In [93]:
```
#importing the libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

In [94]:
```
#reading the dataset
data=pd.read_csv('car data.csv')
print(data.shape)
data.head()
```

```
(301, 9)
```

Out[94]:

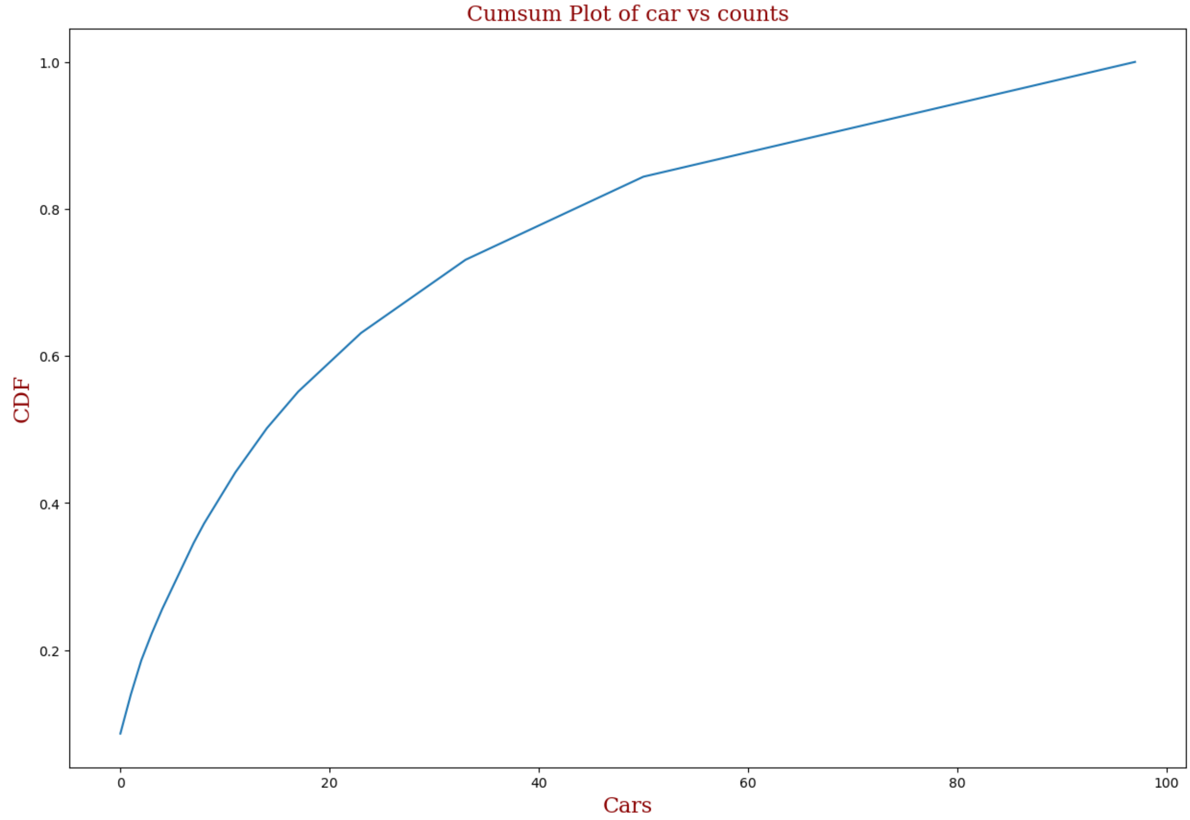
	Car_Name	Year	Selling_Price	Present_Price	Kms_Driven	Fuel_Type	Seller_Type	Transmission
0	ritz	2014	3.35	5.59	27000	Petrol	Dealer	Manual
1	sx4	2013	4.75	9.54	43000	Diesel	Dealer	Manual
2	ciaz	2017	7.25	9.85	6900	Petrol	Dealer	Manual
3	wagon r	2011	2.85	4.15	5200	Petrol	Dealer	Manual
4	swift	2014	4.60	6.87	42450	Diesel	Dealer	Manual

From the dataset preview, Selling_Price is the dependent variable and the rest are independent variables

In [95]:
```
print("Top 10 cars:\n")
print(data.Car_Name.value_counts().head(10))

y = data.Car_Name.value_counts(normalize=True).cumsum()
x = len(y)

font = {'family': 'serif',
        'color':  'darkred',
        'weight': 'normal',
        'size': 16,
        }

plt.figure(figsize=(15,10))
plt.plot(range(x),y);
plt.title('Cumsum Plot of car vs counts', fontdict = font)
plt.xlabel('Cars', fontdict = font)
plt.ylabel('CDF', fontdict = font)
```

```
Top 10 cars:

city              26
corolla altis     16
verna             14
fortuner          11
brio              10
ciaz               9
innova             9
i20                9
grand i10          8
jazz               7
Name: Car_Name, dtype: int64
```

Out[95]:
```
Text(0, 0.5, 'CDF')
```



Checking if there are any missing values

In [96]:
```
data.isnull().sum()
```

Out[96]:
```
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
```

Checking cardinality of independent categorical variables in the dataset

In [97]:
```
print('Unique elements in Seller_Type are',data['Seller_Type'].unique())
print('Unique elements in Fuel_Type are',data['Fuel_Type'].unique())
print('Unique elements in Transmission are',data['Transmission'].unique())
print('Unique elements in Owner are',data['Owner'].unique())
print('Unique elements in Year are',data['Year'].unique())
```

```
Unique elements in Seller_Type are ['Dealer' 'Individual']
Unique elements in Fuel_Type are ['Petrol' 'Diesel' 'CNG']
Unique elements in Transmission are ['Manual' 'Automatic']
Unique elements in Owner are [0 1 3]
Unique elements in Year are [2014 2013 2017 2011 2018 2015 2016 2009 2010 2012 200
3 2008 2006 2005
 2004 2007]
```

In [98]:
```
print('Unique elements in Car_Name are',data['Car_Name'].nunique())
#98 unique elements
#so, rather than encoding it, we can just drop this columbn as it doesn' make sense
```

```
Unique elements in Car_Name are 98
```

In [99]:
```
data.describe()
```

Out[99]:

	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

Feature Engineering

In [100…
```
dataset=data[['Year','Selling_Price','Present_Price','Kms_Driven','Fuel_Type','Sel
dataset.head()
```

Out[100]:

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

defining a feature variable 'Present_Year' which has all the element values as 2020. On subtracting 'Present_Year' and 'Year', we can make another feature variable as 'Number_of_Years_Old', which gives us idea about how old the car is.

In [101…
```
dataset['Present_Year']=2020
dataset['Number_of_Years_Old']=dataset['Present_Year']- dataset['Year']
dataset.head()
```

Out[101]:

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

So, we can now safely drop 'Year' and 'Present_Year' columns

In [102…

```
dataset.drop(labels=['Year', 'Present_Year'],axis=1,inplace=True)
dataset.head()
```

Out[102]:

	Selling_Price	Present_Price	Kms_Driven	Fuel_Type	Seller_Type	Transmission	Owner	Number
0	3.35	5.59	27000	Petrol	Dealer	Manual	0	
1	4.75	9.54	43000	Diesel	Dealer	Manual	0	
2	7.25	9.85	6900	Petrol	Dealer	Manual	0	
3	2.85	4.15	5200	Petrol	Dealer	Manual	0	
4	4.60	6.87	42450	Diesel	Dealer	Manual	0	

Encoding the Categorical Variables

In [103…

```
#select categorical variables from then dataset, and then implement categorical enc
Fuel_Type=dataset[['Fuel_Type']]
Fuel_Type=pd.get_dummies(Fuel_Type, drop_first=True)

Seller_Type=dataset[['Seller_Type']]
Seller_Type=pd.get_dummies(Seller_Type, drop_first=True)

Transmission=dataset[['Transmission']]
Transmission=pd.get_dummies(Transmission, drop_first=True)

dataset=pd.concat([dataset,Fuel_Type, Seller_Type, Transmission], axis=1)

dataset.drop(labels=['Fuel_Type', 'Seller_Type', 'Transmission'], axis=1, inplace=

dataset.head()
```

Out[103]:

	Selling_Price	Present_Price	Kms_Driven	Owner	Number_of_Years_Old	Fuel_Type_Diesel	Fuel_T
0	3.35	5.59	27000	0	6	0	
1	4.75	9.54	43000	0	7	1	
2	7.25	9.85	6900	0	3	0	
3	2.85	4.15	5200	0	9	0	
4	4.60	6.87	42450	0	6	1	

to reduce the multicollinearity we dropped cng --Multicollinearity occurs when two or more independent variables in a data frame have a high correlation with one another in a regression model.

In [104…

```
dataset.columns
```

Out[104]:

```
Index(['Selling_Price', 'Present_Price', 'Kms_Driven', 'Owner',
       'Number_of_Years_Old', 'Fuel_Type_Diesel', 'Fuel_Type_Petrol',
       'Seller_Type_Individual', 'Transmission_Manual'],
      dtype='object')
```

In [105…

```
# Dataset Correlation
dataset.corr()
```

Out[105]:

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

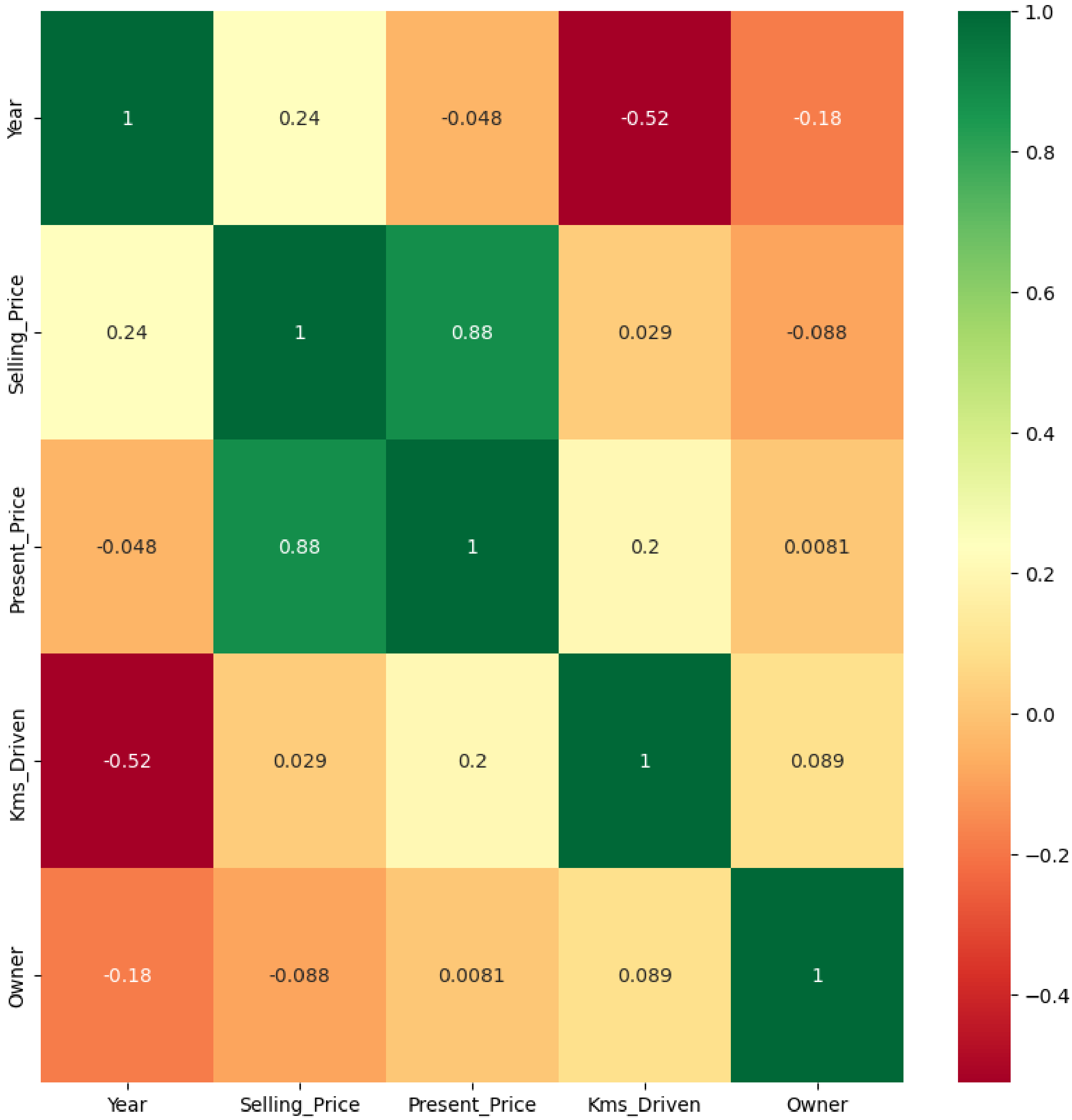
Data Visualization and Correlation

In [106…

```
#Correlations of features in dataset
corrmat = data.corr()
top_corr_features = corrmat.index
plt.figure(figsize=(10,10))
```

```
#Plot heat map
sns.heatmap(data[top_corr_features].corr(),annot=True,cmap="RdYlGn")
```

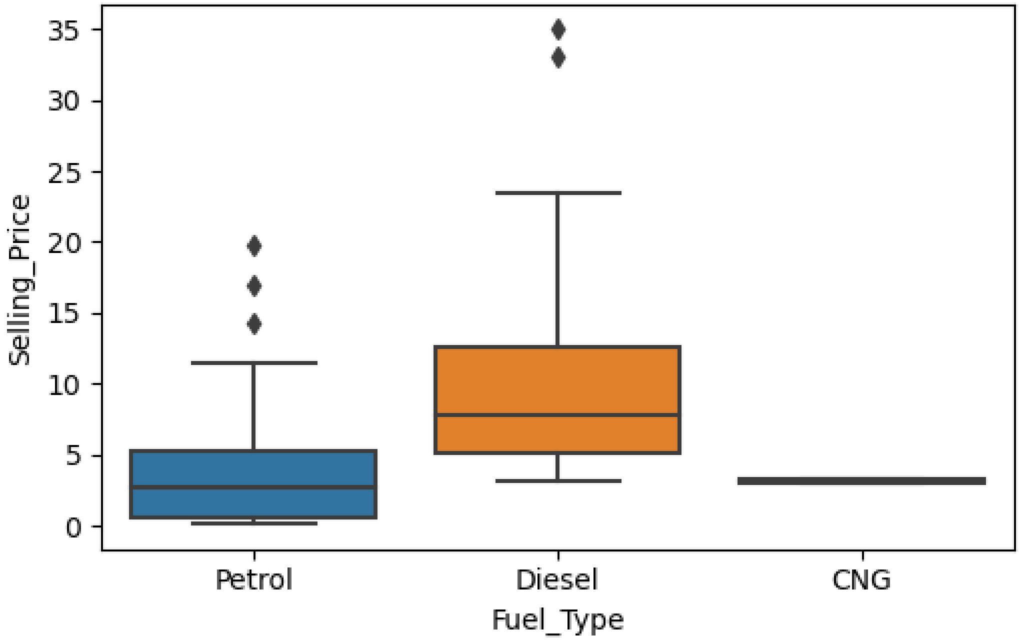
Out[106]: <AxesSubplot:>



In [107…

```
plt.figure(figsize = (20,12))
plt.subplot(3,3,1)
sns.boxplot(x = 'Fuel_Type', y = 'Selling_Price', data = data)
```

Out[107]: <AxesSubplot:xlabel='Fuel_Type', ylabel='Selling_Price'>

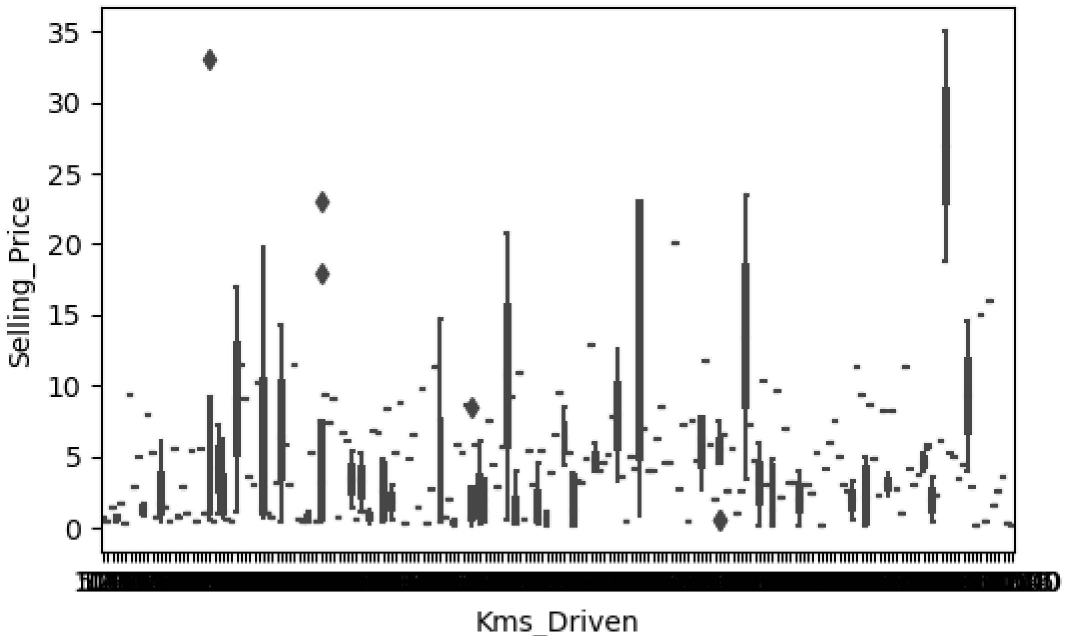


In [108…

```
plt.figure(figsize = (20,12))
plt.subplot(3,3,1)
sns.boxplot(x = 'Kms_Driven', y = 'Selling_Price', data = data)
```

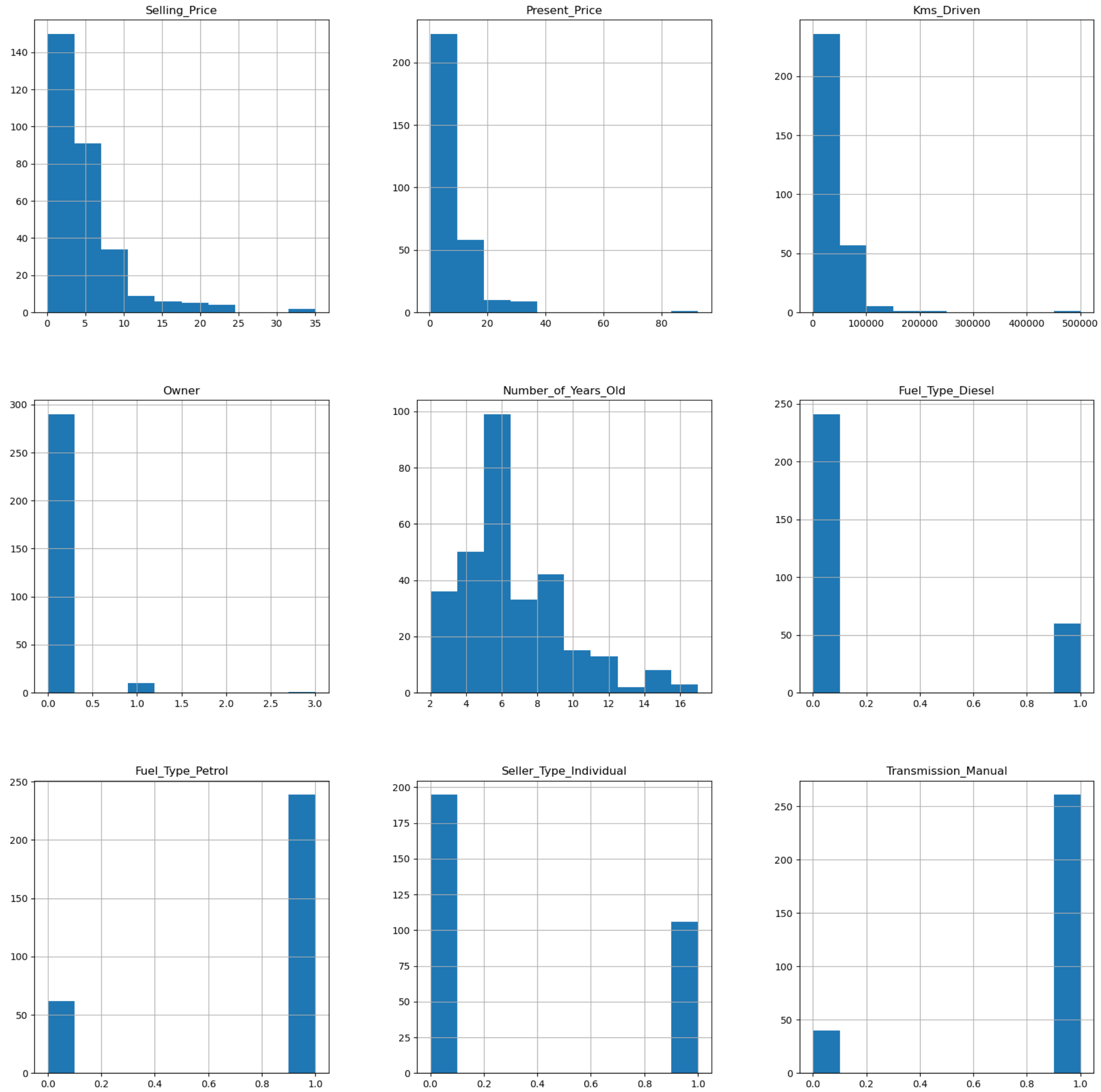
Out[108]:

```
<AxesSubplot:xlabel='Kms_Driven', ylabel='Selling_Price'>
```



In [109…

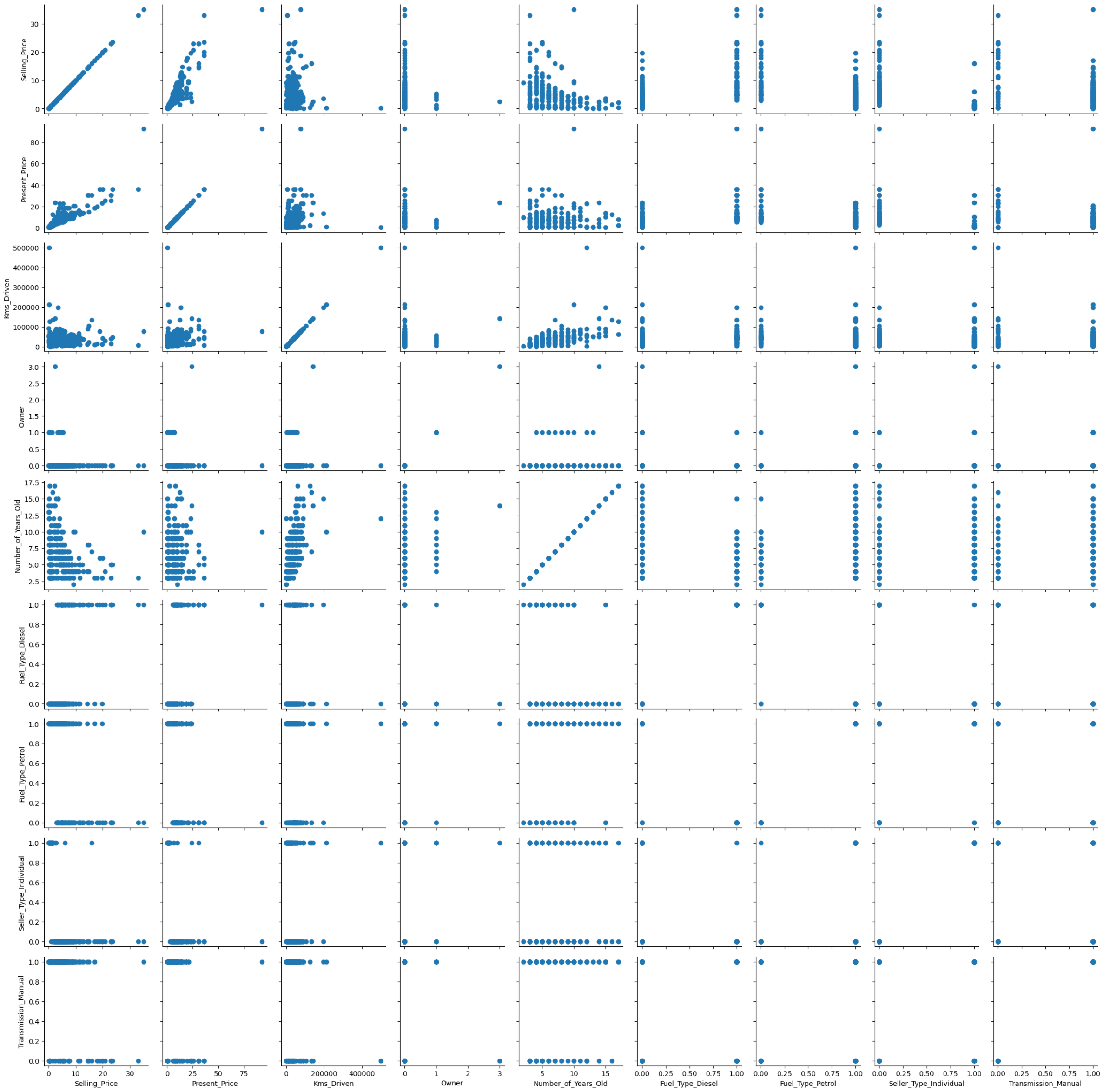
```
p = dataset.hist(figsize = (20,20))
```



In [110…

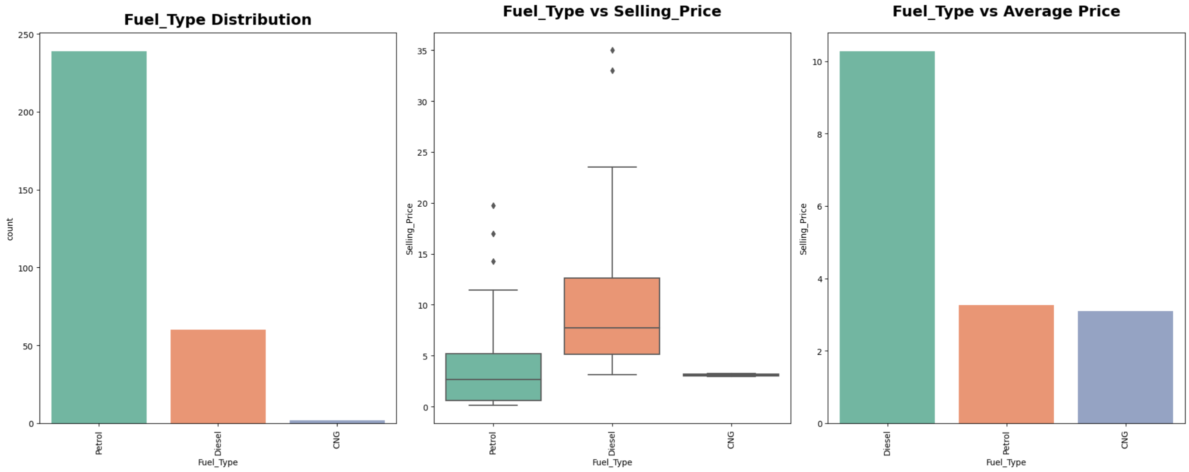
```
g=sns.PairGrid(dataset)
g.map(plt.scatter)
```

Out[110]: <seaborn.axisgrid.PairGrid at 0x1844965cd30>



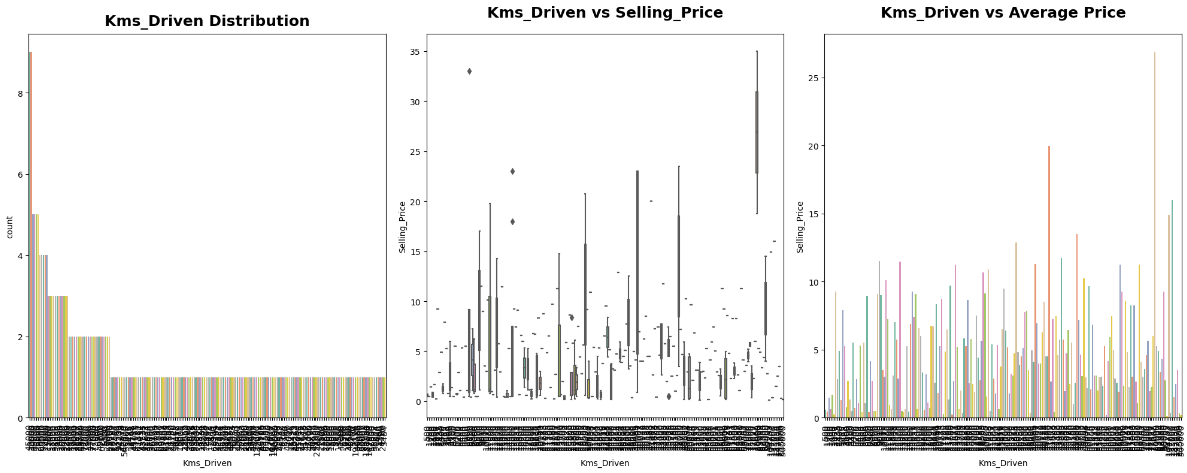
In [111…

```
def categorical_visualization(cols):
    plt.figure(figsize=(20,8))
    plt.subplot(1,3,1)
    sns.countplot(x=cols,data=data,palette="Set2",order=data[cols].value_counts().
    plt.title(f"{cols} Distribution",pad=10,fontweight="black",fontsize=18)
    plt.xticks(rotation=90)

    plt.subplot(1,3,2)
    sns.boxplot(x=cols,y="Selling_Price",data=data,palette="Set2")
    plt.title(f"{cols} vs Selling_Price",pad=20,fontweight="black",fontsize=18)
    plt.xticks(rotation=90)

    plt.subplot(1,3,3)
    x=pd.DataFrame(data.groupby(cols)["Selling_Price"].mean().sort_values(ascendin
    sns.barplot(x=x.index,y="Selling_Price",data=x,palette="Set2")
    plt.title(f"{cols} vs Average Price",pad=20,fontweight="black",fontsize=18)
    plt.xticks(rotation=90)
    plt.tight_layout()
    plt.show()

categorical_visualization("Fuel_Type")
```



In [112...

```
categorical_visualization("Kms_Driven")
```



In [113...

```
sell=dataset['Selling_Price']
dataset.drop(['Selling_Price'], axis=1, inplace=True)
dataset=dataset.join(sell)
dataset.head()
```

Out[113]:

	Present_Price	Kms_Driven	Owner	Number_of_Years_Old	Fuel_Type_Diesel	Fuel_Type_Petrol	S
0	5.59	27000	0	6	0	1	
1	9.54	43000	0	7	1	0	
2	9.85	6900	0	3	0	1	
3	4.15	5200	0	9	0	1	
4	6.87	42450	0	6	1	0	

In [114...

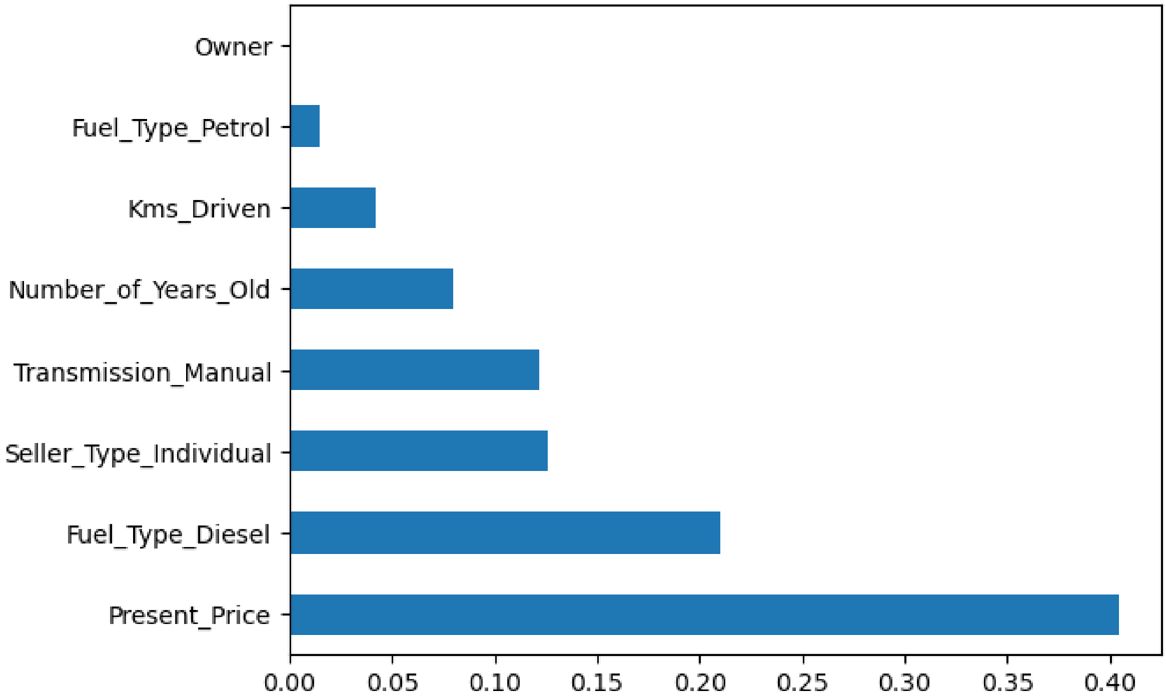
```
X=dataset.iloc[:,:-1]
y=dataset.iloc[:,-1]
```

In [115...

```
### To determine important features, make use of ExtraTreesRegressor
from sklearn.ensemble import ExtraTreesRegressor
model = ExtraTreesRegressor()
model.fit(X,y)

print(model.feature_importances_)

#plot graph of feature importances for better visualization
feat_importances = pd.Series(model.feature_importances_, index=X.columns)
```

```
feat_importances.nlargest(10).plot(kind='barh')
plt.show()
```

```
[0.4046579  0.04194815 0.0008649  0.07983709 0.21022608 0.01428844
 0.12603296 0.12214448]
```



'Owner' has zero feature importance i.e. nil on the dependent variable, 'Selling_Price'

Model Building and Training

In [116…

```
X=dataset.iloc[:,:-1].values
y=dataset.iloc[:,-1].values
```

In [117…

```
from sklearn.model_selection import cross_val_score
from sklearn import metrics
from sklearn.metrics import mean_absolute_error
from sklearn.metrics import mean_squared_error
#from sklearn.model_selection import RandomizedSearchCV
#from sklearn.model_selection import GridSearchCV
#from sklearn.model_selection import StratifiedKFold
#kfold = StratifiedKFold(n_splits=3)
```

In [118…

```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_st
```

In [119…

```
accuracy = []
r2score = []
mean2=[]
meanabsoulte=[]
rmse=[]
```

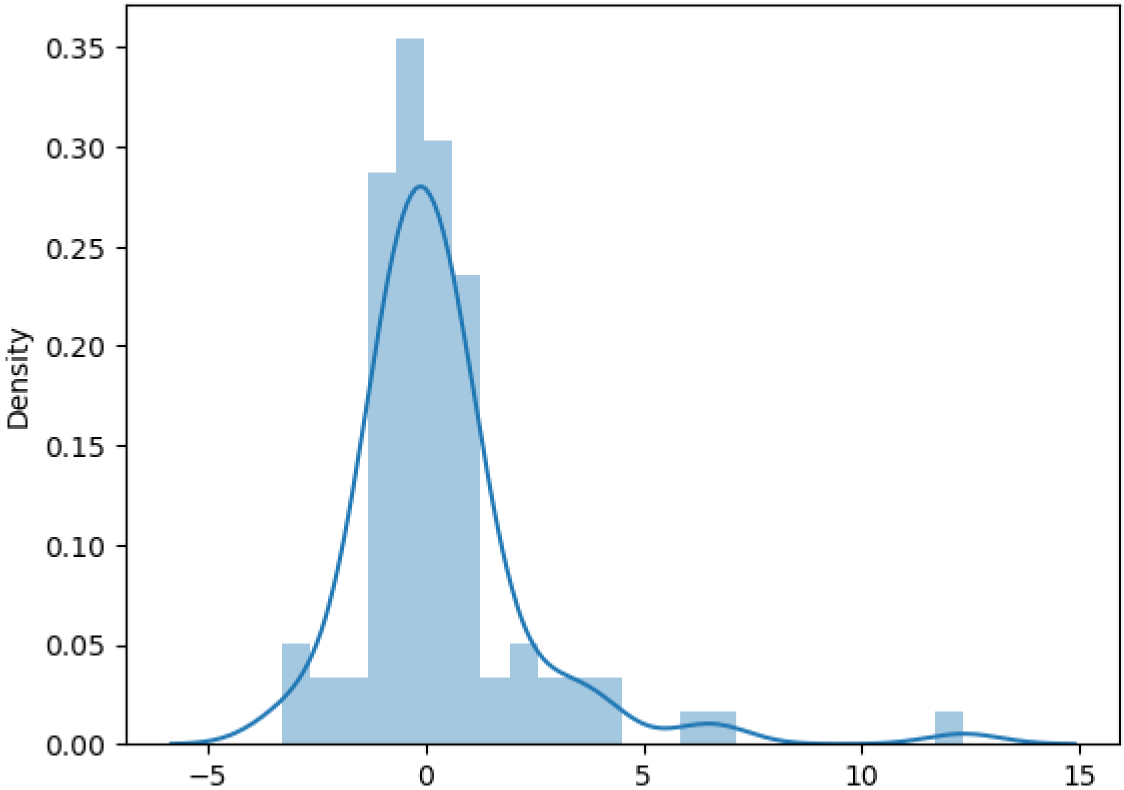
Linear Regressor

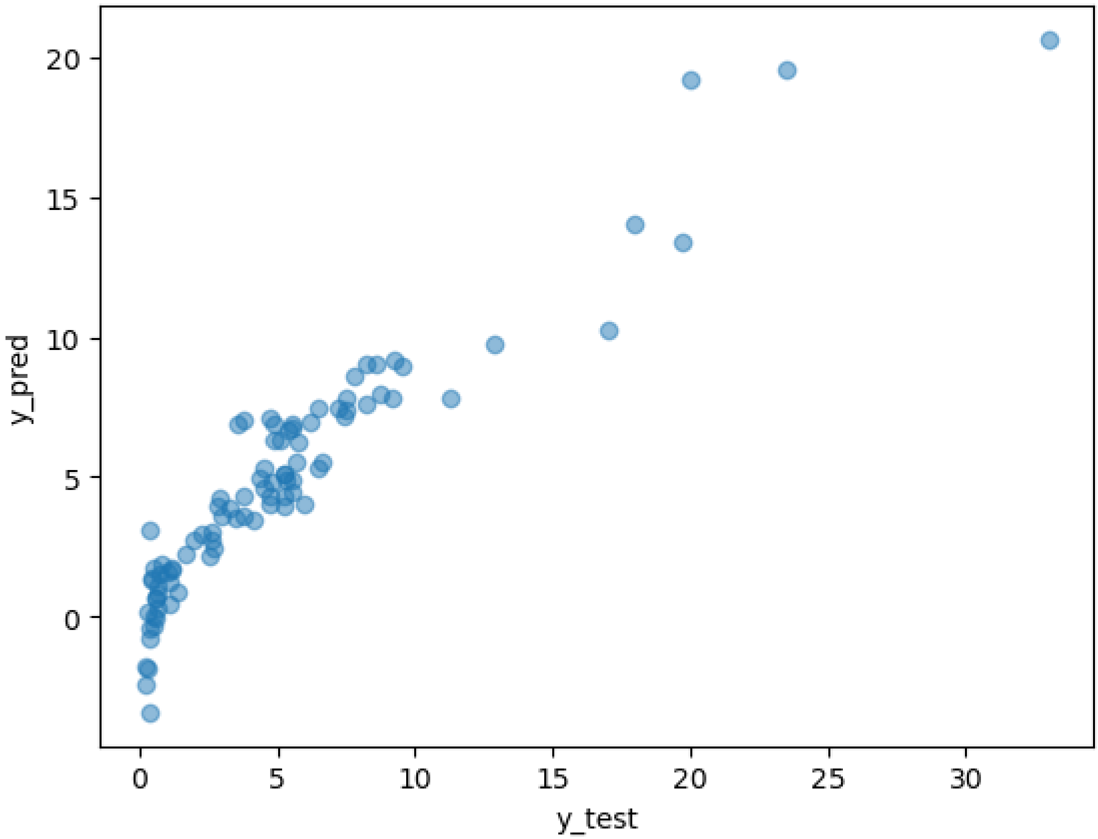
In [120…

```
from sklearn.linear_model import LinearRegression
model = LinearRegression()
```

```
model.fit(X_train, y_train)

y_pred = model.predict(X_test)


print("Linear Regressor Score on Training set is",model.score(X_train, y_train))#T
print("Linear Regressor Score on Test Set is",model.score(X_test, y_test))#Testing

accuracies = cross_val_score(model, X_train, y_train, cv = 5)
print(accuracies)
print("Accuracy: {:.2f} %".format(accuracies.mean()*100))
print("Standard Deviation: {:.2f} %".format(accuracies.std()*100))

mae=mean_absolute_error(y_pred, y_test)
print("Mean Absolute Error:" , mae)

mse=mean_squared_error(y_test, y_pred)
print("Mean Squared Error:" , mse)

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

print('The r2_score is', metrics.r2_score(y_test, y_pred))
accuracy.append(accuracies.mean()*100)
r2score.append(metrics.r2_score(y_test, y_pred))
mean2.append(mse)
meanabsoulte.append(mae)
rmse.append(np.sqrt(metrics.mean_squared_error(y_test, y_pred)))

sns.distplot(y_test-y_pred)
plt.show()

plt.scatter(y_test, y_pred, alpha = 0.5)
plt.xlabel("y_test")
plt.ylabel("y_pred")
plt.show()
```

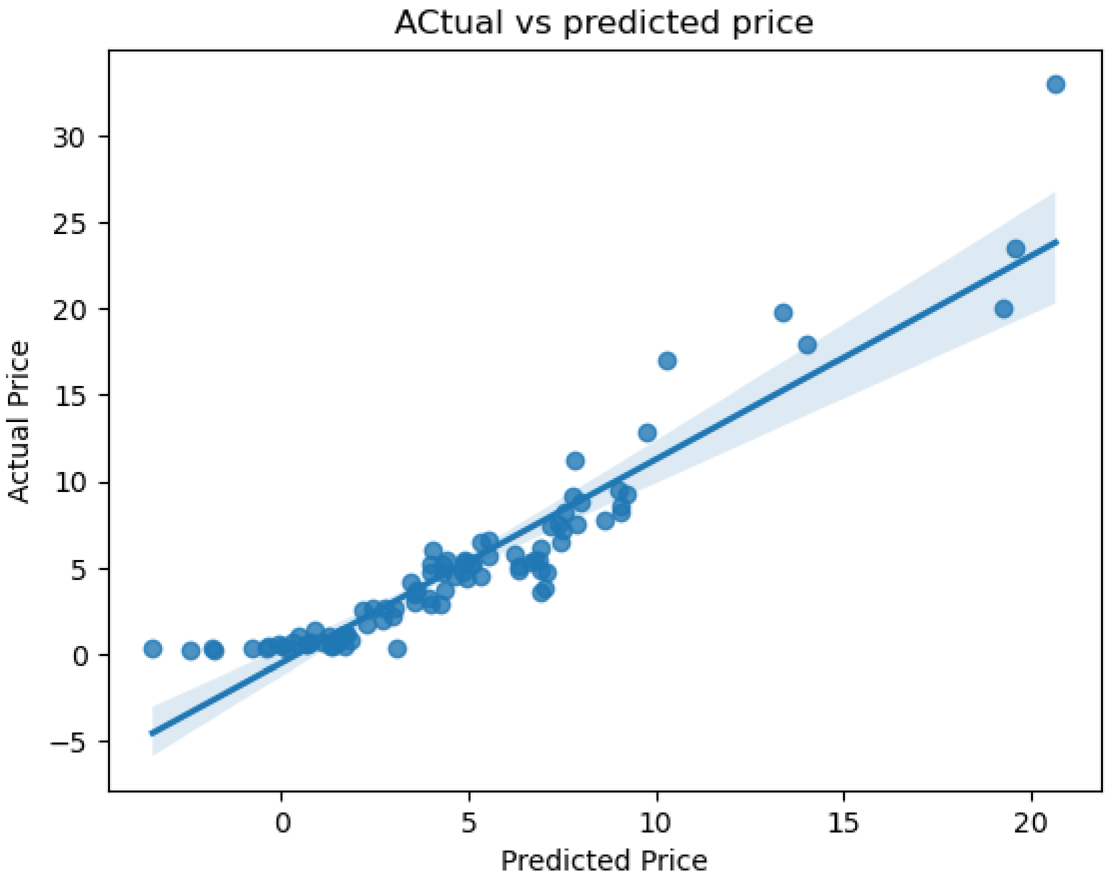
```
Linear Regressor Score on Training set is 0.8926207626208046
Linear Regressor Score on Test Set is 0.8517983059778262
[0.84989767 0.91045493 0.75641733 0.66228803 0.84093716]
Accuracy: 80.40 %
Standard Deviation: 8.62 %
Mean Absolute Error: 1.2426713915033707
Mean Squared Error: 4.432128265667619
RMSE: 2.1052620420431323
The r2_score is 0.8517983059778262
C:\Users\DELL\anaconda3\lib\site-packages\seaborn\distributions.py:2619: FutureWar
ning: `distplot` is a deprecated function and will be removed in a future version.
Please adapt your code to use either `displot` (a figure-level function with simil
ar flexibility) or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```





In [121…

```
sns.regplot(x=y_pred, y=y_test)
plt.xlabel("Predicted Price")
plt.ylabel('Actual Price')
plt.title("ACtual vs predicted price")
plt.show()
```



Decision Tree Regressor

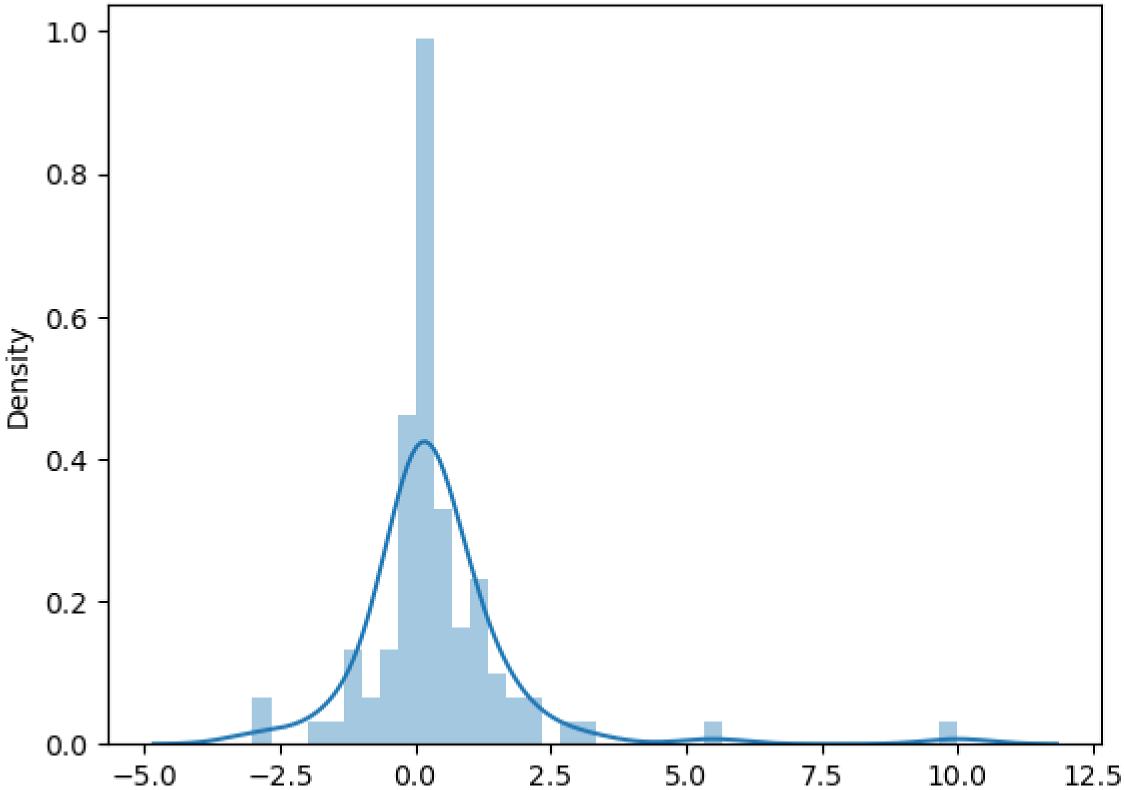
In [122…

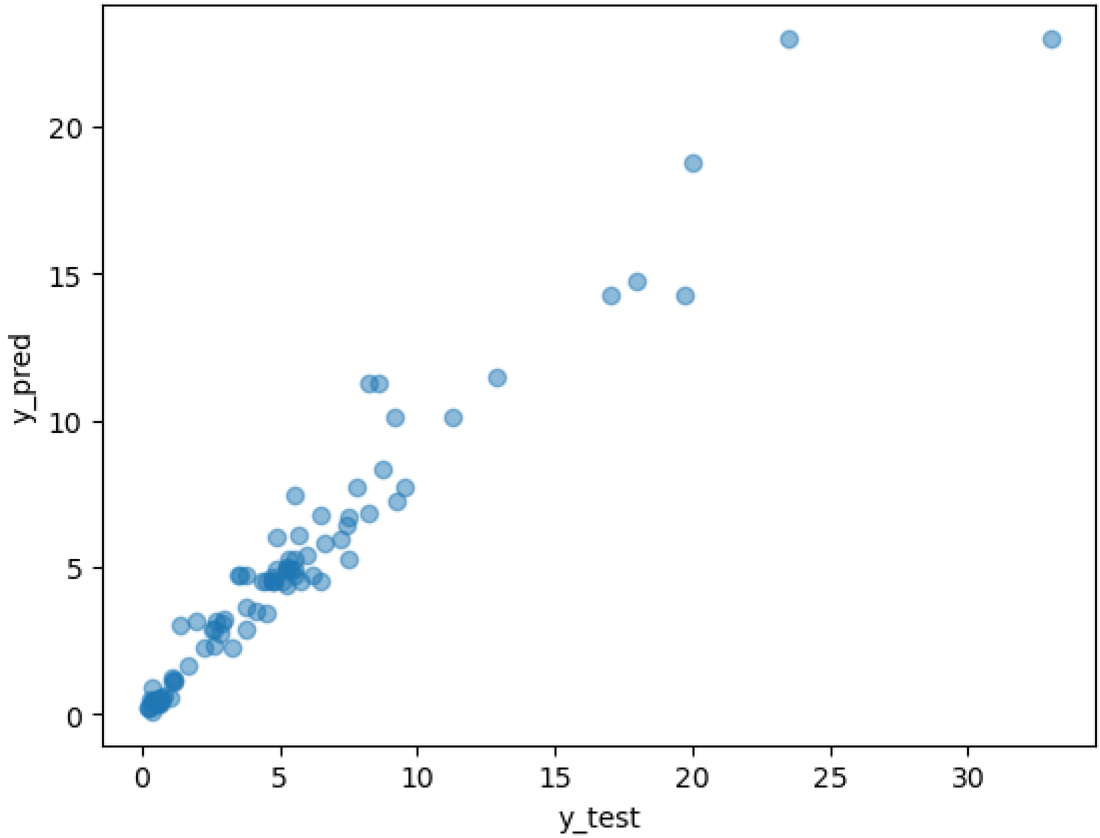
```
#Decision Tree Regressor
from sklearn.tree import DecisionTreeRegressor
dt_reg = DecisionTreeRegressor(random_state = 0)
dt_reg.fit(X_train, y_train)
y_pred=dt_reg.predict(X_test)

print("Decision Tree Score on Training set is",dt_reg.score(X_train, y_train))#Tra
print("Decision Tree Score on Test Set is",dt_reg.score(X_test, y_test))#Testing A

accuracies = cross_val_score(dt_reg, X_train, y_train, cv = 5)
print(accuracies)
print("Accuracy: {:.2f} %".format(accuracies.mean()*100))
print("Standard Deviation: {:.2f} %".format(accuracies.std()*100))

mae=mean_absolute_error(y_pred, y_test)
print("Mean Absolute Error:" , mae)

mse=mean_squared_error(y_test, y_pred)
print("Mean Squared Error:" , mse)

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

print('The r2_score is', metrics.r2_score(y_test, y_pred))

accuracy.append(accuracies.mean()*100)
r2score.append(metrics.r2_score(y_test, y_pred))
mean2.append(mse)
meanabsoulte.append(mae)
rmse.append(np.sqrt(metrics.mean_squared_error(y_test, y_pred)))

sns.distplot(y_test-y_pred)
```

```
plt.show()

plt.scatter(y_test, y_pred, alpha = 0.5)
plt.xlabel("y_test")
plt.ylabel("y_pred")
plt.show()
```

```
Decision Tree Score on Training set is 1.0
Decision Tree Score on Test Set is 0.9202815383374512
[0.9542394  0.84409548 0.69916028 0.924205   0.92156403]
Accuracy: 86.87 %
Standard Deviation: 9.22 %
Mean Absolute Error: 0.8102197802197801
Mean Squared Error: 2.3840648351648355
RMSE: 1.5440417206684653
The r2_score is 0.9202815383374512
```

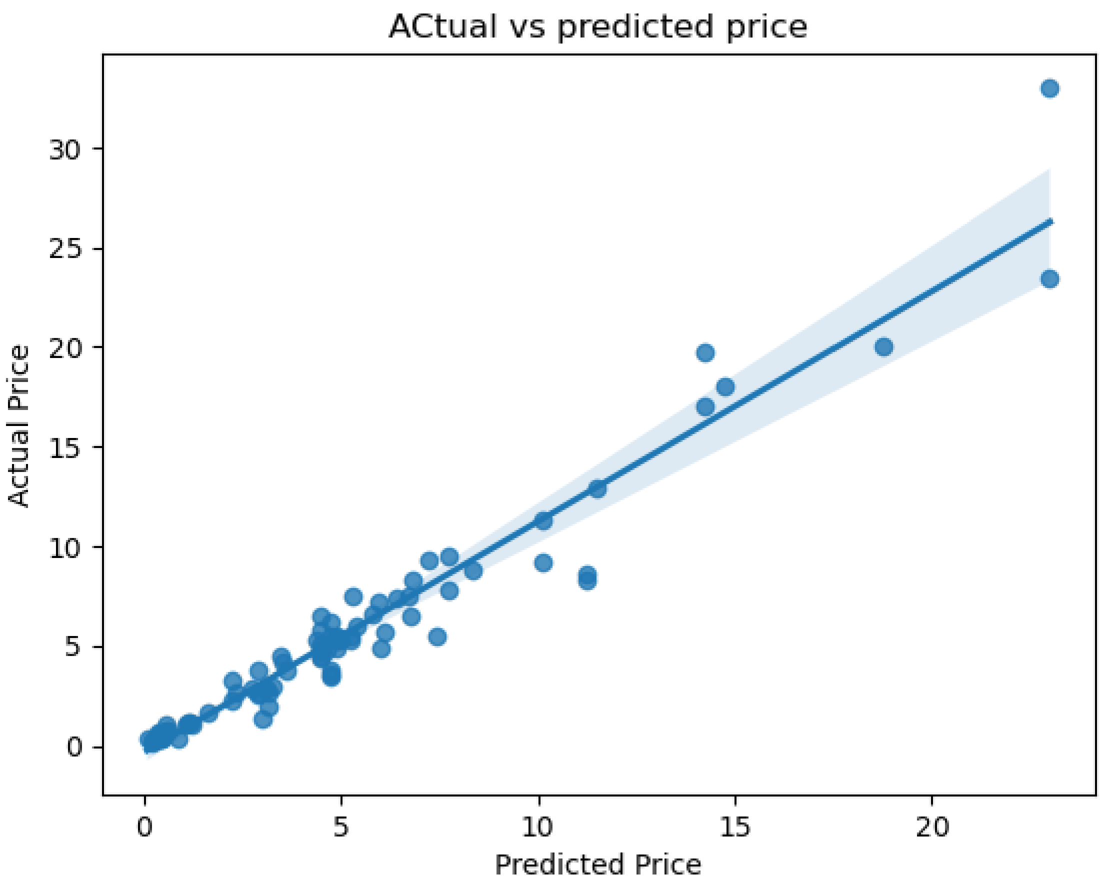
```
C:\Users\DELL\anaconda3\lib\site-packages\seaborn\distributions.py:2619: FutureWar
ning: `distplot` is a deprecated function and will be removed in a future version.
Please adapt your code to use either `displot` (a figure-level function with simil
ar flexibility) or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```





In [123…

```
sns.regplot(x=y_pred, y=y_test)
plt.xlabel("Predicted Price")
plt.ylabel('Actual Price')
plt.title("ACtual vs predicted price")
plt.show()
```



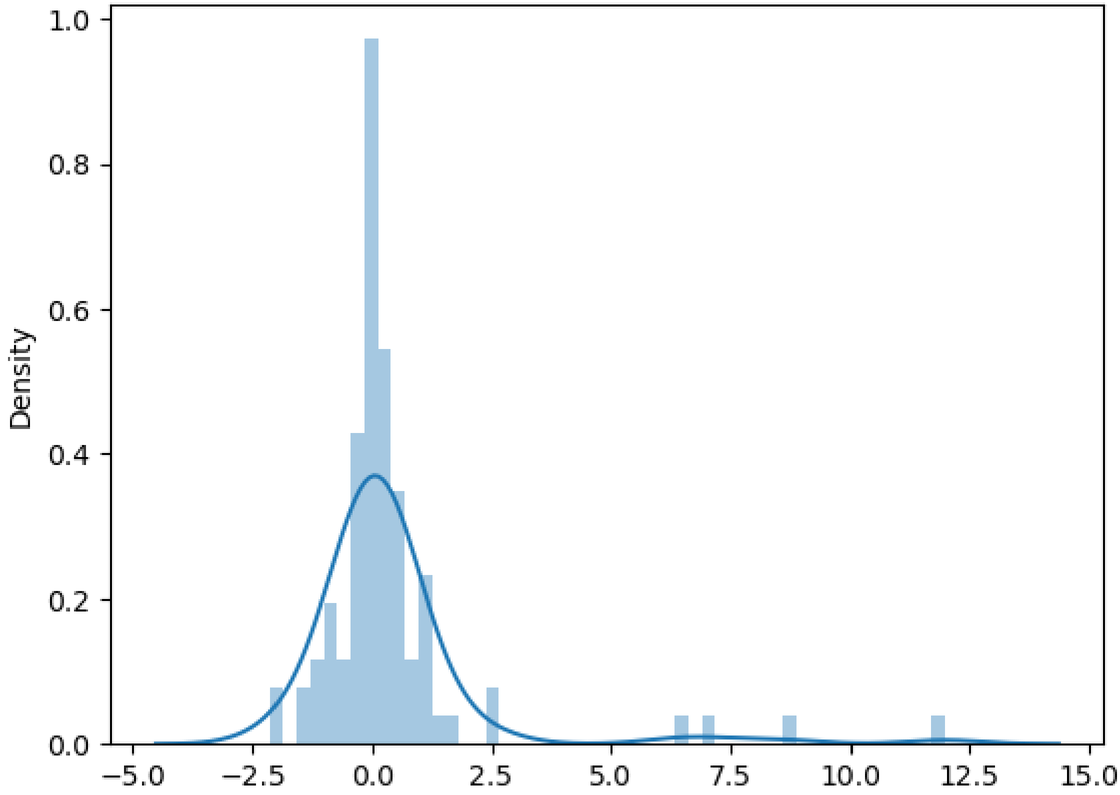
Random Forest Regressor

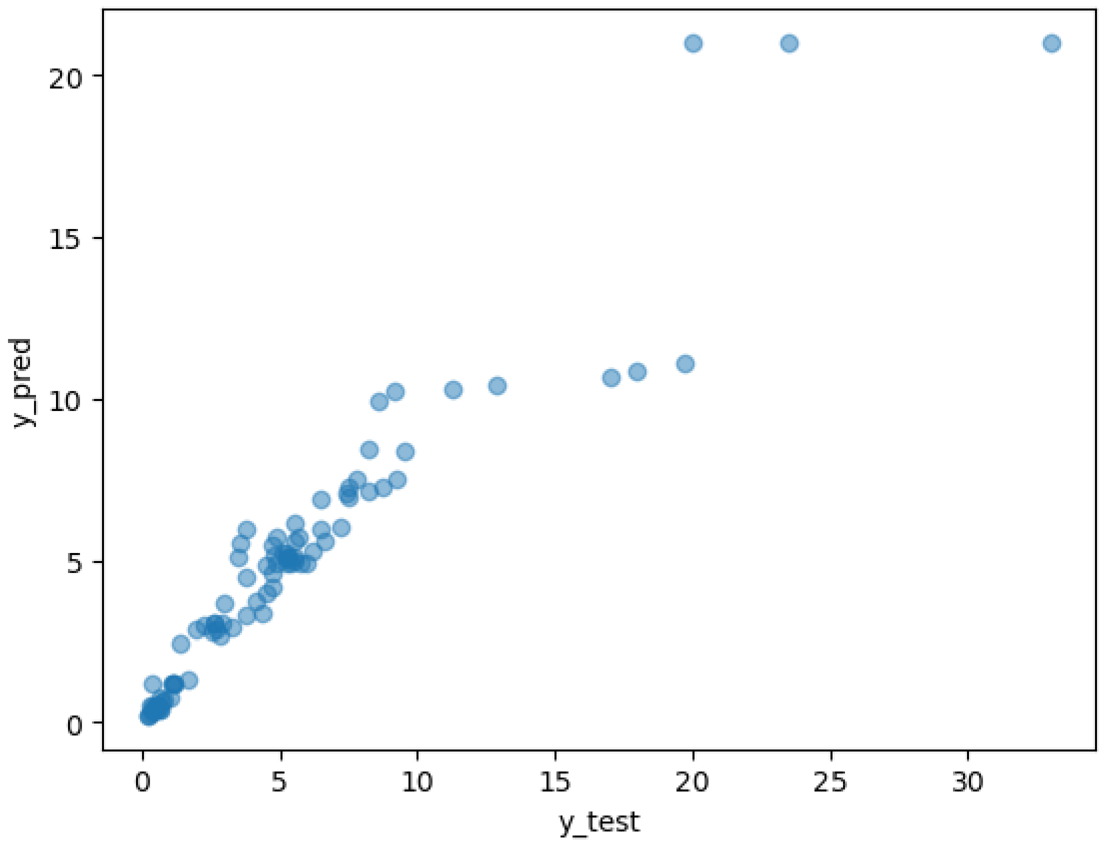
In [124…

```
#Random Forest Regression
from sklearn.ensemble import RandomForestRegressor
rf_reg = RandomForestRegressor(n_estimators=400,min_samples_split=15,min_samples_le
max_features='auto', max_depth=30)
rf_reg.fit(X_train, y_train)
y_pred=rf_reg.predict(X_test)

print("Random Forest Score on Training set is",rf_reg.score(X_train, y_train))#Tra
print("Random Forest Score on Test Set is",rf_reg.score(X_test, y_test))#Testing Ac

accuracies = cross_val_score(rf_reg, X_train, y_train, cv = 5)
print(accuracies)
print("Accuracy: {:.2f} %".format(accuracies.mean()*100))
print("Standard Deviation: {:.2f} %".format(accuracies.std()*100))

mae=mean_absolute_error(y_pred, y_test)
print("Mean Absolute Error:" , mae)

mse=mean_squared_error(y_test, y_pred)
print("Mean Squared Error:" , mse)

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

print('The r2_score is', metrics.r2_score(y_test, y_pred))
accuracy.append(accuracies.mean()*100)
r2score.append(metrics.r2_score(y_test, y_pred))
mean2.append(mse)
meanabsoulte.append(mae)
rmse.append(np.sqrt(metrics.mean_squared_error(y_test, y_pred)))

sns.distplot(y_test-y_pred)
plt.show()

plt.scatter(y_test, y_pred, alpha = 0.5)
plt.xlabel("y_test")
plt.ylabel("y_pred")
plt.show()
```

```
Random Forest Score on Training set is 0.910266568514969
Random Forest Score on Test Set is 0.8671354048467697
[0.94820538 0.816767   0.62988664 0.83125856 0.93028691]
Accuracy: 83.13 %
Standard Deviation: 11.34 %
Mean Absolute Error: 0.8836663992663134
Mean Squared Error: 3.973456117154846
RMSE: 1.993352983581896
The r2_score is 0.8671354048467697
```

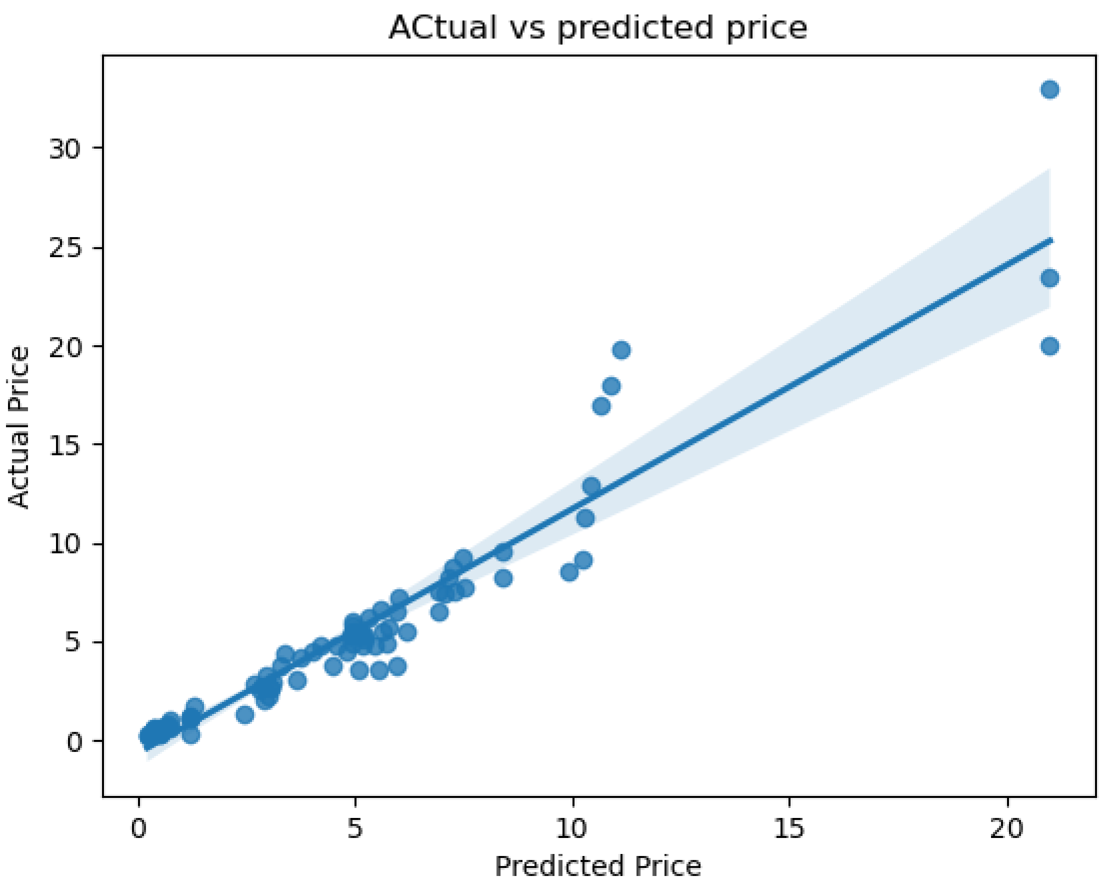
```
C:\Users\DELL\anaconda3\lib\site-packages\seaborn\distributions.py:2619: FutureWar
ning: `distplot` is a deprecated function and will be removed in a future version.
Please adapt your code to use either `displot` (a figure-level function with simil
ar flexibility) or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```





In [125…

```
sns.regplot(x=y_pred, y=y_test)
plt.xlabel("Predicted Price")
plt.ylabel('Actual Price')
plt.title("ACtual vs predicted price")
plt.show()
```



Voting Regressor

Voting Regressor is an ensemble meta-estimator that fits several base regressors, each on the whole dataset to average the individual predictions to form a final prediction.

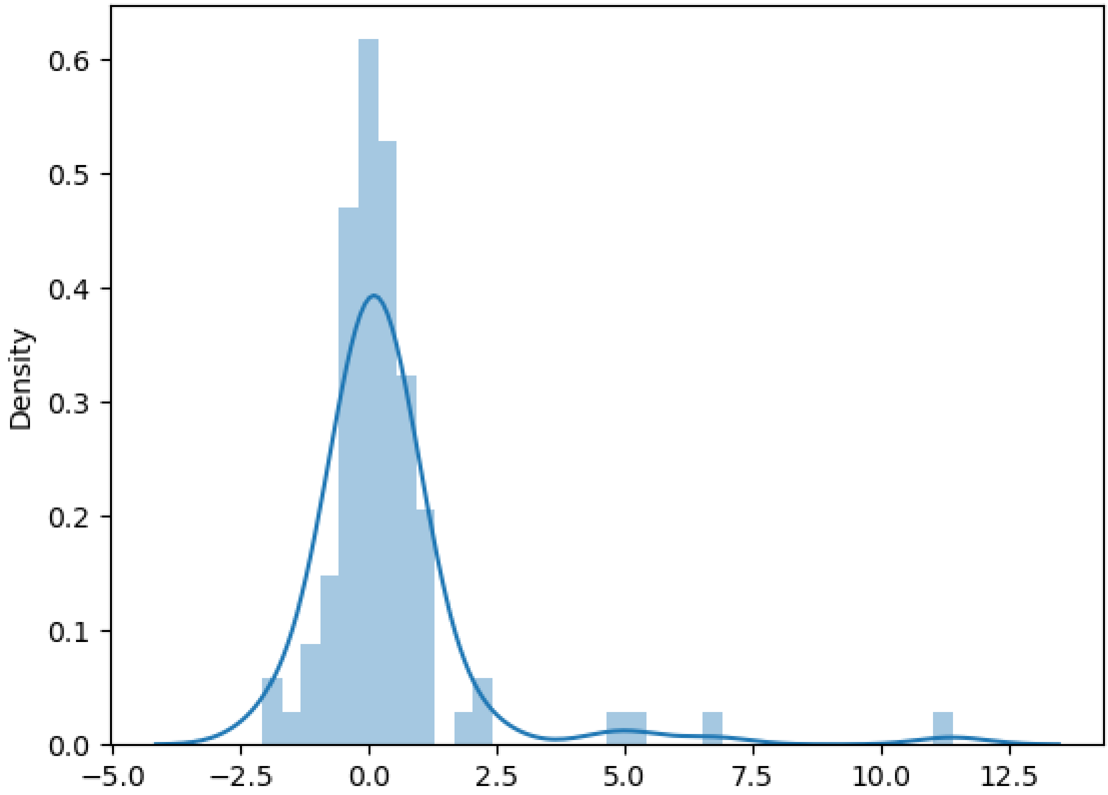
In [126…

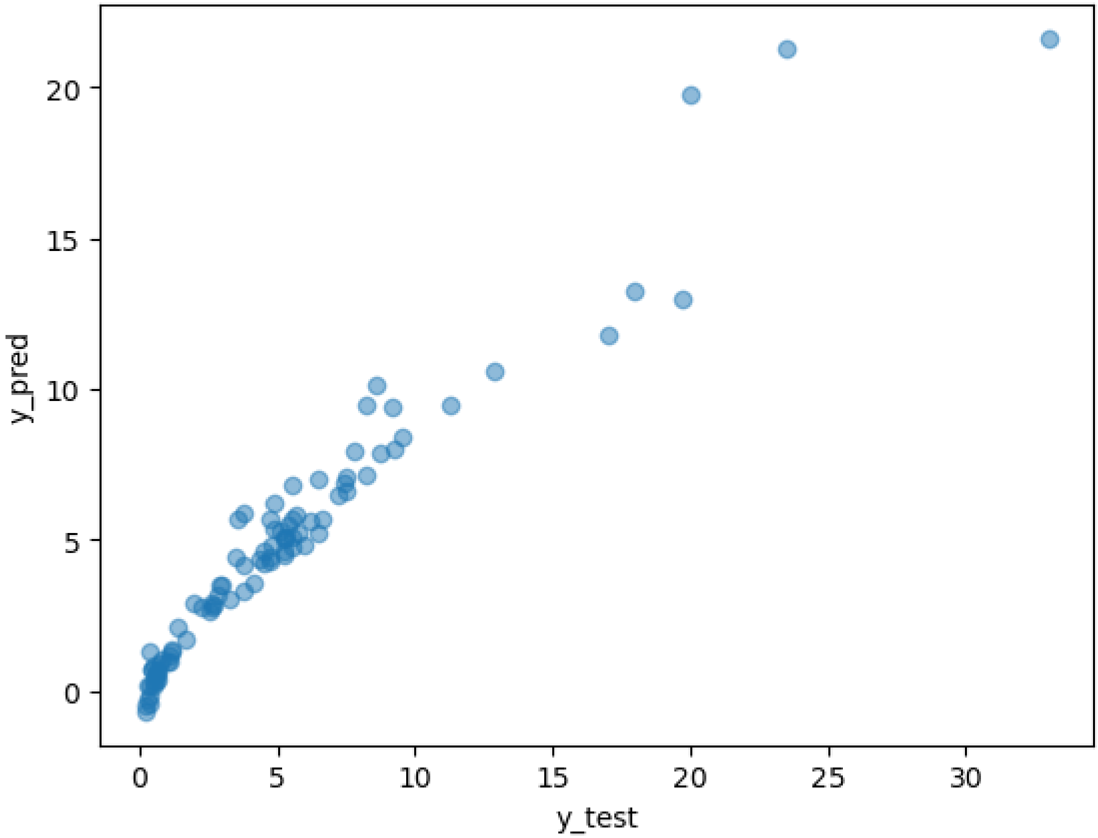
```
from sklearn.ensemble import VotingRegressor
vot_reg = VotingRegressor([('DecisionTree', dt_reg), ('RandomForestRegressor', rf_
vot_reg.fit(X_train, y_train)
y_pred=vot_reg.predict(X_test)

print("Voting Regresssor Score on Training set is",vot_reg.score(X_train, y_train)
print("Voting Regresssor Score on Test Set is",vot_reg.score(X_test, y_test))#Test

accuracies = cross_val_score(vot_reg, X_train, y_train, cv = 5)
print(accuracies)
print("Accuracy: {:.2f} %".format(accuracies.mean()*100))
print("Standard Deviation: {:.2f} %".format(accuracies.std()*100))

mae=mean_absolute_error(y_pred, y_test)
print("Mean Absolute Error:" , mae)

mse=mean_squared_error(y_test, y_pred)
print("Mean Squared Error:" , mse)

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

print('The r2_score is', metrics.r2_score(y_test, y_pred))

accuracy.append(accuracies.mean()*100)
r2score.append(metrics.r2_score(y_test, y_pred))
mean2.append(mse)
meanabsoulte.append(mae)
```

```
rmse.append(np.sqrt(metrics.mean_squared_error(y_test, y_pred)))

sns.distplot(y_test-y_pred)
plt.show()

plt.scatter(y_test, y_pred, alpha = 0.5)
plt.xlabel("y_test")
plt.ylabel("y_pred")
plt.show()
```

```
Voting Regresssor Score on Training set is 0.9747670501881848
Voting Regresssor Score on Test Set is 0.8983795201953172
[0.95785591 0.93777113 0.73902928 0.89954763 0.95815186]
Accuracy: 89.85 %
Standard Deviation: 8.25 %
Mean Absolute Error: 0.8544876881826632
Mean Squared Error: 3.039067831745924
RMSE: 1.743292239340818
The r2_score is 0.8983795201953172
```

```
C:\Users\DELL\anaconda3\lib\site-packages\seaborn\distributions.py:2619: FutureWar
ning: `distplot` is a deprecated function and will be removed in a future version.
Please adapt your code to use either `displot` (a figure-level function with simil
ar flexibility) or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```

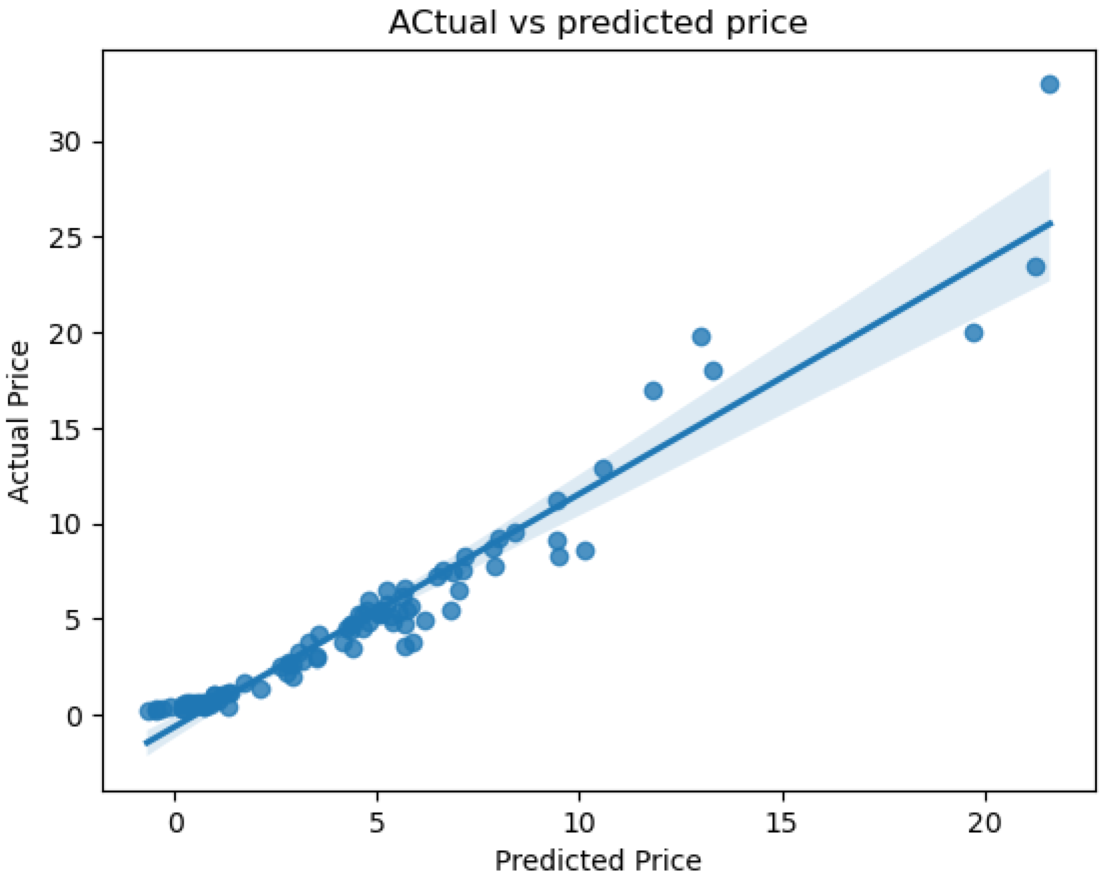




So, the XGBoost Regressor gave us best scores on the Training Dataset

In [127…

```
sns.regplot(x=y_pred, y=y_test)
plt.xlabel("Predicted Price")
plt.ylabel('Actual Price')
plt.title("ACtual vs predicted price")
plt.show()
```



In [128…

```
models = ["Linear Regression","Decision Tree","Random Forest","X_boost"]
```

In [129…

```
df = pd.DataFrame({"Algorithms":models,
                   "Accuracy Score":accuracy,
                   "r^2 Score":r2score,
                  "mse":mean2,
                  "mae":meanabsoulte,
                  "rmse":rmse})
```

In [130…

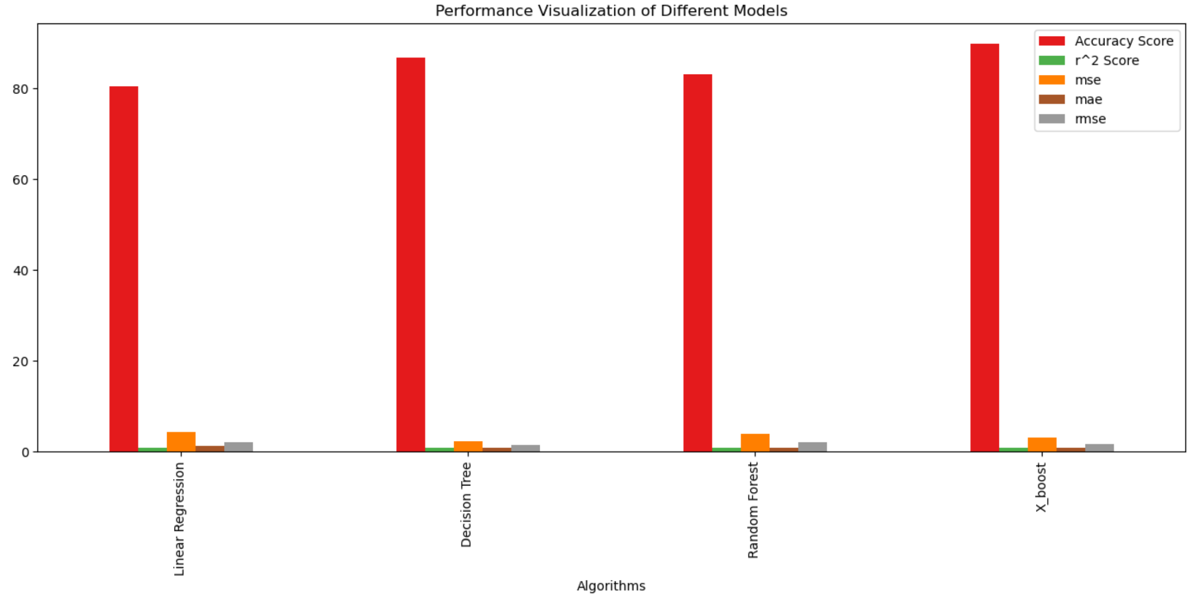
```
df
```

Out[130]:

	Algorithms	Accuracy Score	r^2 Score	mse	mae	rmse
0	Linear Regression	80.399903	0.851798	4.432128	1.242671	2.105262
1	Decision Tree	86.865284	0.920282	2.384065	0.810220	1.544042
2	Random Forest	83.128090	0.867135	3.973456	0.883666	1.993353
3	X_boost	89.847116	0.898380	3.039068	0.854488	1.743292

In [135…

```
df.plot(x="Algorithms",y=["Accuracy Score","r^2 Score","mse","mae","rmse"], figsiz
        title="Performance Visualization of Different Models",colormap="Set1")
plt.show()
```



Model deployment by Dumping the model selected as a Pickle File

In [ ]:

In [131…

```
import pickle
pickle.dump(vot_reg, open("vot_reg.pkl", "wb"))

# Load model from file
model1 = pickle.load(open("vot_reg.pkl", "rb"))
```

In [132…

```
model1.predict([[9.85, 6900, 0, 3, 0, 1, 0, 1]])
```

Out[132]: array([7.19241174])

In [133…

```
model.predict([[7.85, 8000, 0, 2, 1, 2, 0, 1]])
```

Out[133]: array([9.69233381])

In [134…

```
model.predict([[11.0, 2000, 0, 1, 1, 2, 0, 1]])
```

Out[134]: array([11.34874994])

The car has more Selling price when the kms driven is less