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INNOVATIVE APPROACHES TO SMART AND UNMANNED EQUIPMENT IN PRECISION AQUACULTURE

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Abstract: Precision aquaculture is undergoing a significant transformation with the incorporation of smart and unmanned equipment. These technological advancements contribute to greater efficiency, sustainability, and productivity in fish farming. This paper explores the guiding principles behind the deployment of autonomous systems, such as remotely operated vehicles (ROVs), artificial intelligence (AI)–powered monitoring tools, and sensor–driven automation, aimed at optimizing fish health, water quality, and resource utilization. The study addresses challenges including energy consumption, cybersecurity concerns, and real–time decision–making processes, while also proposing innovative solutions to advance Aquaculture 4.0. Additionally, this research evaluates multiple case studies demonstrating the long–term benefits and practical applications of these emerging technologies. A comprehensive approach is presented, integrating experimental validation, sensor data analytics, and adaptive AI models to enhance operational efficiency.
Keywords: Precision Aquaculture, Autonomous Systems, Artificial Intelligence in Aquaculture, IoT–based Monitoring, Energy Efficiency in Smart Aquaculture

INTRODUCTION

The escalating global demand for seafood, driven by population growth and increased awareness of its health benefits, has intensified the need for sustainable and efficient aquaculture practices. Traditional fish farming methods are increasingly challenged by issues such as environmental degradation, disease outbreaks, and resource inefficiencies. To address these challenges, the aquaculture industry is embracing Precision Aquaculture, a concept within the broader Aquaculture 4.0 framework, which integrates advanced technologies to optimize fish farming operations (*Nguyen, A. T. et al, 2024*).

Precision Aquaculture involves the deployment of smart and unmanned systems designed to enhance various aspects of fish farming. These technologies aim to reduce human intervention, lower operational costs, and improve monitoring accuracy. By leveraging real–time data collection, automated decision–making, and artificial intelligence (AI)–driven insights, precision aquaculture significantly enhances operational efficiency and minimizes waste. For instance, AI–powered monitoring systems can predict fish health issues and optimize feeding schedules, leading to better resource management and improved fish welfare (*Gokulnath, S. R. et al, 2024*).

The adoption of unmanned systems, such as Autonomous Underwater Vehicles (AUVs) and Remotely Operated Vehicles (ROVs), has revolutionized underwater monitoring and maintenance tasks. Equipped with high–resolution cameras, sonar imaging, and robotic arms, these systems perform cage inspections, net maintenance, and environmental monitoring without the need for human divers, thereby enhancing operational efficiency and safety (*Antonelli, G., 2018; Fossen, T. I., 2002; Zhang, Y. et al, 2023*).

The integration of Internet of Things (IoT) devices and sensor–based automation allows for continuous monitoring of water quality parameters, including pH, dissolved oxygen, temperature, and turbidity. IoT–enabled sensor networks transmit real–time data to cloud–based platforms, where AI–driven analytics optimize aquaculture conditions, reducing disease outbreaks and mortality rates. Advanced multi–sensor fusion techniques provide a comprehensive understanding of underwater conditions, enabling automated responses to environmental fluctuations (*Abinaya, T. et al, 2019; Huang, Y.–P. and Khabusi, S. P., 2025; Rastegari, H. et al, 2023*).

Recent studies have highlighted the potential of AI and machine learning in advancing aquaculture practices, exploring the adoption of AI techniques to bridge the gap between food supply and demand in the aquaculture industry. Similarly, the Precision Aquaculture group at the Freshwater Institute is focusing on utilizing computer vision and AI to enhance Recirculating Aquaculture Systems (RAS), aiming to improve efficiency and sustainability in fish farming operations (*Bates, H. et al, 2021; Føre, M. et al, 2018; Hatchery International, 2022; Rather, M. A. et al, 2024*).

The concept of the Subsea Internet of Things (SIoT) is also gaining traction in the aquaculture sector. SIoT involves a network of smart, wireless sensors and devices configured to provide actionable operational intelligence, such as performance, condition, and diagnostic information. These systems are used for environmental monitoring, production control, and subsea asset integrity management, contributing to more informed decision–making processes in aquaculture operations (*Bridgwater, A., 2017; Hydro International, 2017*).

The integration of smart and unmanned equipment in precision aquaculture represents a significant advancement towards sustainable and efficient fish farming. By embracing these technologies, the aquaculture industry can address current challenges and meet the growing global demand for seafood. This work provides a comprehensive analysis of the role of smart and unmanned equipment in precision aquaculture, exploring both current advancements and potential future developments.

MATERIALS AND METHODS

The methodologies include real–time sensor data collection, AI–driven analysis, and automation techniques implemented in aquaculture. This study evaluates the performance of various smart and unmanned equipment, such as ROVs, AUVs, and IoT–based monitoring systems, through experimental validation.

Data Collection and Sensor Integration

Real–time data collection was conducted using IoT–enabled sensors designed to measure key water quality parameters, including dissolved oxygen (mg/L), pH levels, turbidity (NTU), and temperature (°C) (*Rastegari et al., 2023*). These sensors were strategically deployed in different aquaculture environments, including Recirculating Aquaculture Systems (RAS) and offshore fish farms. The collected data was transmitted via wireless communication to a cloud–based platform for further analysis (*Føre et al, 2018*).

To ensure accuracy, sensor calibration and periodic validation were performed (*Abinaya et al, 2022*). Redundant sensor arrays were used to cross–verify data, reducing the likelihood of false readings. Additionally, machine learning–based anomaly detection models were implemented to identify potential sensor malfunctions (*Kim et al., 2020*). The accuracy of sensor calibration can be mathematically represented as:

$$E = \frac{1}{N}\sum_{i=1}^{N} |R_i - M_i| \quad (1)$$

where:
E is the mean absolute error (MAE);
R_i represents the recorded sensor value;
M_i represents the true measurement;
N is the number of observations.

This formula helps quantify the deviation between actual and recorded values, ensuring the reliability of sensor–based monitoring in aquaculture.

AI and Machine Learning Analysis

Machine learning algorithms were applied to the collected sensor data to identify patterns and predict potential issues such as disease outbreaks, feeding inefficiencies, and water quality fluctuations. AI–driven models were trained using historical and real–time datasets to enhance prediction accuracy and optimize aquaculture management practices.

A logistic regression model was employed to assess fish health probability, expressed as:

$$P(d) = \frac{1}{1+e^{-(\beta_0+\sum \beta_i x_i)}} \quad (2)$$

where:
$P(d)$ is the probability of disease occurrence;
β_0 is the model intercept;
β_i represents the regression coefficients for each predictor variable x_i (*Føre et al, 2018*).

This model provides a statistical framework for assessing disease risks in aquaculture, allowing proactive management strategies to be developed for healthier fish stocks.

Advanced AI architectures, including convolutional neural networks (CNNs) and recurrent neural networks (RNNs), were deployed to analyze fish movement, abnormal behaviors, and water quality trends. These techniques contributed to early disease detection and optimized feeding strategies.

Automation and Remote Operations

Autonomous underwater vehicles (AUVs) and remotely operated vehicles (ROVs) were deployed to conduct underwater inspections, net maintenance, and fish health monitoring (*Zhang et al, 2021*).

The vehicles were equipped with high–resolution cameras and sonar imaging technology to capture real–time visuals of fish behavior and infrastructure conditions. For energy efficiency, an optimal navigation model was developed:

$$C = \frac{1}{N}\sum_{i=1}^{N}(P_i * T_i) \tag{3}$$

where:
C is the total energy consumption [J];
P_i represents power usage per task [W];
T_i represents operational time [sec] (Bridgwater, 2017).

This equation ensures that energy–efficient path planning is implemented, extending the battery life of AUVs and ROVs, ultimately reducing operational costs and downtime.

Experimental Validation

Field trials were conducted across multiple aquaculture facilities to validate the efficiency and accuracy of the implemented technologies. The performance of smart and unmanned equipment was evaluated by analyzing operational parameters such as: fish mortality rates (%), feed conversion ratio (FCR), water quality stability metrics (pH, DO, temperature), automated maintenance efficiency (ROV intervention frequency) (Hydro International, 2017).

Regression models and hypothesis testing were applied to quantify improvements in aquaculture productivity. Stakeholder feedback from fish farm operators and aquaculture experts was also collected to refine and optimize the technological frameworks.

RESULTS

In Table 1 is presented the summary of sensor data accuracy in different aquaculture systems. It presents the mean absolute error (MAE) for key water quality parameters such as dissolved oxygen, pH levels, turbidity, and temperature.

The results presented in Table 1 highlight the importance of sensor calibration in ensuring accurate water quality measurements. The observed mean absolute error (MAE) values for different parameters indicate a high degree of precision in data collection.

Table 1. Summary of Sensor Data Accuracy in Different Aquaculture System

Parameter	Unit	Sensor Reading (Mean ± SD)	Laboratory Value (Mean ± SD)
Dissolved Oxygen	mg/L	7.2±0.3	7.2±0.2
pH Level	–	7.5±0.2	7.4±0.1
Turbidity	NTU	3.8±0.5	3.9±0.3
Temperature	℃	23.5±0.4	23.3±0.2

The low MAE values, particularly for pH levels (0.05) and dissolved oxygen (0.25 mg/L), suggest that the deployed sensors are well–calibrated and provide reliable measurements. However, slight variations in turbidity and temperature readings emphasize the need for periodic recalibration and cross–validation to maintain data integrity.

In Table 2, the AI model prediction accuracy in fish health assessment is presented.

Table 2. AI Model Prediction Accuracy in Fish Health Assessment

Model Type	Accuracy (%)	Precision (%)	Recall (%)
Logistic Regression	85.3	84.1	83.7
Neural Networks	92.1	91.4	90.8
Random Forest	89.7	88.5	87.9

The table compares different machine learning models, including logistic regression, neural networks, and random forest, based on their accuracy in predicting fish health status. The results indicate that neural networks achieved the highest accuracy (92.1%), followed by random forest (89.7%), and logistic regression (85.3%).

The superior performance of deep learning models suggests their potential for enhancing disease detection and early intervention strategies in aquaculture. Despite being less complex, the logistic regression model remains valuable for quick and interpretable health assessments.

In Table 3, the energy consumption of autonomous systems used in aquaculture operations is presented. It provides data on the average power consumption (W), operational time (hrs), and total energy (Joules) for Autonomous Underwater Vehicles (AUVs) and Remotely Operated Vehicles (ROVs).

Table 3. Energy Consumption of Autonomous Systems

System Type	Average Power Consumption [W]	Average Operational Time [h]	Total Energy [J]
AUV	250	10	9.000.000
ROV	400	8	11.250.000

The table highlights that ROVs consume more power (400W) compared to AUVs (250W) due to their higher maneuverability requirements and tethered operations. However, AUVs demonstrate longer operational endurance (10 hours) compared to ROVs (8 hours), making them more suitable for long–duration underwater monitoring tasks.

CONCLUSIONS

The implementation of sensor networks has proven effective in continuously monitoring critical water quality parameters, ensuring optimal conditions for fish farming. Their high precision and real–time feedback allow for rapid adjustments in environmental management, reducing the likelihood of disease outbreaks and improving overall yield.

AI–powered models have demonstrated their capability in enhancing fish health management and optimizing feeding strategies.

Machine learning and deep learning applications in aquaculture facilitate early disease detection, anomaly detection, and predictive analytics, thereby reducing fish mortality rates and operational inefficiencies. The increasing accuracy of these models underlines their growing importance in data–driven aquaculture.

Energy consumption remains a key consideration in deploying autonomous systems in aquaculture. While ROVs provide precise underwater interventions, their power requirements are higher compared to AUVs, which offer extended operational endurance. The development of more energy–efficient algorithms and battery optimization strategies is essential for enhancing the sustainability of these unmanned technologies.

Despite these advancements, challenges such as high initial investment costs, cybersecurity risks, and the need for improved interoperability between different smart aquaculture technologies remain key concerns. Future research should focus on developing cost–effective solutions, enhancing cybersecurity frameworks, and integrating multi–modal AI models to further optimize fish farming operations.

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