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WATER QUALITY ANALYSIS PHASE5-DATA ANALYTICS WITH COGNOS: GROUP2

INTRODUCTION:

Water is a fundamental resource essential for sustaining life, supporting ecosystems, and facilitating various human activities. The quality of water, determined by its chemical, physical, and biological characteristics, plays a pivotal role in its suitability for different purposes. Water quality analysis is the systematic assessment of these attributes to ensure the safety, health, and sustainability of water resources.

OBJECTIVE:

The primary objective of water quality analysis is to assess and measure the physical, chemical, and biological characteristics of water to determine its suitability for various purposes and to ensure it meets established standards and regulations.

DESIGN THINKING:

Designing a water quality analysis system using Python involves several steps. Here's a simplified design thinking process for such a project:

PREPARING OF DATA:

First we have to understand what was the data we are going to analyse for this we have to clean and process the data by using suitable techniques like dropping the null values, data types, remove the duplicate values, visualize the missing values drop the duplicates, by using the suitable functions like drop, is null etc....

EXPLORATORY DATA ANALYSIS:

This was the most important step in this project so we have to represent our data in the understandable visualization tools like pie Scattered plot, histogram, heat map to represent the relation and variation .

PREDICTIVE MODEL:

Random Forest (RF) and Logistic Regression (LG) are two different types of predictive models used in data analysis, but they are typically used for different types of tasks, and they may not be directly applicable to water quality analysis.

the model also depends on the quality and quantity of your data and the domain-specific knowledge you incorporate into feature engineering and model selection. It's a good practice to try different models and evaluate their performance to choose the one that best fits your particular analysis task.

DAC-phase5

```
[1]: import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import plotly.express as px
```

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

```
[3]: df.head
```

```
[3]: <bound method NDFrame.head of
Chloramines      Sulfate \
0      NaN      204.890456  20791.31898    7.300212  368.516441
1    3.716080    129.422921  18630.05786    6.635246         NaN
2    8.099124    224.236259  19909.54173    9.275884         NaN
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         NaN
3273  9.419510    175.762646  33155.57822    7.350233         NaN
3274  5.126763    230.603758  11983.86938    6.303357         NaN
3275  7.874671    195.102299  17404.17706    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      18.436525     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      327.459761      16.140368      78.698446      2.309149          1
```

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

```
[4]: df.info(memory_usage="deep")
```

```
<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
```

```
[5]: print(df.shape)
print(len(df))
print(f"Number of rows: {df.shape[0]} \nNumber of columns: {df.shape[1]}")
```

```
(3276, 10)
```

```
3276
```

```
Number of rows: 3276
```

```
Number of columns: 10
```

```
[6]: df.describe()
```

```
[6]:
```

	ph	Hardness	Solids	Chloramines	Sulfate	\
count	2785.000000	3276.000000	3276.000000	3276.000000	2495.000000	
mean	7.080795	196.369496	22014.092526	7.122277	333.775777	
std	1.594320	32.879761	8768.570828	1.583085	41.416840	
min	0.000000	47.432000	320.942611	0.352000	129.000000	
25%	6.093092	176.850538	15666.690300	6.127421	307.699498	
50%	7.036752	196.967627	20927.833605	7.130299	333.073546	
75%	8.062066	216.667456	27332.762125	8.114887	359.950170	
max	14.000000	323.124000	61227.196010	13.127000	481.030642	

	Conductivity	Organic_carbon	Trihalomethanes	Turbidity	Potability
count	3276.000000	3276.000000	3114.000000	3276.000000	3276.000000
mean	426.205111	14.284970	66.396293	3.966786	0.390110
std	80.824064	3.308162	16.175008	0.780382	0.487849
min	181.483754	2.200000	0.738000	1.450000	0.000000
25%	365.734414	12.065801	55.844536	3.439711	0.000000

50%	421.884968	14.218338	66.622485	3.955028	0.000000
75%	481.792305	16.557652	77.337473	4.500320	1.000000
max	753.342620	28.300000	124.000000	6.739000	1.000000

```
[7]: df.describe?
```

```
[8]: df.isnull().sum()
```

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

```
[9]: def isnull_prop(df):
     total_rows = df.shape[0]
     missing_val_dict = {}
     for col in df.columns:
         missing_val_dict[col] = [df[col].isnull().sum(), (df[col].isnull().
         ↳sum() / total_rows)]
     return missing_val_dict
     null_dict = isnull_prop(df)
     print(null_dict.items())
```

```
dict_items([('ph', [491, 0.14987789987789987]), ('Hardness', [0, 0.0]),
('Solids', [0, 0.0]), ('Chloramines', [0, 0.0]), ('Sulfate', [781,
0.23840048840048841]), ('Conductivity', [0, 0.0]), ('Organic_carbon', [0, 0.0]),
('Trihalomethanes', [162, 0.04945054945054945]), ('Turbidity', [0, 0.0]),
('Potability', [0, 0.0])])
```

```
[10]: import pandas as pd
```

```
# Check for NaN values in your DataFrame (assuming df is your DataFrame)
print(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
```

```
[11]: df_missing = pd.DataFrame.from_dict(null_dict,
                                         orient="index",
                                         columns=["missing", "miss_percent"])

df_missing
```

```
[11]:
```

	missing	miss_percent
ph	491	0.149878
Hardness	0	0.000000
Solids	0	0.000000
Chloramines	0	0.000000
Sulfate	781	0.238400
Conductivity	0	0.000000
Organic_carbon	0	0.000000
Trihalomethanes	162	0.049451
Turbidity	0	0.000000
Potability	0	0.000000

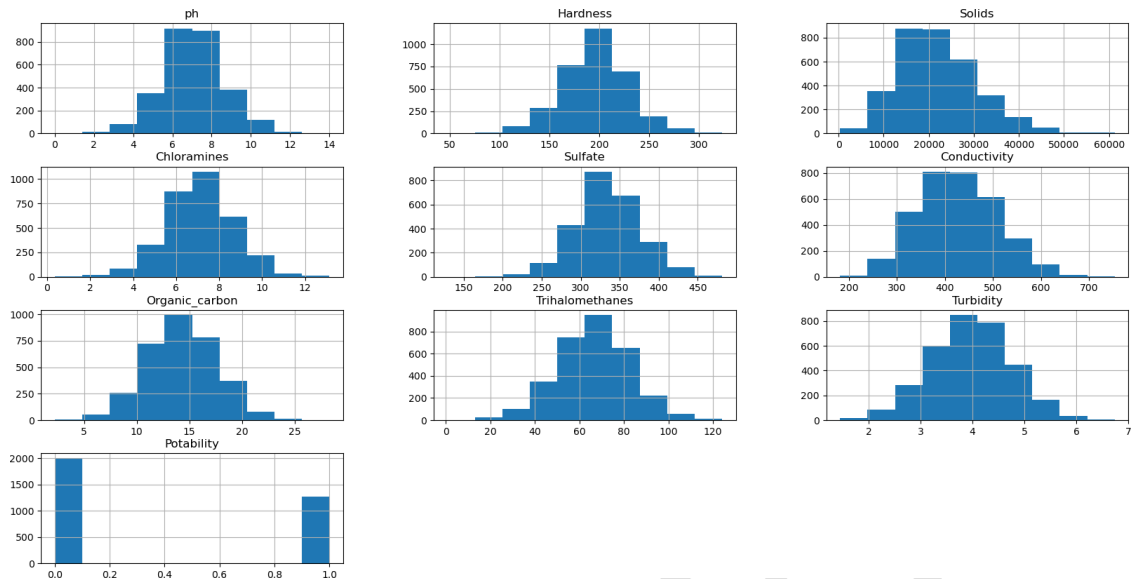
```
[33]: import numpy as np

# Check for infinite values
print(np.isinf(X_train).sum())
```

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

1 visualization

```
[13]: plt.rcParams["figure.figsize"] = [20,10]
df.hist()
plt.show()
```



```
[14]: fig = px.scatter(df, x = "ph", y = "Sulfate", color = "Potability", template = _
↳ "plotly_dark", trendline="ols")
fig.show()
```

```
[15]: fig = px.scatter(df, x = "Organic_carbon", y = "Hardness", color = _
↳ "Potability", template = "plotly_dark", trendline="lowess")
fig.show()
```

2 logistic regression

```
[16]: import seaborn as sns
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split
from sklearn.metrics import confusion_matrix, accuracy_score, _
↳ classification_report
```

```
[17]: # Creating model object
model_lg = LogisticRegression(max_iter=120, random_state=0, n_jobs=20)
```

```
[18]: df.fillna(df.mean(), inplace=True) # Replace NaN with mean of the column
```

```
[19]: X_train=df[["ph", "Hardness", "Solids", "Chloramines", "Sulfate", "Conductivity", "Organic_carbon", "
y_train= df["Potability"]
```

```
[20]: # Training Model
model_lg.fit(X_train, y_train)
```

```
[20]: LogisticRegression(max_iter=120, n_jobs=20, random_state=0)
```

```
[21]: X_train, X_test, y_train, y_test = train_test_split(
    df[["ph", "Hardness", "Solids", "Chloramines", "Sulfate", "Conductivity", "Organic_carbon", "Trihalomethanes", "Potability"]],
    test_size=0.2, # You can adjust the test size as needed
    random_state=42 # You can set a random seed for reproducibility
)
pred_lg = model_lg.predict(X_test)
```

```
[22]: lg = accuracy_score(y_test, pred_lg)
print(lg)
```

0.6280487804878049

```
[23]: print(classification_report(y_test, pred_lg))
```

	precision	recall	f1-score	support
0	0.63	1.00	0.77	412
1	0.00	0.00	0.00	244
accuracy			0.63	656
macro avg	0.31	0.50	0.39	656
weighted avg	0.39	0.63	0.48	656

C:\Users\lab\anaconda3\lib\site-packages\sklearn\metrics_classification.py:1318: UndefinedMetricWarning:

Precision and F-score are ill-defined and being set to 0.0 in labels with no predicted samples. Use `zero_division` parameter to control this behavior.

C:\Users\lab\anaconda3\lib\site-packages\sklearn\metrics_classification.py:1318: UndefinedMetricWarning:

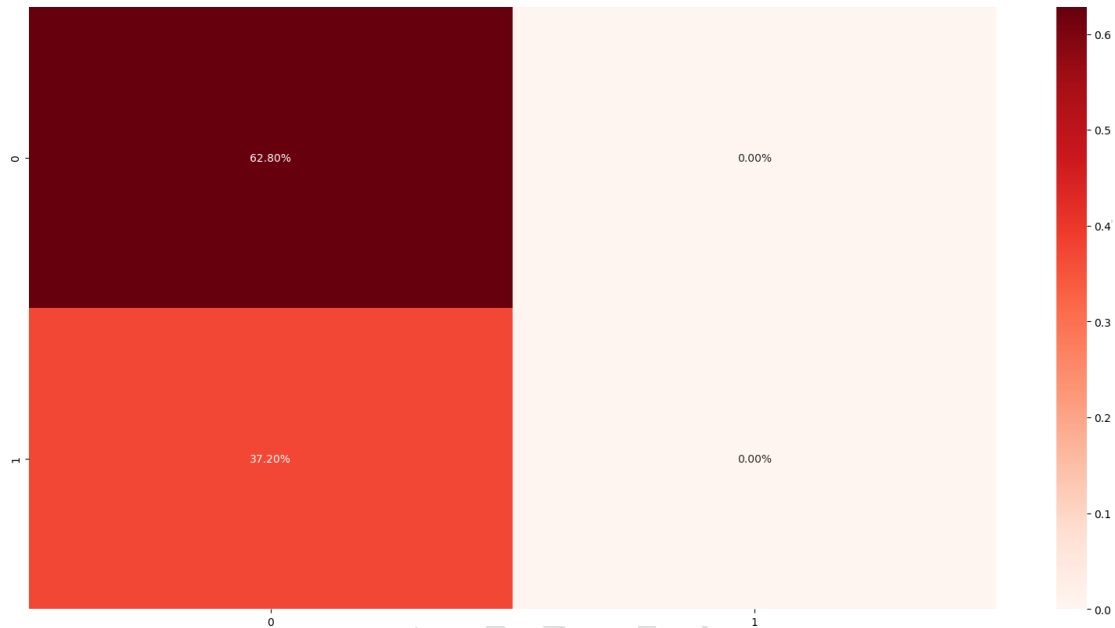
Precision and F-score are ill-defined and being set to 0.0 in labels with no predicted samples. Use `zero_division` parameter to control this behavior.

C:\Users\lab\anaconda3\lib\site-packages\sklearn\metrics_classification.py:1318: UndefinedMetricWarning:

Precision and F-score are ill-defined and being set to 0.0 in labels with no predicted samples. Use `zero_division` parameter to control this behavior.

```
[24]: cm1 = confusion_matrix(y_test, pred_lg)
      sns.heatmap(cm1/np.sum(cm1), annot = True, fmt= '0.2%', cmap = 'Reds')
```

[24]: <AxesSubplot:>



3 RandomForest

```
[25]: from sklearn.ensemble import RandomForestClassifier
```

```
[26]: model_rf = RandomForestClassifier(n_estimators=300,min_samples_leaf=1,
      random_state=32)
```

```
[27]: model_rf.fit(X_train, y_train)
```

[27]: RandomForestClassifier(n_estimators=300, random_state=32)

```
[28]: pred_rf = model_rf.predict(X_test)
```

```
[29]: rf = accuracy_score(y_test, pred_rf)
      print(rf)
```

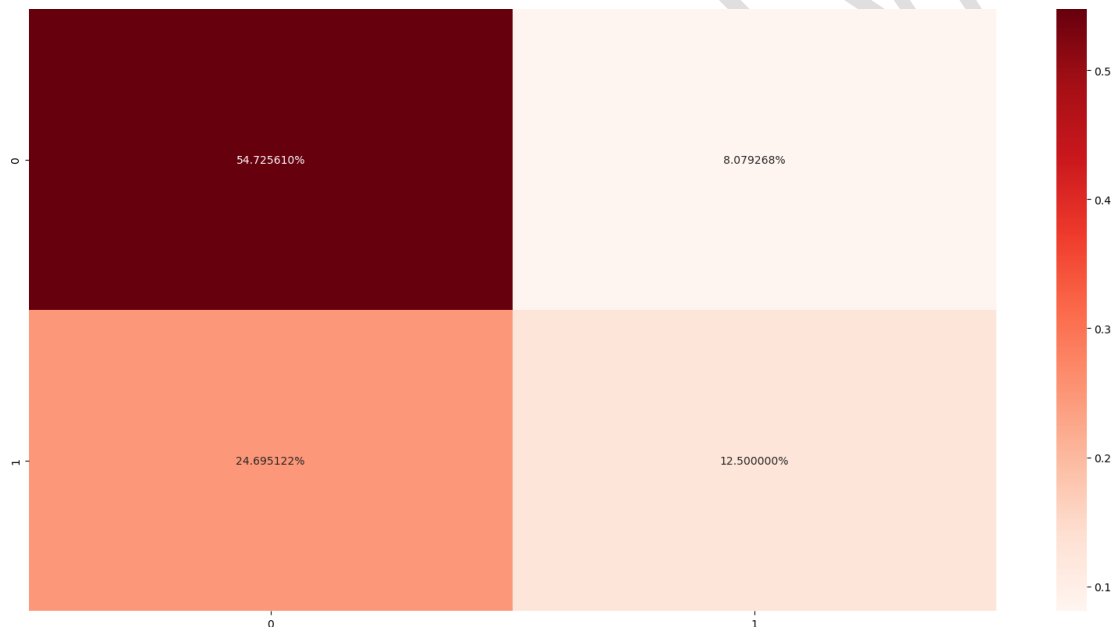
0.6722560975609756

```
[30]: print(classification_report(y_test,pred_rf))
```


	precision	recall	f1-score	support
0	0.69	0.87	0.77	412
1	0.61	0.34	0.43	244
accuracy			0.67	656
macro avg	0.65	0.60	0.60	656
weighted avg	0.66	0.67	0.64	656

```
[31]: cm3 = confusion_matrix(y_test, pred_rf)
sns.heatmap(cm3/np.sum(cm3), annot = True, fmt= '%1%', cmap = 'Reds')
```

[31]: <AxesSubplot:>

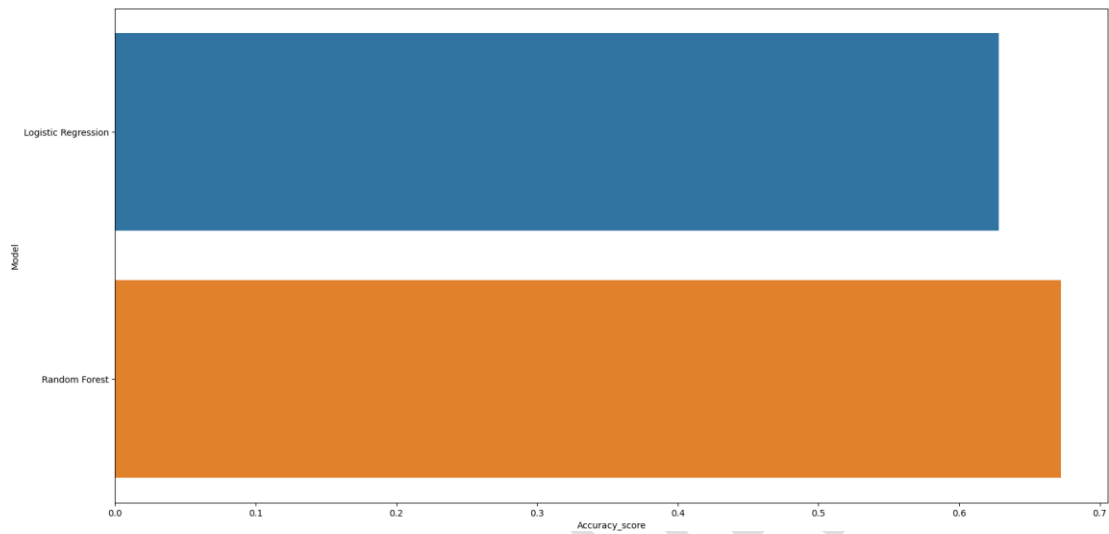


4 logistic regression vs random forest

```
[32]: models = pd.DataFrame({
    'Model': ['Logistic Regression', 'Random Forest'],
    'Accuracy_score': [lg, rf]
})
models
sns.barplot(x='Accuracy_score', y='Model', data=models)
models.sort_values(by='Accuracy_score', ascending=False)
```

[32]:

	Model	Accuracy_score
1	Random Forest	0.672256
0	Logistic Regression	0.628049



INSIGHTS:

To assess water quality and determine its portability, an analysis should involve collecting and examining various water quality parameters and data. By analyzing parameters and factors, you can gain insights into the overall water quality. A comprehensive assessment would involve statistical analysis, data visualization, and the application of relevant models to predict and monitor water quality. Regular monitoring and testing are essential to ensure that water meets the required standards for portability and safety. If contaminants or quality issues are identified, appropriate water treatment and remediation measures should be implemented to make the water potable.