```python
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import sklearn
from sklearn.model_selection import train_test_split
from sklearn.metrics import
confusion_matrix,accuracy_score,classification_report
import warnings
warnings.filterwarnings("ignore")

df=pd.read_csv("water_potability.csv")
df
```

```
            ph    Hardness        Solids  Chloramines     Sulfate  \
0          NaN  204.890455  20791.318981     7.300212  368.516441
1     3.716080  129.422921  18630.057858     6.635246         NaN
2     8.099124  224.236259  19909.541732     9.275884         NaN
3     8.316766  214.373394  22018.417441     8.059332  356.886136
4     9.092223  181.101509  17978.986339     6.546600  310.135738
...        ...         ...           ...          ...         ...
3271  4.668102  193.681735  47580.991603     7.166639  359.948574
3272  7.808856  193.553212  17329.802160     8.061362         NaN
3273  9.419510  175.762646  33155.578218     7.350233         NaN
3274  5.126763  230.603758  11983.869376     6.303357         NaN
3275  7.874671  195.102299  17404.177061     7.509306         NaN

      Conductivity  Organic_carbon  Trihalomethanes  Turbidity
Potability
0       564.308654       10.379783        86.990970   2.963135
0
1       592.885359       15.180013        56.329076   4.500656
0
2       418.606213       16.868637        66.420093   3.055934
0
3       363.266516       18.436524       100.341674   4.628771
0
4       398.410813       11.558279        31.997993   4.075075
0
...            ...             ...              ...        ...
...
3271    526.424171       13.894419        66.687695   4.435821
1
3272    392.449580       19.903225              NaN   2.798243
1
3273    432.044783       11.039070        69.845400   3.298875
1
3274    402.883113       11.168946        77.488213   4.708658
1
3275    327.459760       16.140368        78.698446   2.309149
1
```

```
[3276 rows x 10 columns]
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3276 entries, 0 to 3275
Data columns (total 10 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   ph               2785 non-null   float64
 1   Hardness         3276 non-null   float64
 2   Solids           3276 non-null   float64
 3   Chloramines      3276 non-null   float64
 4   Sulfate          2495 non-null   float64
 5   Conductivity     3276 non-null   float64
 6   Organic_carbon   3276 non-null   float64
 7   Trihalomethanes  3114 non-null   float64
 8   Turbidity        3276 non-null   float64
 9   Potability       3276 non-null   int64
dtypes: float64(9), int64(1)
memory usage: 256.1 KB
```

```
df.isnull().sum()
```

```
ph                 491
Hardness             0
Solids               0
Chloramines          0
Sulfate            781
Conductivity         0
Organic_carbon       0
Trihalomethanes    162
Turbidity            0
Potability           0
dtype: int64
```

```
df.duplicated().sum()
```

```
np.int64(0)
```

REPLACING THE NULL VALUES TO MEAN OF EACH COLUMN

```
for i in df.columns:
    if df[i].isnull().sum()>0:
        df[i].fillna(df[i].mean(),inplace=True)
```

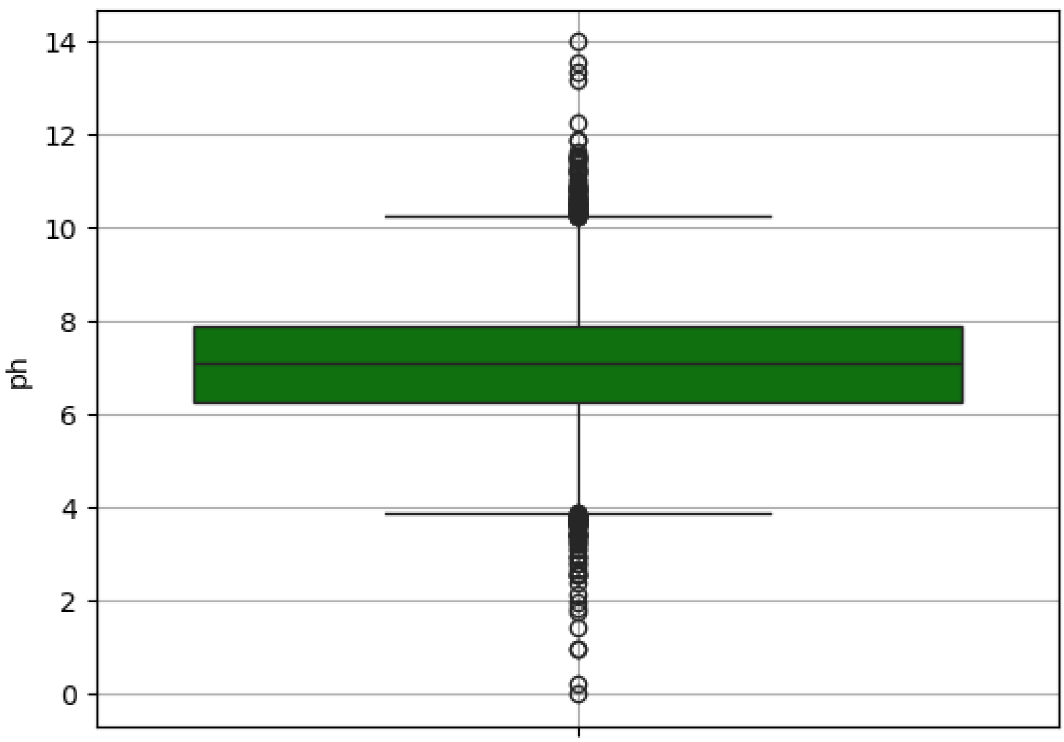
```
df.isnull().sum()
```

```
ph                 0
Hardness           0
Solids             0
Chloramines        0
Sulfate            0
Conductivity       0
Organic_carbon     0
Trihalomethanes    0
Turbidity          0
Potability         0
dtype: int64
```

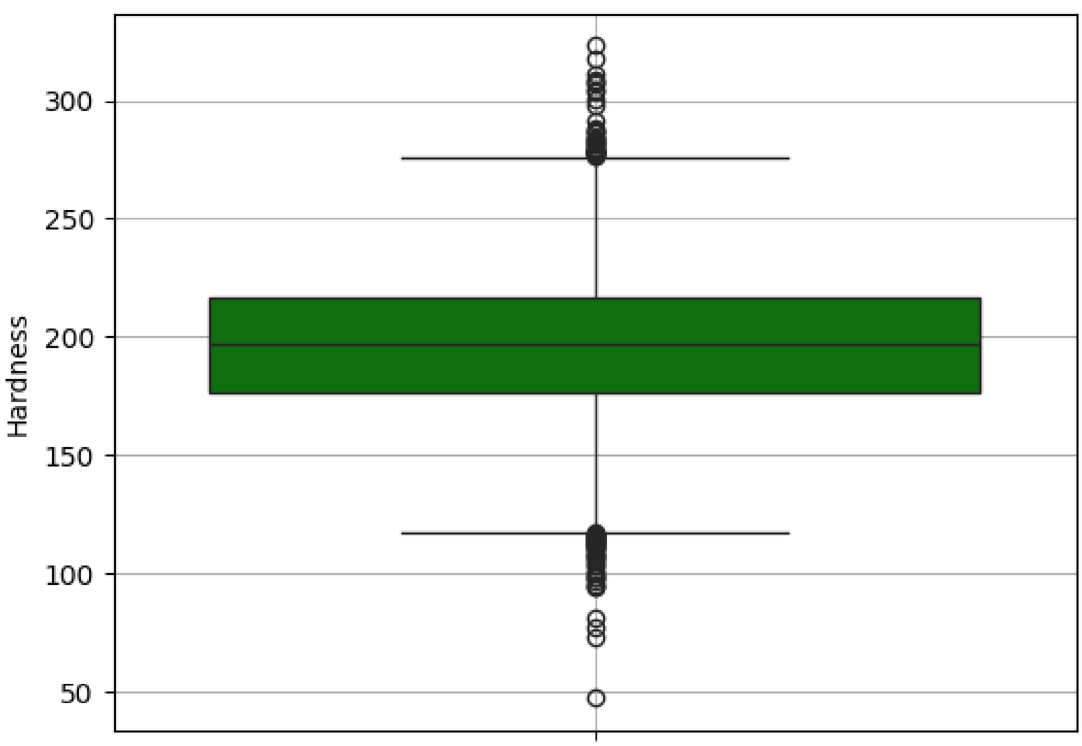
SHOWING OUTLIERS

```
for i in df.columns:
    if i == "Potability":
        pass
    else:
        print(f'                    -----------------
{i}-------------------                 \n')
        sns.boxplot(df[i],color='g')
        plt.grid()
        plt.show()
```

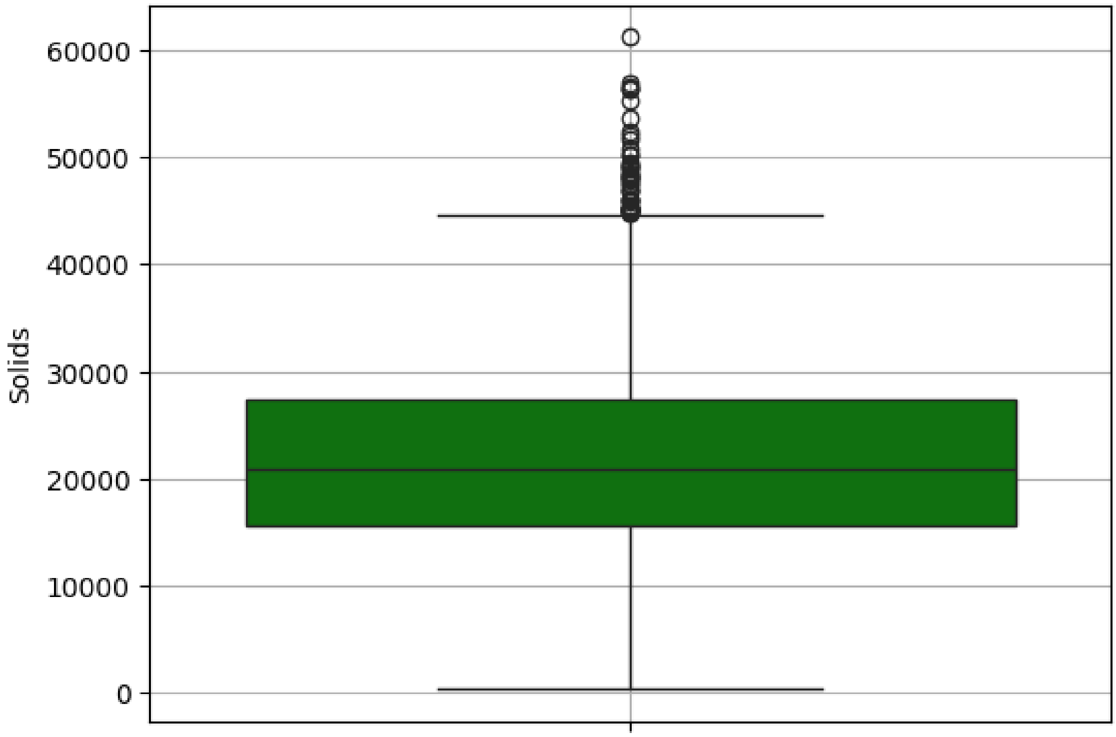
```
                    -----------------ph-------------------
```



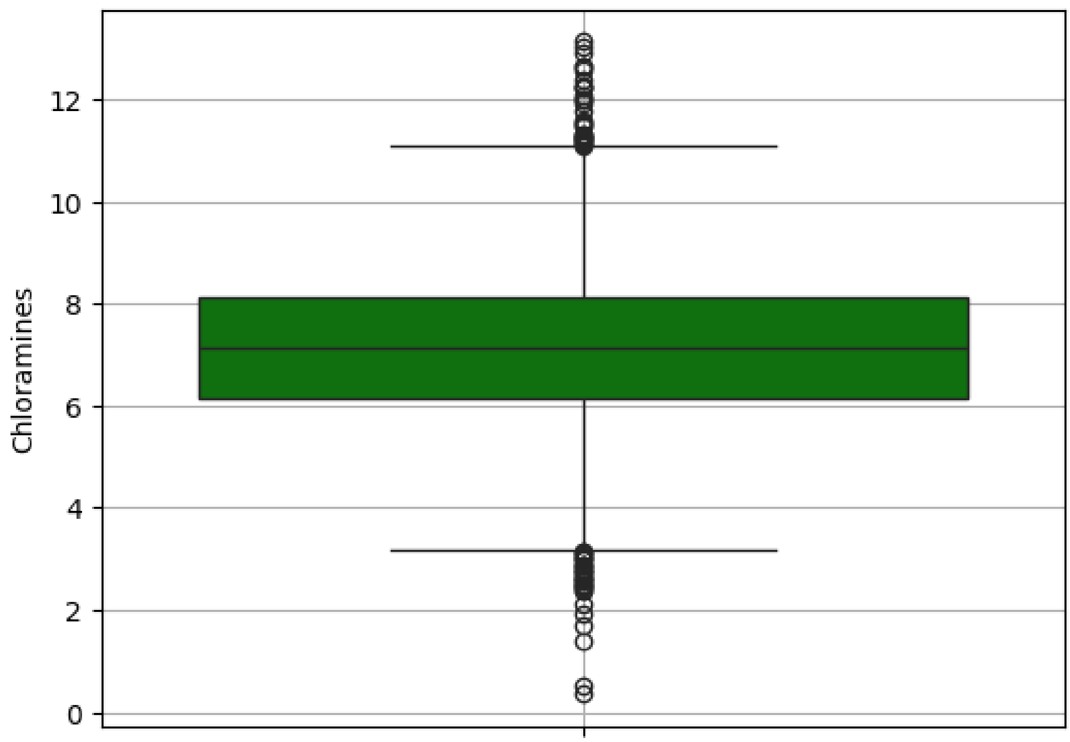

```
-----------------Hardness-------------------
```



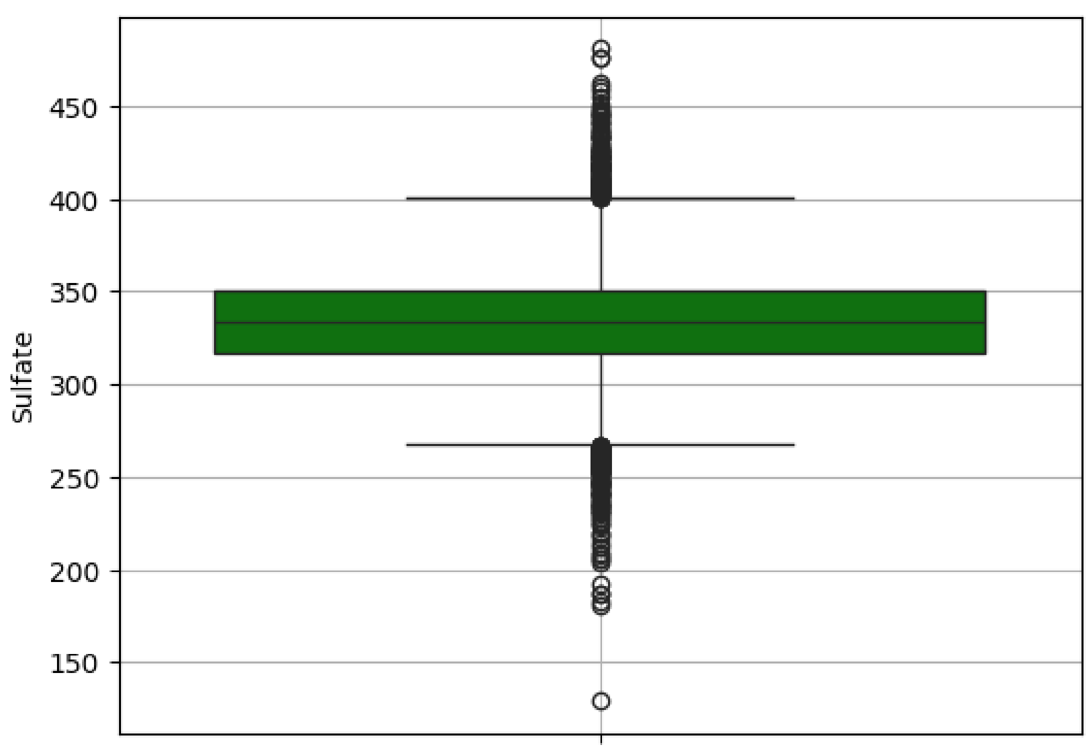
```
----------------Solids------------------
```



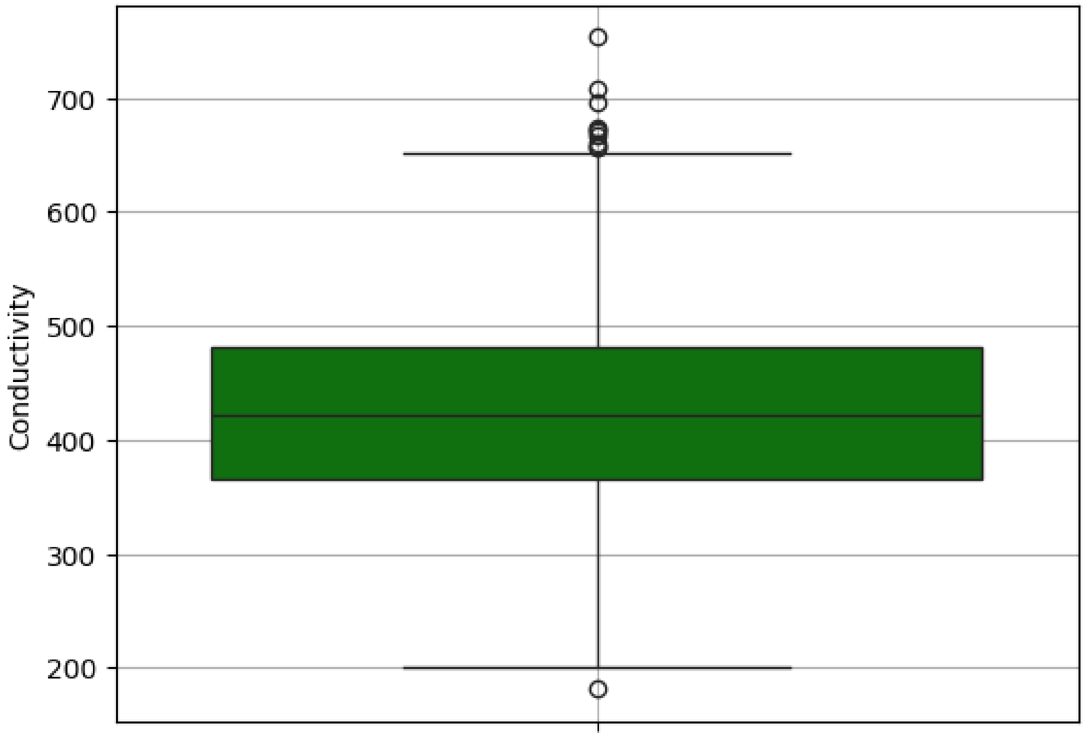

```
----------------Chloramines------------------
```



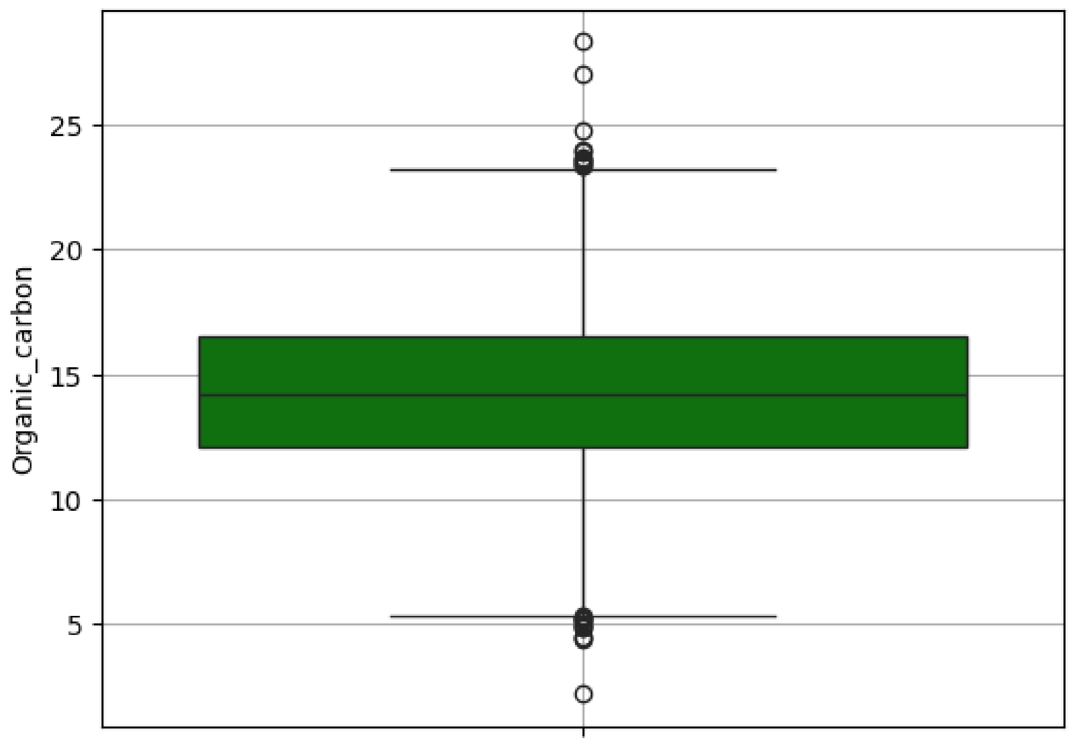

```
----------------Sulfate------------------
```



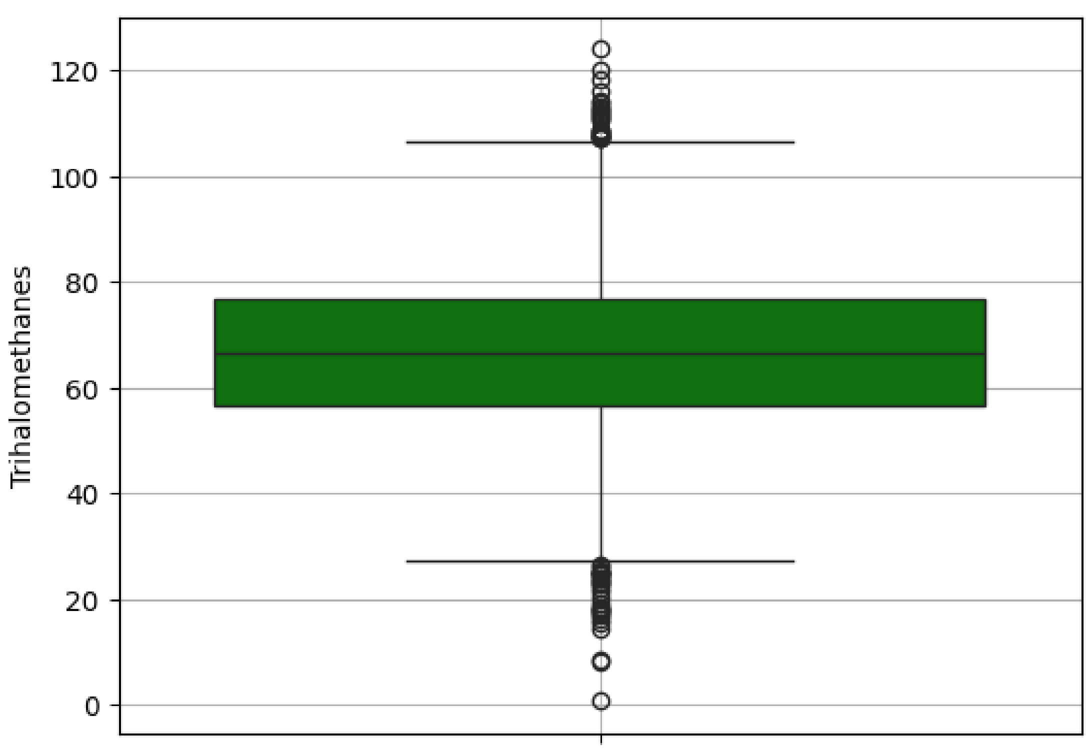
```
-----------------Conductivity-------------------
```



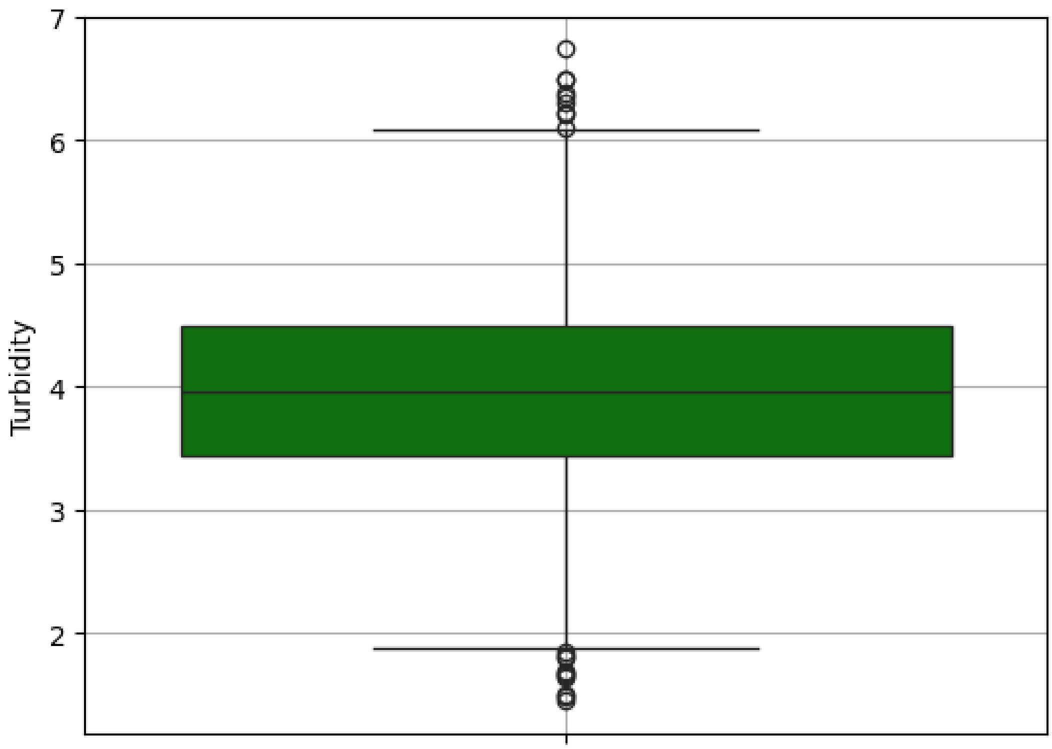

```
-----------------Organic_carbon-------------------
```




```
                       -----------------
Trihalomethanes-----------------
```



```
                    -----------------Turbidity-------------------
```



removing outliers

```
q1=df.quantile(0.25)
q3=df.quantile(0.75)
IQR=q3-q1
print(f'IQR--------> \n\n{IQR}')
```

```
IQR-------->

ph                     1.592377
Hardness              39.816918
Solids             11666.071830
Chloramines            1.987466
Sulfate               33.291119
Conductivity         116.057890
Organic_carbon         4.491850
Trihalomethanes       20.018954
Turbidity              1.060609
Potability             1.000000
dtype: float64
```

```python
lower_limit=q1-1.5*IQR
upper_limit=q3+1.5*IQR
print(lower_limit)
```

```
ph                    3.889107
Hardness            117.125160
Solids            -1832.417449
Chloramines           3.146221
Sulfate             267.157960
Conductivity        191.647579
Organic_carbon        5.328026
Trihalomethanes      26.619225
Turbidity             1.848797
Potability           -1.500000
dtype: float64
```

```python
df[((df<lower_limit)|(df>upper_limit)).any(axis=1)]
```

```
             ph    Hardness        Solids  Chloramines     Sulfate  \
1      3.716080  129.422921  18630.057858     6.635246  333.775777
9     11.180284  227.231469  25484.508491     9.077200  404.041635
18     8.975464  279.357167  19460.398131     6.204321  333.775777
26     3.445062  207.926260  33424.768678     8.782147  384.007006
32    10.433291  117.791230  22326.892046     8.161505  307.707509
...         ...         ...           ...          ...         ...
3246  10.667364  173.381945  28912.202201     7.071294  276.634391
3249  10.808157  198.596751  29614.348790     5.782418  304.622061
3261   3.629922  244.187392  24856.633209     6.618071  366.967873
3269  11.491011   94.812545  37188.826022     9.263166  258.930600
3271   4.668102  193.681735  47580.991603     7.166639  359.948574

      Conductivity  Organic_carbon  Trihalomethanes  Turbidity
Potability
1       592.885359       15.180013        56.329076   4.500656
0
9       563.885481       17.927806        71.976601   4.370562
0
18      431.443990       12.888759        63.821237   2.436086
0
26      441.785876       13.805902        30.284597   4.184397
0
32      412.986834       12.890709        65.733478   5.057311
0
...            ...             ...              ...        ...
...
3246    286.063394       17.685651        55.147364   4.135569
1
3249    383.269410       14.902820        47.896406   4.362542
1
3261    442.076337       13.302880        59.489294   4.754826
```

```
1
3269    439.893618       16.172755        41.558501   4.369264
1
3271    526.424171       13.894419        66.687695   4.435821
1

[610 rows x 10 columns]
```

outliers removal

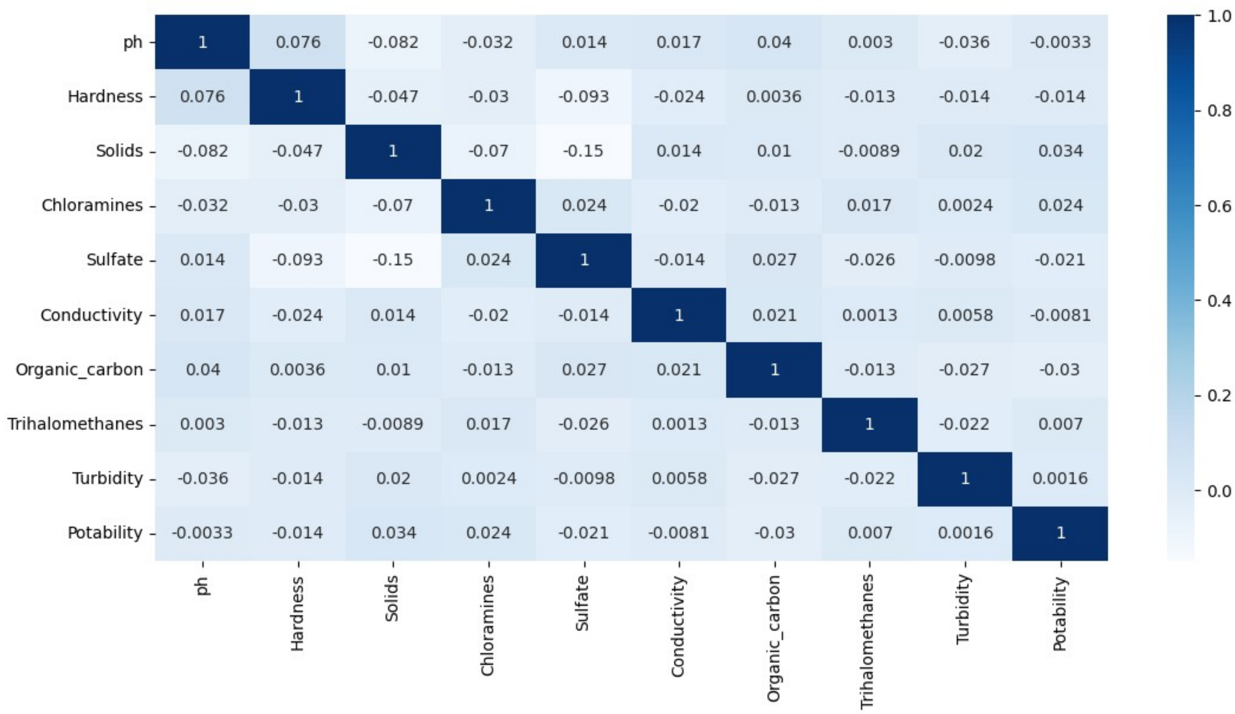
```
df[~((df<lower_limit)|(df>upper_limit)).any(axis=1)]
```

```
            ph    Hardness        Solids  Chloramines     Sulfate  \
0     7.080795  204.890455  20791.318981     7.300212  368.516441
2     8.099124  224.236259  19909.541732     9.275884  333.775777
3     8.316766  214.373394  22018.417441     8.059332  356.886136
4     9.092223  181.101509  17978.986339     6.546600  310.135738
5     5.584087  188.313324  28748.687739     7.544869  326.678363
...        ...         ...           ...          ...         ...
3270  6.069616  186.659040  26138.780191     7.747547  345.700257
3272  7.808856  193.553212  17329.802160     8.061362  333.775777
3273  9.419510  175.762646  33155.578218     7.350233  333.775777
3274  5.126763  230.603758  11983.869376     6.303357  333.775777
3275  7.874671  195.102299  17404.177061     7.509306  333.775777

      Conductivity  Organic_carbon  Trihalomethanes  Turbidity  
Potability
0       564.308654       10.379783        86.990970   2.963135
0
2       418.606213       16.868637        66.420093   3.055934
0
3       363.266516       18.436524       100.341674   4.628771
0
4       398.410813       11.558279        31.997993   4.075075
0
5       280.467916        8.399735        54.917862   2.559708
0
...            ...             ...              ...        ...
...
3270    415.886955       12.067620        60.419921   3.669712
1
3272    392.449580       19.903225        66.396293   2.798243
1
3273    432.044783       11.039070        69.845400   3.298875
1
3274    402.883113       11.168946        77.488213   4.708658
1
3275    327.459760       16.140368        78.698446   2.309149
```

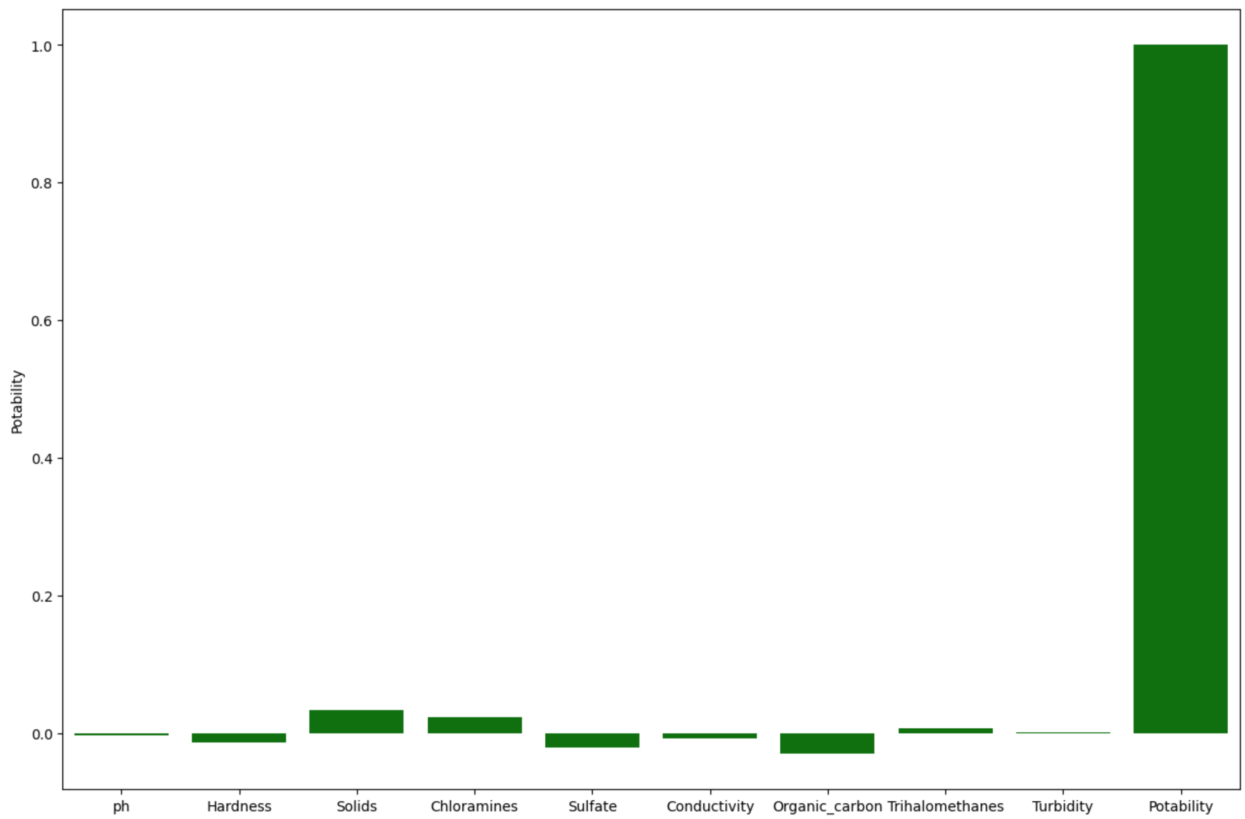
```
1

[2666 rows x 10 columns]
```

checking for collinearity and removing if any

```
plt.figure(figsize=(13,6))
sns.heatmap(df.corr(),annot=True,cmap="Blues")
plt.show()
```




```
plt.figure(figsize=(15,10))
sns.barplot(df.corr()["Potability"],color='g')
plt.show()
```



seperating dependent and independent

```
x=df.drop(columns='Potability')
y=df['Potability']
```

splitting

```
X_train, X_test, y_train, y_test = train_test_split(x, y,
test_size=0.3, random_state=42)

for i in df.columns:
    print('------max values----------')
    print(f"max value in {i}---->{df[i].max()}\n")
    print('----------min values----------')
    print(f'min value in {i}----->{df[i].min()}\n')


------max values----------
max value in ph---->13.999999999999998

----------min values-----------
min value in ph----->0.0
```

```
------max values----------
max value in Hardness---->323.124

---------min values-----------
min value in Hardness----->47.432

------max values----------
max value in Solids---->61227.19600771213

---------min values-----------
min value in Solids----->320.942611274359

------max values----------
max value in Chloramines---->13.127000000000002

---------min values-----------
min value in Chloramines----->0.3520000000000003

------max values----------
max value in Sulfate---->481.0306423059972

---------min values-----------
min value in Sulfate----->129.00000000000003

------max values----------
max value in Conductivity---->753.3426195583046

---------min values-----------
min value in Conductivity----->181.483753985146

------max values----------
max value in Organic_carbon---->28.300000000000001

---------min values-----------
min value in Organic_carbon----->2.1999999999999886

------max values----------
max value in Trihalomethanes---->124.0

---------min values-----------
min value in Trihalomethanes----->0.7379999999999995

------max values----------
max value in Turbidity---->6.739

---------min values-----------
min value in Turbidity----->1.45

------max values----------
max value in Potability---->1
```

```
----------min values-----------
min value in Potability----->0
```

```python
from sklearn.preprocessing import StandardScaler
```

```python
s=StandardScaler()
X_train_s=s.fit_transform(X_train)
X_test_s=s.fit_transform(X_test)
```

```python
X_train
```

```
            ph    Hardness        Solids  Chloramines     Sulfate  \
2985  7.080795  188.445469  28791.614416     8.040356  382.009477
1073  7.203439  168.445358  22826.484697     6.283250  271.892045
3140  7.080795  242.827588  29298.074262     5.853840  340.348645
2643  6.056818  211.765886   4440.277357     9.507303  333.775777
2174  9.581189  223.296216  28292.780318     5.665431  333.775777
...        ...         ...           ...          ...         ...
1095  4.187491  208.374188  21809.709834     5.846112  327.474203
1130  7.793915  164.958947  25506.912237     7.868036  358.259200
1294  6.630364  186.761088  30939.023214     7.703481  333.775777
860   8.783168  218.032840  16183.586649     7.390474  334.053885
3174  6.698154  198.286268  34675.862845     6.263602  360.232834

      Conductivity  Organic_carbon  Trihalomethanes  Turbidity
2985    422.234861       10.575690        63.235365   3.228379
1073    437.370863       16.410654        64.505923   6.389161
3140    463.115174        5.426650        66.396293   3.522586
2643    316.921776       17.766397        53.541191   3.358061
2174    398.479317       11.350768        44.574120   3.929178
...            ...             ...              ...        ...
1095    264.508083       11.235144        46.682597   4.592959
1130    398.460312       15.297496        66.396293   4.220028
1294    330.876083       13.815757        86.753117   3.490588
860     389.021616       16.354520        47.100982   4.274137
3174    430.935009       12.176678        66.396293   3.758180

[2293 rows x 9 columns]
```

```python
pd.DataFrame(X_train_s,columns=X_train.columns)
```

```
            ph  Hardness    Solids  Chloramines   Sulfate
Conductivity  \
0    -0.008982 -0.246998  0.750536     0.587582  1.335674     -
0.054682
1     0.074882 -0.856455  0.080096    -0.527665 -1.709476
0.130717
2    -0.008982  1.410171  0.807459    -0.800215  0.183599
0.446057
```

```
3    -0.709177  0.463637 -1.986388     1.518663  0.001836     -
1.344653
4     1.700785  0.814997  0.694470    -0.919799  0.001836     -
0.345662
...        ...       ...       ...          ...       ...              ..
.
2288 -1.987422  0.360283 -0.034182    -0.805120 -0.172426     -
1.986664
2289  0.478649 -0.962696  0.381358     0.478209  0.678892     -
0.345895
2290 -0.316987 -0.298326  0.991890     0.373764  0.001836     -
1.173728
2291  1.155099  0.654608 -0.666520     0.175097  0.009526     -
0.461509
2292 -0.270632  0.052877  1.411885    -0.540136  0.733470
0.051885

      Organic_carbon  Trihalomethanes  Turbidity
0          -1.117452        -0.202345  -0.938934
1           0.656002        -0.122326   3.126131
2          -2.682430        -0.003271  -0.560556
3           1.068061        -0.812882  -0.772151
4          -0.881878        -1.377626  -0.037641
...              ...              ...        ...
2288       -0.917020        -1.244835   0.816045
2289        0.317674        -0.003271   0.336420
2290       -0.132680         1.278797  -0.601709
2291        0.638941        -1.218485   0.406009
2292       -0.630854        -0.003271  -0.257561

[2293 rows x 9 columns]
```

```python
from sklearn.neighbors import KNeighborsClassifier
```

```python
model=KNeighborsClassifier(n_neighbors=5)
model.fit(X_train_s,y_train)
```

```
KNeighborsClassifier()
```

```python
model.score(X_train_s,y_train)
```

```
0.7592673353685129
```

```python
model.score(X_test_s,y_test)
```

```
0.6205493387589013
```

```python
from sklearn.svm import SVC
```

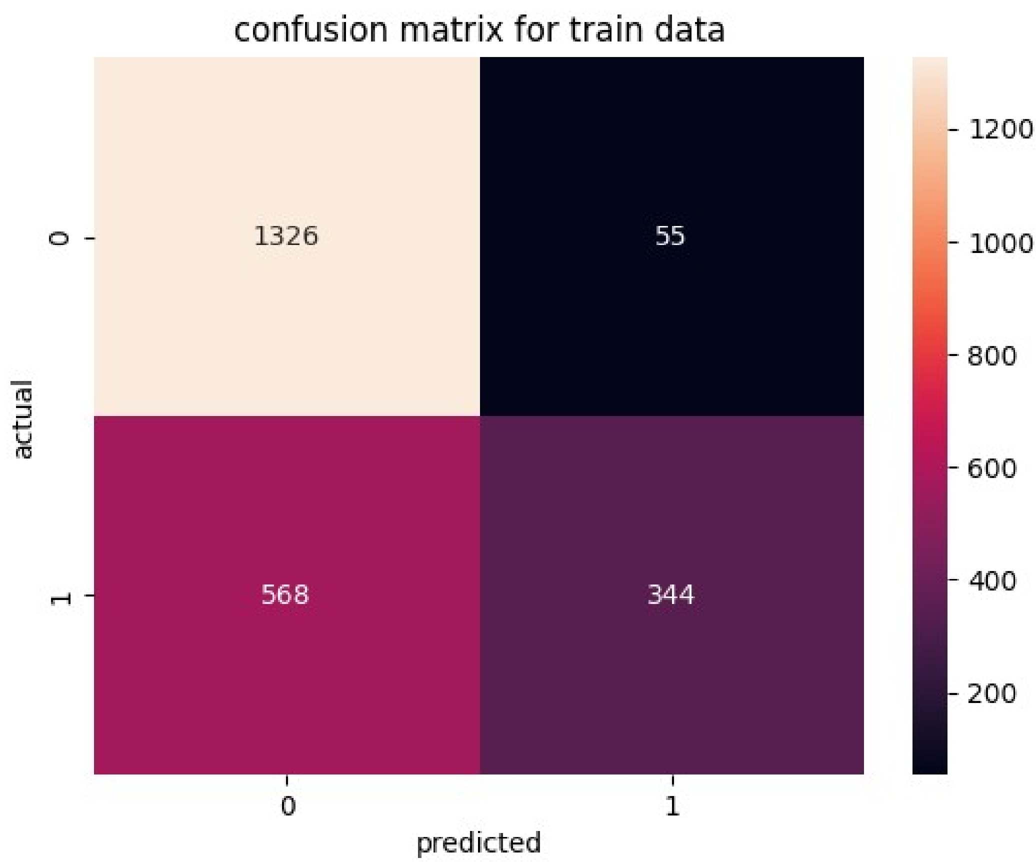
```python
model_2=SVC(kernel="rbf")
model_2.fit(X_train_s,y_train)
```

```
SVC()

model_2.score(X_train_s,y_train)

0.7283035324901875

model_2.score(X_test_s,y_test)

0.6958290946083419

from sklearn.linear_model import LogisticRegression

model_3=LogisticRegression()
model_3.fit(X_train_s,y_train)

LogisticRegression()

model_3.score(X_train_s,y_train)

0.6022677714784126

model_3.score(X_test_s,y_test)

0.6286876907426246

from sklearn.tree import DecisionTreeClassifier

model_4=DecisionTreeClassifier(max_depth=13)
model_4.fit(X_train_s,y_train)

DecisionTreeClassifier(max_depth=13)

model_4.score(X_train_s,y_train)

0.7845617095508068

model_4.score(X_test_s,y_test)

0.6256358087487284
```

model selected is model_2

```
y_pred_train=model_2.predict(X_train_s)
y_pred_test=model_2.predict(X_test_s)

y_train[:5]

2985    0
1073    1
3140    1
2643    0
```

```
2174    0
Name: Potability, dtype: int64

y_pred_train[:5]

array([0, 1, 0, 0, 0])

sns.heatmap(confusion_matrix(y_train,y_pred_train),annot=True,fmt=".4g
")
plt.title("confusion matrix for train data")
plt.xlabel("predicted")
plt.ylabel("actual")

Text(50.72222222222214, 0.5, 'actual')
```




```
sns.heatmap(confusion_matrix(y_test,y_pred_test),annot=True,fmt=".4g")
plt.title("confusion matrix for test data")
plt.xlabel("predicted")
plt.ylabel("actual")

Text(50.72222222222214, 0.5, 'actual')
```


```
print(f'train data accuracy:
{round(accuracy_score(y_train,y_pred_train),2)*100}%')

train data accuracy: 73.0%

print(f'test data accuracy:
{round(accuracy_score(y_test,y_pred_test),2)*100}%')

test data accuracy: 70.0%

print(f'   train data classification report:- \n\n
{classification_report(y_train,y_pred_train)}')

   train data classification report:-

               precision    recall  f1-score   support

           0       0.70      0.96      0.81      1381
           1       0.86      0.38      0.52       912

    accuracy                           0.73      2293
   macro avg       0.78      0.67      0.67      2293
weighted avg       0.76      0.73      0.70      2293
```

```
print(f'   test data classification report:- \n\n
{classification_report(y_test,y_pred_test)}')
```

```
   test data classification report:- 

              precision    recall  f1-score   support

           0       0.69      0.93      0.79       617
           1       0.71      0.31      0.43       366

    accuracy                           0.70       983
   macro avg       0.70      0.62      0.61       983
weighted avg       0.70      0.70      0.66       983
```

sample testing

```
x[:1]
```

```
         ph    Hardness        Solids  Chloramines     Sulfate 
Conductivity  \
0  7.080795  204.890455  20791.318981     7.300212  368.516441 
564.308654   

   Organic_carbon  Trihalomethanes  Turbidity  
0       10.379783         86.99097   2.963135  
```

```
data=[[9.0927288,101.133503,18978.98632332,6.523,310.135738,298.41813,
18.558279,34.992323,4.075075]]
```

```
print(f'predicted potability: {int(model_2.predict(data)[0])}')
```

```
predicted potability: 1
```