KEMENTERIAN PENDIDIKAN MALAYSIA

SINGLE DISCIPLINARY PROJECT

APPLICATION FORM
FUNDAMENTAL RESEARCH GRANT SCHEME (FRGS)
Skim Geran Penyelidikan Fundamental
(Pindaan 1/2012)

JABATAN PENDIDIKAN TINGGI
KEMENTERIAN PENDIDIKAN MALAYSIA

A. Application Details

Application ID	358605
A(i). Selected Grant	FRGS 2020-1
A(ii). Title Of Proposed Research Project	A dynamic IoT management framework for water quality assessment and classification
A(iii). Keyword	Drone, water collection, water sampling, water quality, IoT

B. Details of Project Leader

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B(xii). Type of Service (Permanent/Contract)	Permanent

C. Research Information

C(i). Research Domain

Research Domain	Sub Research Domain
Information and Communication Technology	Artificial Intelligence

C(ii). Research Cluster

Cluster: Climate Change & Environment

C(ii). National Priority Area

Priority Area: Water Security

C(iii). Location of Research

Location
Faculty of Computer Science and Information Technology, University of Malaya

C(iv). Duration of this research

From	June/2020
To	May/2022
Duration	2 years

C(v). Other Researchers

Researcher Id	Name	IC / Passport Number	Faculty/ School/ Centre/ Unit	Position	Area of Expertise	Invitation Status	Next Appointed Leader	Role
36581	Zeeda Fatimah Binti Mohamad	761124055000	Universiti Malaya	Associate Professor (Dr)	Environmental Ethics, Environmental Management and Policy, Science, Technology and Innovation Policy , Socio-technical Analysis, Innovation Systems , Sustainable Development	Accepted	☐	
66935	Zati Binti Sharip	730626045302	Kementerian Air, Tanah dan Sumber Asli	Senior Lecturer (Senior researcher)	Aquatic plant biology, Environmental Engineering, Limnology, freshwater ecology	Accepted	☐	
95403	Darween Reza Bin Sabri	921004086363	My Conceptual Robotics Sdn Bhd	Others (Mr)		Accepted	☐	

C(vi). Research projects that have been completed or ongoing by project leader for the last three years

Title	Grant Name	Role	Progress (%)	Status	Duration	Start Date	End Date
Evaluation of Image Processing and Simulation Software Framework for the Diagnosis and outcome prediction of Mycardial Infarction (RP028C-14HTM)	UMRG programme	Member	N/A	Complete - KPI Achieved	3 years 7 months	16/07/2014	15/02/2018

C(vii). Academic publications that has been published by the project leader for the last five years

Title	Name of Journal	Year
Capacity and Frequency Optimization of Wireless Backhaul Network Using Traffic Forecasting	IEEE Access	2020
QRDPSO: A new optimization method for swarm robot searching and obstacle avoidance in dynamic environment	Journal of Intelligent Automation and Soft Computing	2019
Blending Big Data Analytics: Review on Challenges and a Recent Study	IEEE Access	2019
Application of Robotics in STEM education	Best Practices in STEM Mentor Mentee	2019
Computational Thinking in STEM	Best Practices in STEM Mentor Mentee	2019
How Rovio navigates in its environment	Regional Conference on Computer and Information Engineering 2017	2017
Detecting arm and hand flapping movement disorder in children using human pose estimation and skeletal representation algorithms	IEEE AUN/SEED-Net Regional Conference for Computer and Information Engineering	2016
Wearable robots: trends and challenges in industrial exoskeleton	International Seminar on Palm Oil Mechanisation (PalmMech)	2016
Fuzzy-based framework for the selection of image processing software for diagnosis and outcome prediction of cardiac diseases.	The 3rd International Conference on Computational Science and Technology	2016
Detecting arm flapping in children with Autism Spectrum Disorder using human pose estimation and skeletal representation algorithms	The IEEE 2016 International Conference on Advanced Informatics	2016

Classification of Image Processing Software Tools for Cardiovascular Image Analysis	International Conference for Innovation in Biomedical Engineering and Life Sciences (ICIBEL)	2015
Autonomous robot mapping by landmark association	EuroAsianPasific Joint Conference on Cognitive Science	2015

C(viii). Executive Summary of Research Proposal

(Please include the problem statement, objectives, research methodology, expected output/outcomes/implication, and significance of output from the research project)

The conservation of water ecosystems and resources is an important agenda under the United Nations Sustainable Development Goals (SDGs).
The SDGs is a blueprint of sustainable development priorities until 2030, formulated to promote coordinated planning and development for
the planet to survive and thrive in multiple dimensions. Among the 17 SDGs, this research aspires to contribute to SDG6 that sets out to
ensure equitable access to clean water and sanitation for all. This includes the conservation of water resources such as lakes. As Malaysia
experience rapid urbanization and population growth - levels of water pollution have also increased, which are severely affecting the water
quality of our natural and man-made lakes. This requires improvement in water quality monitoring and mitigation measures. The aim of this
research is to experiment with the proposed AI and IoT technology to improve the efficiency of current water quality methods, which are
predominant conducted manually at present.

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 and industrialization which is deteriorating the water quality on the surface and underground (Putra & Harsono, 2016; Gafri et al., 2018). As a result, water resource management has become more important than ever (Siyang & Kerdcharoen, 2016). Water sampling (spatially separated and high frequency) is crucial in managing freshwater resources and maintaining public health (Ore et al., 2015) and 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). Real-time data collected using IoT can benefit water conservation management and policy-makers to take appropriate action. 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).

This proposal involves the design and building of a dynamic IoT framework for water quality assessment and classification for real-time lake conservation management. In particular, this work will look into eutrophication risk level at lakes as case study. The dynamic IoT framework proposed will consists of multi-parameter probes mounted on a visual flying drone with special light sensor for in-situ sampling at lakes. Data from probes or sensors will go through pre-processing, predictive parameters modeling using machine learning (ML) techniques, and evaluation to determine lake eutrophication risk levels. The risk levels include oligotrophic (none-existing nutrients), mesotrophic (moderate level of nutrients) and eutrophic (true or heavy level of nutrients). The framework is completed with real-time data communication and intuitive visualization for end-users through web-pages and mobile platforms.

C(ix). Detail Planning

(a) Research background

1. Problem Statement

Water quality is currently estimated through expensive and time-consuming lab and statistical analyses, which require sample collection, transport to labs, and a considerable amount of time and calculation. This is inefficient given water is vital to life and horrific consequences of water pollution necessitate a quicker and cheaper alternative. In this regard, the main motivation in this study is to propose and evaluate an alternative method based on ML techniques for the efficient prediction of water parameters in real-time. To our best knowledge, most works focus on rivers, watershed and drinking water, but none specifically on lake eutrophication. The literature also shows machine learning (ML) models have only been applied on manually collected data.

Most of the research used too many parameters to be efficient enough for real-time water profiling, in particular in lake eutrophication cases. One way to improve is to employ ML methodologies to optimize statistical solution for the water quality problem. One of the main challenges in this work is to deal with the time series nature of water data and several ML techniques will be evaluated for water parameters prediction. Six parameters are minimally taken in manual water surface sampling; temperature, pH, dissolved oxygen (DO), turbidity, electric conductivity (EC) and most importantly, clorophyll-a for eutrophication identification. With electronic probe or sonde, these parameters can be measured in-situ, except clorophyll-a, which requires lab testing and time to confirm presence. In this work, our proposed dynamic IoT framework will retrieve clorophyll-a in real time through ML prediction by reflectance of special light sensor mounted on the visual flying drone.

2. Hypothesis

Currently, trained personnel use boats to perform fieldwork sampling at multiple checkpoint depending on lake size, and require lab testing and considerable time to confirm eutrophication risk level at lakes. We propose a dynamic IoT framework to perform in-situ sampling and real-time prediction of water parameters using ML techniques saves time and money, and improve lake conservation management in this country.

3. Research Questions

1. What are the various methods used for lake surface water sampling?
2. What are the discriminative features that distinguish lake eutrophication risk levels?
3. Which ML techniques are appropriate for water parameters prediction and classification?
4. How to ensure unbroken communication between IoT nodes and the backend server for region with and without cellular coverage?
5. How does the performance of the proposed framework differ from existing solutions?

4. Literature Reviews

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 eutrophication can be anticipated. Currently, for lake sampling, trained personnel has to use boats and hire safety officers for the fieldwork. They need to collect large volumes of water samples and transport them back to the laboratory to test algae and nutrients present in the water (Azizul, 2019). To address these widespread challenges, improving sampling quantity and quality is necessary for improving lake water quality.

Lake sampling is a fieldwork associated with the collection and transport of water samples. A sampling expedition may include in-situ analysis and/or co-ordination with laboratory for analysis. For example, temperature, DO, EC, and pH are measured in-situ as field parameters while other physical, chemical and bacteriological parameters are analyzed in the laboratory (Al-Badaii et al., 2013). At present, a successful sampling expedition include a comprehensive checklist (Ballance and Bartram, 2002) which usually involve a team of water, geographical and safety personnels. In addition, safety of field personnel, suitability of the equipment for analysis, field measurement profiles, temporal and spatial heterogeneity, ecological characteristics, weather conditions, fluvial-sediment transport, and sources of contaminations are other considerations for choosing an appropriate water sampling method. These considerations is required to minimize biases in water profiling.

Biases caused by the water collection process can be curbed with good selection of sampling method and strategic sampling location. Surface water sampling methods include (i) surface dip sample taken at deepest point, (ii) a surface dip sample taken at water edge, (iii) a surface dip sample about 30m from the shore and (v) surface dip sample taken along a short transect out from the shore. For national survey purposes, samples taken from the edge of the lake are the most cost effective. However, for accurate lake profiling, considering multiple sampling stations is the practice to represent the lake's condition at a given time. Fig. 1 shows the stations selected for water sampling at the Cempaka lake, Bangi (Gasim et al., 2015).

According to the Surface water sampling (2013) guidelines, the physical location of the investigator when collecting a sample may influence bias too. The guidelines reported sampling from accessible location such as steam banks by wading or from low platforms (from small boats or piers), may cause the re-suspension of bottom deposits and bias the sample. If the stream is too deep to wade, or if the sample must be collected from more than one water depth, or if the sample must be collected from an elevated platform (bridge, pier, etc.), supplemental sampling equipment must be used which is cost prohibitive. Fig. 2 shows grab sampling which has been the practice traditionally before sonde technology become available. Fig. 3 shows the data sonde, an electronic multi-parameter probe which auto profiles water properties upon contact with water samples.

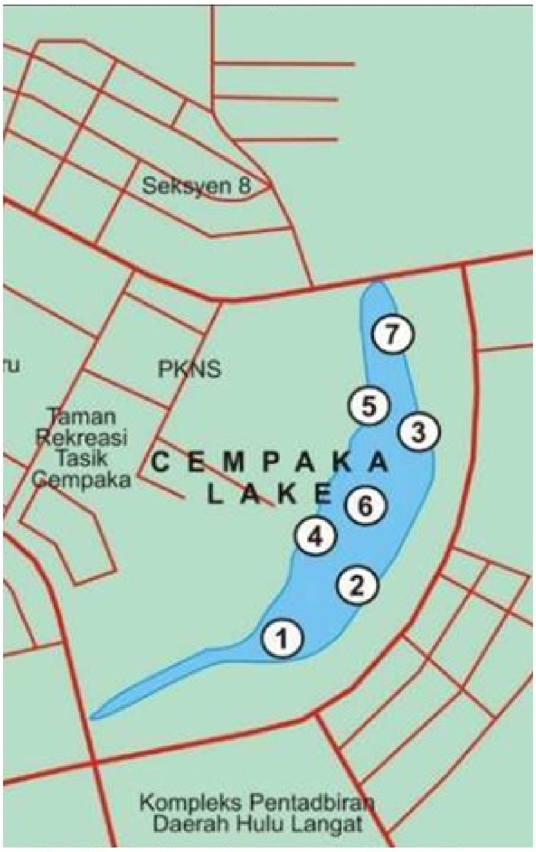


Fig. 1: Location of seven sampling stations in the Cempaka lake (taken from Gasim et al., 2015)


Fig. 2: Grab sampling (taken from Ore et al., 2015)

Fig. 3: Electronic Multi-parameters data sonde by EXO

Several significant deployment of drones for water sampling have been recorded and the design of the drone including its sampling mechanism is decribed in Table 1. The aerial works did not specifically followed any guideline for lake water sampling however their considerations for the drone design and sampling mechanism is in accordance to the guideline proposed by Ore et al. (2015)

following a discussion with their hydrologist partners:

1. The drone must capture at least three 20 ml water samples at predefined locations within 1 km.
2. The drone must be light and small enough to be carried by a single scientist.
3. The drone samples autonomously once target locations are identified.
4. The drone must be reliable and safe to reduce cost and risk, since these are the primary barriers for adoption.
5. The drone must be cost effective.
6. The drone must not influence water properties.

In terms of the type of drone technology, most of the drones proposed for water sampling in the last 5 years are airborne and only one is water-bound. Generally, multi-copters such as quad-copter (4-rotor), hexa-copter (6-rotor) and octa-copter (8-rotor) are preferred over fixed-wing for their vertical take-off and landing capability similar to a helicopter with fixed pitch propellers and symmetrical design. Other design and developmental considerations in building an appropriate drone for water sampling include:

1. Frame design and analysis
Most off the shelf drones are aluminium-based, strong and rigid for overall rigidity and strength however fiber glass is opted for the water-bound drone. SolidWorks are preferred for simulation and most of the works simulated the structure properties to get the load distribution, maximum strain, displacement and von Mises stress at given conditions by balancing parameters such as:
a) Material used
b) Total mass (quad/hexa/octa-gonal base + arm)
c) Volume
d) Density
e) Thrust calculation
f) Weight of each motor
g) Length of each arm
h) Edge length of centre hexagon

2. Dynamic analysis
For acceleration estimation, the drone design must consider:
a) Mass and acceleration
b) Gravity
c) Propeller thrust
d) Drag force
e) Disturbances

3. Electronic system
To ensure stability, off the shelf electronic boards are sufficient and available open market source are preferred. The main concentration was towards increasing flight time and payload, while consuming the least power. This depends greatly on how much thrust generated as a consequence of the motor-propeller combination. Some electronic aspects for consideration include:
a) Brushless DC motor
b) Propeller (length plays a factor. The longer the lenght, the higher the thrust but more power is consumed)
c) Electronic speed controller (ESC). ESC is an electrical circuit which is used to vary speed of the (BLDC) motor. The speed that is produced depends on the received frequency from controller board. The burst current of each ESC is 30amp with 25gm of weight.
d) Flight controller. The multicopter controller board should include integrated gyroscopic sensors and accelerometer to ensure flight stability.
e) Remote controller for radio control systems (2.4 GHz signal technology and a 6 channels receiver with a range of 100m is usually the base).
f) Battery. To balance weight and power, most design opted for light weighted lithium-ion polymer batteries.

4. Assembly and system integration
For custom-built drones, most of the components are purchased separately from the open market following considerations of above mentioned specifications and assembled into the prototype. However it is a practice to purchase off the shelf drones (preference for 4 out of 6 works in the last 5 years). The advantages of off-the-shelf drones include:
a) Cheaper: It is economically efficient to buy a drone than making it.
b) Ready to fly: A purchased drone can be put into flight almost immediately. The Ready-to-Fly quadcopters only require a camera, battery, and propellers attachment to take to the skies.
c) Assistance: support for snags and breakage while under warranty, with option to dispatch to the manufacturer for fix or replacements.
d) Nil technical know-how required: You need no technical knowledge for purchasing a drone. However, if you construct your own drone technical know-how is a must.
e) Better performance: calibration and vibration analysis is perfected prior to sales

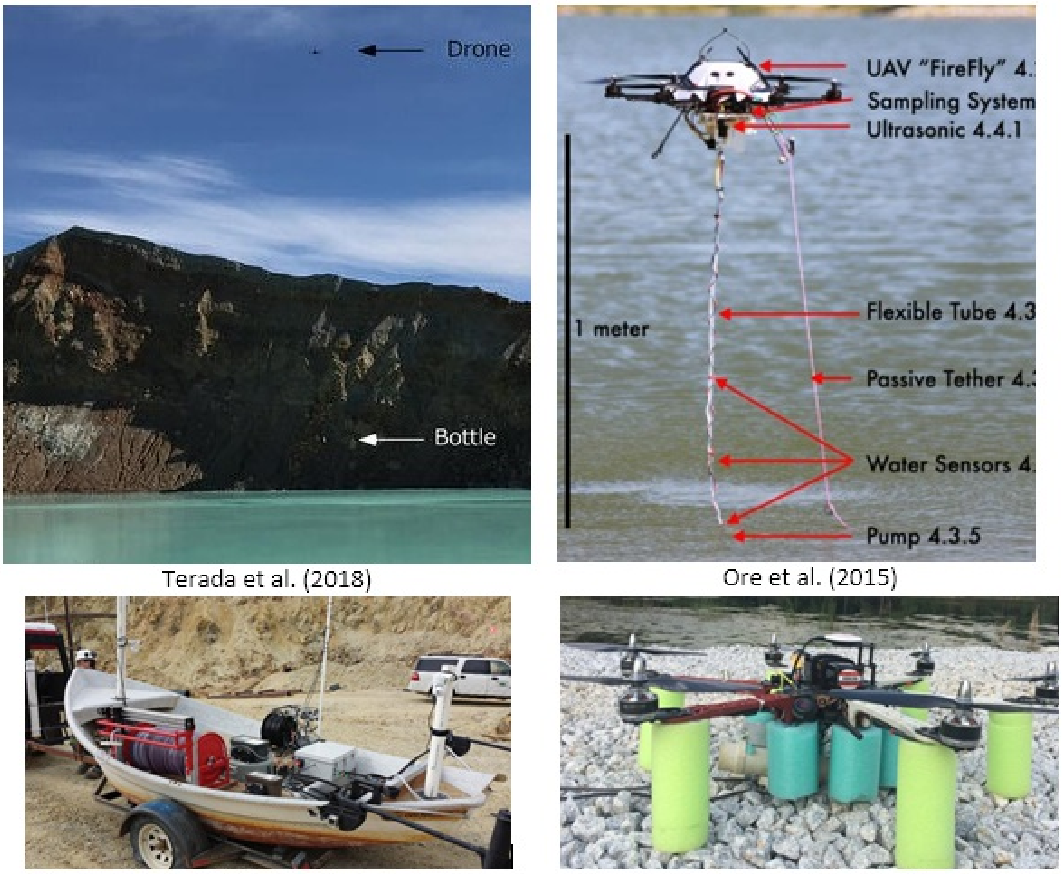
Table 1: Comparison on latest drone designs for lake water sampling

Ref & Aim	Drone design	Limitation
Terada et al. (2018) Airborne sampling of lake crater	• Off the shelf 6-rotor LAB645 (by Enroutelab, Japan) • 12kg take-off load • 40mins flight duration • 4km return flight route • 2 x battery 2kg, 350 Wh, 22.5V • Manual take-off and landing • Bottle with auto inlet shut when reach max water capacity	• Small amount of water sample (250ml) • 30m suspended tether • Rope may snagged on trees • Operator catches bottle before landing • Manual water profiling (no sondes on board) • Maintain 30m above water so to maintain drone communication with operator
Castendyk et al. (2018) Airborne sampling of pit lakes	• Off the shelf 6-rotor DJI Matrice600 • 6kg take-off load • 15mins flight duration • Bottle requires separate messenger down static tether to shut inlet • Messenger with sonde for in-situ profiling • Data transfer available upon landing • Recorded 80m depth sampling • USD4,500 price (low-cost)	• 100m suspended tether • Tether may snagged on trees and powerlines • Sampling bottle may pendulum below drone making landing the payload difficult • Weight of payload limits flight duration to <15mins and negates the use of multi-parameter sonde that needs about 2mins to stabilize readings • Moderate wind and light rain may delay drone operations
Castendyk et al. (2018) Water-based sampling of pit lakes	• Custom-built drone-boat (by Uni of Montana) • 4m length, flat bottomed, drift boat • Fiber glass body • Raspberry Pi as central controller • Uses MS5 data sonde by Hydrolab • Data sonde comes with reeled data cable of 200m length • Online data log	• The need to maintain a stable, obstacle-free access road leading to pit lake shoreline • Requires humans to drive inside the pit and manually deploy the boat • Only able to study at 200m depth (pit is close to 370m depth) • USD80,000 price tag (costly to reproduce)
Koparan et al., (2018) Airborne sampling of lakes	• Custom-built 6-rotor design • Autonomous sampling • Fabricated water capturing mechanism (FWCM) with messenger and floatation attachments • 18s water sampling duration • 1.8m suspended tether	• 2.8kg take-off load • <6mins max flight duration limits to 1.5min flight each testing • 73 cases, 66% water collection success • Messenger failure (25 cases), servo motor malfunction (4 cases) and instability (1 case). • Instable when wind speed >28.97km/h • Stable when wind speed < 24.14km/h
Ore et al., (2015) Airborne sampling of lakes	• Off the shelf 6-rotor design (by Ascending Technology Firefly) • Fabricated water capturing mechanism • 1m suspended tether	• 600g take-off load (300g used to load 3 x 20ml sampling vials) • <20mins max flight duration • 2km max flight distance • In-situ analysis upon landing

For the drone to be compatible for water sampling activities, the works reviewed proposed differing mechanism to fetch water samples. Interestingly, all of the air-bound drones opted for suspended tethered solution in which a sampling bottle (Terada et al., 2018; Castendyk et al., 2018; Koparan et al., 2018) or several sampling vials (Ore et al., 2015) are attached to it. The difference is in the length of the tether. Some prefers >30m tether length and some prefers <2m length. Regardless of the length, non of the drones touches the surface of the water for sampling and all have issues with the bottle or vials pendulum beneath the drone, disturbing the flight stability. It is also reported that the longer the length of the tether, the harder it is for the operator to maneuvre sampling based on camera input due to the distance to surface of water. In terms of water being let into the bottles or vials, some proposed fabricated mechanism with auto-inlet upon max fill and others proposed a messenger going down the tether to shut the inlet of the bottles or vials. Noted also that most drones perform surface dip sampling except for the ones sampling in pit lakes. None of the works reported sampling along the transact or areas in which the water may experience re-suspension.

In regards to payload, only 2 works consider air-bound drone to have max take-off load >6kg. For this reason, non of the works carry a sonde on-board except for Castendyk et al. (2018) which performs data transfer upon water collection. This is due to the weight of multi-parameter sonde which is usually over 1kg. In terms of performance, the custom-built drones have more freedom in designing and controlling the sampling mechanism, depending on the budget or resources available. If given an option most would prefer to adopt lighter frame to counter payload and power consumption however materials such as carbon fiber are expensive. It is noted that none of the works considered lengthier propeller to improve thrust. All of the works reported efficiency of their drones is highly influenced by environmental factors such as change in wind direction and speed. At times, flight and sampling is delayed or completely abandoned even in moderate wind and light rain.

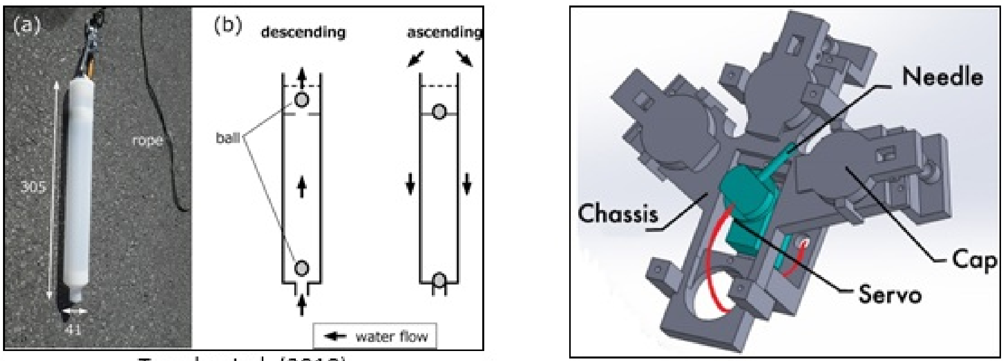
In summary, developing a drone specific for lake water profiling requires serious considerations on drone specifications as well as the water sampling requirements. For the drone, concentration must be given on the trade-offs between the electromechanical design to push for highest payload and flight time while minimizing battery consumption. On the other hand, implementing efficient sampling mechanism must consider the guidelines used by lake researchers and experts so the solution improves sampling time and is cost effective. Fig. 4 shows example of drones used for lake profiling, all using suspended tether and Fig. 5 shows examples of auto shut inlet for sampling mechanism.



Terada et al. (2018) Ore et al. (2015)

Castendyk et al. (2018) water-based drone Koparan et al. (2018)

Fig. 4: Example of drones used for lake profiling, all using suspended tether



Terada et al. (2018) Ore et al. (2015)

Fig. 5: Examples of auto shut inlet for sampling mechanism

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).

Smart Water Quality Sensors

The global system for mobile communication (GSM) is used to inform water conservation management authorities by sending SMS for any abnormality in the reading. Mo et al. (2012) used the GSM to relay automatic measurements and analysis of pH, turbidity, temperature, EC and DO. In another study, an automatic sampler was designed by Wiranto et al. (2015) that collect 20 ml of water samples whenever the value of 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. 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 fairly 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 the 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, 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) developed water quality sensors for potable water measuring DO, pH, temperature and 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 and ORP in the study conducted by Li et al. (2017). It provided high-resolution spatio-temporal 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.

From this literature review, it is 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 are able to provide high-resolution spatio-temporal data about the quality of water in the water bodies. The sensors can also be attached to drone 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 IoT framework to be ubiquitous and widely used by the water conservation community. Most of the research used too many parameters to be efficient enough for real-time water profiling, in particular in lake eutrophication cases. One way to improve is to employ AI methodologies to optimize statistical solution for the water quality problem.

AI techniques in water quality prediction

Water quality prediction is a time series prediction problem and conventional Neural Networks (NN) are not suitable. Wang et al. (2017) performed prediction of the DO parameter using the LSTM neural network and it was found to perform better than Back Propagation NN and Online Sequential Extreme Learning Machine. For training, monthly data of DO is collected from 2000 to 2006. 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. Due to the challenging behavior of the time-series data, 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. The results show that all algorithms are vulnerable but SVM, ANN and logistic regressions are less vulnerable. They observed the 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). Table 2 shows the numerical WQI and its classifications. Appearance, alkalinity, temperature Hardness as CaCO3, EC, calcium, TDS, chlorides, nitrite as NO2, turbidity, pH and fecal coliforms WQI was found using the unsupervised learning technique of Average Linkage (within Groups) method of Hierarchical Clustering using Euclidean distance which performed well in Ali & Qamar (2013). For classification, the multi-layer perceptron (MLP) proved to be an accurate supervised learning technique.

Table 2: Sample range of WQI and classification

Range of WQI	Qualification
90 - 100	Excellent
70 - 90	Good
50 - 70	Medium
25 - 50	Bad
0 - 25	Very Bad

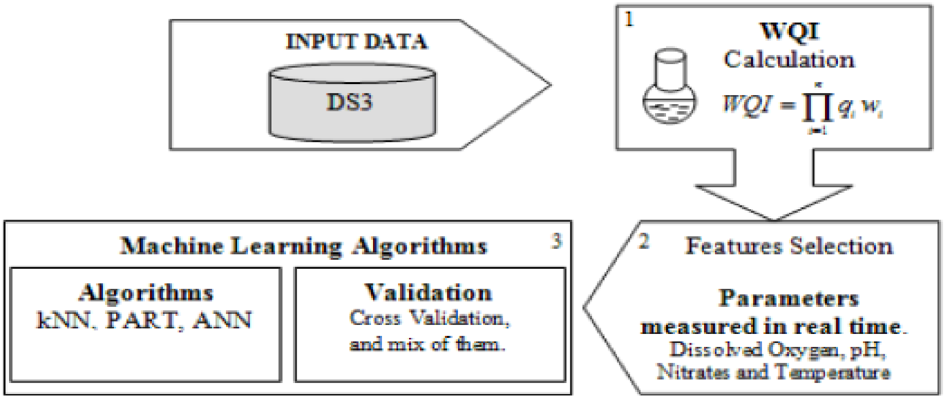


Fig.6: Framework to parameter prediction using ML (taken from Camero et al. (2013)

Chlorophyll-A

A 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 tune 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 showed faster in training speed and more accurate than Back Propagation NN.

The clorophyll-a parameter prediction and evaluation

One work forecasts the water quality parameters to determine the concentration of the parameters which include 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 was used to evaluate the model. Another work which involve the clorophyll-a parameter (together with Colored Dissolved Organic Matter (CDOM) and Total Suspended Matter (TSM)) is Ruescas et al. (2018) which proposed ML algorithms to retrieve water quality parameters from simulated remote sensing reflectance by mapping reflectances to WQ parameters. The work 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.

IoT framework for real-time water quality monitoring

One work is found to propose an IoT based solution with AI techniques to monitor water quality in real time. Shafi et al. (2018) provide 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 suggests that the deep neural network outperformed all with accuracy of 93%.

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 clorophyll-a is considered in-situ. The ML techniques can be useful to support chlorophyll-a parameter prediction in relation to the WQI for framework completion. Visual flying drone as medium to perform sampling can lower operational cost, require minimal training and can give rapid access to inaccessible and hostile environments.

5. Relevance to Government Policy (if any)

This research contributes to the improvement of water quality monitoring of water bodies (lakes) in Malaysia. Specifically, it addresses the mitigation measures under the Environmental Quality Act (1974) and more generally, the National Water Resources Policy (2012). It is also related to the SDG6 aspects in the upcoming Rancangan Malaysia ke-12, especially on integrated water resource management.

(b) References

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(c) Objective (s) of the Research

1. To study appropriate discriminators in distinguishing lake eutrophication risk levels.
2. To extract features for water parameter prediction and classification using appropriate ML techniques.
3. To ensure communication between IoT nodes and backend server in region with or without cellular coverage.
4. To evaluate and compare the performance of the proposed framework with existing solutions.

(d) Methodology:

1. Description of Methodology

In this section description of the methodology will be presented in 3 phases; the methods to ensure data transfer is intact between the IoT nodes and the backend server, the methods to perform data prediction and classification using ML techniques, and finally the methods to perform data visualization for completion of framework. Fig. 7 shows an overview of the proposed IoT framework for water quality assessment and classification.

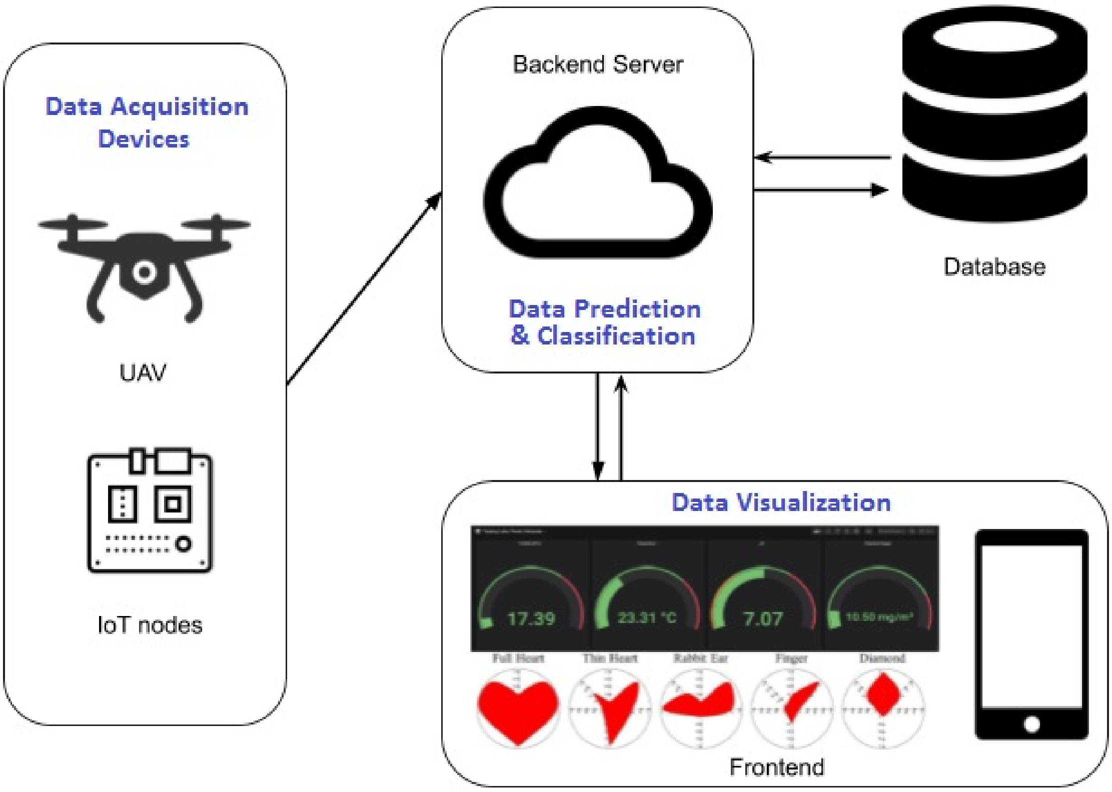


Fig. 7: Overview of the IoT framework proposed

Phase I: Methods to ensure unbroken communication for IoT framework

In this phase, 2 important processes are described, the data acquisition and the data transfer and storage. The data acquisition involves data transfer from the IoT nodes (such as the water quality sensors and sensors on the drone) to the backend server. The IoT devices are resource-constrained and therefore are not able to run any AI-based algorithm on the fly. Sampling data collected by the IoT devices must be transferred to the backend server for further processing. The processes for the active data acquisition are as follows.

Active data acquisition:
a) A visual flying drone fitted with water quality sensors will be deployed to skim over the surface of the water of a targeted water source to gather water samples for analysis.
b) To obtain good average measurement, multiple water samples will be taken from multiple locations of the water source, depending of lake size and other requirements by the sampling officers.
c) Each time the water quality probe touches water surface, raw readings of the 6 parameters (temperature, pH, DO, clorophyll-a, turbidity and EC) are recorded on an IoT logging nodes. Table 3 shows sample raw readings taken for 4 parameters (pH, temperature, turbidity and DO). Note that it is important to log reading taken time and the server recorded time to ensure

Table 3: Sample raw reading logged on IoT nodes for 4 parameters

Reading Taken Time	Server Recorded Time	pH	Temperature (°C)	Turbidity (NTU)	Dissolved Oxygen (mg/L)
02/01/2020 11:08	02/01/2020 11:08	3.36	30.13 °C	3.84 NTU	4.43 mg/L
02/01/2020 11:08	02/01/2020 11:08	3.35	30.13 °C	3.81 NTU	4.43 mg/L
02/01/2020 11:08	02/01/2020 11:08	0	9 °C	4.43 NTU	0 mg/L
02/01/2020 11:07	02/01/2020 11:07	4.36	3 °C	3.32 NTU	0 mg/L
02/01/2020 11:07	02/01/2020 11:07	0	6 °C	0 NTU	0 mg/L
02/01/2020 11:06	02/01/2020 11:06	0	0 °C	0 NTU	0 mg/L

Data transfer and storage:

Data transfer and storage becomes an important component for the proposed IoT framework. Once the raw readings are obtained by means of active data acquisition, the data must be transferred from the node devices (drone and IoT nodes) to the backend server for storage and processing. Data transfer protocols between drone and the backend server is not the same as the data transfer protocol between the IoT nodes and the backend server. The methods are described as follows:

Data transfer between drone and backend server:
a) To transfer the water quality measurements data from the drone to the backend server, the drone deployed needs to be equipped with long range wireless communication to communicate with the ground station.
b) The data will then be transferred through the wireless communication to the ground station
c) After receiving the data from the drone, the ground station will upload the data to the backend server through more robust communication method (e.g. the internet)
d) The uploaded measurement data can then be stored in a database for storage and processing.

Data transfer between IoT nodes and backend server:
a) Transfer of measurement data collected by the IoT devices depends on the coverage of available networks in the deployed region.
b) For regions with cellular coverage, cellular networks will be used to transfer the data from the nodes to the backend server.
c) While for regions with no cellular coverage, a mesh network will be deployed in the region to transfer the data from the nodes to the backend server.

d) Decentralized Cellular Transfer
-- IoT devices will be equipped with cellular communication modules such as GSM, 3G, LTE or NB-IoT modules.
-- Each IoT node will then upload the measurement data directly to the backend server using cellular networks, without relaying the data to another data station.
-- This method is suitable for deployment that uses low volume of node.

e) Centralized Cellular Transfer
-- This method employs the usage of data stations; a ground station which all the IoT nodes will be connected to and act as a router
-- The IoT devices will be equipped with medium-ranged wireless communication modules such as 2.4GHz transceivers to connect to the nearby data station.
-- While for the data station, it will be equipped with medium-ranged wireless communication modules to connect with the IoT nodes, and cellular communication modules such as GSM, 3G, LTE or NB-IoT modules for data transfer.
-- The IoT nodes will send the measured water quality data to the data station.
-- The data station will then collect all the received data and upload them to the backend server using cellular networks.
-- This method is suitable for deployment that uses a huge volume of nodes, as it will greatly reduce the cost and network load in the region.

f) Mesh Network Transfer
-- This method also employs the usage of data stations; ground stations that act as a router for the nodes to relay the data to the backend server
-- IoT devices will be equipped with medium-ranged wireless communication module such as 2.4GHz transceivers
-- The IoT devices will be configured to form a mesh network; each of the node will act as message router to route data to the data station, which are located at a region where connectivity to the Internet is available
-- The data station will be equipped with 2.4GHz transceivers to receive the data from the IoT devices, and equipped with robust connection to connect to the backend server.
-- Data from the IoT nodes will be routed through the mesh network to the data station
-- The data station will then upload the received data to the backend server.
-- This method is suitable for deployment in regions where there is no cellular coverage to transfer the data to the backend server

After the data had been received from the data acquisition devices, it will then be stored into a database for further processing and analysis.

Phase II: Data prediction and classification using ML techniques

With the development of industry and becoming of urbanization, water resources such as lakes are becoming seriously polluted. In the process of lake quality monitoring and eutrophication controlling, the accuracy of water quality evaluation is crucial. Water quality has been conventionally estimated through expensive and time-consuming lab and statistical analyses, and an alternative method, real-time and in-situ will boost lake conservation management in this country. To perform in-situ sampling for lake eutrophication, the ML techniques is proposed in this work to estimate the water quality class (WQS), which is a distinctive class defined on the basis of the water quality index (WQI), the singular index which describe general water quality.

Data collection for network training:

In the early stages, data from online repository will be searched for the purpose of network training. It is predicted that the online repository will not have data from local studies. For completion of data collection, data taken at local lakes in recent years will be retrieved with the cooperation by co-researchers of this team. These data will act as ground truth for the network training. Fig. 8 shows the methodology flow required to achieve WQC for eutrophication risk levels.

<IMAGE691194 WIDTH=900 HEIGHT=752>

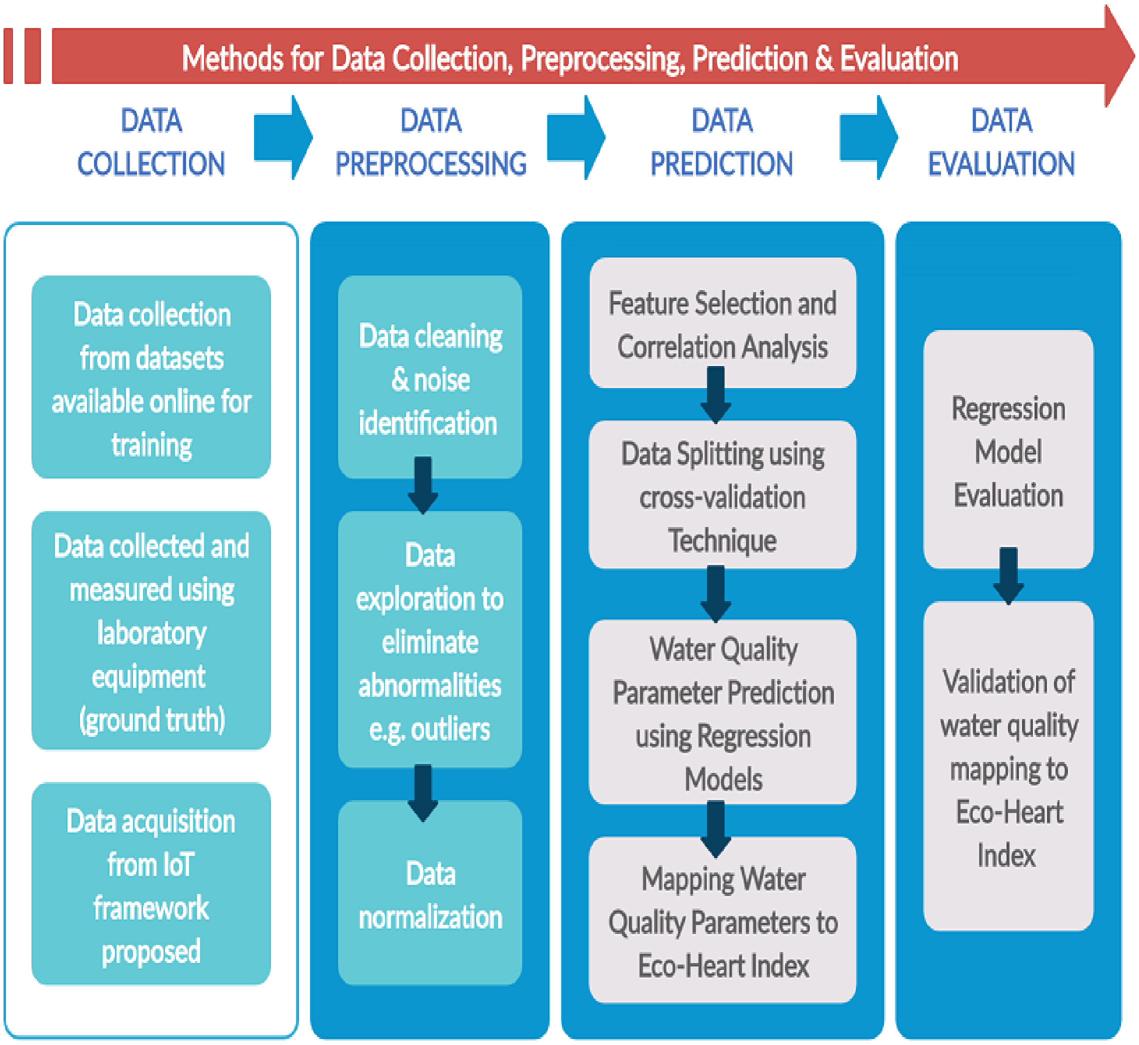


Fig. 8: Methods for data collection, processing, prediction and evaluation

Data Preprocessing:

Real world data are noisy and highly imbalanced which makes prediction difficult. To clean the raw water data, the boxplot analysis is a common standardized way of displaying the distribution of data based on a five number summary ("minimum", first quartile (Q1), median, third quartile (Q3), and "maximum"). It can describe outliers and what their values are. For example, the boxplots can show the mean, range and standard deviation of water quality parameters at numerous sampling sites over sampling seasons and can depict the seasonal variation existing in their concentrations. In tropical countries, it is common to define sampling over pre-monsoon and monsoon seasons.

The boxplot is also useful for outlier detection as most of the water parameters are diversed enough and can be on the higher end of the values. The boxplot can provide intuitive visualization to support outlier detection threshold values depending upon the problem domain. For example, if the boxplot computed that most parameters lied outside the box, deeming outliers normal, an upper cap/ceiling strategy can be utilize to filter out outliers. Consequently, parameter values that were very different from other values can be replaced with the max threshold value for example, for normalization. The goal is to remove outliers without risking data loss and to not introduce bias to the dataset.

For normalization, the z-score is a conventional standardization and normalization method that represents the number of standard deviations; a raw data point is above or below the population mean. It ideally lies between -3 and +3. It normalizes the dataset to the aforementioned scale to convert all the data with varying scales to the default scale. To normalize the data using the z-score, the mean of the population from a raw data point can be subtracted and divided by the standard deviation, which gives a score ideally varying between -3 and +3. Therefore, reflecting how many standard deviations a point is above or below the mean as computed by following equation where x represents the value of a particular sample, μ represents the mean and σ represents the standard deviation (Jayalakshmi & Santhakumaran, 2011).

$$z\_score = ((x-\mu))/\sigma$$

Data Analysis:

To perform data analysis, this work proposed several ML algorithms to predict the WQI and WQC using minimal number of parameters. In preparation for computation with a ML algorithm, the data must first go through the correlation analysis and data splitting. Briefly, the correlation analysis focuses on extracting possible relationships between the 6 parameters. The Pearson correlation method is a popular approach to find the dependent variables and to predict hard-to-estimate variables through easily attainable parameters. The Pearson's correlation coefficient can be applied on the normalized raw values of the 6 parameters used in the proposed framework to measure the statistical relationship, or association, between two continuous variables. Some correlation studies between water quality parameters are reported as follows:

a) Redox is positively correlated with pH while Chlorine dioxide is negatively correlated with temperature (Muharemi et al., 2019).
b) Color in water may result from the presence of natural metallic ions (iron and manganese), humus and peat materials, plankton, weeds, and industrial wastes (Singh, 2017).
c) EC is highly correlated with total dissolved solids, chlorides and fecal coliform count, and loosely correlated with calcium and temperature.

It is important that this work look into correlation possibilities between the 6 parameters proposed and determine distinguish discriminator which determine risk level of lake eutrophication. A correlation analysis chart specifically for lake eutrophication using 6 water quality parameters will be contributed as an outcome if this study.

Data splitting is done prior to computing data using ML model. The goal of data splitting is to check parts of the data and compute the accuracy measures to establish model's performance. One common approach to data splitting is the use of the k-fold cross validation, which splits the data into k subsets and iterates over all the subsets. This technique considers the k-1 subsets as the training dataset and 1 subset as the testing dataset. An efficient split is usually computationally expensive, but it has been considered that text-based water quality datasets are rarely huge thus suitable to employ the k-fold cross validation.

The ML algorithms for data prediction and classification

Following successful retrieval of cloropyll-a in Ruecas et al. (2018) and Khan & See (2016), the linear and non-linear regression methods of ML will be investigated in this work. The regression methods can be used to estimate the WQI and the classification algorithms can be used to classify samples into the pre-defined WQC. The following algorithms are among those to be considered in our study:

a) Regularized linear

b) Random forest
Random forest is a model that uses multiple base models on subsets of the given data and makes decisions based on all the models. In random forest, the base model is a decision tree, carrying benefits of a decision tree with efficiency of using multiple models.

c) Kernel ridge
The Ridge regression works on the same principles as linear regression, in which it just adds a certain bias to negate the effect of large variances and to void the requirement of unbiased estimators. It penalizes the coefficients that are far from zero and minimizes the sum of squared residuals

d) Gaussian process
Naive Bayes is a simple and a fast algorithm that works on the principle of Bayes theorem with the assumption that the probability of the presence of one feature is unrelated to the probability of the presence of the other feature

e) Support vector machine
Support vector machines (SVMs) are mostly used for classification but they can be used for regression as well. Visualizing data points plotted on a plane, SVMs define a hyperplane between the classes and extend the margin in order to maximize the distinction between two classes, which results in fewer close miscalculations.

f) k Nearest Neighbor
The K nearest neighbor algorithm classifies by finding the given points nearest n neighbors and assigns the class of majority of n neighbors to it. In the case of a draw, one could employ different techniques to resolve it, e.g., increase n or add bias towards one class. However, the k nearest neighbor will not be considered if this study requires processing large datasets as the iterations considers whole training data and computes nearest neighbors each time.

For evaluation and model validation this work will look into the following techniques:

a) Mean absolute error (MAE)
The MAE is a measure of accuracy for regression. It sums up absolute values of errors and divides them by the total number of values. It gives equal weight to each error value. The formula for calculating MAE is shown as follows where x_obs refers to the actual value, x_pred refers to the predicted value, and n refers to the total number of samples considered.

MAE = (∑(||x_obs- x_pred ||))/n

b) Mean Square Error (MSE)
The MSE is the sum of squares of errors divided by the total number of predicted values. This attributes greater weight to larger errors. This is particularly useful in problems where there needs to be a larger weight for larger errors. It is measured by following equation where x_obs is the actual value, x_pred is the predicted value, and n is the total number of samples considered

MSE = (∑(x_obs- x_pred)^2)/n

c) Root Mean Squared Error (RMSE)
The RMSE is just the square root of MSE and scales the values of MSE near to the ranges of observed values. It is estimated from its equation (see follows) that the x_{obs} points to the actual value, x_{pred} points to the predicted value, and n points to the total number of samples considered

$$RMSE = \sqrt{(\Sigma (x_{obs}-x_{pred})^2)/n}$$

Phase 3: Data Visualization
Once the model has been evaluated and a WQC is decided for the sampling data, the data is prepared for display. The following steps shows the processes to publish visualization online for end-user perusal

a) The stored data will be displayed by the backend server
b) Numerical data will be scaled according to the type of the measurement the data represents (e.g.: water pH will be scaled to fit between 0 and 14)
c) The scaled data will then be sent to the frontend through HTTP request or real time communication protocols such as WebSocket and TCPSocket.
d) The frontend will then display the received data by using simple charts such as meter bar
e) The frontend will also render an intuitive heart-shaped radar chart following recommendation by Sakai et al., (2018) towards an Eco-Heart Index as a tool for community-based water quality monitoring and assessment (see Fig. 9).

Fig. 9: Meter bar and the Eco-Heart index for intuitive data visualization

In summary, the methodology adopts the SMART approach as seen in Fig. 10. For completion, the mapping of the research questions (RQs), research objectives (ROs), the methodology and the research outcome is presented in Table 4.

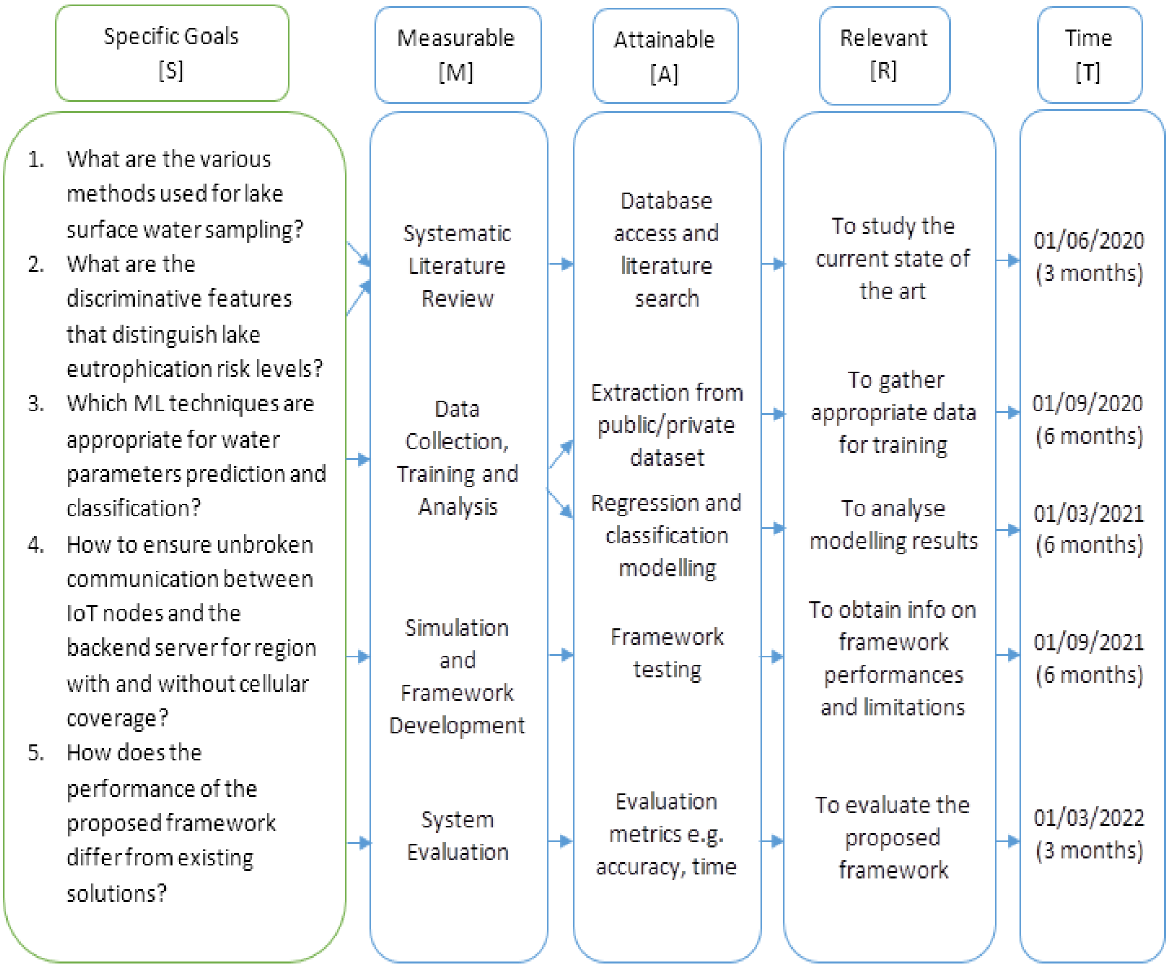

Specific Goals [S]
Measurable [M]
Attainable [A]
Relevant [R]
Time [T]
1. What are the various methods used for lake surface water sampling?
2. What are the discriminative features that distinguish lake eutrophication risk levels?
3. Which ML techniques are appropriate for water parameters prediction and classification?
4. How to ensure unbroken communication between IoT nodes and the backend server for region with and without cellular coverage?
5. How does the performance of the proposed framework differ from existing solutions?
Systematic Literature Review
Data Collection, Training and Analysis
Simulation and Framework Development
System Evaluation
Database access and literature search
Extraction from public/private dataset
Regression and classification modelling
Framework testing
Evaluation metrics e.g. accuracy, time
To study the current state of the art
To gather appropriate data for training
To analyse modelling results
To obtain info on framework performances and limitations
To evaluate the proposed framework
01/06/2020 (3 months)
01/09/2020 (6 months)
01/03/2021 (6 months)
01/09/2021 (6 months)
01/03/2022 (3 months)

Table 4: Mapping of RQ, RQ, Methodology and Outcome

Research Questions	Research Objectives	Methodology	Outcome
What are the various methods used for lake water sampling? What are the discriminative features that distinguish lake eutrophication risk levels?	To study appropriate discriminators in distinguishing lake eutrophication risk levels.	a) Literature search b) Systematic literature review	a) Findings on the performance of existing approaches b) Novel features to distinguish lake eutrophication risk levels
Which ML techniques are appropriate for water parameters prediction and classification?	To extract features for water parameter prediction and classification using appropriate ML techniques.	a) Data collection b) Data training c) Regression and classification modelling d) Test	a) Correlation analysis chart for lake eutrophication using 6 water parameters b) An algorithm for optimized prediction and classification of eutrophication water parameters
How to ensure unbroken communication between IoT nodes and the backend server for region with and without cellular coverage?	To ensure communication between IoT nodes and backend server in region with or without cellular coverage.	a) Testing solution b) Validating and fine-tuning c) Proof-of-concept	a) A dynamic IoT framework for real-time water parameter prediction and classification
How to ensure unbroken communication between IoT nodes and the backend server for region with and without cellular coverage?	To ensure communication between IoT nodes and backend server in region with or without cellular coverage.	a) Testing solution b) Validating and fine-tuning c) Proof-of-concept	a) A dynamic IoT framework for real-time water parameter prediction and classification
How does the performance of the proposed framework differ from existing solutions?	To evaluate and compare the performance of the proposed framework with existing solutions.	a) Comparative evaluation	a) Results of performance comparison with existing solutions

2. Flow Chart of Research Activities	flowchart.pdf

3. Research Activities

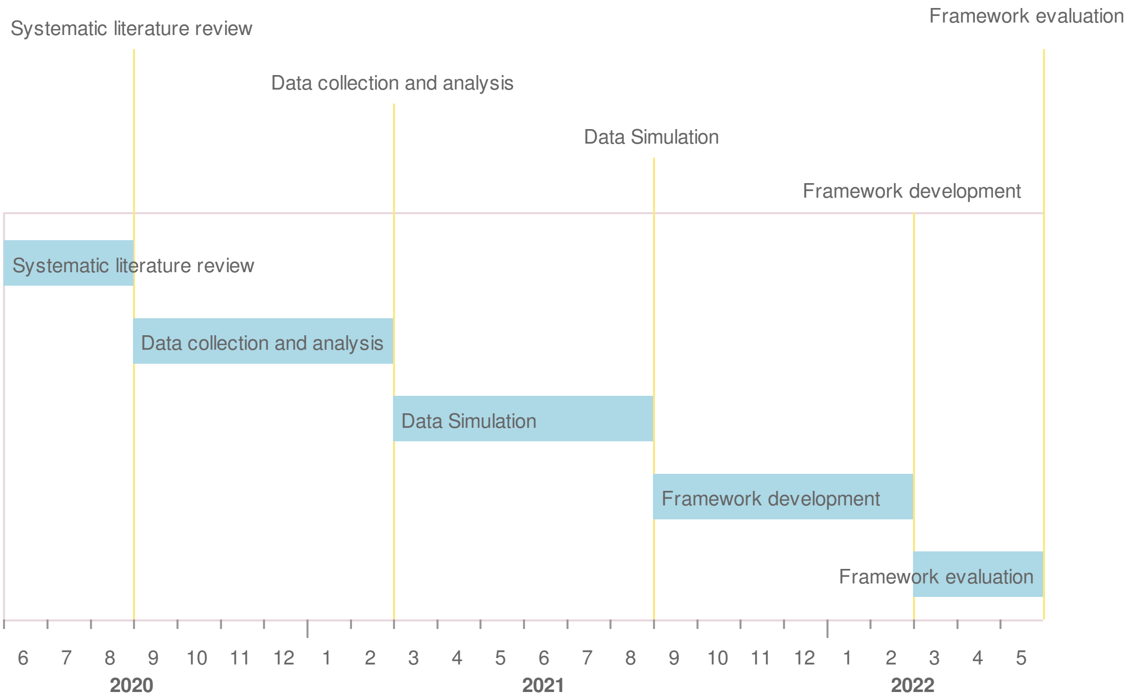
Activity	Start Date	End Date
Systematic literature review	01/06/2020	31/08/2020
Data collection and analysis	01/09/2020	28/02/2021
Data Simulation	01/03/2021	31/08/2021
Framework development	01/09/2021	28/02/2022
Framework evaluation	01/03/2022	31/05/2022

4. Milestones and Dates

Description	Date	Cumulative Project Completion Percentage(%)
Systematic literature review	31/08/2020	10

Data collection and analysis	28/02/2021	40
Data Simulation	31/08/2021	70
Framework development	28/02/2022	90
Framework evaluation	31/05/2022	100

Gantt Chart of Research Activities with Milestones



(e) Expected Results/Benefit

1. Novel theories/New findings/Knowledge

An algorithm for optimized prediction and classification of eutrophication water parameters

2. Impact Statement on Society, Economy and Nation (delineate/describe expected research deliverables)

The world's freshwater resources contribute to every activity that is essential to human health and well-being, ranging from agriculture to cleaning, drinking, and industrial manufacturing. This precious resources must be protected and conserved for current and future generations. Conventional water quality monitoring system involves collection of water at various locations within a lake or river and transporting the samples to a field station or laboratory for analytical testing. Such approaches are laborious and not cost effective, may delay detection of contaminants and considered not efficient due to the unavailability of real time water quality information. In recent years, as the technology for water quality management becomes more sophisticated, the water sector has seen a proliferation of solutions that uses digital technology such as sensors, data analytics software and remote-controlled devices to improve how water is properly managed. Distributed wireless sensor networks are being utilized to collect data over a larger area and send the data to a centralized data storage server using wireless communication technology. Dynamic IoT framework, the main output of this research is an experiment towards this direction by improving the efficiency of our water quality monitoring systems through the provision of real time data, which will enable faster responses for mitigation measures.

3. Research Publications

2 ISI journals

Total Number of Publications: 2

4. Specific or Potential Applications

A dynamic IoT framework for real-time water parameter prediction and classification

Total Number of Applications: 1

5. Number of PhD and Masters (by research) Students

Number of PhD Students:

0

Number of Masters (by research) Students:

1

Remark (if any):

6. Intellectual Property(IP)

An algorithm for optimized prediction and classification of eutrophication water parameters

Total Number of IP: 1

D. Access to Equipment & Material

E. Budget

Budget Type	Description	Year 1	Year 2	Grand Total	-
11000 - Salary and Wages	1 MSc GRA RM2,200 x 24months =RM52,800	26400	26400	**52800**	
Vot-Total		**26400**	**26400**	**52800**	
21000 - Travelling and Transportation **Local**				**0**	
Sub-Total		0	0	0	
Overseas				**0**	
Sub-Total		0	0	0	
Field work	Field work for testing		1500	**1500**	
Sub-Total		0	1500	1500	
Vot-Total		**0**	**1500**	**1500**	
24000 - Rental				**0**	
Vot-Total		**0**	**0**	**0**	
27000 - Research Materials and Supplies	Multi-parameter water quality sensor (without casing or IOT-enabled solution)	76039		**76039**	
	Casing for multi-parameter sensor with water proofing material	3000		**3000**	
	Battery RM600 x 6 unit = RM3,600	3600		**3600**	
	Daylight capture unit 1080p 60fps RM3,000 x 1 unit = RM3,000	3000		**3000**	
	Electronic support unit RM2,000 x 1 unit = RM2,000	2000		**2000**	
Vot-Total		**87639**	**0**	**87639**	
28000 - Maintenance and Minor Repair Services	Aerial and attachment maintenance		4000	**4000**	
	Multi-parameter sampling chemical solution for sensor calibration maintenance		4000	**4000**	
Vot-Total		**0**	**8000**	**8000**	
29000 - Professional Services **Services/Consultancy**	Journal page charges x 2 ISI journal	3600	3600	**7200**	
Sub-Total		3600	3600	7200	
Short term course				**0**	
Sub-Total		0	0	0	
Vot-Total		**3600**	**3600**	**7200**	
35000 - Accessories and Equipment				**0**	
Vot-Total		**0**	**0**	**0**	
50000 - Goods and Services Tax (GST)		117639	39500	**157139**	
Vot-Total		**117639**	**39500**	**157139**	

Grand Total	**117639**	**39500**	**(100.00%) 157139**	
Grand Total With GST	**117639**	**39500**	**157139**	

F(i). Patent Search (describe how your research output shall produce an innovation idea or technology that has the potential to be a solution to future stakeholders (community, industry, government etc.) and offer a unique proposition not found in potential competitors)

To identify if the researcher is able to coherently present a compelling argument for their proposal in light of the IP landscape and factors identified in the (Yes/No) Section. The answer would reflect an understanding of their research advantage and limitations and the prospect of moving the completed research beyond this stage of funding.

I have identified 4 keywords appropriate for patent search: Drone Water Quality Water Collection Water Sampling On their own, each patent search through Lens.org with jurisdiction Malaysia, Indonesia, Singapore and Thailand gives the following results: Drone: 26 patents Water Quality: 156 patents Water Sampling: 69 patents Water Collection: 285 patents However, when combine “drone” AND “any of the other keywords”, under the same jurisdictions return 0 results

Patent search results.pdf

F(ii). Research Collaborator

☑ International/Industrial Linkages (Please identify any industry or end-user group involved in the project, and describe its role/contribution to the project)

My Conceptual Robotics Sdn Bhd will support in 3D printing and sensor chip/microcontroller design and development for the IoT nodes and devices

☑ Agency/Organisation (Please identify all agencies/organisations collaborating in the project, and describe their role/contribution to the project)

Kementerian Air, Tanah dan Sumber Asli will provide method and expertise on eutrophication issues for inland water bodies in Malaysia in the early stages and involve in proof of concept and testing in later stages.

F(iii). Risk Assessment (Please describe factors that may cause delays in, or prevent implementation of, the project as proposed above; estimate the degree of risk)

Risk in delay depending on how much field work is involved during the testing phase. Due to budget constraint, a ready-made IOT-enabled water quality device (see Appendix C, RM145k++) will not be available to this research. In substitute, the team will develop our own.

Risk	Low	Medium	High
1. Technical	☑	☐	☐
2. Timing	☐	☑	☐
3. Budget	☐	☑	☐

G. Declaration

☑ 1. All information stated here are accurate, KPM and IPT has right to reject or to cancel the offer without prior notice if there is any inaccurate information given.

☑ 2. Application of this research is presented for the Fundamental Research Grant Scheme (FRGS).

☑ 3. Application of this research is also presented for the other research grant/s (grant's name and total amount)

Grant Name	Grant Source	Grant Amount(RM)
IIRG	Univerity Malaya	92367

☐ 4. Application of this research is subject to Ethical Committee approval.

☐ 5. Project Leader have ongoing Fundamental Research Grant Scheme (FRGS) project.

Name: Zati Hakim Binti Azizul Hasan

Signature:

Date: 24/02/2020

Approved By:

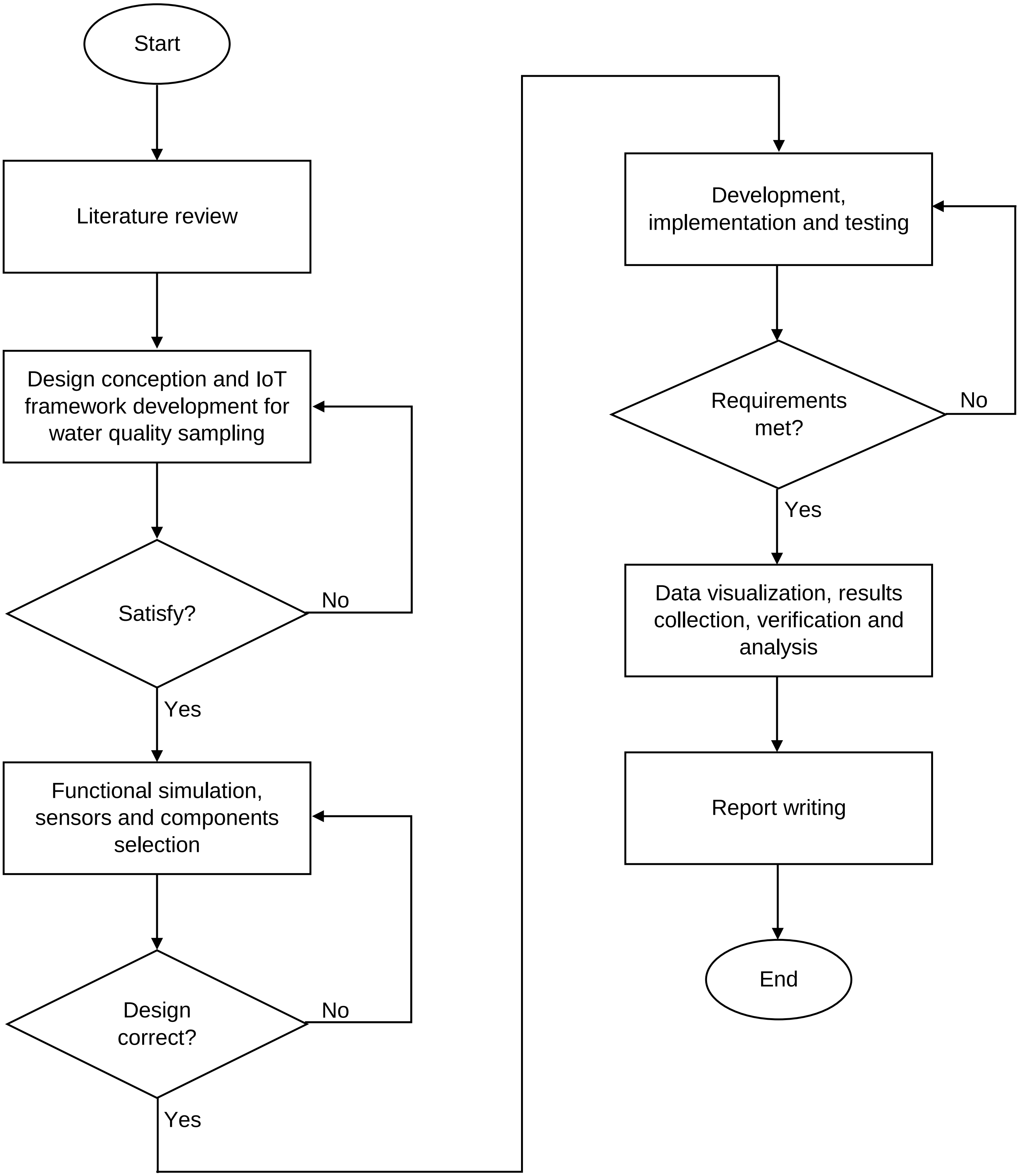
Signature:

RMC
Date:

Appendix	
Flow Chart	flowchart.pdf

Appendix	Name	File Name
A	Quotation Drone	VQT-00382 - UNIVERSITI MALAYA.pdf
B	Quotation Multi Parameter Sensor	QV20039317 (UM DSS).pdf
C	Quotation Commercial Sonde with IOT enabled	QV20039315 (UM Sonde EXO).pdf

Appendix B: Flow Chart



VISIONCRAFT INDUSTRIES SDN BHD (126900-X)
Poladrone-L1-Futurise Centre,
Persiaran Apec, Cyber 8,
63000 Cyberjaya, Selangor, Malaysia

QUOTATION : VQT-00382

Universiti Malaya
Department of Artificial Intelligence,
Faculty of Computer Science and Information Technology,
University of Malaysia 50603 Kuala Lumpur, Malaysia.

Attn : Zati Hakim Azizul Hasan, PhD
TEL : FAX :

Your Ref.	:
Our Ref.	:
Vendor Code	: 1000036268
C. C.	:
Date	: 26/2/2019
Page	: 1 of 1

Thank you for your inquiry. We are pleased to submit our quote as follows:

Item	Item Code	Description	Qty	Unit Price	Disc	Amount
1	DJI-M600.00001	MATRICE 600 Pro - 1 x Matrice 600 Pro (Aircraft Body) - 2 x Landing Gear - 2 x Landing Skid - 2 x Spring - 1 x Remote Controller - 6 x TB47S Intelligent Flight Battery - 1 x Hex Battery Charging Hub - 1 x Inner Foam Case - 1 x Power Cable - 2 x RC Charging Cable - 1 x Micro USB Cable - 6 x Red Knob (With Casket) - Tape, Stickers, Spare Screws	1.00 UNIT	18,000.00		18,000.00
2	DJI-M600.00010	MATRICE 600-PART01-ZENMUSE X3/X5 Gimbal Mounting Bracket	1.00 UNIT	800.00		800.00
3	DJI-Z001.00011	Zenmuse Z3	1.00 UNIT	3,500.00		3,500.00
4	DJI-M600.00002	MATRICE 600 Intelligent Flight Battery TB47S (6 PCS)	1.00 BOX	3,900.00		3,900.00

Validity : 14 Days
Delivery Term : Ex-Stock
Payment Term : PREPAYMENT

Total (RM)	**26,200.00**

Note:
1. Prices are subjected to change without prior notice.
2. Payment to be remitted via bank transfer to Visioncraft Industries Sdn Bhd. **Maybank: A/C No.: 012147209685**
3. One (1) year local and international manufacturer warranty included for aircraft, Six (6) months for batteries.
4. By agreeing to purchase and operate a DJI product, the client will be deemed to have read and agreed to the DJI UAS Terms of Use as listed at: www.dji.com/terms
5. Non-refundable deposit unless agreed upon by both parties.

We hope that our quotation is favourable to you and looking forward to receive your valued orders in due course.

Thank you.

We confirm the order by accepting the terms & conditions stated above.

This is a Computer Generated Document.
No Signature is Required.

Person incharge : *chop & sign*
Date :

ARACHEM (M) SDN BHD (127181-D)
GST NO: 001727176704
11, Persiaran Industri, Taman Perindustrian Sri Damansara,
Bandar Sri Damansara, 52200 Kuala Lumpur, Malaysia.
Tel: +603-6276 2323 Fax: +603-6273 3555
Email: marketing@arachem.com.my
Website : www.arachem.com.my

Quotation

To: UNIVERSITI MALAYA
Lembah Pantai
50603 Kuala Lumpur
Wilayah Persekutuan
Attn : Dr Zati Hakim abdul Hassan
Phone : +60-3-7967 7022/3273 Fax : +60-3-7956 0027
Email : zati@um.edu.my

Date : 27-Feb-2019
Quotation No : QV20039317
Quoted By : Azrin Farha
Sales Person : Azrin Farha (+6019 - 3551915)
Quotation Currency : MYR

We thank you for your recent enquiry and are pleased to quote you as follows:
Re : Quotation on YSI Multiparameter Grab In-situ Testing

No.	Item Code & Description	Qty	Unit Price	Total
1.0	**PRODSS-2 PH/DO/CONDUCTIVITY METER WITH 10M CABLE WITH GPS WITH DEPTH**			
1.1	**PRODSS-2 - 626870-2 Pro DSS Handheld Multiparameter Instrument with GPS** ProDSS Meter provide extreme flexibility for the measurement of a variety of combinations for parameters selected Specification: Barometer: Built in Data Management: KorDSS desktop PC software (included) Data Memory: >100,000 data sets; 400 GLP files Dimensions: 8.3 x 21.6 x 5.6 cm (WxLxD) Warranty: 3 year instrument, 2 year bulkhead	1	11,579.00	11,579.00
1.2	**3075 - 603075 Carry Case, Soft Sided**	1	722.00	722.00
1.3	**6900 - 626900 ProDSS ODO Optical Dissolved Oxygen Smart Sensor** Specification: Range: 0 to 50 mg/L Accuracy: 0-20 mg/L (+/- 0.1 mg/L) 20-50 mg/L (+/- 8% of reading) Resolution: 0.1 or 0.01 mg/L Max operation depth: 100m Warranty: 2 years DO sensor, 1 year DO sensor cap	1	6,002.00	6,002.00
1.4	**6902 - 626902 ProDSS Conductivity/Temp Smart Sensor** Specification:	1	4,200.00	4,200.00

	Conductivity Range: 0 to 200 ms/cm Max operational Depth: 100m Warranty: 2 years			
1.5	**6903 - 626903 ProDSS pH Smart Sensor with Module** Specification: Range: 0 to 14 units Max operational Depth: 100m Warranty: 2 years for ph sensor, 1 year for ph module	1	2,707.00	2,707.00
1.6	**3821-1 - YSI pH 4 Buffer, 1 pint/475 ml**	1	78.00	78.00
1.7	**3822-1 - YSI pH 7 Buffer, 1 pint/475 ml**	1	78.00	78.00
1.8	**3823-1 - YSI pH10 Buffer, 1 pint/475ml**	1	78.00	78.00
1.9	**3167-1 - Conductivity Std., 1 mS/cm, 475ml**	1	89.00	89.00
1.10	**6910-10 - 626910-10 DSS-10 Meter, 4 Port Cable Assembly, With Depth** Depth Specification: Type: Pressure Tranducer Range: 0 to 100m Resolution: 0.001m	1	15,474.00	15,474.00
1.11	**6210 - 626210 ProDSS Total Algae-Phycocyanin (TAL-PC) Sensor** TAL-PC sensors detect chlorophyll and phycocyanin and are ideal for monitoring freshwater cyanobacteria.	1	17,516.00	17,516.00
1.12	**6211 - 626211 ProDSS Total Algae-Phycoerythrin (TAL-PE) Sensor** TAL-PC sensors detect chlorophyll and phycoerythrin and are ideal for monitoring marine cyanobacteria.	1	17,516.00	17,516.00
		Grand Total		**76,039.00**

Price : Nett-delivered
Delivery : 4 - 6 weeks upon confirmation of order
Terms : 30 DAYS
Validity : 2 Weeks

Regards,

Azrin Farha

+6019 - 3551915

NOTE : PLEASE INDICATE OUR QUOTATION REFERENCE NUMBER IN ALL PURCHASE ORDER.

ARACHEM (M) SDN BHD (127181-D)
GST NO: 001727176704
11, Persiaran Industri, Taman Perindustrian Sri Damansara,
Bandar Sri Damansara, 52200 Kuala Lumpur, Malaysia.
Tel: +603-6276 2323 Fax: +603-6273 3555
Email: marketing@arachem.com.my
Website : www.arachem.com.my

IRRECOVERABLE TERMS AND CONDITIONS OF SUPPLY:-

1. GOODS RETURNED OR EXCHANGED

All goods sold are not returnable, unless WRITTEN APPROVAL is obtained from Arachem.
Goods returned or exchanged are subject to restocking fees as follow:
Common item : restocking fee - 30% of total ordered amount
Non-common item: restocking fee - 50% of total ordered amount

2. CANCELLATION OF CONFIRMED ORDER

30% of the total ordered value will be charged for order cancelled.

3. SPECIAL DELIVERY ARRANGEMENT

Freight charges and incidental costs to speed up the delivery process will be imposed.

4. MINIMUM ORDER CHARGES

Order less than RM 500 are subject to handling charge of
RM 15 - West Malaysia
RM 20 - East Malaysia (apply to non-dangerous goods)

5. DANGEROUS GOODS (DG) – DELIVERY TO EAST MALAYSIA

Customers are encouraged to arrange for own collection. Otherwise, a minimum DG surcharge of RM 500 shall be imposed.

ARACHEM (M) SDN BHD (127181-D)
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11, Persiaran Industri, Taman Perindustrian Sri Damansara,
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Tel: +603-6276 2323 Fax: +603-6273 3555
Email: marketing@arachem.com.my
Website : www.arachem.com.my

Quotation

To: UNIVERSITI MALAYA
Lembah Pantai
50603 Kuala Lumpur
Wilayah Persekutuan
Attn : Dr Zati Hakim abdul Hassan
Phone : +60-3-7967 7022/3273 Fax : +60-3-7956 0027
Email : zati@um.edu.my

Date : 27-Feb-2019
Quotation No : QV20039315
Quoted By : Azrin Farha
Sales Person : Azrin Farha (+6019 - 3551915)
Quotation Currency : MYR

We thank you for your recent enquiry and are pleased to quote you as follows:
Re : Quotation on YSI Multiparameter Online System (Real time Data Installation OR Grab Sample Meter)

No.	Item Code & Description	Qty	Unit Price	Total
1.0	**Real Time Datalogging Sensor System**			
1.1	**599503-01 - EXO3 Sonde, 10 m Depth, 4 Sensor Ports, 1 Wiper Port** Offering the greatest value of any sonde available in the market, EXO3 combines the maneuverability of EXO1 with the powerful antifouling wiper of the EXO2. EXO3 is a purpose-built sonde for monitoring major water quality parameters, including: pH, conductivity, temperature, turbidity, dissolved oxygen and etc. **<u>General Specification</u>** Connectivity / Communications: Sonde: Bluetooth wireless technology, USB, RS-485, and integral SDI-12 Output Options with Adapters: USB, RS-232, or Modbus Depth Rating: 0 to 10m Desktop Software Compatible: KorEXO Flow Cell: Yes Medium: Fresh, sea or polluted waterMemory: 512 MB total memory; >1,000,000 logged readings Monitoring: Yes Multiparameter: Yes Operating Temperature: -5 to 50 °C (23 to 122 °F) Power: 2 Alkaline Batteries (D-Cell) Sampling: Yes Size: Diameter: 7.62 cm (3.00 in) Length: 58.67 cm (23.1 inc) Smart Sensors / Ports: 5 sensor ports (4 ports available when central wiper in use) Peripheral ports: 1 power communication port Storage Temperature: -20 to 80 °C (-4 to 176 °F). Exception: 0 to 60 °C (32 to 140 °F) for pH and pH/ORP sensors	1	30,032.00	30,032.00

ARACHEM (M) SDN BHD (127181-D)
GST NO: 001727176704
11, Persiaran Industri, Taman Perindustrian Sri Damansara,
Bandar Sri Damansara, 52200 Kuala Lumpur, Malaysia.
Tel: +603-6276 2323 Fax: +603-6273 3555
Email: marketing@arachem.com.my
Website : www.arachem.com.my

	User Calibratable: Yes Waterproof: Yes Weight: 2.00 kg (4.41 lbs) with a full payload of 4 probes, 1 wiper, and probe guard installed			
1.2	**599090-01 - EXO Central Wiper, EXO2 , TI**	1	8,758.00	8,758.00
1.3	**599101-01 - EXO Turbidity Sensor, TI** Range: 0-4000 FNU or NTU Accuracy: 0-999 FNU: +/- 2%; NTU: +/- 5% Resolution: 0.01 FNU (LR), 0.1 FNU (HR)	1	13,263.00	13,263.00
1.4	**599702 - EXO pH Sensor Assembly, Unguarded, Ti** For Use With YSI EXO 2 Range: 0-14 units Accuracy: +/- 0.1 ph Resolution: 0.01 units	1	4,137.00	4,137.00
1.5	**599100-01 - EXO Optical DO sensor, TI** Range: 0-50 mg/L Accuracy: 0 – 20 mg/L: +/- 1%, 20 – 50 mg/L: +/- 5% Resolution: 0.01 mg/L	1	14,421.00	14,421.00
1.6	**599102-01 - EXO Total Algae - PC Sensor, TI** Optimized for freshwater use - Phycocyanin Blue Green Algae: Range: 0 to 100 ug/L PC; 0 to 100 RFU Resolution: 0.01 ug/L PC: 0.01 RFU Chlorophyll: Range: 0 to 400 ug/L Chl; 0 to 100 RFU Resolution: 0.01 ug/L Chl; 0.01 RFU	1	24,947.00	24,947.00
1.7	**599103-01 - EXO Total Algae - PE Sensor, Ti** Optimized for Saltwater use - Phycoerythrin Blue Green Algae: Range: 0 to 100 ug/L PC; 0 to 100 RFU Resolution: 0.01 ug/L PC: 0.01 RFU	1	24,947.00	24,947.00

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	Chlorophyll: Range: 0 to 400 ug/L Chl; 0 to 100 RFU Resolution: 0.01 ug/L Chl; 0.01 RFU			
1.8	**599827 - EXO Wiped Conductivity/Temperature Sensor** Range: 0 – 100 mS/cm Accuracy: ±1% of the reading or 0.002 mS/cm, whichever is greater Resolution: 0.0001 to 0.01 mS/cm (range dependent) **Temperature** Range: -5 to 50 °C Accuracy: ±0.2°C Resolution: 0.001 °C **Saliniy (Calculated from Cond & Temp)** Range: 0-70 ppt Accuracy: ±2% of the reading or 0.2 ppt, whichever is greater Resolution: 0.01 ppt **TDS (Calculated from Cond & Temp)** Range: 0-100,000 g/L Resolution: Variable	1	10,737.00	10,737.00
1.9	**599040-10 - EXO 10m Field Cable**	1	4,389.00	4,389.00
1.10	**599008-10 - EXO 10 meter Flying Lead Cable**	1	3,411.00	3,411.00
1.11	**577400 - YSI EXO GO Wireless Bluetooth Communication Device**	1	6,526.00	6,526.00
			Grand Total	**145,568.00**

Price : Nett-delivered
Delivery : 4 - 6 weeks upon confirmation of order
Terms : 30 DAYS
Validity : 2 Weeks

Regards,

ARACHEM (M) SDN BHD (127181-D)
GST NO: 001727176704
11, Persiaran Industri, Taman Perindustrian Sri Damansara,
Bandar Sri Damansara, 52200 Kuala Lumpur, Malaysia.
Tel: +603-6276 2323 Fax: +603-6273 3555
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Website : www.arachem.com.my

Dedicated to 1990-2015 Cutting-edge Technologies & Innovative Solutions

Azrin Farha

+6019 - 3551915

NOTE : PLEASE INDICATE OUR QUOTATION REFERENCE NUMBER IN ALL PURCHASE ORDER.

ARACHEM (M) SDN BHD (127181-D)
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Goods returned or exchanged are subject to restocking fees as follow:
Common item : restocking fee - 30% of total ordered amount
Non-common item: restocking fee - 50% of total ordered amount

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30% of the total ordered value will be charged for order cancelled.

3. SPECIAL DELIVERY ARRANGEMENT

Freight charges and incidental costs to speed up the delivery process will be imposed.

4. MINIMUM ORDER CHARGES

Order less than RM 500 are subject to handling charge of
RM 15 - West Malaysia
RM 20 - East Malaysia (apply to non-dangerous goods)

5. DANGEROUS GOODS (DG) – DELIVERY TO EAST MALAYSIA

Customers are encouraged to arrange for own collection. Otherwise, a minimum DG surcharge of RM 500 shall be imposed.

I have identified keywords appropriate to my proposal:

Drone

Water Quality

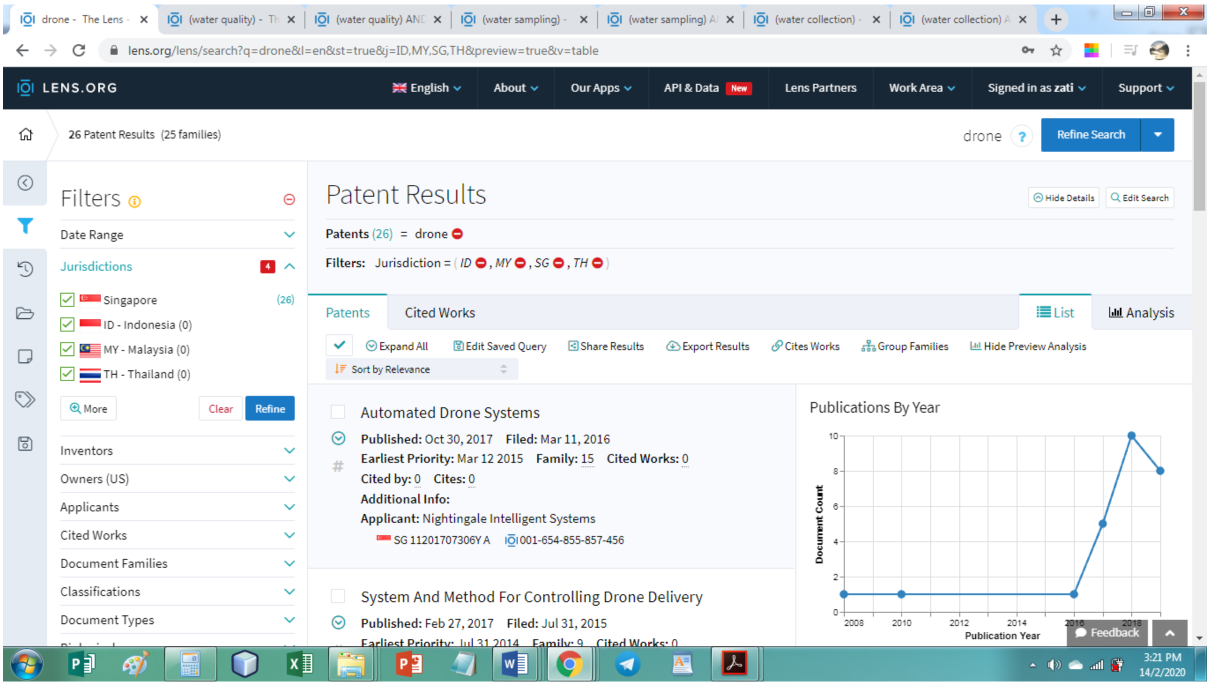
Water Collection

Water Sampling

On their own, each patent search through Lens.org with jurisdiction Malaysia, Indonesia, Singapore and Thailand gives the following results:

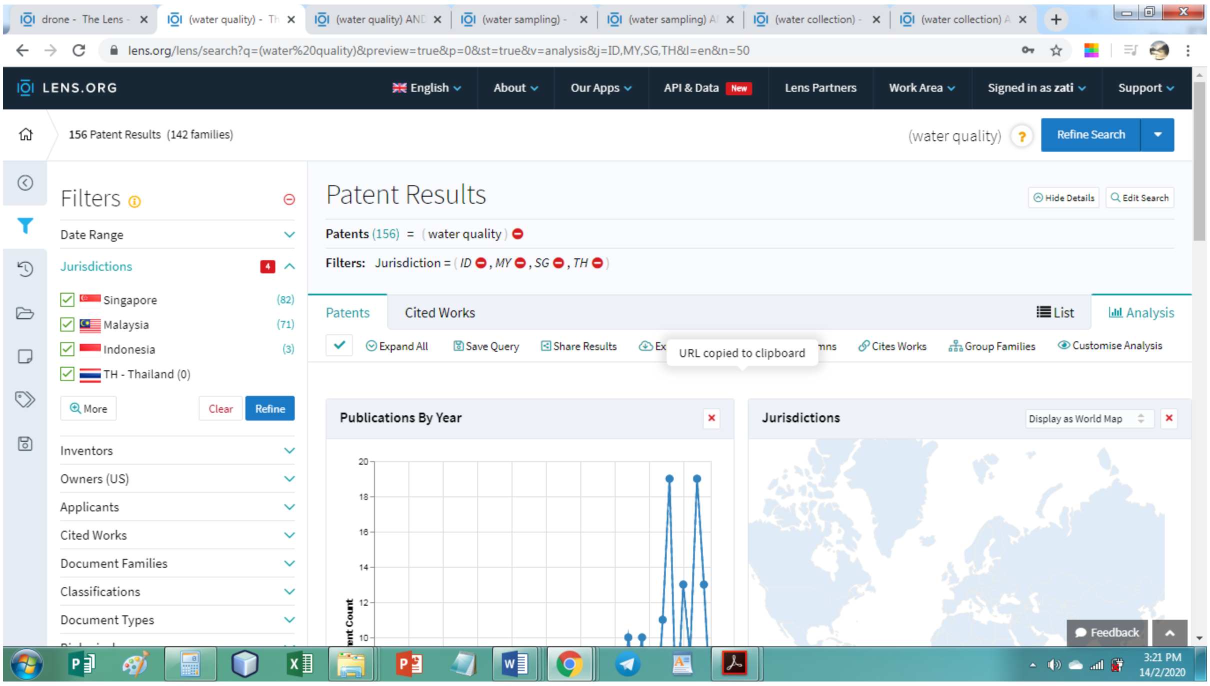
Drone: 26 patents

https://link.lens.org/jWAnhZz9kHd



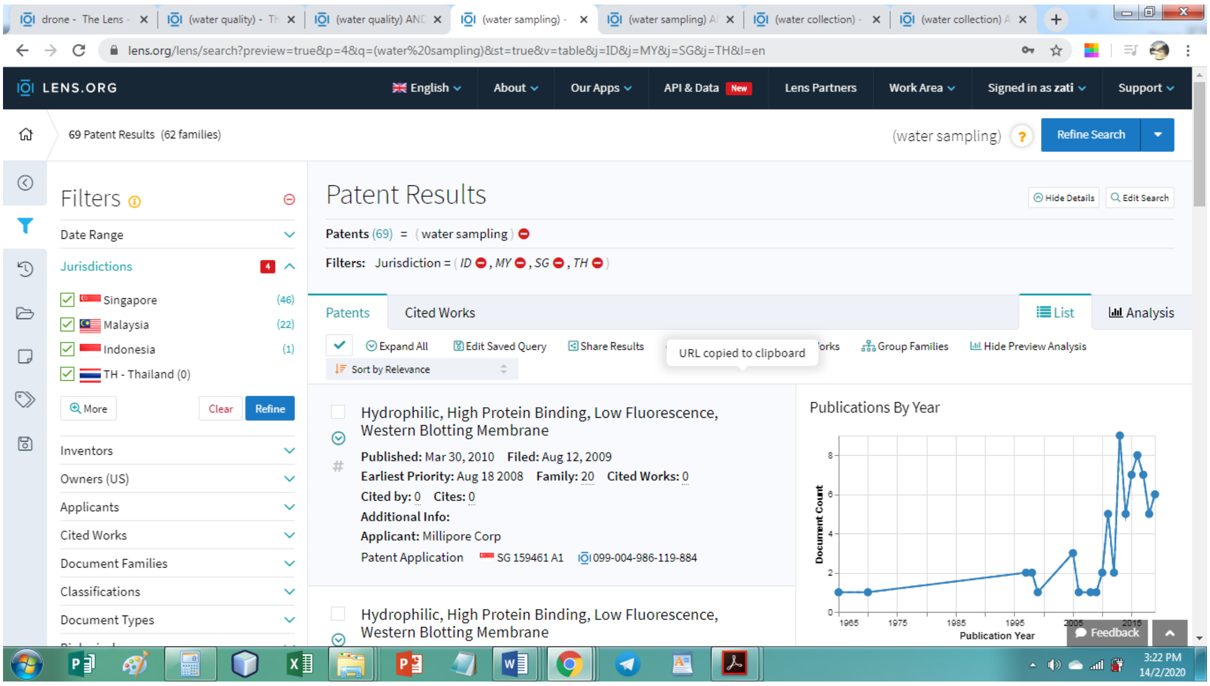
Water Quality: 156 patents

https://link.lens.org/s5vHnTXSBDi



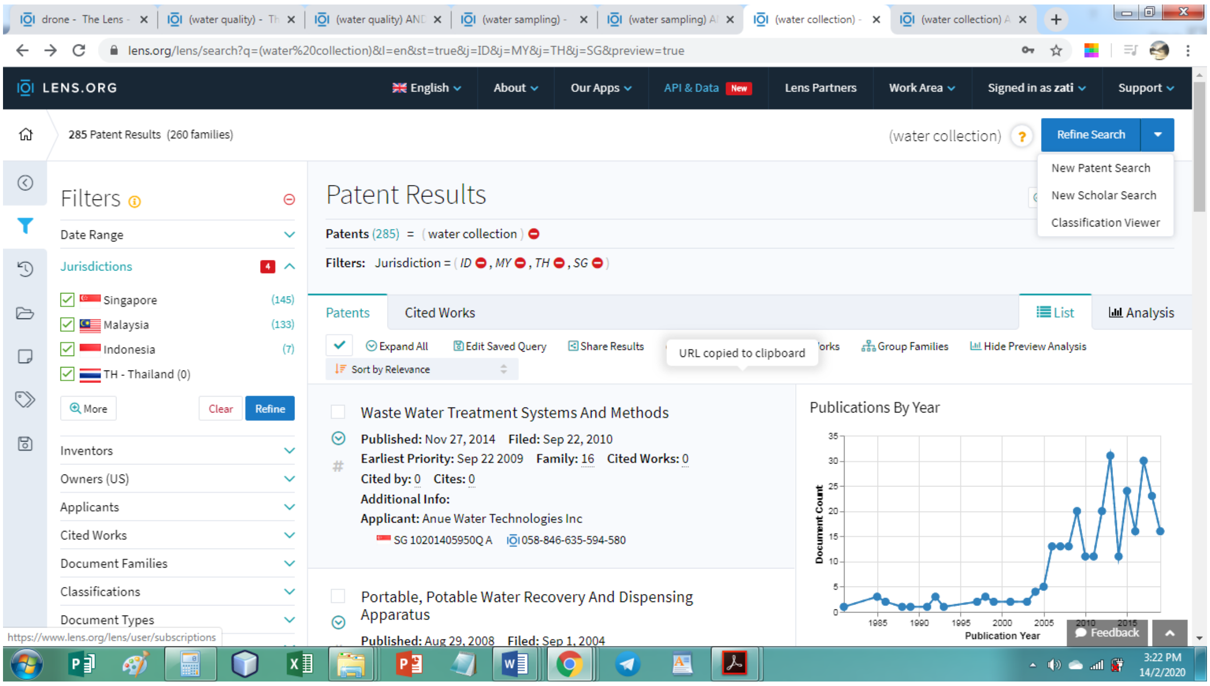
Water Sampling: 69 patents

https://link.lens.org/kuVYcUOcXNe



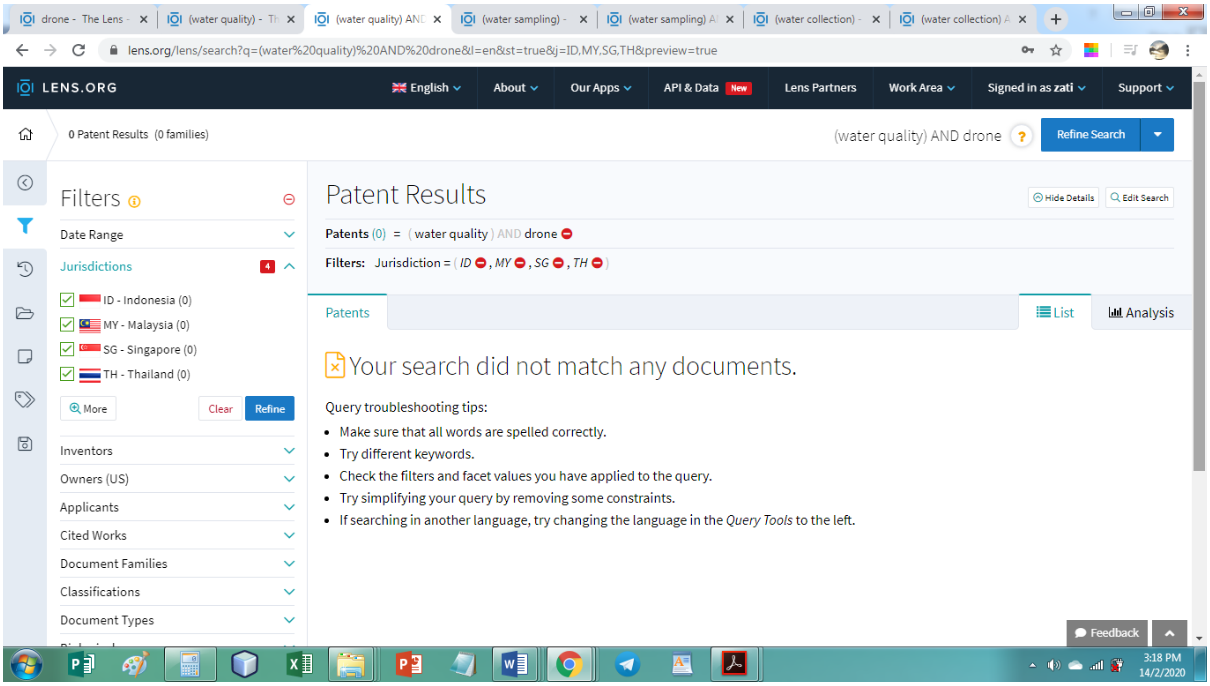
Water Collection: 285 patents

https://link.lens.org/rv7N4uC6tDc

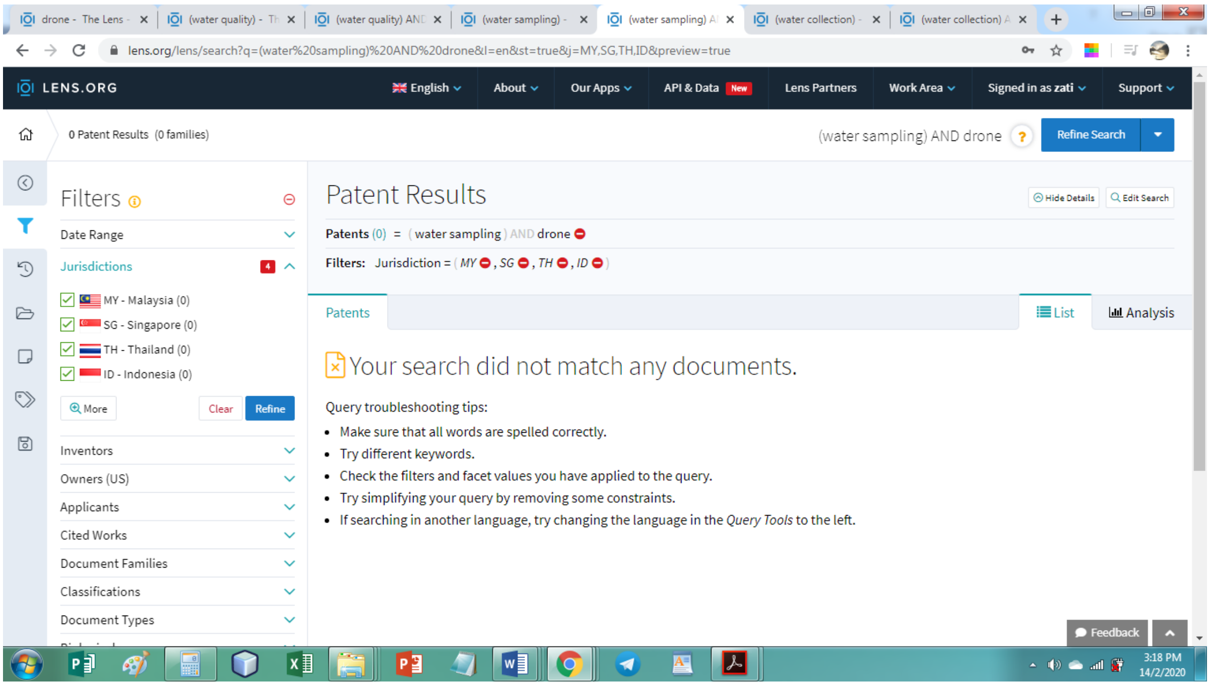


However, when combine “drone” AND “any of the other keywords”, under the same jurisdictions return 0 results

Water quality + Drone:



Water Sampling + Drone:



Water Collection + Drone: