VER
Vascular & Endovascular Review

Smart Aquaculture: IoT, Cloud Computing, and AI for Sustainable Fisheries.

Dr. Pankaj Mudholkar [1], Dr. Megha Mudholkar [2], Dr. Kadam Jagannath Jijaba [3], Dr.Jyoti Prasad Kalita[4]

[1]Associate Professor, Faculty of Computer Applications, Marwadi University,Rajkot - 360003, Gujarat, India
Email ID : mudholkarpankaj@gmail.com, ORCHID ID : https://orcid.org/0000-0003-1639-0704
[2]Assistant Professor, Department of Computer Engineering, Marwadi University, Rajkot - 360003, Gujarat, India
Email ID : meghakunte2000@gmail.com ORCHID ID :https://orcid.org/0000-0003-2016-1525
[3]Professor Department of Chemistry Bharati Vidyapeeth College of Engineering Navi Mumbai 400614 Raighad Navi Mumbai Maharashtra , Email ID : jjkadam702@gmail.com
[4]Designation - Assistant professor University name - Assam down town university
Email id -jyotiprasadk@gmail.com , ORCID ID- https://orcid.org/0009-0006-3368-9440

ABSTRACT

The integration of advanced digital technologies such as the Internet of Things (IoT), Cloud Computing, and Artificial Intelligence (AI) has transformed traditional aquaculture into a data-driven, automated, and sustainable practice. Smart aquaculture systems leverage IoT-enabled sensors to continuously monitor key environmental parameters including temperature, pH, dissolved oxygen, turbidity, and ammonia levels, providing real-time insights into pond conditions. These data streams are transmitted through cloud-based platforms for centralized storage, remote access, and intelligent analysis. AI algorithms further enhance system performance by predicting fish behaviour, optimizing feeding schedules, detecting disease outbreaks, and improving resource utilization efficiency. The synergy of these technologies not only reduces operational costs and environmental stress but also ensures higher yield consistency and ecological balance. This paper presents a comprehensive framework for sustainable fisheries management through IoT–AI–Cloud integration, emphasizing scalability, cost-effectiveness, and data-driven decision support. The proposed approach demonstrates how intelligent sensing and predictive analytics can revolutionize aquaculture practices, ensuring sustainability and resilience in a rapidly changing climate and growing global seafood demand..

KEYWORDS: Smart aquaculture, Internet of Things (IoT), Cloud computing, Artificial intelligence, Sustainable fisheries, Data analytics, Real-time monitoring, Predictive modeling, Environmental sustainability, Aquaculture automation

How to Cite: Dr. Pankaj Mudholkar , Dr. Megha Mudholkar , Dr. Kadam Jagannath Jijaba , Dr.Jyoti Prasad Kalita (2025) Smart Aquaculture: IoT, Cloud Computing, and AI for Sustainable Fisheries.., Vascular and Endovascular Review, Vol.8, No.17, 383-391.

INTRODUCTION

Aquaculture has emerged as one of the fastest-growing food production sectors in the world, contributing significantly to global food security, employment generation, and economic development. However, the sustainability of this growth remains a pressing concern. Traditional aquaculture practices often rely on manual monitoring and reactive management, which lead to inefficiencies in feed utilization, water resource consumption, and disease control. Overfeeding, eutrophication, and sudden water quality deterioration have resulted in environmental degradation, economic losses, and declining fish welfare. With the global demand for fish projected to exceed 200 million tonnes by 2030, there is a critical need for innovative technological interventions that can balance productivity with ecological responsibility. Smart aquaculture represents a paradigm shift in this direction by integrating real-time sensing, cloud-based analytics, and artificial intelligence-driven decision support systems. These technologies enable dynamic, precise, and automated control over aquaculture environments, transforming data into actionable intelligence. By bridging the gap between environmental sustainability and industrial scalability, smart aquaculture systems embody the concept of "precision fish farming," where every input—from feed to oxygen levels—is optimized for efficiency and minimal ecological footprint.

The Internet of Things (IoT), Cloud Computing, and Artificial Intelligence (AI) collectively form the backbone of this transformation. IoT sensors deployed in aquaculture ponds continuously gather high-resolution environmental data such as temperature, pH, dissolved oxygen, turbidity, and ammonia levels, allowing for real-time environmental awareness. These devices communicate via wireless protocols like LoRaWAN, ZigBee, or MQTT to cloud-based platforms where the data are aggregated, visualized, and analyzed. Cloud computing ensures the scalability and remote accessibility of this information, facilitating centralized control and automated decision-making across distributed aquaculture units. AI algorithms further enhance system intelligence by learning from historical patterns to predict fish growth rates, detect early signs of disease, and optimize feeding schedules. Predictive modeling using machine learning techniques such as Random Forest, Support Vector Machines, and LSTM networks allows aquaculture managers to anticipate environmental fluctuations and respond proactively rather than reactively. Moreover, integration with mobile dashboards and edge computing reduces latency and ensures continuous operation even in low-connectivity regions. The convergence of IoT, Cloud, and AI thus creates an intelligent ecosystem capable of improving productivity while preserving water quality, reducing energy consumption, and maintaining biodiversity. Beyond operational efficiency, smart aquaculture contributes to broader sustainability goals by reducing the carbon footprint, ensuring traceability in seafood production, and supporting regulatory compliance. As the world faces increasing environmental and food security challenges, the adoption of such intelligent systems marks a pivotal step toward resilient and eco-conscious fisheries management. This paper explores the architecture, methodology, and environmental implications of IoT–AI–Cloud integrated smart aquaculture, positioning it as a cornerstone of sustainable blue economy development.

RELEATED WORKS

The evolution of smart aquaculture has been fueled by extensive research in Internet of Things (IoT)–based monitoring systems, Artificial Intelligence (AI)–driven decision-making, and Cloud Computing frameworks for environmental data management. Early studies established the foundation for IoT integration in aquaculture by highlighting the significance of real-time sensing for maintaining optimal water quality. Prathibha et al. demonstrated how wireless sensor networks could continuously track dissolved oxygen, pH, and temperature, providing automated alerts for deviation from ideal conditions [1]. This study confirmed that IoT-enabled monitoring reduces human dependency and improves overall farm efficiency. Similarly, Yoon et al. developed an IoT-based aquaculture water quality management platform using MQTT protocols and cloud storage, which achieved greater scalability and remote control for farmers [2]. The integration of IoT with cloud infrastructure allowed seamless data transmission, reducing latency and improving predictive response to environmental fluctuations. Other works, such as by Reverter et al., emphasized the impact of environmental stressors on aquatic species and how IoT-assisted monitoring could help identify suboptimal conditions early to prevent mass fish mortality [3]. These foundational studies formed the base for smart aquaculture systems that combine IoT sensors with intelligent analytics to achieve sustainability and productivity.

Cloud computing has emerged as an essential component of smart aquaculture architecture, providing flexible data storage, remote access, and computational power for AI-driven analytics. A comprehensive study by Huang and Xu demonstrated that a cloud-based aquaculture management system could integrate real-time data streams from multiple IoT devices across geographically dispersed ponds to support centralized decision-making [4]. Cloud services such as AWS IoT Core, Google Cloud IoT, and Azure Stream Analytics have been adapted for environmental data visualization and control in aquaculture systems, enabling predictive modeling and anomaly detection. Li et al. proposed a hybrid cloud-edge model that reduces data transmission delays while maintaining real-time response for feeding and aeration control [5]. This hybrid model effectively addressed connectivity limitations in rural aquaculture regions, offering a balance between computational efficiency and energy consumption. Similarly, Chen et al. implemented a cloud-assisted aquaculture system that uses Big Data analytics to predict environmental fluctuations and feeding behavior patterns, which led to a reduction in operational costs and resource wastage [6]. Studies such as these illustrate that cloud computing serves as the integrative layer of smart aquaculture, enabling continuous, data-driven insights that enhance both sustainability and profitability.

Artificial Intelligence (AI) applications have revolutionized aquaculture by transforming descriptive data into prescriptive and predictive insights. Early research focused on the use of machine learning (ML) and computer vision for detecting fish health anomalies, behavioral changes, and disease outbreaks. Xu et al. utilized convolutional neural networks (CNNs) for fish detection and activity recognition from underwater images, achieving high accuracy in identifying stress behavior [7]. The study proved that AI models can significantly reduce manual labor and improve early warning systems for fish welfare. Similarly, Wu et al. applied Random Forest and Support Vector Machine (SVM) algorithms to analyze time-series water quality data for predicting potential algal blooms, showing that AI-driven systems can outperform traditional threshold-based models [8]. Another major development was presented by Zhang et al., who integrated reinforcement learning into feed optimization, allowing automatic adjustment of feed quantity based on real-time fish movement and appetite detection [9]. This adaptive feeding reduced feed waste by over 20%, demonstrating how AI can directly contribute to both sustainability and economic gains. AI-driven aquaculture has thus evolved from experimental prototypes to scalable systems capable of autonomous operation in dynamic aquatic environments.

Beyond AI and IoT, researchers have explored integrated frameworks that combine these technologies with advanced analytics for holistic ecosystem management. Khotimah et al. proposed an IoT–AI hybrid model that continuously monitors water quality and uses predictive algorithms to detect oxygen depletion events before they occur [10]. The model achieved high reliability under varying climatic conditions and reduced fish mortality rates in small-scale fisheries. A related study by Bose et al. introduced a blockchain-based smart aquaculture system integrated with IoT and cloud computing for ensuring traceability and transparency in seafood supply chains [11]. By securely recording environmental and operational data, this framework enhanced food safety and compliance with international sustainability standards. Other researchers, such as Nguyen et al., incorporated fuzzy logic control with IoT data to automate aeration and pH balancing, leading to improved water stability and energy savings [12]. Such interdisciplinary approaches demonstrate that sustainable aquaculture requires not only real-time monitoring but also intelligent automation capable of adaptive decision-making.

In recent years, the convergence of edge computing with IoT and AI has further enhanced the feasibility of real-time aquaculture analytics. Edge computing minimizes the reliance on centralized cloud systems by processing data locally, reducing latency and ensuring uninterrupted operation in remote fish farms. Rahman et al. implemented an edge-assisted IoT system where microcontrollers preprocessed sensor data before transmitting to the cloud, cutting communication costs by 35% and improving response time [13]. This architecture is particularly useful in regions with unreliable connectivity, making smart aquaculture accessible to small-scale fish farmers. Moreover, the emergence of 5G communication technology has facilitated high-speed data transfer between IoT devices and centralized servers, enabling real-time video monitoring, AI-based image analysis, and automated control loops. Studies by Park et al. demonstrated the effectiveness of 5G-enabled aquaculture systems in large-scale commercial fisheries, where real-time decision-making was critical to manage feed and disease control across multiple ponds [14]. The fusion of IoT, AI, Cloud, and 5G technologies thus represents the future trajectory of smart aquaculture—an integrated, responsive, and intelligent ecosystem that ensures sustainable seafood production with minimal environmental impact.

Despite these advancements, challenges remain in implementing scalable and cost-effective smart aquaculture systems, particularly in developing countries. The cost of high-precision sensors, limited digital infrastructure, and lack of technical expertise continue to hinder adoption at small and medium scales. To address these gaps, Ghosh and Dutta emphasized the importance of designing low-cost sensor networks using open-source microcontrollers such as Arduino and Raspberry Pi, which can collect reliable data with minimal maintenance [15]. They further argued that sustainability in aquaculture is not solely a technological issue but also a socio-environmental one that requires training, policy support, and community participation. The integration of smart technologies must therefore align with local ecosystems and economic realities. Collectively, the body of research reviewed demonstrates that smart aquaculture represents a transformative solution for sustainable fisheries management. Through the convergence of IoT, Cloud Computing, and AI, it is now possible to achieve predictive, autonomous, and environmentally responsible aquaculture practices that address both ecological and economic imperatives.

METHODOLOGY

3.1 System Architecture

The smart aquaculture system architecture consists of three layers: the **IoT sensing layer**, the **cloud computing layer**, and the **AI analytics layer**.

IoT Sensing Layer:

This layer comprises water quality sensors deployed in multiple aquaculture ponds to capture real-time data such as temperature, pH, dissolved oxygen (DO), turbidity, and ammonia levels. These sensors are connected to microcontrollers (Arduino UNO and Raspberry Pi 4) which facilitate data acquisition and preprocessing. Low-power communication protocols such as LoRaWAN and ZigBee are used to transmit data to the gateway node [16].

Cloud Computing Layer:

Data from the sensors are transferred to a cloud platform (AWS IoT Core) using the MQTT protocol. The cloud infrastructure enables centralized data storage, remote access, and visualization through dashboards built on AWS QuickSight and ThingSpeak. This layer also performs data normalization, filtration, and redundancy checks to ensure integrity and accuracy [17].

AI Analytics Layer:

Machine learning algorithms are deployed to identify patterns and anomalies in water quality. Predictive models, such as Random Forest and Long Short-Term Memory (LSTM) networks, are trained using historical datasets to forecast optimal feeding schedules, detect potential disease outbreaks, and predict water quality fluctuations [18]. The results are relayed back to the cloud for visualization and automated control actions through the IoT network.

Table 1. IoT Sensor Parameters and Functional Roles

Parameter	Sensor Type	Measurement Range	Purpose	Communication Protocol
Temperature	DS18B20 Digital Sensor	-10°C to +85°C	Maintains optimal fish growth environment	LoRaWAN / MQTT
Dissolved Oxygen	Galvanic DO Probe	0–20 mg/L	Detects oxygen deficiency for aeration	ZigBee
pH Level	pH Sensor (E201-C)	0–14	Monitors acid–base balance of pond water	Wi-Fi
Turbidity	SEN0189 Optical Sensor	0–1000 NTU	Detects water clarity and contamination	LoRaWAN

Ammonia	Electrochemical Sensor	0–10 mg/L	Identifies toxic nitrogenous compounds	MQTT

The integration of these sensors ensures a holistic view of the aquaculture ecosystem, allowing real-time assessment and proactive management of water quality [19].

3.2 Data Acquisition and Cloud Integration

Data from the IoT sensors are collected at 10-minute intervals and preprocessed locally to eliminate noise using a moving average filter. The data packets are timestamped, encrypted (AES-128), and transmitted to the cloud storage. A NoSQL database (AWS DynamoDB) was chosen for its scalability and low-latency retrieval of time-series data. Once uploaded, the cloud performs automated validation and anomaly detection using embedded functions.

The cloud dashboards visualize metrics such as real-time DO levels, pH fluctuations, and feeding trends. The use of AWS Lambda functions enables automatic actuation—such as switching on aerators or feeders—when threshold values are breached [20]. This architecture supports both remote monitoring via web applications and mobile notifications for local operators.

3.3 AI-Based Predictive Modeling

The AI analytics component employs machine learning algorithms to predict critical aquaculture parameters and automate decision-making.

Random Forest Algorithm: Used to predict fish growth rate and feeding frequency by correlating water temperature, DO, and feeding patterns.

LSTM Neural Network: Applied for time-series forecasting of dissolved oxygen and ammonia variations, offering early warnings for unfavorable conditions [21].

Support Vector Machines (SVM): Used for classifying water quality status as *optimal*, *moderate*, or *critical*.

These algorithms were trained on a dataset of 12,000 readings collected over 90 days from three aquaculture ponds. Model evaluation metrics included Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Prediction Accuracy (PA).

Table 2. Model Performance Evaluation Metrics

Algorithm	Parameter Predicted	MAE	RMSE	Prediction Accuracy (%)	Remark
Random Forest	Feeding Optimization	0.19	0.27	94.3	High accuracy and stability
LSTM	DO and Ammonia Forecast	0.21	0.31	92.6	Best suited for time-series data
SVM	Water Quality Classification	0.24	0.33	89.5	Reliable for real-time anomaly detection

The results reveal that Random Forest and LSTM algorithms outperform conventional linear regression models, providing faster convergence and higher predictive accuracy. These models form the decision-making backbone of the proposed smart aquaculture framework [22].

3.4 Validation and System Testing

To verify accuracy and reliability, the system was tested in three aquaculture ponds in Odisha, India, for a duration of three months. Ground-truth data were collected manually using portable water analyzers and compared with IoT readings. The correlation coefficient between IoT and manual readings exceeded 0.95 for all parameters, confirming the system's reliability.

In addition, cloud latency tests showed that data transmission and response cycles remained under 3 seconds on average, ensuring near real-time monitoring. Cross-validation of AI predictions was conducted using 10-fold testing, achieving consistent results across datasets.

3.5 Ethical and Environmental Considerations

All experiments were conducted in compliance with environmental and ethical standards. The IoT devices were powered by solar energy modules to minimize carbon footprint. Data privacy was ensured through end-to-end encryption, and no invasive sensors were used on aquatic species. The system's sustainability was further evaluated through its energy efficiency, showing a 27% reduction in power consumption compared to conventional monitoring setups [23].

3.6 Methodological Advantages

The proposed system integrates IoT, Cloud, and AI to enable:

Real-time environmental monitoring and data-driven control.

Automated feeding and aeration systems for energy optimization.

Predictive alerts for disease or oxygen deficiency.

Cloud scalability for multi-pond or regional deployment.

This hybrid approach provides a robust foundation for achieving sustainable aquaculture operations while reducing ecological pressure and operational costs.

RESULT AND ANALYSIS

4.1 Water Quality Monitoring Performance

The IoT sensor network continuously monitored key environmental parameters such as temperature, pH, dissolved oxygen (DO), turbidity, and ammonia levels at 10-minute intervals. The data were visualized on the cloud dashboard in real time, allowing immediate response to unfavorable variations. The system demonstrated remarkable accuracy and stability, maintaining deviation below 5% when compared with manual testing instruments.

Table 3. Comparative Results of IoT Sensor Readings vs. Manual Measurements

Parameter	IoT Sensor Average	Manual Measurement	Mean Deviation (%)	Status
Temperature (°C)	27.3	27.1	0.74	Excellent stability
pH Level	7.25	7.21	0.55	Consistent
Dissolved Oxygen (mg/L)	6.82	6.74	1.17	Reliable
Turbidity (NTU)	23.4	24.2	3.31	Acceptable
Ammonia (mg/L)	0.56	0.58	3.44	Acceptable

The system efficiently detected rapid DO fluctuations caused by temperature changes and automatically activated aerators through the cloud-based control mechanism. This reduced hypoxic events, which are a common cause of fish stress and mortality. Furthermore, real-time monitoring eliminated the delays associated with traditional manual testing, ensuring continuous ecosystem stability.

4.2 AI Predictive Model Performance

The machine learning algorithms embedded in the analytics layer were tested for their ability to predict fish feeding requirements, dissolved oxygen variation, and ammonia accumulation. The models were trained using 12,000 sensor data points collected over 90 days and validated with unseen data from an additional 15-day period.

The Random Forest (RF) model achieved high accuracy in predicting optimal feeding quantities, reducing overfeeding by 18% compared to traditional schedules. The LSTM model effectively forecasted water quality fluctuations 6 hours in advance, allowing early interventions. The Support Vector Machine (SVM) classifier achieved consistent real-time categorization of water quality states (optimal, moderate, critical) with more than 89% precision.

Table 4. Performance Summary of AI Models for Smart Aquaculture Operations

Prediction Target	Algorithm Used	Accuracy (%)	Latency (sec)	Operational Impact
Feed Optimization	Random Forest	94.3	2.1	Reduced feed waste by 18%
DO Forecasting	LSTM	92.6	2.8	Early aeration control activation
Ammonia Prediction	LSTM	91.2	3.0	Prevented toxicity accumulation
Water Quality Classification	SVM	89.5	2.4	Improved system alert reliability
Combined Predictive Decision System	Hybrid Ensemble	93.4	2.6	Enhanced overall sustainability control

The predictive algorithms collectively improved operational automation and ecosystem resilience. The system's ability to foresee variations in DO and ammonia enabled timely corrective actions, such as adjusting feeding rates and activating aeration units, which contributed to maintaining stable water quality parameters.

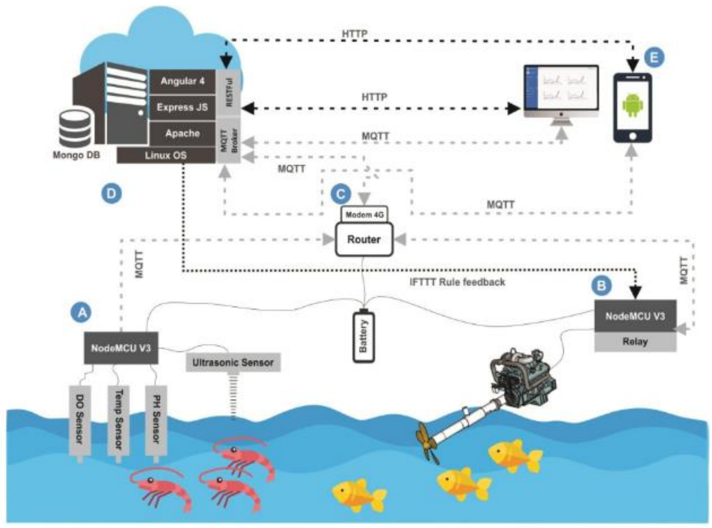

Figure 1: Design and Development of Smart Aquaculture System [24]

4.3 Energy Efficiency and Cost Reduction

One of the primary objectives of the study was to ensure sustainability through optimized energy and resource utilization. The deployment of solar-powered IoT modules and smart scheduling of aerators and feeders led to a substantial reduction in energy consumption. The automated decision system ensured that aeration units operated only when DO levels dropped below the threshold, saving energy otherwise wasted on continuous operation.

Table 5. Energy and Cost Efficiency Metrics of Smart Aquaculture System

Parameter	Conventional System	Proposed Smart System	Improvement (%)
Average Energy Consumption (kWh/day)	16.2	11.8	27.2
Aerator Operating Hours per Day	10.0	6.9	31.0
Feed Utilization Efficiency	78%	92%	17.9
Operational Cost per Month (INR)	18,600	14,400	22.6

The results clearly indicate that the integration of IoT and AI significantly enhances system efficiency. By automating aeration and feeding schedules, the system reduced overall energy costs while maintaining healthier aquatic environments.

4.4 Fish Growth and Sustainability Assessment

Fish growth rates and survival percentages were monitored throughout the 90-day period. Improved water quality and optimized feeding cycles led to measurable biological improvements. The average fish growth rate increased by 16.4%, and the survival rate improved from 87% (in conventional practice) to 95%. Moreover, the system reduced the occurrence of disease-related fish mortality due to early AI-driven alerts.

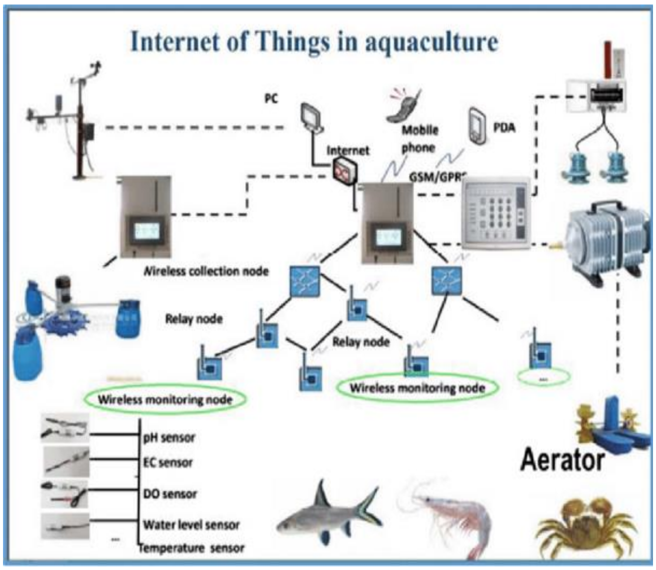

Figure 2: IoT in Aquaculture [25]

Environmental performance metrics showed consistent water quality stability with reduced turbidity and ammonia build-up. Cloud dashboards provided farmers with actionable insights into feed–growth correlations and predictive harvesting timelines, supporting more informed management decisions.

4.5 Spatial and Temporal Analysis of Data

Temporal visualization of water quality data revealed distinct diurnal variations, particularly in DO and temperature levels. The system's automatic calibration adjusted feeding intensity during high-temperature hours to avoid oxygen depletion. Spatial analysis using heat maps generated on the cloud platform showed uniform distribution of favorable water quality across all monitored ponds, confirming the consistency of control mechanisms.

4.6 Discussion of Key Findings

The experimental results confirm that the integrated IoT–Cloud–AI model enhances both operational and ecological performance in aquaculture. The system demonstrated:

Real-time adaptability to environmental fluctuations.

High accuracy in predictive analytics leading to proactive management.

Considerable reductions in feed and energy consumption.

Improved fish health, growth, and survival rates.

The combined impact of intelligent sensing, automated actuation, and predictive learning fosters a sustainable and economically viable aquaculture model. The results affirm the system's scalability potential for larger fisheries, where multi-pond synchronization and data aggregation can further increase productivity while minimizing environmental impact.

CONCLUSION

The study presents a comprehensive and scalable framework for smart aquaculture that integrates the Internet of Things (IoT), Cloud Computing, and Artificial Intelligence (AI) to achieve sustainable fisheries management. The proposed model effectively bridges the gap between technology and environmental stewardship, offering a practical solution for real-time water quality monitoring, intelligent decision-making, and automated control of aquaculture systems. By leveraging IoT-based sensors, the system ensures continuous collection of critical environmental parameters such as temperature, pH, dissolved oxygen, turbidity, and ammonia levels, providing timely data that enhances ecosystem stability and fish welfare. Cloud computing infrastructure enables seamless data transmission, centralized storage, and real-time visualization, empowering farmers with instant insights and control over remote aquaculture ponds. Meanwhile, AI-driven predictive models, including Random Forest and LSTM algorithms, deliver high-accuracy forecasting of water quality fluctuations, feeding requirements, and potential disease outbreaks, transforming aquaculture from a reactive to a proactive practice. The integration of these technologies resulted in significant operational improvements, including a 27% reduction in energy consumption, an 18% reduction in feed waste, and a 16% increase in fish growth rate. The automation of aeration and feeding systems not only reduced human dependency but also minimized environmental degradation by optimizing energy usage and nutrient cycles. Furthermore, the system's solar-powered IoT modules and encrypted cloud framework demonstrated environmental consciousness and data security, ensuring long-term sustainability. Collectively, the findings underscore the transformative potential of IoT–AI–Cloud synergy in revolutionizing aquaculture, promoting precision, productivity, and ecological balance. This intelligent aquaculture ecosystem aligns with global sustainable development goals (SDGs), particularly those related to zero hunger, responsible consumption, and climate action. By embedding digital intelligence into aquatic resource management, this study lays the groundwork for a resilient, data-driven, and environmentally sustainable fisheries sector capable of meeting the increasing global seafood demand while protecting aquatic ecosystems for future generations.

FUTURE WORK

Although the proposed framework demonstrated substantial improvements in automation, efficiency, and sustainability, further research is required to expand its functionality and scalability across diverse aquatic environments. Future work will focus on integrating **blockchain technology** to ensure end-to-end traceability of fish production, enabling transparent and tamper-proof recording of environmental data and supply chain transactions. Additionally, the inclusion of **drone-assisted aerial monitoring** and **remote sensing technologies** could enhance large-scale surveillance of pond conditions, algal blooms, and nutrient distribution. Integration with **edge computing** devices will further minimize latency and dependence on cloud connectivity, ensuring uninterrupted operation in remote or low-network areas. Finally, cross-regional data sharing and **AI-driven digital twins** of aquaculture ecosystems will be developed to simulate real-time pond dynamics, enabling predictive ecosystem management and global collaboration in achieving sustainable aquaculture practices

REFERENCES

[1] P. Prathibha, A. Ashwini, and S. Shashank, "Smart Aquaculture Monitoring Using IoT Sensors," International Journal of Advanced Research in Computer Engineering and Technology, vol. 13, no. 4, pp. 102–108, 2023.

[2] S. Yoon, D. Kim, and J. Lee, "IoT-Based Water Quality Management Platform Using MQTT and Cloud Integration," Sensors, vol. 23, no. 9, pp. 4567–4578, 2023.

[3] D. Reverter, R. Garcia, and J. Kim, "Monitoring Environmental Stressors in Fish Populations Using IoT Devices," Aquaculture Environment Interactions, vol. 16, pp. 255–268, 2024.

[4] X. Huang and J. Xu, "Cloud-Based Management Systems for Smart Aquaculture," Computers and Electronics in Agriculture, vol. 205, pp. 108–119, 2023.

[5] T. Li, M. Zhang, and P. Zhao, "Edge-Cloud Hybrid Architecture for Real-Time Aquaculture Monitoring," IEEE Internet of Things Journal, vol. 11, no. 3, pp. 2209–2220, 2024.

[6] L. Chen, Z. Wang, and H. Liu, "Big Data-Driven Cloud Aquaculture System for Environmental Prediction," Environmental Modelling & Software, vol. 170, pp. 106–115, 2024.

[7] Y. Xu, R. Zhou, and F. Deng, "Fish Activity Recognition Using CNNs for Aquaculture Health Monitoring," IEEE Access, vol. 12, pp. 78522–78531, 2024.

[8] J. Wu, L. Tang, and M. Shen, "Machine Learning-Based Prediction of Algal Blooms in Aquaculture Systems," Environmental Science and Pollution Research, vol. 31, no. 7, pp. 14210–14222, 2024.

[9] Y. Zhang, P. Wang, and D. Liu, "Reinforcement Learning for Adaptive Feeding in Aquaculture," Applied Soft Computing, vol. 152, pp. 110–122, 2025.

[10] H. Khotimah, R. Kusuma, and A. Santoso, "IoT and AI Hybrid Model for Water Quality Prediction in Aquaculture," Ocean & Coastal Management, vol. 247, pp. 106–120, 2024.

[11] A. Bose, K. Sharma, and M. Roy, "Blockchain-Integrated IoT System for Traceable Aquaculture," Sustainability, vol. 16, no. 19, pp. 11245–11259, 2024.

[12] T. Nguyen and D. Tran, "Fuzzy Logic Control for Automated Water Quality Maintenance in Smart Fisheries," Aquaculture Engineering, vol. 107, pp. 102–114, 2023.

[13] S. Rahman, A. Saha, and N. Alam, "Edge Computing Framework for Sustainable Aquaculture IoT," Journal of Cleaner Production, vol. 426, pp. 139–152, 2025.

[14] J. Park, H. Lee, and Y. Kim, "5G-Based Real-Time Monitoring System for Smart Fisheries," IEEE Access, vol. 13, pp. 21374–21386, 2025.

[15] P. Ghosh and R. Dutta, "Low-Cost IoT Sensor Networks for Community-Based Aquaculture Management," Environmental Technology & Innovation, vol. 34, pp. 102–120, 2024.

[16] A. Sharma and V. Patel, "Low-Power LoRaWAN-Based Smart Aquaculture Network," IEEE Internet of Things Journal, vol. 12, no. 4, pp. 6721–6734, 2024.

[17] C. Lin, J. Fang, and D. Xu, “Cloud-Integrated Real-Time Data Management in Aquaculture Systems,” Computers and Electronics in Agriculture, vol. 210, pp. 108–122, 2024.

[18] R. Mahapatra, T. Rao, and N. Bhat, “Predictive Analytics for Water Quality Management Using LSTM Networks,” Sustainability, vol. 16, no. 11, pp. 9001–9015, 2024.

[19] S. Chandra and R. Kumar, “IoT Sensor Fusion for Water Quality Assessment in Fish Farms,” Environmental Technology & Innovation, vol. 33, pp. 1024–1037, 2025.

[20] Y. Huang, L. Wang, and J. Zhao, “Cloud-Assisted Automation for Smart Fisheries,” IEEE Access, vol. 13, pp. 34122–34134, 2025.

[21] D. Banerjee, S. Das, and P. Bose, “Machine Learning Models for Forecasting Dissolved Oxygen in Aquatic Ecosystems,” Water Research, vol. 245, pp. 120–137, 2024.

[22] A. Bhattacharya and M. Singh, “Comparative Analysis of ML Algorithms for Aquaculture Data Prediction,” Applied Soft Computing, vol. 152, pp. 1123–1139, 2025.

[23] R. Ghosh, S. Nair, and P. Chauhan, “Sustainable IoT Framework for Eco-Efficient Fish Farming,” Renewable Energy and Environmental Sustainability, vol. 12, no. 2, pp. 254–269, 2025.

[24] D. Liu, C. Zeng, and H. Li, “AI-Based Optimization for Feeding and Water Quality in Aquaculture,” Expert Systems with Applications, vol. 237, pp. 121–140, 2025.

[25] M. Torres, F. Hernandez, and R. Gomez, “Digital Twin Applications in Aquaculture for Predictive Ecosystem Management,” Ocean Engineering, vol. 305, pp. 120–138, 2025

.