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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             ph    Hardness        Solids  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]:
```python
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

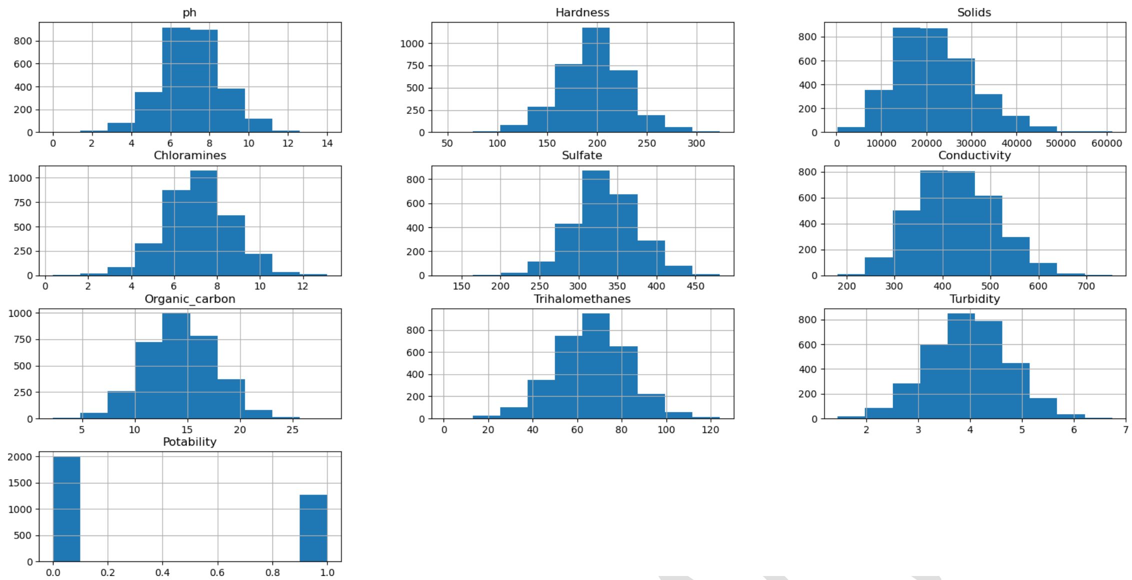
[33]:
```python
import numpy as np

# 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]:
```python
plt.rcParams['figure.figsize'] = [20,10]
df.hist()
plt.show()
```



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

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

2 logestic regression

[16]:
```python
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]:
```python
# Creating model object
model_lg = LogisticRegression(max_iter=120,random_state=0, n_jobs=20)
```

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

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

[20]:
```python
# 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","Triha
    df["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:

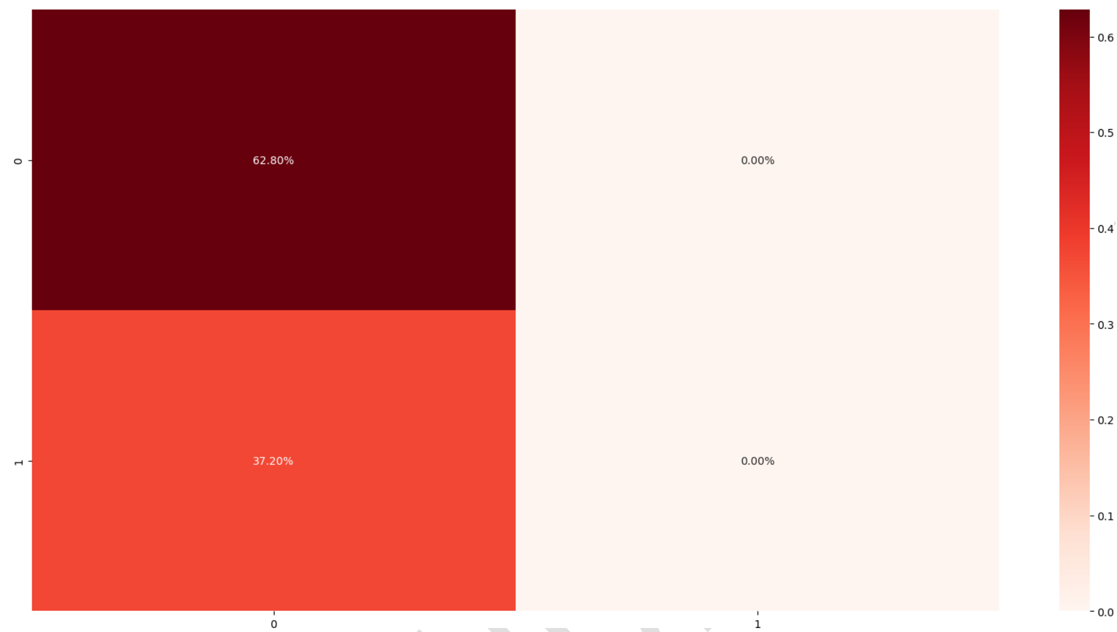
Precision and F-score are ill-defined and being set to 0.0 in labels with no predicted samples. Use `zero_division` parameter to control this behavior.

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))
```

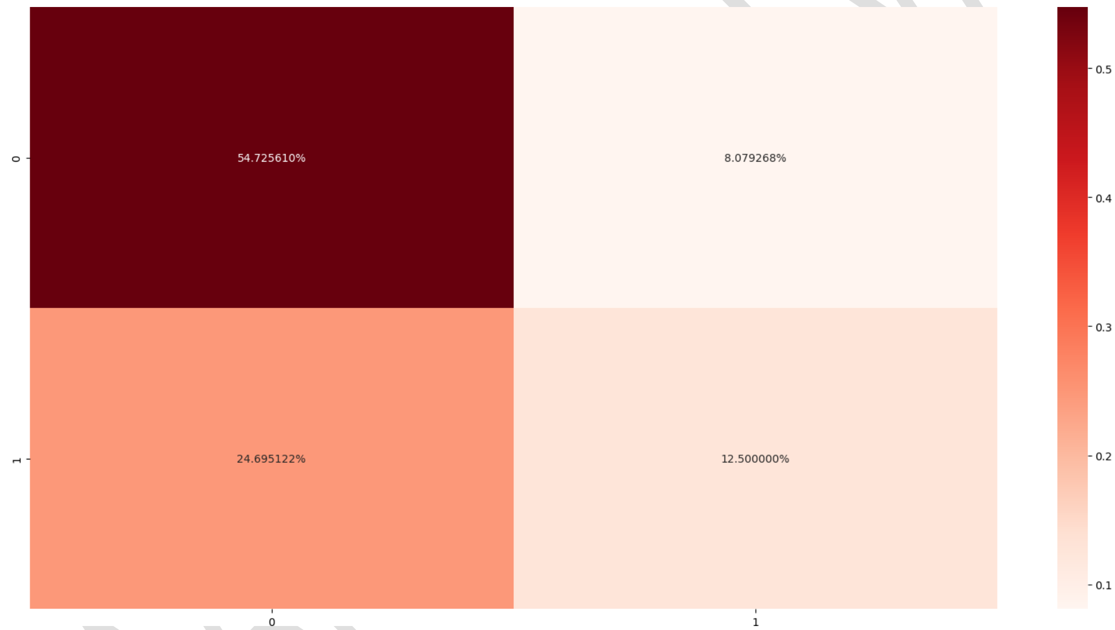
```
              precision    recall  f1-score   support

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

[31]: <AxesSubplot:>



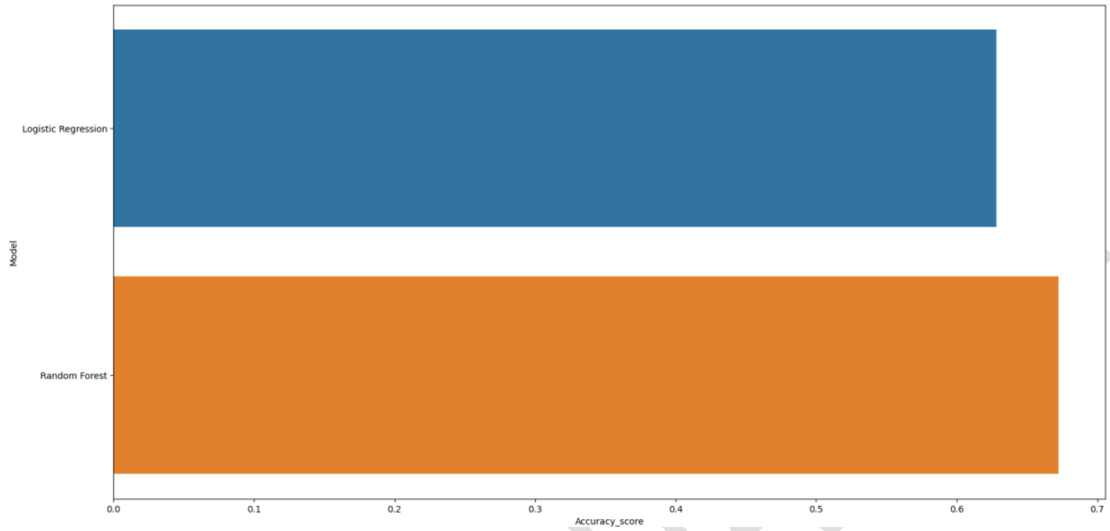
4 logestic regression vs random forest

[32]:
```python
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.