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Reg No :- 23122110
Class :- 3MScDS B

Water Quality Classification Using KNN

Dataset Used :- Click Here

In this project, we aim to classify the potability of water samples using the K-Nearest Neighbors (KNN) algorithm. Ensuring safe and potable water is crucial for public health, and machine learning techniques can provide valuable insights and predictions about water quality based on various chemical and physical attributes.

By utilizing a dataset from Kaggle, we preprocess the data, standardize the features, and explore the optimal parameters for the KNN model. The KNN algorithm is a simple yet effective method for classification tasks, making it an ideal choice for this water quality classification problem. Through cross-validation and parameter tuning, we aim to achieve a robust model that can accurately predict whether a given water sample is drinkable or not.

Credits :- ChatGPT(For Commenting and Understanding Bugs)

References :-Elastic

In [ ]:
```
#Importing All Libraries
import numpy as np
import matplotlib.pyplot as plt
from sklearn.neighbors import KNeighborsClassifier
import pandas as pd
import seaborn as sns
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import classification_report, confusion_matrix
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import train_test_split
```

In [ ]:
```
#Reaading the Dataset
df = pd.read_csv('water_potability.csv')
df.head()
```

Out[ ]:

	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

In [ ]:
```
#Checking is there any Missing Values
missing_values = df.isnull().sum()
print(missing_values)
```

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

In [ ]:
```
#Replacing the Numerical rows if there is any Missing Values in that entire Column
def replace_NAN(d):
    missing_values = d.isnull().sum()
    means = d.mean()
    for col in d.columns:
        if missing_values[col] > 0:
            d[col].fillna(means[col], inplace=True)
    return d
```

In [ ]:
```
#Printing the Average of all Columns
means = df.mean()
print(means)
```

```
ph                   7.080795
Hardness           196.369496
Solids           22014.092526
Chloramines          7.122277
Sulfate            333.775777
Conductivity       426.205111
Organic_carbon      14.284970
Trihalomethanes     66.396293
Turbidity            3.966786
Potability           0.390110
dtype: float64
```

In [ ]:
```
df = replace_NAN(df)
```

In [ ]:
```
missing_values = df.isnull().sum()
print(missing_values)
```

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

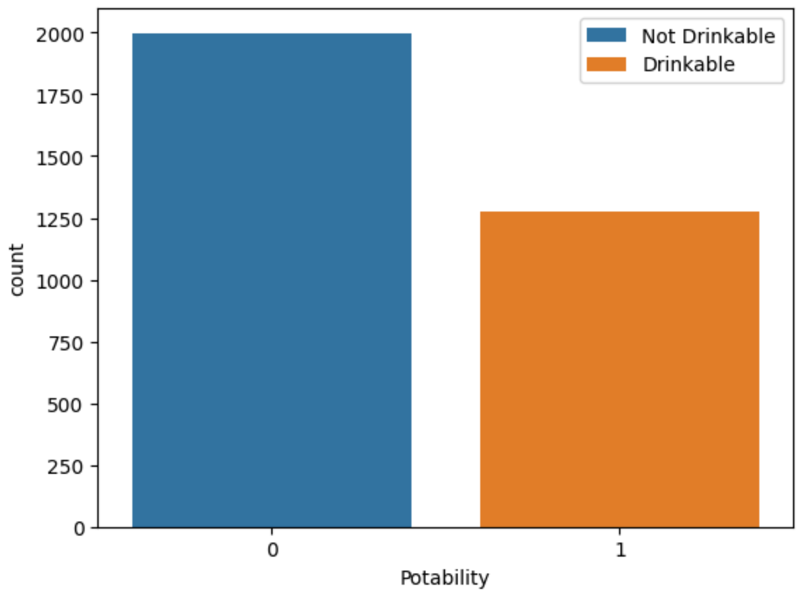
In [ ]:
```
#Descriptive Statistics
df.describe()
```

Out[ ]:

	ph	Hardness	Solids	Chloramines	Sulfate	Conductivity	Organic_carbon	Trihalomethanes	Turbidit
count	3276.000000	3276.000000	3276.000000	3276.000000	3276.000000	3276.000000	3276.000000	3276.000000	3276.00000
mean	7.080795	196.369496	22014.092526	7.122277	333.775777	426.205111	14.284970	66.396293	3.96678
std	1.469956	32.879761	8768.570828	1.583085	36.142612	80.824064	3.308162	15.769881	0.78038
min	0.000000	47.432000	320.942611	0.352000	129.000000	181.483754	2.200000	0.738000	1.45000
25%	6.277673	176.850538	15666.690297	6.127421	317.094638	365.734414	12.065801	56.647656	3.43971
50%	7.080795	196.967627	20927.833607	7.130299	333.775777	421.884968	14.218338	66.396293	3.95502
75%	7.870050	216.667456	27332.762127	8.114887	350.385756	481.792304	16.557652	76.666609	4.50032
max	14.000000	323.124000	61227.196008	13.127000	481.030642	753.342620	28.300000	124.000000	6.73900

In [ ]:
```
# Create a count plot for 'Potability', with different colors for each category.
sns.countplot(data=df, x='Potability', hue='Potability')

# Set custom legend labels: 'Not Drinkable' and 'Drinkable'.
plt.legend(labels=['Not Drinkable', 'Drinkable'])
```

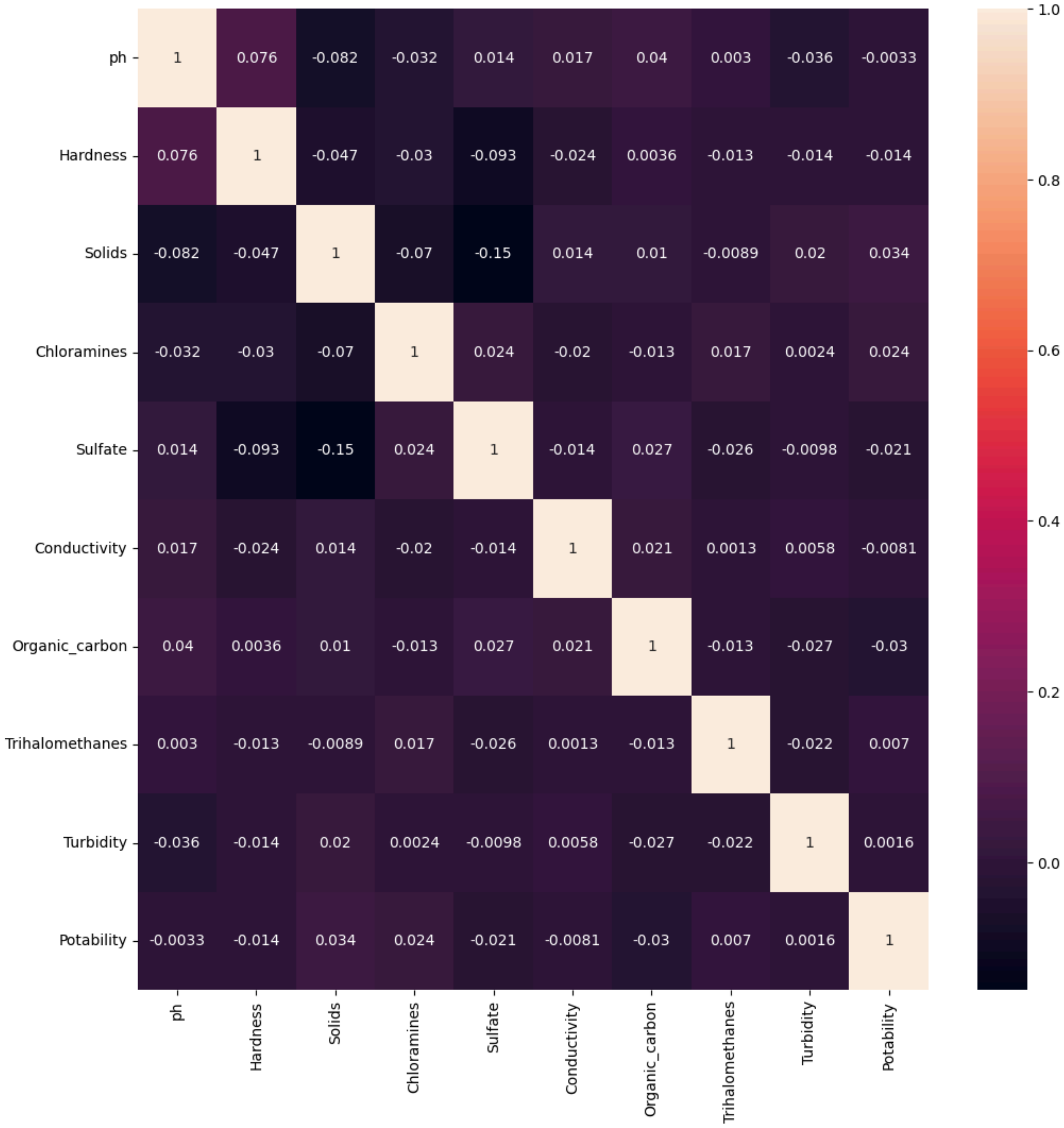
Out[ ]: <matplotlib.legend.Legend at 0x1e48280a650>



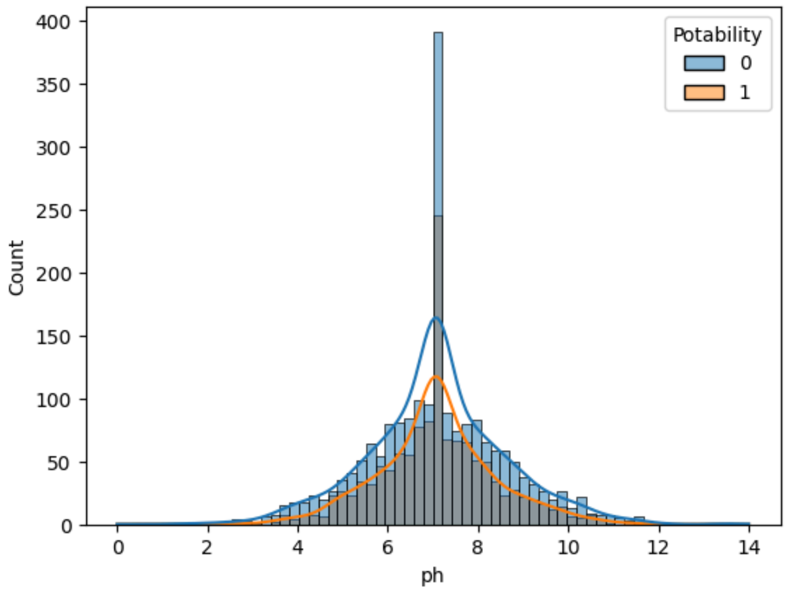
In [ ]:
```
# Calculate the correlation matrix for the DataFrame 'df'.
cor = df.corr()
```

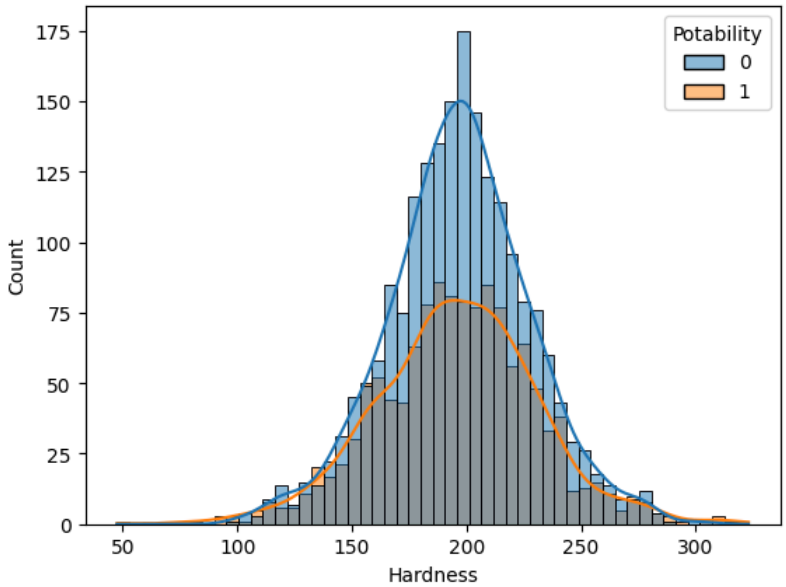
```python
# Create a new figure for the plot with a size of 12x12 inches.
plt.figure(figsize=(12, 12))

# Create a heatmap of the correlation matrix.
# annot=True adds the correlation coefficient values to the heatmap cells.
sns.heatmap(cor, annot=True)
```

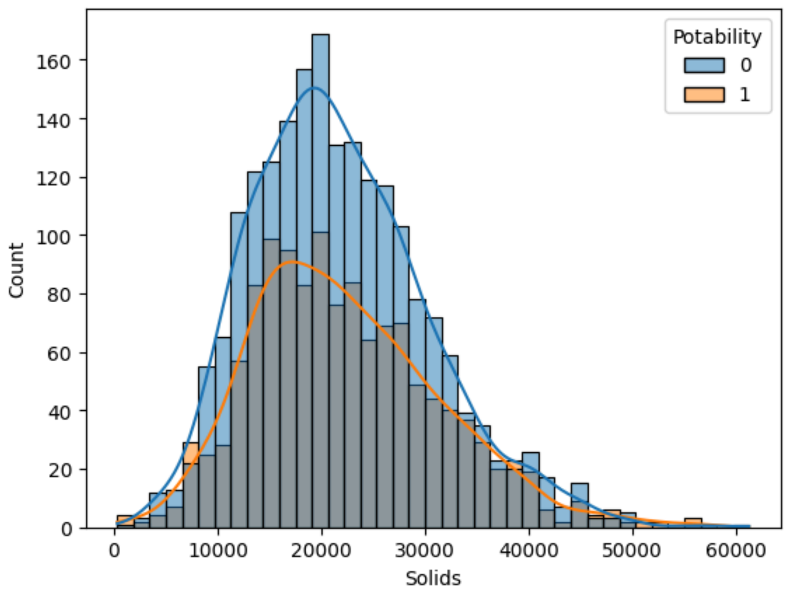
Out[ ]: <Axes: >

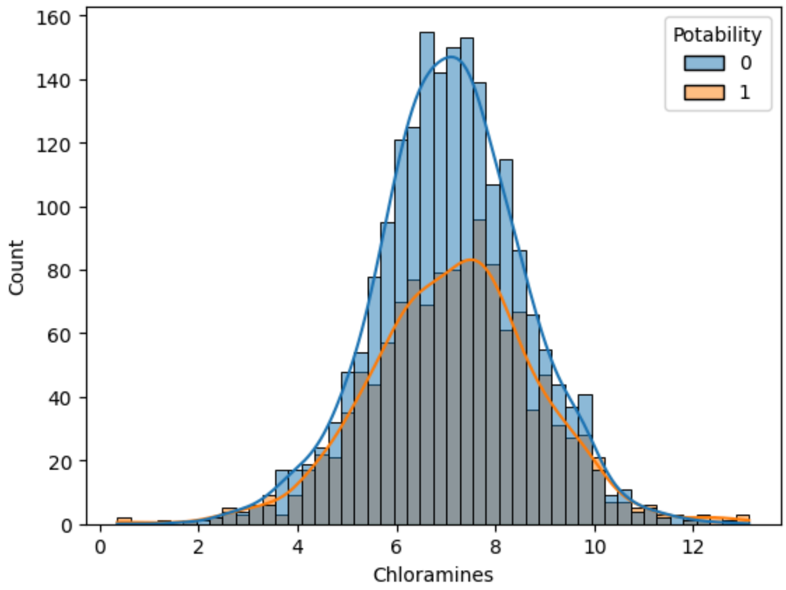


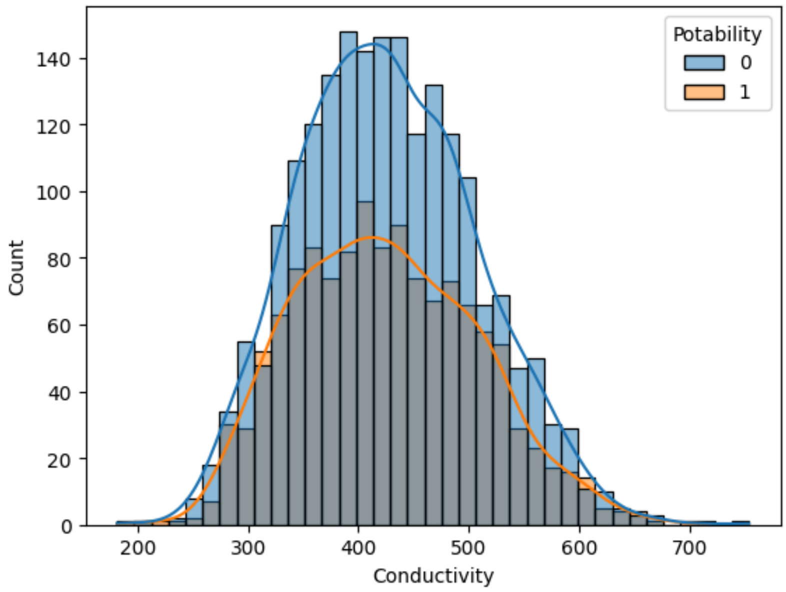
In [ ]:
```python
# Loop through each column in the DataFrame.
for col in df.columns:
    # Create a histogram with a kernel density estimate (kde) for each column, colored by 'Potability'.
    sns.histplot(data=df, x=col, kde=True, hue='Potability')
    # Show the plot.
    plt.show()
```

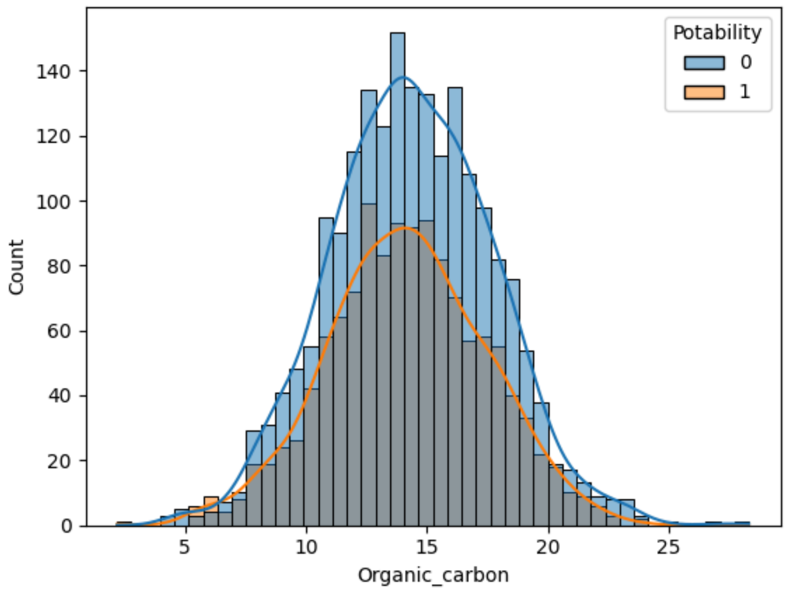

Potability
0
1
Count
ph
0
2
4
6
8
10
12
14
0
50
100
150
200
250
300
350
400

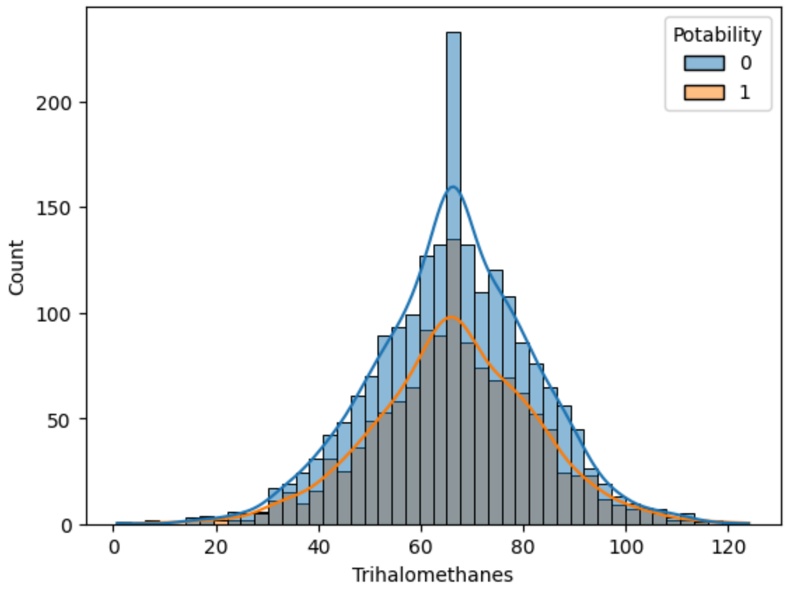

Potability
0
1
Count
Hardness
50
100
150
200
250
300
0
25
50
75
100
125
150
175

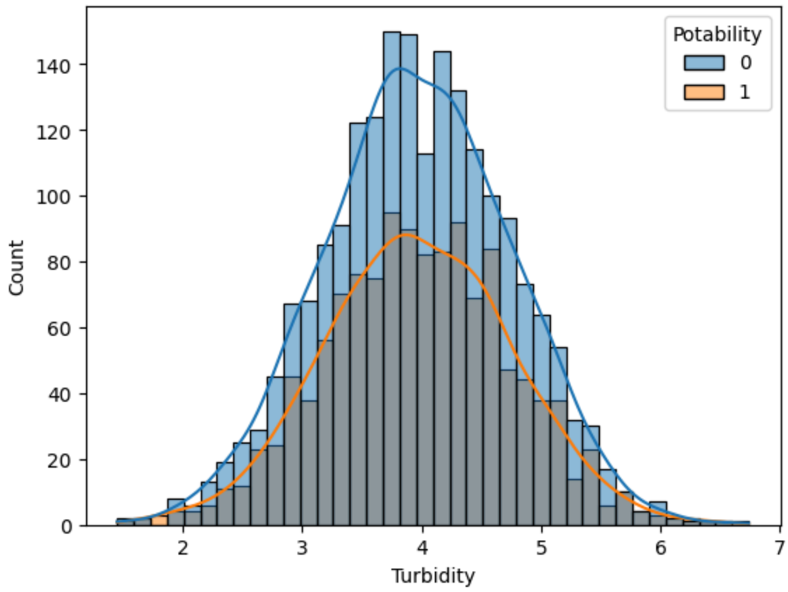

Potability
0
1
Count
Solids
0
10000
20000
30000
40000
50000
60000
0
20
40
60
80
100
120
140
160

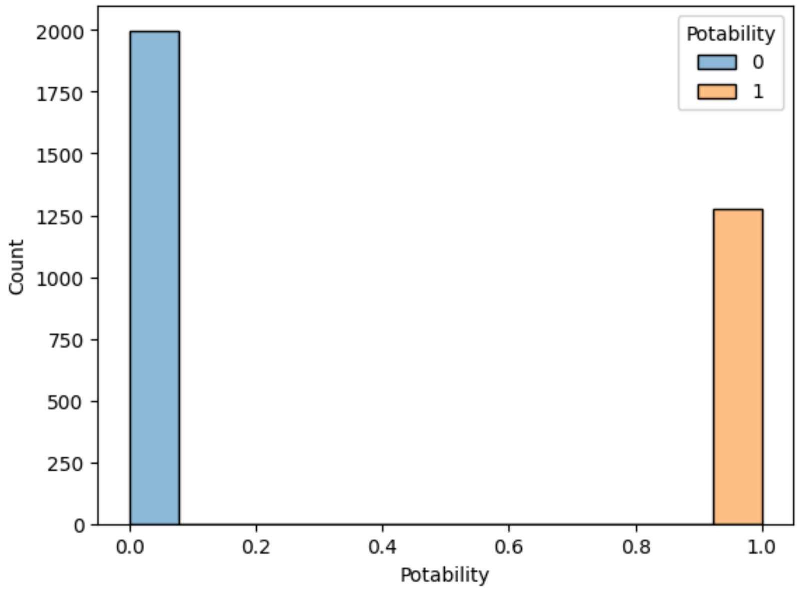

Potability
0
1
Count
Chloramines


Potability
0
1
Count
Conductivity


Potability
0
1
Count
Organic_carbon





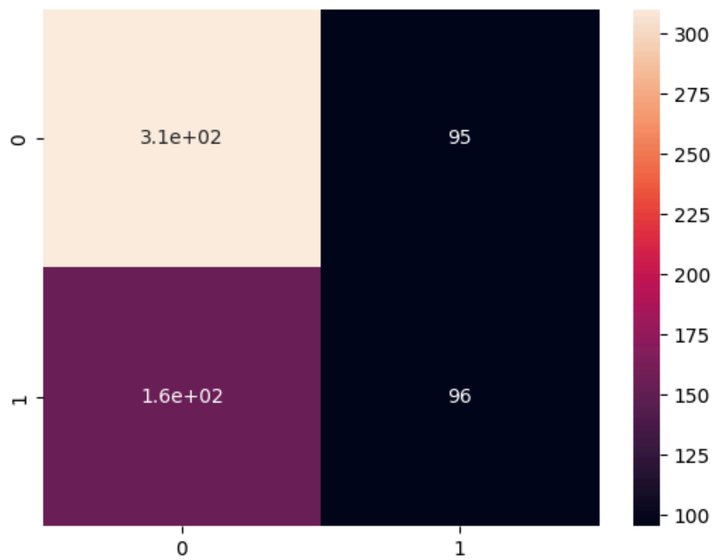


In [ ]:

```
#Most of the attributes follow normal distribution

def train_eval(data):

        # Shuffle the data and separate features (data_x) and target (data_y).
    data = data.sample(frac=1)
    data_x = data.iloc[:, :-1]
    data_y = data.iloc[:, -1]
```

```
    # Standardize the features.
    scaler = StandardScaler()
    data_x = pd.DataFrame(scaler.fit_transform(data_x), columns=data_x.columns)

    # Split the data into training and testing sets.
    x_train, x_test, y_train, y_test = train_test_split(data_x, data_y, test_size=0.2, random_state=41)

    # Train the KNeighborsClassifier model.
    model = KNeighborsClassifier()
    model.fit(x_train, y_train)

    # Evaluate the model.
    predictions = model.predict(x_test)
    report = classification_report(y_test, predictions)
    print(report)

    # Plot the confusion matrix.
    matrix = confusion_matrix(y_test, predictions)
    sns.heatmap(matrix, annot=True)

# Call the function with the DataFrame 'df'.
train_eval(df)
```

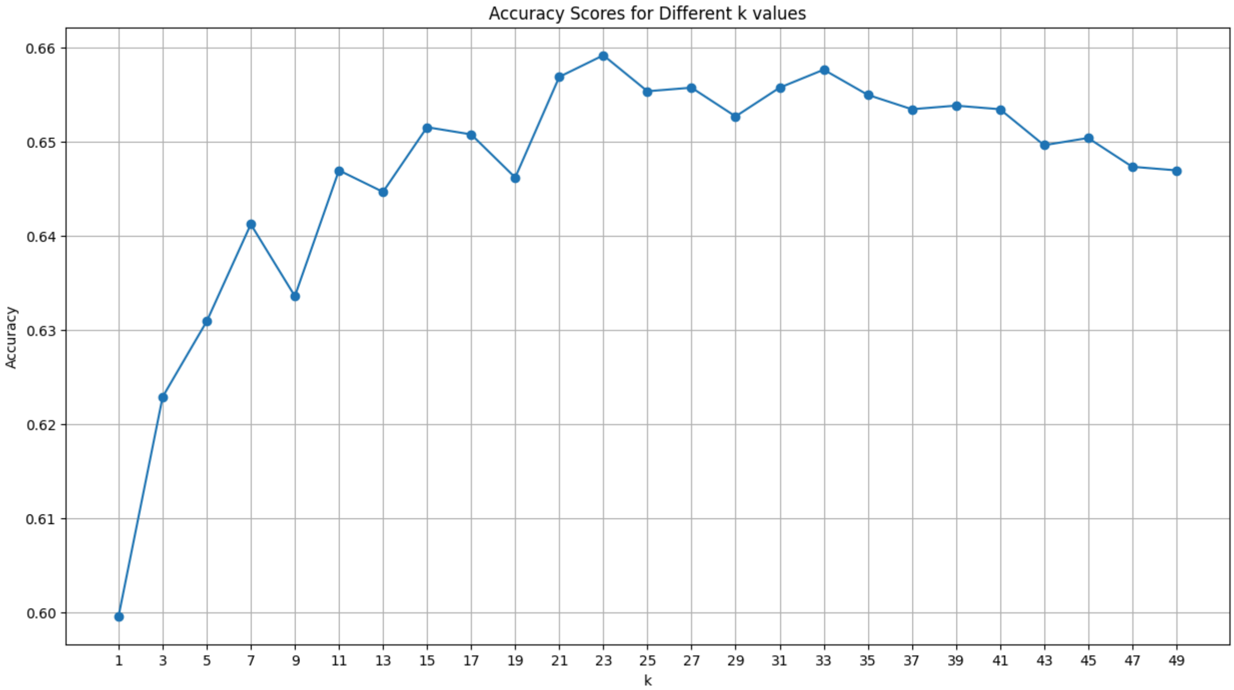
```
              precision    recall  f1-score   support

           0       0.67      0.77      0.71       405
           1       0.50      0.38      0.43       251

    accuracy                           0.62       656
   macro avg       0.58      0.57      0.57       656
weighted avg       0.60      0.62      0.61       656
```



In [ ]:

```
# Shuffle the data and separate features (data_x) and target (data_y).
data = df.sample(frac=1)
data_x = data.iloc[:, :-1]
data_y = data.iloc[:, -1]

# Standardize the features.
scaler = StandardScaler()
data_x = pd.DataFrame(scaler.fit_transform(data_x), columns=data_x.columns)

# Split the data into training and testing sets.
x_train, x_test, y_train, y_test = train_test_split(data_x, data_y, test_size=0.2, random_state=41)

# List of odd k values from 1 to 50.
k_values = list(range(1, 51, 2))
accu = []

# Evaluate KNeighborsClassifier for each k using cross-validation.
for k in k_values:
    m = KNeighborsClassifier(n_neighbors=k)
    scores = cross_val_score(m, x_train, y_train, cv=10, scoring='accuracy')
    accu.append(scores.mean())

# Plot accuracy scores versus k values.
plt.figure(figsize=(15, 8))
plt.plot(k_values, accu, marker='o')
plt.xlabel('k')
plt.ylabel('Accuracy')
plt.xticks(k_values)
```

```
plt.title('Accuracy Scores for Different k values')
plt.grid(True)
plt.show()
```



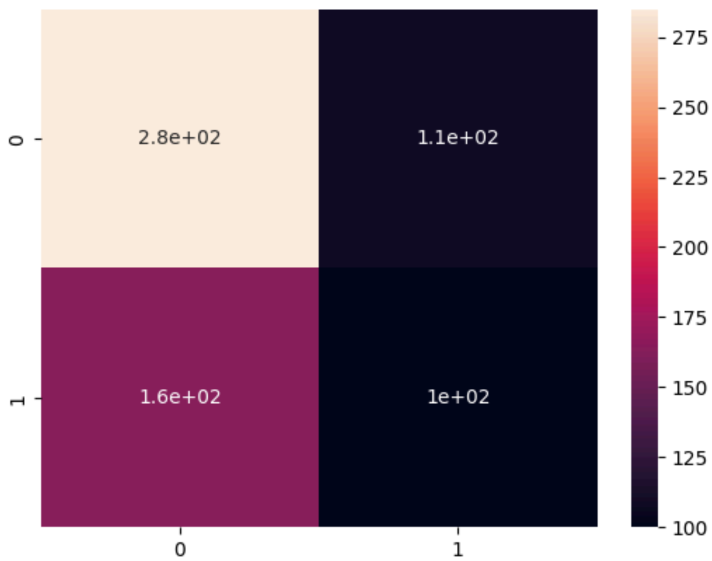
In [ ]:
```
df = df.drop(columns = 'Sulfate', axis =1 )
df.head(5)
```

Out[ ]:

	ph	Hardness	Solids	Chloramines	Conductivity	Organic_carbon	Trihalomethanes	Turbidity	Potability
0	7.080795	204.890455	20791.318981	7.300212	564.308654	10.379783	86.990970	2.963135	0
1	3.716080	129.422921	18630.057858	6.635246	592.885359	15.180013	56.329076	4.500656	0
2	8.099124	224.236259	19909.541732	9.275884	418.606213	16.868637	66.420093	3.055934	0
3	8.316766	214.373394	22018.417441	8.059332	363.266516	18.436524	100.341674	4.628771	0
4	9.092223	181.101509	17978.986339	6.546600	398.410813	11.558279	31.997993	4.075075	0

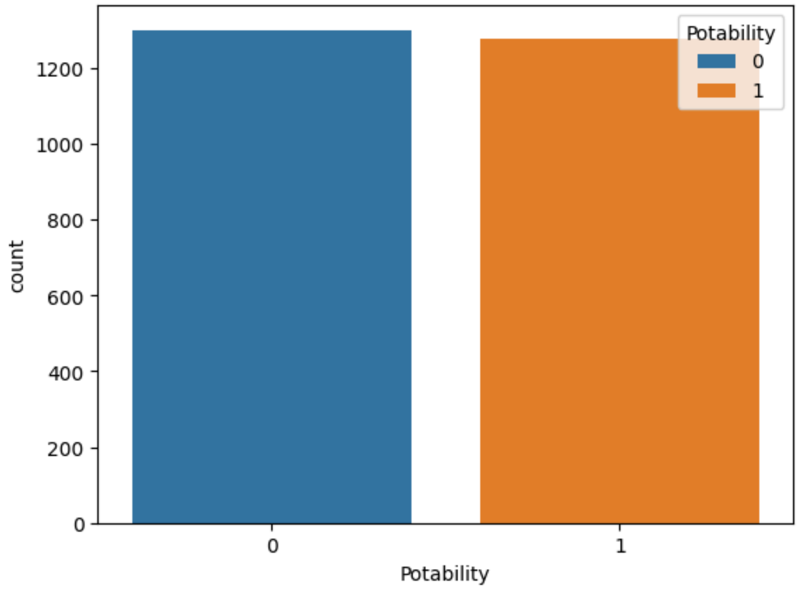
In [ ]:
```
train_eval(df)
```

```
              precision    recall  f1-score   support

           0       0.64      0.73      0.68       393
           1       0.48      0.38      0.42       263

    accuracy                           0.59       656
   macro avg       0.56      0.55      0.55       656
weighted avg       0.57      0.59      0.58       656
```



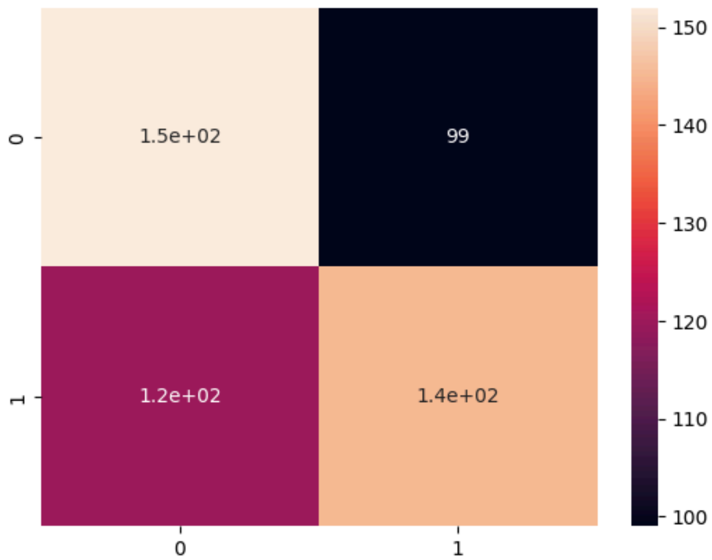
In [ ]:
```
#Lets tackle class imbalance problem, by downsampaling not drinkable instances(np)

p = data[data['Potability']==1]
not_p = data[data['Potability']==0]
sampled_data = not_p.sample(n=1300)

#Shuffle the sampled data
data_new = pd.concat([p, sampled_data], axis =0)
#shuffle
s_data = data_new.sample(frac=1)
s_data.head()

sns.countplot(data=s_data, x= 'Potability', hue= 'Potability')
```

Out[ ]:
```
<Axes: xlabel='Potability', ylabel='count'>
```



In [ ]:
```
train_eval(s_data)
```

```
              precision    recall  f1-score   support

           0       0.56      0.61      0.58       251
           1       0.59      0.55      0.57       265

    accuracy                           0.58       516
   macro avg       0.58      0.58      0.58       516
weighted avg       0.58      0.58      0.58       516
```

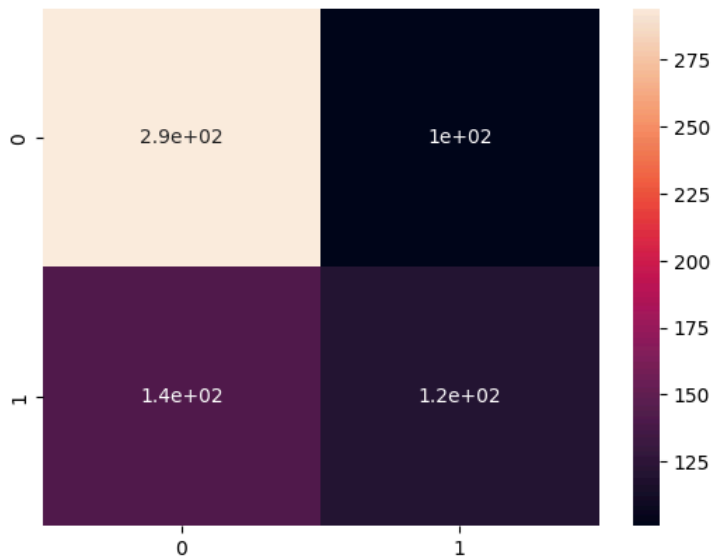


In [ ]:
```
data_x= data.iloc[:, :-1]
data_y = data.iloc[:,-1]
scaler = StandardScaler()
data_x = pd.DataFrame(scaler.fit_transform(data_x), columns = data_x.columns)

#test train split
x_train, x_test, y_train, y_test = train_test_split(data_x, data_y, test_size = 0.2, random_state=41)
```

```
#model creation
model = KNeighborsClassifier(metric = 'cosine')
model.fit(x_train, y_train)

#evaluation
predictions = model.predict(x_test)
report = classification_report(y_test, predictions)
print(report)
matrix = confusion_matrix(y_test, predictions)
sns.heatmap(matrix, annot= True)
```

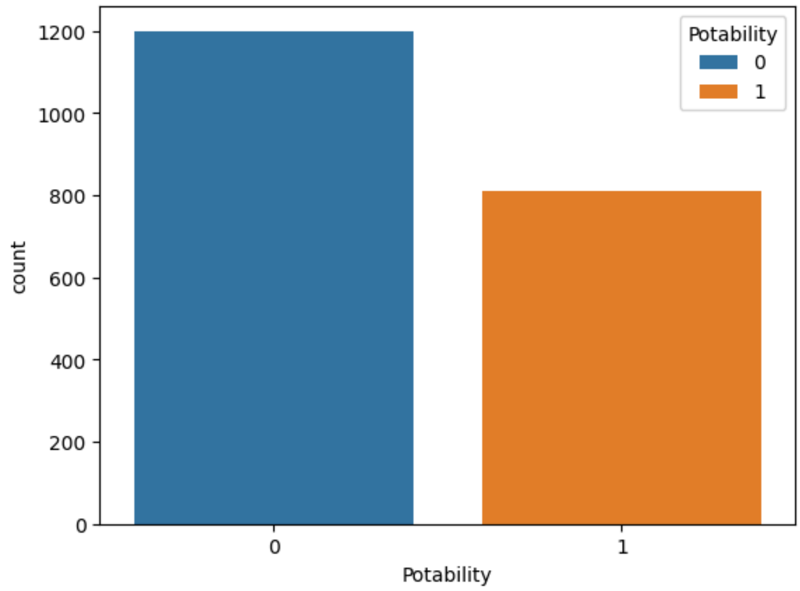
```
              precision    recall  f1-score   support

           0       0.68      0.74      0.71       395
           1       0.54      0.46      0.50       261

    accuracy                           0.63       656
   macro avg       0.61      0.60      0.60       656
weighted avg       0.62      0.63      0.62       656
```

Out[ ]: <Axes: >



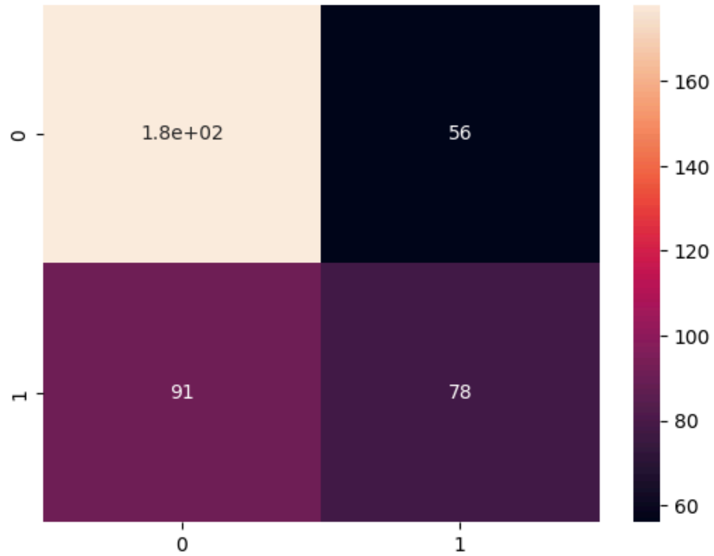
In [ ]:
```
# Lets try dropping all the rows with missing values
data = pd.read_csv('water_potability.csv')
data.dropna(inplace =True)

sns.countplot(data=data, x = 'Potability', hue = 'Potability' )
print(data.shape)
```

```
(2011, 10)
```

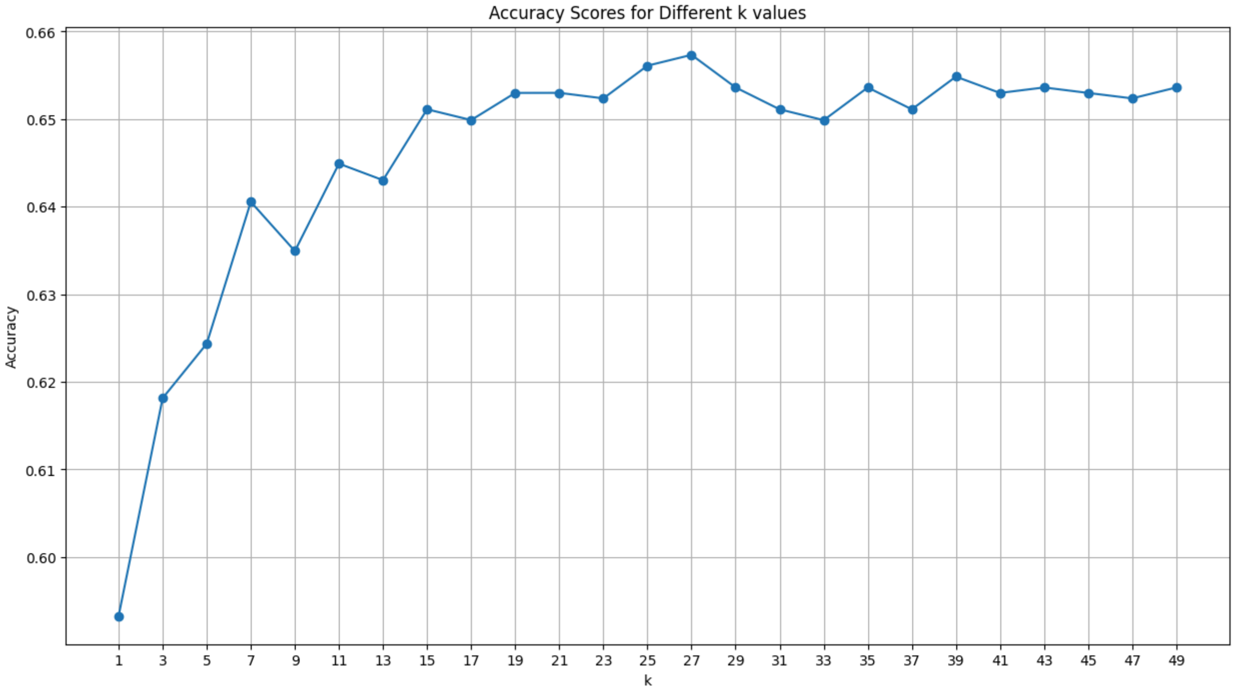


In [ ]:
```
train_eval(data)
```

```
              precision    recall  f1-score   support

           0       0.66      0.76      0.71       234
           1       0.58      0.46      0.51       169

    accuracy                           0.64       403
   macro avg       0.62      0.61      0.61       403
weighted avg       0.63      0.64      0.63       403
```



In [ ]:
```
data = data.sample(frac=1)
data_x= data.iloc[:, :-1]
data_y = data.iloc[:,-1]
scaler = StandardScaler()
data_x = pd.DataFrame(scaler.fit_transform(data_x), columns = data_x.columns)

#test train split
x_train, x_test, y_train, y_test = train_test_split(data_x, data_y, test_size = 0.2, random_state=41)




k_values = list(range(1,51, 2))
accu = []
for k in k_values:
    m = KNeighborsClassifier(n_neighbors =k)
    scores = cross_val_score(m, x_train, y_train, cv=10,  scoring='accuracy')
    accu.append(scores.mean())

# Plotting accuracy scores versus k values
plt.figure(figsize =(15,8))
plt.plot(k_values, accu, marker='o')
plt.xlabel('k')
plt.ylabel('Accuracy')
plt.xticks(k_values)
plt.title('Accuracy Scores for Different k values')
plt.grid(True)
plt.show()
```


Accuracy Scores for Different k values
Accuracy
0.66
0.65
0.64
0.63
0.62
0.61
0.60
k
1
3
5
7
9
11
13
15
17
19
21
23
25
27
29
31
33
35
37
39
41
43
45
47
49