Literature Review: The Role of IoT and AI in Water Quality Monitoring in Aquaculture

Fittrie Meyllianawaty Pratiwy[1] & Aisyah[1]
Faculty of Fisheries and Marine Sciences, Universitas Padjadjaran
Corresponding author: vthreemeyllia@gmail.com

Abstract

Water quality monitoring is an essential aspect of aquaculture practices to maintain the health of cultured organisms and production stability. The development of the Internet of Things (IoT) enables real-time data acquisition from various environmental sensors, while Artificial Intelligence (AI) provides analytical and predictive capabilities for early detection of critical conditions. The purpose of this paper is to further explore the application of IoT and AI in water quality monitoring by highlighting advantages, limitations, and future development opportunities. The results indicate that the implementation of IoT and AI in aquaculture has shifted cultivation management paradigms from reactive toward proactive and predictive approaches. Real-time monitoring of water quality parameters enables early problem detection and timely intervention.

Keywords:

IoT; Artificial Intelligence; Aquaculture; Water Quality; Sensor; Machine Learning.

Introduction

The main challenge in modern aquaculture is meeting increasing production demands while simultaneously facing various environmental pressures. Water quality parameters such as temperature, pH, dissolved oxygen, ammonia, and salinity play central roles because they directly influence organism growth and health. Instability in these parameters may trigger mass mortality and significant economic losses, thereby encouraging the need for reliable monitoring systems (Al Mamun, 2024; Jais, 2024). To overcome the limitations of traditional practices that are manual and not real-time, the Internet of Things (IoT) offers solutions through sensor infrastructures capable of continuous data acquisition and transmission. Field implementations vary, ranging from buoy modules to stationary solar-powered systems that facilitate remote monitoring and cloud-based data visualization (Shete, 2024; Abdillah, 2025). Beyond mere data collection, information value is enhanced through Artificial Intelligence (AI) analytical capabilities. Various Machine Learning and Deep Learning algorithms (such as Random Forest, SVM, and LSTM) have been applied for time prediction, anomaly detection, and automated

control (Mahesh, 2024; Alluhaidan, 2025). This IoT–AI synergy promises more proactive management systems. The IoT–AI combination essentially forms a new paradigm in aquaculture management that is precise, adaptive, and efficient. However, several challenges such as sensor durability, network dependency, and lack of data standardization still hinder implementation. This paper aims to further explore IoT and AI applications in water quality monitoring as well as their future development opportunities.

1. IoT in Aquaculture

The Internet of Things (IoT) can fundamentally be understood as an integrated cyber-physical infrastructure that converts conventional cultivation practices into an interconnected and intelligent ecosystem. Singh et al. (2024) describe this system as a comprehensive architecture consisting of a perception layer acting as the sensory nervous system through the use of multi-parameter sensors. This layer connects to a network layer functioning as the data circulation pathway utilizing wireless communication protocols, and finally converges at the application layer.

The application layer serves as a control center through cloud-based platforms that not only store but also analyze data to generate actionable insights. Martinez et al. (2022) further clarify that the main goal of IoT implementation in water quality contexts is to establish monitoring systems capable of identifying fluctuations in critical parameters such as pH, temperature, dissolved oxygen, and turbidity at high frequency. This system is designed to provide early warning functions against environmental condition changes that could harm aquatic biota before reaching critical levels, while simultaneously eliminating subjectivity and inconsistency inherent in manual measurement methods.

A comparative study by Martinez et al. (2022) on communication protocols revealed that LoRaWAN offers optimal performance for aquaculture applications. This protocol excels due to its coverage range reaching 3.5 km, sufficient to cover large pond areas, its very low power consumption allowing sensor operation for months with a single battery charge, its ability to penetrate vegetation and pond structures, and its economically feasible operational cost for commercial scales. Practical IoT applications in this field continue to develop with the emergence of edge computing frameworks specifically designed to monitor water quality parameters, as demonstrated by Gupta et al. (2021). The core approach involves performing preliminary sensor data processing locally to filter noise and measurement anomalies before data transmission to the cloud, implementing automatic calibration algorithms correcting sensor drift in real time, and executing basic control logic to provide immediate responses to emergency conditions such as sudden dissolved oxygen depletion. The implementation of edge computing by Gupta et al. (2021) successfully reduced transmitted data volume by up to 65% without reducing information quality while maintaining system operational reliability even under limited connectivity conditions, a situation commonly encountered in remote aquaculture facilities.

2. AI in Aquaculture

In modern aquaculture contexts, Artificial Intelligence (AI) represents a paradigm leap from conventional monitoring systems toward intelligent cognitive ecosystems capable of predictive and precision analysis. According to Taylor et al. (2025), AI functions as a cognitive engine that not only processes historical data but is also capable of identifying complex patterns and nonlinear relationships among water quality parameters that cannot be detected through conventional statistical analysis.

The study developed a Long Short-Term Memory (LSTM) model achieving 94% prediction accuracy for dissolved oxygen parameters by utilizing the algorithm's ability to capture long-term temporal dependencies from time-series data. Kumar et al. (2023) further explain that the fundamental essence of AI implementation is creating predictive systems capable of anticipating environmental condition changes before reaching critical thresholds, where developed machine learning algorithms not only predict individual parameters but also understand synergistic relationships among variables such as temperature, pH, and ammonia concentration. The implementation of such systems demonstrates impressive capability in predicting hypoxic conditions 4–6 hours before occurrence with 89% accuracy, thereby enabling preventive interventions that significantly reduce the risk of mass mortality. Computer vision applications in aquaculture, as studied by Harris et al. (2023), represent a revolutionary dimension in AI utilization by adding biological monitoring layers through non-invasive visual analysis of fish conditions. Developed Convolutional Neural Network (CNN) algorithms are capable of detecting behavioral abnormalities with 92% sensitivity and 95% specificity, providing early warning systems for fish health problems based on swimming patterns, spatial distribution, and responses to environmental stimuli. Hall et al. (2021) further refined this approach by developing YOLO-based systems for biomass estimation and fish stress detection, aiming to create non-invasive monitoring tools that reduce the need for physical handling, which often causes additional stress. Implementation results show error rates below 7% for biomass estimation and early stress detection accuracy reaching 90%, contributing significantly to fish welfare while optimizing production processes through more precise harvest scheduling.

3. Machine Learning in Aquaculture

Machine Learning (ML) acts as a cognitive engine capable of classifying and categorizing complex data patterns derived from water quality parameters that cannot be identified through conventional statistical approaches. Various algorithms, including Random Forest and Support Vector Machine (SVM), have demonstrated effectiveness in grouping water conditions into categories such as optimal, sub-optimal, and critical through multivariable analysis of parameters including pH, temperature, dissolved oxygen, and ammonia simultaneously (Mahesh, 2024).

Beyond classification capability, ML also excels in time-series data modeling implemented through Long Short-Term Memory (LSTM) architecture. This model effectively captures temporal dependencies in water quality data, enabling prediction of fluctuations in

critical parameters such as dissolved oxygen 4–6 hours ahead with accuracy exceeding 90%, which is crucial for early preventive action (Taylor et al., 2025).

Modern ML systems continue advancing through adaptive learning capabilities and continuous optimization via reinforcement learning implementation. These systems continuously improve as operational data increases, particularly in optimizing feeding strategies based on environmental conditions, which significantly improve feed conversion ratios (Alluhaidan, 2025). Furthermore, ML facilitates integration of multimodal data including physicochemical sensor readings, computer vision imaging data, and other environmental parameters. This integration enables the creation of digital twin systems representing actual cultivation conditions more comprehensively and holistically (Abdillah, 2025). From a technical implementation perspective, edge machine learning development enables local data processing without full dependence on cloud connectivity. This approach successfully reduces latency to below 500 milliseconds and saves bandwidth usage up to 65% through optimal preprocessing and feature selection mechanisms (Gupta et al., 2021). Model interpretability aspects also receive increasing attention through Explainable AI (XAI) techniques using SHAP methods, enabling operators to understand contributions of each variable toward prediction results, ultimately increasing trust in applied automation systems (Schmidt, 2025).

4. Research on Water Quality Using IoT Systems

The following are several studies on water quality assisted by IoT, AI, or Machine Learning, presented in the table below:

Measured Parameters / Method	Results	Reference
Temperature, DO, and pH	The biofloc system integrated with the developed IoT prototype demonstrated positive results.	Blancalfor & Baccay (2022)
Temperature, TDS, pH, salinity, and EC	The designed IoT system assists farmers in Bangladesh in monitoring water quality in real time and accurately.	Ahmed et al. (2024)
Literature study regarding IoT and AI in biofloc and aquaculture	IoT and AI development in biofloc systems shows promising future development opportunities.	Alghamdi & Haraz (2025)

DO, Ammonia, Turbidity, pH, Temperature, and TDS	The system achieved high accuracy levels: 90.5% (5.33 mg/L) for DO, 88.9% (0.0067) for ammonia, 96.4% (33.32 NTU) for turbidity, 94.8% (8.17) for pH, 99.1% (26.33) for temperature, and 94.9% (741.25 mg/L) for TDS.	Zuhaer et al. (2025)
Temperature, pH, DO, Ammonia, and Salinity	Comparison between IoT sensor and manual measurement shows accuracy levels ranging from 76% to 97%.	Jais et al. (2024)
DO, pH, and Temperature	The IoT system was able to comprehensively analyze data with regular and positively correlated data distribution, proving effective real-time monitoring capability.	Shete et al. (2024)
Temperature, DO, pH, and Turbidity	Real-time measurement enables continuous monitoring and environmental condition analysis.	Hridoy et al. (2025)
Temperature, DO, and pH	The system operates stably, produces accurate real-time data, meets production requirements, and provides strong technical support for aquaculture management.	Huan et al. (2020)
Nitrate, pH, Temperature, Ammonia, DO, Turbidity, BOD, Conductivity, Total Coliform, and Manganese	The DSTCNN model effectively describes spatial and temporal pond dynamics, enabling pattern and trend detection related to water quality.	Arepalli & Naik (2024)
DO, Temperature, pH, and Turbidity	Developed IoT devices collect and analyze data and also analyze images in real time, enabling monitoring of water quality and fish growth.	Chiu et al. (2022)
pH, Temperature, and Turbidity	The study supports researchers utilizing tested	Islam (2023)

	fish species, and developed IoT systems successfully obtain real-time water quality data influencing fish growth and survival rate.	
Temperature, pH, turbidity with fish breeding tracking	Two modules, AI and aquatic tracking, successfully collected real-time data on water quality and fish growth development through tagging.	Gao et al. (2019)
DO, Salinity, pH, Turbidity, and Temperature	Machine Learning approaches show strong potential in supporting aquaculture decision-making for improved pond performance.	Rana et al. (2021)
pH, Temperature, and Turbidity	Systems transmit real-time water quality data accessible remotely and provide alerts when parameters exceed predefined thresholds.	Raghavendra et al. (2021)
Temperature, pH, DO, Nitrate, and others	The model achieved high performance with accuracy reaching 98.69% for public datasets and 99.89% for real-time datasets.	Arepalli & Naik (2024)
pH, light, water level, temperature, TDS, EC, ammonia, nitrate, nitrite	IoT design expected to be interoperable, secure, scalable, low-cost, fully automated, and flexible.	Khaoula et al. (2021)
Temperature, salinity, light intensity, DO, TDS, and pH	The approach effectively maintains optimal cultivation conditions, reduces ecological risks such as eutrophication, and improves monitoring of Sargassum sp. growth.	Misbahuddin et al. (2025)
Temperature, DO, pH, turbidity	Integration with predictive models such as Random Forest shows excellent predictive capability.	Navarro et al. (2025)
pH, temperature, turbidity influenced by climate variability	Cloud-based real-time monitoring integrated with predictive analytics supports proactive water quality management.	Kanwal et al. (2024)

5. Benefits and Opportunities in Aquaculture in the Future

The implementation of integrated IoT and AI systems has provided measurable benefits in various operational aspects of aquaculture. Nelson et al. (2024) reported an increase in survival rate from 74% to 89% and a reduction in labor costs of up to 42% through automation of monitoring and routine control. Integration with blockchain technology offers opportunities for enhanced traceability and transparency, where Perez et al. (2023) proposed recording water quality data in a distributed ledger to provide product assurance verifiable by consumers and create value-added products through guaranteed farming practices.

The development of Digital Twin technology represents the next frontier, enabling system simulation and optimization prior to physical implementation, aiming to reduce operational risks through virtual testing of various management scenarios (Baker et al., 2024). Advances in energy harvesting and edge AI open opportunities for truly autonomous systems, demonstrated by Adams et al. (2024), who developed a hybrid energy system combining solar and microbial fuel cells, as well as the implementation of TinyML for real-time analytics on edge devices by Campbell et al. (2024), aiming to create self-sufficient and intelligent systems for remote aquaculture operations.

6. Conclusion

The implementation of IoT and AI in aquaculture has transformed cultivation management paradigms from reactive to proactive and predictive approaches. Real-time monitoring of water quality parameters such as temperature, pH, dissolved oxygen, salinity, ammonia, nitrate, and turbidity enables early detection of problems and timely intervention. Integration of sensors with actuators creates automatic control systems that maintain optimal conditions for fish growth and health. Sensor technology continues to develop toward higher accuracy, long-term stability, and better resilience under challenging environmental conditions. Advances in material science and nanotechnology produce sensors with improved selectivity, faster response time, and reduced maintenance requirements. Simultaneously, advances in AI and machine learning enable smarter data analysis, more accurate predictions, and increasingly autonomous systems.

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