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Data-Driven Water Monitoring System with Descriptive Analytics for Aquaculture Prawn Farms

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Abstract: This study aimed to develop a data-driven water monitoring system with descriptive analytics for aquaculture prawn farms. This system was designed to automate the monitoring of the water quality of the prawn farm so as to minimize labor and time spent for manually testing the water. Utilizing a rapid prototyping methodology, which is a rapid or quick creation of a prototype or a physical model of a device used in the development of a project, the said monitoring system was evaluated through a comparative analysis between the data gathered manually and the data collected by the monitoring system. To ensure reliability and validity of this monitoring system, it was used various times over several consecutive days. Also, a t-test was used to determine the significant differences between manual and system readings. Findings of the study showed that the designed water monitoring system provided accurate results, and the objectives of the study were met, particularly in terms of integrating a Raspberry Pi 3 microprocessor to automate the system in monitoring the water quality. It was also found out that the use of different sensors to test the water condition in terms of its temperature, pH level, salinity, dissolved oxygen, and turbidity was accurate. Furthermore, the system also met its objective of developing an Android mobile application to monitor the status remotely. With this, it is recommended for prawn farmers to utilize the system (with internet connectivity) for their efficient water quality management and to improve their remote monitoring capabilities.

Keywords: Aquaculture, Water monitoring system device, Microprocessor, Sensors

1. Introduction

Water monitoring plays a vital role in prawn farming. The quality of water affects the growth and production of prawns. According to the company named Alune [1], which was posted on The Fish Site, maintaining great water quality was crucial for several reasons. Great water quality makes ideal conditions for shrimp development. Decreasing the measures of alkali and natural particles lessens the

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chances of sickness. It ought to likewise decrease natural contamination from shrimp ranches' wastewater.

Furthermore, the prawn industry was one of the Philippines' most viable and profitable industries. The shrimp farming business was a significant source of revenue in Southeast Asia's inter-tropical countries and other developing inter-tropical countries. The shrimp business has developed quickly, generating billions of dollars in annual commerce, and employing millions of people throughout the world. Shrimp output worldwide, including wild and farmed, was estimated to be approximately seven (7) million metric tons [2].

Meanwhile, the quality of the water directly influences the growth, survival, and total output of shrimp. Disease, mortality, delayed development, and reduced shrimp output all affect poor water quality [3]. Good water quality was one of the most crucial requirements for prawn farming. A farmer should consider the water supply's seasonal availability, quality, and quantity while choosing his agricultural location [4]. Maintaining clean water and keeping all parameters within the usual range was crucial for shrimp farming to have healthy development and speedy growth [5].

Moreover, with the integration of the right and advanced technology in the system, the industry will produce undeniably great income and a sustainable livelihood for the people. However, the current system needs to be manually monitored in terms of its water quality to maximize the yield. It was therefore conceptualized to create an automated system, which is the data-driven water monitoring system with descriptive analytics for aquaculture prawn farms, that automatically checks their water condition to lessen the working time allotted for monitoring different parameters in the system.

The study aimed to create a Data-Driven Water Monitoring System with Descriptive Analytics for prawn farms. It focused on four main objectives:

1. Automating Monitoring: Integrate a Raspberry Pi 3 microprocessor to automate the water quality monitoring process.
2. Testing Water Conditions: Use various sensors to measure key water parameters, including temperature, pH level, salinity, dissolved oxygen, and turbidity.
3. Developing a Mobile App: Create an Android app to allow remote monitoring of water quality.
4. Validating Sensor Accuracy: Compare the data from the sensors with manually collected data to evaluate and confirm the accuracy of the system.

2. Review of Related Literature

The Raspberry Pi 3 has gained popularity for automating water quality monitoring in prawn farms due to its low cost, compact size, and ease of programming. Literature highlights its various applications, including Internet of Things (IoT), robotics, and industrial use, and details its technical specifications like processor speed, random access memory (RAM), and connectivity options. Its open-source nature and affordability make it accessible for small-scale farmers. The Raspberry Pi 3 shows great potential for revolutionizing aquaculture with real-time water monitoring and sustainable practices [6][7].

According to Chen *et al.* [8], Parra *et al.* [9], Razman *et al.* [10] and Olanubi *et al.* [11], sensor applications in water quality monitoring are essential for managing key parameters like temperature, pH, salinity, dissolved oxygen (DO), and turbidity, which directly impact prawn health and farm productivity. This study highlights the use of various sensors, such as thermistors, resistance temperature detectors (RTDs), electrochemical pH probes, and dissolved oxygen (DO) probes, to deliver accurate, real-time data for farm management. Calibration is crucial for maintaining sensor accuracy, with regular recalibration needed to account for environmental conditions. These sensors enable continuous monitoring and automation of water treatment systems, optimizing prawn farming efficiency and sustainability. The integration of sensors with microprocessors offers a data-driven approach, enhancing operational effectiveness in aquaculture.

Another study on mobile application development has become a vital tool in enabling farmers to remotely monitor and manage water quality in prawn farms. This section discusses the development of IoT-enabled Android applications, allowing farmers to track key metrics like temperature, pH, salinity, and dissolved oxygen in real-time, regardless of their location. These applications enhance farm productivity by providing timely alerts and facilitating proactive decision-making. Several studies highlight the integration of mobile apps with IoT technology, such as those by Mahmud *et al.* [12], and Olanubi *et al.* [11], which demonstrate improved monitoring capabilities, operational efficiency, and resource optimization in aquaculture. This study further developed a mobile app for prawn farms, offering users remote access to sensor data, empowering efficient farm management and improving yields. Furthermore, Tsai *et al.* [13], Chiu *et al.* [14], and Ya'acob *et al.* [15] emphasized the significance of IoT-based aquaculture systems in enhancing sustainability and resource efficiency, further emphasizing the potential of these technologies in revolutionizing the aquaculture industry.

The study by Yasin *et al.* [16] focuses on developing an automated system to control and monitor the pH levels in prawn breeding tanks, addressing the inefficiencies of manual methods traditionally used by farmers in Malaysia. Using an Arduino Uno controller, the system monitors pH levels and adjusts them automatically by adding alkaline or acidic substances as needed. The system also includes a Graphical User Interface (GUI) that allows farmers to monitor and control the water conditions in real-time. The automated pH control system ensures optimal water conditions, promoting prawn growth and reducing the need for manual labor. This solution is particularly beneficial for small-scale prawn farmers, offering a low-cost, efficient method to maintain water quality.

The study by Orozco-Lugo *et al*. [17] presents the development of a flying ad-hoc network (FANET) architecture for monitoring water quality in shrimp farms. The system focuses on critical water quality parameters, which are essential for shrimp survival and growth. The FANET platform, designed for mobile sensing, enables high-resolution spatial monitoring of water conditions without the need for extensive infrastructure. This mobile network offers a cost-effective and efficient solution for shrimp farmers, enhancing water quality management. The system is set to be deployed in shrimp farms in Colima, Mexico, after successful laboratory trials. The study highlights the potential of IoT technology to automate and streamline farm operations, allowing farmers to monitor water quality remotely via mobile apps, thus enhancing decision-making and productivity. This system represents a step toward more efficient and accessible prawn farming for small-scale farmers [8][18].

3. Methodology

The data-driven water monitoring system for prawn farms was designed to automate water quality checks, reducing manual labor and time. It uses five sensors to measure crucial water parameters—temperature, pH, salinity, dissolved oxygen, and turbidity—connected to a Raspberry Pi 3 microprocessor, which processes the data and controls the system. Data collected every five minutes is sent to a database and accessed via an Android app, providing remote monitoring with graphical displays and descriptive analysis. The project followed a rapid prototyping methodology with three phases: Concept (developing the idea and selecting components), Prototype (building, testing, and refining the system), and Production (validating performance and planning for patenting and commercialization). The system architecture includes the Raspberry Pi 3 Board, which controls the sensors and processes data, and relies on Wi-Fi to connect to the internet and transfer data to the mobile app. Hardware requirements include a personal computer, mobile device, Raspberry Pi 3 Model B, and various sensors, while software requirements encompass Raspberry Pi OS, MySQL, and development tools like Thonny IDE and Visual Studio Code.

3.1 Evaluation of the Study

The study assessed the effectiveness and accuracy of sensor systems by comparing data from manual methods with system sensor readings. A paired samples t-test was used to check for statistically significant differences between the two data sets, helping to evaluate how well the sensors match manual measurements. SPSS software was employed to analyze these differences, providing insights into the reliability and validity of the sensor system by calculating the mean, standard deviation, and standard error. Table 1 indicates the recommended range of water quality parameters as discussed by Van Wyk *et al.* [19] and Table 2 depicts the sustainability classification of recommended range for water quality parameters for prawn farms as cited by Uddin *et al.* [20].

Table 1. Recommended Range of Water Quality Parameters for Prawn Farms

Water Quality Parameter	Recommended Range
Temperature	28 – 32 °C
Dissolved Oxygen (DO)	5.0 – 9.0 mg/L
Turbidity	30 – 40 ntu
Salinity	0.5 – 35 μS/cm
pH	7.0 – 8.3

Table 2. Suitability Classification of Recommended Range for Water Quality Parameters

Water Quality Parameter	Suitability Classification		
	Most Suitable	Moderately Suitable	Least Suitable
Temperature	25 – 31	12 – 25	<12 – >32
Dissolved Oxygen (DO)	5.0 – 9.0	2.5 – 4.0	<2.5 – >9.0
Turbidity	30 – 40	18 – 35	<18 – >40
Salinity	1 – 15	15 – 35	>35
pH	6 – 8	4 – 6.8 – 9	<4 – >9

3.2 Data Gathering Instrument

To verify the accuracy of sensor-generated data, the study compared system readings with manually collected data over several days. A paired samples t-test was performed using SPSS software to assess if the differences between manual and system readings were statistically significant. The analysis involved consolidating both datasets, comparing readings, and using the t-test to evaluate the mean, standard deviation, and standard error of the differences. This statistical validation supports the reliability of the automated monitoring system and ensures that data-driven decisions are based on accurate information.

4. Results and Discussion

The analysis and interpretation of data from the study on the Data-Driven Water Monitoring System for Aquaculture Prawn Farms. The system was developed with a floating device protected by a polycarbonate twin wall roofing for water safety, Styrofoam boards for dryness, and swimming pool chlorine dispensers to secure the sensors, all held together by a Polyvinyl Chloride (PVC) pipe for buoyancy. Central to the system is the Raspberry Pi 3 Microprocessor, which automates and processes data from five different sensors — temperature, pH, salinity, dissolved oxygen, and turbidity — connected through 40 general-purpose input/output (GPIO) pins on the board. These sensors were chosen for their effectiveness, affordability, and practicality, and they continuously collect and transmit data to the Raspberry Pi for processing, as illustrated in the figures provided.

4.1 Evaluate and Validate the Accuracy of the Sensors by Comparing the System Generated Data to the Manually Generated Data

Table 3. Comparison of Temperature between Manual and System Readings

Time	Parameter Temperature	Time	Parameter Temperature
September 3, 2023	Manual Reading		System Reading
8:00	26.7	8:00	26.9
12:00	36.0	12:00	36.5
16:00	33.5	16:00	33.6
8:00	26.8	8:00	26.9
12:00	26.3	12:00	26.5
September 4, 2023			
4:00	25.8	4:00	25.5
8:00	26.4	8:00	26.4
12:00	34.9	12:00	34.5

16:00	32.8	16:00	32.9
8:00	26.4	8:00	26.5
12:00	25.4	12:00	25.4
September 5, 2023			
4:00	25.2	4:00	25.4
8:00	26.4	8:00	26.6
12:00	35.2	12:00	35.0
16:00	32.8	16:00	32.8
8:00	27.0	8:00	27.8
12:00	25.7	12:00	25.0
September 6, 2023			
4:00	25.2	4:00	25.5
8:00	26.4	8:00	26.2
12:00	35.2	12:00	35.2
16:00	33.1	16:00	33.0
8:00	28.0	8:00	27.9
12:00	26.3	12:00	26.0
September 7, 2023			
4:00	25.3	4:00	25.3
8:00	26.8	8:00	26.5
12:00	36.6	12:00	36.0
16:00	33.5	16:00	33.1
8:00	28.3	8:00	28.0
12:00	25.6	12:00	25.5

Table 3 compares water temperature measurements between manual and system readings. The data shows that the system's temperature measurements closely match those obtained manually, with only minor differences in decimal places. This indicates that the system provides nearly identical temperature readings compared to manual methods. The results suggest that the system is highly accurate and capable of automating temperature monitoring effectively. This automation is particularly valuable for real-time decision-making where precise temperature data is crucial. Overall, the system demonstrated strong accuracy and consistency, supporting its use in similar monitoring scenarios.

Table 4. Comparison of pH Level between Manual and System Readings

Time	**Parameter pH Level**	**Time**	**Parameter pH Level**
September 3, 2023	Manual Reading		System Reading
8:00	8.01	8:00	8.06
12:00	8.81	12:00	8.80
16:00	8.78	16:00	8.80
8:00	8.81	8:00	8.81
12:00	7.58	12:00	7.68
September 4, 2023			
4:00	7.83	4:00	7.90
8:00	8.23	8:00	8.20
12:00	8.59	12:00	8.60
16:00	8.72	16:00	8.70
8:00	8.16	8:00	8.18
12:00	8.16	12:00	8.16
September 5, 2023			
4:00	8.13	4:00	8.15
8:00	8.16	8:00	8.16
12:00	8.85	12:00	8.80
16:00	8.72	16:00	8.75
8:00	8.22	8:00	8.27

12:00	8.21	12:00	8.20
September 6, 2023			
4:00	8.10	4:00	8.10
8:00	8.09	8:00	8.10
12:00	8.79	12:00	8.75
16:00	8.78	16:00	8.76
8:00	8.10	8:00	8.10
12:00	8.10	12:00	8.10
September 7, 2023			
4:00	8.82	4:00	8.80
8:00	8.81	8:00	8.81
12:00	8.88	12:00	8.85
16:00	8.72	16:00	8.79
8:00	8.82	8:00	8.82
12:00	8.82	12:00	8.82

Table 4 compares pH level measurements recorded manually and by the system over several days. The pH levels varied between 7.58 and 8.88, with some minor differences between manual and system readings. For example, on September 3, 2023, at 8:00, the manual reading showed 8.01, while the system recorded 8.06. Despite these small variations, both methods generally provided similar results, indicating that the system is reliable for monitoring pH levels. The system consistently captured pH changes within an acceptable range, reflecting a mostly neutral to slightly alkaline environment. While occasional deviations were noted, the system's overall performance was reliable, though ongoing monitoring and adjustments are needed to maintain accuracy.

Table 5. Comparison of Salinity Level between Manual and System Readings

Time	Parameter Salinity	Time	Parameter Salinity
September 3, 2023	Manual Reading		System Reading
8:00	0.97	8:00	1.00

12:00	1.06	12:00	1.01
16:00	1.00	16:00	1.00
8:00	1.01	8:00	1.00
12:00	1.00	12:00	1.00
September 4, 2023			
4:00	0.97	4:00	1.00
8:00	0.98	8:00	1.00
12:00	0.96	12:00	1.00
16:00	1.00	16:00	1.00
8:00	0.97	8:00	1.00
12:00	1.00	12:00	1.00
September 5, 2023			
4:00	1.00	4:00	1.00
8:00	1.04	8:00	1.00
12:00	0.97	12:00	0.97
16:00	0.98	16:00	0.98
8:00	1.00	8:00	1.00
12:00	1.00	12:00	1.00
September 6, 2023			
4:00	1.00	4:00	1.00
8:00	0.98	8:00	1.00
12:00	1.02	12:00	0.98
16:00	1.00	16:00	0.98
8:00	0.98	8:00	1.00
12:00	1.00	12:00	1.00

September 7, 2023			
4:00	1.00	4:00	1.00
8:00	1.01	8:00	1.00
12:00	1.06	12:00	0.98
16:00	1.00	16:00	1.00
8:00	1.01	8:00	1.00
12:00	1.00	12:00	1.00

Table 5 compares manual and system readings of salinity levels in a prawn farm over several days. The results show that both methods produce consistent and aligned readings, indicating that the system is accurate and reliable for monitoring salinity. The minor fluctuations observed are within an acceptable range, reflecting stable water conditions. This consistency highlights the system's effectiveness in providing continuous and reliable salinity data, which is crucial for maintaining optimal prawn health. The close agreement between manual and system readings confirms that the Raspberry Pi 3 microprocessor is successfully integrated for real-time monitoring. This setup allows for timely data collection and prompt detection of any salinity changes, enabling farm operators to make quick interventions. The study shows how modern technology, like the Raspberry Pi 3, can enhance environmental monitoring and improve the efficiency and sustainability of prawn farming.

Table 6. Comparison of Dissolved Oxygen between Manual and System Readings

Time	**Parameter Dissolved Oxygen**	**Time**	**Parameter Dissolved Oxygen**
September 3, 2023	Manual Reading		System Reading
8:00	7.1	8:00	7.4
12:00	7.3	12:00	7.0
16:00	7.4	16:00	7.0
8:00	7.0	8:00	8.7
12:00	7.2	12:00	9.0
September 4, 2023			
4:00	8.5	4:00	8.5
8:00	9.1	8:00	8.6

12:00	8.5	12:00	8.5
16:00	8.6	16:00	8.5
8:00	9.0	8:00	7.0
12:00	9.0	12:00	7.0
September 5, 2023			
4:00	7.0	4:00	7.0
8:00	7.1	8:00	7.0
12:00	7.2	12:00	7.5
16:00	7.0	16:00	7.0
8:00	7.6	8:00	7.2
12:00	7.0	12:00	7.2
September 6, 2023			
4:00	7.0	4:00	7.2
8:00	7.2	8:00	7.2
12:00	7.2	12:00	7.2
16:00	7.2	16:00	7.2
8:00	7.2	8:00	7.2
12:00	7.1	12:00	7.2
September 7, 2023			
4:00	7.2	4:00	7.2
8:00	7.2	8:00	7.2
12:00	7.1	12:00	7.2
16:00	7.2	16:00	7.2
8:00	7.0	8:00	7.2
12:00	7.2	12:00	7.2

Table 6 shows a detailed comparison between manual and system readings of dissolved oxygen levels in an aquatic environment over several days. Dissolved oxygen is a critical parameter for assessing water quality, as it directly affects the survival and health of aquatic organisms. The data reveals variations in dissolved oxygen levels recorded at different times throughout the observation period. Both manual and system readings display fluctuations, but there are instances where significant differences between the two datasets are observed. Some variations are expected due to natural fluctuations in water quality.

Despite these differences, most of the data gathered from manual and system readings closely align, indicating the system's potential to accurately monitor dissolved oxygen levels. For instance, on September 6, 2023, at 8:00, both manual and system readings recorded a dissolved oxygen level of 7.2, demonstrating consistency between the two datasets. Overall, ongoing calibration of the monitoring system is crucial to maintaining the accuracy and reliability in measuring dissolved oxygen levels and ensuring the health and sustainability of the aquatic environment.

Table 7. Comparison of Turbidity Level between Manual and System Readings

Time	Parameter Turbidity	Time	Parameter Turbidity
September 3, 2023	Manual Reading		System Reading
8:00	11.1	8:00	11.0
12:00	11.1	12:00	11.0
16:00	11.0	16:00	11.0
8:00	11.7	8:00	11.1
12:00	11.0	12:00	11.0
September 4, 2023			
4:00	11.3	4:00	11.3
8:00	11.2	8:00	11.2
12:00	10.5	12:00	11.0
16:00	12.1	16:00	11.9
8:00	10.9	8:00	11.1
12:00	10.9	12:00	11.0
September 5, 2023			
4:00	11.0	4:00	11.0

8:00	11.7	8:00	11.5
12:00	11.2	12:00	11.0
16:00	10.6	16:00	11.0
8:00	11.0	8:00	11.0
12:00	11.0	12:00	11.0
September 6, 2023			
4:00	11.2	4:00	11.0
8:00	11.3	8:00	11.2
12:00	11.2	12:00	11.0
16:00	10.7	16:00	11.0
8:00	10.8	8:00	11.0
12:00	11.2	12:00	11.2
September 7, 2023			
4:00	10.6	4:00	11.0
8:00	11.2	8:00	11.2
12:00	13.7	12:00	13.0
16:00	12.0	16:00	12.0
8:00	11.2	8:00	11.1
12:00	10.0	12:00	11.0

Table 7 compares turbidity levels measured manually and by the system over several days. Turbidity, which indicates water clarity affected by suspended particles, showed some fluctuations in both readings. Generally, manual and system readings were closely aligned, showing consistency in turbidity measurement. For instance, on September 3, 2023, at 8:00, manual readings recorded a turbidity of 11.1, while the system showed 11.0. These minor differences did not affect the overall agreement between the two methods, confirming the system's effectiveness in monitoring turbidity. This consistency is crucial for assessing water quality and understanding environmental conditions. The reliable alignment between readings across different days suggests the system is a valuable tool for ongoing turbidity monitoring and environmental management. By using this monitoring system, stakeholders can make informed decisions to protect and preserve aquatic environments.

Table 8. Difference in the Measurements between Manual and System Readings

Parameter	Test	t/f value	Significance	Remarks
Temperature	t-test	0.708	0.485	Not Significant
pH Level	t-test	– 1.195	0.242	Not Significant
Salinity	t-test	0.511	0.613	Not Significant
Dissolved Oxygen	t-test	1.259	0.218	Not Significant
Turbidity	t-test	– 0.176	0.862	Not Significant

Table 8 shows that t-tests revealed no significant differences between manual and system readings for temperature, pH, salinity, dissolved oxygen, and turbidity. The pH, salinity, dissolved oxygen, and turbidity tests had significance levels of 0.242, 0.613, 0.218, and 0.862, respectively, indicating that both methods provide consistent and reliable measurements across all parameters.

4.2 Develop an Android Mobile Application to Monitor the Status Remotely

Figure 1. Mobile Application

The Android mobile application was developed to allow users to monitor water quality remotely. Once installed, the app’s home page, as shown in Figure 1, provides an overview of the latest reading from the floating device, along with tabs for accessing graphs and logs. On the Graph Page, users can view a graphical representation of the collected data. This page allows users to select a date range to see data trends over time, with both visual graphs and written interpretations of the data displayed below the graph. The Log Page presents the data in a numerical format. This page shows detailed logs of all collected readings, providing users with precise information about water quality parameters.

5. Conclusion and Recommendations

The study assessed the sensor system's accuracy by comparing data collected manually with readings from the system sensors, focusing on water quality parameters. It used suitability classification and a t-test to validate the sensor system’s reliability. The results showed:

1. Minimal differences between manual and system readings demonstrated high accuracy, suggesting the system's potential for reliable real-time temperature monitoring.
2. Although there were slight differences between manual and system readings, both methods generally matched, indicating the system’s reliability in capturing pH levels accurately.
3. Consistent results between manual and system readings affirmed the system's accuracy in monitoring salinity, supporting stable water conditions for prawns.
4. Strong alignment between manual and system readings highlighted the system’s effectiveness in monitoring dissolved oxygen levels precisely.
5. Despite minor fluctuations, consistent alignment between manual and system readings underscored the system’s reliability in turbidity monitoring.
6. The t-test confirmed no significant differences between manual and system readings, validating the system's reliability.

The study concluded that the Data-Driven Water Monitoring System successfully integrated the Raspberry Pi 3 for automation, effectively utilizing five sensors to monitor water quality. The mobile application provided accurate graphical data and enabled remote monitoring. Additionally, the comparison between manual and system readings revealed no significant differences, confirming the reliability of the sensors.

Based on the results, the study recommends the following:

1. Deploy the system in prawn farms with internet access.
2. Conduct future studies to explore integrating solar panels for improved power supply.
3. Add sensors for Nitrate, Phosphate, and advanced turbidity to enhance monitoring capabilities.
4. Incorporate SMS notifications and recommend mitigation activities for better decision-making.

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