Regression Model on Household Electricity Consumption

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Problem Statement

- Predict the household power counsumtion

Task Peformed in this Notebook:-

1. Load Data
2. Exploratory data analysis
3. Check and remove any special character
4. Handle the null Values
5. Graphical Analysis
6. Check and Handle the outliers
7. Train Test Split
8. Model building for :
    - Linear Regression
    - Ridge Regression
    - Lasso Regression
    - ElasticNet Regression
    - Support Vector Regression
    - Decision Tree Regressor
    - Random Forest Regressor
    - Bagging Regressor
9. check for all models:
    - mean_squared_error
    - mean_absolute_error
    - r2_score
    - Adjusted r2_score
10. Hyper-Parameter tuning using RandomSearchCV on:
    - Random Forest Regessor
    - Bagging Regressor
11. Summary
12. Store the best model in pickle file

Description

- The dataset is collected from UCI website, provided by Senior Researchers from France.
- More then 2 million records
- Data of 47 months ranging from December 2006 to November 2010.
- Dataset has 9 attributes, out of which 3 are meter readings stating how much electricity unit appliances of various type has consumed.

In [8]:

```
## comment
## Observation
```

Importing required libraries

In [48]:

```
# Data Analysing
import pandas as pd
import numpy as np

# Graphical analysis
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')

# for model building
from sklearn.linear_model import LinearRegression,Ridge,Lasso,ElasticNe
from sklearn.svm import SVR
from sklearn.metrics import accuracy_score,r2_score,mean_squared_error,
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.ensemble import RandomForestRegressor
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import BaggingRegressor
from sklearn.model_selection import RandomizedSearchCV

# save the model
import pickle

```

Load dataset

In [4]:

```
## Loading Dataset
df = pd.read_csv(r"household_power_consumption.txt",sep=';')
df.head()
```

Out[4]:

	Date	Time	Global_active_power	Global_reactive_power	Voltage
0	16/12/2006	17:24:00	4.216	0.418	234.840
1	16/12/2006	17:25:00	5.360	0.436	233.630
2	16/12/2006	17:26:00	5.374	0.498	233.290
3	16/12/2006	17:27:00	5.388	0.502	233.740
4	16/12/2006	17:28:00	3.666	0.528	235.680

In [5]:

```
## Checking Shape of Dataset
df.shape
```

Out[5]:

```
(2075259, 9)
```

Observations

- Data is very big so we have to take small sample for model building

In [6]:

```
## Creating 60,000 Sample Data from Original dataset
df_sample = df.sample(60000)
```

In [7]:

```
## Checking Sample shape of newly created sample dataset.
df_sample.shape
```

Out[7]:

```
(60000, 9)
```

Observations

- We have taken 60000 samples out of 2 million to build model

EDA

In [9]:

```
## Checking all Columns Available in a dataset
df_sample.columns
```

Out[9]:

```
Index(['Date', 'Time', 'Global_active_power', 'Global_reactiv
e_power',
       'Voltage', 'Global_intensity', 'Sub_metering_1', 'Sub_
metering_2',
       'Sub_metering_3'],
      dtype='object')
```

Drop Date and time columns

In [10]:

```
## Droping Unnecessary columns from dataset
df_sample.drop(['Date','Time'],axis = 1, inplace = True)
```

In [11]:

```
## checking Top 5 rows from dataset
df_sample.head()
```

Out[11]:

	Global_active_power	Global_reactive_power	Voltage	Global_intens
1773	0.914	0.206	246.160	3.8
1874584	0.346	0.000	240.160	1.4
604094	0.296	0.082	244.350	1.2
1998496	0.474	0.000	240.940	2.0
1636101	2.670	0.118	236.060	11.2

Check any special character

In [12]:

```
## Checking any special character are present in a dataset or not.
special_char = df_sample[df_sample['Voltage'] == "?"]
special_char
```

Out[12]:

	Global_active_power	Global_reactive_power	Voltage	Global_intensi
1931833	?	?	?	
1985001	?	?	?	
1713833	?	?	?	
1987508	?	?	?	
192536	?	?	?	
...	...	...	...	
1930378	?	?	?	
1988688	?	?	?	
1988393	?	?	?	
1619355	?	?	?	
1934148	?	?	?	

739 rows × 7 columns

Drop these records having special character

In [13]:

```
print("Data before special characters", df_sample.shape)
df_sample.drop(special_char.index,axis= 0,inplace=True)
print("Data before removal of special characters", df_sample.shape)
```

```
Data before special characters (60000, 7)
Data before removal of special characters (59261, 7)
```

Check duplicated

In [14]:

```
## Checking Total Duplicate rows present in a dataset.
df_sample.duplicated().sum()
```

Out[14]:

```
276
```

In [15]:

```
## Droping Duplicate Rows from dataset and also checking shape of datas
print("Data before duplicate records", df_sample.shape)
df_sample.drop_duplicates(inplace=True)
print("Data after removal of duplicate records", df_sample.shape)
```

```
Data before duplicate records (59261, 7)
Data after removal of duplicate records (58985, 7)
```

Check the null values

In [17]:

```
## Checking Total Null Value present in a dataset.
df_sample.isna().sum()
```

Out[17]:

```
Global_active_power      0
Global_reactive_power    0
Voltage                  0
Global_intensity         0
Sub_metering_1           0
Sub_metering_2           0
Sub_metering_3           0
dtype: int64
```

Observations

- No Null Value

Convert all dtypes to float

In [18]:

```
## Checking dtypes for all Columns present in a dataset
df_sample.dtypes
```

Out[18]:

```
Global_active_power      object
Global_reactive_power    object
Voltage                  object
Global_intensity         object
Sub_metering_1           object
Sub_metering_2           object
Sub_metering_3          float64
dtype: object
```

In [19]:

```
## Converting all Columns dtype to Float type
df_sample = df_sample.astype(float)
```

In [20]:

```
## Checking dtypes after converting all columns dtype to float
df_sample.dtypes
```

Out[20]:

```
Global_active_power     float64
Global_reactive_power   float64
Voltage                 float64
Global_intensity        float64
Sub_metering_1          float64
Sub_metering_2          float64
Sub_metering_3          float64
dtype: object
```

Combine reading of sub_metering_1,sub_metering_2 and sub_metering_3

In [21]:

```
## Checking all Columns name Present in a dataset
df_sample.columns
```

Out[21]:

```
Index(['Global_active_power', 'Global_reactive_power', 'Volta
ge',
       'Global_intensity', 'Sub_metering_1', 'Sub_metering_
2',
       'Sub_metering_3'],
      dtype='object')
```

In [22]:

```
## Combining 3 submeter into one main meter.
df_sample['meter'] =df_sample['Sub_metering_1'] + df_sample['Sub_meteri
```

Drop 3 columns

In [23]:

```
## Droping 3 Sub-meter columns from dataset.
df_sample.drop(['Sub_metering_1','Sub_metering_2','Sub_metering_3'],axi
```

In [24]:

```
## Checking top 5 rows from dataset
df_sample.head()
```

Out[24]:

	Global_active_power	Global_reactive_power	Voltage	Global_intensi
1773	0.914	0.206	246.16	3
1874584	0.346	0.000	240.16	1
604094	0.296	0.082	244.35	1
1998496	0.474	0.000	240.94	2
1636101	2.670	0.118	236.06	11

In [25]:

```
## Checking basic Statistics method with the help of Describe()
df_sample.describe().T
```

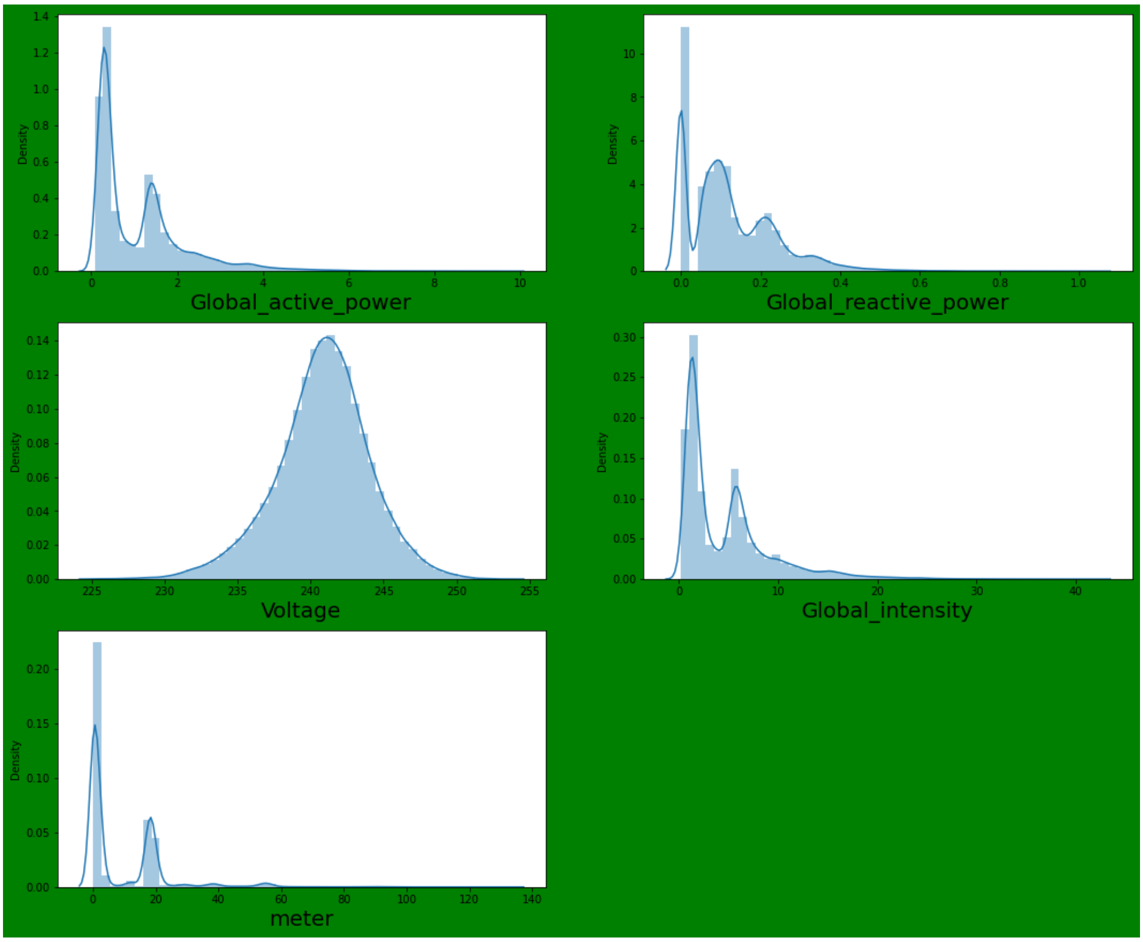
Out[25]:

	count	mean	std	min	25%
Global_active_power	58985.0	1.104116	1.068752	0.078	0.310
Global_reactive_power	58985.0	0.123839	0.112869	0.000	0.048
Voltage	58985.0	240.829027	3.239738	225.250	239.000
Global_intensity	58985.0	4.680766	4.495246	0.200	1.400
meter	58985.0	8.983013	13.037285	0.000	0.000

Graphical Representation

In [28]:

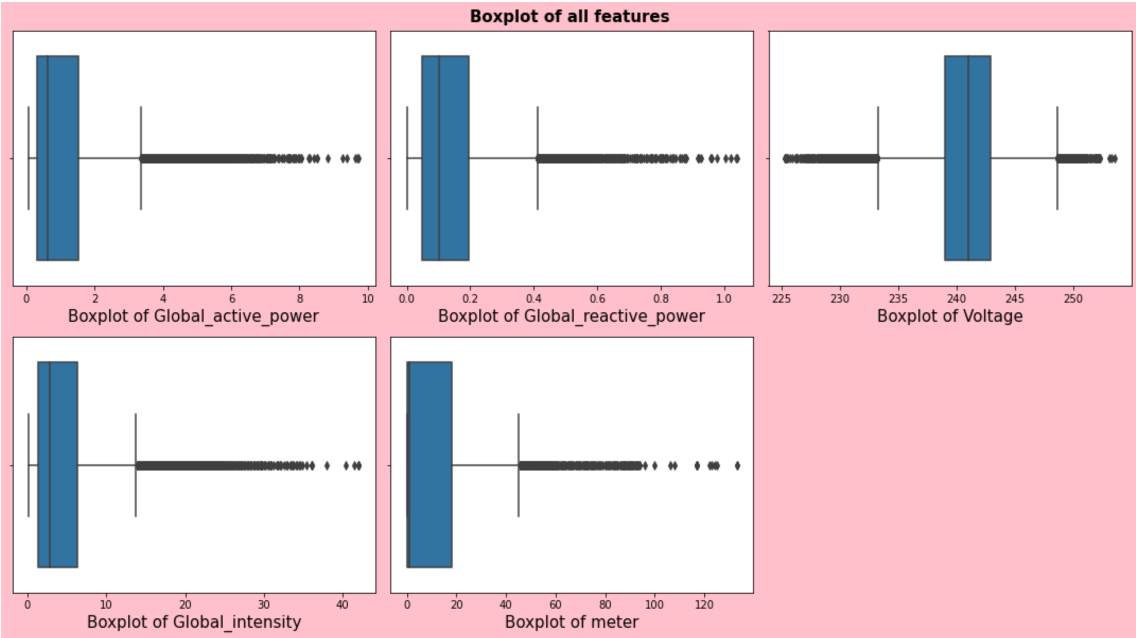
```
## Let's see data distribution in each column

plt.figure(figsize=(18,15), facecolor='green')
plotnumber = 1

for column in df_sample.columns[:]:
    if plotnumber<=5 :
        ax = plt.subplot(3,2,plotnumber)
        sns.distplot(df_sample[column])
        plt.xlabel(column,fontsize=20)
    plotnumber+=1
plt.show()
```



Check the outliers

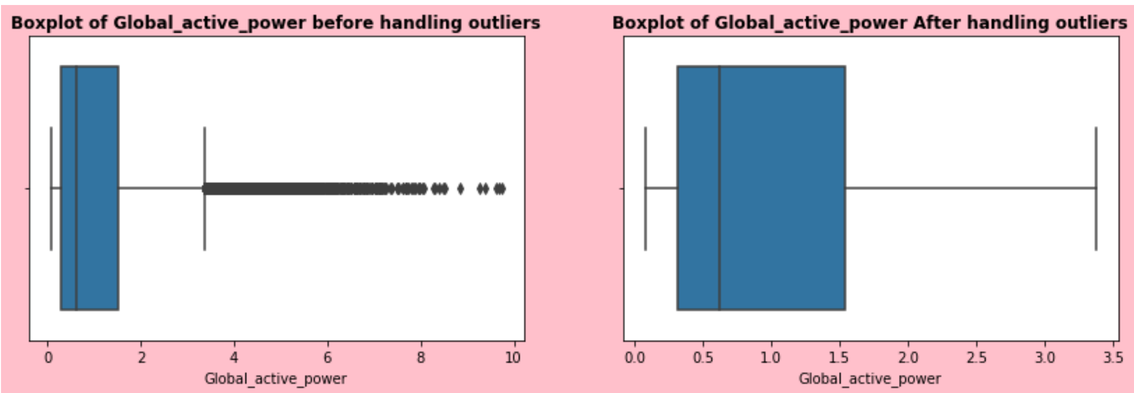
In [33]:

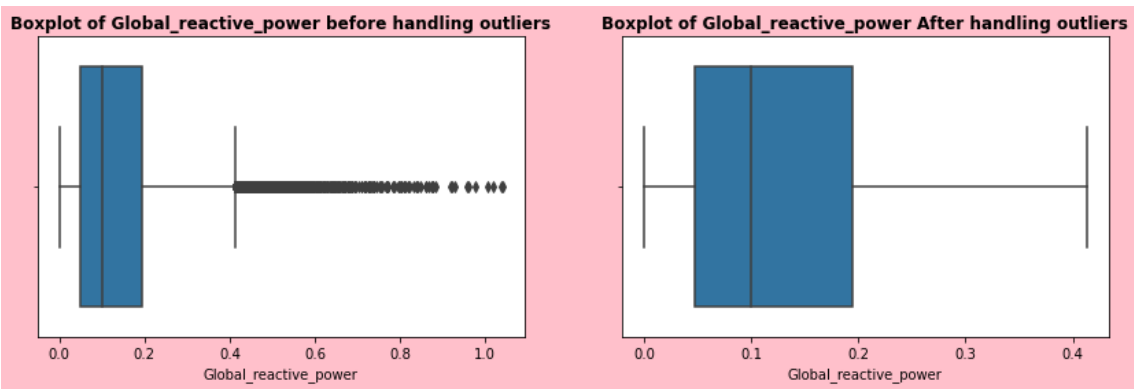
```
## Checking Outlier in Dataset
plt.figure(figsize=(15,20),facecolor='pink')
plt.suptitle("Boxplot of all features", fontweight = 'bold', fontsize =
for i in range(0,len(df_sample.columns)):
    plt.subplot(5,3,i+1)
    sns.boxplot(x = df_sample.columns[i], data = df_sample)
    plt.xlabel("Boxplot of {}".format(df_sample.columns[i]),fontsize =
    plt.tight_layout()
```

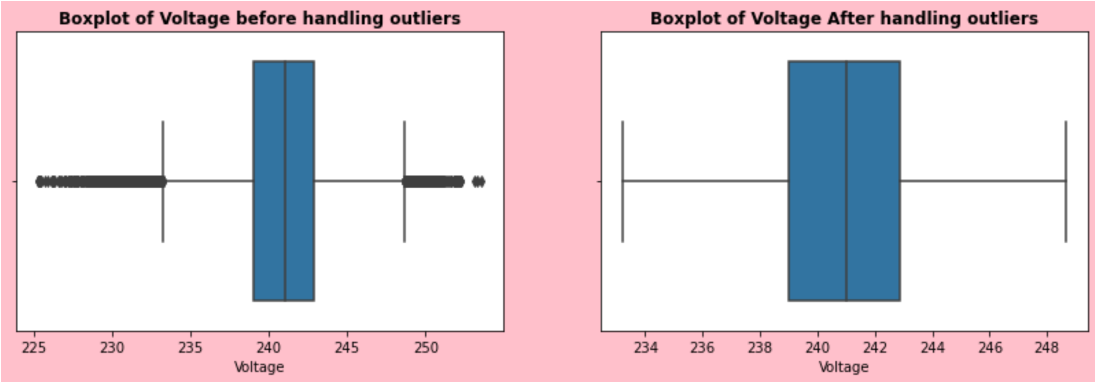


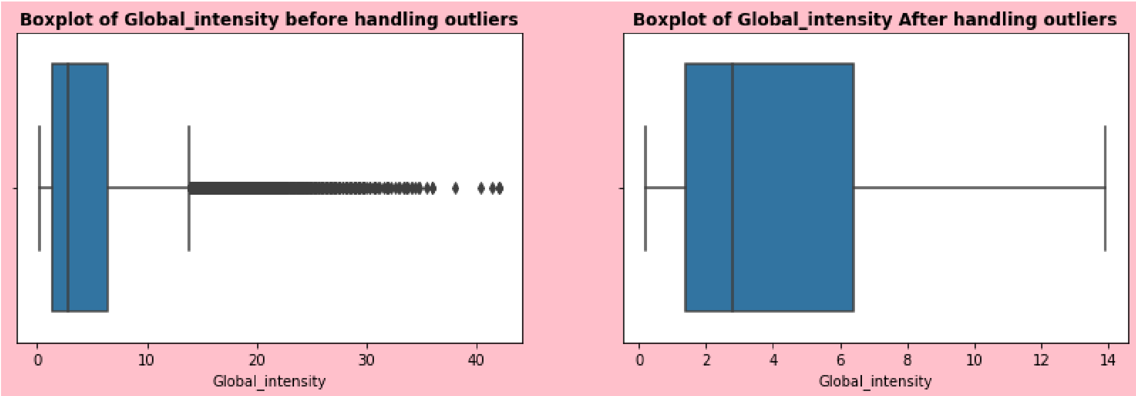
In [68]:

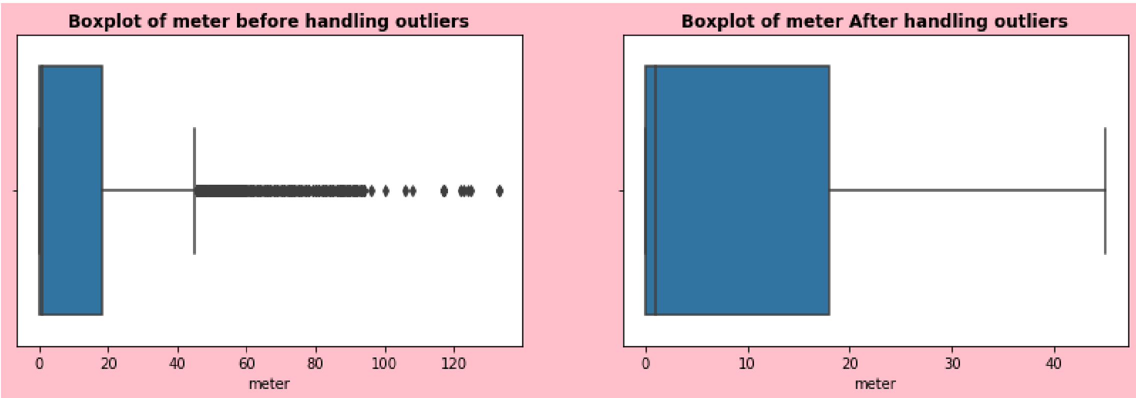
```
## Handling the outliers
df1 = df_sample.copy()
feature_to_use = df1.columns

for i in range(len(feature_to_use)):
    IQR = df1[feature_to_use[i]].quantile(0.75) - df1[feature_to_use[i]
    Lower_Limit = df1[feature_to_use[i]].quantile(0.25) - (1.5*IQR)
    UPPER_LIMIT = df1[feature_to_use[i]].quantile(0.75) + (1.5*IQR)
    df1[feature_to_use[i]]= np.where(df1[feature_to_use[i]]>UPPER_LIMIT
                                    np.where(df1[feature_to_use[i]]<Lower_L


for fea in feature_to_use:
    plt.figure(figsize = (14,4),facecolor='pink')
    plt.subplot(121)
    sns.boxplot(x = fea, data = df_sample)
    plt.title("Boxplot of {} before handling outliers".format(fea),font

    plt.subplot(122)
    sns.boxplot(x = fea, data = df1)
    plt.title("Boxplot of {} After handling outliers".format(fea),fontw
    plt.show()
```











Seperate Independent and Dependent Features

In [37]:

```
x = df1.drop('meter', axis = 1)
y = df1['meter']
```

In [40]:

```
## Cheking Shape of x and y
x.shape, y.shape
```

Out[40]:

```
((58985, 4), (58985,))
```

Train Test Split

.

In [41]:

```
x_train,x_test,y_train,y_test = train_test_split(x,y,test_size = 0.33,r
```

In [44]:

```
## Ckecking the shape of Training Data
x_train.shape,y_train.shape
```

Out[44]:

```
((39519, 4), (39519,))
```

In [45]:

```
## Ckecking the shape of Testing Data
x_test.shape,y_test.shape
```

Out[45]:

```
((19466, 4), (19466,))
```

Standardization

In [46]:

```
scaler = StandardScaler()
x_train = scaler.fit_transform(x_train)
x_test = scaler.fit_transform(x_test)
```

Model Building

In [47]:

```
report = []
```

In [49]:

```
models = {
    "Linear Regression" : LinearRegression(),
    "Ridge Regression" : Ridge(),
    "Lasso Regression" : Lasso(),
    "ElasticNet Regression" : ElasticNet(),
    "Support Vector Regression" : SVR(),
    "Decision Tree Regressor" : DecisionTreeRegressor(),
    "Random Forest Regressor" : RandomForestRegressor()
}

for i in range(len(list(models))):
    model = list(models.values())[i]
    model.fit(x_train,y_train)   # Training Model

    # Prediction
    y_train_pred = model.predict(x_train)
    y_test_pred = model.predict(x_test)

    # Training Data perfomance Matrix
    model_train_mse = mean_squared_error(y_train,y_train_pred)   # Calc
    model_train_mae = mean_absolute_error(y_train,y_train_pred)  # Calc
    model_train_r2 = r2_score(y_train,y_train_pred)              # Calc
    model_train_ad_r2 = 1 - (1-model_train_r2)*(len(y_train)-1) / (len(


    # Test Data perfomance Matrix
    model_test_mse = mean_squared_error(y_test,y_test_pred)   # Calcula
    model_test_mae = mean_absolute_error(y_test,y_test_pred)  # Calcula
    model_test_r2 = r2_score(y_test,y_test_pred)              # Calcula
    model_test_ad_r2 = 1 - (1-model_test_r2)*(len(y_test)-1) / (len(y_t


    report.append({
                    "model" : (list(models.keys()))[i],
                    'Train Mean Squared Error ' : model_train_mse,
                    'Test Mean Squared Error' : model_test_mse,
                    'Train Mean Absolute Error' : model_train_mae,
                    'Test Mean Absolute Error' : model_test_mae,
                    'Train R Sqaure' : model_train_r2,
                    'Test R Sqaure' : model_test_r2,
                    'Train Adj R Sqaure' : model_train_ad_r2,
                    'Test Adj R Sqaure' : model_test_ad_r2
    })

all_model = pd.DataFrame(report)
all_model
```

Out[49]:

	model	Train Mean Squared Error	Test Mean Squared Error	Train Mean Absolute Error	Test Mean Absolute Error	Train R Sqaure	Test R Sqaure
0	Linear Regression	40.317066	38.626226	4.227816	4.118774	0.692251	0.697878
1	Ridge Regression	40.317870	38.619047	4.226963	4.117645	0.692245	0.697934
2	Lasso Regression	42.259282	40.205873	4.489305	4.388920	0.677426	0.685522
3	ElasticNet Regression	46.791558	44.627403	5.048629	4.955296	0.642830	0.650939
4	Support Vector Regression	39.213283	39.200943	3.114148	3.059588	0.700677	0.693383
5	Decision Tree Regressor	0.583525	61.139598	0.045608	3.666033	0.995546	0.521786
6	Random Forest Regressor	5.270498	34.186604	1.164584	3.039165	0.959769	0.732603

Hyper-Parameter Tunning on RandomSearchCV

In [50]:

```
Ran_param = {
    "max_depth" : [5,8,15,None,10],
    'max_features' : [3,'auto'],
    'min_samples_split' : [2,8,15,20],
    'n_estimators' : [50,100,200,500]
}
```

In [51]:

```
random = RandomizedSearchCV(estimator = RandomForestRegressor(),
                   param_distributions = Ran_param,
                   n_iter= 100,
                   cv = 3,
                   verbose = 2,
                   n_jobs=-1)
```

In [52]:

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

```
Fitting 3 folds for each of 100 candidates, totalling 300 fit
s
```

Out[52]:

```
RandomizedSearchCV

RandomizedSearchCV(cv=3, estimator=RandomForestRegressor
(), n_iter=100,
                   n_jobs=-1,
                   param_distributions={'max_depth': [5,
8, 15, None, 10],
                                        'max_features':
[3, 'auto'],
                                        'min_samples_spl
it': [2, 8, 15, 20],
                                        'n_estimators':

         estimator: RandomForestRegressor

              RandomForestRegressor
```

In [53]:

```
random.best_params_,random.best_estimator_
```

Out[53]:

```
({'n_estimators': 500,
  'min_samples_split': 20,
  'max_features': 3,
  'max_depth': 10},
 RandomForestRegressor(max_depth=10, max_features=3, min_samp
les_split=20,
                       n_estimators=500))
```

In [54]:

```
rf_best_para = RandomForestRegressor(max_depth=10, max_features=3, min_
                                     n_estimators=500)

rf_best_para.fit(x_train,y_train)

# make predictions
rf_pred_train = rf_best_para.predict(x_train)
rf_pred_test = rf_best_para.predict(x_test)

# Training dataset performance matrix
rf_train_mse = mean_squared_error(y_train,rf_pred_train)   # Calculate
rf_train_mae = mean_absolute_error(y_train,rf_pred_train)  # Calculate
rf_train_r2 = r2_score(y_train,rf_pred_train)              # Calculate
rf_train_ad_r2 = 1 - (1-rf_train_r2)*(len(y_train)-1) / (len(y_train)-


# Test Data perfomance Matrix
rf_test_mse = mean_squared_error(y_test,rf_pred_test)   # Calculate MSE
rf_test_mae = mean_absolute_error(y_test,rf_pred_test)  # Calculate MAE
rf_test_r2 = r2_score(y_test,rf_pred_test)              # Calculate 2 s
rf_test_ad_r2 = 1 - (1-rf_test_r2)*(len(y_test)-1) / (len(y_test)- x_te

print("\n")
print("Hyperparameter tuning on random forest")

print("Model Performance For Training Data")
print("-Mean Squared Error : {:4f}".format(rf_train_mse))
print("-Mean Absolute Error : {:.4f}".format(rf_train_mae))
print("-R Sqaure : {:.4f}".format(rf_train_r2))
print("-Adj R Sqaure : {:.4f}".format(rf_train_ad_r2))

print("-----------------------------------------------------------------

print("Model Performance For Test Data")
print("-Mean Squared Error : {:4f}".format(rf_test_mse))
print("-Mean Absolute Error : {:.4f}".format(rf_test_mae))
print("-R Sqaure : {:.4f}".format(rf_test_r2))
print("-Adj R Sqaure : {:.4f}".format(rf_test_ad_r2))
```

```
Hyperparameter tuning on random forest
Model Performance For Training Data
-Mean Squared Error : 27.816961
-Mean Absolute Error : 2.8878
-R Sqaure : 0.7877
-Adj R Sqaure : 0.7876
-------------------------------------------------------------
```

```
----------
Model Performance For Test Data
-Mean Squared Error : 31.002924
-Mean Absolute Error : 2.9927
-R Sqaure : 0.7575
-Adj R Sqaure : 0.7575
```

In [55]:

```
rf_record = []
rf_record.append({
                    "model" : "Hyper-Parameter Tunning on random forest
                    "Train Mean Squared Error " : rf_train_mse,
                    "Test Mean Squared Error" : rf_test_mse,
                    "Train Mean Absolute Error" : rf_train_mae,
                    "Test Mean Absolute Error" : rf_test_mae,
                    "Train R Sqaure" : rf_train_r2,
                    "Test R Sqaure" : rf_test_r2,
                    "Train Adj R Sqaure" : rf_train_ad_r2,
                    "Test Adj R Sqaure" : rf_test_ad_r2
                    })

Hypertuned_rf = pd.DataFrame(rf_record)
Hypertuned_rf
```

Out[55]:

	model	Train Mean Squared Error	Test Mean Squared Error	Train Mean Absolute Error	Test Mean Absolute Error	Train R Sqaure	Test R Sqaure
0	Hyper-Parameter Tunning on random forest	27.816961	31.002924	2.887815	2.992724	0.787667	0.757505

Bagging Regressor

In [70]:

```
report2 = []
# Bagging using DecisionTreeRegressor
dt_bag = BaggingRegressor(n_estimators=100)
#If None, then the base estimator is a DecisionTreeRegressor.
dt_bag.fit(x_train,y_train)

# Make predictions
train_pred_bag =dt_bag.predict(x_train)
test_pred_bag = dt_bag.predict(x_test)

# Training dataset performance matrix
bag_train_mse = mean_squared_error(y_train,train_pred_bag)   # Calculat
bag_train_mae = mean_absolute_error(y_train,train_pred_bag)  # Calculat
bag_train_r2 = r2_score(y_train,train_pred_bag)              # Calculat
bag_train_ad_r2 = 1 - (1-bag_train_r2)*(len(y_train)-1) / (len(y_train)


# Test Data perfomance Matrix
bag_test_mse = mean_squared_error(y_test,test_pred_bag)   # Calculate M
bag_test_mae = mean_absolute_error(y_test,test_pred_bag)  # Calculate M
bag_test_r2 = r2_score(y_test,test_pred_bag)              # Calculate 2
bag_test_ad_r2 = 1 - (1-bag_test_r2)*(len(y_test)-1) / (len(y_test)- x_



report2.append({
                "model" : 'Bagging Regressor',
                'Train Mean Squared Error ' : bag_train_mse,
                'Test Mean Squared Error' : bag_test_mse,
                'Train Mean Absolute Error' : bag_train_mae,
                'Test Mean Absolute Error' : bag_test_mae,
                'Train R Sqaure' : bag_train_r2,
                'Test R Sqaure' : bag_test_r2,
                'Train Adj R Sqaure' : bag_train_ad_r2,
                'Test Adj R Sqaure' : bag_test_ad_r2
})

Bagging_report = pd.DataFrame(report2)
Bagging_report
```

Out[70]:

model	Train Mean Squared Error	Test Mean Squared Error	Train Mean Absolute Error	Test Mean Absolute Error	Train R Sqaure	Test R Sqaur

Hyper-parameter tunning of bagging regressor

In [58]:

```
bag_param = {
            'n_estimators' : [50,100,200,500],
            'max_samples' : range(2,5,1),
            'max_features' : [2,3]
}
```

In [59]:

```
bag_ran_search = RandomizedSearchCV(estimator=dt_bag,
                    param_distributions= bag_param,
                    n_iter=100,
                    n_jobs=-1,
                    cv = 3,
                    verbose= 2
                    )
```

In [60]:

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

```
Fitting 3 folds for each of 24 candidates, totalling 72 fits
```

Out[60]:

```
RandomizedSearchCV
estimator: BaggingRegressor
  BaggingRegressor
```

In [61]:

```
bag_ran_search.best_params_,bag_ran_search.best_estimator_
```

Out[61]:

```
({'n_estimators': 50, 'max_samples': 4, 'max_features': 3},
 BaggingRegressor(max_features=3, max_samples=4, n_estimators
=50))
```

In [62]:

```python
bag_model_hyp =  BaggingRegressor(max_features=4, max_samples=10, n_est
bag_model_hyp.fit(x_train,y_train)

# Make predictions
train_pred_baghyp =bag_model_hyp.predict(x_train)
test_pred_baghyp = bag_model_hyp.predict(x_test)

# Training dataset performance matrix
baghy_train_mse = mean_squared_error(y_train,train_pred_baghyp)   # Cal
baghy_train_mae = mean_absolute_error(y_train,train_pred_baghyp)  # Cal
baghy_train_r2 = r2_score(y_train,train_pred_baghyp)              # Cal
baghy_train_ad_r2 = 1 - (1-baghy_train_r2)*(len(y_train)-1) / (len(y_tr

# Test Data perfomance Matrix
baghy_test_mse = mean_squared_error(y_test,test_pred_baghyp)   # Calcul
baghy_test_mae = mean_absolute_error(y_test,test_pred_baghyp)  # Calcul
baghy_test_r2 = r2_score(y_test,test_pred_baghyp)              # Calcul
baghy_test_ad_r2 = 1 - (1-baghy_test_r2)*(len(y_test)-1) / (len(y_test)

print("Hyperparameter tunning of Bagging Regressor")

print("Model Performance For Training Data")
print("-Mean Squared Error : {:4f}".format(baghy_train_mse))
print("-Mean Absolute Error : {:.4f}".format(baghy_train_mae))
print("-R Sqaure : {:.4f}".format(baghy_train_r2))
print("-Adj R Sqaure : {:.4f}".format(baghy_train_ad_r2))

print("----------------------------------------------------------------

print("Model Performance For Test Data")
print("-Mean Squared Error : {:4f}".format(baghy_test_mse))
print("-Mean Absolute Error : {:.4f}".format(baghy_test_mae))
print("-R Sqaure : {:.4f}".format(baghy_test_r2))
print("-Adj R Sqaure : {:.4f}".format(baghy_test_ad_r2))

```

```
Hyperparameter tunning of Bagging Regressor
Model Performance For Training Data
-Mean Squared Error : 40.121305
-Mean Absolute Error : 3.7882
-R Sqaure : 0.6937
-Adj R Sqaure : 0.6937
-----------------------------------------------------------
------------
Model Performance For Test Data
-Mean Squared Error : 38.382493
-Mean Absolute Error : 3.6898
```

```
-R Sqaure : 0.6998
-Adj R Sqaure : 0.6997
```

In [63]:

```
bag_record = []
bag_record.append({
                    "model" : "Hyper-Parameter Tunning on Bagging Regre
                    "Train Mean Squared Error " : baghy_train_mse,
                    "Test Mean Squared Error" : baghy_test_mse,
                    "Train Mean Absolute Error" : baghy_train_mae,
                    "Test Mean Absolute Error" : baghy_test_mae,
                    "Train R Sqaure" : baghy_train_r2,
                    "Test R Sqaure" : baghy_test_r2,
                    "Train Adj R Sqaure" : baghy_train_ad_r2,
                    "Test Adj R Sqaure" : baghy_test_ad_r2
                    })

Hypertuned_bag = pd.DataFrame(bag_record)
Hypertuned_bag
```

Out[63]:

	model	Train Mean Squared Error	Test Mean Squared Error	Train Mean Absolute Error	Test Mean Absolute Error	Train R Sqaure	Test R Sqaure
0	Hyper-Parameter Tunning on Bagging Regressor	40.121305	38.382493	3.788187	3.689813	0.693746	0.699784

Summary

- Accuracy report of all columns

In [65]:

```
frames3 = [all_model,Bagging_report,Hypertuned_rf,Hypertuned_bag]
all_records = pd.concat(frames3)
all_records.reset_index(inplace=True)
all_records.drop('index',axis = 1,inplace = True)
all_records.sort_values(by = 'Test R Sqaure',ascending=False)
```

Out[65]:

	model	Train Mean Squared Error	Test Mean Squared Error	Train Mean Absolute Error	Test Mean Absolute Error	Train R Sqaure	Test R Sqaure
8	Hyper-Parameter Tunning on random forest	27.816961	31.002924	2.887815	2.992724	0.787667	0.757505
7	Bagging Regressor	5.296305	34.156389	1.164451	3.039126	0.959572	0.732840
6	Random Forest Regressor	5.270498	34.186604	1.164584	3.039165	0.959769	0.732603
9	Hyper-Parameter Tunning on Bagging Regressor	40.121305	38.382493	3.788187	3.689813	0.693746	0.699784
1	Ridge Regression	40.317870	38.619047	4.226963	4.117645	0.692245	0.697934
0	Linear Regression	40.317066	38.626226	4.227816	4.118774	0.692251	0.697878
4	Support Vector Regression	39.213283	39.200943	3.114148	3.059588	0.700677	0.693383
2	Lasso Regression	42.259282	40.205873	4.489305	4.388920	0.677426	0.685522
3	ElasticNet Regression	46.791558	44.627403	5.048629	4.955296	0.642830	0.650939
5	Decision Tree Regressor	0.583525	61.139598	0.045608	3.666033	0.995546	0.521786

Store the best model in pickle file

In [66]:

```
import pickle
pickle.dump(rf_best_para, open('random_forest_hypertuned.sav','wb'))
```

Thank you