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Water Quality Analysis for the Sustainability of Aquaculture Industry using IoT and Big Data

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ABSTRACT

The water quality is the most important parameter for aquatic species' health and growth. The state is critical and is essential to monitor the water quality continuously in real-time. Poor water quality will affect health, growth and ability of the animal to breed. These also affected their yields value based on the amount and size of the animal. The main water parameters such Dissolved Oxygen (DO), pH, temperature, ammonia and Electrical Conductivity (EC) are monitored in real time. The data were acquired by the developed instrument and send wirelessly through wireless GSM communication module to cloud-based database. The data were retrieved, and the water quality parameters are classifying and predicted using deep learning algorithm. Results show that the performance of deep learning algorithm had improve system performance in monitoring the water quality. This system also provides alert signals to farmers based on condition of the water quality parameters. This will ensure suitable water quality for the animal in aquaculture system.

1. Introduction

Internet of Things (IoT) and other advancements have contributed to the innovation of conventional agricultural practices over the past few years [1]. The aquaculture monitoring system should be automated operations and managed remotely. By applying the Internet of Things (IOT), operation costs will reduce because less workers are needed to supervise the farms and increase productivity. The IoT and big data will have a significant impact on the industry monitoring and analytics [2]. The system will integrate the water quality parameter sensors node that acquire, store, and analyse the data [3].

Water quality is one of the most essential elements for aquatic survival in aquaculture farm. Any pollution will reduce its feeding, waste excretion, growth and can end with death [1]. So, in aquaculture farm, the water quality needs to monitor continuously to ensure the survival of the

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animal [4]. The IoT-based system should be implemented to automate the monitoring and data analytic operations that managed remotely. The system will integrate IoT-based sensors node to acquired data that being stored and analysed [1]. Data collection, analysis, and processing of water temperature, electrical conductivity, pH, turbidity, and dissolved oxygen [5] are crucial for the animal wellbeing. The farmer will know the real time information about the farm water quality parameter status which are important for the animal that sensitive to changes or further action.

Aquaculture intelligent systems that using IoT-based monitoring system will acquire data in real time using sensor nodes, store and analyse it. The system will monitor the water quality parameter, microclimate, and provide early warning alarm. The system can use the acquired information to control the farm water wheels, pumps, feeding system, CCTV and alarms. The farmer accesses IoT-based application with pond controller and the sensors for water management, feeding system and equipped with others application. This will enable the farmers to solve the labour shortage issue, water quality stability and optimum feeding. It will be reducing unconsumed the animal feed which reduce water pollution, increasing emphasis on fish health and growth rate which reducing the mortality rate, that make aquaculture industry more productive and sustainability. Advances in IoT technology have led to significant progress in the application of environmental remote monitoring. IoT-based has been applied to aquaculture farm water quality monitoring using wireless data transmission [6].

The development of IoT-based water quality monitoring system. The water quality parameters sensors are Dissolved Oxygen (DO), pH, Temperature, electrical conductivity (EC) level and ammonia are acquired by the microcontroller in real-time. The measurement data is stored in remote server database and being process by machine learning. The microcontroller also controls the feeding system, and others related devices [7].

The used of machine learning such as Artificial Neural Network (ANN), Radial Basis Function (RBF), Deep Belief Network, Decision Tree, Support Vector Machine (SVM), adaptive neural fuzzy inference system and K-Means clustering algorithm is used for classification and prediction of the water quality. Big data analysis is used for real time water quality monitoring [8]. The farmer can get information at regular intervals through web and remote mobile monitoring. This system will reduce labour cost, enrich animal health, saving operational costs and increasing efficiency [9].

2. System Structure

The developed system main components as shown in Figure 1 consist of water quality parameter sensors, ESP32 microcontroller and wireless GSM communication module which are integrated and known as node. The node and GSM communication module are integrated in the control box. An embedded microcontroller and application program are being developed as the system software. The real time data from the node is transmitted to cloud database @ web server using wireless GSM communication module for data storage. The data will be analyse (classify and predicted) using deep learning method and the results is submitted to the website and mobile devices.

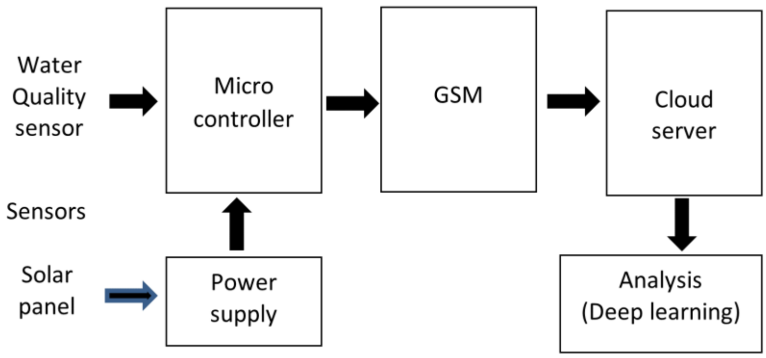

Fig. 1. The system architecture

2.1 The Sensors

The sensors will collect data from the aquaculture farm and can detect the changes in the water. The quality must be controlled to ensure within limits for good animal breeding environment [10]. Main requirements of sensors are small size, high sensitivity, high selectivity, low power consumption, robust, reliable, and affordable [11].

The selected water quality parameter sensors are DO, pH, temperature, ammonia and turbidity which will be generated electric signals which based on the parameter's concentration. The multi-sensory are placed inside a close-fitting sensing chamber to enhance the data acquisition process. The water quality parameters sensors are acquired by the ESP32 microcontroller in real-time. The developed system is placed in the pond to acquire in-situ data and transmit wirelessly by using GSM communication module. The data is stored in cloud database. The Big data are being process by deep learning for classification and prediction for provides a good result with low error rates.

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2.1.1 Dissolved Oxygen (DO)

DO is the most important parameter in the marine species life and metabolic activities, that represent the oxygen in dissolved state. The DO source is either from air or generated by plant photosynthesis. The DO is higher at lower water temperature, low altitude and water flow. The animal DO requirement depending on type, activity, size, temperature and feeding rate [12]. The level of DO can be increased through plants such as floating tree and mechanical devices e.g. paddle wheel. Lower and higher DO will reduce the growth and responsible for animal death [13]. The DO level is the main parameter to control in aquaculture system [14]. The amount of oxygen that can be dissolved (saturated) in water also depends on temperature and salinity level [14]. The DO is measured in milligram per liter (mg/L) or parts per million (ppm). Normally the animal is comfortable with DO value around 5 to 9 ppm [15]. The animal will stress when its level falls below 5 mg/L [1]. DO levels below 2 mg/L will make the animal fall to death [16]. The system is developed using the DO Galvanic Probe Sensor from DFRobot which ranges from 0 to 20 ppm.

2.1.2 pH (Power of Hydrogen)

The measure of acidity or alkalinity of water is pH (hydrogen ion concentration) which ranges from 0 to 14 where 7 is considered neutral. For pure water the pH is between 6.5 to 8 [17]. An increase of pH, the hydrogen ion concentration reduces about ten times and the water will less acidic. Metabolism of aquatic species and bacterial nitrification contribute to acid formation in aquaculture farms which reduce the water pH value. The pH value also dependent on the temperature and DO [10]. A large number of animals can tolerate pH between 5 to 10, but for most of aquatic species the range is from 6.5 to 8.5. Changes in pH can undesirably affect animal wellbeing. This pH range will ensure the animal health and good growth [18]. The developed system is using a pH sensor from DFRobot and the range is from 0 to 14 with 0.1 accuracy.

2.1.3 Temperature

The water temperature will influence the animal behavior, feeding, growth, breeding, and detoxification rate [19]. It is influenced by ambient temperature and depth. The body temperature of cold blooded aquatic species follow the ambient water where this affects their chemical, biological reactions and toxicity of the water. The water temperature should be controlled and kept at suitable for the health of the animals for their optimum. The suitable temperature for most of the animals is between 20 to 35 °C. A temperature sensor, the DS18B20 from DFRobot is used to measure the water temperature because of its good control and design capabilities. Itis waterproof, and resistant to moisture and rust because its encapsulation in a high-quality stainless-steel tube. The sensor operating range is from -10°C to +85°C with ±0.5°C accuracy.

2.1.4 Ammonia

The ammonia generated from animal waste is a serious threat to the aquaculture industry. The ammonia in aquaculture systems is the ionized form (NH_4^+) which is not toxic and un-ionized very toxic NH_3. To harmless nitrates, toxic ammonia can be degraded through biological processes [1].

2.1.5 Electrical Conductivity (EC)

The EC sensor is used to measure the ability to deliver electric current by ions in the water. Any contaminants in the water tank will increase the EC value, indicating a change in the salt content in the water. If the EC value is higher than the appropriate range, osmotic water is used to lower its value and if the value is lower than the range, calcium carbonate solutions or salt is used to increase it [10].

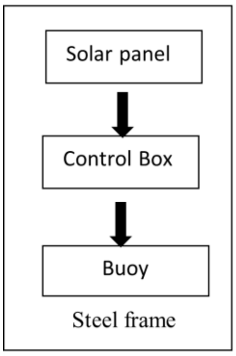
2.2 Energy Harvesting System

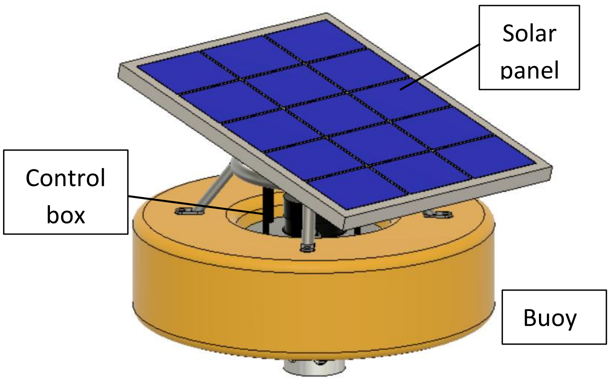
An energy harvesting system is being used as power source for the system because of the outdoor pond location that must rely on batteries to operate. The design and deployment of the node needs special attention due to impact of the environment and water on the sensitive electronic component. The fabricated water quality parameter sensor node includes control box, transmission module and energy harvesting system which situated inside the buoy, steel frame and as shown by Figure 2.

Energy harvesting system is situated on the buoy is composed of one 50W solar panel, 12 volts 3.6 amp. hour (Ah) rechargeable sealed lead acid battery, charge controller is locating on top of the buoy. The charge controller is used to control the charging process and protect the battery from overcurrent. The battery is used as energy source to power the node with 3.3 V and 5.0 V DC to DC voltage converter. The solar panel converts the sun irradiated energy into electrical energy and then stores in the battery. It constantly charges the battery for sustain the continuous monitoring.

2.2.1 The buoy

The buoy is used to float the system system on the pond water surface. It is composed of a rubber tube buoy with 750 cm in diameter and 250 cm in height. The buoy was wrapped with steel frame to protect and combines the control box and energy harvesting system together and protect it from collusion with others floating materials. The buoy will be deployed in the pond for a specific period. Figure 2(a) shows the flow of the energy harvesting system, and the concept of the system is depicted in Figure 2(b).





(a) (b)

Fig. 2. (a) The energy harvesting system flow (b) CAD drawing of the assembly of the buoy equipped with PV and sensors

2.2.2 Control box

The control box was designed to waterproof acrylic board with 15 × 15 × 10 cm dimensions which provide protection for the node. The sensing chamber is position just slightly under water surface, by suspended it under the bottom of steel frame. This ensure that the sensor have good contact with the pond water for optimum data measurement. The sensors respond output signal will correspond with the water quality parameter concentration. A signal conditioning circuits is used to regulate the sensors output signal before being acquired by the microcontroller. A Low Pass Filter (LPF) is used to eliminate unwanted frequencies from the output signal.

An ESP32 microcontroller function is to control the developed system. The microcontroller embedded program is downloaded from PC via USB interface. The microcontroller is controlling the water quality sensors data acquisition time and location.

The sensors output response that being acquire at periodic time frame in real time will be converted into a digital signal by the microcontroller on-board Analog to Digital Converter (ADC). Then, the wireless GSM communication module that connected with the microcontroller will send the data using SMS to the cloud-based server for data storage via SIM card. Then it will wait for an acknowledgment from server for confirms of the data transmission. After that the system will switches to sleep mode (standby) for power optimization. Later based on program (30 minute), the system will again wake up for another data acquisition mode. An alphanumeric Liquid Crystal Display (LCD) is used to display the operating status of the system, data acquisition and transmission.

3. Data Analysis

3.1 Big Data Analysis

Big data in the IoT environment refers to the large volumes of data generated by interconnected devices and sensors. Machine learning algorithms can process and analyze this data to extract valuable insights. Machine learning enables computers to learn from data and make predictions or decisions without explicit programming. Neural Networks (NN) are a type of supervised learning algorithm that learns from labeled data. They mimic the structure and functionality of biological neural networks and are used for various tasks like pattern recognition and decision-making. Deep Neural Networks (DNN) are an extension of NN with multiple hidden layers, capable of representing complex patterns. DNN requires high computational capabilities, often utilizing multicore GPUs.. DNN which is have a deeper network and many hidden layers as illustrated in Figure 3 required more higher computation capability that always performed using multicore GPU.

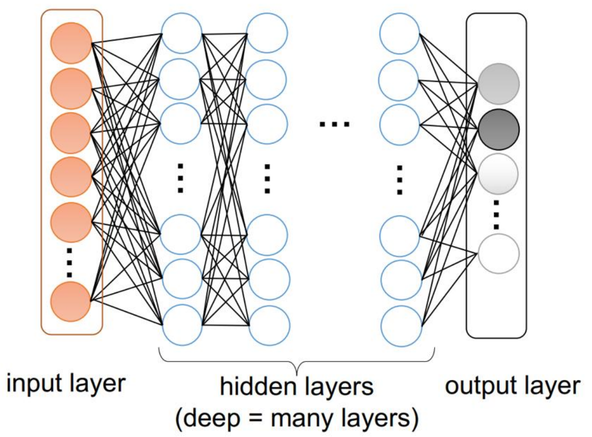


Fig. 3. Input layer, hidden layers and output layer of DNN

Deep neural networks have have demonstrated remarkable success in various domains, including computer vision, natural language processing, speech recognition, recommendation systems, and more. Their ability to learn and model complex patterns and representations from data has led to significant advancements in areas such as image recognition, object detection, machine translation, and speech synthesis.

Another type of deep learning algorithm called Recurrent Neural Network (RNN). RNN more suitable to processing that involved with handling the sequential data such as time series, speech data and natural language. This is because the ability of the RNN to store and maintain the memory and capture dependencies across different time steps.

The key characteristic of an RNN architecture as in Figure 4 is its recurrent connections, which allow information to flow from one step or time unit to the next. This enables the network to process sequential data by considering the current input along with the previous information stored in its hidden state. The hidden state of an RNN can be thought of as the memory of the network that retains information from previous steps.

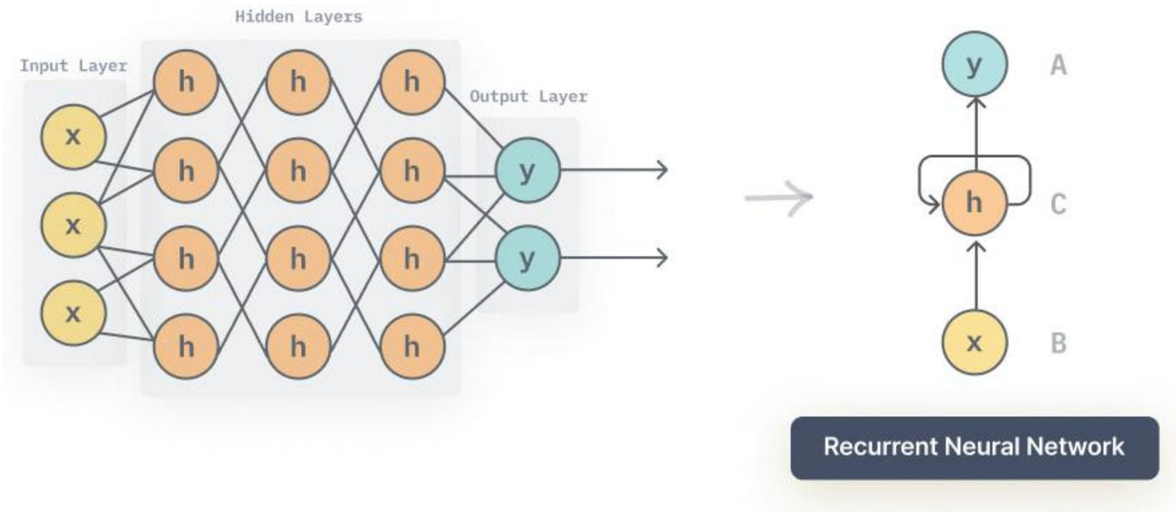


Fig. 4. Architecture of RNN

RNNs have been successfully applied in various domains, including natural language processing, machine translation, sentiment analysis, speech recognition, and time series prediction. Their ability to model sequences and capture temporal dependencies makes them a powerful tool for tasks that involve sequential data.

3.2 Prediction Model
3.2.1 Data pre-processing

Data Pre-processing is an important part in developing the efficient prediction model. In this data processing, there were several stages such as Data Cleaning, Data Integration, Data Transformation, Feature Selection, Feature Engineering, Data Reduction, Data Discretization, Data Normalization, Handling Imbalanced Data and Splitting Data.

In this study, Data cleaning was applied to all 9-sensor nodes before Data Integration was performed to each sensor node on the same pond. The data cleaning process used in this study was nearest neighbor interpolation which it used to estimate value for new or missing data points based on the values of the nearest existing data points. Let say Eq. (1)

$$(x_i, y_i), i = 1,2, \dots., n \quad (1)$$

where $x_i$represent the input or independent variable, and $y_i$represent the corresponding output or dependent variable. To estimate value $y_a$at the new or missing point x_a using nearest neighbor interpolation by using Eq. (2)

$$y_a = y_j \quad (2)$$

where is the index of the nearest existing data point to the new input point x_a.

The Nearest Neighbor Interpolation method selects the closest data point and assigns its output value to the new input point without any interpolation or calculation. This approach assumes that the output value remains constant within the neighborhood of the nearest data point which makes this method suitable for this study due to dataset may consist of some missing value or outlier conditions.

3.2.2 Deep learning model

As a comparison, two methods from machine learning and deep learning itself have been performed in this study. Support Vector Regression (SVR) which is an extension from SVM that specially design for regression and Multilayer Perceptron (MLP) which is feedforward neural network have been selected as machine learning algorithm [20]. While Gated Recurrent Unit (GRU) and Long Short-term Memory (LSTM) from Recurrent Neural Network (RNN) composed as Deep Learning algorithm.

These four models are chosen to be a predictor for water quality due to their ability to deal and provide a good performance in dealing with time-series data. Furthermore, time-series data used in this study are constructed as three-dimensional data. The models process the data feed from the node sensors such as Dissolved Oxygen (DO), potential of Hydrogen (pH), Ammonia ($NH3$), Electrical Conductivity (EC) and temperature. Originally these stand-alone data were represented in 2-dimensional data before it been combined based on time-series to become three-dimensional data as illustrated in Figure 5.

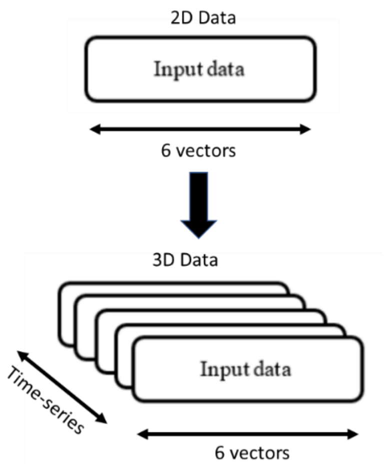


Fig. 5. Transforming isolated data from 2D to 3D through time-series function

The structure of this multiple sequence prediction method is used to predict water quality in a step-by-step sequence. To predict value X ˆ_(t + 1) at timestamp t + 1, previous historical data X_1, X_2, X_3, . . . , X_t, which are known as time lags, are required. When generating the next prediction value of X ˆ_(t + 2), X ˆ_(t + 1), data is fed back into the dataset. The process flow will continue until the designed moving windows are completed. The GRU model is composed of three hidden layers with a sigmoid activation function applied to each layer. The output layer is computed using a dense function, which compresses the three-dimensional data to one-dimensional data. Adam optimization is then implemented in the training model to calculate the probabilistic errors between the ground truth and output of the prediction model.

3.2.3 Hyperparameter testing

Hyperparameter testing or tuning is the next step to apply in this study. This is the process where optimal parameter or configuration for machine or deep learning were obtained from the process of systematically searching and evaluating different combinations of hyperparameters. In this study Random Search used to obtain the hyperparameters due to their easy to implement and computational efficiency compared to Grid Search and Brute Force method. In random search, each hyperparameters will be picked randomly and evaluate the model's performance for a certain number of iterations until get the optimum result. Table 1 shows the range hyperparameter obtained from the models and being used in this study.

Table 1
Range hyperparameter obtained used in this study

Hyperparameter	Values
Hidden Layer	1 – 5
Hidden Node	2^3 - 2^{10}
Learning Rate	0.001, 0.005, 0.01, 0.05, 0.1, 0.5
Iteration	2^3 - 2^{12}
Split	1 – 5

4. Methodology

An experiment was conducted to verify the function and operation of the developed instrument that correlated with the aquaculture pond water quality. The samples were collected from an aquaculture farm in Penang Malaysia. The size of the pond is approximately 30m × 40m × 1.5 m. The sampling process is illustrated in Figure 6 and Figure 7 shows the data acquisition process flow chart.

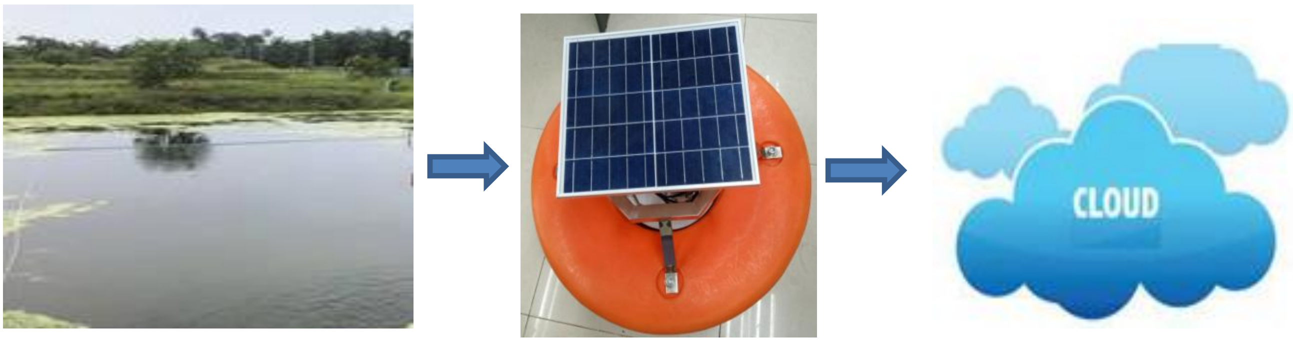


Fig. 6. Transforming isolated data from 2D to 3D through time-series function

The sampling process begins with the developed instrument is manually placed into the left side of the pond at a designated time for data acquisition process. The water will fill the sensing chamber and the process will continue for one minute for optimum sensor response. Then, the microcontroller will acquire the sensor response data. The acquisition process was repeated three times to ensure its repetition for stable sensor response data. After that, the average of the acquired data will be sent wirelessly to the cloud server for storage through GSM communication module. Once the process is completed, the system will return to sleep mode. Then the equipment sensor is cleaned by using water. The acquisition process will be repeated for the middle and right side of the pond. Then the instrument will be used for the other two ponds. So, for the experiment, data are acquired from nine locations of the aquaculture farm ponds. The process flow chart is as depicted in Figure 7.

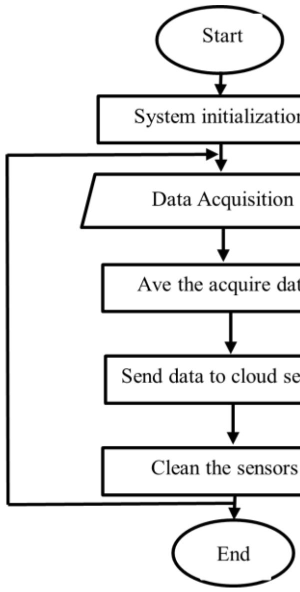


Fig. 7. The data acquisition process flow chart

5. Experimental Results

In this study, SVM and MLP declared as ML method which it does not have the recurrent feedback process to update the weight and bias like GRU and LSTM. The performance comparison has been performed between all four types of learning processes in terms of predicting the water quality. Hyperparameter for all methods have been decided using random-search method as the result can be seen in Table 2. The hyperparameter structure for MLP, LSTM and GRU is look similar compared to SVR due to those three coming from same branch of learning model.

Table 2
Hyperparameter for SVR, MLP, LSTM and GRU

Hyperparameter	Machine Learning		Deep Learning	
	SVR	MLP	GRU	LSTM
Kernal	RBF	-	-	-
Regularization	499.2	-	-	-
Hidden Layer	1	1	3	3
Hidden Node	-	128	64+512+256	64+512+128
Learning Rate	0.001	0.001	0.001	0.01
Iteration	10,000	200	1800	1500
Split	0.8	0.8	0.8	0.8
Optimizer	-	Gradient descent	Adam	Adam
Activation Function	-	Sigmoid	Hyperbolic tangent	Hyperbolic tangent

The gained hyperparameter in Table 2 was used to build the water quality prediction model for three ponds from nine sensor nodes. Three sensor nodes placed for one pond to collect the data of DO, pH, EC, NH3, Temperature and EC. The validation process from the input data was separated by 80% for training and 20% for validating. This training and validating process was conducted toward approximately 466,560 data for a month with each node sending six sensors' data every 5 minutes to the cloud. Table 3 presents the performance for each developed model. As it clearly illustrated that GRU perform better compared with SVR, MLP and LSTM with R^2 value for all pond are above 0.9 and the average value was 0.9567.

Table 3
The performance for SVR, MLP, GRU and LSTM

Pond	Evaluation	Machine Learning		Deep Learning	
		SVR	MLP	GRU	LSTM
1	R^2	0.85	0.82	0.97	0.96
	MSE	31.26	116.45	8.59	32.16
	RMSE	5.59	10.79	2.93	5.67
	MAE	0.92	9.45	0.95	0.79
2	R^2	0.96	0.72	0.95	0.93
	MSE	23.62	212.48	6.45	19.96
	RMSE	4.86	14.58	2.54	4.47
	MAE	0.97	11.57	0.82	1.22
3	R^2	0.91	0.86	0.95	0.89
	MSE	17.89	98.65	10.24	28.18
	RMSE	4.23	9.93	3.20	5.31
	MAE	2.53	10.65	1.21	0.82

4. Conclusions

It can be concluded that the proposed Deep learning model for big data prediction performed better compared to conventional machine learning with GRU and LSTM achieve R^2 value 0.89 and above. While GRU recorded an average R^2 value above 0.95 for all three ponds. Furthermore, the GRU model also provides the lowest MSE, RMSE and MAE value compared to other models. Random-search method also proved suitable for hyperparameter tuning that affects a good result in prediction.

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