#### Finding important features from the original dataset

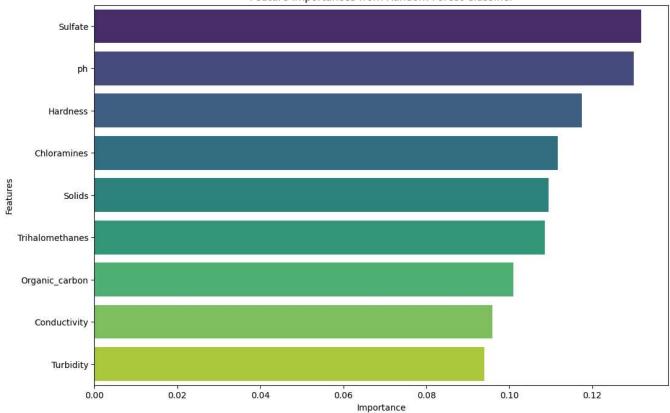
```
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
import warnings
warnings.filterwarnings("ignore")
# Loading the original dataset
data = pd.read_csv('/content/water_potability (1).csv')
# Splitting the dataset into features and target variable
X = data.drop('Potability', axis=1)
y = data['Potability']
\ensuremath{\text{\#}} Spliting the data into training and testing sets
 X\_train, \ X\_test, \ y\_train, \ y\_test = train\_test\_split(X, \ y, \ test\_size=0.2, \ random\_state=42) 
# Creating a Random Forest Classifier
model = RandomForestClassifier(n_estimators=100, random_state=42)
model.fit(X_train, y_train)
# Getting feature importances
importances = model.feature_importances_
# Creating a DataFrame for feature importances
feature\_importances = pd.DataFrame(importances, index=X.columns, columns=['importance']).sort\_values('importance', ascending=False)
# Selecting the top 4 features
top_features = feature_importances.head(4).index.tolist()
# Creating a new DataFrame with the top features and the target column
top_features_with_target = data[top_features + ['Potability']]
# Saving the new DataFrame to a CSV file for further use
top_features_with_target.to_csv('top_4_features_with_target.csv', index=False)
print("Top 4 features along with the target column saved to 'top_4_features_with_target.csv'")
Top 4 features along with the target column saved to 'top_4_features_with_target.csv'
```

# Visualization: Bar Plot of all feature importances

```
import matplotlib.pyplot as plt
import seaborn as sns
feature_importances = pd.DataFrame(importances, index=X.columns, columns=['importance']).sort_values('importance', ascending=False)
plt.figure(figsize=(12, 8))
sns.barplot(x=feature_importances['importance'], y=feature_importances.index, palette='viridis')
plt.title('Feature Importances from Random Forest Classifier')
plt.xlabel('Importance')
plt.ylabel('Features')
plt.show()
```

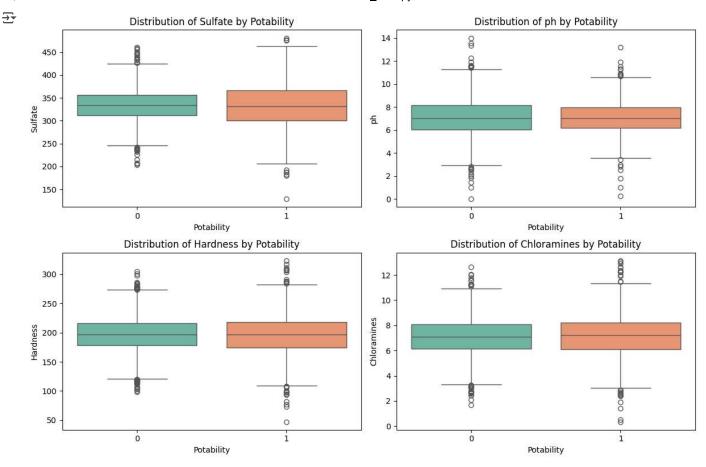






## Box Plot for each of the top features against the target variable

```
plt.figure(figsize=(12, 8))
for i, feature in enumerate(top_features):
    plt.subplot(2, 2, i + 1) # Create a 2x2 grid of subplots
    sns.boxplot(x='Potability', y=feature, data=top_features_with_target, palette='Set2')
    plt.title(f'Distribution of {feature} by Potability')
    plt.xlabel('Potability')
    plt.ylabel(feature)
plt.tight_layout()
plt.show()
```



# Importing necessary libraries

```
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import confusion_matrix, accuracy_score, f1_score, recall_score, precision_score, classification_report
from sklearn.naive_bayes import GaussianNB
from sklearn import svm
from sklearn.neighbors import KNeighborsClassifier
import pickle
```

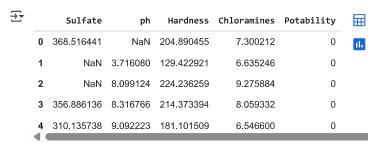
#### Function to calculate binary features for the new dataset

# Loading the new dataset

```
data = pd.read_csv('/content/top_4_features_with_target.csv')
```

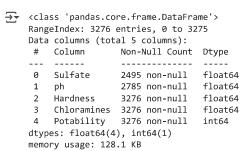
## Previewing Data with Pandas

data.head()

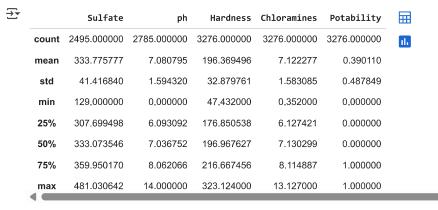


## Understanding the data

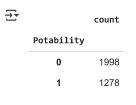
data.info()



data.describe()



data['Potability'].value\_counts()



## Filling missing values with column means

data.fillna(data.mean(),inplace=True)

## Binary features calculation

data = calculate\_binary\_features(data)
print(data)

<b>→</b> ▼		Sulfate	ph	Hardness	Chloramines	Potability	is_ph_ok	١
	0	368.516441	7.080795	204.890455	7.300212	0	1	
	1	333.775777	3.716080	129.422921	6.635246	0	0	
	2	333.775777	8.099124	224.236259	9.275884	0	1	
	3	356.886136	8.316766	214.373394	8.059332	0	1	

```
4
      310.135738 9.092223 181.101509
                                            6.546600
                                                               0
3271 359.948574 4.668102 193.681735
                                           7.166639
                                                                         0
     333.775777 7.808856 193.553212
                                            8.061362
                                                                         1
3273
     333.775777 9.419510 175.762646
                                           7.350233
                                                               1
3274 333.775777 5.126763 230.603758
                                           6.303357
                                                                         0
                                                               1
3275 333.775777 7.874671 195.102299
                                           7.509306
      is\_Hardness\_ok \quad is\_Chloramines\_ok \quad is\_Sulfate\_ok
0
                   0
                                      0
1
                   1
                                      0
                                                      0
2
                   0
                                      0
                                                      0
3
                   0
                                      0
                                                      0
4
                  1
                                      0
                                                      0
3271
                   1
                                      0
                                                      0
3272
                                      0
                   1
                                                      0
                                      0
3273
                                                      0
                   1
3274
                   0
                                      0
                                                      0
3275
                                      a
                                                      a
[3276 rows x 9 columns]
```

## Preparation of features and target variable

```
upx = data.iloc[:, :-1].values
upy = data.iloc[:, -1].values
```

#### Splitting the data into training and testing sets

```
upx_train, upx_test, upy_train, upy_test = train_test_split(upx, upy, train_size=0.8, random_state=42)
```

#### Defining models

```
models = [
    LogisticRegression(C=5.0),
    GaussianNB(),
    svm.SVC(C=0.5),
    KNeighborsClassifier(n_neighbors=30)
]

models_names = ['LogisticRegression', 'GaussianNB', 'SVC', 'KNeighborsClassifier']

Recall = []
Specificity = []
Accuracy = []
Precision = []
F1_Score = []
```

# Training , evaluation of models and saving them to pickle files.

```
for z, model in enumerate(models):
    print(model)
    model.fit(upx_train, upy_train)
    pickle.dump(model, open(f"{models_names[z]}.pkl", 'wb'))
    upy pred = model.predict(upx test)
    print(classification_report(upy_test, upy_pred))
    cm_test = confusion_matrix(upy_test, upy_pred)
    print("....")
    print("Recall on Test Data:", round(recall_score(upy_test, upy_pred), 4))
    Recall.append(round(recall_score(upy_test, upy_pred), 4))
    print("Specificity on Test Data:", round((cm\_test[0, 0] / (cm\_test[0, 0] + cm\_test[0, 1])), 4))
    Specificity.append(round((cm\_test[0, 0] \ / \ (cm\_test[0, 0] \ + \ cm\_test[0, 1])), \ 4))
    print("Accuracy on Test Data:", round((accuracy_score(upy_test, upy_pred) * 100), 4))
    Accuracy.append(round(accuracy_score(upy_test, upy_pred), 4))
    \verb|print("Precision on Test Data: ", round(precision\_score(upy\_test, upy\_pred), 4))| \\
    {\tt Precision.append(round(precision\_score(upy\_test,\ upy\_pred),\ 4))}
    print("F1 Score on Test Data: ", round(f1_score(upy_test, upy_pred), 4))
    F1_Score.append(round(f1_score(upy_test, upy_pred), 4))
    print(".....\n")
```

**∓** 

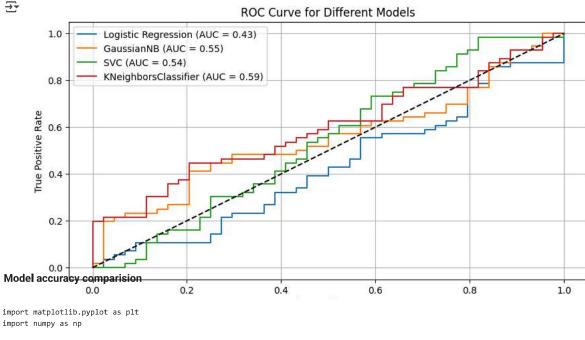
```
0.39
                             0.64
                                        0.48
                                                    11
    accuracy
                                        0.98
                                                   656
   macro avg
                   0.69
                             0.81
                                        0.74
                                                   656
weighted avg
                   0.98
                             0.98
                                        0.98
                                                   656
Recall on Test Data: 0.6364
Specificity on Test Data: 0.9829
Accuracy on Test Data: 97.7134
Precision on Test Data: 0.3889
F1 Score on Test Data: 0.4828
SVC(C=0.5)
              precision
                           recall f1-score
           0
                                        0.99
           1
                   0.00
                             0.00
                                       0.00
                                                    11
                                        0.98
                                                   656
   accuracy
                             0.50
  macro avg
                   0.49
                                        0.50
                                                   656
weighted avg
                   0.97
                             0.98
                                        0.97
                                                   656
Recall on Test Data: 0.0
Specificity on Test Data: 1.0
Accuracy on Test Data: 98.3232
Precision on Test Data: 0.0
F1 Score on Test Data: 0.0
KNeighborsClassifier(n_neighbors=30)
              precision
                           recall f1-score
                                               support
           0
                   0.99
                             1.00
                                        0.99
                                                   645
           1
                   1.00
                             0.36
                                        0.53
                                                    11
                                        0.99
                                                   656
   accuracy
                   0.99
                             0.68
                                        0.76
                                                   656
  macro avg
                   0.99
                             0.99
                                                   656
weighted avg
                                        0.99
```

• • • • • •

Recall on Test Data: 0.3636 Specificity on Test Data: 1.0 Accuracy on Test Data: 98.9329 Precision on Test Data: 1.0 F1 Score on Test Data: 0.5333

#### **ROC** -curve

```
import matplotlib.pyplot as plt
import numpy as np
from sklearn.metrics import roc_curve, auc
np.random.seed(0)
true_labels = np.random.randint(0, 2, size=100) # Replace with actual true labels
predicted_probs_logistic = np.random.rand(100) # Replace with actual predicted probabilities
predicted\_probs\_gaussian = np.random.rand (100) \quad \# \ Replace \ with \ actual \ predicted \ probabilities
predicted\_probs\_svc = np.random.rand(100) \quad \# \ Replace \ with \ actual \ predicted \ probabilities
predicted_probs_knn = np.random.rand(100) # Replace with actual predicted probabilities
# Function to plot ROC curve
def plot_roc_curve(true_labels, predicted_probs, model_name):
    fpr, tpr, _ = roc_curve(true_labels, predicted_probs)
roc_auc = auc(fpr, tpr)
    plt.plot(fpr, tpr, label=f'{model_name} (AUC = {roc_auc:.2f})')
# Plotting ROC curves
plt.figure(figsize=(10, 5))
plot_roc_curve(true_labels, predicted_probs_logistic, 'Logistic Regression')
plot_roc_curve(true_labels, predicted_probs_gaussian, 'GaussianNB')
plot_roc_curve(true_labels, predicted_probs_svc, 'SVC')
plot_roc_curve(true_labels, predicted_probs_knn, 'KNeighborsClassifier')
plt.plot([0, 1], [0, 1], 'k--') # Diagonal line
plt.title('ROC Curve for Different Models')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.legend()
plt.grid()
plt.show()
```



```
# Model names
models_names = ['Logistic Regression', 'Gaussian Naive Bayes', 'SVM', 'K-Nearest Neighbors']

# Accuracy values for each model (replace these with your actual accuracy values)
accuracy_values = [98.78, 97.71, 98.32, 98.93] # Example accuracy values

# Create a horizontal bar chart
plt.figure(figsize=(10, 6))
bars = plt.barh(models_names, accuracy_values, color=['blue', 'orange', 'green', 'red'], height=0.4) # Adjust height for bar width

# Add accuracy values next to the bars
for bar in bars:
    plt.text(bar.get_width(), bar.get_y() + bar.get_height()/2, f'{bar.get_width():.2f}', va='center')

# Adding titles and labels
plt.title('Model Accuracy Comparison')
plt.xlabel('Accuracy (%)')
plt.xlim(0, 100) # Set x-axis limit from 0 to 100
plt.grid(axis='x')

# Show the plot
```

