EVALUATING AND CLASSIFYING WATER QUALITY USING MACHINE LEARNING

A PROJECT REPORT

Submitted by

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3.HARITHA R

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ABSTRACT

Water pollution can be described as one of the most dangerous threats that the humanity ever faced. Great damage is caused to crops ,animals, forests etc. To prevent this problem we have to predict water quality from pollutants using machine learning techniques. Hence, water quality evaluation and prediction has become an important research area. The aim is to investigate machine learning based techniques for water quality forecasting by predicting results in best accuracy. Our analysis provides a comprehensive guide to sensitivity analysis of model parameters with regard to performance in prediction of water quality by accuracy calculation. To propose a machine learning-based method to accurately predict the Water Quality Index value by prediction results in the form of best accuracy from comparing supervised classification machine learning algorithms. Additionally, to compare and discuss the performance of various machine learning algorithms from the given water supply department dataset with evaluation classification report. Precision, Recall, and F1 Score are used to determine the success of the proposed machine learning algorithm technique.

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LIST OF ABBREVIATIONS

S.NO	ABBREVIATION	EXPANSION
1	ML	Machine Learning
2	WQM	Water Quality Monitoring
3	WQI	Water Quality Index
4	LR	Logistic Regression
5	RF	Random Forest
6	DT	Decision Tree
7	SVM	Support Vector Machine
8	PCB	Physical-chemical-Biological
9	TP	True Positive
10	TN	True Negative
11	FP	False Positive
12	FN	False Negative

CHAPTER- 1

1.INTRODUCTION

1.1 OVERVIEW

One of the biggest fears of the world is water pollution. The of water needs to be monitored in real time to supply a safe drinking water. In the 21st century a lot of inventions have been developed but at the same time global warming ,pollutions are also being formed, which has lead to unsafe drinking water for the worlds population. Nowadays, water quality monitoring in real time faces challenges because of growing population, and limited water resources, growing population, etc. Therefore better methods need to be developed to predict the water quality whether it is safe or unsafe for drinking.

1.2 PROBLEM DEFINITION

Water pollution can be described as one of the most dangerous threats that the humanity ever faced. Great damage is caused to crops ,animals, forests etc. To prevent this problem we have to predict water quality from pollutants using machine learning techniques. Hence, water quality evaluation and prediction has become an important research area. The aim is to investigate machine learning based techniques for water quality forecasting by predicting results in best accuracy. Our analysis provides a comprehensive guide to sensitivity analysis of model parameters with regard to performance in prediction of water quality by accuracy calculation. To propose a machine learning-based method to accurately predict the Water Quality Index value by prediction results in the form of best accuracy from comparing supervised classification machine learning algorithms. Additionally, to compare and discuss the performance of various machine learning algorithms from the given water supply department dataset with evaluation classification report. Precision, Recall, and F1 Score are used to determine the success of the proposed machine learning algorithm technique.

CHAPTER - 2

2. LITERATURE SURVEY

1.Title: Comparison of Water Quality Classification Models using Machine Learning

Author: Neha Radhakrishnan; Anju S Pillai

Year: July 2021

Published in: Fifth International Conference on Communication and Electronics Systems

Observation: In this paper, machine learning methods such as SVM, Decision Tree, and Nave Bayes are used to compare water quality classification models. pH, DO, BOD, and electrical conductivity are among factors examined when determining water quality. The water quality was determined using only four factors. Only three methods are compared, resulting in lower accuracy. As a result, the decision tree algorithm was discovered to be a better classification model, with a 98.50 percent accuracy.

2. Title: Water quality prediction and classification based on principal component regression and gradient boosting classifier

Year: June2021

Author: Md.Saikat islam khan

Published in : Journal of King Saud University-Computer and Information Science

Observation: Gradient Boosting Regression, Multiple Linear Regression, and Support Vector Regression are three machine learning techniques used in this work to compare water quality classification models. The data set is separated into two parts: 75 percent for training and 25% for testing. WQI is calculated

using nine parameters (PH, DO, TDS, Chloride, COD, EC, SS, Turbidity, Alkalinity). As a result, Support Vector Regression produces excellent results.

3.Title: Prediction of groundwater quality indices using Machine Learning algorithms

Year: Dec 2021

Authors: Hemant Raheja, Arun Goel, Mahesh Pal

Published in: International journal of machine learning and computing
Observation: The number of parameters considered in this study was 12. The data set is separated into two parts: 75 percent for training and 25% for testing. Two indices are used to calculate water quality. Entropy water quality index and Water quality index are the two. EWQI is efficient as a result of two indexes. Gradient Boosting Model, DNN, and XGBoost are the algorithms employed in this paper. Some user-defined parameter is required by this algorithm. Correlation coefficient, Root mean square error, and Index of agreement are examples of output parameters. As a result, DNN generates great accuracy.

4.Title: Research on water quality prediction method based on AE-LSTM

Author : Huizinga Zhang, Kimie Jinx

Year : October 2021

Published in: 5th International Conference on Automation, Control Engineering

Observation: A water quality parameter prediction technique based on automatic encoder (AE) spatial property reduction and long and short time memory (LSTM) neural networks is proposed. The Lang Fang Water Quality Automatic Observation Station data collection is used to assess the tactic's efficacy. The strategy is discovered to have higher forecast accuracy and

toughness by estimating total phosphorus (TP) and total atomic number 7 (TN) concentrations. Results, The prediction model with AE-LSTM input had a higher prediction impact and accuracy than the prediction model with LSTM input, and it could effectively forecast water quality parameters.

5.Title: Water quality analysis in a lake using deep learning methodology

Year: Aug 2020

Author: P.Senthil Kumar, Prasannamedha G, Soumya K

Published in: International journal of environmental analytical chemistry

Observation: Korattur Lake in Chennai was used to collect samples. This paper's parameter was 9. (PH ,TDS ,COD ,Nitrate ,Iron ,Sodium ,Phosphate ,Turbidity ,chloride). Artificial Neural Networks, Recurrent Neural Networks, and Long Short Term Memory are the algorithms employed. As a result, LSTM has the highest accuracy, around 94%.

6. Title: Predicting Water Quality Parameters Using Machine Learning

Author: Nikhil M Ragi; Ravishankar Holla; G Manju

Year : March 2020

Published in: 4th International Conference on Recent Trends on Electronics, Information, Communication Technology (RTEICT)

Observation: ANN (Artificial Neural Network) is used. This method eliminates the use of chemicals in the evaluation of water quality indicators and is also cost effective. This paper presents a transient methodology for predicting unknown parameters such as pH, chloride, and sulphate values using well-known parameters such as pH scale, electrical physical phenomena, and TDS, as well as

the Levenberg-Marquardt algorithmic programme, which aids in the classification of water bodies for various applications. In forecasting chloride, total-hardness, sulphate, and total alkalinity, the accuracy was 83.94 percent, 87.9%, 81.736 percent, and 79.48 percent, respectively.

7.Title: Ground Water Quality Prediction using Machine Learning Algorithms

Author : S.Vijay & Dr.K.Kamaraj

Year: March 01, 2019

Published in: International Journal of Research and Analytical Reviews

Observation: It examines the physico-chemical properties of ground water quality in the Vellore district towns of Ranipet, Arcot, and Walljah Pet. For the objective of investigating the quality of groundwater, water samples were obtained from various designated bore wells. In the Vellore district, there are two major types of water contamination: high and low. Water quality metrics like PH, TDS, EC, Chloride, Sulphate, Nitrate, Carbonate, Bicarbonate, metal ions, and trace elements have all been calculated. Water quality prediction algorithms employing Machine Learning classifier algorithm C5.0, Nave Bayes, and Random Forest as leaner. With accuracy and classification error, Nave Bayes and Random Forest generated better results.

8.Title: Predictive Analysis of Water Quality Parameters using Deep Learning

Author: Archana Solanki, Himanshu Agrawal, Kanchan Khare

Year: September 2019

Published in: International journal of computer application

Observation: When compared to other techniques, deep learning algorithms that use unsupervised learning provide proper results. Stack denoising autoencoder, deep belief network, regression, and multilayer perception are examples of algorithms. The results show that toughness can be achieved using a denoising autoencoder and a deep belief network, as well as successfully managing information variability. The benefit of unsupervised learning algorithms is assessed using metrics such as mean absolute error and mean square error to examine the prediction error rate. Area unit pH scale, dissolved oxygen, and turbidity were employed as parameters. Modules include data collecting (krishna stream), data preparation, and modelling.

CHAPTER-3

3. SYSTEM ANALYSIS

3.1 EXISTING SYSTEM

The sensor technology for WQM has improved. The cost-effective sensorised tools have been implemented which measures the PCB values are available and are deployed on boats ,buoys ,ships. The connected sensors technology has been a bridging solution for the disconnect between data quality, data gathering and data analysis and enhances the global data inter-comparability. They has reviewed the sensor deployment strategies, key deployment strategies, emerging methods for data analysis.

EXISTING SYSTEM DRAWBACKS

- Sensor technology is being used
- It is expensive to deploy
- No machine learning concept is used
- No accuracy is found

3.2 PROPOSED SYSTEM:

The proposed method is to build a machine learning model for water quality. Data collecting include gathering historical data on water quality. Data mining is a technique used for processing enormous data in the domain If discovered before treatment, the water can save lives . Machine learning concept is applied in this system which reduces the manual effort to make a better model which is error less. Data analysis and data visualization are being done on the dataset . Then machine learning algorithms are applied on the dataset. After applying the algorithms each one produces different accuracy. Finally the algorithm with highest accuracy is selected and deployed.

Advantages:

- Machine learning concept is used.
- Various algorithms are used.
- Highest accuracy is attained

3.3 FEASIBILITY STUDY

3.3.1 SOCIAL FEASIBILITY

Water pollution is one of the greatest threats to the humanity which destroys animals, plants, crops ,environment etc. To prevent this problem various machine learning techniques have to be developed to predict the water quality. The aim is to predict the water quality using various ML algorithms and predict their highest accuracy. Hence this system predicts the water quality and predicts whether the water is safe to drink or not.

3.3.2 TECHNICAL FEASIBILITY

The Requirements of this system are:

Operating System : Windows 10

Tool : Anaconda with Jupyter Notebook

Processor : intel i5

Hard disk : 500 GB

RAM : 8 GB

- **Python :**
- It's a multipurpose language. It's utilised for a wide range of purposes, including software development and machine learning apps.
- It is simple to learn
- It has a legible syntax.

• Python's features include flexibility, readability, scalability, portability, and speed.

- Flask: Flask is a Python-based microweb framework. The flask framework is used to deploy this system.
- As a result, this system is technically viable.
- **USED PACKAGES:**

- **sklearn:**
- Sklearn is a machine learning library for Python that includes many machine learning methods.
- **NumPy:**

- It's a python module that provides quick math functions for calculations. It's utilised to read information.**NumPy:**
- It is a numeric python module which provides fast maths functions for calculations.
- It is used to read data in numpy arrays and for manipulation purpose.
- **Pandas**
- Pandas can read and write a variety of files, and data frames make data processing simple.
- **Matplotlib:**
- Data visualisation is an effective tool for identifying trends in a dataset.
- Data frames make it simple to manipulate data.

3.3.3 ECONOMIC FEASIBILITY

- Total number of lines of code (LOC)=1200K
- KLOC=1200/1000=1.2

- Effort = 2.4 (1.2)1.05 =>2.906 person-month
- Development time = 2.5(2.906)0.38=>3.747months
- Average staff size=2.906/3.747 =>0.775 person
- Productivity = 1.2/2.906 > 0.412 KLOC/person-month
- Hence this system is economically feasible.

3.4 HARDWARE REQUIREMENTS:

Processor : intel i5

Hard disk : 500 GB

RAM : 8 GB

3.5 SOFTWARE REQUIREMENTS:

Operating System : Windows 10

Tool : Anaconda with Jupyter Notebook

CHAPTER - 4

4. SYSTEM DESIGN

4.1 E-R DIAGRAM

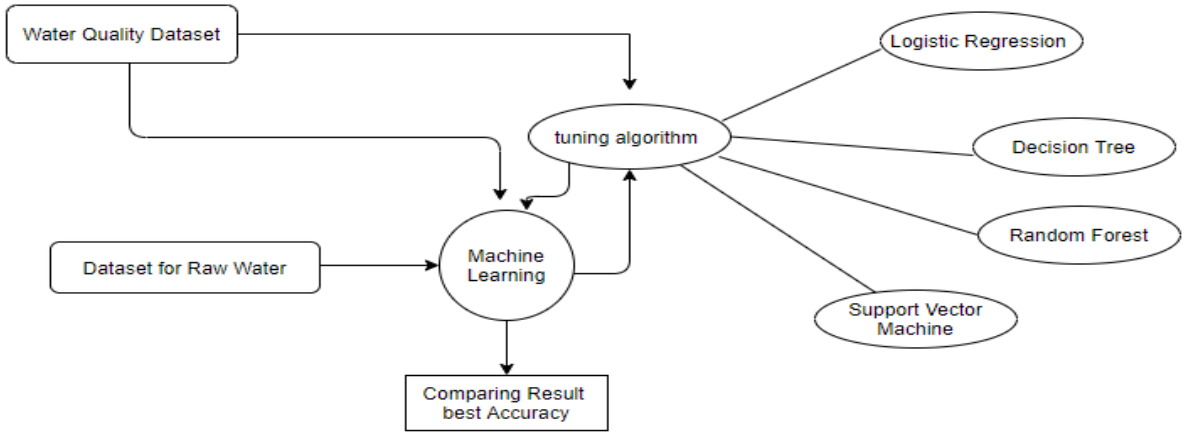


FIG 4.1 E-R DIAGRAM

4.2 DATA FLOW DIAGRAM:

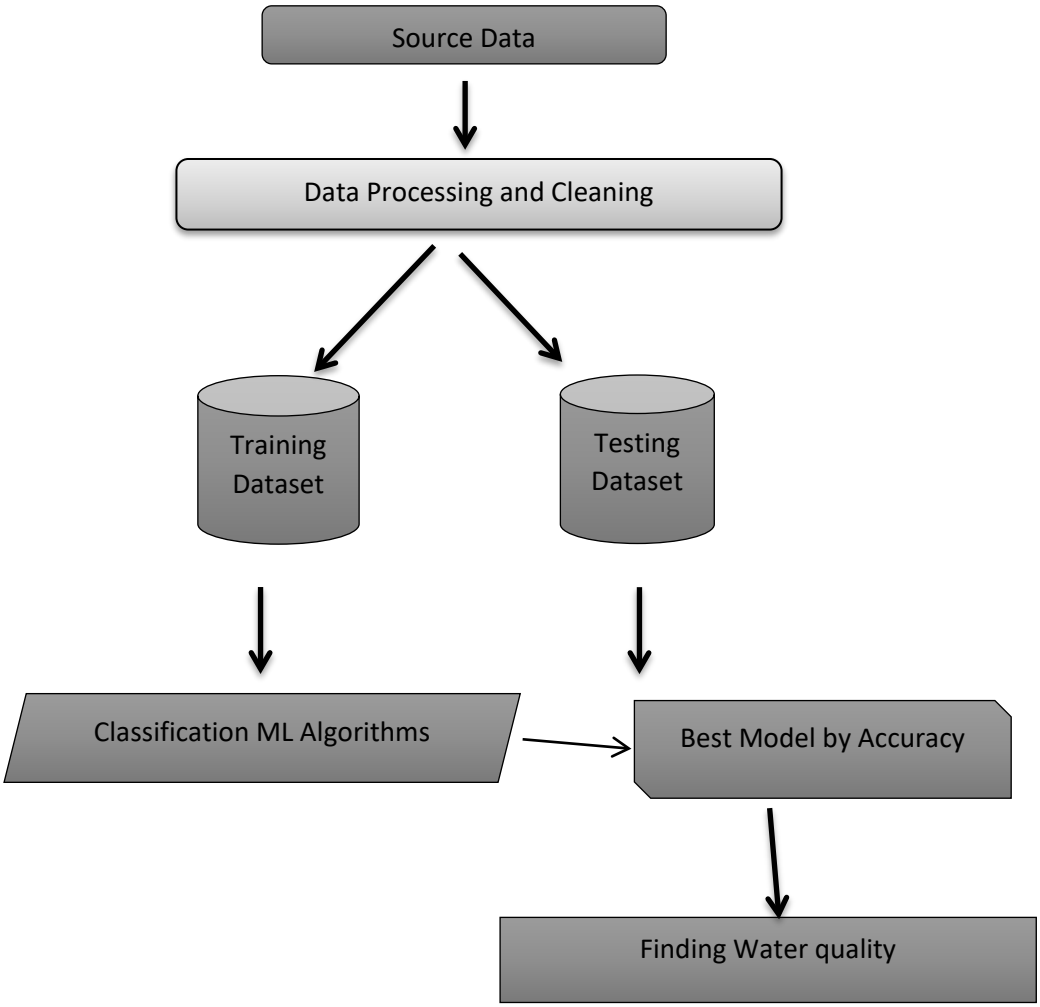


FIG 4.2 DATA FLOW DIAGRAM

4.3 USE CASE DIAGRAM:

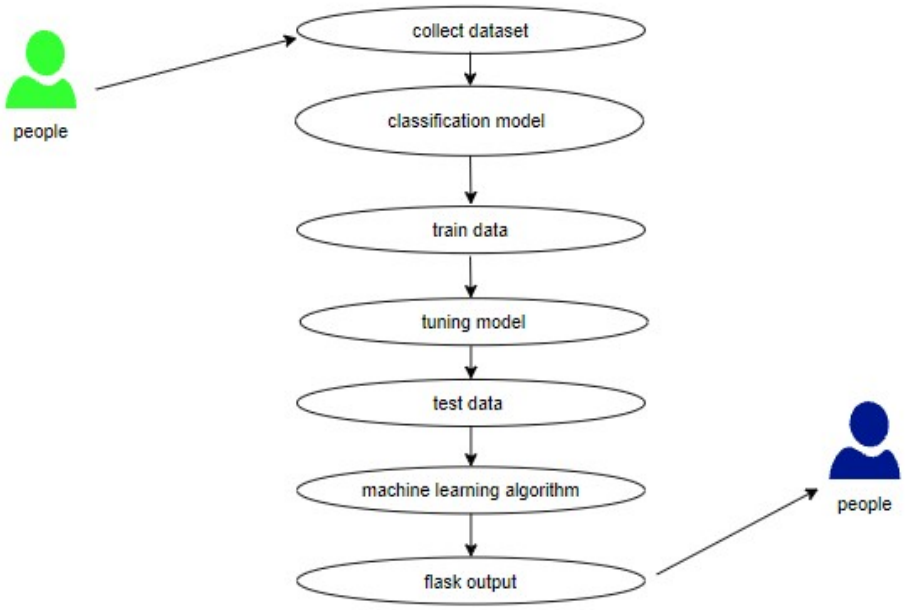


FIG 4.3 USE CASE DIAGRAM

4.4 CLASS DIAGRAM:

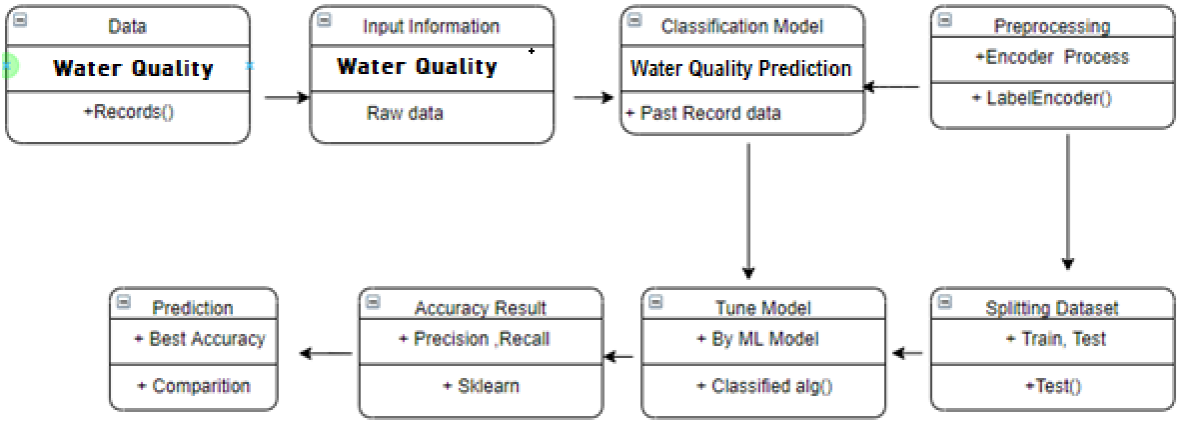


FIG 4.4 CLASS DIAGRAM

4.5 ACTIVITY DIAGRAM:

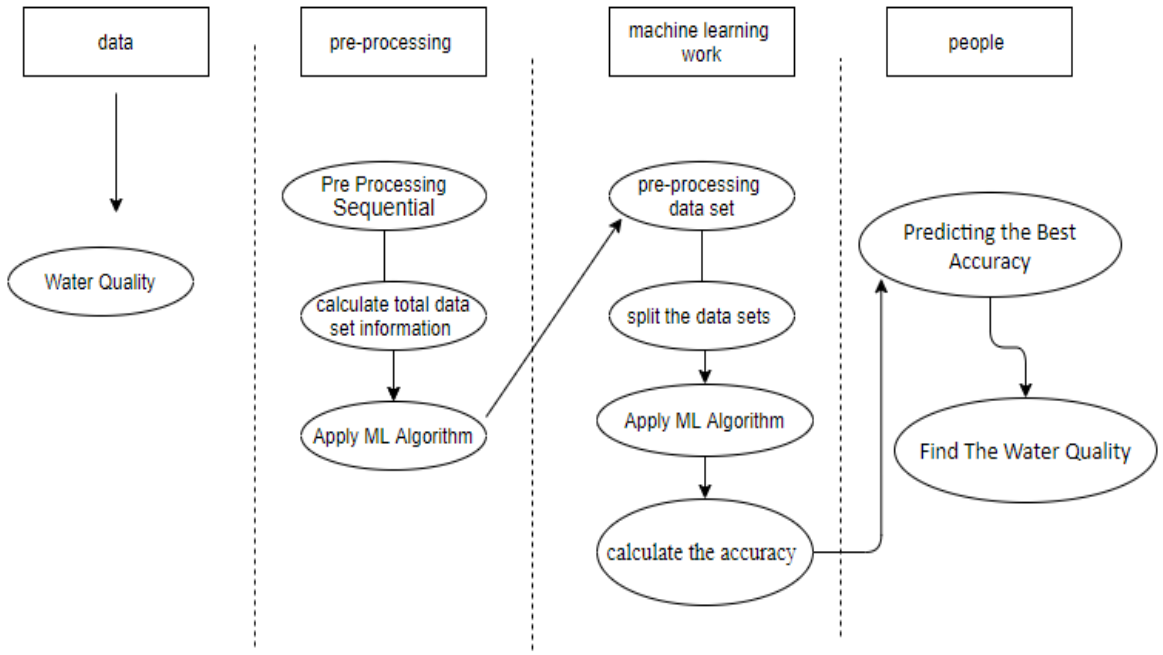


FIG 4.5 ACTIVITY DIAGRAM

4.6 SEQUENCE DIAGRAM:

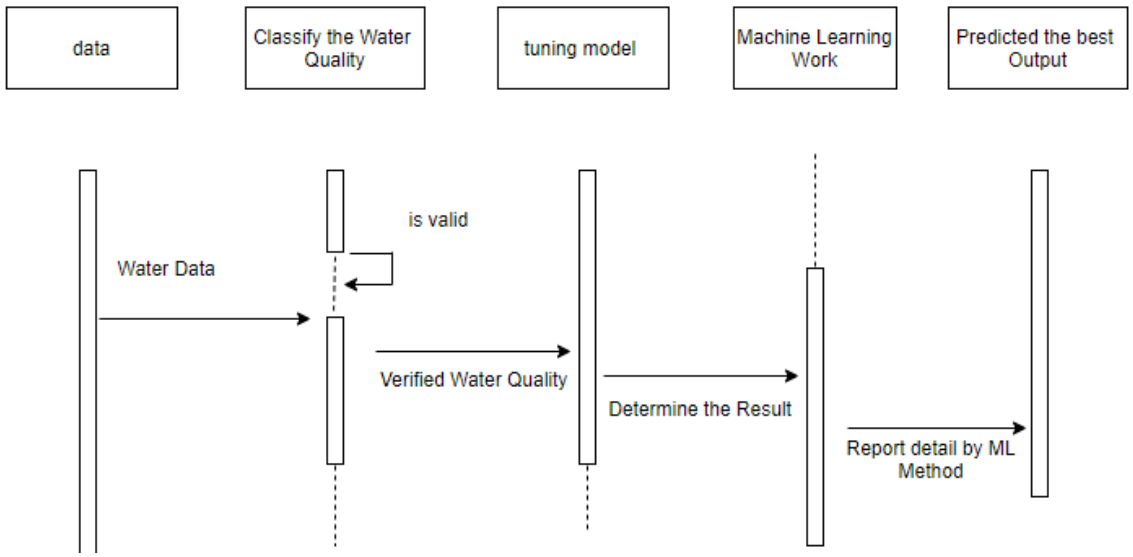


FIG 4.6 SEQUENCE DIAGRAM

CHAPTER -5

5. SYSTEM ARCHITECTURE

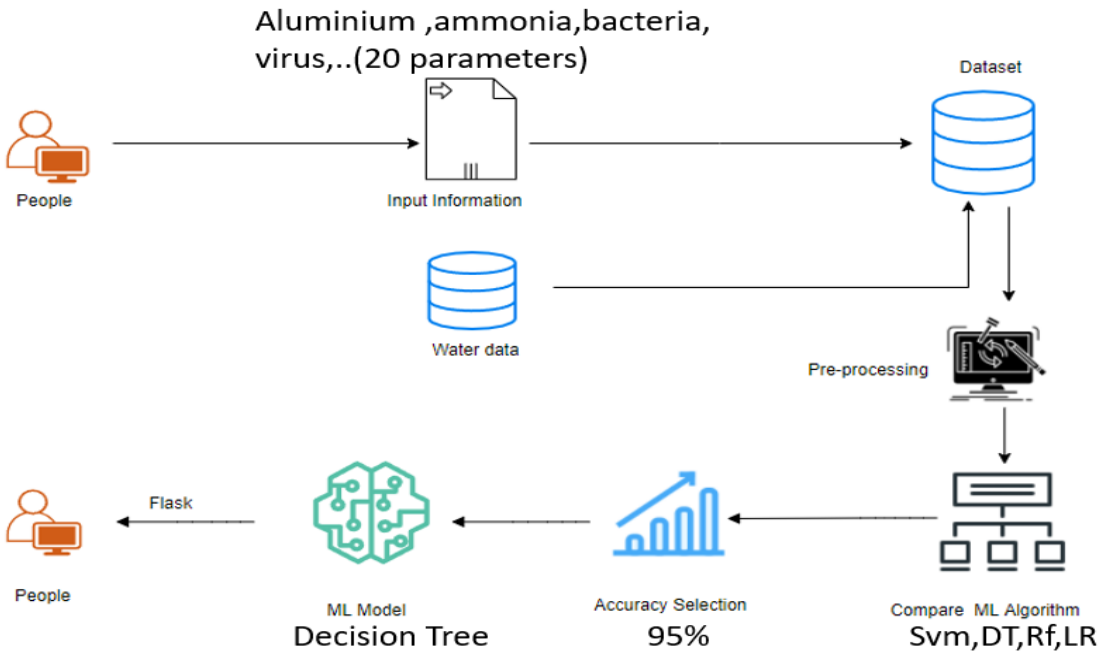


FIG 5.1 SYSTEM ARCHITECTURE

Water pollution is one of the greatest fears of the world. So as to provide a safe drinking water there is a need to predict the quality of water in real time. But, since the real time water monitoring faces challenges due to growing pollution limited water resources etc. There is a need to develop new and better technologies to predict the water quality parameters.

5.1 MODULE DESIGN SPECIFICATION

5.1.1 DATA PRE-PROCESSING

Validation techniques in ML is used to get the error rate which is close to true error rate pf the dataset. If the volume of the data is too large the validation techniques are not needed. This is concerned with locating the missing or duplicate value.Datatype is found-that is whether integer or float. Fine tuning of model hyper parameters are finetuned by ML engineers. Data gathering, data analysis, and the process of dealing with data content, quality, and organisation

can be time-consuming. Understanding data and its properties is done during the data identification step, which aids in the selection of an algorithm to build the model.

A number data is cleaned by pythons pandas library, It focuses specifically on biggest data cleaning task , missing values, it spends less time cleaning the data and more time exploring and modelling.

MODULE DIAGRAM:

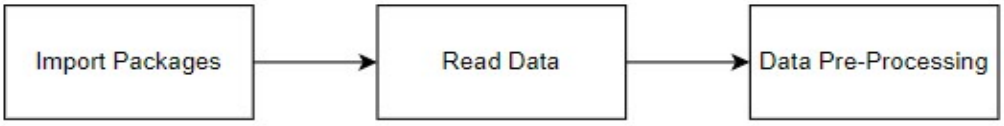


FIG 5.2 MODULE DIAGRAM

5.1.2 DATA VALIDATION OR DATA CLEANING PROCESS

The specified dataset is being loaded. The library packages are being imported. Variables are identified by data shape and type, and missing values and duplicate values are evaluated. A validation dataset is a sample of data kept back from training your model that is used to measure model skill when tweaking models and techniques for making the most of validation and test datasets while evaluating your models. Drop the column and rename the dataset. The steps for cleaning data vary depending on the dataset. The main purpose is to find and fix problems so that data may be used for better decision-making and analytics.

5.1.3 DATA VISUALISATION

It is an important skill in machine learning and applied statistics. Statistics focuses on estimating data and quantitative descriptions. Data visualisation provides qualitative comprehension tools that are useful for comprehending

datasets, exploring datasets, and spotting outliers, patterns, and corrupt data, among other things. it is used to express the key relationship in charts plots .

Expressing the data in visual form makes it more understandable. Visualising data samples is an important skill in both applied ML and applied statistics. It will discover the different plots that will be known while visualising data in python and how to use them for better understanding of data.

- How to use line plots to visualise time series data and bar charts to visualise categorical variables.
- How to summarise data distributions with histograms and box plots

Pre-processing refers to the adjustments made to our data before it is fed into the algorithm.. Data pre-processing is used to clean the raw dataset . In other words, In other words, anytime data is acquired from various sources, it is obtained in raw format, which makes analysis impossible.. The data has to be in better manner for achieving better results. Some Machine Learning models require data in a specific format; for example, the Random Forest(RF) algorithm does not tolerate null values. To implement RF algorithm null values have to be eliminated from the original raw dataset. Dataset should be formatted in such a way that more than one machine learning and deep learning algorithms are executed using the same dataset.

False Positives (FP) occur when the actual class is not the same as the projected class.

False Negatives (FN) are situations in which the real class is yes but the expected class is no.

True Positives (TP) are accurately predicted positive values, indicating that the value of the actual class and the value of the projected class are both yes.

True Negatives (TN): These are correctly predicted negative values, indicating that the actual class value is no and the predicted class value is also no.

MODULE DIAGRAM:

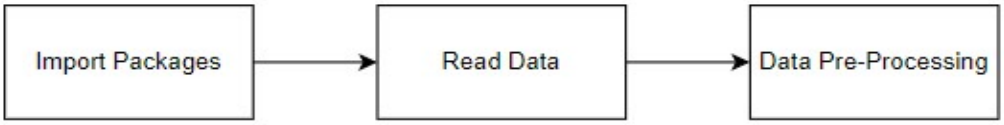


FIG 5.3 MODULE DIAGRAM

5.1.4 COMPARING ALGORITHMS

It is necessary to compare the performance of different machine learning algorithms which creates a test harness to compare different machine learning algorithms in python using scikit-learn. This test harness is used as a template to build your own ML problems and is able to add more different algorithms to compare. Different models have different performance characteristics. Resampling methods like cross validation is used to estimate accuracy of each model on unseen data. This estimate is used to choose one or two best models. For a new dataset it is good idea to visualize the data using different techniques to look at the data from different perspectives. The same idea applies to model selection. Different visualisation methods are used to show variance, average accuracy and other properties of the model accuracies. Each algorithm is tested in the same way on the same data, which can be accomplished by requiring each algorithm to be tested with the same test harness. In this system 4 different algorithms are compared:

- Logistic Regression

- Decision Tree
- Random Forest
- Support Vector Machine

Machine Learning Model is built using install Scikit-Learn libraries. This library package has to do pre-processing, linear model with logistic regression method, cross validating by K-Fold method, ensemble with random forest method and tree with decision tree classifier. Then it splits the data into train set and test set then finally predicting the result by comparing accuracy.

5.1.5 PREDICTING RESULT BY ACCURACY

To predict a value, the logistic regression process uses a linear equation with independent predictors. The anticipated value ranges from negative infinity to positive infinity. Logistic regression is a high-accuracy model that is created by comparing the best accuracy

True Positive Rate(TPR) = TP / (TP + FN)

False Positive rate(FPR) = FP / (FP + TN)

Accuracy: Accuracy is the percentage of right predictions out of a total number of forecasts.

Accuracy = (TP + TN) / (TP + TN + FP + FN)

It's only the proportion of accurately anticipated observations to total observations. Only when the dataset is symmetric and the values of false negative and false positive are almost equal is accuracy a good measure.

Precision: Precision refers to the percentage of positive predictions that are correct.

Precision = TP / (TP + FP)

The ratio of accurately anticipated positive observations to total predicted positive observations is known as precision. The low false positive rate is related to high precision. We have a precision of 0.788, which is rather good.

Recall: Recall that the proportion of positive observed values that was correctly predicted is the proportion of positive observed values that was correctly predicted.

Recall = TP / (TP + FN)

Recall(Sensitivity) Yes, recall (Sensitivity) is the ratio of accurately predicted positive observations to all observations in the actual class.

F1 Score The weighted average of Precision and Recall is the F1 Score. As a result, this score considers both false positives and false negatives. When the class distribution is unequal, F1 is frequently more valuable than accuracy. When false positives and false negatives have equivalent costs, accuracy works well. If the costs of a false negative and a false positive are significantly different, it's wiser to consider both Precision and Recall.

General Formula:

F- Measure = 2TP / (2TP + FP + FN)

F1-Score Formula:

F1 Score = 2*(Recall * Precision) / (Recall + Precision)

5.2 ALGORITHM:

5.2.1 LOGISTIC REGRESSION:

It's a statistical technique for analysing a data set with one or more independent factors that influence the outcome. A dichotomous variable is used to assess the outcome (in which there are only two possible outcomes). The purpose of logistic regression is to identify the best-fitting model to represent the

relationship between a set of independent (predictor or explanatory) factors and a dichotomous feature of interest (dependent variable = response or outcome variable). A Machine Learning classification approach called logistic regression is used to predict the likelihood of a categorical dependent variable. The dependent variable in logistic regression is a binary variable that comprises data coded as 1 (yes, success, etc.) or 0 (no) (no, failure, etc.).

```
Classification report of Logistic Regression Results:

              precision    recall  f1-score   support

           0       0.91      0.98      0.95      2125
           1       0.68      0.27      0.38       274

    accuracy                           0.90      2399
   macro avg       0.79      0.62      0.66      2399
weighted avg       0.89      0.90      0.88      2399

Accuracy result of Logisticregression is: 90.1625677365569

Confusion Matrix result of Logistic Regression is:
 [[2090   35]
 [ 201   73]]

Sensitivity :  0.9835294117647059

Specificity :  0.2664233576642336

Cross validation test results of accuracy:
[0.2525     0.8905566  0.91869919 0.90494059 0.88617886]

Accuracy result of Logistic Regression is: 77.05750469043153
```

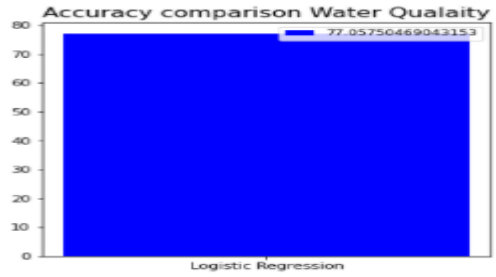


FIG 5.4 LOGISTIC REGRESSION RESULT

5.2.2 DECISION TREE:

Decision tree analysis is a prophetic modelling fashion that can be used in a variety of situations. An algorithmic strategy that can resolve the dataset in multitudinous ways grounded on different conditions can be used to produce decision trees. The most important algorithms in the sphere of supervised algorithms are decision trees. They can be used for bracket as well as retrogression. Decision bumps, where the data is resolve, and leaves, where we

get the result, are the two main ingredients of a tree.

```
Classification report DecisionTree classifier Results:

              precision    recall  f1-score   support

           0       0.98      0.97      0.97      2125
           1       0.76      0.81      0.78       274

    accuracy                           0.95      2399
   macro avg       0.87      0.89      0.88      2399
weighted avg       0.95      0.95      0.95      2399


Accuracy result of DecisionTree  is: 94.8311796581909

Confusion Matrix result of DecissionTree Classifier is:
 [[2053   72]
 [  52  222]]

Sensitivity :  0.9661176470588235

Specificity :  0.8102189781021898

Cross validation test results of accuracy:
[0.21       0.86241401 0.79612258 0.95747342 0.89868668]

Accuracy result of DecisionTree Classifier is: 74.49393370856787
```

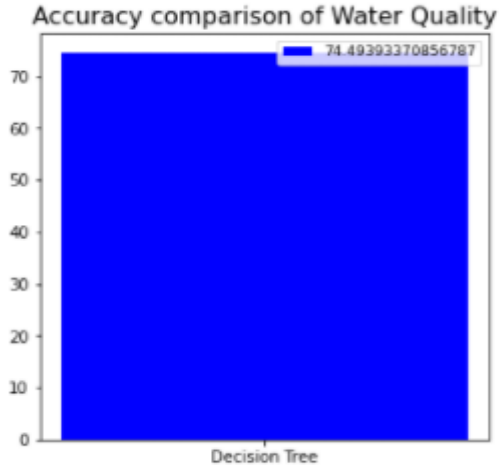


FIG 5.5 DECISION TREE RESULT

IMPORTANT TERMS IN DECISION TREE

The root node symbolises the total population or sample, which is then separated into two or more homogeneous groups.

Decision Knot - When a sub-node splits into several sub-nodes, it's referred to as a decision knot.

Bumps that do not resolve are referred to as Leaf or Terminal knots.

Cutting - Pruning Pruning is the process of removing sub-nodes from a decision knot. Splitting in the opposite direction, as it were.

Branch/Sub-Tree A branch or sub-tree is a portion of the overall tree.

Knot between parent and child A parent knot of sub-nodes is a knot that is divided into sub-nodes, whereas sub-nodes are the children of a parent knot.

5.2.3 RANDOM FOREST:

Random Forest is a popular machine learning algorithm that belongs to the supervised learning technique. It can be used for both Classification and Regression problems in ML. It is based on the concept of ensemble learning, which is a process of combining multiple classifiers to solve a complex problem and to improve the performance of the model. "Random Forest is a classifier that contains a number of decision trees on various subsets of the given dataset and takes the average to improve the predictive accuracy of that dataset." Instead of relying on one decision tree, the random forest takes the prediction from each tree and based on the majority votes of predictions, and it predicts the final output.

```
Classification report of Random Forest Results:

              precision    recall  f1-score   support

           0       0.96      0.99      0.98      2125
           1       0.93      0.66      0.77       274

    accuracy                           0.96      2399
   macro avg       0.94      0.83      0.87      2399
weighted avg       0.95      0.96      0.95      2399

Accuracy result of Random Forest is: 95.58149228845352

Confusion Matrix result of Random Forest is:
 [[2111   14]
 [  92  182]]

Sensitivity :  0.9934117647058823

Specificity :  0.6642335766423357

Cross validation test results of accuracy:
[0.234375   0.89430894 0.91744841 0.94121326 0.88680425]

Accuracy result of Random Forest is: 77.48299718574108
```

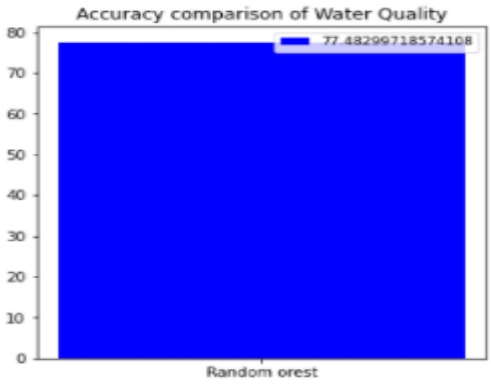


FIG 5.6 RANDOM FOREST RESULT

5.2.4 SUPPORT VECTOR MACHINE:

An SVM training algorithm creates a model that assigns new exemplifications to one of two orders, making it anon-probabilistic double direct classifier, given a series of training exemplifications that are collectively designated as belonging to one of two orders. The thing of using SVMs is to detect the stylish line in two confines or the stylish hyperplane in further than two confines to help us in classifying our space. The largest periphery, or the maximum distance between data points of both classes, is used to find the hyperplane (line).

```
Classification report of Support Vector Machines Results:

              precision    recall  f1-score   support

           0       0.89      1.00      0.94      2125
           1       0.00      0.00      0.00       274

    accuracy                           0.89      2399
   macro avg       0.44      0.50      0.47      2399
weighted avg       0.78      0.89      0.83      2399

Accuracy result of Support Vector Machines is: 88.5785744060025

Confusion Matrix result of Support Vector Machines is:
 [[2125    0]
 [ 274    0]]

Sensitivity :  1.0

Specificity :  0.0

Cross validation test results of accuracy:
[0.495625   0.88555347 0.88617886 0.88617886 0.88617886]

Accuracy result of Support Vector Machine is: 80.79430112570357
```

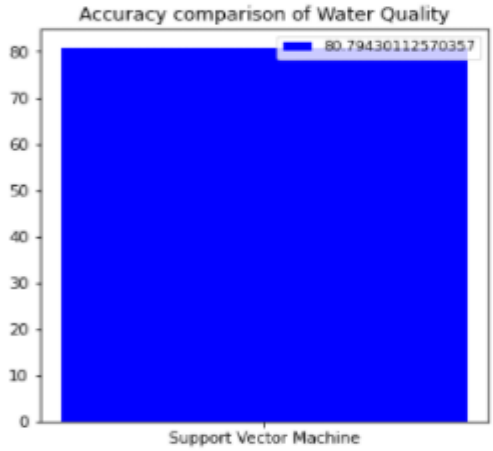


FIG 5.7 SUPPORT VECTOR MACHINE RESULT

CHAPTER - 6

6 .SYSTEM IMPLEMENTATION:

6.1 SERVER SIDE CODING

```
#import package

import pandas as pd
import numpy as ny
#read dataset
data = pd.read_csv('water.csv')
# view head
data.head()
#view tail
data.tail()
# shape of the project
data.shape
# size ofthe data
data.size
#columns
data.columns
data.isnull()
data.isnull().sum()
data.dropna()
# information about dataset
data.info()
data.duplicated()
data.duplicated().sum()
# describe
data.describe()
data['arsenic'].nunique()
data['barium'].nunique()
```

```
data["uranium"].nunique()
# check the unique values
data["aluminium"].nunique()
data["viruses"].nunique()
data["mercury"].nunique()
data["silver"].unique()
data["mercury"].unique()
data["arsenic"].unique()
data["uranium"].unique()
data["chloramine"].unique()
data["aluminium"].unique()
data.head()
#min max values
print("minimum values of aluminium :", data["aluminium"].min())
print("mean values of alumimum :",data["aluminium"].mean())
print("maximum values of aluminium :", data["aluminium"].max())
#min max values
print("minimum values of aluminium :", data["chloramine"].min())
print("mean values of alumimum :",data["chloramine"].mean())
print("maximum values of aluminium :", data["chloramine"].max())
#min max values
print("minimum values of aluminium :", data["copper"].min())
print("mean values of alumimum :",data["copper"].mean())
print("maximum values of aluminium :", data["copper"].max())
In [ ]:
#min max values
print("minimum values of aluminium :", data["flouride"].min())
print("mean values of alumimum :",data["flouride"].mean())
```

```
print("maximum values of aluminium :", data["flouride"].max())
#min max values
print("minimum values of aluminium :", data["lead"].min())
print("mean values of alumimum :",data["lead"].mean())
print("maximum values of aluminium :", data["lead"].max())
#min max values
print("minimum values of aluminium :", data["nitrates"].min())
print("mean values of alumimum :",data["nitrates"].mean())
print("maximum values of aluminium :", data["nitrates"].max())
#min max values
print("minimum values of aluminium :", data["radium"].min())
print("mean values of alumimum :",data["radium"].mean())
print("maximum values of aluminium :", data["radium"].max())
data.corr()
data.corr().describe()
data["mercury"].value_counts()
pd.Categorical(data["uranium"]).describe()
data.info()
data.columns
from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()
var_mod = (['aluminium', 'ammonia', 'arsenic', 'barium', 'cadmium', 'chloramine',
    'chromium', 'copper', 'flouride', 'bacteria', 'viruses', 'lead',
    'nitrates', 'nitrites', 'mercury', 'perchlorate', 'radium', 'selenium',
    'silver', 'uranium', 'is_safe'])
for i in var_mod:
        data[i] = le.fit_transform(data[i]). astype(int)
data.head()
```

Model-2:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
data = pd.read_csv("water.csv")
data.head()
data["is_safe"].unique()
data["is_safe"].unique()
data[data["is_safe"]=='#NUM!']
data = data.drop(data[data["is_safe"]=='#NUM!'].index)
data["is_safe"].unique()
data["is_safe"] = data["is_safe"].astype(float)
data.info()
data.columns
data.isnull().sum()
data =data.dropna()
plt.figure(figsize= (10,8))
sns.heatmap(data.isnull())
plt.show()
plt.figure(figsize=(9,6))
sns.scatterplot(x=data['aluminium'],y=data["barium"])
plt.show()
plt.figure(figsize = (14,8))
sns.stripplot(x = data["cadmium"], y = data["chromium"])
data.columns
plt.figure(figsize= (12,8))
```

```
plt.subplot(2,2,1)
data["cadmium"].plot(kind='density')
plt.subplot(2,2,2)
data["copper"].plot(kind='density')
plt.subplot(2,2,3)
data["viruses"].plot(kind='density')
plt.subplot(2,2,4)
data["chromium"].plot(kind='density')
plt.show()
data.hist(figsize=(20,35),layout =(19,3) )
plt.show()
plt.figure(figsize=(12,4))
plt.subplot(1,2,1)
plt.title("mercury")
sns.boxplot(data["mercury"])
plt.subplot(1,2,2)
plt.title("perchlorate")
sns.boxplot(data["perchlorate"])
plt.show()
#Propagation by variable
def PropByVar(data, variable):
    dataframe_pie = data[variable].value_counts()
    ax = dataframe_pie.plot.pie(figsize=(10,10), autopct='%1.2f%%', fontsize =
12)
    ax.set_title(variable + ' \n', fontsize = 15)
    return np.round(dataframe_pie/data.shape[0]*100,2)

PropByVar(data, 'is_safe')
plt.figure(figsize=(15,12))
```

```
sns.heatmap(data.corr(), annot =True)
plt.show()
data.columns
from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()
var = ['aluminium', 'ammonia', 'arsenic', 'barium', 'cadmium', 'chloramine',
      'chromium', 'copper', 'flouride', 'bacteria', 'viruses', 'lead',
      'nitrates', 'nitrites', 'mercury', 'perchlorate', 'radium', 'selenium',
      'silver', 'uranium', 'is_safe']
for i in var:
   data[i] = le.fit_transform(data[i])
data.head()
```

Module 3 : Performance measurements of Logistic regression

```
#import library packages
import pandas as p
import matplotlib.pyplot as plt
import seaborn as s
import numpy as n
#Load given dataset
data = p.read_csv("water.csv")
import warnings
warnings.filterwarnings('ignore')
data.head(5)
data.tail(5)
data.isnull().sum()
data = data.dropna()
data.shape
data.duplicated().sum()
data.info()
```

```
data["is_safe"].unique()
data[data["is_safe"]=='#NUM!']
data = data.drop(data[data["is_safe"]=='#NUM!'].index)
data["is_safe"].unique()
data.describe()
data.corr()
df = data
df.columns
#According to the cross-validated MCC scores, the random forest is the best-performing model, so now let's evaluate its performance on the test set.
from sklearn.metrics import confusion_matrix, classification_report,
matthews_corrcoef, cohen_kappa_score, accuracy_score,
average_precision_score, roc_auc_score
X = data.drop(labels='is_safe', axis=1)
#Response variable
y = data.loc[:,'is_safe']
#We'll use a test size of 30%. We also stratify the split on the response variable, which is very important to do because there are so few fraudulent transactions.
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3,
random_state=0, stratify=y)
```

Logistic Regression :

```
from sklearn.metrics import accuracy_score, confusion_matrix
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import cross_val_score

logR= LogisticRegression()
```

```
logR.fit(X_train,y_train)

predictLR = logR.predict(X_test)

print("")
print('Classification report of Logistic Regression Results:')
print("")
print(classification_report(y_test,predictLR))
x = (accuracy_score(y_test,predictLR)*100)

print('Accuracy result of Logisticregression is:', x)

print("")

cm2=confusion_matrix(y_test,predictLR)
print('Confusion Matrix result of Logistic Regression is:\n',cm2)
print("")
sensitivity2 = cm2[0,0]/(cm2[0,0]+cm2[0,1])
print('Sensitivity : ', sensitivity2 )
print("")
specificity2 = cm2[1,1]/(cm2[1,0]+cm2[1,1])
print('Specificity : ', specificity2)
print("")

accuracy = cross_val_score(logR, X, y, scoring='accuracy')
print('Cross validation test results of accuracy:')
print(accuracy)
#get the mean of each fold
print("")
```

```
print("Accuracy result of Logistic Regression is:",accuracy.mean() * 100)
LR=accuracy.mean() * 100




def graph():
    import matplotlib.pyplot as plt
    data=[LR]
    alg="Logistic Regression"
    plt.figure(figsize=(5,5))
    b=plt.bar(alg,data,color=("b"))
    plt.title("Accuracy comparison Water Qualaity",fontsize=15)
    plt.legend(b,data,fontsize=9)




graph()
TN = cm2[1][0]
FN = cm2[0][0]
TP = cm2[1][1]
FP = cm2[0][1]
print("True Positive :",TP)
print("True Negative :",TN)
print("False Positive :",FP)
print("False Negative :",FN)
print("")
TPR = TP/(TP+FN)
```

```
TNR = TN/(TN+FP)
FPR = FP/(FP+TN)
FNR = FN/(TP+FN)
print("True Positive Rate :",TPR)
print("True Negative Rate :",TNR)
print("False Positive Rate :",FPR)
print("False Negative Rate :",FNR)
print("")
PPV = TP/(TP+FP)
NPV = TN/(TN+FN)
print("Positive Predictive Value :",PPV)
print("Negative predictive value :",NPV)

cm2=confusion_matrix(y_test, predictLR)
print('Confusion matrix-LR:')
print(cm2)

s.heatmap(cm2/n.sum(cm2), annot=True, cmap = 'Blues', annot_kws={"size":
16}, fmt='.2%',)
plt.show()
```

Module 4 : Performance measurements of DecisionTree:

```
#import library packages
import pandas as p
import matplotlib.pyplot as plt
import seaborn as s
import numpy as n
#Load given dataset
```

```
data = p.read_csv("water.csv")
import warnings
warnings.filterwarnings('ignore')
data.head(5)
data.tail(5)
data.isnull().sum()
data = data.dropna()
data.shape
data.duplicated().sum()
data["is_safe"].unique()
data[data["is_safe"]=='#NUM!']
data = data.drop(data[data["is_safe"]=='#NUM!'].index)
data["is_safe"].unique()
data.info()
data.describe()
data.corr()
df = data
df.columns
#According to the cross-validated MCC scores, the random forest is the best-performing model, so now let's evaluate its performance on the test set.
from sklearn.metrics import confusion_matrix, classification_report,
matthews_corrcoef, cohen_kappa_score, accuracy_score,
average_precision_score, roc_auc_score
X = data.drop(labels='is_safe', axis=1)
#Response variable
y = data.loc[:,'is_safe']
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3,
random_state=0, stratify=y)
```

DecisionTree:

```
from sklearn.metrics import accuracy_score, confusion_matrix
from sklearn.tree import DecisionTreeClassifier
from sklearn.model_selection import cross_val_score

DT=DecisionTreeClassifier()

DT.fit(X_train,y_train)

predictDT = DT.predict(X_test)

print("")
print('Classification report DecisionTree classifier Results:')
print("")
print(classification_report(y_test,predictDT))

print("")
x = (accuracy_score(y_test,predictDT)*100)

print('Accuracy result of DecisionTree  is:', x)
print("")

cm2=confusion_matrix(y_test,predictDT)
print('Confusion Matrix result of DecissionTree Classifier is:\n',cm2)
print("")
sensitivity2 = cm2[0,0]/(cm2[0,0]+cm2[0,1])
print('Sensitivity : ', sensitivity2 )
print("")
specificity2 = cm2[1,1]/(cm2[1,0]+cm2[1,1])
```

```
print('Specificity : ', specificity2)
print("")

accuracy = cross_val_score(DT, X, y, scoring='accuracy')
print('Cross validation test results of accuracy:')
print(accuracy)
#get the mean of each fold
print("")
print("Accuracy result of DecisionTree Classifier is:",accuracy.mean() * 100)
dt=accuracy.mean() * 100




def graph():
    import matplotlib.pyplot as plt
    data=[dt]
    alg="Decision Tree"
    plt.figure(figsize=(5,5))
    b=plt.bar(alg,data,color=("b"))
    plt.title("Accuracy comparison of Water Quality",fontsize=15)
    plt.legend(b,data,fontsize=9)




graph()
TN = cm2[1][0]
FN = cm2[0][0]
```

```
TP = cm2[1][1]
FP = cm2[0][1]
print("True Positive :",TP)
print("True Negative :",TN)
print("False Positive :",FP)
print("False Negative :",FN)
print("")
TPR = TP/(TP+FN)
TNR = TN/(TN+FP)
FPR = FP/(FP+TN)
FNR = FN/(TP+FN)
print("True Positive Rate :",TPR)
print("True Negative Rate :",TNR)
print("False Positive Rate :",FPR)
print("False Negative Rate :",FNR)
print("")
PPV = TP/(TP+FP)
NPV = TN/(TN+FN)
print("Positive Predictive Value :",PPV)
print("Negative predictive value :",NPV)

cm2=confusion_matrix(y_test, predictDT)
print('Confusion matrix-DT:')
print(cm2)
s.heatmap(cm2/n.sum(cm2), annot=True, cmap = 'Blues', annot_kws={"size":
16}, fmt='.2%',)
plt.show()
```

Module 5 : Performance measurements of Random Forest algorithms

```
#import library packages
import pandas as p
import matplotlib.pyplot as plt
import seaborn as s
import numpy as n
#Load given dataset
data = p.read_csv("water.csv")
import warnings
warnings.filterwarnings('ignore')
data.head(5)
data.tail(5)
data.isnull().sum()
data = data.dropna()
data.shape
data.duplicated().sum()
data["is_safe"].unique()
data[data["is_safe"]=='#NUM!']
data = data.drop(data[data["is_safe"]=='#NUM!'].index)
data["is_safe"].unique()
data.info()
data.describe()
data.corr()
df = data
df.columns
#According to the cross-validated MCC scores, the random forest is the best-performing model, so now let's evaluate its performance on the test set.
```

```
from sklearn.metrics import confusion_matrix, classification_report,
matthews_corrcoef, cohen_kappa_score, accuracy_score,
average_precision_score, roc_auc_score
X = data.drop(labels='is_safe', axis=1)
#Response variable
y = data.loc[:,'is_safe']
#We'll use a test size of 30%. We also stratify the split on the response variable,
which is very important to do because there are so few fraudulent transactions.
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3,
random_state=0, stratify=y)
```

Random Forest:

```
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score, confusion_matrix
from sklearn.model_selection import cross_val_score

rfc = RandomForestClassifier()

rfc.fit(X_train,y_train)

predictR = rfc.predict(X_test)

print("")
print('Classification report of Random Forest Results:')
print("")

print(classification_report(y_test,predictR))
x = (accuracy_score(y_test,predictR)*100)
```

```
print('Accuracy result of Random Forest is:', x)
print("")
cm1=confusion_matrix(y_test,predictR)
print('Confusion Matrix result of Random Forest is:\n',cm1)
print("")
sensitivity1 = cm1[0,0]/(cm1[0,0]+cm1[0,1])
print('Sensitivity : ', sensitivity1 )
print("")
specificity1 = cm1[1,1]/(cm1[1,0]+cm1[1,1])
print('Specificity : ', specificity1)
print("")

accuracy = cross_val_score(rfc, X, y, scoring='accuracy')
print('Cross validation test results of accuracy:')
print(accuracy)
#get the mean of each fold
print("")
print("Accuracy result of Random Forest is:",accuracy.mean() * 100)
RFC=accuracy.mean() * 100


def graph():
    import matplotlib.pyplot as plt
    data=[RFC]
    alg="Random orest"
    plt.figure(figsize=(5,5))
    b=plt.bar(alg,data,color=("b"))
    plt.title("Accuracy comparison of Water Quality")
```

```
    plt.legend(b,data,fontsize=9)


graph()
TN = cm1[0][1]
FN = cm1[1][1]
TP = cm1[0][0]
FP = cm1[1][0]
print("True Positive :",TP)
print("True Negative :",TN)
print("False Positive :",FP)
print("False Negative :",FN)
print("")
TPR = TP/(TP+FN)
TNR = TN/(TN+FP)
FPR = FP/(FP+TN)
FNR = FN/(TP+FN)
print("True Positive Rate :",TPR)
print("True Negative Rate :",TNR)
print("False Positive Rate :",FPR)
print("False Negative Rate :",FNR)
print("")
PPV = TP/(TP+FP)
NPV = TN/(TN+FN)
print("Positive Predictive Value :",PPV)
print("Negative predictive value :",NPV)


cm2=confusion_matrix( predictR,y_test)
```

```
print('Confusion matrix-RF:')
print(cm2)

s.heatmap(cm2/n.sum(cm2), annot=True, cmap = 'Blues', annot_kws={"size":
16},fmt='.2%')
plt.show()
```

Module 6 : Performance measurements of SVM

```
#import library packages
import pandas as p
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as n
#Load given dataset
data = p.read_csv("water.csv")
import warnings
warnings.filterwarnings('ignore')
data.head(5)
data.isnull().sum()
data = data.dropna()
data.duplicated().sum()
data["is_safe"].unique()
data[data["is_safe"]=='#NUM!']
data = data.drop(data[data["is_safe"]=='#NUM!'].index)
data["is_safe"].unique()
data.info()
df = data
```

```
df.columns
#According to the cross-validated MCC scores, the random forest is the best-performing model, so now let's evaluate its performance on the test set.
from sklearn.metrics import confusion_matrix, classification_report, matthews_corrcoef, cohen_kappa_score, accuracy_score, average_precision_score, roc_auc_score
X = data.drop(labels='is_safe', axis=1)
#Response variable
y = data.loc[:,'is_safe']
#We'll use a test size of 30%. We also stratify the split on the response variable, which is very important to do because there are so few fraudulent transactions.
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=0, stratify=y)

svc
from sklearn.svm import SVC
from sklearn.metrics import accuracy_score, confusion_matrix
from sklearn.model_selection import cross_val_score



s = SVC()

s.fit(X_train,y_train)

predicts = s.predict(X_test)

print("")
print('Classification report of Support Vector Machines Results:')
```

```
print("")

print(classification_report(y_test,predicts))
x = (accuracy_score(y_test,predicts)*100)

print('Accuracy result of Support Vector Machines is:', x)
print("")
cm2=confusion_matrix(y_test,predicts)
print('Confusion Matrix result of Support Vector Machines is:\n',cm2)
print("")
sensitivity1 = cm2[0,0]/(cm2[0,0]+cm2[0,1])
print('Sensitivity : ', sensitivity1 )
print("")
specificity1 = cm2[1,1]/(cm2[1,0]+cm2[1,1])
print('Specificity : ', specificity1)
print("")

accuracy = cross_val_score(s,X, y, scoring='accuracy')
print('Cross validation test results of accuracy:')
print(accuracy)
#get the mean of each fold
print("")
print("Accuracy result of Support Vector Machine is:",accuracy.mean() * 100)
S=accuracy.mean() * 100

def graph():
    import matplotlib.pyplot as plt
    data=[S]
    alg="Support Vector Machine"
```

```
    plt.figure(figsize=(5,5))
    b=plt.bar(alg,data,color=("b"))
    plt.title("Accuracy comparison of Water Quality")
    plt.legend(b,data,fontsize=9)


graph()
TN = cm2[1][0]
FN = cm2[0][0]
TP = cm2[1][1]
FP = cm2[0][1]
print("True Positive :",TP)
print("True Negative :",TN)
print("False Positive :",FP)
print("False Negative :",FN)
print("")
TPR = TP/(TP+FN)
TNR = TN/(TN+FP)
FPR = FP/(FP+TN)
FNR = FN/(TP+FN)
print("True Positive Rate :",TPR)
print("True Negative Rate :",TNR)
print("False Positive Rate :",FPR)
print("False Negative Rate :",FNR)
print("")
PPV = TP/(TP+FP)
NPV = TN/(TN+FN)
print("Positive Predictive Value :",PPV)
print("Negative predictive value :",NPV)
```

```
cm2=confusion_matrix(y_test, predicts)
print('Confusion matrix-SVM:')
print(cm2)

sns.heatmap(cm2/n.sum(cm2), annot=True, cmap = 'Blues',
annot_kws={"size": 16}, fmt='.2%',)
plt.show()
```

6.2 CLIENT SIDE CODING

```
  import numpy as np
from flask import Flask, request, jsonify, render_template
import pickle
import joblib
app = Flask(__name__)
model = joblib.load('dt.pkl')
@app.route('/')
def home():
   return render_template('index.html')


@app.route('/predict',methods=['POST'])
def predict():
```

```
    '''
    For rendering results on HTML GUI
    '''
    int_features = [(x) for x in request.form.values()]
    final_features = [np.array(int_features)]
    print(final_features)
    prediction = model.predict(final_features)


    output = prediction[0]
    print(output)
    if output == '0':
        output ='water is not safe'
    elif output =='1':
        output = 'Water is safe'
    return render_template('index.html', prediction_text='WATER QUALITY
{}'.format(output))
if __name__ == "__main__":
    app.run(host="localhost", port=8012)
```

CHAPTER - 7

7. PERFORMANCE ANALYSIS

7.1 RESULTS AND DISCUSSIONS

The proposed model was used to prognosticate the water quality. For this purpose the dataset mentioned before was used to estimate the model performance to find out the stylish one, comparisons with RF, LR, SVC, DT were displayed. The dataset was resolve into 70 and 30for training and testing purposes independently. For the results performance of 4 algorithms were compared in which Decision Tree has attained the loftiest delicacy of 96 when compared to 3 other algorithms. Eventually the system is stationed as a web operation. This system predicts the water quality status as safe or unsafe for drinking.

7.2 PERFORMANCE ANALYSIS

Evaluation Criteria are used to measure the quality of the machine literacy model. Assessing machine literacy models or algorithms is essential for any design. By using evaluation criteria, we can insure that the model is operating rightly and optimally.

It's veritably important to use multiple evaluation criteria to estimate your model. This is because a model may perform well using one dimension from one evaluation metric, but may perform inadequately using another dimension from another evaluation metric. There are numerous different types of evaluation criteria

available to test a model. They're confusion matrix, delicacy, perfection, recall, F1- score, false positive rate, Receiver driver characteristics wind (ROC), Precision-Recall (PR) wind, Logarithmic loss, mean absolute error and root mean squared error.

In this design, we include confusion matrix and bracket delicacy.

A confusion matrix gives us a matrix as affair and describes the complete performance of the model.

Bracket of a test dataset produces four issues – true positive, false positive, true negative, and false negative.

True positive (TP) correct positive vaticination

False positive (FP) incorrect positive vaticination

True negative(TN) correct negative vaticination

False negative (FN) incorrect negative vaticination

Bracket delicacy is the rate of the number of correct prognostications to the total number of input samples, which is generally what we relate to when we use the term delicacy. The stylish delicacy is1.0, whereas the worst is0.0. It can also be calculated by 1 – ERR.

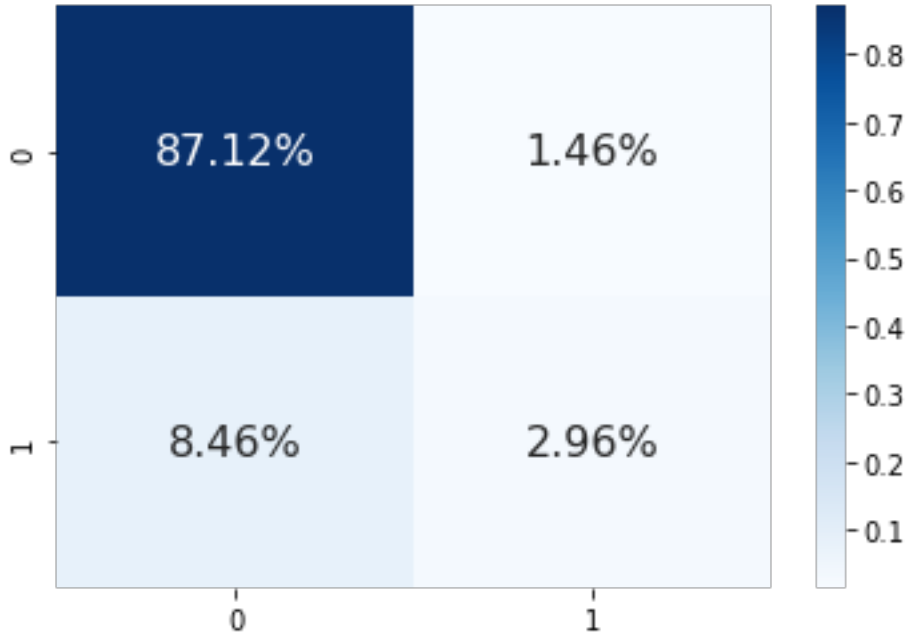
Delicacy is calculated as the total number of two correct prognostications (TP TN) divided by the total number of a dataset (P N).

Delicacy = (TP TN)/ (TP TN FN FP)

Delicacy = (TP TN)/ (P N)

7.2.1 CONFUSION MATRIX:

LOGISTIC REGRESSION:



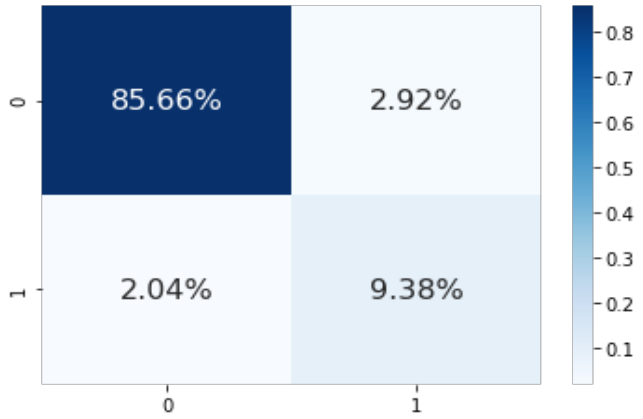
True Positive Rate : 0.03285515964831097

True Negative Rate : 0.8529411764705882

False Positive Rate : 0.14705882352941177

False Negative Rate : 0.967144840351689

DECISION TREE:

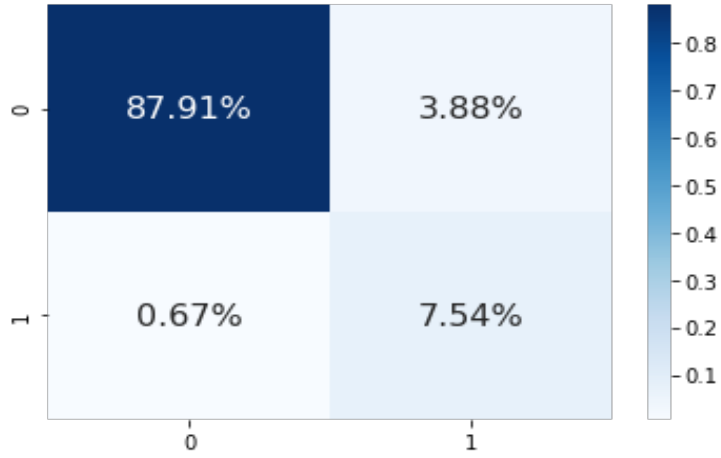


True Positive Rate : 0.09868421052631579

True Negative Rate : 0.4117647058823529

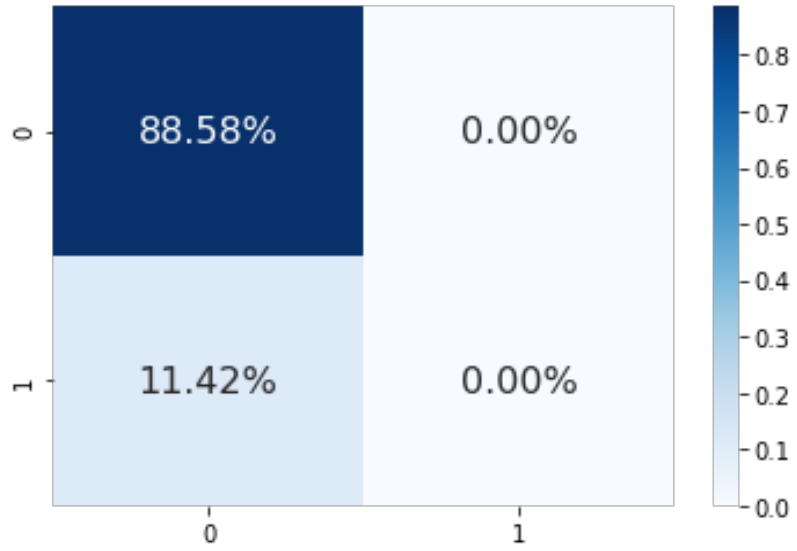
False Positive Rate : 0.5882352941176471
False Negative Rate : 0.9013157894736842

RANDOM FOREST:



True Positive Rate : 0.9209606986899563
True Negative Rate : 0.14678899082568808
False Positive Rate : 0.8532110091743119
False Negative Rate : 0.07903930131004366

SUPPORT VECTOR MACHINE:



True Positive Rate : 0.0

True Negative Rate : 1.0

False Positive Rate : 0.0

False Negative Rate : 1.0

7.2.2 ACCURACY

METHOD	ACCURACY
Logistic regression	90%
Decision Tree	95%
Random Forest	95%
Support Vector Machine	88%

The above table shows Decision Tree and Random Forest has maximum accuracy of 95% hence decision tree is deployed used flask framework.

CHAPTER - 8

8. CONCLUSION AND FUTURE ENHANCEMENT

In this system the analytical process started from data cleaning and processing , finding the missing values, exploratory analysis of data ,applying different algorithms and finally model building and evaluation and finding the highest accuracy. The best accuracy on public test set is the highest accuracy score which will be found out. This application is helpful in predicting Water Quality status. As a future enhancement Water Quality prediction will be done using a using AI model. This process can be automated by showing the prediction result in web application or desktop application. The work can be optimized and implemented in Artificial Intelligence environment.

APPENDICES

A.1 SAMPLE SCREENS

FIG A.1 OUTPUT SCREEN

FIG A.2 ENTERING VALUES OF 20 PARAMETERS

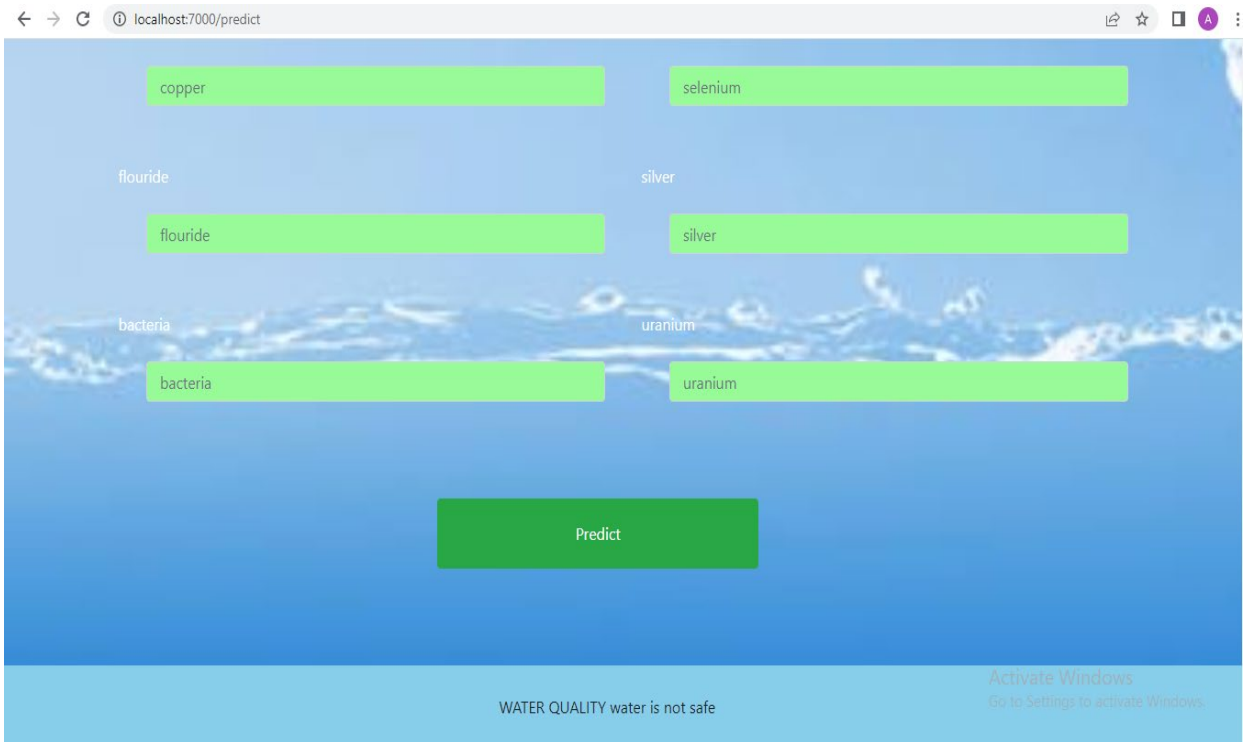


FIG A.3 PREDICTING WATER QUALITY

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