PROJECT DEVELOPMENT PHASE

SPRINT-1

TEAM ID	PNT2022TMID37730
PROJECT TITLE	Efficient Water Quality Analysis And Prediction
	Using machine Learning
MAXIMUM MARKS	8 Marks

pip install matplotlib In [427... # pip install seaborn In [428... # import all needed libraries import pandas as pd import numpy as np import os import matplotlib.pyplot as plt import seaborn as sns from sklearn.model_selection import train_test_split from sklearn.preprocessing import StandardScaler from sklearn.preprocessing import OneHotEncoder from sklearn.preprocessing import LabelEncoder from sklearn.preprocessing import MinMaxScaler from sklearn.ensemble import RandomForestRegressor from sklearn.tree import DecisionTreeRegressor from sklearn.linear_model import LogisticRegression from sklearn.linear_model import LinearRegression from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score,r2_score from sklearn.metrics import confusion_matrix, classification_report # read csv file using pandas df=pd.read_csv('Book0.1.csv') df.head() NITRATENAN N+ D.O. PH TOTAL COLIFORM Unnamed: STATION CONDUCTIVITY B.O.D. LOCATIONS STATE Temp NITRITENANN COLIFORM (MPN/100ml)Mean year CODE (mg/l) (µmhos/cm) (mg/l) (MPN/100ml) ZUARI AT D/S OF PT. WHERE KUMBARURIA GOA 29.8 5.7 7.2 2 0.2 4953 8391 2014 1399 189 CANAL JOI... 1475 ZUARI AT PANCHAWADI GOA 29.5 6.3 6.9 0.1 3243 5330 2014 RIVER ZUARI AT BORIM GOA 29.7 3181 8443 2014 3 5.8 6.9 64 3.8 0.5 5382

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Out[429			

429		Unnamed: 0	STATION CODE	LOCATIONS	STATE	Temp	D.O. (mg/l)	PH	CONDUCTIVITY (µmhos/cm)	B.O.D. (mg/l)	NITRATENAN N+ NITRITENANN (mg/l)	FECAL COLIFORM (MPN/100ml)	TOTAL COLIFORM (MPN/100ml)Mean	year
	0	1	1399	ZUARI AT D/S OF PT. WHERE KUMBARIRIA CANAL JOI	GOA	29.8	5.7	7.2	189	2	0.2	4953	8391	2014
	1	2	1475	ZUARI AT PANCHAWADI	GOA	29.5	6.3	6.9	179	1.7	0.1	3243	5330	2014
	2	3	3181	RIVER ZUARI AT BORIM BRIDGE	GOA	29.7	5.8	6.9	64	3.8	0.5	5382	8443	2014
	3	4	3182	RIVER ZUARI AT MARCAIM JETTY	GOA	29.5	5.8	7.3	83	1.9	0.4	3428	5500	2014
	4	5	1400	MANDOVI AT NEGHBOURHOOD OF PANAJI, GOA	GOA	30	5.5	7.4	81	1.5	0.1	2853	4049	2014

In [430...

no need this because it give value error of continuous value error
df.drop(['Unnamed: 0'],inplace=True,axis=1)

n [431.

1=['Temp','D.O. (mg/l)','PH','CONDUCTIVITY (μmhos/cm)','B.O.D. (mg/l)','NITRATENAN N+ NITRITENANN (mg/l)','FECAL COLIFORM (MPN/100ml)','TOTAL COLIFORM df[df[l]=="NAN"]

Out[431.

	STATION CODE	LOCATIONS	STATE	Temp	D.O. (mg/l)	PH	CONDUCTIVITY (µmhos/cm)	B.O.D. (mg/l)	NITRATENAN N+ NITRITENANN (mg/l)	FECAL COLIFORM (MPN/100ml)	TOTAL COLIFORM (MPN/100ml)Mean	Vear
0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
1	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
2	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
3	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
4	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
	_						***					
890	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
891	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN

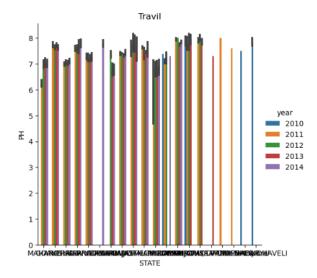
```
In [432...
          # drop the all nan and empty data
           for i in 1:
               df.drop(df.index[df[i]=="NAN"],inplace=True,axis=0)
               df.drop(df.index[df[i]==" "],inplace=True,axis=0)
In [433...
           # convert all data type into float
           for i in 1:
               df[i]=df[i].astype('float')
In [434...
           df.describe()
Out[434...
                     STATION
                                              D.O.
                                                                  CONDUCTIVITY
                                                                                     B.O.D.
                                                                                                 NITRATENAN N+
                                                                                                                    FECAL COLIFORM
                                                                                                                                           TOTAL COLIFORM
                                                          PH
                                  Temp
                                                                                                                                                                  year
                       CODE
                                            (mg/l)
                                                                     (µmhos/cm)
                                                                                     (mg/l)
                                                                                              NITRITENANN (mg/l)
                                                                                                                       (MPN/100ml)
                                                                                                                                          (MPN/100ml)Mean
           count 879.000000 879.000000 879.000000 879.000000
                                                                      879.000000 879.000000
                                                                                                       879.000000
                                                                                                                       8.790000e+02
                                                                                                                                               8.790000e+02 879.000000
                 2194.318544 26.093743
                                          6.310728
                                                     7.232628
                                                                      1650.803185
                                                                                   4.924061
                                                                                                         1.644994
                                                                                                                       6.869346e+05
                                                                                                                                               1.110502e+06 2012.559727
           mean
                   807.389674
                               3.261618
                                           1.300479
                                                     0.606125
                                                                     4927.777303
                                                                                  12.770214
                                                                                                         2.896984
                                                                                                                       1.209315e+07
                                                                                                                                               2.069025e+07
                                                                                                                                                             1.102190
                    17.000000 16.000000
                                          0.200000
                                                     2.600000
                                                                       27.000000
                                                                                   0.100000
                                                                                                         0.000000
                                                                                                                       2.000000e+00
                                                                                                                                               4.000000e+00 2010.000000
            min
            25%
                  1548.000000 24.450000
                                          5.900000
                                                     6.950000
                                                                       75.000000
                                                                                   1.200000
                                                                                                         0.280000
                                                                                                                       2.550000e+01
                                                                                                                                               9.000000e+01 2012.000000
            50%
                 2290.000000 27.000000
                                          6.700000
                                                     7.200000
                                                                      159.000000
                                                                                   1.800000
                                                                                                         0.590000
                                                                                                                       1.990000e+02
                                                                                                                                               5.000000e+02 2013.000000
                 2708.000000 28.400000
                                          7.100000
                                                     7.600000
                                                                      505.500000
                                                                                   3.300000
                                                                                                         1.775000
                                                                                                                       9.965000e+02
                                                                                                                                               2.425000e+03 2014.000000
                 3473.000000 33.000000
                                          9.900000
                                                     8.400000
                                                                    37227.000000 185.800000
                                                                                                        20.300000
                                                                                                                       2.725216e+08
                                                                                                                                               5.110909e+08 2014.000000
           # viewing the column of state
            color=sns.color_palette()
           int_level = df['STATE'].value_counts()
           plt.figure(figsize=(25,8))
            sns.barplot(int_level.index,int_level.values,alpha=0.9,color=color[5])
           plt.ylabel('count of data ',fontsize=12)
```

```
# viewing the column of state
            color=sns.color_palette()
            int_level = df['STATE'].value_counts()
            plt.figure(figsize=(25,8))
            sns.barplot(int_level.index,int_level.values,alpha=0.9,color=color[5])
            plt.ylabel('count of data ',fontsize=12)
            plt.xlabel('State',fontsize=12)
            plt.show()
           C:\ProgramData\Anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWarning: Pass the following variables as keyword args: x, y. From version
           0.12, the only valid positional argument will be 'data', and passing other arguments without an explicit keyword will result in an error or misinterpr
           etation.
           warnings.warn(
             200
             150 -
                                                                                                                                        Tripura MADHANGRADESHIDADRA NAGKANNISWEDU DAMAN & DIU
In [436...
           # viewing the column data of year
            color=sns.color_palette()
            int_level = df['year'].value_counts()
           \# State and year comparision with ph rate
           plt.figure(figsize=(20,20))
g=sns.catplot(data=df,kind="bar",x="STATE",y="PH",hue="year")
plt.title("Travil")
```

```
In [437—
# State and year comparision with ph rate

plt.figure(figsize=(20,20))
g=sns.catplot(data=df,kind="bar",x="STATE",y="PH",hue="year")
plt.title("Travil")
```

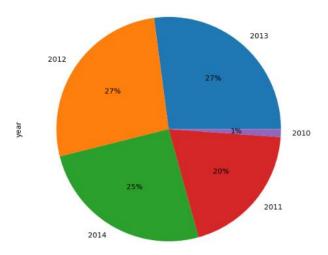
Out[437... Text(0.5, 1.0, 'Travil')



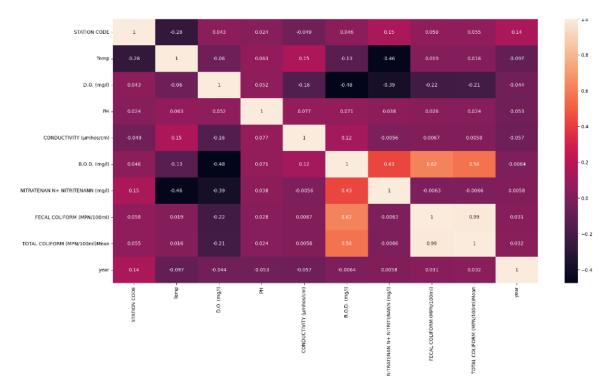
In [438_
df['year'].value_counts().plot(kind='pie',figsize=(7,7),autopct='%1.0f%%')

df['year'].value_counts().plot(kind='pie',figsize=(7,7),autopct='%1.0f%%')

Out[438_



plt.figure(figsize=(20,10))
sns.heatmap(df.corr(),annot=True)
plt.show()



In [448_ # Create column for the pure water range and split with undrikingable water

df['PH Range']=pd.cut(x=df['PH'],bins=[0,6.49,7.5,14],labels=['0-6.49','6.5-7.5','7.5-14'])

df['Water Qu']=df['PH Range'].map({'6.5-7.5':1,'7.5-14':0,'0-6.49':0})

df.drop(df.index[df['PH Range']=="NaN"],inplace=True,axis=0)

In [441... df.describe()

Out[441.

	STATION CODE	Temp	D.O. (mg/l)	PH	CONDUCTIVITY (µmhos/cm)	B.O.D. (mg/l)	NITRATENAN N+ NITRITENANN (mg/l)	COLIFORM (MPN/100ml)	TOTAL COLIFORM (MPN/100ml)Mean	year	Water Qu
count	879.000000	879.000000	879.000000	879.000000	879.000000	879.000000	879.000000	8.790000e+02	8.790000e+02	879.000000	879.000000
mean	2194.318544	26.093743	6.310728	7.232628	1650.803185	4.924061	1.644994	6.869346e+05	1.110502e+06	2012.559727	0.673493
std	807.389674	3.261618	1.300479	0.606125	4927.777303	12.770214	2.896984	1.209315e+07	2.069025e+07	1.102190	0.469202
min	17.000000	16.000000	0.200000	2.600000	27.000000	0.100000	0.000000	2.000000e+00	4.000000e+00	2010.000000	0.000000
25%	1548.000000	24.450000	5.900000	6.950000	75.000000	1.200000	0.280000	2.550000e+01	9.000000e+01	2012.000000	0.000000
50%	2290.000000	27.000000	6.700000	7.200000	159.000000	1.800000	0.590000	1.990000e+02	5.000000e+02	2013.000000	1.000000
75%	2708.000000	28.400000	7.100000	7.600000	505.500000	3.300000	1.775000	9.965000e+02	2.425000e+03	2014.000000	1.000000
max	3473.000000	33.000000	9.900000	8.400000	37227.000000	185.800000	20.300000	2.725216e+08	5.110909e+08	2014.000000	1.000000

In []:

In [442_ # Box plot for comparing the ph with other column and finding the outliers

col_pruning=['Temp','D.O. (mg/l)','CONDUCTIVITY (µmhos/cm)','B.O.D. (mg/l)','NITRATENAN N+ NITRITENANN (mg/l)','FECAL COLIFORM (MPN/100m1)']

for col in col_pruning:
 print("\a\n")
 coldescedf[col].describe()
 col_lower=coldesc[6]-coldesc[4]
 col_lower=coldesc[4]-(1.5*col_IQR)

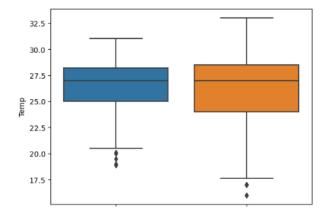
```
# Box plot for comparing the ph with other column and finding the outliers

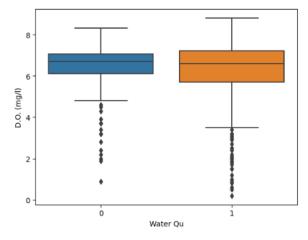
col_pruning=['Temp','D.O. (mg/l)','CONDUCTIVITY (µmhos/cm)','B.O.D. (mg/l)','NITRATENAN N+ NITRITENANN (mg/l)','FECAL COLIFORM (MPN/l00ml)']

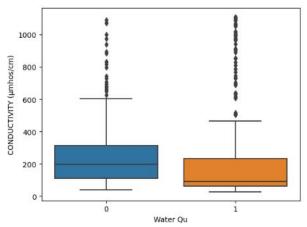
for col in col_pruning:
    print("\n\n")
    coldesc=df[col].describe()
    col_IQR=coldesc[6]-coldesc[4]
    col_Lower=coldesc[6]-coldesc[4]
    col_Higher=coldesc[6]+(1.5*col_IQR)

# print(col_Lower,col_Higher)
# df.drop(df.index[(df[col]col_Higher)],inplace=True,axis=0)
    df.drop(df.index[(df[col]col_Higher)],inplace=True,axis=0)
    sns.boxplot(x='Water Qu',y=df[col],data=df)
    plt.show()

print(df[col].describe())
```







Count 745.000000
mean 222.344966
std 243.275990
min 27.0000000
55% 59.000000
55% 120.000000
75% 274.000000
max 1110.000000
Name: CONDUCTIVITY (µmhos/cm), dtype: float64

Water Qu

486.000000 284.436214 383.079776 2.000000 22.000000 count mean std min 25% 50% 75% 25% 221.000000 50% 131.500000 75% 380.750000 max 1850.000000 Name: FECAL COLIFORM (MPN/100ml), dtype: float64

In [443... df.drop(['year'],inplace=True,axis=1)

In [444... df.drop(['STATION CODE','LOCATIONS','STATE','PH Range','Water Qu'],inplace=True,axis=1)

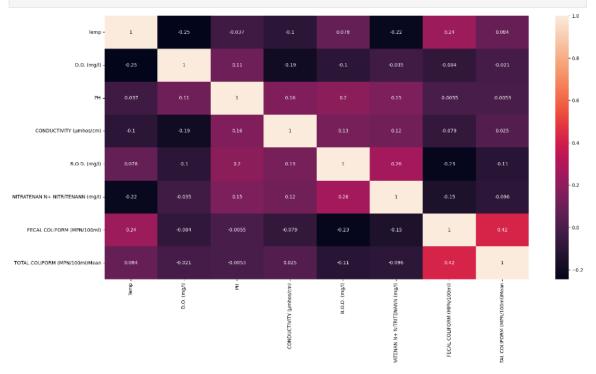
In [445... # transforming your data so that it fits within a specific scale

mm=MinMaxScaler()
df[1]=mm.fit_transform(df[1])
df.describe()

	Temp	D.O. (mg/l)	PH	CONDUCTIVITY (µmhos/cm)	B.O.D. (mg/l)	NITRATENAN N+ NITRITENANN (mg/l)	FECAL COLIFORM (MPN/100ml)	TOTAL COLIFORM (MPN/100ml)Mean
count	486.000000	486.000000	486.000000	486.000000	486.000000	486.000000	486.000000	486.000000
mean	0.600061	0.724280	0.813046	0.147103	0.307922	0.254203	0.152833	0.013122
std	0.157548	0.118957	0.101386	0.177769	0.204720	0.214196	0.207294	0.047275
min	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
25%	0.534091	0.695122	0.754386	0.038853	0.150000	0.095238	0.010823	0.001265
50%	0.629870	0.743902	0.807018	0.077706	0.233333	0.190476	0.070076	0.005544
75%	0.701299	0.792683	0.877193	0.184089	0.450000	0.351190	0.204951	0.014127
max	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000

w near map for finaing the correction between columns

plt.figure(figsize=(20,10))
sns.heatmap(df.corr(),annot=True)
plt.show()



Split the Data

In [449...

train and test date spliting

 $x_train, \ x_test, \ y_train, \ y_test= \ train_test_split(x, \ y, \ test_size= \ 0.25, \ random_state=42)$

In [450...

x_train

Out[450.

ð		Temp	D.O. (mg/l)	CONDUCTIVITY (µmhos/cm)	B.O.D. (mg/l)	NITRATENAN N+ NITRITENANN (mg/l)	FECAL COLIFORM (MPN/100ml)	TOTAL COLIFORM (MPN/100ml)Mean
	795	0.577922	0.804878	0.023127	0.083333	0.071429	0.160173	0.010290
	105	0.623377	0.560976	0.025902	0.083333	0.333333	0.091450	0.004655
	355	0.785714	0.573171	0.066605	0.450000	0.376190	0.056277	0.007819
	830	0.662338	0.682927	0.015726	0.100000	0.100000	0.385823	0.024496
	775	0.500000	0.768293	0.164662	0.350000	0.442857	0.000000	0.000768
				-			•	***
	226	0.642857	0.573171	0.730805	0.450000	0.476190	0.003788	0.000286
	532	0.545455	0.731707	0.037003	0.166667	0.252381	0.147727	0.010033
	661	0.415584	0.658537	0.407956	0.216667	0.204762	0.001623	0.000181
	808	0.584416	0.817073	0.024977	0.200000	0.195238	0.223485	0.013694
	220	0.629870	0.682927	0.127660	0.333333	0.000000	0.151515	0.005062

364 rows × 7 columns

In [451...

print(List(x_train.iloc[1]))

LinearRegression

Pickle

```
# Load the model into pickle for serializing and deserializing a Python object structure
In [463...
In [464...
               with open('model_pkl', 'wb') as files:
    pickle.dump(regressor, files)
with open('model_pkl' , 'rb') as f:
    lr = pickle.load(f)
                lr.predict([list(x_train.iloc[1])])
               C:\ProgramData\Anaconda3\lib\site-packages\sklearn\base.py:450: UserWarning: X does not have valid feature names, but LinearRegression was fitted with
               feature names
                warnings.warn(
Out[464... array([0.74676269])
In Γ465...
               with open('model_pkl', 'wb') as files:
    pickle.dump(clf_gini, files)
with open('model_pkl', 'rb') as f:
    lr = pickle.load(f)
lr.predict([list(x_train.iloc[1])])
               C:\ProgramData\Anaconda3\lib\site-packages\sklearn\base.py:450: UserWarning: X does not have valid feature names, but DecisionTreeRegressor was fitted
               with feature names
warnings.warn(
             array([0.73684211])
In [466...
               with open('model_pkl', 'wb') as files:
    pickle.dump(forest_model, files)
with open('model pkl' . 'rb') as f:
```