

IoT-enabled sensor for water quality prediction using machine learning

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### 1. Introduction

Eutrophication or algal bloom is prevalent in Malaysian inland aquatic bodies such as lakes and ponds which hinder the performance of its ecosystems (Sharip & Suratman, 2017). About 60% of Malaysian lakes suffer from eutrophication because of the organic nutrients (a byproduct of human activities) present in the water (NAHRIM, 2009). To address this issue, water sampling must be carried out at regular intervals to detect the degradation of water quality at early stages so that it can be prevented. Continuous water quality monitoring is also important to ensure proper functioning of the ecosystem, protection of water supplies and public health (García, 2020). Currently, for lake sampling, trained personnel are required to use boats and hire safety officers for the fieldwork. Also, large volumes of water samples must be collected and transported back to the laboratory to test algae and nutrients present in the water (Azizul, 2019).

Commercially available in-situ water quality sensors are of three types: Ion-selective electrode (ISE), Wet Chemical and Optical Sensor. Out of these, ISE is the most cost-effective but is susceptible to inaccuracies and drifting. On the other hand, wet chemical and optical sensors are very precise but are very expensive and requires routine maintenance which adds more cost (Castrillo & García, 2020). In situ water parameter sensing sondes that measures the physicochemical properties of the water are often used alongside manual water sampling where the samples are used for bacteriological analysis in the laboratory (Al-Badaii et al., 2013). Often these sondes used in situ measurements are not IoT enabled but there is a demand for cost-effective online sensors that can be used for telemonitoring.

For parameters that are difficult to measure in-situ or requires an expensive sensor, it is possible to predict the parameter based on other available water quality parameters using a machine learning model and is termed a soft sensor (Castrillo & García, 2020). Prediction models of water quality parameters are generally of two types: deductive and inductive. Deductive models require an in depth understanding of the complex biological, chemical and physical processes and is often time consuming. Inductive, on the other hand, solely focuses only on the statistical correlation of features and patterns of the measured data to form a comprehensive understanding of the system. Algorithms like Artificial Neural Network (ANN) is a good example of inductive modelling that can model complexities of natural processes and predict parameters like Chlorophyll-a (Tian et al., 2017).

Temperature, Turbidity, Electrical Conductivity (EC), Dissolved Oxygen (DO) and pH are commonly measured in situ along with manual sampling to detect water quality impairment (Koparan et al., 2018). Low cost sensors for the aforementioned parameters are easily available but there is no cost-effective sensor for chlorophyll-a. However, chlorophyll-a can be predicted using machine learning models and studies found chlorophyll-a to be significantly correlated with temperature, DO, pH, Transparency, Total Suspended Solids (TSS) and nutrients namely, total nitrogen (TN) and total phosphorus (TP) (Huo et al. 2013; Mamun et al. 2020). These nutrients (Phosphorus and Nitrogen compounds) in turn are correlated with Electrical Conductivity, Turbidity and pH. Hence, the hypothesis is IoT enabled Temperature, Turbidity, EC, DO, pH sensors will be able to effectively model Chlorophyll-a concentration needed to determine eutrophication.

#### 1.1 Proposed Solution

A cost-effective, IoT enabled multiparameter sonde and Chlorophyll-a soft sensor will be designed and developed in this study to provide physicochemical properties of water in real-time. The data collected will be transmitted to the backend for analysis and will also be used to predict Chlorophyll-a concentration using machine learning. To assess the accuracy and precision of the sensors developed, it will be compared with laboratory-grade sensors. The machine learning models to be studied and compared are Support Vector Machine (SVM), Support Vector Regression (SVR), Deep Learning, Extreme Learning Model (ELM), Random Forest (RF) and Artificial Neural Network (ANN). After training the models with water quality data, it will be validated using k-fold cross-validation to find the optimum model. The architecture of the proposed system is depicted in Fig-1.1.

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**Fig-1.1: Architecture of the water quality sensor. Diagram shows communication between IoT enabled sensor and the backend and visualization in the frontend.**

***Sensor Selection***

DFRobot produces low-cost water quality sensors that can be easily integrated with any microcontroller are used for developing the IoT sonde. The list of different sensors is given below:

1. Analog Turbidity Sensor (SKU SEN0189)
2. Analog pH Sensor (SEN0161-V2)
3. Analog Dissolved Oxygen Sensor (SEN0237-A)
4. Analog Electrical Conductivity Sensor Meter (SKU DFR0300)
5. Digital Temperature Sensor (DS18B20)

***Microcontroller Selection & Firmware***

ESP32 microcontroller, a 32-bit low cost, low power system on a chip (SoC) with Wi-Fi connectivity is chosen for this application. It uses the FreeRTOS, a real-time operating system which is robust and reliable, and the firmware is written in C programming language. The microcontroller is also interfaced with an LCD display, as seen in figure-1.1 for displaying water quality parameters

***Backend Communication and Functionality***

Lightweight Message Queuing Telemetry Transport (MQTT) protocol over SSL is used for bidirectional communication with the backend. The sensor data is sent using MQTT in a json packet. MQTT event can also be triggered by the backend to initiate Over-the-air firmware update so that it can update the firmware and calibration parameters remotely if required as seen in figure-1.1. Before sending the firmware update, the backend authenticates the water quality device using Oauth2.0 protocol and streams the data over https. The data sent to the backend are stored in a database which will then be used to predict chlorophyll-a values instantaneously. The frontend application in the browser visualizes all these data by communicating with the backend using REST APIs.

#### 1.2 Problem Statement

The effective functioning of inland aquatic bodies like lakes and ponds are being severely hindered by Eutrophication. Not only the ecosystem, eutrophication also plagues drinking water supply and affects public health. This effect is on the rise due to rapid urbanization and other anthropogenic factors including farming, industrialization, etc. which is deteriorating the water quality on the surface and underground. (Taufiqurrahman et al., 2017; Gafril et al., 2018). As a result, water resource management has become more important than ever (Siyang & Kerdcharoen, 2016).

Eutrophication detection requires high-frequency monitoring so that it can be prevented in the early stages but it is challenging because field monitoring is expensive, depends on the availability of staff, safety considerations and the significant delay between sample collection and relaying the information to the stakeholders (Tian et al. 2017). Traditional laboratory testing methods to determine water quality, albeit accurate, are also not ideal for early detection of contamination and lead to a slow response in an event of an emergency such as natural disasters (Yang et al., 2018). Therefore, a timely informed decision cannot be made with traditional methods of water sampling. (Siyang & Kerdcharoen, 2016; Zhu et al., 2018).

Water sampling (spatially separated and high frequency) is crucial in managing freshwater resources and maintaining public health (Ore et al., 2015). Water quality parameters including nutrients (phosphorus and nitrogen compounds, predictors of eutrophication) are usually measured using grab sampling which is infrequent because of the cost and manpower required (Castrillo & García, 2020). Real-time monitoring is required to detect the onset of algal blooms or contamination of water bodies in early stages (Dunbabin & Grinham, 2010; Saab et al., 2017). This real-time data collected using IoT can benefit water conservation management, policymakers, etc. to take appropriate action. However, contemporary studies show that commercially available IoT-enabled sensors for telemonitoring are often expensive (Yang et al., 2018).

#### 1.3 Significance of the Study

A cost-effective IoT enabled multiparameter probe with Chlorophyll-a soft sensor is proposed in this study. It has an accompanying backend that stores the data and a frontend to visualize data in an easy manner to practitioners, and citizens alike. The backend analyzes the real-time data to predict Chlorophyll-a instantaneously to simulate a soft sensor. Firstly, the system provides automatic measurements that have many advantages compared to manual methods like structuring of data, repeatability, eliminating human error etc. Secondly, the handheld sonde is low-cost and can be used by anyone to inspect water bodies thereby promoting citizen science. The sensor can be also deployed in UAVs, USVs etc. to measure water quality in remote locations and provide high-resolution spatiotemporal data. Thirdly, real-time water quality measurement is also potentially useful in the distribution system, industries, aquafarming, etc. and can also predict the onset of algal bloom.

In summary, the proposed study has the potential to streamline water conservation management and has the following advantages:

1. Inexpensive water sampling
2. Accurate water sampling in real-time
3. Cutting down the need for trained personnel for sampling.
4. User-friendly and effective visualization of water quality parameters
5. Prediction of Chlorophyll-a without the need of an expensive sensor.

#### 1.4 Scope and Limitations

The IoT water quality measuring sonde is reliant on cellular networks for internet access. Physical sensors may also require routine calibration and maintenance and soft-sensor measurements will be constrained to a specific water body based on the training data. Also, benchmarking with several other commercially available sondes and cost-benefit analysis of the proposed system is outside the scope of this study.

### 2. Literature Review

Significant research was carried out in the past few years in order to improve water quality monitoring since there is no single solution to tackle the multifarious issues that come with water conservation management (Behmel et al., 2016). With rapid urbanization, population growth, industrialization, and climate change, real-time monitoring and analysis will be crucial to streamline decision making and rapid action in response to pollution (Gafri et al., 2018). With this growing need, researchers aimed to optimize water quality monitoring programs by improving the sensors and employing various data collection methods both static (fixed-site monitoring) and dynamic (sensor attached to a mobile vehicle). Several parameters are also being predicted using other parameters for the past two decades with machine learning techniques to provide fast and reliable data without the need for a physical sensor or laboratory tests (Tian et al. 2017). Development on the sensor side and different monitoring methods are presented in the first and second sections of this review and water quality prediction using machine learning models are covered in the third section.

***Smart Water Quality Sensors***

GSM is used to inform water conservation management authorities by sending SMS when there is an abnormality in the reading (Mo et al., 2012). Their system made automatic measurements of pH, Turbidity, Temperature, EC & DO and analyzed the data to determine and abnormalities. In another study, an automatic sampler was designed that collect 20 ml of water samples whenever the value of Dissolved Oxygen (DO) or pH exceeds a certain programmed threshold. The parameters are measured using in situ probes and transmitted wirelessly using the XBee module to the control station where the parameters are graphically displayed (Wiranto et al., 2015).

A low-cost sensor that measures four parameters was designed by Indu & Choondal (2017) which measures pH, Total Dissolved Solids (TDS), EC and Temperature electronically. The sensor has good accuracy and could be developed under $60 without any IoT capabilities. Also, Taufiqurrahman et al. (2017) developed wireless sensors that measure temperature, TDS, Turbidity, and pH of potable water and transmits the data wirelessly using XBee module to a local control unit that determines the quality of the water using fuzzy logic but has no IoT features as well.

Smart sensors for water distribution networks (S::CAN and Eventlab) were evaluated by Saab et al. (2017) and they concluded that smart sensors are as effective as laboratory tests of water samples. For testing potable water, Gopavanitha & Nagaraju (2018) developed smart sensors that can measure physicochemical properties like Temperature, Turbidity, Electrical Conductivity (EC), pH and flow in real-time. The system used a Raspberry Pi module and the data was relayed to the backend for further analysis.

***Distributed Water Quality Sensor Network***

Vaddadi et al. (2012) also developed water quality sensors for potable water measuring DO, pH, temperature, EC and the sensors were deployed on a floating platform anchored to a fixed location. Several of these solar-powered floating sensors distributed across a water body measured and transmitted data to the central unit wirelessly through ZigBee from where the data was uploaded to the cloud to enable

remote monitoring.

Another grid-based distributed surface water measurement was proposed by Konyha (2016) which can forecast the spread of contamination in rivers or lakes. Five solar-powered monitoring stations with submersible sensors were deployed in this study to measure the water quality and the stations communicated with the communication column. The communication column communicates with the server via GPRS. The sensors measured Oxidation Reduction Potential (ORP), pH, EC, Temperature, DO, Nitrate ions and Chloride ions.

Solar-powered IoT enabled Mobile Sensor Nodes (MSN) were deployed to monitor Temperature, pH, DO, EC & ORP in the study conducted by Li et al. (2017). It provided high-resolution spatiotemporal data surface water quality which is useful for monitoring large water bodies. The MSN communicates with the base station wirelessly which then uploads the data to the server for further analysis using GPRS/3G/4G. The MSN also followed specified trajectories determined by the path planning algorithm to collect data across the water body.

***Water Quality Prediction using Machine Learning***

Water Quality Prediction uses various machine learning techniques and predicts various parameters which are grouped and summarized in Table 2.1 below:

**Table-2.1: Summary of Water Quality Prediction using Machine Learning**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| ***Chlorophyll-A Prediction*** | | | | |
| **Reference** | **Aim** | **Algorithm** | **Findings** | **Gap** |
| Huo et al. (2013), | Eutrophication (Algal bloom) prediction and tropic state of the water body is determined by predicting chlorophyll-a which is the prime indicator for eutrophication | Back Propagation NN, | 1. Nonlinear relationship between Chl-a and input parameters | 1. Requires a lot of input parameters |
| Zhang et al. (2016), | Deep Belief Network, | 2. Dependent on meteorological, hydrological and other biochemical processes | 2. Most input parameters cannot be measured in real time |
| Tian et al. (2017), | Back Propagation NN, | 3. Temp, TSS, TP & NP influence Chl-a and Transparency | 3. Trained on a limited dataset |
| Yi et al. (2018), | Extreme Learning Model, | 4. Region of rivers have different | 4. Predictive models are specific to a particular waterbody |
| Mamun et al. (2020) , | Support Vector Machine, | 5. Rainfall, solar radiation | 5. Relies on expensive sensors and sensitive to de-calibration |
| Jimeno-Sáez et al. (2020) | Support Vector Regression | 6. Chl-a data is a non-stationary time series process which makes prediction difficult |  |
| ***Nutrients Prediction*** | | | | |
| **Reference** | **Aim** | **Algorithm** | **Findings** | **Gap** |
| Nieto et al. (2019), | Eutrophication assessment using predicted nutrients and supporting water quality management through continuous monitoring | Support Vector Machine (SVM), | 1. Nonlinear ML models have clear advantages over linear models | 1. SVM relies on parameters that cannot be measured in real time |
| García (2020) | Random Forest (RF) | 2. Meteorological, seasonal factors, flow and time are important parameters for prediction | 2. Accuracy of RF relatively low |
|  |  | 3. Covariance between input variables should be assessed | 3. Lot of preprocessing required before feeding the RF model |
| ***DO, BOD, COD Prediction*** | | | | |
| **Reference** | **Aim** | **Algorithm** | **Findings** | **Gap** |
| Xu & Liu. (2013), | Determination of water quality in order to aid aquaculture management and detect pollution | Wavelet NN | 1. Water Quality is heavily influenced by hydrological and meteorological factors | 1. Trained on extremely small dataset |
| Najafzadeh & Ghaemi (2019) | Least Square Support Vector Machine |  | 2. Lot of input data required where some of them can't be measured in real time |
|  |  |  |
| ***Time Series WQ Prediction*** | | | | |
| **Reference** | **Aim** | **Algorithm** | **Findings** | **Gap** |
| Khan & See (2016), | Event detection, anomaly detection like decalibraion or faults and water quality trend prediction is done to forecast near future events | Feedforward Neural Network with Non-Linear Autoregressive (NAR), | 1. DO and Turbidity are important parameters for Water Quality Management | 1. Time series prediction is vulnerable in the presence of imbalanced data |
| Wang et al. (2017), | Long- and Short-Term Memory NN, | 2. Real world data are usually very noisy and imbalanced | 2. Training usually takes a long time |
| Cao et al. (2018), | Least Square Support Vector Machine, |  | 3. Datasets are scarce, and models are trained over limited datasets |
| Joslyn & Lipor (2018), | Support Vector Regression |  | 4. Real time prediction is not possible |
| Muharemi et al. (2019) |  |  |  |
| ***WQI Prediction*** | | | | |
| **Reference** | **Aim** | **Algorithm** | **Findings** | **Gap** |
| Camejo et al. (2013), | Water Quality is assessed to estimate the WQI and also water is also classified according to the water quality standards | k-Nearest Neighbour, | 1. Deep learning outperforms other models like kNN & SVM | 1. SVR relies on a lot of input parameters |
| Yan et al. (2017), | Extreme Learning Machine |  | 2. Trained on a limited dataset |
| Shafi et al. (2018), | Deep Neural Network |  | 3. Some parameters cannot be measured in real time |
| Ahmed et al. (2019), | Gradient Boosting & Polynomial Regression |  |  |
| Li et al. (2019) | Hybrid Support Vector Regression |  |  |
| ***Parameter Retrieval*** | | | | |
| **Reference** | **Aim** | **Algorithm** | **Findings** | **Gap** |
| Keller et al. (2018), | Retrieved certain water quality parameters that cannot be measured in situ in order to enable instantaneous remote sensing | ANN, SVM, Extremely Randomized trees (ET), | 1. Neural Networks are superior when it comes to parameter retrieval compared to other ML models | 1. Satellite images are not available in cloudy and dusty weather |
| Ruescas et al. (2018), | Random Forest Regression, Gaussian Process Regression |  | 2. Hyperspectral or Multispectral radiometers are very expensive |
| Hafeez et al. (2019), | ANN |  |  |
| Shehhi & Kaya (2020) | Regression & Neural Network (Nonlinear Auto Regressive) |  |  |

From this literature review, it was observed that smart sensors have allowed in situ measurement of water quality parameters and it has also been proven to be as effective as laboratory tests. These sensors deployed in a large number in static stations can provide high-resolution spatiotemporal data about the quality of water in the water bodies. Several parameters were accurately estimated, and successful predictions are made about the trends of water quality, event detection, pollution etc. Remote monitoring also proven to be closely related to the standards of traditional sampling methods. However, there are certain limitations in these solutions that are still preventing the solution to be ubiquitous and widely used by the water conservation community.

Firstly, most of the research article failed to provide proper accuracy measurements and lacked robust comparison with standard laboratory devices for the low-cost sensors that were developed. Moreover, the cost to develop the sensors and the calibration strategies involved were not addressed. Many of these standalone sensors stored the data locally in their control station and data was not uploaded to the cloud. Also, the stationary sensors require periodical maintenance which is again arduous and costly (Xu et al. 2013). Secondly, the distributed sensor networks deployed sensors that are expensive and deploying it in large numbers to cover a large water body becomes very costly. Also, many of the standalone sensors and distributed sensors communicated with a central control station. Implementation of this architecture is also expensive and time-consuming.  
  
The machine learning models for prediction were mostly trained using a small dataset where the data were collected over a narrow period. The accuracy of prediction in some of the machine learning models were average and usually required a lot of input parameters for the prediction. Moreover, the predictions were not done with real-time data and the models were trained and tested with data generated using expensive sensors by government bodies or private institutions.

In summary, the development of a cost-effective IoT sensor framework with accompanying chlorophyll-a soft sensor for real-time lake eutrophication profiling is practical and an interesting area to explore. Using five hardware sensors and one soft sensor to predict eutrophication in real time will aid water conservation management and relevant authorities can act quickly to curb the effects of eutrophication.

### 3. Methodology

#### 3.1 Research Methodology

The study commences with a literature search and systematic review to identify problems in the field regarding water quality monitoring. The IoT prototype is built after identifying the important water quality parameters (Temperature, Turbidity, EC, DO, pH & Chlorophyll-a) that determine eutrophication in lakes. Few promising machine learning models are selected that will be used to build the chlorophyll-a soft sensor based on the literature review. Table 3.1 summarizes research methodology and Figure 3.1 shows the graphical representation of the SMART methodology. Section 3.2 and 3.3 discusses IoT sensor development and Machine Learning model validation methodology in detail.

A screenshot of a cell phone

Description automatically generated**Fig 3.1: SMART Research Methodology**

**Table 3.1: Mapping of RQ, RO, Methodology, and Outcome**

|  |  |  |  |
| --- | --- | --- | --- |
| **Research Questions** | **Research Objectives** | **Methodology** | **Outcome** |
| What are the various methods used for lake water sampling? | To study different monitoring methods and parameters for efficient lake water sampling and parameters required to accurately predict Chlorophyll-a | a) Literature search  b) Systematic literature review | a) Findings on the performance of existing approaches  b) Core parameters for water quality monitoring and Chlorophyll-a prediction |
| What are the parameters important for Chl-a prediction? |
| How accurate are the in-situ measurements compared to laboratory equipment? | To compare the IoT sensor data with laboratory equipment for the same water samples. | a) Proof-of-concept  b) Calibration of sensors  c) Data collection from IoT sensor and lab equipment  d) Accuracy and precision test | a) Custom-built IoT-enabled sensor.  b) Develop firmware and integrate with the backend  c) Training and Validating appropriate machine learning model for prediction  d) Visualize the data on the backend |
| Is the proposed prototype a feasible solution for a real-time lake water sampling? | To test the performance of the proposed prototype in real-time | a) Providing water quality researchers our sensor for data collection | 1. New findings on the proposed prototype in terms of feasibility and accuracy |
| How does the performance of the proposed prototype differ from standard methods? | To evaluate and compare the performance of the proposed prototype with standard methods of measurement | a) Comparative evaluation | a) Results of performance comparison with existing solutions |

#### 3.2 IoT enabled Sensor Evaluation

The IoT enabled multiparameter sonde developed will first be calibrated using standard solutions for different parameters. After calibration, it will be tested with real water samples collected from lake. The same samples will also be tested with laboratory grade sensors. The data measured from IoT sensors will then be evaluated against the precise laboratory sensors to determine accuracy and precision. The process flow for this evaluation is summarized in figure 3.2.

**A screenshot of a cell phone

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#### 3.3 Machine Learning Model Validation

First step in this process is to collect water quality data for Malaysian lakes. The data must be preprocessed to clean the data and deal with missing values. Also, it is useful to test the data for normality, linear relationships and covariance between parameters according to the literature.

The machine learning models selected for this study (SVM, SVR, Deep Learning, ELM, RF and ANN) will be trained from the preprocessed training set. Finally, to assess which model performs best, k-fold cross validation test will be carried out for the models as depicted in figure 3.3.

**Figure-3.3: Data preprocessing, Machine learning model training & Validation**

A close up of a sign

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### References

Al-Badaii, F., Shuhaimi-Othman, M., & Gasim, M. B. (2013). Water quality assessment of the Semenyih river, Selangor, Malaysia. Journal of chemistry, 2013.

Ali, M., & Qamar, A. M. (2013, September). Data analysis, quality indexing and prediction of water quality for the management of rawal watershed in Pakistan. In *Eighth International Conference on Digital Information Management (ICDIM 2013)* (pp. 108-113). IEEE.

Azizul, Z. H. (2019). Internal discussion with SPAN and NAHRIM on challenges of lake sampling in Malaysia. Unpublished manuscript.

Behmel, S., Damour, M., Ludwig, R., & Rodriguez, M. J. (2016). Water quality monitoring strategies — A review and future perspectives. Science of the Total Environment, 571, 1312–1329. <https://doi.org/10.1016/j.scitotenv.2016.06.235>

Beloev, I. H. (2016). A review on current and emerging application possibilities for unmanned aerial vehicles. Acta technological agricultural, 19(3), 70-76.

Camejo, J., Pacheco, O., & Guevara, M. (2013, January). Classifier for drinking water quality in real time. In *2013 International Conference on Computer Applications Technology (ICCAT)* (pp. 1-5). IEEE.

Cao, S., Wang, S., & Zhang, Y. (2018, December). Design of River Water Quality Assessment and Prediction Algorithm. In *2018 17th IEEE International Conference on Machine Learning and Applications (ICMLA)* (pp. 901-906). IEEE.

Castrillo, M., & García, Á. L. (2020). Estimation of high frequency nutrient concentrations from water quality surrogates using machine learning methods. Water Research, 115490.

Detweiler, C., Ore, J. P., Anthony, D., Elbaum, S., Burgin, A., & Lorenz, A. (2015). Environmental Reviews and Case Studies: Bringing Unmanned Aerial Systems Closer to the Environment. Environmental Practice, 17(3), 188–200. <https://doi.org/10.1017/S1466046615000174>

Dunbabin, M., & Grinham, A. (2010). Experimental evaluation of an autonomous surface vehicle for water quality and greenhouse gas emission monitoring. Proceedings - IEEE International Conference on Robotics and Automation, 5268–5274. <https://doi.org/10.1109/ROBOT.2010.5509187>

Esakki, B., Ganesan, S., Mathiyazhagan, S., Ramasubramanian, K., Gnanasekaran, B., & Son, B. et al. (2018). Design of Amphibious Vehicle for Unmanned Mission in Water Quality Monitoring Using Internet of Things. *Sensors*, *18*(10), 3318. doi: 10.3390/s18103318

Gafri, H., Zuki, F., Zeeda, F., Affan, N., Sulaiman, A., & Norasiah, S. (2018). A Study on Water Quality Status of Varsity Lake and Pantai River, Anak Air Batu River in UM Kuala Lumpur, Malaysia and Classify it based on (WQI) Malaysia. International Journal of Environmental Quality, Vol. 29, pp. 51–65. <https://doi.org/10.6092/issn.2281-4485/7967>

Gopavanitha, K., & Nagaraju, S. (2018). A low cost system for real time water quality monitoring and controlling using IoT. 2017 International Conference on Energy, Communication, Data Analytics and Soft Computing, ICECDS 2017, 3227–3229. <https://doi.org/10.1109/ICECDS.2017.8390054>

Hidalgo, F., Mendoza, J., & Cuellar, F. (2016). ROV-based acquisition system for water quality measuring. OCEANS 2015 - MTS/IEEE Washington, 1–5. <https://doi.org/10.23919/oceans.2015.7404435>

Hongmin, G., Hui, G., Chenming, L., Junlin, Q., & Lizhong, X. (2013). Water quality data measurement and analysis system equipped in underwater navigation robot. Sensors and Transducers, 155(8), 128–135.

Huo, S., He, Z., Su, J., Xi, B., & Zhu, C. (2013). Using artificial neural network models for eutrophication prediction. Procedia Environmental Sciences, 18, 310-316.

Siregar, M. (2004). On-line water quality monitoring on Brantas river East Java Indonesia. *2004 IEEE International Conference On Semiconductor Electronics*. doi: 10.1109/smelec.2004.1620825

Indu, K., & Choondal, J. J. (2017). Modeling, development & analysis of low cost device for water quality testing. 2016 IEEE Annual India Conference, INDICON 2016, 1–6. <https://doi.org/10.1109/INDICON.2016.7839131>

Joslyn, K., & Lipor, J. (2018, December). A Supervised Learning Approach to Water Quality Parameter Prediction and Fault Detection. In *2018 IEEE International Conference on Big Data (Big Data)* (pp. 2511-2514). IEEE.

Khan, Y., & See, C. S. (2016, April). Predicting and analyzing water quality using Machine Learning: A comprehensive model. In *2016 IEEE Long Island Systems, Applications and Technology Conference (LISAT)* (pp. 1-6). IEEE.

Konyha, J. (2016). Grid-based wide area water quality measurement system for surface water. Proceedings of the 2016 17th International Carpathian Control Conference, ICCC 2016, 341–344. <https://doi.org/10.1109/CarpathianCC.2016.7501120>

Koparan, C., Koc, A. B., Privette, C. V., & Sawyer, C. B. (2018). In situ water quality measurements using an unmanned aerial vehicle (UAV) system. Water (Switzerland), 10(3). <https://doi.org/10.3390/w10030264>

Koparan, C., Koc, A. B., Privette, C. V., & Sawyer, C. B. (2019). Autonomous in situ measurements of noncontaminant water quality indicators and sample collection with a UAV. Water (Switzerland), 11(3). <https://doi.org/10.3390/w11030604>

Koprowski, R., Wróbel, Z., Kleszcz, A., Wilczyński, S., Woźnica, A., & Łozowski, B. et al. (2013). Mobile sailing robot for automatic estimation of fish density and monitoring water quality. *Biomedical Engineering Online*, *12*(1), 60. doi: 10.1186/1475-925x-12-60

Lally, H. T., O’Connor, I., Jensen, O. P., & Graham, C. T. (2019). Can drones be used to conduct water sampling in aquatic environments? A review. Science of the Total Environment, 670, 569–575. <https://doi.org/10.1016/j.scitotenv.2019.03.252>

Li, T., Xia, M., Chen, J., Zhao, Y., & de Silva, C. (2017). Automated water quality survey and evaluation using an IoT platform with mobile sensor nodes. Sensors (Switzerland), 17(8). <https://doi.org/10.3390/s17081735>

Linchant, J., Lisein, J., Semeki, J., Lejeune, P., & Vermeulen, C. (2015). Are unmanned aircraft systems (UAS s) the future of wildlife monitoring? A review of accomplishments and challenges. Mammal Review, 45(4), 239-252.

Liu, J., Wu, Z., & Yu, J. (2016). Design and implementation of a robotic dolphin for water quality monitoring. 2016 IEEE International Conference on Robotics and Biomimetics, ROBIO 2016, 835–840. <https://doi.org/10.1109/ROBIO.2016.7866427>

Mamun, M., Kim, J. J., Alam, M. A., & An, K. G. (2020). Prediction of Algal Chlorophyll-a and Water Clarity in Monsoon-Region Reservoir Using Machine Learning Approaches. Water, 12(1), 30.

Mo, D., Zhao, Y., & Chen, S. (2012). Automatic measurement and reporting system of water quality based on GSM. Proceedings - 2012 International Conference on Intelligent Systems Design and Engineering Applications, ISDEA 2012, 1007–1010. <https://doi.org/10.1109/ISdea.2012.595>

Mooney, J. G., & Johnson, E. N. (2014). A Comparison of Automatic Nap-of-the-earth Guidance Strategies for Helicopters. Journal of Field Robotics, 32(8), 1–17. https://doi.org/10.1002/rob

Nilsson, C. (2009). Reservoirs. Encyclopedia of Inland Waters, 625–633. <https://doi.org/10.1016/B978-012370626-3.00039-9>

Muharemi, F., Logofătu, D., & Leon, F. (2019). Machine learning approaches for anomaly detection of water quality on a real-world data set. *Journal of Information and Telecommunication*, *3*(3), 294-307.

NAHRIM. 2009. Study on the Status of Eutrophication of Lakes in Malaysia. NAHRIM, Seri Kembangan.

Nishar, A., Richards, S., Breen, D., Robertson, J., & Breen, B. (2016). Thermal infrared imaging of geothermal environments and by an unmanned aerial vehicle (UAV): A case study of the Wairakei–Tauhara geothermal field, Taupo, New Zealand. Renewable Energy, 86, 1256-1264.

Ore, J., Elbaum, S., Burgin, A., & Detweiler, C. (2015). Autonomous Aerial Water Sampling. Journal Of Field Robotics, 32(8), 1095-1113. doi: 10.1002/rob.21591

Osborne, P., Hoffman, E., Lovelady, R., Holloway, R., & Ferguson, R. (1981). A Water Quality Monitoring Robot. *OCEANS 81*. doi: 10.1109/oceans.1981.1151651

Park, J., Sohn, J., Kim, S., & Park, J. (2013). Design and field testing of water quality sensor modules designed for round-the-clock operations from buoys and biomimetic underwater robots. Studies in Computational Intelligence, Vol. 466, pp. 209–216. <https://doi.org/10.1007/978-3-642-35485-4_16>

Podnar, G., Dolan, J. M., Low, K. H., & Elfes, A. (2010). Telesupervised remote surface water quality sensing. IEEE Aerospace Conference Proceedings, (Figure 1), 1–9. <https://doi.org/10.1109/AERO.2010.5446668>

Ruescas, A. B., Mateo-Garcia, G., Camps-Valls, G., & Hieronymi, M. (2018, July). Retrieval of Case 2 Water Quality Parameters with Machine Learning. In *IGARSS 2018-2018 IEEE International Geoscience and Remote Sensing Symposium* (pp. 124-127). IEEE.

Saab, C., Shahrour, I., & Chehade, F. H. (2017). Smart technology for water quality control: Feedback about use of water quality sensors. 2017 Sensors Networks Smart and Emerging Technologies, SENSET 2017, 2017-Janua, 1–4. <https://doi.org/10.1109/SENSET.2017.8125060>

Sakai, N., Mohamad, Z. F., Nasaruddin, A., Abd Kadir, S. N., Mohd Salleh, M. S. A., & Sulaiman, A. H. (2018). Eco-Heart Index as a tool for community-based water quality monitoring and assessment. Ecological Indicators, 91(March), 38–46. <https://doi.org/10.1016/j.ecolind.2018.03.079>

Shafi, U., Mumtaz, R., Anwar, H., Qamar, A. M., & Khurshid, H. (2018, October). Surface water pollution detection using internet of things. In *2018 15th International Conference on Smart Cities: Improving Quality of Life Using ICT & IoT (HONET-ICT)* (pp. 92-96). IEEE.

Sharip, Z., & Suratman, S. (2017). Formulating Specific Water Quality Criteria for Lakes: A Malaysian Perspective. In Water Quality. InTech.

Shunmuga Perumal, P., Samson Arun Raj, A., Bharathi, B. M. S., Mohan Raju, G., & Yogeswari, K. (2017). UAV assisted automated remote monitoring and control system for smart water bodies. Proceedings - 2017 2nd International Conference on Recent Trends and Challenges in Computational Models, ICRTCCM 2017, 116–120. <https://doi.org/10.1109/ICRTCCM.2017.85>

Siyang, S., & Kerdcharoen, T. (2016). Development of unmanned surface vehicle for smart water quality inspector. 2016 13th International Conference on Electrical Engineering/Electronics, Computer, Telecommunications and Information Technology, ECTI-CON 2016, 1–5. <https://doi.org/10.1109/ECTICon.2016.7561370>

Taufiqurrahman, Tamami, N., Putra, D. A., & Harsono, T. (2017). Smart sensor device for detection of water quality as anticipation of disaster environment pollution. Proceedings - 2016 International Electronics Symposium, IES 2016, 87–92. <https://doi.org/10.1109/ELECSYM.2016.7860981>

Tian, W., Liao, Z., & Zhang, J. (2017). An optimization of artificial neural network model for predicting chlorophyll dynamics. Ecological Modelling, 364, 42-52.

Turner, I. L., Harley, M. D., & Drummond, C. D. (2016). UAVs for coastal surveying. Coastal Engineering, 114, 19-24.

Vaddadi, S. K., Sadistap, S. S., & Kumar, P. (2012). Development of embedded wireless network and water quality measurement systems for aquaculture. Proceedings of the International Conference on Sensing Technology, ICST, 637–641. <https://doi.org/10.1109/ICSensT.2012.6461757>

Wang, Y., Zhou, J., Chen, K., Wang, Y., & Liu, L. (2017, November). Water quality prediction method based on LSTM neural network. In *2017 12th International Conference on Intelligent Systems and Knowledge Engineering (ISKE)* (pp. 1-5). IEEE.

Wiranto, G., Mambu, G. A., Hiskia, Hermida, I. D. P., & Widodo, S. (2015). Design of online data measurement and automatic sampling system for continuous water quality monitoring. 2015 IEEE International Conference on Mechatronics and Automation, ICMA 2015, 2331–2335. <https://doi.org/10.1109/ICMA.2015.7237850>

Xu, L., Gu, H., Li, C., Shi, A., & Shen, J. (2013). System design of water quality monitoring robot with automatic navigation and self-test capability. International Journal of Control and Automation, 6(5), 67–82. <https://doi.org/10.14257/ijca.2013.6.5.07>

Yan, H., Liu, Y., Han, X., & Shi, Y. (2017, August). An evaluation model of water quality based on DSA-ELM method. In *2017 16th International Conference on Optical Communications and Networks (ICOCN)* (pp. 1-3). IEEE.

Yang, T., Hsiung, S., Kuo, C., Tsai, Y., Peng, K., & Peng, K. et al. (2018). Development of unmanned surface vehicle for water quality monitoring and measurement. 2018 IEEE International Conference On Applied System Invention (ICASI). doi: 10.1109/icasi.2018.8394316

Zhu, C., Liu, X., Chen, H., & Tian, X. (2018). Automatic cruise system for water quality monitoring. International Journal of Agricultural and Biological Engineering, 11(4), 220–228. <https://doi.org/10.25165/j.ijabe.20181104.2658>