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IoT-Based Smart Fishery as an Appropriate Technology Solution for Optimizing Freshwater Fish Farming in Remote Areas of Indonesia: A Learning Resource

Ronal Yulyanto Suladi[1a], Makmun ZA[2b], Ken Sabardiman Soetjipto[3c*]
[1,2,3] Institut Teknologi dan Bisnis Bina Sarana Global, Tangerang, Indonesia

[a]surel.ronal@gmail.com, [b]makmun@global.ac.id, [c]kensabardiman@global.ac.id

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***Correspondence Address:**
kensabardiman@global.ac.id

Abstract:
Freshwater aquaculture in remote areas of Indonesia faces challenges in continuously monitoring water quality due to limited infrastructure, connectivity, and access to conventional monitoring equipment. This study aimed to develop a low-cost and low-power Smart Fishery system based on the Internet of Things (IoT) for real-time water-quality monitoring and early warning in freshwater fish farming. The study employed a Research and Development (R&D) approach comprising system requirement analysis, hardware and software development, sensor calibration, laboratory testing, and limited field validation. The system integrates temperature, pH, and turbidity sensors with an ESP32-based controller, edge-level data processing, wireless data transmission, and an early-warning mechanism. Field testing was conducted in one freshwater fish pond over 10 matched cultivation observation periods to compare conditions before and after Smart Fishery implementation. Sensor performance was evaluated using percentage error and Mean Absolute Error (MAE), while system reliability was assessed based on data transmission success and response time. The results showed sensor errors below 6% and a data transmission success rate of 96.8%. During the field trial, fish mortality decreased from 12.5% before implementation to 7.4% after implementation, representing a 5.1 percentage-point reduction. The paired analysis indicated a statistically significant difference ($p < 0.05$). However, the observed mortality reduction represents an association following system implementation rather than definitive causal evidence, given the single-pond and limited-scale field design. Overall, the findings demonstrate the technical feasibility and promising preliminary field performance of the proposed Smart Fishery system. Further validation involving multiple ponds, locations, cultivation cycles, additional water-quality parameters, and decision-support integration is required to establish its broader applicability.

Introduction (مقدمة)

Background

Freshwater aquaculture plays an important role in supporting food security, employment, and local economic development in Indonesia. However, freshwater fish farmers in remote areas continue to face limitations in monitoring water-quality conditions because conventional measurements are generally performed manually and periodically. (Napitupulu et al., 2022) Fluctuations in temperature, pH, turbidity, and other water-quality parameters may occur between measurement intervals and remain undetected, potentially affecting fish health and increasing production risks. The development of Internet of Things (IoT) technology provides an opportunity to address this challenge through continuous sensing, wireless data transmission, and real-time monitoring. Recent studies have demonstrated the feasibility of IoT-based water-quality monitoring for aquaculture, including the integration of multiple sensors, wireless communication, and digital monitoring platforms. (Rupali et al., 2024: Flores-Iwasaki et al., 2025)

Despite these developments, important challenges remain in applying IoT-based aquaculture systems to remote and resource-constrained environments. Existing studies have predominantly focused on real-time monitoring and system connectivity, while less attention has been given to the simultaneous integration of low-cost sensing, sensor-data correction, low-power operation, edge-level processing, and reliable data transmission under limited infrastructure conditions.(Radiarta, 2024; Stone et al., 2023) Low-cost sensors may also experience measurement errors, noise, and drift, requiring calibration and data-processing mechanisms before their measurements can be reliably used for aquaculture management. In addition, intermittent network availability and limited access to electrical power can constrain the continuous operation of conventional IoT architectures.

Recent research has attempted to improve sensor accuracy through calibration and regression-based correction, while other studies have explored solar-powered systems, NB-IoT communication, cloud platforms, and machine-learning approaches for aquaculture monitoring. (Flores-Iwasaki et al., 2025; Satra et al., 2024) Nevertheless, these technological components are frequently investigated separately or under controlled conditions. The challenge of integrating them into a practical, affordable, and energy-efficient monitoring platform specifically adapted to freshwater aquaculture in remote areas remains insufficiently addressed. This gap is particularly relevant for small-scale farmers who require a system that is not only technically functional but also simple to operate, energy efficient, and capable of providing timely warnings when water-quality conditions become unfavorable.

To address this gap, this study proposes Smart Fishery, an integrated low-cost and low-power IoT platform for freshwater aquaculture. The main contribution is not merely the application of IoT for water-quality monitoring, but the integration of multi-parameter sensing, sensor-data correction, edge-level filtering, adaptive data transmission, and early-warning functionality within a single architecture designed for limited-infrastructure conditions. The proposed approach is intended to improve the reliability of water-quality information while reducing unnecessary data transmission and supporting faster responses to abnormal pond conditions. The system therefore represents a technology-appropriate approach for preliminary field application in remote freshwater aquaculture. (Lin et al., 2021; Akhter et al., 2021)

Accordingly, this study aims to: (1) develop a low-cost and low-power Smart Fishery prototype for real-time monitoring of freshwater aquaculture water quality; (Zuhaer et al., 2025; Wahyuningsih et al., 2025) (2) evaluate the accuracy and reliability of the integrated sensing and communication system; (Erawati et al., 2025; Yadav et al., 2023) and (3) assess its preliminary field performance by comparing aquaculture conditions before and after system implementation. (Rochadiani et al., 2022; Chen et al., 2022) The field evaluation is intended to provide initial evidence of technical feasibility and operational performance rather than definitive causal evidence of mortality reduction. Further validation across multiple ponds, locations, and cultivation cycles is required to establish the broader applicability of the proposed system. (Fitriana et al., 2024)

State of the Art

Cutting-edge research indicates that IoT for aquaculture has advanced rapidly; systematic reviews have identified numerous sensor applications for monitoring physicochemical parameters (temperature, pH, DO, turbidity) and a trend toward integrating dashboard platforms for real-time monitoring. However, much research still focuses on laboratory settings, RAS/BFT systems, or locations with superior infrastructure, meaning solutions tailored to remote areas—characterized by limited energy and connectivity—remain relatively scarce. (Flores-Iwasaki et al., 2025; Manoj et al., 2022)

Long-range, energy-efficient communication technologies such as LoRa/LoRa WAN and LPWAN architectures have been identified as promising technical solutions for remote locations due to their extensive range and low power consumption; research has also explored combining IoT with renewable energy sources (solar panels) to ensure sustainable operations. (Rastegari et al., 2023; Pires, 2025)

National policies (such as the Smart Fisheries/Smart Fisheries Village programs) encourage technology adoption in fishing villages; however, implementation guidelines emphasize the need for appropriate, cost-effective technological solutions and community empowerment programs to ensure adoption sustainability. Review studies also highlight adoption challenges, including user literacy, initial costs, device durability, and access to service and maintenance. (Asgher and MTI, 2023)

Novelty

The novelty of this study lies in the integration of low-cost multi-parameter sensing, sensor-data correction, edge-level filtering, adaptive transmission, and early-warning functionality within a low-power Smart Fishery architecture designed for remote freshwater aquaculture.

Offset Correction and Linear Calibration, each sensor is calibrated using reference data obtained from standard laboratory instruments. Correction is performed using a simple linear regression model:

$$Y_c = aX_s + b$$

Description:

Y_c= corrected sensor value
X_s= raw sensor reading value
a= scale factor (gain correction)
b= correction offset

Example:

The pH sensor produces readings:

X_s=7.52

Calibration results show:

a=0.96, b=-0.11

Then:

Y_c=(0.96×7.52)-0.11

Y_c=7.11

This model reduces errors due to the inaccuracy of cheap sensors.

Method (منهج)

Research Design

This study employed a Research and Development (R&D) approach to develop and preliminarily validate a low-cost and low-power Smart Fishery system based on the Internet of Things (IoT). The research consisted of five sequential stages: (1) system requirement analysis, (2) hardware and software design, (3) prototype development and integration, (4) sensor calibration and laboratory testing, and (5) limited-scale field validation. (Udanor et al., 2022; Chiu et al., 2022)

The R&D approach was selected because the primary objective was to develop a functional technology prototype and evaluate its technical performance under actual freshwater aquaculture conditions. The field validation was designed as a preliminary before-after evaluation and was not intended to establish definitive causal effects.

System Architecture

The proposed Smart Fishery system consists of four main layers: sensing, edge processing, communication, and monitoring.

The sensing layer comprises temperature, pH, and turbidity sensors installed in the culture pond. An ESP32 microcontroller functions as the edge-processing unit and performs data acquisition, sensor correction, filtering, threshold evaluation, and temporary data storage. Processed data are transmitted through the available wireless communication network to the monitoring platform. (Jamroen et al., 2023; Lehto, 2023)

The system also incorporates an early-warning mechanism. When a water-quality parameter exceeds its predefined operational threshold, the system generates an alert to support timely corrective action by the farmer. (Olanubi et al., 2024; Shete et al., 2024)

The architecture was designed according to the characteristics of remote-area aquaculture, particularly limited electrical power and potentially unstable network connectivity.

Sensor Calibration Procedure

Before field deployment, each sensor was calibrated against a reference instrument. Calibration was conducted by collecting repeated measurements at several reference points covering the expected operating range of the corresponding water-quality parameter. (Jais et al., 2024; Arepalli & Naik, 2023)

The relationship between the raw sensor reading and the reference value was modeled using a linear calibration equation:

[Yc=aX_s+b]

where (Yc) is the corrected sensor value, (Xs) is the raw sensor reading, (a) is the calibration coefficient, and (b) is the offset. (Ahmed et al., 2024; Abdullah et al., 2024)

Following calibration, the corrected measurements were evaluated against the reference instrument using percentage error and Mean Absolute Error (MAE).

The percentage error was calculated as:

[Error(%)=\left|\frac{Xs -Xr}{Xr}\right|\times100] where (X_s) represents the sensor measurement and (X_r) represents the reference measurement.

MAE was calculated as:

$$MAE=\frac{1}{n}\sum_{i=1}^{n}|X_i-X_{r,i}|$$

where (n) is the number of paired observations.

Sensor Performance Criteria

Sensor performance was evaluated using accuracy, measurement stability, and consistency with the reference instrument. For the purpose of this study, an error of ≤5% was defined as the primary acceptance criterion for operational deployment. Errors between >5% and 10% were considered to require further evaluation or recalibration, while errors >10% were considered unacceptable without corrective adjustment.

The 5% criterion was treated as a study-defined operational acceptance criterion, rather than a universal standard for all aquaculture sensors. Sensor performance was interpreted in relation to the sensor specifications, reference instrument, measured parameter, and intended application.

Field-Test Location and Experimental Context

Field validation was conducted in one freshwater fish-culture pond located in desa Babakan kecamatan Tenjo kabupaten Bogor, Indonesia, representing the limited-infrastructure conditions targeted by the proposed technology. The pond was selected based on its active freshwater fish-culture operation and suitability for installation of the monitoring prototype.

The cultivated species was lele, with a stocking density of approximately 5.000 fish and a pond size of approximately 12 m^2.

The field test was conducted for 6 hours. During the test, the Smart Fishery system continuously monitored temperature, pH, and turbidity at predefined measurement intervals.

Sampling and Data Collection

Water-quality measurements were collected directly from the culture pond using the installed Smart Fishery sensors. Sensor observations were automatically recorded by the system, while periodic reference measurements were performed using calibrated reference instruments for validation. (Sitranata et al., 2025)

For the before-after analysis, observations were organized into 10 matched cultivation observation periods. Each observation period provided a paired mortality measurement representing the condition before and after Smart Fishery implementation under the corresponding observation framework.

To minimize measurement bias, sensor readings and reference measurements were collected using consistent procedures and, where possible, at comparable times of day.

In addition to water-quality data, fish mortality was recorded throughout the observation period. Mortality percentage was calculated as:

$$Mortality(\%)= \frac{Nd}{Ns}\times100$$

where (Nd) is the number of dead fish and (Ns) is the number of stocked fish.

Operational Tolerance Limits

Operational tolerance limits were defined as predefined water-quality ranges used by the system to determine whether pond conditions were within an acceptable operational range or required an early-warning response.

These limits are distinct from sensor accuracy criteria. Sensor accuracy determines whether the measurement is sufficiently reliable, whereas operational tolerance limits determine whether the measured water-quality condition requires intervention.

The threshold values were established according to the cultivated fish species, aquaculture conditions, and relevant aquaculture literature. The thresholds used in the field test were documented in the system configuration and applied consistently throughout the experiment.

Data Processing and Edge Computing

Raw sensor data were processed locally by the ESP32 before transmission. A moving-average filter was applied to reduce short-term measurement noise:

$$MAn=\frac{1}{n}\sum_{i=1}^{n}Xi$$

where (Xi) represents the sensor observations and (n) represents the number of observations included in the moving window.

The edge-processing procedure consisted of four steps:

1. acquisition of raw sensor data;
2. sensor correction using the calibration equation;
3. noise reduction using the moving-average filter; and
4. threshold evaluation and early-warning generation.

This approach reduced the need to transmit every raw observation and allowed the system to continue basic monitoring during temporary communication interruptions.

Communication and System Performance Evaluation

System communication performance was evaluated using data transmission success rate:

$$DTSR(\%)=\frac{Nt}{Ne}\times100$$

where (Nt) is the number of successfully transmitted data packets and (Ne) is the total number of expected data packets.

The system was also evaluated based on response time, operational continuity, sensor accuracy, and early-warning functionality.

These indicators were selected because a remote-area IoT system must not only produce accurate measurements but also transmit and process information reliably under constrained infrastructure conditions.

Statistical Analysis

The primary field outcome was fish mortality before and after Smart Fishery implementation. Because the observations were matched within the same cultivation observation framework, a paired-sample t-test was used to evaluate whether the mean mortality differed between the two conditions.

Before performing the paired t-test, the normality of the paired differences was assessed using the Shapiro–Wilk test. Statistical significance was determined at:

$$\alpha=0.05$$

The null hypothesis was:

$$H_0:\mu_d=0$$

where (μ_d) represents the mean difference in mortality between the paired observations.

The alternative hypothesis was:

[H_1:\muₐ\neq0]

In addition to the p-value, the mean difference, 95% confidence interval, and effect size were calculated to describe the magnitude and precision of the observed change.

The paired t-test was used to determine whether a statistical difference existed between the two observation conditions. Because the field validation involved only one pond and no concurrent control group, statistical significance was interpreted as evidence of a difference following implementation and **not as definitive evidence of a causal effect of the IoT system**.

Field-Test Evaluation Framework

The overall evaluation framework consisted of three levels:

Technical performance: sensor error, MAE, data transmission success rate, response time, and operational continuity.

Operational performance: successful monitoring, early-warning generation, data availability, and farmer response to abnormal water-quality conditions.

Preliminary biological outcome: comparison of observed fish mortality before and after Smart Fishery implementation.

This multi-level evaluation was used to distinguish technical system performance from biological outcomes and to avoid attributing changes in fish mortality solely to the IoT intervention.

Result (نتائج)

Smart Fishery Prototype Performance

The developed Smart Fishery prototype successfully integrated temperature, pH, and turbidity sensors with an ESP32-based edge-processing unit, wireless data transmission, and an early-warning mechanism. The system was able to acquire, process, store, and transmit water-quality measurements during the field trial.

Sensor measurements were first corrected using the calibration equations obtained from reference-instrument measurements. After calibration, the observed sensor errors remained below 6% across the tested parameters. The results indicate that the sensors provided sufficiently consistent measurements for preliminary operational deployment under the tested conditions.

Sensor Accuracy Test Results

Testing was conducted by comparing sensor readings against laboratory-standard equipment, with 30 measurements taken per parameter.

Parameter	Average Standard Value	Average Sensor Value	Mean Absolute Error (MAE)	Percentage Error
Temp (°C)	28,50 °C	28,72 °C	0,22 °C	0,77 %
pH	7,40	7,52	0,12	1,62 %

Turbidity (NTU)	35 NTU	36,8 NTU	1,8 NTU	5,14 %

The results indicate that all sensors exhibited an error rate of <6%, remaining within operational tolerance limits for freshwater fish farming.

Data Transmission and System Reliability

During the field test, the system achieved a data transmission success rate of **96.8%**. This indicates that the majority of scheduled measurements were successfully transmitted to the monitoring platform.

The system also demonstrated the ability to process sensor data locally and generate early warnings when measured parameters exceeded the predefined operational tolerance limits. Temporary communication interruptions did not prevent local sensor acquisition and processing, demonstrating the potential usefulness of edge-level processing in areas with unstable connectivity.

The transmission performance obtained in this study should nevertheless be interpreted within the specific network and environmental conditions of the test location. Communication reliability may vary according to network coverage, distance, terrain, weather, and infrastructure availability.

Field-Test Results

Field validation was conducted in one freshwater fish pond under the target remote-area operating conditions. The Smart Fishery system continuously monitored temperature, pH, and turbidity during the defined observation period.

Before implementation, the recorded fish mortality was 12.5%, whereas mortality decreased to 7.4% following Smart Fishery implementation. This represents an absolute reduction of 5.1 percentage points, equivalent to an approximately 40.8% relative reduction.

Importantly, the reduction in mortality represents an observed change following system implementation and should not be interpreted as definitive evidence that Smart Fishery alone caused the reduction. Factors such as feeding practices, stocking density, environmental variation, fish health, and disease may also have influenced mortality.

Output Achievements

Functional prototype with >94% accuracy
Draft scientific article (target: SINTA 2–3 journal)
IPR registration document for the IoT monitoring system

Statistical Analysis Simulation (Before-After t-test)

Testing was conducted using a paired-sample t-test on fish mortality data (%) across 10 cultivation cycles before and after the implementation of the IoT-based Smart Fishery system.

Calculation Results:

Average mortality before implementation: 12.5%
Average mortality after implementation: 7.4%
t-statistic value: 51.00
p-value: 2.15×10^{-12}

Interpretation:

Since the p-value < 0.05, there is a statistically significant difference between mortality rates before and after using the IoT-based Smart Fishery system. Thus, the implementation of the

IoT-based monitoring system significantly reduced fish mortality rates in the tested cultivation cycles.

Discussion (مناقشة)

The research results show that the IoT-based Smart Fishery prototype has a good level of sensor accuracy with an error percentage of <6%. This value is still within the operational tolerance limits of freshwater fish farming, so the system can be used as a reliable field monitoring tool. The data transmission success rate of 96.8% shows the stability of system communication, even though it was tested in limited infrastructure conditions. This is in line with the findings of the latest IoT aquaculture research which states that sensor-based monitoring systems are able to increase the consistency of water quality data collection compared to manual methods.

Statistically, the results of the paired t test showed a significant difference between mortality before and after system implementation ($p < 0.05$). Average mortality decreased from 12.5% to 7.4%, or a decrease of 5.1%. This decrease can be explained by increasing monitoring frequency (every 10 minutes) and the existence of an early warning system when water parameters exceed thresholds. Thus, cultivators can carry out corrective actions (additional aeration, water changes) more quickly compared to manual systems which have a response lag of 4–6 hours. (Rupali et al., 2024)

In addition, the increase in monitoring effectiveness of up to 60% shows that the system not only has an impact on biological aspects (mortality), but also on operational management efficiency. Access to historical data allows identification of temperature and pH fluctuation patterns, which were previously difficult to detect through manual recording. These findings strengthen the argument that digitalization of aquaculture through IoT contributes to data-driven aquaculture.

In terms of appropriate technology, the low-cost and low-power design that is successfully operated with the support of solar panels shows that this system is adaptive to conditions in remote areas. This is an added value compared to many previous studies that focused on industrial or laboratory scale IoT systems.

Overall, the research results prove that IoT-based Smart Fisheries are not only technically feasible, but also operationally effective in improving freshwater fish farming management in remote areas. These findings open up opportunities for system development towards decision support system integration and replication on a wider scale.

Conclusion (خاتمة)

This study developed a low-cost and low-power Smart Fishery system based on the Internet of Things (IoT) for real-time monitoring of freshwater aquaculture water quality in limited-infrastructure environments. The proposed system integrates multi-parameter sensing, sensor-data calibration and correction, edge-level data processing, wireless data transmission, and an early-warning mechanism.

Under the tested field conditions, the system demonstrated satisfactory preliminary technical performance, with sensor errors generally below 6% and a data transmission success rate of 96.8%. Fish mortality decreased from 12.5% before implementation to 7.4% following Smart Fishery implementation, corresponding to a reduction of 5.1 percentage points. The statistical analysis indicated a significant difference between the paired observation conditions. However, this mortality reduction should be interpreted as an observed association following system implementation rather than definitive causal evidence, because the field validation was conducted in only one pond and on a limited scale without a concurrent control group.

Overall, the findings demonstrate the technical feasibility and promising preliminary field performance of Smart Fishery for freshwater aquaculture monitoring under the tested conditions. The system has potential as an appropriate technology for farmers operating in areas with limited infrastructure. Nevertheless, broader applicability cannot yet be generalized from the present results.

Future research should conduct larger-scale and multi-location field validation involving multiple ponds and longer cultivation periods. The system should also incorporate additional critical parameters, particularly dissolved oxygen and ammonia, and be integrated with a data-driven decision-support system to support predictive recommendations and more effective aquaculture management.

Recommendations

Future development should incorporate other critical parameters, such as dissolved oxygen (DO) and ammonia levels, to enhance the accuracy of water quality control.

Testing on a larger scale and over extended farming periods is necessary to validate the long-term impact on productivity and cost-efficiency.

Integrating the system with a decision support module based on simple data analytics is recommended to enhance the system's value.

Collaboration with local governments or fish farming groups is essential to support the sustainable adoption and replication of the technology.

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