In [ ]:
```
# importing libraries
```

In [1]:
```
import numpy as np
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.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier

import xgboost
from xgboost import XGBClassifier
from sklearn.svm import SVC

from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import GridSearchCV , RandomizedSearchCV
from sklearn.metrics import confusion_matrix, accuracy_score , classification_report

import warnings
warnings.filterwarnings('ignore')
```

In [ ]:
```
# loading and analysing data through eda
```

In [2]:
```
df=pd.read_csv('water_potability.csv')
```

In [3]:
```
df.head(10)
```

Out[3]:

	ph	Hardness	Solids	Chloramines	Sulfate	Conductivity	Organic_carbon	Trihalometh
0	NaN	204.890455	20791.318981	7.300212	368.516441	564.308654	10.379783	86.99
1	3.716080	129.422921	18630.057858	6.635246	NaN	592.885359	15.180013	56.32
2	8.099124	224.236259	19909.541732	9.275884	NaN	418.606213	16.868637	66.42
3	8.316766	214.373394	22018.417441	8.059332	356.886136	363.266516	18.436524	100.34
4	9.092223	181.101509	17978.986339	6.546600	310.135738	398.410813	11.558279	31.99
5	5.584087	188.313324	28748.687739	7.544869	326.678363	280.467916	8.399735	54.91
6	10.223862	248.071735	28749.716544	7.513408	393.663396	283.651634	13.789695	84.60
7	8.635849	203.361523	13672.091764	4.563009	303.309771	474.607645	12.363817	62.79
8	NaN	118.988579	14285.583854	7.804174	268.646941	389.375566	12.706049	53.92
9	11.180284	227.231469	25484.508491	9.077200	404.041635	563.885481	17.927806	71.97

In [4]:
```
df.tail()
```

Out[4]:

	ph	Hardness	Solids	Chloramines	Sulfate	Conductivity	Organic_carbon	Trihalome
3271	4.668102	193.681735	47580.991603	7.166639	359.948574	526.424171	13.894419	66.
3272	7.808856	193.553212	17329.802160	8.061362	NaN	392.449580	19.903225	
3273	9.419510	175.762646	33155.578218	7.350233	NaN	432.044783	11.039070	69.
3274	5.126763	230.603758	11983.869376	6.303357	NaN	402.883113	11.168946	77.
3275	7.874671	195.102299	17404.177061	7.509306	NaN	327.459760	16.140368	78.

In [5]:
```
df.columns
```

Out[5]:
```
Index(['ph', 'Hardness', 'Solids', 'Chloramines', 'Sulfate', 'Conductivity',
       'Organic_carbon', 'Trihalomethanes', 'Turbidity', 'Potability'],
      dtype='object')
```

In [6]:
```
df.shape
```

Out[6]:
```
(3276, 10)
```

In [7]:
```
df.describe()
```

Out[7]:

	ph	Hardness	Solids	Chloramines	Sulfate	Conductivity	Organic_carbon	Tri
count	2785.000000	3276.000000	3276.000000	3276.000000	2495.000000	3276.000000	3276.000000	
mean	7.080795	196.369496	22014.092526	7.122277	333.775777	426.205111	14.284970	
std	1.594320	32.879761	8768.570828	1.583085	41.416840	80.824064	3.308162	
min	0.000000	47.432000	320.942611	0.352000	129.000000	181.483754	2.200000	
25%	6.093092	176.850538	15666.690297	6.127421	307.699498	365.734414	12.065801	
50%	7.036752	196.967627	20927.833607	7.130299	333.073546	421.884968	14.218338	
75%	8.062066	216.667456	27332.762127	8.114887	359.950170	481.792304	16.557652	
max	14.000000	323.124000	61227.196008	13.127000	481.030642	753.342620	28.300000	

In [8]:
```
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
```

In [ ]:
```
# imbalance data
```

In [10]:
```
df['Potability']
```

Out[10]:
```
0       0
1       0
2       0
3       0
4       0
       ..
3271    1
3272    1
3273    1
3274    1
3275    1
Name: Potability, Length: 3276, dtype: int64
```

In [11]:
```
df['Potability'].value_counts()
```

Out[11]:
```
Potability
0    1998
1    1278
Name: count, dtype: int64
```

In [12]:
```
len(df)
```

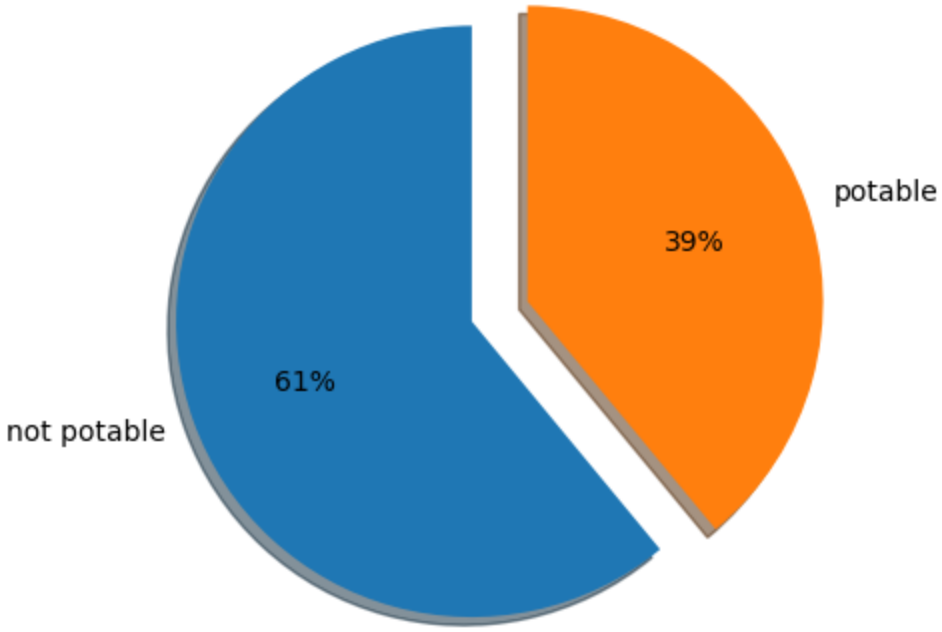
Out[12]:
```
3276
```

In [13]:
```
print(len(df[df['Potability']==0])/len(df)*100)
print(len(df[df['Potability']==1])/len(df)*100)
```

```
60.98901098901099
39.010989010989015
```

In [14]:
```
plt.pie(df['Potability'].value_counts(),autopct='%1.0f%%',shadow=True,startangle=90,
        labels=['not potable','potable'],explode=(0,0.2))

plt.show()
```



In [15]:
```
# missing data
```

In [17]:
```
df.isnull().sum()
```

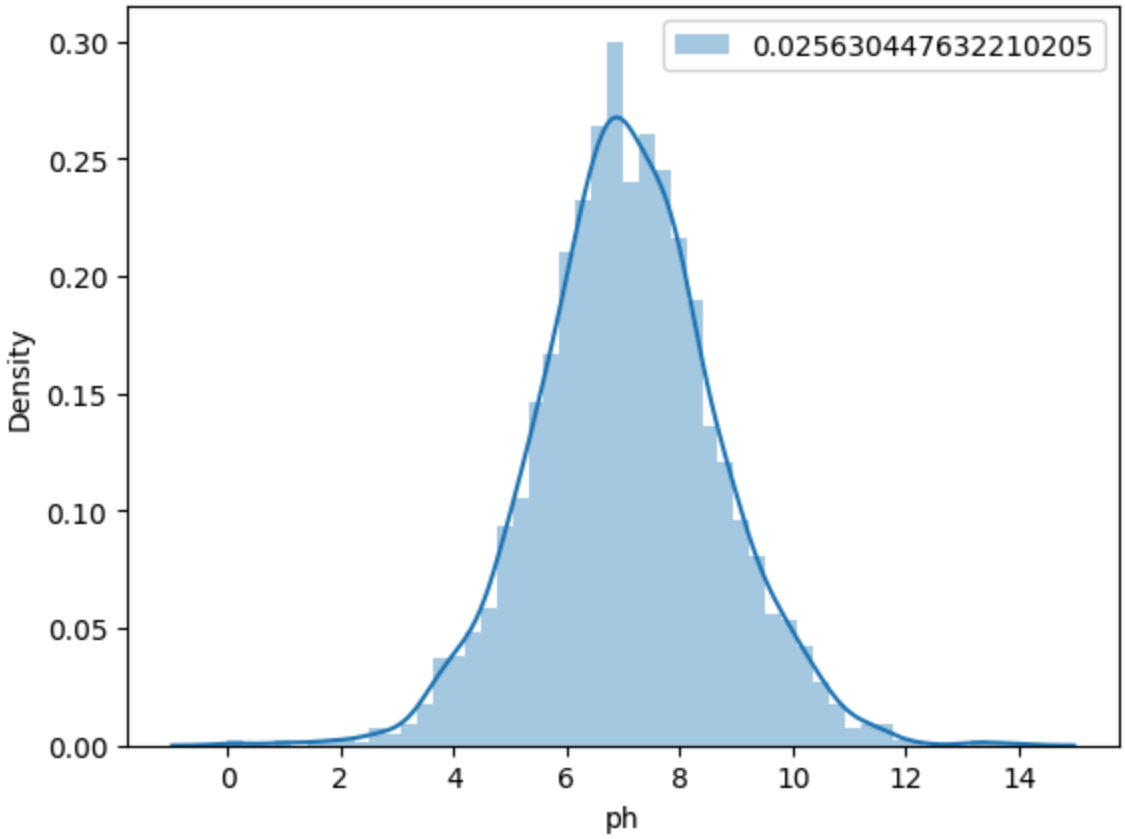
Out[17]:
```
ph                491
Hardness            0
Solids              0
Chloramines         0
Sulfate           781
Conductivity        0
Organic_carbon      0
Trihalomethanes   162
Turbidity           0
Potability          0
dtype: int64
```

In [18]:
```
round(df.isnull().mean()*100,2)
```

Out[18]:
```
ph                14.99
Hardness           0.00
Solids             0.00
Chloramines        0.00
Sulfate           23.84
Conductivity       0.00
Organic_carbon     0.00
Trihalomethanes    4.95
Turbidity          0.00
Potability         0.00
dtype: float64
```

In [19]:
```
sns.distplot(df['ph'],label=df.ph.skew())
plt.legend()
```

Out[19]:
```
<matplotlib.legend.Legend at 0x2cd2a974690>
```



In [20]:
```
df.ph.mean()
```

Out[20]:
```
7.080794504276835
```

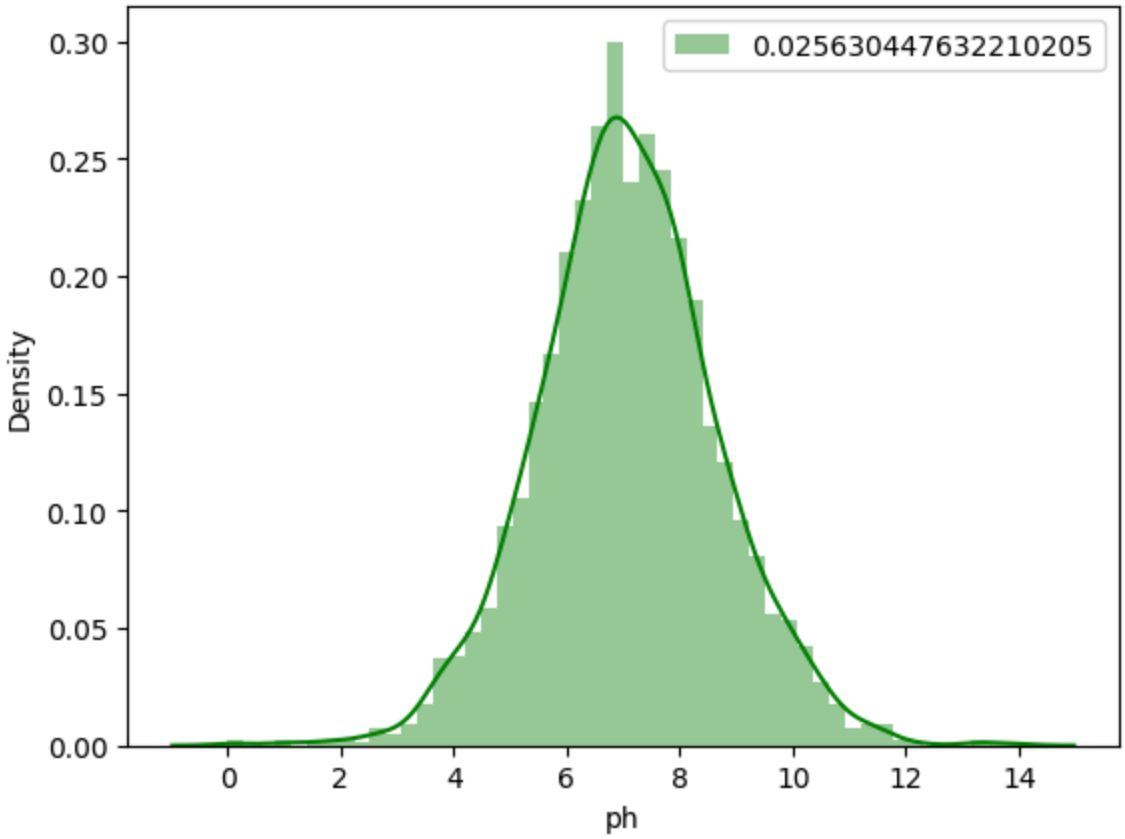
In [21]:
```
df.ph.median()
```

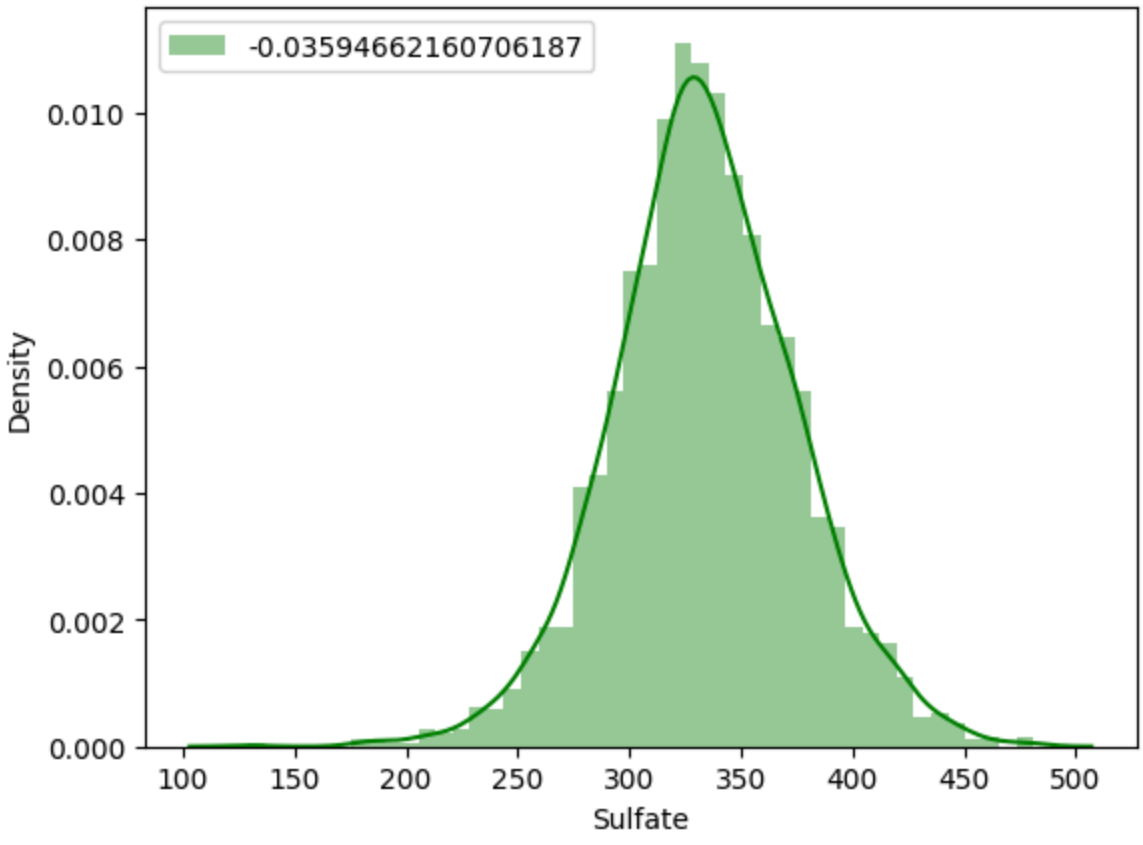
Out[21]:
```
7.036752103833548
```

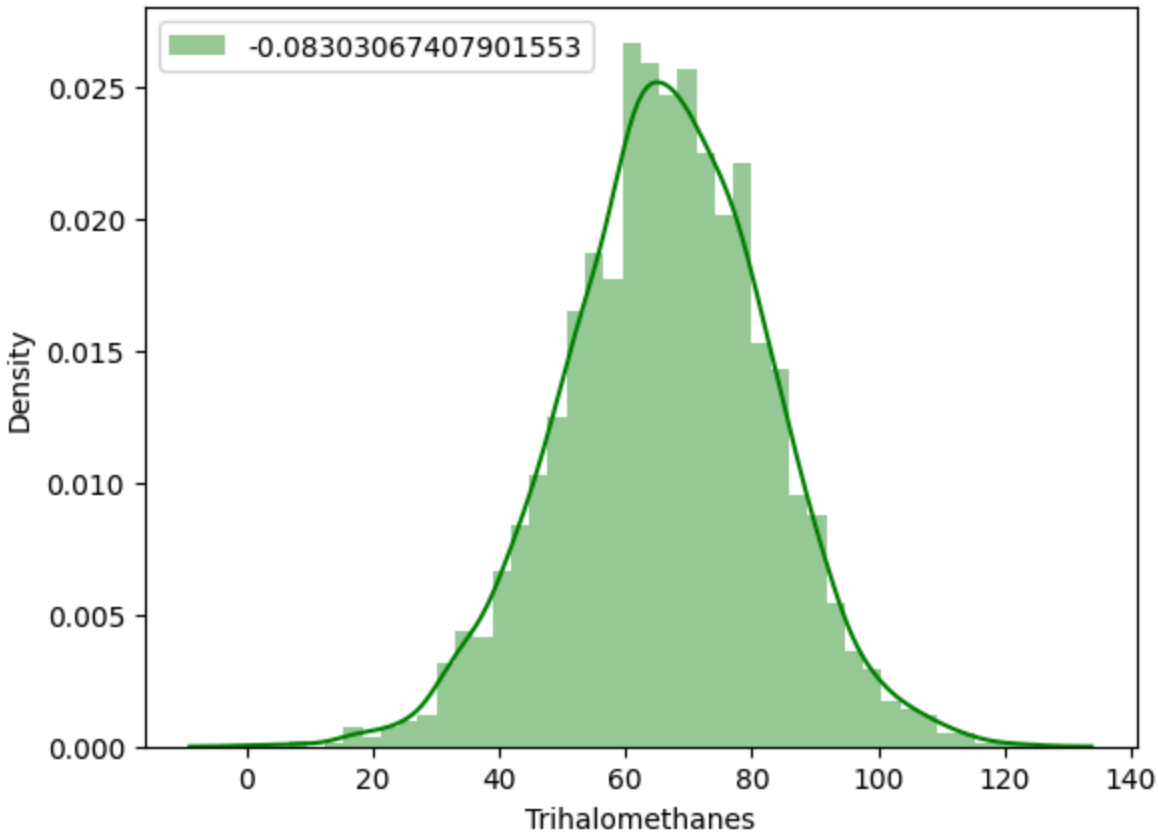
In [22]:
```
for i in df:
    if df[i].isna().sum()>0:
        print(i)
```

```
ph
Sulfate
Trihalomethanes
```

In [24]:
```
cols=np.random.choice(['r','g','b'])
for i in df:
    if df[i].isna().sum()>0:
        sns.distplot(df[i],color=cols,label=df[i].skew())
        plt.legend()
        plt.show()
```







In [25]:
```
for i in df:
    if df[i].isna().sum()>0:
        print(f'{i} : {df[i].mean()}')
```

```
ph : 7.080794504276835
Sulfate : 333.7757766108135
Trihalomethanes : 66.39629294676803
```

In [26]:
```
for i in df:
    if df[i].isna().sum()>0:
        print(f'{i} : {df[i].mean()}')
        df[i].fillna(df[i].mean(),inplace=True)
```

```
ph : 7.080794504276835
Sulfate : 333.7757766108135
Trihalomethanes : 66.39629294676803
```

In [27]:
```
df.isnull().sum()
```

Out[27]:
```
ph                0
Hardness          0
Solids            0
Chloramines       0
Sulfate           0
Conductivity      0
Organic_carbon    0
Trihalomethanes   0
Turbidity         0
Potability        0
dtype: int64
```

In [28]:
```
# duplicate data
```

In [29]:
```
df.duplicated().sum()
```

Out[29]:
```
0
```

In [30]:
```
df[df.duplicated()]
```

Out[30]:

	ph	Hardness	Solids	Chloramines	Sulfate	Conductivity	Organic_carbon	Trihalomethanes	Turbidity	Pot

In [31]:
```
# outliers
```

In [34]:
```
q1=df.quantile(0.25)
q3=df.quantile(0.75)
IQR=q3-q1
IQR
```

Out[34]:
```
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
```

In [35]:
```
print(q1-1.5*IQR)
print()
print(q3+1.5*IQR)
```

```
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

ph                   10.258615
Hardness            276.392834
Solids            44831.869873
Chloramines          11.096086
Sulfate             400.322434
Conductivity        655.879140
Organic_carbon       23.295427
Trihalomethanes     106.695040
Turbidity             6.091233
Potability            2.500000
dtype: float64
```

In [36]:
```
upper=q3+1.5*IQR
lower=q1-1.5*IQR
```

In [37]:
```
df.shape
```

Out[37]:
```
(3276, 10)
```

In [40]:
```
data=df[~((df<lower)|(df>upper)).any(axis=1)]
data
```

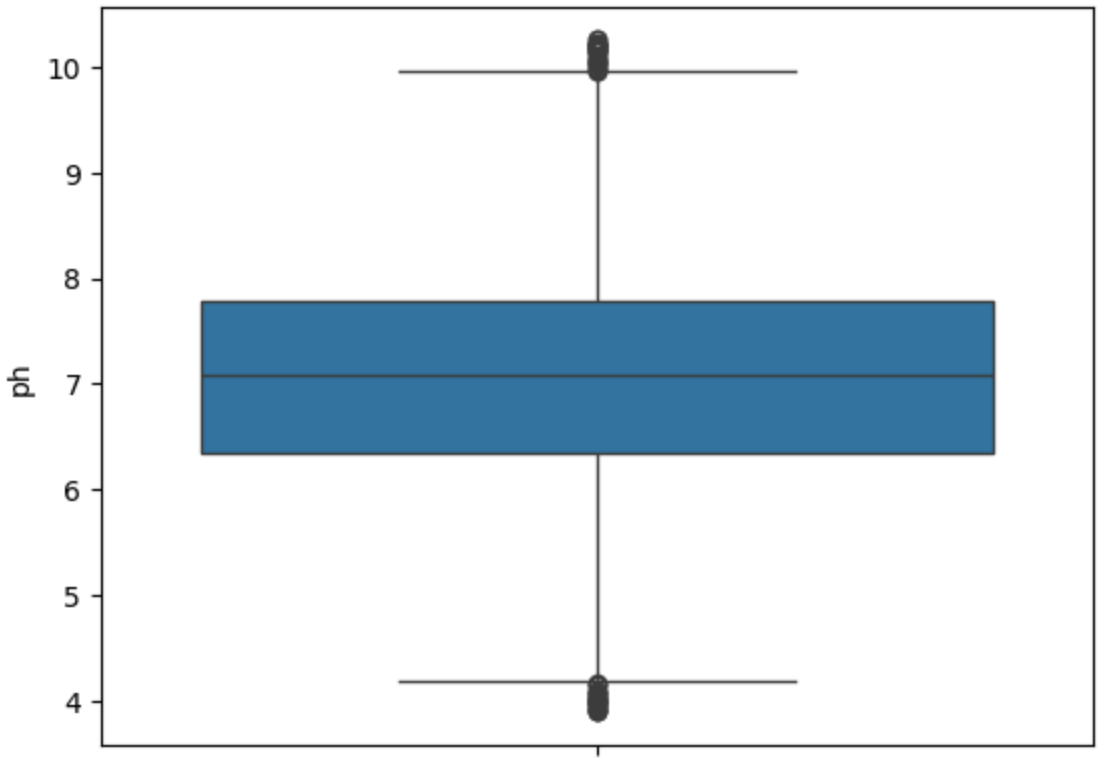
Out[40]:

	ph	Hardness	Solids	Chloramines	Sulfate	Conductivity	Organic_carbon	Trihalome
0	7.080795	204.890455	20791.318981	7.300212	368.516441	564.308654	10.379783	86.
2	8.099124	224.236259	19909.541732	9.275884	333.775777	418.606213	16.868637	66.
3	8.316766	214.373394	22018.417441	8.059332	356.886136	363.266516	18.436524	100.
4	9.092223	181.101509	17978.986339	6.546600	310.135738	398.410813	11.558279	31.
5	5.584087	188.313324	28748.687739	7.544869	326.678363	280.467916	8.399735	54.
...	...	...	...	...	...	...	...	
3270	6.069616	186.659040	26138.780191	7.747547	345.700257	415.886955	12.067620	60.
3272	7.808856	193.553212	17329.802160	8.061362	333.775777	392.449580	19.903225	66.
3273	9.419510	175.762646	33155.578218	7.350233	333.775777	432.044783	11.039070	69.
3274	5.126763	230.603758	11983.869376	6.303357	333.775777	402.883113	11.168946	77.
3275	7.874671	195.102299	17404.177061	7.509306	333.775777	327.459760	16.140368	78.

2666 rows × 10 columns

In [41]:
```
sns.boxplot(data['ph'])
```

Out[41]:
```
<Axes: ylabel='ph'>
```



In [42]:
```
data.shape
```

Out[42]:
```
(2666, 10)
```

In [43]:
```
data
```

Out[43]:

	ph	Hardness	Solids	Chloramines	Sulfate	Conductivity	Organic_carbon	Trihalome
0	7.080795	204.890455	20791.318981	7.300212	368.516441	564.308654	10.379783	86.
2	8.099124	224.236259	19909.541732	9.275884	333.775777	418.606213	16.868637	66.
3	8.316766	214.373394	22018.417441	8.059332	356.886136	363.266516	18.436524	100.
4	9.092223	181.101509	17978.986339	6.546600	310.135738	398.410813	11.558279	31.
5	5.584087	188.313324	28748.687739	7.544869	326.678363	280.467916	8.399735	54.
...	...	...	...	...	...	...	...	
3270	6.069616	186.659040	26138.780191	7.747547	345.700257	415.886955	12.067620	60.
3272	7.808856	193.553212	17329.802160	8.061362	333.775777	392.449580	19.903225	66.
3273	9.419510	175.762646	33155.578218	7.350233	333.775777	432.044783	11.039070	69.
3274	5.126763	230.603758	11983.869376	6.303357	333.775777	402.883113	11.168946	77.
3275	7.874671	195.102299	17404.177061	7.509306	333.775777	327.459760	16.140368	78.

2666 rows × 10 columns

In [44]:
```
# feature selection
```

In [45]:
```
data.corr()
```

Out[45]:

	ph	Hardness	Solids	Chloramines	Sulfate	Conductivity	Organic_carbon	Trih
ph	1.000000	0.131362	-0.087036	-0.062888	0.016894	0.001943	0.026160	
Hardness	0.131362	1.000000	-0.045552	-0.035832	-0.027939	-0.030415	0.012463	
Solids	-0.087036	-0.045552	1.000000	-0.040392	-0.110090	0.007087	0.026793	
Chloramines	-0.062888	-0.035832	-0.040392	1.000000	0.024502	-0.015277	-0.000684	
Sulfate	0.016894	-0.027939	-0.110090	0.024502	1.000000	-0.005850	-0.007588	
Conductivity	0.001943	-0.030415	0.007087	-0.015277	-0.005850	1.000000	0.006515	
Organic_carbon	0.026160	0.012463	0.026793	-0.000684	-0.007588	0.006515	1.000000	
Trihalomethanes	0.009172	-0.007093	-0.024550	0.016574	-0.022269	-0.001138	-0.000059	
Turbidity	-0.043034	-0.022362	0.022801	-0.005415	-0.017310	0.007674	-0.016705	
Potability	-0.005949	-0.000710	0.005600	0.013195	-0.003741	-0.001886	-0.027090	

In [46]:
```
data.corr()['Potability']
```

Out[46]:
```
ph                -0.005949
Hardness          -0.000710
Solids             0.005600
Chloramines        0.013195
Sulfate           -0.003741
Conductivity      -0.001886
Organic_carbon    -0.027090
Trihalomethanes    0.014351
Turbidity          0.004761
Potability         1.000000
Name: Potability, dtype: float64
```

In [47]:
```
# seperate dependent and independent
```

In [48]:
```
X=data.iloc[:,:-1]
X
```

Out[48]:

	ph	Hardness	Solids	Chloramines	Sulfate	Conductivity	Organic_carbon	Trihalome
0	7.080795	204.890455	20791.318981	7.300212	368.516441	564.308654	10.379783	86.
2	8.099124	224.236259	19909.541732	9.275884	333.775777	418.606213	16.868637	66.
3	8.316766	214.373394	22018.417441	8.059332	356.886136	363.266516	18.436524	100.
4	9.092223	181.101509	17978.986339	6.546600	310.135738	398.410813	11.558279	31.
5	5.584087	188.313324	28748.687739	7.544869	326.678363	280.467916	8.399735	54.
...	...	...	...	...	...	...	...	
3270	6.069616	186.659040	26138.780191	7.747547	345.700257	415.886955	12.067620	60.
3272	7.808856	193.553212	17329.802160	8.061362	333.775777	392.449580	19.903225	66.
3273	9.419510	175.762646	33155.578218	7.350233	333.775777	432.044783	11.039070	69.
3274	5.126763	230.603758	11983.869376	6.303357	333.775777	402.883113	11.168946	77.
3275	7.874671	195.102299	17404.177061	7.509306	333.775777	327.459760	16.140368	78.

2666 rows × 9 columns

In [49]:
```
y=data['Potability']
y
```

Out[49]:
```
0       0
2       0
3       0
4       0
5       0
       ..
3270    1
3272    1
3273    1
3274    1
3275    1
Name: Potability, Length: 2666, dtype: int64
```

In [50]:
```
# splitting data
```

In [51]:
```
X_train,X_test,y_train,y_test=train_test_split(X,y,test_size=0.2,random_state=42)
```

In [52]:
```
# feature selection
```

In [53]:
```
sc=StandardScaler()
```

In [54]:
```
X_train_sc=sc.fit_transform(X_train)
X_test_sc=sc.fit_transform(X_test)
```

In [55]:
```
X_test_sc
```

Out[55]:
```
array([[ 0.76955275,  0.0591837 ,  2.49249786, ..., -0.07283378,
         0.16249225, -0.52065935],
       [-1.37679259, -0.49759241, -0.77389725, ...,  1.02418171,
        -1.04356868, -1.15747579],
       [-0.50185216, -0.87086   , -0.85715381, ..., -1.40586274,
        -0.60781891,  0.9004857 ],
       ...,
       [-1.46694886,  0.23524254,  0.15325569, ..., -0.16535897,
         1.1010898 , -1.35989889],
       [ 0.35343507, -0.42462971,  0.42181357, ...,  0.19609378,
         0.55484498, -0.21437106],
       [ 0.26376863,  0.44151539,  1.28298512, ...,  0.76844349,
        -1.60818106, -0.33879065]])
```

In [56]:
```
X_train_sc
```

Out[56]:
```
array([[ 1.08790956,  2.09056478, -0.59647931, ..., -1.05584236,
        -0.76370666, -0.13696497],
       [-1.74032936, -1.54115475, -0.18021947, ..., -0.74586468,
         0.12902908, -0.11598472],
       [ 0.0119423 , -1.41562152,  0.19157245, ...,  1.52916801,
         1.0208548 ,  2.11818687],
       ...,
       [ 0.35677911,  0.49545104,  0.26969765, ...,  1.1716937 ,
        -0.91406427,  0.65386741],
       [ 0.55136958,  0.99173017, -0.2579827 , ...,  0.27335131,
         0.56043327, -0.33985365],
       [ 0.0119423 ,  2.10605667, -1.585393  , ...,  0.79325653,
         0.41990686, -0.77401858]])
```

In [57]:
```
# logistic regression
```

In [58]:
```
### on original data
```

In [59]:
```
lr=LogisticRegression()
lr.fit(X_train,y_train)
```

Out[59]:
```
LogisticRegression()
```
In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

In [63]:
```
print(f'Training accuracy:{lr.score(X_train,y_train)} ')
print(f'Test accuracy:{lr.score(X_test,y_test)} ')
```

```
Training accuracy:0.623358348968105
Test accuracy:0.6404494382022472
```

In [64]:
```
# on scaled data
```

In [65]:
```
lr=LogisticRegression()
lr.fit(X_train_sc,y_train)
```

Out[65]:
```
LogisticRegression()
```
In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

In [66]:
```
print(f'Training accuracy:{lr.score(X_train_sc,y_train)} ')
print(f'Test accuracy:{lr.score(X_test_sc,y_test)} ')
```

```
Training accuracy:0.623358348968105
Test accuracy:0.6404494382022472
```

In [67]:
```
# decision tree
```

In [68]:
```
dt=DecisionTreeClassifier(max_depth=5)
dt.fit(X_train,y_train)
```

Out[68]:
```
DecisionTreeClassifier(max_depth=5)
```
In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

In [69]:
```
print(f'Training accuracy:{dt.score(X_train,y_train)} ')
print(f'Test accuracy:{dt.score(X_test,y_test)} ')
```

```
Training accuracy:0.6965290806754222
Test accuracy:0.6329588014981273
```

In [ ]:
```
# xgb
```

In [70]:
```
xgb=XGBClassifier(gamma=0.7,reg_alpha=0.5,red_lambda=0.2)
xgb.fit(X_train,y_train)
```

Out[70]:
```
XGBClassifier(base_score=None, booster=None, callbacks=None,
              colsample_bylevel=None, colsample_bynode=None,
              colsample_bytree=None, device=None, early_stopping_rounds=None,
              enable_categorical=False, eval_metric=None, feature_types=None,
              gamma=0.7, grow_policy=None, importance_type=None,
              interaction_constraints=None, learning_rate=None, max_bin=None,
              max_cat_threshold=None, max_cat_to_onehot=None,
              max_delta_step=None, max_depth=None, max_leaves=None,
              min_child_weight=None, missing=nan, monotone_constraints=None,
              multi_strategy=None, n_estimators=None, n_jobs=None,
              num_parallel_tree=None, random_state=None, ...)
```

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

In [71]:
```
print(f'Training accuracy{xgb.score(X_train,y_train)} ')
print(f'Test accuracy{xgb.score(X_test,y_test)} ')
```

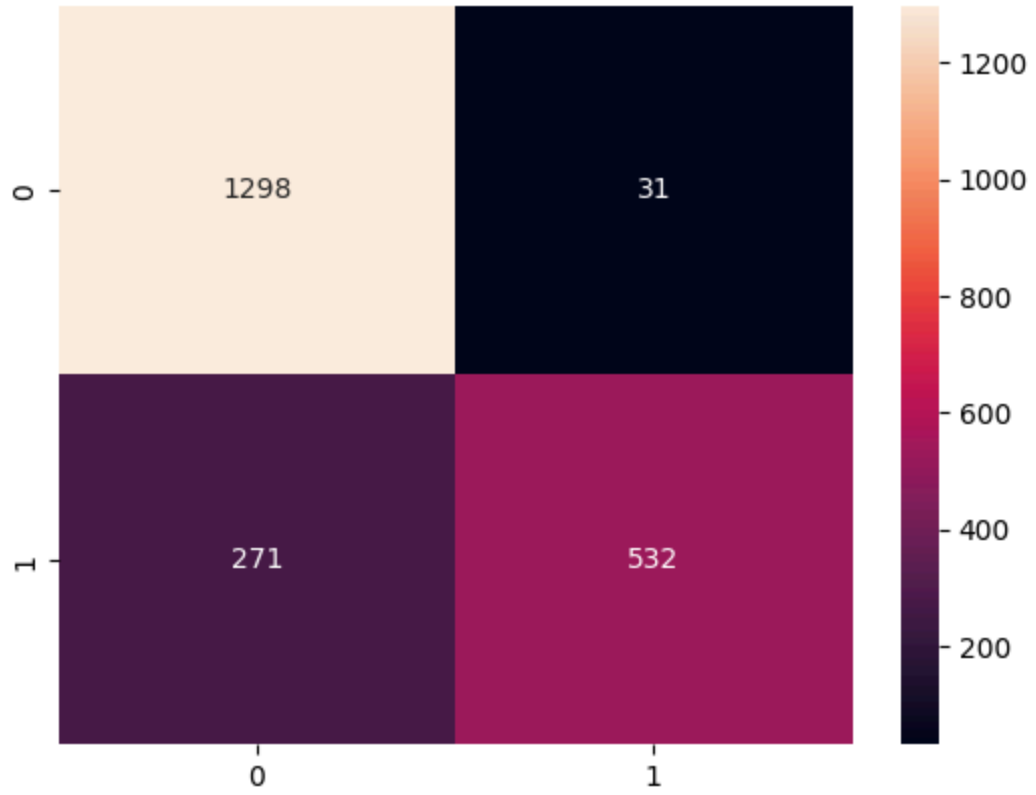
```
Training accuracy0.8583489681050657
Test accuracy0.649812734082397
```

In [76]:
```
y_train_pred_xgb=xgb.predict(X_train)
y_test_pred_xgb=xgb.predict(X_test)
```

In [77]:
```
# model evaluation
```

In [78]:
```
sns.heatmap(confusion_matrix(y_train,y_train_pred_xgb),annot=True,fmt='.4g')
```

Out[78]: <Axes: >



In [79]:
```
accuracy_score(y_train,y_train_pred_xgb)
```

Out[79]: 0.8583489681050657

In [80]:
```
print(classification_report(y_train,y_train_pred_xgb))
```

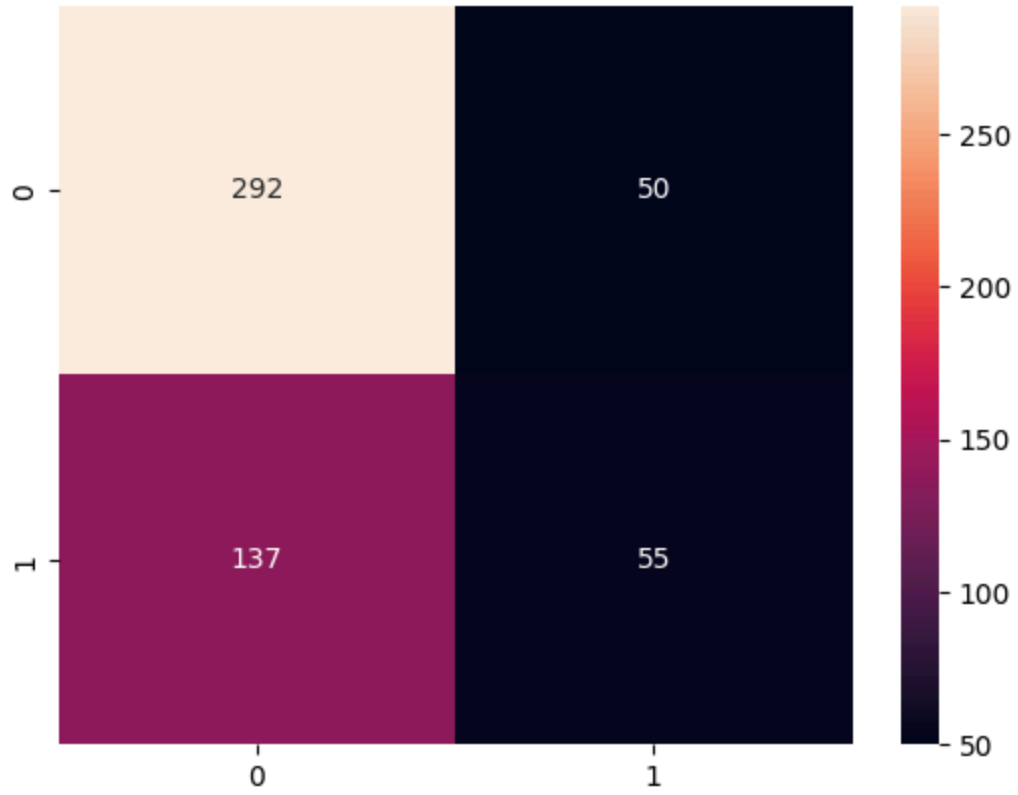
```
              precision    recall  f1-score   support

           0       0.83      0.98      0.90      1329
           1       0.94      0.66      0.78       803

    accuracy                           0.86      2132
   macro avg       0.89      0.82      0.84      2132
weighted avg       0.87      0.86      0.85      2132
```

In [81]:
```
sns.heatmap(confusion_matrix(y_test,y_test_pred_xgb),annot=True,fmt='.4g')
```

Out[81]: <Axes: >



In [83]:
```
accuracy_score(y_test,y_test_pred_xgb)
```

Out[83]: 0.649812734082397

In [87]:
```
parameters= {
    'n_estimators':[100,200],
    'learning_rate':[0.1,0.01,1.0,0.05],
    'max_depth':[3,4,5],
    'gamma':[0.2,0.3],
    'reg_alpha':[0.1,0.2,1],
    'reg_lambda':[0.1,1]
}
parameters
```

Out[87]:
```
{'n_estimators': [100, 200],
 'learning_rate': [0.1, 0.01, 1.0, 0.05],
 'max_depth': [3, 4, 5],
 'gamma': [0.2, 0.3],
 'reg_alpha': [0.1, 0.2, 1],
 'reg_lambda': [0.1, 1]}
```

In [88]:
```
grid_search=GridSearchCV(estimator=xgb,param_grid=parameters,scoring='accuracy',
                         cv=5,verbose=3)
grid_search.fit(X_train,y_train)
```

```
Fitting 5 folds for each of 288 candidates, totalling 1440 fits
[CV 1/5] END gamma=0.2, learning_rate=0.1, max_depth=3, n_estimators=100, reg_alpha=
0.1, reg_lambda=0.1;, score=0.630 total time=   0.1s
[CV 2/5] END gamma=0.2, learning_rate=0.1, max_depth=3, n_estimators=100, reg_alpha=
0.1, reg_lambda=0.1;, score=0.616 total time=   0.1s
[CV 3/5] END gamma=0.2, learning_rate=0.1, max_depth=3, n_estimators=100, reg_alpha=
0.1, reg_lambda=0.1;, score=0.660 total time=   0.1s
[CV 4/5] END gamma=0.2, learning_rate=0.1, max_depth=3, n_estimators=100, reg_alpha=
0.1, reg_lambda=0.1;, score=0.638 total time=   0.1s
[CV 5/5] END gamma=0.2, learning_rate=0.1, max_depth=3, n_estimators=100, reg_alpha=
0.1, reg_lambda=0.1;, score=0.646 total time=   0.1s
[CV 1/5] END gamma=0.2, learning_rate=0.1, max_depth=3, n_estimators=100, reg_alpha=
0.1, reg_lambda=1;, score=0.616 total time=   0.1s
[CV 2/5] END gamma=0.2, learning_rate=0.1, max_depth=3, n_estimators=100, reg_alpha=
0.1, reg_lambda=1;, score=0.611 total time=   0.1s
[CV 3/5] END gamma=0.2, learning_rate=0.1, max_depth=3, n_estimators=100, reg_alpha=
0.1, reg_lambda=1;, score=0.669 total time=   0.1s
[CV 4/5] END gamma=0.2, learning_rate=0.1, max_depth=3, n_estimators=100, reg_alpha=
0.1, reg_lambda=1;, score=0.634 total time=   0.1s
```

In [89]:
```
print(f'best selected parameters : {grid_search.best_params_}')
print(f'best estimators:{grid_search.best_estimator_}')
```

```
best selected parameters : {'gamma': 0.3, 'learning_rate': 0.05, 'max_depth': 5, 'n_es
timators': 100, 'reg_alpha': 1, 'reg_lambda': 0.1}
best estimators:XGBClassifier(base_score=None, booster=None, callbacks=None,
              colsample_bylevel=None, colsample_bynode=None,
              colsample_bytree=None, device=None, early_stopping_rounds=None,
              enable_categorical=False, eval_metric=None, feature_types=None,
              gamma=0.3, grow_policy=None, importance_type=None,
              interaction_constraints=None, learning_rate=0.05, max_bin=None,
              max_cat_threshold=None, max_cat_to_onehot=None,
              max_delta_step=None, max_depth=5, max_leaves=None,
              min_child_weight=None, missing=nan, monotone_constraints=None,
              multi_strategy=None, n_estimators=100, n_jobs=None,
              num_parallel_tree=None, random_state=None, ...)
```

In [90]:
```
print(f'Training accuracy{grid_search.score(X_train,y_train)} ')
print(f'Test accuracy{grid_search.score(X_test,y_test)} ')
```

```
Training accuracy0.8030018761726079
Test accuracy0.6554307116104869
```

In [ ]: