# Water Quality Classification

CIND820: Big Data Analytics Project

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**Spring-Summer 2022** 





#### Why classify water?

- Basic necessity for all human life
- Process of water testing is time consuming: water collection and laboratory testing
- Costly

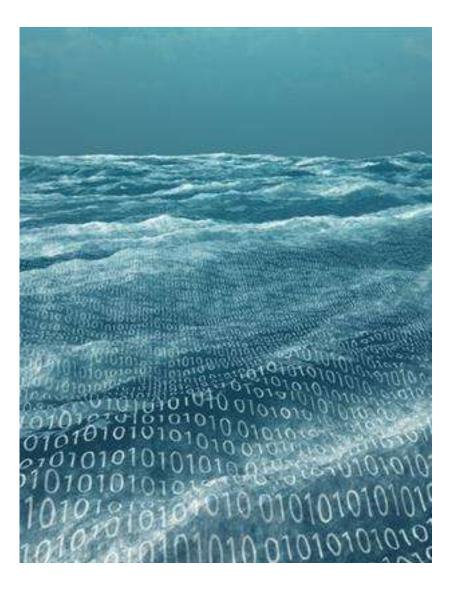
Can machine learning improve the process of water classification?







# **Predicting Water Potability**

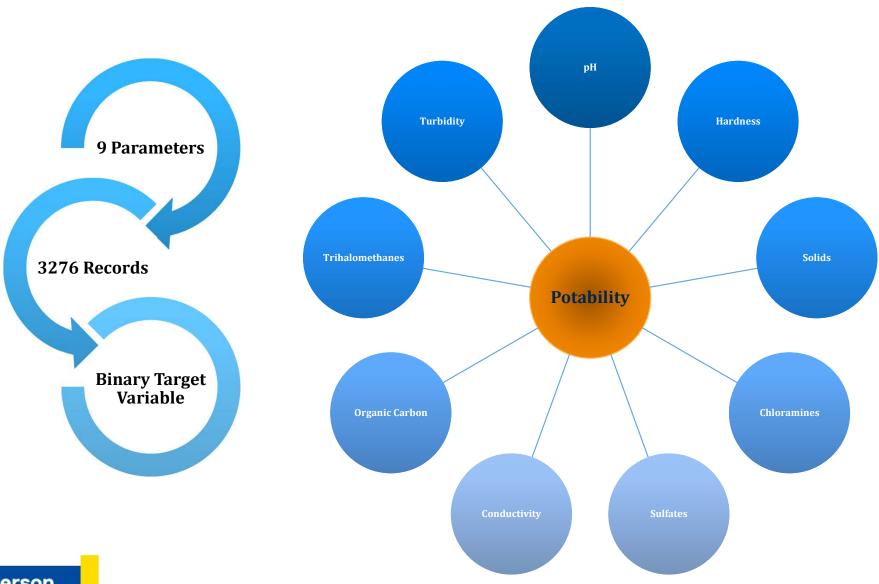


- Can we predict water potability?
- Which machine learning algorithms can yield the most efficient and accurate results?
- Can the parameters within the ML algorithms be tuned to yield the best results?
- Are the parameters within the dataset affective in water quality prediction?
- Should there be other parameters to consider?
- How confident are we in our findings?



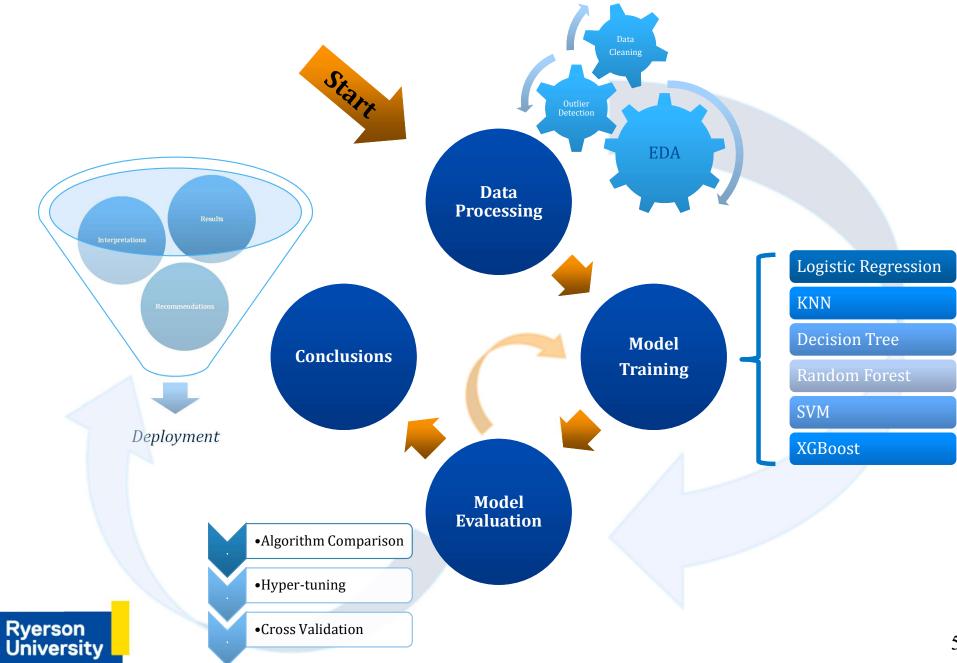
#### The Dataset

https://www.kaggle.com/datasets/adityakadiwal/water-potability/

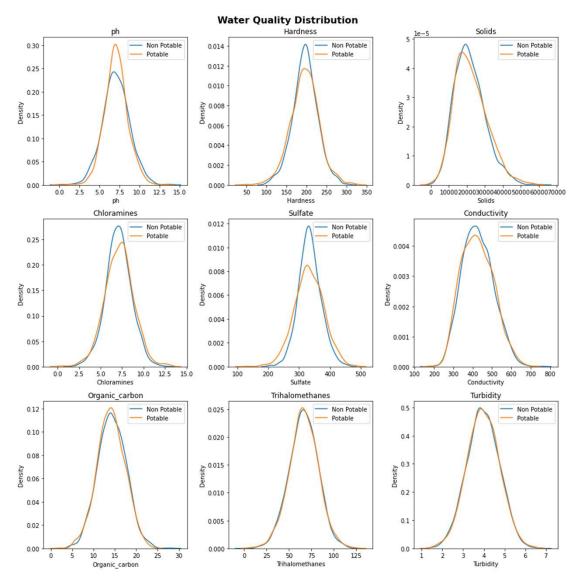


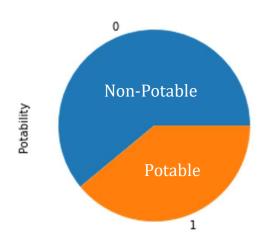


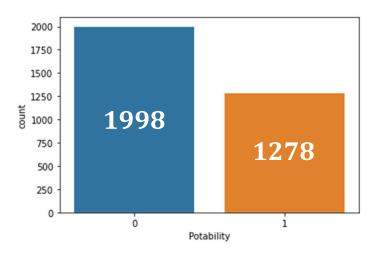
# **Approach Process**



#### **EDA: Visual Analyses**

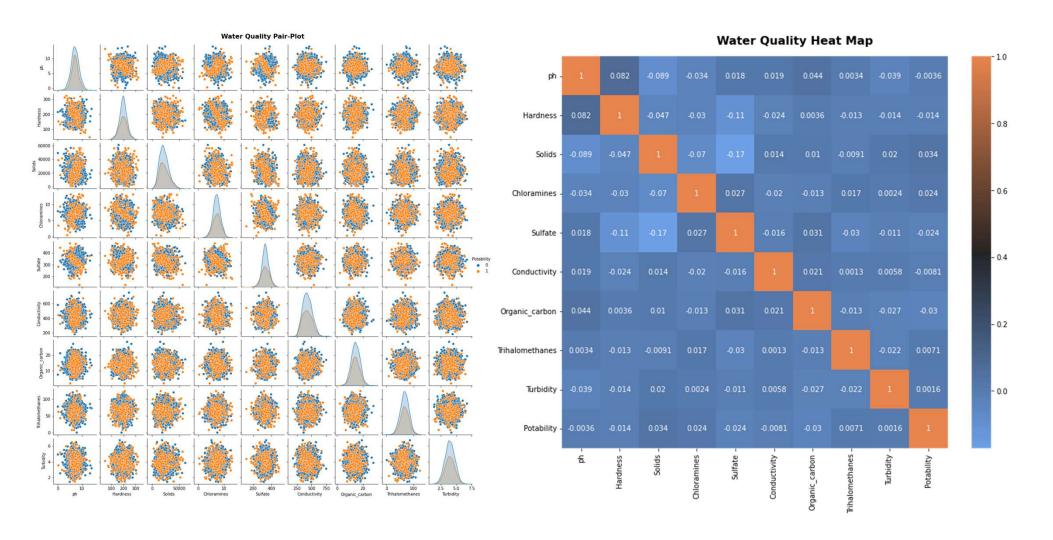






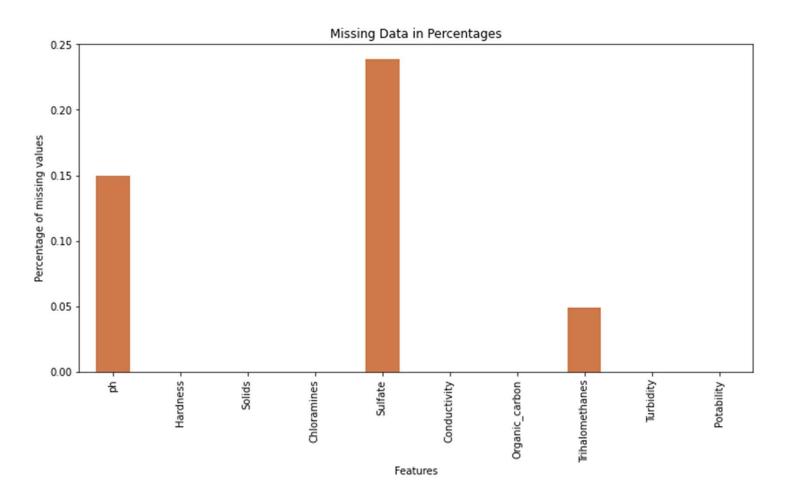


# **EDA: Visual Analyses**





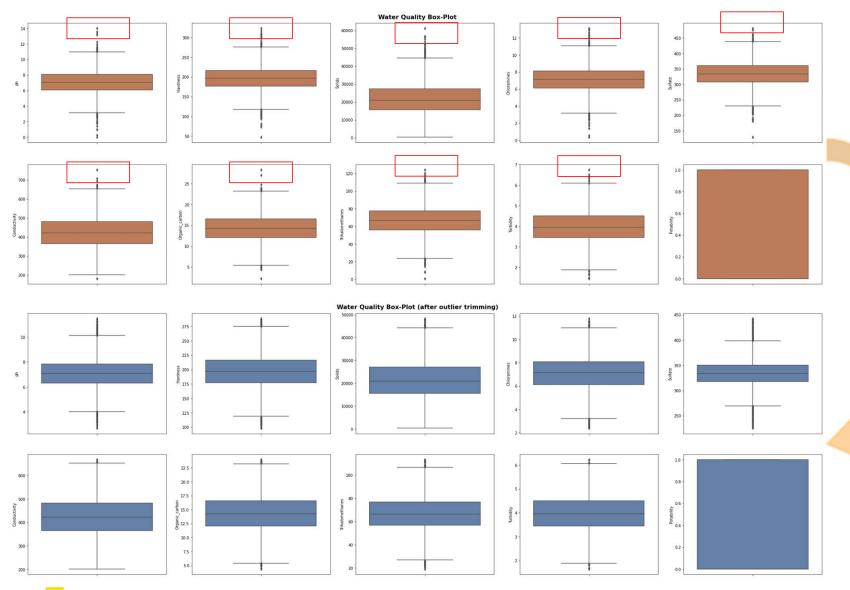
# **Missing Values**



 The majority of the parameters have a Gaussian distribution therefore it was safe to replace missing values with the mean value

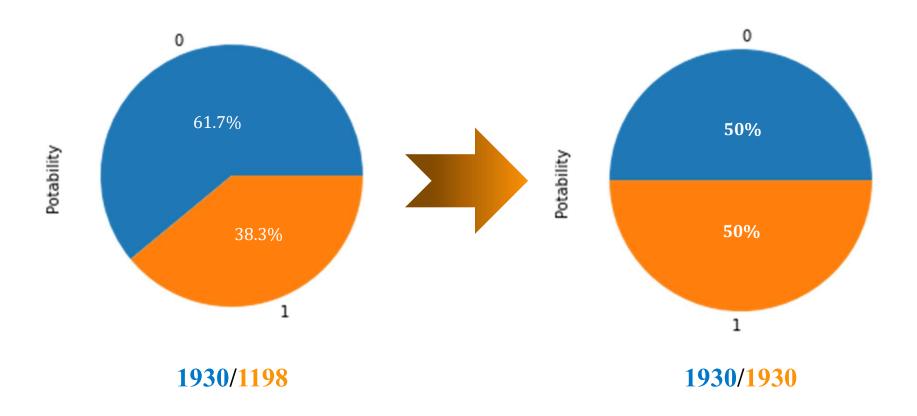


#### **Outlier Detection**





#### **Class Imbalance**

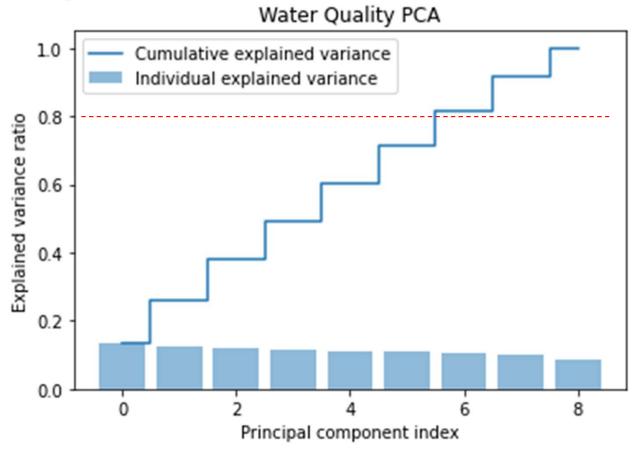


• Up-sampling the minority class to balance the data for training to prevent bias to the majority class



# **Principle Component Analysis**

• Exploring dimensionality reduction using **PCA** tells us that all the variables are independent from each other and further confirms our previous observations from the heatmap.

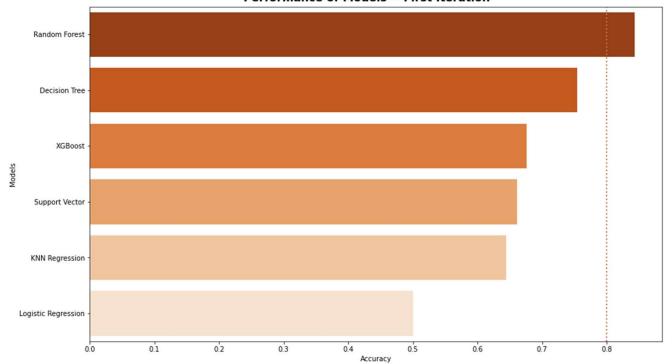




# Algorithm Comparison 1st Iteration

|   | Model               | Accuracy | Precision | Recall   | F1 Score |
|---|---------------------|----------|-----------|----------|----------|
| 3 | Random Forest       | 0.843264 | 0.827676  | 0.852151 | 0.839735 |
| 2 | Decision Tree       | 0.753886 | 0.698690  | 0.860215 | 0.771084 |
| 5 | XGBoost             | 0.676166 | 0.654822  | 0.693548 | 0.673629 |
| 4 | Support Vector      | 0.660622 | 0.632212  | 0.706989 | 0.667513 |
| 1 | KNN Regression      | 0.643782 | 0.620347  | 0.672043 | 0.645161 |
| 0 | Logistic Regression | 0.500000 | 0.483645  | 0.556452 | 0.517500 |

#### Performance of Models -- First Iteration

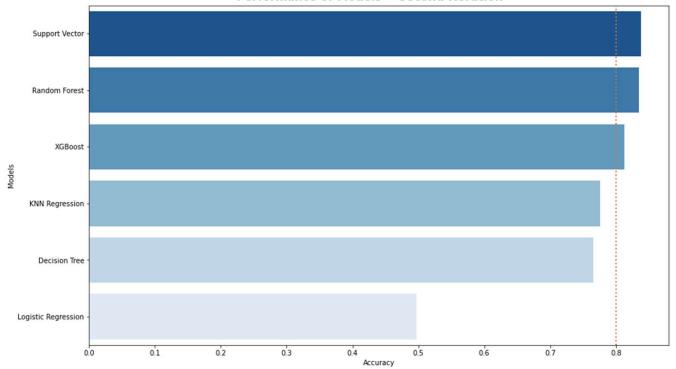




# Algorithm Comparison 2<sup>nd</sup> Iteration

|   | Model               | Accuracy | Precision | Recall   | F1 Score |
|---|---------------------|----------|-----------|----------|----------|
| 4 | Support Vector      | 0.838083 | 0.853868  | 0.801075 | 0.826630 |
| 3 | Random Forest       | 0.834197 | 0.808081  | 0.860215 | 0.833333 |
| 5 | XGBoost             | 0.812176 | 0.763341  | 0.884409 | 0.819427 |
| 1 | KNN Regression      | 0.775907 | 0.722595  | 0.868280 | 0.788767 |
| 2 | Decision Tree       | 0.765544 | 0.714607  | 0.854839 | 0.778458 |
| 0 | Logistic Regression | 0.497409 | 0.481132  | 0.548387 | 0.512563 |

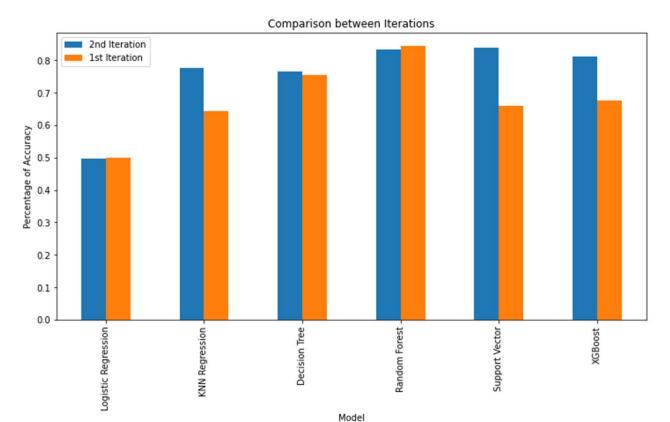
#### Performance of Models -- Second Iteration





#### **Model Evaluation**

|   | Model               | 2nd Iteration | 1st Iteration | Difference in<br>Accuracy |
|---|---------------------|---------------|---------------|---------------------------|
| 0 | Logistic Regression | 49.74%        | 50.00%        | -0.26%                    |
| 1 | KNN Regression      | 77.59%        | 64.38%        | 13.21%                    |
| 2 | Decision Tree       | 76.55%        | 75.39%        | 1.17%                     |
| 3 | Random Forest       | 83.42%        | 84.33%        | -0.91%                    |
| 4 | Support Vector      | 83.81%        | 66.06%        | 17.75%                    |
| 5 | XGBoost             | 81.22%        | 67.62%        | 13.60%                    |

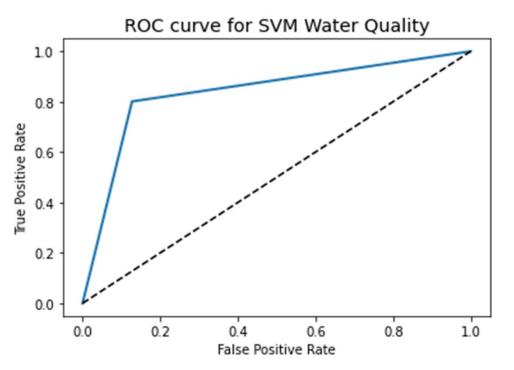




#### **Cross Validation**

**K-Fold CV** 

| Algorithm     | Mean Accuracy<br>Score | Standard<br>Deviation |  |
|---------------|------------------------|-----------------------|--|
| Random Forest | 85.28 %                | 1.84 %                |  |
| SVM           | 87.98 %                | 1.91 %                |  |
| XGBoost       | 80.73 %                | 1.77%                 |  |



ROC AUC: **0.8368** CV ROC AUC: **0.8674** 



#### **Interpretation & Recommendations**

- After 2<sup>nd</sup> iteration and hyper-tunning parameters, SVM performed with the greatest accuracy 84.33%
- After k-Fold cross validation, SVM's accuracy increased to 87.98%



- Increasing parameters: coliforms and heavy metals
- Explore deeper machine learning such as ANN (artificial neural network)



#### **Conclusions**

- Can we predict water potability?
- Which machine learning algorithms can yield the most efficient and accurate results?
- Can the parameters within the ML algorithms be tuned to yield the best results?
- Are the parameters within the dataset affective in water quality prediction?
- Should there be other parameters to consider?
- How confident are we in our findings?

- ✓ Using ML it is possible to predict water potability
- ✓ Support Vector Machine Classifier best performance 87.98% accuracy
- ✓ Hyper-tunning did increased accuracy in modeling for most of the algorithms
- ✓ The parameters within the dataset were affective in prediction although had low correlation
- ✓ Through research from other studies, additional attributes such as coliform and heavy metals should be included
- ✓ Confident in our findings but room for improvement

