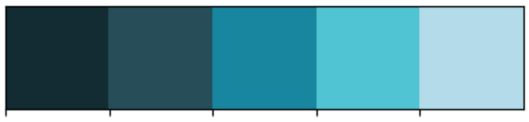
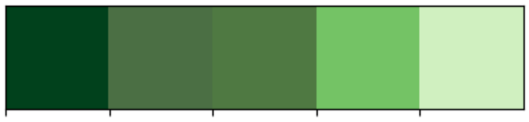
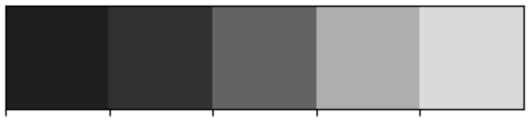
```
# Basic Libraries
import numpy as np
import pandas as pd
from warnings import filterwarnings
from collections import Counter

# Visualizations Libraries
import matplotlib.pyplot as plt
import seaborn as sns
import plotly
import plotly.offline as pyo
import plotly.express as px
import plotly.graph_objs as go
pyo.init_notebook_mode()
import plotly.figure_factory as ff
import missingno as msno

# Data Pre-processing Libraries
from sklearn.preprocessing import StandardScaler,MinMaxScaler
from sklearn.model_selection import train_test_split

# Modelling Libraries
from sklearn.linear_model import LogisticRegression,RidgeClassifier,SGDClassifier,PassiveAggressiveClassifier
from sklearn.linear_model import Perceptron
from sklearn.svm import SVC,LinearSVC,NuSVC
from sklearn.neighbors import KNeighborsClassifier,NearestCentroid
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier,AdaBoostClassifier,GradientBoostingClassifier
from sklearn.naive_bayes import GaussianNB,BernoulliNB
from sklearn.ensemble import VotingClassifier

# Evaluation & CV Libraries
from sklearn.metrics import precision_score,accuracy_score
from sklearn.model_selection import RandomizedSearchCV,GridSearchCV,RepeatedStratifiedKFold
```

Colors

```
colors_blue = ["#132C33", "#264D58", '#17869E', '#51C4D3', '#B4DBE9']
colors_dark = ["#1F1F1F", "#313131", '#636363', '#AEAEAE', '#DADADA']
colors_green = ['#01411C','#4B6F44','#4F7942','#74C365','#D0F0C0']
sns.palplot(colors_blue)
sns.palplot(colors_green)
sns.palplot(colors_dark)
```







Importing The Dataset

```
df=pd.read_csv('/content/water_potability.csv')
```

```
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.head()
```

	ph	Hardness	Solids	Chloramines	Sulfate	Conductivity	Organic_carbon	Trihalomethanes	Turbidity	Potability
0	NaN	204.890455	20791.318981	7.300212	368.516441	564.308654	10.379783	86.990970	2.963135	0
1	3.716080	129.422921	18630.057858	6.635246	NaN	592.885359	15.180013	56.329076	4.500656	0
2	8.099124	224.236259	19909.541732	9.275884	NaN	418.606213	16.868637	66.420093	3.055934	0
3	8.316766	214.373394	22018.417441	8.059332	356.886136	363.266516	18.436524	100.341674	4.628771	0
4	9.092223	181.101509	17978.986339	6.546600	310.135738	398.410813	11.558279	31.997993	4.075075	0

Visualizations

```
d= pd.DataFrame(df['Potability'].value_counts())
fig = px.pie(d,values='Potability',names=['Not Potable','Potable'],hole=0.4,opacity=0.6,
            color_discrete_sequence=[colors_green[3],colors_blue[3]],
             labels={'label':'Potability','Potability':'No. Of Samples'})

fig.add_annotation(text='We can resample the data<br> to get a balanced dataset',
                  x=1.2,y=0.9,showarrow=False,font_size=12,opacity=0.7,font_family='monospace')
fig.add_annotation(text='Potability',
                  x=0.5,y=0.5,showarrow=False,font_size=14,opacity=0.7,font_family='monospace')

fig.update_layout(
    font_family='monospace',
    title=dict(text='Q. How many samples of water are Potable?',x=0.47,y=0.98,
               font=dict(color=colors_dark[2],size=20)),
    legend=dict(x=0.37,y=-0.05,orientation='h',traceorder='reversed'),
    hoverlabel=dict(bgcolor='white'))

fig.update_traces(textposition='outside', textinfo='percent+label')

fig.show()
```

```
fig = px.histogram(df,x='Hardness',y=Counter(df['Hardness']),color='Potability',template='plotly_white',
                  marginal='box',opacity=0.7,nbins=100,color_discrete_sequence=[colors_green[3],colors_blue[3]],
                  barmode='group',histfunc='count')

fig.add_vline(x=151, line_width=1, line_color=colors_dark[1],line_dash='dot',opacity=0.7)
fig.add_vline(x=301, line_width=1, line_color=colors_dark[1],line_dash='dot',opacity=0.7)
fig.add_vline(x=76, line_width=1, line_color=colors_dark[1],line_dash='dot',opacity=0.7)

fig.add_annotation(text='<76 mg/L is<br> considered soft',x=40,y=130,showarrow=False,font_size=9)
fig.add_annotation(text='Between 76 and 150<br> (mg/L) is<br>moderately hard',x=113,y=130,showarrow=False,font_size=9)
fig.add_annotation(text='Between 151 and 300 (mg/L)<br> is considered hard',x=250,y=130,showarrow=False,font_size=9)
fig.add_annotation(text='>300 mg/L is<br> considered very hard',x=340,y=130,showarrow=False,font_size=9)

fig.update_layout(
    font_family='monospace',
    title=dict(text='Hardness Distribution',x=0.53,y=0.95,
               font=dict(color=colors_dark[2],size=20)),
    xaxis_title_text='Hardness (mg/L)',
    yaxis_title_text='Count',
    legend=dict(x=1,y=0.96,bordercolor=colors_dark[4],borderwidth=0,tracegroupgap=5),
    bargap=0.3,
)
fig.show()
```

```
fig = px.histogram(df,x='ph',y=Counter(df['ph']),color='Potability',template='plotly_white',
                  marginal='box',opacity=0.7,nbins=100,color_discrete_sequence=[colors_green[3],colors_blue[3]],
                  barmode='group',histfunc='count')

fig.add_vline(x=7, line_width=1, line_color=colors_dark[1],line_dash='dot',opacity=0.7)

fig.add_annotation(text='<7 is Acidic',x=4,y=70,showarrow=False,font_size=10)
fig.add_annotation(text='>7 is Basic',x=10,y=70,showarrow=False,font_size=10)


fig.update_layout(
    font_family='monospace',
    title=dict(text='pH Level Distribution',x=0.5,y=0.95,
               font=dict(color=colors_dark[2],size=20)),
    xaxis_title_text='pH Level',
    yaxis_title_text='Count',
    legend=dict(x=1,y=0.96,bordercolor=colors_dark[4],borderwidth=0,tracegroupgap=5),
    bargap=0.3,
)
fig.show()
```

```
fig = px.histogram(df,x='Chloramines',y=Counter(df['Chloramines']),color='Potability',template='plotly_white',
                  marginal='box',opacity=0.7,nbins=100,color_discrete_sequence=[colors_green[3],colors_blue[3]],
                  barmode='group',histfunc='count')

fig.add_vline(x=4, line_width=1, line_color=colors_dark[1],line_dash='dot',opacity=0.7)

fig.add_annotation(text='<4 ppm is considered<br> safe for drinking',x=1.8,y=90,showarrow=False)

fig.update_layout(
    font_family='monospace',
    title=dict(text='Chloramines Distribution',x=0.53,y=0.95,
               font=dict(color=colors_dark[2],size=20)),
    xaxis_title_text='Chloramines (ppm)',
    yaxis_title_text='Count',
    legend=dict(x=1,y=0.96,bordercolor=colors_dark[4],borderwidth=0,tracegroupgap=5),
    bargap=0.3,
)
fig.show()
```

```
fig = px.histogram(df,x='Sulfate',y=Counter(df['Sulfate']),color='Potability',template='plotly_white',
                  marginal='box',opacity=0.7,nbins=100,color_discrete_sequence=[colors_green[3],colors_blue[3]],
                  barmode='group',histfunc='count')

fig.add_vline(x=250, line_width=1, line_color=colors_dark[1],line_dash='dot',opacity=0.7)

fig.add_annotation(text='<250 mg/L is considered<br> safe for drinking',x=175,y=90,showarrow=False)

fig.update_layout(
    font_family='monospace',
    title=dict(text='Sulfate Distribution',x=0.53,y=0.95,
               font=dict(color=colors_dark[2],size=20)),
    xaxis_title_text='Sulfate (mg/L)',
    yaxis_title_text='Count',
    legend=dict(x=1,y=0.96,bordercolor=colors_dark[4],borderwidth=0,tracegroupgap=5),
    bargap=0.3,
)
fig.show()
```

```
fig = px.histogram(df,x='Conductivity',y=Counter(df['Conductivity']),color='Potability',template='plotly_white',
                  marginal='box',opacity=0.7,nbins=100,color_discrete_sequence=[colors_green[3],colors_blue[3]],
                  barmode='group',histfunc='count')

fig.add_annotation(text='The Conductivity range <br> is safe for both (200-800),<br> Potable and Non-Potable water',
                   x=600,y=90,showarrow=False)

fig.update_layout(
    font_family='monospace',
    title=dict(text='Conductivity Distribution',x=0.5,y=0.95,
               font=dict(color=colors_dark[2],size=20)),
    xaxis_title_text='Conductivity (μS/cm)',
    yaxis_title_text='Count',
    legend=dict(x=1,y=0.96,bordercolor=colors_dark[4],borderwidth=0,tracegroupgap=5),
    bargap=0.3,
)
fig.show()
```

```
fig = px.histogram(df,x='Organic_carbon',y=Counter(df['Organic_carbon']),color='Potability',template='plotly_white',
                  marginal='box',opacity=0.7,nbins=100,color_discrete_sequence=[colors_green[3],colors_blue[3]],
                  barmode='group',histfunc='count')

fig.add_vline(x=10, line_width=1, line_color=colors_dark[1],line_dash='dot',opacity=0.7)

fig.add_annotation(text='Typical Organic Carbon<br> level is upto 10 ppm',x=5.3,y=110,showarrow=False)

fig.update_layout(
    font_family='monospace',
    title=dict(text='Organic Carbon Distribution',x=0.5,y=0.95,
               font=dict(color=colors_dark[2],size=20)),
    xaxis_title_text='Organic Carbon (ppm)',
    yaxis_title_text='Count',
    legend=dict(x=1,y=0.96,bordercolor=colors_dark[4],borderwidth=0,tracegroupgap=5),
    bargap=0.3,
)
fig.show()
```

```
fig = px.histogram(df,x='Trihalomethanes',y=Counter(df['Trihalomethanes']),color='Potability',template='plotly_white',
                  marginal='box',opacity=0.7,nbins=100,color_discrete_sequence=[colors_green[3],colors_blue[3]],
                  barmode='group',histfunc='count')

fig.add_vline(x=80, line_width=1, line_color=colors_dark[1],line_dash='dot',opacity=0.7)

fig.add_annotation(text='Upper limit of Trihalomethanes<br> level is 80 μg/L',x=115,y=90,showarrow=False)

fig.update_layout(
    font_family='monospace',
    title=dict(text='Trihalomethanes Distribution',x=0.5,y=0.95,
               font=dict(color=colors_dark[2],size=20)),
    xaxis_title_text='Trihalomethanes (μg/L)',
    yaxis_title_text='Count',
    legend=dict(x=1,y=0.96,bordercolor=colors_dark[4],borderwidth=0,tracegroupgap=5),
    bargap=0.3,
)
fig.show()
```

```
fig = px.scatter_matrix(df,df.drop('Potability',axis=1),height=1250,width=1250,template='plotly_white',opacity=0.7,
                        color_discrete_sequence=[colors_blue[3],colors_green[3]],color='Potability',
                       symbol='Potability',color_continuous_scale=[colors_green[3],colors_blue[3]])

fig.update_layout(font_family='monospace',font_size=10,
                  coloraxis_showscale=False,
                 legend=dict(x=0.02,y=1.07,bgcolor=colors_dark[4]),
                 title=dict(text='Scatter Plot Matrix b/w Features',x=0.5,y=0.97,
                   font=dict(color=colors_dark[2],size=24)))
fig.show()
```

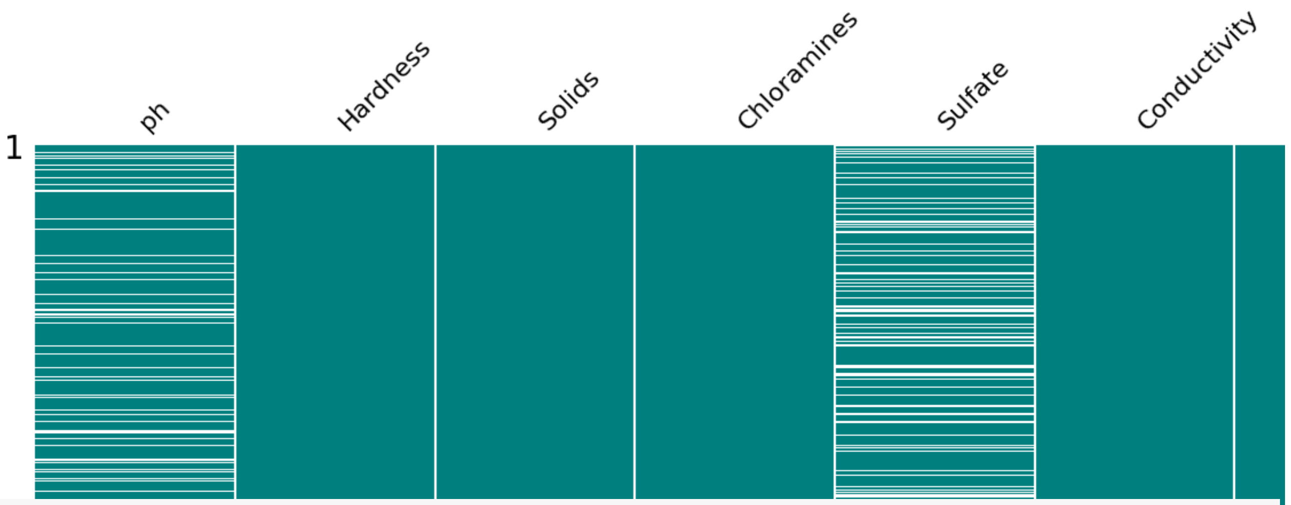
```
cor=df.drop('Potability',axis=1).corr()
cor
```

	ph	Hardness	Solids	Chloramines	Sulfate	Conductivity	Organic_carbon	Trihalomethanes	Turbidity
ph	1.000000	0.082096	-0.089288	-0.034350	0.018203	0.018614	0.043503	0.003354	-0.039057
Hardness	0.082096	1.000000	-0.046899	-0.030054	-0.106923	-0.023915	0.003610	-0.013013	-0.014449
Solids	-0.089288	-0.046899	1.000000	-0.070148	-0.171804	0.013831	0.010242	-0.009143	0.019546
Chloramines	-0.034350	-0.030054	-0.070148	1.000000	0.027244	-0.020486	-0.012653	0.017084	0.002363
Sulfate	0.018203	-0.106923	-0.171804	0.027244	1.000000	-0.016121	0.030831	-0.030274	-0.011187
Conductivity	0.018614	-0.023915	0.013831	-0.020486	-0.016121	1.000000	0.020966	0.001285	0.005798
Organic_carbon	0.043503	0.003610	0.010242	-0.012653	0.030831	0.020966	1.000000	-0.013274	-0.027308
Trihalomethanes	0.003354	-0.013013	-0.009143	0.017084	-0.030274	0.001285	-0.013274	1.000000	-0.022145

```
fig = px.imshow(cor,height=800,width=800,color_continuous_scale=colors_blue,template='plotly_white')

fig.update_layout(font_family='monospace',
                title=dict(text='Correlation Heatmap',x=0.5,y=0.93,
                           font=dict(color=colors_dark[2],size=24)),
                coloraxis_colorbar=dict(len=0.85,x=1.1)
                 )

fig.show()
```

Data Preparation

```
fig = msno.matrix(df,color=(0,0.5,0.5))
```



```
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[df['Potability']==0].describe()
```

	ph	Hardness	Solids	Chloramines	Sulfate	Conductivity	Organic_carbon	Trihalomethanes	Turbidity	Po
count	1684.000000	1998.000000	1998.000000	1998.000000	1510.000000	1998.000000	1998.000000	1891.000000	1998.000000	
mean	7.085378	196.733292	21777.490788	7.092175	334.564290	426.730454	14.364335	66.303555	3.965800	
std	1.683499	31.057540	8543.068788	1.501045	36.745549	80.047317	3.334554	16.079320	0.780282	
min	0.000000	98.452931	320.942611	1.683993	203.444521	181.483754	4.371899	0.738000	1.450000	
25%	6.037723	177.823265	15663.057382	6.155640	311.264006	368.498530	12.101057	55.706530	3.444062	
50%	7.035456	197.123423	20809.618280	7.090334	333.389426	422.229331	14.293508	66.542198	3.948076	
75%	8.155510	216.120687	27006.249009	8.066462	356.853897	480.677198	16.649485	77.277704	4.496106	
max	14.000000	304.235912	61227.196008	12.653362	460.107069	753.342620	28.300000	120.030077	6.739000	

```
df[df['Potability']==1].describe()
```

	ph	Hardness	Solids	Chloramines	Sulfate	Conductivity	Organic_carbon	Trihalomethanes	Turbidity	Pot
count	1101.000000	1278.000000	1278.000000	1278.000000	985.000000	1278.000000	1278.000000	1223.000000	1278.000000	
mean	7.073783	195.800744	22383.991018	7.169338	332.566990	425.383800	14.160893	66.539684	3.968328	
std	1.448048	35.547041	9101.010208	1.702988	47.692818	82.048446	3.263907	16.327419	0.780842	
min	0.227499	47.432000	728.750830	0.352000	129.000000	201.619737	2.200000	8.175876	1.492207	
25%	6.179312	174.330531	15668.985035	6.094134	300.763772	360.939023	12.033897	56.014249	3.430909	
50%	7.036752	196.632907	21199.386614	7.215163	331.838167	420.712729	14.162809	66.678214	3.958576	
75%	7.933068	218.003420	27973.236446	8.199261	365.941346	484.155911	16.356245	77.380975	4.509569	
max	13.175402	323.124000	56488.672413	13.127000	481.030642	695.369528	23.604298	124.000000	6.494249	

```
df[df['Potability']==0][['ph','Sulfate','Trihalomethanes']].median()
```

```
ph                   7.035456
Sulfate            333.389426
```

```
Trihalomethanes     66.542198
dtype: float64
```

```
df[df['Potability']==1][['ph','Sulfate','Trihalomethanes']].median()
```

```
ph                   7.036752
Sulfate            331.838167
Trihalomethanes     66.678214
dtype: float64
```

```
df['ph'].fillna(value=df['ph'].median(),inplace=True)
df['Sulfate'].fillna(value=df['Sulfate'].median(),inplace=True)
df['Trihalomethanes'].fillna(value=df['Trihalomethanes'].median(),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
```

Standardizing The Data

```
X = df.drop('Potability',axis=1).values
y = df['Potability'].values
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=101)
scaler = StandardScaler()
scaler.fit(X_train)
X_train = scaler.transform(X_train)
X_test = scaler.transform(X_test)
```

Modelling

```
filterwarnings('ignore')
models =[("LR", LogisticRegression(max_iter=1000)),("SVC", SVC()),('KNN',KNeighborsClassifier(n_neighbors=10)),
         ("DTC", DecisionTreeClassifier()),("GNB", GaussianNB()),
        ("SGDC", SGDClassifier()),("Perc", Perceptron()),("NC",NearestCentroid()),
        ("Ridge", RidgeClassifier()),("NuSVC", NuSVC()),("BNB", BernoulliNB()),
         ('RF',RandomForestClassifier()),('ADA',AdaBoostClassifier()),
        ('XGB',GradientBoostingClassifier()),('PAC',PassiveAggressiveClassifier())]

results = []
names = []
finalResults = []

for name,model in models:
    model.fit(X_train, y_train)
    model_results = model.predict(X_test)
    score = precision_score(y_test, model_results,average='macro')
    results.append(score)
    names.append(name)
    finalResults.append((name,score))

finalResults.sort(key=lambda k:k[1],reverse=True)
```

```
finalResults
```

```
[('SVC', 0.6928617374229805),
 ('XGB', 0.6630921227291691),
 ('RF', 0.6371248936111797),
 ('NuSVC', 0.6227085849916291),
 ('GNB', 0.6012450851900393),
 ('KNN', 0.599731034904334),
 ('ADA', 0.5730733082706767),
 ('PAC', 0.5446198830409357),
 ('DTC', 0.526067736800721),
 ('SGDC', 0.5245597775718258),
 ('NC', 0.5180221380172848),
 ('Perc', 0.47848552636610453),
 ('LR', 0.3045801526717557),
 ('Ridge', 0.3045801526717557),
 ('BNB', 0.3045801526717557)]
```

Hyperparameter Tuning

```
model_params = {
    'XGB':
    {
        'model':GradientBoostingClassifier(),
        'params':
        {
            'learning_rate':[0.0001,0.001,0.01,0.1],
            'n_estimators':[100,200,500,1000],
            'max_features':['sqrt','log2'],
            'max_depth':list(range(11))
        }
    },
    'Random Forest':
    {
        'model':RandomForestClassifier(),
        'params':
        {
            'n_estimators':[10,50,100,200],
            'max_features':['auto','sqrt','log2'],
            'max_depth':list(range(1,11))
        }
    }
}
cv = RepeatedStratifiedKFold(n_splits=5,n_repeats=2)
scores=[]
for model_name,params in model_params.items():
    rs = RandomizedSearchCV(params['model'],params['params'],cv=cv,n_iter=20)
    rs.fit(X,y)
    scores.append([model_name,dict(rs.best_params_),rs.best_score_])
data=pd.DataFrame(scores,columns=['Model','Parameters','Score'])
data
```

	Model	Parameters	Score
0	XGB	{'n_estimators': 500, 'max_features': 'sqrt', ...	0.663919
1	Random Forest	{'n_estimators': 100, 'max_features': 'sqrt', ...	0.666813

Final Model

```
param=data['Parameters']
model = VotingClassifier(estimators=[
                                     ('XGB',GradientBoostingClassifier(**param[0])),
                                     ('RF',RandomForestClassifier(**param[1])),
                                    ],voting='hard')

accuracy=[]
scaler = StandardScaler()
skf = RepeatedStratifiedKFold(n_splits=5,n_repeats=2)
skf.get_n_splits(X,y)

for train_index, test_index in skf.split(X,y):

    X_train, X_test = X[train_index], X[test_index]
    y_train, y_test = y[train_index], y[test_index]

    scaler.fit(X_train)
    X_train = scaler.transform(X_train)
    X_test = scaler.transform(X_test)

    model.fit(X_train,y_train)
    predictions=model.predict(X_test)
    score=accuracy_score(y_test,predictions)
    accuracy.append(score)
```

```
np.mean(accuracy)
```

```
0.6639138428598026
```

Conclusion

1. The TDS levels seem to contain some descripency since its values are on an average 40 folds more than the upper limit for safe drinking water.

2. The data contains almost equal number of acidic and basic pH level water samples.

3. 92% of the data was considered Hard.

4. Only 2% of the water samples were safe in terms of Chloramines levels.

5. Only 1.8% of the water samples were safe in terms of Sulfate levels.

6. 90.6% of the water samples had higher Carbon levels than the typical Carbon levels in drinking water (10 ppm).

7. 76.6% of water samples were safe for drinking in terms of Trihalomethane levels in water.

8. 90.4% of the water samples were safe for drinking in terms of the Turbidity of water samples.

9. The correlation coefficients between the features were very low.

10. Random Forest and XGBoost worked the best to train the model.

11. The ensemble method of using the Voting Classfier on Stratified K-folded samples gave an accuracy of >64%