In [1]: import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)
import matplotlib.pyplot as plt
df=pd.read_csv('C:\\ds project\\water_potability.csv')
df

Out[1]: Solids Chloramines ph Hardness Sulfate Conductivity Organic_car NaN 204.890456 20791.31898 0 7.300212 368.516441 10.379 564.308654 6.635246 **1** 3.716080 129.422921 18630.05786 592.885359 15.180 NaN **2** 8.099124 224.236259 19909.54173 16.868 9.275884 NaN 418.606213 8.059332 356.886136 **3** 8.316766 214.373394 22018.41744 363.266516 18.436 9.092223 181.101509 17978.98634 6.546600 310.135738 398.410813 11.558 **3271** 4.668102 193.681736 47580.99160 7.166639 359.948574 526.424171 13.894 **3272** 7.808856 193.553212 17329.80216 19.903 8.061362 NaN 392.449580 **3273** 9.419510 175.762646 33155.57822 7.350233 NaN 432.044783 11.039 **3274** 5.126763 230.603758 11983.86938 6.303357 NaN 402.883113 11.168 **3275** 7.874671 195.102299 17404.17706 7.509306 NaN 327.459761 16.140 3276 rows × 10 columns

In [2]: 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

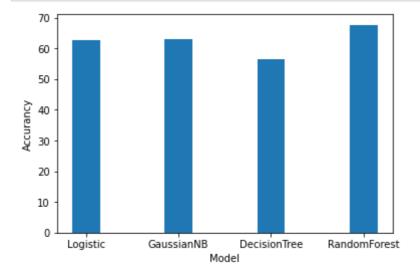
```
In [3]: df.isnull().sum()
Out[3]: ph
                            491
        Hardness
                              0
        Solids
                              0
        Chloramines
                              0
                            781
        Sulfate
        Conductivity
                              0
        Organic_carbon
                              0
        Trihalomethanes
                            162
        Turbidity
                              0
                              0
        Potability
        dtype: int64
In [4]: df["ph"].fillna(df["ph"].mean(skipna=True), inplace=True)
        df["Sulfate"].fillna(df["Sulfate"].mean(skipna=True), inplace=True)
        df["Trihalomethanes"].fillna(df["Trihalomethanes"].mean(skipna=True), inplace
In [5]: df.isnull().sum()
Out[5]: ph
                            0
        Hardness
                            0
        Solids
                            0
        Chloramines
                            0
        Sulfate
                            0
        Conductivity
                            0
        Organic_carbon
                            0
        Trihalomethanes
                            0
        Turbidity
                            0
        Potability
                            0
        dtype: int64
```

```
In [6]:
       from sklearn.model selection import train test split
        X = df.drop('Potability', axis=1)
        y = df['Potability']
        print(X)
        print(y)
        X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, ra
                   ph
                         Hardness
                                        Solids Chloramines
                                                               Sulfate
                                                                       \
             7.080795 204.890456 20791.31898
        0
                                                  7.300212 368.516441
        1
             3.716080
                       129.422921 18630.05786
                                                  6.635246 333.775777
        2
                       224.236259 19909.54173
             8.099124
                                                  9.275884 333.775777
        3
             8.316766 214.373394 22018.41744
                                                  8.059332 356.886136
        4
             9.092223 181.101509 17978.98634
                                                  6.546600 310.135738
        3271 4.668102
                       193.681736 47580.99160
                                                  7.166639 359.948574
        3272 7.808856 193.553212 17329.80216
                                                  8.061362 333.775777
        3273 9.419510 175.762646 33155.57822
                                                  7.350233 333.775777
        3274 5.126763 230.603758 11983.86938
                                                  6.303357 333.775777
             7.874671 195.102299 17404.17706
                                                  7.509306 333.775777
        3275
             Conductivity Organic_carbon Trihalomethanes Turbidity
        0
               564.308654
                                10.379783
                                                86.990970
                                                            2.963135
        1
               592.885359
                                15.180013
                                                56.329076
                                                            4.500656
        2
               418.606213
                                16.868637
                                                66.420093
                                                            3.055934
                                               100.341674 4.628771
        3
               363.266516
                                18.436525
        4
               398.410813
                                11.558279
                                                31.997993
                                                            4.075075
               526.424171
                                13.894419
                                                66.687695
                                                            4.435821
        3271
               392.449580
                                                            2.798243
        3272
                                19.903225
                                                66.396293
        3273
               432.044783
                                11.039070
                                                69.845400
                                                            3.298875
        3274
               402.883113
                                                77.488213
                                                            4.708658
                                11.168946
        3275
               327.459761
                                16.140368
                                               78.698446
                                                            2.309149
        [3276 rows x 9 columns]
        0
               0
        1
               0
        2
               0
        3
               a
        4
               0
        3271
               1
        3272
               1
        3273
               1
        3274
               1
        3275
               1
        Name: Potability, Length: 3276, dtype: int64
In [7]:
       # LOGISTIC REGRESSION
        from sklearn.linear model import LogisticRegression
        model=LogisticRegression()
        model.fit(X_train,y_train)
```

```
Out[7]: LogisticRegression()
```

```
In [8]: | lr= model.score(X_test,y_test) * 100
         print("Accuracy:",lr)
         Accuracy: 62.80487804878049
 In [9]: #GAUSSIAN
         from sklearn.naive_bayes import GaussianNB
         classifire=GaussianNB()
         classifire.fit(X_train,y_train)
 Out[9]: GaussianNB()
In [10]: vr=classifire.score(X_test,y_test)*100
         print("Accuracy:",vr)
         Accuracy: 63.109756097560975
In [11]: #DECISIONTREE CLASSIFIER
         from sklearn.tree import DecisionTreeClassifier
         modelDT = DecisionTreeClassifier()
         modelDT.fit(X_train,y_train)
Out[11]: DecisionTreeClassifier()
In [12]: vr1=modelDT.score(X_test,y_test)*100
         print("Accuracy:", vr1)
         Accuracy: 56.40243902439024
In [13]: #RANDOM FOREST CLASSIFIER
         from sklearn.ensemble import RandomForestClassifier
         modelRF = RandomForestClassifier()
         modelRF.fit(X_train,y_train)
Out[13]: RandomForestClassifier()
In [14]: r1=modelRF.score(X_test,y_test)*100
         print("Accuracy:",r1)
         Accuracy: 67.6829268292683
In [15]: print("hello")
         hello
```

```
In [16]: X=["Logistic","GaussianNB","DecisionTree","RandomForest"]
Y=[lr,vr,vr1,r1]
plt.bar(X,Y,width=0.3)
plt.xlabel("Model")
plt.ylabel("Accurancy")
plt.show()
```



```
In [19]: ph = eval(input())
         h = eval(input())
         s= eval(input())
         c = eval(input())
         su = eval(input())
         co = eval(input())
         o = eval(input())
         t = eval(input())
         tu = eval(input())
         a = {
              'ph': [ph],
              'Hardness': [h],
              'Solids': [s],
              'Chloramines': [c],
              'Sulfate': [su],
              'Conductivity': [co],
              'Organic_carbon': [o],
              'Trihalomethanes': [t],
              'Turbidity': [tu]
         }
         res = modelRF.predict(pd.DataFrame(a))
         if res:
             print("POTABLE,YOU CAN!!!")
         else:
             print("IMPOTABILITY, YOU MAY USE IT FOR GARDENING OR RECYCLE IT!!!")
         23.4
         34.5
         65.7
         65.43
         32.11
         32.23
         34.321
         234.56
         56.78
         POTABLE, YOU CAN!!!
In [ ]:
```