car_brand'],␣
 ↪axis=1)
y2 = cars['car_price']
# Create a Linear Regression model
linear_model = LinearRegression()

# Split the data into training and testing sets
X_train2, X_test2, y_train2, y_test2 = train_test_split(X2, y2, test_size=0.3)

# Train the Linear Regression model
```

```
linear_model.fit(X_train2, y_train2)

# Make predictions on the test set
y_pred2 = linear_model.predict(X_test2)

# Evaluate the model
mse = mean_squared_error(y_test2, y_pred2)
r2 = r2_score(y_test2, y_pred2)

print(f'Mean Squared Error: {mse}')
print(f'R-squared: {r2}')
```

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Cell was canceled due to an error in a previous cell.
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[ ]:
```
print("Grandient boosting Regression")

# Generate a baseline using DummyRegressor
dummy_model = DummyRegressor(strategy='mean')
dummy_model.fit(X_train, y_train)
y_pred_baseline = dummy_model.predict(X_test)

# Evaluate baseline model
mae_baseline = mean_absolute_error(y_test, y_pred_baseline)
print(f'Baseline Mean Absolute Error: {mae_baseline}')
mse_baseline = mean_squared_error(y_test, y_pred_baseline)
print(f'Baseline Mean Squared Error: {mse_baseline}')
print(f'Baseline Root Mean Squared Error: {mse_baseline**0.5}')

print("Hyperparameter Optimization Step")
# objective function for Optuna
def objective(trial):
    params = {
        'n_estimators': trial.suggest_int('n_estimators', 100, 1000),
        'max_depth': trial.suggest_int('max_depth', 1, 150),
        'learning_rate': trial.suggest_float('learning_rate', 0.01, 0.2),
        'subsample': trial.suggest_float('subsample', 0.5, 1.0),
        'colsample_bytree': trial.suggest_float('colsample_bytree', 0.5, 1.0),
    }
    xgb_model = xgb.XGBRegressor(random_state=42, **params)
    xgb_model.fit(X_train, y_train)
    y_pred = xgb_model.predict(X_test)
    return mean_squared_error(y_test, y_pred)

# Create an Optuna study and optimize the objective function
study = optuna.create_study(direction='minimize')
study.optimize(objective, n_trials=100)
```

```
# Get the best hyperparameters
xgb_best_params = study.best_params
print(f'Best Hyperparameters: {xgb_best_params}')
# xgb_best_params = {'n_estimators': 888, 'max_depth': 12, 'learning_rate': 0.
↪059265067129644175, 'subsample': 0.6710882119982516, 'colsample_bytree': 0.
↪9147549947728586}
# Train the model with the best hyperparameters
best_xgb_model = xgb.XGBRegressor(random_state=42, **xgb_best_params)
best_xgb_model.fit(X_train, y_train)
y_pred = best_xgb_model.predict(X_test)
y_pred_xgb = y_pred
# Evaluate the best model
mse = mean_squared_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)
mae = mean_absolute_error(y_test, y_pred)
print(f'Mean Absolute Error: {mae}')
print(f'Mean Squared Error: {mse}')
print(f'Root Mean Squared Error: {mse**0.5}')
print(f'R-squared: {r2}')

# Calculate accuracy metrics
errors = abs(y_pred - y_test)
mape = 100 * (errors / y_test)
accuracy = 100 - np.mean(mape)
print('Accuracy:', round(accuracy, 2), '%.')
```

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[ ]:
```
# Model Visualization and Analysis
from sklearn.model_selection import cross_val_score
# # Use cross_val_score for cross-validation
scores = cross_val_score(best_rf_model, X, y, cv=5,␣
↪scoring='neg_mean_squared_error')

# Display the mean squared error scores
print("RF Cross-Validation Mean Squared Error:", -scores.mean())

scores2 = cross_val_score(best_xgb_model, X, y, cv=5,␣
↪scoring='neg_mean_squared_error')

# Display the mean squared error scores
print("RF Cross-Validation Mean Squared Error:", -scores2.mean())



# Random Forest Visualization
```

```
plt.figure(figsize=(12, 8))

# Actual Prices
plt.scatter(X_test['car_driven'], y_test, label='Actual Prices', alpha=0.5)

# Random Forest Predictions
y_pred_rf = best_rf_model.predict(X_test)
plt.scatter(X_test['car_driven'], y_pred_rf, label='RF Predictions', alpha=0.5)

plt.xlabel('Distance Traveled (car_driven)')
plt.ylabel('Car Price')
plt.title('Random Forest: Actual vs. Predicted Prices over Distance Traveled')
plt.legend()
plt.show()

# XGBoost Visualization
plt.figure(figsize=(12, 8))

# Actual Prices
plt.scatter(X_test['car_driven'], y_test, label='Actual Prices', alpha=0.5)

# XGBoost Predictions
y_pred_xgb = best_xgb_model.predict(X_test)
plt.scatter(X_test['car_driven'], y_pred_xgb, label='XGB Predictions', alpha=0.
↪5)

plt.xlabel('Distance Traveled (car_driven)')
plt.ylabel('Car Price')
plt.title('XGBoost: Actual vs. Predicted Prices over Distance Traveled')
plt.legend()
plt.show()

# Random Forest Visualization by Top 10 Car Brands
top_brands_rf = feature_importance_df['Feature'].str.extract(r'car_brand_(.*)').
↪dropna()[0]

plt.figure(figsize=(15, 8))

for brand in top_brands_rf:
    brand_indices = X_test[X_test[f'car_brand_{brand}'] == 1].index

    if not brand_indices.empty:  # Check if there are samples for the current␣
↪brand
        plt.scatter(X_test.loc[brand_indices, 'car_driven'], y_test.
↪loc[brand_indices], label=f'Actual Prices - {brand}', alpha=0.5)

        y_pred_rf_brand = best_rf_model.predict(X_test.loc[brand_indices])
```

```
        plt.scatter(X_test.loc[brand_indices, 'car_driven'], y_pred_rf_brand,␣
↪label=f'RF Predictions - {brand}', alpha=0.5)

plt.xlabel('Distance Traveled (car_driven)')
plt.ylabel('Car Price')
plt.title('Random Forest: Actual vs. Predicted Prices by Top 10 Car Brands over␣
↪Distance Traveled')
plt.legend()
plt.show()

# XGBoost Visualization by Top 10 Car Brands
top_brands_xgb = feature_importance_df['Feature'].str.extract(r'car_brand_(.
↪*)').dropna()[0]

plt.figure(figsize=(15, 8))

for brand in top_brands_xgb:
    brand_indices = X_test[X_test[f'car_brand_{brand}'] == 1].index

    if not brand_indices.empty:  # Check if there are samples for the current␣
↪brand
        plt.scatter(X_test.loc[brand_indices, 'car_driven'], y_test.
↪loc[brand_indices], label=f'Actual Prices - {brand}', alpha=0.5)

        y_pred_xgb_brand = best_xgb_model.predict(X_test.loc[brand_indices])
        plt.scatter(X_test.loc[brand_indices, 'car_driven'], y_pred_xgb_brand,␣
↪label=f'XGB Predictions - {brand}', alpha=0.5)

plt.xlabel('Distance Traveled (car_driven)')
plt.ylabel('Car Price')
plt.title('XGBoost: Actual vs. Predicted Prices by Top 10 Car Brands over␣
↪Distance Traveled')
plt.legend()
plt.show()
```

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[ ]:
```
# Feature Engineering
cars['actual_depreciation_rate'] = cars['car_price'] / cars['car_driven']

# Select relevant features
X = cars[['car_brand', 'car_driven']]  # Add other relevant features
y = cars['actual_depreciation_rate']

# Encode categorical variables
```

```python
X_encoded = pd.get_dummies(X, columns=['car_brand'])
X_encoded = X_encoded.drop(['car_brand_Hummer', 'car_brand_Other'], axis=1)
# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X_encoded, y, test_size=0.
 ↪3, random_state=42)
# print(X_test.columns)

# Random Forest model
rf_model = RandomForestRegressor(random_state=42, **rf_best_params)
rf_model.fit(X_train, y_train)
y_pred_rf = rf_model.predict(X_test)

# XGBoost model
xgb_model = xgb.XGBRegressor(random_state=42, **xgb_best_params)
xgb_model.fit(X_train, y_train)
y_pred_xgb = xgb_model.predict(X_test)

# Evaluate models
mse_rf = mean_squared_error(y_test, y_pred_rf)
mse_xgb = mean_squared_error(y_test, y_pred_xgb)

print(f'RF Mean Squared Error: {mse_rf}')
print(f'XGB Mean Squared Error: {mse_xgb}')

# Compare model predictions with actual depreciation rates
results_rf = pd.DataFrame({'Actual_Price': y_test, 'Predicted_RF': y_pred_rf})
results_xgb = pd.DataFrame({'Actual_Price': y_test, 'Predicted_XGB':␣
 ↪y_pred_xgb})

# Outliers removal to make viewing easier
results_rf = results_rf[results_rf['Actual_Price'] < 5000]
results_xgb = results_xgb[results_xgb['Actual_Price'] < 5000]

# Visualize the results with a line of best fit
plt.figure(figsize=(12, 6))

plt.subplot(1, 2, 1)
sns.regplot(x='Actual_Price', y='Predicted_RF', data=results_rf,␣
 ↪line_kws={'color': 'red'})
plt.title('Random Forest Model: Actual_Price vs Predicted Depreciation Rate')
plt.xlabel('Actual Depreciation Rate')
plt.ylabel('Predicted Depreciation Rate (RF)')

plt.subplot(1, 2, 2)
sns.regplot(x='Actual_Price', y='Predicted_XGB', data=results_xgb,␣
 ↪line_kws={'color': 'red'})
plt.title('XGBoost Model: Actual_Price vs Predicted Depreciation Rate')
```

```
plt.xlabel('Actual Depreciation Rate')
plt.ylabel('Predicted Depreciation Rate (XGB)')

plt.tight_layout()
plt.show()

results_rf['Depreciation_Rate_RF'] = ((results_rf['Actual_Price'] -␣
↪results_rf['Predicted_RF']) / results_rf['Actual_Price']) * 100

# Extract encoded 'car_brand' columns from the original dataset for 'results_rf'
brand_columns = [col for col in X_encoded.columns if col.
↪startswith('car_brand_')]
results_rf['Car_Brand'] = X_test[brand_columns].idxmax(axis=1).apply(lambda x:␣
↪x.split('_')[-1])

# Group by Car Brand and calculate average depreciation rate
depreciation_by_brand_rf = results_rf.
↪groupby('Car_Brand')['Depreciation_Rate_RF'].mean().reset_index()

# Create a bar plot
plt.figure(figsize=(12, 6))
sns.barplot(x='Car_Brand', y='Depreciation_Rate_RF',␣
↪data=depreciation_by_brand_rf)
plt.xticks(rotation=90)
plt.title('Average Depreciation Rate by Car Brand (Random Forest)')
plt.show()

# Calculate depreciation rate for XGBoost
results_xgb['Depreciation_Rate_XGB'] = ((results_xgb['Actual_Price'] -␣
↪results_xgb['Predicted_XGB']) / results_xgb['Actual_Price']) * 100

brand_columns_xgb = [col for col in X_encoded.columns if col.
↪startswith('car_brand_')]
results_xgb['Car_Brand'] = X_test[brand_columns_xgb].idxmax(axis=1).
↪apply(lambda x: x.split('_')[-1])

# Group by Car Brand and calculate average depreciation rate for XGBoost
depreciation_by_brand_xgb = results_xgb.
↪groupby('Car_Brand')['Depreciation_Rate_XGB'].mean().reset_index()

# Create a bar plot for XGBoost
plt.figure(figsize=(12, 6))
sns.barplot(x='Car_Brand', y='Depreciation_Rate_XGB',␣
↪data=depreciation_by_brand_xgb)
plt.xticks(rotation=90)
plt.title('Average Depreciation Rate (XGBoost) by Car Brand')
```

```
plt.show()
```

```
Cell was canceled due to an error in a previous cell.
```

[ ]:
```
# Data Manipulation
import numpy as np
import pandas as pd
import warnings
# Visualization
import matplotlib.pyplot as plt
import seaborn as sns
from datetime import datetime
from sklearn.tree import export_graphviz
import pydot
#Train Test Split
from sklearn.model_selection import train_test_split

#Scaling
from sklearn.preprocessing import StandardScaler

#Models
import optuna
import xgboost as xgb
from sklearn.dummy import DummyRegressor
from skopt import BayesSearchCV
from sklearn.ensemble import RandomForestRegressor
from xgboost import XGBRegressor
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LinearRegression
from sklearn.svm import SVR
from sklearn.neighbors import KNeighborsRegressor
from sklearn.tree import DecisionTreeRegressor
from sklearn.model_selection import GridSearchCV

#Deep Neural Networks:
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Activation
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.callbacks import EarlyStopping

#Evaluation
from sklearn.model_selection import cross_val_score
from sklearn.metrics import classification_report
from sklearn.metrics import mean_absolute_error
from sklearn.metrics import mean_squared_error
from sklearn.metrics import r2_score
```

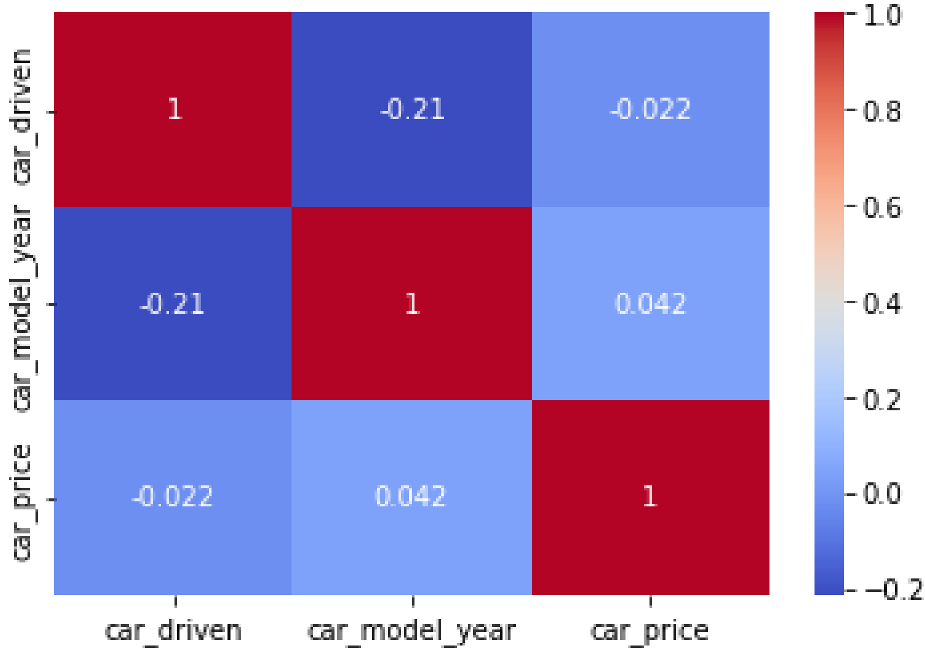
```
from sklearn.metrics import explained_variance_score

cars = pd.read_csv(r'C:\Users\rocke\Downloads\used_cars\used_car_cleaned.csv',␣
 ↪delimiter=',')
cars2 = pd.read_csv(r'C:\Users\rocke\Downloads\used_cars\archive␣
 ↪(2)\UsedCarsSA_Clean_EN.csv', delimiter=',')
warnings.filterwarnings("ignore")


# print(cars.head())
# print(cars2.head())

# CLEANING CODE

cars2 = cars2.drop(['Origin', 'Color', 'Options', 'Engine_Size', 'Fuel_Type',␣
 ↪'Region', 'Negotiable'], axis=1)
cars2 = cars2.rename(columns={'Make': 'car_brand', 'Type': 'car_model', 'Year':␣
 ↪'car_model_year', 'Gear_Type': 'car_transmission', 'Mileage': 'car_driven',␣
 ↪'Price': 'car_price'})
cars2 = cars2[cars.columns]
cars2 = cars2[cars2['car_price'] != 0]
cars = pd.concat([cars, cars2], ignore_index=True)
print(cars)
cars.to_csv("used_car_data.csv")
# Calculate correlations for selected columns
correlation_columns = ['car_driven', 'car_model_year', 'car_price']
correlation_matrix = cars[correlation_columns].corr()

# Create a heatmap to visualize the correlation matrix
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm')
plt.show()
sns.pairplot(data=cars,hue='car_transmission')
plt.show()

# price distribution

plt.figure(figsize=(15,8))

plt.subplot(1,2,1)
plt.title('Price Distribution Plot')
sns.histplot(cars['car_price'])
plt.ticklabel_format(useOffset=False, style='plain', axis=('x'))

plt.subplot(1,2,2)
plt.title('Price Spread')
sns.boxplot(y=cars['car_price'])
plt.ticklabel_format(useOffset=False, style='plain', axis=('y'))
```

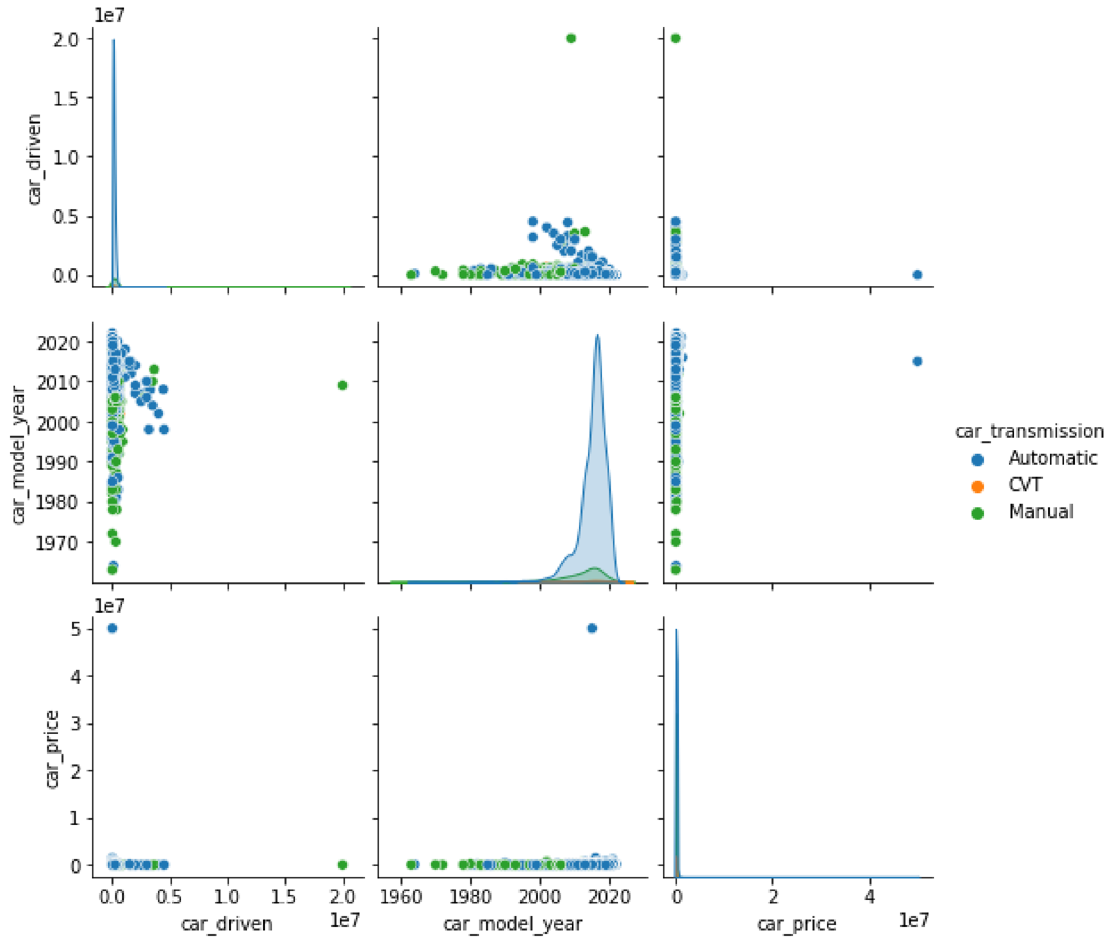
```
plt.show()

#price outliers
expensive = cars.loc[cars['car_price'] > 200000]
cars = cars[cars['car_price'] <= 200000]
cars = cars[cars['car_price'] >= 5000]

plt.figure(figsize=(15,8))

plt.subplot(1,2,1)
plt.title('Price Distribution Plot')
sns.histplot(cars['car_price'])
plt.ticklabel_format(useOffset=False, style='plain', axis=('x'))

plt.subplot(1,2,2)
plt.title('Price Spread')
sns.boxplot(y=cars['car_price'])
plt.ticklabel_format(useOffset=False, style='plain', axis=('y'))

plt.show()

# Create a box plot to visualize the distribution of car prices by transmission␣
↪type
sns.boxplot(x='car_transmission', y='car_price', data=cars)
plt.show()

plt.figure(figsize=(15,8))

plt.subplot(1,2,1)
plt.title('Year Distribution Plot')
sns.histplot(cars['car_model_year'])
plt.ticklabel_format(useOffset=False, style='plain', axis=('x'))

plt.subplot(1,2,2)
plt.title('Year Spread')
sns.boxplot(y=cars['car_model_year'])
plt.ticklabel_format(useOffset=False, style='plain', axis=('y'))

plt.show()

# Create a bar plot to visualize the average car price by car brand
brandPrice = cars.groupby(['car_brand'])['car_price'].mean().reset_index()
sns.barplot(x='car_brand', y='car_price', data=brandPrice)
plt.xticks(rotation=90)
plt.show()
```

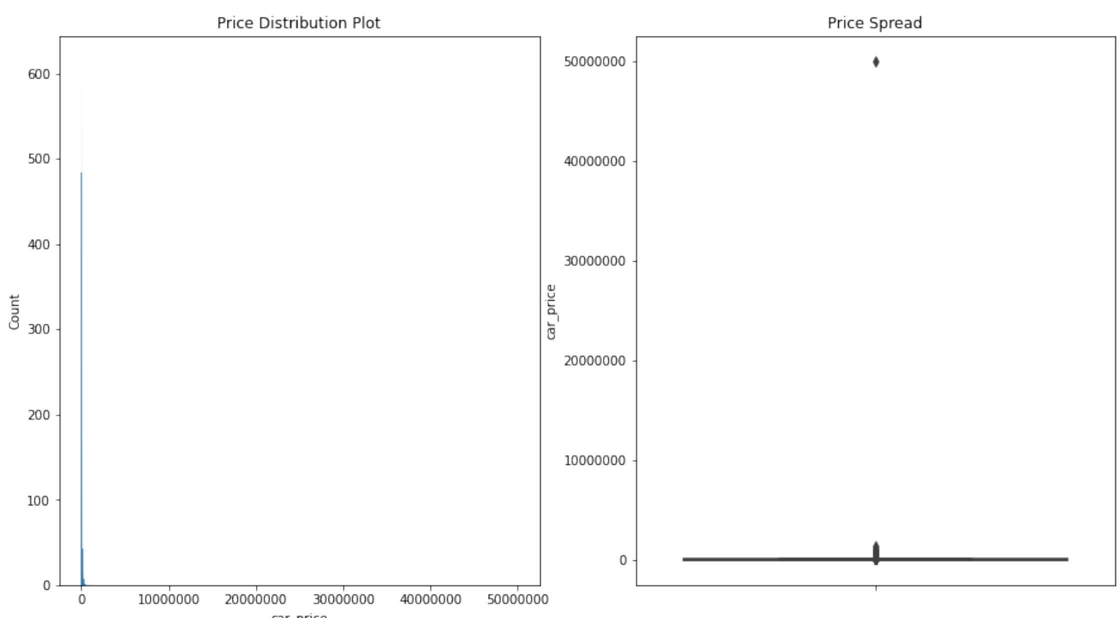
```
# milage outliers

plt.subplot(1,2,1)
plt.title('Mileage Distribution Plot')
sns.histplot(cars['car_driven'])
plt.ticklabel_format(useOffset=False, style='plain', axis=('x'))

plt.subplot(1,2,2)
plt.title('Mileage Spread')
sns.boxplot(y=cars['car_driven'])
plt.ticklabel_format(useOffset=False, style='plain', axis=('y'))

plt.show()

print(cars.loc[cars['car_driven'] > 500000])
cars = cars[cars['car_driven'] <= 500000]
print(cars[cars['car_transmission'] == 118008.5011120378])
sns.boxplot(y='car_driven', x='car_transmission',data=cars)
plt.show()


cars = cars[cars['car_model_year'] >= 2000]
print(cars.dtypes)

plt.figure(figsize=(15,8))

plt.subplot(1,2,1)
plt.title('Mileage Distribution Plot')
sns.histplot(cars['car_driven'])
plt.ticklabel_format(useOffset=False, style='plain', axis=('x'))

plt.subplot(1,2,2)
plt.title('Mileage Spread')
sns.boxplot(y=cars['car_driven'])
plt.ticklabel_format(useOffset=False, style='plain', axis=('y'))

plt.show()


# encoded categorical variables and feature choosing

cars_encoded = pd.get_dummies(cars, columns=['car_brand', 'car_model',␣
 ↪'car_transmission'])

# Split the data into features (X) and target (y)
```

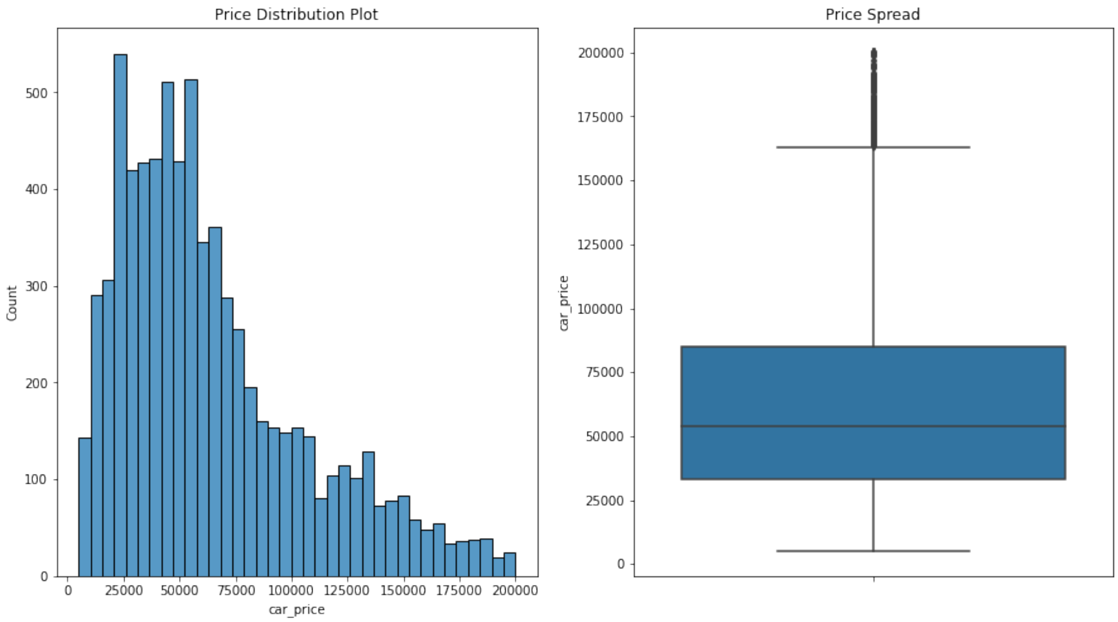
```python
X = cars_encoded.drop('car_price', axis=1)
y = cars_encoded['car_price']

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3,␣
 ↪random_state = 42)
```

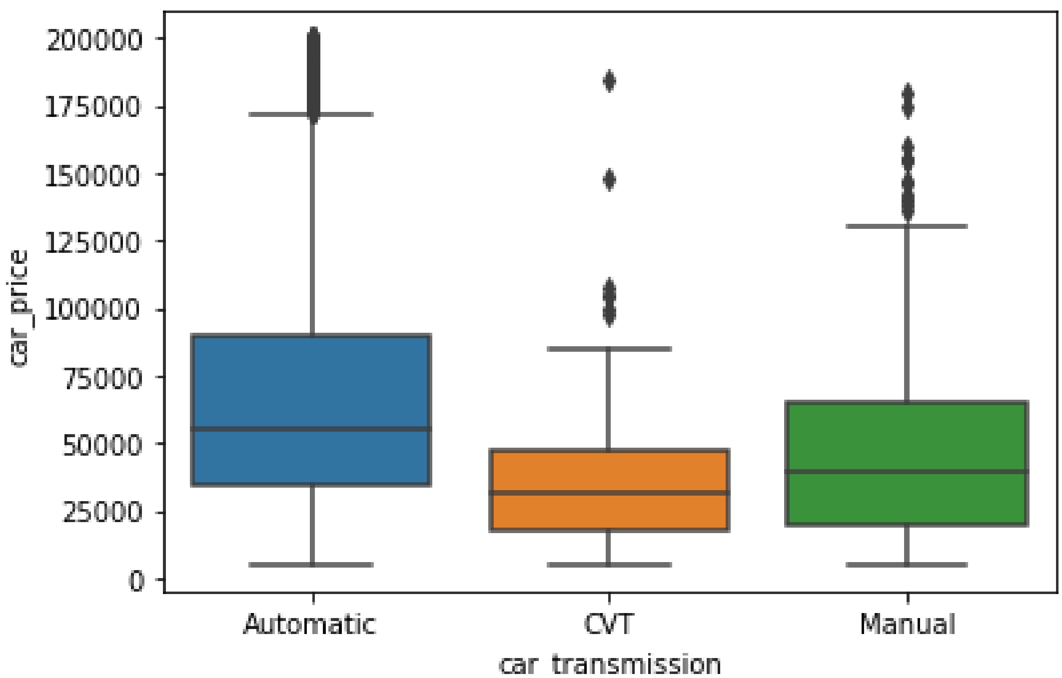
```
       car_brand    car_model  car_driven car_transmission  car_model_year  \
0        Hyundai       Tucson     83491.0        Automatic            2018
1      Chevrolet  Trailblazer    222000.0        Automatic            2009
2          Great         Wall         0.0        Automatic            2022
3           Ford       Fusion    178000.0        Automatic            2012
4     Mitsubishi      Attrage     10500.0        Automatic            2020
…            …          …          …               …              …
7790         Kia      Sorento    257000.0           Manual            2006
7791        Audi           A6     77000.0        Automatic            2015
7792   Chevrolet       Camaro    150000.0        Automatic            2010
7793      Nissan       Altima     18500.0        Automatic            2011
7794    Cadillac        Other    256000.0        Automatic            2013

      car_price
0       64000.0
1       20000.0
2      135000.0
3       23000.0
4       32000.0
…           …
7790    15000.0
7791    75000.0
7792    53000.0
7793    22000.0
7794    40000.0

[7795 rows x 6 columns]
```

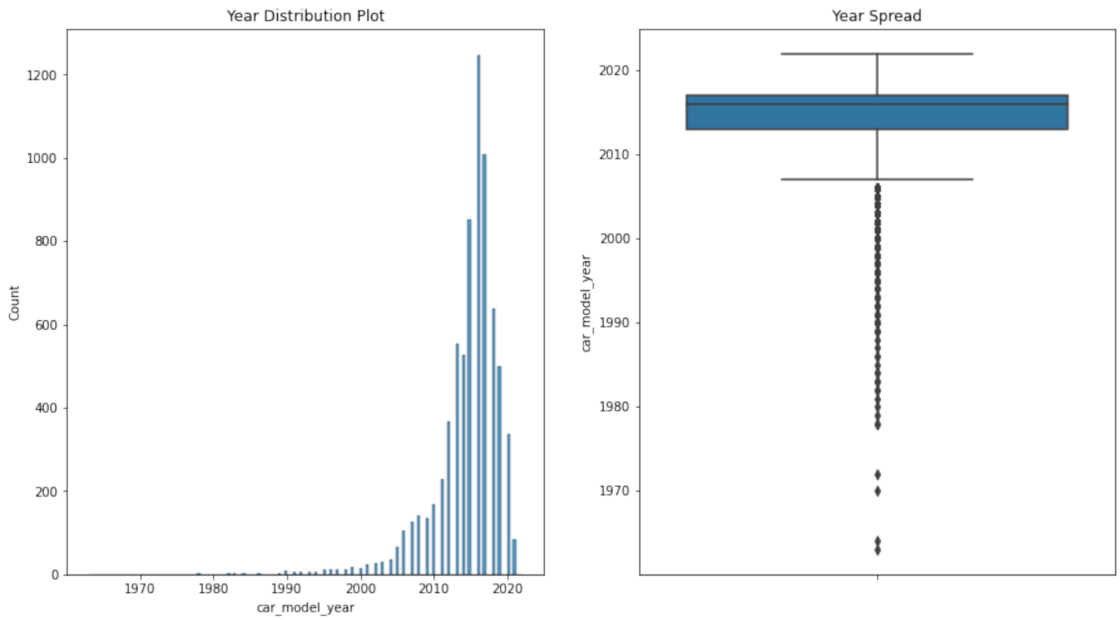

car_driven
car_model_year
car_price
1
-0.21
-0.022
-0.21
1
0.042
-0.022
0.042
1
car_driven
car_model_year
car_price
1.0
0.8
0.6
0.4
0.2
0.0
−0.2


1e7
car_driven
car_model_year
car_price
car_transmission
Automatic
CVT
Manual
1e7
1e7

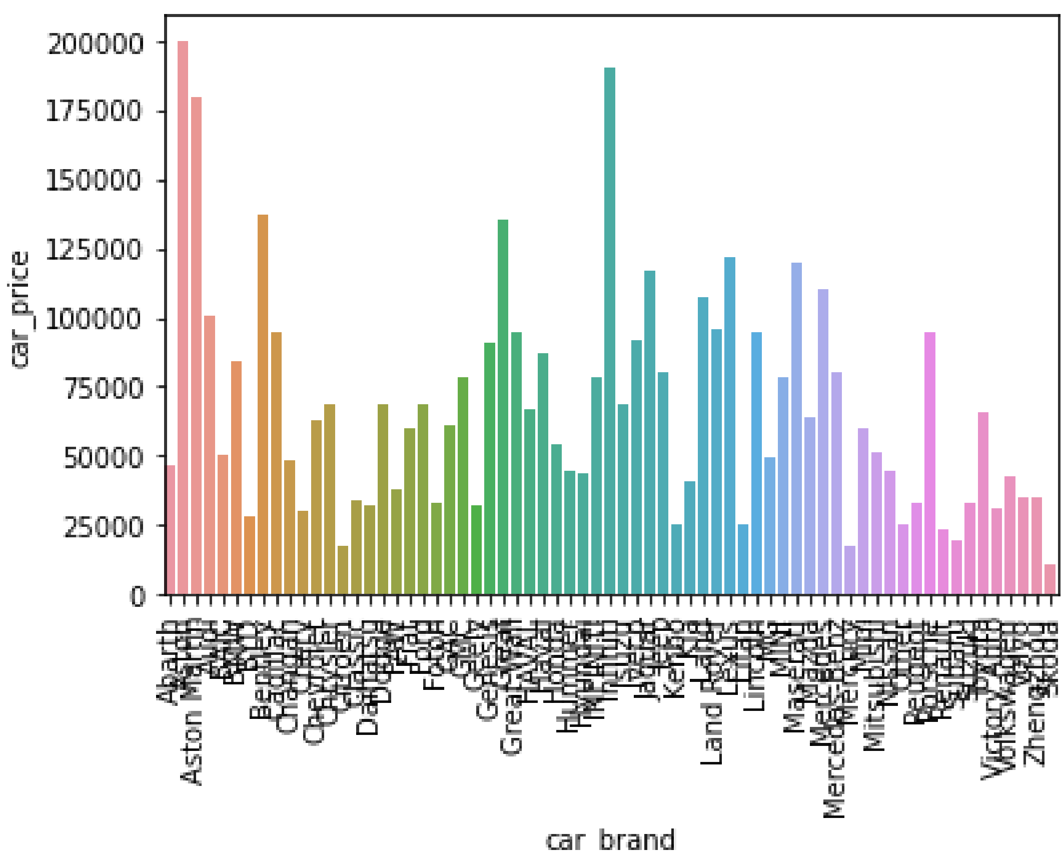

Price Distribution Plot
Count
car_price
Price Spread
car_price


Price Distribution Plot
Count
car_price
Price Spread
car_price

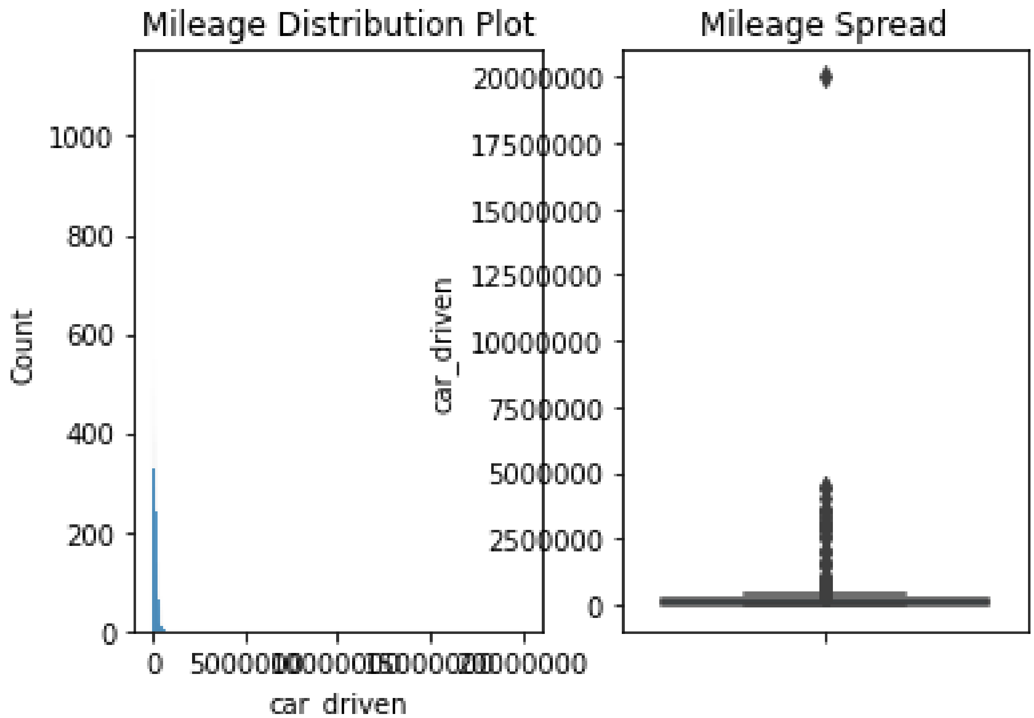

car_price
Automatic
CVT
Manual
car_transmission



Year Distribution Plot
Count
1200
1000
800
600
400
200
0
1970
1980
1990
2000
2010
2020
car_model_year
Year Spread
car_model_year
2020
2010
2000
1990
1980
1970

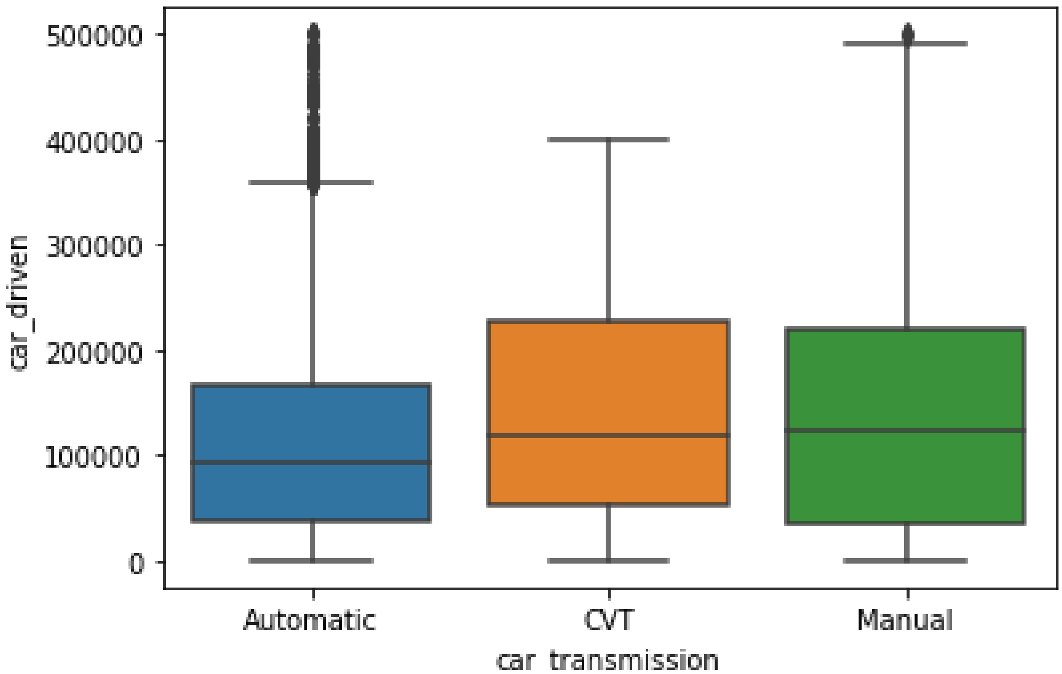


car_price
200000
175000
150000
125000
100000
75000
50000
25000
0
Abarth
Aston Martin
car_brand

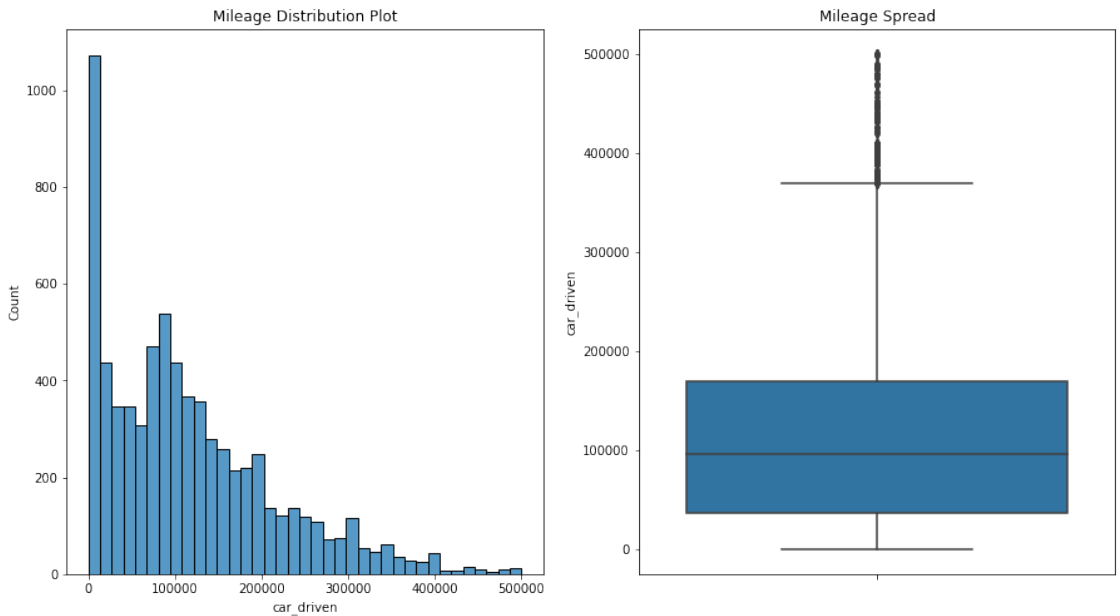



```
      car_brand     car_model  car_driven car_transmission  car_model_year  \
18          Kia        Cerato   1640000.0        Automatic            2012
345      Toyota         Camry    755000.0        Automatic            2018
588     Hyundai        Sonata    625000.0        Automatic            2006
1125     Suzuki         Swift   2680000.0        Automatic            2007
1640     Toyota         Camry    692000.0           Manual            1998
…         …            …          …              …             …
7646      Honda        Accord    547000.0           Manual            2005
7680     Nissan        Patrol    595000.0        Automatic            1998
7702     Toyota         Camry    520000.0        Automatic            2009
7721     Toyota  Land Cruiser   1500000.0        Automatic            2015
7752     Toyota         Camry    550000.0           Manual            2010

       car_price
18       33000.0
345      62500.0
588      15000.0
1125     14500.0
1640      7000.0
…          …
7646     19000.0
7680     20000.0
7702     23000.0
7721    150000.0
```

```
7752    20000.0

[78 rows x 6 columns]
Empty DataFrame
Columns: [car_brand, car_model, car_driven, car_transmission, car_model_year,
car_price]
Index: []
```




```
car_brand            object
car_model            object
car_driven          float64
car_transmission     object
car_model_year        int64
car_price           float64
dtype: object
```




```
[ ]: print('Random Forest Regression')
     # Generate a baseline using DummyRegressor
     dummy_model = DummyRegressor(strategy='mean')
     dummy_model.fit(X_train, y_train)

     # Predict using the baseline model
     y_pred_baseline = dummy_model.predict(X_test)

     # Evaluate the baseline model
     mae_baseline = mean_absolute_error(y_test, y_pred_baseline)
     print(f'Baseline Mean Absolute Error: {mae_baseline}')
     mse_baseline = mean_squared_error(y_test, y_pred_baseline)
     print(f'Baseline Mean Squared Error: {mse_baseline}')
     print(f'Baseline Root Mean Squared Error: {mse_baseline**0.5}')

     print("Hyperparameter Optimization Step")
     def objective(trial):
         params = {
             'n_estimators': trial.suggest_int('n_estimators', 100, 1000),
             'max_depth': trial.suggest_int('max_depth', 1, 150),
             'min_samples_split': trial.suggest_int('min_samples_split', 2, 30),
             'min_samples_leaf': trial.suggest_int('min_samples_leaf', 1, 10),
             'max_features': trial.suggest_categorical('max_features', ['sqrt',␣
      ↪'log2', None])
         }
         rf_model = RandomForestRegressor(random_state=42, **params)
```

```
    rf_model.fit(X_train, y_train)
    y_pred = rf_model.predict(X_test)
    return mean_squared_error(y_test, y_pred)

study = optuna.create_study(direction='minimize')
study.optimize(objective, n_trials=100)

rf_best_params = study.best_params
print(f'Best Hyperparameters: {rf_best_params}')
# rf_best_params = {'n_estimators': 869, 'max_depth': 133, 'min_samples_split':␣
↪7, 'min_samples_leaf': 1, 'max_features': 'sqrt'}

# Use the best model for predictions
best_rf_model = RandomForestRegressor(random_state=42, **rf_best_params)
best_rf_model.fit(X_train, y_train)
feature_importance = best_rf_model.feature_importances_

# Get the feature names
feature_names = X_train.columns

# Create a DataFrame for feature importance
feature_importance_df = pd.DataFrame({
    'Feature': feature_names,
    'Importance': feature_importance
})

# Sort the DataFrame by importance in descending order
feature_importance_df = feature_importance_df.sort_values(by='Importance',␣
↪ascending=False)

# Display the feature importance DataFrame
print("Feature Importance:")
print(feature_importance_df.head(10))


y_pred = best_rf_model.predict(X_test)
y_pred_rf = y_pred
errors = abs(y_pred - y_test)
print('Mean Absolute Error:', round(np.mean(errors), 2))
mape = 100 * (errors / y_test)
# Calculate and display accuracy
accuracy = 100 - np.mean(mape)

# Evaluate the model
mse = mean_squared_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)
feature_importance = best_rf_model.feature_importances_
```

```python
# print(f'Feature Importance: {feature_importance}')
print(f'Mean Squared Error: {mse}')
print(f'Root Mean Squared Error: {mse**0.5}')
print(f'R-squared: {r2}')
print('Accuracy:', round(accuracy, 2), '%.')
```

```
Random Forest Regression

[I 2023-12-12 17:24:05,358] A new study created in memory with name: no-
name-9c395f7c-237a-44aa-9db0-38fd27bcb159


Baseline Mean Absolute Error: 32745.338787888144
Baseline Mean Squared Error: 1649521929.7686503
Baseline Root Mean Squared Error: 40614.30695910802
Hyperparameter Optimization Step

[I 2023-12-12 17:24:08,477] Trial 0 finished with value: 647726445.7002499 and
parameters: {'n_estimators': 691, 'max_depth': 121, 'min_samples_split': 4,
'min_samples_leaf': 6, 'max_features': 'sqrt'}. Best is trial 0 with value:
647726445.7002499.
[I 2023-12-12 17:24:09,446] Trial 1 finished with value: 1343747525.856675 and
parameters: {'n_estimators': 654, 'max_depth': 12, 'min_samples_split': 9,
'min_samples_leaf': 7, 'max_features': 'log2'}. Best is trial 0 with value:
647726445.7002499.
[I 2023-12-12 17:24:10,696] Trial 2 finished with value: 1315632930.8800197 and
parameters: {'n_estimators': 827, 'max_depth': 49, 'min_samples_split': 30,
'min_samples_leaf': 7, 'max_features': 'log2'}. Best is trial 0 with value:
647726445.7002499.
[I 2023-12-12 17:24:11,176] Trial 3 finished with value: 811977958.0078212 and
parameters: {'n_estimators': 124, 'max_depth': 101, 'min_samples_split': 19,
'min_samples_leaf': 9, 'max_features': 'sqrt'}. Best is trial 0 with value:
647726445.7002499.
[I 2023-12-12 17:24:11,354] Trial 4 finished with value: 1578015420.342894 and
parameters: {'n_estimators': 178, 'max_depth': 1, 'min_samples_split': 9,
'min_samples_leaf': 5, 'max_features': 'sqrt'}. Best is trial 0 with value:
647726445.7002499.
[I 2023-12-12 17:24:40,594] Trial 5 finished with value: 334715380.52894765 and
parameters: {'n_estimators': 942, 'max_depth': 65, 'min_samples_split': 16,
'min_samples_leaf': 3, 'max_features': None}. Best is trial 5 with value:
334715380.52894765.
[I 2023-12-12 17:24:58,663] Trial 6 finished with value: 481442651.1890297 and
parameters: {'n_estimators': 709, 'max_depth': 85, 'min_samples_split': 18,
'min_samples_leaf': 9, 'max_features': None}. Best is trial 5 with value:
334715380.52894765.
[I 2023-12-12 17:25:04,465] Trial 7 finished with value: 293494966.68798095 and
parameters: {'n_estimators': 508, 'max_depth': 61, 'min_samples_split': 2,
'min_samples_leaf': 1, 'max_features': 'log2'}. Best is trial 7 with value:
```

```
293494966.68798095.
[I 2023-12-12 17:25:27,567] Trial 8 finished with value: 425810412.5457371 and
parameters: {'n_estimators': 789, 'max_depth': 32, 'min_samples_split': 15,
'min_samples_leaf': 6, 'max_features': None}. Best is trial 7 with value:
293494966.68798095.
[I 2023-12-12 17:25:30,169] Trial 9 finished with value: 511651103.8895053 and
parameters: {'n_estimators': 479, 'max_depth': 37, 'min_samples_split': 18,
'min_samples_leaf': 3, 'max_features': 'sqrt'}. Best is trial 7 with value:
293494966.68798095.
[I 2023-12-12 17:25:36,461] Trial 10 finished with value: 195946876.28859562 and
parameters: {'n_estimators': 410, 'max_depth': 140, 'min_samples_split': 2,
'min_samples_leaf': 1, 'max_features': 'log2'}. Best is trial 10 with value:
195946876.28859562.
[I 2023-12-12 17:25:43,839] Trial 11 finished with value: 196326328.62762597 and
parameters: {'n_estimators': 434, 'max_depth': 146, 'min_samples_split': 2,
'min_samples_leaf': 1, 'max_features': 'log2'}. Best is trial 10 with value:
195946876.28859562.
[I 2023-12-12 17:25:47,399] Trial 12 finished with value: 213232479.50763762 and
parameters: {'n_estimators': 342, 'max_depth': 150, 'min_samples_split': 7,
'min_samples_leaf': 1, 'max_features': 'log2'}. Best is trial 10 with value:
195946876.28859562.
[I 2023-12-12 17:25:48,637] Trial 13 finished with value: 908159440.7022152 and
parameters: {'n_estimators': 338, 'max_depth': 149, 'min_samples_split': 2,
'min_samples_leaf': 3, 'max_features': 'log2'}. Best is trial 10 with value:
195946876.28859562.
[I 2023-12-12 17:25:51,539] Trial 14 finished with value: 236936068.05811873 and
parameters: {'n_estimators': 342, 'max_depth': 123, 'min_samples_split': 12,
'min_samples_leaf': 1, 'max_features': 'log2'}. Best is trial 10 with value:
195946876.28859562.
[I 2023-12-12 17:25:52,666] Trial 15 finished with value: 1071486931.9538132 and
parameters: {'n_estimators': 439, 'max_depth': 126, 'min_samples_split': 24,
'min_samples_leaf': 4, 'max_features': 'log2'}. Best is trial 10 with value:
195946876.28859562.
[I 2023-12-12 17:25:53,754] Trial 16 finished with value: 706289497.5173566 and
parameters: {'n_estimators': 247, 'max_depth': 100, 'min_samples_split': 6,
'min_samples_leaf': 2, 'max_features': 'log2'}. Best is trial 10 with value:
195946876.28859562.
[I 2023-12-12 17:25:56,237] Trial 17 finished with value: 704616652.0272862 and
parameters: {'n_estimators': 572, 'max_depth': 136, 'min_samples_split': 11,
'min_samples_leaf': 2, 'max_features': 'log2'}. Best is trial 10 with value:
195946876.28859562.
[I 2023-12-12 17:25:57,394] Trial 18 finished with value: 1052561958.7243686 and
parameters: {'n_estimators': 412, 'max_depth': 104, 'min_samples_split': 5,
'min_samples_leaf': 4, 'max_features': 'log2'}. Best is trial 10 with value:
195946876.28859562.
[I 2023-12-12 17:26:16,700] Trial 19 finished with value: 304096000.98131555 and
parameters: {'n_estimators': 560, 'max_depth': 135, 'min_samples_split': 22,
'min_samples_leaf': 2, 'max_features': None}. Best is trial 10 with value:
```

```
195946876.28859562.
[I 2023-12-12 17:26:17,380] Trial 20 finished with value: 1053001627.9721396 and
parameters: {'n_estimators': 267, 'max_depth': 89, 'min_samples_split': 13,
'min_samples_leaf': 4, 'max_features': 'log2'}. Best is trial 10 with value:
195946876.28859562.
[I 2023-12-12 17:26:21,067] Trial 21 finished with value: 212939175.77006018 and
parameters: {'n_estimators': 378, 'max_depth': 145, 'min_samples_split': 7,
'min_samples_leaf': 1, 'max_features': 'log2'}. Best is trial 10 with value:
195946876.28859562.
[I 2023-12-12 17:26:27,417] Trial 22 finished with value: 196064542.08750382 and
parameters: {'n_estimators': 421, 'max_depth': 138, 'min_samples_split': 2,
'min_samples_leaf': 1, 'max_features': 'log2'}. Best is trial 10 with value:
195946876.28859562.
[I 2023-12-12 17:26:30,362] Trial 23 finished with value: 683512630.2411408 and
parameters: {'n_estimators': 611, 'max_depth': 109, 'min_samples_split': 2,
'min_samples_leaf': 2, 'max_features': 'log2'}. Best is trial 10 with value:
195946876.28859562.
[I 2023-12-12 17:26:33,299] Trial 24 finished with value: 201462862.69076768 and
parameters: {'n_estimators': 257, 'max_depth': 115, 'min_samples_split': 4,
'min_samples_leaf': 1, 'max_features': 'log2'}. Best is trial 10 with value:
195946876.28859562.
[I 2023-12-12 17:26:33,976] Trial 25 finished with value: 1413504251.5993834 and
parameters: {'n_estimators': 471, 'max_depth': 135, 'min_samples_split': 9,
'min_samples_leaf': 10, 'max_features': 'log2'}. Best is trial 10 with value:
195946876.28859562.
[I 2023-12-12 17:26:36,582] Trial 26 finished with value: 674574083.6745112 and
parameters: {'n_estimators': 543, 'max_depth': 136, 'min_samples_split': 4,
'min_samples_leaf': 2, 'max_features': 'log2'}. Best is trial 10 with value:
195946876.28859562.
[I 2023-12-12 17:26:37,913] Trial 27 finished with value: 906117854.4916769 and
parameters: {'n_estimators': 415, 'max_depth': 131, 'min_samples_split': 8,
'min_samples_leaf': 3, 'max_features': 'log2'}. Best is trial 10 with value:
195946876.28859562.
[I 2023-12-12 17:26:51,557] Trial 28 finished with value: 224082711.13472813 and
parameters: {'n_estimators': 297, 'max_depth': 87, 'min_samples_split': 2,
'min_samples_leaf': 1, 'max_features': None}. Best is trial 10 with value:
195946876.28859562.
[I 2023-12-12 17:26:52,720] Trial 29 finished with value: 609309819.7727457 and
parameters: {'n_estimators': 218, 'max_depth': 117, 'min_samples_split': 5,
'min_samples_leaf': 5, 'max_features': 'sqrt'}. Best is trial 10 with value:
195946876.28859562.
[I 2023-12-12 17:26:53,464] Trial 30 finished with value: 417388072.20297015 and
parameters: {'n_estimators': 113, 'max_depth': 143, 'min_samples_split': 29,
'min_samples_leaf': 2, 'max_features': 'sqrt'}. Best is trial 10 with value:
195946876.28859562.
[I 2023-12-12 17:26:55,725] Trial 31 finished with value: 201497666.4259894 and
parameters: {'n_estimators': 188, 'max_depth': 114, 'min_samples_split': 4,
'min_samples_leaf': 1, 'max_features': 'log2'}. Best is trial 10 with value:
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195946876.28859562.
[I 2023-12-12 17:26:59,175] Trial 32 finished with value: 200447948.56451353 and
parameters: {'n_estimators': 299, 'max_depth': 123, 'min_samples_split': 4,
'min_samples_leaf': 1, 'max_features': 'log2'}. Best is trial 10 with value:
195946876.28859562.
[I 2023-12-12 17:27:01,196] Trial 33 finished with value: 677310280.9162338 and
parameters: {'n_estimators': 400, 'max_depth': 125, 'min_samples_split': 3,
'min_samples_leaf': 2, 'max_features': 'log2'}. Best is trial 10 with value:
195946876.28859562.
[I 2023-12-12 17:27:02,224] Trial 34 finished with value: 912671950.3761346 and
parameters: {'n_estimators': 305, 'max_depth': 142, 'min_samples_split': 6,
'min_samples_leaf': 3, 'max_features': 'log2'}. Best is trial 10 with value:
195946876.28859562.
[I 2023-12-12 17:27:03,092] Trial 35 finished with value: 1307661826.1257915 and
parameters: {'n_estimators': 498, 'max_depth': 127, 'min_samples_split': 11,
'min_samples_leaf': 7, 'max_features': 'log2'}. Best is trial 10 with value:
195946876.28859562.
[I 2023-12-12 17:27:10,286] Trial 36 finished with value: 211087789.40577805 and
parameters: {'n_estimators': 647, 'max_depth': 96, 'min_samples_split': 4,
'min_samples_leaf': 1, 'max_features': 'log2'}. Best is trial 10 with value:
195946876.28859562.
[I 2023-12-12 17:27:13,360] Trial 37 finished with value: 388670046.73784924 and
parameters: {'n_estimators': 447, 'max_depth': 141, 'min_samples_split': 9,
'min_samples_leaf': 2, 'max_features': 'sqrt'}. Best is trial 10 with value:
195946876.28859562.
[I 2023-12-12 17:27:16,783] Trial 38 finished with value: 906917090.7158121 and
parameters: {'n_estimators': 970, 'max_depth': 120, 'min_samples_split': 6,
'min_samples_leaf': 3, 'max_features': 'log2'}. Best is trial 10 with value:
195946876.28859562.
[I 2023-12-12 17:27:36,145] Trial 39 finished with value: 463302334.52915746 and
parameters: {'n_estimators': 719, 'max_depth': 69, 'min_samples_split': 3,
'min_samples_leaf': 8, 'max_features': None}. Best is trial 10 with value:
195946876.28859562.
[I 2023-12-12 17:27:39,360] Trial 40 finished with value: 250792419.1306514 and
parameters: {'n_estimators': 374, 'max_depth': 77, 'min_samples_split': 7,
'min_samples_leaf': 1, 'max_features': 'log2'}. Best is trial 10 with value:
195946876.28859562.
[I 2023-12-12 17:27:42,479] Trial 41 finished with value: 201285984.7837914 and
parameters: {'n_estimators': 284, 'max_depth': 113, 'min_samples_split': 4,
'min_samples_leaf': 1, 'max_features': 'log2'}. Best is trial 10 with value:
195946876.28859562.
[I 2023-12-12 17:27:44,897] Trial 42 finished with value: 201925778.28560516 and
parameters: {'n_estimators': 170, 'max_depth': 108, 'min_samples_split': 2,
'min_samples_leaf': 1, 'max_features': 'log2'}. Best is trial 10 with value:
195946876.28859562.
[I 2023-12-12 17:27:46,403] Trial 43 finished with value: 689078985.9193519 and
parameters: {'n_estimators': 307, 'max_depth': 131, 'min_samples_split': 5,
'min_samples_leaf': 2, 'max_features': 'log2'}. Best is trial 10 with value:
```

195946876.28859562.
[I 2023-12-12 17:27:50,902] Trial 44 finished with value: 196402324.898236 and parameters: {'n_estimators': 357, 'max_depth': 150, 'min_samples_split': 3, 'min_samples_leaf': 1, 'max_features': 'log2'}. Best is trial 10 with value: 195946876.28859562.
[I 2023-12-12 17:27:57,217] Trial 45 finished with value: 196840988.0530377 and parameters: {'n_estimators': 510, 'max_depth': 147, 'min_samples_split': 3, 'min_samples_leaf': 1, 'max_features': 'log2'}. Best is trial 10 with value: 195946876.28859562.
[I 2023-12-12 17:28:00,694] Trial 46 finished with value: 464349707.5310907 and parameters: {'n_estimators': 516, 'max_depth': 146, 'min_samples_split': 2, 'min_samples_leaf': 3, 'max_features': 'sqrt'}. Best is trial 10 with value: 195946876.28859562.
[I 2023-12-12 17:28:22,140] Trial 47 finished with value: 289546721.29249877 and parameters: {'n_estimators': 598, 'max_depth': 150, 'min_samples_split': 8, 'min_samples_leaf': 2, 'max_features': None}. Best is trial 10 with value: 195946876.28859562.
[I 2023-12-12 17:28:22,875] Trial 48 finished with value: 1384486095.639725 and parameters: {'n_estimators': 469, 'max_depth': 6, 'min_samples_split': 3, 'min_samples_leaf': 1, 'max_features': 'log2'}. Best is trial 10 with value: 195946876.28859562.
[I 2023-12-12 17:28:26,212] Trial 49 finished with value: 739920623.246479 and parameters: {'n_estimators': 874, 'max_depth': 54, 'min_samples_split': 20, 'min_samples_leaf': 2, 'max_features': 'log2'}. Best is trial 10 with value: 195946876.28859562.
[I 2023-12-12 17:28:27,173] Trial 50 finished with value: 1252595457.2971034 and parameters: {'n_estimators': 527, 'max_depth': 140, 'min_samples_split': 26, 'min_samples_leaf': 6, 'max_features': 'log2'}. Best is trial 10 with value: 195946876.28859562.
[I 2023-12-12 17:28:31,330] Trial 51 finished with value: 196970662.3711337 and parameters: {'n_estimators': 345, 'max_depth': 130, 'min_samples_split': 3, 'min_samples_leaf': 1, 'max_features': 'log2'}. Best is trial 10 with value: 195946876.28859562.
[I 2023-12-12 17:28:35,869] Trial 52 finished with value: 196457849.4658131 and parameters: {'n_estimators': 360, 'max_depth': 149, 'min_samples_split': 3, 'min_samples_leaf': 1, 'max_features': 'log2'}. Best is trial 10 with value: 195946876.28859562.
[I 2023-12-12 17:28:39,988] Trial 53 finished with value: 207327975.23411897 and parameters: {'n_estimators': 432, 'max_depth': 150, 'min_samples_split': 6, 'min_samples_leaf': 1, 'max_features': 'log2'}. Best is trial 10 with value: 195946876.28859562.
[I 2023-12-12 17:28:41,709] Trial 54 finished with value: 686735507.7481896 and parameters: {'n_estimators': 374, 'max_depth': 139, 'min_samples_split': 5, 'min_samples_leaf': 2, 'max_features': 'log2'}. Best is trial 10 with value: 195946876.28859562.
[I 2023-12-12 17:28:48,173] Trial 55 finished with value: 196331334.48840213 and parameters: {'n_estimators': 460, 'max_depth': 146, 'min_samples_split': 2, 'min_samples_leaf': 1, 'max_features': 'log2'}. Best is trial 10 with value:

195946876.28859562.
[I 2023-12-12 17:28:49,628] Trial 56 finished with value: 770184758.0075164 and parameters: {'n_estimators': 392, 'max_depth': 37, 'min_samples_split': 14, 'min_samples_leaf': 2, 'max_features': 'log2'}. Best is trial 10 with value: 195946876.28859562.
[I 2023-12-12 17:28:50,815] Trial 57 finished with value: 1057500784.9657 and parameters: {'n_estimators': 454, 'max_depth': 138, 'min_samples_split': 2, 'min_samples_leaf': 4, 'max_features': 'log2'}. Best is trial 10 with value: 195946876.28859562.
[I 2023-12-12 17:29:01,223] Trial 58 finished with value: 336625439.010241 and parameters: {'n_estimators': 332, 'max_depth': 134, 'min_samples_split': 16, 'min_samples_leaf': 3, 'max_features': None}. Best is trial 10 with value: 195946876.28859562.
[I 2023-12-12 17:29:04,776] Trial 59 finished with value: 227649843.85300234 and parameters: {'n_estimators': 432, 'max_depth': 144, 'min_samples_split': 10, 'min_samples_leaf': 1, 'max_features': 'log2'}. Best is trial 10 with value: 195946876.28859562.
[I 2023-12-12 17:29:06,275] Trial 60 finished with value: 765818104.8938036 and parameters: {'n_estimators': 369, 'max_depth': 19, 'min_samples_split': 7, 'min_samples_leaf': 5, 'max_features': 'sqrt'}. Best is trial 10 with value: 195946876.28859562.
[I 2023-12-12 17:29:12,263] Trial 61 finished with value: 196810095.22972837 and parameters: {'n_estimators': 496, 'max_depth': 147, 'min_samples_split': 3, 'min_samples_leaf': 1, 'max_features': 'log2'}. Best is trial 10 with value: 195946876.28859562.
[I 2023-12-12 17:29:20,531] Trial 62 finished with value: 196647110.52510384 and parameters: {'n_estimators': 559, 'max_depth': 150, 'min_samples_split': 2, 'min_samples_leaf': 1, 'max_features': 'log2'}. Best is trial 10 with value: 195946876.28859562.
[I 2023-12-12 17:29:23,231] Trial 63 finished with value: 677173529.7911136 and parameters: {'n_estimators': 569, 'max_depth': 129, 'min_samples_split': 2, 'min_samples_leaf': 2, 'max_features': 'log2'}. Best is trial 10 with value: 195946876.28859562.
[I 2023-12-12 17:29:27,415] Trial 64 finished with value: 201905442.42661455 and parameters: {'n_estimators': 413, 'max_depth': 150, 'min_samples_split': 5, 'min_samples_leaf': 1, 'max_features': 'log2'}. Best is trial 10 with value: 195946876.28859562.
[I 2023-12-12 17:29:29,776] Trial 65 finished with value: 674801267.3254457 and parameters: {'n_estimators': 481, 'max_depth': 142, 'min_samples_split': 2, 'min_samples_leaf': 2, 'max_features': 'log2'}. Best is trial 10 with value: 195946876.28859562.
[I 2023-12-12 17:29:35,173] Trial 66 finished with value: 203469006.21814546 and parameters: {'n_estimators': 543, 'max_depth': 134, 'min_samples_split': 5, 'min_samples_leaf': 1, 'max_features': 'log2'}. Best is trial 10 with value: 195946876.28859562.
[I 2023-12-12 17:29:39,465] Trial 67 finished with value: 197143040.42726707 and parameters: {'n_estimators': 348, 'max_depth': 144, 'min_samples_split': 3, 'min_samples_leaf': 1, 'max_features': 'log2'}. Best is trial 10 with value:

195946876.28859562.
[I 2023-12-12 17:29:42,275] Trial 68 finished with value: 683303802.2719265 and parameters: {'n_estimators': 604, 'max_depth': 137, 'min_samples_split': 4, 'min_samples_leaf': 2, 'max_features': 'log2'}. Best is trial 10 with value: 195946876.28859562.
[I 2023-12-12 17:29:45,644] Trial 69 finished with value: 198536859.03068975 and parameters: {'n_estimators': 239, 'max_depth': 139, 'min_samples_split': 2, 'min_samples_leaf': 1, 'max_features': 'log2'}. Best is trial 10 with value: 195946876.28859562.
[I 2023-12-12 17:29:54,790] Trial 70 finished with value: 445448570.2127462 and parameters: {'n_estimators': 324, 'max_depth': 145, 'min_samples_split': 6, 'min_samples_leaf': 7, 'max_features': None}. Best is trial 10 with value: 195946876.28859562.
[I 2023-12-12 17:30:00,789] Trial 71 finished with value: 196348084.515822 and parameters: {'n_estimators': 486, 'max_depth': 150, 'min_samples_split': 3, 'min_samples_leaf': 1, 'max_features': 'log2'}. Best is trial 10 with value: 195946876.28859562.
[I 2023-12-12 17:30:08,394] Trial 72 finished with value: 199523819.48172596 and parameters: {'n_estimators': 645, 'max_depth': 133, 'min_samples_split': 4, 'min_samples_leaf': 1, 'max_features': 'log2'}. Best is trial 10 with value: 195946876.28859562.
[I 2023-12-12 17:30:10,971] Trial 73 finished with value: 673963829.1111953 and parameters: {'n_estimators': 467, 'max_depth': 121, 'min_samples_split': 3, 'min_samples_leaf': 2, 'max_features': 'log2'}. Best is trial 10 with value: 195946876.28859562.
[I 2023-12-12 17:30:11,599] Trial 74 finished with value: 1406859404.3483052 and parameters: {'n_estimators': 434, 'max_depth': 146, 'min_samples_split': 2, 'min_samples_leaf': 10, 'max_features': 'log2'}. Best is trial 10 with value: 195946876.28859562.
[I 2023-12-12 17:30:15,987] Trial 75 finished with value: 201966914.13551953 and parameters: {'n_estimators': 400, 'max_depth': 150, 'min_samples_split': 5, 'min_samples_leaf': 1, 'max_features': 'log2'}. Best is trial 10 with value: 195946876.28859562.
[I 2023-12-12 17:30:20,567] Trial 76 finished with value: 196370889.24122992 and parameters: {'n_estimators': 365, 'max_depth': 128, 'min_samples_split': 3, 'min_samples_leaf': 1, 'max_features': 'log2'}. Best is trial 10 with value: 195946876.28859562.
[I 2023-12-12 17:30:23,479] Trial 77 finished with value: 371004668.2135528 and parameters: {'n_estimators': 370, 'max_depth': 126, 'min_samples_split': 4, 'min_samples_leaf': 2, 'max_features': 'sqrt'}. Best is trial 10 with value: 195946876.28859562.
[I 2023-12-12 17:30:24,073] Trial 78 finished with value: 1335372084.7702785 and parameters: {'n_estimators': 358, 'max_depth': 140, 'min_samples_split': 8, 'min_samples_leaf': 8, 'max_features': 'log2'}. Best is trial 10 with value: 195946876.28859562.
[I 2023-12-12 17:30:27,373] Trial 79 finished with value: 197138913.7257997 and parameters: {'n_estimators': 280, 'max_depth': 129, 'min_samples_split': 3, 'min_samples_leaf': 1, 'max_features': 'log2'}. Best is trial 10 with value:

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195946876.28859562.
[I 2023-12-12 17:30:29,285] Trial 80 finished with value: 684891955.9956049 and
parameters: {'n_estimators': 417, 'max_depth': 136, 'min_samples_split': 6,
'min_samples_leaf': 2, 'max_features': 'log2'}. Best is trial 10 with value:
195946876.28859562.
[I 2023-12-12 17:30:34,827] Trial 81 finished with value: 196701461.7909922 and
parameters: {'n_estimators': 390, 'max_depth': 143, 'min_samples_split': 2,
'min_samples_leaf': 1, 'max_features': 'log2'}. Best is trial 10 with value:
195946876.28859562.
[I 2023-12-12 17:30:40,402] Trial 82 finished with value: 196663936.0529217 and
parameters: {'n_estimators': 458, 'max_depth': 147, 'min_samples_split': 3,
'min_samples_leaf': 1, 'max_features': 'log2'}. Best is trial 10 with value:
195946876.28859562.
[I 2023-12-12 17:30:46,186] Trial 83 finished with value: 199074235.6941391 and
parameters: {'n_estimators': 492, 'max_depth': 142, 'min_samples_split': 4,
'min_samples_leaf': 1, 'max_features': 'log2'}. Best is trial 10 with value:
195946876.28859562.
[I 2023-12-12 17:30:52,601] Trial 84 finished with value: 199329075.33869213 and
parameters: {'n_estimators': 525, 'max_depth': 132, 'min_samples_split': 4,
'min_samples_leaf': 1, 'max_features': 'log2'}. Best is trial 10 with value:
195946876.28859562.
[I 2023-12-12 17:30:53,821] Trial 85 finished with value: 727338684.6540284 and
parameters: {'n_estimators': 318, 'max_depth': 150, 'min_samples_split': 18,
'min_samples_leaf': 2, 'max_features': 'log2'}. Best is trial 10 with value:
195946876.28859562.
[I 2023-12-12 17:30:59,202] Trial 86 finished with value: 196218000.24722683 and
parameters: {'n_estimators': 417, 'max_depth': 138, 'min_samples_split': 3,
'min_samples_leaf': 1, 'max_features': 'log2'}. Best is trial 10 with value:
195946876.28859562.
[I 2023-12-12 17:31:03,607] Trial 87 finished with value: 204306260.83423108 and
parameters: {'n_estimators': 419, 'max_depth': 120, 'min_samples_split': 5,
'min_samples_leaf': 1, 'max_features': 'log2'}. Best is trial 10 with value:
195946876.28859562.
[I 2023-12-12 17:31:05,788] Trial 88 finished with value: 672464338.0398114 and
parameters: {'n_estimators': 452, 'max_depth': 138, 'min_samples_split': 3,
'min_samples_leaf': 2, 'max_features': 'log2'}. Best is trial 10 with value:
195946876.28859562.
[I 2023-12-12 17:31:22,697] Trial 89 finished with value: 221313846.6021739 and
parameters: {'n_estimators': 399, 'max_depth': 126, 'min_samples_split': 7,
'min_samples_leaf': 1, 'max_features': None}. Best is trial 10 with value:
195946876.28859562.
[I 2023-12-12 17:31:27,783] Trial 90 finished with value: 202035352.22851175 and
parameters: {'n_estimators': 356, 'max_depth': 136, 'min_samples_split': 3,
'min_samples_leaf': 1, 'max_features': 'sqrt'}. Best is trial 10 with value:
195946876.28859562.
[I 2023-12-12 17:31:37,120] Trial 91 finished with value: 196610902.90252313 and
parameters: {'n_estimators': 580, 'max_depth': 146, 'min_samples_split': 2,
'min_samples_leaf': 1, 'max_features': 'log2'}. Best is trial 10 with value:
```

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195946876.28859562.
[I 2023-12-12 17:31:44,905] Trial 92 finished with value: 196145957.74070337 and
parameters: {'n_estimators': 485, 'max_depth': 142, 'min_samples_split': 2,
'min_samples_leaf': 1, 'max_features': 'log2'}. Best is trial 10 with value:
195946876.28859562.
[I 2023-12-12 17:31:50,298] Trial 93 finished with value: 199097287.54993477 and
parameters: {'n_estimators': 476, 'max_depth': 142, 'min_samples_split': 4,
'min_samples_leaf': 1, 'max_features': 'log2'}. Best is trial 10 with value:
195946876.28859562.
[I 2023-12-12 17:31:55,718] Trial 94 finished with value: 197003033.98066035 and
parameters: {'n_estimators': 437, 'max_depth': 132, 'min_samples_split': 3,
'min_samples_leaf': 1, 'max_features': 'log2'}. Best is trial 10 with value:
195946876.28859562.
[I 2023-12-12 17:31:57,546] Trial 95 finished with value: 685320767.7834516 and
parameters: {'n_estimators': 380, 'max_depth': 139, 'min_samples_split': 5,
'min_samples_leaf': 2, 'max_features': 'log2'}. Best is trial 10 with value:
195946876.28859562.
[I 2023-12-12 17:32:05,100] Trial 96 finished with value: 196965641.8653651 and
parameters: {'n_estimators': 510, 'max_depth': 147, 'min_samples_split': 2,
'min_samples_leaf': 1, 'max_features': 'log2'}. Best is trial 10 with value:
195946876.28859562.
[I 2023-12-12 17:32:07,653] Trial 97 finished with value: 674831208.1464149 and
parameters: {'n_estimators': 487, 'max_depth': 143, 'min_samples_split': 3,
'min_samples_leaf': 2, 'max_features': 'log2'}. Best is trial 10 with value:
195946876.28859562.
[I 2023-12-12 17:32:12,297] Trial 98 finished with value: 214815323.6373171 and
parameters: {'n_estimators': 419, 'max_depth': 93, 'min_samples_split': 4,
'min_samples_leaf': 1, 'max_features': 'log2'}. Best is trial 10 with value:
195946876.28859562.
[I 2023-12-12 17:32:14,178] Trial 99 finished with value: 692540957.2982405 and
parameters: {'n_estimators': 337, 'max_depth': 81, 'min_samples_split': 6,
'min_samples_leaf': 2, 'max_features': 'log2'}. Best is trial 10 with value:
195946876.28859562.

Best Hyperparameters: {'n_estimators': 410, 'max_depth': 140,
'min_samples_split': 2, 'min_samples_leaf': 1, 'max_features': 'log2'}
Feature Importance:
                    Feature  Importance
1            car_model_year    0.221827
0                car_driven    0.185057
300  car_model_Land Cruiser    0.035441
43          car_brand_Lexus    0.034641
32        car_brand_Hyundai    0.022447
50       car_brand_Mercedes    0.021416
235          car_model_Figo    0.014856
326       car_model_Mustang    0.013660
102        car_model_Accent    0.013349
462         car_model_Yaris    0.013110
```

```
Mean Absolute Error: 8454.4
Mean Squared Error: 195946876.28859562
Root Mean Squared Error: 13998.102596016204
R-squared: 0.8808643164493225
Accuracy: 80.61 %.
```

[ ]:
```
print("Linear Regression")
X2 = cars.drop(['car_price', 'car_transmission', 'car_model', 'car_brand'],␣
 ↪axis=1)
y2 = cars['car_price']
# Create a Linear Regression model
linear_model = LinearRegression()

# Split the data into training and testing sets
X_train2, X_test2, y_train2, y_test2 = train_test_split(X2, y2, test_size=0.3)

# Train the Linear Regression model
linear_model.fit(X_train2, y_train2)

# Make predictions on the test set
y_pred2 = linear_model.predict(X_test2)

# Evaluate the model
mse = mean_squared_error(y_test2, y_pred2)
r2 = r2_score(y_test2, y_pred2)

print(f'Mean Squared Error: {mse}')
print(f'R-squared: {r2}')
```

```
Linear Regression
Mean Squared Error: 1394215604.8679054
R-squared: 0.20886080400806872
```

[ ]:
```
print("Grandient boosting Regression")

# Generate a baseline using DummyRegressor
dummy_model = DummyRegressor(strategy='mean')
dummy_model.fit(X_train, y_train)
y_pred_baseline = dummy_model.predict(X_test)

# Evaluate baseline model
mae_baseline = mean_absolute_error(y_test, y_pred_baseline)
print(f'Baseline Mean Absolute Error: {mae_baseline}')
mse_baseline = mean_squared_error(y_test, y_pred_baseline)
print(f'Baseline Mean Squared Error: {mse_baseline}')
print(f'Baseline Root Mean Squared Error: {mse_baseline**0.5}')

print("Hyperparameter Optimization Step")
```

```python
# objective function for Optuna
def objective(trial):
    params = {
        'n_estimators': trial.suggest_int('n_estimators', 100, 1000),
        'max_depth': trial.suggest_int('max_depth', 1, 150),
        'learning_rate': trial.suggest_float('learning_rate', 0.01, 0.2),
        'subsample': trial.suggest_float('subsample', 0.5, 1.0),
        'colsample_bytree': trial.suggest_float('colsample_bytree', 0.5, 1.0),
    }
    xgb_model = xgb.XGBRegressor(random_state=42, **params)
    xgb_model.fit(X_train, y_train)
    y_pred = xgb_model.predict(X_test)
    return mean_squared_error(y_test, y_pred)

# Create an Optuna study and optimize the objective function
study = optuna.create_study(direction='minimize')
study.optimize(objective, n_trials=100)

# Get the best hyperparameters
xgb_best_params = study.best_params
print(f'Best Hyperparameters: {xgb_best_params}')
# xgb_best_params = {'n_estimators': 888, 'max_depth': 12, 'learning_rate': 0.
↪059265067129644175, 'subsample': 0.6710882119982516, 'colsample_bytree': 0.
↪9147549947728586}
# Train the model with the best hyperparameters
best_xgb_model = xgb.XGBRegressor(random_state=42, **xgb_best_params)
best_xgb_model.fit(X_train, y_train)
y_pred = best_xgb_model.predict(X_test)
y_pred_xgb = y_pred
# Evaluate the best model
mse = mean_squared_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)
mae = mean_absolute_error(y_test, y_pred)
print(f'Mean Absolute Error: {mae}')
print(f'Mean Squared Error: {mse}')
print(f'Root Mean Squared Error: {mse**0.5}')
print(f'R-squared: {r2}')

# Calculate accuracy metrics
errors = abs(y_pred - y_test)
mape = 100 * (errors / y_test)
accuracy = 100 - np.mean(mape)
print('Accuracy:', round(accuracy, 2), '%.')
```

```
[I 2023-12-12 17:32:20,925] A new study created in memory with name: no-
name-b64f83d9-c309-4642-bc8d-17f719049684
```

```
Grandient boosting Regression
```

```
Baseline Mean Absolute Error: 32745.338787888144
Baseline Mean Squared Error: 1649521929.7686503
Baseline Root Mean Squared Error: 40614.30695910802
Hyperparameter Optimization Step
```

```
[I 2023-12-12 17:32:32,919] Trial 0 finished with value: 204479863.83711797 and
parameters: {'n_estimators': 630, 'max_depth': 58, 'learning_rate':
0.07376617711138349, 'subsample': 0.5486640157115119, 'colsample_bytree':
0.6326548431302376}. Best is trial 0 with value: 204479863.83711797.
[I 2023-12-12 17:32:47,716] Trial 1 finished with value: 230107527.58014816 and
parameters: {'n_estimators': 329, 'max_depth': 70, 'learning_rate':
0.05368036923143994, 'subsample': 0.980823545806747, 'colsample_bytree':
0.5344162065211611}. Best is trial 0 with value: 204479863.83711797.
[I 2023-12-12 17:32:51,558] Trial 2 finished with value: 179072160.2740198 and
parameters: {'n_estimators': 943, 'max_depth': 16, 'learning_rate':
0.13812619132003406, 'subsample': 0.712199452044775, 'colsample_bytree':
0.8470823132098337}. Best is trial 2 with value: 179072160.2740198.
[I 2023-12-12 17:33:05,264] Trial 3 finished with value: 200375711.06501725 and
parameters: {'n_estimators': 663, 'max_depth': 88, 'learning_rate':
0.0386857716306806, 'subsample': 0.525851808786641, 'colsample_bytree':
0.5906967764942724}. Best is trial 2 with value: 179072160.2740198.
[I 2023-12-12 17:33:10,051] Trial 4 finished with value: 200064285.41673547 and
parameters: {'n_estimators': 749, 'max_depth': 22, 'learning_rate':
0.17258611852951475, 'subsample': 0.8085028022683538, 'colsample_bytree':
0.7022907358440036}. Best is trial 2 with value: 179072160.2740198.
[I 2023-12-12 17:33:10,540] Trial 5 finished with value: 1018569570.337943 and
parameters: {'n_estimators': 154, 'max_depth': 1, 'learning_rate':
0.04163266616550462, 'subsample': 0.5865059111499702, 'colsample_bytree':
0.8549522351694697}. Best is trial 2 with value: 179072160.2740198.
[I 2023-12-12 17:33:22,098] Trial 6 finished with value: 255529101.15232596 and
parameters: {'n_estimators': 486, 'max_depth': 79, 'learning_rate':
0.1761934465327932, 'subsample': 0.630136386845763, 'colsample_bytree':
0.611069181414892}. Best is trial 2 with value: 179072160.2740198.
[I 2023-12-12 17:33:37,505] Trial 7 finished with value: 197100251.2073858 and
parameters: {'n_estimators': 372, 'max_depth': 74, 'learning_rate':
0.02565821653053102, 'subsample': 0.7842638914061356, 'colsample_bytree':
0.7790333925878399}. Best is trial 2 with value: 179072160.2740198.
[I 2023-12-12 17:33:38,756] Trial 8 finished with value: 249539695.48918492 and
parameters: {'n_estimators': 585, 'max_depth': 3, 'learning_rate':
0.07525834342686008, 'subsample': 0.9952231608308255, 'colsample_bytree':
0.8983957327278695}. Best is trial 2 with value: 179072160.2740198.
[I 2023-12-12 17:33:49,552] Trial 9 finished with value: 236792950.89391083 and
parameters: {'n_estimators': 534, 'max_depth': 85, 'learning_rate':
0.15891045705279763, 'subsample': 0.5442977289452868, 'colsample_bytree':
0.5699202946488475}. Best is trial 2 with value: 179072160.2740198.
[I 2023-12-12 17:34:26,631] Trial 10 finished with value: 203032206.175274 and
parameters: {'n_estimators': 997, 'max_depth': 138, 'learning_rate':
0.12456215535271017, 'subsample': 0.6991088127773158, 'colsample_bytree':
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0.9737483195732508}. Best is trial 2 with value: 179072160.2740198.
[I 2023-12-12 17:34:37,075] Trial 11 finished with value: 184058189.45357895 and
parameters: {'n_estimators': 962, 'max_depth': 40, 'learning_rate':
0.010733426531717516, 'subsample': 0.7722329154175709, 'colsample_bytree':
0.7760065346433914}. Best is trial 2 with value: 179072160.2740198.
[I 2023-12-12 17:34:48,264] Trial 12 finished with value: 180604264.17189604 and
parameters: {'n_estimators': 995, 'max_depth': 42, 'learning_rate':
0.010646535314077252, 'subsample': 0.7095047335380091, 'colsample_bytree':
0.7790451997463047}. Best is trial 2 with value: 179072160.2740198.
[I 2023-12-12 17:34:58,744] Trial 13 finished with value: 193987515.8477752 and
parameters: {'n_estimators': 829, 'max_depth': 36, 'learning_rate':
0.11419622311360825, 'subsample': 0.6888462596396938, 'colsample_bytree':
0.8470920512924425}. Best is trial 2 with value: 179072160.2740198.
[I 2023-12-12 17:35:22,132] Trial 14 finished with value: 229658536.76529786 and
parameters: {'n_estimators': 858, 'max_depth': 111, 'learning_rate':
0.14368001230842067, 'subsample': 0.685800879114726, 'colsample_bytree':
0.7165085427358692}. Best is trial 2 with value: 179072160.2740198.
[I 2023-12-12 17:35:30,555] Trial 15 finished with value: 191478491.4913136 and
parameters: {'n_estimators': 885, 'max_depth': 25, 'learning_rate':
0.1959086859197891, 'subsample': 0.843549443257874, 'colsample_bytree':
0.8136064567280747}. Best is trial 2 with value: 179072160.2740198.
[I 2023-12-12 17:35:44,598] Trial 16 finished with value: 197769449.16373786 and
parameters: {'n_estimators': 744, 'max_depth': 52, 'learning_rate':
0.09926069148234976, 'subsample': 0.6264458522567324, 'colsample_bytree':
0.9287894714692493}. Best is trial 2 with value: 179072160.2740198.
[I 2023-12-12 17:35:49,661] Trial 17 finished with value: 187880683.9298918 and
parameters: {'n_estimators': 929, 'max_depth': 20, 'learning_rate':
0.13469452846166485, 'subsample': 0.7344900257697683, 'colsample_bytree':
0.7253706591147919}. Best is trial 2 with value: 179072160.2740198.
[I 2023-12-12 17:36:04,741] Trial 18 finished with value: 201445708.0755163 and
parameters: {'n_estimators': 775, 'max_depth': 45, 'learning_rate':
0.09696420903344917, 'subsample': 0.8360660274281746, 'colsample_bytree':
0.8775388981566055}. Best is trial 2 with value: 179072160.2740198.
[I 2023-12-12 17:36:36,284] Trial 19 finished with value: 192700762.3470516 and
parameters: {'n_estimators': 996, 'max_depth': 101, 'learning_rate':
0.010842340640761424, 'subsample': 0.7311256022644517, 'colsample_bytree':
0.8100192154030418}. Best is trial 2 with value: 179072160.2740198.
[I 2023-12-12 17:36:36,985] Trial 20 finished with value: 199352916.37495083 and
parameters: {'n_estimators': 147, 'max_depth': 13, 'learning_rate':
0.07802738971124473, 'subsample': 0.6435665357085874, 'colsample_bytree':
0.9995494173596471}. Best is trial 2 with value: 179072160.2740198.
[I 2023-12-12 17:36:45,077] Trial 21 finished with value: 176034285.11191586 and
parameters: {'n_estimators': 936, 'max_depth': 35, 'learning_rate':
0.011751459616146267, 'subsample': 0.7367778714701413, 'colsample_bytree':
0.781915232394115}. Best is trial 21 with value: 176034285.11191586.
[I 2023-12-12 17:36:52,923] Trial 22 finished with value: 182007350.80913603 and
parameters: {'n_estimators': 874, 'max_depth': 33, 'learning_rate':
0.029394884771824392, 'subsample': 0.745225643899293, 'colsample_bytree':
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0.7500374902354099}. Best is trial 21 with value: 176034285.11191586.
[I 2023-12-12 17:37:11,377] Trial 23 finished with value: 194294093.76189548 and
parameters: {'n_estimators': 808, 'max_depth': 60, 'learning_rate':
0.056705451704519905, 'subsample': 0.6637619515711256, 'colsample_bytree':
0.826457778596482}. Best is trial 21 with value: 176034285.11191586.
[I 2023-12-12 17:37:14,249] Trial 24 finished with value: 182206113.4478264 and
parameters: {'n_estimators': 908, 'max_depth': 12, 'learning_rate':
0.018733684148665365, 'subsample': 0.7164320058389596, 'colsample_bytree':
0.6732279738128434}. Best is trial 21 with value: 176034285.11191586.
[I 2023-12-12 17:37:18,882] Trial 25 finished with value: 173088934.94701123 and
parameters: {'n_estimators': 708, 'max_depth': 29, 'learning_rate':
0.02933704295848803, 'subsample': 0.6043503852812897, 'colsample_bytree':
0.7729749973754705}. Best is trial 25 with value: 173088934.94701123.
[I 2023-12-12 17:37:23,903] Trial 26 finished with value: 176855035.4463434 and
parameters: {'n_estimators': 688, 'max_depth': 30, 'learning_rate':
0.03342763763977619, 'subsample': 0.5852586728577721, 'colsample_bytree':
0.6682687691082791}. Best is trial 25 with value: 173088934.94701123.
[I 2023-12-12 17:37:28,878] Trial 27 finished with value: 174040755.41350827 and
parameters: {'n_estimators': 710, 'max_depth': 31, 'learning_rate':
0.030988710986717818, 'subsample': 0.5028988856126074, 'colsample_bytree':
0.6706826094703771}. Best is trial 25 with value: 173088934.94701123.
[I 2023-12-12 17:37:35,737] Trial 28 finished with value: 187998099.87280968 and
parameters: {'n_estimators': 452, 'max_depth': 50, 'learning_rate':
0.04772520459755165, 'subsample': 0.5039497624349677, 'colsample_bytree':
0.7420433218866751}. Best is trial 25 with value: 173088934.94701123.
[I 2023-12-12 17:37:47,554] Trial 29 finished with value: 194207723.048829 and
parameters: {'n_estimators': 698, 'max_depth': 57, 'learning_rate':
0.06162052558026434, 'subsample': 0.5008275109482093, 'colsample_bytree':
0.6507178064161404}. Best is trial 25 with value: 173088934.94701123.
[I 2023-12-12 17:37:59,910] Trial 30 finished with value: 190092334.92324397 and
parameters: {'n_estimators': 607, 'max_depth': 63, 'learning_rate':
0.024379639127533326, 'subsample': 0.5722302703649008, 'colsample_bytree':
0.6940467621450253}. Best is trial 25 with value: 173088934.94701123.
[I 2023-12-12 17:38:05,351] Trial 31 finished with value: 183509266.17887378 and
parameters: {'n_estimators': 681, 'max_depth': 32, 'learning_rate':
0.035860526863527524, 'subsample': 0.5913098741038858, 'colsample_bytree':
0.647759067400207}. Best is trial 25 with value: 173088934.94701123.
[I 2023-12-12 17:38:09,969] Trial 32 finished with value: 174280921.10175082 and
parameters: {'n_estimators': 716, 'max_depth': 29, 'learning_rate':
0.03575599658443237, 'subsample': 0.5476444223766668, 'colsample_bytree':
0.6610744744879948}. Best is trial 25 with value: 173088934.94701123.
[I 2023-12-12 17:38:11,623] Trial 33 finished with value: 181145908.7134415 and
parameters: {'n_estimators': 629, 'max_depth': 8, 'learning_rate':
0.04574560001271236, 'subsample': 0.5406214406753505, 'colsample_bytree':
0.6213588545968514}. Best is trial 25 with value: 173088934.94701123.
[I 2023-12-12 17:38:14,485] Trial 34 finished with value: 172710599.2393609 and
parameters: {'n_estimators': 530, 'max_depth': 24, 'learning_rate':
0.020467685143818016, 'subsample': 0.5597295299045244, 'colsample_bytree':
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0.6997618967547052}. Best is trial 34 with value: 172710599.2393609.
[I 2023-12-12 17:38:17,300] Trial 35 finished with value: 170571607.8692759 and
parameters: {'n_estimators': 549, 'max_depth': 24, 'learning_rate':
0.060910345653761716, 'subsample': 0.5618172213028187, 'colsample_bytree':
0.5188266909178267}. Best is trial 35 with value: 170571607.8692759.
[I 2023-12-12 17:38:19,270] Trial 36 finished with value: 165764937.60187286 and
parameters: {'n_estimators': 407, 'max_depth': 22, 'learning_rate':
0.06400417655928553, 'subsample': 0.5205569959331067, 'colsample_bytree':
0.5404031667426825}. Best is trial 36 with value: 165764937.60187286.
[I 2023-12-12 17:38:20,530] Trial 37 finished with value: 172069693.68318364 and
parameters: {'n_estimators': 279, 'max_depth': 19, 'learning_rate':
0.05846785260580809, 'subsample': 0.568138043767049, 'colsample_bytree':
0.5032256014890338}. Best is trial 36 with value: 165764937.60187286.
[I 2023-12-12 17:38:21,740] Trial 38 finished with value: 169697502.6010387 and
parameters: {'n_estimators': 283, 'max_depth': 16, 'learning_rate':
0.06457399175909617, 'subsample': 0.5615880615369441, 'colsample_bytree':
0.5131891519336426}. Best is trial 36 with value: 165764937.60187286.
[I 2023-12-12 17:38:22,350] Trial 39 finished with value: 789606129.2171105 and
parameters: {'n_estimators': 229, 'max_depth': 1, 'learning_rate':
0.06621455915761508, 'subsample': 0.5315401972843705, 'colsample_bytree':
0.502417726495519}. Best is trial 36 with value: 165764937.60187286.
[I 2023-12-12 17:38:23,844] Trial 40 finished with value: 166440824.4781451 and
parameters: {'n_estimators': 327, 'max_depth': 17, 'learning_rate':
0.08400035380135468, 'subsample': 0.563031738463942, 'colsample_bytree':
0.5492953155797445}. Best is trial 36 with value: 165764937.60187286.
[I 2023-12-12 17:38:25,116] Trial 41 finished with value: 168747624.64625633 and
parameters: {'n_estimators': 314, 'max_depth': 17, 'learning_rate':
0.08298731326403626, 'subsample': 0.5772610262868618, 'colsample_bytree':
0.5448847425700243}. Best is trial 36 with value: 165764937.60187286.
[I 2023-12-12 17:38:26,207] Trial 42 finished with value: 177652697.1991753 and
parameters: {'n_estimators': 380, 'max_depth': 8, 'learning_rate':
0.08273771483125131, 'subsample': 0.6114919086884965, 'colsample_bytree':
0.5538121002536343}. Best is trial 36 with value: 165764937.60187286.
[I 2023-12-12 17:38:27,819] Trial 43 finished with value: 163828546.53070742 and
parameters: {'n_estimators': 416, 'max_depth': 17, 'learning_rate':
0.06868936602060988, 'subsample': 0.5254351696480434, 'colsample_bytree':
0.5348554247342359}. Best is trial 43 with value: 163828546.53070742.
[I 2023-12-12 17:38:29,268] Trial 44 finished with value: 162917639.05829144 and
parameters: {'n_estimators': 400, 'max_depth': 15, 'learning_rate':
0.08550262266434973, 'subsample': 0.5334605068452769, 'colsample_bytree':
0.5417482083535005}. Best is trial 44 with value: 162917639.05829144.
[I 2023-12-12 17:38:30,468] Trial 45 finished with value: 170920686.81433877 and
parameters: {'n_estimators': 421, 'max_depth': 8, 'learning_rate':
0.08729741241407245, 'subsample': 0.5239137329737872, 'colsample_bytree':
0.5447976567829562}. Best is trial 44 with value: 162917639.05829144.
[I 2023-12-12 17:38:39,624] Trial 46 finished with value: 213440493.6626385 and
parameters: {'n_estimators': 356, 'max_depth': 138, 'learning_rate':
0.07266658264836981, 'subsample': 0.5195173850096391, 'colsample_bytree':
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0.5818080821735724}. Best is trial 44 with value: 162917639.05829144.
[I 2023-12-12 17:38:40,536] Trial 47 finished with value: 175382873.40963146 and
parameters: {'n_estimators': 209, 'max_depth': 16, 'learning_rate':
0.09138968031097913, 'subsample': 0.5338823217208967, 'colsample_bytree':
0.5974033774909914}. Best is trial 44 with value: 162917639.05829144.
[I 2023-12-12 17:38:41,744] Trial 48 finished with value: 207376940.94356093 and
parameters: {'n_estimators': 482, 'max_depth': 5, 'learning_rate':
0.07348354665790113, 'subsample': 0.5810479407345112, 'colsample_bytree':
0.5632207842435264}. Best is trial 44 with value: 162917639.05829144.
[I 2023-12-12 17:38:46,463] Trial 49 finished with value: 211050896.65759456 and
parameters: {'n_estimators': 307, 'max_depth': 43, 'learning_rate':
0.10810058658340045, 'subsample': 0.6088535606736128, 'colsample_bytree':
0.5386900263179599}. Best is trial 44 with value: 162917639.05829144.
[I 2023-12-12 17:38:47,811] Trial 50 finished with value: 162898863.92896238 and
parameters: {'n_estimators': 406, 'max_depth': 13, 'learning_rate':
0.08250233370869499, 'subsample': 0.5476978675392475, 'colsample_bytree':
0.5300935892377621}. Best is trial 50 with value: 162898863.92896238.
[I 2023-12-12 17:38:56,733] Trial 51 finished with value: 206053578.2383488 and
parameters: {'n_estimators': 416, 'max_depth': 147, 'learning_rate':
0.08557206488770251, 'subsample': 0.5496358162569547, 'colsample_bytree':
0.5246597849333642}. Best is trial 50 with value: 162898863.92896238.
[I 2023-12-12 17:38:58,216] Trial 52 finished with value: 175313028.72883818 and
parameters: {'n_estimators': 333, 'max_depth': 20, 'learning_rate':
0.09387847659734658, 'subsample': 0.518670457783464, 'colsample_bytree':
0.5731926047805801}. Best is trial 50 with value: 162898863.92896238.
[I 2023-12-12 17:38:59,652] Trial 53 finished with value: 164754587.9675566 and
parameters: {'n_estimators': 398, 'max_depth': 14, 'learning_rate':
0.08062180496657416, 'subsample': 0.5419310159120212, 'colsample_bytree':
0.5323635258140921}. Best is trial 50 with value: 162898863.92896238.
[I 2023-12-12 17:39:00,996] Trial 54 finished with value: 167154272.53298435 and
parameters: {'n_estimators': 389, 'max_depth': 12, 'learning_rate':
0.0696038726307506, 'subsample': 0.5409521339021074, 'colsample_bytree':
0.5939501437356236}. Best is trial 50 with value: 162898863.92896238.
[I 2023-12-12 17:39:02,149] Trial 55 finished with value: 272883208.6719514 and
parameters: {'n_estimators': 457, 'max_depth': 3, 'learning_rate':
0.07968259016422649, 'subsample': 0.5208878508910832, 'colsample_bytree':
0.5276255976162494}. Best is trial 50 with value: 162898863.92896238.
[I 2023-12-12 17:39:08,815] Trial 56 finished with value: 211309948.52989823 and
parameters: {'n_estimators': 504, 'max_depth': 40, 'learning_rate':
0.09897400844443738, 'subsample': 0.5522121241945702, 'colsample_bytree':
0.6085454944385756}. Best is trial 50 with value: 162898863.92896238.
[I 2023-12-12 17:39:11,193] Trial 57 finished with value: 175192730.06047842 and
parameters: {'n_estimators': 422, 'max_depth': 24, 'learning_rate':
0.06924000647751197, 'subsample': 0.5951392087799257, 'colsample_bytree':
0.5595078682481185}. Best is trial 50 with value: 162898863.92896238.
[I 2023-12-12 17:39:12,109] Trial 58 finished with value: 212384955.92934448 and
parameters: {'n_estimators': 235, 'max_depth': 11, 'learning_rate':
0.051798363086414445, 'subsample': 0.620100837851487, 'colsample_bytree':
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0.5771524426524319}. Best is trial 50 with value: 162898863.92896238.
[I 2023-12-12 17:39:15,969] Trial 59 finished with value: 193727819.35590786 and
parameters: {'n_estimators': 344, 'max_depth': 38, 'learning_rate':
0.07748533203396114, 'subsample': 0.5302985992460675, 'colsample_bytree':
0.5390747994914775}. Best is trial 50 with value: 162898863.92896238.
[I 2023-12-12 17:39:26,418] Trial 60 finished with value: 219933707.10501355 and
parameters: {'n_estimators': 455, 'max_depth': 70, 'learning_rate':
0.08876953459034959, 'subsample': 0.6375555964405566, 'colsample_bytree':
0.5279560314974134}. Best is trial 50 with value: 162898863.92896238.
[I 2023-12-12 17:39:27,712] Trial 61 finished with value: 168863776.08834577 and
parameters: {'n_estimators': 359, 'max_depth': 13, 'learning_rate':
0.06973192348802836, 'subsample': 0.544045218655931, 'colsample_bytree':
0.5862047238589285}. Best is trial 50 with value: 162898863.92896238.
[I 2023-12-12 17:39:28,579] Trial 62 finished with value: 609495485.5372561 and
parameters: {'n_estimators': 396, 'max_depth': 1, 'learning_rate':
0.07604242262359981, 'subsample': 0.5153967228248342, 'colsample_bytree':
0.5593943905496963}. Best is trial 50 with value: 162898863.92896238.
[I 2023-12-12 17:39:29,866] Trial 63 finished with value: 176638101.1774782 and
parameters: {'n_estimators': 392, 'max_depth': 11, 'learning_rate':
0.05368074160653403, 'subsample': 0.5435437851331061, 'colsample_bytree':
0.5919115589898002}. Best is trial 50 with value: 162898863.92896238.
[I 2023-12-12 17:39:36,674] Trial 64 finished with value: 207615598.605675 and
parameters: {'n_estimators': 267, 'max_depth': 95, 'learning_rate':
0.06692865627952267, 'subsample': 0.5767270665973939, 'colsample_bytree':
0.5142880960346682}. Best is trial 50 with value: 162898863.92896238.
[I 2023-12-12 17:39:39,774] Trial 65 finished with value: 183735538.01309478 and
parameters: {'n_estimators': 499, 'max_depth': 26, 'learning_rate':
0.09131740877843846, 'subsample': 0.5112953050692487, 'colsample_bytree':
0.5512883163093542}. Best is trial 50 with value: 162898863.92896238.
[I 2023-12-12 17:39:42,313] Trial 66 finished with value: 183528928.99124333 and
parameters: {'n_estimators': 572, 'max_depth': 20, 'learning_rate':
0.10173767325678015, 'subsample': 0.5016924066387225, 'colsample_bytree':
0.5298254882206347}. Best is trial 50 with value: 162898863.92896238.
[I 2023-12-12 17:39:43,507] Trial 67 finished with value: 174299539.3580011 and
parameters: {'n_estimators': 428, 'max_depth': 8, 'learning_rate':
0.08099878469480838, 'subsample': 0.5329871064361662, 'colsample_bytree':
0.5674530405066542}. Best is trial 50 with value: 162898863.92896238.
[I 2023-12-12 17:39:45,246] Trial 68 finished with value: 167548551.2912306 and
parameters: {'n_estimators': 386, 'max_depth': 16, 'learning_rate':
0.07271131721981394, 'subsample': 0.558923936283162, 'colsample_bytree':
0.6036539624571152}. Best is trial 50 with value: 162898863.92896238.
[I 2023-12-12 17:39:50,474] Trial 69 finished with value: 203727409.48070636 and
parameters: {'n_estimators': 307, 'max_depth': 48, 'learning_rate':
0.06286912605622244, 'subsample': 0.5921520882921012, 'colsample_bytree':
0.6236846422879471}. Best is trial 50 with value: 162898863.92896238.
[I 2023-12-12 17:39:52,532] Trial 70 finished with value: 189288383.0437542 and
parameters: {'n_estimators': 193, 'max_depth': 36, 'learning_rate':
0.08570700032887522, 'subsample': 0.5697870109012374, 'colsample_bytree':
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0.539778301705887}. Best is trial 50 with value: 162898863.92896238.
[I 2023-12-12 17:39:53,936] Trial 71 finished with value: 166761428.17038292 and
parameters: {'n_estimators': 380, 'max_depth': 15, 'learning_rate':
0.0729004957333407, 'subsample': 0.5563922547322576, 'colsample_bytree':
0.5941965053316921}. Best is trial 50 with value: 162898863.92896238.
[I 2023-12-12 17:39:57,056] Trial 72 finished with value: 178179350.46789402 and
parameters: {'n_estimators': 468, 'max_depth': 27, 'learning_rate':
0.07791776112229024, 'subsample': 0.537972113382718, 'colsample_bytree':
0.5909141186813825}. Best is trial 50 with value: 162898863.92896238.
[I 2023-12-12 17:39:58,085] Trial 73 finished with value: 224691508.42581627 and
parameters: {'n_estimators': 368, 'max_depth': 6, 'learning_rate':
0.057861768002674334, 'subsample': 0.5555916051025767, 'colsample_bytree':
0.573004923660717}. Best is trial 50 with value: 162898863.92896238.
[I 2023-12-12 17:40:00,455] Trial 74 finished with value: 180830493.00564682 and
parameters: {'n_estimators': 518, 'max_depth': 21, 'learning_rate':
0.0952459555839364, 'subsample': 0.5000429561398103, 'colsample_bytree':
0.5050731997201652}. Best is trial 50 with value: 162898863.92896238.
[I 2023-12-12 17:40:01,045] Trial 75 finished with value: 239365696.09162584 and
parameters: {'n_estimators': 101, 'max_depth': 14, 'learning_rate':
0.06827477056226283, 'subsample': 0.521558998260577, 'colsample_bytree':
0.5526139046041324}. Best is trial 50 with value: 162898863.92896238.
[I 2023-12-12 17:40:02,096] Trial 76 finished with value: 173392773.11592695 and
parameters: {'n_estimators': 329, 'max_depth': 11, 'learning_rate':
0.08142050386536011, 'subsample': 0.5992159775115349, 'colsample_bytree':
0.5001697531381731}. Best is trial 50 with value: 162898863.92896238.
[I 2023-12-12 17:40:11,743] Trial 77 finished with value: 204424873.40421 and
parameters: {'n_estimators': 433, 'max_depth': 112, 'learning_rate':
0.07336555735530935, 'subsample': 0.5822600234058937, 'colsample_bytree':
0.5216083676128166}. Best is trial 50 with value: 162898863.92896238.
[I 2023-12-12 17:40:13,683] Trial 78 finished with value: 164423690.2636961 and
parameters: {'n_estimators': 395, 'max_depth': 22, 'learning_rate':
0.06280358896085023, 'subsample': 0.5695042638199586, 'colsample_bytree':
0.538342303587254}. Best is trial 50 with value: 162898863.92896238.
[I 2023-12-12 17:40:16,696] Trial 79 finished with value: 174877916.12075946 and
parameters: {'n_estimators': 406, 'max_depth': 31, 'learning_rate':
0.06168880604280532, 'subsample': 0.5695222853944352, 'colsample_bytree':
0.5353128794093289}. Best is trial 50 with value: 162898863.92896238.
[I 2023-12-12 17:40:18,206] Trial 80 finished with value: 171841125.3107747 and
parameters: {'n_estimators': 260, 'max_depth': 23, 'learning_rate':
0.053663449979827936, 'subsample': 0.554607743287777, 'colsample_bytree':
0.5166644473817816}. Best is trial 50 with value: 162898863.92896238.
[I 2023-12-12 17:40:19,696] Trial 81 finished with value: 166897293.2751273 and
parameters: {'n_estimators': 362, 'max_depth': 18, 'learning_rate':
0.06555396922224849, 'subsample': 0.5362171493549865, 'colsample_bytree':
0.565342416274202}. Best is trial 50 with value: 162898863.92896238.
[I 2023-12-12 17:40:21,304] Trial 82 finished with value: 173382632.7487265 and
parameters: {'n_estimators': 363, 'max_depth': 19, 'learning_rate':
0.08953431567332858, 'subsample': 0.5281151870152418, 'colsample_bytree':
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0.5562313357509456}. Best is trial 50 with value: 162898863.92896238.
[I 2023-12-12 17:40:24,061] Trial 83 finished with value: 173504490.90120307 and
parameters: {'n_estimators': 444, 'max_depth': 27, 'learning_rate':
0.06340974096589713, 'subsample': 0.5128566270987467, 'colsample_bytree':
0.5659820607998574}. Best is trial 50 with value: 162898863.92896238.
[I 2023-12-12 17:40:24,953] Trial 84 finished with value: 288925842.52462226 and
parameters: {'n_estimators': 336, 'max_depth': 5, 'learning_rate':
0.04750921024958174, 'subsample': 0.5862941668717919, 'colsample_bytree':
0.5467364108887839}. Best is trial 50 with value: 162898863.92896238.
[I 2023-12-12 17:40:27,771] Trial 85 finished with value: 188376874.5642109 and
parameters: {'n_estimators': 293, 'max_depth': 34, 'learning_rate':
0.08359292788104997, 'subsample': 0.5664981292100146, 'colsample_bytree':
0.5294765803368799}. Best is trial 50 with value: 162898863.92896238.
[I 2023-12-12 17:40:29,585] Trial 86 finished with value: 167447797.33747607 and
parameters: {'n_estimators': 477, 'max_depth': 17, 'learning_rate':
0.07444355318033452, 'subsample': 0.540297710428185, 'colsample_bytree':
0.5790449656042025}. Best is trial 50 with value: 162898863.92896238.
[I 2023-12-12 17:40:31,676] Trial 87 finished with value: 163694041.75534335 and
parameters: {'n_estimators': 411, 'max_depth': 23, 'learning_rate':
0.05726509932969867, 'subsample': 0.5480616709702739, 'colsample_bytree':
0.5384637372767708}. Best is trial 50 with value: 162898863.92896238.
[I 2023-12-12 17:40:33,643] Trial 88 finished with value: 168980075.64664716 and
parameters: {'n_estimators': 404, 'max_depth': 22, 'learning_rate':
0.04155549846291431, 'subsample': 0.5507415327294322, 'colsample_bytree':
0.5133279353368488}. Best is trial 50 with value: 162898863.92896238.
[I 2023-12-12 17:40:34,875] Trial 89 finished with value: 171388384.1914216 and
parameters: {'n_estimators': 318, 'max_depth': 15, 'learning_rate':
0.05748463161099249, 'subsample': 0.6020057943374633, 'colsample_bytree':
0.541848773066799}. Best is trial 50 with value: 162898863.92896238.
[I 2023-12-12 17:40:36,168] Trial 90 finished with value: 166959600.57242513 and
parameters: {'n_estimators': 433, 'max_depth': 9, 'learning_rate':
0.08587582657947286, 'subsample': 0.5124388097683437, 'colsample_bytree':
0.5316776087857422}. Best is trial 50 with value: 162898863.92896238.
[I 2023-12-12 17:40:38,618] Trial 91 finished with value: 177476509.42338118 and
parameters: {'n_estimators': 352, 'max_depth': 29, 'learning_rate':
0.06990720251808633, 'subsample': 0.5272131375646798, 'colsample_bytree':
0.5688404391831807}. Best is trial 50 with value: 162898863.92896238.
[I 2023-12-12 17:40:40,159] Trial 92 finished with value: 166142058.093121 and
parameters: {'n_estimators': 379, 'max_depth': 18, 'learning_rate':
0.06589270156478014, 'subsample': 0.561084363822098, 'colsample_bytree':
0.5584126105529779}. Best is trial 50 with value: 162898863.92896238.
[I 2023-12-12 17:40:42,136] Trial 93 finished with value: 171262387.54487723 and
parameters: {'n_estimators': 387, 'max_depth': 23, 'learning_rate':
0.08032854522080085, 'subsample': 0.5607558822224379, 'colsample_bytree':
0.5508127695289587}. Best is trial 50 with value: 162898863.92896238.
[I 2023-12-12 17:40:43,733] Trial 94 finished with value: 165883319.7380634 and
parameters: {'n_estimators': 447, 'max_depth': 14, 'learning_rate':
0.06101378466200673, 'subsample': 0.5819444989521456, 'colsample_bytree':
```
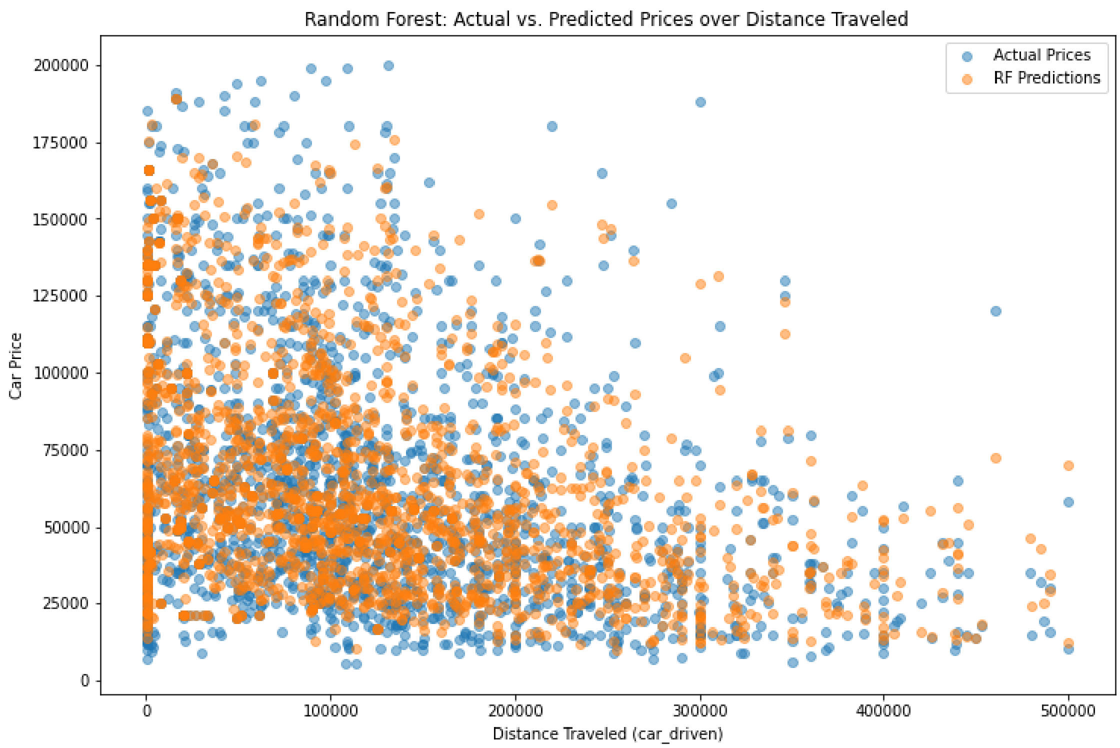

```
0.5196966342069795}. Best is trial 50 with value: 162898863.92896238.
[I 2023-12-12 17:40:44,772] Trial 95 finished with value: 314164734.8607198 and
parameters: {'n_estimators': 454, 'max_depth': 3, 'learning_rate':
0.059674695374935395, 'subsample': 0.5770930255725314, 'colsample_bytree':
0.5206344912122307}. Best is trial 50 with value: 162898863.92896238.
[I 2023-12-12 17:40:46,451] Trial 96 finished with value: 173698046.19088113 and
parameters: {'n_estimators': 490, 'max_depth': 10, 'learning_rate':
0.05353835445581905, 'subsample': 0.5452192234283928, 'colsample_bytree':
0.510180180329851 4}. Best is trial 50 with value: 162898863.92896238.
[I 2023-12-12 17:40:49,155] Trial 97 finished with value: 173848979.9579455 and
parameters: {'n_estimators': 421, 'max_depth': 28, 'learning_rate':
0.05054020934585571, 'subsample': 0.5914404249800073, 'colsample_bytree':
0.5403860624227373}. Best is trial 50 with value: 162898863.92896238.
[I 2023-12-12 17:40:51,637] Trial 98 finished with value: 166616575.83444664 and
parameters: {'n_estimators': 546, 'max_depth': 20, 'learning_rate':
0.06597292620173688, 'subsample': 0.5258487432429673, 'colsample_bytree':
0.5212864188288127}. Best is trial 50 with value: 162898863.92896238.
[I 2023-12-12 17:40:52,680] Trial 99 finished with value: 198749775.88212192 and
parameters: {'n_estimators': 407, 'max_depth': 6, 'learning_rate':
0.07672823885165489, 'subsample': 0.6119313588946045, 'colsample_bytree':
0.5093232704243466}. Best is trial 50 with value: 162898863.92896238.

Best Hyperparameters: {'n_estimators': 406, 'max_depth': 13, 'learning_rate':
0.08250233370869499, 'subsample': 0.5476978675392475, 'colsample_bytree':
0.5300935892377621}
Mean Absolute Error: 8167.862993379832
Mean Squared Error: 162898863.92896238
Root Mean Squared Error: 12763.183926002257
R-squared: 0.9009575050575315
Accuracy: 83.17 %.
```

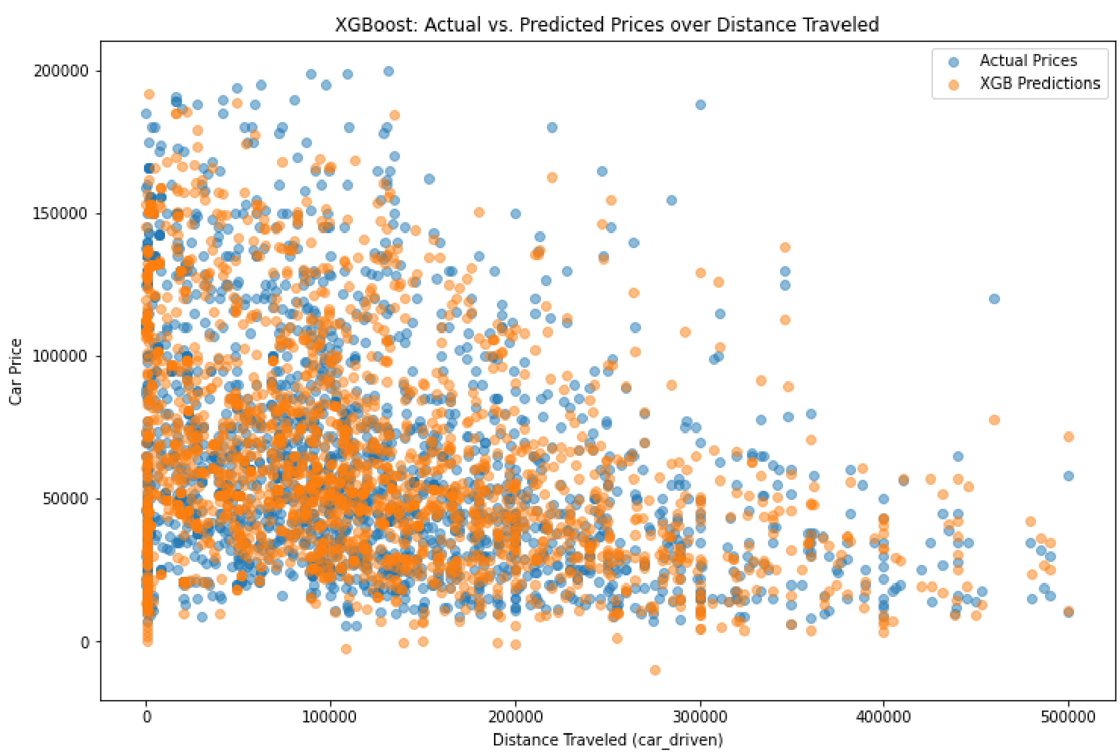
[ ]:
```
# Model Visualization and Analysis
from sklearn.model_selection import cross_val_score
# # Use cross_val_score for cross-validation
scores = cross_val_score(best_rf_model, X, y, cv=5,␣
 ↪scoring='neg_mean_squared_error')

# Display the mean squared error scores
print("RF Cross-Validation Mean Squared Error:", -scores.mean())

scores2 = cross_val_score(best_xgb_model, X, y, cv=5,␣
 ↪scoring='neg_mean_squared_error')

# Display the mean squared error scores
print("RF Cross-Validation Mean Squared Error:", -scores2.mean())


# Random Forest Visualization
```

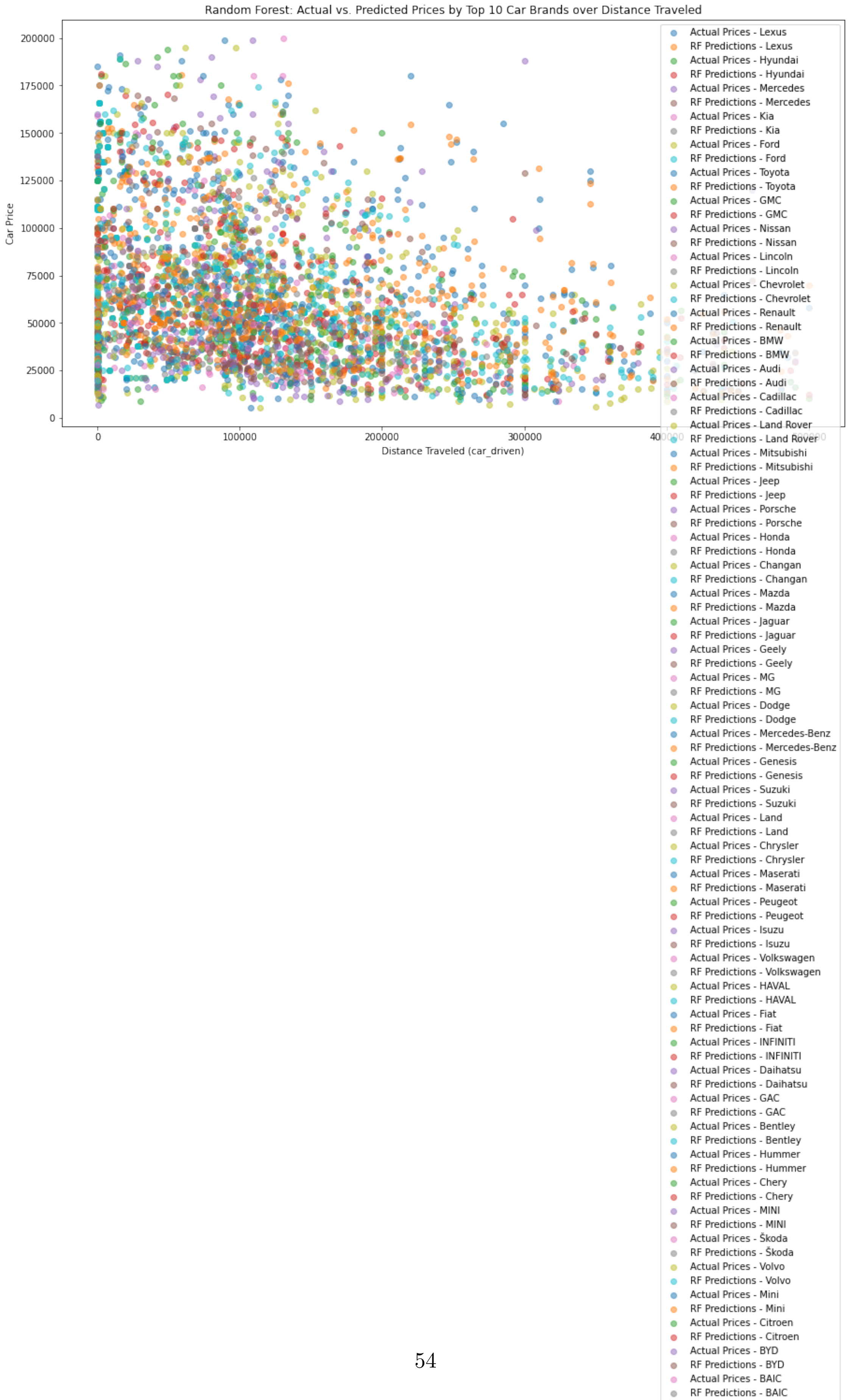
```python
plt.figure(figsize=(12, 8))

# Actual Prices
plt.scatter(X_test['car_driven'], y_test, label='Actual Prices', alpha=0.5)

# Random Forest Predictions
y_pred_rf = best_rf_model.predict(X_test)
plt.scatter(X_test['car_driven'], y_pred_rf, label='RF Predictions', alpha=0.5)

plt.xlabel('Distance Traveled (car_driven)')
plt.ylabel('Car Price')
plt.title('Random Forest: Actual vs. Predicted Prices over Distance Traveled')
plt.legend()
plt.show()

# XGBoost Visualization
plt.figure(figsize=(12, 8))

# Actual Prices
plt.scatter(X_test['car_driven'], y_test, label='Actual Prices', alpha=0.5)

# XGBoost Predictions
y_pred_xgb = best_xgb_model.predict(X_test)
plt.scatter(X_test['car_driven'], y_pred_xgb, label='XGB Predictions', alpha=0.
 ↪5)

plt.xlabel('Distance Traveled (car_driven)')
plt.ylabel('Car Price')
plt.title('XGBoost: Actual vs. Predicted Prices over Distance Traveled')
plt.legend()
plt.show()

# Random Forest Visualization by Top 10 Car Brands
top_brands_rf = feature_importance_df['Feature'].str.extract(r'car_brand_(.*)').
 ↪dropna()[0]

plt.figure(figsize=(15, 8))

for brand in top_brands_rf:
    brand_indices = X_test[X_test[f'car_brand_{brand}'] == 1].index

    if not brand_indices.empty:  # Check if there are samples for the current␣
 ↪brand
        plt.scatter(X_test.loc[brand_indices, 'car_driven'], y_test.
 ↪loc[brand_indices], label=f'Actual Prices - {brand}', alpha=0.5)

        y_pred_rf_brand = best_rf_model.predict(X_test.loc[brand_indices])
```

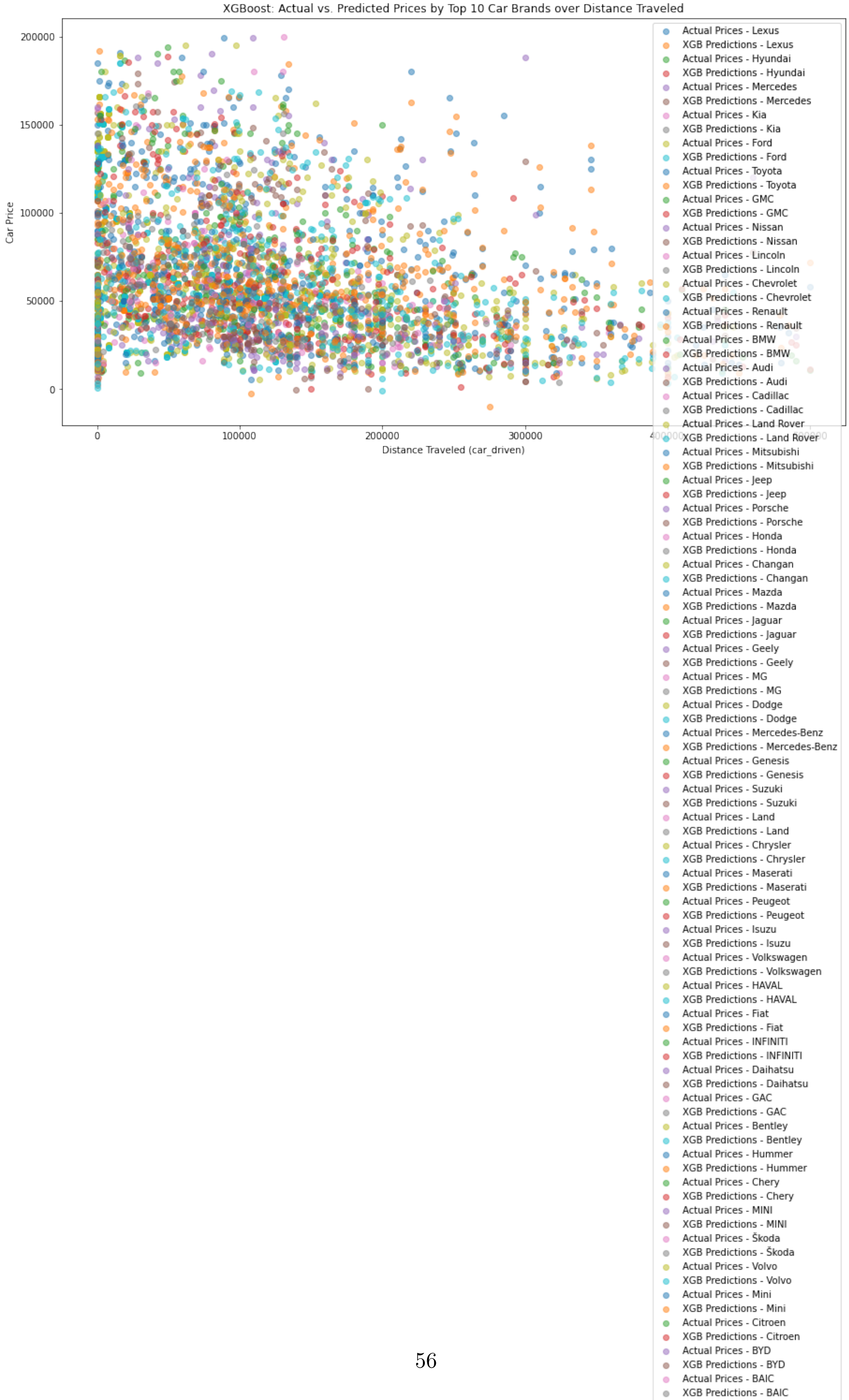
```
        plt.scatter(X_test.loc[brand_indices, 'car_driven'], y_pred_rf_brand,␣
↪label=f'RF Predictions - {brand}', alpha=0.5)

plt.xlabel('Distance Traveled (car_driven)')
plt.ylabel('Car Price')
plt.title('Random Forest: Actual vs. Predicted Prices by Top 10 Car Brands over␣
↪Distance Traveled')
plt.legend()
plt.show()

# XGBoost Visualization by Top 10 Car Brands
top_brands_xgb = feature_importance_df['Feature'].str.extract(r'car_brand_(.
↪*)').dropna()[0]

plt.figure(figsize=(15, 8))

for brand in top_brands_xgb:
    brand_indices = X_test[X_test[f'car_brand_{brand}'] == 1].index

    if not brand_indices.empty:  # Check if there are samples for the current␣
↪brand
        plt.scatter(X_test.loc[brand_indices, 'car_driven'], y_test.
↪loc[brand_indices], label=f'Actual Prices - {brand}', alpha=0.5)

        y_pred_xgb_brand = best_xgb_model.predict(X_test.loc[brand_indices])
        plt.scatter(X_test.loc[brand_indices, 'car_driven'], y_pred_xgb_brand,␣
↪label=f'XGB Predictions - {brand}', alpha=0.5)

plt.xlabel('Distance Traveled (car_driven)')
plt.ylabel('Car Price')
plt.title('XGBoost: Actual vs. Predicted Prices by Top 10 Car Brands over␣
↪Distance Traveled')
plt.legend()
plt.show()
```

```
RF Cross-Validation Mean Squared Error: 238135352.76941156
RF Cross-Validation Mean Squared Error: 207643152.5300929
```


Random Forest: Actual vs. Predicted Prices over Distance Traveled
Actual Prices
RF Predictions
Car Price
Distance Traveled (car_driven)
0
25000
50000
75000
100000
125000
150000
175000
200000
0
100000
200000
300000
400000
500000


XGBoost: Actual vs. Predicted Prices over Distance Traveled
Actual Prices
XGB Predictions
Car Price
Distance Traveled (car_driven)
0
50000
100000
150000
200000
0
100000
200000
300000
400000
500000


Random Forest: Actual vs. Predicted Prices by Top 10 Car Brands over Distance Traveled
Car Price
200000
175000
150000
125000
100000
75000
50000
25000
0
0
100000
200000
300000
400000
Distance Traveled (car_driven)
Actual Prices - Lexus
RF Predictions - Lexus
Actual Prices - Hyundai
RF Predictions - Hyundai
Actual Prices - Mercedes
RF Predictions - Mercedes
Actual Prices - Kia
RF Predictions - Kia
Actual Prices - Ford
RF Predictions - Ford
Actual Prices - Toyota
RF Predictions - Toyota
Actual Prices - GMC
RF Predictions - GMC
Actual Prices - Nissan
RF Predictions - Nissan
Actual Prices - Lincoln
RF Predictions - Lincoln
Actual Prices - Chevrolet
RF Predictions - Chevrolet
Actual Prices - Renault
RF Predictions - Renault
Actual Prices - BMW
RF Predictions - BMW
Actual Prices - Audi
RF Predictions - Audi
Actual Prices - Cadillac
RF Predictions - Cadillac
Actual Prices - Land Rover
RF Predictions - Land Rover
Actual Prices - Mitsubishi
RF Predictions - Mitsubishi
Actual Prices - Jeep
RF Predictions - Jeep
Actual Prices - Porsche
RF Predictions - Porsche
Actual Prices - Honda
RF Predictions - Honda
Actual Prices - Changan
RF Predictions - Changan
Actual Prices - Mazda
RF Predictions - Mazda
Actual Prices - Jaguar
RF Predictions - Jaguar
Actual Prices - Geely
RF Predictions - Geely
Actual Prices - MG
RF Predictions - MG
Actual Prices - Dodge
RF Predictions - Dodge
Actual Prices - Mercedes-Benz
RF Predictions - Mercedes-Benz
Actual Prices - Genesis
RF Predictions - Genesis
Actual Prices - Suzuki
RF Predictions - Suzuki
Actual Prices - Land
RF Predictions - Land
Actual Prices - Chrysler
RF Predictions - Chrysler
Actual Prices - Maserati
RF Predictions - Maserati
Actual Prices - Peugeot
RF Predictions - Peugeot
Actual Prices - Isuzu
RF Predictions - Isuzu
Actual Prices - Volkswagen
RF Predictions - Volkswagen
Actual Prices - HAVAL
RF Predictions - HAVAL
Actual Prices - Fiat
RF Predictions - Fiat
Actual Prices - INFINITI
RF Predictions - INFINITI
Actual Prices - Daihatsu
RF Predictions - Daihatsu
Actual Prices - GAC
RF Predictions - GAC
Actual Prices - Bentley
RF Predictions - Bentley
Actual Prices - Hummer
RF Predictions - Hummer
Actual Prices - Chery
RF Predictions - Chery
Actual Prices - MINI
RF Predictions - MINI
Actual Prices - Škoda
RF Predictions - Škoda
Actual Prices - Volvo
RF Predictions - Volvo
Actual Prices - Mini
RF Predictions - Mini
Actual Prices - Citroen
RF Predictions - Citroen
Actual Prices - BYD
RF Predictions - BYD
Actual Prices - BAIC
RF Predictions - BAIC


XGBoost: Actual vs. Predicted Prices by Top 10 Car Brands over Distance Traveled
Car Price
200000
150000
100000
50000
0
0
100000
200000
300000
Distance Traveled (car_driven)
Actual Prices - Lexus
XGB Predictions - Lexus
Actual Prices - Hyundai
XGB Predictions - Hyundai
Actual Prices - Mercedes
XGB Predictions - Mercedes
Actual Prices - Kia
XGB Predictions - Kia
Actual Prices - Ford
XGB Predictions - Ford
Actual Prices - Toyota
XGB Predictions - Toyota
Actual Prices - GMC
XGB Predictions - GMC
Actual Prices - Nissan
XGB Predictions - Nissan
Actual Prices - Lincoln
XGB Predictions - Lincoln
Actual Prices - Chevrolet
XGB Predictions - Chevrolet
Actual Prices - Renault
XGB Predictions - Renault
Actual Prices - BMW
XGB Predictions - BMW
Actual Prices - Audi
XGB Predictions - Audi
Actual Prices - Cadillac
XGB Predictions - Cadillac
Actual Prices - Land Rover
XGB Predictions - Land Rover
Actual Prices - Mitsubishi
XGB Predictions - Mitsubishi
Actual Prices - Jeep
XGB Predictions - Jeep
Actual Prices - Porsche
XGB Predictions - Porsche
Actual Prices - Honda
XGB Predictions - Honda
Actual Prices - Changan
XGB Predictions - Changan
Actual Prices - Mazda
XGB Predictions - Mazda
Actual Prices - Jaguar
XGB Predictions - Jaguar
Actual Prices - Geely
XGB Predictions - Geely
Actual Prices - MG
XGB Predictions - MG
Actual Prices - Dodge
XGB Predictions - Dodge
Actual Prices - Mercedes-Benz
XGB Predictions - Mercedes-Benz
Actual Prices - Genesis
XGB Predictions - Genesis
Actual Prices - Suzuki
XGB Predictions - Suzuki
Actual Prices - Land
XGB Predictions - Land
Actual Prices - Chrysler
XGB Predictions - Chrysler
Actual Prices - Maserati
XGB Predictions - Maserati
Actual Prices - Peugeot
XGB Predictions - Peugeot
Actual Prices - Isuzu
XGB Predictions - Isuzu
Actual Prices - Volkswagen
XGB Predictions - Volkswagen
Actual Prices - HAVAL
XGB Predictions - HAVAL
Actual Prices - Fiat
XGB Predictions - Fiat
Actual Prices - INFINITI
XGB Predictions - INFINITI
Actual Prices - Daihatsu
XGB Predictions - Daihatsu
Actual Prices - GAC
XGB Predictions - GAC
Actual Prices - Bentley
XGB Predictions - Bentley
Actual Prices - Hummer
XGB Predictions - Hummer
Actual Prices - Chery
XGB Predictions - Chery
Actual Prices - MINI
XGB Predictions - MINI
Actual Prices - Škoda
XGB Predictions - Škoda
Actual Prices - Volvo
XGB Predictions - Volvo
Actual Prices - Mini
XGB Predictions - Mini
Actual Prices - Citroen
XGB Predictions - Citroen
Actual Prices - BYD
XGB Predictions - BYD
Actual Prices - BAIC
XGB Predictions - BAIC

[ ]:
```python
# Feature Engineering
# Depreciation rate of car based on mileage and accounting for inf values
cars['actual_depreciation_rate'] = cars['car_price'] / np.
 ↪where(cars['car_driven'] == 0, 1, cars['car_driven'])
# print(cars['actual_depreciation_rate'].describe())

# print(cars['car_brand'].value_counts())

X = cars[['car_brand', 'car_driven']]
y = cars['actual_depreciation_rate']

X_encoded = pd.get_dummies(X, columns=['car_brand'])
X_encoded = X_encoded.drop(['car_brand_Hummer', 'car_brand_Other'], axis=1)

X_train, X_test, y_train, y_test = train_test_split(X_encoded, y, test_size=0.
 ↪3, random_state=42)
# print(X_test.columns)

# Random Forest model
rf_model = RandomForestRegressor(random_state=42, **rf_best_params)
rf_model.fit(X_train, y_train)
y_pred_rf = rf_model.predict(X_test)

# XGBoost model
xgb_model = xgb.XGBRegressor(random_state=42, **xgb_best_params)
xgb_model.fit(X_train, y_train)
y_pred_xgb = xgb_model.predict(X_test)

# Evaluate models
mse_rf = mean_squared_error(y_test, y_pred_rf)
mse_xgb = mean_squared_error(y_test, y_pred_xgb)

print(f'RF Mean Squared Error: {mse_rf}')
print(f'XGB Mean Squared Error: {mse_xgb}')

# Compare model predictions with actual depreciation rates
results_rf = pd.DataFrame({'Actual_Price': y_test, 'Predicted_RF': y_pred_rf})
results_xgb = pd.DataFrame({'Actual_Price': y_test, 'Predicted_XGB':␣
 ↪y_pred_xgb})

# Outliers removal to make viewing easier
results_rf = results_rf[results_rf['Actual_Price'] < 5000]
results_xgb = results_xgb[results_xgb['Actual_Price'] < 5000]
```

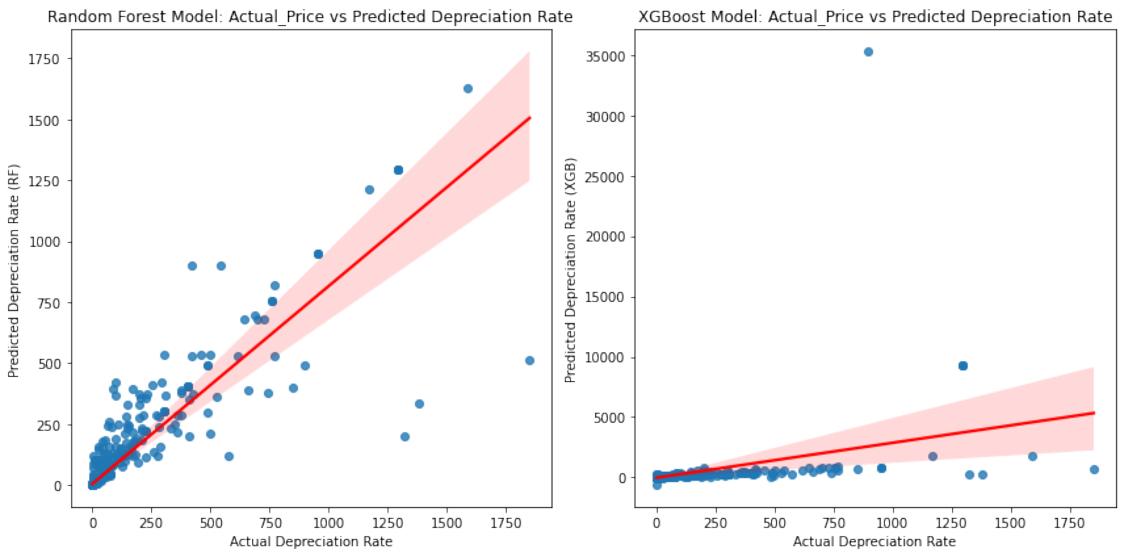
```python
# Visualize the results with a line of best fit
plt.figure(figsize=(12, 6))

plt.subplot(1, 2, 1)
sns.regplot(x='Actual_Price', y='Predicted_RF', data=results_rf,␣
 ↪line_kws={'color': 'red'})
plt.title('Random Forest Model: Actual_Price vs Predicted Depreciation Rate')
plt.xlabel('Actual Depreciation Rate')
plt.ylabel('Predicted Depreciation Rate (RF)')

plt.subplot(1, 2, 2)
sns.regplot(x='Actual_Price', y='Predicted_XGB', data=results_xgb,␣
 ↪line_kws={'color': 'red'})
plt.title('XGBoost Model: Actual_Price vs Predicted Depreciation Rate')
plt.xlabel('Actual Depreciation Rate')
plt.ylabel('Predicted Depreciation Rate (XGB)')

plt.tight_layout()
plt.show()

results_rf['Depreciation_Rate_RF'] = ((results_rf['Actual_Price'] -␣
 ↪results_rf['Predicted_RF']) / results_rf['Actual_Price']) * 100

# Extract encoded 'car_brand' columns
brand_columns = [col for col in X_encoded.columns if col.
 ↪startswith('car_brand_')]
results_rf['Car_Brand'] = X_test[brand_columns].idxmax(axis=1).apply(lambda x:␣
 ↪x.split('_')[-1])

# Group by Car Brand and calculate average depreciation rate
depreciation_by_brand_rf = results_rf.
 ↪groupby('Car_Brand')['Depreciation_Rate_RF'].mean().reset_index()


# Create a bar plot
plt.figure(figsize=(12, 6))
sns.barplot(x='Car_Brand', y='Depreciation_Rate_RF',␣
 ↪data=depreciation_by_brand_rf)
plt.xticks(rotation=90)
plt.title('Average Depreciation Rate by Car Brand (Random Forest)')
plt.show()

# Calculate depreciation rate for XGBoost
results_xgb['Depreciation_Rate_XGB'] = ((results_xgb['Actual_Price'] -␣
 ↪results_xgb['Predicted_XGB']) / results_xgb['Actual_Price']) * 100
```

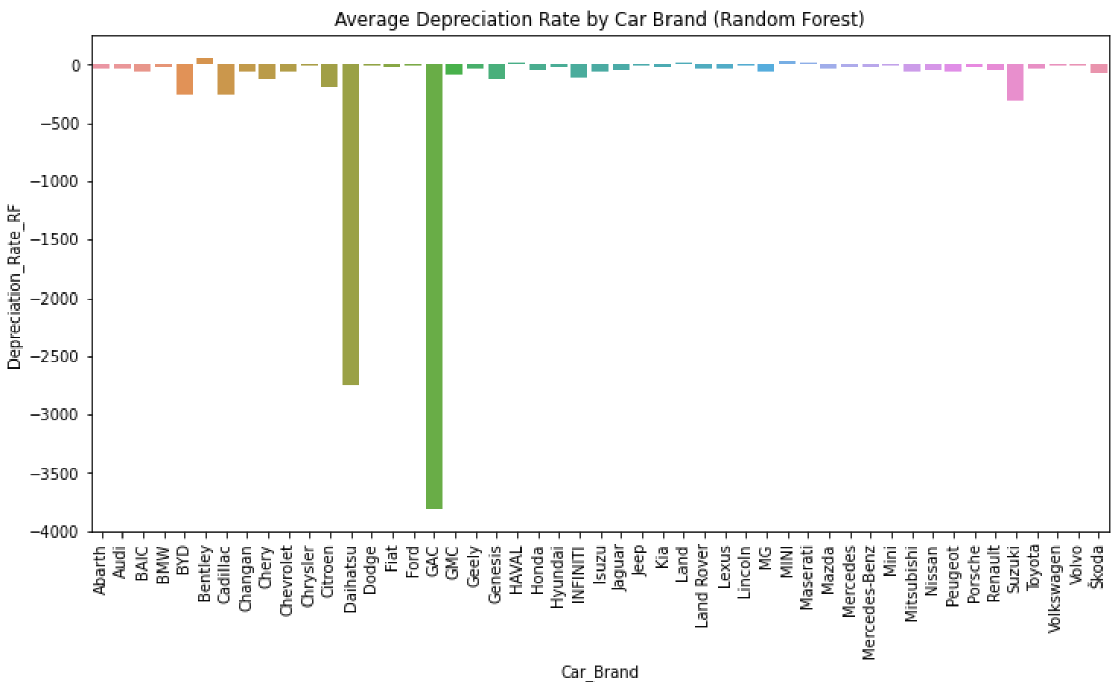
```
brand_columns_xgb = [col for col in X_encoded.columns if col.
 ↪startswith('car_brand_')]
results_xgb['Car_Brand'] = X_test[brand_columns_xgb].idxmax(axis=1).
 ↪apply(lambda x: x.split('_')[-1])

# Group by Car Brand and calculate average depreciation rate for XGB
depreciation_by_brand_xgb = results_xgb.
 ↪groupby('Car_Brand')['Depreciation_Rate_XGB'].mean().reset_index()

# Create a bar plot for XGBoost
plt.figure(figsize=(12, 6))
sns.barplot(x='Car_Brand', y='Depreciation_Rate_XGB',␣
 ↪data=depreciation_by_brand_xgb)
plt.xticks(rotation=90)
plt.title('Average Depreciation Rate (XGBoost) by Car Brand')
plt.show()

# Filter car brands with more than 75 cars
popular_brands = cars['car_brand'].value_counts()[cars['car_brand'].
 ↪value_counts() > 75].index

# Filter results for popular brands
popular_results_rf = results_rf[results_rf['Car_Brand'].isin(popular_brands)]
popular_results_xgb = results_xgb[results_xgb['Car_Brand'].isin(popular_brands)]

# Get the lowest 3 depreciation rates for Random Forest
lowest_depreciation_rf = popular_results_rf.
 ↪groupby('Car_Brand')['Depreciation_Rate_RF'].mean().nsmallest(3).
 ↪reset_index()

# Get the lowest 3 depreciation rates for XGBoost
lowest_depreciation_xgb = popular_results_xgb.
 ↪groupby('Car_Brand')['Depreciation_Rate_XGB'].mean().nsmallest(3).
 ↪reset_index()

print("Lowest 3 Depreciation Rates (Random Forest):")
print(lowest_depreciation_rf)

print("\nLowest 3 Depreciation Rates (XGBoost):")
print(lowest_depreciation_xgb)

# Filter car brands with more than 75 cars
popular_brands = cars['car_brand'].value_counts()[cars['car_brand'].
 ↪value_counts() > 50].index

# Filter results for popular brands
```

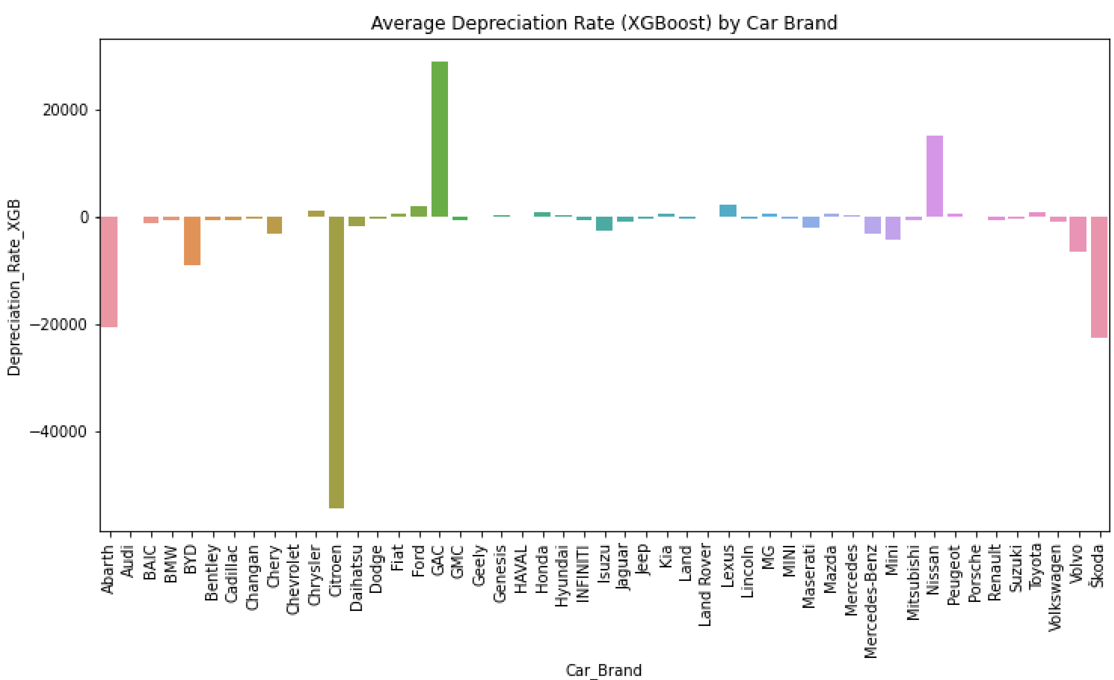
```
popular_results_rf = results_rf[results_rf['Car_Brand'].isin(popular_brands)]
popular_results_xgb = results_xgb[results_xgb['Car_Brand'].isin(popular_brands)]


top_brands_rf = depreciation_by_brand_rf[depreciation_by_brand_rf['Car_Brand'].
 ↪isin(popular_brands)].nlargest(5, 'Depreciation_Rate_RF')
top_brands_xgb =␣
 ↪depreciation_by_brand_xgb[depreciation_by_brand_xgb['Car_Brand'].
 ↪isin(popular_brands)].nlargest(5, 'Depreciation_Rate_XGB')

low_brands_rf = depreciation_by_brand_rf[depreciation_by_brand_rf['Car_Brand'].
 ↪isin(popular_brands)].nsmallest(5, 'Depreciation_Rate_RF')
low_brands_xgb =␣
 ↪depreciation_by_brand_xgb[depreciation_by_brand_xgb['Car_Brand'].
 ↪isin(popular_brands)].nsmallest(5, 'Depreciation_Rate_XGB')


print("Top 5 Car Brands with Highest Depreciation Rates (Random Forest):")
print(top_brands_rf)

print("\nTop 5 Car Brands with Highest Depreciation Rates (XGBoost):")
print(top_brands_xgb)

plt.figure(figsize=(12, 6))
sns.barplot(x='Car_Brand', y='Depreciation_Rate_RF', data=top_brands_rf,␣
 ↪palette='viridis')
plt.title('Top 5 Car Brands with Highest Depreciation Rates (Random Forest)')
plt.xlabel('Car Brand')
plt.ylabel('Average Depreciation Rate')
plt.xticks(rotation=45)
plt.show()

plt.figure(figsize=(12, 6))
sns.barplot(x='Car_Brand', y='Depreciation_Rate_XGB', data=top_brands_xgb,␣
 ↪palette='viridis')
plt.title('Top 5 Car Brands with Highest Depreciation Rates (XGBoost)')
plt.xlabel('Car Brand')
plt.ylabel('Average Depreciation Rate')
plt.xticks(rotation=45)
plt.show()

plt.figure(figsize=(12, 6))
sns.barplot(x='Car_Brand', y='Depreciation_Rate_RF', data=low_brands_rf,␣
 ↪palette='viridis')
plt.title('Top 5 Car Brands with Lowest Depreciation Rates (Random Forest)')
plt.xlabel('Car Brand')
```

```
plt.ylabel('Average Depreciation Rate')
plt.xticks(rotation=45)
plt.show()

plt.figure(figsize=(12, 6))
sns.barplot(x='Car_Brand', y='Depreciation_Rate_XGB', data=low_brands_xgb,␣
  ↪palette='viridis')
plt.title('Top 5 Car Brands with Lowest Depreciation Rates (XGBoost)')
plt.xlabel('Car Brand')
plt.ylabel('Average Depreciation Rate')
plt.xticks(rotation=45)
plt.show()
```

```
RF Mean Squared Error: 3104.655806191558
XGB Mean Squared Error: 713289.2907992633
```

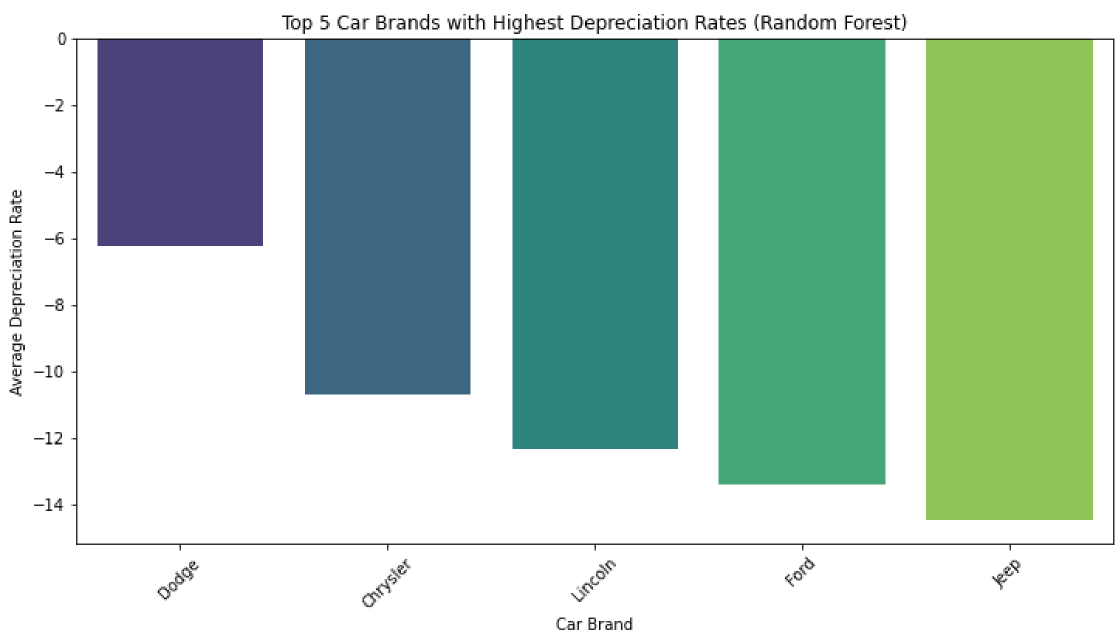


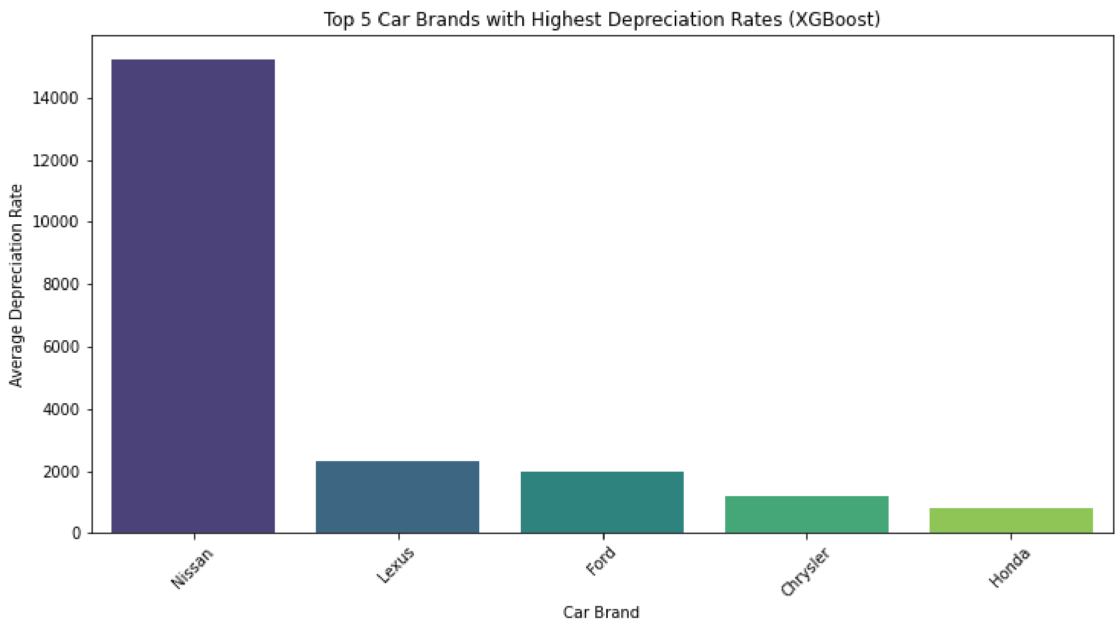


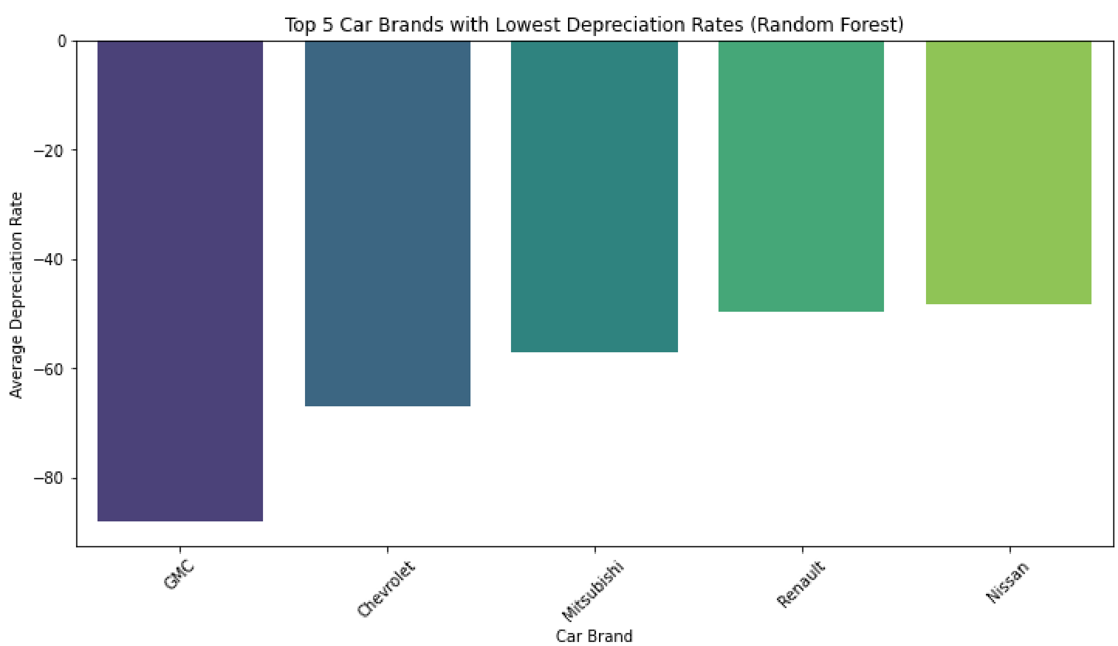


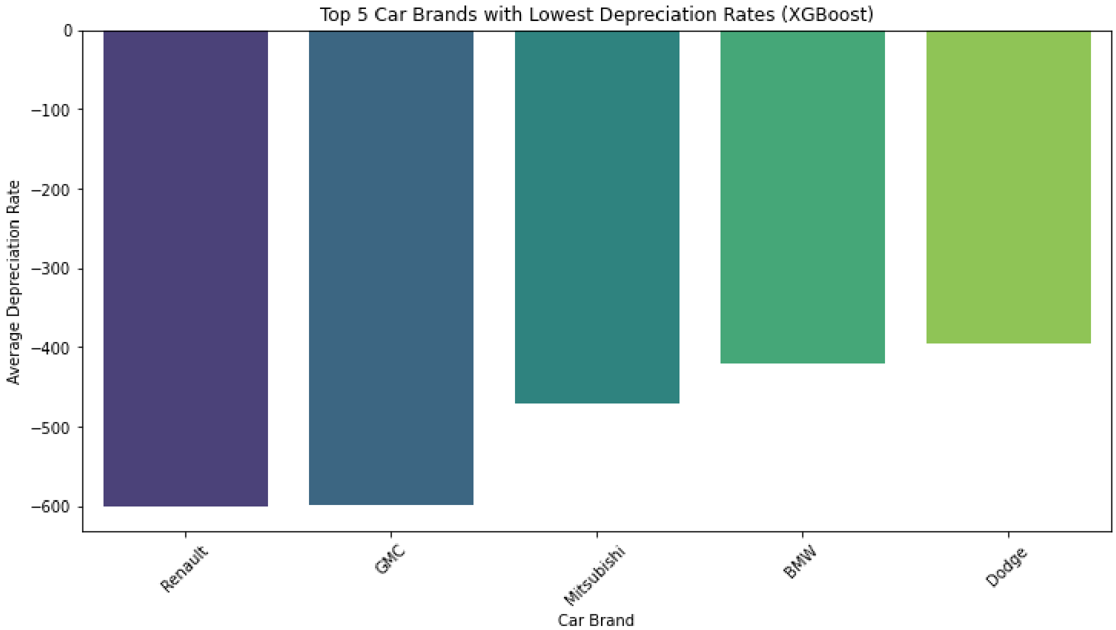

```
Lowest 3 Depreciation Rates (Random Forest):
    Car_Brand  Depreciation_Rate_RF
0         GMC            -88.152534
```

```
1   Chevrolet           -66.994621
2  Mitsubishi           -57.225495

Lowest 3 Depreciation Rates (XGBoost):
    Car_Brand  Depreciation_Rate_XGB
0         GMC            -598.801743
1  Mitsubishi            -470.295595
2         BMW            -421.187602
Top 5 Car Brands with Highest Depreciation Rates (Random Forest):
   Car_Brand  Depreciation_Rate_RF
13     Dodge             -6.205036
10  Chrysler            -10.698451
31   Lincoln            -12.328297
15      Ford            -13.365128
26      Jeep            -14.433586

Top 5 Car Brands with Highest Depreciation Rates (XGBoost):
   Car_Brand  Depreciation_Rate_XGB
40    Nissan           15237.331452
30     Lexus            2329.814842
15      Ford            1982.935608
10  Chrysler            1177.632464
21     Honda             805.085869
```




Top 5 Car Brands with Highest Depreciation Rates (XGBoost)
Average Depreciation Rate
0
2000
4000
6000
8000
10000
12000
14000
Nissan
Lexus
Ford
Chrysler
Honda
Car Brand


Top 5 Car Brands with Lowest Depreciation Rates (Random Forest)
Average Depreciation Rate
0
−20
−40
−60
−80
GMC
Chevrolet
Mitsubishi
Renault
Nissan
Car Brand


Top 5 Car Brands with Lowest Depreciation Rates (XGBoost)
Average Depreciation Rate
0
−100
−200
−300
−400
−500
−600
Renault
GMC
Mitsubishi
BMW
Dodge
Car Brand