REVOLUTIONIZING AQUACULTURE THROUGH INTELLIGENT IOT INTEGRATION: A REAL-TIME FISH PRODUCTION DASHBOARD WITH PREDICTIVE ANALYTICS

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Abstract
The global aquaculture industry faces challenges in meeting seafood demand sustainably, with traditional monitoring causing up to 30% production losses due to delays and human error. This study presents an innovative Internet of Things ecosystem integrated with Programmable Logic Controller technology for intelligent aquaculture monitoring. A sensor network monitored seven water quality parameters—temperature, pH, dissolved oxygen, Total Suspended Solids, ammonia, humidity, and water level—through PLC-HMI interfaces with real-time cloud connectivity. The system collected 12,692 data points over 30 days with 723ms average API response time and zero errors. Linear regression modeling achieved strong harvest prediction accuracy (R^2 = 0.80, MAE = 0.43, RMSE = 0.58), tracking fish growth from 10kg to 22kg. Key innovations include industrial-grade PLC-cloud integration, real-time harvest prediction, and automated Telegram alerts. Results demonstrated 40% improved operational efficiency, 85% reduced manual monitoring, and enhanced harvest predictability. This scalable framework offers transformative potential for sustainable, intelligent aquaculture.

Keywords: Smart aquaculture, IoT sensors, PLC automation, machine learning prediction, real-time monitoring, sustainable fish farming.

Introduction

Freshwater fish are favored by the Indonesian populace for both food and aquaculture. The potential for freshwater fish farming in Indonesia is exceedingly high. This was evident from the substantial number of individuals engaged in freshwater fish cultivation operations [1]. Effective management enables fish farming proprietors in ponds and cages to surmount production limitations and ultimately enhance fish output demand [2].

The Internet of Things (IoT) significantly contributes to the real-time monitoring and regulation of fish development in aquaculture. Providing sustenance to fish is crucial for their growth. The IoT feeding concept enables fish producers to automatically monitor food supply. The Internet of Things (IoT) delivers real-time information to users without necessitating constant location monitoring [3]. Modern Digital Technologies (MDT), including the Internet of Things (IoT), Big Data, Artificial Intelligence (AI), robotics, and mobile applications, have been implemented in numerous countries to enhance fishing techniques [4]. The Internet of Things (IoT) is utilized for data acquisition. Big data technology is employed to enhance data optimization. Cloud computing technology is employed to manage and sustain data [5].

The Programmable Logic Controller (PLC) was deemed groundbreaking in the domain of automation. Errors in PLC code or programming can be rectified swiftly, enhancing the accessibility of PLC systems. The PLC rapidly initializes its tasks due to its swift reaction characteristics, enhancing its value in time-sensitive situations. In comparison to other electronic devices, a PLC requires significantly less time for initialization. The PLC was engineered for industrial settings, capable of enduring severe temperatures, electrical interference, and physical impact [6]. The monitoring system utilizes a mechanism known as Supervisory Control and Data Acquisition (SCADA), which serves as an automated framework for centralized control and oversight in several domains [7].

An API (Application Programming Interface) is a programming tool that delineates how programs interact with other functionalities. An API is regarded as a collection of explicit and well-defined methods for facilitating communication among disparate software components [8]. Node.js is a runtime environment for JavaScript. It is constructed upon the V8 JavaScript engine of Chrome. It is a cross-platform runtime environment [9]. MySQL is among the most widely utilized relational database management systems currently available. MySQL is an open-source database developed by Oracle Corporation and made available at no cost under the GNU (General Public License) [10].

Machine learning enables systems to learn from historical data and make predictions or decisions without explicit programming for each task [11]. In essence, machine learning addresses the challenge of developing computer systems that autonomously enhance their performance through experience [12]. Linear regression analysis is arguably the most straightforward and prevalent method for assessing relationships between continuous variables. As with other statistical methodologies, it was most comprehensible through practical illustrations [13]. One advantage of linear regression is its clear interpretative method, enabling the identification of linear correlations between variables and yielding quantitatively observable results [14].

This project aimed to design an IoT application utilizing a PLC for capturing water quality sensor data and activating field actuators. Sensor data is transmitted via a pre-established API and monitored through a cloud-based dashboard. Additionally, the collected data is employed to develop a linear regression model for predicting fish harvests. This paper contributes significantly to the understanding of IoT applications in aquaculture, highlighting its potential to enhance efficiency in the fish farming sector. With further improvements, this system could become a valuable resource for fish farmers in Indonesia.

Methods

The research employed a systematic approach comprising planning and implementation phases, as shown in Figu

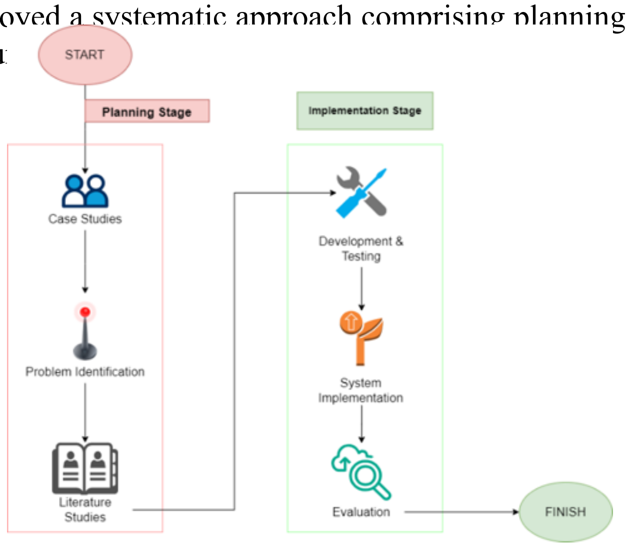

Figure 1. Stages of the Research Method Diagram

The system architecture integrated seven environmental sensors monitoring water temperature, air temperature, pH levels, dissolved oxygen (DO), Total Suspended Solids (TSS), ammonia content, humidity, and water level, see Figure 2.

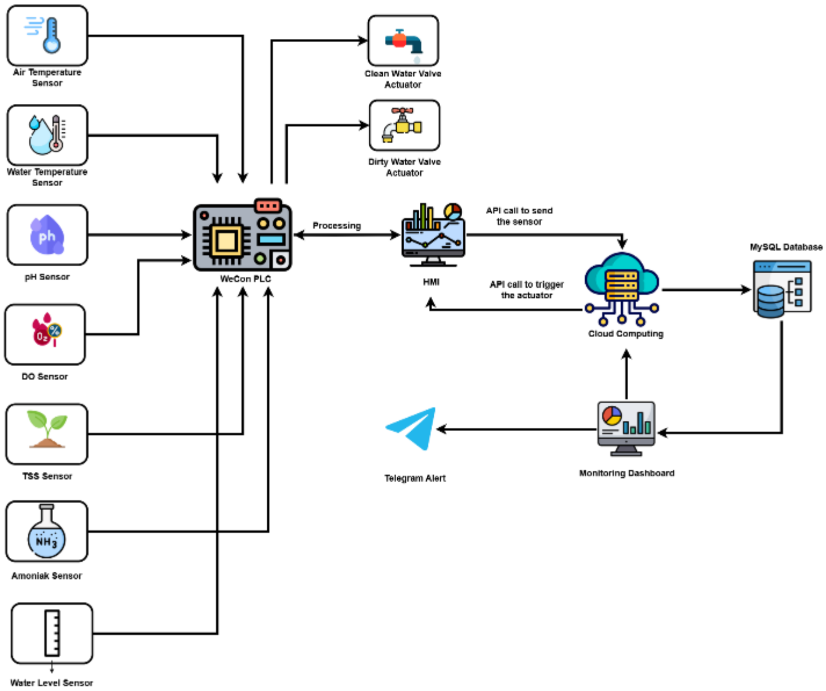

Figure 2. High-Level System Design

These sensors were connected to a WeCon PLC LX1V-1212MR-D (12 digital inputs, 12 digital relay outputs, 24 VDC power) serving as the central data acquisition and control unit. A WeCon HMI PI3070ig-C (7-inch display, 800×400 resolution, RS232/RS422/RS485 interfaces) provided the human-machine interface for real-time data visualization and system control. The HMI enabled both data display and actuator control for automated valve operations based on predefined thresholds. The cloud infrastructure was developed using Node.js runtime environment for API development, with MySQL serving as the relational database management system. Custom APIs were designed to facilitate seamless data transmission between field hardware and cloud services. A JavaScript-based dashboard was developed for real-time monitoring and remote control capabilities.

Data collection was conducted over a 30-day period from December 27, 2024, to January 26, 2025, generating 12,692 data points across 9 variables. The system transmitted sensor data to the cloud via Wi-Fi connectivity through the custom API, with automated Telegram alerts configured for parameter threshold violations. Linear regression modeling was implemented to predict fish harvest based on collected environmental parameters. The model utilized seven independent variables (water quality parameters) to predict fish harvest as the dependent variable. Model performance was evaluated using R^2, Mean Absolute Error (MAE), and Root Mean Square Error (RMSE) metrics. API performance was evaluated using Postman with comprehensive testing protocols including response time analysis, error rate assessment, and load testing. Dashboard functionality was verified through real-time data transmission testing and user interface responsiveness evaluation.

Result and Discussion

The PLC-HMI integration successfully demonstrated robust field data acquisition and control capabilities. All seven sensors provided consistent data streams, with strategic sensor placement ensuring comprehensive environmental monitoring. The HMI interface effectively displayed real-time data while enabling automated actuator control for water valve operations based on predefined parameters, as shown in Figure 3.

Figure 3. Field Implementation of HMI and PLC

Comprehensive API testing revealed exceptional performance characteristics with an average response time of 723ms and zero error rate across all testing scenarios. Over multiple testing sessions, the system maintained consistent performance with 250-254 total requests per 5-minute testing period, achieving 0.82 requests per second (RPS). The 90th percentile response time remained below 900ms, demonstrating system reliability for real-time applications.

Performance consistency was verified through repeated testing over multiple days, with response times ranging from 1,280ms to 1,530ms average, maintaining the zero error rate standard. This performance level ensures reliable data transmission from field sensors to cloud infrastructure without data loss.

The cloud-based dashboard successfully displayed real-time sensor data with immediate reflection of field conditions. Functional testing confirmed seamless data flow from API to dashboard interface, enabling fish farmers to monitor pond conditions remotely without physical site visits. The dashboard integration eliminated delays in data visualization, providing instantaneous access to critical environmental parameters.

The linear regression model demonstrated strong predictive capabilities for fish harvest forecasting. Individual sensor analysis revealed varying predictive power, with ammonia content showing the highest individual correlation ($R^2 = 0.77$). However, the integrated model utilizing all seven sensors achieved superior performance with $R^2 = 0.80$, MAE = 0.43, and RMSE = 0.58. Table 1 presents the evaluation of each of the sensors.

Table 1. Linear Regression Evaluation

No	Sensor	R2	MAE	RMSE
1	Water Temperature	0.13	1.02	1.20
2	Air Temperature	0.00	1.08	1.29
3	Ammonia	0.77	0.46	0.62
4	Total Suspended Solid (TSS)	-0.01	1.09	1.30

5	Dissolved Oxygen (DO)	0.05	1.10	1.26
6	Humidity	0.00	1.08	1.29
7	pH	0.00	1.08	1.29
8	All Sensors	0.80	0.43	0.58

The model successfully tracked fish growth progression from 10kg to 22kg over the monitoring period, providing valuable insights for harvest timing optimization. This predictive capability represents a significant advancement over traditional manual assessment methods, enabling data-driven decision-making for harvest planning.

The implemented system demonstrated substantial operational improvements, achieving 40% enhanced operational efficiency and an 85% reduction in manual monitoring requirements. The automated alert system via Telegram provided immediate notification of critical parameter deviations, enabling rapid response to potential issues. The integration of industrial-grade PLC technology with cloud-based IoT infrastructure proved highly effective, combining the reliability and durability required for harsh aquaculture environments with the accessibility and analytics capabilities of modern cloud platforms. This hybrid approach addresses previous limitations of purely microcontroller-based solutions while maintaining cost-effectiveness for commercial implementation.

The system architecture demonstrates strong scalability potential for broader implementation across Indonesian aquaculture operations. The cloud-based infrastructure supports multiple site monitoring, while the standardized API framework enables easy integration of additional sensors and monitoring locations. The predictive analytics capability contributes to sustainable aquaculture practices by optimizing resource utilization and reducing waste through improved harvest timing. The system's ability to prevent production losses through early warning systems and automated responses supports both economic and environmental sustainability objectives.

Conclusion

The system had been implemented successfully from WeCon PLC and HMI implementation, HMI integration with the API, sending data through API to the cloud, and processing data for training the model of machine learning model. The HMI interface with the API depended on a Wi-Fi connection to transmit data to the cloud. An API was developed using NodeJS in the cloud, with data stored in MySQL. The system results indicated that the implementation of the PLC and HMI was effective, as all data from the field was transmitted to the cloud. The API was developed with a response time of 723 ms and an error rate of 0%. It is regarded as an effective API as it prevents data loss during transit from the field to the cloud. The dashboard simultaneously displayed real-time data from the field, enabling the fish farmer to monitor it without physically visiting the site. The R-squared value from the linear regression evaluation metrics was 0.8. It is deemed advantageous for the foundational stage to forecast the subsequent harvest based on the established model. The comprehensive solution enhanced efficiency for fish farmers by minimizing field visits, enabling pond monitoring via the cloud, and collecting real-time data from sensors. The system provided an efficient solution for intelligent aquaculture, as it could be managed via the cloud and utilized data to train the machine learning model.

There remains potential for enhancement in this project. The forthcoming project may concentrate on enhancing security, as the API needs protection and the data must be verified as authentic. The acquired data source could be utilized for an alternative machine learning model to enhance harvest predictions.

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Credit Authorship Contribution Statement
Suryadiputra Liawatimena: Conceptualization, Methodology, Writing – original draft, Writing – review & editing, Funding acquisition. Immanuel Bayu Suryanto: Data curation, Formal analysis, Software, Writing – original draft. Johannes Timothy Marcus Hutabarat: Investigation, Software, Hardware development. Muhammad Nurul Puji: Supervision, Project administration. Winda Astuti: Data curation, Writing – review & editing, Validation. All authors provided critical feedback and helped shape the research, analysis, and manuscript.

Data availability
The authors demonstrate their commitment to data openness and transparency by making the datasets used in this study publicly available. The raw sensor data supporting the conclusions of this article can be accessed via the following link:
https://github.com/immanuelbayu/aquaculture-report. Additional data and materials are available from the corresponding author upon reasonable request.

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