

Development of 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 has to be carried out at regular intervals to detect the degradation of water quality at early stages so that it can be prevented. Currently, for lake sampling, trained personnel have to use boats and hire safety officers for the fieldwork. Also, large volumes of water samples have to be collected and transported back to the laboratory to test algae and nutrients present in the water (Azizul, 2019).

In situ water parameter sensing equipment that measures the physicochemical properties of the water are also used sometimes alongside water sample collection. Water quality parameters such as pH, Dissolved Oxygen (DO), Electrical Conductivity (EC) and temperature are measured on-site and the samples are used for bacteriological analysis in the laboratory (Al-Badaii et al., 2013). Often the water quality sondes used in situ measurements are quite expensive and usually not IoT enabled. There are several issues when it comes to sampling remote water bodies such as transporting equipment, boats, and people to the site which is extremely challenging if the site is far away.

##### 1.1 Proposed Solution

A cost-effective, IoT enabled multiparameter sonde will be designed and developed in this study to provide physicochemical properties of water in real-time. Temp, EC, DO and pH are the most common parameters to detect water quality impairment in rivers and lakes (Koparan et al., 2018) and these sensors will be used to make the IoT enabled sonde. The data collected will be transmitted to the backend for analysis and visualization will be done in the form of the Eco-heart index developed by Sakai et al. (2018). This is useful especially for non-technical stakeholders and the raw parameters will also be available for scientists and researchers. To assess the accuracy of the sensors developed, it will be compared with laboratory analyzers using the paired t-test. The t-test will be carried out by finding the mean difference between the two sets by taking random data samples.

##### 1.2 Problem Statement

The effective functioning of inland aquatic bodies like lakes and ponds are being severely hindered by Eutrophication. 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).

Traditional laboratory testing methods to determine water quality, albeit accurate, are 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). 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 that demonstrate telemonitoring of water parameters using IoT are often expensive (Yang et al., 2018).

Another issue when it comes to conventional water quality monitoring is that the information is constrained within the practitioners and doesn’t help much when it comes to informing the general population (Indu & Choondal, 2017). The data is published as Water Quality Index (WQI) which integrates all the measured parameters and hence individual parameters are lost. Also, the numerical value of WQI is not engaging or informative enough to the laymen community (Sakai et al., 2018).

##### 1.3 Significance of the Study

A cost-effective IoT enabled multiparameter probe is proposed in this study. It has an accompanying backend for data analytics to communicate and visualize data in an easy manner to practitioners, and citizens alike. Firstly, it provides automatic measurements that have many advantages compared to manual methods like structuring of data, repeatability, etc. According to Gopavanitha and Nagaraju (2018), real-time water quality measurement is also potentially useful in the distribution system, industries, aquafarming, etc.

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

1. Inexpensive water sampling
2. Fast and accurate water sampling
3. Cutting down the need for trained personnel for sampling.
4. User-friendly and effective visualization of water quality parameters
5. Prediction of water quality using machine learning algorithms.

##### 1.4 Scope and Limitations

The IoT water quality measuring sonde is also reliable on cellular networks for internet access and there are some water quality parameters that cannot be measured on-site. There is a limitation on the number of parameters to be measured due to constraints in time and resources. Also, benchmarking with several other commercially available sondes and assessing the efficacy 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). Development on the sensor side and different monitoring methods are presented in the first and second sections of this review.

***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 measured pH, Total Dissolved Solids (TDS), EC and Temperature electronically. The sensor was accurate 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 communicated with the base station wirelessly and the base station 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.

***Underwater Robots for Water Quality Sampling***

Osborne et al. (1981) proposed a submersible buoy capable of in situ water quality measurement (Temperature, Turbidity, pressure, EC, pH, ORP, DO and Fluoride) and transmitted data to the ground control station via an underwater communication channel. In a similar study by Park et al. (2013), the effectiveness of water quality sensors (Turbidity, Temperature, pH, DO & EC) were realized that can be deployed to buoys and underwater robots The studies concluded that automatic measurements have a lot of advantages including fast and reliable data over manual methods.

An underwater robot dolphin was developed by Liu et al. (2016) with an on-board water quality sensing probe and demonstrated the feasibility of automatic water quality monitoring. Also, Hidalgo et al. (2016) measured underwater parameters like Salinity, Turbidity, EC, pH, DO and Depth using probes mounted on a Remotely Operated Vehicle (ROV).

In a study by Xu et al. (2013), a multiparameter water quality probe was developed for underwater robots and the accuracy was benchmarked against XZ-001 and 5B-3B water quality analyzers. In a similar study, an underwater robot equipped with a multiprobe water quality sensor measured water quality and tagged it with to their respective latitude and longitudinal values. The underwater robot floats to the surface of the water to communicate with the control station on the ground to send the measured parameters. Experimental results demonstrated errors of the measurement were within 5% when compared to the lab water analyzers. Both the studies measured the underwater parameters like Temperature, Turbidity, Blue/Green Algae, Chlorophyll A, DO, pH & ORP

***Unmanned Surface Vehicle (USV) Water Quality Sampling***

Siyang & Kerdcharoen (2016) mounted water quality sensors on a USV to make it mobile and take measurements from different locations to overcome the constraints of a fixed-location sensor. The sensors were manufactured by Atlas Scientific and the data (Temperature, pH, DO, ORP and EC) were obtained in real-time from the ground station which communicated with the sensor onboard the USV wirelessly via the XBee module. The ground station uploads the data to the internet from where the data is accessible from any location. In a similar study, ARK sensor buoy by AQUAS was carried by a UAV developed by Yang et al. (2018) which was used to measure Temperature, Turbidity, pH, EC, DO, Chlorophyll A & Potassium Ion. The buoy communicated with the computer in the ground station via Bluetooth and uploaded the measured data to the cloud using a 4G network.

To assess the quality of freshwater in lakes and rivers, a fleet of autonomous Robot Sensing Boats (RSB) was implemented to monitor water quality parameters (Temperature, pH & DO) that were sent to the server in real-time by the RSBs. They conducted in situ water quality assessments using a multiparameter sonde and experimented in fresh and algae-laden water for over three months to prove the proposed telesupervision architecture. The RSBs navigated using an architecture named Multilevel Autonomy Telesupervison Architecture (MARTA) developed for water quality sampling tasks. Another automatic cruise system for water sampling was proposed by Zhu, Liu, Chen & Tian. (2018). The ship mounted with a multiparameter water quality sonde that measured DO, pH, Temperature and Ammonia-Nitrogen in real-time while navigating autonomously to widen the range of measurements. The remote monitoring and control were assisted by an Android app they developed for this study.

Autonomous catamaran type boats were also quite popular when it came to automatic water sampling due to their stability of sailing. Koprowski et al. (2013) used an autonomous boat to measure the physicochemical properties of drinking water and used to measure fish density using the fish’s spatial location. The robot followed a designated path to measure the parameters and allowed remote monitoring and saved the data locally. Dunbabin & Grinham (2010) also used a solar-powered autonomous catamaran and experimentally evaluated the capabilities of monitoring water quality parameters such as Temperature, EC, DO and Chlorophyll using YSI Sonde. The catamaran was also referred to as Autonomous Surface Vehicles (ASV) and could navigate complex environments and continuously monitoring the water parameters in real-time. The collected data is relayed back to the shore-based facility for further analysis. They also proved the efficacy of the remote water profiling as it was strongly correlated with the manual methods.

***Unmanned Aerial Vehicle (UAV) Water Quality Sampling***

In order to conduct in situ water quality measurement, a hexacopter was equipped with floatation gears and water quality acquisition probes (Temperature, EC, DO & pH) in the research conducted by Koparan et al. (2018). The UAV allowed multipoint sensing to cover a wide area accurately with the error staying below 4%. The floatation equipment allowed landing and take-off from the surface of the water and the water parameter data was stored locally in an SD card. In a later study by Koparan et al. (2019), three cartridges were used to sample water at different depths along with the in-situ measurements of the previous parameters. Their research concluded that UAVs lower operational and logistics cost and allows quick access to inaccessible and hostile environments with flight time being the only bottleneck.

Similarly, a hybrid of a UAV and a hovercraft was designed for water quality monitoring in this study by Esakki et al. (2018) which had a payload capacity of 7 kg. This allowed the amphibious vehicle to collect 500ml of water samples from water bodies using a pump and containers. Moreover, the UAV was also equipped with water quality acquisition probes for Turbidity, pH, DO & EC that were IoT enabled allowing the data to be uploaded in the cloud using a wifi hotspot. In another study by Shunmuga et al. (2017), a LIDAR was attached to the drone to measure water level and capacity which is relayed to the ground control station wirelessly. The control station is also connected to stationary water quality sensors and rainfall sensors installed in the water reservoir. The control station collects and processes the data and transforms it into a knowledge base.

Detweiler et al. (2015) installed a pump and cartridges on the drone that samples water from different remote locations and brings back water samples for laboratory testing. They found that water quality parameters obtained from aerial sampling correlate with the conventional manual sampling methods. Given the good accuracies of the water quality parameters from aerial sampling, Ore et al. (2015) also found that UAV sampling provides high-resolution spatiotemporal data quickly while cutting down labor and cost.

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

Wang et al. (2017) carried out a study that predicted Dissolved Oxygen (DO) using Long & Short term Memory Neural Network (LSTM NN) using monthly DO data collected from 2000 to 2006. The study concluded that water parameter prediction problem is caused mainly due to the time series nature of the data where conventional NN fails. Hence, they suggested LSTM NN that outperformed Back Propagation and Online Sequential Extreme Learning Machine. Muharemi et al. (2019) discusses the approaches to detect anomalies on water quality data for parameters such as temperature, chlorine dioxide, pH, redox potential, EC, and turbidity. Logistic regression, linear discriminant analysis, support vector machines (SVM), artiﬁcial neural network (ANN), deep neural network (DNN), recurrent neural network (RNN) and long short-term memory (LSTM) were evaluated using F-score metric due to the challenging behavior of the time-series data. The results show that all algorithms are vulnerable but SVM, ANN and logistic regressions are less vulnerable. They also found that real-world data are noisy and highly imbalanced which makes prediction difficult.

Joslyn & Lipor (2018) investigated corrupted DO and turbidity data due to sensor faults, fouling and decalibration through supervised ML techniques using SVMs. Water quality is also evaluated using four parameters; pH, DO, potassium permanganate index (CODMn) and ammonia-nitrogen (NH3-N), using Extreme Learning Machine Algorithm optimized by Dolphin Swarm Algorithm (DSA-ELM) which was proven to be highly accurate (Yan et al., 2017). Older ML techniques such as decision trees, ANN and k-nearest neighbors (kNN) have also been used to classify drinking water quality into two categories (good and medium) out of five classes (excellent, good, medium, bad, very bad) (Camejo et al., 2013).

Appearance, alkalinity, temperature Hardness as CaCO3, EC, calcium, TDS, chlorides, nitrite as NO2, turbidity, pH and fecal coliforms were found using the unsupervised learning technique of Average Linkage (within Groups) method of Hierarchical Clustering using Euclidean distance which performed well in the study by Ali & Qamar (2013). For classification, the multi-layer perceptron (MLP) proved to be an accurate supervised learning technique.

Water quality assessment models are developed which analyzes water quality parameters and makes further predictions of the trend regarding water pollution. Cao et al. (2018) fine-tuned hyperparameters taken from readings of pH, DO, Chemical Oxygen Demand (COD), and NH-3 using the Mutation Genetic Algorithm with Particle Swarm Optimization (PSO) and Least Squares SVM based on PSO. The proposed algorithm proved to be faster in training speed and more accurate than Back propagation NN. Another study analyzed water quality parameters to determine the concentration of the parameters including Chlorophyll-A, EC, DO and turbidity (Khan & See, 2016). The ANN with Non-Linear Autoregressive (NAR) time series analysis was used to predict Water Quality and the Mean-Squared Error (MSE). Root Mean-Squared Error (RMSE) and Regression Analysis were used to evaluate the model.

In another work by Ruescas et al. (2018), Chlorophyll-A (together with Colored Dissolved Organic Matter (CDOM) and Total Suspended Matter (TSM)) is proposed where ML algorithms are used to retrieve water quality parameters from simulated remote sensing reflectance by mapping reflectance to WQ parameters. This work also reported that the ML linear and non-linear regression methods (regularized linear, random forest, Kernel ridge, Gaussian process and support vector regressors) performed efficiently and effectively.

Shafi et al. (2018) proposed an IoT-based solution with AI techniques to monitor water quality in real-time. It provides remote monitoring and assessment of several parameters including pH, turbidity, hardness as CaCo3, EC, alkalinity, TDS, nitrate, fecal coliform, and calcium. They applied the SVM, kNN, single-layer neural network and the deep neural network to classify the water quality and found that the deep neural network outperformed all with accuracy of 93%.

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. The sensors can also be attached to an underwater robot, USV or UAV to collect data from diverse spatial locations and it also gives access to remote and inaccessible areas in a fast and convenient way. These various methods were 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.

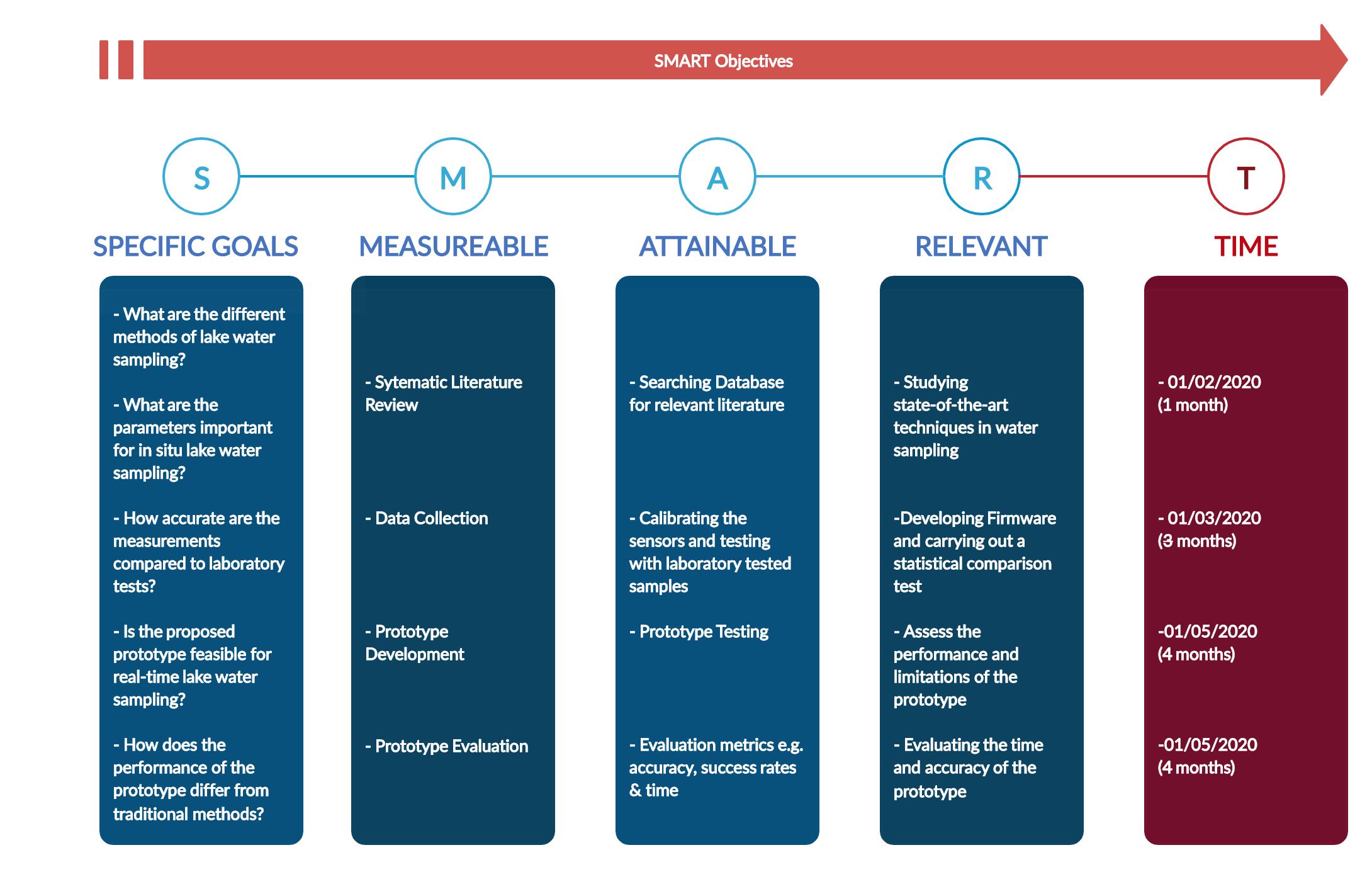
In summary, the development of a dynamic IoT framework with accompanying data analysis and visualization for real-time lake eutrophication profiling is practical and an interesting area to explore. Using six parameters to predict eutrophication risk level is feasible but only if Chlorophyll-A is considered in-situ. The ML techniques can be useful to support Chlorophyll-A parameter prediction by analyzing other measured parameters for framework completion.

### **3. Methodology**

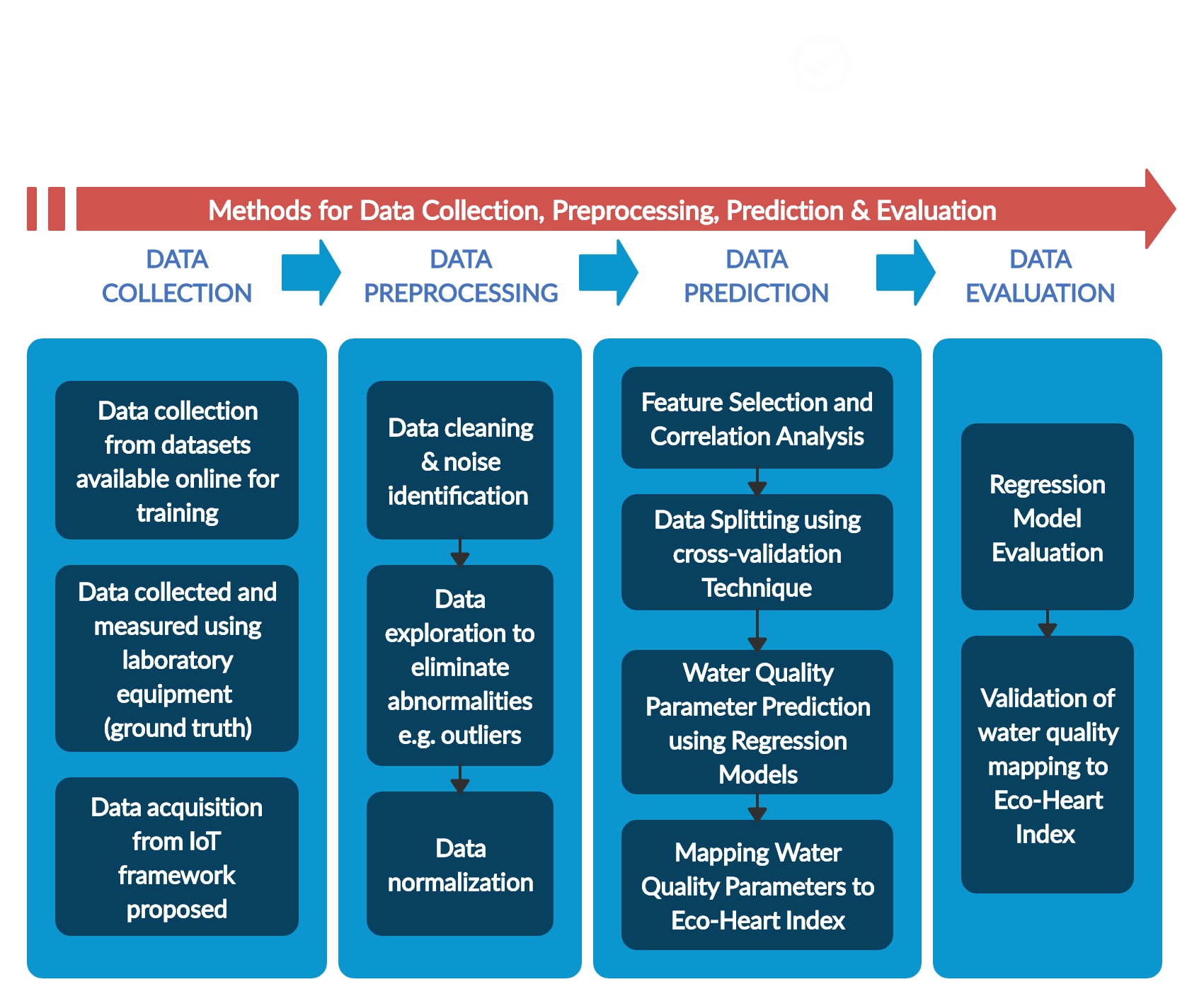
Table 3.1 shows the mapping of the research methodology and Figure 3.1 shows the graphical representation of the SMART methodology. The study commences with a literature search and systematic review to identify discriminators before the development of the proposed prototype. The water quality sensors are then calibrated and benchmarked with laboratory equipment for all the parameters (Temp, EC, DO and pH). The multiparameter sonde and floatation gears will be mounted on an off-the-shelf UAV-drone. After the integration, functionality testing will be carried at the Tasik Varsity, UM where results taken by prototype will be compared against conventional sampling techniques to evaluate the performance of the proposed prototype. Figure 3.2 summarizes the process of data collection and preprocessing which allows the machine learning models to analyze and predict based on the input data.

**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 appropriate discriminators in distinguishing different monitoring methods and parameters for efficient lake water sampling. | a) Literature search  b) Systematic literature review | a) Findings on the performance of existing approaches  b) Core parameters for water quality monitoring |
| What are the parameters important for in situ water sampling? |
| How accurate are the in situ measurements compared to laboratory equipment? | To compare the sensor data with laboratory measurements | a) Proof-of-concept  b) Calibration of sensors  c) Data collection from lab equipment  d) Comparison test | a) Custom-built IoT-enabled sensor.  b) Develop firmware and integrate with the backend  c) Calibrate the Sensor  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) Development and integration of the sensor with the drone  b) Validating and fine-tuning | 1. New findings on the proposed prototype in terms of time 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 |

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**Fig 3.1: SMART Research Methodology**

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**Fig 3.2: Data Collection, Processing, Prediction & Evaluation Methodology**

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