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Research on the Development and Application of an Intelligent Aquaculture System

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ABSTRACT

This research addresses the pressing need for sustainable practices in aquaculture, which faces challenges, like environmental degradation. The study aims to evaluate the effectiveness of an intelligent aquaculture system (IAS) in improving key performance indicators in shrimp farming. Methodologically, it focuses on a specific shrimp farm divided into 10 breeding zones, with the number 3 area selected for experimentation. Data on environmental parameters and performance metrics were collected for comparative analysis against traditional practices. Results showed significant improvements: The IAS achieved a feed conversion rate of 90.22% and a growth rate of 50 g/week, outperforming traditional methods. Additionally, it exhibited lower disease incidence and mortality rates, indicating enhanced safety. The study concludes that IASs can substantially improve operational efficiency and sustainability, offering valuable insights for the future of aquaculture practices.

KEYWORDS

Intelligentization, Aquaculture, System Development, Applied Research

INTRODUCTION

Aquaculture occupies an important position in the global food supply chain and has a far-reaching impact on human dietary health and economic growth in many regions. However, with the rapid growth of the global population and increasing pressure on resources, traditional aquaculture methods have become inadequate. The main problems faced by the industry include disease outbreaks, water quality deterioration, low feed utilization efficiency, and difficulties in growth cycle management, all of which seriously hinder the sustainable development and efficiency improvement of aquaculture (Singh et al., 2023; Vo et al., 2021).

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To meet these challenges, the development and application of intelligent aquaculture systems (IASs) has become particularly critical. With the help of advanced technologies, such as the Internet of Things (IoT; Rastegari et al., 2023), big data analysis (Duan et al., 2018), artificial intelligence (AI; Capetillo-Contreras et al., 2024), and cloud computing (Mustapha et al., 2021), these systems enable real-time monitoring of environmental parameters and precise operational management, thus solving the inefficiency problems associated with traditional methods (Olanubi et al., 2024; Wang et al., 2021). Compared with traditional manual operations, intelligent transformation not only improves efficiency but also reduces labor and material costs, enhances product quality, and brings remarkable economic, social, and environmental benefits (Chiu et al., 2022).

This study focuses on the development and application of IASs, aiming to clearly demonstrate how these systems address the challenges faced by traditional aquaculture by discussing their core technologies, operational principles, and practical impacts. Specifically, this study will evaluate the role of IAS in improving production efficiency, reducing costs, enhancing product quality, and promoting sustainable development, and it will highlight their significant advantages through detailed case analysis and benefit evaluation.

The core purpose of this study is to deeply explore the following aspects of IASs: (1) to analyze in detail the key technologies used to enable intelligent transformation, such as IoT sensor networks, data analysis algorithms, and AI model training platforms. This paper will explain how these technologies can be integrated into daily management and decision-making processes to optimize resource allocation and the production process. Through specific case studies and quantitative analysis, the effectiveness of intelligent systems in improving output, controlling costs, and protecting the environment will be demonstrated. Through this research, we hope to provide valuable reference information for policymakers, industry practitioners, and related researchers, as well as to jointly promote the modernization of the aquaculture industry, ensuring its long-term and stable development.

LITERATURE REVIEW

In recent years, aquaculture has undergone a remarkable transformation, mainly driven by the growth of global demand for seafood and the urgent need for sustainable practices. With the continuous growth of the world population, traditional aquaculture methods are facing unprecedented challenges, including disease outbreaks, water quality deterioration, and low feed utilization efficiency. These problems not only threaten the productivity of aquaculture but also pose a challenge to its sustainability. In order to address these urgent issues, the development and application of IASs have become promising solutions, as they can improve productivity and sustainability by integrating advanced technologies (An et al., 2021; Chen et al., 2022).

Importance and Technical Progress of Water Quality Management

In aquaculture, water quality management is a key factor in ensuring the health and growth of aquatic organisms. Poor water quality can lead to higher mortality, slower growth, and increased disease susceptibility. Therefore, effective water quality management is crucial for the sustainability of aquaculture. Recent research shows that monitoring key water quality parameters, such as dissolved oxygen, pH, temperature, and nutrient levels, is essential (Huan et al., 2020; Yusoff et al., 2024). By adopting real-time monitoring technology, practitioners can make informed decisions to maintain optimal water quality conditions, thus ensuring the health and stability of the system.

Modern technologies, such as the IoT (Rastegari et al., 2023) and AI (Capetillo-Contreras et al., 2024), have revolutionized the way water quality is managed in aquaculture. IASs continuously monitor water quality parameters and environmental conditions using sensor networks and equipment (Li & Liu, 2020; Zhang & Gui, 2023). These data are transmitted to cloud-based platforms for analysis, enabling timely intervention when water quality deviates from the acceptable range. For example, the automatic system can adjust aeration, filtration, and water exchange processes based on real-time data to maintain the most suitable conditions for aquatic organisms. This shift from manual management to automated management not only improves operational efficiency but also reduces the risk of human error (Ubina et al., 2022; Yadav et al., 2023).

Challenges and Solutions of Technology Implementation

Although the advantages of IASs are obvious, there are still some challenges to be overcome for their successful implementation. One of the major challenges is the high initial investment required, which may be unbearable for many small farmers and become an obstacle to the adoption of these technologies. To alleviate this problem, innovative financing models, such as public-private partnerships or microfinance, can be explored to reduce the economic burden on small farmers and promote the widespread application of intelligent systems (Munguti et al., 2023; Munyua et al., 2022).

The experiences of other industries also provide valuable references for aquaculture. For example, precision agriculture uses similar IoT and AI technologies to optimize crop management, improve resource utilization efficiency, and increase yield by monitoring soil conditions, weather patterns, and crop health. Similarly, intelligent manufacturing uses real-time data analysis to enhance production processes, reduce waste, and improve product quality (SS et al., 2024; Senoo et al., 2024). By learning from the successful experiences and best practices of these industries, aquaculture can adopt data-driven decision-making methods, thus improving its operational efficiency and sustainability.

Feed Utilization Efficiency and Economic Impact

In addition to water quality management, feed utilization efficiency is also a key factor affecting aquaculture productivity. Traditional feeding methods usually result in a high feed conversion rate, increasing costs and negatively impacting the environment. IASs can optimize feeding strategies by analyzing data on fish behavior and environmental conditions. Determining the optimal feeding time and quantity can improve feed conversion rates and reduce waste, thus enhancing the economic benefits of aquaculture while promoting environmental protection by reducing the ecological footprint of feed production (Akinsorotan et al., 2024; Saad et al., 2024).

Socio-Economic Impact and Capacity Building

The social and economic impact of IASs cannot be ignored. Although these technologies bring many benefits, they also pose challenges for small farmers who lack the technical and financial resources to implement them. Transitioning to automation and data-driven practices requires a certain level of technological knowledge, which may not be common among all aquaculture practitioners. Therefore, it is necessary to carry out capacity-building initiatives and training programs to equip farmers with the skills needed to operate and maintain these advanced systems. By addressing these socio-economic obstacles, the aquaculture industry can ensure the fair distribution of the benefits of intelligent technology (Er-rousse & Qafas, 2024).

Environmental Considerations and Sustainable Practices

Finally, the environmental impact of IASs also needs careful assessment. Although these systems can improve resource utilization efficiency and reduce waste, their implementation should not lead to unexpected consequences, such as increased energy consumption or dependence on nonrenewable resources. To ensure a positive contribution to the environment, sustainable practices should be integrated into the design and operation of IASs, including the use of renewable energy, optimization of water use, and minimization of chemical inputs (Kassem et al., 2021; Mustafa et al., 2021).

The Latest Research Progress Based on Different Regions

In China, the integration of IoT sensors and AI algorithms has notably improved water quality monitoring and automated feeding systems, which, in turn, optimizes breeding efficiency and the quality of aquatic products (Chen et al., 2024; Wang et al., 2021). These systems enable more precise control over farm conditions, reducing resource consumption and increasing yields. In Europe, particularly in Norway, the combination of machine learning and big data is being used to predict fish growth rates and disease risks, optimizing the use of resources, such as feed and energy. A key example includes a study in northern Norway, where an integrated approach using geographic information systems and machine learning identified the most suitable sites for salmon farming, providing a pathway to more sustainable farming practices (Aspen, 2022). Additionally, precision fish farming systems have been developed to enhance production through real-time monitoring, improving farm management and reducing operational risks (Føre et al., 2018). In North America, innovations, such as blockchain technology, are being explored for tracking the supply chains of aquatic products, aiming to improve food safety and supply chain transparency in the United States (Howson, 2020). In Canada, the development of intelligent farming systems that adapt to cold climates has been a focus. These systems utilize advanced environmental control technologies to optimize farm yield and streamline farming cycles in the country's offshore aquaculture sites (Asgher, 2024). In Southeast Asia, the application of solar-powered sensor networks in Thailand is improving water quality monitoring in remote aquaculture locations, offering a sustainable and efficient solution for local farmers (Pant et al., 2004). In Vietnam, the adoption of automation technologies by small-scale farmers has contributed to improved farming practices, resulting in better income and quality of life for the local community (Tri et al., 2022). These global developments illustrate how IASs are transforming the industry by addressing region-specific challenges. The diverse applications of these technologies—from precision farming and machine learning to blockchain and automation—highlight their potential to enhance sustainability, food safety, and productivity in aquaculture worldwide.

To sum up, this study aims to fill the gap in the existing knowledge base by discussing the core technology and practical application of IASs. We not only emphasize the advantages of intelligent systems in improving production efficiency, reducing costs, and improving product quality but also deeply analyze their role in promoting sustainable development and social and economic equity. Through a comprehensive review of the latest literature, this study clarifies the contribution of IASs and provides valuable references for future research and development.

MATERIALS AND METHODS

Overview of IASs

An IAS, as the product of the deep integration of modern information technology and traditional aquaculture industry, integrates the advantages of advanced technologies, such as the IoT (Rastegari et al., 2023), big data analysis (Duan et al., 2018), AI (Capetillo-Contreras et al., 2024), and cloud computing (Mustapha et al., 2021), so as to achieve accurate monitoring of the farming environment, intelligent regulation, and automatic management of the farming process, thereby improving the farming efficiency, reducing costs and improving product quality.

System Definition and Characteristics

An IAS, in short, is a use of modern information technology to the whole process of aquaculture intelligent management system. It collects key parameters, such as water quality, temperature, light, and dissolved oxygen, in the farming environment in real time, through various sensors, cameras, and other IoT devices deployed in the farm, and it sends these data to the cloud or edge computing platform for processing and analysis through wireless transmission technology. Then, the results of big data analysis are mapped to the behavior, so that the system can automatically adjust the farming environment, such as adjusting water temperature, oxygen, feeding, and other farming activities, to achieve the optimal way to help the growth and development of aquatic organisms (Yang et al., 2021).

System Architecture and Components

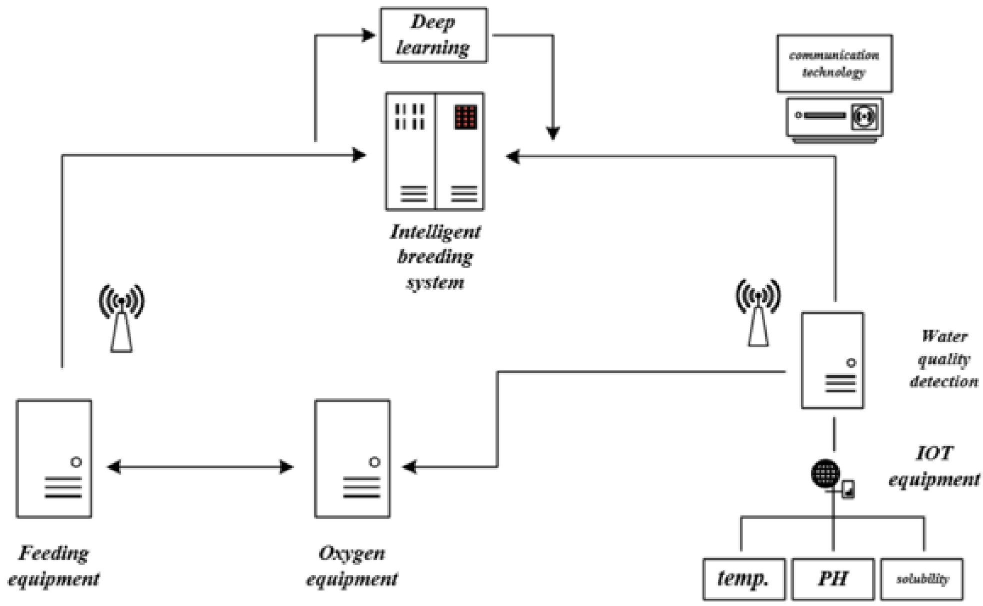
An IAS usually consists of several key components (Hu et al., 2020):

1. IoT sensing layer: This layer includes water quality monitoring sensors, temperature sensors, light sensors, cameras, etc., responsible for real-time collection of all kinds of data of aquaculture environment.
2. Network communication layer: Through Wi-Fi, long range, narrowband-IoT, and other wireless communication technologies, the data collected by the perception layer is transmitted to the cloud or local data center.
3. Data processing and analysis layer: This layer uses big data processing technology and deep learning algorithm to clean, integrate, and analyze the received data and extract valuable information, such as water quality assessment and disease risk prediction.
4. Intelligent control layer: This layer automatically adjusts the breeding environment according to the data analysis results. For example, the aquatic organisms are currently in the stage of rapid growth and development and need to increase the frequency of feeding. At this time, the intelligent feeding machine can feed one or more breeding areas regularly and quantitatively for multiple times through the system instruction. The same is true of aerators, temperature control equipment, etc., to achieve precise regulation.
5. User interaction layer: This component is the most frequently contacted by users, which provides an intuitive interface, enabling farmers to remotely and real-time monitor the farming environment, receive various early warning information from the system, view the system analysis report, and make decisions accordingly.

Working Principle and Process

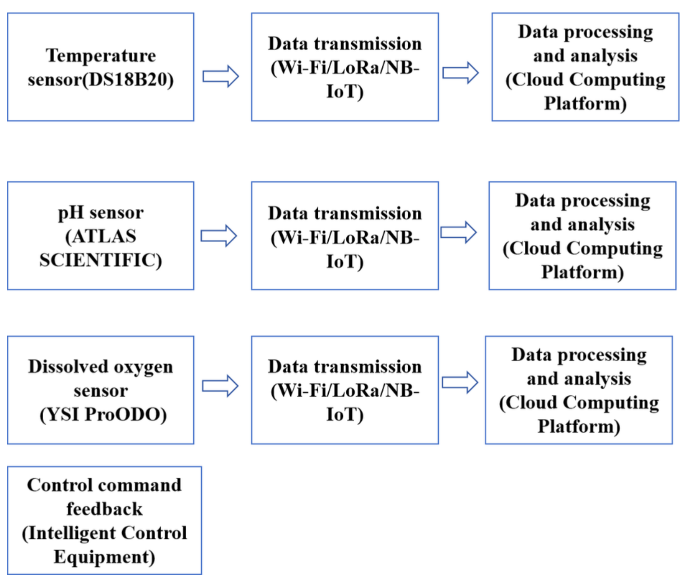
The main workflow of the IAS is shown in Figure 1 and Figure 2, which can be summarized as follows: Firstly, the system collects real-time aquaculture environment data, such as water quality, temperature, and other key indicators, through various sensors deployed in the IoT sensing layer; subsequently, these data are transmitted to the data processing and analysis layer through the network communication layer, and deep mining and intelligent analysis are carried out using big data technology and machine learning algorithms to identify the changing trends and potential risks of the farming environment. Based on the analysis results, the intelligent control layer automatically generates control instructions, such as adjusting feeding strategy and optimizing water quality conditions, and executes them through intelligent devices. Finally, the system continuously monitors the regulation effect and adjusts the strategy according to the real-time feedback, forming a closed-loop and dynamically optimized aquaculture management process. This process not only realizes the precise control and intelligent management of the breeding environment but also significantly improves the breeding efficiency and product quality.

Figure 1. Workflow diagram of intelligent aquaculture system (IAS)



Note. IAS = intelligent aquaculture system; IoT = Internet of Things; PH =Pondus Hydrogenii .

Figure 2. Workflow diagram of equipment



Note. LoRa =Long Range; NB =Narrowband ; YSI ProODO =It is a portable dissolved oxygen (DO) meter produced by YSI ; IoT = Internet of Things.

Technical Advantages and Highlights

The technical advantages and highlights of the IAS are concentrated in its comprehensive and accurate management capabilities. Through the deep application of the IoT technology, the system can monitor the key indicators of the farming environment in real time, ensure the immediacy and accuracy of the data, and provide timely and effective early warning information for farmers. The introduction of big data analysis technology enables the system to dig deeply into the laws behind the data, achieve precise regulation and strategy optimization of the breeding environment, and greatly improve the breeding efficiency and product quality. Moreover, the system uses AI algorithms for intelligent decision support, automatically analyzes data, and generates scientific breeding suggestions, which greatly reduces the decision-making burden of farmers. In addition, the realization of remote management and automatic control functions makes the breeding process more convenient and efficient, as well as further improves the intelligent level of the breeding industry.

Key Technologies and Their Functions

The successful implementation of an IAS is inseparable from the support and application of a series of key technologies. These technologies not only promote the intelligent monitoring and management of the aquaculture environment but also effectively promote the precision and personalization of aquaculture strategies, bringing unprecedented changes to the aquaculture industry.

IoT Technology to Achieve Real-Time Monitoring of Farming Environment

IoT technology is the cornerstone of IASs. First of all, in terms of the overall system design level, we need to focus on the three core functions of real-time monitoring, data analysis, and intelligent regulation.

First of all, we need to build an IoT sensing layer, specifically through the deployment of water quality monitoring sensor equipment and comprehensive and reasonable coverage of the entire farming area, so as to collect real-time farming environment data. Through Zigbee (also known as purple bee), we achieve a stable connection between the sensor and the data center, to ensure real-time data transmission.

Secondly, build the data analysis and processing layer, which is the key to the intelligence of the entire system. The cloud computing platform is used to centrally store and process the collected data, and big data analysis and machine learning algorithms are used to mine the correlation and regularity among the data, identify abnormal changes in the breeding environment, predict the growth trend and disease risk of breeding organisms, and provide a basis for intelligent decision-making.

Finally, the intelligent control layer is designed to automatically trigger the control instructions according to the data analysis results to realize the precise control of the breeding environment. At the same time, if conditions permit, we can also develop mobile application and web site, which is convenient to provide remote monitoring and manual regulation functions, so that farmers can grasp the breeding dynamics at any time, and they can respond to emergencies more flexibly.

Big Data Technology: Mining the Law Behind the Data

Big data technology plays a crucial role in IASs. The system needs to use big data processing technology and machine learning algorithms to clean, integrate, and analyze the massive data received and extract valuable information. Its main role is that, through data analysis, the system is able to identify changing trends in the farming environment, predict disease risks, optimize feed formulations, and improve farming efficiency.

AI Technology: Intelligent Decision Support

AI technology is the core of the IAS. The system uses AI algorithms, such as deep learning and neural networks, to conduct intelligent analysis of breeding data and automatically generate regulatory instructions. For example, we set in the system development: When the water quality monitoring data shows that the dissolved oxygen concentration is lower than 4 mg/L, the system can automatically start the aerator and adjust the dissolved oxygen concentration to the appropriate range of 6–8 mg/L to effectively improve the water quality conditions. At the same time, if the disease warning model analyzes that the probability of a farmed organism contracting a disease is more than 10%, the system will trigger preventive measures in advance, such as adjusting the feed formula and increasing the frequency of disinfection, so as to significantly reduce the incidence of disease to less than 2%.

Cloud Computing Technology: Data Sharing and Remote Management

Cloud computing technology, from the surface point of view may be the smallest part of the entire system, but its "heritage effect" is immeasurable. Through the cloud computing platform, the centralized data storage, processing, and analysis can provide farmers and even breeding cooperative organizations with remote monitoring, data analysis, decision support, and other one-stop services. In other words, the expansion and upgrading of the industrial scale is closely related to cloud computing technology.

Fifth Generation Communication Technology: Improve Data Transmission Efficiency and Reliability

The introduction of 5th generation communication technology has brought double improvement of data transmission efficiency and reliability to the IAS. It plays a decisive role for the system to collect and transmit more abundant breeding environment data in real time, as well as plays a decisive role for accurate regulation and intelligent decision-making.

System Development Example

Water Quality Monitoring Module

Water quality monitoring is a key link in the development practice of the IAS. We use Python programming language and related libraries to achieve this function. The following is a simplified code example of water quality monitoring, which aims to show how to read data through sensors and make preliminary processing.

```
       def read_ph(self):
           # Reading pH
           return round(random.uniform(6.5, 9.0), 2)  # Set the pH
range to 6.5 to 9.0
       def read_dissolved_oxygen(self):
           # Read dissolved oxygen (mg/L)
           return round(random.uniform(5.0, 15.0), 2)  # Let the
dissolved oxygen range be 5.0 to 15.0 mg/L
       def read_temperature(self):
           # Read temperature (degrees Celsius)
           return round(random.uniform(20.0, 30.0), 2)  # Set the
temperature range to 20 to 30 degrees Celsius
   def monitor_water_quality():
       sensor = WaterQualitySensor()

       while True:
           ph_value = sensor.read_ph()
           dissolved_oxygen = sensor.read_dissolved_oxygen()
           temperature = sensor.read_temperature()
```

```
            print(f"Current water quality monitoring data:")
            print(f"pH: {ph_value}")
            print(f"Dissolved oxygen: {dissolved_oxygen} mg/L")
            print(f"temperature: {temperature} °C")

            # Of course, you can add data storage or alarm logic
here
            # e.g., if ph_value < 6.5 or dissolved_oxygen < 5.0:
            #           print("Warning: Water quality is not up to
standard！")
```

Notes: Simulation data generation: this code segment uses random.uniform to generate simulated water quality parameters (water temperature, pH value, and dissolved oxygen). In practical application, this part needs to be adjusted according to the specific sensor interface library, such as using Adafruit's Digital Humidity and Temperature sensor library to read the temperature and humidity sensor data.

Data storage: The collected data is stored in an SQLite database for subsequent analysis and visualization. In actual deployment, data can be sent to the cloud platform for more advanced data processing and real-time monitoring.

Application of Deep Learning Algorithm

Deep learning algorithm is used to optimize feeding strategy in the IAS. By analyzing the growth stage, health status, and environmental conditions of aquatic organisms (such as water temperature, dissolved oxygen, pH value, and light intensity), the system can intelligently adjust the feeding amount, time, and type.

```
   # Split features and labels
   X = data[['growth_stage', 'health_status', 'water_temperature',
'dissolved_oxygen',
     'ph_value', 'light_intensity']]
   y = data[['feed_amount', 'feed_time', 'feed_type']]

   # Data preprocessing
   X_train, X_test, y_train, y_test = train_test_split(X, y, test_
size=0.2, random_state=42)
   scaler = StandardScaler()
   X_train = scaler.fit_transform(X_train)
   X_test = scaler.transform(X_test)

   # Build a deep learning model
   model = Sequential()
   model.add(Dense(64, input_dim=X_train.shape[1],
activation='relu'))
   model.add(Dense(32, activation='relu'))
   model.add(Dense(3))  # In the output layer, the three outputs
correspond to the feeding amount, feeding time and feeding type

   # Compilation model
   model.compile(optimizer=Adam(learning_rate=0.001), loss='mean_
squared_error')

   # Training model
```

```
    model.fit(X_train, y_train, epochs=100, batch_size=32,
validation_split=0.2)

    # Make a forecast
    predictions = model.predict(X_test)
    predicted_feed_amount = predictions[:, 0]
    predicted_feed_time = predictions[:, 1]
    predicted_feed_type = np.round(predictions[:, 2]).astype(int)
```

Notes: Model construction: The model adopts multi-layer perceptron structure and is suitable for regression tasks. Adam optimizer and mean square error loss function are used to minimize the difference between the predicted value and the real value.

Training and prediction: The training data is generated randomly, and the real data collected from sensors should be used in practical application. The prediction part shows how to predict the feeding amount based on the model and round the result to an integer, which is convenient for practical application.

Combined With Application Scenarios

In order to better understand the practical application of these technologies, the following are specific scenarios of water quality monitoring and feeding optimization in the IAS:

- Water quality monitoring: Through the sensor network deployed in the farm, the key parameters, such as water temperature, pH value, and dissolved oxygen, are collected in real time. These data are not only used to adjust the breeding environment immediately but also transmitted to the cloud platform for big data analysis to help farmers identify potential problems and take preventive measures.
- Feeding optimization: Based on the deep learning model, the system can automatically adjust the feeding strategy according to the growth stage, health status, and environmental conditions of aquatic organisms. This not only improves the utilization rate of feed and reduces waste but also promotes the healthy growth of organisms.

RESULTS AND ANALYSIS

Basic Principles of Dataset Selection

Relevance of the Dataset

The dataset selected for this study is directly aligned with the objectives of evaluating the performance of IASs. By focusing on a specific shrimp aquaculture farm with a total area of 10 mu, subdivided into 10 equally sized breeding zones, the study aims to assess the effectiveness of the intelligent system in improving key performance indicators, such as growth rates, feed conversion efficiency, and overall sustainability, in shrimp farming. This targeted approach ensures that the findings are highly relevant and applicable to real-world aquaculture practices, providing valuable insights for enhancing operational efficiency and sustainability in the industry.

Representativeness

The experimental design incorporates a representative sample of the aquaculture environment by selecting the number 3 breeding area as the experimental site. This area was chosen randomly to minimize bias and ensure that the results reflect typical conditions encountered in the shrimp farming sector. Additionally, the inclusion of similar number 4 and distant number 10 areas as reference points allows for comparative analysis, enhancing the representativeness of the dataset across different breeding conditions.

Sampling Methodology

The sampling methodology employed in this study is designed to reduce human interference and experimental error. By randomly selecting the number 3 breeding area and using adjacent areas for comparison, the study ensures that the data collected is not influenced by external factors that could skew the results. This approach enhances the reliability of the findings and supports the validity of the conclusions drawn from the dataset.

Diversity of Aquaculture Conditions

The dataset captures a range of aquaculture conditions by including multiple breeding areas within the same shrimp base. This diversity allows for an examination of how the IAS performs under varying environmental conditions, such as differences in water quality, temperature, and stocking density. By analyzing data from these different areas, the study can provide insights into the adaptability and effectiveness of the intelligent system across diverse aquaculture settings.

Acknowledgment of Limitations

While the dataset provides valuable insights, it is important to acknowledge its limitations. For instance, the study is conducted within a single shrimp base, which may not fully represent the broader aquaculture industry. Additionally, factors, such as seasonal variations and specific management practices in the selected areas, may influence the results. By transparently discussing these limitations, the study enhances its credibility and allows for a more nuanced interpretation of the findings.

Data Analysis Results

The data shown in Figures 3, 4, 5, 6, and 7 was finally obtained.

Figure 3. Comparison of feed conversion rate and growth rate in different farming methods

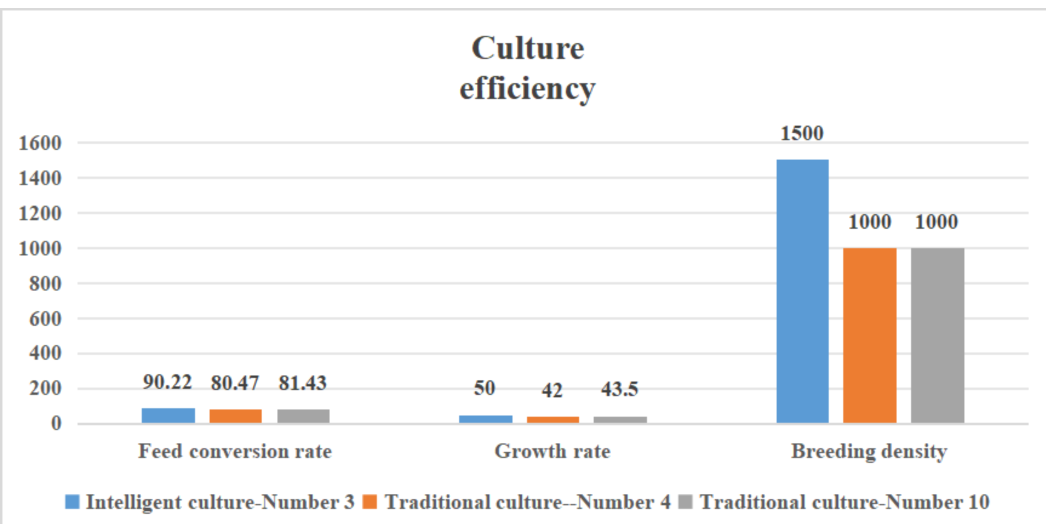


Figure 4. Trends of disease incidence and mortality

Figure 5. Comparison of water resource utilization rate and tail water treatment efficiency

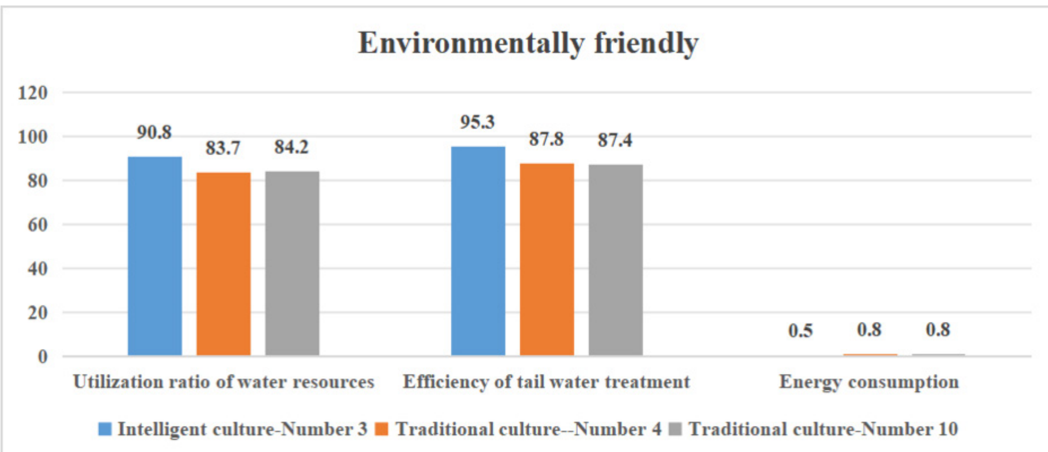


Figure 6. Comparison of labor cost, feed cost, and water quality monitoring cost

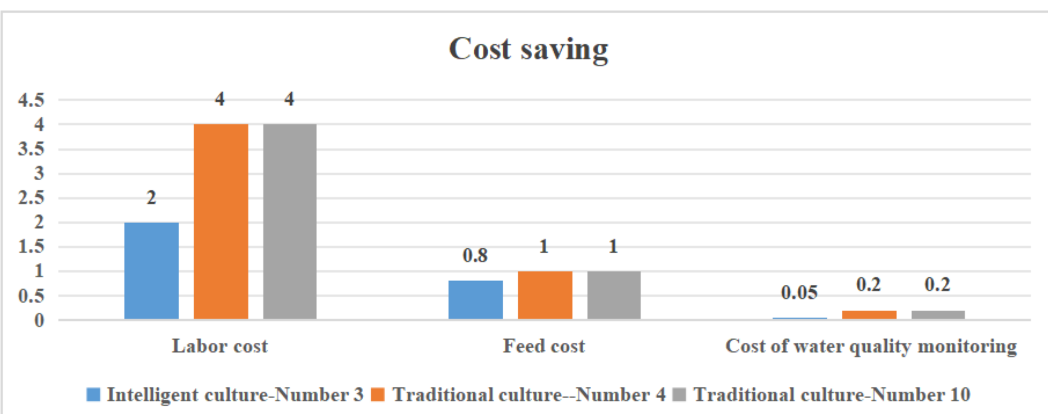
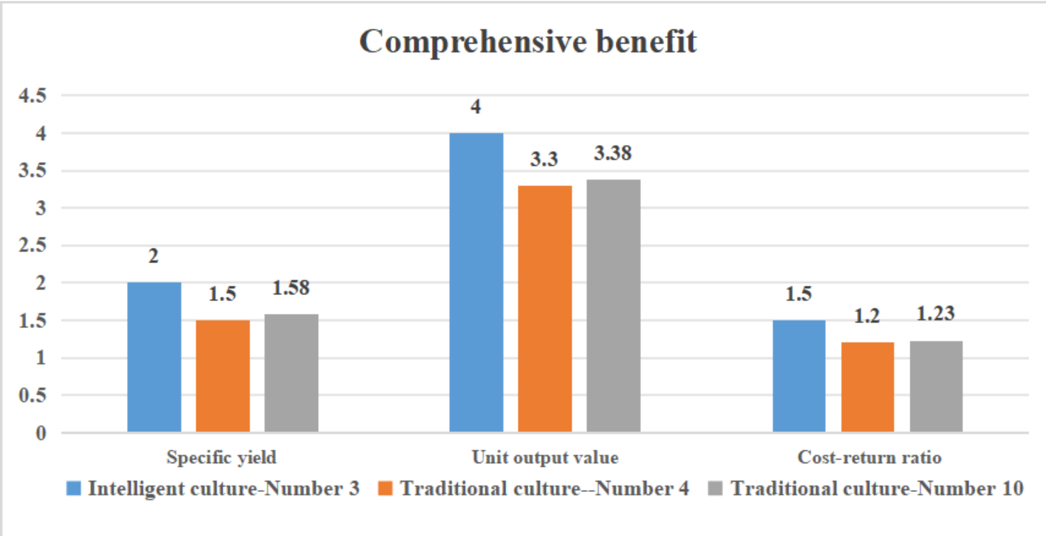


Figure 7. Comparison of unit output and unit output value



Culture Efficiency

The IAS demonstrates superior culture efficiency compared to traditional methods. The breeding density in the intelligent system is set at 1,500 tails/m^3, which is 50% higher than the traditional systems at 1,000 tails/m^3. Moreover, the intelligent system achieves a feed conversion rate of 90.22%, outperforming the traditional methods (80.47% for number 4 and 81.43% for number 10), indicating better utilization of feed. Additionally, the intelligent system leads in growth rate, with a weekly growth of 50 grams per tail, surpassing both traditional systems (42 grams for number 4 and 43.5 grams for number 10). This efficiency in both feed and growth results in better overall performance for the intelligent system in terms of culture productivity.

Culture Safety

The intelligent culture system significantly enhances safety by reducing the incidence of diseases and mortality rates. The disease incidence rate is 2.75% in the intelligent system, which is much lower than the 7.86% and 7.13% observed in the traditional systems. Additionally, the intelligent system shows a mortality rate of 1.2%, compared to 4.1% and 3.9% in the traditional methods. Another important factor is the reduced frequency of abnormal water quality events; the intelligent system only faces one event per month, while traditional systems experience four and three events per month. These results highlight the intelligent system's ability to maintain a healthier and safer environment for aquatic organisms.

Environmentally Friendly

In terms of environmental sustainability, the IAS proves to be more efficient in water usage and energy consumption. The water utilization rate in the intelligent system stands at 90.8%, higher than the 83.7% and 84.2% in the traditional methods. Moreover, the intelligent system achieves a water treatment efficiency of 95.3%, which is noticeably higher than the 87.8% and 87.4% in the traditional systems. The energy consumption is also more efficient, with the intelligent system using only 0.5 kWh/tail, as opposed to the 0.8 kWh/ tail required by the traditional methods. This efficiency leads to significant resource savings and a reduced environmental impact in intelligent aquaculture.

Cost Saving

Cost analysis reveals the substantial savings offered by the intelligent system across several key areas. The intelligent system reduces labor costs, requiring only two persons per day, compared to four persons in the traditional methods. Additionally, feed costs are lower in the intelligent system (0.8 yuan per tail) versus 1.0 yuan per tail in traditional aquaculture. The water quality monitoring cost in the intelligent system is also lower (0.05 yuan per cubic meter) compared to 0.2 yuan in traditional systems. These savings in labor, feed, and water quality monitoring contribute to the overall cost-effectiveness of the intelligent aquaculture approach.

Comprehensive Benefit

In terms of overall productivity and profitability, the IAS offers clear advantages. The specific yield in the intelligent system reaches 2,000 kg/m^3, which is 500 kg/m^3 higher than the traditional systems (1,500 kg/m^3 for number 4 and 1,580 kg/m^3 for number 10). This higher yield translates into a significantly better unit output value of 40,000 yuan/m^3 for the intelligent system, compared to 33,000 yuan/m^3 for the traditional systems. As a result, the cost-return ratio for the intelligent system is 1.5, compared to 1.2 and 1.23 in the traditional systems, further illustrating the economic benefits and increased profitability of the intelligent aquaculture approach.

In conclusion, the IAS significantly outperforms traditional methods in several key areas, including culture efficiency, safety, environmental sustainability, cost savings, and overall profitability. It achieves higher breeding density, better feed conversion, and faster growth, while also reducing disease incidence, mortality rates, and water quality issues. The system's superior water and energy efficiency lead to reduced environmental impact, and its lower labor, feed, and monitoring costs make it more cost-effective. With higher productivity and a better cost-return ratio, the intelligent system provides a more sustainable and profitable solution for modern aquaculture, offering clear advantages over traditional methods.

DISCUSSION

Comparison of Research Results With Previous Studies

This study highlights the great potential of IASs in improving efficiency and sustainability. Compared with traditional methods, IAS integrates advanced technologies, such as the IoT, big data analysis, and AI, to enable real-time monitoring and optimal management of water quality parameters, environmental conditions, and feeding strategies. These technologies not only improve production efficiency but also reduce resource waste, mitigate environmental pollution, and enhance product quality. For example, in Zhejiang province, in China, after the introduction of IoT sensors and AI algorithms, reproductive efficiency and product quality were significantly improved (Zhang & Gui, 2023). In contrast, traditional methods rely on experience and regular inspections, making it difficult to achieve the same level of accuracy and timeliness.

Cause Analysis of Results

The success of IASs can largely be attributed to their effective use of advanced technologies. First, real-time data collection and analysis enable practitioners to respond swiftly to changes and maintain the optimal breeding environment. Second, automation reduces the possibility of human error, ensuring operational consistency and accuracy. Additionally, intelligent systems improve feed conversion rates, reduce costs, and lower the ecological footprint by optimizing feed delivery time and quantity. These technological advancements are crucial factors in achieving higher efficiency and sustainability.

However, despite the many advantages of intelligent systems, there are also challenges and potential disadvantages. For example, the high dependence on technology means that any failure or error in data collection could negatively affect the entire aquaculture environment. Therefore, it is essential to establish robust backup systems and maintenance protocols. Moreover, the high initial investment and technical complexity pose significant challenges, particularly for small farmers, and may hinder the widespread adoption of intelligent systems.

Socio-Economic Impact

In order to strengthen the social and economic benefits of IASs, especially in their application to small-scale farmers, it is important to discuss their social and economic impact in depth. The high initial investment required for intelligent systems may become an obstacle for small farmers to adopt this technology. It is estimated that the initial equipment and installation costs of intelligent systems are about 30% to 50% higher than those of traditional methods. In addition, intelligent systems require a certain level of technical expertise, which may be difficult for farmers who lack the necessary skills. To address these challenges, public-private partnerships, micro-credit schemes, or government subsidies could help reduce the economic burden. Research shows that, with proper training, the technology adoption rate among farmers can increase to more than 70%. Therefore, implementing training programs to help farmers master the operation of intelligent systems is a key measure to promote the widespread adoption of this technology.

The Role of Stakeholders

The implementation of IASs involves many stakeholders, including the government, scientific research institutions, enterprises, farmers, and technology suppliers. The government should formulate policies and support measures, such as providing subsidies, tax incentives, and technology extension services. Scientific research institutions conduct basic research and technical development to provide theoretical and technical support for intelligent systems. Enterprises develop and sell intelligent devices and software, as well as provide technical support and services. Farmers, as end users, participate in the use and feedback of the system, which helps drive technical improvements. Technology suppliers provide the necessary hardware and software solutions to ensure the stable operation of the system. The cooperation and joint efforts of all parties will contribute to the successful popularization and application of intelligent systems.

Environmental Impact Assessment

IASs have both positive and potentially negative impacts on the environment. The utilization rate of water resources increased from 83.7% to 90.8%, and the efficiency of tailwater treatment increased from 87.8% to 95.3%, which helps reduce the impact on the environment. Energy consumption decreased from 0.8 kWh/tail to 0.5 kWh/tail, thereby reducing carbon emissions. However, the replacement of smart devices may lead to an increase in electronic waste, necessitating the establishment of a recycling mechanism. Excessive reliance on technology may also weaken farmers' traditional knowledge and skills, which requires balanced development. A comprehensive environmental assessment is essential to identify and address these potential problems and ensure the long-term sustainability of intelligent systems.

Future Research Direction

In order to further promote the development of IASs, the following specific areas deserve further study:

- Cost reduction: Explore low-cost sensors and simplify system design to reduce the initial investment threshold. Study how technological innovation and large-scale production can further reduce the cost of intelligent systems, making them more accessible to a broader audience.

- Improvement of adaptability: Customize intelligent systems based on the climate and geographical characteristics of different regions to improve their applicability and effectiveness. For example, in Southeast Asia, solar-powered sensor networks have proven to be an effective solution for remote water quality monitoring (Kumar & Aravindh, 2020).
- Multidisciplinary cooperation: Combine the expertise of disciplines, such as biology, engineering, economics, and sociology, to address complex problems. Interdisciplinary cooperation can enhance the scientific and practical aspects of technology and provide a better understanding of how it operates within various socio-economic contexts.
- Policy support: Investigate how policy guidance and support can facilitate the widespread adoption of intelligent systems. The government can encourage more farmers to adopt intelligent technologies through legislation, financial incentives, education, and public outreach.
- Long-term impact assessment: Continuously monitor the long-term environmental and socio-economic impacts of intelligent systems to ensure their sustainable development. Establish a long-term monitoring mechanism to collect and analyze extensive data, assess the performance of intelligent systems over time, and provide a foundation for future improvements.

By deepening socio-economic analysis, providing more data support, clarifying the roles of stakeholders, conducting comprehensive environmental assessments, and planning future research directions, we can accelerate the modernization of the aquaculture industry and ensure its long-term stability. This will not only help improve the efficiency and competitiveness of the industry but also promote environmental protection, social equity, and the achievement of sustainable development goals.

CONCLUSION

The purpose of this study was to explore the development and application of IASs, with a focus on their core technologies, operational principles, and real-world impacts. The findings reveal that these systems significantly enhance operational efficiency, reduce costs, and improve product quality, while also promoting environmental sustainability. By integrating advanced technologies, such as the IoT, big data analysis, and AI, IASs enable precise monitoring and automated management of aquaculture environments. This technological transformation not only addresses the inefficiencies of traditional practices but also positions the industry to better meet the challenges posed by a growing global population and increasing resource constraints.

From these findings, it can be concluded that the continued advancement and widespread adoption of IASs will be crucial for the future of the industry. However, it is important to recognize the challenges associated with these innovations, including dependency on technology and financial barriers. To fully realize the potential of these systems, collaboration among researchers, policymakers, and industry stakeholders will be essential to create a supportive ecosystem that promotes equitable access and addresses any emerging drawbacks.

In conclusion, IASs have the potential to revolutionize the industry by boosting productivity, improving sustainability, and contributing to global food security. Embracing these technologies will be critical for overcoming future challenges in aquaculture and ensuring the responsible management of natural resources for future generations.

COMPETING INTERESTS

The authors of this publication declare there are no competing interests.

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