Car Price Prediction

In [1]:
```
import warnings
warnings.filterwarnings("ignore")

import re
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import scipy as st

from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder
from sklearn.metrics import confusion_matrix

from sklearn.metrics import accuracy_score

from sklearn.tree import DecisionTreeRegressor
from sklearn.neighbors import KNeighborsRegressor,KNeighborsClassifier
from sklearn.ensemble import RandomForestRegressor

from sklearn.metrics import mean_squared_error
from sklearn.metrics import mean_absolute_error
from sklearn.metrics import mean_absolute_percentage_error
from sklearn.metrics import r2_score

sns.set_style("darkgrid")
```

Loading Data

In [2]:
```
link = "C:/Users/parsh/Downloads/Car details v3.csv"
```

In [3]:
```
df = pd.read_csv(link)
```

In [4]:
```
df.head()
```

Out[4]:

	name	year	selling_price	km_driven	fuel	seller_type	transmission	owner	mileage	engine	max_power	torque	seats
0	Maruti Swift Dzire VDI	2014	450000	145500	Diesel	Individual	Manual	First Owner	23.4 kmpl	1248 CC	74 bhp	190Nm@ 2000rpm	5.0
1	Skoda Rapid 1.5 TDI Ambition	2014	370000	120000	Diesel	Individual	Manual	Second Owner	21.14 kmpl	1498 CC	103.52 bhp	250Nm@ 1500-2500rpm	5.0
2	Honda City 2017-2020 EXi	2006	158000	140000	Petrol	Individual	Manual	Third Owner	17.7 kmpl	1497 CC	78 bhp	12.7@ 2,700(kgm@ rpm)	5.0
3	Hyundai i20 Sportz Diesel	2010	225000	127000	Diesel	Individual	Manual	First Owner	23.0 kmpl	1396 CC	90 bhp	22.4 kgm at 1750-2750rpm	5.0
4	Maruti Swift VXI BSIII	2007	130000	120000	Petrol	Individual	Manual	First Owner	16.1 kmpl	1298 CC	88.2 bhp	11.5@ 4,500(kgm@ rpm)	5.0

Cleaning the Data

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

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 8128 entries, 0 to 8127
Data columns (total 13 columns):
 #   Column         Non-Null Count  Dtype  
---  ------         --------------  -----  
 0   name           8128 non-null   object 
 1   year           8128 non-null   int64  
 2   selling_price  8128 non-null   int64  
 3   km_driven      8128 non-null   int64  
 4   fuel           8128 non-null   object 
 5   seller_type    8128 non-null   object 
 6   transmission   8128 non-null   object 
 7   owner          8128 non-null   object 
 8   mileage        7907 non-null   object 
 9   engine         7907 non-null   object 
 10  max_power      7913 non-null   object 
 11  torque         7906 non-null   object 
 12  seats          7907 non-null   float64
dtypes: float64(1), int64(3), object(9)
memory usage: 825.6+ KB
```

In [6]:
```
df.isna().sum()
```

Out[6]:
```
name               0
year               0
selling_price      0
km_driven          0
fuel               0
seller_type        0
transmission       0
owner              0
mileage          221
engine           221
max_power        215
torque           222
seats            221
dtype: int64
```

Create a column of Brand

In [7]:
```python
l = lambda x:x.split()[0]

df["Brand"] = df["name"].apply(l)
```

In [8]:
```python
df.head()
```

Out[8]:

	name	year	selling_price	km_driven	fuel	seller_type	transmission	owner	mileage	engine	max_power	torque	seats
0	Maruti Swift Dzire VDI	2014	450000	145500	Diesel	Individual	Manual	First Owner	23.4 kmpl	1248 CC	74 bhp	190Nm@ 2000rpm	5.0
1	Skoda Rapid 1.5 TDI Ambition	2014	370000	120000	Diesel	Individual	Manual	Second Owner	21.14 kmpl	1498 CC	103.52 bhp	250Nm@ 1500-2500rpm	5.0
2	Honda City 2017-2020 EXi	2006	158000	140000	Petrol	Individual	Manual	Third Owner	17.7 kmpl	1497 CC	78 bhp	12.7@ 2,700(kgm@ rpm)	5.0
3	Hyundai i20 Sportz Diesel	2010	225000	127000	Diesel	Individual	Manual	First Owner	23.0 kmpl	1396 CC	90 bhp	22.4 kgm at 1750-2750rpm	5.0
4	Maruti Swift VXI BSIII	2007	130000	120000	Petrol	Individual	Manual	First Owner	16.1 kmpl	1298 CC	88.2 bhp	11.5@ 4,500(kgm@ rpm)	5.0

Create a column of Model

In [9]:
```
def mod(x):
    x = x.split()
    x = x[1::]
    x = " ".join(x)
    return x
```

In [10]:
```
df["Model"] = df["name"].apply(mod)
```

In [11]:
```
df.head()
```

Out[11]:

	name	year	selling_price	km_driven	fuel	seller_type	transmission	owner	mileage	engine	max_power	torque	seats
0	Maruti Swift Dzire VDI	2014	450000	145500	Diesel	Individual	Manual	First Owner	23.4 kmpl	1248 CC	74 bhp	190Nm@ 2000rpm	5.0
1	Skoda Rapid 1.5 TDI Ambition	2014	370000	120000	Diesel	Individual	Manual	Second Owner	21.14 kmpl	1498 CC	103.52 bhp	250Nm@ 1500-2500rpm	5.0
2	Honda City 2017-2020 EXi	2006	158000	140000	Petrol	Individual	Manual	Third Owner	17.7 kmpl	1497 CC	78 bhp	12.7@ 2,700(kgm@ rpm)	5.0
3	Hyundai i20 Sportz Diesel	2010	225000	127000	Diesel	Individual	Manual	First Owner	23.0 kmpl	1396 CC	90 bhp	22.4 kgm at 1750-2750rpm	5.0
4	Maruti Swift VXI BSIII	2007	130000	120000	Petrol	Individual	Manual	First Owner	16.1 kmpl	1298 CC	88.2 bhp	11.5@ 4,500(kgm@ rpm)	5.0

Delete the column of name

In [12]:
```
df.drop(columns=["name"],inplace=True)
```

In [13]:
```
df.head()
```

Out[13]:

	year	selling_price	km_driven	fuel	seller_type	transmission	owner	mileage	engine	max_power	torque	seats	Brand	
0	2014	450000	145500	Diesel	Individual	Manual	First Owner	23.4 kmpl	1248 CC	74 bhp	190Nm@ 2000rpm	5.0	Maruti	
1	2014	370000	120000	Diesel	Individual	Manual	Second Owner	21.14 kmpl	1498 CC	103.52 bhp	250Nm@ 1500-2500rpm	5.0	Skoda	Ar
2	2006	158000	140000	Petrol	Individual	Manual	Third Owner	17.7 kmpl	1497 CC	78 bhp	12.7@ 2,700(kgm@ rpm)	5.0	Honda	2(
3	2010	225000	127000	Diesel	Individual	Manual	First Owner	23.0 kmpl	1396 CC	90 bhp	22.4 kgm at 1750-2750rpm	5.0	Hyundai	
4	2007	130000	120000	Petrol	Individual	Manual	First Owner	16.1 kmpl	1298 CC	88.2 bhp	11.5@ 4,500(kgm@ rpm)	5.0	Maruti	Sv

Cleaning all columns one by one

In [14]:
```
df["mileage"].fillna(df["mileage"].mode()[0],inplace=True)
```

In [15]:
```
l = lambda x:x.split()[0]
```

In [16]:
```
df["Mileage"] = df["mileage"].apply(l)
```

In [17]:
```
a = lambda x:x.split()[-1]
```

In [18]:
```
df["Mileage_Unit"] = df["mileage"].apply(a)
```

In [19]:
```
df.drop(columns=["mileage"],inplace=True)
```

In [20]:
```
df["Mileage"].dtype
```

Out[20]:
```
dtype('O')
```

In [21]:
```
df["Mileage"] = df["Mileage"].astype(float)
```

In [22]:
```
df["Mileage"].dtype
```

Out[22]:
```
dtype('float64')
```

In [23]:
```
df.head()
```

Out[23]:

	year	selling_price	km_driven	fuel	seller_type	transmission	owner	engine	max_power	torque	seats	Brand	Model	M
0	2014	450000	145500	Diesel	Individual	Manual	First Owner	1248 CC	74 bhp	190Nm@ 2000rpm	5.0	Maruti	Swift Dzire VDI	
1	2014	370000	120000	Diesel	Individual	Manual	Second Owner	1498 CC	103.52 bhp	250Nm@ 1500-2500rpm	5.0	Skoda	Rapid 1.5 TDI Ambition	
2	2006	158000	140000	Petrol	Individual	Manual	Third Owner	1497 CC	78 bhp	12.7@ 2,700(kgm@ rpm)	5.0	Honda	City 2017-2020 EXi	
3	2010	225000	127000	Diesel	Individual	Manual	First Owner	1396 CC	90 bhp	22.4 kgm at 1750-2750rpm	5.0	Hyundai	i20 Sportz Diesel	
4	2007	130000	120000	Petrol	Individual	Manual	First Owner	1298 CC	88.2 bhp	11.5@ 4,500(kgm@ rpm)	5.0	Maruti	Swift VXI BSIII	

In [24]:

```
df["max_power"].unique
```

Out[24]:

```
<bound method Series.unique of 0           74 bhp
1       103.52 bhp
2           78 bhp
3           90 bhp
4         88.2 bhp
           ...
8123     82.85 bhp
8124       110 bhp
8125      73.9 bhp
8126        70 bhp
8127        70 bhp
Name: max_power, Length: 8128, dtype: object>
```

In [25]:

```
df["max_power"] = df["max_power"].str.replace("bhp","")
df["max_power"] = df["max_power"].str.replace(" ","")
```

In [26]:
```
df["max_power"].fillna(df["max_power"].mode()[0],inplace=True)
```

In [27]:
```
df[df["max_power"]==""]
```

Out[27]:

	year	selling_price	km_driven	fuel	seller_type	transmission	owner	engine	max_power	torque	seats	Brand	Model	Mileage
4933	2000	80000	100000	CNG	Individual	Manual	Second Owner	796 CC		NaN	8.0	Maruti	Omni CNG	10.9

In [28]:
```
df["max_power"] = df["max_power"].str.replace("","0")
```

In [29]:
```
df["max_power"] = df["max_power"].astype(float)
```

In [30]:
```
df.head()
```

Out[30]:

	year	selling_price	km_driven	fuel	seller_type	transmission	owner	engine	max_power	torque	seats	Brand	Model
0	2014	450000	145500	Diesel	Individual	Manual	First Owner	1248 CC	7040.0000	190Nm@ 2000rpm	5.0	Maruti	Swift Dzire VDI
1	2014	370000	120000	Diesel	Individual	Manual	Second Owner	1498 CC	100030.0502	250Nm@ 1500-2500rpm	5.0	Skoda	Rapid 1.5 TDI Ambition
2	2006	158000	140000	Petrol	Individual	Manual	Third Owner	1497 CC	7080.0000	12.7@ 2,700(kgm@ rpm)	5.0	Honda	City 2017-2020 EXi
3	2010	225000	127000	Diesel	Individual	Manual	First Owner	1396 CC	9000.0000	22.4 kgm at 1750-2750rpm	5.0	Hyundai	i20 Sportz Diesel
4	2007	130000	120000	Petrol	Individual	Manual	First Owner	1298 CC	8080.0200	11.5@ 4,500(kgm@ rpm)	5.0	Maruti	Swift VXI BSIII

In [31]:
```
df["engine"].unique
```

Out[31]:
```
<bound method Series.unique of 0       1248 CC
1       1498 CC
2       1497 CC
3       1396 CC
4       1298 CC
          ...
8123    1197 CC
8124    1493 CC
8125    1248 CC
8126    1396 CC
8127    1396 CC
Name: engine, Length: 8128, dtype: object>
```

In [32]:
```
df["engine"] = df["engine"].str.replace("CC","")
```

In [33]:
```
df["engine"] = df["engine"].astype(float)
```

In [34]:
```
df["engine"].fillna(df["engine"].mean(),inplace=True)
```

In [35]:
```
df.head()
```

Out[35]:

	year	selling_price	km_driven	fuel	seller_type	transmission	owner	engine	max_power	torque	seats	Brand	Model	M
0	2014	450000	145500	Diesel	Individual	Manual	First Owner	1248.0	7040.0000	190Nm@ 2000rpm	5.0	Maruti	Swift Dzire VDI	
1	2014	370000	120000	Diesel	Individual	Manual	Second Owner	1498.0	100030.0502	250Nm@ 1500-2500rpm	5.0	Skoda	Rapid 1.5 TDI Ambition	
2	2006	158000	140000	Petrol	Individual	Manual	Third Owner	1497.0	7080.0000	12.7@ 2,700(kgm@ rpm)	5.0	Honda	City 2017-2020 EXi	
3	2010	225000	127000	Diesel	Individual	Manual	First Owner	1396.0	9000.0000	22.4 kgm at 1750-2750rpm	5.0	Hyundai	i20 Sportz Diesel	
4	2007	130000	120000	Petrol	Individual	Manual	First Owner	1298.0	8080.0200	11.5@ 4,500(kgm@ rpm)	5.0	Maruti	Swift VXI BSIII	

In [36]:

```
df["torque"].str.split()
```

Out[36]:

```
0                   [190Nm@, 2000rpm]
1              [250Nm@, 1500-2500rpm]
2           [12.7@, 2,700(kgm@, rpm)]
3        [22.4, kgm, at, 1750-2750rpm]
4           [11.5@, 4,500(kgm@, rpm)]
                    ...
8123              [113.7Nm@, 4000rpm]
8124     [24@, 1,900-2,750(kgm@, rpm)]
8125                [190Nm@, 2000rpm]
8126           [140Nm@, 1800-3000rpm]
8127           [140Nm@, 1800-3000rpm]
Name: torque, Length: 8128, dtype: object
```

In [37]:

```
df["torque"].fillna(df["torque"].mode()[0],inplace=True)
```

In [38]:
```
nm = []
r = []
for i in df["torque"].str.split():
    nm.append(i[0])
    r.append(" ".join(i[1:]))
```

In [39]:
```
df["nm"] = nm
df["rpm"] = r
```

In [40]:
```
df.head()
```

Out[40]:

	year	selling_price	km_driven	fuel	seller_type	transmission	owner	engine	max_power	torque	seats	Brand	Model
0	2014	450000	145500	Diesel	Individual	Manual	First Owner	1248.0	7040.0000	190Nm@ 2000rpm	5.0	Maruti	Swift Dzire VDI
1	2014	370000	120000	Diesel	Individual	Manual	Second Owner	1498.0	100030.0502	250Nm@ 1500-2500rpm	5.0	Skoda	Rapid 1.5 TDI Ambition
2	2006	158000	140000	Petrol	Individual	Manual	Third Owner	1497.0	7080.0000	12.7@ 2,700(kgm@ rpm)	5.0	Honda	City 2017-2020 EXi
3	2010	225000	127000	Diesel	Individual	Manual	First Owner	1396.0	9000.0000	22.4 kgm at 1750-2750rpm	5.0	Hyundai	i20 Sportz Diesel
4	2007	130000	120000	Petrol	Individual	Manual	First Owner	1298.0	8080.0200	11.5@ 4,500(kgm@ rpm)	5.0	Maruti	Swift VXI BSIII

Regular Expression

In [41]:
```
x = []
for i in df["nm"]:
    y = re.sub("[^0-9.]","",i)
    x.append(y)
```

In [42]:
```
df["nm"] = x
```

In [43]:
```
a = []
for i in df["rpm"]:
    b = re.sub("[^0-9-]","",i)
    a.append(b)
```

In [44]:
```
df["rpm"] = a
```

In [45]:
```
df.drop(columns=["torque"],inplace=True)
```

In [46]:
```
df["nm"] = df["nm"].astype(float)
```

In [47]:
```
x = []
for i in df["rpm"]:
    y = i.split("-")
    if y[-1]=="":
        x.append(0)
    else:
        x.append(float(y[-1]))
```

In [48]:
```
df["rpm"] = x
```

In [49]:
```
df.head()
```

Out[49]:

	year	selling_price	km_driven	fuel	seller_type	transmission	owner	engine	max_power	seats	Brand	Model	Mileage	Mile
0	2014	450000	145500	Diesel	Individual	Manual	First Owner	1248.0	7040.0000	5.0	Maruti	Swift Dzire VDI	23.40	
1	2014	370000	120000	Diesel	Individual	Manual	Second Owner	1498.0	100030.0502	5.0	Skoda	Rapid 1.5 TDI Ambition	21.14	
2	2006	158000	140000	Petrol	Individual	Manual	Third Owner	1497.0	7080.0000	5.0	Honda	City 2017-2020 EXi	17.70	
3	2010	225000	127000	Diesel	Individual	Manual	First Owner	1396.0	9000.0000	5.0	Hyundai	i20 Sportz Diesel	23.00	
4	2007	130000	120000	Petrol	Individual	Manual	First Owner	1298.0	8080.0200	5.0	Maruti	Swift VXI BSIII	16.10	

In [50]:

```
df.isna().sum()
```

Out[50]:
```
year              0
selling_price     0
km_driven         0
fuel              0
seller_type       0
transmission      0
owner             0
engine            0
max_power         0
seats           221
Brand             0
Model             0
Mileage           0
Mileage_Unit      0
nm                0
rpm               0
dtype: int64
```

In [51]:
```
df["seats"].fillna(df["seats"].mean(),inplace=True)
```

In [52]:
```
df.isna().sum()
```

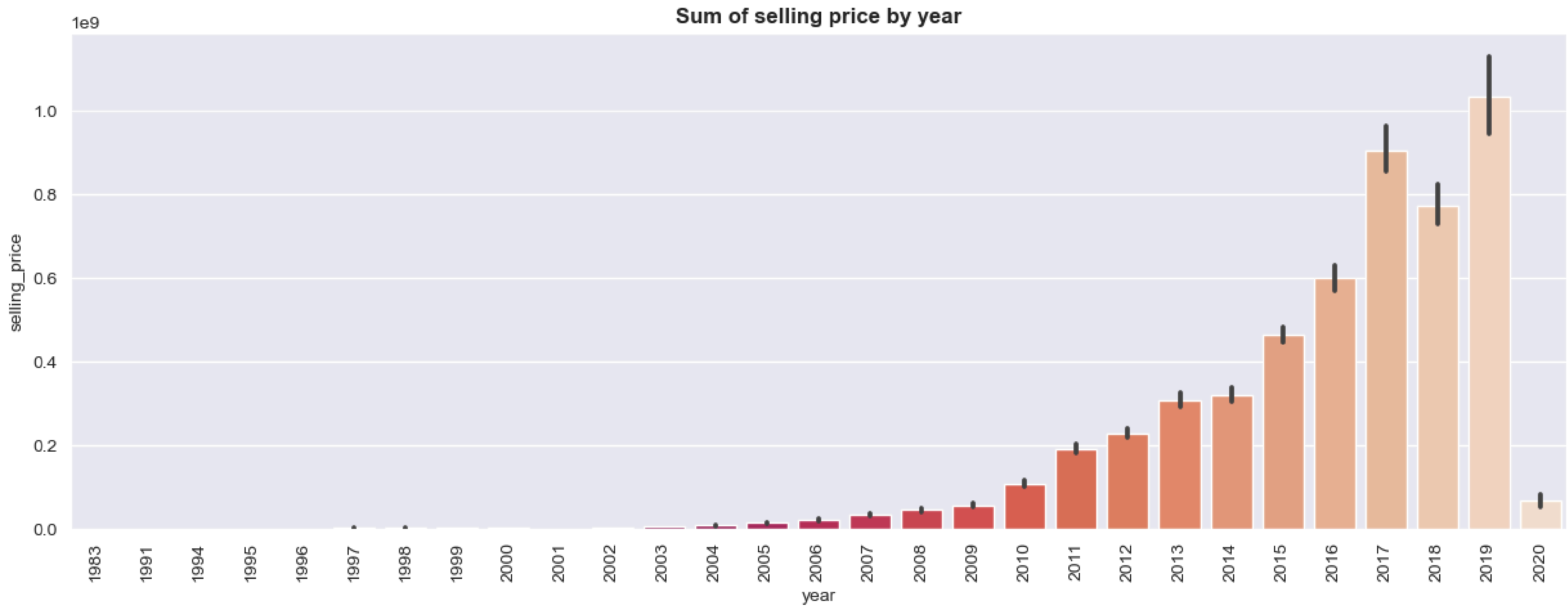
Out[52]:
```
year             0
selling_price    0
km_driven        0
fuel             0
seller_type      0
transmission     0
owner            0
engine           0
max_power        0
seats            0
Brand            0
Model            0
Mileage          0
Mileage_Unit     0
nm               0
rpm              0
dtype: int64
```

In [53]:
```
df.dtypes
```

Out[53]:
```
year                int64
selling_price       int64
km_driven           int64
fuel               object
seller_type        object
transmission       object
owner              object
engine            float64
max_power         float64
seats             float64
Brand              object
Model              object
Mileage           float64
Mileage_Unit       object
nm                float64
rpm               float64
dtype: object
```

EDA = Exploratory Data Analysis

In [54]:
```
plt.figure(figsize=(15,5))
sns.barplot(data = df,x = "year",y = "selling_price",estimator="sum",palette="rocket")
plt.title("Sum of selling price by year",fontweight="bold")
plt.xticks(rotation = 90)
plt.show()
```



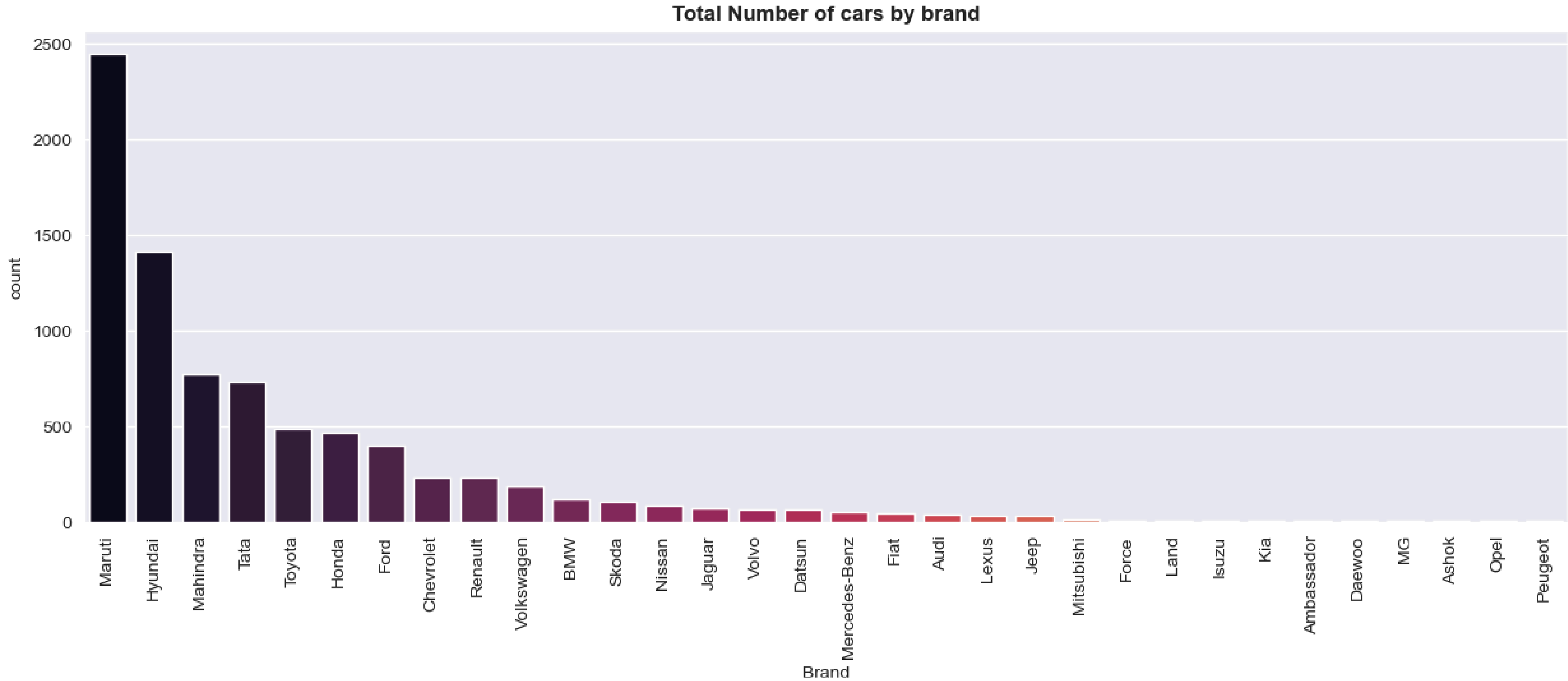
Insights from the Bar Chart:

- Increasing Trend: The bar chart clearly shows a growing trend in the sum of selling prices over the years. The selling price has been significantly increasing over the past two decades.
- Sharp Increase After 2010: The trend becomes more pronounced after the year 2010, indicating a potentially accelerated growth in the market.
- Highest Selling Price in 2020: The year 2020 saw the highest sum of selling price, potentially indicating peak market activity or a significant surge in the value of goods sold.

In [55]:
```
vl = df["Brand"].value_counts().reset_index()
```

In [56]:
```
plt.figure(figsize=(15,5))
sns.barplot(data=vl,x="Brand",y="count",palette="rocket")
plt.title("Total Number of cars by brand",fontweight="bold")
```

```
plt.xticks(rotation=90)
plt.show()
```



Insights from the Bar Chart:

- Dominance of Maruti:

Maruti leads significantly with the highest count, surpassing 2500 units. This indicates a strong market presence and popularity of Maruti vehicles.

- Close Competition:

Hyundai follows as the second largest brand, but with a notable gap from Maruti. This suggests a healthy competition among the top brands. Other Key Players:

- Brands like Mahindra, Tata, and Toyota also show substantial counts, suggesting a strong market share in the automotive sector.
- Honda, Ford, Chevrolet, and Renault appear next, with counts indicating moderate popularity.

In [57]:
```
fl = df.groupby("fuel")["selling_price"].mean().reset_index()
```

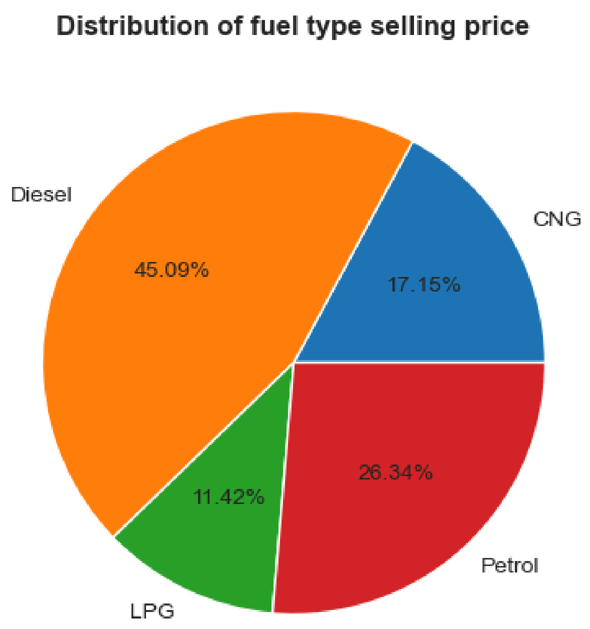
In [58]:
```
tr = df.groupby("transmission")["selling_price"].mean().reset_index()
```

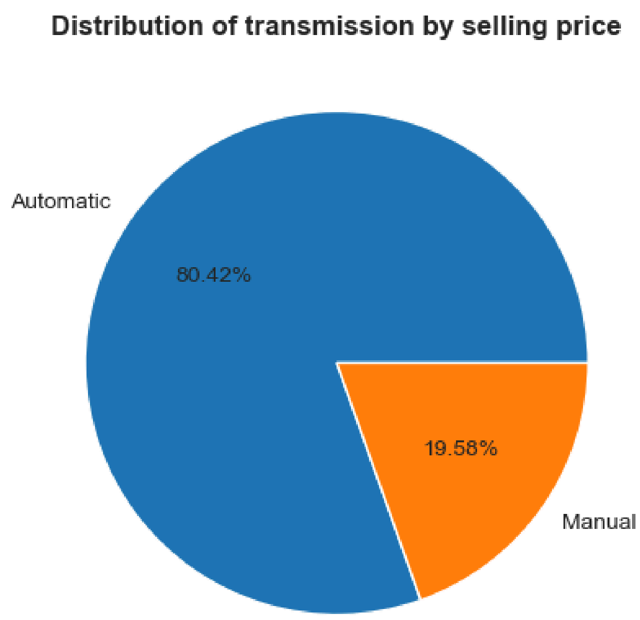
In [59]:
```
plt.figure(figsize=(17,5))

plt.subplot(1,2,1)
plt.pie(fl["selling_price"],labels=fl["fuel"],autopct="%0.2f%%")
plt.title("Distribution of fuel type selling price",fontweight="bold")

plt.subplot(1,2,2)
plt.pie(tr["selling_price"],labels=tr["transmission"],autopct="%0.2f%%")
plt.title("Distribution of transmission by selling price",fontweight="bold")

plt.show()
```





Insights from the Pie Charts:

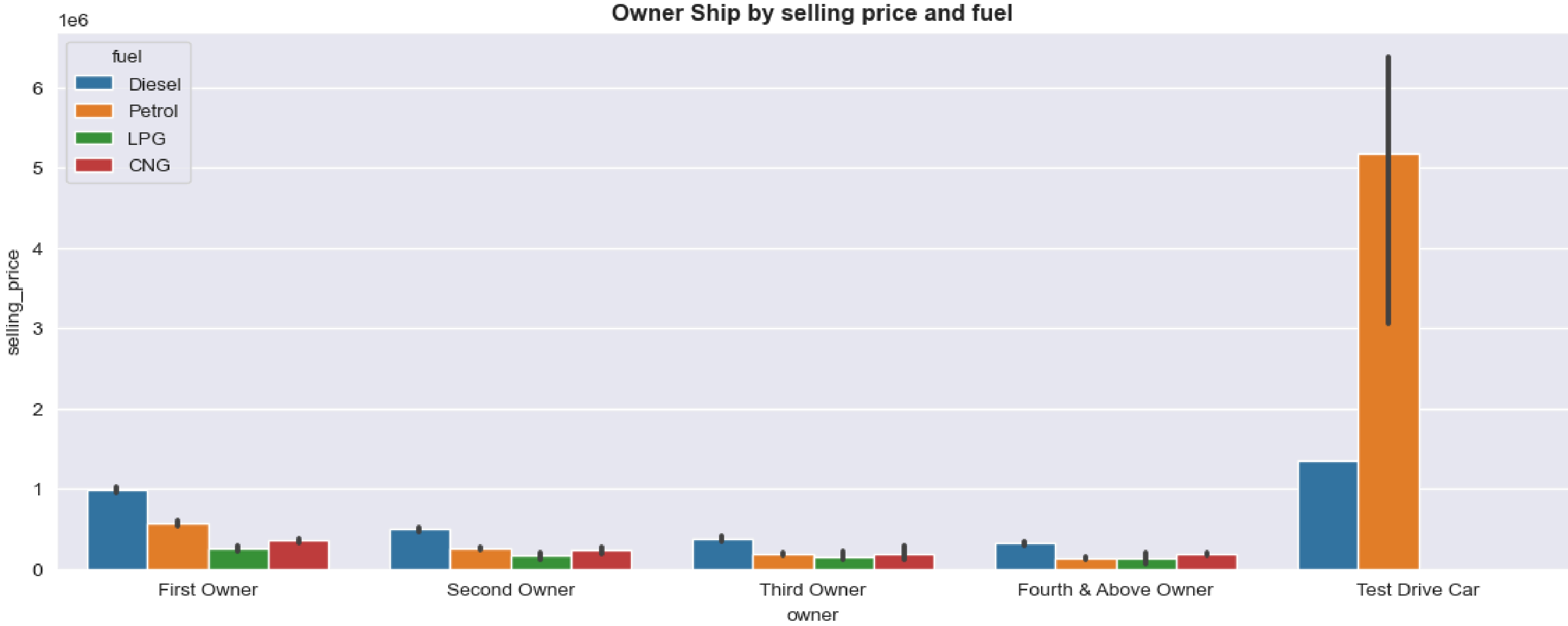
- Trend Towards Diesel and Automatic: There is a significant preference for diesel fuel combined with automatic transmissions, indicating consumer prioritization of performance and convenience.
-

Potential for Growth in Alternative Fuels: The lower percentages of CNG and LPG suggest opportunities for developers and manufacturers to promote alternative fuel vehicles

-

Market Dynamics: The high preference for automatic transmission indicates a potential shift in manufacturing focus to cater to consumer demands, prioritizing automatics over manual options.

In [60]:
```
plt.figure(figsize=(14,5))
sns.barplot(data=df, x="owner", y="selling_price",hue="fuel")
plt.title("Owner Ship by selling price and fuel",fontweight="bold")
plt.show()
```



Insights from the Bar Chart:

- Market Implications:

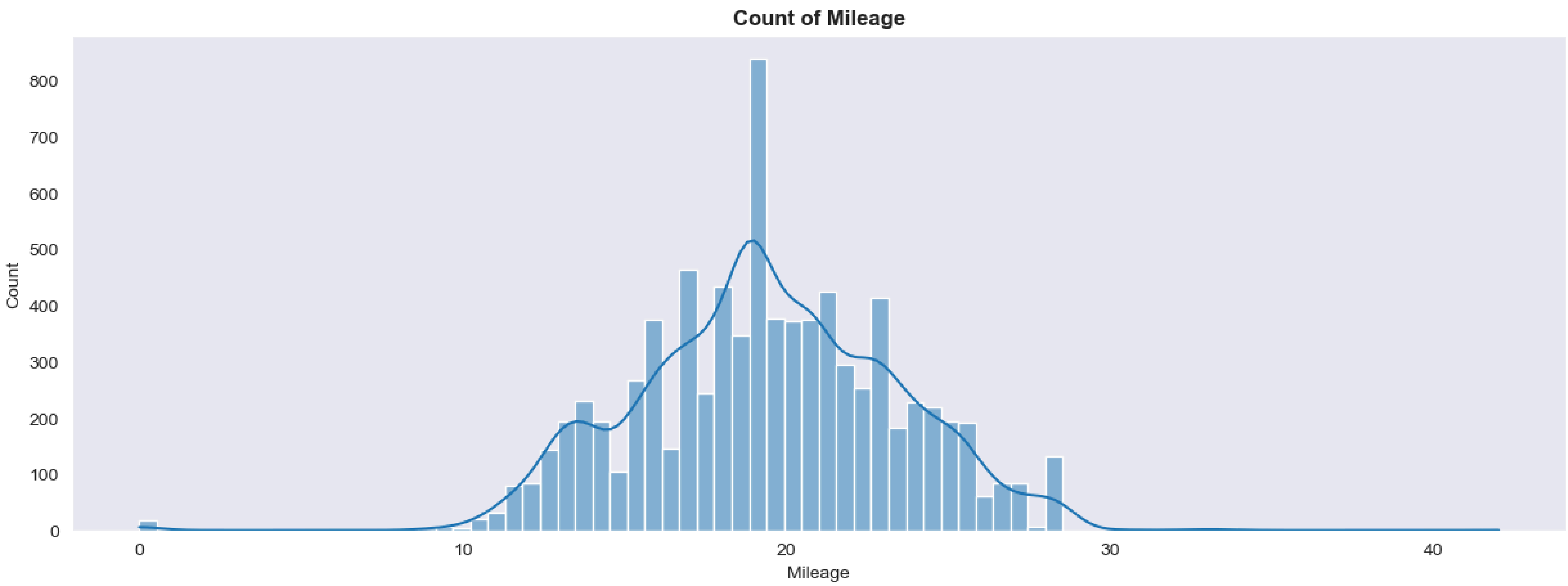
There is a clear differentiation in selling prices based on fuel type and ownership status, which suggests preferences in the used car market.

- Investment Considerations:

Buyers may want to focus on Diesel cars from first owners for better resale value. The significantly higher price for Test Drive Cars indicates a market preference for almost new vehicles.

- The Test Drive Car category shows an extremely high selling price, indicating that these vehicles are likely new or nearly new and might be priced much higher than used cars.

In [61]:
```
plt.figure(figsize=(15,5))
sns.histplot(data=df,x="Mileage",kde=True)
plt.grid()
plt.title("Count of Mileage",fontweight="bold")
plt.show()
```



Insights from the Histogram Chart:

- Mileage values range from 0 to 40 miles, but most occurrences are clustered between 10 to 30 miles.

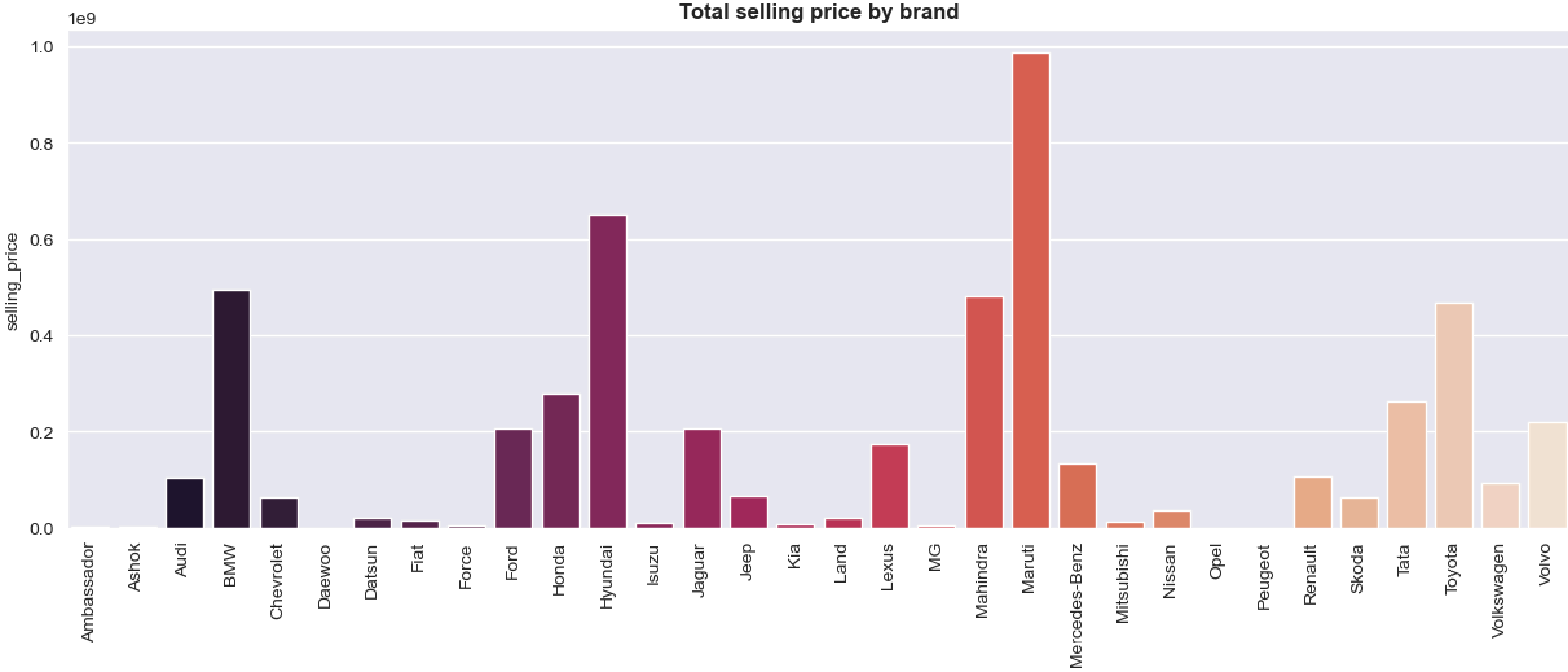
-

Very few instances fall below 5 miles or exceed 35 miles.

- The data suggests that most occurrences of mileage fall within a moderate range, significantly clustered around the 20-mile mark.
- This histogram could be useful for understanding driving patterns or for assessing vehicle usage within a certain limit, indicating a preference for mileage around that peak.

In [62]:
```
pr = df.groupby("Brand")["selling_price"].sum().reset_index()
```

In [63]:
```
plt.figure(figsize=(15,5))
sns.barplot(data=pr,x="Brand",y="selling_price",palette="rocket")
plt.title("Total selling price by brand",fontweight="bold")
plt.xticks(rotation=90)
plt.show()
```



Insights from the Bar Chart.

-

Maruti stands out as the brand with the highest total number of cars sold, significantly surpassing other brands- . Hyundai and Mahindra follow, showing a strong presence in the market, but with lower numbers compared to Marue- s:

Brands like Honda, Ford, and Toyota appear to have a moderate range of sales, indicating a stable yet not dominating market pres- ands:

Several brands like Isuzu, Peugeot, and Datsun show relatively low sales figures. These might be niche brands or could have less market pene- Segment:

Brands like BMW and Mercedes-Benz display some sales but are considerably lower than the top-selling brands. This suggests they cater to a different market segment primarily focused on luxury..

In [64]:
```
df.head()
```

Out[64]:

	year	selling_price	km_driven	fuel	seller_type	transmission	owner	engine	max_power	seats	Brand	Model	Mileage	Mile
0	2014	450000	145500	Diesel	Individual	Manual	First Owner	1248.0	7040.0000	5.0	Maruti	Swift Dzire VDI	23.40	
1	2014	370000	120000	Diesel	Individual	Manual	Second Owner	1498.0	100030.0502	5.0	Skoda	Rapid 1.5 TDI Ambition	21.14	
2	2006	158000	140000	Petrol	Individual	Manual	Third Owner	1497.0	7080.0000	5.0	Honda	City 2017-2020 EXi	17.70	
3	2010	225000	127000	Diesel	Individual	Manual	First Owner	1396.0	9000.0000	5.0	Hyundai	i20 Sportz Diesel	23.00	
4	2007	130000	120000	Petrol	Individual	Manual	First Owner	1298.0	8080.0200	5.0	Maruti	Swift VXI BSIII	16.10	

In [65]:
```
df.dtypes
```

Out[65]:
```
year              int64
selling_price     int64
km_driven         int64
fuel             object
seller_type      object
transmission     object
owner            object
engine          float64
max_power       float64
seats           float64
Brand            object
Model            object
Mileage         float64
Mileage_Unit     object
nm              float64
rpm             float64
dtype: object
```

Changing Text to Number

In [66]:
```
ln = LabelEncoder()

for i in df:
    if df[i].dtypes in ("object","bool"):
        df[i] = ln.fit_transform(df[i])
```

In [67]:
```
df.head()
```

Out[67]:

	year	selling_price	km_driven	fuel	seller_type	transmission	owner	engine	max_power	seats	Brand	Model	Mileage	Mileage_Ur
0	2014	450000	145500	1	1	1	0	1248.0	7040.0000	5.0	20	1562	23.40	
1	2014	370000	120000	1	1	1	2	1498.0	100030.0502	5.0	27	1274	21.14	
2	2006	158000	140000	3	1	1	4	1497.0	7080.0000	5.0	10	331	17.70	
3	2010	225000	127000	1	1	1	0	1396.0	9000.0000	5.0	11	2055	23.00	
4	2007	130000	120000	3	1	1	0	1298.0	8080.0200	5.0	20	1604	16.10	

In [68]:

```
df.dtypes
```

Out[68]:

```
year               int64
selling_price      int64
km_driven          int64
fuel               int32
seller_type        int32
transmission       int32
owner              int32
engine           float64
max_power        float64
seats            float64
Brand              int32
Model              int32
Mileage          float64
Mileage_Unit       int32
nm               float64
rpm              float64
dtype: object
```

In [ ]:

Splitting the Data

In [69]:
```
x = df.drop(columns=["selling_price"])
y = df["selling_price"]
```

In [70]:
```
x
```

Out[70]:

	year	km_driven	fuel	seller_type	transmission	owner	engine	max_power	seats	Brand	Model	Mileage	Mileage_Unit	nm
0	2014	145500	1	1	1	0	1248.0	7040.0000	5.0	20	1562	23.40	1	190.0
1	2014	120000	1	1	1	2	1498.0	100030.0502	5.0	27	1274	21.14	1	250.0
2	2006	140000	3	1	1	4	1497.0	7080.0000	5.0	10	331	17.70	1	12.7
3	2010	127000	1	1	1	0	1396.0	9000.0000	5.0	11	2055	23.00	1	22.4
4	2007	120000	3	1	1	0	1298.0	8080.0200	5.0	20	1604	16.10	1	11.5
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
8123	2013	110000	3	1	1	0	1197.0	8020.0805	5.0	11	2045	18.50	1	113.7
8124	2007	119000	1	1	1	1	1493.0	101000.0000	5.0	11	1767	16.80	1	24.0
8125	2009	120000	1	1	1	0	1248.0	7030.0900	5.0	20	1574	19.30	1	190.0
8126	2013	25000	1	1	1	0	1396.0	7000.0000	5.0	28	886	23.57	1	140.0
8127	2013	25000	1	1	1	0	1396.0	7000.0000	5.0	28	886	23.57	1	140.0

8128 rows × 15 columns

In [71]:
```
y
```

Out[71]:
```
0       450000
1       370000
2       158000
3       225000
4       130000
         ...
8123    320000
8124    135000
8125    382000
8126    290000
8127    290000
Name: selling_price, Length: 8128, dtype: int64
```

In [72]:
```
x_train,x_test,y_train,y_test = train_test_split(x,y,test_size=0.15,random_state=25)
```

In [73]:
```
x_train.head()
```

Out[73]:

	year	km_driven	fuel	seller_type	transmission	owner	engine	max_power	seats	Brand	Model	Mileage	Mileage_Unit	nm
5851	2009	75000	3	1	1	2	1368.0	9000.0000	5.0	28	1075	15.0	1	116.0
6163	2019	1300	3	1	1	0	999.0	6070.0000	5.0	6	1299	22.5	1	91.0
3701	2012	70000	3	1	1	2	1197.0	8050.0800	5.0	20	1616	18.6	1	114.0
2573	2013	90000	0	1	1	0	998.0	5080.0106	5.0	20	1816	26.6	0	77.0
3435	2013	210000	1	1	1	4	1396.0	8080.0706	5.0	11	2053	21.9	1	219.6

In [74]:
```
y_train.head()
```

Out[74]:
```
5851    150000
6163    325000
3701    280000
2573    211000
3435    360000
Name: selling_price, dtype: int64
```

In [75]:
```
print(f"Total number of rows and columns in x_train{x_train.shape}")
```

```
Total number of rows and columns in x_train(6908, 15)
```

In [76]:
```
print(f"Total number of rows and columns in x_test{x_test.shape}")
```
```
Total number of rows and columns in x_test(1220, 15)
```

In [77]:
```
print(f"Total number of rows and columns in y_train{y_train.shape}")
```
```
Total number of rows and columns in y_train(6908,)
```

In [78]:
```
print(f"Total number of rows and columns in y_test{y_test.shape}")
```
```
Total number of rows and columns in y_test(1220,)
```

Building, Training and Testing the Models

In [ ]:

Building K-NN Model

In [79]:
```
kn = KNeighborsRegressor()
kn.fit(x_train,y_train)
```

Out[79]:
```
▾ KNeighborsRegressor
KNeighborsRegressor()
```

In [80]:
```
ac = kn.score(x_train,y_train)
ac1 = kn.score(x_test,y_test)
```

In [81]:
```
print("-"*80)
print("The Accuracy of train data is ",ac)
print("-"*80)
```

```
print("The accuracy of test data is",ac1)
print("-"*80)
```

```
--------------------------------------------------------------------------------
The Accuracy of train data is  0.922589064130468
--------------------------------------------------------------------------------
The accuracy of test data is 0.9186366933769297
--------------------------------------------------------------------------------
```

In [82]:
```
pred = kn.predict(x_test)
```

In [83]:
```
pred
```

Out[83]:
```
array([2418000.,  222000.,  559000., ...,  303400.,  848000.,  660000.])
```

In [84]:
```
y_test.head()
```

Out[84]:
```
4799    2150000
1293     204999
2351     459999
3374     310000
349      434999
Name: selling_price, dtype: int64
```

In [85]:
```
ms = mean_squared_error(y_test,pred)
print("-"*80)
print("Mean squared error is :-",ms)
print("-"*80)
```

```
--------------------------------------------------------------------------------
Mean squared error is :- 57205517818.904
--------------------------------------------------------------------------------
```

In [86]:
```
ma = mean_absolute_error(y_test,pred)
print("-"*80)
print("Mean absolute error is :-",ma)
print("-"*80)
```

```
--------------------------------------------------------------------------------
Mean absolute error is :- 138743.80098360655
--------------------------------------------------------------------------------
```

In [87]:
```
map = mean_absolute_percentage_error(y_test,pred)
print("-"*80)
print("Mean absolute percentage error is :-",map)
print("-"*80)
```

```
--------------------------------------------------------------------------------
Mean absolute percentage error is :- 0.38493022877198146
--------------------------------------------------------------------------------
```

In [88]:
```
r = r2_score(y_test,pred)
print("-"*80)
print("r2_score is :-",r)
print("-"*80)
```

```
--------------------------------------------------------------------------------
r2_score is :- 0.9186366933769297
--------------------------------------------------------------------------------
```

In [ ]:

Building Decision Tree Model

In [89]:
```
dt = DecisionTreeRegressor()
dt.fit(x_train,y_train)
```

Out[89]:
```
▾ DecisionTreeRegressor
DecisionTreeRegressor()
```

In [90]:
```
ac2 = dt.score(x_train,y_train)
ac3 = dt.score(x_test,y_test)
```

In [91]:
```
print("-"*80)
print("The Accuracy of train data is ",ac2)
print("-"*80)
```

```
print("The accuracy of test data is",ac3)
print("-"*80)
```

```
--------------------------------------------------------------------------------
The Accuracy of train data is  0.9998441722246297
--------------------------------------------------------------------------------
The accuracy of test data is 0.9106178288805218
--------------------------------------------------------------------------------
```

In [92]:
```
pred2 = dt.predict(x_test)
```

In [93]:
```
pred2
```

Out[93]:
```
array([2150000.,  220000.,  490000., ...,  250000.,  585000.,  800000.])
```

In [94]:
```
ms1 = mean_squared_error(y_test,pred2)
print("-"*80)
print("Mean squared error is :-",ms1)
print("-"*80)
```

```
--------------------------------------------------------------------------------
Mean squared error is :- 62843480616.57831
--------------------------------------------------------------------------------
```

In [95]:
```
ma1 = mean_absolute_error(y_test,pred2)
print("-"*80)
print("Mean absolute error is :-",ma1)
print("-"*80)
```

```
--------------------------------------------------------------------------------
Mean absolute error is :- 80233.33771085768
--------------------------------------------------------------------------------
```

In [96]:
```
map1 = mean_absolute_percentage_error(y_test,pred2)
print("-"*80)
print("Mean absolute percentage error is :-",map1)
print("-"*80)
```

```
--------------------------------------------------------------------------------
Mean absolute percentage error is :- 0.17913182289176513
--------------------------------------------------------------------------------
```

In [97]:
```
r1 = r2_score(y_test,pred2)
print("-"*80)
print("r2_score is :-",r1)
print("-"*80)
```

```
--------------------------------------------------------------------------------
r2_score is :- 0.9106178288805218
--------------------------------------------------------------------------------
```

In [ ]:

Building Random Forest Model

In [98]:
```
rf = RandomForestRegressor()
rf.fit(x_train,y_train)
```

Out[98]:
```
▾ RandomForestRegressor
RandomForestRegressor()
```

In [99]:
```
ac4 = rf.score(x_train,y_train)
ac5 = rf.score(x_test,y_test)
```

In [100…
```
print("-"*80)
print("The Accuracy of train data is ",ac4)
print("-"*80)
print("The accuracy of test data is",ac5)
print("-"*80)
```

```
--------------------------------------------------------------------------------
The Accuracy of train data is  0.99547751636116
--------------------------------------------------------------------------------
The accuracy of test data is 0.9736343750355003
--------------------------------------------------------------------------------
```

In [101…
```
pred3 = dt.predict(x_test)
```

In [102…

```
pred3
```

Out[102…

```
array([2150000.,  220000.,  490000., ...,  250000.,  585000.,  800000.])
```

In [103…

```
ms2 = mean_squared_error(y_test,pred3)
print("-"*80)
print("Mean squared error is :-",ms2)
print("-"*80)
```

```
--------------------------------------------------------------------------------
Mean squared error is :- 62843480616.57831
--------------------------------------------------------------------------------
```

In [104…

```
ma2 = mean_absolute_error(y_test,pred3)
print("-"*80)
print("Mean absolute error is :-",ma2)
print("-"*80)
```

```
--------------------------------------------------------------------------------
Mean absolute error is :- 80233.33771085768
--------------------------------------------------------------------------------
```

In [105…

```
map2 = mean_absolute_percentage_error(y_test,pred3)
print("-"*80)
print("Mean absolute percentage error is :-",map2)
print("-"*80)
```

```
--------------------------------------------------------------------------------
Mean absolute percentage error is :- 0.17913182289176513
--------------------------------------------------------------------------------
```

In [106…

```
r2= r2_score(y_test,pred3)
print("-"*80)
print("r2_score is :-",r2)
print("-"*80)
```

```
--------------------------------------------------------------------------------
r2_score is :- 0.9106178288805218
--------------------------------------------------------------------------------
```

In [ ]:

```

```

Models Analysis

Accuracy of Training Data.

- K-NN : 0.922589064130468
- Decision Tree : 0.9998441722246297
- Random Forest : 0.9956081941249877

Accuracy of Testing Data.

- K-NN : 0.9186366933769297
- Decision Tree : 0.9514476803980773
- Random Forest : 0.97555855394354

Mean_squared_error

- K-NN : 57205517818.904
- Decision Tree : 38103614870.08943
- Random Forest : 38103614870.08943

Mean_absolute_error

- K-NN : 138743.80098360655
- Decision Tree : 78577.46598954621

- Random Forest : 78577.46598954621

Mean_absolute_percentage_error

- K-NN : 0.38493022877198146
- Decision Tree : 0.18067570289696547
- Random Forest : 0.18067570289696547

r2_score

- K-NN : 0.9186366933769297
- Decision Tree : 0.9458052960915954
- Random Forest : 0.9458052960915954

In [ ]: