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IoT-Enabled Embedded Virtual Sensor for Energy-Efficient Scalable Online Water Quality Monitoring System

Abstract: - Pollutants introduced into water sources by industries and individuals have made it difficult to obtain enough clean drinking water in the modern world. This calls for a mechanism that periodically assesses the water's quality. There are portable instruments available to measure the factors impacting water quality. But the user needs solutions that are inexpensive, automated, reliable, and responsive. For monitoring of large water bodies, a low-cost, scalable, edge processing system in real-time is created to satisfy the current needs. It is designed using a Raspberry Pi, a display unit, and standard sensors for variables including temperature, ORP, pH, conductivity, and DO. Edge intelligence along with tiny ML is used to deploy the virtual sensor for estimation of the degree of pollution in water which otherwise requires a costly and tedious process. With an edge reaction time of 2.70ns and a notable Nash-Sutcliffe efficiency coefficient of 0.99 for BOD and COD estimation in water, this model is created utilizing the randomized tree classification. With the use of a power-efficient algorithm, the 8.4w system energy consumption of the created prototype allows it to operate on AC and solar power and can be effective in difficult climatic conditions.

Keywords: Water quality, Machine Learning, Extra Trees, Edge computing

I. Introduction

Water is regarded as the ultimate survival resource and one of the most important assets. The demand for freshwater has increased dramatically due to the growing human population and the effects of climate change. Industrial trash is frequently thrown in rivers and lakes, which poses a serious risk. As a result, there is a massive concern about water pollution[1]. The peri-urban settlements face the problem of unsafe household water [2]. Increasing lake, and river water pollution leads to global demand for sophisticated environmental monitoring techniques, especially for the monitoring of water quality. Water can either promote good health or contribute to sickness, depending on its quality. Hence, a reliable technique must be implemented for monitoring the water's purity. The current market offers sensors to track the number of water quality indicators that are typically measured manually using portable testers or regular lab tests. However, it is economically unfeasible due to the expensive setting up and maintenance costs of some of these sensors used for online measurements. Hence, a real-time, cost-efficient solution for monitoring water quality is needed to assess the water grade. It is vital to consider the major indications for determining the overall amount of pollutants in the water for efficient water quality monitoring. The primary parameters identified for this study and prototype development are Temperature (Temp),Oxidation Reduction Potential (ORP) PH, Electrical Conductivity (EC), and Dissolved Oxygen (DO), as discussed in [3]. The secondary predicted parameters include Chemical Oxygen Demand (COD) and Biological Oxygen Demand (BOD) which indicate the extent of pollution in water and are predicted by combining data acquired from Atlas Scientific sensors. The Wireless Sensor Network (WSN) can monitor the properties of water in remote places with minimal cost requirements. Sensor network implementations, according to [4], promise broad applicability. WSN applications for the water areas, however, are challenging, as the electrical component makes the task more difficult [5]. In this study [6], a water parameter IOT monitoring for mines has been built employing sensors for five parameters: liquid level, water oil, suspended solids, pH, and EC.

The currently available method of calculating BOD and COD is tedious and costly, and the estimation time for BOD is longer. Machine learning (ML) models have been useful and data-driven learning techniques can be utilized to estimate BOD in real-time. A case study to estimate the value of BOD and demonstrate the superiority

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of the IBK ML technique for BOD prediction, with 0.15s edge response time is presented in [7]. The IBK is a Lazy algorithm, and is a member of the group of Instance-based Classification mcthods. The use of an evolutionary approach influenced by quantum mechanics, to overcome the delayed convergence and weak global hunt ability is demonstrated in [8,9]. Recent studies on optimization algorithms show that hybrid approaches based on wavelet transforms have been developed [10] but are a shift variant and necessitate a large computation. The researchers in [11] suggest an innovative hybrid strategy using a modular network, which provides higher accuracy by grouping the samples for BOD prediction. The authors in [12] verified that the K-Nearest Neighbour (KNN) method is suitable for the COD quantification using ten input parameters for the water from the Ganga stream. This approach uses a lot of memory. A bio-inspired hybrid model is applied to determine the relationship between extracted reflectance values using satellite images [13] and requires appropriate band selection for satisfactory performance. A multivariate model with four parameters is suggested for calculating COD and BOD load [14]. As the number of independent variables rises, fitting the model into a straight line becomes increasingly difficult. Regression equations, according to the researchers [15], would make it easier to assess effluent quality in wastewater. Here the author's state that the averaged BOD and COD are related and can lead to a far more precise and effective study. The authors[16] describe an optimized random forest method for the categorization of arsenic (As) levels in groundwater samples taken from the Indo-Gangetic area. The gradient boost approach is recommended by the authors of [17] for BOD prediction. The created model demonstrated its feasibility, obtaining 0.95 R2. The researchers in [18] suggest the use of XGBoost's algorithm, to develop a soft sensor with five input parameters utilizing a sparse input matrix for the prediction of BOD which is memory intensive and recommends the use of a physical COD sensor.

It can be concluded from the literature survey that the soft sensors are developed with the goal of measuring the physiochemical characteristics of water in real time. The established simulated models either demand a lot of computation or many factors to estimate the biological load and are typically realized using cloud infrastructure. None of the previous studies considered modeled the machine-learning algorithm with fewer inputs used in this work to predict multi-parameters i.e. both BOD and COD, and reported its deployment at the edge. The focus of this research work is on developing an optimal topology that can accurately forecast water parameters BOD & COD, by choosing the best prediction model with minimum computational cost and memory requirement. The advancement of machine learning technologies has made it possible to create a water quality detecting model efficiently.

Therefore this study involves the design and implementation of a soft sensor at the edge to predict biological load and validation through the use of physical sensors for measuring the minimum primary input parameters. The designed online system is portable, energy efficient, and scalable to monitor water quality for large water bodies including biological load. This workable solution can be used for rural or far-off locations without a water quality laboratory. Its ability to monitor in real-time is its key benefit and the entire system is housed in a specifically designed submersible container. The suggested system keeps track of the parameters and alerts the user regarding the water quality as per the WHO guidelines. Solar power is used to address concerns with energy sources and the system integrates a clock for timestamping data. *The suggested work is novel in the following ways.*

(a)By choosing the best feature subset, the Extra tree ensemble feature selection technique shrinks the feature space, increases the prediction accuracy, and decreases model complexity leading to power efficient computations. The mathematical criteria used in the decision of the feature of the split is based on feature importance. (b)Previous works tend to be complex or overfitting-prone. The suggested work resolves both of these problems. The system includes a virtual sensor that has been verified by laboratory test results.

The created framework's contributions are listed below:

(a)Selection of suitable features with filter-based method that may affect BOD and COD levels. Correlation between features and the redundancy between pairs of features were evaluated to select the best features keeping in view the computational cost and the edge device capability(b)To increase prediction accuracy and build a virtual sensor to replace the pricey online sensors for BOD and COD prediction, the proposed system uses a framework that includes an extra-tree ensemble-based regressor. Water samples from various sources are examined on the entire system. (c)Useful metrics: prediction accuracy, NSE, and computation time are evaluated for performance comparison. There are no cases of either underfitting or overfitting in the method as proposed. (d)The developed prototype is low-cost, with minimal sensors(input),and enables real-time action in the IoT environment which can be used for monitoring large water bodies online.

II. HARDWARE DESIGN

Standard water quality sensors [19] are utilized to design the suggested system for monitoring water quality. The system is developed and put into use with the primary goal of monitoring water quality parameters in mind. Other considerations included the system's suitability for large water bodies, its capacity to measure and store data in real-time, its ability to manage power usage, and send timely notifications to system users via onsite display or short message or web display[6]. The developed system disseminates the gathered information graphically and in table form through a tailored web-based portal for the end-users. The designed low-power system is effective in harsh environmental conditions and can run on AC and solar power with system energy consumption equal to 8.4w[19]. It is capable of measuring different parameters at a maximum depth of 100ft. The hardware setup includes includes a plurality of sensors selected for continuous remote monitoring. The System consists of two modules : a transmitter station and receiver station. The transmitter station consists of sensor nodes such as pH, ORP, temperature, conductivity, turbidity, and Microprocessor. The sensor nodes communicate through I2C serial communication protocol over a single wire with the central processing unit (raspberry Pi). The different hardware modules used in the system are Raspberry pi, Decoders, Isolators, pH Sensor, Temperature sensor, ORP Sensor, Conductivity Sensor, Turbidity sensor, and dissolved oxygen are shown as below in figure 1 and 2. By providing electrical isolation, isolators prevent voltage or current spikes from reaching the sensor, thus safeguarding it from potential harm. The receiver station receives the data from the transmitter through a wireless network. The graphical user interface is designed, so that users can observe, investigate and analyze the related data. The measured data is sent to the cloud in real-time and users can receive and monitor information related to different measured parameters and water quality index at predetermined intervals through the internet using display gadgets. The power management module provides 5V input to the sensors and isolators. The system is reproducible and the architecture is scalable to add new sensors in the future at the cost of sensors only, no other component upgrade is required. Also, easy removal of the sensors from the controller without additional cost is possible. The sensor range and its accuracy are available at https://atlas-scientific.com [19].

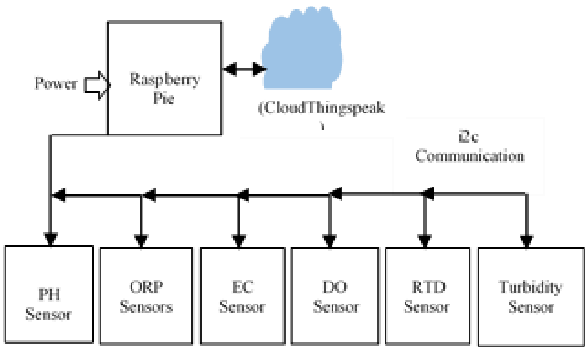

Fig. 1 Sensor Unit

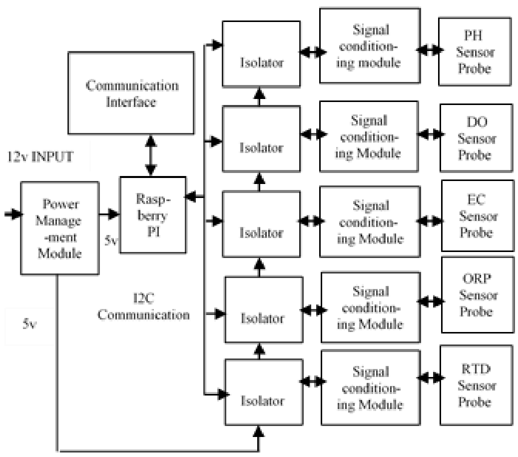

Fig. 2 Control Unit

III. SOFTWARE CONFIGURATION

The system initializes the real-time clock and SD card after the sensor node is installed, making it ready to transmit data. The system begins gathering data using the sensors, and it then sends that data to the users using GSM. Also, data is stored and displayed in real time at the base station. The time interval to acquire the parameters can be configured as per the requirement of the user. The detected values are updated in real-time, and the user interface is simple. Due to limitations of at least five days required for the completion of the BOD measurements in a laboratory setting, the acquired parameters through the designed system are explored to build a cost-efficient rapid soft-sensor for the estimation of COD and BOD in water. Intelligence techniques based on extra tree regression are used for the estimation of the mentioned parameters. Despite the fact that the extra trees algorithm creates a lot of decision trees, each tree's sampling is randomized and without replacement. The work aimed to reveal the empirical relationship of BOD and COD with other acquired parameters including categorical data. The "Namami Ganga", a national mission for the Clean Ganga initiative's real-time data streaming is utilized to create a database of 30,000 samples [20], for six months to account for weather fluctuations. The scrapped data from the Namami ganga project consists of 14 water quality parameters and 2 parameters related to station type. Data transformation and cleansing were carried out to improve the scrapped data quality. A correlation heat chart is employed to determine the order of each variable, which is utilized to simulate the learning model, in order to comprehend the link between the parameters used in this study. Based on the correlation heat map for 14 parameters ,the variables with a correlation coefficient greater than 0.25 were derived and are used to simulate the intelligent learning model based on extra trees. The correlation heat map for the derived parameters is shown in figure 3 .

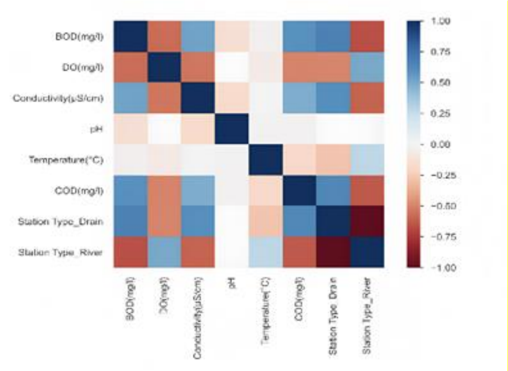

Fig. 3 Correlation Heat Map

The degree of importance given to each variable determines the accuracy of the estimation, and each variable's relative relevance was determined, as illustrated in Figure 4. A few samples of data used for training are shown in Table 1.

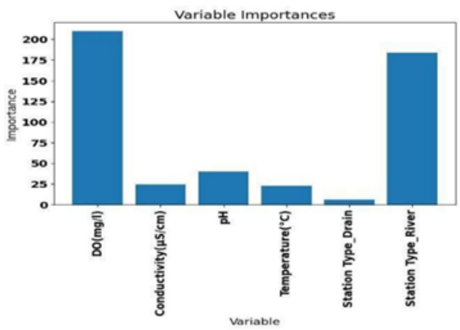

Fig. 4 Relative Importance of Derived Input Parameters

Tab. 1. Sample data used for training the extra tree regression model

Date and Time	BOD (mg/l)	DO (mg/l)	EC (µS/cm)	pH	Temp. (°C)	COD (mg/l)
12-08-2022 07:04	1.58	5.48	160	8.74	26	14.97

12-08-2022 07:01	1.84	6.99	288	7.65	30	13.15
11-08-2022 16:04	1.99	6.83	190	8.53	26.7	17.36
02-05-2022 12:01	4.64	9.06	727	8.3	31.3	25.2
15-08-2022 17:04	5.9	5.4	234.9	8.13	32.4	12.9
15-08-2022 18:03	1.61	7.37	151	8.74	27.7	15.05
15-08-2022 18:04	1.75	7.07	189	8.61	27.3	14.08
15-08-2022 18:04	1.1	8.4	233	7.32	28.3	12.78
15-08-2022 18:00	1.44	5.28	436	8.68	34.4	13.55
26-08-2022 06:01	26.06	0.81	705	7.89	29.7	105.99

Four variables, including pH, DO, EC, and temperature, comprised the model's input based on the correlation graph, the interactions between various factors, and the significance of those interactions. The categorical data served as both the input to the trained model and a means of optimizing the data analysis.The learning-based prediction framework, which is created using a random selection of samples and attributes, provided improved prediction outcomes while using fewer resources, is based on the averaged approach for each output value. Pruning is used to reduce the size of decision trees by deleting areas of the tree that don't have the ability to categorize instances. The Extra Trees Algorithm is represented by Equation 1 where the model inputs are the dataset, base learner ($\epsilon_t(x)$), number of base learner (T), and the model output is G(x).

“(1)”

$$G(x) = \frac{1}{T}\sum_{t=1}^{T} \epsilon_t(x)$$

The complete process of implementation of the system is summarized in figure 5 below. The findings of tests conducted on out-of-bag samples obtained from urban water bodies are used to validate the derived model.

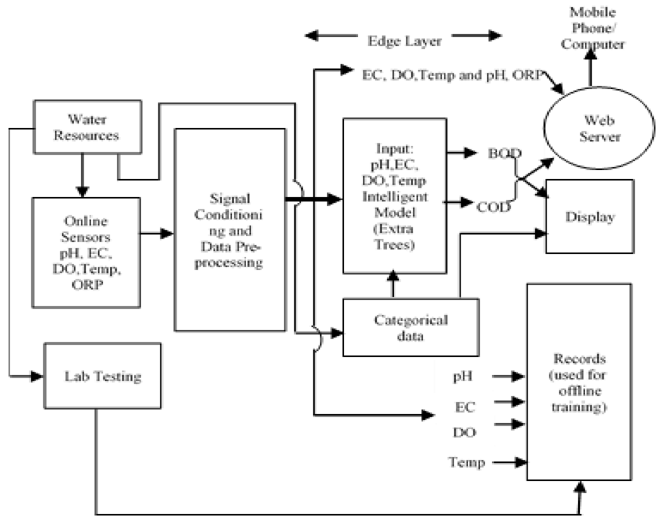

Fig. 5 Overall System Design Flow

The IoT model (Figure 5) contains an edge layer that consists of devices, sensors, and controllers. The connected devices enable the IoT environment, and the controller layer is used for connectivity and edge computing through Wi-Fi. The cloud layer is used to store the data collected from the edge layer. The water parameters acquired through online sensors (ph,EC,DO,ORP and Temp) are displayed locally at the measurement site .The acquired sensor data is processed locally on the IoT device using intelligent machine learning model to predict the values of BOD and COD which is transmitted utilizing MQTT communication protocol to a remote server/user for further analysis. The measured water parameters are compared with standards as prescribed by WHO/CPCB as per their usage to indicate its general quality and usefulness. Here the proposed architecture distributes the training which is carried out offline or can also be performed on the cloud and testing at the edge. The online sensors present in the edge layer acquire the water quality parameter values, and the parameters measured through the offline laboratory approach are also appended in the training data. The proposed architecture has the provision for wired as well as Wi-Fi communication on the site and remotely. Training is carried out using historical data and the validated model file is embedded in the edge controller. The model file and the parameters acquired through an online sensor in the controller are able to predict the values of BOD and COD in real time.

IV. RESULTS AND DISCUSSION

The prototype is developed based on the description in section II, for the water quality prediction. The framework consists of raw data collection from sensors, processing, and virtual sensors for secondary parameter estimation, archiving, and visualization. The extra trees algorithm used for the prediction of secondary parameters randomly selected a split value which made the trees uncorrelated. The developed system is tested for different water quality samples for primary parameters and prediction of secondary parameters which include BOD and COD by the virtual sensor embedded in the system. Figures 6 and 7 show the predicted and actual values of the out-of-the-bag samples for BOD and COD. With a maximum variance of 2% and a Nash-Sutcliffe efficiency (NSE) of 0.99, these results demonstrate high precision for the two parameters. NSE is a potentially reliable statistic for assessing the predictive capability of the model . An efficiency of 1.0 corresponds to a perfect match between model and observed data and 0.99 NSE indicates a close match with an acceptable level of performance. The designed system and the developed GUI are presented in Figure 8,9 and 10.

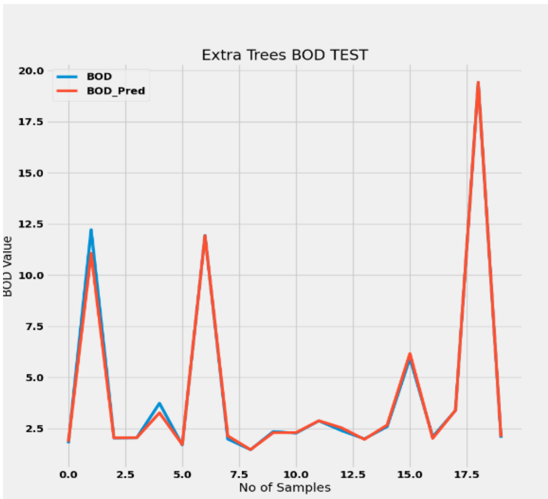

Fig. 6 Performance of predictive model for BOD

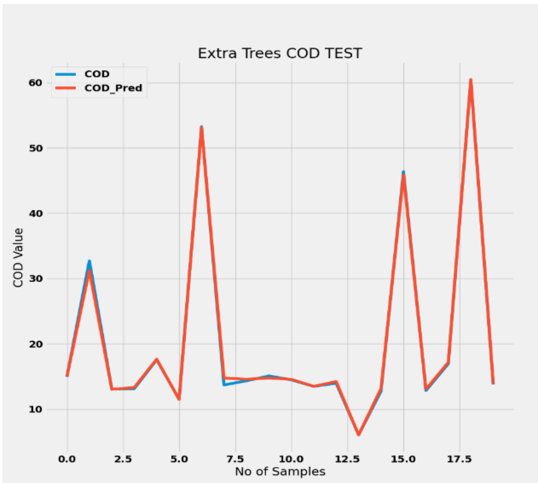

Fig. 7 Performance of predictive model for COD

Shallow trees are used to reduce the memory requirement. It results in a decrease in execution time. The edge response time for the tiny ML model embedded on Rasberry Pi3, Model B, Rev 1.2 with a clock speed of 1.2 GHz is 2.70ns. The parameters that influenced the prediction time are the response time of sensing devices which include online sensors and the data processing environment. By absorbing the data gathered from the sensors, machine learning for IoT is used to forecast the value of BOD and COD and augment intelligence. The prediction time is calculated as the time elapsed from the acquisition of water parameters by the sensors to the availability of the predicted values (COD /BOD) at the output. According to the test results, the model is most suited for assessing BOD and COD levels in water bodies, particularly reservoirs, river streams, and lakes. The inference on water quality is drawn at the remote end by the user by comparing it with prescribed standards.

Fig. 8 Developed system with the Graphical User Interface (GUI)

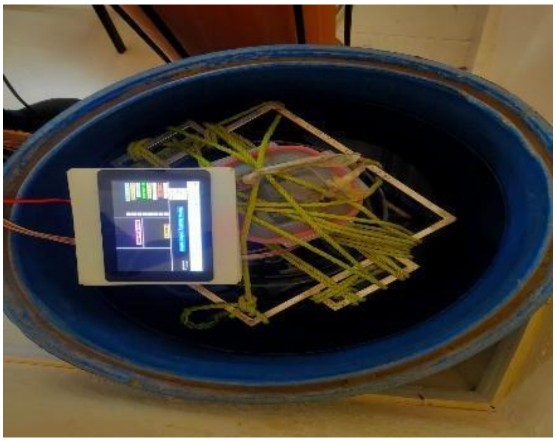

Fig. 9 Deployed system in water tank with the Graphical User Interface (GUI)

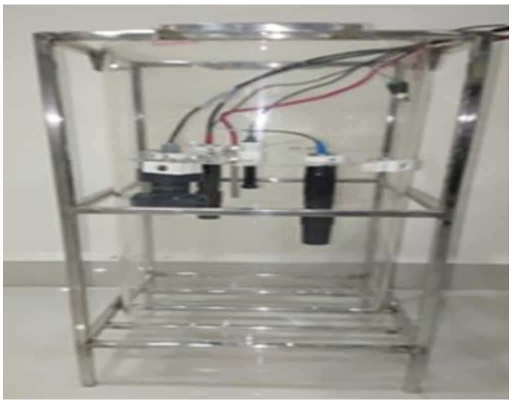

Fig. 10 Developed circular hold along with the sensors

Tab. 2: Comparison of the existing deployed model for prediction of BOD and COD

Multi-parameter Prediction model	**No of inputs**	**MAE**	**MSE**	**RMSE**	**NSE**	**Training time (in sec)**	**Prediction time (in sec)**
BOD and COD prediction with extra trees	4	0.52	2.69	1.64	BOD: 0.994 COD: 0.990		0.053
BOD prediction with IBK approach[7]	6	0.08	-	0.19	--	--	0.15
COD prediction using KNN [12]	5	0.043	--	0.97	-	--	0.02

The results of the suggested approach specifically the soft sensor are contrasted with the most recent literature's results in Table 2. The suggested strategy produces more effective performance metrics while using fewer input variables. Furthermore, this work is focused on the implementation of a two-parameter prediction system along with the requisite hardware as opposed to earlier research, which was based on the prediction of a single parameter. Thus the results indicate that feature selection and deployment of extra trees generate an optimal model with low computational complexity for prediction of both parameters BOD and COD. A single soft sensor can predict both parameters which has not been reported in the literature with minimal inputs. NSE indicates that the plot of observed versus simulated data is well-fitted.

V. CONCLUSION

A scalable, low-cost solar-powered system for monitoring the water quality in large bodies of water has been created during the course of this effort. It uses standard sensors to monitor primary water quality parameters, along with an embedded single soft sensor to monitor secondary parameters and displays the results as per the requirements of the user remotely. The developed system is housed in a customized enclosure to suit the requirements of measuring the parameters at variable depths and is waterproof with the sensors appropriately mounted along with the display. Embedded soft sensors using machine intelligence is able to predict the COD and BOD values within acceptable limits based on measurements made from sensors. It is the first time randomized tree classification is used for the prediction of multiparameters (COD &BOD) with small edge reaction time. Due to its cost and time considerations, this scalable model is preferable to the conventional laboratory method and also avoids the use of costly sensors for secondary parameters. All water parameters are recorded correctly, this makes the model highly versatile and can be used to determine water parameters or check the quality of polluted water.

VI. FUTURE RESEARCH

Currently, the testing is going on to monitor parameters at variable depths to analyze the sensitivity and accuracy of the sensors. Work is in progress to predict other secondary parameters of interest. For the purpose of expanding the study, the inclusion of heavy metal ions as parameters of interest is also taken into consideration. In the future, the design of wireless communication between the sensor to the controller is proposed, and a network of such sensors to monitor and map different water bodies.

A. Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

B. Funding Statement

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C. Data Availability

The data that has been used is available to the public [21]

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