CarDekho Price Prediction

About Car Dehko

CarDekho is a prominent Indian automotive technology company headquartered in Jaipur, Rajasthan. Founded in 2008 by brothers Amit Jain and Anurag Jain, the platform assists users in buying and sellingcars by providing comprehensive automotive content, including expert reviews, detailed specifications,pricing comparisons, and multimedia content for various car brands andmodels available in India.

Dataset Overview

The dataset contains the following columns:

car_name: Name of the car

brand: Car brand

model: Car model

vehicle_age: Age of the vehicle in years

km_driven: Total kilometers driven

seller_type: Type of seller (Individual or Dealer)

fuel_type: Type of fuel (Petrol, Diesel, etc.)

transmission_type: Manual or Automatic

mileage: Mileage of the car

engine: Engine capacity (in cc)

max_power: Maximum power output

seats: Number of seats

selling_price: Price at which the car was sold

Problem Statement:

The used car market in India is a dynamic and ever-changing landscape. Prices can fluctuate wildly based on a variety of factors including the make and model of the car,its mileage, its condition and the current market conditions. As a result, it can be difficult for sellers to accurately price their cars.

Approach:

We propose to develop a machine learning model that can predict the price of a used car based on its features. The model will be trained on a dataset of used cars that have been sold on

Cardekho.com in India.The model will then be able to be used to predict the price of any used car, given its features.

Objective

To build suitable Machine Learning Model for Used Car Price Prediction.

Benefits:

The benefits of this solution include:

Sellers will be able to more accurately price their cars which will help them to sell their cars faster and for a higher price.

Buyers will be able to find cars that are priced more competitively.

The overall used car market in India will become more efficient.

```
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 LabelEncoder, StandardScaler
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import mean_absolute_error, mean_squared_error,
r2_score

# Load dataset
df = pd.read_csv("Cardekho.csv")
df
```

```
              car_name     brand     model  vehicle_age  km_driven  \
0          Maruti Alto    Maruti      Alto            9     120000
1        Hyundai Grand   Hyundai     Grand            5      20000
2          Hyundai i20   Hyundai       i20           11      60000
3          Maruti Alto    Maruti      Alto            9      37000
4        Ford Ecosport      Ford  Ecosport            6      30000
...                ...       ...       ...          ...        ...
15406      Hyundai i10   Hyundai       i10            9      10723
15407    Maruti Ertiga    Maruti    Ertiga            2      18000
15408      Skoda Rapid     Skoda     Rapid            6      67000
15409  Mahindra XUV500  Mahindra    XUV500            5    3800000
15410       Honda City     Honda      City            2      13000

      seller_type fuel_type transmission_type  mileage  engine
max_power  \
0      Individual    Petrol            Manual    19.70     796
46.30
1      Individual    Petrol            Manual    18.90    1197
82.00
2      Individual    Petrol            Manual    17.00    1197
```

```
80.00
3      Individual    Petrol            Manual    20.92     998
67.10
4          Dealer    Diesel            Manual    22.77    1498
98.59
...           ...       ...               ...      ...     ...
...
15406      Dealer    Petrol            Manual    19.81    1086
68.05
15407      Dealer    Petrol            Manual    17.50    1373
91.10
15408      Dealer    Diesel            Manual    21.14    1498
103.52
15409      Dealer    Diesel            Manual    16.00    2179
140.00
15410      Dealer    Petrol         Automatic    18.00    1497
117.60

       seats  selling_price
0          5         120000
1          5         550000
2          5         215000
3          5         226000
4          5         570000
...      ...            ...
15406      5         250000
15407      7         925000
15408      5         425000
15409      7        1225000
15410      5        1200000

[15411 rows x 13 columns]
```

```
# Display basic info
print(df.info())
print(df.head())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 15411 entries, 0 to 15410
Data columns (total 13 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   car_name           15411 non-null  object
 1   brand              15411 non-null  object
 2   model              15411 non-null  object
 3   vehicle_age        15411 non-null  int64
 4   km_driven          15411 non-null  int64
 5   seller_type        15411 non-null  object
 6   fuel_type          15411 non-null  object
 7   transmission_type  15411 non-null  object
```

```
 8   mileage            15411 non-null  float64
 9   engine             15411 non-null  int64
 10  max_power          15411 non-null  float64
 11  seats              15411 non-null  int64
 12  selling_price      15411 non-null  int64
dtypes: float64(2), int64(5), object(6)
memory usage: 1.5+ MB
None
        car_name    brand     model  vehicle_age  km_driven
seller_type  \
0    Maruti Alto   Maruti      Alto            9     120000
Individual
1  Hyundai Grand  Hyundai     Grand            5      20000
Individual
2    Hyundai i20  Hyundai       i20           11      60000
Individual
3    Maruti Alto   Maruti      Alto            9      37000
Individual
4  Ford Ecosport     Ford  Ecosport            6      30000
Dealer

  fuel_type transmission_type  mileage  engine  max_power  seats  \
0    Petrol            Manual    19.70     796      46.30      5
1    Petrol            Manual    18.90    1197      82.00      5
2    Petrol            Manual    17.00    1197      80.00      5
3    Petrol            Manual    20.92     998      67.10      5
4    Diesel            Manual    22.77    1498      98.59      5

   selling_price
0         120000
1         550000
2         215000
3         226000
4         570000

# Handling missing values
df.dropna(inplace=True)

# Encoding categorical variables
label_encoders = {}
categorical_cols = df.select_dtypes(include=['object']).columns
for col in categorical_cols:
    le = LabelEncoder()
    df[col] = le.fit_transform(df[col])
    label_encoders[col] = le

# Splitting data
X = df.drop(columns=['selling_price'])  # Assuming 'Price' is the
target column
y = df['selling_price']
```

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

# Scaling features
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)

# Model training
model = RandomForestRegressor(n_estimators=100, random_state=42)
model.fit(X_train, y_train)
```

```
RandomForestRegressor(random_state=42)
```

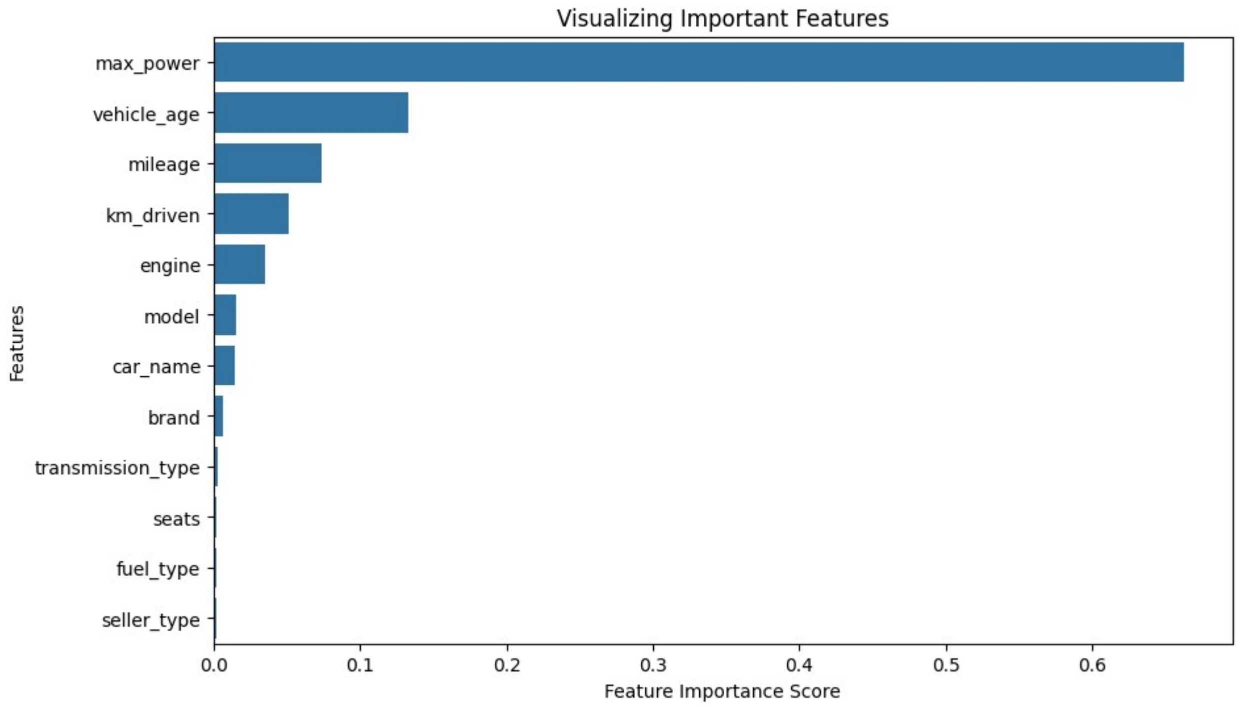
```python
# Predictions
y_pred = model.predict(X_test)

# Evaluation
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(f'MAE: {mae}')
print(f'MSE: {mse}')
print(f'RMSE: {rmse}')
print(f'R² Score: {r2}')
```

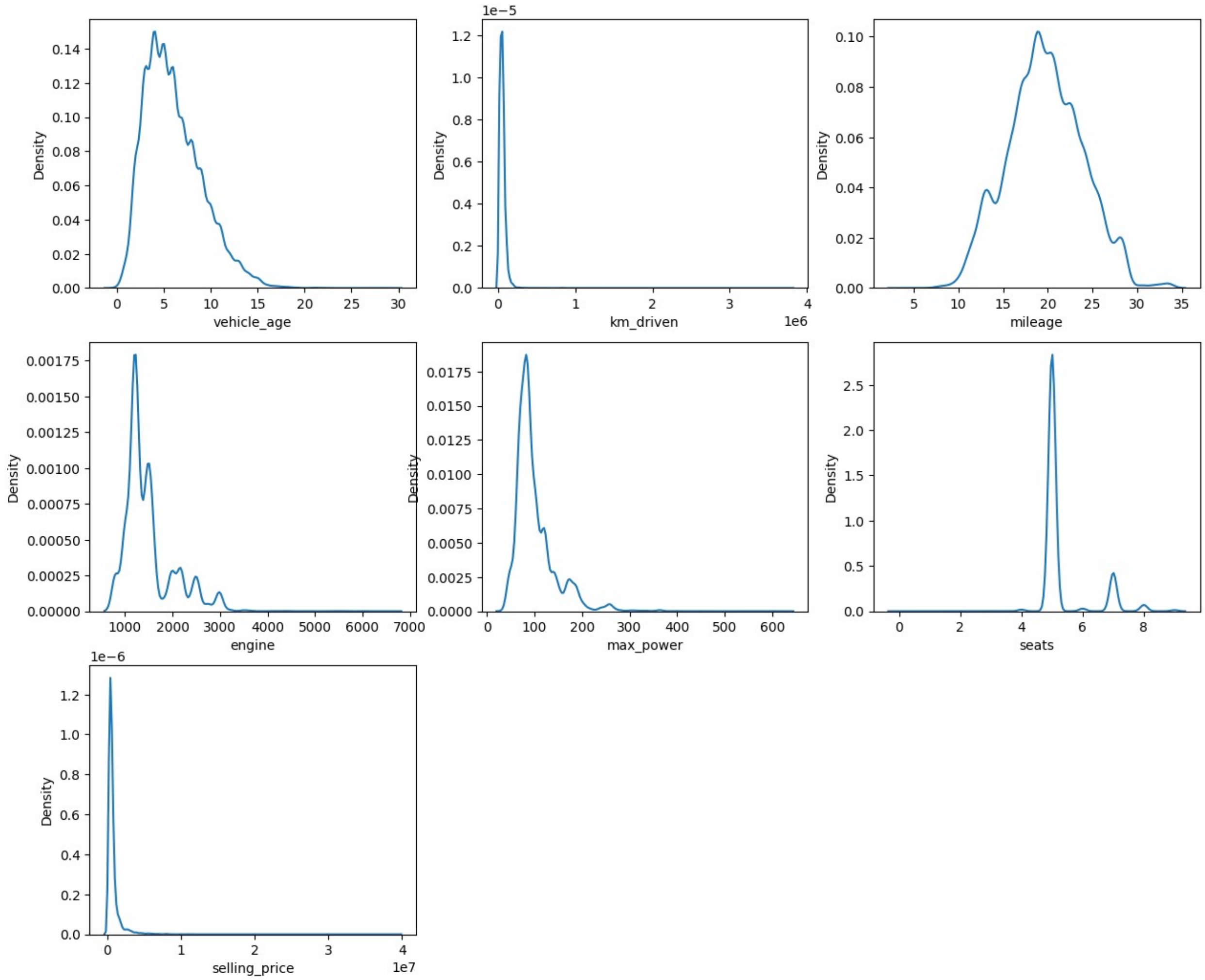
```
MAE: 99264.66682291472
MSE: 44451792219.313156
RMSE: 210835.9367359207
R² Score: 0.9409499634804136
```

```python
# Feature Importance
feature_importance = pd.Series(model.feature_importances_,
index=X.columns).sort_values(ascending=False)
plt.figure(figsize=(10, 6))
sns.barplot(x=feature_importance, y=feature_importance.index)
plt.xlabel('Feature Importance Score')
plt.ylabel('Features')
plt.title('Visualizing Important Features')
plt.show()
```




```
# Plot the density graphs of each of the numerical columns
num_columns = ['vehicle_age', 'km_driven', 'mileage', 'engine',
'max_power', 'seats','selling_price']
plt.figure(figsize=(15, 30))
for i in range(len(num_columns)):
    plt.subplot(7, 3, i+1)
    sns.kdeplot(data = df[num_columns[i]])

plt.show()
```



Overall Insights

Right-Skewed Variables:

Variables like km_driven, selling_price, and max_power show strong right skewness, indicating a dominance of lower or typical values with a few outliers at the higher end. These variables may require transformation (e.g., log or square root) if used for modeling.

Concentrated Distributions:

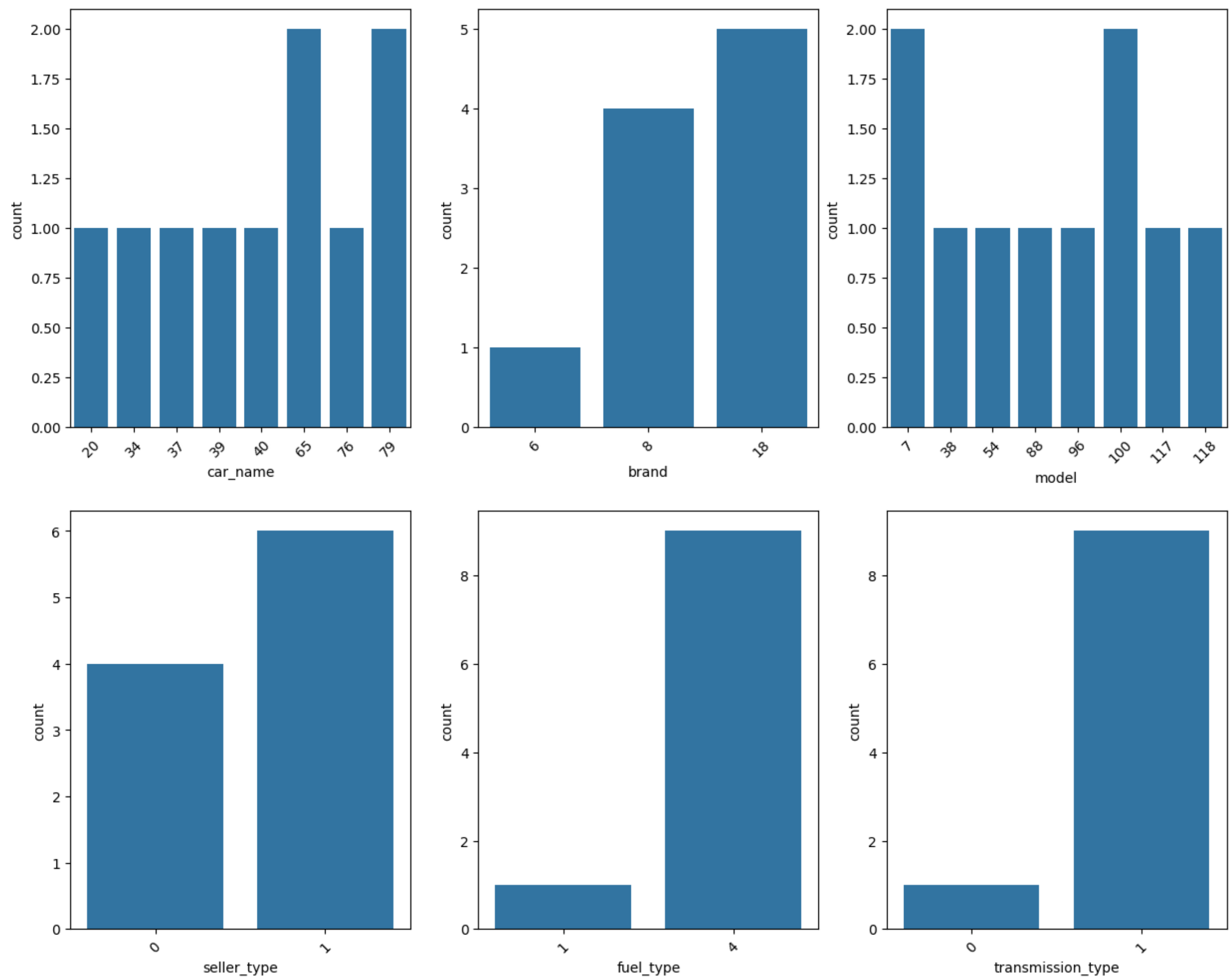
Seats and vehicle_age are highly concentrated around typical values (e.g., 5 seats, 0-10 years). This suggests standard consumer preferences for newer vehicles and compact/mid-sized cars.

Distinct Vehicle Segments:

The multimodal nature of engine and the broad range of max_power suggest that the dataset includes a mix of vehicle classes (e.g., compact, SUV, performance).

```python
# Plot the countplots of each of the categorical columns
cat_columns = ['car_name', 'brand', 'model', 'seller_type',
'fuel_type', 'transmission_type']
plt.figure(figsize=(15, 12))
for i in range(len(cat_columns)):
    plt.subplot(2, 3, i+1)
    plt.xticks(rotation = 45)
    sns.countplot(x = df[cat_columns[i]].head(10))

plt.show()
```



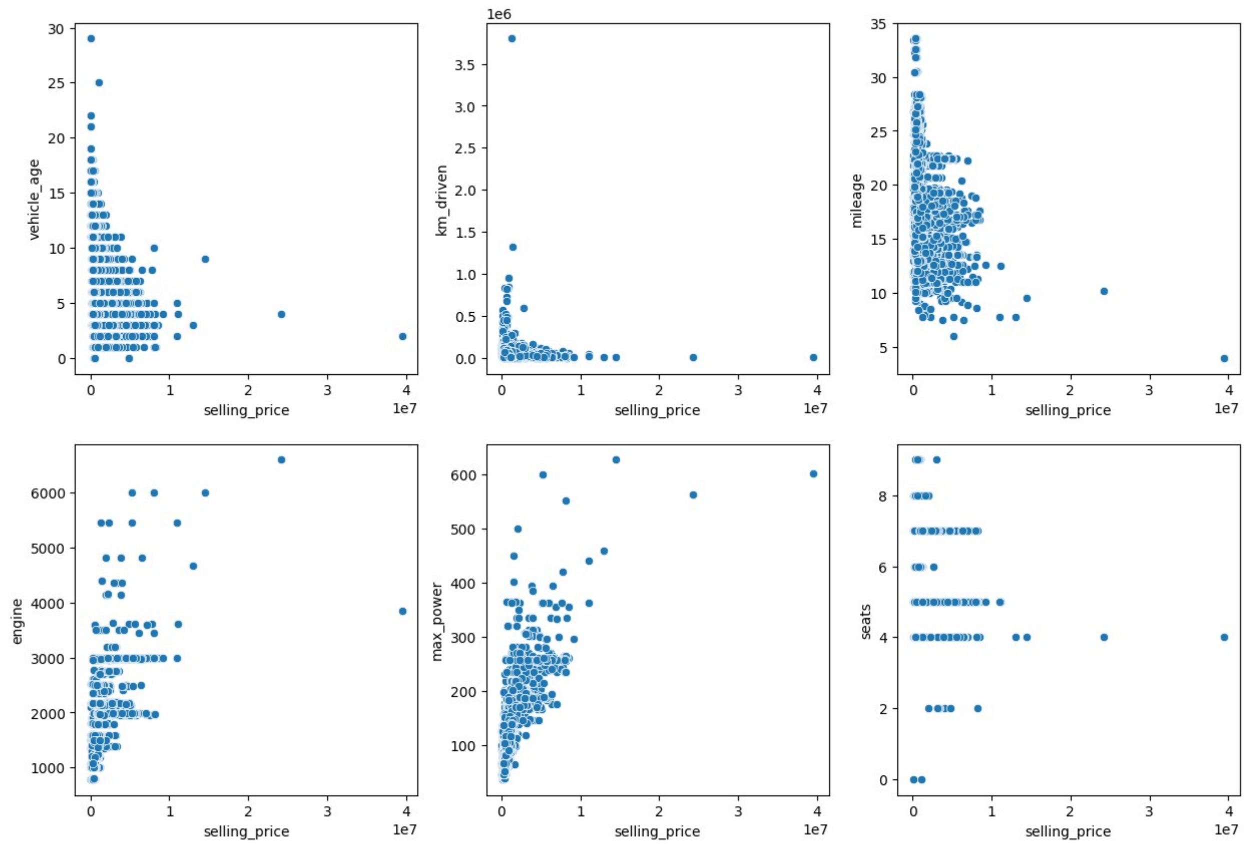
Insights

The dataset skews toward manual transmission and petrol-fueled cars sold by individuals. Maruti is the dominant brand, with the Maruti Alto and Hyundai Grand leading among models. Diesel cars and automatic transmissions are underrepresented, potentially indicating limited availability or demand in the dataset.

```
# Plot the relationship of each variable with the selling price
(Target variable)
numerical_columns = ['vehicle_age', 'km_driven', 'mileage', 'engine',
'max_power', 'seats']

plt.figure(figsize=(15, 10))
for i in range(len(numerical_columns)):
    plt.subplot(2, 3, i+1)
    sns.scatterplot(data = df, x = 'selling_price', y =
numerical_columns[i])

plt.show()
```



Interpretation of the Scatterplots

1. Vehicle Age vs Selling Price Observation:Older vehicles tend to have lower selling prices, indicating an inverse relationship.

Outliers: Some older vehicles show unusually high selling prices.

2. Kilometers Driven vs Selling Price Observation: Cars with fewer kilometers driven are priced higher, while cars with high mileage are clustered at lower prices.

Clusters: There’s a noticeable cluster at low prices and low mileage.

3.*** Mileage vs Selling Price Observation:*** No strong correlation is visible. However, cars with lower mileage seem to cluster around average selling prices.

4. Engine vs Selling Price Observation: A positive relationship is visible: cars with larger engine capacities tend to have higher prices.

5. Max Power vs Selling Price Observation: A positive trend is visible: higher power correlates with higher selling prices.

Outliers: Some extreme outliers are present with very high power values.

6. Seats vs Selling Price Observation: No clear relationship is visible. Most cars have 4 or 5 seats, but prices don’t vary significantly based on seating capacity.