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IoT-Based Water Quality Monitoring: An Application for Optimal Aquaculture Management

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ABSTRACT

Ineffective water quality monitoring and various farming difficulties causing fish kill events are persistent challenges in aquafarming, significantly impacting fish production. This paper presents a scalable, mobile IoT-based aquaculture monitoring application that tackles the challenges so farmers can enhance fish production, reduce labour costs, and improve food security. With the help of sensors, the application can monitor water quality indicators in real-time for optimal fish growth. In addition, we include predictive analytics and alert messages to mitigate aeration system failures, algal blooms, and unpredictable water changes. The application is a four-module architecture with data acquisition, communication, data processing, and user interface, supported by efficient data gathering, storage, and visualisation. For the application development methodology, we use Evolutionary Prototyping to refine the application repeatedly with the help of user feedback. This work addresses limitations through future work in automation, network backup, and machine learning integration.

1. Introduction

The aquaculture industry has experienced significant growth and transformation in recent years, making it a crucial player in the global seafood supply chain. As shown in Figure 1, global aquaculture productivity has substantially increased from the 1990s to the 2020s. Notably, Figure 2 indicates that aquaculture is on the verge of surpassing capture fisheries as the primary source of aquatic products as of 2020 [1]. Despite this growth, a critical research gap remains, signalling an urgent need to develop and expand the aquaculture sector further. This expansion is imperative to meet the escalating food demands of the global population. With many wild fish stocks facing overfishing, relying solely on wild-caught seafood has become unsustainable. Aquaculture stands out as an essential alternative source of seafood that can be produced in a controlled and sustainable manner.

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One sustainable approach to expanding the aquaculture industry is indoor aquaculture, particularly the Recirculating Aquaculture Systems (RAS) approach. The equipment used to monitor and manage aquaculture systems must be improved to achieve this expansion, including implementing advanced aquaculture monitoring systems [2].

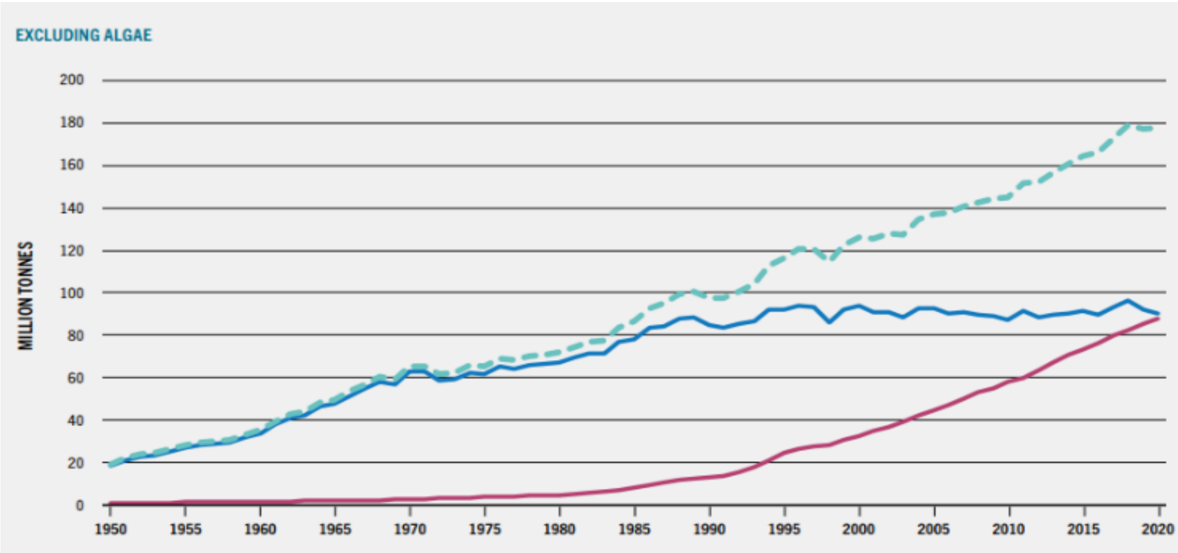

Fig. 1. World capture fisheries and aquaculture production excluding algae [1]

	1990s	2000s	2010s	2018	2019	2020
	Average per year					
			Million tonnes (live weight equivalent)			
Production						
Capture:						
Inland	7.1	9.3	11.3	12.0	12.1	11.5
Marine	81.9	81.6	79.8	84.5	80.1	78.8
Total capture	**88.9**	**90.9**	**91.0**	**96.5**	**92.2**	**90.3**
Aquaculture:						
Inland	12.6	25.6	44.7	**51.6**	**53.3**	**54.4**
Marine	9.2	17.9	26.8	**30.9**	**31.9**	**33.1**
Total aquaculture	**21.8**	**43.4**	**71.5**	**82.5**	**85.2**	**87.5**
Total world fisheries and aquaculture	**110.7**	**134.3**	**162.6**	**178.9**	**177.4**	**177.8**
Utilization[2]						
Human consumption	81.6	109.3	143.2	156.8	158.1	157.4
Non-food uses	29.1	25.0	19.3	22.2	19.3	20.4
Population (billions)[3]	5.7	6.5	7.3	7.6	7.7	7.8
Per capita apparent consumption (kg)	14.3	16.8	19.5	20.5	20.5	20.2
Trade						
Exports – in quantity	39.6	51.6	61.4	66.8	66.6	59.8
Share of exports in total production	*35.8%*	*38.5%*	*37.7%*	*37.3%*	*37.5%*	*33.7%*
Exports – in value (USD 1 billion)	46.6	76.4	141.8	165.3	161.8	150.5

Figure 2: World fisheries and aquaculture production, utilization and trade [1]

Maintaining optimal water quality conditions is a critical factor in the success of aquaculture operations. Temperature, dissolved oxygen (DO), pH, and ammonia levels significantly impact fish growth and overall production [12]. Traditional monitoring methods for aquaculture water quality are often labour- and time-intensive and may not provide real-time data on water quality conditions. Consequently, there has been a growing interest in using sensors to monitor water quality in aquaculture operations.

This work aims to enhance fish growth performance and water quality monitoring in aquaculture through the Internet of Things (IoT) application. The focal point of the work is creating an aquaculture monitoring system that uses sensors to collect data on critical water quality indicators, including temperature, DO, pH, and ammonia levels in a fish farming environment. By using the sensors together with an IoT application, real-time monitoring of the water quality for aquaculture is enabled [13], [14], [15], [16], [21]. Such a monitoring system was also developed by Raju and Varma [16] using Raspberry Pi as their microcontroller to process the captured data. They aim to facilitate the creation of more efficient and effective water quality monitoring systems for aquaculture operations, meeting the growing demand for sustainable seafood by optimising water quality for enhanced fish growth.

The remainder of this paper is organised as follows. Section 2 describes the problem statement along with a case study, followed by Section 3, which presents the proposed technology solution. Section 4 provides an approach for the proposed technology. Section 5 discusses the results, followed by Section 6, which delves deeper into the discussion of the results. Finally, Section 7 concludes this paper.

2. Problem Statement

Urban aquaculture faces many difficulties due to the lack of suitable methods and equipment to monitor the water quality of aquaculture. It will undoubtedly result in the fact that aquafarmers are always too late to take the appropriate measures when there is a problem with the water quality,

Fig. 3. A fish kill event

which will cause the fish in the tank to start dying off and lead to severe damages and losses such as fish kill events as shown in Figure 3.

To understand the real problems fish farmers face, we conducted one case study with a home-based fish farmer from Petaling Jaya, Selangor, Malaysia. It is an ambitious aquafarming work centred around cultivating Tilapia fish, intending to establish an aquafarming system model in the residential area. Knowledge transfer activities and hands-on practical training regarding the aquafarming systems shall be provided to the residents once the aquafarming system is improvised successfully using our proposed IoT application. Three cutting-edge fiberglass tanks were set up in the backyard, equipped with a water pump (Figure 4 and Figure 5).

While the initial harvests were promising, the fish farmer soon encountered significant challenges related to water quality monitoring. The high ambient temperatures and occasional power outages in the region led to fluctuations in the tanks' water temperature, affecting DO levels

Fig. 4. Water pumps

Fig. 5. Fiberglass tanks involved in this work

and pH balance. These fluctuations threatened Tilapia's health and growth, requiring the fish farmer to explore innovative solutions to overcome the challenges. Therefore, the challenges faced by the fish farmer have been detailed in the following section.

2.1 Aeration system failure

The aeration system is supposed to function continuously to provide sufficient oxygen for the fish to survive in the water tank [3]. However, aeration system failure may occur without notice by the farmer. When the aeration system fails, this can result in fish kill events within minutes in the water tank due to a lack of DO [4]. The DO will also affect the fish's growth and metabolism [18]. The rate at which fish consume food can also be impacted, as the DO levels indirectly influence the feeding behaviour of the fish [19]. As a result, a water monitoring system to notify the user when the level of DO in the water tank drops below a safe level is necessary to prevent this risk.

2.2 Algae Bloom

Algae often help aquaculture by giving the farmed fish oxygen and a natural food source [5]. According to Fernando *et al.* [6], previous research has proven that adding algae to fish feed (aquafeed) in small amounts (10% of the diet) had a positive impact on growth performance and feed utilisation efficiency. However, according to the Minnesota Pollution Control Agency,[6] excessive algae growth or, in the event of algae bloom, will result in low DO. Nutrients like Phosphorus and Nitrogen are both factors that contribute to algae growth, and there are many ways that these two elements can reach our water resources [7]. Excessive proliferation of algae in water can lead to an increased surplus of nutrients like phosphorus [17].

DO is used up during the decomposition and death of the algae. As a result, fish may not have access to enough DO, resulting in fish kills. Large-scale fish mortality was caused by an algal bloom in the Mumbai coastal areas in 2018 [6]. Therefore, if aquafarmers utilise sensors to monitor the DO, Nitrogen and Phosphorus levels, they can predict the Algae Bloom events and take the necessary action immediately.

2.3 Unpredictable timing to change water

Changing water maintains good water quality in the tanks to ensure a suitable environment for the best fish growth performance [8]. Unfortunately, aquafarmers have difficulty determining the best timing for water exchange. The water composition constantly changes due to climatic and seasonal changes and pond usage [9]. Aquafarmers cannot know the timing to change the water unless they perform water testing frequently. Keeping water testing may often be too cumbersome for them. Therefore, most aquaculture farmers will choose to change the water when the water looks dirty, but maybe the water is still usable.

Even if the water tank looks clear, water contamination may occur due to food and waste particles. Waste can be converted into chemicals such as nitrate and phosphate. Excessive nitrate and phosphate affect the DO, temperature and others [5]. To solve this problem, a water monitoring system can be installed in the water tanks to monitor water parameters and perform water quality forecasts continuously. According to Li *et al*. [11], historical data collected from the sensors can be used to build Machine-Learning (ML) models to predict water quality. The environmental stability of aquaculture systems can thus be well maintained, and the incidence of fish diseases caused by deteriorating water quality can be reduced with water quality prediction. Based on the forecasts, aquaculture farmers can promptly replace the tank's water.

3. Technology Solution

We tackled the challenges by implementing a viable technology solution - an Internet of Things (IoT) water monitoring system for aquaculture fish tanks. It entails seamlessly integrating water parameter sensors, microcontrollers, and cloud servers and developing a user-friendly Android

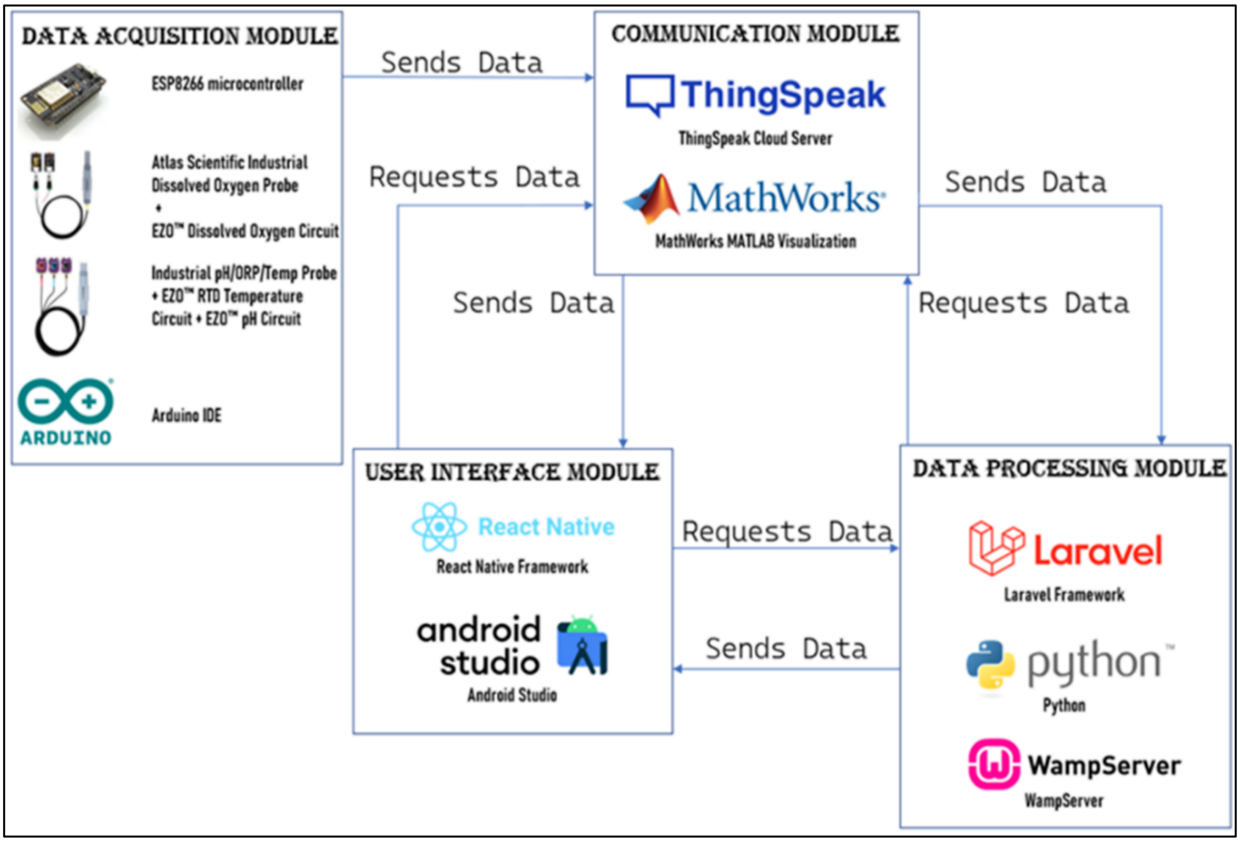

Fig. 6. Our proposed technology solution

application dashboard for real-time monitoring and management. Figure 6 shows the proposed solution that is divided into four modules: (i) Data Acquisition Module, (ii) Communication Module, (iii) Data Processing Module and (iv) User Interface Module.

2.4 Data Acquisition Module

In the Data Acquisition Module, sensors are installed inside the water tank to measure water parameters such as Dissolved Oxygen (DO), pH level, Temperature, and Ammonia Level. The sensors are Atlas Scientific Industrial Dissolved Oxygen Probe and Industrial pH/ORP/Temp Probe, each with

Fig. 7. Prototype

corresponding EZO circuits to improve the sensing accuracy. The communication protocol between the microcontroller and the sensors is the Universal Asynchronous Receiver / Transmitter (UART), a serial communication protocol. The collected sensor data is sent to the microcontroller with a WiFi module supporting 4G. The microcontroller then uses the Internet connection to send the collected data to the Cloud Server in the Communication Module for data storage. The prototype of the data acquisition module is shown in Figure 7.

To reduce the impact of external conditions on sensor performance, we select sensors that are particularly built for outdoor applications and are resistant to elements such as heavy rain. Certain sensors use ultrasonic or optical approaches to reduce vulnerability to poor weather conditions, such as rain, and to defend against fouling, debris collection, and rapid water flows. Optical sensors, in particular, excel in electrochemical devices in terms of resilience in tough environments, decreased maintenance requirements, extended calibration stability, and higher efficiency through real-time data processing and control [27].

2.5 Communication Module

The Communication Module, *ThingSpeak* IoT platform, serves as data storage for the water parameters data sent by the microcontroller in the Data Acquisition Module. Besides storing the sensors' data, it also provides Data Visualization features such as gauges and line graphs. It also provides REST API to retrieve the data for the Data Processing Module and User Interface Module.

2.6 Data Processing Module

The Data Processing Module shall function as a web server to process user account information, perform analysis, handle user authentication and authorisation, and manage other application logic for the mobile application. It is built using the Laravel PHP framework and Python.

2.7 User Interface Module

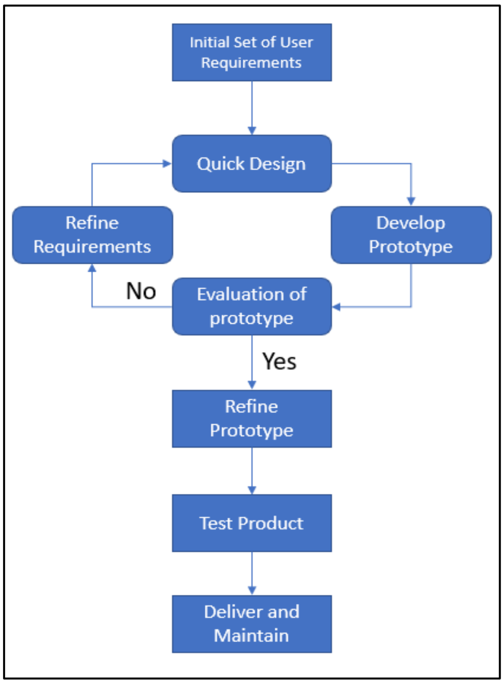

Fig. 8. The evolutionary prototyping

The User Interface Module is developed using React Native, which can communicate with the Data Processing Module and Communication Module with an internet connection. It can request data for Data Visualisation and provide several functions such as a dashboard, alert notification, prediction, activity record and analysis to enhance aquaculture operations.

3. Prototyping Methodology for the Technology Solution

Evolutionary Prototyping is one of the popular variants of prototyping methodology used in work development [11]. Prototyping methodology is a process that repeatedly refines the prototype based on customer feedback until the prototype satisfies the customer's needs. However, there are different ways to perform prototyping methodology. We used Evolutionary Prototyping in this work (Figure 8).

The Evolutionary Prototyping started with getting the initial user requirements. The requirements were collected from stakeholders, especially end-users, for documentation. The initial requirements were also collected by reviewing the existing water quality monitoring applications in the market. Further discussion and requirement specification review were conducted with the aquafarmer to confirm the software requirements.

In the Quick Design phase, a high-level design of the application prototype was produced. It should include an overall basic software architecture, data structure and interfaces. This stage used *ThingSpeak* and *ThingsBoard* to build the dashboard for data visualisation of this application prototype.

We developed the basic application prototype based on the quick design phase. *ThingSpeak* and *ThingsBoard* were used to build the dashboard for data visualisation. This mid-fidelity prototype does not obtain the collected sensor data from the cloud. This prototype is clickable to allow end-users to test whether they can easily understand and use the functions and features provided in this system. This prototype encourages end users to determine whether the software requirements are satisfied.

Stakeholders and end users evaluated the application prototype and provided feedback on its functionality and features. During this evaluation phase, they assess whether the prototype is usable and acceptable, and if not, they shall provide input for improvement. If any requirements are not met or are missing, this leads to modification and redefinition of software requirements. Then, the processes from quick design to evaluation shall be repeated until the stakeholders are satisfied with the prototype.

The basic functionality of the application prototype is read when the stakeholders and end users accept it. However, the prototype may need to be refined by adding new functionalities and features. After the application prototype is refined, stakeholders and end users must test and evaluate the final product to ensure it meets the specification requirements. If unsatisfied, return to the previous stage to refine the prototype.

Once the final product passes all tests and the stakeholders approve, the application can be delivered to the end-users. However, the application should always be maintained and updated to meet the end-users' changing needs and meet quality standards.

4. Final Product

The final product provides user interfaces that display all the water parameter readings, allowing users to check the current water condition in the water tanks. Figure 9 shows the 'Channel' page, listing all the water tanks added by the user for monitoring. It displays three gauges for water parameters: DO, RTD, and pH. A green gauge indicates that the water parameter is within the safety level, while a red gauge indicates that it is out of range. Users can add additional monitoring channels and have the option to delete channels. Figure 10 displays the dashboard for a single channel. The first tab lists all the water parameter gauges, while the second tab lists their corresponding line graphs. Figure 11 displays the dashboard for users to record activities and view activity analyses. It is accessible from the third tab on a single channel's dashboard. There are four tabs for different activities, each containing its respective analysis. Below the tabs is a calendar for users to interact with and record activities. The dots on the calendar indicate recorded activities, with each colour representing a different activity: red for 'Change Water,' spring green for 'Feed Fish,' blue for 'Clean Tank,' and green for 'Clean Sensor. Figure 12 displays the page where users can toggle the notification 'ON' or 'OFF.' Notifications will pop up if the notification function is turned 'ON'. Figure 13 displays the dashboard for monitoring a single water parameter of a specific water tank. Users can access it by clicking on the gauge or line graphs within the water tank's dashboard. The dashboard includes a gauge for the selected water parameter. Additionally, there are four tabs to allow users to change the scale of the line graphs: 'Day-Hour,' 'Week-Day,' 'Month-Day,' and 'An Hour.' In the middle of the dashboard, trend line graphs are plotted based on the selected line graph scale. Below the graphs, users can find an analysis of the water parameter based on the line graph data.

4.1 User Interfaces

Users can monitor three key water quality parameters in real time by utilising the application and receiving data directly from the deployed sensors.

As illustrated in Figure 14, the gauges display two distinct colours: red for dangerous levels and green for safe levels. Users can customise the safe level ranges to suit their specific monitoring needs. This real-time monitoring capability empowers users to take immediate corrective action when the mobile application triggers warning messages for parameter values outside the user-defined safe ranges. This proactive approach helps prevent unnecessary losses, particularly in the aquaculture industry. Early detection of water quality deviations can allow timely corrective actions, such as aeration, pH adjustments, or water exchange. It will help to minimise the potential harm to the aquatic organisms, which enhances their growth performance.

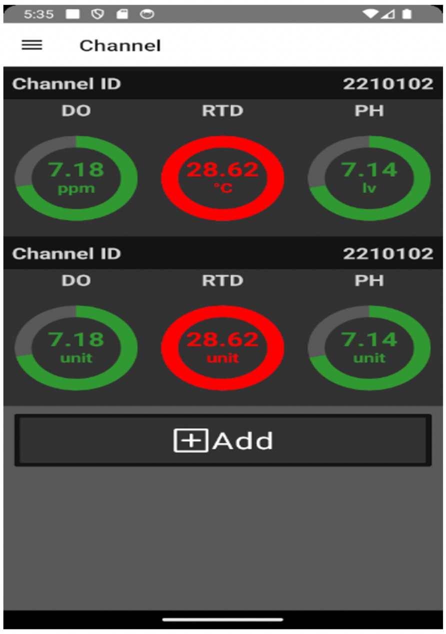

Fig. 9. Dashboard to monitor multiple water tank (channel)

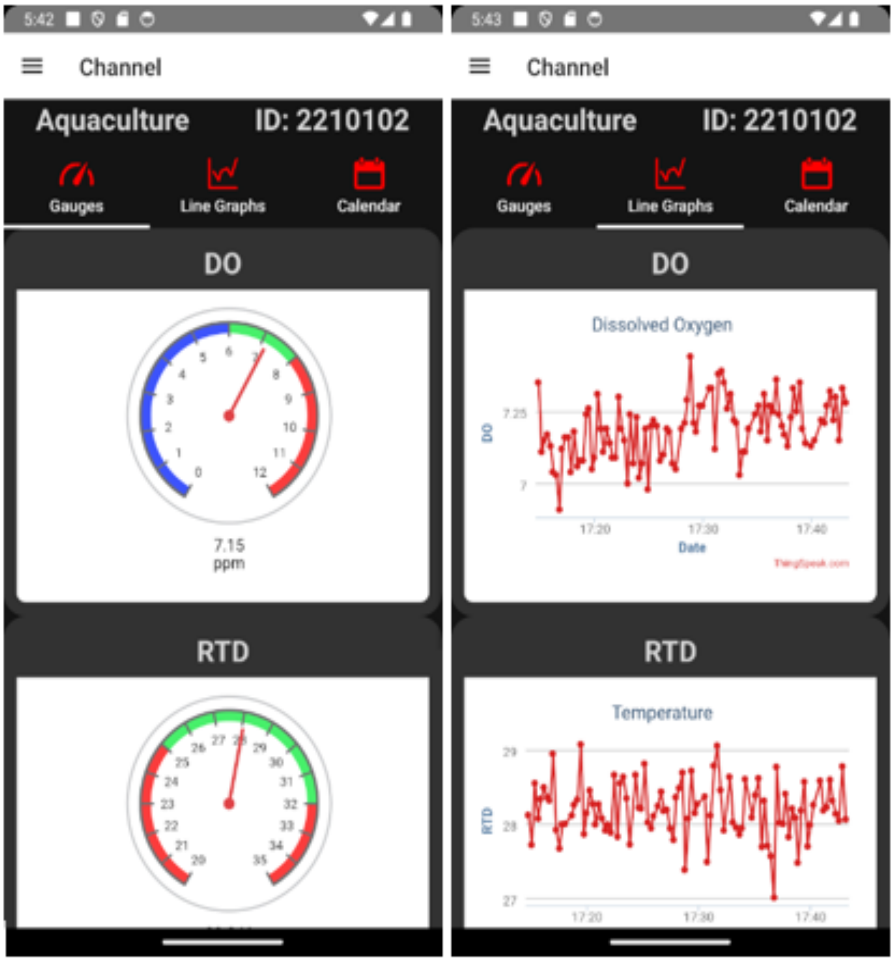

Fig. 10. Dashboard to monitor a single water tank

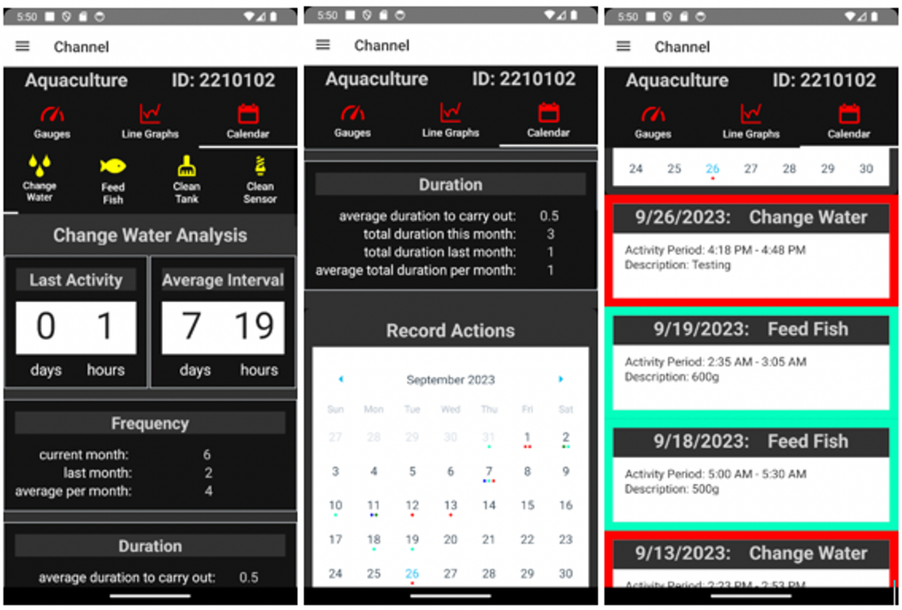

Fig. 11. Dashboard to view and record activity for a single water tank

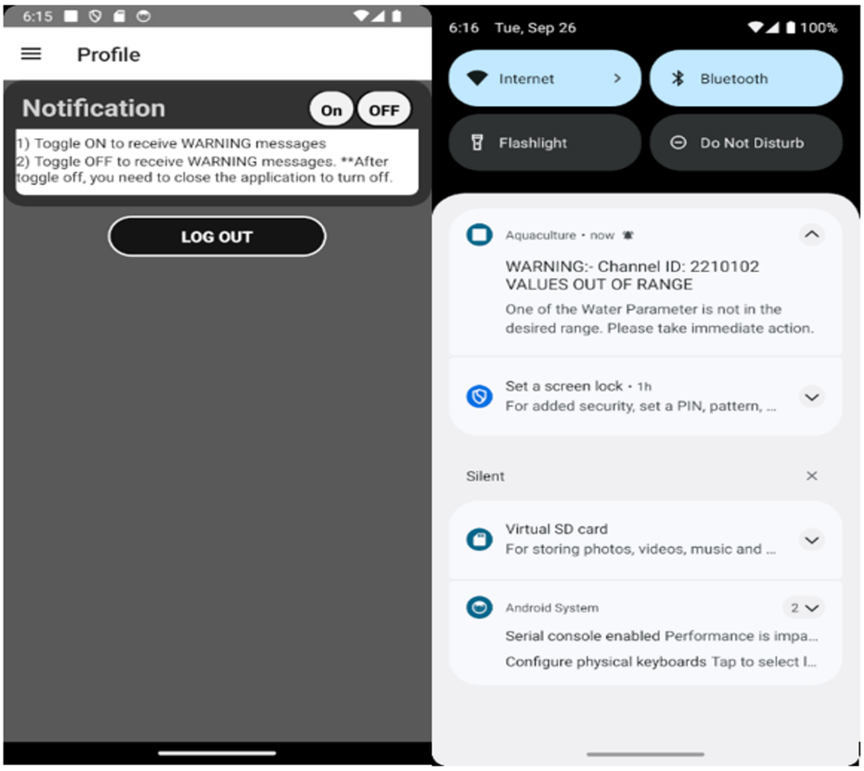

Fig. 12. Notification to alert user on the water tank condition

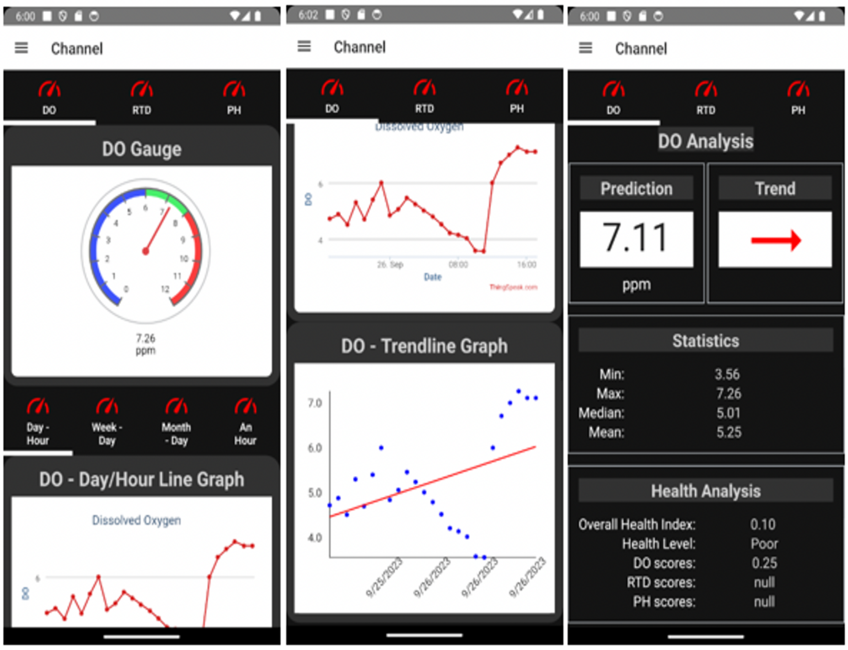

Fig. 13. Dashboard to monitor a single water parameter of a single water tank

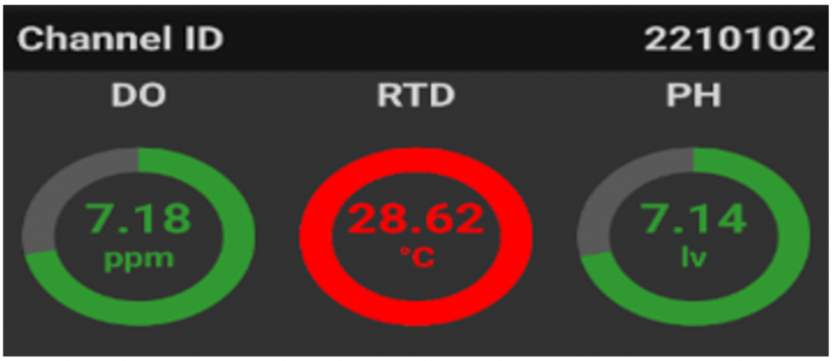

Fig. 14. Gauges which providing real time values with colour indicator

4.2 Alert Notification

As shown in Figure 12, the alert notification feature has been readily implemented into our system. Establishing a background task service allows for the realisation of this ability. The user interface, which permits users to turn the notification service on or off, is shown graphically in Figure 12. When the user chooses to activate notifications, the background service activity starts. The pH gauge is an example of how users can set safety levels for different gauges using the task service, as seen in Figure 15.

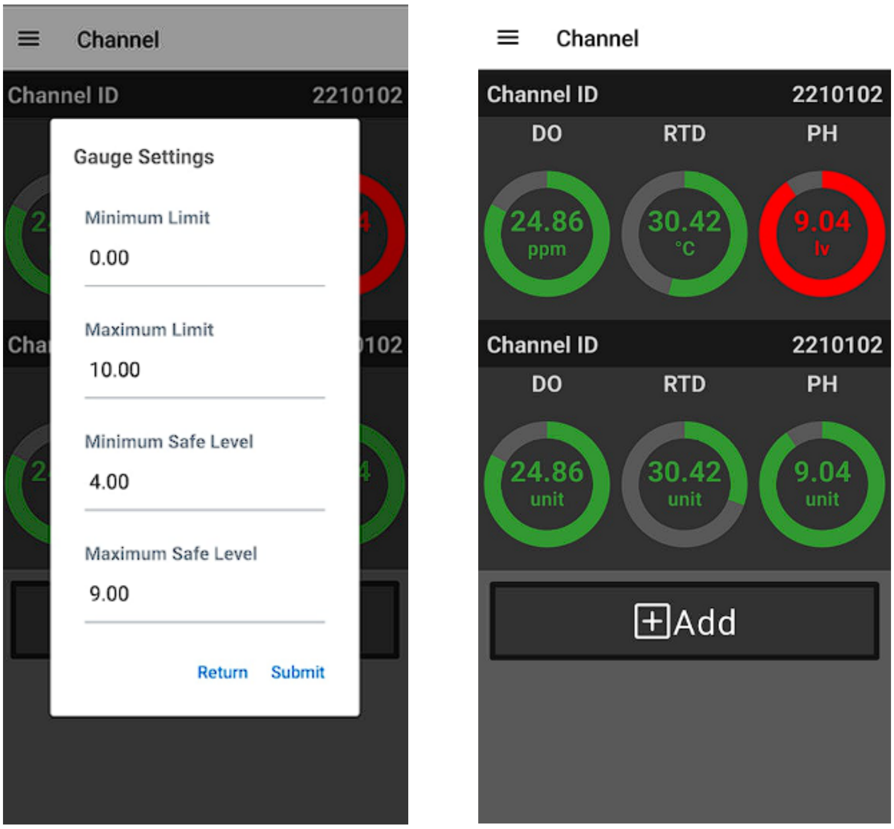

Figure 15: Gauges settings

For the pH gauge, for example, the user can set the maximum safe level (set at 9) and the minimum safe level (set at 4 in this case). These preset gauge settings are used by the background tasks to determine if the current water parameters are within the designated range. An out-of-range pH value in the tank turns the gauge red. As a result, the background service causes a notification to be sent to the user with a warning message informing them of the departure from the safety range, which is between 4 and 9 (Figure 16).

After receiving the message, the user is prompted to address the water quality concern. In the previously described case, for example, the message notifies the user that the pH measurement is 9.04, higher than the designated safety range. The system ensures that users are always aware of the situation by sending notifications every 15 seconds until the water quality is acceptable. This function ensures that people know what is happening until the water quality is considered safe.

It is crucial to keep in mind that users must enable notification sounds on their mobile devices for this functionality to work. This proactive strategy guarantees that users receive and recognise notifications promptly, allowing for rapid intervention in response to fluctuations in water quality.

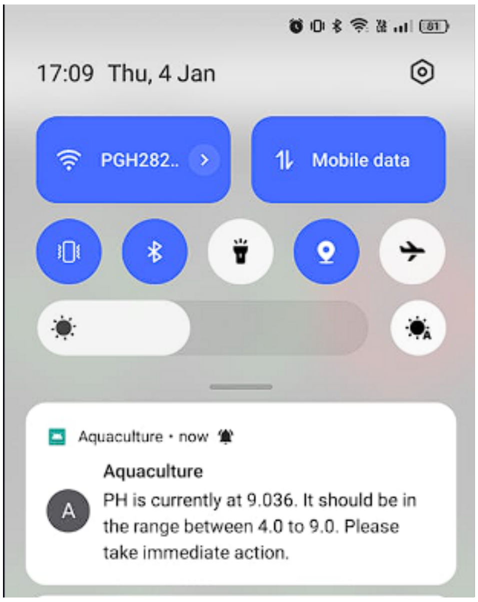

Figure 16: Alert Notification

4.3 Machine Learning

This system can be improved by integrating different machine learning algorithms with the data collected in the ThingSpeak cloud database. The objectives of this integration are to forecast trends, identify abnormalities, and derive insights from water quality data. It is observed that CEEMDAN-RF and CEEMDAN-XGBoost provide better prediction stability when compared to other benchmark models, which is based on research done in 2020 by Lu and Ma. The mean absolute percentage error (MAPE), utilised in assessing prediction performance, is calculated using Eqs. (1).

$$MAPE = \frac{100\%}{n} \sum_{t=1}^{n} \left| \frac{O_t - P_t}{O_t} \right| \quad (1)$$

The prediction performance is evaluated based on Table 1.

Table 1
MAPE grade performance evaluation

MAPE range	Grade
< 10%	excellent
10% - 20 %	good
20% - 50%	reasonable
>50%	inaccurate

With remarkable MAPEs of 0.27% (great), 14.94% (good), and 1.59% (excellent), respectively, CEEMDAN-RF outperforms other models in the prediction of pH, turbidity, and FDOM (dissolved organic matter). In a similar vein, CEEMDAN-XGBoost achieves exceptional MAPEs of 0.27%, 14.94%, and 1.59% in its forecasts of pH value, turbidity, and FDOM.

The water quality characteristics, including temperature, dissolved oxygen, pH, specific conductance, turbidity, and FDOM, were employed in their analysis. This data was collected at one-hour intervals throughout a two-month period. At the moment, this system collects temperature, pH value, dissolved oxygen, and ammonia automatically. However, additional sensors are needed to capture additional variables, such as specific conductance and turbidity, for more robust model training.

According to Lu and Ma [26], decision tree-based machine learning models, such as Random Forest (RF) and XGBoost, offer some important benefits that are critical when discussing water quality:

1) Capable of handling missing values:
   Decision tree-based models can deal with missing values effectively, even in equipment failures or other circumstances.
2) Increased prediction speeds:
   Only one decision tree building is required, so they are appropriate when short-term or real-time forecasts are crucial for monitoring water quality.
3) Preventing overfitting:
   Randomness is used in the training procedures. When working with complex datasets, overfitting is a common concern that is greatly reduced by this intentional unpredictability. Preventing overfitting becomes a crucial benefit in water quality prediction because the model's capacity to generalise to new, unseen data is essential.

Before training the models, the data is decomposed and denoised using CEEMDAN, a data-denoising technique. More obvious and comparable features are present in the same dataset because of this procedure.

Therefore, their study serves as an inspiration for our machine-learning methods. CEEDMAN is used for data decomposition in the prediction process, and data normalisation is then applied to reduce the dimensional influence of the data features. The data is then split into training and testing sets, and the models are trained using XGBoost and RF. Lastly, predictions are made using the trained model, and the final findings are obtained by denormalising the outcomes.

We plan to leverage our existing system in this work for initial data collection and subsequently employ the same methodology to develop prediction models through comparable techniques. These models will be stored on either our cloud server or back-end server to facilitate continuous predictions. This process aims to detect disparities between sensor readings and predicted values, verify potential sensor malfunctions, and forecast future trends and water parameter values.

5 Discussion

After installing our IoT water quality monitoring application at the aquafarm, the submerged sensors in the water tank effectively collect readings and send them via the microcontroller with an internet connection to the ThingSpeak Cloud Server. The readings are then successfully retrieved by our mobile application, giving customers access to a sophisticated, user-friendly dashboard that can be accessed through the mobile application, making it easy to analyse and display the information pertaining to the state of the water. Therefore, our IoT technology can potentially change how aquafarm water quality monitoring is done completely.

Manual testing techniques become outdated when data on water parameters is continuously and automatically collected in the aquafarm. Figure 17 shows that our system can capture and store water parameter conditions in CSV format. Figure 18 shows how to use a REST API to access these records easily.

A	B	C	D	E
created_at	entry_id	field1	field2	field3
2023-10-08 11:22:18 +0800	415466	6.35	29.125	8.092
2023-10-08 11:22:34 +0800	415467	6.28	28.967	8.09
2023-10-08 11:22:51 +0800	415468	6.25	28.625	8.088
2023-10-08 11:23:07 +0800	415469	6.22	28.996	8.089
2023-10-08 11:23:23 +0800	415470	6.29	28.777	8.089
2023-10-08 11:23:40 +0800	415471	6.32	28.635	8.089
2023-10-08 11:23:56 +0800	415472	6.36	29.167	8.078
2023-10-08 11:24:12 +0800	415473	6.42	28.739	8.072
2023-10-08 11:24:29 +0800	415474	6.48	28.73	8.066
2023-10-08 11:24:45 +0800	415475	6.35	28.918	8.077
2023-10-08 11:25:01 +0800	415476	6.28	28.536	8.075

Figure 17: Data records in CSV format

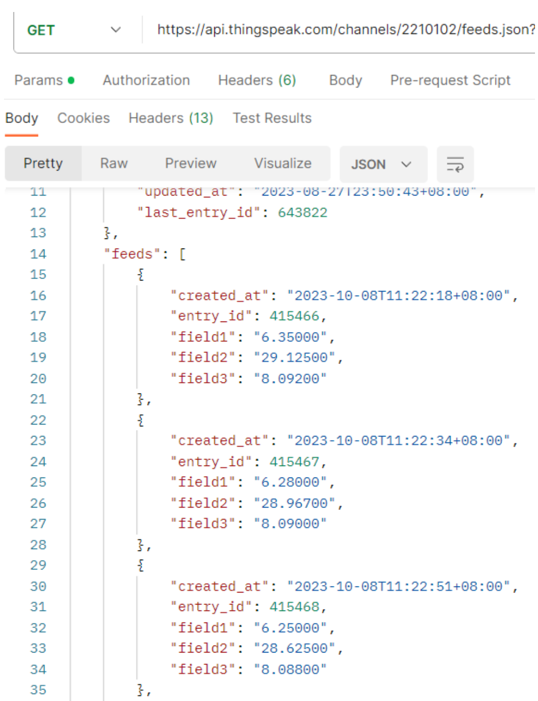

Figure 18: REST API for accessing records in CSV files

Aquafarmers can use the mobile application to monitor trends in water parameters, evaluate the quality of the water, and take preventative action when patterns point to an approaching departure from the safety range. The user-friendly analysis enables consumers to make well-informed judgements regarding whether to replace their water supply, eliminating the necessity for ongoing manual testing and speculation. This helps customers monitor water quality effectively while also streamlining procedures.

A vital component is the notification system, which instantly alerts farmers to any unexpected variables resulting in major shifts in the water parameters. This early information avoids possible fish kill incidents and assists farmers in identifying shortcomings, such as malfunctioning aeration systems. Furthermore, our approach greatly lowers the frequency of algae blooms for better water quality management. Finally, our technology can help farmers determine when to replace their water supply, potentially saving them from a massive loss in a single fish kill incident. The cost includes fish feed, water, energy, and the initial cost of the tilapia fish.

6 Conclusion

This work designs and implements an IoT-based aquaculture monitoring application. This scalable, mobile, and precise application promises to enhance aquaculture production. It saves labour costs by eliminating manual testing, decreasing losses, and averting critical circumstances. Through continuous real-time water quality monitoring, the application addresses the issues of operating fish farms using traditional, non-technical approaches.

Monitoring water quality in aquaculture can have significant social and economic benefits. Monitoring water quality parameters such as temperature, dissolved oxygen, pH, and ammonia levels allows for timely adjustments to create optimal conditions for fish growth. This can lead to healthier and faster-growing fish, ultimately increasing production and profitability. Maintaining optimal water quality conditions also helps reduce stress on fish and lowers the likelihood of disease outbreaks that cause mortality. Lower mortality rates mean higher yields and reduced financial losses.

Implementing IoT sensors for water quality monitoring can provide real-time data, allowing aquaculture farmers to make quick decisions and adjustments. This can result in more efficient resource utilisation, reduced labour costs, and increased productivity. Ensuring that water quality parameters are within acceptable limits helps to comply with environmental regulations, reducing the risk of possible legal issues. Early detection of water quality issues can prevent unnecessary losses. Improving aquaculture practices through water quality monitoring can increase fish production. This can enhance food security in Malaysia by providing a consistent and reliable source of protein for the population.

The aquaculture industry contributes to Malaysia's economy by generating income from domestic consumption and exports. Higher yields and better-quality fish can increase revenue and economic growth [25]. The expansion of aquaculture operations, driven by improved growth performance, can create jobs in rural and coastal areas, helping to reduce unemployment and poverty levels [24].

While our system has progressed significantly, it still has some limitations. Initially, we created the system effectively for data retrieval, dashboard display, and user alerts for water quality monitoring. However, one significant disadvantage is the system's inability to recognise when sensor accuracy recalibration is required. Furthermore, our technology is currently limited to inland farming in water tanks. Besides, network connectivity concerns inhibit the smooth transmission of data from sensors to the cloud and mobile applications. Deploying the application in areas with inadequate network coverage can lead to inconsistent data transfer, hindering users' ability to take prompt action. Network connectivity issues can disrupt data transmission from sensors to the cloud and the mobile application. Environmental factors like heavy rainfall can impact sensor performance, potentially resulting in inconsistent and inaccurate data readings. In addition, there is a recognised need for greater automation to solve this constraint and improve water quality control. Implementing a Recirculating Aquaculture System (RAS) is one possible approach. RAS includes water circulation, oxygenation, temperature management, and pH and chemical control, allowing for a holistic approach to maintaining optimal water conditions within the system. Furthermore, environmental factors such as severe rainfall could potentially disrupt sensor performance, resulting in inconsistent and inaccurate data readings.

In order to address present system constraints, our future work will focus on increasing automation through the deployment of a Recirculating Aquaculture System (RAS). RAS will extend the system's application beyond water tanks by incorporating advanced water quality control features. To solve the inadequate network coverage issue, we would integrate cellular backup into the microcontroller of the Data Acquisition Module to act as secondary communication capabilities when WiFi is unavailable, or the connection is weak.

Concurrently, we intend to use machine learning algorithms to analyse past data, find patterns, and forecast prospective water quality issues. These algorithms will not only allow for proactive decision-making and the prevention of hazardous situations but will also aid in the detection of discrepancies between sensor readings and expected values, the verification of probable sensor malfunctions, and the forecasting of future trends in water parameter values. This comprehensive approach seeks to make our system a strong and intelligent instrument for aquaculture management, assuring optimal conditions and supporting sustainability [22], [23].

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