Project Overview

The used car market in India is one of the fastest-growing automotive segments, with millions of vehicles being bought and sold each year. However, determining the right price for a used car remains a significant challenge. Car prices vary widely depending on several factors such as brand, model, age, mileage, fuel type, transmission, ownership history, and overall market demand.

This project aims to develop a machine learning model that predicts the price of a used car based on its features. The dataset, sourced from Cardekho.com, contains detailed information about cars sold in India. By leveraging data-driven techniques, the model will provide sellers with accurate price estimates and help buyers identify competitively priced vehicles.

Objectives

Perform data cleaning, exploration, and visualization to understand key factors affecting car prices.

Apply feature engineering to prepare the dataset for modeling.

Train and evaluate multiple machine learning algorithms to predict used car prices.

Select the best-performing model based on accuracy and generalizability.

Benefits

Sellers: Price their vehicles more accurately, reducing negotiation time and increasing chances of selling at a fair value.

Buyers: Identify cars that are competitively priced, leading to better purchasing decisions.

Market Efficiency: Enhance transparency and trust in the Indian used car market by reducing pricing uncertainty.

In [1]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt

from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import r2_score
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import classification_report
from sklearn.metrics import confusion_matrix
```

In [2]:
```
df = pd.read_csv("Cardekho.csv")
df
```

Out[2]:

	Unnamed: 0	car_name	brand	model	vehicle_age	km_driven	seller_type	f
0	0	Maruti Alto	Maruti	Alto	9	120000	Individual	
1	1	Hyundai Grand	Hyundai	Grand	5	20000	Individual	
2	2	Hyundai i20	Hyundai	i20	11	60000	Individual	
3	3	Maruti Alto	Maruti	Alto	9	37000	Individual	
4	4	Ford Ecosport	Ford	Ecosport	6	30000	Dealer	
...	...	...	...	...	...	...	...	
15406	19537	Hyundai i10	Hyundai	i10	9	10723	Dealer	
15407	19540	Maruti Ertiga	Maruti	Ertiga	2	18000	Dealer	
15408	19541	Skoda Rapid	Skoda	Rapid	6	67000	Dealer	
15409	19542	Mahindra XUV500	Mahindra	XUV500	5	3800000	Dealer	
15410	19543	Honda City	Honda	City	2	13000	Dealer	

15411 rows × 14 columns

EDA

Checking for null values and handling duplicates

In [3]:
```
df.isnull().sum()
```

Out[3]:
```
Unnamed: 0           0
car_name             0
brand                0
model                0
vehicle_age          0
km_driven            0
seller_type          0
fuel_type            0
transmission_type    0
mileage              0
engine               0
max_power            0
seats                0
selling_price        0
dtype: int64
```

In [4]:
```
# There are no null values according to the above result
```

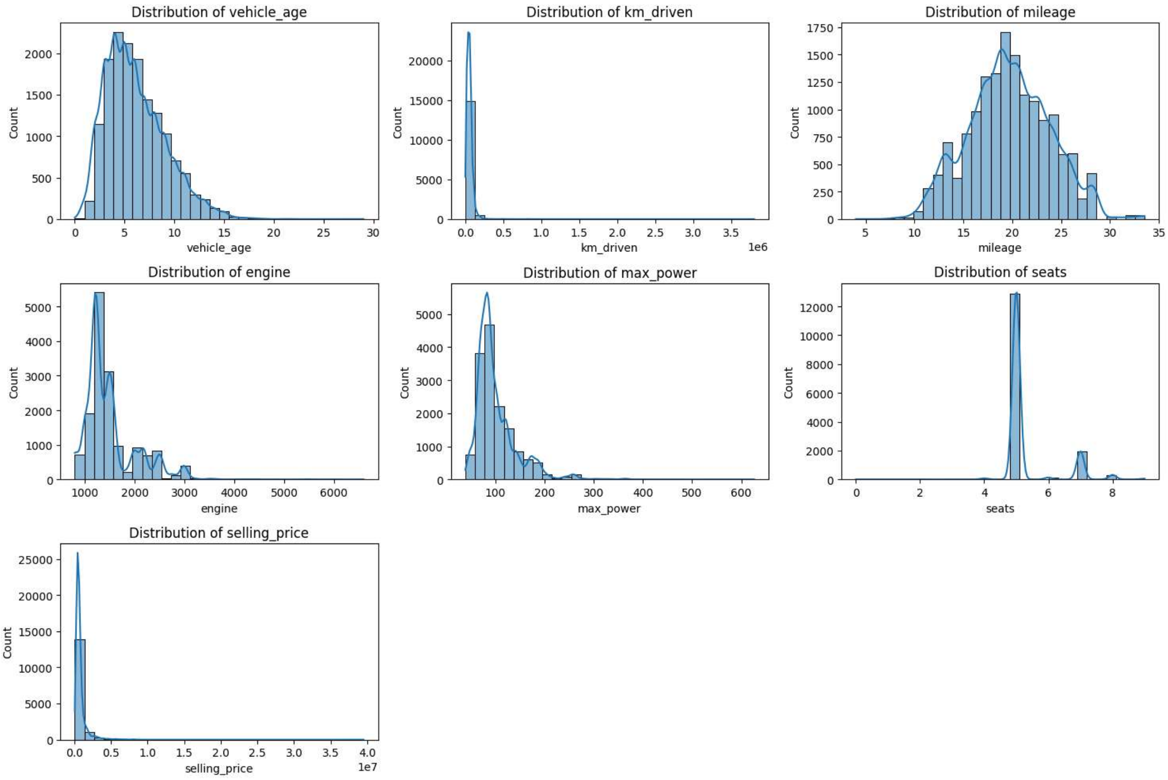
In [5]:
```
df.describe()
```

Out[5]:

	Unnamed: 0	vehicle_age	km_driven	mileage	engine	max_po
count	15411.000000	15411.000000	1.541100e+04	15411.000000	15411.000000	15411.00(
mean	9811.857699	6.036338	5.561648e+04	19.701151	1486.057751	100.58{
std	5643.418542	3.013291	5.161855e+04	4.171265	521.106696	42.972
min	0.000000	0.000000	1.000000e+02	4.000000	793.000000	38.40(
25%	4906.500000	4.000000	3.000000e+04	17.000000	1197.000000	74.00(
50%	9872.000000	6.000000	5.000000e+04	19.670000	1248.000000	88.50(
75%	14668.500000	8.000000	7.000000e+04	22.700000	1582.000000	117.30(
max	19543.000000	29.000000	3.800000e+06	33.540000	6592.000000	626.00(

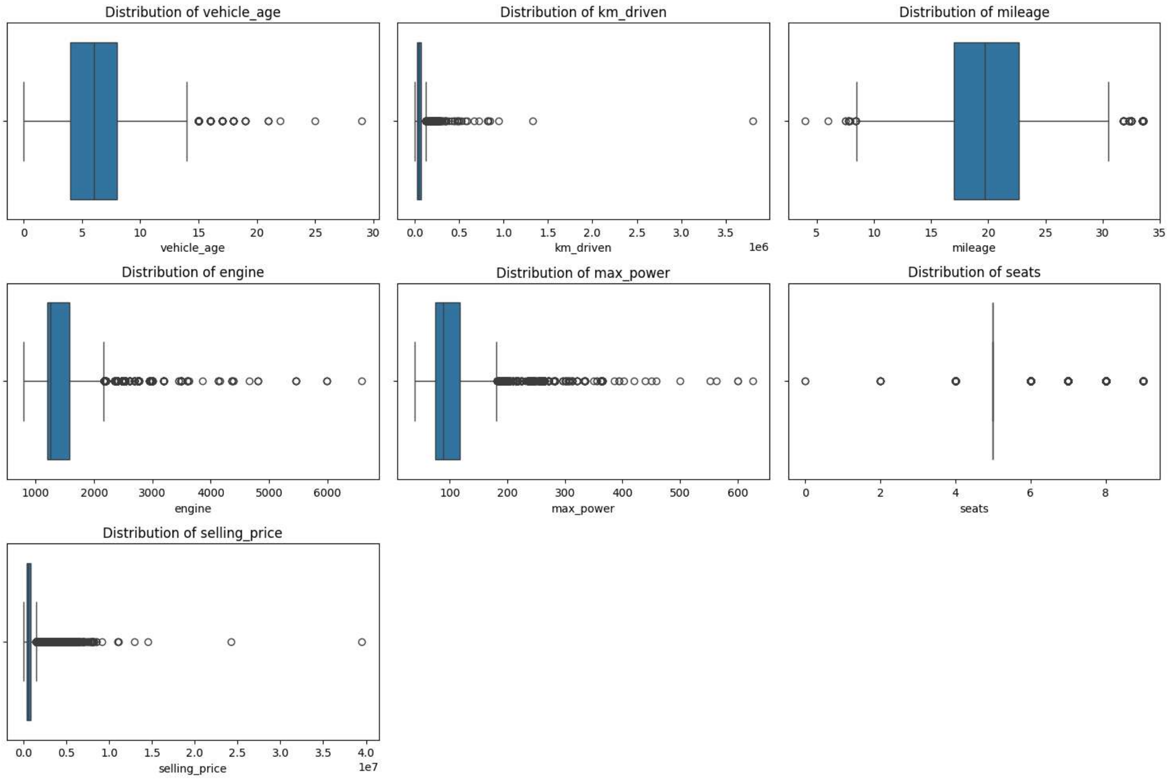
Univariate Analysis

In [6]:
```
plt.figure(figsize = (15, 10))

num_cols = ["vehicle_age", "km_driven", "mileage", "engine", "max_power", "seats

for i in range(len(num_cols)):
    plt.subplot(3, 3, i+1)
    sns.histplot(df[num_cols[i]], kde = True, bins = 30)
    plt.title(f"Distribution of {num_cols[i]}")

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



In [7]:
```
# In the above graphs we can see graphs like "vehicle_age", "km_driven", "engine
```

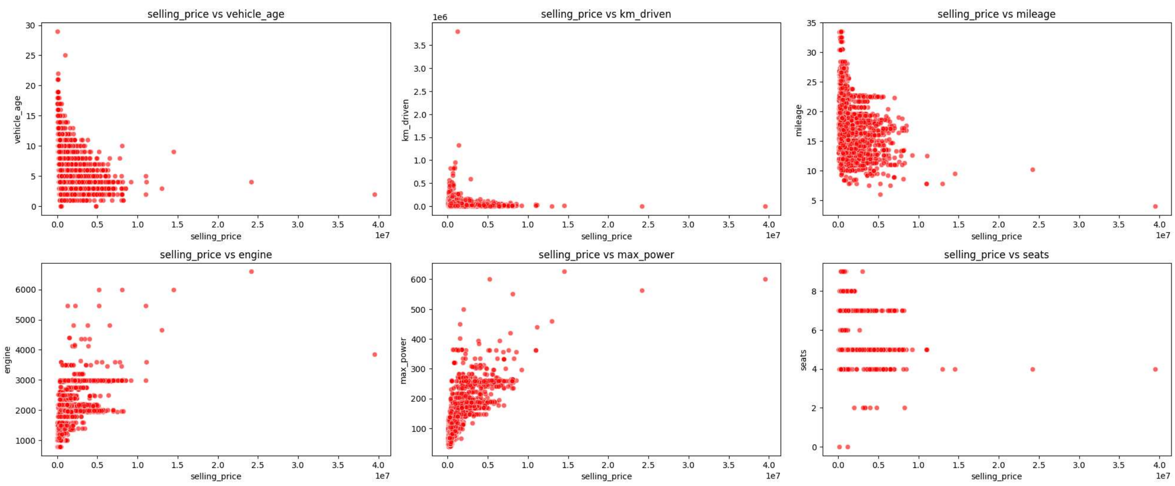
In [8]:
```
# Checking if we have outliers in these cols

plt.figure(figsize = (15, 10))

num_cols = ["vehicle_age", "km_driven", "mileage", "engine", "max_power", "seats

for i in range(len(num_cols)):
    plt.subplot(3, 3, i+1)
    sns.boxplot(x = df[num_cols[i]])
    plt.title(f"Distribution of {num_cols[i]}")

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



In [9]:
```
# All the cols have outliers.
```

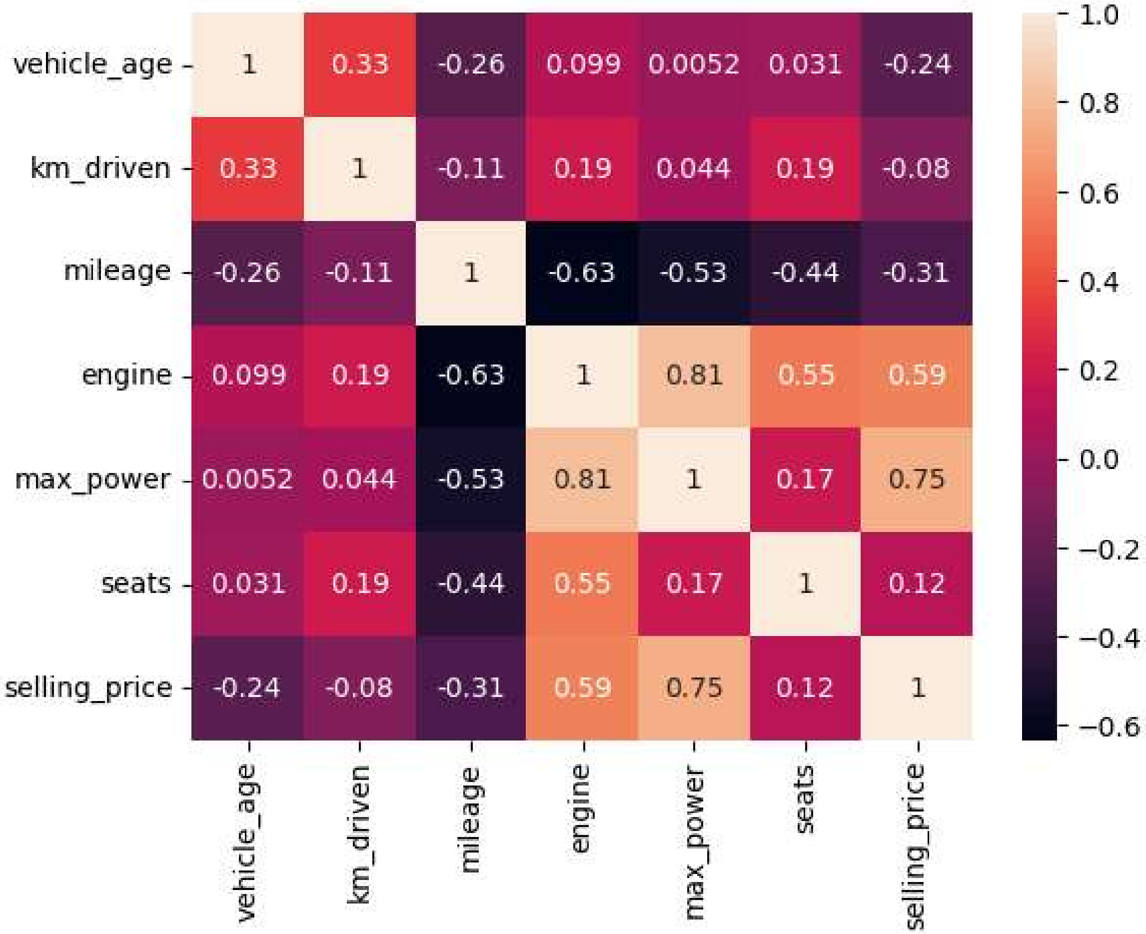
Bivariate Analysis

In [10]:
```
plt.figure(figsize=(20, 20))

num_cols = ["vehicle_age", "km_driven", "mileage", "engine", "max_power", "seats

for i in range(len(num_cols)):
    plt.subplot(5, 3, i + 1)  # 3 rows × 3 cols grid
    sns.scatterplot(data = df, x = 'selling_price', y = num_cols[i], color = 'r'
    plt.title(f'selling_price vs {num_cols[i]}')

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



Multivariate Analysis

In [11]:
```
num_cols = ["vehicle_age", "km_driven", "mileage", "engine", "max_power", "seats

sns.heatmap(data = df[num_cols].corr(), annot = True, cmap = 'rocket')
plt.show()
```



In [12]:
```
# In the above graph we can see that
# selling_price is negatively correlated with vehicle_age, km_driven, mileage
# selling_price is positively correlated with engine, max_power, seats
```

Data Preprocessing

In [13]:
```
# feature engineering
model_data = df.copy()
```

In [14]:
```
df.columns
```

Out[14]:
```
Index(['Unnamed: 0', 'car_name', 'brand', 'model', 'vehicle_age', 'km_driven',
       'seller_type', 'fuel_type', 'transmission_type', 'mileage', 'engine',
       'max_power', 'seats', 'selling_price'],
      dtype='object')
```

In [15]:
```
# Dropping unnecessary columns
model_data.drop(labels = ['Unnamed: 0', 'car_name', 'brand', 'model'], axis = 1,
```

In [16]:
```
model_data.head()
```

Out[16]:

	vehicle_age	km_driven	seller_type	fuel_type	transmission_type	mileage	engine	r
0	9	120000	Individual	Petrol	Manual	19.70	796	
1	5	20000	Individual	Petrol	Manual	18.90	1197	
2	11	60000	Individual	Petrol	Manual	17.00	1197	
3	9	37000	Individual	Petrol	Manual	20.92	998	
4	6	30000	Dealer	Diesel	Manual	22.77	1498	

In [17]:

```
# Will use one-hot encoding to create dummies of the categorical variable
model_data = pd.get_dummies(model_data, dtype = int)
model_data
```

Out[17]:

	vehicle_age	km_driven	mileage	engine	max_power	seats	selling_price	selle
0	9	120000	19.70	796	46.30	5	120000	
1	5	20000	18.90	1197	82.00	5	550000	
2	11	60000	17.00	1197	80.00	5	215000	
3	9	37000	20.92	998	67.10	5	226000	
4	6	30000	22.77	1498	98.59	5	570000	
...	...	...	...	...	...	...	...	
15406	9	10723	19.81	1086	68.05	5	250000	
15407	2	18000	17.50	1373	91.10	7	925000	
15408	6	67000	21.14	1498	103.52	5	425000	
15409	5	3800000	16.00	2179	140.00	7	1225000	
15410	2	13000	18.00	1497	117.60	5	1200000	

15411 rows × 17 columns

In [18]:

```
# Feature Separation
y = model_data['selling_price']
x = model_data.drop('selling_price',axis = 1)
```

In [19]:

```
# Train / Test split
x_train,x_test,y_train,y_test = train_test_split(x,y,test_size = 0.2)
```

In [20]:

```
# Model building
# Linear Regression

regressor = LinearRegression().fit(x_train,y_train)
pred = regressor.predict(x_test)
```

In [21]:

```
r_square_value = r2_score(y_true = y_test,y_pred = pred)
```

```
r_square_value
```

Out[21]: 0.6586796359312257

In [22]:
```
# Linear regression is not a good model for this data because r2 is very less
```

In [23]:
```
x_test['predicted_selling_price'] = pred

x_test['Actual_selling_price'] = y_test
x_test
```

Out[23]:

	vehicle_age	km_driven	mileage	engine	max_power	seats	seller_type_Dealer
14854	4	43318	19.56	1197	81.80	5	1
5693	8	93000	12.05	2179	120.00	8	1
6807	5	60000	20.14	1498	88.00	5	0
8308	3	73185	19.67	1582	126.20	5	1
15109	4	55000	26.21	1248	88.50	5	1
...	...	...	...	...	...	...	...
12450	2	5000	21.70	998	67.00	5	0
15014	8	44000	15.04	1598	103.60	5	1
7141	7	120000	23.40	1248	74.00	5	0
15166	5	20012	21.79	998	67.05	5	1
10541	10	60251	12.99	2494	100.60	7	1

3083 rows × 18 columns

In [24]:
```
pred = pred.astype(int)

pred
```

Out[24]: array([691255, 845516, 622561, ..., 259543, 319529, 508619], shape=(3083,))

In [ ]: