With the covid 19 impact in the market, we have seen 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. One of our clients works with small traders, who sell used cars. With the change in market due to covid 19 impact, our client is facing problems with their previous car price valuation machine learning models. So, they are looking for new machine learning models from new data. We have to make car price valuation model.

In [74]:
```
# To start, we will import some libraries that will allow us to explore the datas

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

In [75]:
```
df=pd.read_csv(r'E:\DS Intenship projects\Project form Mentor\Car Price Predictio
df
```

Out[75]:

	Unnamed: 0	Brand	Model	Variant	Manufacturing_Year	Driven_KiloMeters	Fuel
0	0	Maruti	2015 Maruti Swift Dzire	VXI Manual	2015	92,630 km	Petrol
1	1	Tata	2018 Tata Tiago	XZA 1.2 REVOTRON Automatic	2018	15,548 km	Petrol
2	2	Ford	2014 Ford Ecosport	1.5 TITANIUMTDCI OPT Manual	2014	93,737 km	Diesel
3	3	Hyundai	2013 Hyundai Verna	FLUIDIC 1.6 EX VTVT Manual	2013	10,546 km	Petrol
4	4	Datsun	2016 Datsun Redi Go	T (O) Manual	2016	31,546 km	Petrol
...	...	...	...	...	...	...	...
5368	5368	Hyundai	2014 Hyundai Grand i10	MAGNA 1.2 KAPPA VTVT Manual	2014	65,015 km	Petrol
5369	5369	Maruti	2017 Maruti Ertiga	VXI CNG Manual	2017	68,439 km	Petrol + CNG
5370	5370	Maruti	2011 Maruti Alto	LXI Manual	2011	25,012 km	Petrol
5371	5371	Hyundai	2017 Hyundai Verna	1.6 EX CRDI Manual	2017	91,495 km	Diesel
5372	5372	Maruti	2015 Maruti Ertiga	VXI CNG Manual	2015	73,123 km	Petrol + CNG

5373 rows × 9 columns

As we can see overview of dataset which I have scrapped on car24.com and we have here 5373 rows and 9 columns

In [76]:
```
#I would like to drop "Unnamed: 0" Column from the dataset becasue we do not requ

df.drop(['Unnamed: 0'],axis=1,inplace=True)
```

In [77]:
```
df.head()
```

Out[77]:

	Brand	Model	Variant	Manufacturing_Year	Driven_KiloMeters	Fuel	Number_of_Ow
0	Maruti	2015 Maruti Swift Dzire	VXI Manual	2015	92,630 km	Petrol	1st O
1	Tata	2018 Tata Tiago	XZA 1.2 REVOTRON Automatic	2018	15,548 km	Petrol	2nd O
2	Ford	2014 Ford Ecosport	1.5 TITANIUMTDCI OPT Manual	2014	93,737 km	Diesel	1st O
3	Hyundai	2013 Hyundai Verna	FLUIDIC 1.6 EX VTVT Manual	2013	10,546 km	Petrol	1st O
4	Datsun	2016 Datsun Redi Go	T (O) Manual	2016	31,546 km	Petrol	2nd O

Above are top 5 rows

In [78]:
```
df.tail()
```

Out[78]:

	Brand	Model	Variant	Manufacturing_Year	Driven_KiloMeters	Fuel	Number_of_Owners
5368	Hyundai	2014 Hyundai Grand i10	MAGNA 1.2 KAPPA VTVT Manual	2014	65,015 km	Petrol	1st Owne
5369	Maruti	2017 Maruti Ertiga	VXI CNG Manual	2017	68,439 km	Petrol + CNG	1st Owne
5370	Maruti	2011 Maruti Alto	LXI Manual	2011	25,012 km	Petrol	1st Owne
5371	Hyundai	2017 Hyundai Verna	1.6 EX CRDI Manual	2017	91,495 km	Diesel	1st Owne
5372	Maruti	2015 Maruti Ertiga	VXI CNG Manual	2015	73,123 km	Petrol + CNG	1st Owne

Above we can observe bottom five rows to have better understading of our data.

In [79]:
```
df.shape
```

Out[79]:
```
(5373, 8)
```

We can see shape of Data by looking at the above output we have now 5373 rows and 8 column as we already deleted one column

In [80]:
```
df.dtypes
```

Out[80]:
```
Brand                  object
Model                  object
Variant                object
Manufacturing_Year      int64
Driven_KiloMeters      object
Fuel                   object
Number_of_Owners       object
Car_Price              object
dtype: object
```

We can see almost all columns are having "Object" data and as machine learning model does not understand object data. we need to convert data in numerical data by using feasible Encoding technique

In [81]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5373 entries, 0 to 5372
Data columns (total 8 columns):
 #   Column              Non-Null Count  Dtype 
---  ------              --------------  ----- 
 0   Brand               5373 non-null   object
 1   Model               5373 non-null   object
 2   Variant             5373 non-null   object
 3   Manufacturing_Year  5373 non-null   int64 
 4   Driven_KiloMeters   5373 non-null   object
 5   Fuel                5373 non-null   object
 6   Number_of_Owners    5373 non-null   object
 7   Car_Price           5373 non-null   object
dtypes: int64(1), object(7)
memory usage: 335.9+ KB
```

Above table gives us more inforation about our data as below

- Dataset consume 335KB space which is very low
- There is no null value present in dataset
- we can again see datatype in above table as well
- Name of the all columns

In [82]:
```
df.sample(6)
```

Out[82]:

	Brand	Model	Variant	Manufacturing_Year	Driven_KiloMeters	Fuel	Number_of_Owner
577	Honda	2017 Honda City	ZX CVT Automatic	2017	88,451 km	Petrol	1st Own
4822	Hyundai	2019 Hyundai Eon	ERA PLUS Manual	2019	53,001 km	Petrol	1st Own
5342	Honda	2012 Honda City	S MT PETROL Manual	2012	47,085 km	Petrol	1st Own
306	Hyundai	2018 Hyundai Creta	1.6 VTVT SX AUTO Automatic	2018	21,198 km	Petrol	2nd Own
1710	Renault	2021 Renault Kwid	RXL Manual	2021	25,134 km	Petrol	2nd Own
3203	Maruti	2019 Maruti Alto K10	VXI AMT Automatic	2019	24,566 km	Petrol	1st Own

If we would like to see random line from dataset then we can use above code to see random line. in will pick any random lines always and count will be as per we provided

In [83]:
```
df['Model'] = df['Model'].str[4:]
df
```

Out[83]:

	Brand	Model	Variant	Manufacturing_Year	Driven_KiloMeters	Fuel	Number_of_
0	Maruti	Maruti Swift Dzire	VXI Manual	2015	92,630 km	Petrol	1s
1	Tata	Tata Tiago	XZA 1.2 REVOTRON Automatic	2018	15,548 km	Petrol	2n
2	Ford	Ford Ecosport	1.5 TITANIUMTDCI OPT Manual	2014	93,737 km	Diesel	1s
3	Hyundai	Hyundai Verna	FLUIDIC 1.6 EX VTVT Manual	2013	10,546 km	Petrol	1s
4	Datsun	Datsun Redi Go	T (O) Manual	2016	31,546 km	Petrol	2n
...	...	...	...	...	...	...	
5368	Hyundai	Hyundai Grand i10	MAGNA 1.2 KAPPA VTVT Manual	2014	65,015 km	Petrol	1s
5369	Maruti	Maruti Ertiga	VXI CNG Manual	2017	68,439 km	Petrol + CNG	1s
5370	Maruti	Maruti Alto	LXI Manual	2011	25,012 km	Petrol	1s
5371	Hyundai	Hyundai Verna	1.6 EX CRDI Manual	2017	91,495 km	Diesel	1s
5372	Maruti	Maruti Ertiga	VXI CNG Manual	2015	73,123 km	Petrol + CNG	1s

5373 rows × 8 columns

In [84]:
```
df.nunique()
```

Out[84]:
```
Brand                   22
Model                  128
Variant                822
Manufacturing_Year      14
Driven_KiloMeters     3941
Fuel                     3
Number_of_Owners         3
Car_Price             1240
dtype: int64
```

We can see uniquness of our data

- we can see there are total 22 brands present in dataset
- 128 models are present
- we have three different fuel catagories.

Checking all values in each columns

In [85]:
```
for i in df.columns:
    print(df[i].value_counts(),"\n\n", "-"*100, "\n\n")
```

```
Maruti        2283
Hyundai       1342
Honda          451
Tata           251
Renault        242
Mahindra       141
Ford           133
Toyota         129
KIA            116
Volkswagen      88
Skoda           54
Datsun          41
MG              40
Jeep            21
Nissan          19
MARUTI           6
Audi             6
Jaguar           3
BMW              3
```

As We observed previously that we have "Driven_KiloMeters" and "Car_Price" Present in dataset as Object datatype which we need to convert in numbers. So lets do it first

In [86]:
```
# Car price

df["Car_Price"]= df["Car_Price"].str.replace('₹', '')
df["Car_Price"]= df["Car_Price"].str.replace(',', '')
```

In [87]:
```
# Converting Datatype to numeric datatype
df["Car_Price"]=pd.to_numeric(df['Car_Price'],errors='coerce')
```

In [88]:
```
# Driven_KiloMeters

df["Driven_KiloMeters"]= df["Driven_KiloMeters"].str.replace('km', '')
df["Driven_KiloMeters"]= df["Driven_KiloMeters"].str.replace(',', '')
```

In [89]:
```
# Converting Datatype to numeric datatype
df["Driven_KiloMeters"]=pd.to_numeric(df['Driven_KiloMeters'],errors='coerce')
```

In [90]:
```
df.dtypes
```

Out[90]:
```
Brand                 object
Model                 object
Variant               object
Manufacturing_Year     int64
Driven_KiloMeters      int64
Fuel                  object
Number_of_Owners      object
Car_Price              int64
dtype: object
```

We can see above both columns are converted in to Int64

Checking Null Values in Dataset

In [91]:
```
df.isnull().sum()
```

Out[91]:
```
Brand                 0
Model                 0
Variant               0
Manufacturing_Year    0
Driven_KiloMeters     0
Fuel                  0
Number_of_Owners      0
Car_Price             0
dtype: int64
```

We Don't have Null Values present in Dataset

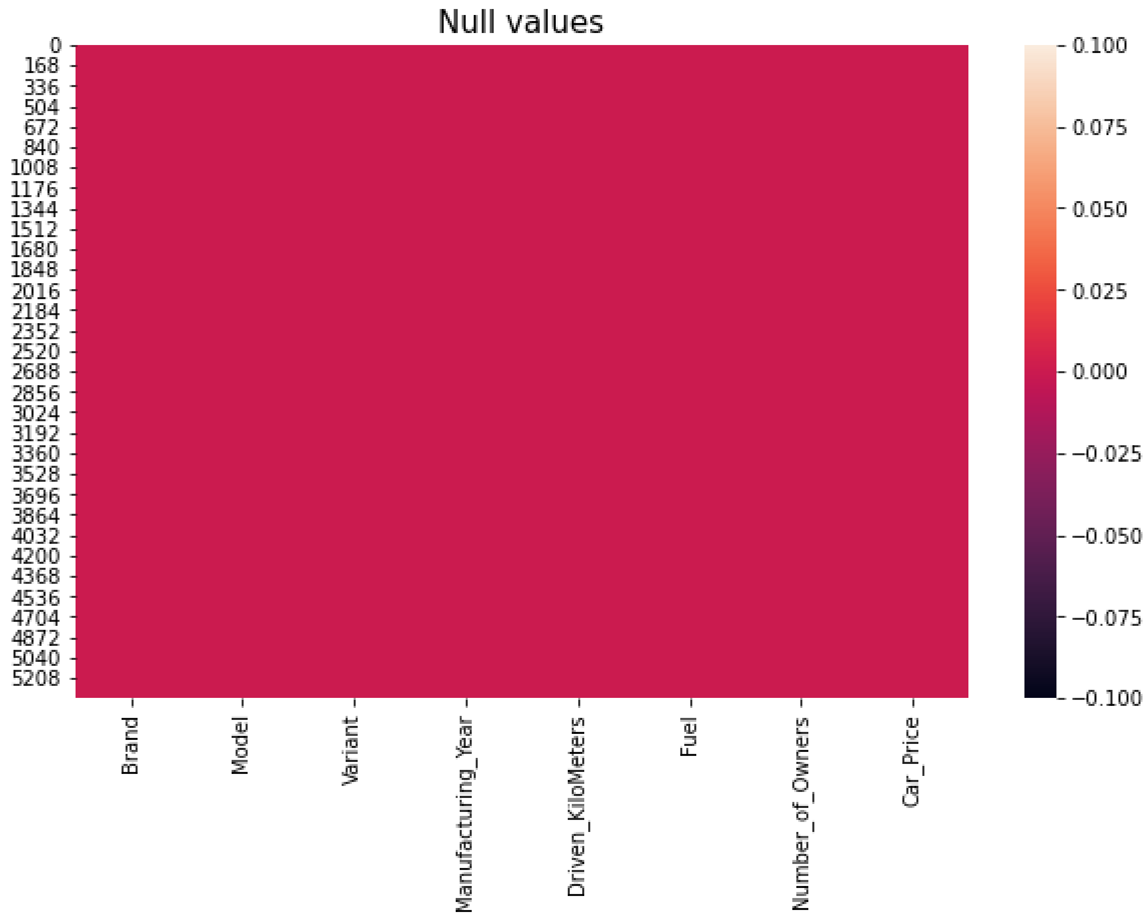
In [92]:
```
df.loc[df['Brand']==" "]
```

Out[92]:

Brand	Model	Variant	Manufacturing_Year	Driven_KiloMeters	Fuel	Number_of_Owners	Car_Pri

I am just checking if any blank space available in datset or not and we dont have nay blank space

In [93]:
```
plt.figure(figsize=(10,6))
plt.title("Null values",fontsize=15)
sns.heatmap(df.isnull());
```



We can also check Null values using above heat map. we can clearly observe that there is not null values present in Data set

In [94]:
```
# Checking for duplicate data
df.duplicated().sum()
```

Out[94]: 1351

We can see that we have total 1351 duplicated rows which we dont required and we can drop them to avoid Bias in model Learning

In [95]:
```
# DropPing duplicate rows
df=df.drop_duplicates()
```

In [96]:
```
df.shape
```

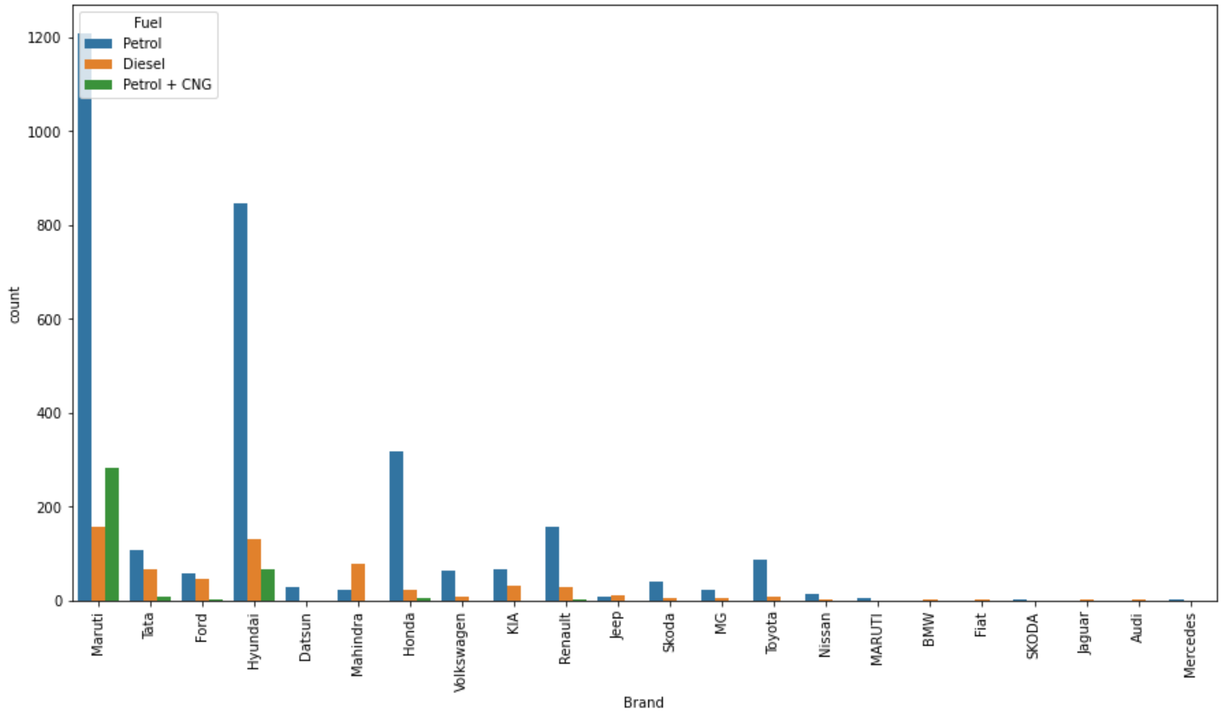
Out[96]:
```
(4022, 8)
```

We have removed duplciate rows from data set

In [97]:
```
#Lest separate catogorical and numarical columns just if we required

categorical_col=[]
for i in df.dtypes.index:
    if df.dtypes[i]=='object':
        categorical_col.append(i)
print("Categorical columns are:\n",categorical_col)
print("\n")

# Now checking for numerical columns
numerical_col=[]
for i in df.dtypes.index:
    if df.dtypes[i]!='object':
        numerical_col.append(i)
print("Numerical columns are:\n",numerical_col)
```

```
Categorical columns are:
 ['Brand', 'Model', 'Variant', 'Fuel', 'Number_of_Owners']


Numerical columns are:
 ['Manufacturing_Year', 'Driven_KiloMeters', 'Car_Price']
```

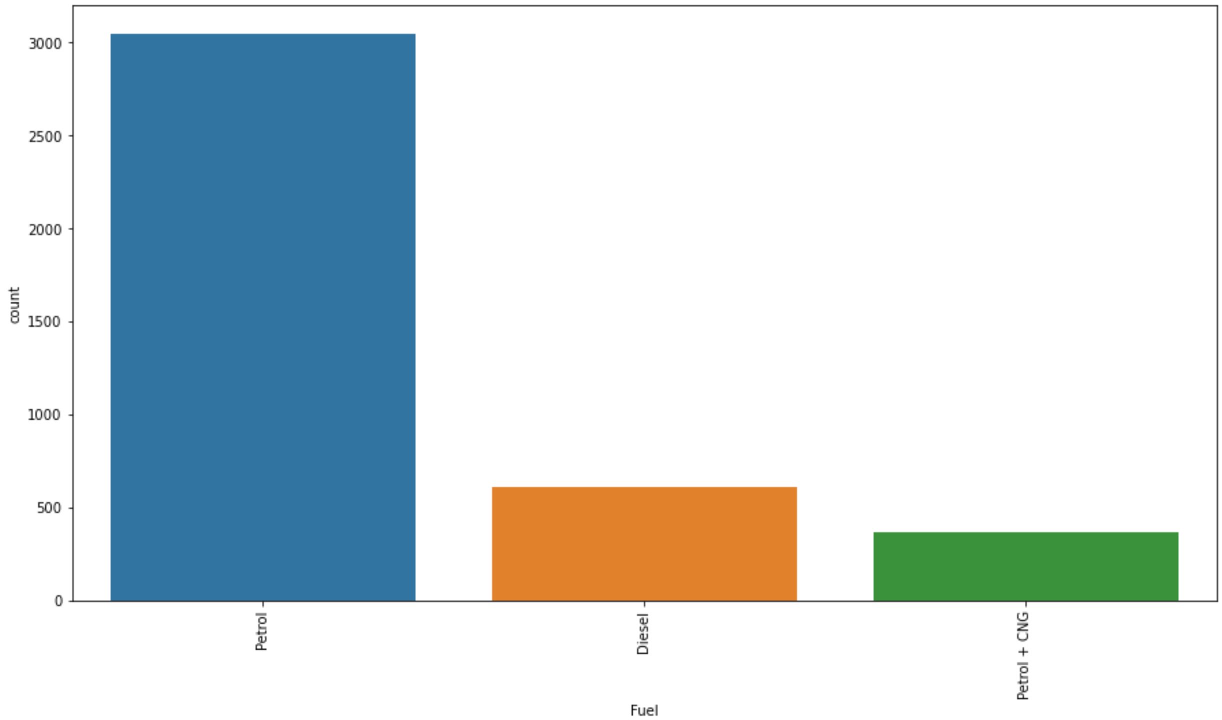
In [98]:
```
plt.figure(figsize=(15,8))
sns.countplot(df['Brand'],hue=df['Fuel'])
plt.xticks(rotation=90)
plt.show()
```



We can Observe below points from above graph

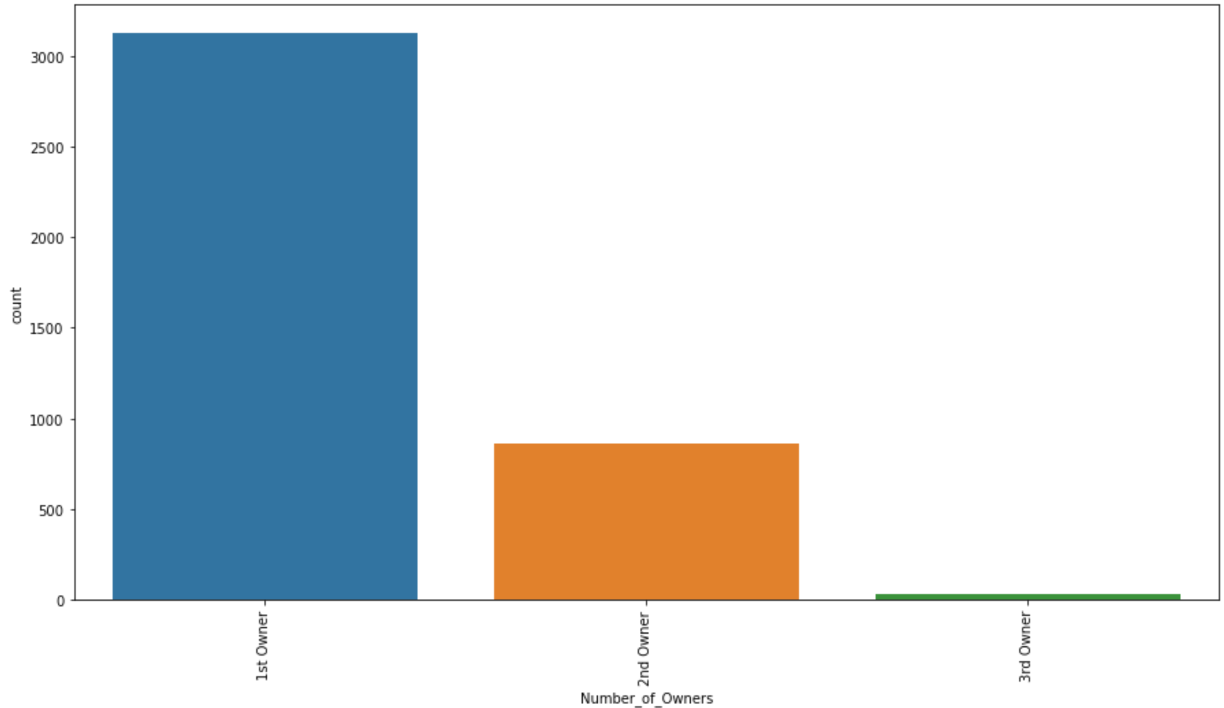
- we can see that maruti has highetst market in second hand car selling
- Maruti has highest count with combine fuel Petrol + CNG
- BMW,SKODA,Jaguar these are premimum car and very less market in second hand selling.
- Sencond largest market is Hyundai followed by Honda

In [99]:
```
plt.figure(figsize=(15,8))
sns.countplot(df['Fuel'],)
plt.xticks(rotation=90)
plt.show()
```



- Petrol car's has highest market
- diesel car's are second one
- We can see Petrol+CNG cars are very less

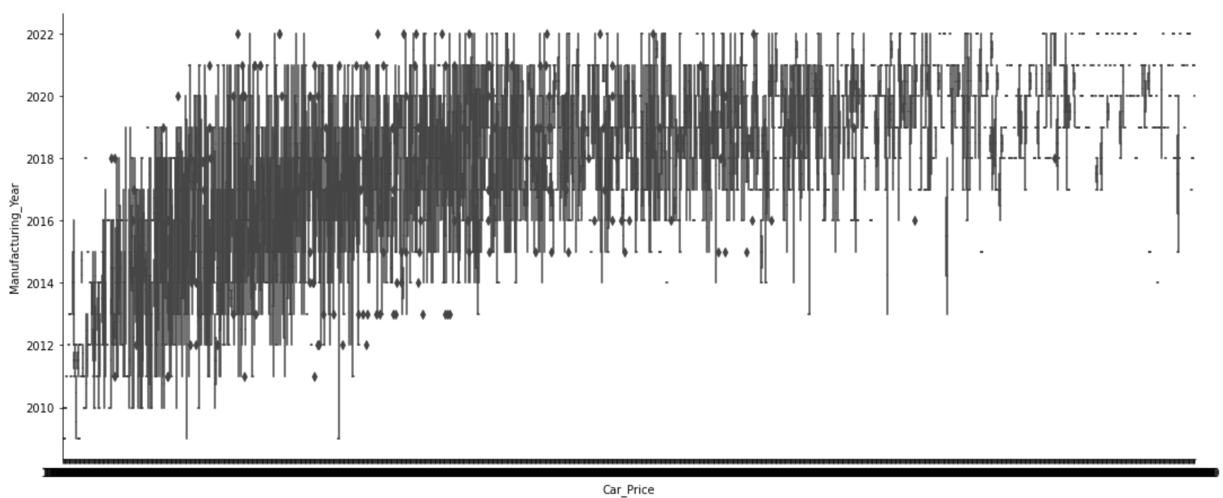
In [100]:
```
plt.figure(figsize=(15,8))
sns.countplot(df['Number_of_Owners'],)
plt.xticks(rotation=90)
plt.show()
```



We can see that highest car's are getting sold by 1st owner and lowest are 3rd owner

In [102]:
```
sns.catplot(x='Car_Price', y = 'Manufacturing_Year',
            data = df,
            kind = 'box',
            height = 6,
            aspect=2.5)
```

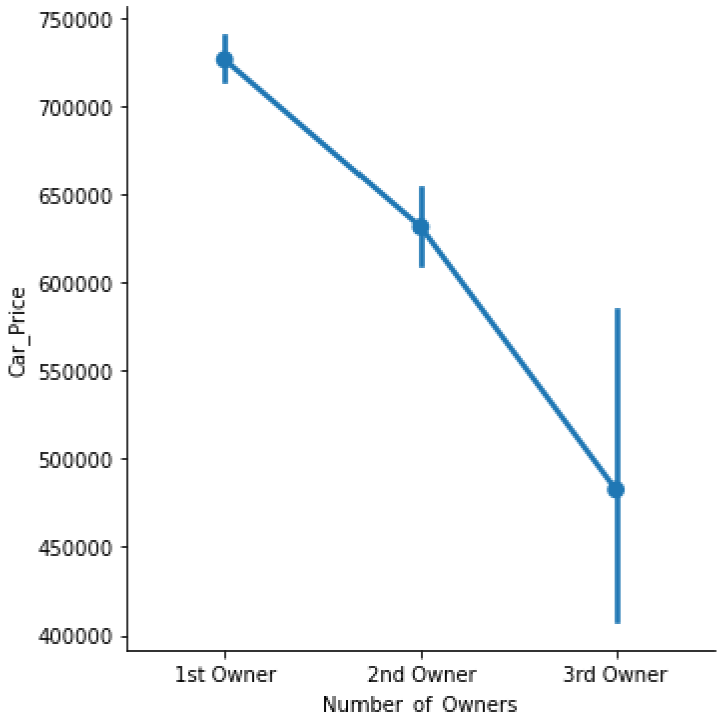
Out[102]: <seaborn.axisgrid.FacetGrid at 0x2313b2f80a0>



We can see that car prices are getting higher when car model is manufctured in recent years. if car model is from 2010 then we can see price is lowest

In [103]:
```
sns.catplot(x="Number_of_Owners",
            y="Car_Price",

            kind="point",
            data=df)
```

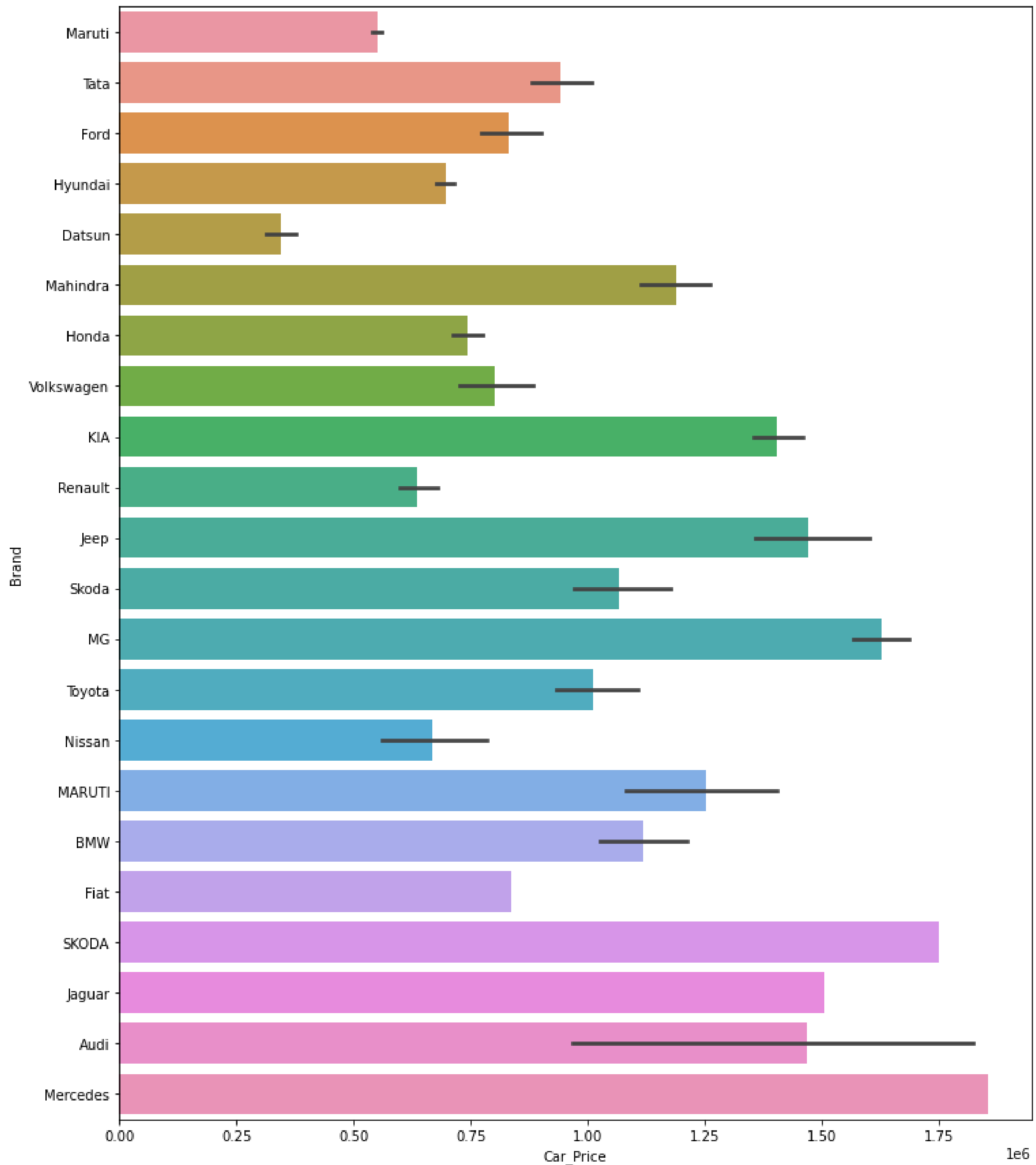
Out[103]: <seaborn.axisgrid.FacetGrid at 0x23137546be0>



We can see that 1st owner is asking for high price and 3rd owner is looking for low price

In [104]:
```
plt.figure(figsize=(12,15))
sns.barplot(x=df["Car_Price"], y=df["Brand"])
```

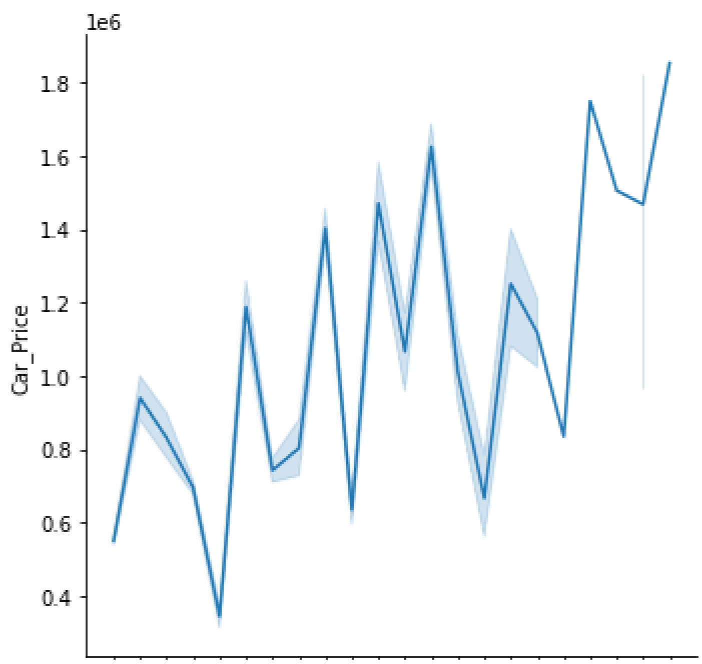
Out[104]: <AxesSubplot:xlabel='Car_Price', ylabel='Brand'>



We can see price range of all brand where detsun and maruti has lowest price in market and Mercedes, AUdi jagaur are highest price.

In [105]:

```
index = 0
features = df.drop("Car_Price", axis=1)
for col, value in features.items():
    sns.relplot(x=col, y="Car_Price", kind="line", data=df)
    index += 1
plt.show()
```

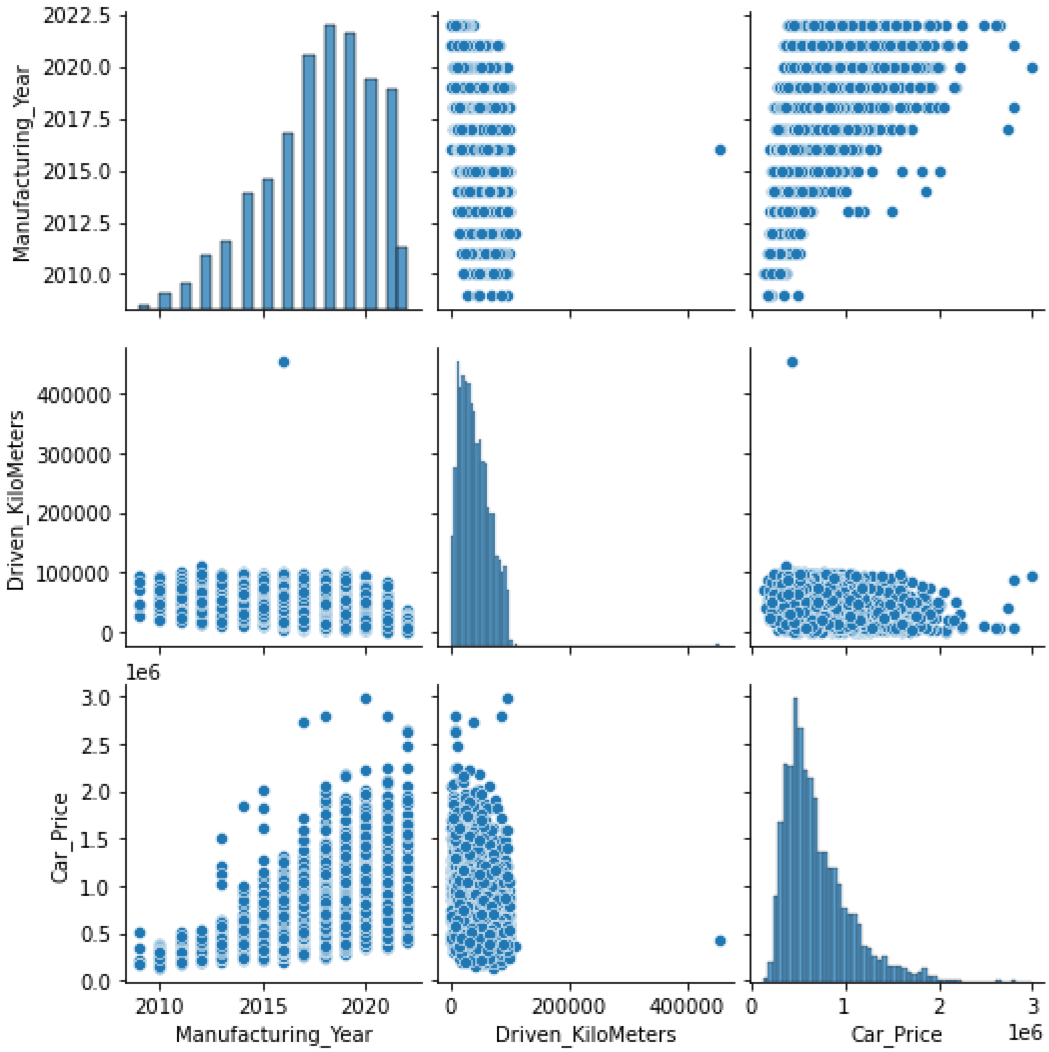


Below are some importatnt observation from above graphs

- Maruti has lowest rates and cars like audi,mercedes are having high rates
- We can see that car prices are positvely correlated with year of manufactring. Most new car will get sell with high value
- Car which has less driven KM has good value and car which driven more than 1lac KM has low value
- Diesel cars are getting sell in high rates
- Maximum owner cars are listed with low price and if car is being sold by fist ownner then rate is high

In [106]:
```
sns.pairplot(df)
```

Out[106]:
```
<seaborn.axisgrid.PairGrid at 0x23143680e50>
```



Above Plots allow as to understand relationship between all our variable.

- Manufacturing year and Car price has postive relation

Label Encoding

In [107]:
```
#Encoding car Dataset

from sklearn.preprocessing  import LabelEncoder
enc = LabelEncoder()
for i in df.columns:
    if df[i].dtypes=="object":
        df[i]=enc.fit_transform(df[i].values.reshape(-1,1))
```

In [108]:
```
df.dtypes
```

Out[108]:
```
Brand                 int32
Model                 int32
Variant               int32
Manufacturing_Year    int64
Driven_KiloMeters     int64
Fuel                  int32
Number_of_Owners      int32
Car_Price             int64
dtype: object
```

We can see all Object data is transfomred into integers and we are good to go ahead

Descriptive statistics

In [109]:
```
df.describe().T
```

Out[109]:

	count	mean	std	min	25%	50%	75%
Brand	4022.0	10.786425	4.661364	0.0	6.00	13.0	13.0
Model	4022.0	59.264794	30.071055	0.0	30.00	66.0	80.0
Variant	4022.0	450.616360	233.885861	0.0	254.00	472.0	654.0
Manufacturing_Year	4022.0	2017.579811	2.696534	2009.0	2016.00	2018.0	2020.0
Driven_KiloMeters	4022.0	40953.383889	25557.530967	64.0	20429.75	37304.0	58167.5
Fuel	4022.0	0.940080	0.487741	0.0	1.00	1.0	1.0
Number_of_Owners	4022.0	0.231477	0.441982	0.0	0.00	0.0	0.0
Car_Price	4022.0	703994.454749	354345.119015	131000.0	454000.00	617000.0	875000.0

We can have statistical look of our data and I see bwlow points here to observe.

- mean of car price in 70K and standered deviation is 35K max car value is 29.8lac and min is 4.5 lac 75% car pricess are under 9lac
- Average car running is 40K KM and highest is 45K km. 75% cars running is under 58K km

In [110]:
```
# Checking correlation for all colouns

df.corr()
```

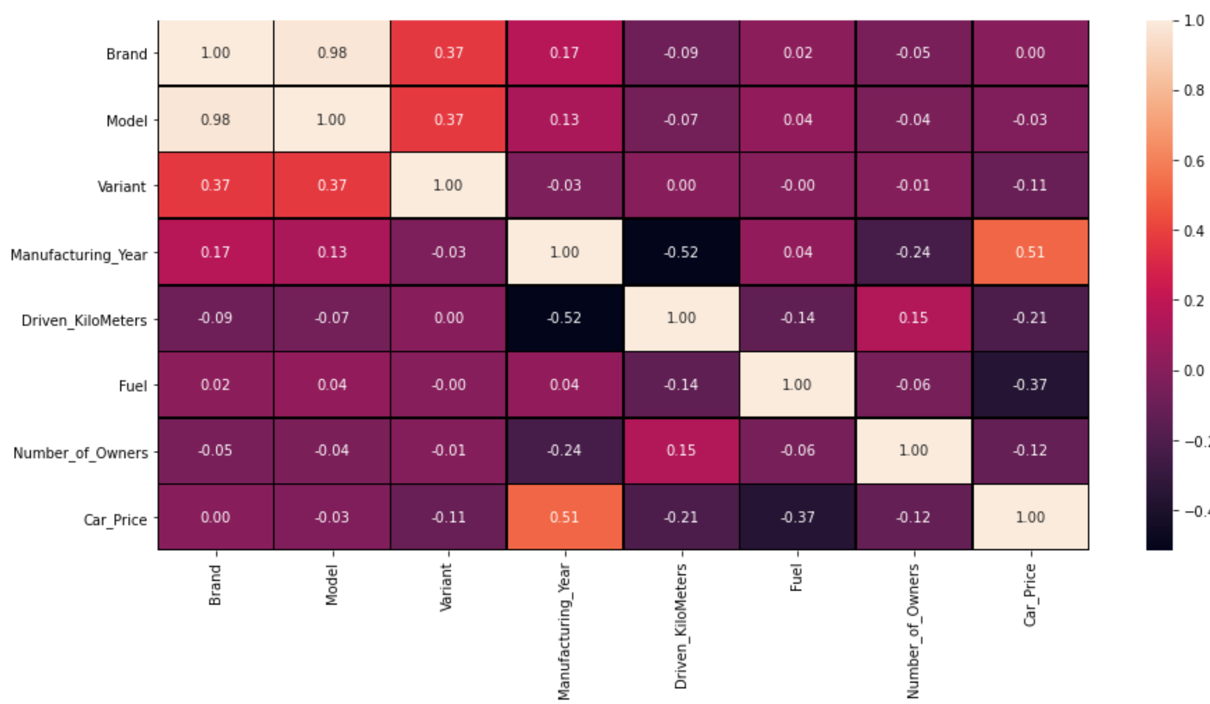
Out[110]:

	Brand	Model	Variant	Manufacturing_Year	Driven_KiloMeters	Fu
Brand	1.000000	0.979400	0.369480	0.168257	-0.086665	0.0218
Model	0.979400	1.000000	0.374283	0.127757	-0.070835	0.0389
Variant	0.369480	0.374283	1.000000	-0.030159	0.000506	-0.0019
Manufacturing_Year	0.168257	0.127757	-0.030159	1.000000	-0.515161	0.0366
Driven_KiloMeters	-0.086665	-0.070835	0.000506	-0.515161	1.000000	-0.1374
Fuel	0.021826	0.038996	-0.001900	0.036633	-0.137453	1.0000
Number_of_Owners	-0.049873	-0.038462	-0.011081	-0.236588	0.152522	-0.0590
Car_Price	0.002962	-0.029308	-0.111315	0.511054	-0.213019	-0.3656

Above chart shows us correaltion of all columns with each other

In [111]:
```
# we will plot all aboev values on hitmap just for good visualisation

import matplotlib.pyplot as plt
plt.figure(figsize=(15,7))
sns.heatmap(df.corr(),annot=True,linewidths=0.6,linecolor="black",fmt='.2f')
```

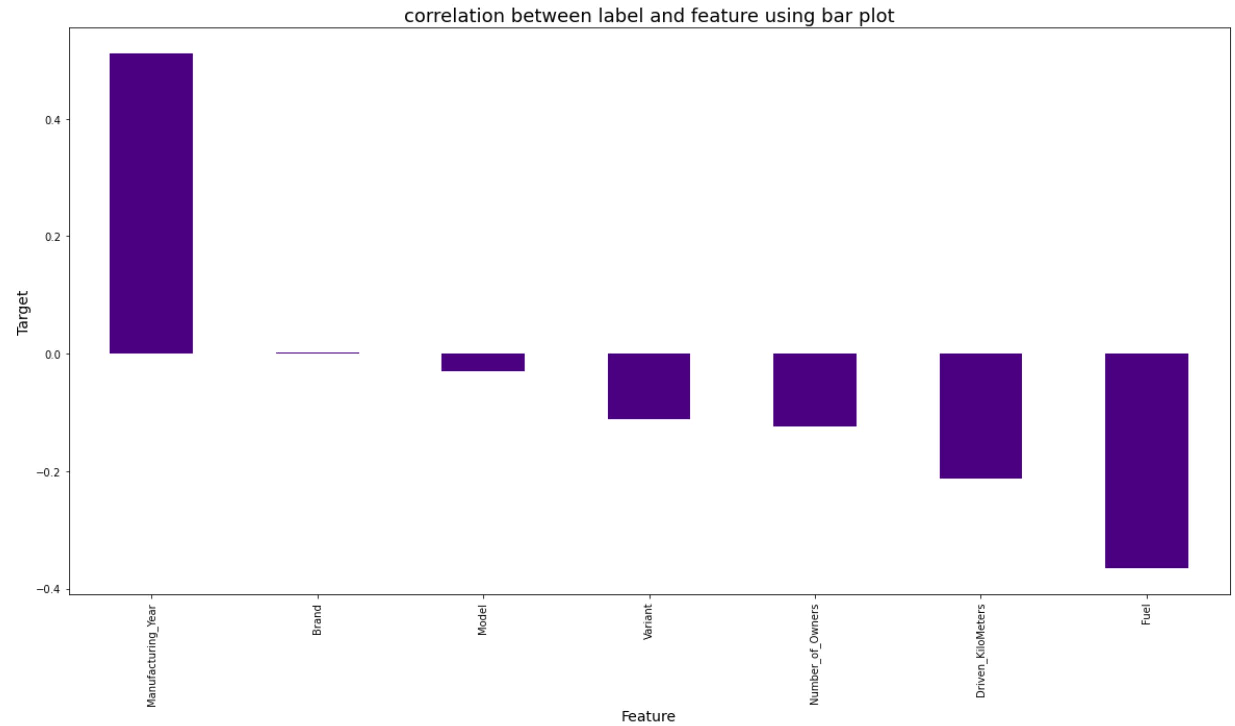
Out[111]: <AxesSubplot:>



- Very important variable is Manufacturing year which has highest positive correlation

- Second inportat variable is Fuel type, there we can see negative correalation but as it is not countineous variable.
- Brand plays very less role in price predication

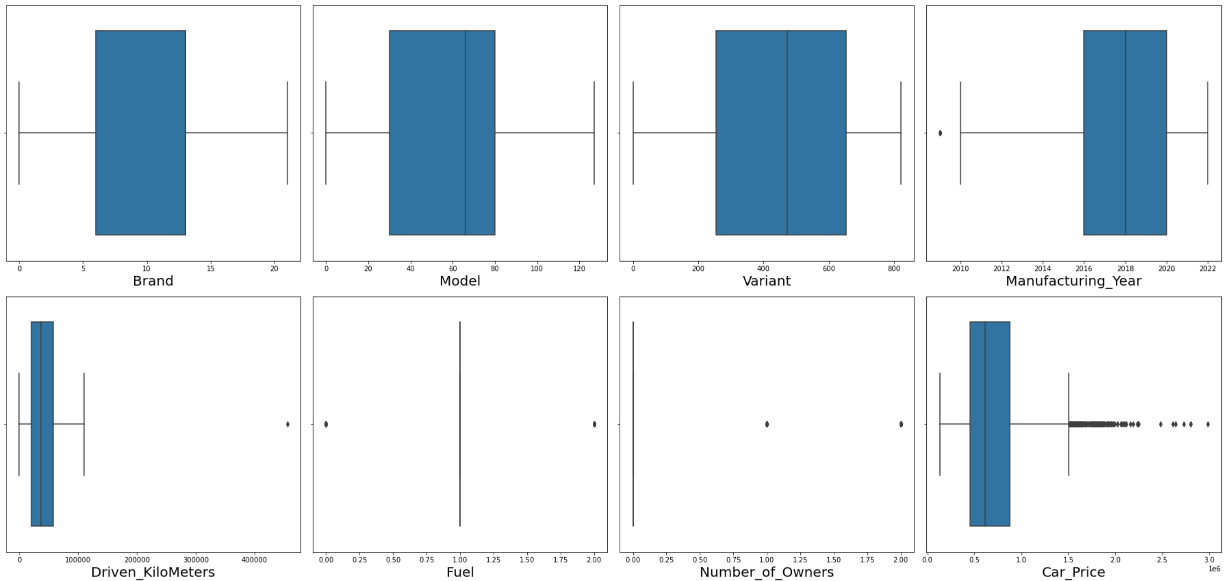
In [112]:
```
plt.figure(figsize=(20,10))
df.corr()['Car_Price'].sort_values(ascending=False).drop(['Car_Price']).plot(kinc
plt.xlabel('Feature',fontsize=14)
plt.ylabel('Target',fontsize=14)
plt.title('correlation between label and feature using bar plot',fontsize=18)
plt.show()
```



- Here we can we can see only one variable has positive corre;ation as we have seen on previous chart.
- All others are negatively correalted
- Brand has almost neutral realtion

Outliers Handling

In [113]:
```
plt.figure(figsize=(25,35))
plotnumber=1
for column in df:
    if plotnumber<=23:
        ax=plt.subplot(6,4,plotnumber)
        sns.boxplot(df[column])
        plt.xlabel(column,fontsize=20)
    plotnumber+=1
plt.tight_layout()
```



We can able to see outliers in two main bariable which are Car_price and Driven_kilometers

Outliers Handling

In [114]:
```
# Lets Treat outliers

from scipy.stats import zscore
zscore=zscore(df)
zabs=np.abs(zscore)

z=df[(zabs<3).all(axis=1)]
```

In [115]:
```
z.shape
```
Out[115]:
```
(3911, 8)
```

In [116]:
```
df.shape
```
Out[116]:
```
(4022, 8)
```

In [117]:
```
loss=(4022-3911)/4022*100
loss
```
Out[117]:
```
2.759820984584784
```

we have 2% data loss if we treat outliers and we can accept this loss to train good model

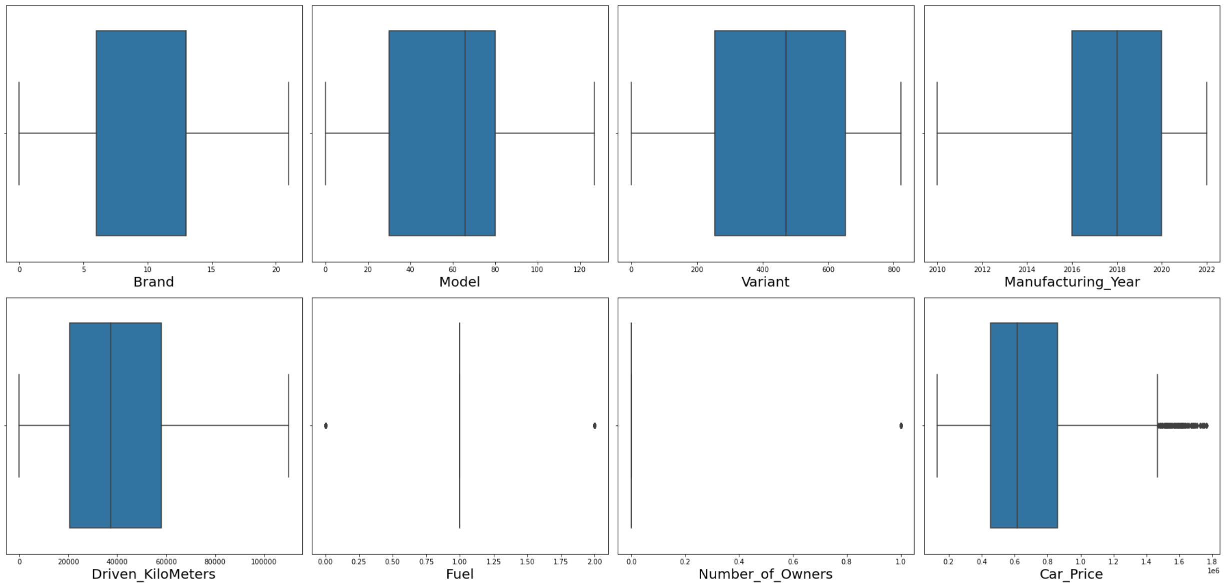
In [118]:
```
dropindex=df.index.difference(z.index)
dropindex
```
Out[118]:
```
Int64Index([  47,   90,  133,  176,  188,  217,  246,  273,  278,  428,
            ...
            5043, 5052, 5126, 5198, 5222, 5245, 5258, 5302, 5324, 5337],
           dtype='int64', length=111)
```

In [119]:
```
df.drop(dropindex,inplace=True)
df
```
Out[119]:

	Brand	Model	Variant	Manufacturing_Year	Driven_KiloMeters	Fuel	Number_of_Owners	Ca
0	13	81	654	2015	92630	1	0	
1	19	111	745	2018	15548	1	1	
2	4	8	124	2014	93737	0	0	
3	6	38	322	2013	10546	1	0	
4	2	6	598	2016	31546	1	1	
...	...	...	...	...	...	...	...	
5368	6	30	431	2014	65015	1	0	
5369	13	73	650	2017	68439	2	0	
5370	13	64	419	2011	25012	1	0	
5371	6	38	143	2017	91495	0	0	
5372	13	73	650	2015	73123	2	0	

3911 rows × 8 columns

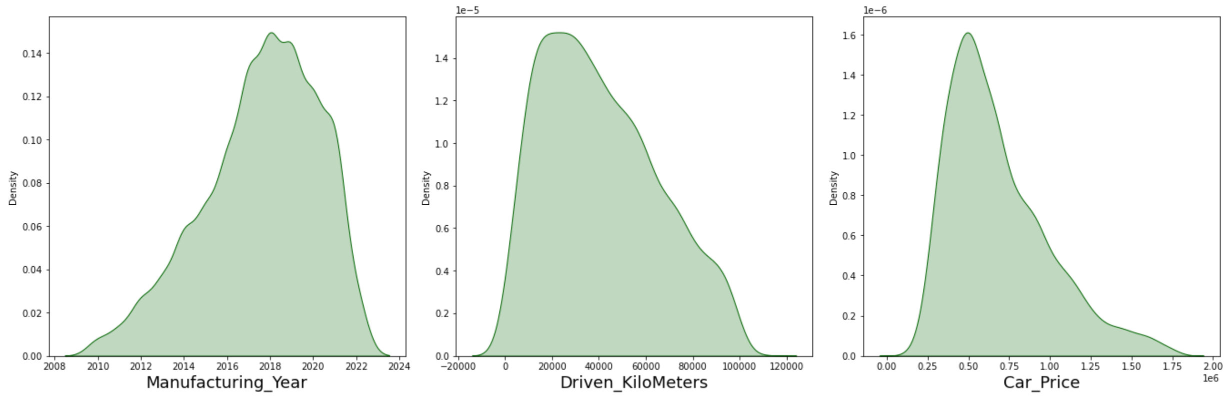
In [120]:
```
plt.figure(figsize=(25,35))
plotnumber=1
for column in df:
    if plotnumber<=23:
        ax=plt.subplot(6,4,plotnumber)
        sns.boxplot(df[column])
        plt.xlabel(column,fontsize=20)
    plotnumber+=1
plt.tight_layout()
```



We can observe chmages now. if we obeserve we observe above box plot with first one then we can see difference between Driven_kilometers and Car_proice columns

Finding Skewness

In [121]:
```
plt.figure(figsize=(25,35))
plotnumber=1
for column in numerical_col:
    if plotnumber<=8:
        ax=plt.subplot(6,4,plotnumber)
        sns.distplot(df[column],color="darkgreen",hist=False,kde_kws={"shade": Tr
        plt.xlabel(column,fontsize=18)
    plotnumber+=1
plt.tight_layout()
```



In [122]:
```
df.skew()
```

Out[122]:
```
Brand                  0.167868
Model                  0.110196
Variant               -0.343922
Manufacturing_Year    -0.558509
Driven_KiloMeters      0.455637
Fuel                  -0.133010
Number_of_Owners       1.367601
Car_Price              1.006157
dtype: float64
```

We have skewness present in dataset which we need to handle to achieve good model performance and reduce chances of Bias

Lets treat skewness using powerTransform

I will skip car_price just becasue that it target column and we need actual price to be predicated not

In [123]:
```
skew=['Manufacturing_Year','Driven_KiloMeters']
from sklearn.preprocessing import PowerTransformer
scaler = PowerTransformer(method='yeo-johnson')

df[skew] = scaler.fit_transform(df[skew].values)
df[skew].head()
```

Out[123]:

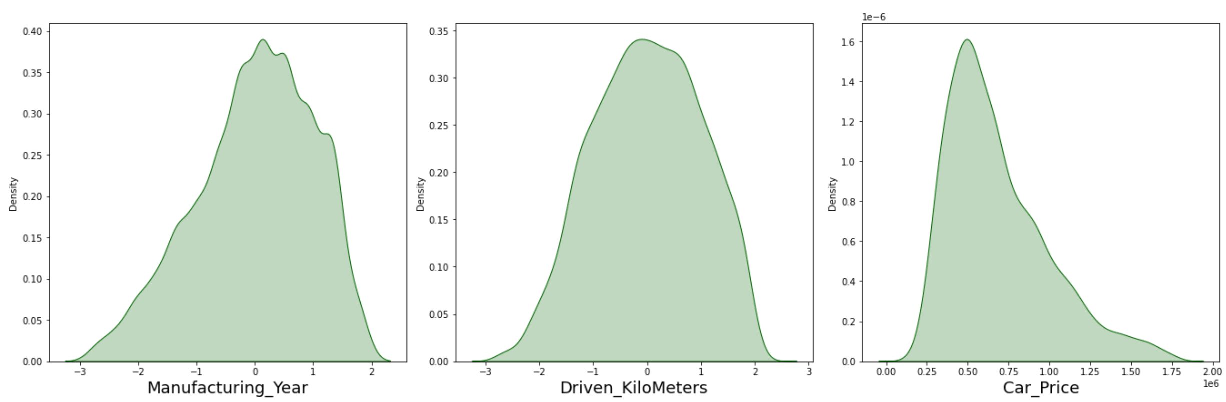
	Manufacturing_Year	Driven_KiloMeters
0	-0.983667	1.763965
1	0.131714	-1.035349
2	-1.338831	1.793026
3	-1.685986	-1.363016
4	-0.620311	-0.230475

In [124]:
```
df.skew()
```

Out[124]:
```
Brand                 0.167868
Model                 0.110196
Variant              -0.343922
Manufacturing_Year   -0.427569
Driven_KiloMeters    -0.115416
Fuel                 -0.133010
Number_of_Owners      1.367601
Car_Price             1.006157
dtype: float64
```

Checking skewness after removing

In [125]:
```
plt.figure(figsize=(25,35))
plotnumber=1
for column in numerical_col:
    if plotnumber<=8:
        ax=plt.subplot(6,4,plotnumber)
        sns.distplot(df[column],color="darkgreen",hist=False,kde_kws={"shade": Tr
        plt.xlabel(column,fontsize=18)
    plotnumber+=1
plt.tight_layout()
```



Looks Good symentric view that previous one

We have cleaned our dataset and now data is ready to build and train Models

Lest define our x and y now

In [126]:
```
x = df.drop('Car_Price', axis=1)
y = df['Car_Price']
x.shape
```

Out[126]: (3911, 7)

In [127]:
```
y.shape
```

Out[127]: (3911,)

Scaling Data using standardScaler

In [128]:
```
from sklearn.preprocessing import StandardScaler

scaler = StandardScaler()
x = pd.DataFrame(scaler.fit_transform(x), columns=x.columns)
x.head()
```

Out[128]:

	Brand	Model	Variant	Manufacturing_Year	Driven_KiloMeters	Fuel	Number_of_O
0	0.483436	0.729599	0.868812	-0.983667	1.763965	0.105203	-0.5
1	1.779188	1.731318	1.257871	0.131714	-1.035349	0.105203	1.8
2	-1.460192	-1.707916	-1.397133	-1.338831	1.793026	-1.962381	-0.5
3	-1.028274	-0.706198	-0.550610	-1.685986	-1.363016	0.105203	-0.5
4	-1.892109	-1.774698	0.629392	-0.620311	-0.230475	0.105203	1.8

Finding Best Random State

In [129]:
```
#Importing models and matrix

import sklearn
from sklearn.tree import DecisionTreeRegressor
from sklearn.neighbors import KNeighborsRegressor
from sklearn.ensemble import AdaBoostRegressor
from sklearn.ensemble import ExtraTreesRegressor
from sklearn.ensemble import GradientBoostingRegressor
from sklearn.ensemble import RandomForestClassifier
from sklearn.svm import SVC
from sklearn.linear_model import SGDClassifier
from sklearn.linear_model import LinearRegression, Ridge, Lasso
from sklearn.ensemble import RandomForestRegressor
from sklearn.svm import SVR

#metrics
from sklearn.metrics import confusion_matrix, classification_report
from sklearn.metrics import accuracy_score
from sklearn.metrics import r2_score,mean_squared_error
from sklearn.model_selection import train_test_split, GridSearchCV, cross_val_sco
```

In [130]:
```
maxAcc = 0
maxRS = 0

for i in range(1,200):
    x_train,x_test,y_train,y_test = train_test_split(x,y,test_size=.20, random_st
    modRF = RandomForestRegressor()
    modRF.fit(x_train,y_train)
    pred = modRF.predict(x_test)
    acc = r2_score(y_test,pred)
    if acc>maxAcc:
        maxAcc = acc
        maxRs=i
print(f"Best Accuracy is: {maxAcc} on Random State: {maxRs}")
```

```
Best Accuracy is: 0.9416279073939675 on Random State: 55
```

We Found best Random state. which is 55 with 94% accuracy

In [131]:
```
# Best Parameter for Lasso

parameters = {'alpha':[0.0001,0.001,0.01,0.1,1,10],'random_state':list(range(0,1(
lasso = Lasso()
clf = GridSearchCV(lasso,parameters)
clf.fit(x_train,y_train)
print(clf.best_params_)
```

```
{'alpha': 10, 'random_state': 0}
```

Defining train and test data with best random state

In [132]:
```
x_train,x_test,y_train,y_test = train_test_split(x,y,test_size=.20, random_state=
```

In [133]:
```
dt=DecisionTreeRegressor()
kn=KNeighborsRegressor()
adb=AdaBoostRegressor()
gdb=GradientBoostingRegressor()
lnr=LinearRegression()
rfr=RandomForestRegressor()
sv=SVR()
lss=Lasso(alpha=0.0001,random_state=0)

model=[dt,kn,adb,gdb,lnr,rfr,sv,lss]

for i in model:
    i.fit(x_train,y_train)
    predi=i.predict(x_test)
    print('performance matrix of',i,'is:')
    print("RMSE Score is:",mean_squared_error(y_test,predi))
    r2 = r2_score(y_test, predi)*100
    print("R2 Score is:", r2)
    cv_score = (cross_val_score(i, x, y, cv=5).mean())*100
    print("Cross Validation Score:", cv_score)
    result = r2 - cv_score
    print("R2 Score - Cross Validation Score is", result)
    print("******************************************************************")
```

```
performance matrix of DecisionTreeRegressor() is:
RMSE Score is: 8409680131.803321
R2 Score is: 90.69015556431556
Cross Validation Score: 80.32976042631843
R2 Score - Cross Validation Score is 10.36039513799713
******************************************************************
performance matrix of KNeighborsRegressor() is:
RMSE Score is: 29492475966.796936
R2 Score is: 67.3506769614596
Cross Validation Score: 63.79880839909029
R2 Score - Cross Validation Score is 3.5518685623693074
******************************************************************
performance matrix of AdaBoostRegressor() is:
RMSE Score is: 49895042441.36229
R2 Score is: 44.76423883421259
Cross Validation Score: 48.812315277492445
R2 Score - Cross Validation Score is -4.048076443279854
******************************************************************
performance matrix of GradientBoostingRegressor() is:
RMSE Score is: 16341405281.45134
R2 Score is: 81.90942596550804
Cross Validation Score: 79.84159946823947
R2 Score - Cross Validation Score is 2.0678264972685696
******************************************************************
performance matrix of LinearRegression() is:
RMSE Score is: 52309202977.306145
R2 Score is: 42.09166881012698
Cross Validation Score: 41.01037931931106
R2 Score - Cross Validation Score is 1.0812894908159194
******************************************************************
performance matrix of RandomForestRegressor() is:
RMSE Score is: 5167621993.167944
R2 Score is: 94.27924057695417
```

```
Cross Validation Score: 88.71224441904954
R2 Score - Cross Validation Score is 5.566996157904626
*****************************************************************
performance matrix of SVR() is:
RMSE Score is: 92515663308.83241
R2 Score is: -2.418453469132764
Cross Validation Score: -7.200993137347611
R2 Score - Cross Validation Score is 4.782539668214847
*****************************************************************
performance matrix of Lasso(alpha=0.0001, random_state=0) is:
RMSE Score is: 52309202992.78418
R2 Score is: 42.09166879299219
Cross Validation Score: 41.01037932627494
R2 Score - Cross Validation Score is 1.0812894667172444
*****************************************************************
```

Considering above all matrix I would select GradientBoostingRegressor as a best performing parameter becasue we can see high r2 score and less diffrence between r2 score and cross validation score

Hyperparameter tuning for GradientBoostingRegressor

In [136]:

```python
from sklearn.model_selection import GridSearchCV
from sklearn.ensemble import RandomForestRegressor

parameters={'loss' : ['squared_error', 'absolute_error', 'huber', 'quantile'],
           'max_features' : ['auto', 'sqrt', 'log2'],
           'learning_rate':[0.1,.2,.4,.5],
           'criterion' : ['friedman_mse', 'squared_error', 'mse'],}


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

In [137]:

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

Out[137]:

```
▸ GridSearchCV
▸ estimator: GradientBoostingRegressor
    ▸ GradientBoostingRegressor
```

In [138]:

```python
GCV.best_params_
```

Out[138]:

```
{'criterion': 'friedman_mse',
 'learning_rate': 0.4,
 'loss': 'squared_error',
 'max_features': 'auto'}
```

In [139]:
```
car_model = GradientBoostingRegressor(criterion='friedman_mse', learning_rate= 0.
car_model.fit(x_train, y_train)
pred = car_model.predict(x_test)
print("RMSE value:",np.sqrt(mean_squared_error(y_test, gdb.predict(x_test))))
print('R2_Score:',r2_score(y_test,pred)*100)
```

```
RMSE value: 127833.50609856298
R2_Score: 91.78569771667927
```

Here we can see that after hypertuning parameter we have increased accuracy upto 92% and RMSE is also very less that mean model id trained well

In [140]:
```
#saving the model
import joblib
joblib.dump(car_model,'car_model.pkl')
```

Out[140]: ['car_model.pkl']

In [141]:
```
# Loading our saved model so that we can predict using it

loadmodel = joblib.load('car_model.pkl')
```

In [142]:
```
import numpy as np
a = np.array(y_test)
predicted = np.array(loadmodel.predict(x_test))
df_final = pd.DataFrame({"Original":a,"Predicted":predicted},index=range(len(a)))
df_final
```

Out[142]:

	Original	Predicted
0	313599	547117.572686
1	637000	672323.948869
2	403000	475625.603890
3	484000	495820.236159
4	1009000	826886.412777
...	...	...
778	249000	380597.855386
779	380000	458238.156483
780	624000	655097.397502
781	584000	500687.316232
782	515000	518867.397311

783 rows × 2 columns

Finally we have used trained model to predit value and we can see certain closeness between actual values and predicated values

In [ ]:

```

```