import pandas as pd

df=pd.read_csv('/content/car data.csv')

df.shape

```
(301, 9)
```

print(df['Seller_Type'].unique())

print(df['Transmission'].unique())

print(df['Owner'].unique())

```
['Dealer' 'Individual']
['Manual' 'Automatic']
[0 1 3]
```

df.isnull().sum()

```
Car_Name         0
Year             0
Selling_Price    0
Present_Price    0
Kms_Driven       0
Fuel_Type        0
Seller_Type      0
Transmission     0
Owner            0
dtype: int64
```

df.describe()

	Year	Selling_Price	Present_Price	Kms_Driven	Owner
count	301.000000	301.000000	301.000000	301.000000	301.000000
mean	2013.627907	4.661296	7.628472	36947.205980	0.043189
std	2.891554	5.082812	8.644115	38886.883882	0.247915
min	2003.000000	0.100000	0.320000	500.000000	0.000000
25%	2012.000000	0.900000	1.200000	15000.000000	0.000000
50%	2014.000000	3.600000	6.400000	32000.000000	0.000000
75%	2016.000000	6.000000	9.900000	48767.000000	0.000000
max	2018.000000	35.000000	92.600000	500000.000000	3.000000

df.columns

```
Index(['Car_Name', 'Year', 'Selling_Price', 'Present_Price', 'Kms_Driven',
       'Fuel_Type', 'Seller_Type', 'Transmission', 'Owner'],
      dtype='object')
```

final_dataset=df[['Year','Selling_Price','Present_Price','Kms_Driven','Fuel_Type','Seller_Type','Transmission','Owner']
]

#creating new feature bcz we need no of years for a car and not just year , this feature will help us find out the same by = current year-year

final_dataset['Current_Year']=2022

final_dataset['no_of_year']=final_dataset['Current_Year']-final_dataset['Year']

final_dataset.head()

	Year	Selling_Price	Present_Price	Kms_Driven	Fuel_Type	Seller_Type	Transmission	Owner	Current_Year	no_of_year
0	2014	3.35	5.59	27000	Petrol	Dealer	Manual	0	2022	8
1	2013	4.75	9.54	43000	Diesel	Dealer	Manual	0	2022	9
2	2017	7.25	9.85	6900	Petrol	Dealer	Manual	0	2022	5
3	2011	2.85	4.15	5200	Petrol	Dealer	Manual	0	2022	11
4	2014	4.60	6.87	42450	Diesel	Dealer	Manual	0	2022	8

#now year and current year is not required , therefore dropping it

final_dataset.drop(['Year'],axis=1,inplace=True)

final_dataset.drop(['Current_Year'],axis=1,inplace=True) #inplace because we need operation to take place like a permanent one

final_dataset=pd.get_dummies(final_dataset,drop_first=True)

final_dataset

	Selling_Price	Present_Price	Kms_Driven	Owner	no_of_year	Fuel_Type_Diesel	Fuel_Type_Petrol	Seller_Type_Individual	Transmission_Manual
0	3.35	5.59	27000	0	8	0	1	0	1
1	4.75	9.54	43000	0	9	1	0	0	1
2	7.25	9.85	6900	0	5	0	1	0	1
3	2.85	4.15	5200	0	11	0	1	0	1
4	4.60	6.87	42450	0	8	1	0	0	1
...	...	...	...	...	...	...	...	...	...
296	9.50	11.60	33988	0	6	1	0	0	1
297	4.00	5.90	60000	0	7	0	1	0	1
298	3.35	11.00	87934	0	13	0	1	0	1
299	11.50	12.50	9000	0	5	1	0	0	1
300	5.30	5.90	5464	0	6	0	1	0	1

301 rows × 9 columns

#finding correlation

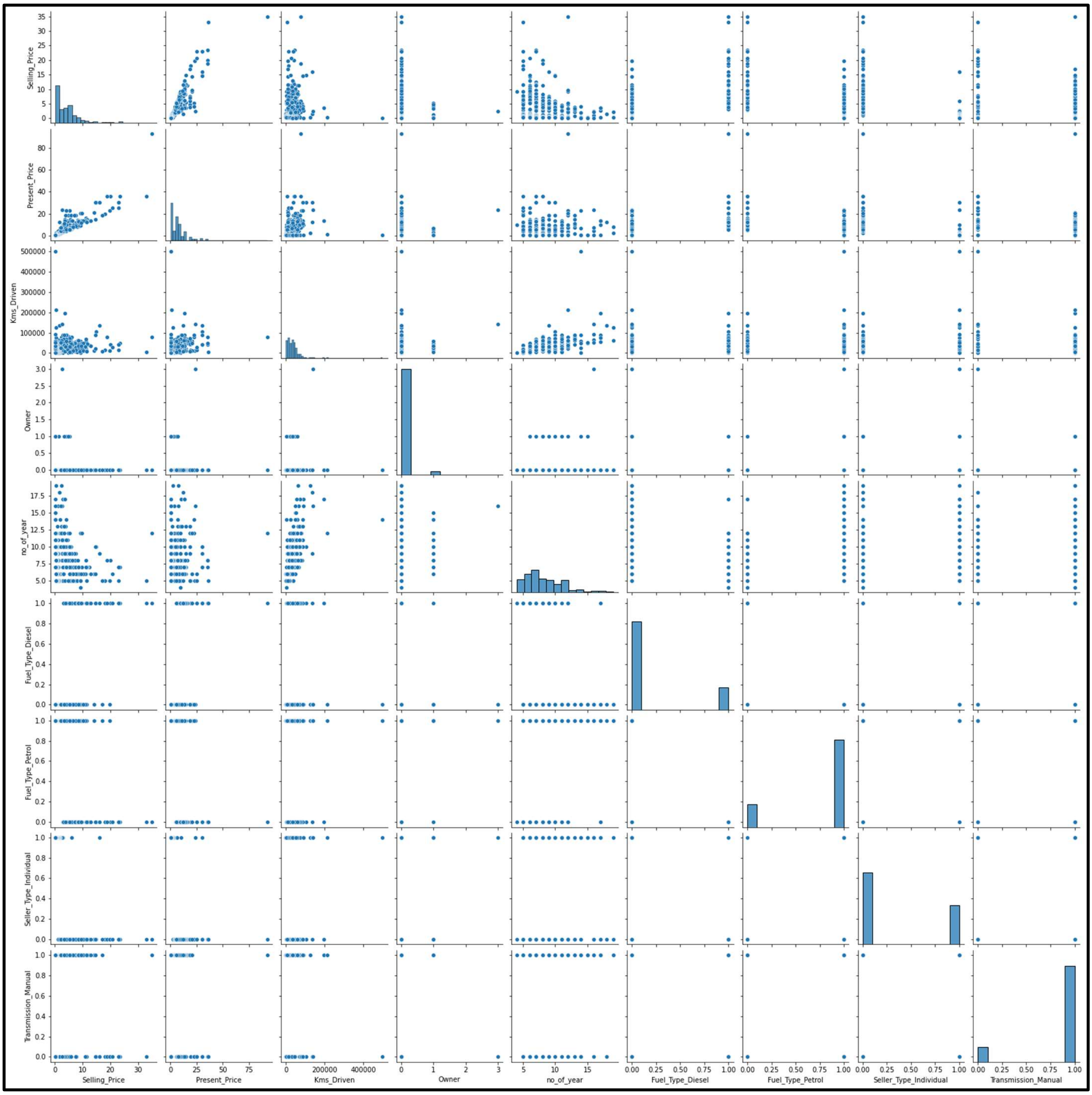
final_dataset.corr()

	Selling_Price	Present_Price	Kms_Driven	Owner	no_of_year	Fuel_Type_Diesel	Fuel_Type_Petrol	Seller_Type_Individual	Transmission_Manual
Selling_Price	1.000000	0.878983	0.029187	-0.088344	-0.236141	0.552339	-0.540571	-0.550724	-0.367128
Present_Price	0.878983	1.000000	0.203647	0.008057	0.047584	0.473306	-0.465244	-0.512030	-0.348715
Kms_Driven	0.029187	0.203647	1.000000	0.089216	0.524342	0.172515	-0.172874	-0.101419	-0.162510
Owner	-0.088344	0.008057	0.089216	1.000000	0.182104	-0.053469	0.055687	0.124269	-0.050316
no_of_year	-0.236141	0.047584	0.524342	0.182104	1.000000	-0.064315	0.059959	0.039896	-0.000394
Fuel_Type_Diesel	0.552339	0.473306	0.172515	-0.053469	-0.064315	1.000000	-0.979648	-0.350467	-0.098643
Fuel_Type_Petrol	-0.540571	-0.465244	-0.172874	0.055687	0.059959	-0.979648	1.000000	0.358321	0.091013
Seller_Type_Individual	-0.550724	-0.512030	-0.101419	0.124269	0.039896	-0.350467	0.358321	1.000000	0.063240
Transmission_Manual	-0.367128	-0.348715	-0.162510	-0.050316	-0.000394	-0.098643	0.091013	0.063240	1.000000

```
import seaborn as sns

#plotting in form of pairplot using seaborn

sns.pairplot(final_dataset)
```




```
#independent and dependent feautre

x=final_dataset.iloc[:,1:] #from 1st col = independent

y=final_dataset.iloc[:,0] #first as dependent
```

x.head()

	Present_Price	Kms_Driven	Owner	no_of_year	Fuel_Type_Diesel	Fuel_Type_Petrol	Seller_Type_Individual	Transmission_Manual
0	5.59	27000	0	8	0	1	0	1
1	9.54	43000	0	9	1	0	0	1
2	9.85	6900	0	5	0	1	0	1
3	4.15	5200	0	11	0	1	0	1
4	6.87	42450	0	8	1	0	0	1

y.head()

```
0    3.35
1    4.75
2    7.25
3    2.85
4    4.60
Name: Selling_Price, dtype: float64
```

#feature importance

from sklearn.ensemble import ExtraTreesRegressor

model=ExtraTreesRegressor()

model.fit(x,y)

```
ExtraTreesRegressor()
```

#train test split

from sklearn.model_selection import train_test_split

x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.2)

x_train.shape

```
(240, 8)
```

from sklearn.ensemble import RandomForestRegressor

rf_random=RandomForestRegressor()

import numpy as np

#hypeparametes

n_estimators=[int(x) for x in np.linspace(start=100, stop = 1200, num = 12)]

print(n_estimators)

```
[100, 200, 300, 400, 500, 600, 700, 800, 900, 1000, 1100, 1200]
```

#first create the base model to tune

rf=RandomForestRegressor()

#applying randimize search cv

rf_random = RandomizedSearchCV(estimator=rf, param_distributions = random_grid, scoring='neg_mean_squared_error',n_iter=10, cv=5, verbose=2, random_state=42,n_jobs=1)

rf_random.fit(x_train,y_train)

```
RandomForestRegressor()
```

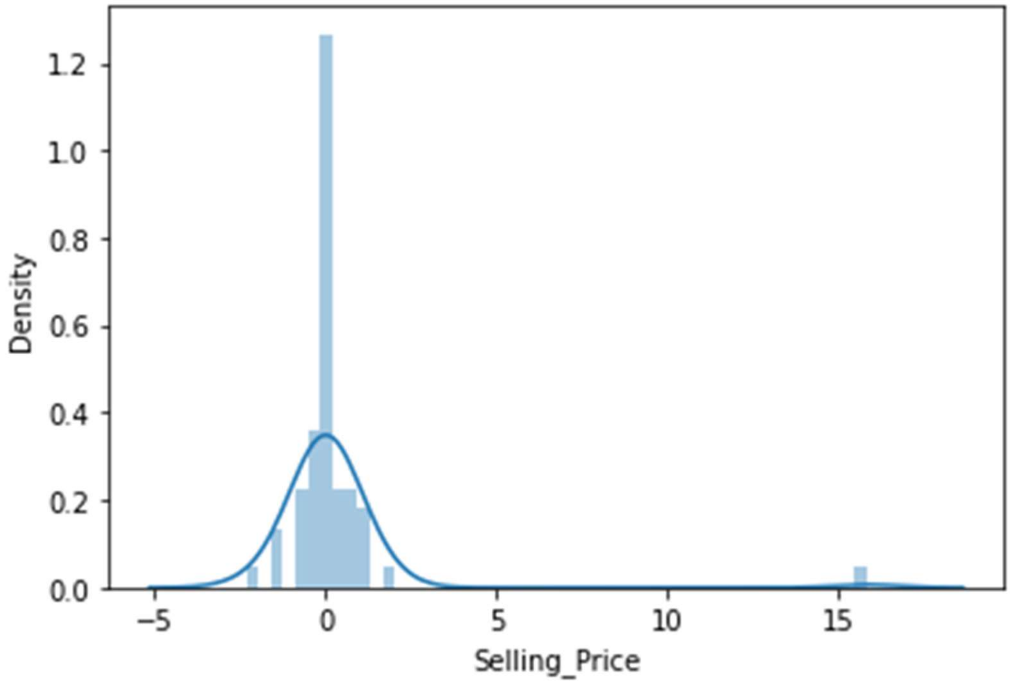
prediction=rf_random.predict(x_test)

prediction

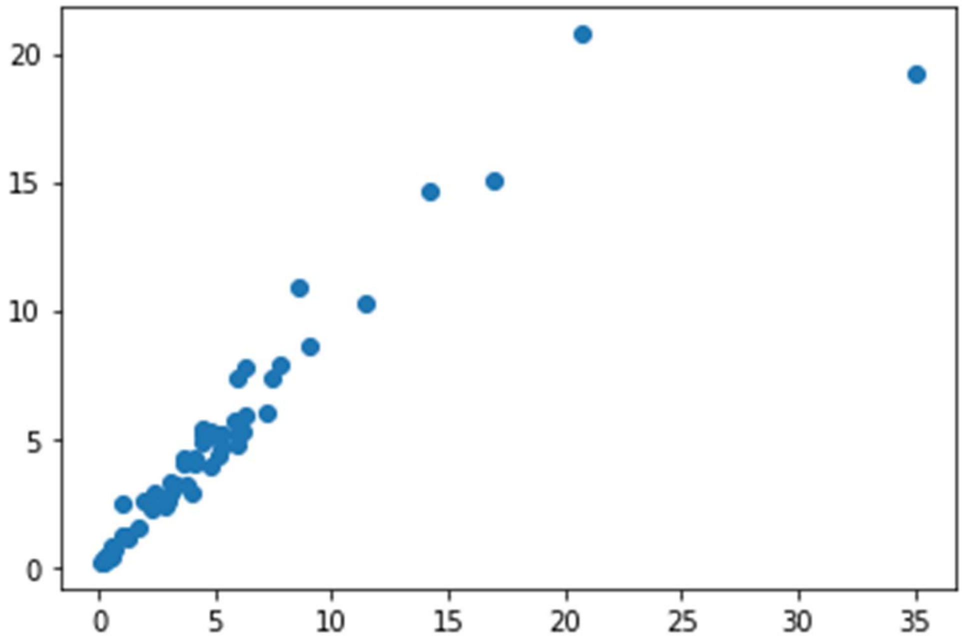
```
array([ 0.3583,  5.2288,  8.6604,  1.555 ,  1.1764,  5.2329,  0.3305,
        4.7845,  4.219 ,  2.6015,  2.922 ,  0.8053, 10.2285,  5.2459,
        0.4249,  0.2142,  1.144 ,  6.037 ,  3.971 ,  4.0639,  0.7048,
        2.857 , 15.0204,  0.2457,  7.8805,  4.1935,  4.3345,  3.9905,
        5.149 ,  7.3655,  2.2765,  0.456 ,  0.2714,  3.2735,  1.1812,
        5.2268,  4.8889,  5.1415,  4.6775, 19.1748,  1.1831,  5.177 ,
        5.911 ,  0.3463,  3.1537,  2.376 ,  0.4647, 14.6703,  2.9275,
        5.746 ,  3.253 ,  0.4153,  7.378 ,  0.1927, 20.7582,  5.2246,
        5.348 ,  2.4835, 10.861 ,  7.7821,  2.625 ])
```

import seaborn as sns

sns.distplot(y_test-prediction)



plt.scatter(y_test,prediction)



from sklearn import metrics

print('MAE:', metrics.mean_absolute_error(y_test, prediction))

print('MSE:', metrics.mean_squared_error(y_test, prediction))

print('RMSE:', np.sqrt(metrics.mean_squared_error(y_test, prediction)))

```
MAE: 0.7062967213114754
MSE: 4.574107365737702
RMSE: 2.138716289211288
```