CAR PRICE PREDICTION

Submitted by:
Puram Naga Raju
Internship-23

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INTRODUCTION

With the covid 19 impact in the market, we have seen a lot of changes in the car market. Now some cars are in demand hence making them costly and some are not in demand hence cheaper. Predicting the price of used cars is both an important and interesting problem. The market value is based on a number of factors, including demand, supply, options, and incentives. The market value of a vehicle usually falls somewhere between the sticker price and the invoice price. Because the market value is an average, some people will pay more than that amount, while others will pay less.

A car's value is determined by many factors: the popularity of the make and model of your car, vehicle specifications, trim levels, physical appearance, mileage, consistent maintenance and working condition. Using this as a base, I have collected the data from “Cars24” website and here I have collected and scrapped the information of the cars with definite and significant features required for predicting the better model.

Once the data is collected, the data will be cleaned and pre-processed with all the necessary tools and the same will be used to build machine learning models in order to predict the price of the same.

Analytical Problem Framing:

Here our dataset has 7039 rows and 16 columns, using this dataset we will be building the model followed by training the data and then finally the model is tested by using 70% of the training data and 30% of the testing data. ➢ As we have pre-processed the data by removing the null values there may be chances of getting outliers and certain unknown values.

These columns are named when the data is collected but during the pre-processing there are few newly created columns which are extracted from the existing data and thus the number of columns increases and the columns are renamed.

Importing libraries :

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
```

Primarily these are the basic libraries which are imported and further the libraries necessary are imported.

Collecting the data :

```
data1 = pd.read_csv("cars1.csv")
data2 = pd.read_csv("cars2.csv")
data3 = pd.read_csv("cars3.csv")
data4 = pd.read_csv("cars4.csv")
data5 = pd.read_csv("cars5.csv")
data6 = pd.read_csv("cars6.csv")
data7 = pd.read_csv("cars7.csv")
data8 = pd.read_csv("cars8.csv")
data9 = pd.read_csv("cars9.csv")
data10 = pd.read_csv("cars10.csv")
data11 = pd.read_csv("cars11.csv")
data12 = pd.read_csv("cars12.csv")
data13 = pd.read_csv("cars13.csv")
```

- Here we have just collected the scraped data into different dataframes which needs to be concatenated for the complete data frame.

Combining the data into a dataframe :

```
data = pd.concat([data1,data2,data3,data4,data5,data6,data7,data8,data9,data10,data11,data12,data13], axis = 0, ignore_index=True)
data.head()
```

	Name	Brand	Model	Transmission	Year of Purchase	Kilometers Driven	Last Service	Fuel Type	Owner	Insurance	History	Location	EMI per month	Price
0	Swift VDI ABS MANUAL	Maruti	['VDI', 'ABS']	MANUAL	Mar-15	76,264 km	76,264km (22 Nov 2021)	Diesel	1st Owner	Valid upto Mar 2023 3rd Party	Non-Accidental	DELHI	₹9,840/month	₹4,26,499
1	Swift ZDI MANUAL	Maruti	['ZDI']	MANUAL	Jul-14	92,088 km	92,088km (08 Mar 2022)	Diesel	1st Owner	Valid upto Mar 2023 3rd Party	Non-Accidental	DELHI	₹9,710/month	₹4,20,799
2	Baleno ALPHA DDIS 190 MANUAL	Maruti	['ALPHA', 'DDIS', '190']	MANUAL	Jan-16	67,332 km	67,332km (16 Nov 2021)	Diesel	1st Owner	Valid upto Jul 2022 Third Party	Non-Accidental	DELHI	₹13,612/month	₹5,92,199
3	Baleno ALPHA DDIS 190 MANUAL	Maruti	['ALPHA', 'DDIS', '190']	MANUAL	Nov-15	76,135 km	76,135km (07 Mar 2022)	Diesel	2nd Owner	Valid upto Mar 2023 3rd Party	Non-Accidental	DELHI	₹12,672/month	₹5,50,899
4	Baleno ZETA 1.2 K12 MANUAL	Maruti	['ZETA', '1.2', 'K12']	MANUAL	Mar-18	37,786 km	37,786km (09 Feb 2022)	Petrol	1st Owner	Valid upto Mar 2023 3rd Party	Non-Accidental	DELHI	₹14,546/month	₹6,33,199

Observation : Here we can see that there is a lot of preprocessing to be done in the data for the better model and accuracy.

Information of the data :

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7039 entries, 0 to 7038
Data columns (total 14 columns):
 #   Column              Non-Null Count  Dtype
---  ------              --------------  -----
 0   Name                7039 non-null   object
 1   Brand               7039 non-null   object
 2   Model               7039 non-null   object
 3   Transmission        6956 non-null   object
 4   Year of Purchase    7039 non-null   object
 5   Kilometers Driven   7039 non-null   object
 6   Last Service        7039 non-null   object
 7   Fuel Type           7039 non-null   object
 8   Owner               7039 non-null   object
 9   Insurance           7039 non-null   object
 10  History             7039 non-null   object
 11  Location            6498 non-null   object
 12  EMI per month       7039 non-null   object
 13  Price               7039 non-null   object
dtypes: object(14)
memory usage: 770.0+ KB
```

Observation : Here we can see that all the columns are with Object datatype and also we can see that the data has null values in few columns which we have fill during the preprocessing of the data.

Null values of the data :

```
data.isnull().sum()
```

```
Name                   0
Brand                  0
Model                  0
Transmission          83
Year of Purchase       0
Kilometers Driven      0
Last Service           0
Fuel Type              0
Owner                  0
Insurance              0
History                0
Location             541
EMI per month          0
Price                  0
dtype: int64
```

Observation : Here we can see that the columns "Transmission" and "Location" have null values in them.

Description of the data :

```
pd.set_option("display.max_columns",None)
data.describe()
```

	Name	Brand	Model	Transmission	Year of Purchase	Kilometers Driven	Last Service	Fuel Type	Owner	Insurance	History	Location	EMI per month	Price
count	7039	7039	7039	6956	7039	7039	7039	7039	7039	7039	7039	6498	7039	7039
unique	791	24	669	2	256	4371	4473	4	4	96	1	14	2906	3170
top	Baleno DELTA 1.2 K12 MANUAL	Maruti	[VXI]	MANUAL	Jan-14	36,696 km	1,12,006km (03 Jan 2022)	Petrol	1st Owner	Valid upto Mar 2023 3rd Party	Non-Accidental	DELHI	₹0/month	₹3,44,999
freq	241	3636	816	6024	167	7	7	4501	5610	5032	7039	1853	541	14

Observation : Here we can see the unique values,frequently repeated values of the columns and also we can observe that the statistical information of the data is not presented as all the columns are with object type of the data.

➢ The dataset has only object datatype and so statistical description is not done over here.

➢ **Here the pre-processing of the data starts:** Here I have used splitting concept for the extraction of the required data from the extracted data and thus created new columns.

```
x = data["Name"]
```

```
list0 = []
for i in x:
    list0.append(i.split(' ')[0])
print(list0)
```

```
['Swift', 'Swift', 'Baleno', 'Baleno', 'Baleno', 'Swift', 'Swift', 'Swift', 'Ciaz', 'Ciaz', 'Baleno', 'Ertiga', 'Baleno', 'Sw
ift', 'Ciaz', 'Swift', 'Swift', 'Baleno', 'Ertiga', 'Alto', 'Swift', 'Swift', 'Swift', 'Ritz', 'Swift', 'Baleno', 'Baleno',
'Swift', 'Swift', 'Swift', 'Swift', 'Ciaz', 'Swift', 'Swift', 'Swift', 'Baleno', 'Swift', 'Baleno', 'Swift', 'Swift', 'Swif
t', 'Swift', 'Swift', 'Ciaz', 'Alto', 'Swift', 'Dzire', 'Baleno', 'Swift', 'Baleno', 'Swift', 'Baleno', 'Baleno', 'Swift', 'S
wift', 'Alto', 'Baleno', 'Swift', 'Swift', 'Swift', 'Swift', 'Swift', 'Swift', 'Ritz', 'Swift', 'Baleno', 'Baleno', 'Swift',
'Swift', 'Swift', 'Swift', 'Ciaz', 'Swift', 'Swift', 'Swift', 'Baleno', 'Swift', 'Baleno', 'Swift', 'Swift', 'IGNIS', 'Swif
t', 'Swift', 'Ertiga', 'Swift', 'Alto', 'Swift', 'Swift', 'Swift', 'Swift', 'IGNIS', 'Swift', 'Swift', 'Ertiga', 'Swift', 'Sw
ift', 'Swift', 'Ertiga', 'Baleno', 'Swift', 'Swift', 'Baleno', 'Swift', 'Swift', 'Baleno', 'Baleno', 'Swift', 'Swift', 'Swif
t', 'Ciaz', 'Swift', 'Swift', 'Baleno', 'Swift', 'Swift', 'Baleno', 'Swift', 'Swift', 'Swift', 'Swift', 'Baleno', 'Swift', 'S
wift', 'Swift', 'Swift', 'Dzire', 'Ritz', 'Dzire', 'Swift', 'Swift', 'Swift', 'Ritz', 'Baleno', 'Dzire', 'Dzire', 'Ertiga',
'Baleno', 'Ritz', 'Swift', 'Ertiga', 'Celerio', 'Swift', 'Swift', 'Swift', 'Celerio', 'Swift', 'Swift', 'Alto', 'Swift', 'Swi
ft', 'Swift', 'Ciaz', 'Dzire', 'Swift', 'Ciaz', 'Ertiga', 'Baleno', 'Swift', 'Baleno', 'Swift', 'Swift', 'Ciaz', 'Swift', 'Sw
ift', 'Baleno', 'Swift', 'Swift', 'Baleno', 'Swift', 'Swift', 'Swift', 'Swift', 'Swift', 'Ritz', 'Swift', 'Swift', 'Baleno',
'Baleno', 'Dzire', 'IGNIS', 'Baleno', 'Dzire', 'Celerio', 'Swift', 'Baleno', 'Baleno', 'Swift', 'Swift', 'Swift', 'Swift', 'S
wift', 'Swift', 'Baleno', 'Ciaz', 'Swift', 'Baleno', 'Swift', 'Swift', 'Ritz', 'IGNIS', 'Swift', 'Ertiga', 'Baleno', 'Swift',
'Swift', 'Swift', 'Swift', 'IGNIS', 'Swift', 'Swift', 'Ertiga', 'Swift', 'Ertiga', 'Swift', 'Ertiga', 'Swift', 'Swift', 'Alt
o', 'Swift', 'Dzire', 'Swift', 'Baleno', 'Swift', 'Swift', 'Alto', 'Swift', 'Swift', 'Swift', 'Swift', 'Ciaz', 'Alto', 'Alt
o', 'S', 'Swift', 'Alto', 'Alto', 'Swift', 'S', 'Vitara', 'Swift', 'Alto', 'Swift', 'Vitara', 'Vitara', 'Swift', 'Vitara', 'V
itara', 'Swift', 'Vitara', 'Alto', 'Alto', 'S', 'Alto', 'Celerio', 'Swift', 'Alto', 'S', 'Alto', 'Vitara', 'Swift', 'Alto',
```

```
Name_of_the_car = list0
```

```
df = pd.DataFrame()
df["Name_of_the_car"] = list0
df
```

	Name_of_the_car
0	Swift
1	Swift
2	Baleno
3	Baleno
4	Baleno
...	...
7034	Alto
7035	
7036	maze
7037	
7038	

7039 rows × 1 columns

```
Car_name = df
```

```
data.insert(len(data.columns),"Car_name",Car_name.values)
```

Observation : Here we have inserted the craeted column into the dataframe.

```
data.drop(['Name'],axis = 1,inplace = True)
```

Observation : Here we have dropped the parent column "Name".

➢ Here the preprocessing the column "name" is done and the new column got created.

Year of Purchase :

```
yea = data["Year of Purchase"]
```

```
list1 = []
for j in yea:
    list1.append(j.strip(' ')[0:3])
print(list1)
```

```
'Apr', 'Jan', 'Jul', 'Apr', 'Dec', 'May', 'Apr', 'May', 'May', 'Aug', 'Nov', 'May', 'Feb', 'Mar', 'Oct', 'Feb', 'Mar', 'Jun',
'Mar', 'Oct', 'Jan', 'Apr', 'Nov', 'Jan', 'Aug', 'Jan', 'Nov', 'Sep', 'Oct', 'Jul', 'Dec', 'Nov', 'Jul', 'May', 'Jan', 'Nov',
'Sep', 'Mar', 'Feb', 'Apr', 'May', 'May', 'Mar', 'Aug', 'Apr', 'Apr', 'Mar', 'Oct', 'Mar', 'Jan', 'Jan', 'Nov', 'Feb', 'Mar',
'Jun', 'Feb', 'Mar', 'Oct', 'Aug', 'Apr', 'Feb', 'Jan', 'Aug', 'Feb', 'Apr', 'Jan', 'Nov', 'Dec', 'Feb', 'Nov', 'May', 'May',
'Sep', 'Jul', 'Nov', 'Jul', 'Feb', 'Aug', 'Sep', 'Nov', 'Aug', 'Jan', 'Mar', 'Jan', 'May', 'Jan', 'Aug', 'Jan', 'Jun', 'Jan',
'Feb', 'Jun', 'Nov', 'Nov', 'Jul', 'Feb', 'Jan', 'Aug', 'Apr', 'Oct', 'Jun', 'Nov', 'Jul', 'Oct', 'Feb', 'Apr', 'Feb', 'Feb',
'Mar', 'Oct', 'Aug', 'Apr', 'Feb', 'Jan', 'Aug', 'Feb', 'Apr', 'Jan', 'Nov', 'Feb', 'Sep', 'Nov', 'Dec', 'Nov', 'Oct', 'Jun',
'Jan', 'Dec', 'Jun', 'May', 'Mar', 'Jan', 'May', 'Jan', 'Jan', 'Aug', 'Jan', 'May', 'Apr', 'Aug', 'Jan', 'Jan', 'Mar', 'Mar',
'Jul', 'Oct', 'Jun', 'Mar', 'Jan', 'Aug', 'Jul', 'Nov', 'Jan', 'Jul', 'Nov', 'Mar', 'Mar', 'Sep', 'Apr', 'Jul', 'May', 'Aug',
'Dec', 'Nov', 'May', 'Jul', 'Apr', 'Oct', 'Dec', 'Sep', 'May', 'Apr', 'Feb', 'Oct', 'Nov', 'Jun', 'Dec', 'May', 'Jan', 'Jan',
'Aug', 'Jan', 'Mar', 'Mar', 'Jan', 'Jan', 'Apr', 'Aug', 'Aug', 'Aug', 'Jul', 'Feb', 'Jan', 'Feb', 'Aug', 'Feb', 'Mar', 'Jul',
'Oct', 'Apr', 'Jan', 'Mar', 'Mar', 'Nov', 'Jul', 'Feb', 'Apr', 'Jan', 'Mar', 'Mar', 'Jan', 'Jan', 'Apr', 'Jan', 'Mar', 'Mar',
'Jan', 'Sep', 'Apr', 'Apr', 'Jan', 'Mar', 'Jan', 'Mar', 'Sep', 'Apr', 'Jun', 'Nov', 'Jan', 'Feb', 'May', 'Oct', 'Aug', 'Apr',
'Apr', 'Jan', 'Jan', 'Jul', 'Nov', 'Feb', 'Feb', 'Oct', 'Jan', 'Feb', 'Jan', 'Jun', 'Apr', 'Apr', 'Jan', 'Jan', 'Feb', 'May',
'Oct', 'Oct', 'Jul', 'Jan', 'Jan', 'Aug', 'Jan', 'Aug', 'Feb', 'Jan', 'Nov', 'Feb', 'May', 'Feb', 'Mar', 'Mar', 'Mar', 'Nov',
'Aug', 'Oct', 'May', 'Apr', 'Jan', 'Aug', 'Nov', 'Dec', 'Jan', 'Dec', 'Sep', 'May', 'Feb', 'Sep', 'Jan', 'Oct', 'Aug', 'Apr',
'Jul', 'Mar', 'Jun', 'Jan', 'May', 'Mar', 'Aug', 'Dec', 'Feb', 'Mar', 'Aug', 'Jan', 'Jun', 'Jul', 'May', 'Mar', 'Sep', 'May',
'Jan', 'Oct', 'Mar', 'May', 'Jun', 'Dec', 'Apr', 'Mar', 'Oct', 'Jan', 'Nov', 'Jun', 'Sep', 'Feb', 'May', 'Aug', 'Apr', 'Jun',
'Mar', 'Jun', 'Mar', 'Jun', 'Jan', 'Apr', 'Mar', 'Sep', 'Mar', 'Feb', 'Feb', 'Oct', 'Dec', 'Oct', 'Dec', 'Nov', 'Jan', 'Apr',
```

```
Purchase_month = list1
```

```
df1 = pd.DataFrame()
df1["Purchase_month"] = list1
df1
```

	Purchase_month
0	Mar
1	Jul
2	Jan
3	Nov
4	Mar
...	...
7034	Feb
7035	Jan
7036	Sep
7037	Aug
7038	Feb

```
list2 = []
for k in yea:
    list2.append(k.strip('')[-2:])
print(list2)
```

```
'14', '10', '14', '17', '18', '13', '14', '15', '14', '17', '14', '15', '15', '15', '17', '17', '15', '14', '17', '15', '13',
'13', '13', '20', '13', '13', '14', '15', '18', '15', '15', '14', '14', '16', '18', '17', '16', '15', '13', '18', '17', '15',
'15', '17', '15', '14', '14', '17', '14', '13', '17', '13', '15', '17', '13', '15', '15', '14', '15', '15', '13', '13', '17',
'17', '15', '17', '14', '15', '14', '14', '15', '18', '18', '15', '17', '18', '14', '14', '19', '13', '13', '15', '16', '14',
'15', '19', '13', '12', '13', '17', '17', '17', '14', '13', '18', '14', '16', '12', '14', '17', '14', '13', '17', '13', '15',
'17', '13', '15', '15', '14', '15', '13', '12', '15', '17', '18', '17', '18', '18', '18', '18', '13', '19', '16', '15', '14',
'12', '14', '13', '13', '15', '20', '17', '13', '16', '13', '13', '14', '19', '15', '14', '19', '13', '13', '13', '14', '18',
'16', '15', '17', '13', '15', '18', '13', '13', '13', '20', '15', '17', '14', '19', '13', '15', '20', '14', '13', '17', '15',
'17', '20', '18', '20', '14', '18', '15', '14', '20', '17', '14', '19', '15', '18', '18', '12', '19', '17', '14', '16', '15',
'17', '16', '15', '18', '13', '12', '20', '19', '16', '14', '18', '15', '14', '20', '17', '14', '19', '18', '19', '15', '19',
'16', '19', '15', '19', '16', '14', '16', '19', '16', '17', '20', '13', '17', '16', '18', '18', '13', '16', '16', '09', '18',
'18', '16', '13', '11', '21', '19', '18', '18', '13', '17', '20', '13', '17', '16', '16', '16', '17', '16', '21', '18', '11',
'13', '09', '18', '18', '18', '18', '16', '18', '12', '15', '14', '13', '14', '13', '14', '16', '17', '19', '17', '18', '12',
'16', '18', '14', '17', '16', '17', '16', '14', '16', '17', '18', '12', '20', '12', '19', '15', '17', '17', '15', '14', '09',
'13', '17', '13', '18', '20', '18', '13', '13', '11', '10', '17', '18', '20', '20', '18', '14', '13', '18', '18', '14', '19',
'17', '19', '17', '13', '18', '09', '10', '19', '18', '17', '14', '19', '16', '16', '16', '18', '16', '12', '17', '18', '15',
'17', '18', '18', '18', '19', '16', '19', '19', '17', '18', '16', '16', '16', '19', '15', '16', '16', '12', '16', '18', '15',
'18', '16', '18', '18', '15', '14', '17', '15', '17', '14', '19', '17', '18', '17', '18', '16', '16', '16', '19', '15', '16',
'16', '12', '16', '18', '15', '18', '16', '16', '16', '16', '18', '19', '14', '17', '13', '17', '12', '18', '14', '17', '17',
```

```python
purchase_year = list2
```

```python
df2 = pd.DataFrame()
df2["purchase_year"] = list2
df2
```

	purchase_year
0	15
1	14
2	16
3	15
4	18
...	...
7034	19
7035	19
7036	20
7037	17
7038	18

```python
data.insert(len(data.columns),"Purchase_month",Purchase_month.values)
```

```python
data.insert(len(data.columns),"Purchase_year",Purchase_year.values)
```

Observation : Here we can see that we are inserting the created columns into the dataframe.

```python
data.shape
```

```
(7039, 16)
```

```python
data.drop(['Year of Purchase'],axis = 1,inplace = True)
```

Observation : Here we can see that we have dropped the parent column "Year of Purchase".

➢ Here the new columns like "Purchase month" and "purchase year" are created and after creating these new columns the parent columns are dropped.

Kilometers Driven :

```python
kms = data["Kilometers Driven"]
```

```python
list3 = []
for i in kms:
    list3.append(i.split(" ")[0].replace(",",""))
print(list3)
```

```
['76264', '32088', '67332', '76135', '37786', '74447', '70112', '68749', '121025', '83877', '18364', '27611', '88392', '7726
[illegible]
```

```python
kilometers_driven = list3
```

```python
df3 = pd.DataFrame()
df3["Kilometers_Driven"] = list3
df3
```

	Kilometers_Driven
0	76264
1	32088
2	67332
3	76135
4	37786
...	...
7034	95530
7035	31962
7036	15472
7037	6427
7038	30407

```python
data.insert(len(data.columns),"Kilometers_Driven",Kilometers_Driven.values)
```

Observation : Here we have inserted the created column into the dataframe.

```python
data.drop(['Kilometers Driven'],axis = 1,inplace = True)
```

Observation : Here we have dropped the parent column "Kilometers Driven" .

➢ Here the column "Kilometres Driven" is deleted and the column with the same name but different extracted data is created.

```python
service= data["Last Service"].str.split( '(' )
```

```python
list4=[]
for m in range(len(service)):
    print(service[m][1][:-1])
    list4 += [service[m][1][:-1]]
print(list4)
```

```
14 Mar 2022
23 Feb 2022
11 Mar 2022
07 Feb 2022
```

```python
service = df4
service
```

	service
0	22 Nov 2021
1	08 Mar 2022
2	16 Nov 2021
3	07 Mar 2022
4	09 Feb 2022
...	...
7034	24 Dec 2021
7035	01 Mar 2022
7036	21 Dec 2021
7037	21 Dec 2021
7038	11 Jan 2022

```python
data.insert(len(data.columns),"service",service.values)
```

Observation : Here we have inserted the column into the dataframe.

```python
data.drop(['Last Service'],axis = 1,inplace = True)
```

Observation : Here we can see that we can see that we have dropped the parent column "Last Service".

Owner :

```python
own = data["Owner"]
```

```python
list5 = []
for n in own:
    list5.append(n.strip(" ")[0])
print(list5)
```

```
['1', '1', '1', '2', '1', '1', '1', '1', '2', '1'
'2', '2', '1', '1', '1', '1', '1', '1', '1', '1',
'1', '1', '1', '1', '1', '1', '1', '1', '1', '1',
'1', '1', '1', '1', '2', '3', '1', '1', '3', '1',
```

```python
owner = list5
```

```python
df4 = pd.DataFrame()
df4["owner"] = list5
df4
```

	owner
0	1
1	1
2	1
3	2
4	1
...	...
7034	2
7035	1
7036	1
7037	1
7038	1

```python
data.insert(len(data.columns),"owner",owner.values)
```

Observation : Here we have inserted the created column into the dataframe.

```python
data.drop(['Owner'],axis = 1,inplace = True)
```

Observation : Here we have dropped the parent column "Owner".

- Here we have created the new column named "owner" and the parent column is deleted.

Insurance :

```python
ins = data["Insurance"]
```

```python
list5 = []   ## insurance year
for p in ins:
    list5.append(p.split(" ")[2:4][1])
print(list5)
```

```
[illegible]
```

```python
Year_of_insurance = list5
```

```python
df5 = pd.DataFrame()
df5["Year_of_insurance"] = list5
df5
```

	Year_of_insurance
0	2023
1	2023
2	2022
3	2023
4	2023
...	...
7034	2023
7035	2023
7036	2023
7037	2023
7038	2022

```python
data.insert(len(data.columns),"Year_of_insurance",Year_of_insurance.values)
```

```python
list6 = []
for q in ins:
    list6.append(q.split(" ")[2:4][0])
print(list6)
```

```
['Mar', 'Mar', 'Jul', 'Mar', 'Mar', 'Mar', 'Mar', 'Mar', 'Mar', 'Mar', 'Mar', 'Mar', 'Sept', 'Mar', 'Sept', 'Mar', 'Mar', 'Ma
r', 'Mar', 'Mar', 'Aug', 'Mar', 'Mar', 'Mar', 'Mar', 'Sept', 'Mar', 'Mar', 'Mar', 'Jul', 'Mar', 'Mar', 'Mar', 'Mar', 'Mar',
'Dec', 'Mar', 'Nov', 'Mar', 'Mar', 'Dec', 'Mar', 'Mar', 'Mar', 'Mar', 'Mar', 'Nov', 'Mar', 'Mar', 'Dec', 'Mar', 'Mar', 'Mar',
'Mar', 'Mar', 'Dec', 'Mar', 'Mar', 'Mar', 'Mar', 'Aug', 'Mar', 'Mar', 'Mar', 'Mar', 'Sept', 'Mar', 'Mar', 'Mar', 'Jul', 'Ma
r', 'Mar', 'Mar', 'Mar', 'Mar', 'Dec', 'Mar', 'Nov', 'Mar', 'Mar', 'Sept', 'Nov', 'Mar', 'Mar', 'Nov', 'Aug', 'Mar', 'Mar',
'Mar', 'Mar', 'Mar', 'Mar', 'Mar', 'Mar', 'Mar', 'Mar', 'Mar', 'Mar', 'Mar', 'Mar', 'Mar', 'Mar', 'Mar', 'Mar', 'Dec', 'Sep
t', 'Jul', 'Mar', 'Mar', 'Mar', 'Mar', 'Mar', 'Mar', 'Mar', 'Mar', 'Nov', 'Mar', 'Mar', 'Mar', 'Mar', 'Dec', 'Mar', 'Mar', 'M
ar', 'Mar', 'Mar', 'Mar', 'Mar', 'Mar', 'Mar', 'Aug', 'Mar', 'Mar', 'Nov', 'Jan', 'Mar', 'Feb', 'Mar', 'Mar', 'Aug', 'Jul',
'Aug', 'Mar', 'Mar', 'Mar', 'Mar', 'Mar', 'Jul', 'Mar', 'Mar', 'Mar', 'Mar', 'Nov', 'Mar', 'Mar', 'Mar', 'Mar', 'Mar', 'Mar',
'Mar', 'Mar', 'Mar', 'Mar', 'Mar', 'Mar', 'Mar', 'Mar', 'Nov', 'Mar', 'Mar', 'Mar', 'Mar', 'Mar', 'Mar', 'Mar', 'Mar', 'Nov',
'Mar', 'Sept', 'Mar', 'Mar', 'Jul', 'Mar', 'Jun', 'Mar', 'Jun', 'Mar', 'Mar', 'Jan', 'Mar', 'Mar', 'Mar', 'Mar', 'Jan', 'Fe
b', 'Mar', 'Mar', 'Mar', 'Mar', 'Mar', 'Mar', 'Mar', 'Mar', 'Aug', 'Mar', 'Mar', 'Mar', 'Mar', 'Mar', 'Mar', 'Mar', 'Mar', 'M
ar', 'Mar', 'Mar', 'Mar', 'Nov', 'Mar', 'Aug', 'Mar', 'Nov', 'Mar', 'Dec', 'Mar', 'Mar', 'Mar', 'Dec', 'Mar', 'Mar', 'Mar',
'Mar', 'Mar', 'Mar', 'Oct', 'Mar', 'Mar', 'Jul', 'Mar', 'Jan', 'Mar', 'Mar', 'Oct', 'Mar', 'Aug', 'Mar', 'Mar', 'Mar', 'Mar',
'Mar', 'Mar', 'Mar', 'Mar', 'Mar', 'Mar', 'Mar', 'Mar', 'Mar', 'Mar', 'Mar', 'Mar', 'Mar', 'Mar', 'Jul', 'Mar', 'Jan', 'Mar',
'Mar', 'Mar', 'Mar', 'Mar', 'Mar', 'Mar', 'Mar', 'Mar', 'Mar', 'Mar', 'Mar', 'Dec', 'Mar', 'Jul', 'Mar', 'Mar', 'Mar', 'Mar',
'Mar', 'Mar', 'Mar', 'Mar', 'Mar', 'Mar', 'Mar', 'Mar', 'Mar', 'Mar', 'Mar', 'Oct', 'Mar', 'Mar', 'Mar', 'Mar', 'Mar', 'Mar',
'Mar', 'Mar', 'Mar', 'Mar', 'Mar', 'Oct', 'Mar', 'Mar', 'Mar', 'Mar', 'Mar', 'Dec', 'Mar', 'Mar', 'Mar', 'Mar', 'Mar', 'Mar',
'Mar', 'Mar', 'Mar', 'Nov', 'Aug', 'Nov', 'Jan', 'Mar', 'Mar', 'Mar', 'Dec', 'Mar', 'Mar', 'Mar', 'Mar', 'Mar', 'Mar', 'Mar',
```

```
Month_of_insurance = lists
```

```
df6 = pd.DataFrame()
df6["Month_of_insurance"] = lists
df6
```

	Month_of_insurance
0	Mar
1	Mar
2	Jul
3	Mar
4	Mar
...	...
7034	Mar
7035	Mar
7036	Mar
7037	Mar
7038	Oct

```
data.insert(len(data.columns),"Month_of_insurance",Month_of_insurance.values)
```

```
data.drop(['Insurance'],axis = 1,inplace = True)
```

- Here we have dropped the parent column after creating the new columns "Year of insurance" and "Month of insurance".

EMI per month :

```
em = data["EMI per month"]
```

```
listx = []   #yes
for i in em:
    listx.append(i.split("₹")[1].split("/")[0].replace(",",""))
print(listx)
```

[illegible]

```
EMI = listx
```

```
df8 = pd.DataFrame()
df8["EMI"] = listx
df8
```

	EMI
0	9840
1	9710
2	13812
3	12672
4	14546
...	...
7034	0
7035	0
7036	0
7037	0
7038	0

```
data.insert(len(data.columns),"EMI",EMI.values)
```

Observation : here we have inserted the created column into the dataframe

```
data.drop(['EMI per month'],axis = 1,inplace = True)
```

Observation : Here we have seen that we have dropped the parent column.

- Here we have added the column into the dataframe and deleted the parent column.

Price :

```
pric = data["Price"]
```

```
list11 = []  #service #
for x in pric:
    list11.append(x.replace("₹","").replace(",",""))
print(list11)
```

```
Car_Price = list11
```

```
df11 = pd.DataFrame()
df11["Car_Price"] = list11
df11
```

	Car_Price
0	420499
1	420799
2	582199
3	550899
4	633199
...	...
7034	385699
7035	630899
7036	774899
7037	631399
7038	533099

```
data.insert(len(data.columns),"Car_Price",Car_Price.values)
```

Observation : Here we have inserted the created column into dataframe

```
data.drop(['Price'],axis = 1,inplace = True)
```

Here I have dropped the parent column and in place the extracted new column is replaced.

Now here we drop the unnecessary column “History” in which we have the same data in all the records and is not useful for our prediction and so we delete the column.

```
data["History"].unique()
```

```
array(['Non-Accidental'], dtype=object)
```

```
data.drop(['History'],axis = 1,inplace = True)
```

Observation : Here we have seen that the column "History" is with single value "Non-Accidental" and is also of no effect in the model and so we can drop this column.

Filling the null-values :

```
data['Location'] = data['Location'].fillna(data['Location'].mode()[0])
```

```
data['Transmission'] = data['Transmission'].fillna(data['Transmission'].mode()[0])
```

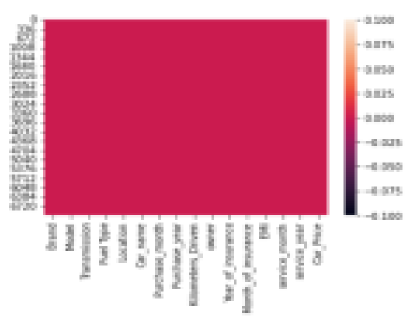
```
data.isnull().sum()
```

```
Brand                  0
Model                  0
Transmission           0
Fuel Type              0
Location               0
Car_name               0
Purchase_month         0
Purchase_year          0
Kilometers_Driven      0
owner                  0
Year_of_insurance      0
Month_of_insurance     0
EMI                    0
service_month          0
service_year           0
Car_Price              0
dtype: int64
```

➢ Here we have filled all the null values.

```
sns.heatmap(data.isnull())
```

```
<AxesSubplot:>
```



Here we can see that there are no null values in our dataset now and thus we can continue for model building.

Here we know that all our features are of the same object data type even after extracting the required data from the parent columns and so here we are going to change the datatype of the columns where it is necessary

Changing the datatypes :

```
data['Purchase_year'] = data['Purchase_year'].astype('int')
```

```
data['Purchase_year'].dtype
```

```
dtype('int32')
```

Observation : Here we have converted the created column "Purchase_year" into "int" datatype.

```
data['Kilometers_Driven'] = data['Kilometers_Driven'].astype('int')
```

```
data['Kilometers_Driven'].dtype
```

```
dtype('int32')
```

Observation : Here we have converted the created column "Kilometers_Driven" into "int" datatype.

```
data['owner'] = data['owner'].astype('int')
```

```
data['owner'].dtype
```

```
dtype('int32')
```

Observation : Here we have converted the created column "owner" into "int" datatype.

```
data['Year_of_insurance'] = data['Year_of_insurance'].astype('int')
```

```
data['Year_of_insurance'].dtype
```

```
dtype('int32')
```

Observation : Here we have converted the created column "Year_of_insurance" into "int" datatype.

```
data['EMI'] = data['EMI'].astype('int')
```

```
data['EMI'].dtype
```

```
dtype('int32')
```

Observation : Here we have converted the created column "EMI" into "int" datatype.

```
data['service_year'] = data['service_year'].astype('int')
```

```
data['service_year'].dtype
```

```
dtype('int32')
```

Observation : Here we have converted the created column "service_year" into "int" datatype.

```
data['Car_Price'] = data['Car_Price'].astype('int')
```

```
data['Car_Price'].dtype
```

```
dtype('int32')
```

Observation : Here we have converted the created column "Car_Price" into "int" datatype

Checking the datatypes of the columns again:

```
data.dtypes
```

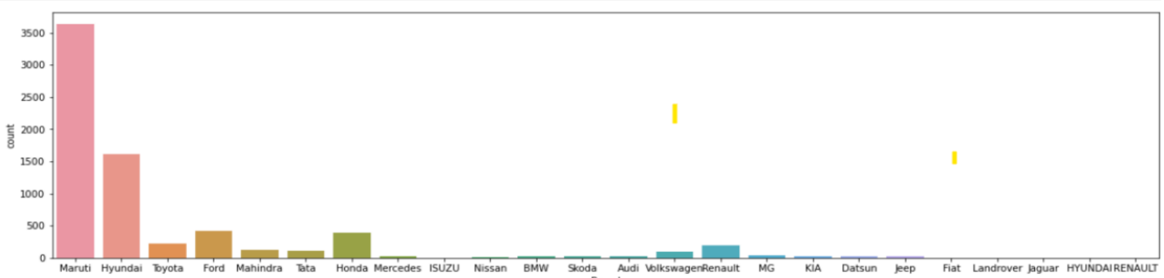
```
Brand                  object
Model                  object
Transmission           object
Fuel Type              object
Location               object
Car_name               object
Purchase_month         object
Purchase_year           int32
Kilometers_Driven       int32
owner                   int32
Year_of_insurance       int32
Month_of_insurance     object
EMI                     int32
service_month          object
service_year            int32
Car_Price               int32
dtype: object
```

Observation : Here we can see that the columsn have changed their datatypes.

Now here we will move to the visualization part where we will be going to visualize the features of our dataset and analyze them.

Brand :

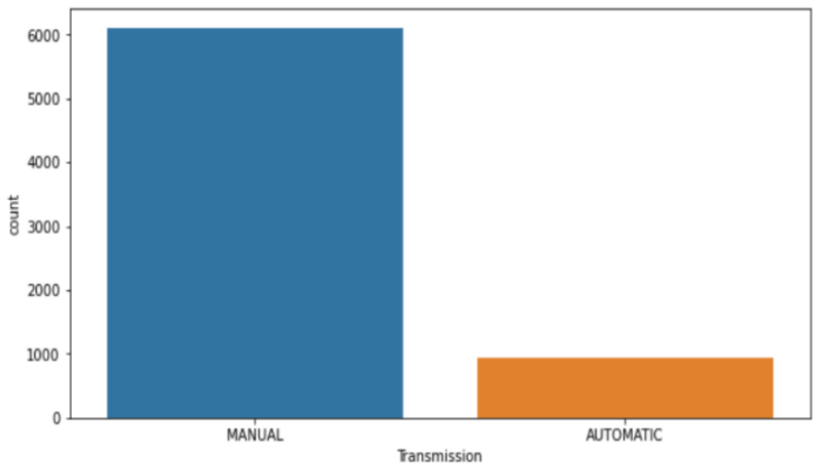
```
# Brand
plt.figure(figsize=(20,5))
sns.countplot(data.Brand);
```



Observation : Here we have seen that the column has the highest count for the attribute "Maruti" followed by "Hyundai" and the least count is for "Nissan".

Transmission :

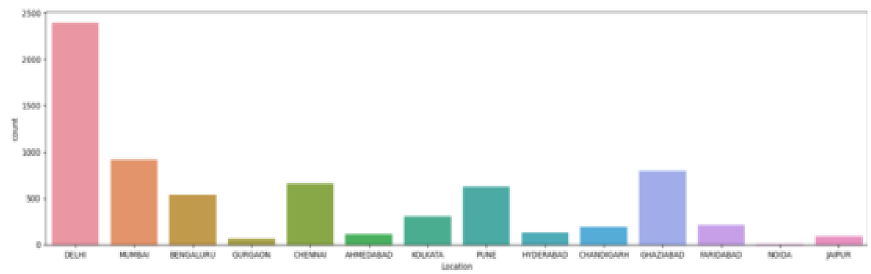
```
# Transmission
plt.figure(figsize=(10,5))
sns.countplot(data.Transmission);
```



Observation : here we can see that the column has the highest count for the attribute "Manual" and the least count is for "Automatic".

Location :

```
plt.figure(figsize=(20,5),dpi = 100)
sns.countplot(data.Location);
```

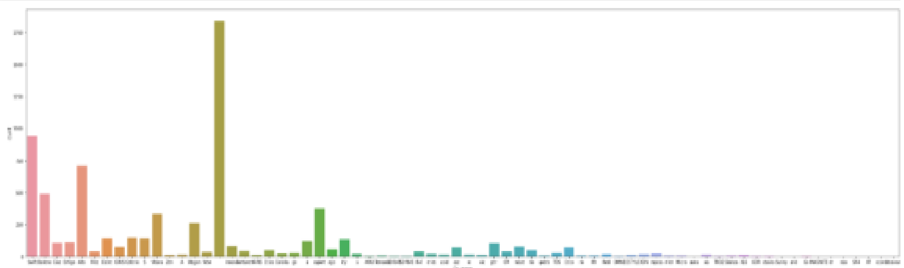


Observation : here we can see that the highest count is for the attribute "Delhi" followed by "Ghazlabad" and the least count is for the category "Noida".

Car_name :

```
Car_name

plt.figure(figsize=(40,10))
sns.countplot(data.Car_name);
```

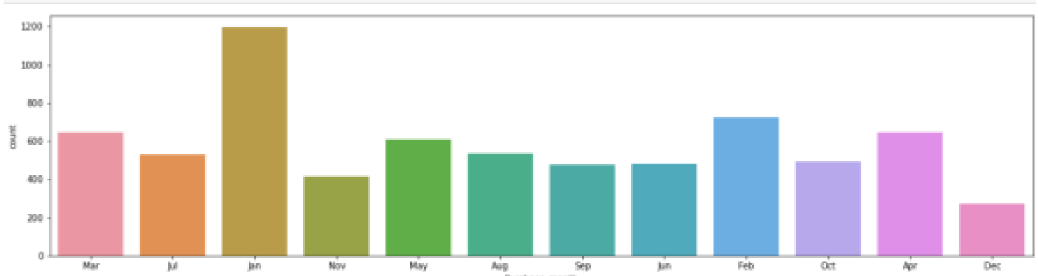


Observation : here we can see that the highest count is for the attribute "Innova" followed by "Swift" and the least count is for thye attribute "Aris".

Purchase_month :

```
Purchase_month

plt.figure(figsize=(20,5))
sns.countplot(data.Purchase_month);
```



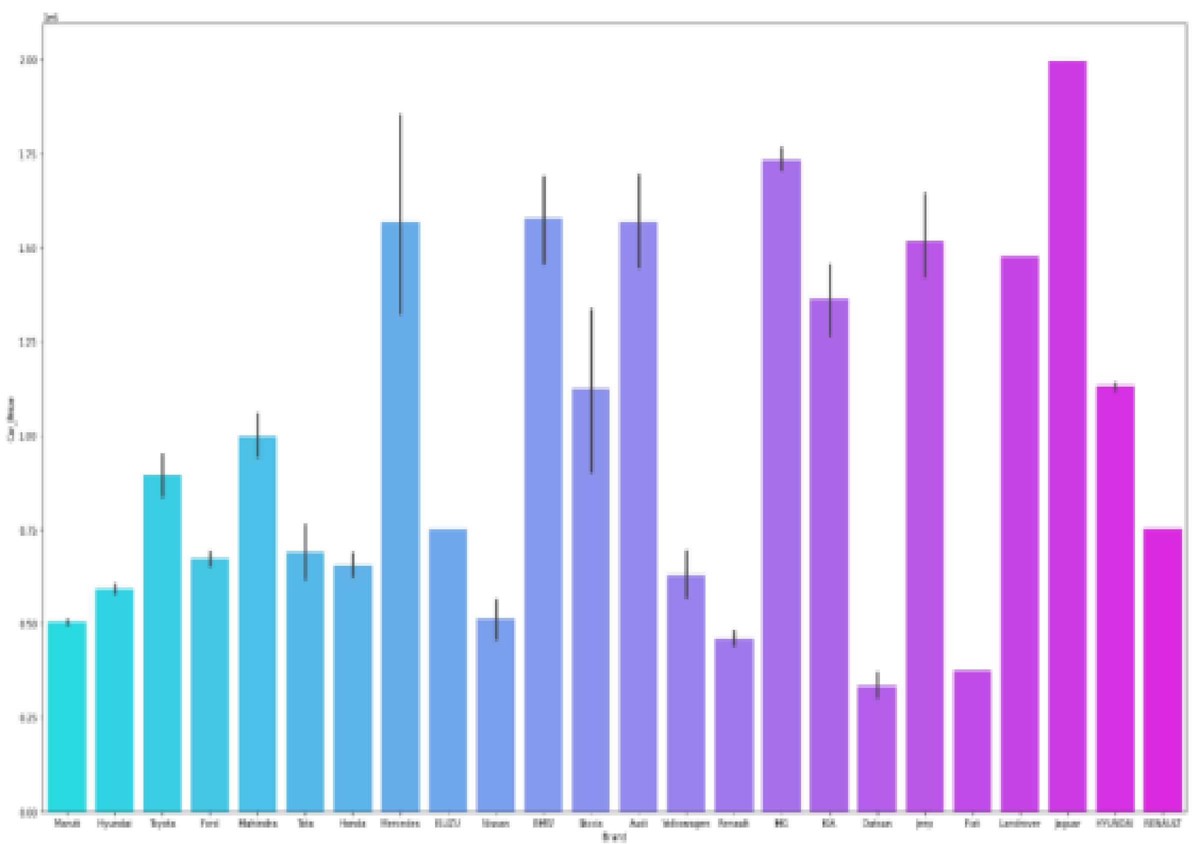
Observation : here we can see that the attribute with the highest count in the column is "Jan" followed by "Feb" and the least count is for the attribute "Dec".

These are a few features for which we have done Univariate analysis, now let’s move to Bivariate analysis of the features of the data.

Brand with Car_price :

```
plt.figure(figsize = (25,15))
sns.barplot(x = 'Brand', y = 'Car_Price', data = data, palette = 'cool')
```

<AxesSubplot:xlabel='Brand', ylabel='Car_Price'>



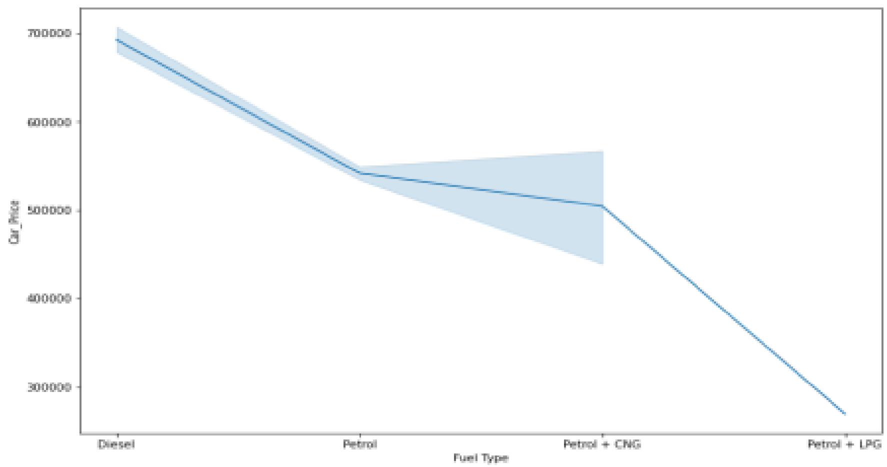
Observation : here we can see that the brand with highest price is "Jaguar" and the least price is "Datsun".

Fuel Type with car_price :

```
#Fuel Type

plt.figure(figsize = (12,8))
sns.lineplot(x = 'Fuel Type', y = 'Car_Price', data = data, palette = 'Blues')
```

```
<AxesSubplot:xlabel='Fuel Type', ylabel='Car_Price'>
```



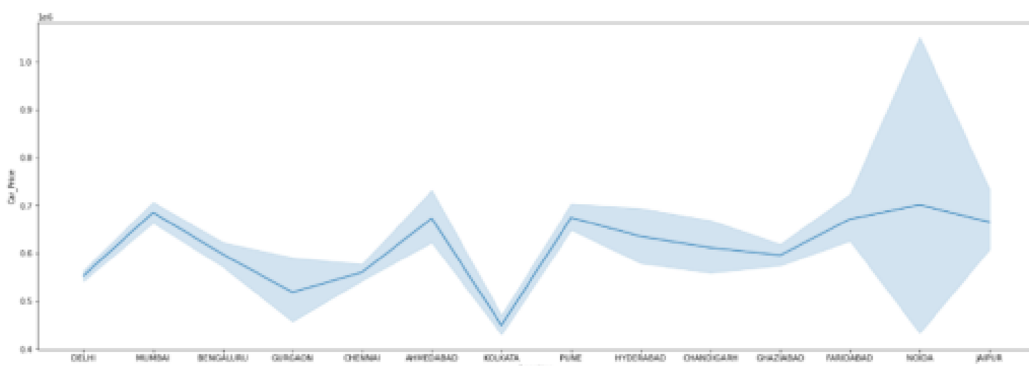
Observation : here we can see that the highest price is for the category "Diesel" and the least price is for the category "Petrol + LPG"

Location with car_price :

```
#Location

plt.figure(figsize = (22,8))
sns.lineplot(x = 'Location', y = 'Car_Price', data = data, palette = 'Blues')
```

```
<AxesSubplot:xlabel='Location', ylabel='Car_Price'>
```



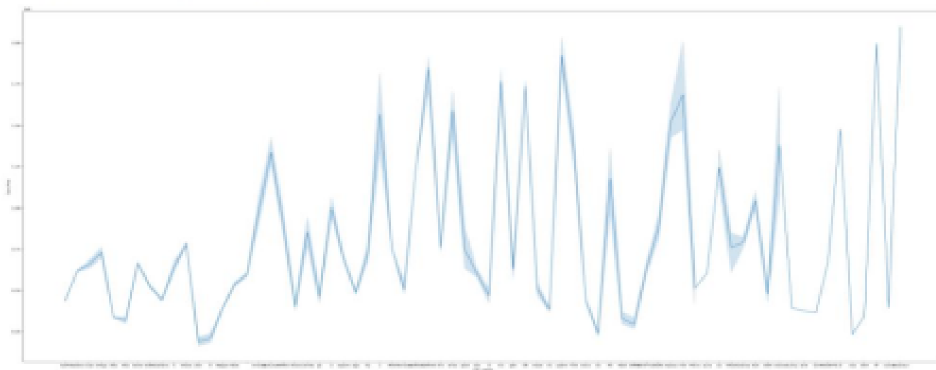
Observation : here we can see that all the locations the car_price is almost similar .

Car_name with car_price :

```
# Car_name

plt.figure(figsize = (42,20),dpi = 500)
sns.lineplot(x = 'Car_name', y = 'Car_Price', data = data, palette = 'Blues')
```

```
<AxesSubplot:xlabel='Car_name', ylabel='Car_Price'>
```



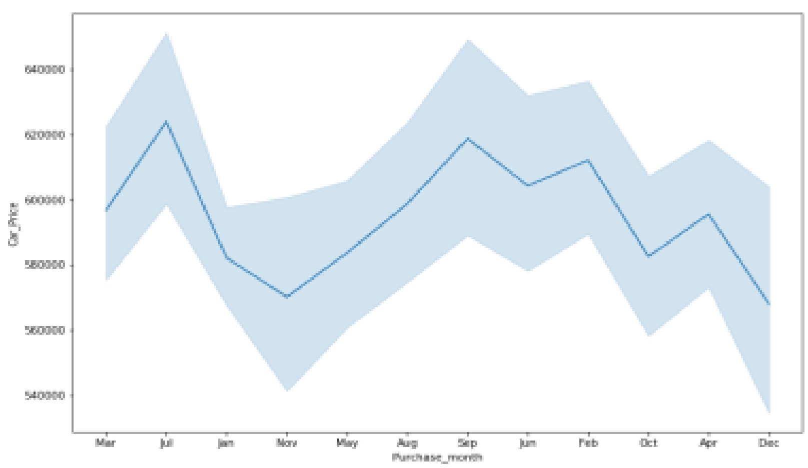
Observation : Here we can see that the highest car_price is for the category XF.Cardeavour and most of them have similar price ranges.

Purchase_month with car_price :

```
# Purchase_month

plt.figure(figsize = (12,8))
sns.lineplot(x = 'Purchase_month', y = 'Car_Price', data = data, palette = 'Blues')
```

```
<AxesSubplot:xlabel='Purchase_month', ylabel='Car_Price'>
```

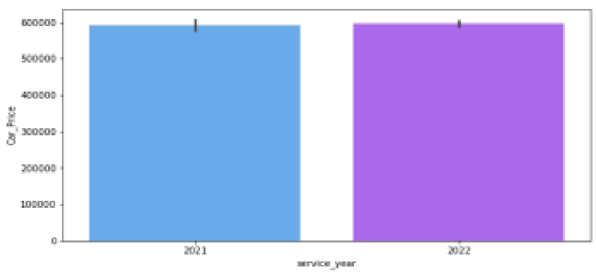


Observation : here we can see that the column has the highest price for the category "jul" with 620000 and the least is for the category "Dec".

service_year with Car_Price :

```
plt.figure(figsize = (10,5))
sns.barplot(x = 'service_year', y = 'Car_Price', data = data, palette = 'cool')
```

<AxesSubplot:xlabel='service_year', ylabel='Car_Price'>

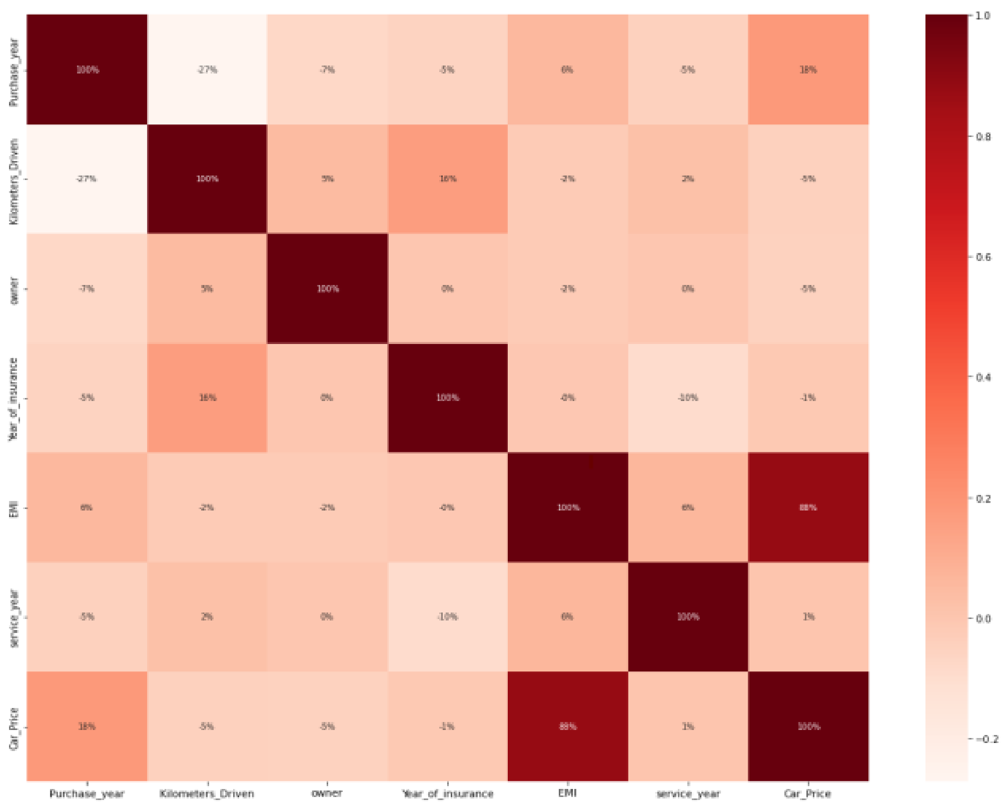


Observation : Here we can see that the categories present in the column are almost at the same price range almost at 600000

Correlation :

```
corr = data.corr()
```

```
plt.figure(figsize = (20,15))
sns.heatmap(corr,annot = True,fmt = ".0%",cbar = True,square = True,annot_kws = {'size':8}, cmap = 'Reds')
plt.show()
```



Encoding the data through Label Encoder:

```
from sklearn.preprocessing import LabelEncoder
```

Observation : Here we have imported the "LabelEncoder" for encoding the data.

```
for column in data.columns:
    if data[column].dtype == np.number:
        continue
    data[column] = LabelEncoder().fit_transform(data[column])
```

Here we have used for loop to encode the complete data ie., all the column of the data.

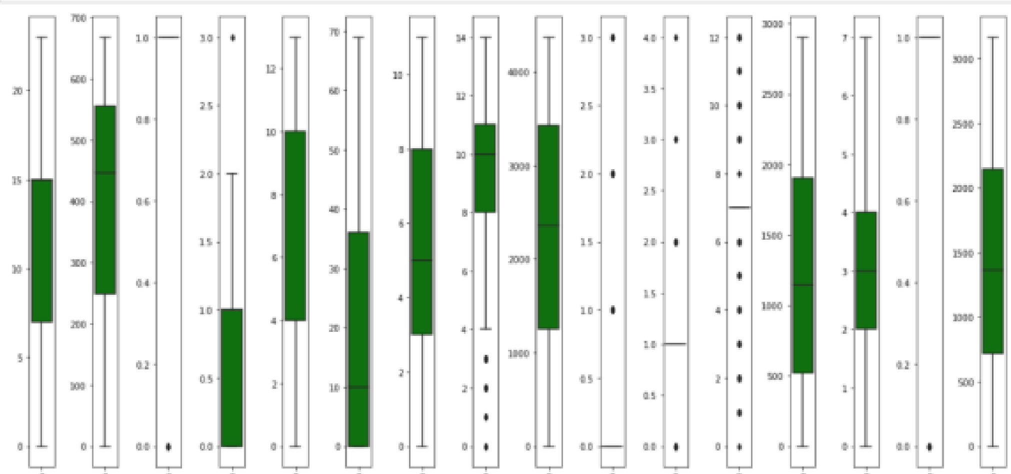
```
data.head()
```

	Brand	Model	Transmission	Fuel Type	Location	Car_name	Purchase_month	Purchase_year	Kilometers_Driven	owner	Year_of_insurance	Month_of_insurance
0	15	528	1	0	4	32	7	8	3712	0	1	7
1	15	626	1	0	4	32	5	7	4006	0	1	7
2	15	227	1	0	4	4	4	9	3463	0	0	5
3	15	227	1	0	4	4	9	8	3706	1	1	7
4	15	633	1	1	4	4	7	11	2122	0	1	7

Observation : Here we can see that we have encoded all the columns of the data.

Now we will Check the outliers present in the data:

```
col_list = data.columns.values
ncol = 30
nrows = 12
plt.figure(figsize = (ncol,3*ncol))
for i in range (0, len(col_list)):
    plt.subplot(nrows,ncol,i+1)
    sns.boxplot(data = data[col_list[i]],color = 'green', orient = 'v')
    plt.tight_layout()
```



Observation : Here we can see that there are few columns which have outliers which are to be treated further for better model accuracy.

Regression Algorithms :

```
from sklearn.ensemble import RandomForestRegressor
from sklearn.tree import DecisionTreeRegressor
from sklearn.neighbors import KNeighborsRegressor as KNN
from sklearn.svm import SVR
from sklearn.model_selection import cross_val_score
from sklearn import metrics
```

Observation : Here we can see that we have imported the necessary libraries to train and test the model.

Linear Regression :

```
# Checking r2score for Linear Regression
LR = LinearRegression()
LR.fit(x_train,y_train)

# prediction
predLR=LR.predict(x_test)
print('R2_score:',metrics.r2_score(y_test,predLR))
```

```
R2_score: 0.8569831256498824
```

```
# Mean Absolute Error (MAE)

print(metrics.mean_absolute_error(y_test, predLR))

# Mean Squared Error (MSE)
print(metrics.mean_squared_error(y_test, predLR))

# Root Mean Squared Error (RMSE)
print(np.sqrt(metrics.mean_squared_error(y_test, predLR)))
```

```
188.33710470714834
106638.76215756004
326.5559096962724
```

Observation : Here we can see that we have achieved 85.6% accuracy with Linear regression model

Random Forest Regressor:

```
#Checking R2 score for Random Forest Regressor:

RFR=RandomForestRegressor()
RFR.fit(x_train,y_train)

# prediction
predRFR=RFR.predict(x_test)
print('R2_Score:',metrics.r2_score(y_test,predRFR))
```

```
R2_Score: 0.984098786719313
```

```
# Mean Absolute Error (MAE)
print(metrics.mean_absolute_error(y_test, predRFR))

# Mean Squared Error (MSE)
print(metrics.mean_squared_error(y_test, predRFR))

# Root Mean Squared Error (RMSE)
print(np.sqrt(metrics.mean_squared_error(y_test, predRFR)))
```

```
19.886629213483147
11856.542864338055
108.88775350946521
```

\ Observation : Here we can see that we have achieved 98.4% for Random Forest Regressor model

Decision Tree Regressor :

```
# Checking R2 score for Decision Tree Regressor
DTR=DecisionTreeRegressor()
DTR.fit(x_train,y_train)

# prediction
predDTR=DTR.predict(x_test)
print('R2_Score:',metrics.r2_score(y_test,predDTR))
```

```
R2_Score: 0.9739385316014878
```

```
# Mean Absolute Error (MAE)
print(metrics.mean_absolute_error(y_test, predDTR))

# Mean Squared Error (MSE)
print(metrics.mean_squared_error(y_test, predDTR))

# Root Mean Squared Error (RMSE)
print(np.sqrt(metrics.mean_squared_error(y_test, predDTR)))
```

```
24.37420615534929
19432.411333659013
139.400184123476
```

Observation : Here we have seen that we have achieved 97.3% accuracy with Decision Tree Regressor model.

KNN regressor :

```
# Checking R2 score for KNN regressor

knn=KNN()
knn.fit(x_train,y_train)

#prediction
predknn=knn.predict(x_test)
print('R2_Score:',metrics.r2_score(y_test,predknn))
```

```
R2_Score: 0.781359340265938
```

```
# Mean Absolute Error (MAE)
print(metrics.mean_absolute_error(y_test, predknn))

# Mean Squared Error (MSE)
print(metrics.mean_squared_error(y_test, predknn))

# Root Mean Squared Error (RMSE)
print(np.sqrt(metrics.mean_squared_error(y_test, predknn)))
```

```
289.6653639472399
163026.70169027845
403.76565194463785
```

Observation : here we can see that we have achieved 78% accuracy with KNN Regressor model

Checking the Cross Validation Score :

```
from sklearn.model_selection import cross_val_score
```

```
# Checking cv score for Linear Regression
print(cross_val_score(LR,x,y,cv=5).mean())
```

```
0.7836850757481711
```

```
# Checking cv score for Random Forest Regression
print(cross_val_score(RFR,x,y,cv=5).mean())
```

```
0.9709442195306274
```

```
# Checking cv score for Decision Tree Regression
print(cross_val_score(DTR,x,y,cv=5).mean())
```

```
0.9616810327158174
```

```
# Checking cv score for KNN Regression
print(cross_val_score(knn,x,y,cv=5).mean())
```

```
0.7384108581236906
```

Observation: Here we can see that among all the models “Random Forest Regressor” has a high CV Score.

Hyper parameter Tuning :

```
from sklearn.model_selection import GridSearchCV
```

```
#RandomForestRegressor

parameters = {'criterion':['mse', 'mae'],
             'max_features':['auto', 'sqrt', 'log2'],
             'n_estimators':[0,200],
             'max_depth':[2,4,6]}
```

```
GCV=GridSearchCV(RandomForestRegressor(),parameters,cv=5)
```

```
GCV.fit(x_train,y_train)
```

```
GridSearchCV(cv=5, estimator=RandomForestRegressor(),
             param_grid={'criterion': ['mse', 'mae'], 'max_depth': [2, 4, 6],
                         'max_features': ['auto', 'sqrt', 'log2'],
                         'n_estimators': [0, 200]})
```

```
GCV.best_params_
```

```
{'criterion': 'mse',
 'max_depth': 6,
 'max_features': 'auto',
 'n_estimators': 200}
```

```
Cars_model = RandomForestRegressor(criterion='mse', max_depth=6, max_features='auto', n_estimators=200)
Cars_model.fit(x_train, y_train)
pred = Cars_model.predict(x_test)
print("RMSE value:",np.sqrt(metrics.mean_squared_error(y_test, predRFR)))
print('R2_Score:',r2_score(y_test,pred)*100)
```

```
RMSE value: 108.88775350946521
R2_Score: 97.2158311996941
```

Observation : Here we can see that our best model is Random Forest model and the model is with 98.4% accuracy before hyper parameter tuning and got reduced after hyper parameter tuning.

Saving the model :

```
# Saving the model using .pkl
import pickle
filename='Cars.pkl'
pickle.dump(RFR,open(filename,'wb'))
```

Observation : Here we have saved our model with ".pkl" method

CONCLUSION

We have successfully built a model using multiple models and found that the Random Forest Regressor model is the best model with a good accuracy.

Below are the details of the model's metrics predicting the dataset • R2- score of 0.98 • RMSE of 108.88.

You can view the same from the visualizations on the correlation of independent variable over dependent variable (target) As we can see from the boxplot,

I couldn't remove all the outliers yet since the data is expensive, I have to proceed with the dataset with outliers.

Further, I couldn't get skewness under control for a few variables through a couple of transformation techniques, yet I have proceeded with building the model. Looking at the heatmap for correlation, I could see there were few independent variables which were correlated with each other, yet I have not removed any variable based on their correlation because multicollinearity will not affect prediction. Limitations of this work and Scope for Future Work: Due to the presence of a lot of outliers, we are unsure whether the model is going to perform well to a completely new dataset.

During data-collection, there are certain websites that do not provide the necessary information on the used car due to which the data collected was not precise which had to be pre-processed for building a better model.

Thank You….