

PROJECT DOCUMENT – PHASE 3

WATER QUALITY ANALYSIS

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About Dataset

Context

Access to safe drinking-water is essential to health, a basic human right and a component of effective policy for health protection. This is important as a health and development issue at a national, regional and local level. In some regions, it has been shown that investments in water supply and sanitation can yield a net economic benefit, since the reductions in adverse health effects and health care costs outweigh the costs of undertaking the interventions.

Content

The water_potability.csv file contains water quality metrics for 3276 different water bodies.

1. pH value:

PH is an important parameter in evaluating the acid–base balance of water. It is also the indicator of acidic or alkaline condition of water status. WHO has recommended maximum permissible limit of pH from 6.5 to 8.5. The current investigation ranges were 6.52–6.83 which are in the range of WHO standards.

2. Hardness:

Hardness is mainly caused by calcium and magnesium salts. These salts are dissolved from geologic deposits through which water travels. The length of time water is in contact with hardness producing material helps determine how much hardness there is in raw water. Hardness was originally defined as the capacity of water to precipitate soap caused by Calcium and Magnesium.

3. Solids (Total dissolved solids - TDS):

Water has the ability to dissolve a wide range of inorganic and some organic minerals or salts such as potassium, calcium, sodium, bicarbonates, chlorides, magnesium, sulfates etc. These minerals produced un-wanted taste and diluted color in appearance of water. This is the important parameter for the use of water. The water with high TDS value indicates that water is highly mineralized. Desirable limit for TDS is 500 mg/l and maximum limit is 1000 mg/l which prescribed for drinking purpose.

4. Chloramines:

Chlorine and chloramine are the major disinfectants used in public water systems. Chloramines are most commonly formed when ammonia is added to chlorine to treat drinking water. Chlorine levels up to 4 milligrams per liter (mg/L or 4 parts per million (ppm)) are considered safe in drinking water.

5. Sulfate:

Sulfates are naturally occurring substances that are found in minerals, soil, and rocks. They are present in ambient air, groundwater, plants, and food. The principal commercial use of sulfate is in the chemical industry. Sulfate concentration in seawater is about 2,700 milligrams per liter (mg/L). It ranges from 3 to 30 mg/L in most freshwater supplies, although much higher concentrations (1000 mg/L) are found in some geographic locations.

6. Conductivity:

Pure water is not a good conductor of electric current rather's a good insulator. Increase in ions concentration enhances the electrical conductivity of water. Generally, the amount of dissolved solids in water determines the electrical conductivity. Electrical conductivity (EC) actually measures the ionic process of a solution that enables it to transmit current. According to WHO standards, EC value should not exceeded 400 $\mu\text{S}/\text{cm}$.

7. Organic_carbon:

Total Organic Carbon (TOC) in source waters comes from decaying natural organic matter (NOM) as well as synthetic sources. TOC is a measure of the total amount of carbon in organic compounds in pure water. According to US EPA < 2 mg/L as TOC in treated / drinking water, and < 4 mg/Lit in source water which is use for treatment.

8. Trihalomethanes:

THMs are chemicals which may be found in water treated with chlorine. The concentration of THMs in drinking water varies according to the level of organic material in the water, the

amount of chlorine required to treat the water, and the temperature of the water that is being treated. THM levels up to 80 ppm is considered safe in drinking water.

9. Turbidity:

The turbidity of water depends on the quantity of solid matter present in the suspended state. It is a measure of light emitting properties of water and the test is used to indicate the quality of waste discharge with respect to colloidal matter. The mean turbidity value obtained for Wondo Genet Campus (0.98 NTU) is lower than the WHO recommended value of 5.00 NTU.

10. Potability:

Indicates if water is safe for human consumption where 1 means Potable and 0 means Not potable.

Data Gathering

```
In [1]: import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

```
In [2]: df = pd.read_csv('C:\\Users\\Roshni\\Downloads\\archive\\water_potability.csv')
df.head()
```

Out[2]:

	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

Exploratory Data Analysis

```
In [3]: df.shape
```

Out[3]: (3276, 10)

```
In [4]: df.isnull().sum()
```

```
Out[4]: ph          491
Hardness          0
Solids            0
Chloramines       0
Sulfate           781
Conductivity      0
Organic_carbon    0
Trihalomethanes   162
Turbidity         0
Potability        0
dtype: int64
```

In [5]: 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 [6]: df.describe()

Out[6]:

	ph	Hardness	Solids	Chloramines	Sulfate	Conductivity	Organic_carbon	Trihalomethanes	Turbidity	Potability
count	2785.000000	3276.000000	3276.000000	3276.000000	2495.000000	3276.000000	3276.000000	3114.000000	3276.000000	3276.000000
mean	7.080795	196.369496	22014.092526	7.122277	333.775777	426.205111	14.284970	66.396293	3.966786	0.390110
std	1.594320	32.879761	8768.570828	1.583085	41.416840	80.824064	3.308162	16.175008	0.780382	0.487849
min	0.000000	47.432000	320.942611	0.352000	129.000000	181.483754	2.200000	0.738000	1.450000	0.000000
25%	6.093092	176.850538	15666.690297	6.127421	307.699498	365.734414	12.065801	55.844536	3.439711	0.000000
50%	7.036752	196.967627	20927.833607	7.130299	333.073546	421.884968	14.218338	66.622485	3.955028	0.000000
75%	8.062066	216.667456	27332.762127	8.114887	359.950170	481.792304	16.557652	77.337473	4.500320	1.000000
max	14.000000	323.124000	61227.196008	13.127000	481.030642	753.342620	28.300000	124.000000	6.739000	1.000000

In [7]: df.fillna(df.mean(), inplace=True)
df.isnull().sum()

Out[7]:

ph	0
Hardness	0
Solids	0
Chloramines	0
Sulfate	0
Conductivity	0
Organic_carbon	0
Trihalomethanes	0
Turbidity	0
Potability	0

dtype: int64

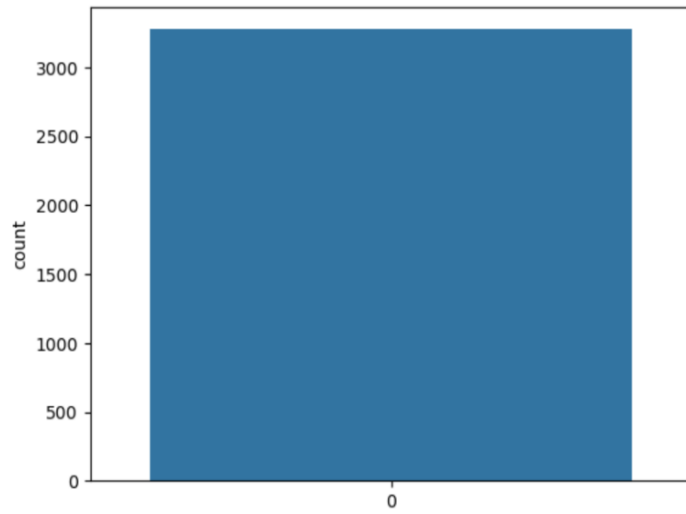
In [8]: df.Potability.value_counts()

Out[8]:

0	1998
1	1278

Name: Potability, dtype: int64

```
In [9]: sns.countplot(df['Potability'])  
plt.show()
```



```
In [10]: sns.distplot(df['ph'])  
plt.show()
```

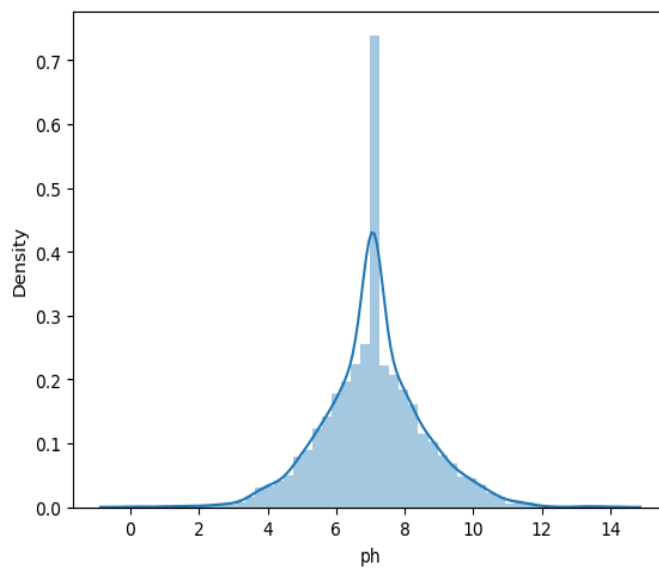
C:\Users\Roshni\AppData\Local\Temp\ipykernel_5356\3057384885.py:1: UserWarning:

'distplot' is a deprecated function and will be removed in seaborn v0.14.0.

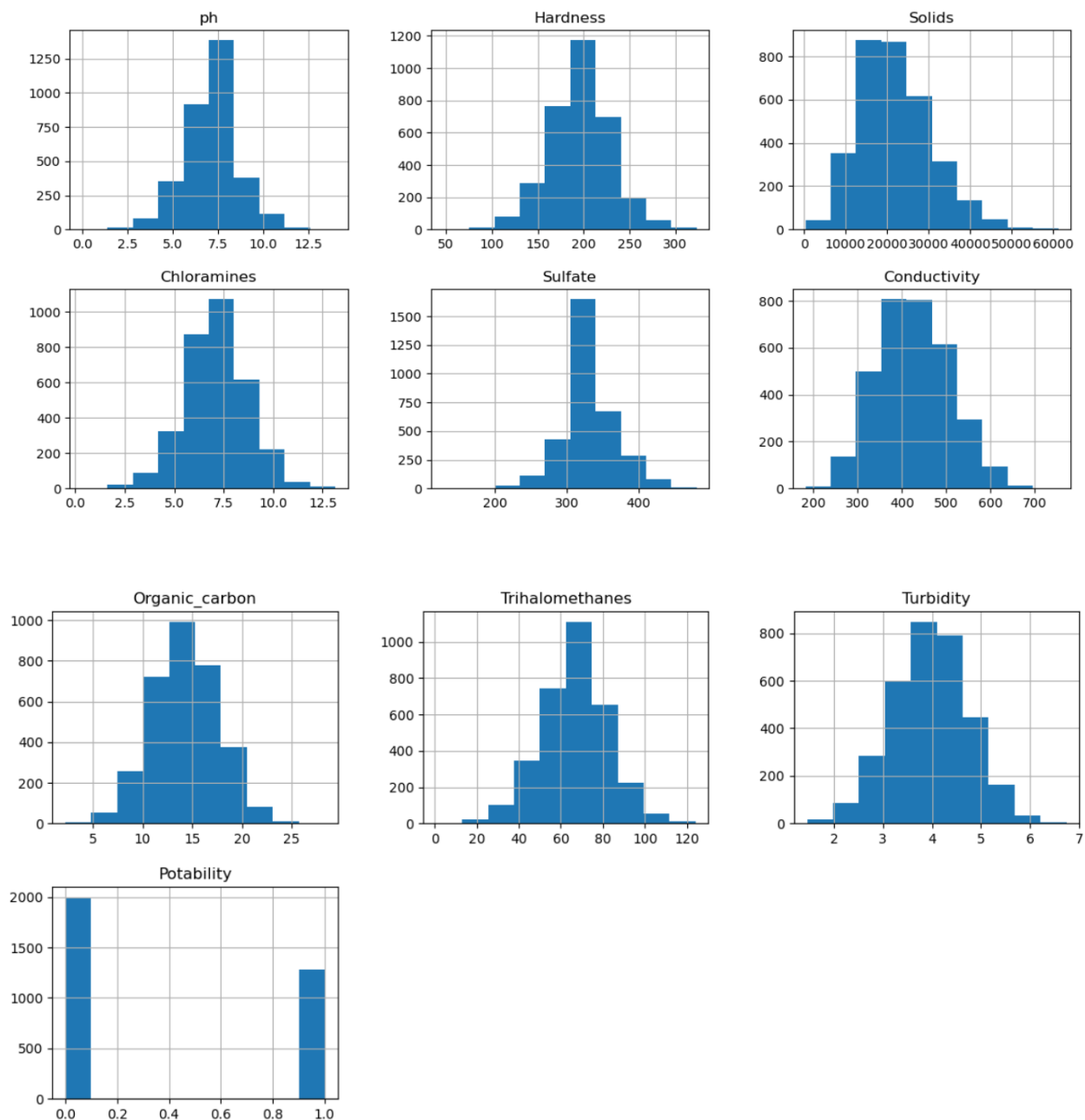
Please adapt your code to use either 'displot' (a figure-level function with similar flexibility) or 'histplot' (an axes-level function for histograms).

For a guide to updating your code to use the new functions, please see
<https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751>

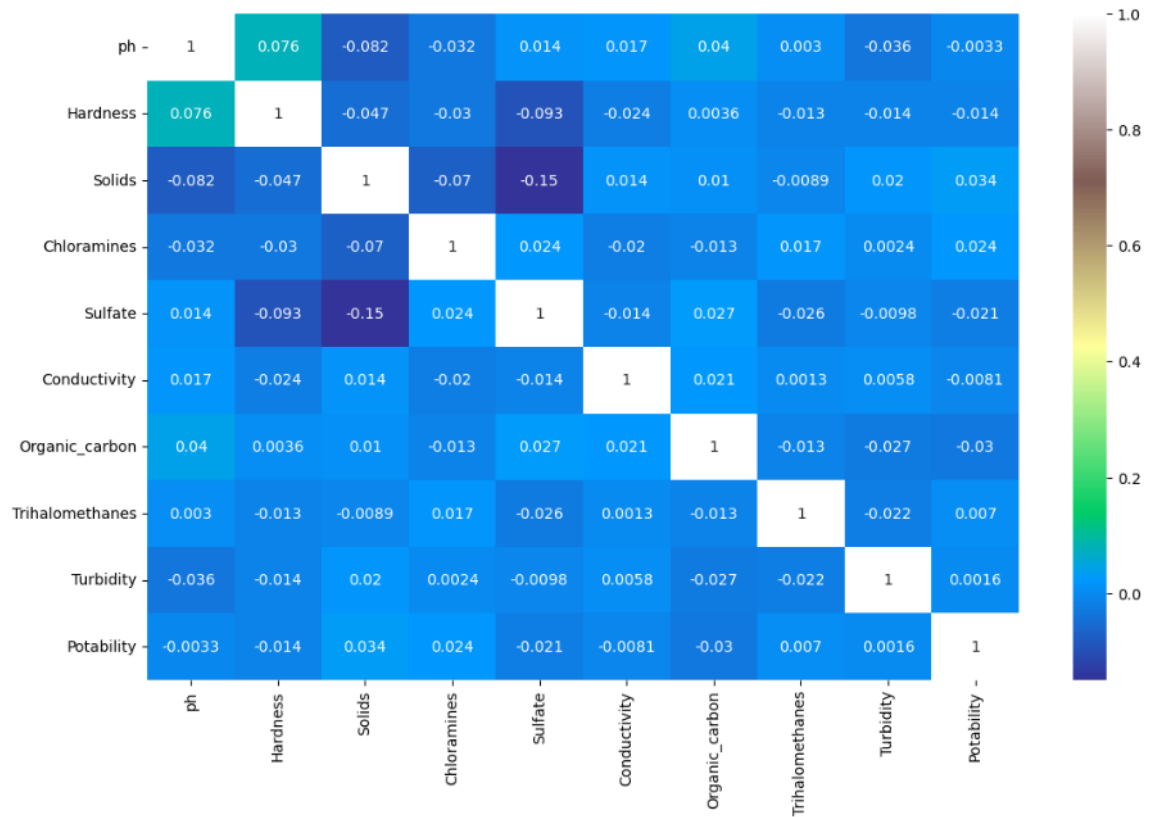
```
sns.distplot(df['ph'])
```



```
In [11]: df.hist(figsize=(14,14))  
plt.show()
```

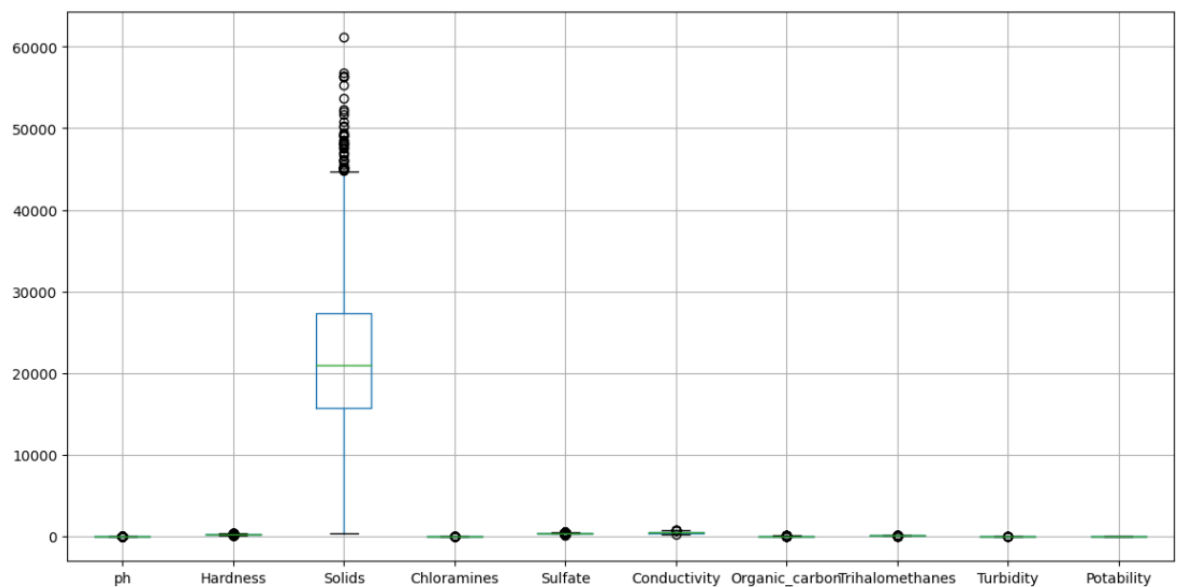


```
In [12]: plt.figure(figsize=(13,8))
sns.heatmap(df.corr(),annot=True,cmap='terrain')
plt.show()
```



```
In [13]: df.boxplot(figsize=(14,7))
```

Out[13]: <Axes: >



Train Decision Tree Classifier and checking accuracy

```
In [14]: X = df.drop('Potability',axis=1)
Y= df['Potability']
```

```
In [15]: from sklearn.model_selection import train_test_split
X_train, X_test, Y_train, Y_test = train_test_split(X,Y, test_size= 0.2, random_state=101,shuffle=True)
```

```
In [16]: from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import accuracy_score,confusion_matrix,classification_report
dt=DecisionTreeClassifier(criterion= 'gini', min_samples_split= 10, splitter= 'best')
dt.fit(X_train,Y_train)
```

```
Out[16]: ▾ DecisionTreeClassifier
DecisionTreeClassifier(min_samples_split=10)
```

```
In [17]: prediction=dt.predict(X_test)
print(f"Accuracy Score = {accuracy_score(Y_test,prediction)*100}")
print(f"Confusion Matrix =\n {confusion_matrix(Y_test,prediction)}")
print(f"Classification Report =\n {classification_report(Y_test,prediction)}")
```

```
Accuracy Score = 59.45121951219512
Confusion Matrix =
[[276 126]
 [140 114]]
Classification Report =
```

	precision	recall	f1-score	support
0	0.66	0.69	0.67	402
1	0.47	0.45	0.46	254
accuracy			0.59	656
macro avg	0.57	0.57	0.57	656
weighted avg	0.59	0.59	0.59	656

```
In [18]: res = dt.predict([[5.735724, 158.318741,25363.016594,7.728601,377.543291,568.304671,13.626624,75.952337,4.732954]])[0]
res
```

```
C:\ProgramData\anaconda3\lib\site-packages\sklearn\base.py:420: UserWarning: X does not have valid feature names, but DecisionTreeClassifier was fitted with feature names
warnings.warn(
```

```
Out[18]: 1
```

Apply hyper parameter tuning

```
In [20]: from sklearn.model_selection import RepeatedStratifiedKFold
from sklearn.model_selection import GridSearchCV

# define models and parameters
model = DecisionTreeClassifier()
criterion = ["gini", "entropy"]
splitter = ["best", "random"]
min_samples_split = [2,4,6,8,10,12,14]

# define grid search
grid = dict(splitter=splitter, criterion=criterion, min_samples_split=min_samples_split)
cv = RepeatedStratifiedKFold(n_splits=10, n_repeats=3, random_state=1)
grid_search_dt = GridSearchCV(estimator=model, param_grid=grid, n_jobs=-1, cv=cv,
                             scoring='accuracy',error_score=0)
grid_search_dt.fit(X_train, Y_train)
```

```
Out[20]: ▸ GridSearchCV
▸ estimator: DecisionTreeClassifier
▸ DecisionTreeClassifier
```



```

In [21]: print(f"Best: {grid_search_dt.best_score_:.3f} using {grid_search_dt.best_params_}")
means = grid_search_dt.cv_results_['mean_test_score']
stds = grid_search_dt.cv_results_['std_test_score']
params = grid_search_dt.cv_results_['params']

for mean, stdev, param in zip(means, stds, params):
    print(f"mean: {mean:.3f} (std: {stdev:.3f}) with: {param}")

print("Training Score:", grid_search_dt.score(X_train, Y_train)*100)
print("Testing Score:", grid_search_dt.score(X_test, Y_test)*100)

Best: 0.593 using {'criterion': 'gini', 'min_samples_split': 6, 'splitter': 'random'}
0.583 (0.030) with: {'criterion': 'gini', 'min_samples_split': 2, 'splitter': 'best'}
0.567 (0.026) with: {'criterion': 'gini', 'min_samples_split': 2, 'splitter': 'random'}
0.586 (0.031) with: {'criterion': 'gini', 'min_samples_split': 4, 'splitter': 'best'}
0.581 (0.023) with: {'criterion': 'gini', 'min_samples_split': 4, 'splitter': 'random'}
0.582 (0.033) with: {'criterion': 'gini', 'min_samples_split': 6, 'splitter': 'best'}
0.593 (0.031) with: {'criterion': 'gini', 'min_samples_split': 6, 'splitter': 'random'}
0.588 (0.034) with: {'criterion': 'gini', 'min_samples_split': 8, 'splitter': 'best'}
0.583 (0.031) with: {'criterion': 'gini', 'min_samples_split': 8, 'splitter': 'random'}
0.589 (0.029) with: {'criterion': 'gini', 'min_samples_split': 10, 'splitter': 'best'}
0.581 (0.028) with: {'criterion': 'gini', 'min_samples_split': 10, 'splitter': 'random'}
0.588 (0.028) with: {'criterion': 'gini', 'min_samples_split': 12, 'splitter': 'best'}
0.581 (0.029) with: {'criterion': 'gini', 'min_samples_split': 12, 'splitter': 'random'}
0.590 (0.025) with: {'criterion': 'gini', 'min_samples_split': 14, 'splitter': 'best'}
0.591 (0.030) with: {'criterion': 'gini', 'min_samples_split': 14, 'splitter': 'random'}
0.583 (0.032) with: {'criterion': 'entropy', 'min_samples_split': 2, 'splitter': 'best'}
0.571 (0.027) with: {'criterion': 'entropy', 'min_samples_split': 2, 'splitter': 'random'}
0.584 (0.029) with: {'criterion': 'entropy', 'min_samples_split': 4, 'splitter': 'best'}
0.578 (0.033) with: {'criterion': 'entropy', 'min_samples_split': 4, 'splitter': 'random'}
0.587 (0.028) with: {'criterion': 'entropy', 'min_samples_split': 6, 'splitter': 'best'}
0.589 (0.024) with: {'criterion': 'entropy', 'min_samples_split': 6, 'splitter': 'random'}
0.587 (0.028) with: {'criterion': 'entropy', 'min_samples_split': 8, 'splitter': 'best'}
0.580 (0.031) with: {'criterion': 'entropy', 'min_samples_split': 8, 'splitter': 'random'}
0.588 (0.026) with: {'criterion': 'entropy', 'min_samples_split': 10, 'splitter': 'best'}
0.586 (0.027) with: {'criterion': 'entropy', 'min_samples_split': 10, 'splitter': 'random'}
0.588 (0.032) with: {'criterion': 'entropy', 'min_samples_split': 12, 'splitter': 'best'}
0.593 (0.026) with: {'criterion': 'entropy', 'min_samples_split': 12, 'splitter': 'random'}
0.587 (0.031) with: {'criterion': 'entropy', 'min_samples_split': 14, 'splitter': 'best'}
0.590 (0.023) with: {'criterion': 'entropy', 'min_samples_split': 14, 'splitter': 'random'}
Training Score: 90.64885496183206
Testing Score: 56.40243902439024

```