Importing Libraries

```
import pandas as pd
import numpy as np
# for visualization
import seaborn as sns
import matplotlib.pyplot as plt
from datetime import datetime
# for evaluating
from sklearn import metrics
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
from sklearn import metrics
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import GridSearchCV
from sklearn.linear_model import LinearRegression
from sklearn.ensemble import RandomForestRegressor
from sklearn.svm import SVR
from sklearn.metrics import accuracy_score
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import KFold
from sklearn.ensemble import GradientBoostingRegressor
```

Importing Data files using DATE as index value

```
df_monthlysupply = pd.read_csv(r"C:\Users\nites\Downloads\Monthly Supply.csv", parse_dates=[0]).set_index('DATE')
df_unemprate = pd.read_csv(r"C:\Users\nites\Downloads\Unemployment Rate.csv",parse_dates=[0]).set_index('DATE')
df_mortgaerate = pd.read_csv(r"C:\Users\nites\Downloads\Mortgage Rate.csv",parse_dates=[0]).set_index('DATE')
df_federalfund = pd.read_csv(r"C:\Users\nites\Downloads\Federal Funds Rate.csv",parse_dates=[0]).set_index('DATE')
df_gdp = pd.read_csv(r"C:\Users\nites\Downloads\USA GDP.csv",parse_dates=[0]).set_index('DATE')
df_personalincome = pd.read_csv(r"C:\Users\nites\Downloads\Real Disposable Personal Income.csv",parse_dates=[0]).set_index('DATE')
df_delinquency = pd.read_csv(r"C:\Users\nites\Downloads\Delinquency Rate.csv",parse_dates=[0]).set_index('DATE')
df_personalsaving = pd.read_csv(r"C:\Users\nites\Downloads\Personal Saving.csv",parse_dates=[0]).set_index('DATE')
df_personalconexp = pd.read_csv(r"C:\Users\nites\Downloads\Personal Consumption Expenditures.csv",parse_dates=[0]).set_index('DATE')
df_weeklynomear = pd.read_csv(r"C:\Users\nites\Downloads\Weekly Nominal Earnings.csv",parse_dates=[0]).set_index('DATE')
df_realgdp = pd.read_csv(r"C:\Users\nites\Downloads\Real GDP.csv",parse_dates=[0]).set_index('DATE')
df_priceindex = pd.read_csv(r"C:\Users\nites\Downloads\Price Index.csv",parse_dates=[0]).set_index('DATE')
```

Converting quarterly data into monthly

```
df_delinquency_monthly = df_delinquency.resample('MS').mean()
df_weeklynomear_monthly = df_weeklynomear.resample('MS').mean()
df_realgdp_monthly = df_realgdp.resample('MS').mean()
#df_delinquency_monthly = df_delinquency_monthly.interpolate()
#df_weeklynomear_monthly = (df_weeklynomear_monthly.ffill()
+df_weeklynomear_monthly.bfill())/2

df_delinquency_monthly.head()

            DRSFRMACBS
DATE
2000-01-01        1.95
2000-02-01         NaN
2000-03-01         NaN
2000-04-01        1.89
2000-05-01         NaN

df_weeklynomear_monthly.head()

            LEU0252887700Q
DATE
2000-01-01           603.0
2000-02-01             NaN
2000-03-01             NaN
2000-04-01           606.0
2000-05-01             NaN

df_realgdp_monthly.head()

                GDPC1
DATE
2000-01-01  12935.252
2000-02-01        NaN
2000-03-01        NaN
2000-04-01  13170.749
2000-05-01        NaN
```

Mergeing all csv files into single csv file

```
df_price =
pd.merge(pd.merge(pd.merge(pd.merge(pd.merge(pd.merge(pd.merge(pd.merg
e(pd.merge(pd.merge(pd.merge(df_monthlysupply,df_unemprate,on
='DATE'),df_mortgaerate, on ='DATE'),df_federalfund,on
='DATE'),df_gdp, on ='DATE'),df_personalincome, on
='DATE'),df_personalsaving, on='DATE'),df_personalconexp, on =
'DATE'),df_delinquency_monthly, on ='DATE'),df_weeklynomear_monthly,
on ='DATE'),df_realgdp_monthly, on ='DATE'),df_priceindex, on ='DATE')

df_price.head(10)

            MSACSR  UNRATE  MORTGAGE30US       DFF  USALORSGPNOSTSAM
DSPIC96  \
```

```
DATE

2000-01-01     4.3     4.0        8.2100  5.448387        101.491397
9309.1
2000-02-01     4.3     4.1        8.3250  5.734828        101.552445
9345.2
2000-03-01     4.3     4.0        8.2400  5.853548        101.626906
9370.3
2000-04-01     4.4     3.8        8.1525  6.019667        101.698161
9418.3
2000-05-01     4.4     4.0        8.5150  6.268065        101.740194
9457.3
2000-06-01     4.8     4.0        8.2880  6.528333        101.732697
9483.3
2000-07-01     4.1     4.0        8.1475  6.544516        101.678298
9533.3
2000-08-01     4.4     4.1        8.0275  6.496774        101.588896
9591.5
2000-09-01     4.0     3.9        7.9120  6.517000        101.475487
9601.5
2000-10-01     4.0     3.9        7.7950  6.509355        101.340753
9627.4

            PMSAVE     PCE  DRSFRMACBS  LEU0252887700Q      GDPC1
CSUSHPISA
DATE

2000-01-01   358.9  6542.9        1.95           603.0  12935.252
100.552
2000-02-01   324.3  6625.3         NaN             NaN        NaN
101.339
2000-03-01   311.8  6686.5         NaN             NaN        NaN
102.127
2000-04-01   347.8  6679.1        1.89           606.0  13170.749
102.922
2000-05-01   351.1  6709.7         NaN             NaN        NaN
103.677
2000-06-01   355.3  6746.9         NaN             NaN        NaN
104.424
2000-07-01   383.8  6768.5        2.07           611.0  13183.890
105.054
2000-08-01   389.9  6802.8         NaN             NaN        NaN
105.767
2000-09-01   340.8  6888.6         NaN             NaN        NaN
106.537
2000-10-01   360.3  6893.8        2.42           614.0  13262.250
107.382
```

```
df_price.tail(10)
```

DATE	MSACSR	UNRATE	MORTGAGE30US	DFF	USALORSGPNOSTSAM	DSPIC96 \
2021-04-01	4.7	6.0	3.0600	0.069000	99.112250	16146.9
2021-05-01	5.4	5.8	2.9625	0.058065	99.272288	15669.5
2021-06-01	5.8	5.9	2.9750	0.078000	99.450967	15603.3
2021-07-01	6.0	5.4	2.8680	0.098065	99.638899	15735.2
2021-08-01	6.5	5.2	2.8425	0.092258	99.831176	15720.0
2021-09-01	6.1	4.7	2.9000	0.079333	100.017229	15466.3
2021-10-01	6.9	4.6	3.0675	0.079032	100.170256	15472.4
2021-11-01	6.2	4.2	3.0675	0.079667	100.259331	15470.8
2021-12-01	5.6	3.9	3.0980	0.079677	100.263970	15442.7
2022-01-01	5.7	4.0	3.4450	0.079355	100.193185	15163.5

DATE	PMSAVE	PCE	DRSFRMACBS	LEU0252887700Q	GDPC1	CSUSHPISA
2021-04-01	2331.1	15618.7	2.41	1048.0	19368.310	250.094
2021-05-01	1872.8	15624.4	NaN	NaN	NaN	254.556
2021-06-01	1713.2	15802.0	NaN	NaN	NaN	259.249
2021-07-01	1920.5	15814.9	2.30	1068.0	19478.893	263.349
2021-08-01	1795.2	15991.1	NaN	NaN	NaN	267.028
2021-09-01	1463.7	16088.9	NaN	NaN	NaN	270.258
2021-10-01	1362.4	16309.5	2.33	1069.0	19806.290	273.154
2021-11-01	1384.4	16390.9	NaN	NaN	NaN	276.429
2021-12-01	1593.2	16242.3	NaN	NaN	NaN	280.190
2022-01-01	1047.7	16543.3	2.13	1100.0	19727.918	284.767

Exploratory Data Analysis

```
df_price.reset_index(drop=True, inplace=True)  #as a index date  is
not useful for the model so using reset index method i removed date
index

df_price.head(10)

   MSACSR  UNRATE  MORTGAGE30US       DFF  USALORSGPNOSTSAM  DSPIC96
PMSAVE  \
0     4.3     4.0        8.2100  5.448387        101.491397   9309.1
358.9
1     4.3     4.1        8.3250  5.734828        101.552445   9345.2
324.3
2     4.3     4.0        8.2400  5.853548        101.626906   9370.3
311.8
3     4.4     3.8        8.1525  6.019667        101.698161   9418.3
347.8
4     4.4     4.0        8.5150  6.268065        101.740194   9457.3
351.1
5     4.8     4.0        8.2880  6.528333        101.732697   9483.3
355.3
6     4.1     4.0        8.1475  6.544516        101.678298   9533.3
383.8
7     4.4     4.1        8.0275  6.496774        101.588896   9591.5
389.9
8     4.0     3.9        7.9120  6.517000        101.475487   9601.5
340.8
9     4.0     3.9        7.7950  6.509355        101.340753   9627.4
360.3

      PCE  DRSFRMACBS  LEU0252887700Q      GDPC1  CSUSHPISA
0  6542.9        1.95           603.0  12935.252    100.552
1  6625.3         NaN             NaN        NaN    101.339
2  6686.5         NaN             NaN        NaN    102.127
3  6679.1        1.89           606.0  13170.749    102.922
4  6709.7         NaN             NaN        NaN    103.677
5  6746.9         NaN             NaN        NaN    104.424
6  6768.5        2.07           611.0  13183.890    105.054
7  6802.8         NaN             NaN        NaN    105.767
8  6888.6         NaN             NaN        NaN    106.537
9  6893.8        2.42           614.0  13262.250    107.382

df_price.tail(10)

     MSACSR  UNRATE  MORTGAGE30US       DFF  USALORSGPNOSTSAM  DSPIC96
\
255     4.7     6.0        3.0600  0.069000         99.112250  16146.9

256     5.4     5.8        2.9625  0.058065         99.272288  15669.5

257     5.8     5.9        2.9750  0.078000         99.450967  15603.3
```

```
258     6.0     5.4        2.8680  0.098065         99.638899  15735.2
259     6.5     5.2        2.8425  0.092258         99.831176  15720.0
260     6.1     4.7        2.9000  0.079333        100.017229  15466.3
261     6.9     4.6        3.0675  0.079032        100.170256  15472.4
262     6.2     4.2        3.0675  0.079667        100.259331  15470.8
263     5.6     3.9        3.0980  0.079677        100.263970  15442.7
264     5.7     4.0        3.4450  0.079355        100.193185  15163.5

     PMSAVE      PCE  DRSFRMACBS  LEU0252887700Q      GDPC1  CSUSHPISA
255  2331.1  15618.7        2.41          1048.0  19368.310    250.094
256  1872.8  15624.4         NaN             NaN        NaN    254.556
257  1713.2  15802.0         NaN             NaN        NaN    259.249
258  1920.5  15814.9        2.30          1068.0  19478.893    263.349
259  1795.2  15991.1         NaN             NaN        NaN    267.028
260  1463.7  16088.9         NaN             NaN        NaN    270.258
261  1362.4  16309.5        2.33          1069.0  19806.290    273.154
262  1384.4  16390.9         NaN             NaN        NaN    276.429
263  1593.2  16242.3         NaN             NaN        NaN    280.190
264  1047.7  16543.3        2.13          1100.0  19727.918    284.767
```

Removing NaN values using ffill and bfill method

```
df_price = (df_price.ffill()+df_price.bfill())/2

df_price.head()
```

```
   MSACSR  UNRATE  MORTGAGE30US       DFF  USALORSGPNOSTSAM  DSPIC96
PMSAVE  \
0     4.3     4.0        8.2100  5.448387        101.491397   9309.1
358.9
1     4.3     4.1        8.3250  5.734828        101.552445   9345.2
324.3
```

```
2     4.3     4.0        8.2400  5.853548        101.626906   9370.3
311.8
3     4.4     3.8        8.1525  6.019667        101.698161   9418.3
347.8
4     4.4     4.0        8.5150  6.268065        101.740194   9457.3
351.1

      PCE  DRSFRMACBS  LEU0252887700Q       GDPC1  CSUSHPISA
0  6542.9        1.95           603.0  12935.2520    100.552
1  6625.3        1.92           604.5  13053.0005    101.339
2  6686.5        1.92           604.5  13053.0005    102.127
3  6679.1        1.89           606.0  13170.7490    102.922
4  6709.7        1.98           608.5  13177.3195    103.677
```

```
df_price.shape
```

```
(265, 12)
```

Renaming Columns name

```
df_price.rename(columns = {'MSACSR':'Monthly Supply',
'UNRATE':'Unemployment Rate', 'MORTGAGE30US':'Mortgage Rate',
'DFF':'Federal Funds Rate', 'USALORSGPNOSTSAM':'USA GDP',
'DSPIC96':'Disposable Income', 'PMSAVE':'Personal Saving',
'PCE':'Consumption Expenditures', 'DRSFRMACBS':'Delinquency Rate',
'LEU0252887700Q':'Nominal Earnings', 'GDPC1':'Real GDP',
'CSUSHPISA':'Price Index'}, inplace = True)
```

```
df_price.head()
```

```
   Monthly Supply  Unemployment Rate  Mortgage Rate  Federal Funds
Rate  \
0             4.3                4.0         8.2100
5.448387
1             4.3                4.1         8.3250
5.734828
2             4.3                4.0         8.2400
5.853548
3             4.4                3.8         8.1525
6.019667
4             4.4                4.0         8.5150
6.268065

      USA GDP  Disposable Income  Personal Saving  Consumption
Expenditures  \
0  101.491397             9309.1            358.9
6542.9
1  101.552445             9345.2            324.3
6625.3
2  101.626906             9370.3            311.8
6686.5
3  101.698161             9418.3            347.8
```

```
6679.1
4  101.740194             9457.3           351.1
6709.7

   Delinquency Rate  Nominal Earnings    Real GDP  Price Index
0              1.95             603.0  12935.2520      100.552
1              1.92             604.5  13053.0005      101.339
2              1.92             604.5  13053.0005      102.127
3              1.89             606.0  13170.7490      102.922
4              1.98             608.5  13177.3195      103.677
```

```
df_price.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 265 entries, 0 to 264
Data columns (total 12 columns):
 #   Column                    Non-Null Count  Dtype
---  ------                    --------------  -----
 0   Monthly Supply            265 non-null    float64
 1   Unemployment Rate         265 non-null    float64
 2   Mortgage Rate             265 non-null    float64
 3   Federal Funds Rate        265 non-null    float64
 4   USA GDP                   265 non-null    float64
 5   Disposable Income         265 non-null    float64
 6   Personal Saving           265 non-null    float64
 7   Consumption Expenditures  265 non-null    float64
 8   Delinquency Rate          265 non-null    float64
 9   Nominal Earnings          265 non-null    float64
 10  Real GDP                  265 non-null    float64
 11  Price Index               265 non-null    float64
dtypes: float64(12)
memory usage: 25.0 KB
```

Checking any missing value in the dataset

```
df_price.isnull().sum()
```

```
Monthly Supply              0
Unemployment Rate           0
Mortgage Rate               0
Federal Funds Rate          0
USA GDP                     0
Disposable Income           0
Personal Saving             0
Consumption Expenditures    0
Delinquency Rate            0
Nominal Earnings            0
Real GDP                    0
Price Index                 0
dtype: int64
```

```
df_price.describe()
```

	Monthly Supply	Unemployment Rate	Mortgage Rate	Federal Funds Rate
count	265.000000	265.000000	265.000000	265.000000
mean	5.758491	5.950566	4.989968	1.636559
std	1.880103	1.944536	1.371733	1.884929
min	3.300000	3.500000	2.684000	0.049000
25%	4.300000	4.600000	3.890000	0.129000
50%	5.300000	5.400000	4.714000	1.004516
75%	6.500000	6.900000	6.095000	2.377667
max	12.200000	14.700000	8.515000	6.544516

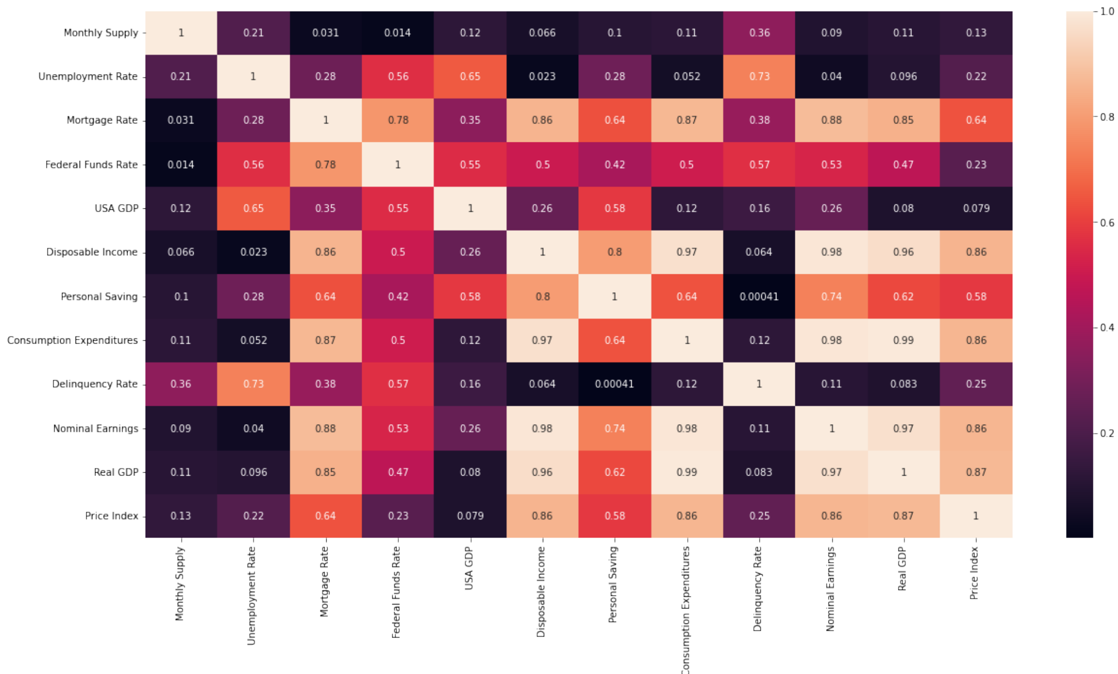
	USA GDP	Disposable Income	Personal Saving
count	265.000000	265.000000	265.000000
mean	99.889733	12304.084528	873.528679
std	1.294200	1849.055814	738.496949
min	91.580035	9309.100000	193.400000
25%	99.543817	10839.000000	418.700000
50%	99.930092	12060.900000	752.200000
75%	100.544633	13567.100000	1048.500000
max	101.829671	19119.500000	6392.500000

	Consumption Expenditures	Delinquency Rate	Nominal Earnings
count	265.000000	265.000000	265.000000
mean	10769.224906	4.631660	803.811321
std	2542.163077	3.232384	125.751710
min	6542.900000	1.400000	603.000000
25%	8850.100000	2.130000	697.000000
50%	10514.300000	2.960000	791.000000
75%	12701.700000	7.135000	886.000000
max	16543.300000	11.360000	1100.000000

	Real GDP	Price Index
count	265.000000	265.000000
mean	16164.514445	166.582038
std	1870.768617	37.080033
min	12935.252000	100.552000
25%	14956.291000	141.646000
50%	15807.995000	163.666000
75%	17671.535000	184.329000
max	19806.290000	284.767000

```
plt.figure(figsize=(20, 10))
sns.heatmap(df_price.corr().abs(), annot = True)
```

```
<AxesSubplot:>
```



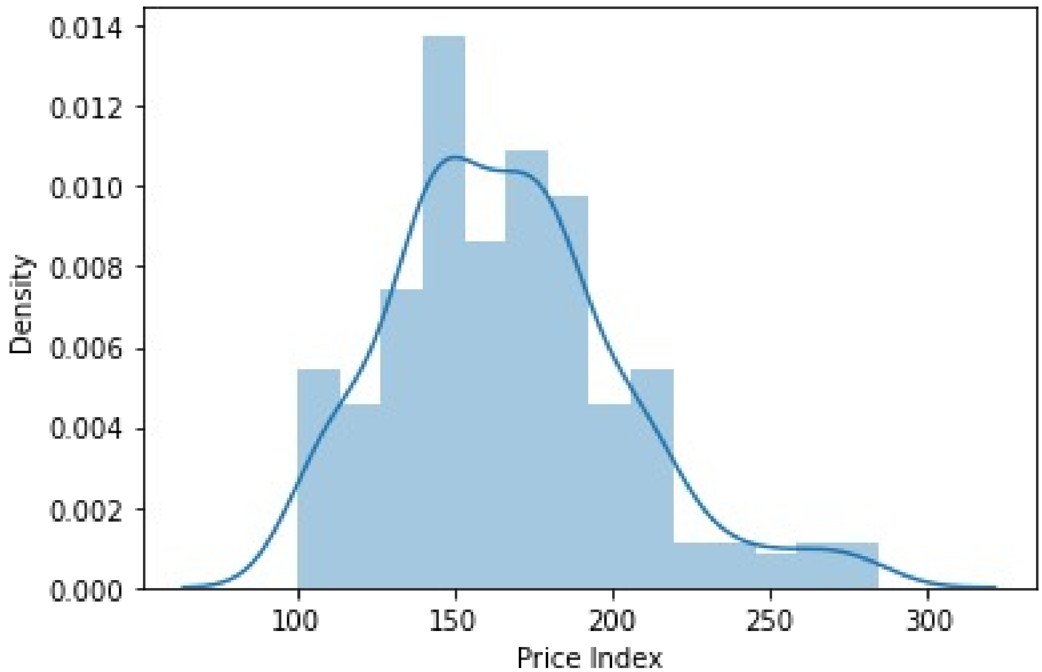
In corr graph we can see some columns have positive correlation and some have negative corr. like USA GDP have negative correlation with price Index unemployment rate also have some negative corr. with price Index.

```
sns.pairplot(df_price)
plt.tight_layout()
```

Pairplot show monthly supply, unemployment Rate, personal svaing have long right skewed data and USA GDP have left skewed data. some features have linearity in distribution.

```
sns.distplot(df_price['Price Index']);
```

```
E:\ProgramData\Anaconda3\lib\site-packages\seaborn\
distributions.py:2619: FutureWarning: `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 similar
flexibility) or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```



Seperating X(Independent) and Y(Dependent) variable

```
x = df_price.drop('Price Index', axis =1)
y = df_price['Price Index']

#x.skew(axis = 0, skipna = True)

#y.skew(axis = 0, skipna = True)

#for col in x.columns:
   # if np.abs(x[col].skew()) > 0.7:
       # x[col] = np.log1p(x[col])

#y =  np.log1p(y)
```

spliting data into train and test using train_test_split

```
x_train,x_test,y_train,y_test = train_test_split(x,y, test_size = 0.2,
random_state = 0 )

x_train.head()

     Monthly Supply  Unemployment Rate  Mortgage Rate  Federal Funds
Rate  \
196             5.1                4.8         3.6000
0.365161
55              4.3                5.4         5.8675
1.429355
157             4.1                7.7         3.5325
0.145000
44              3.8                6.1         6.1475
1.010000
```

```
190              5.5                5.1        3.9425
0.117667

        USA GDP  Disposable Income  Personal Saving  Consumption
Expenditures  \
196   99.851573            13515.1            976.1
12624.4
55    99.886847            10693.5            450.6
8271.6
157   99.880367            12224.9            698.3
11282.1
44    99.309835            10369.1            439.1
7853.7
190  100.103871            13417.7           1010.7
12397.5

     Delinquency Rate  Nominal Earnings    Real GDP
196             4.385             883.0  17671.5350
55              1.530             686.5  14531.7135
157             9.450             827.5  16452.9435
44              1.805             664.5  14050.7680
190             5.050             875.0  17514.0220
```

```
#x_test.head()
y_test.head()
```

```
110    148.659
97     171.542
83     184.141
8      106.537
161    154.194
Name: Price Index, dtype: float64
```

Scaling Data because some features values are different and are not normally distributed

```
x_train_scaled = StandardScaler().fit_transform(x_train)
x_test_scaled = StandardScaler().fit_transform(x_test)
```

Model Building Using Linear regression, GradientBoostingRegressor, RandomForestRegressor

```
lr = LinearRegression()
lr.fit(x_train_scaled,y_train)
pred = lr.predict(x_test_scaled)
print(lr.score(x_train_scaled, y_train))
print(lr.score(x_test_scaled, y_test))
```

```
0.9527388015010082
0.8978483997231272
```

```
print('Root Mean Squared Error:',
np.sqrt(metrics.mean_squared_error(y_test, pred)))
```

```
Root Mean Squared Error: 10.951537246546923
```

```
output_lr =
pd.DataFrame({'actual':np.array(y_test).flatten(),'pred':np.array(pred
).flatten()})
output_lr
```

	actual	pred
0	148.659	155.932734
1	171.542	170.628210
2	184.141	171.205009
3	106.537	112.371122
4	154.194	151.236776
5	163.400	161.723099
6	168.058	168.473227
7	179.111	174.050686
8	159.330	156.054471
9	184.364	171.574661
10	181.868	193.434410
11	142.525	151.793648
12	284.767	273.041513
13	139.860	149.771792
14	188.032	191.812842
15	111.651	115.250529
16	218.139	256.555859
17	193.786	204.361003
18	168.663	170.542532
19	160.075	156.722535
20	173.133	179.175547
21	137.532	143.520811
22	200.038	206.833538
23	105.767	112.965277
24	149.965	147.907978
25	208.947	228.328652
26	151.504	151.020512
27	219.702	252.644131
28	169.138	170.511105
29	184.156	171.163340
30	222.539	246.223640
31	145.717	142.735324
32	180.848	190.713343
33	167.339	172.492834
34	119.611	129.000149
35	156.142	137.071744
36	188.818	197.186489
37	129.355	139.813765
38	165.909	167.256358
39	114.811	113.176764
40	161.989	162.744994
41	169.351	163.524677
42	152.854	156.048125
43	139.306	148.849199

```
44  104.424  114.944772
45  115.855  122.924705
46  172.948  176.861015
47  167.501  165.794121
48  109.846  119.243358
49  143.600  141.460835
50  205.464  219.457937
51  140.011  146.601794
52  180.254  175.557509
```

Gradient Boosting Regressor using Hyperparameter tuning

```
num_folds = 10
scoring = 'neg_mean_squared_error'

param_grid = {'n_estimators':[100,200,250,300,400]}

model = GradientBoostingRegressor(random_state=1313, learning_rate =
0.1,
                                  max_depth = 4, min_samples_leaf = 3)
kfold = KFold(n_splits=num_folds, random_state=1313, shuffle=True)
grid = GridSearchCV(estimator=model, param_grid=param_grid,
                    scoring=scoring, cv=kfold)
grid_result = grid.fit(x_train_scaled, y_train)
```

```
print("Best: %f using %s" % (grid_result.best_score_,
                             grid_result.best_params_))
means = grid_result.cv_results_['mean_test_score']
stds = grid_result.cv_results_['std_test_score']
params = grid_result.cv_results_['params']
for mean, stdev, param in zip(means, stds, params):
    print("%f (%f) with: %r" % (mean, stdev, param))
```

```
Best: -11.209296 using {'n_estimators': 400}
-11.310681 (22.494929) with: {'n_estimators': 100}
-11.228173 (22.529470) with: {'n_estimators': 200}
-11.221059 (22.553471) with: {'n_estimators': 250}
-11.213234 (22.554856) with: {'n_estimators': 300}
-11.209296 (22.546869) with: {'n_estimators': 400}
```

Random Forest Regressor using hyperparameter Tuning

```
rf =RandomForestRegressor()
param = dict(max_depth=[10,11,12,13,14,15,19,20],
max_features=[3,4,5,6,7])
grid_rf = GridSearchCV(estimator=rf , param_grid = param, n_jobs = -1)
grid_rf.fit(x_train,y_train)
print(grid_rf.best_score_)
print(grid_rf.best_estimator_)
```

```
0.9957240823927249
RandomForestRegressor(max_depth=15, max_features=4)
```

```
rf=RandomForestRegressor(max_depth=15,max_features=4)
results_rt = cross_val_score(rf, x_train, y_train , cv=10,
scoring='neg_mean_squared_error')
print(results_rt.mean())
```

```
-5.360414667596172
```

```
rf.fit(x_train,y_train)
pred_rf = rf.predict(x_test)
np.sqrt(metrics.mean_squared_error(y_test,pred_rf))
```

```
5.824471106594633
```

```
output =
pd.DataFrame({'actual':np.array(y_test).flatten(),'pred':np.array(pred
_rf).flatten()})
output
```

	actual	pred
0	148.659	150.348119
1	171.542	172.424454
2	184.141	183.325235
3	106.537	107.303280
4	154.194	150.032252
5	163.400	162.184385
6	168.058	169.435239
7	179.111	178.670346
8	159.330	160.040979
9	184.364	182.401014
10	181.868	182.362800
11	142.525	142.733812
12	284.767	247.598430
13	139.860	139.716178
14	188.032	188.515697
15	111.651	112.078500
16	218.139	226.041450
17	193.786	192.858640
18	168.663	169.007347
19	160.075	160.145532
20	173.133	174.291939
21	137.532	135.530730
22	200.038	200.818730
23	105.767	105.939950
24	149.965	149.826512
25	208.947	208.814110
26	151.504	151.523278
27	219.702	228.646560
28	169.138	170.657789

29	184.156	182.521599
30	222.539	229.749690
31	145.717	145.349475
32	180.848	179.458844
33	167.339	167.931723
34	119.611	119.836450
35	156.142	154.224732
36	188.818	189.308007
37	129.355	129.336030
38	165.909	165.374002
39	114.811	115.446710
40	161.989	164.049506
41	169.351	170.319874
42	152.854	150.035575
43	139.306	139.028966
44	104.424	105.977810
45	115.855	117.202590
46	172.948	173.406067
47	167.501	166.975120
48	109.846	110.225650
49	143.600	144.852064
50	205.464	204.821950
51	140.011	139.921463
52	180.254	181.098071