NAALAIYA THIRAN PROJECT-2022
ECI01-PROFESSIONAL READINESS FORINNOVATION,
EMPLOYABILITY ANDENTREPRENEURSHIP

Efficient Water Quality Analysis and Prediction Using Machine Learning

Submitted by

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PROJECT CALENDER

Phase	Phase Description	Week	Dates	Activity Details
1	Preparation Phase (Pre-requisites, Registrations, Environment Setup, etc.)	2	22 - 27Aug 2022	Creation GitHub account & collaborate with Project repository in project workspace
2	Ideation Phase (Literature survey, Empathize, Defining Problem Statement, Ideation)	2	29 Aug – 03 Sept 2022	Literature survey (Aim, objective, problem statement and need for the project)
		3	5-10thSept 2022	Preparing Empathy Map Canvas to capture the user Pains & Gains
		4	12-17 Sept 2022	Listing of the ideas using brain storming session
3	Project Design Phase -I (Proposed Solution, Problem- Solution Fit, Solution Architecture)	5	19-24 Sept 2022	Preparing document The proposed solution
		6	26Sept-01 Oct2022	Preparing problem-solution fit document & Solution Architecture
4	Project Design Phase –II (Requirement Analysis, Customer Journey, Data Flow Diagrams, Technology Architecture)	7	3-8Oct 2022	Preparing the customer journey maps
		8	10 -15Oct 2022	Preparing the Functional Requirement Document & Data Flow Diagrams and Technology Architecture
5	Project Planning Phase (Milestones &Tasks, Sprint Schedules)	9	17 -22Oct 2022	Preparing Milestone & Activity List, Sprint Delivery Plan
6	Project Development Phase (Coding & Solution, acceptance Testing, Performance Testing)	10	24 -29Oct 2022	Preparing Project Development Delivery of Sprint - 1
		11	31Oct -5 Nov2022	Preparing Project Development Delivery of Sprint - 2
		12	7 - 12Nov 2022	Preparing Project Development Delivery of Sprint-3
		13	14 - 19Nov 2022	Preparing Project Development Delivery of Sprint - 4

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1 INTRODUCTION

Water quality has a direct impact on public health and the environment. Water is used for various practices, such as drinking, agriculture, and industry. Recently, development of water sports and entertainment has greatly helped to attract tourists (Jennings 2007). Among various sources of water supply, due to easy access, rivers have been used more frequently for the development of human societies. Using other water resources such as groundwater and seawater sometimes assisted with problems. For example, using groundwater without suitable recharge will lead to land subsidence

1.1 PROJECT OVERVIEW

With the rapid increase in the volume of data on the aquatic environment, machine leaning has become an important tool for data analysis, classification, and prediction. Unlike traditional models used in water-related research, data-driven models based on machine learning can efficiently solve more complex nonlinear problems. In water environment research, models and conclusions derived from machine learning have been applied to the construction, monitoring, simulation, evaluation, and optimization of various water treatment and management systems. Additionally, machine learning can provide solutions for water pollution control water quality improvement, and watershed ecosystem security management. In this review, we describe the cases in which machine learning algorithms have been applied to evaluate the water quality in different water environments, such as surface water, groundwater, drinking water, sewage, and seawater. Furthermore, we propose possible future applications of machine learning approaches to water environments.

1.2. PURPOSE

Hence, rapid industrial development has prompted the decay of water quality at a disturbing rate. Furthermore, infrastructures, with the absence of public awareness, and less hygienic qualities, significantly affect the quality of drinking water. In fact, the consequences of polluted drinking water are so dangerous and can badly affect health, the environment, and infrastructures. As per the United Nations (UN) report, about 1.5 million people die each year because of contaminated water-driven diseases. In developing countries, it is announced that 80% of health problems are caused by contaminated water. Five million deaths and 2.5 billion illnesses are reported annually -Such a mortality rate is higher than deaths resulting from accidents, crimes, and terrorist attacks .

Therefore, it is very Important to suggest new approaches to analyze and, ifpossible, to predict the water quality (WQ). It is recommended to consider the temporal dimension for forecasting the WQ patterns to ensure the monitoring of the seasonal change of the WQ . However, using a special variation ofmodels together to predict the WQ grants better results than using a single model . There are several methodologies proposed for the prediction and modeling of the WQ. These methodologies include statistical approaches, visual modeling, analyzingalgorithms, and predictive algorithms. For the sake of the determination of the correlation and relationship among different water quality parameters, multivariate statistical techniques have been employed . The geostatistical approaches were used for transitional probability, multivariate interpolation, and regression analysis .

Massive Increases in population, the industrial revolution, and the use of fertilizers and pesticides have led to serious effects on the WQ environments . Thus, having models for the prediction of the WQ is of great help for monitoring water contamination.

2 LITERATURE SURVERY

Many works had been conducted to predict water quality using Machine Learning (ML) approaches. Some researchers used the traditional Machine Learning models, such as Decision Tree Artificial Neural NetworkSupport Vector Machine K-Nearest Neighbors and Naive Bayes However, in recent years, some researchers are moving towards more advanced ML ensemble models, such as Gradient Boosting and Random Forest [[1]]
Traditional Machine Leaming models, such as the Decision Tree model, are frequently found in the literature and performed well on water quality data. However, decision-tree-based ensemble models, including Random Forest (RF) and Gradient Boosting (GB), always outperform the single decision tree Among the reasons for this are its ability to manage both regular attributes and data, not being sensitive to missing values and being highly efficient. Compared to other ML

models, decision-tree-based models are more favorable to short-term prediction and may have a quicker calculation speed Gakii and Jepkoech [3] compared five different decision tree classifiers, which are Logistic Model Tree (LMT), J48, Hoeffding tree, Random Forest and Decision Stump. They found that J48 showed the highest accuracy of 94%, while Decision Stump showed the lowest accuracy. Another study by Jeihouni et al. [4] also compared five decision-tree-based models, which are Random Tree, Random Forest, Ordinary Decision Tree (ODT), Chisquare Automatic Interaction Detector and Iterative Dichotomiser 3 (ID3), to determine high water quality zones. They found that ODT and Random Forest produce higher accuracy compared to the other algorithms and the methods are more suitable for continuous datasets.

Another popular Machine Learning model to predict water quality is Artificial Neural Network (ANN). ANN is a remarkable data-driven model that can cater both linear and non-linear associations among output and input data. It is used to treat the non-linearity of water quality data and the uncertainty of contaminant source. However, the performance of ANN can be obstructed if the training data are imbalanced and when all initial weights of the parameter have the same value. In India, Aradhana and Singh [s] used ANN algorithms to predict water quality. They found that Lavenberg Marquardt (LM) algorithm has a better performance than the Gradient Descent Adaptive (GDA) algorithm. Abyaneh [5] used ANN and multivariate linear regression models in his research and found that the ANN model outperforms the MLR model. However, the research only assessed the performance of the ANN model using root-mean-square error (RMSE), coefficient of correlation (r) and bias values. Although ANN models are the most broadly used, they have a drawback as the prediction power becomes weak if they are used with a small dataset and the testing data are outside the range of the training data .

Support Vector Machine has also been extensively used in water quality studies.

Some studies proved that SVM is the best model in predicting water quality compared to other models. A study by Babbar and Babbar found that Support Vector Machine and Decision Tree are the best classifiers because they have the lowest error rate, which is 0%, in classifying water quality class compared to ANN, Naive Bayes and K-NN classifiers. It also revealed that ML models can quickly determine the water quality class if the data provided represent an accurate representation of domain knowledge. In China, Liu and Lu developed the SVM and ANN model to predict phosphorus and nitrogen. They found that SVM model achieves a better forecasting accuracy compared to the ANN model. This is because the SVM model optimizes a smaller number of parameters acquired from the principle of structural risk minimization, hence avoiding the occurrence of overtraining data to have a better generalization ability This is supported by another study in Eastern Azerbaijan, Iran They found that SVM has a better performance compared to the K-Nearest Neighbor algorithm in estimating two water quality parameters, which are total dissolved solid and conductivity. The results showed smaller error and higher R^2 than the results attained in Abbasi et al. 's report Naive Bayes has also been widely used for predicting water quality. A study by Vijay and Kamaraj [Z] found that Random Forest and Naive Bayes produce better accuracy and low classification error compared to the C5.0 classifier. However, traditional ML models, for example, Decision Tree, ANN, Naive Bayes and SVM, do not perform well. They have some weaknesses, such as a high tendency to be biased and a high

variance [z*]. For example, SVM uses the structural risk minimization principle to address over fitting problem in Machine Learning by reducing the model's complexity and fitting the training data successfully [2] .
Meanwhile, the Bayes model uses prior and posterior probabilities in order to prevent over fitting problems and bias from using only sample information. In ANN, the training process takes a longer time and over fitting problems may occur if there are too many layers, while the prediction error may be affected if there are not enough layers [30]. Over fitting is a fundamental issue in supervised Machine Learning that prevents the perfect generalization of the model to fit the data observed on the training data, as well as unseen data on the testing set. Hence, over fitting occurs due to the presence of noise, a limited training set size, and classifier complexity a-m. One of the strategies considered by many previous works to reduce the effects of over fitting is to adopt more advanced methods, such as the ensemble method.

The ensemble method is a Machine Learning technique that combines several base learners' decisions to produce a more precise prediction than what can be achieved with having each base learner's decision This method has also gained wide attention among researchers recently. The diversity and accuracy of each base learner are two important features to make the ensemble learners work properly .The ensemble method ensures the two features in several ways based on its working principle. There are two commonly used ensemble families in Machine Learning, which are baggmg and boosting. Both the bagging and boosting methods provide a higher stability to the classifiers and are good in reducing variance. Boosting can reduce the bias, while baggmg can solve the overfitting problem A famous ensemble model that uses the baggmg algorithm is Random Forest. It is a classification model that uses multiple base models, typically decision trees, on a given subset of data independently and makes decisions based on all models It uses feature randomness and baggmg when building each individual decision tree to produce an independent forest of trees. Random Forest carries all the advantages of a decision tree with the added effectiveness of using several models Another popular ensemble model is Gradient Boosting. Gradient Boosting is a Machine Learning technique that trains multiple weak classifiers, typically decision trees, to create a robust classifier for regression and classification problems. It assembles the model in a stage-wise way similar to other boosting techniques and it generalizes them by optimizing a suitable cost function. In the GB algorithm, incorrectly classified cases for a step are given increased weight during the next step. The advantages of GB are that it has exceptional accuracy in predicting and fast process E]. Therefore, advanced models, such as Random Forest and Gradient Boosting, should be employed to cater for the lack of basic ML models.

2.1 EXISITNG PROBLEM

The main problem lies here. For testing the water quality we have to conduct lab tests on the water which is costly and time-consuming as well. So, in this paper, we propose an alternative approach using artificial intelligence to predict water quality. This method uses a significant and easily available water quality index which is set by the WHO(World Health Organization). The data taken in this paper is taken from the PCPB India which includes 3277 examples of the distinct wellspring. In this paper, WQI(Water Quality Index) is calculated using Al techniques. So in future work, we can integrate this with 10T based framework to study large datasets and to expand our study to a larger scale. By using that it can predict the water quality fast and more accurately than any other 10T framework. That 10T framework system uses some limits for the sensor to check the parameters like ph, Temperature, Turbidity, and so on. And further after reading this parameter pass these readings to the Arduino microcontroller and ZigBee handset for further prediction

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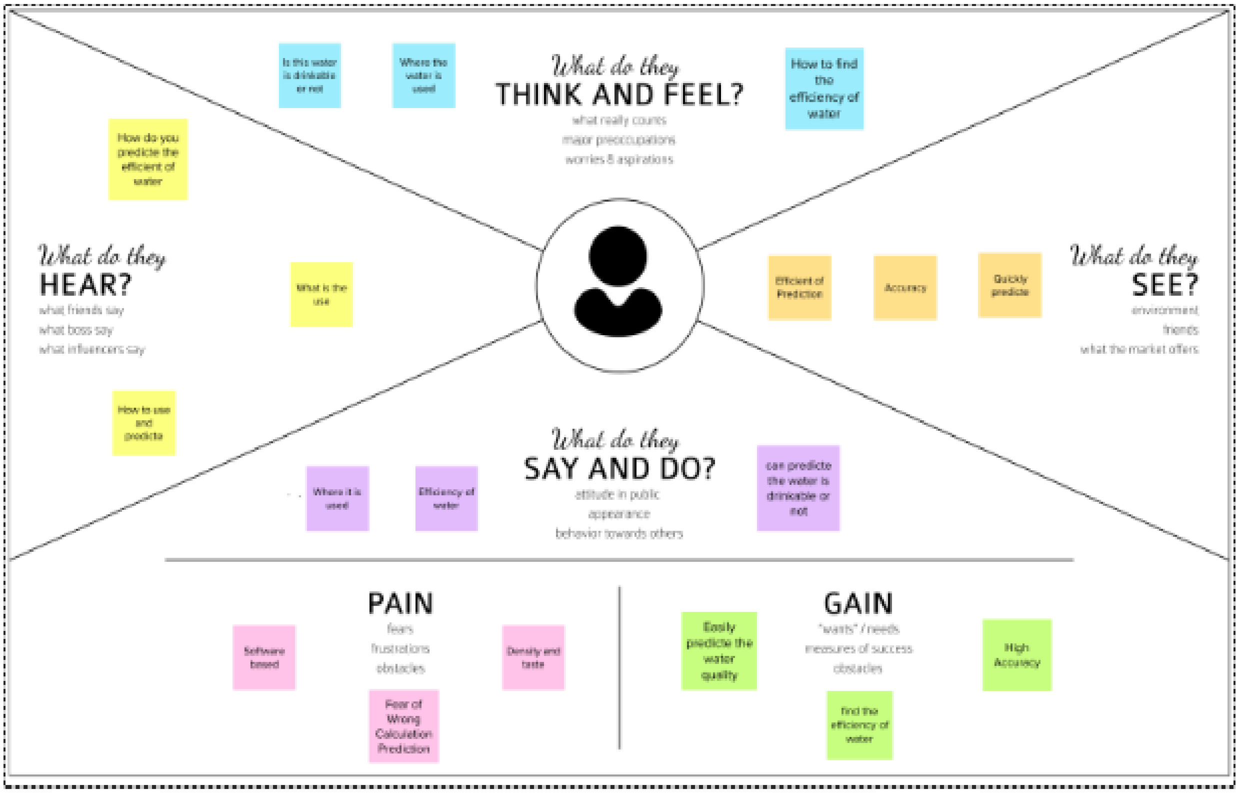
2.3 PROBLEM STATEMENT DEFINITION

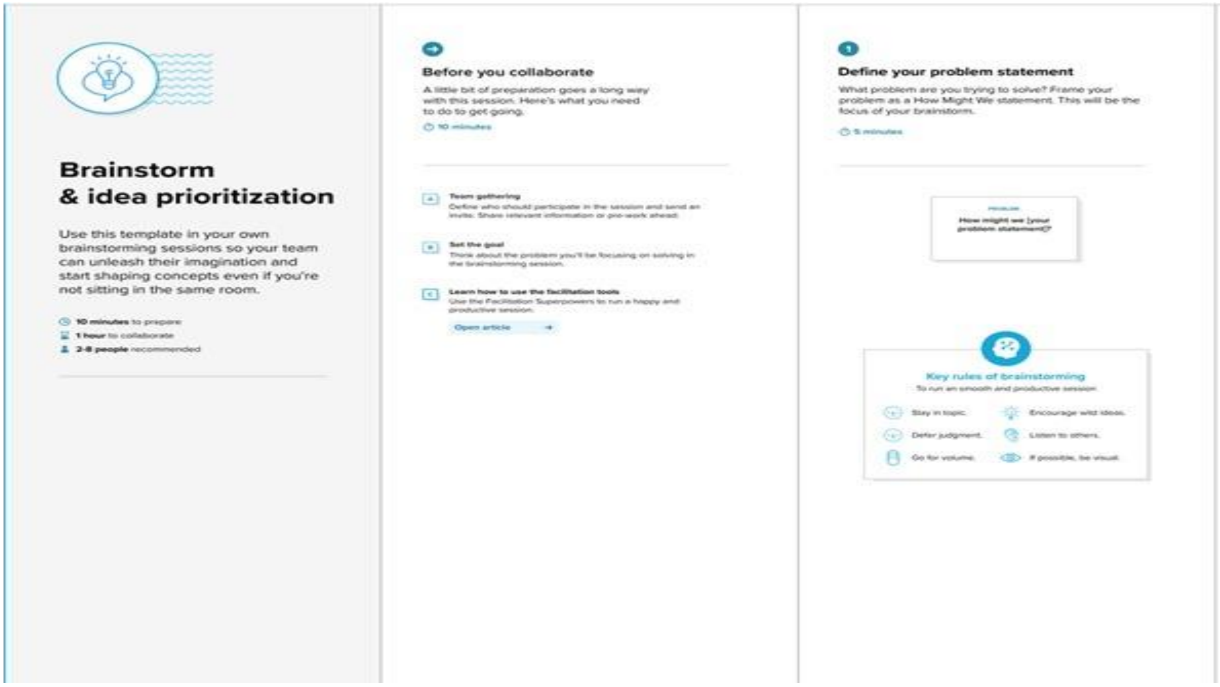
To predict the water safe or not for Access to safe drinking-water is essential to health, a basic human right and a component of effective policy for health protection. This is important as a health and development issue at a national, regional and 10 cal level. In some regions, it has been shown that 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.

3 IDEATION & PROPOSEDSOLUTION

3.1 EMPATHY MAP



3.2 IDEATION AND BRAINSTORMING



Brainstorm & idea prioritization

Use this template in your own brainstorming sessions so your team can unleash their imagination and start shaping concepts even if you're not sitting in the same room.

10 minutes to prepare
1 hour to collaborate
2-8 people recommended

Before you collaborate

A little bit of preparation goes a long way with this session. Here's what you need to do to get going.

10 minutes

A Team gathering
Define who should participate in the session and send an invite. Share relevant information or pre-work ahead.

B Set the goal
Think about the problem you'll be focusing on solving in the brainstorming session.

C Learn how to use the facilitation tools
Use the Facilitation Superpowers to run a happy and productive session.

Open article →

1 Define your problem statement

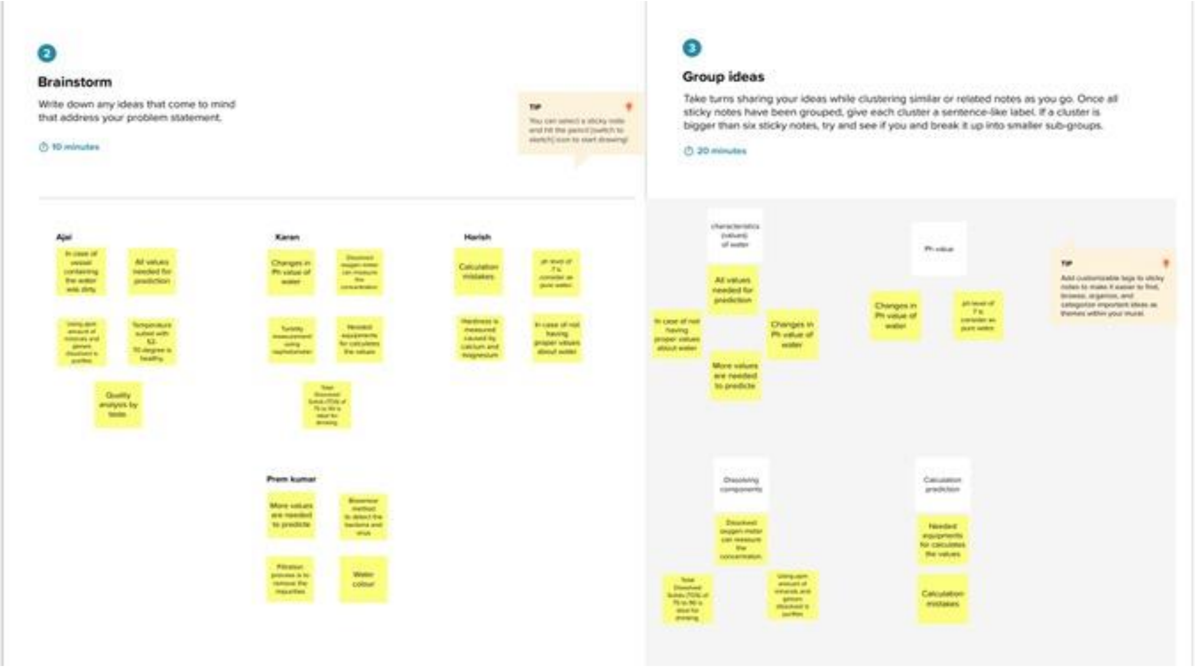
What problem are you trying to solve? Frame your problem as a How Might We statement. This will be the focus of your brainstorm.

5 minutes

PROBLEM
How might we [your problem statement]?

Key rules of brainstorming
To run an smooth and productive session

Stay in topic.
Encourage wild ideas.
Defer judgment.
Listen to others.
Go for volume.
If possible, be visual.



2 Brainstorm

Write down any ideas that come to mind that address your problem statement.

10 minutes

TIP
You can select a sticky note and hit the pencil [switch to sketch] icon to start drawing!

Ajai
In case of vessel containing the water was dirty
All values needed for prediction
Using ppm amount of minerals and gases dissolved is purifies
Temperature suited with 52-70 degree is healthy
Quality analysis by taste

Karan
Changes in Ph value of water
Dissolved oxygen meter can measure the concentration
Turbidity measurement using nephelometer
Needed equipments for calculates the values
Total Dissolved Solids (TDS) of 75 to 90 is ideal for drinking

Harish
Calculation mistakes
ph level of 7 is consider as pure water
Hardness is measured caused by calcium and magnesium
In case of not having proper values about water

Prem kumar
More values are needed to predicte
Biosensor method to detect the bacteria and virus
Filtration process is to remove the impurities
Water colour

3 Group ideas

Take turns sharing your ideas while clustering similar or related notes as you go. Once all sticky notes have been grouped, give each cluster a sentence-like label. If a cluster is bigger than six sticky notes, try and see if you and break it up into smaller sub-groups.

20 minutes

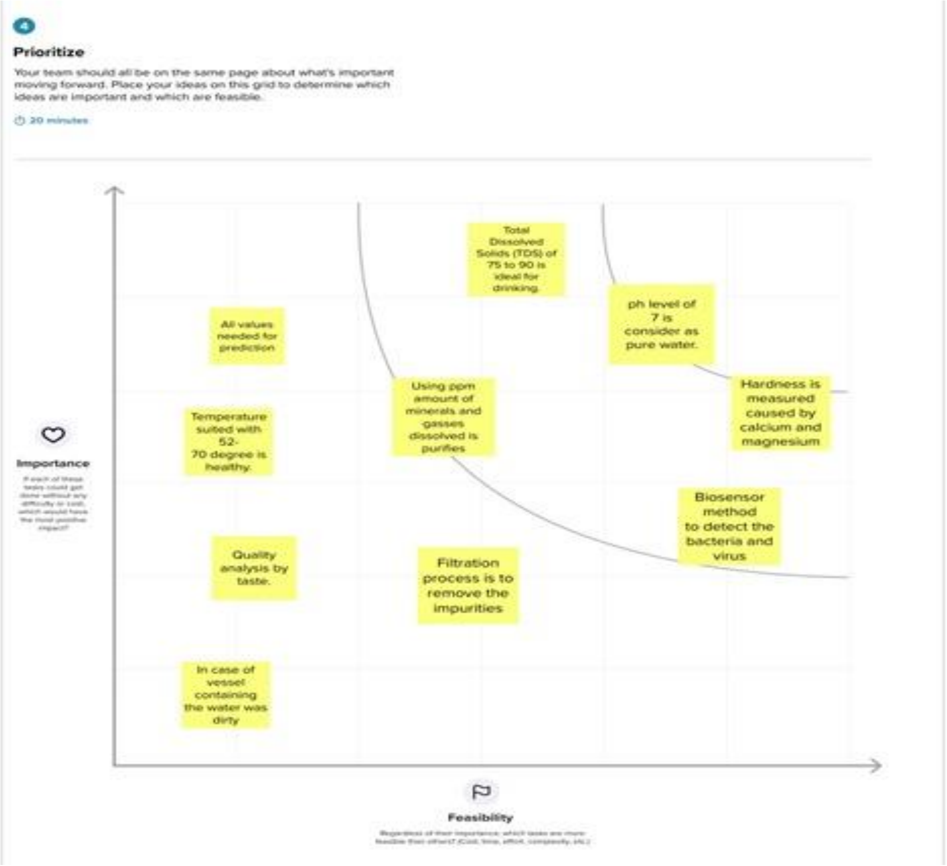
characteristics (values) of water
All values needed for prediction
In case of not having proper values about water
Changes in Ph value of water
More values are needed to predicte

Ph value
Changes in Ph value of water
ph level of 7 is consider as pure water

TIP
Add customizable tags to sticky notes to make it easier to find, browse, organize, and categorize important ideas as themes within your mural.

Dissolving components
Dissolved oxygen meter can measure the concentration
Total Dissolved Solids (TDS) of 75 to 90 is ideal for drinking
Using ppm amount of minerals and gases dissolved is purifies

Calculation prediction
Needed equipments for calculates the values
Calculation mistakes



4

Prioritize

Your team should all be on the same page about what's important moving forward. Place your ideas on this grid to determine which ideas are important and which are feasible.

20 minutes

Importance

If each of these tasks could get done without any difficulty or cost, which would have the most positive impact?

Feasibility

Regardless of their importance, which tasks are more feasible than others? (Cost, time, effort, complexity, etc.)

Total Dissolved Solids (TDS) of 75 to 90 is ideal for drinking.
All values needed for prediction
ph level of 7 is consider as pure water.
Using ppm amount of minerals and gasses dissolved is purifies
Hardness is measured caused by calcium and magnesium
Temperature suited with 52-70 degree is healthy.
Biosensor method to detect the bacteria and virus
Quality analysis by taste.
Filtration process is to remove the impurities
In case of vessel containing the water was dirty

3.3 PROPOSED SOLUTION

S.No.	Parameter	Description
1.	Problem Statement (Problem to be solved)	Water is seen as a major resource that has an impact on many elements of human health and survival. People who live in metropolitan areas are often concerned about the quality of the water.
2.	Idea / Solution description	This project aims at building a machine learning model to predict a water quality by considering all water quality standard indicators.
3.	Novelty / Uniqueness	The proposed method is utilized to test portability. It has two phases: testing and training. working on past historical data.
4.	Social Impact / Customer Satisfaction	The quality of water services as a powerful environmental determinant and a foundation for the prevention and control of water borne diseases.
5.	Business Model (Revenue Model)	This model should be licensed by the machine learning as well as data analytics and make more impression among the people.
6.	Scalability of the Solution	A system that scales well will be able to maintain or increase its level of performance even as it is tested by larger than its operational demands.

3.4 PROBLEM SOLUTION FIT

1.CUSTOMER SEGMENTS There are various categories of customer of high-quality water in the public, private, and government sectors.	**6.CUSTOMER CONSTRAINS** Customers can use a web application to analyse the water quality by simply providing a few water characteristic data, but they do need some fundamental prerequisites, such as a network connection, a system or a mobile.	**5.AVAILABLE SOLUTIONS** Have information on the water's colour, odour, pH level, and other characteristics to evaluate if it is safe to drink or not. **PROS** Solution within a second **CONS** Accuracy is not 100 %
2.JOBS TO BE DONE/PROBLEM Gather the historical information about the quality of the water based on its many features and qualities in the chemical and physical compositions of nature.	**9.PROBLEM ROOT CAUSE** All living things are harmed by improper maintenance of rainwater and surface water from rivers that are combined with industrial waste and certain other human-generated contaminants.	**7.BEHAVIOUR** Customers must have up-to-date information about the water's status in order for machine learning models to accurately anticipate whether the water is excellent or harmful. Basic knowledge of water characteristics and web usage for the easy way to solution.
3.TRIGGERS General information about the water by using sensors and give those values to the application will give all the details of water quality. **4.EMOTIONS:BEFORE/AFTER** Without prior knowledge of water quality and drinking it leads to be causing various diseases and loss of life.	**10.YOUR SOLUTION** **Simply entering the current water data to the web app which gives the analysis of water prediction.** **Using past historical data of water to predict and analyse the water in current scenarios.**	**8.CHANNELS OF BEHAVIOUR** **ONLINE** Customer can use the web app by simply entering the current URL of the website.

4. REQUIREMENT ANALYSIS

4.3 FUNCTIONAL REQUIREMENTS

FR No.	**Functional Requirement (Epic)**	**Sub Requirement (Story / Sub-Task)**
FR-1	Enter the Inputs	Input get through the form and Check the input data
FR-2	User Essential	User needs the result with correct accuracy
FR-3	Data Preprocessing	Get the tested and trained data from the raw dataset
FR-4	User input Evaluation	Evaluate the input with model and predicte the efficiency of water
FR-5	Prediction	Efficient for use or not

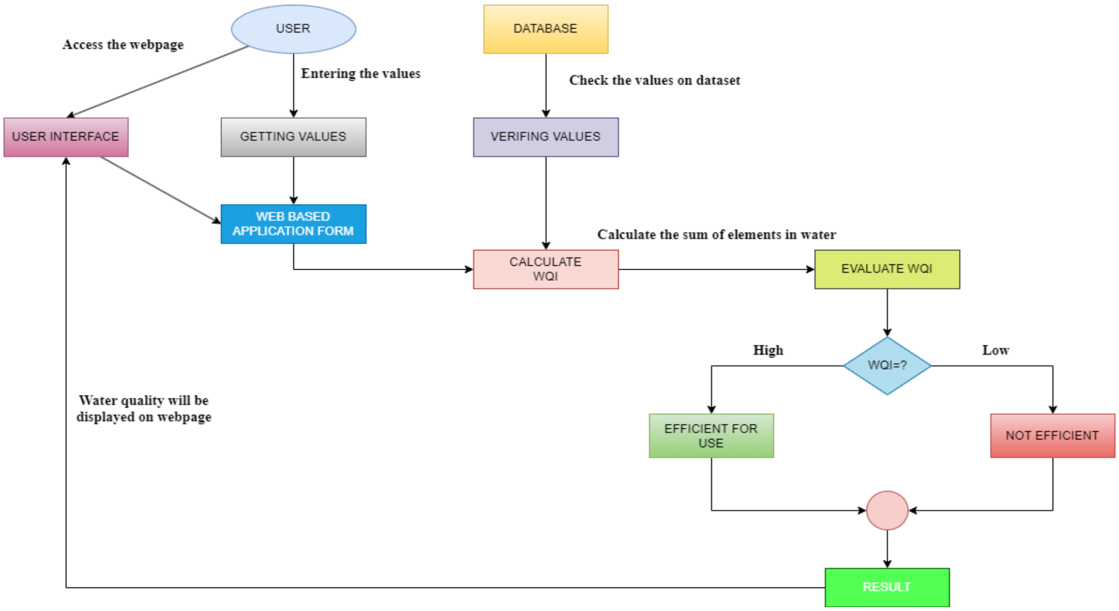
4.4 NONFUCTIONAL REQUIREMENTS

NFR No.	**Non-Functional Requirement**	**Description**
NFR-1	Usability	User friendly web application
NFR-2	Security	Website doesn’t have any harmful virus and it didn’t ask any permission
NFR-3	Reliability	Many type of water values are trained to model so prediction accuracy high
NFR-4	Performance	Quickly get the results
NFR-5	Availability	Available at any time in internet
NFR-6	Scalability	• Can access the website through computer and mobile • Lightweight web application

5 PROJECT DESIGN

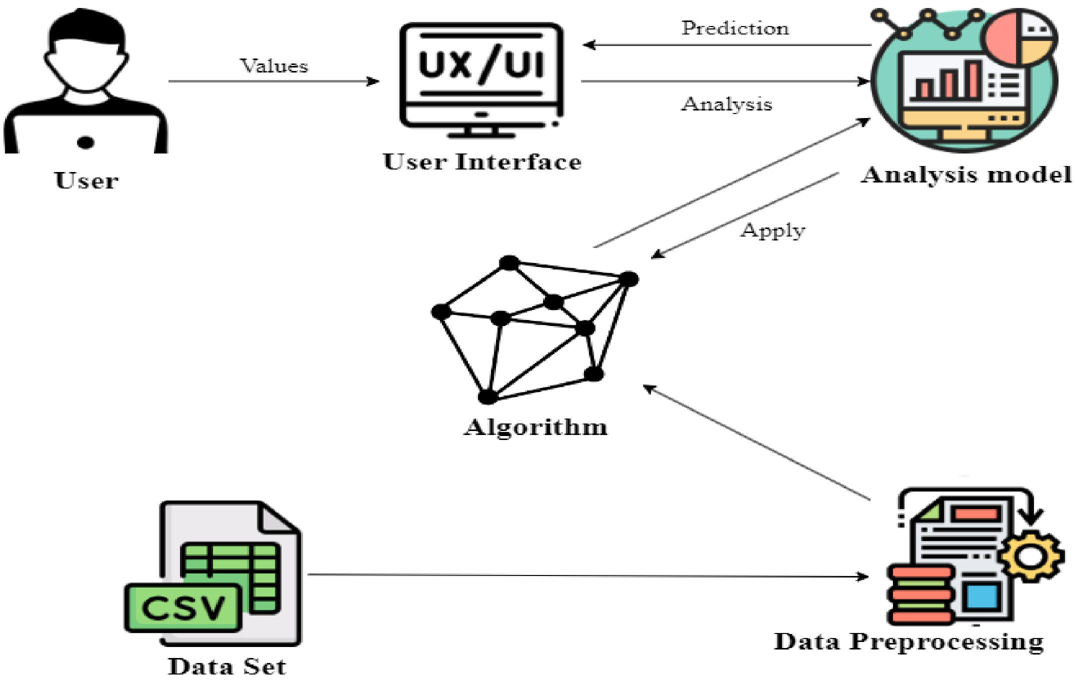
5.1 DATA FLOW DIAGRAMS

Data Flow Diagram



5.2 SOLUTION AND TECHNICAL ARCHITECTURE

SOLUTION ARCHITECTURE



6 PROJECT PLANNING & SCHEDULING

6.1 SPRINT PLANNING AND ESTIMATION

Sprint	Functional Requirement (Epic)	User Story Number	User Story / Task	Story Points	Priority	Team Members
Sprint-1	Data Preparation	USN-1	Collecting water dataset and pre-processing it	20	High	Ajai B
Sprint-2	Model Building	USN-2	Create a ML model to predict water quality	10	Medium	Ajai B Karan L Harish T Prem Kumar B
Sprint-2	Model Evaluation	USN-3	Calculate the performance, error rate and complexity of ML model	10	Medium	
Sprint-3	Model Deployment	USN-4	Using flask and deploy model finally in IBM cloud using IBM storage and Watson Studio	10	Medium	
Sprint-3	Web page (Form)	USN-5	As a user, I can use the application by enter the water data in form	10	Medium	Ajai B Karan L Harish T Prem Kumar B
Sprint-4	Dashboard	USN-6	As a user, I can predict the water quality by click the submit button and the application will show the water is efficient for use or not	20	High	Ajai B

6.2 SPRINT DELIVERY SCHEDULE

Sprint	Total Story Points	Duration	Sprint Start Date	Sprint End Date	Story Points Completed	Sprint Release Date
Sprint-1	20	6 Days	24 Oct 2022	29 Oct 2022	20	29 Oct 2022
Sprint-2	20	6 Days	31 Oct 2022	05 Nov 2022	20	05 Nov 2022
Sprint-3	20	6 Days	07 Nov 2022	12 Nov 2022	20	12 Nov 2022
Sprint-4	20	6 Days	14 Nov 2022	19 Nov 2022	20	19 Nov 2022

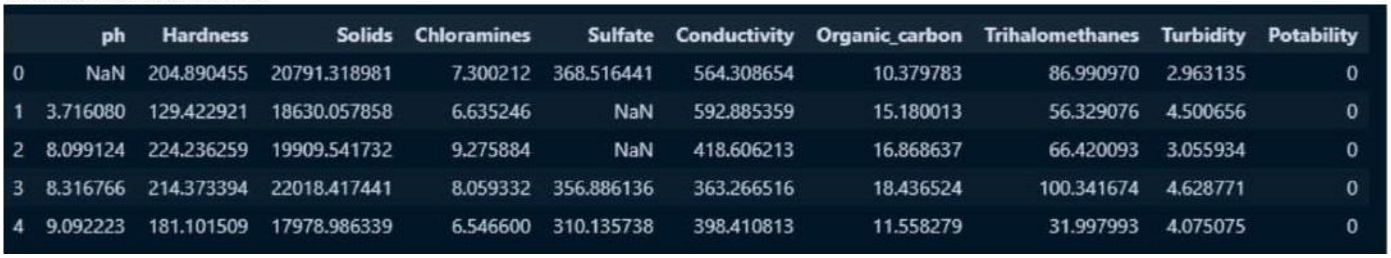
7 CODING & SOLUTIONING

FEATURE 1

Data collection and creation

Data mining techniques require domain knowledge in order to generate predictions. For water quality applications, it is vital to understand how various water quality parameters influence water quality. This information can come from a domain expert or historical data collections. For the forecasting task, two types of data sets were used: a carefully created huge synthetic data set and an available real data set

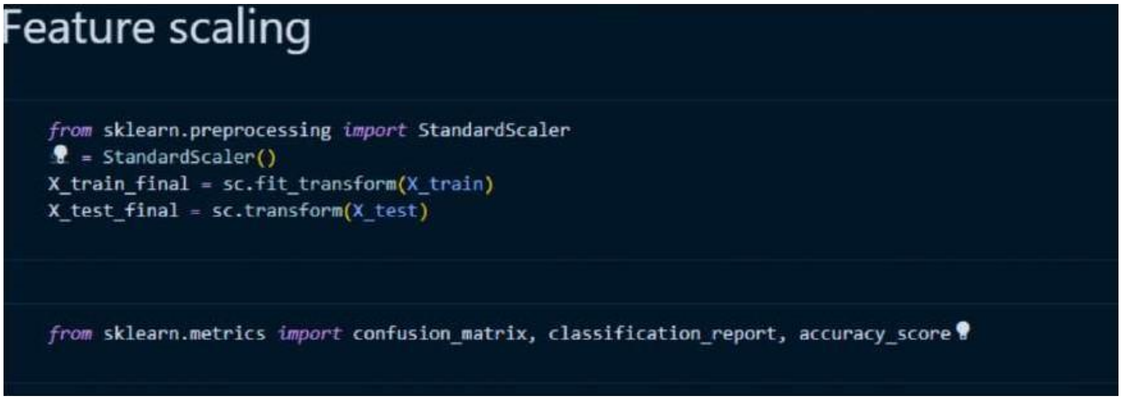
an available real data set



	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

Data Preprocessing

The processing phase IS very important in data analysis to improve the data quality. In this phase, the WQI has been calculated from the most significant parameters of the dataset. Then, water samples have been classified on the basis of the WQI values. For obtaining superior accuracy, the -score method has been used as a data normalization technique.



Feature scaling

```
from sklearn.preprocessing import StandardScaler
💡 = StandardScaler()
X_train_final = sc.fit_transform(X_train)
X_test_final = sc.transform(X_test)


from sklearn.metrics import confusion_matrix, classification_report, accuracy_score💡
```

Water Quality Index Calculation

To measure water quality, WQI is used to be calculated using various parameters that significantly affect WQ [40—42]. In this study, a published dataset IS considered to test the proposed model, and seven significant water quality parameters are Included. The WQI has been calculated using the following formula:

WQI - $\frac{\sum_{i=1}^{N} q_i \times w_i}{\sum_{i=1}^{N} w_i}$,

where: is the total number of parameters Included m the WQI calculations is the quality rating scale for each parameter calculated by equation (2) below, and is the unit weight for each parameter calculated by equation(3).

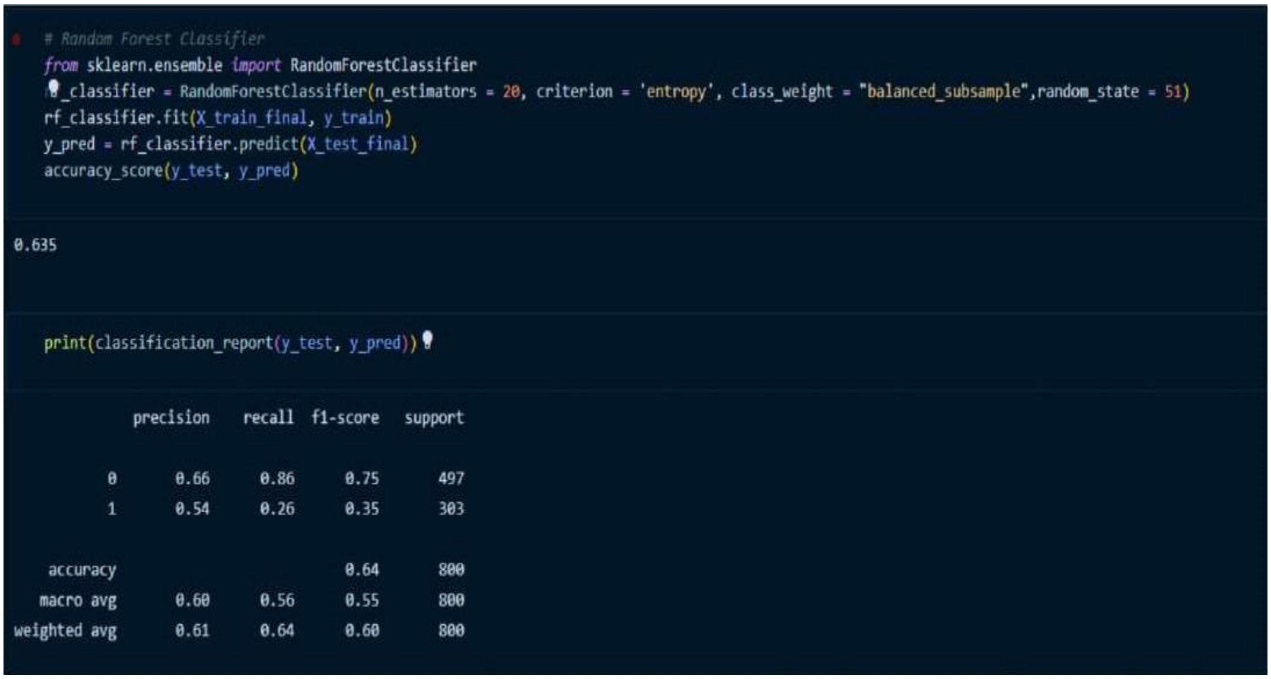
q_i =100 x(STG),

where: is the measured value of parameter in the tested water samples is the ideal value of parameter m pure water (0 for all parameters except and and is the recommended standard value of parameter (as shown in Table J)

FEATURE 2

Performance Measures Results True Positives (TP) are when the model predicts the positive class properly. True Negatives (TN) is one of the components of a confusion matrix designed to demonstrate how classification algorithms work. Positive outcomes that the model predicted correctly are own as False Positives (FP). False Negatives (FN) are negative outcomes that the model predicts negative class. Accuracy is the most basic and Intuitive performance metric, consisting of the ratio of successfully predicted observations to total observations.

Accuracy - TP+TN/(TP+FP+FN+IN)

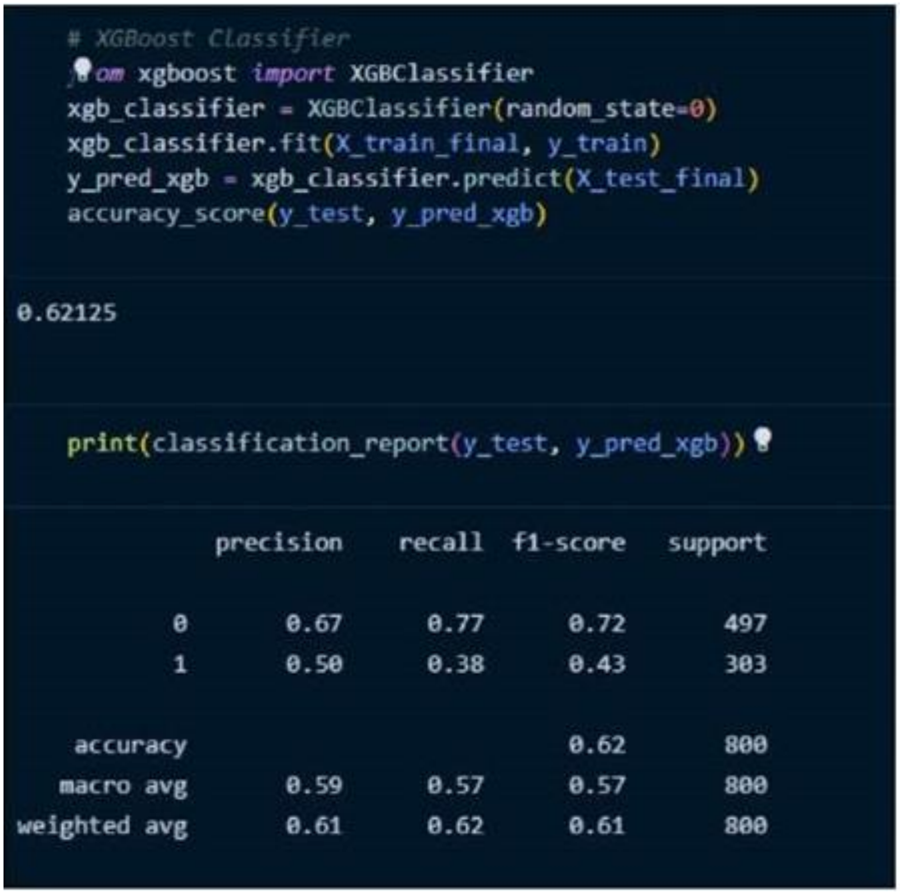


```
# Random Forest Classifier
from sklearn.ensemble import RandomForestClassifier
rf_classifier = RandomForestClassifier(n_estimators = 20, criterion = 'entropy', class_weight = "balanced_subsample",random_state = 51)
rf_classifier.fit(X_train_final, y_train)
y_pred = rf_classifier.predict(X_test_final)
accuracy_score(y_test, y_pred)
```

```
0.635
```

```
print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

           0       0.66      0.86      0.75       497
           1       0.54      0.26      0.35       303

    accuracy                           0.64       800
   macro avg       0.60      0.56      0.55       800
weighted avg       0.61      0.64      0.60       800
```

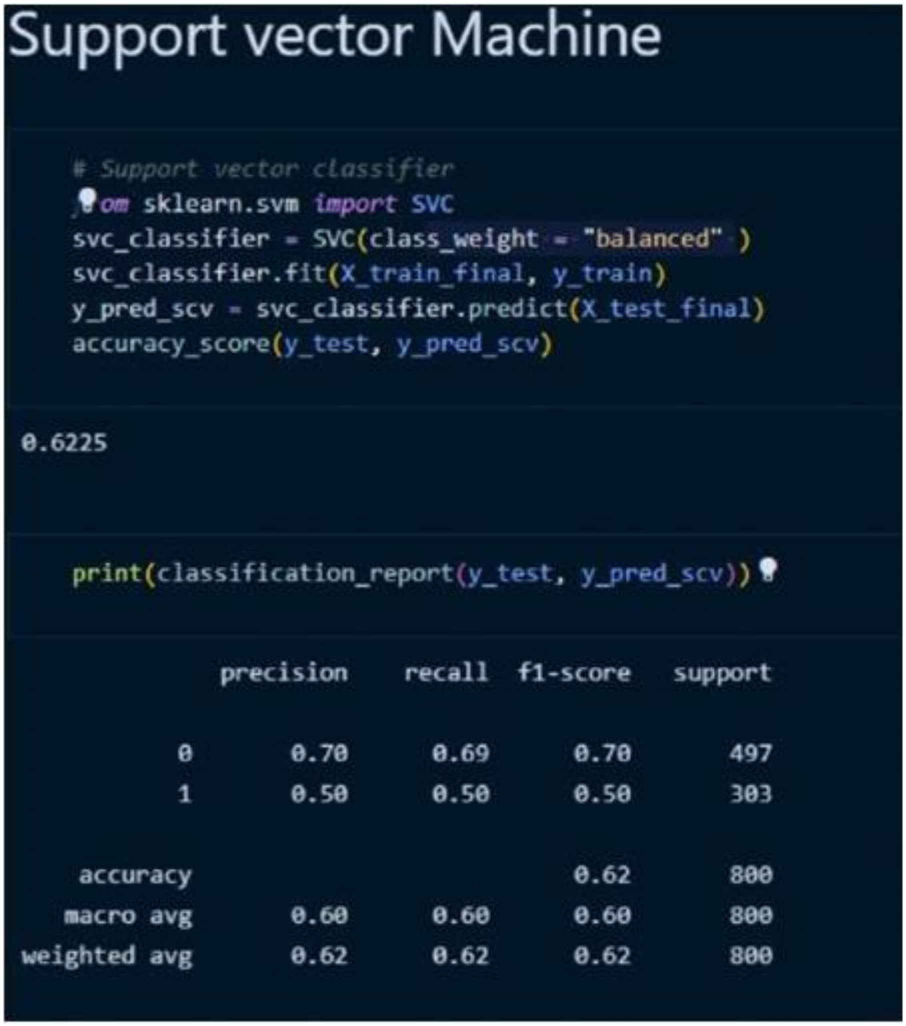


```
# XGBoost Classifier
from xgboost import XGBClassifier
xgb_classifier = XGBClassifier(random_state=0)
xgb_classifier.fit(X_train_final, y_train)
y_pred_xgb = xgb_classifier.predict(X_test_final)
accuracy_score(y_test, y_pred_xgb)
```

```
0.62125
```

```
print(classification_report(y_test, y_pred_xgb))
```

```
              precision    recall  f1-score   support

           0       0.67      0.77      0.72       497
           1       0.50      0.38      0.43       303

    accuracy                           0.62       800
   macro avg       0.59      0.57      0.57       800
weighted avg       0.61      0.62      0.61       800
```



Support vector Machine

```
# Support vector classifier
om sklearn.svm import SVC
svc_classifier = SVC(class_weight = "balanced" )
svc_classifier.fit(X_train_final, y_train)
y_pred_scv = svc_classifier.predict(X_test_final)
accuracy_score(y_test, y_pred_scv)
```

```
0.6225
```

```
print(classification_report(y_test, y_pred_scv))
```

```
              precision    recall  f1-score   support

           0       0.70      0.69      0.70       497
           1       0.50      0.50      0.50       303

    accuracy                           0.62       800
   macro avg       0.60      0.60      0.60       800
weighted avg       0.62      0.62      0.62       800
```

The SVM model was developed in 1995 by Corinna Cortes and Vapnik. It has several unique benefits in solving small samples, and nonlinear and high-dimensional pattern recognition. It can be extended to function in the simulation of other machine learning problems. It uses the hyper plane to separate the points of the input vectors and finds the needed coefficients. The best hyper plane IS the line with the largest margin, which is meant the distance between the hyper plane and the nearest input objects The input points defined in the hyper plane are called support vectors. In this work, the linear SVM model along with the Gaussian radial basis function (equation (U)) is used to classify the tested water samples based on their quality.

8. TESTING AND RESULT

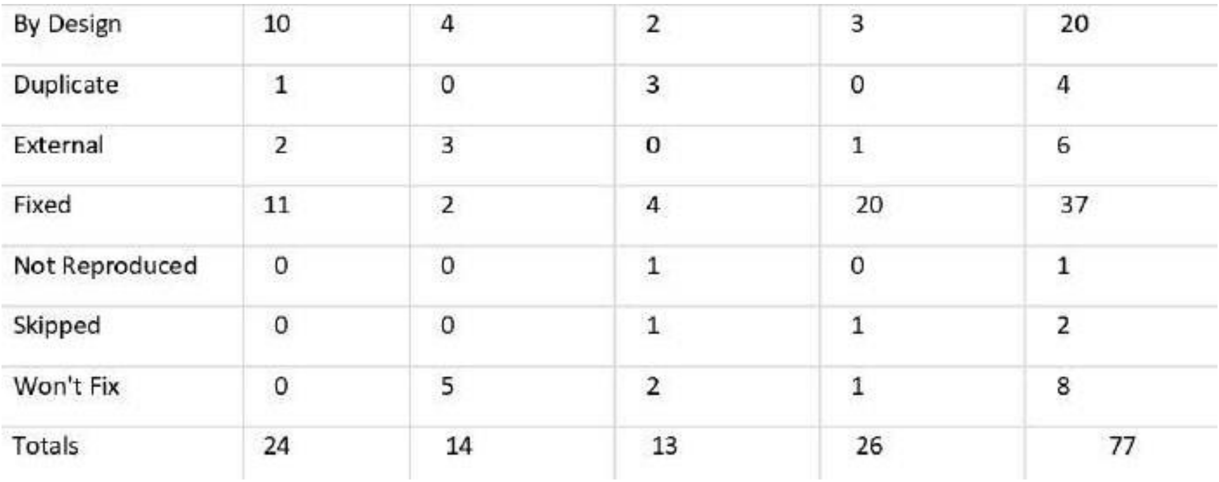
8.1 USER ACCEPTANCE TESTING

8.1.1 Purpose of Document

The purpose of this document is to briefly explain the test coverage and open issues of the [Product Name] project at the time of the release to User Acceptance Testing (UAT).

8.1.2 Defect Analysis

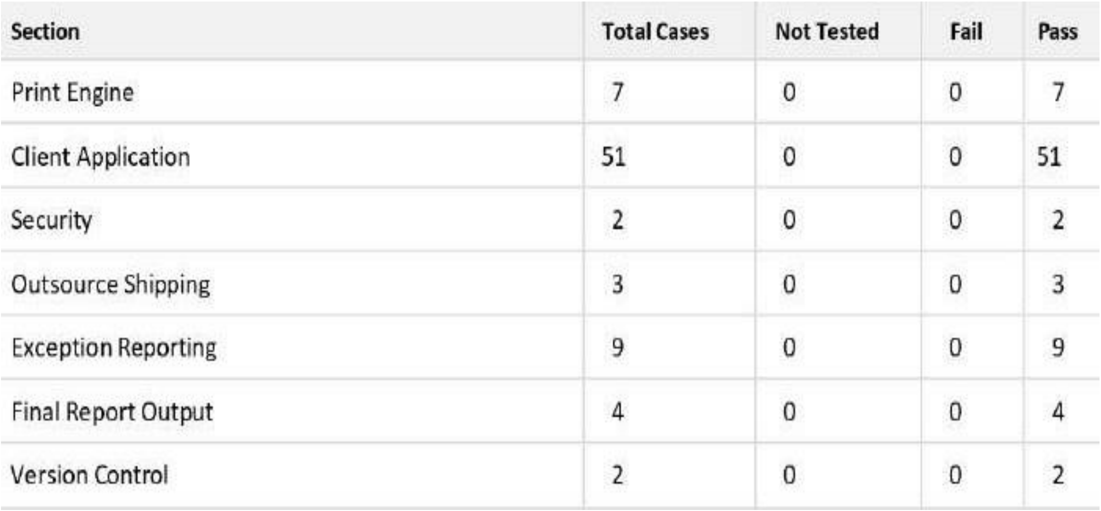
This report shows the number of resolved or closed bugs at each severity level, and how they were resolved



Resolution	%verity 1	Severity 2	Sever ity 3	Severity 4	Qlbtotal
By Design	10	4	2	3	20
Duplicate	1	0	3	0	4
External	2	3	0	1	6
Fixed	11	2	4	20	37
Not Reproduced	0	0	1	0	1
Skipped	0	0	1	1	2
Won't Fix	0	5	2	1	8
Totals	24	14	13	26	77

8.1.3 Test Case Analysis

This report shows the number of test cases that have passed, failed, and untested

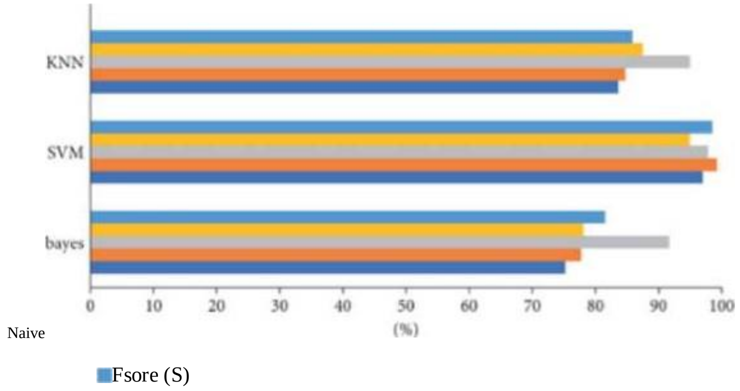


Section	Total Cases	Not Tested	Fail	Pass
Print Engine	7	0	0	7
Client Application	51	0	0	51
Security	2	0	0	2
Outsource Shipping	3	0	0	3
Exception Reporting	9	0	0	9
Final Report Output	4	0	0	4
Version Control	2	0	0	2

9. PERFORMANCE AND RESULTS

9.1 PERFORMANCE METRICS

For validating the developed model, the dataset has been divided into 70% training and 30% testing subsets. the ANN and LSTM models were used to predict the WQI, the SVM, KNN, and Naive Bayes were utilized for the water quality classification prediction



Performance Measures Results Time Positives (TP) are when the model predicts the positive class properly. True Negatives (TN) is one of the components of a confusion matrix designed to demonstrate how classification algorithms work. Positive outcomes that the model predicted incorrectly are known as False Positives (FP). False Negatives (FN) are negative outcomes that the model predicts negative class. Accuracy is the most basic and intuitive performance metric, consisting of the ratio of successfully predicted observations to total observations.
Accuracy = TP+TN/(TP+FP+FN+TN)

S NO	**Algorithm**	**Type**	**ACCURACY**	**Precision**	**Recall FI-Score**
1	RANDOM FOREST	58.5	0.42	0.38	0.40
2	XGBOOST	61.7	0.43	0.12	0.18

10. ADVANTAGES & DISADVANTAGES

10.1 ADVANTAGES

Whether it be for groundwater, surface water or open water, there are a number of reasons why it is Important for you to undertake regular water quality testing. If you're wanting to create a solid foundation on which to build a broader water management plan, then investing in water quality testing should be your first point of action. This testing will also allow you to adhere to strict permit regulations and be m compliance with Australian laws.

Identifying the health of your water will help you to discover where it may need some help. Ultimately, finding a source of pollution, or remaining proactive with your momtormg will enable you to save money in the long term. The more information that you can obtain will assist you with your decision on what product you may need to improve the condition of your water. Simply guessing and buying products based on a hunch or a general trend is ill-advised, as each body of water has unique properties that can only be discovered through testing.

Measuring the amount of dissolved oxygen in your water is another important advantage of water quality testing, as typically the less oxygen, the higher the water temperature, resulting in a more harmful environment for aquatic life. These levels do fluctuate slightly across the seasons, but regular monitoring of your water quality will allow you to discover trends over time, and whether there are other factors that may be contributing to the results you discover.

10.2 DISADVANTAGES

Training necessary Somewhat difficult to manage over time and with large data sets
Requires manual operation to submit data, some configuration required
Costly, usually only feasible under Exchange Network grants Technical expertise and network server required
Requires manual operation to submit data Cannot respond to data queries from other nodes, and therefore cannot interact with the Exchange Network Technical expeltize and network server required

11. CONCLUSION

Probability determines the quality of water, which is one of the most important resources for existence. Traditionally, testing water quality required an expensive and time-consuming lab analysis. This study looked into an alternative machine learning method for predicting water quality using only a few simple water quality criteria. To estimate, a set of representative supervised machine learning algorithms was used. It would detect water of bad quality before it was released for consumption and notify the appropriate authorities It will hopefully reduce the number of individuals who drink low-quality water, lowering the risk of diseases like typhoid and diarrhea. In this case, using a prescriptive analysis based on projected values would result in future capabilities to assist decision and policy makers.

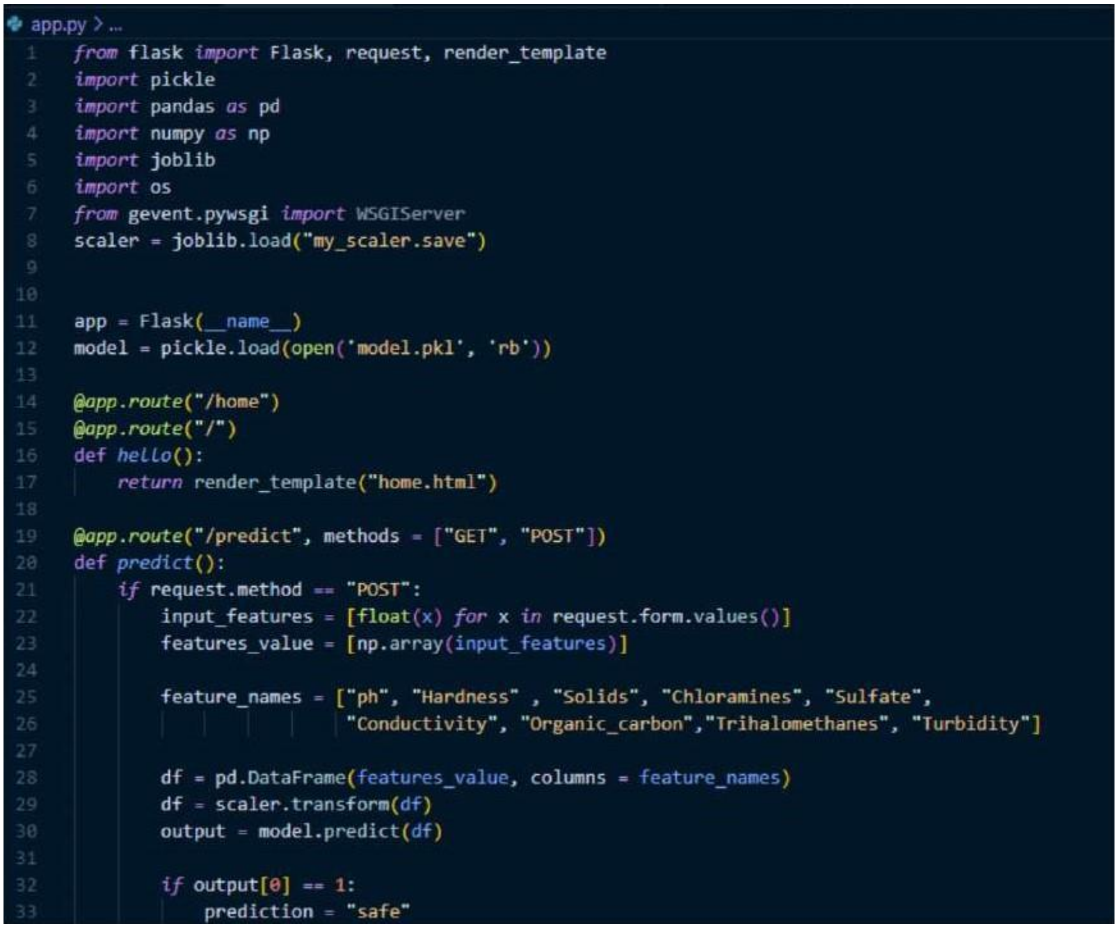
12 SOURCE CODE

Machine learning has been widely used as a powerful tool to solve problems m the water environment because it can be applied to predict water quality, optimize water resource allocation, manage water resource shortages, etc. Despite this, several challenges remain in fully applying machine learning approaches in this field to evaluate water quality: (l) Machine learning is usually dependent on large amounts of high-quality data. Obtaining sufficient data with high accuracy in   and management systems is often difficult owing to the cost or technology limitations. (2) As the conditions in real water treatment and management systems can be extremely complex, the current algorithms may only be applied to specific systems, which hinders the wide application of machine learning approaches. (3) The implementation of machine learning algorithms in practical applications requires researchers to have certain professional background knowledge.

To overcome the above-mentioned challenges, the following aspects should be considered future research and engineering practices: (1) More advanced sensors, including soft sensors, should be developed and applied in water quality monitoring to collect sufficiently accurate data to facilitate the application of machine learning approaches. (2) The feasibility and reliability of the algorithms should be improved, and more universal algorithms and models should be developed according to the water treatment and management requirements. (3) Interdisciplinary talent with knowledge in different fields should be trained to develop more advanced machine learning techniques and apply them in engineering practices.

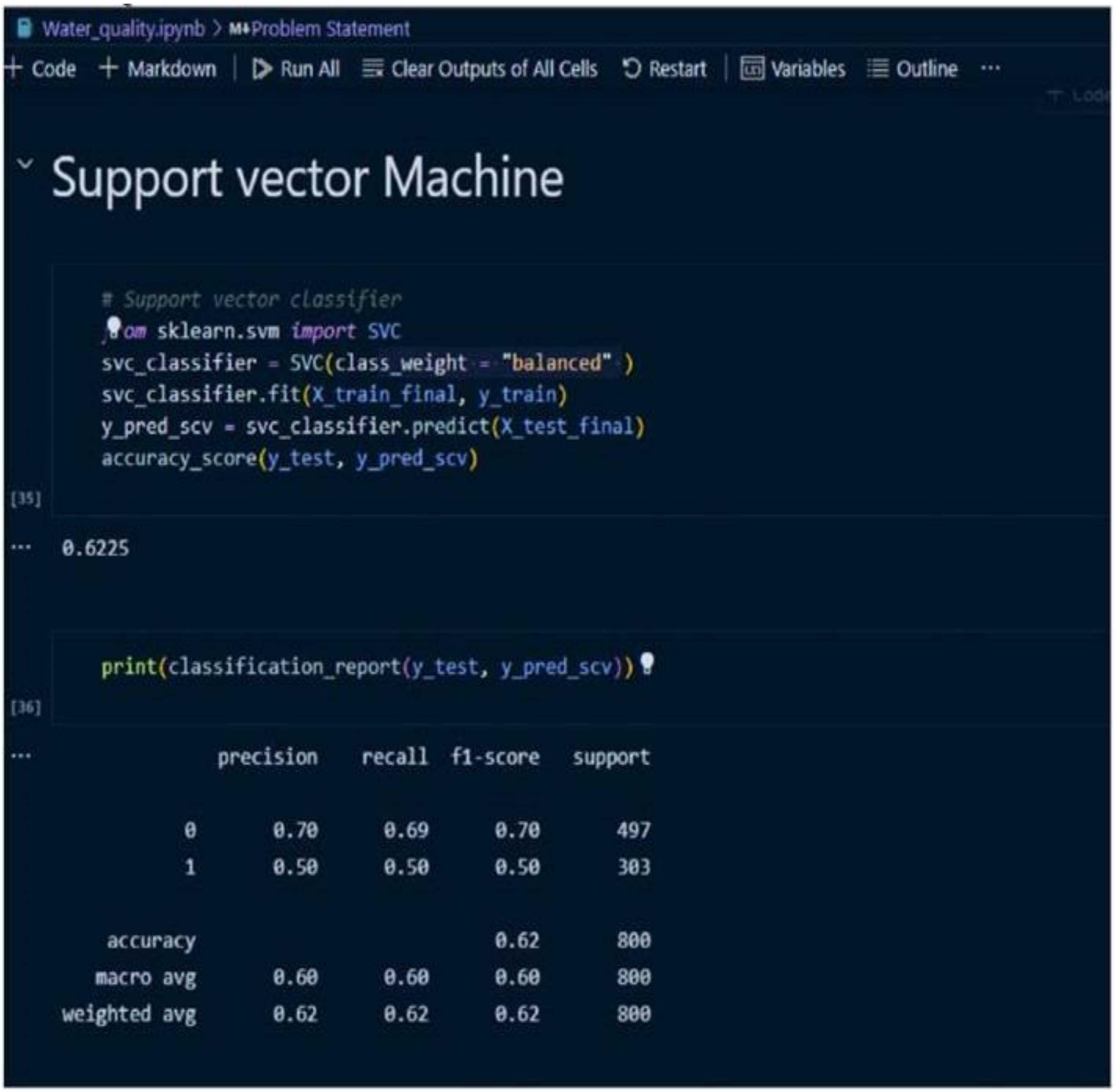
13. APPENDIX

App.py :



```python
from flask import Flask, request, render_template
import pickle
import pandas as pd
import numpy as np
import joblib
import os
from gevent.pywsgi import WSGIServer
scaler = joblib.load("my_scaler.save")


app = Flask(__name__)
model = pickle.load(open('model.pkl', 'rb'))

@app.route("/home")
@app.route("/")
def hello():
    return render_template("home.html")

@app.route("/predict", methods = ["GET", "POST"])
def predict():
    if request.method == "POST":
        input_features = [float(x) for x in request.form.values()]
        features_value = [np.array(input_features)]

        feature_names = ["ph", "Hardness" , "Solids", "Chloramines", "Sulfate",
                         "Conductivity", "Organic_carbon","Trihalomethanes", "Turbidity"]

        df = pd.DataFrame(features_value, columns = feature_names)
        df = scaler.transform(df)
        output = model.predict(df)

        if output[0] == 1:
            prediction = "safe"
```

Water Quality.ipynb



Water_quality.ipynb > M↓Problem Statement
+ Code
+ Markdown
Run All
Clear Outputs of All Cells
Restart
Variables
Outline
···
[35]
[36]

Support vector Machine

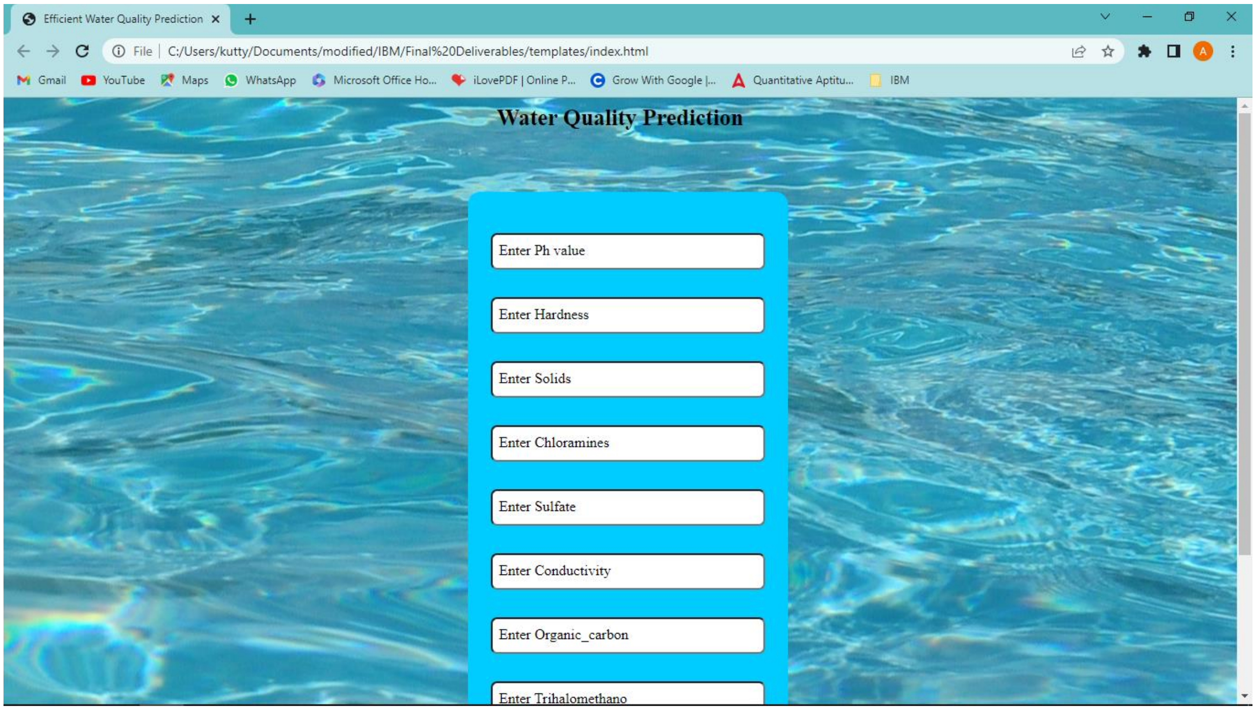
```
# Support vector classifier
from sklearn.svm import SVC
svc_classifier = SVC(class_weight = "balanced" )
svc_classifier.fit(X_train_final, y_train)
y_pred_scv = svc_classifier.predict(X_test_final)
accuracy_score(y_test, y_pred_scv)
```

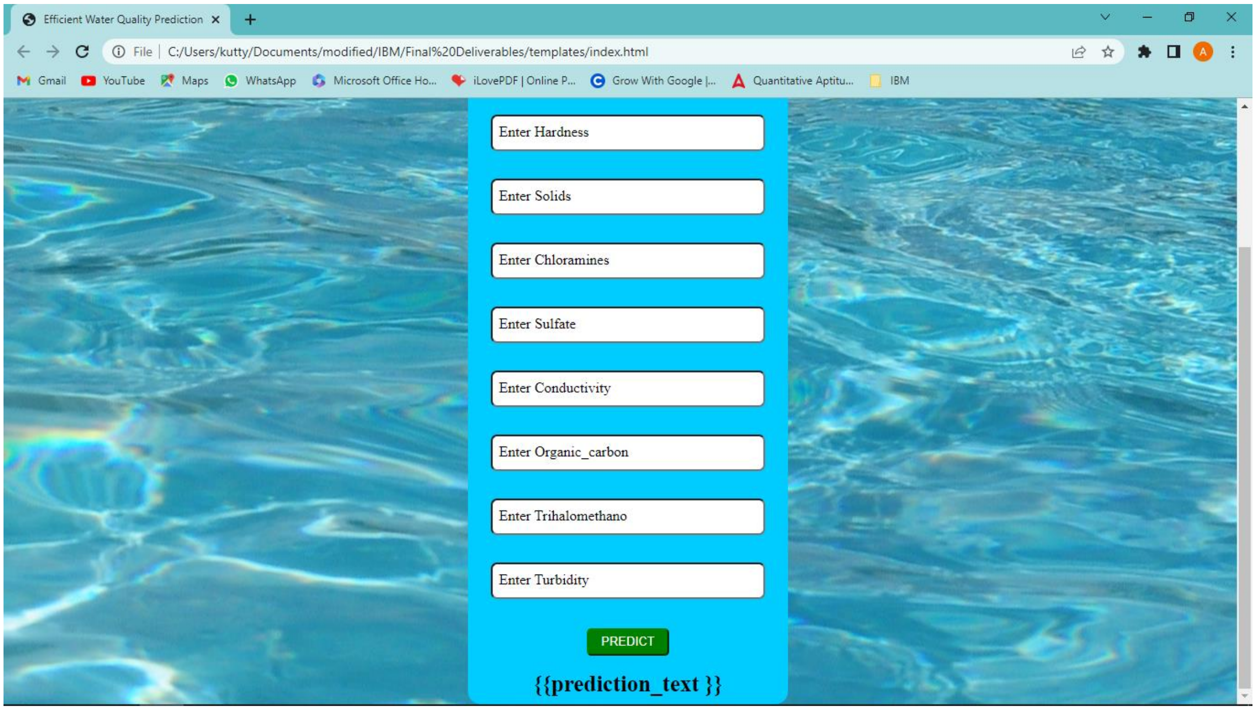
```
0.6225
```

```
print(classification_report(y_test, y_pred_scv))
```

```
              precision    recall  f1-score   support

           0       0.70      0.69      0.70       497
           1       0.50      0.50      0.50       303

    accuracy                           0.62       800
   macro avg       0.60      0.60      0.60       800
weighted avg       0.62      0.62      0.62       800
```

Web Application:


Efficient Water Quality Prediction
File | C:/Users/kutty/Documents/modified/IBM/Final%20Deliverables/templates/index.html
Gmail
YouTube
Maps
WhatsApp
Microsoft Office Ho...
iLovePDF | Online P...
Grow With Google |...
Quantitative Aptitu...
IBM
Water Quality Prediction
Enter Ph value
Enter Hardness
Enter Solids
Enter Chloramines
Enter Sulfate
Enter Conductivity
Enter Organic_carbon
Enter Trihalomethano


Efficient Water Quality Prediction
File | C:/Users/kutty/Documents/modified/IBM/Final%20Deliverables/templates/index.html
Gmail
YouTube
Maps
WhatsApp
Microsoft Office Ho...
iLovePDF | Online P...
Grow With Google |...
Quantitative Aptitu...
IBM
Enter Hardness
Enter Solids
Enter Chloramines
Enter Sulfate
Enter Conductivity
Enter Organic_carbon
Enter Trihalomethano
Enter Turbidity
PREDICT
{{prediction_text }}