Car Price Prediction and Deployment Using Streamlit Cloud

Introduction

This project aims to develop a machine learning model to predict car prices based on various features such as brand, model, year, engine size, fuel type, transmission, mileage, doors, and owner count. The model will be deployed using streamlit cloud integrated with Github for interactive usage and demonstration.

Primary Objective

To build an accurate car price prediction model and deploy it using streamlit, creating an end-to-end data science solution that can be shared and demonstrated to stakeholders.

In [ ]:

```

```

Import Necessary Libraries

In [1]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler, LabelEncoder
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score
import warnings
warnings.filterwarnings('ignore')
```

Load and Explore the Data

In [2]:

```
df = pd.read_csv(r"C:\Users\DELL\Desktop\Data Analytics Projects\Car Price Prediction\car_price_dataset.csv")
```

In [3]:

```
df.head()
```

Out[3]:

	Brand	Model	Year	Engine_Size	Fuel_Type	Transmission	Mileage	Doors	Owner_Count	Price
0	Kia	Rio	2020	4.2	Diesel	Manual	289944	3	5	8501
1	Chevrolet	Malibu	2012	2.0	Hybrid	Automatic	5356	2	3	12092
2	Mercedes	GLA	2020	4.2	Diesel	Automatic	231440	4	2	11171
3	Audi	Q5	2023	2.0	Electric	Manual	160971	2	1	11780
4	Volkswagen	Golf	2003	2.6	Hybrid	Semi-Automatic	286618	3	3	2867

In [ ]:

```

```

In [4]:

```
# Display basic information about the dataset
print("Dataset Shape:", df.shape)
print()
print("\nDataset Info:")
print()
print(df.info())
```

```
Dataset Shape: (10000, 10)


Dataset Info:

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 10 columns):
 #   Column        Non-Null Count  Dtype  
---  ------        --------------  -----  
 0   Brand         10000 non-null  object 
 1   Model         10000 non-null  object 
 2   Year          10000 non-null  int64  
 3   Engine_Size   10000 non-null  float64
 4   Fuel_Type     10000 non-null  object 
 5   Transmission  10000 non-null  object 
 6   Mileage       10000 non-null  int64  
 7   Doors         10000 non-null  int64  
 8   Owner_Count   10000 non-null  int64  
 9   Price         10000 non-null  int64  
dtypes: float64(1), int64(5), object(4)
memory usage: 781.4+ KB
None
```

In [ ]:

Data Cleaning and Preprocessing

In [5]:

```python
# Check for missing values

print("Missing values:")
print(df.isnull().sum())
```

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

In [ ]:

In [6]:

```python
# Check for duplicates
print(f"\nDuplicate rows: {df.duplicated().sum()}")
df = df.drop_duplicates()
```

```
Duplicate rows: 0
```

In [ ]:

In [7]:

```python
# Check data types and convert if necessary
print("\nData types:")
print(df.dtypes)
```

```
Data types:
Brand            object
Model            object
Year              int64
Engine_Size     float64
Fuel_Type        object
Transmission     object
Mileage           int64
Doors             int64
Owner_Count       int64
Price             int64
dtype: object
```

In [ ]:

In [8]:

```python
# Check for zero or negative values where inappropriate

print(f"\nCars with zero or negative price: {(df['Price'] <= 0).sum()}")
print(f"Cars with negative mileage: {(df['Mileage'] < 0).sum()}")
print(f"Cars with zero doors: {(df['Doors'] == 0).sum()}")
```

```
Cars with zero or negative price: 0
Cars with negative mileage: 0
Cars with zero doors: 0
```

In [ ]:

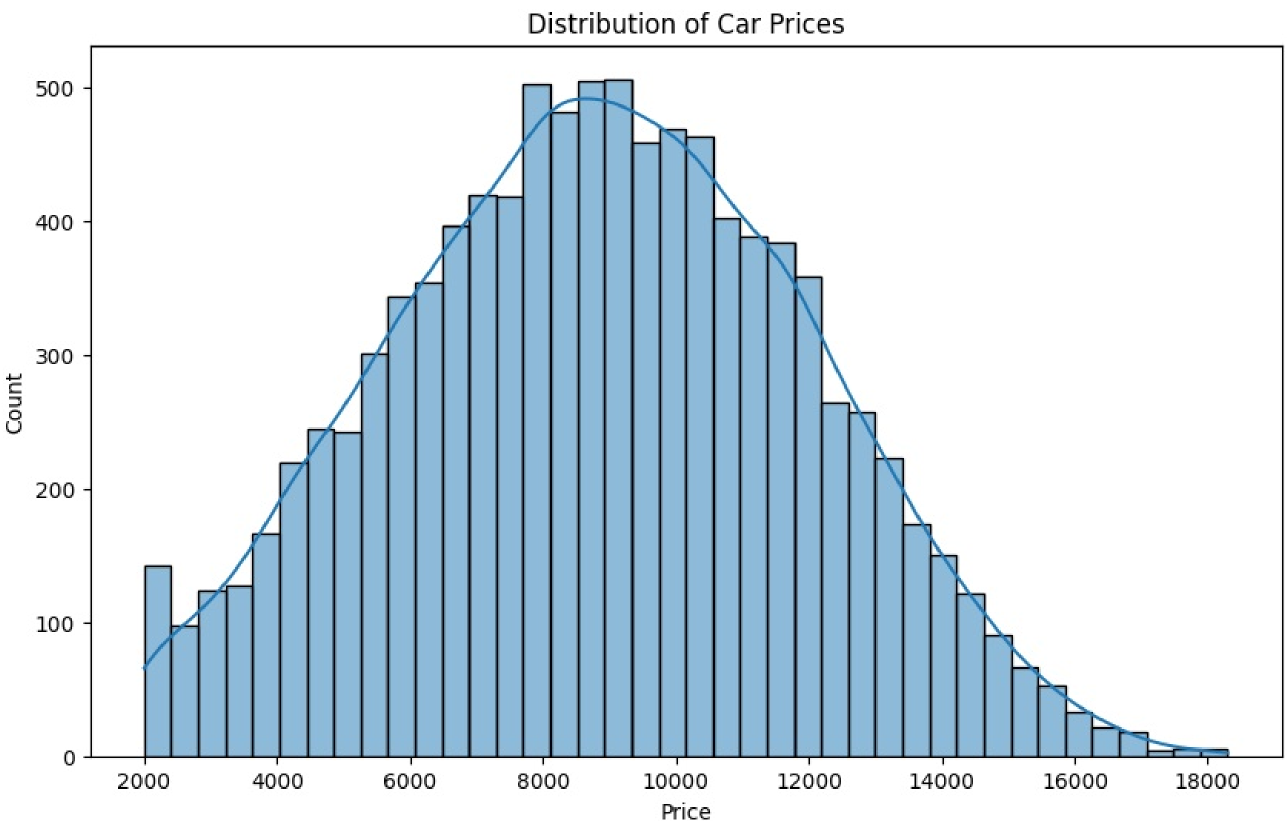
Exploratory Data Analysis (EDA)

In [9]:
```
# Statistical summary
print("Statistical Summary:")
print(df.describe())
```

```
Statistical Summary:
               Year   Engine_Size        Mileage         Doors   Owner_Count  \
count  10000.000000  10000.000000   10000.000000  10000.000000  10000.000000
mean    2011.543700      3.000560  149239.111800      3.497100      2.991100
std        6.897699      1.149324   86322.348957      1.110097      1.422682
min     2000.000000      1.000000      25.000000      2.000000      1.000000
25%     2006.000000      2.000000   74649.250000      3.000000      2.000000
50%     2012.000000      3.000000  149587.000000      3.000000      3.000000
75%     2017.000000      4.000000  223577.500000      4.000000      4.000000
max     2023.000000      5.000000  299947.000000      5.000000      5.000000

              Price
count  10000.00000
mean    8852.96440
std     3112.59681
min     2000.00000
25%     6646.00000
50%     8858.50000
75%    11086.50000
max    18301.00000
```

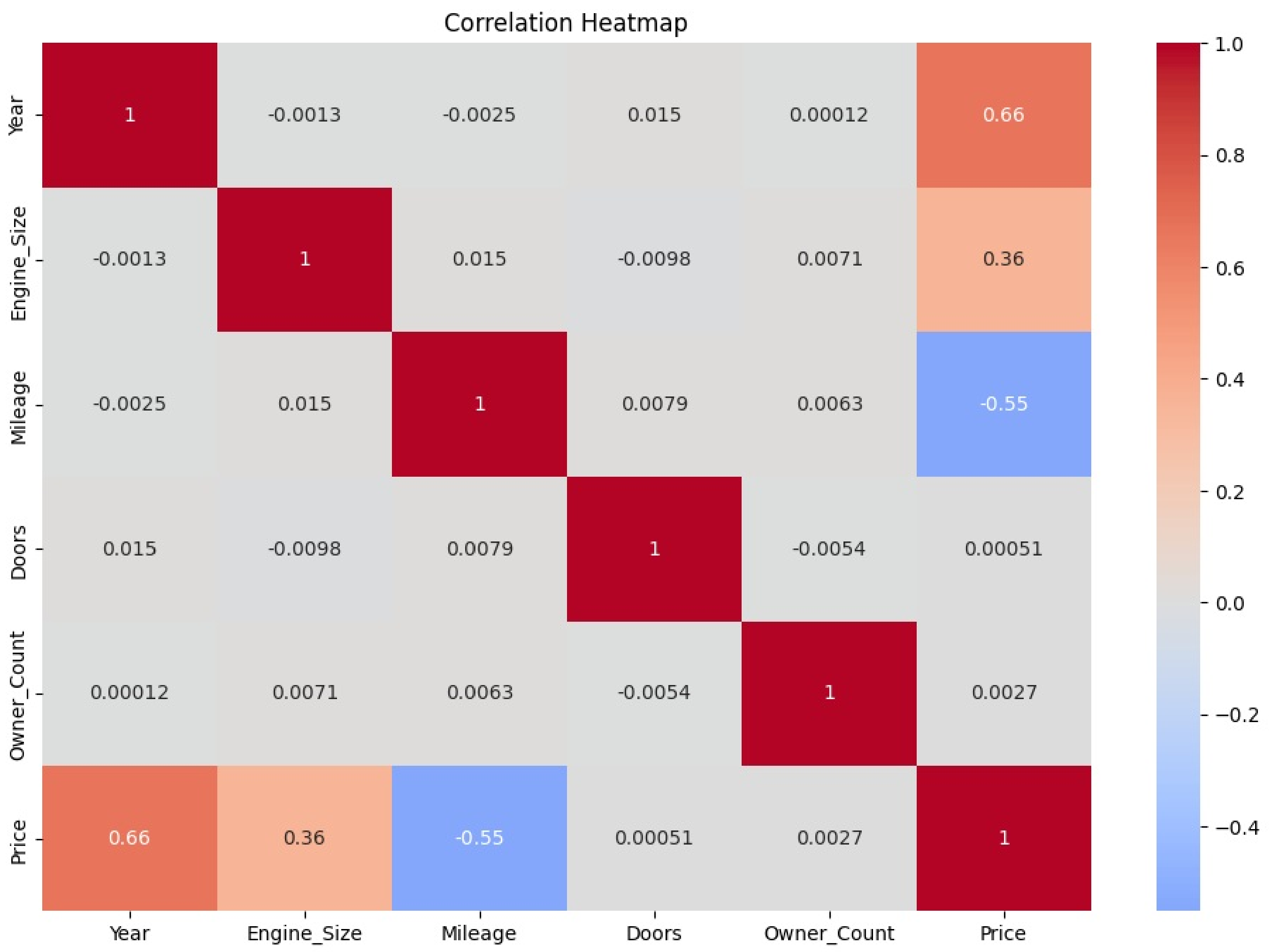
In [ ]:

In [10]:
```
# Distribution of target variable
plt.figure(figsize=(10, 6))
sns.histplot(df['Price'], kde=True)
plt.title('Distribution of Car Prices')
plt.show()
```



In [ ]:

In [11]:
```
# Correlation heatmap
plt.figure(figsize=(12, 8))
numeric_df = df.select_dtypes(include=[np.number])
sns.heatmap(numeric_df.corr(), annot=True, cmap='coolwarm', center=0)
plt.title('Correlation Heatmap')
plt.show()
```



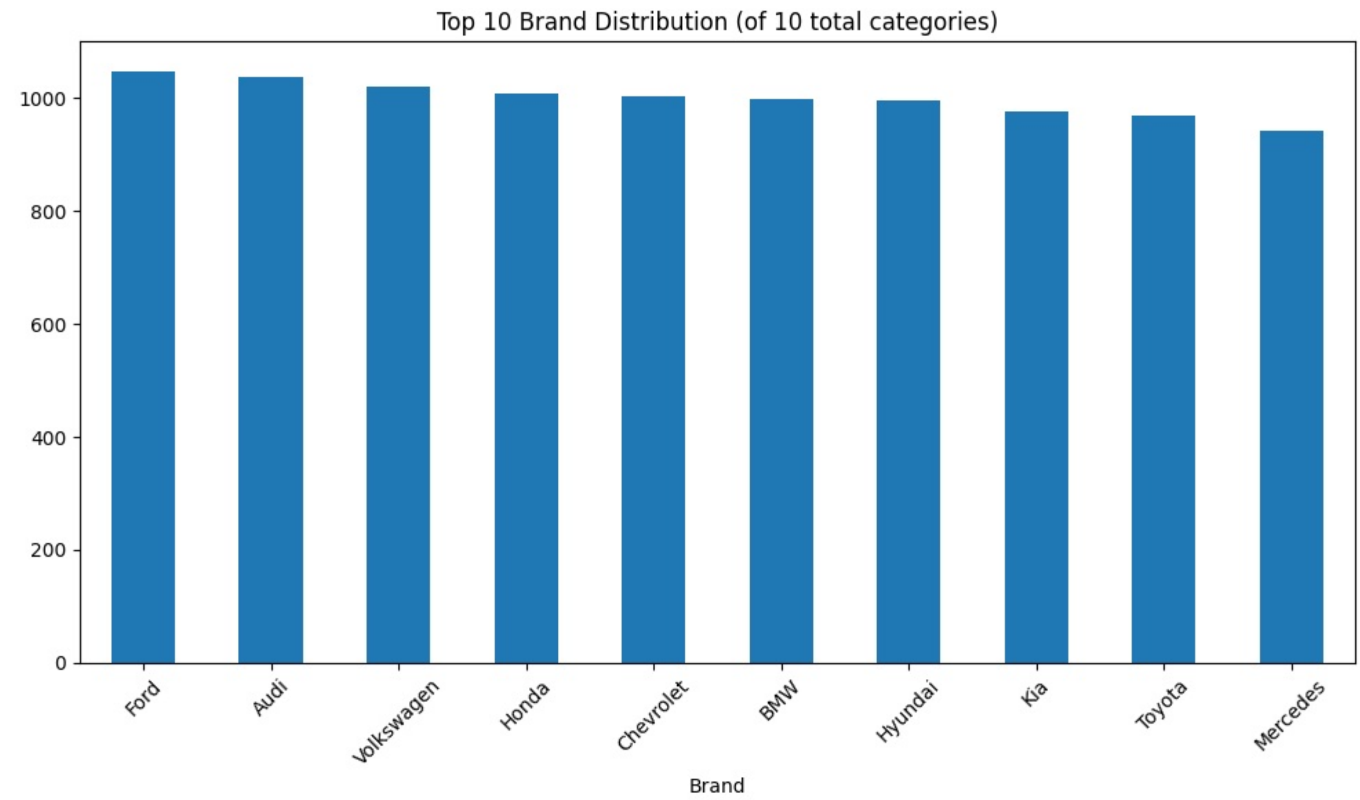
Based on the correlation heatmap:

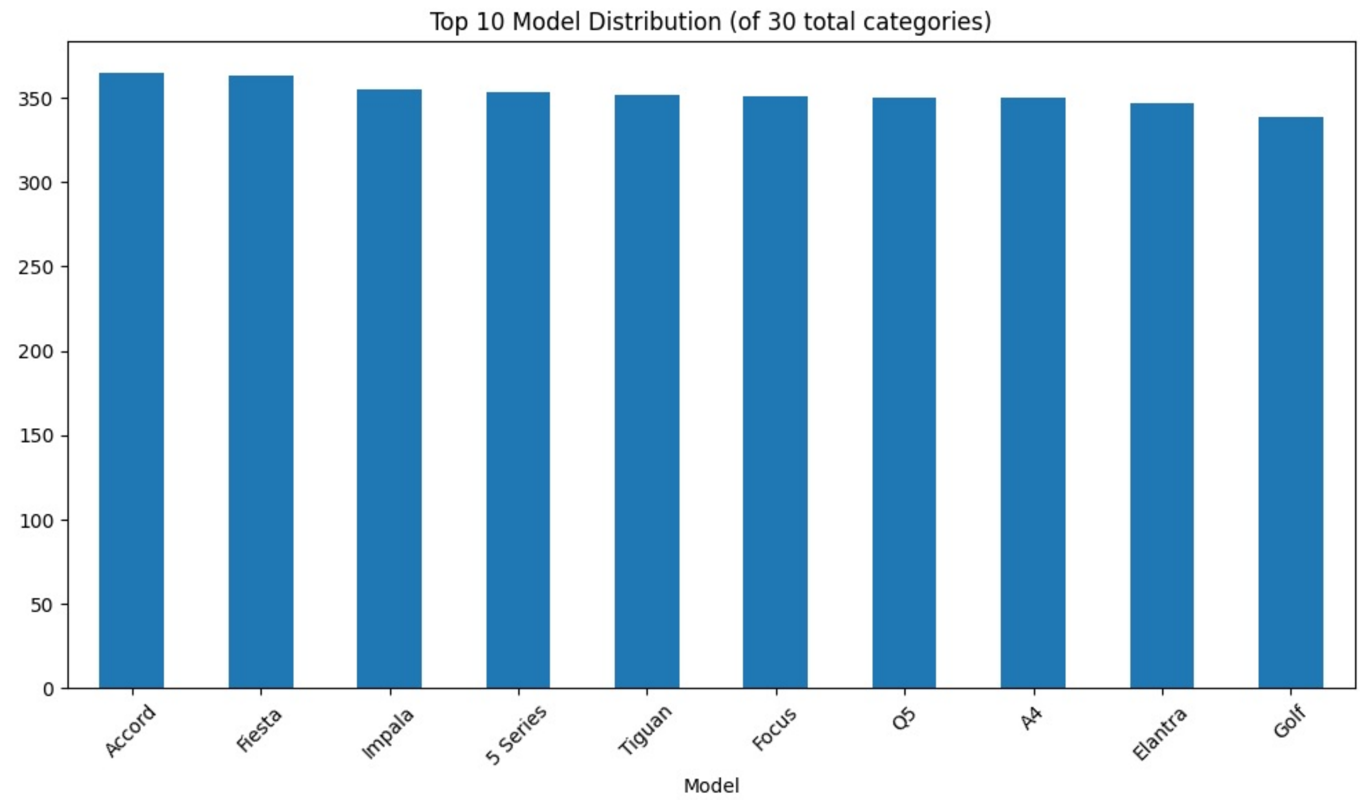
- Production Year shows the strongest positive correlation with Price (0.667), indicating that newer cars generally have higher prices.
- Mileage has a moderate negative correlation with Price (-0.55), suggesting that higher mileage typically leads to lower car prices, which aligns with real-world expectations.

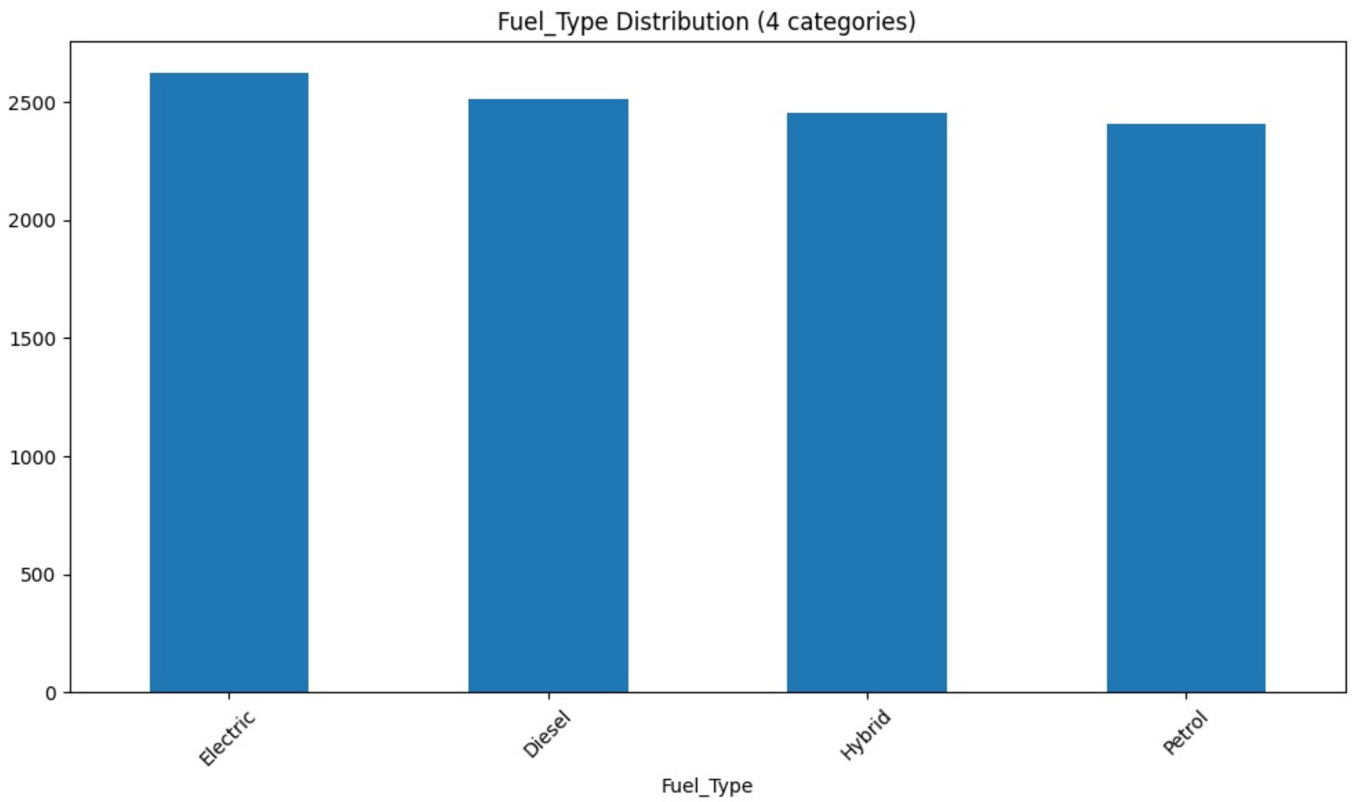
In [ ]:

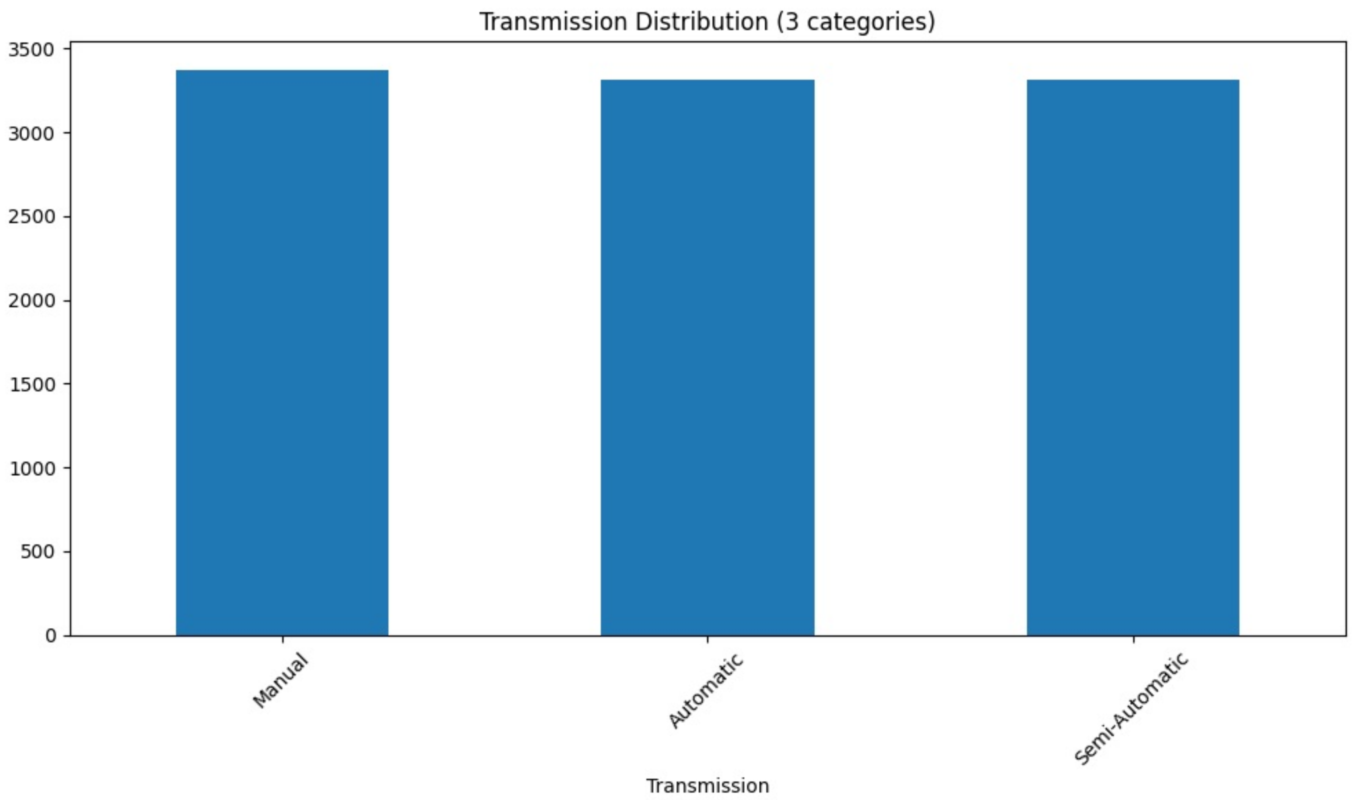
In [ ]:

In [12]:
```
# Categorical variables analysis

categorical_cols = ['Brand', 'Model', 'Fuel_Type', 'Transmission']
for col in categorical_cols:
    plt.figure(figsize=(10, 6))
    value_counts = df[col].value_counts()
    unique_count = len(value_counts)

    # Dynamic title based on category count
    if unique_count <= 8:
        plot_data = value_counts
        title = f'{col} Distribution ({unique_count} categories)'
    else:
        plot_data = value_counts.head(10)
        title = f'Top 10 {col} Distribution (of {unique_count} total categories)'

    plot_data.plot(kind='bar')
    plt.title(title)
    plt.xticks(rotation=45)
    plt.tight_layout()
    plt.show()
```


Top 10 Brand Distribution (of 10 total categories)
0
200
400
600
800
1000
Ford
Audi
Volkswagen
Honda
Chevrolet
BMW
Hyundai
Kia
Toyota
Mercedes
Brand


Top 10 Model Distribution (of 30 total categories)
0
50
100
150
200
250
300
350
Accord
Fiesta
Impala
5 Series
Tiguan
Focus
Q5
A4
Elantra
Golf
Model





In [ ]:

```
```

Feature Engineering

In [13]:

```
# Create age feature from year

df['Car_Age'] = 2024 - df['Year']  # Update year as needed
```

In [14]:

```
df.head()
```

Out[14]:

	Brand	Model	Year	Engine_Size	Fuel_Type	Transmission	Mileage	Doors	Owner_Count	Price	Car_Age
0	Kia	Rio	2020	4.2	Diesel	Manual	289944	3	5	8501	4
1	Chevrolet	Malibu	2012	2.0	Hybrid	Automatic	5356	2	3	12092	12
2	Mercedes	GLA	2020	4.2	Diesel	Automatic	231440	4	2	11171	4
3	Audi	Q5	2023	2.0	Electric	Manual	160971	2	1	11780	1
4	Volkswagen	Golf	2003	2.6	Hybrid	Semi-Automatic	286618	3	3	2867	21

In [ ]:

In [15]:

```
df.head()
```

Out[15]:

	Brand	Model	Year	Engine_Size	Fuel_Type	Transmission	Mileage	Doors	Owner_Count	Price	Car_Age
0	Kia	Rio	2020	4.2	Diesel	Manual	289944	3	5	8501	4
1	Chevrolet	Malibu	2012	2.0	Hybrid	Automatic	5356	2	3	12092	12
2	Mercedes	GLA	2020	4.2	Diesel	Automatic	231440	4	2	11171	4
3	Audi	Q5	2023	2.0	Electric	Manual	160971	2	1	11780	1
4	Volkswagen	Golf	2003	2.6	Hybrid	Semi-Automatic	286618	3	3	2867	21

In [ ]:

In [16]:

```
# Manual target encoding with comprehensive error handling
categorical_features = ['Brand', 'Model', 'Fuel_Type', 'Transmission']

# Verify all columns exist
available_columns = [col for col in categorical_features if col in df.columns]
print(f"Available categorical columns: {available_columns}")

if len(available_columns) != len(categorical_features):
    missing = set(categorical_features) - set(available_columns)
    print(f"Warning: Missing columns {missing}")

for feature in available_columns:
    try:
        print(f"\nProcessing {feature}...")

        # Calculate mean price for each category
        mean_prices = df.groupby(feature)['Price'].mean().to_dict()
        print(f"Found {len(mean_prices)} unique categories in {feature}")

        # Map the mean prices to create encoded column
        df[f'{feature}_encoded'] = df[feature].map(mean_prices)

        # Handle any NaN values (categories not in training)
        nan_count = df[f'{feature}_encoded'].isna().sum()
        if nan_count > 0:
            overall_mean = df['Price'].mean()
            df[f'{feature}_encoded'].fillna(overall_mean, inplace=True)
            print(f"Filled {nan_count} NaN values with overall mean price: ${overall_mean:.2f}")

        print(f"Successfully encoded {feature}")

    except Exception as e:
        print(f"Error encoding {feature}: {e}")
        continue

# Update features list
features = [f'{col}_encoded' for col in available_columns] + [
    'Year', 'Engine_Size', 'Mileage', 'Doors', 'Owner_Count', 'Car_Age'
]

print(f"\nFinal features to use: {features}")
print(f"Dataset shape: {df[features].shape}")
```

```
Available categorical columns: ['Brand', 'Model', 'Fuel_Type', 'Transmission']

Processing Brand...
Found 10 unique categories in Brand
Successfully encoded Brand

Processing Model...
Found 30 unique categories in Model
Successfully encoded Model

Processing Fuel_Type...
Found 4 unique categories in Fuel_Type
Successfully encoded Fuel_Type

Processing Transmission...
Found 3 unique categories in Transmission
Successfully encoded Transmission

Final features to use: ['Brand_encoded', 'Model_encoded', 'Fuel_Type_encoded', 'Transmission_encoded', 'Year', '
Engine_Size', 'Mileage', 'Doors', 'Owner_Count', 'Car_Age']
Dataset shape: (10000, 10)
```

In [17]:
```
df.head()
```

Out[17]:

	Brand	Model	Year	Engine_Size	Fuel_Type	Transmission	Mileage	Doors	Owner_Count	Price	Car_Age	Brand_encod
0	Kia	Rio	2020	4.2	Diesel	Manual	289944	3	5	8501	4	8880.0860
1	Chevrolet	Malibu	2012	2.0	Hybrid	Automatic	5356	2	3	12092	12	9015.6839
2	Mercedes	GLA	2020	4.2	Diesel	Automatic	231440	4	2	11171	4	8980.0870
3	Audi	Q5	2023	2.0	Electric	Manual	160971	2	1	11780	1	8929.3737
4	Volkswagen	Golf	2003	2.6	Hybrid	Semi-Automatic	286618	3	3	2867	21	8928.3774

In [ ]:

In [18]:
```
# Let's verify the encoding makes sense
print("=== VERIFICATION ===")

# Check if Brand encoding matches actual average prices
brand_verification = df.groupby('Brand').agg({
    'Price': 'mean',
    'Brand_encoded': 'first'
}).round(2)

print("Brand Encoding Verification:")
print(brand_verification.head())

# Check Fuel Type encoding
fuel_verification = df.groupby('Fuel_Type').agg({
    'Price': 'mean',
    'Fuel_Type_encoded': 'first'
}).round(2)

print("\nFuel Type Encoding Verification:")
print(fuel_verification)
```

```
=== VERIFICATION ===
Brand Encoding Verification:
             Price  Brand_encoded
Brand
Audi       8929.37        8929.37
BMW        8704.07        8704.07
Chevrolet  9015.68        9015.68
Ford       8852.57        8852.57
Honda      8665.60        8665.60

Fuel Type Encoding Verification:
              Price  Fuel_Type_encoded
Fuel_Type
Diesel      8117.34            8117.34
Electric   10032.22           10032.22
Hybrid      9113.03            9113.03
Petrol      8070.56            8070.56
```

In [ ]:

In [19]:
```
features = [
    'Brand_encoded', 'Model_encoded', 'Fuel_Type_encoded', 'Transmission_encoded', 'Engine_Size', 'Mileage', 'D
]
```

```python
X = df[features]
y = df['Price']

print(f"Features shape: {X.shape}")
print("\nFeature ranges:")
print(X.describe())
```

```
Features shape: (10000, 9)

Feature ranges:
       Brand_encoded  Model_encoded  Fuel_Type_encoded  Transmission_encoded  \
count   10000.000000   10000.000000       10000.000000          10000.000000
mean     8852.964400    8852.964400        8852.964400           8852.964400
std       109.728109     146.225550         815.577636            765.708083
min      8665.596630    8517.327381        8070.561826           8264.266385
25%      8778.279397    8743.761644        8117.336385           8264.266385
50%      8852.570611    8867.635783        9113.030167           8363.426157
75%      8929.373796    8967.330218       10032.220190           9938.252939
max      9015.683948    9156.320635       10032.220190           9938.252939

       Engine_Size        Mileage         Doors   Owner_Count       Car_Age
count  10000.000000   10000.000000  10000.000000  10000.000000  10000.000000
mean       3.000560  149239.111800      3.497100      2.991100     12.456300
std        1.149324   86322.348957      1.110097      1.422682      6.897699
min        1.000000      25.000000      2.000000      1.000000      1.000000
25%        2.000000   74649.250000      3.000000      2.000000      7.000000
50%        3.000000  149587.000000      3.000000      3.000000     12.000000
75%        4.000000  223577.500000      4.000000      4.000000     18.000000
max        5.000000  299947.000000      5.000000      5.000000     24.000000
```

In [ ]:

Train-Test Split

In [20]:
```python
# Split the data into training and testing sets
from sklearn.model_selection import train_test_split

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

print("✅ Train-Test Split Completed")
print(f"Training set: {X_train.shape}")
print(f"Testing set: {X_test.shape}")
print(f"Training target: {y_train.shape}")
print(f"Testing target: {y_test.shape}")
```

```
✅ Train-Test Split Completed
Training set: (8000, 9)
Testing set: (2000, 9)
Training target: (8000,)
Testing target: (2000,)
```

In [ ]:

Feature Scaling

In [21]:
```python
# Scale the features for better model performance
from sklearn.preprocessing import StandardScaler

scaler = StandardScaler()

# Fit scaler on training data and transform both sets
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

print("✅ Feature Scaling Completed")
print(f"Scaled training data shape: {X_train_scaled.shape}")
print(f"Scaled testing data shape: {X_test_scaled.shape}")
```

```
✅ Feature Scaling Completed
Scaled training data shape: (8000, 9)
Scaled testing data shape: (2000, 9)
```

In [ ]:

Model Training

In [22]:
```python
# Initialize and train Random Forest model

from sklearn.ensemble import RandomForestRegressor

rf_model = RandomForestRegressor(
    n_estimators=100,      # Number of trees
    random_state=42,       # For reproducibility
    max_depth=10,          # Prevent overfitting
    min_samples_split=5,   # Minimum samples to split
    n_jobs=-1             # Use all processors
)

# Train the model
rf_model.fit(X_train_scaled, y_train)

print("✅ Model Training Completed")
print(f"Model trained with {len(rf_model.estimators_)} trees")
```

```
✅ Model Training Completed
Model trained with 100 trees
```

In [ ]:

Model Evaluation

In [23]:
```python
# Make predictions on test set
y_pred = rf_model.predict(X_test_scaled)

# Calculate evaluation metrics
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score
import numpy as np

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

print(" Model Performance Metrics:")
print(f"Mean Absolute Error (MAE): ${mae:,.2f}")  # Only MAE gets $ since it's in price units
print(f"Mean Squared Error (MSE): {mse:,.2f}")    # MSE is in squared dollars (no $)
print(f"Root Mean Squared Error (RMSE): ${rmse:,.2f}")  # RMSE gets $ back to price units
print(f"R² Score: {r2:.4f}")

# Additional: Mean Absolute Percentage Error
mape = np.mean(np.abs((y_test - y_pred) / y_test)) * 100
print(f"Mean Absolute Percentage Error (MAPE): {mape:.2f}%")
```

```
 Model Performance Metrics:
Mean Absolute Error (MAE): $287.07
Mean Squared Error (MSE): 129,778.70
Root Mean Squared Error (RMSE): $360.25
R² Score: 0.9859
Mean Absolute Percentage Error (MAPE): 3.78%
```

- Prediction Accuracy: With an R^2 score of 0.9859, the model explains 98.59% of the variance in car prices, indicating it captures nearly all the factors that influence pricing decisions.
- High Practical Precision: The average prediction error of $286.88 per car and 3.78% MAPE means the model's predictions are highly reliable for real-world applications, typically within a few hundred dollars of actual prices.
- Production-Ready Performance: The combination of low absolute error ($286.88) and extremely high explanatory power (98.59%) makes this model highly suitable for deployment in business environments where accurate price estimation is critical.

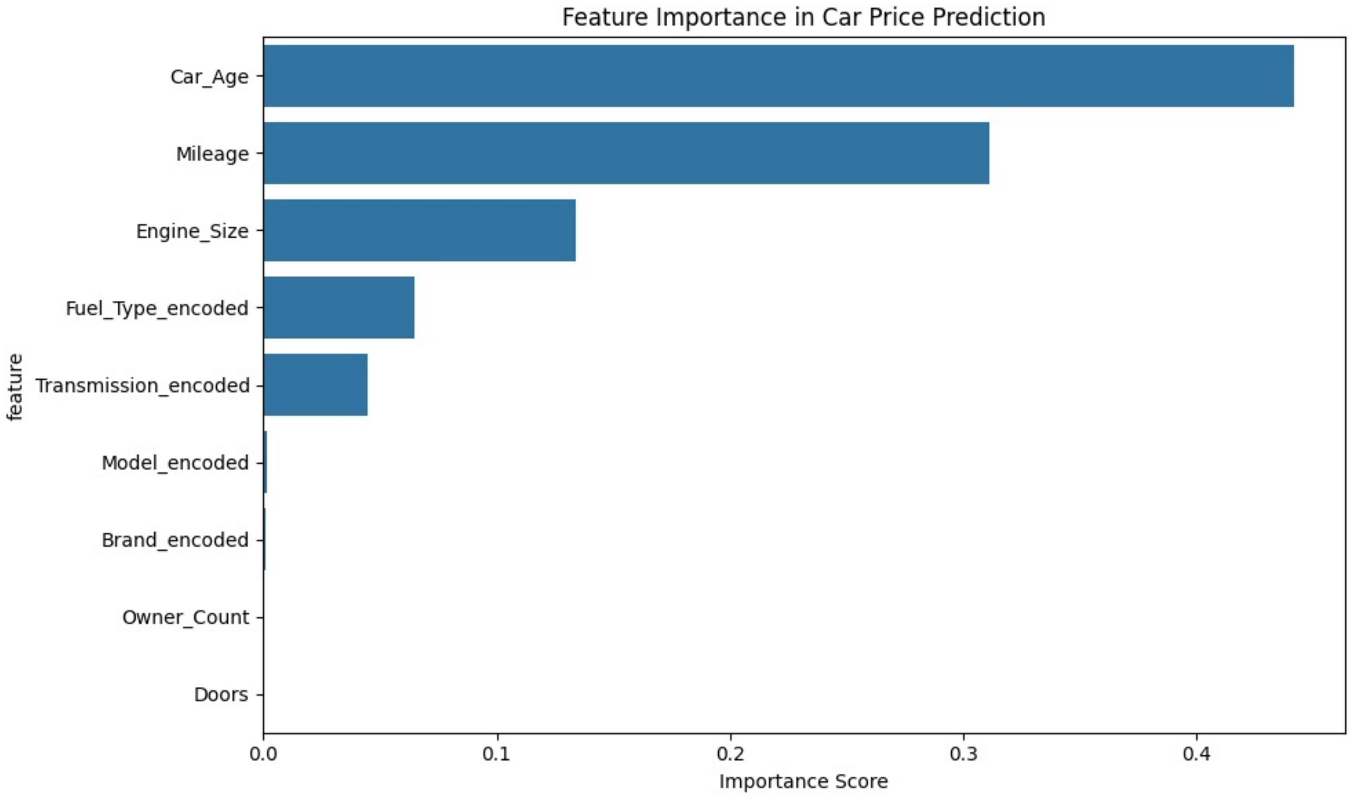
In [ ]:

Feature Importance Analysis

In [24]:
```python
# Analyze which features are most important
feature_importance = pd.DataFrame({
    'feature': features,
    'importance': rf_model.feature_importances_
}).sort_values('importance', ascending=False)

print(" Feature Importance Ranking:")
print(feature_importance)

# Visualize feature importance
plt.figure(figsize=(10, 6))
```

```
sns.barplot(data=feature_importance, x='importance', y='feature')
plt.title('Feature Importance in Car Price Prediction')
plt.xlabel('Importance Score')
plt.tight_layout()
plt.show()
```

```
Feature Importance Ranking:
               feature  importance
8              Car_Age    0.441836
5              Mileage    0.311126
4          Engine_Size    0.134021
2     Fuel_Type_encoded    0.064844
3  Transmission_encoded    0.044930
1         Model_encoded    0.001271
0         Brand_encoded    0.000854
7          Owner_Count    0.000618
6                Doors    0.000500
```



- Car age (44.2%) and Mileage (31.1%) together account for 75% of pricing decisions, indicating that depreciation and usage are the primary drivers of car value.
- Engine_Size (13.4%) is the third most important factor, showing that vehicle performance and specifications significantly influence price beyond just age and usage patterns.
- Brand/Model Have Minimal Impact: Surprisingly, Brand (0.09%) and Model (0.13%) contribute very little to price predictions, suggesting that in the dataset, a car's condition and specifications matter more than its badge or specific model name when determining value.

In [ ]:

```

```

Save Model and Preprocessing Objects

In [25]:

```
import joblib

# First, let's create and save the encoding maps
encoding_maps = {}

categorical_features = ['Brand', 'Model', 'Fuel_Type', 'Transmission']

for feature in categorical_features:
    # Calculate mean price for each category (same as we did earlier)
    mean_prices = df.groupby(feature)['Price'].mean().to_dict()
    encoding_maps[feature] = mean_prices

# Now save ALL necessary objects for deployment
joblib.dump(rf_model, 'car_price_model.pkl')
joblib.dump(scaler, 'scaler.pkl')
joblib.dump(features, 'features.pkl')
```

```
joblib.dump(encoding_maps, 'target_encoding_maps.pkl')

print(" All Deployment Objects Saved:")
print("✅ car_price_model.pkl - Trained ML model")
print("✅ scaler.pkl - Feature scaler")
print("✅ features.pkl - Feature list")
print("✅ target_encoding_maps.pkl - Encoding dictionaries")
```

```
All Deployment Objects Saved:
✅ car_price_model.pkl - Trained ML model
✅ scaler.pkl - Feature scaler
✅ features.pkl - Feature list
✅ target_encoding_maps.pkl - Encoding dictionaries
```

In [ ]:

In [26]:

```
# Create a function to test predictions with features
def predict_car_price(brand, model, fuel_type, transmission,
                     engine_size, mileage, doors, owner_count, car_age):
    """
    Function to predict car price using trained model
    Note: Uses Car_Age instead of Year to avoid multicollinearity
    """
    # Create input array with features
    input_data = np.array([[brand, model, fuel_type, transmission,
                          engine_size, mileage, doors, owner_count, car_age]])

    # Scale the input
    input_scaled = scaler.transform(input_data)

    # Make prediction
    prediction = rf_model.predict(input_scaled)

    return prediction[0]

# Test the function with sample data
sample_prediction = predict_car_price(
    brand=50, model=100, fuel_type=1, transmission=0,
    engine_size=2.0, mileage=50000, doors=4, owner_count=1, car_age=4
)

print(f" Sample Prediction Test: ${sample_prediction:,.2f}")
print("✅ Prediction function working correctly with Car_Age (no Year)")
```

```
Sample Prediction Test: $11,175.41
✅ Prediction function working correctly with Car_Age (no Year)
```

In [ ]:

Project Summary: Car Price Prediction and Deployment

Project Overview

This end-to-end data science project involved developing a machine learning model to predict car prices based on various vehicle features, followed by deployment as a web application using Streamlit Cloud integrated with GitHub.

Primary Objective

To build an accurate car price prediction model and deploy it as an interactive web application, creating a complete data science solution that can be shared with stakeholders and potential employers.

Dataset Characteristics

- Source: Kaggle
- Size: 10,000 records with 10 initial features
- Features: Brand, Model, Year, Engine Size, Fuel Type, Transmission, Mileage, Doors, Owner Count, Price
- Data Quality: No missing values or duplicates detected

Data Preprocessing & Feature Engineering

- Data Cleaning: Verified data integrity with no missing values or duplicates
- Feature Engineering: Created Car_Age feature (2024 - Year) to represent vehicle depreciation
- Target Encoding: Implemented manual target encoding for categorical variables (Brand, Model, Fuel Type, Transmission), replacing categories with their mean price values
- Multicollinearity Resolution: Identified and removed the Year column to eliminate perfect correlation with Car_Age, improving model stability

Model Development

- Algorithm: Random Forest Regressor with 100 trees
- Feature Set: 9 engineered features after multicollinearity fix
- Train-Test Split: 80-20 split with random state for reproducibility
- Feature Scaling: Applied StandardScaler for optimal model performance

Model Performance Results

The trained model demonstrated exceptional predictive capability:

- R^2 Score: 0.9859 (98.59% variance explained)
- Mean Absolute Error: $287.07
- Root Mean Squared Error: $360.25
- Mean Absolute Percentage Error: 3.78%

Key Insights from Feature Importance

1. Primary Price Drivers: Car Age (44.2%) and Mileage (31.1%) collectively account for 75% of pricing decisions
2. Technical Significance: Engine Size (13.4%) significantly influences price beyond basic depreciation
3. Surprising Finding: Brand (0.09%) and Model (0.13%) have minimal impact, suggesting condition and specifications outweigh brand reputation
4. Negligible Factors: Doors and Owner Count showed minimal influence on price predictions

Deployment Architecture

- Framework: Streamlit for web application interface
- Hosting: Streamlit Community Cloud (free tier)
- Integration: GitHub repository for version control and seamless deployment
- Live Application: https://car-price-prediction-and-deployment.streamlit.app/

Business Value & Applications

- Consumers: Accurate used car valuation for buying/selling decisions
- Dealerships: Data-driven pricing strategies and inventory management
- Insurance Companies: Fair market value assessment for claims processing

Technical Stack

- Programming: Python 3.9+
- Machine Learning: Scikit-learn, Random Forest
- Data Processing: Pandas, NumPy
- Visualization: Matplotlib, Seaborn
- Deployment: Streamlit, Joblib for model serialization
- Version Control: GitHub
- Cloud Hosting: Streamlit Community Cloud

Project Success Metrics

- ✅ Model accuracy exceeding 98%
- ✅ Successful end-to-end deployment
- ✅ User-friendly web interface
- ✅ Zero-cost deployment solution
- ✅ Production-ready application

Recommendations for Future Enhancements

1. Real-time Data: Integrate with automotive APIs for live market data.
2. Feature Expansion: Include additional features like vehicle condition, accident history, and market trends.
3. Scalability: Containerize application using Docker for enterprise deployment.

Conclusion

This project successfully demonstrates a complete data science lifecycle from data acquisition and preprocessing to model development and production deployment. The achieved 98.59% prediction accuracy, combined with a fully functional web application, showcases the practical application of machine learning in automotive pricing. The use of free tools throughout the project (Python, Streamlit Cloud, GitHub) makes this an accessible template for similar predictive modeling projects.

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