Water Quality Evaluation Using Machine Learning Techniques

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***Abstract*—One of the most significant and serious issues currently affecting mankind is the degradation of natural water resources, such as rivers and lakes. Polluted water has longterm repercussions on all facets of existence. In order to maximiseyour water quality, it is crucial to manage your water resources. The impacts of water contents can be efficiently managed if data are analysed and water quality can be forecasted. This study's objective is to develop a model for predicting quality of water is based on measurements of water quality using machine learning. With some data obtained through machine learning, models made of algorithms can be created. The collected data will be preprocessed, divided into training and testing portions, and exposed to machine learning classification techniques for a better assessment of parametric findings. Some of the classification typetechniques used in this work are Decision Tree, LinearSVC, Random Forest, GradientBoosting, SGD, and KNeighbour. Each model's performance indicators are computed and are different from one another. Hyper tuning is a method for raising performance metrics for models of machine learning.**

***Index Terms*—Machine learning, prediction, monitoring, data mining, classification, water quality index, water quality parameters.**

I. INTRODUCTION

Many factors that influence water quality make it a com- plicated topic to study. The diverse uses of water are intimately related to this notion in particular. Different demands require different standards. Water quality forecasting is a topic of extensive research. Water quality is often assessed using a number of chemical and physical components which are directly connected to the water's meant use. Then, it's necessary to decide what values of each variable are acceptable and unacceptable. When its variables meet the specifications outlined in advance, water is seen as appropriate for an application. If the water doesn't fullfil these specifications, it needs to be processed before being used. Numerous chemical and physical properties can be utilised to evaluate the water quality. As a result, it is not possible to analyse the activity of each individual variable separately in order to precisely describe water quality, either spatially or chronologically. The difficult alternative is to construct a single metric, like an overall or global index, by combining the values of several physical and chemical factors. An index of quality is a water quality index that may be built for any water application by simply specifying the prerequisites. There are several chemical and physical characteristics of this indicator. Each variable's index had a value function for quality that described how The parameter and its degree of quality were equal (typically this function was linear). A substance's concentration or a number directly measured These functions were defined in terms of physical variables examined in water samples. This paper's main objective is to look into machine learning methods for predicting water quality utilising four different factors,including temperature, conductivity, pH and turbidity.

II. RELATED WORK

Eustace M. Dogo [1] In this work, a wide variety of different combinations of strategies to handle unbalanced classes in relation to a abnormality in binary imbalanced water quality detection problem and existence of abscent values compared thoroughly. Diana Di Luccio , Angelo Riccio [2] In this work, they first describe the idea of the Internet of Floating Things (IoFT), a development of the Internet of Things that applies to marine environments. which uses sensors and gadgets to collect data,is then displayed. Najmeh Sadat and Salwani Abdullah Jaddi, [3] quote

A novel simulation of the co-operation between the kidneys in the human body is used in this paper to propose the Dual- population Kidney-inspired Algorithm (Dual-KA), which im- proves the diversity of solutions and, as a result, better exploresthe search space.

Martin Brandl [4] Different fluorescence indices can be usedto identify various aspects of DOM, including its origin or production.

G.M. Maciel [5] The output of this optimised model is fed into the Conv3DLSTM estimator to yield the final findings. Results from this grey estimator model can be produced quickly and precisely.

A. Al-Sultani, Mustafa Al-Mukhtar [6] Five alternative machine learning (ML) models, including Random Forest (RF), Quantile regression forest (QRF), radial support vector machine, and Gradient Boosting classification, were created in order to forecast on monthly basis for biochemical oxygen demand (BOD) in Iraq. Abilio C. Da Silva Jr. The ultimate objective for this initiative is to create the Internet of Water Things (IoWT), a new online system for managing and monitoring water resources.

Abilio C. Da Silva Jnior [7] The initiative is to create the Internet of Water Things (IoWT), a new online system for managing and monitoring water resources.

Libu Manjakkal and Srinjoy Mitra quote this at [8] The technologies for WQM’s sensors, deployment, and analysisare covered in-depth in this article.

Zhihui Li , Lu Peng, and Feng Wu [9]Impervious surfaces are thus acknowledged as crucial factors when evaluating how urbanisation affects water quality.

Gehad Hassan, Mohamed E. Goher [10] In order to deal with this issue of lacking samples and reduce the time and expense of sample collection, this research provides a unique automated approach for remotely monitoring water quality.

The first Forel Ule index (FUI) water colour product witha determination of 30 m was created for China utilising the generated the Google Earth Engine computing platform and BAP composite, according to Xidong Chen, Liangyun Liu,and Xiao Zhang [11] in this study.

Nur Aqilah Paskhal Rostam [12]In order to develop a reliable prediction algorithm for algal growth, this study arguesthat discussion from the perspective of the entire framework based on the execution of each step is crucial. This understanding of the elements influencing algae development and the challenges associated with prediction must also be provided.

Ni-Bin Chang and Zhibin Sun [13] mention the decom- position of higher order singular values (IDCF-HOSVD) for fusion of integrated data and classifiers, an ensemble learning method is presented in this paper.

Roberto Munoz and Ablio C. Da Silva Junior cite this at [14]. The main goal of this initiative is to create the Internetof Water Things (IoWT), a new online tool for managing and monitoring water resources.

O. O. Ajayi and A. B. Bagula cite this at [15]. These measures, the Irrigation WQI (IWQI) and Water Quality Index (WQI), are used to express the magnitude of these characteristics and ascertain the general water quality.

Bilal Aslam, Ahsen Maqsoom [16] In order to create WQI prediction models, water samples from the study area (North Pakistan) wells were collected.

Ling Cheng and Dhruti Dheda [17]. In order to reduce differences in prediction model performance that occur whena model is used to various datasets, this work focuses onenhancing LSTM model tolerance.

Varun Jeoti and Kasyap Suresh [18] In this article based reader infrastructure and a method that makes it easier to retrieve sensor data, like conductivity, through passive sensor are described.

K. P. Rasheed Abdul HaqFor the aquaculture WQP, we suggest hybrid deep learning (DL) models, a convolutional neural network (CNN) with an LSTM, and a gated recurrent unit (GRU) [19].

Y. Sudriani, V. Sebestyn and J. Abonyi [20]The current study’s research goals are to analyse the current water monitoring systems using the most recent methodology and then to offer insights into the variables influencing sensor implementation at sampling locations.

III. METHODOLOGY

The suggested system’s goal is to forecast the water quality index. It is divided into two parts: a hardware part depictedas Data acquisition system and a software part depicted as Machine learning model. Figure 1 depicts the block diagram of the suggested system. Sensor data is collected using microcontroller and shown on LCD display. This data is further diven to ML model to predict the index of water quality. The next steps are carried out in both the sections.

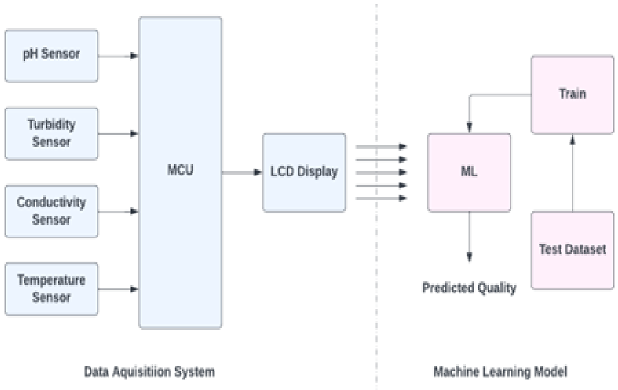


Fig. 1: Overall design framework of the system.

IV. HARDWARE SYSTEM DESIGN

A. Sensors

Sensors are used to collect data of water parameters, suchas pH, temperature, turbidity, and conductivity. There are a variety of sensors available, each with its own advantages and disadvantages. For example, optical sensors are nonintrusive and can be used to measure a wide range of parameters, but they can be expensive. Electrochemical sensors are more affordable, but they can only be used to measure a limited number of parameters. Data from sensors is stored using devices called data loggers. They can be either stand alone devices or integrated into larger systems. Stand alone data loggers are typically used for small scale monitoring projects, while integrated data loggers are often used for larger scale projects or for projects that require long term data storage. To send data collected by sensors and data loggers to a central location, communication devices are utilised. There are a variety of communication devices available, including cellularmodems, radio modems, and satellite modems. The type of communication device used will depend on the size and location of the monitoring project.

B. Microcontroller (MCU)

A microcontroller (MCU) is a type of microcomputer thatis designed to perform a specific task, typically in an embedded system. MCUs are often used in devices that require precise control, such as automotive systems, industrial automation, robotics, medical devices, and many other applications. MCUs typically include a central processing unit (CPU), memory (both volatile and non-volatile), input/output peripherals, and other interfaces for communicating with external devices. The size and power consumption of MCUs are typically much smaller than those of a full-sized computer or microprocessor, making them ideal for applications with limited space or power constraints.

C. pH sensor

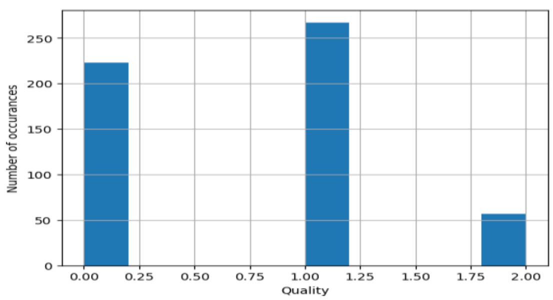
A pH sensor is a tool that determines whether a solutionis acidic or alkaline. The neutral pH value is 7, and the pH scale score from 0-14. The pH of 7 or above is alkaline,whereas a pH of 7 or below is acidic. A pH module is acircuit board that provides an interface between a pH sensor and a microcontroller or computer. The pH module amplifies the signal from the pH sensor and converts it into a digital signal that can be read by the microcontroller or computer. The pH sensor with module is a popular choice for DIY projects that involve measuring the pH of water or other solutions. The pH sensor with module is both affordable and simpleto use. It can be used with a variety of microcontrollers and computers, making it a versatile tool for a variety of projects. The pH sensor based on E201-C pH composite electrode is composed of the glass electrode and reference electrode, which has strong anti-interference ability, convenient connection and good stability. The measurement accuracy of the module is 0.05pH and the resolution is 0.01pH. The pH sensor module communicates with the microcontroller through the simulated serial port.

D. Turbidity sensor

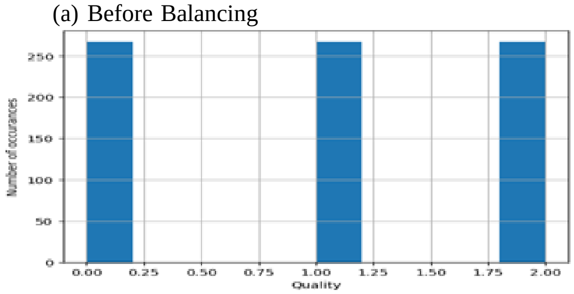
A TDS sensor measures the total dissolved solids (TDS)in water. TDS is a measure of the concentration of dissolvedions in water. There is an infrared emitting diode anda phototransistor inside the sensor. The infrared emitting diode is responsible for emitting the infrared light, and the phototransistor is responsible for receiving the light. When the light passes through a certain amount of water, the turbidity of the water determines how much light passes through. The lower the degree of turbidity, the lighter is transmitted, andthe higher the current is. On the other hand, the less light is transmitted, the lower the current is and more turbidity.

E. Conductivity sensor

A conductivity sensor measures the ability of water to conduct electricity. The dissolved ions in water, such as salt, minerals, and contaminants, have an impact on conductivity. The DJS1 laboratory level electrode conductance cell is used in this design. Conductivity is one of the key indicators used in the monitoring of water quality. Water with a higher conductivity value has a higher TDS value. The amount of contaminants in water increases with the TDS value. In contrast, clean water has a lower conductivity and a higher impurity level.



(a) Before Balancing



(b) After Balancing

Fig. 2: Quality vs Number of occurences before and afterbalancing the dataset

F. Temperature sensor

A temperature sensor measures the temperature of water. The solubility of chemicals can be impacted by the temperature of water, as well as the growth of bacteria and algae. The DS18B20 is a more accurate and reliable temperature sensor module. It has an accuracy of 0.5C and a resolution of 0.01C. A DS18B20-based temperature sensor is distinguished by its potent anti-interference capabilities, little hardware overhead, and excellent precision.

G. LCD display

LCD-display will be used to display sensor's output, this data will be collected in excel sheets for further use to predict water quality using machine learning algorithms.

V. SOFTWARE SYSTEM DESIGN

A. Selection of data set and clustering

The choice is a data collection of water quality requirement for building a model and depending on a number of factors, such as the gathering of crucial parameters that influence water quality, counting how many data samples are present, as well as specifying the labels for each data sample's class. This investigation, four indicator parameters were chosen as the data sets. These variables include turbidity, conductivity, pH, and temperature. The dataset consist of pH, conductivity, turbidity, temperature unsupervised data. Then Elbow method is used to find K-mean clustering plot. After clustering we came to know that there can be maximum of 4 cluster can happen in given dataset. Then we clusterd this dataset into 3 clusters to make this dataset a supervised dataset. Again this dataset was highly imbalanced. We used Synthetic minority over-sampling technique (SMOTE) package from python to make this data balanced so we will have more number of data shown in Fig 2. Then this dataset is used for futher processes.

B. Designing, learning and testing machine learning algorithms

The clusered supervied dataset is the used to check different machine learning algorithms. First selected dataset is divided into 80-20% parts. 80% data is used to train the model and 20% data is used for testing the trained model. Then we applied some classification type machine learning algorithms to this dataset shown in Table I.

TABLE I: Classifiction of algorithms and respective score

Sr. No.	Classifire	Score
1	KNeighbour	0.9130%
2	Decision Tree	0.9875%
3	Random Forest	0.9937%
4	Linear SVC	0.4223%
5	Gradient Boosting	0.9937%
6	SGD	0.4658%

Then we applied folding and hyper tuning technique to improve the score of KNeighbourClassifier algorithm. then we got 99% accuracy for the predictive model.

C.Building predictive model

Each time the cross validation process iterates, a training data set is created, and a prediction model is constructed using six different strategies. KNeighbour, Decision Tree, RandomForest, LinearSVC, GradientBoosting, and SGD are some examples of these methods. Each of these tactics has a different modus approach depending on the underlying relationship structure involving the class label, the indicator parameters, and Consequently. it is anticipated for same data set, the performance of each technique will vary. From the all above KNeighbour Classifier's model is selected based on accuracy and applied some folding and hyper tuning algorithms to improve accuracy. Then Model is created for this KNeighbourClassifier algorithm.

D.Machine Learning Algorithms And Classifier

Five data mining techniques were utilised to estimate the water quality class: Decision Tree (DT), KNeighbour (KN), LinearSVC, GradientBoosting (GB), SGD classifier and Random Forest (RF). These techniques fall under the wide area of parametric and nonparametric classifiers, the function's form is unknown. The parametric learning-based classifier makes more data-related assumptions. If the assumptions are verified to be true for any given data set, these classifiers take corrective action. But the same classifier works. LinearSVC and rule- based classifiers fall under this category frequently. These classifiers' operating principal is their assumptions rather thanthe amount of the sample dataset in order to learn tasks. The data set's features are assumed to be completely independent of one another using SGD. This classifier's parametric design makes it susceptible to bias and other prediction errors. The rules generated by a rule-based classifier, on the other hand, must abide by exhaustive and mutually exclusive features. Theshape of the mapping function is not an assumption made by nonparametric classifiers, in contrast to parametric learning classifiers, and by not making any assumptions.

VI. EXPRIMENTAL RESULTS FOR ML ALGORITHMS

A. Data Collection And Formation

To use data mining techniques to produce predictions, do- main knowledge is necessary. Understanding how the various water quality factors affect water quality is essential for water quality applications. Both historical data sets and subject ex- perts can provide this information. In this study, the forecastingjob was carried out using two different type of data sets: a big,meticulously created artificial data collection and a readily accessible original data set. The similarity between the two data sets is that they are both evaluated using the same numberof indicator parameters. The amount of samples that each dataset takes into account makes a difference in the data sets. The actual data set has a finite number of different observations. The over sampled data set was created since there were not many substantial authentic data sets. However, the proposed synthetic data set captures comparable relationship structures, and the distribution of the water parameters is consistent with the real-world case. Four water quality criteria were employedfor each batch of data to assess the general level of water quality, as measured in terms of Water. The variables includedtemperature, pH, conductivity, and turbidity. The fact that they are all frequently observed critical parameters and that the water quality requirements for these parameters are widely known had an impact on the decision to employ these specific criteria. The predictive modelling approach put out in thispaper, however, is adaptable enough to function with countlessparameters.

B. Data set

Four water quality criteria for each batch of data were utilised to assess the general level of water quality measured in terms of the WQI. Temperature, pH, conductivity, and turbidityused these parameters. The predictive modelling suggested in this work can, however, be adjusted to function with any number of parameters. The Table II displays range of these parameters according to their purpose.

TABLE II: Water quality and purpose depending on pH, conductivity and turbidity

pH	Conducativity	Turbidity	Quality	Purpose
6.5-8	≤ 1000	≤ 3.5	0	Drinking
16-9	≤ 3000	≤ 50	1	Agriculture
3-12	≤ 6000	≤ 160	2	Industry

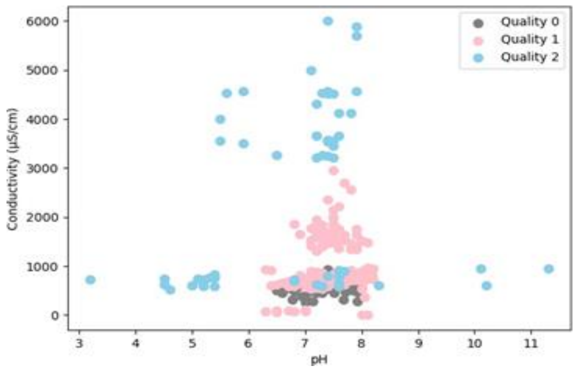


Fig. 3: ph Vs Conductivity scatter plot with Quality.

Precision - Precision is defined as the ratio of correctly predicted positive observations to all expected positive observations.

Precision = TP/(TP+FP)

Recall (Sensitivity) -

Recall quantifies the ratio of accurately predicted positive observations to all of the actual observations made by the class.

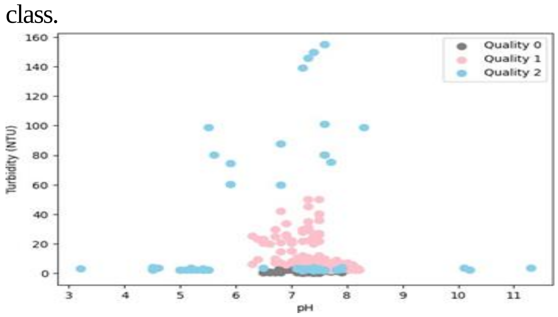


Fig. 4: ph Vs Turbidity scatter plot with Quality.

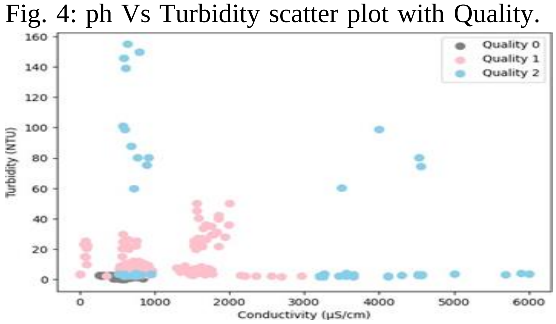


Fig. 5: Conductivity vs Turbidity scatter plot with Quality.

C. Results of Performance measures

The suggested sliding window approach's effectiveness is assessed using the following metrics: Accuracy, Sensitivity, Specificity, Precision, Recall, and F1score. The precisely fore-seen positive values are known as True Positives (TP), this show that the anticipated class values and the actual class values are both accurate. For instance, you will know the same thing if both the projected class and the actual class result indicate that this passenger survived. Indicating that both the actual and projected class values are negative, True Negatives (TN) are accurately anticipated negative values. For instance, suppose you are informed that this traveller did not surviveby both the actual and projected classes. When the expected class is present but the actual class is not, this is known as a false positive (FP). In this scenario, the projected class would have told you that the passenger would live, but the actual class would have informed you that the person did not. When the expected class is not present when the actual class ispresent, this is known as a false negative (FN). For instance, the passenger might be predicted to die, but their actual class value indicates that they survived. These values false positivesand false negatives occur when your actual class differs from the anticipated class.

Accuracy - The most logical performance metric is accuracy, this simply measures how many observations were correctly predicted out of all the observations.

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

Recall = TP/(TP+FN)

F1score - The F1 Score is calculated as the weighted average of Precision and Recall. As a result, when determiningthis score, both FP and FN are considered. F1 is not as simple to comprehend as accuracy, while being generally more beneficial than accuracy, particularly if you have an uneven class distribution. When false positive and false negative costsare about similar, accuracy performs best. It is preferable to include both Precision and Recall if the costs of false positivesand false negatives differ significantly.

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

The performance of the suggested strategy using various classifiers, including Decision Tree, Random Forest, LinearSVC, GradientBoost, SGD and KNeighbour is shown in Table III below. The next Figure 6 show its equivalent graphical representations.

TABLE III: Performance measures for classification algorithm

Methods	Accuracy	Precision	Recall	F1score
KN	0.91	0.88	0.91	0.90
DT	0.99	0.98	0.98	0.98
RF	0.99	0.98	0.98	0.98
LSVC	0.42	0.54	0.42	0.35
GB	0.99	0.98	0.1	0.99
SGD	0.47	0.44	0.47	0.39

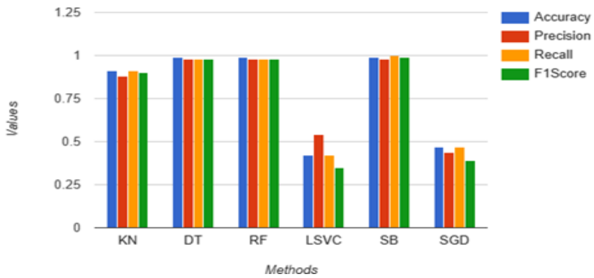


Fig. 6: Accurancy, Precision, Recall and F1score Vs Clissifiers.

It is evident from the findings that every type of classifier, with the exception of RF and DT, achieves up to 98% to 99% across all measures. The Radom Forest classifier produces the best results out of the five different types. The DT classifier also discovered the level of RF performance. This conclusion makes it evident that the eight type factors that were chosen play a significant impact in predicting water quality.

CONCLUSION

In this study, water quality was categorised into three categories 0, 1 and 2. Here, 0 means water can be used for drinking, agriculture and industrial purposes.1 means water can be utilized in agriculture and industrial usage. 3 means water can only be used within industries based on industrial requirement but not suitable for drinking and agriculture usage.The six well-known data mining classification methods listed below are used before defining final model for the prediction of the same: KKneighbour, Decision Tree, Random Forest, LinearSVC, GradientBoosting, SGD. The Overall Index ofPollution served as the foundation for each classifier's models.Temperature, turbidity, pH, and conductivity are the four water quality indicators that were used to create the synthetic data set. These ranges met both domestic and foreign standards. The DAS can be used to collect above parameters and givento ML model to predict the quality of water. The parametersof each classifier were changed during the learning phase to choose the ideal parameter values to learn a certain waterquality class from the data sets. During testing, each predictive model was verified using fictitious data and assessed using parameters like accuracy, sensitivity, specificity, recall, and F1score. Radom Forest classifier achieves the highest results out of the five different types of classifier. The good performance was obtained by RF and DT classifiers.

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