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Design and Implementation of an AIoT-Oriented Aquaponics System: Integrated Application of Environmental Sensing and Remote Control

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Abstract

Limited arable land, climate variability, and workforce aging challenge experience-driven agricultural management, reducing system stability and scalability. The absence of real-time monitoring, standardized decision mechanisms, and cross-site replicability further constrains the deployment of smart agriculture systems. To address these challenges, this study proposes an intelligent management architecture integrating artificial intelligence of things (AIoT) with a rule-based expert system, using aquaponics as a validation testbed. The layered architecture links endpoint sensing, edge processing, cloud-based knowledge governance, and user interfaces to form a closed-loop mechanism connecting sensing, inference, and actuation. A desktop-scale prototype is implemented to evaluate operational feasibility. Results indicate that the system achieves response times of approximately 2–5 seconds, consistent rule-based decisions, and stable multi-day operation, as evidenced by event logs and repeated rule-trigger observations. These findings demonstrate the feasibility of AIoT-enabled intelligent aquaponics management in practical deployment environments.

Keywords: smart agriculture, artificial intelligence of things (AIoT), expert system, aquaponics

1. Introduction

Against this backdrop, urbanization, limited arable land, and increasing climate variability are exerting structural pressure on agricultural production systems. Conventional agricultural management approaches, which rely on manual inspection and experience-based judgment, are increasingly insufficient to cope with rapidly changing environmental conditions. In particular, water resource management, energy utilization, and production stability face growing inefficiencies and resilience constraints. In parallel, the advancement of sustainable development and net-zero policies has intensified the demand for real-time monitoring, precise regulation, and low-carbon operation in agricultural environments. As a result, innovative agricultural technologies have become a major research focus. However, their stability in real-world settings and replicability across sites remain insufficiently validated.

Among innovative agriculture applications, aquaponics systems have attracted attention due to their advantages in water recirculation, closed-loop nutrient utilization, and reduced dependence on chemical inputs. These characteristics make aquaponics an approach for sustainable food production. However, most systems still rely on operators' experience for parameter configuration and daily management, with limited support from real-time, data-driven decision mechanisms. When

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environmental conditions deviate from expected ranges, timely responses are difficult to achieve, potentially affecting fish health and crop growth. Moreover, inconsistencies in equipment interfaces and management logic across installations hinder the replication of successful practices, thereby constraining large-scale deployment.

In agricultural environments, artificial intelligence of things (AIoT) and expert systems are leveraged to improve management timeliness, precision, and consistency. AIoT architectures enable continuous environmental sensing and rapid decision-making through edge computing and cloud analytics, while expert systems encode agricultural knowledge as explicit decision-making rules. However, most existing studies treat sensing, automation, or analytics separately, and lack validation of integrated AIoT–expert system architectures in continuous real-world operation. This gap is particularly evident in aquaponics, where empirical deployment examining the combination of real-time sensing, expert knowledge, and closed-loop control remains to be explored.

Despite these advances, a challenge remains in achieving coordinated, real-time sensing, decision-making, and control within a unified architecture. Based on this research gap, this study proposes an intelligent agricultural management architecture that integrates AIoT with a rule-based expert system and emphasizes deployment rather than algorithmic optimization. In this study, AIoT is interpreted as an architectural integration paradigm that combines real-time sensing, edge processing, and rule-based decision-making, rather than relying solely on machine learning-based intelligence. A prototype system is implemented to evaluate whether the proposed architecture can support responsiveness, consistent decision-making, and stable long-term operation in farming environments.

In this study, the aquaponics system is not treated as the research objective, but rather as an empirical testbed for validating the deployability of innovative agricultural technologies. Through desktop-scale prototype experiments, this work evaluates whether an AIoT-oriented management architecture can be deployed and sustained in an agricultural environment, thereby providing system-level evidence beyond conventional performance evaluation.

Accordingly, the present work makes three primary contributions to the field: (i) it proposes an AIoT–expert system architecture that emphasizes system deployability rather than algorithmic optimization; (ii) it provides a system-level, data-driven validation framework using real-time event logs, repeated rule-trigger observations, and long-term operational records to evaluate traceability, reproducibility, and cross-site deployment potential; and (iii) it demonstrates the practical feasibility of closed-loop, AIoT-based aquaponics management through a desktop-scale empirical testbed.

2. Related Work

Previous studies related to AIoT architectures, expert systems, and smart aquaponics technologies are reviewed in this section. The literature covers real-time sensing, intelligent decision-making, and system integration in smart agriculture environments. Research on agricultural monitoring, knowledge-based systems, and aquaponics management is further examined to identify current limitations and establish the theoretical background of this study.

2.1. Smart agriculture technologies and AIoT architecture

As agricultural production environments become complex, management approaches that rely solely on human experience are no longer sufficient to address challenges such as climate variability, resource constraints, and production stability. The core objective of smart agriculture is to leverage information technologies to transform environmental conditions into measurable, analyzable, and actionable data flows. This transformation enables production management to shift from experience-driven to data-driven practices. Recent studies indicate that integrating the internet of things (IoT) and artificial intelligence (AI) technologies provides the infrastructure for real-time monitoring and decision support in agricultural environments [1-2].

In innovative agriculture architectures, AIoT is a critical technology for improving system responsiveness and decision quality. Compared with conventional IoT approaches that emphasize data collection and remote monitoring, AIoT incorporates intelligent analysis and inference capabilities, enabling systems to adjust control strategies in response to environmental changes. Related studies have shown that integrated sensor networks, edge computing, and cloud-based analytics reduce data transmission latency while maintaining control functions under unstable network conditions, thereby improving the reliability and resilience of agricultural systems [1, 3-4].

At the architectural level, most smart agriculture systems adopt a layered design to separate the requirements of real-time control from long-term data governance. The sensing layer collects data on crop growth and environmental conditions, including temperature, humidity, light intensity, and water quality parameters. The edge layer performs preliminary data processing and real-time decision-making to ensure system operation during communication interruptions. Meanwhile, the cloud layer handles tasks such as data storage, model updates, and cross-site analysis to support long-term decision optimization and knowledge accumulation. Wolfert et al. suggested that layered architectures help address challenges associated with large data volumes, high real-time demands, and environmental heterogeneity in agricultural settings, and form a foundation for big data governance in smart agriculture [3]. Gubbi et al. suggested that layered IoT architectures enhance system scalability and maintainability, making them suitable for deployment in resource-constrained or network-unstable environments [4].

In practical agricultural applications, AIoT technologies are used for crop environment monitoring, precision irrigation, and early disease warning. Real-time AIoT sensing and data analytics help reduce production risks and improve crop quality and resource-use efficiency. However, AIoT sensing and data visualization alone are insufficient to support the long-term operation of complex agricultural systems. In the absence of explicit decision logic and control mechanisms, the operation remains dependent on user experience, limiting the effectiveness of smart agriculture technologies.

Accordingly, recent smart agriculture research has shifted its focus from “data collection” toward “decision support and automated control.” By integrating AI analytical models, rule-based inference, and real-time control architectures, systems can adjust operational parameters based on environmental conditions, reduce the frequency of manual intervention, and improve management consistency [2, 5-6]. AIoT is not merely an extension of sensing and communication technologies but plays a crucial role in linking data, knowledge, and action.

The existing literature on AIoT architectures provides a foundation for real-time monitoring and layered governance in smart agriculture and has demonstrated application potential across agricultural environments. Nevertheless, most studies focus on single crops or simple production settings. For systems characterized by high interdependence and strong interactions among environmental factors, decision consistency and long-term stability remain challenging issues. This research gap is further addressed by integrating decision logic and knowledge governance mechanisms into existing AIoT architectures, thereby establishing a theoretical basis for subsequent research on expert system integration.

2.2. Applications of expert systems in agricultural decision-making

Throughout the development of smart agriculture, a key challenge has been how to transform the experience and judgment logic of agricultural experts into decision-making mechanisms that can be processed by information systems. Recent review studies indicate that expert systems based on knowledge-based reasoning remain an important approach in intelligent decision-support architectures, particularly in domains requiring structured knowledge representation [7]. Compared with purely data-driven analytical models, expert systems emphasize knowledge bases and inference mechanisms as their core components. By preserving and reproducing experts’ reasoning processes through rule-based representations, expert systems enable decision outcomes to be consistent. These characteristics have long positioned expert systems as decision support tools in agriculture, a domain that relies heavily on experience and is subject to frequent environmental variation [8-9].

The basic architecture of an expert system consists of a knowledge base, an inference engine, and a user interface. The knowledge base stores expert experience and domain knowledge, while the inference engine generates decision outcomes based on predefined rules and real-time input conditions. In agricultural applications, such systems are used for crop growth management, irrigation scheduling, and disease diagnosis, reducing risks associated with insufficient experience [10]. Related studies showed that applying expert systems for parameter configuration and operational guidance can improve management consistency and mitigate variability arising from individual operator judgment.

However, the application of traditional expert systems in agricultural environments faces limitations. First, most systems rely on statically designed rules. Once the rule sets are established, their update frequency is limited, making it challenging to reflect rapid changes in environmental conditions. When confronted with climate anomalies or unexpected events, existing rules may become unsuitable, thereby reducing decision reliability [11]. Second, when expert systems are not integrated with real-time sensing data, their inference results may diverge from actual environmental states. This discrepancy leads them to function as advisory tools rather than as core management components with control capabilities.

To address these limitations, recent studies began integrating expert systems with IoT or AI technologies, forming decision-support architectures with real-time data feedback capabilities. By collecting environmental data from sensors and feeding it into inference engines, expert systems can adjust their reasoning outcomes based on current conditions while retaining established rule structures. This integration thereby improves system responsiveness and stability [1, 9]. Through such integration, expert systems move beyond providing recommendations to driving control actions.

In agricultural decision-making applications, another important value of expert systems is their support for knowledge governance and sharing. Through version-controlled and structured rule repositories, agricultural knowledge can be preserved, traced, and reused, enabling successful practices to be transferred across different sites rather than remaining confined to individuals or single farms. Related studies showed that knowledge visualization and traceability mechanisms enhance system credibility and provide a foundation for optimization and dissemination.

Nevertheless, most existing studies apply expert systems to single crops or independent agricultural processes, and their application in environments involving multiple interacting factors and interdependent subsystems is still limited. In aquaponics systems, environmental parameters interact closely, and isolated rules or single-point decisions are insufficient to maintain overall system stability. How to combine real-time sensing data with expert knowledge to establish decision architectures with closed-loop control capabilities in such systems remains an issue.

Expert systems offer advantages in agricultural decision support and knowledge governance by reducing operational barriers and improving management consistency. However, their effectiveness depends on the degree of integration with real-time data sources and control mechanisms. Integrating expert systems within AIoT architectures and validating their feasibility in complex agricultural systems through real-world applications remains an underexplored direction in innovative agriculture research.

2.3. Management challenges and smartization research in aquaponics systems

Aquaponics systems integrate aquaculture and soilless cultivation into a single production model. This combination forms a circular framework for water and nutrient utilization through microbial conversion mechanisms that transform fish excreta into nutrients absorbable by plants. Related studies indicated that, compared with conventional agriculture or standalone aquaculture systems, aquaponics demonstrates advantages in water conservation, reduced chemical fertilizer use, and lower environmental pollution. Therefore, it is regarded as a production model aligned with sustainable agriculture. However, because aquaponics involves multiple biological and ecological subsystems, its system structure also leads to increased management complexity [12-13].

From a practical operational perspective, the stability of aquaponics systems depends on the interactions among water quality parameters, nutrient balance, and environmental conditions. Parameters such as water temperature, dissolved oxygen (DO), pH, and ammonia concentration are closely interrelated, and deviations in any single indicator can affect fish health, nitrifying bacterial activity, and plant growth. While small-scale aquaponics systems may be adjusted through manual experience, rapid environmental changes or system scale expansion present significant challenges. Consequently, reliance on manual monitoring and experience-based judgment is prone to delayed responses and management errors [12-15].

Existing literature showed that management difficulties in aquaponics systems arise not only from the complexity of individual parameters but also from the tacit nature of operational knowledge. Successful operation depends on long-term accumulated experience, including an understanding of the relationships among fish species, crop types, growth stages, and environmental conditions. However, such expertise is difficult to transfer in standardized forms, making successful practices hard to replicate across different sites and limiting the development of aquaponics systems in industrial-scale applications [16].

To address these challenges, recent studies began introducing sensing technologies and automated control mechanisms into aquaponics systems to enhance management timeliness and stability. Related research on real-time monitoring of water quality and environmental parameters, combined with automated equipment for aeration, circulation, and water replenishment control, can reduce system fluctuation risks. As a result, these approaches improve fish survival rates and crop growth performance. Nevertheless, when innovative applications are confined to individual control elements and lack system-level decision-making logic, they remain insufficient to address the complex problems arising from simultaneous multi-parameter variations.

In innovative management research, some studies introduced data analysis models and decision support systems to assist operators with parameter adjustment and risk warning. Such studies mainly focus on historical data analysis or single-factor prediction, and their support for real-time decision-making and cross-system integration remains limited. In addition, some models adopt black-box inference approaches that lack interpretability, making them difficult to apply in practical applications.

Smartization research on aquaponics systems evolves from point-based automated control toward system integration and decision support. However, most existing studies still address sensing, control, and analysis layers separately, and few simultaneously integrate real-time sensing data, expert knowledge, and closed-loop control mechanisms to address the coupled characteristics of aquaponics systems. In particular, concrete and practically verifiable integrated architectures remain lacking in areas such as knowledge standardization, decision consistency, and cross-site applicability.

Therefore, incorporating expert decision-making mechanisms into AIoT-based architectures and validating their feasibility through real-world operational environments may help address limitations in system stability and replicability within innovative aquaponics research. This approach also provides directions for future studies.

2.4. Literature synthesis and research gaps

Based on the reviewed literature, research on smart agriculture has accumulated substantial outcomes in sensing technologies, data acquisition, and system architecture design. Through layered architectures and real-time data processing mechanisms, AIoT provides a foundation for real-time monitoring and long-term data governance in agricultural environments. This framework enables agricultural production to shift from experience-driven to data-driven practices. AIoT demonstrates advantages in improving system responsiveness, reducing communication latency, and enhancing system resilience, and has been validated across various agricultural application scenarios.

At the level of agricultural decision support, expert systems offer an approach for structuring and standardizing agricultural experience through knowledge bases and inference mechanisms. Expert systems help lower operational barriers, improve management consistency, and provide value in knowledge preservation and sharing. However, most expert systems still rely on static rule sets, and their effectiveness depends on rule quality and update frequency. When expert systems are not integrated with real-time sensing data and control mechanisms, decision outcomes may diverge from actual environmental conditions.

In studies on aquaponics systems, the literature acknowledges their potential for resource circulation and sustainable agriculture, while highlighting challenges of management complexity and system stability. Aquaponics systems involve multiple biological and environmental subsystems with coupled parameters, making single-sensor approaches or isolated automated control insufficient to respond to overall system dynamics. Although existing smartization research has introduced sensing devices, computerized control, and data analysis models, most studies address these layers separately and lack system-level decision-integration architectures.

From an overall perspective, AIoT and expert systems each demonstrate their application value in smart agriculture; however, a gap remains in their integrated application within complex agricultural systems. In particular, for highly interdependent production systems such as aquaponics, verifiable application models that simultaneously address real-time sensing responsiveness, decision consistency, and long-term knowledge governance remain limited. In addition, most existing studies focus on single sites or short-term experiments, with limited attention to cross-site replicability and operational feasibility. Previous innovative agriculture research has emphasized algorithmic and model-level performance, particularly approaches based on digital twins and model-driven methods [17], while issues related to system-level deployment and validation in real operational environments remain underexplored.

Based on the synthesis, current smart agriculture research lacks systematic studies that simultaneously integrate AIoT architectures, expert knowledge inference, and closed-loop control mechanisms, and that conduct validation within aquaponics environments. Further development is needed in areas such as knowledge standardization and cross-site applicability. Accordingly, this work proposes an innovative aquaponics management architecture with deployment capability and provides a direction for subsequent research methodology and system design. In contrast to existing studies, this work emphasizes system-level validation by demonstrating real-time responsiveness, decision consistency, and long-term operational stability through deployment in an actual aquaponics testbed.

3. Methodology

This section describes the methodological design and validation process of the proposed AIoT-oriented smart agriculture architecture. The methodology covers system architecture planning, module configuration, expert-system integration, and validation procedures. The validation design focuses on deployment under real operational conditions rather than isolated algorithmic evaluation.

3.1. System design concept and validation-oriented architecture

IoT-based system integration is adopted to enable real-time environmental sensing and data-driven decision support in innovative agricultural applications [1, 4]. The system design in this study is centered on the deployment of innovative agriculture technologies, emphasizing the integration of sensing, decision-making, and control functions into an intelligent management architecture capable of long-term, stable operation in agricultural environments. Innovative agriculture systems must handle large volumes of real-time data and long-term management decisions in applications. Adopting layered architectures to support data governance, decision support, and system scalability is a design principle [3]. In addition, dividing IoT systems into sensing, computing, and application layers improves system maintainability and flexibility, providing an architectural foundation for innovative agriculture system design [4].

In terms of architectural planning, this study incorporates modular and layered design concepts to separate real-time sensing, edge-level decision-making, and control execution. Such separation aims to reduce system complexity while enhancing flexibility for adjustment and expansion. In innovative aquaponics systems, the effectiveness of management decisions depends on the system’s ability to perceive and coordinate multiple environmental parameters in real time and on the system's architecture in ensuring operational stability [12-13].

To validate the feasibility of the proposed design concepts in complex agricultural systems, an aquaponics system is selected as the empirical validation environment in this study. Aquaponics systems involve aquaculture and plant cultivation, within which water quality parameters, nutrient conversion processes, and biological loading are coupled. Variations in any single condition may trigger cascading effects on system operation. Such coupled production system characteristics make aquaponics a suitable test platform for evaluating the integration performance and stability of innovative agriculture management architectures [13]. By deploying the proposed intelligent management architecture within this system, the applicability of the design concepts under operational conditions can be examined, thereby providing a foundation for system validation.

The proposed AIoT-oriented management architecture features a layered design to support real-time sensing, decision-making, and automated control in agricultural environments. The system integrates endpoint sensing devices, edge processing modules, cloud-based knowledge governance, and user interaction interfaces to coordinate sensing, inference, and control processes. Expert-system reasoning and closed-loop control mechanisms are incorporated to improve operational stability and management consistency in highly coupled agricultural systems. Fig. 1 illustrates the overall system architecture and the relationships among the major functional layers.

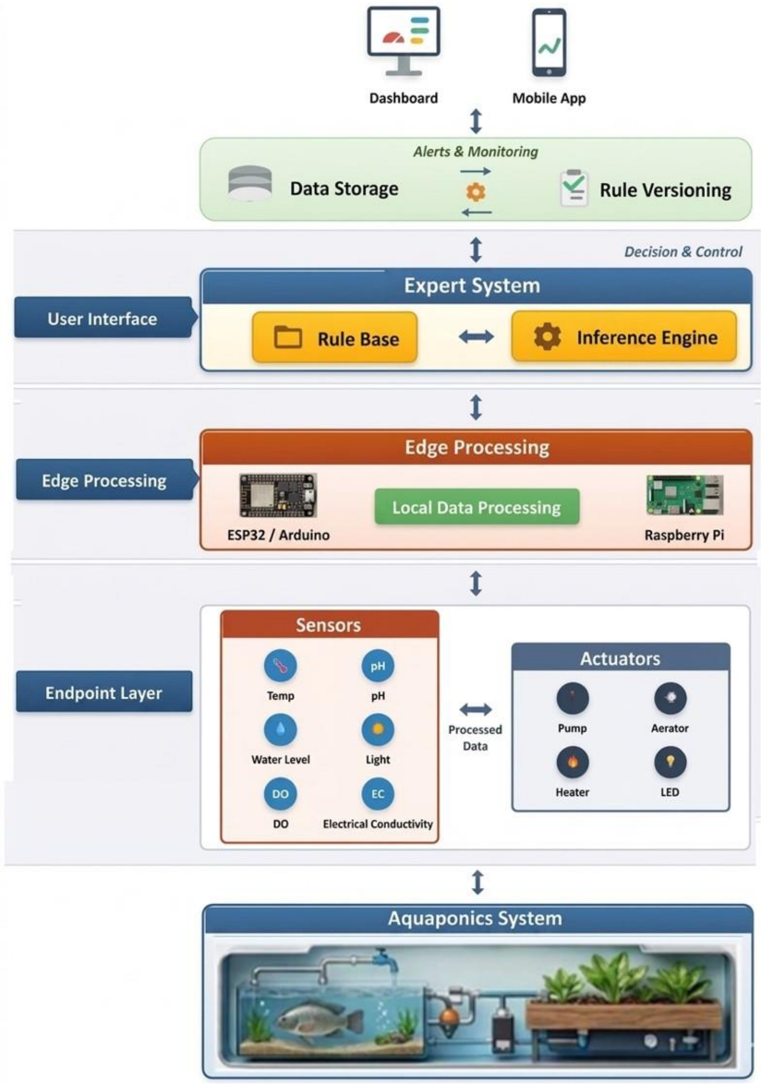

Fig. 1 System architecture for validating smart agriculture technology deployment (using an aquaponics system as the empirical testbed)

3.2. System architecture and module configuration

The innovative agriculture management system proposed in this study is structured upon a layered architecture. The overall system comprises four distinct layers: an endpoint layer, an edge layer, a cloud layer, and a user layer. This architectural arrangement enables the system to address real-time responsiveness and long-term management requirements in agricultural environments, serving as the foundation for validating the deployment of innovative agriculture technologies.

3.2.1 Endpoint layer: sensing and actuation modules

The endpoint layer functions as the data source and control entry point for the intelligent management architecture. It facilitates the collection of real-time environmental and water-quality information from the aquaponics system and executes basic control actions. In this study, multiple sensing components are deployed at the endpoint layer to measure key parameters that affect the stable operation of the aquaponics system, including temperature, water level, pH value, DO, electrical conductivity (EC), and light intensity. These sensing data reflect fish living conditions and plant growth status, forming the basis for decision inference and control actions.

In addition to sensing functions, the endpoint layer integrates various actuation components to support automated regulation, such as water pumps, fans, light-emitting diode (LED) lighting, and heating devices. When the system determines that environmental conditions deviate from expected ranges, it activates actuators in real time to adjust operating conditions. This mechanism mitigates the impact of ecological abnormalities on system operation.

3.2.2 Edge layer: real-time processing and state assessment

The edge layer, comprising microcontrollers and single-board computers, is responsible for real-time processing of data collected from the endpoint layer and for preliminary state assessment. In this study, devices such as ESP32, Arduino, and Raspberry Pi are used at the edge layer to perform data acquisition, real-time control, and computational integration, respectively. Through the edge layer's real-time processing, the system rapidly responds to environmental changes without relying on cloud communication, thereby enhancing operational responsiveness and resilience.

The edge layer performs system-state monitoring and basic decision execution. When sensed data trigger predefined conditions, corresponding control actions can be initiated to ensure the aquaponics system returns to a stable state. This design effectively reduces the impact of communication delays or network interruptions on system operation. This ensures that the innovative agriculture management architecture maintains operational capability in real-world environments.

3.2.3 Cloud layer: data governance and decision support

The cloud layer handles long-term data storage, rule management, and advanced analytical functions, serving as the knowledge governance core of the innovative agriculture management system. By leveraging cloud platforms, historical data from different operational stages of the aquaponics system are collected and analyzed to identify trends and compare system states, thereby supporting decision-making and system optimization.

In addition, the cloud layer is responsible for managing and maintaining the expert rule base, which stores agricultural experience and management logic in a structured manner and provides references for real-time judgment at the edge layer. This design reduces reliance on individual operator experience and enables management knowledge to be accumulated as reusable resources, thereby enhancing system replicability across different deployment sites.

3.2.4 User layer: management interface and interaction modules

The user layer provides interfaces for system managers to monitor and interact with the system, including modules such as mobile applications and management platforms. Through this layer, managers can view real-time system status, environmental parameter variations, and records of control actions, while performing parameter configuration and annotation.

The purpose of this layer is to enhance operational intuitiveness and transparency, allowing users to understand system decision logic and operational states while preventing intelligent systems from becoming opaque black boxes. The real-time feedback and historical record functions provided by the user layer support system validation and management behavior analysis.

3.3. Validation design and expert system decision-making process

Fig. 2 presents the closed-loop decision-making and validation workflow of the proposed AIoT expert system architecture, illustrating how the expert system is operationally integrated into the overall framework. The workflow shows how sensor data are transformed into system states, evaluated through rule-based inference, and translated into control actions, while decision records and system responses are logged to support traceability and validation.

To ensure the feasibility of the innovative agriculture management architecture in real agricultural environments, this study incorporates a rule-based expert system as the decision-making core within the AIoT framework, serving as a mechanism that links sensing data with automated control actions. The methodological design utilizes a validation-oriented approach. Through rule-based inference, the expert system generates consistent decisions based on real-time environmental states and feeds them back to the aquaponics system via automated control actions, thereby supporting long-term operation. This section explains how the expert system is integrated into the AIoT architecture and details the corresponding decision-making process and validation approach.

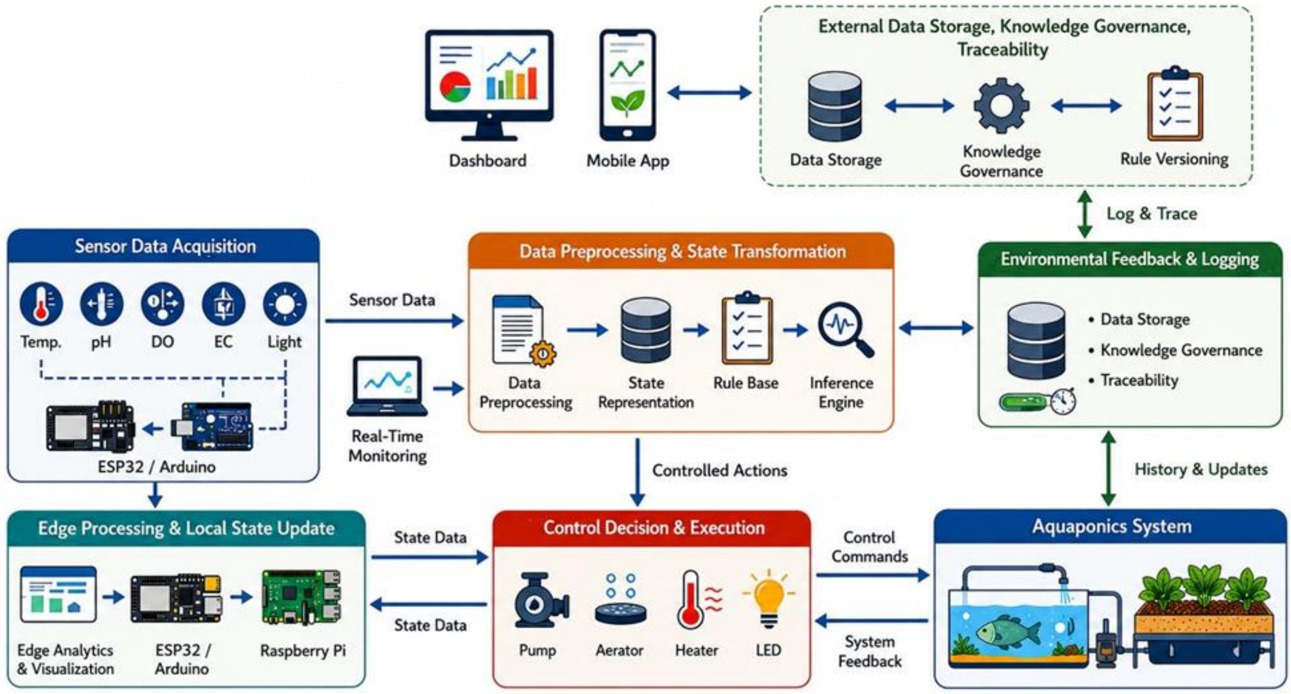

Fig. 2 Closed-loop decision-making and validation workflow of the proposed AIoT–expert system architecture

3.3.1 Sensing data input and state assessment mechanism

During system operation, environmental and water quality sensing data collected at the endpoint layer are processed in real time by the edge layer and subsequently used as primary inputs for expert system inference. To reduce the influence of noise and transient fluctuations on decision outcomes, basic data validation and state assessment are performed during the data input stage. Continuous sensing values are transformed into state-based information suitable for rule matching. This processing workflow helps ensure that subsequent inference results reflect actual system conditions rather than being affected by isolated abnormal values.

3.3.2 Expert system rule inference and decision output

The expert system is centered on a rule base, with rule contents designed based on operational experience and management logic. These rules cover decision scenarios related to water quality regulation, environmental stabilization, and equipment activation and deactivation. Once state information is received from the edge layer, the inference engine performs rule matching and reasoning to generate corresponding control recommendations or executable commands.

To support decision-making in the expert system, environmental parameter are established according to the compatibility requirements of fish and plant species commonly used in aquaponics systems. Table 1 summarizes representative pH ranges for different fish–plant combinations and the corresponding target pH values adopted by the system. These settings serve as knowledge-base references for subsequent rule evaluation and decision-making processes.

Table 1 Representative pH parameter settings for fish–plant combinations

Fish species	Plant species	Fish optimal pH range	Plant optimal pH range	System target pH (Compromised)
Tilapia	Lettuce	7.0 – 8.5	5.5 – 6.5	6.8 – 7.2
Perch	Tomato	6.5 – 8.0	5.5 – 6.5	6.5 – 7.0
Carp	Strawberry	7.0 – 7.5	5.5 – 6.0	6.2 – 6.8

Compared with decision-making approaches that rely on individual sensor thresholds or operator judgment, the proposed expert system incorporates environmental and domain knowledge into a standardized framework. As a result, system decisions are traceable to predefined evaluation criteria and environmental conditions, reducing dependence on individual experience while supporting system tuning, validation, and knowledge-base refinement.

By formalizing expert knowledge into structured rules, the expert system functions as a real-time decision engine and a knowledge governance mechanism within the AIoT architecture. This design supports reproducibility and facilitates knowledge transfer across different deployment contexts, thereby providing a foundation for the validation-oriented methodology adopted in this study.

3.3.3 Decision feedback and control action execution

After the expert system completes inference and generates decision outcomes, the edge layer transmits the corresponding control commands to the actuation components at the endpoint layer. These components then execute regulation tasks, such as starting or stopping water pumps, adjusting aeration equipment, or changing lighting states. This closed-loop process—spanning from sensing to inference to control execution—enables the innovative agriculture management architecture to respond to changes in environmental conditions, thereby reducing the risk of the system deviating from stable operating states.

During system operation, all decision actions and corresponding environmental states are recorded and transmitted back to the cloud layer as a basis for analysis and validation. This design ensures decision traceability and supports correlation analysis between management actions and system performance.

3.3.4 Validation approach and evaluation dimensions

The validation design of this study focuses on examining the effectiveness of the expert system in supporting the stable operation of the innovative agriculture management architecture under operational conditions. It does not prioritize the evaluation of individual control actions. The validation emphasizes three dimensions: real-time responsiveness, decision consistency, and system stability.

Real-time responsiveness assesses whether the system can generate decisions through the expert system and initiate corresponding control actions in a timely manner when environmental conditions deviate from expected ranges. Decision consistency examines whether the expert system produces identical or consistent decision outcomes under similar environmental conditions, thereby reducing management variability caused by differences among operators. System stability is evaluated through long-term continuous operation observations to determine whether the system can maintain operational balance under the interaction of multiple environmental factors in the absence of manual intervention.

Based on this validation design, the proposed system is deployed to examine the integration of expert-system reasoning and AIoT architecture in complex agricultural environments. Continuous sensing, event logging, and repeated rule-trigger observations are used to track environmental changes, decision-making processes, and actuator responses during operation. These operational records are subsequently used to analyze system responsiveness, decision consistency, and closed-loop control behavior under real deployment conditions.

4. Results and Validation

This section presents the validation results of the proposed AIoT-oriented smart agriculture architecture under real operational conditions. The validation examines system responsiveness, decision consistency, and long-term operational stability through prototype deployment and repeated operational observations. The results provide evidence of stable sensing, inference, and control behavior in a highly coupled agricultural environment.

4.1. Validation results of system real-time responsiveness

To verify the real-time responsiveness of the proposed innovative agriculture management architecture in agricultural environments, this study employs a desktop-scale innovative aquaponics prototype system to observe system behavior under conditions of environmental variation or abnormal events. The verification focuses on whether the system can activate expert system inference. It also examines whether the system executes corresponding control actions when sensing data indicate that environmental conditions deviate from predefined ranges, thereby maintaining operational stability. Fig. 3 illustrates the real-time monitoring interface and operational event log of the AIoT-based innovative aquaponics system, providing evidence of sensor-triggered decision-making and actuator responses during system operation.

During operation, when water quality or environmental parameters change, sensing modules at the endpoint layer transmit the relevant data to the edge layer for processing. The system then performs state assessment based on real-time sensing results and inputs the transformed state information into the expert system for rule matching. Once sensing data trigger predefined conditions, the system can complete state assessment and decision inference within a short response interval (typically within a few seconds based on repeated system log observations) and transmit control commands through the edge layer to the corresponding actuators to initiate regulatory actions.

As shown in Fig. 3, transitions from normal to alert states are accompanied by explicit decision outputs and corresponding actuator activations, all recorded with precise timestamps. Although precise quantitative latency measurements are not the primary focus, system logs consistently indicate rapid response behavior following state transitions. To further support these qualitative observations, a quantitative summary of representative system response performance is provided in Table 2.

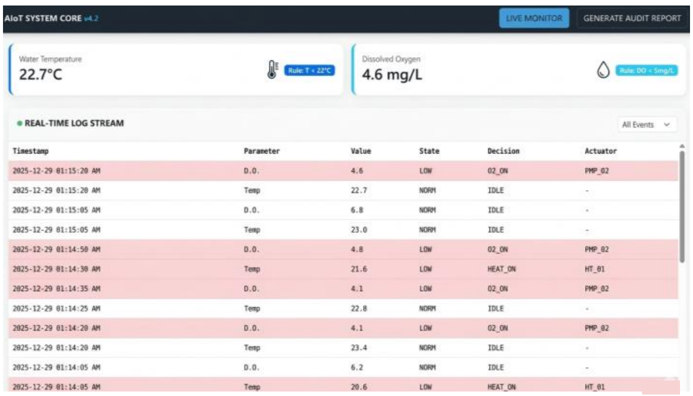

Fig 3 Real-time monitoring interface and operational event log of the AIoT-based innovative aquaponics system

Table 2 Quantitative summary of system response performance under observed operational conditions

Metric	Description	Observed result
Response time	Time between abnormal state detection and actuator activation	Approximately 2–5s
Control latency	Time required for command transmission and actuator response	Typically below 5s
Successful trigger rate	Successful actuator activations after rule triggering	100% in observed cases
Event traceability	Availability of timestamped sensing and control records	Fully traceable
Repeated response consistency	Consistency of decision outputs under repeated identical state conditions	No inconsistent responses observed

The observed results indicate that the proposed system maintains stable and traceable response behavior under repeated operational conditions, providing evidence of real-time responsiveness and control reliability. Repeated observations under identical environmental states consistently produce uniform decision outputs and actuator responses across different operational timestamps. These results demonstrate the stability and reproducibility of the proposed rule-based control mechanism within the AIoT-oriented management architecture.

In addition, across multiple tests, the system exhibits the same response sequence under similar abnormal scenarios, including sensing data updates, state assessment, decision generation, and control action execution. The results indicate that deploying real-time processing and decision-making mechanisms at the edge reduces the impact of communication latency on system response time, enabling the system to maintain real-time control capabilities independently of cloud computing.

The validation results show that the proposed innovative agriculture management architecture can complete the closed-loop sensing, inference, and control process in response to changes in environmental conditions. This characteristic is critical for agricultural systems that are highly coupled and subject to frequent dynamic variations.

4.2. Validation results of expert system decision consistency

To verify the expert system's decision consistency within the innovative agriculture management architecture, this study further examines whether its decision behavior remains stable and consistent under similar environmental conditions. The verification focuses on whether the expert system produces consistent decision outcomes when presented with similar or identical sensing-state information, and whether management inconsistencies arising from sensing fluctuations or operator differences can be reduced.

During the validation process, similar environmental conditions, including deviations in water quality parameters and changes in ecological states, are repeatedly simulated across multiple tests. When sensing data are transformed into identical state determination conditions, the expert system generates the same control recommendations based on predefined rules and triggers the same types of control actions. The results show that identical rule references (e.g., TEMP_LOW_01) consistently lead to the same decision outputs and actuator activations across different timestamps, as shown in Table 3.

Table 3 Representative rule-based decision logs under identical state conditions

Timestamp	Parameter	Sensor value	Rule reference	Decision	Actuator	Status
2025-12-29 00:05:12	Water Temp	21.2℃	TEMP_LOW_01	HEATER_ON	Heater_01	SUCCESS
2025-12-29 00:35:45	Water Temp	20.8℃	TEMP_LOW_01	HEATER_ON	Heater_01	SUCCESS
2025-12-29 01:05:22	Water Temp	21.5℃	TEMP_LOW_01	HEATER_ON	Heater_01	SUCCESS
2025-12-29 01:35:10	Water Temp	20.9℃	TEMP_LOW_01	HEATER_ON	Heater_01	SUCCESS

Note: No inconsistent decision outputs are observed under repeated identical state conditions during the validation process.

In addition, across different testing stages, the system maintains identical decision processes and output results without manual intervention. Compared with traditional management approaches that rely on operator experience for judgment, decision workflows constructed using the expert system reduce management inconsistencies caused by differences in human judgment.

The validation results indicate that the proposed expert system, when integrated into the AIoT architecture, can generate consistent decision-making under similar environmental conditions. This characteristic is imperative for agricultural systems that require long-term operation and involve highly coupled management conditions.

4.3. Analysis of long-term operational stability

To further evaluate the feasibility of the proposed innovative agriculture management architecture, long-term continuous operation is conducted to analyze system stability under the interaction of multiple environmental factors. The validation focuses on examining whether the system can maintain stable sensing, decision-making, and control processes without frequent manual intervention. It also examines whether system failures can be sustained under environmental fluctuations or changes in equipment status, as summarized in Fig. 4.

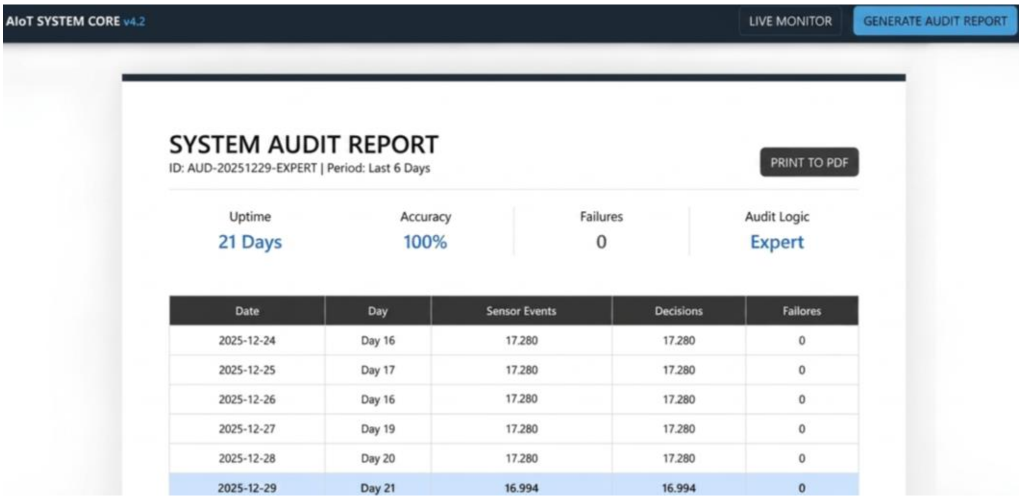

Fig. 4 System audit report summarizing long-term operational records of the AIoT–expert system architecture

During long-term operation, the system continuously collects environmental and water-quality sensing data from the aquaponics system and performs state assessment and decision inference using the expert system. Over multiple consecutive days of operation, the system completes sensing data updates, decision-making, and control action execution without interruption or failure. Even when environmental conditions exhibit gradual changes or short-term fluctuations, the system proactively adjusts control actions via predefined decision mechanisms, enabling the overall operational state to return to acceptable ranges. In addition, throughout the observation period, system decision behaviors exhibit consistent and predictable patterns; the expert system rules do not produce abnormal inference results despite data accumulation or state variation during continuous operation. Although quantitative statistical measures are not explicitly calculated, observed stability across multiple operational cycles indicates consistent system behavior.

To validate the closed-loop control performance of the proposed system, an analysis of environmental parameters and control signals is presented in Fig. 5. The data shown in Fig. 5 are derived from system logs recorded during continuous operation of the prototype system. The time-series curves are constructed by extracting representative segments of environmental parameters and corresponding control signals.

As shown in Fig. 5, the DO level initially remains stable, followed by a gradual decrease, indicating an abnormal environmental condition. Once the predefined threshold is reached, the system activates the control mechanism, as reflected by the control signal switching from OFF to ON. Following the activation of the control mechanism, the DO level increases progressively and returns to a stable range. After stabilization is achieved, the control signal is deactivated. The synchronized variation between the environmental parameter and the control signal demonstrates that the system is capable of recognizing deviations and responding effectively through closed-loop control.

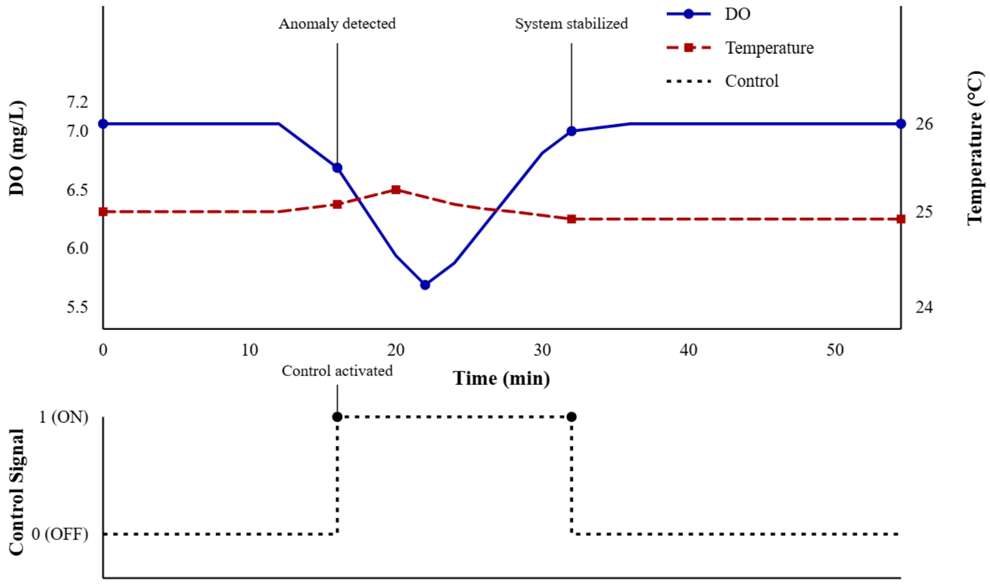

Fig. 5 Time-series response of DO, temperature, and control signal under AIoT-based closed-loop control.

5. Discussion

This section discusses the practical implications of the proposed AIoT-oriented smart agriculture architecture and the contribution of expert systems in agricultural management. System deployability, decision consistency, operational stability, and research limitations are examined based on the validation results and operational observations. The discussion is further related to existing smart agriculture research and practical deployment requirements.

5.1. Implications of practical validation for smart agriculture technologies

This study validates an innovative agricultural management architecture through an aquaponics prototype system, focusing on whether integrating AIoT and expert systems can support stable operation under highly coupled agricultural conditions. Unlike approaches that evaluate algorithmic performance primarily in simulated or isolated sensing scenarios, the present validation considers the operational constraints and environmental variability encountered during practical deployment.

The validation results demonstrate that the proposed architecture maintains real-time responsiveness under changing environmental conditions. Furthermore, it supports consistent decision-making through the expert system, thereby enabling stable long-term operation. These findings indicate that integrating sensing, decision-making, and control mechanisms with explainable decision logic reduces dependence on operator experience and improves the replicability and maintainability of agricultural management practices.

The aquaponics system is employed not as the research objective itself, but as an empirical testbed for evaluating the deployability of innovative agriculture technologies. Because aquaponics simultaneously involves aquaculture and plant cultivation with highly coupled environmental parameters, it provides a suitable environment for assessing system integration capability and operational stability. Validation within such a coupled environment serves as a reference for deploying related technologies in other smart agriculture contexts.

The findings further indicate that the practical value of innovative agriculture technologies depends more on system-level integration, coordinated decision-making, and long-term operational stability than on isolated sensing or algorithmic performance alone.

5.2. The role of expert systems in smart agriculture management

AI techniques in smart agriculture are commonly applied to prediction, classification, and decision optimization. However, decision-making based solely on black-box models often faces limitations in explainability, adaptability, and practical trust under real agricultural conditions. In contrast, expert systems employ explicit rules and inference logic to integrate agricultural management knowledge into structured decision-making processes, providing a more explainable and operationally transparent management mechanism.

In the proposed architecture, the expert system functions as an intermediate decision layer linking sensing data with control actions rather than replacing other AI techniques. By evaluating multiple environmental states simultaneously, the system supports consistent management behavior without relying solely on individual sensor readings or real-time operator judgment. This characteristic is particularly relevant for agricultural systems that require stable, long-term operation.

The explainability of expert systems also improves the transparency of system decisions and facilitates rule adjustment, fault diagnosis, and system maintenance during practical deployment. Compared with black-box models, whose decision rationale is difficult to interpret directly, rule-based systems provide greater operational transparency in environments involving complex interactions and uncertainty [18].

From a practical perspective, expert systems enable the transformation of experience-driven management practices into reusable and transferable knowledge resources. Through systematic, rule-based design, agricultural management knowledge can be preserved and applied across diverse operational contexts, thereby improving the replicability and scalability of smart agricultural management architectures. The rule-based framework adopted in this study also ensures decision traceability, consistent with existing discussions on AI explainability [14].

Compared with existing approaches, conventional threshold-based systems generally rely on simple rule triggering without system-level coordination, limiting adaptability in complex environments. Traditional IoT-based monitoring systems primarily focus on data acquisition and visualization, lacking integrated decision-making and control mechanisms. In contrast, the proposed architecture integrates environmental sensing, rule-based decision-making, and automated control within a unified framework. The resulting closed-loop mechanism enables coordinated responses to environmental changes, as demonstrated in the time-series observations. Compared with machine learning-based approaches, the rule-based design adopted in this study emphasizes interpretability, consistency, and real-time responsiveness, making it suitable for resource-constrained or operationally sensitive environments.

5.3. Research limitations and future work

Although this study conducts field-oriented validation through a desktop-scale aquaponics prototype system, several limitations remain. First, the validation primarily adopts a qualitative system-behavior approach focusing on real-time responsiveness, decision consistency, and long-term operational stability. Large-scale quantitative comparisons and systematic cross-model evaluations are beyond the scope of this study. Accordingly, the results demonstrate the practical feasibility of the proposed architecture rather than comparing the performance of different algorithms or control strategies.

Second, the empirical validation is conducted using a desktop-scale aquaponics system. Although the system captures the highly coupled, dynamic characteristics of real agricultural environments, its scale differs from that of large-scale farm production. Future studies may extend deployment across agricultural systems of different scales and operational contexts to further evaluate system applicability and stability.

In addition, the expert system rules are constructed based on existing management experience and operational logic. Although this design improves decision explainability and consistency, rule modification and expansion still require manual updates. Future research may therefore explore hybrid decision-making architectures integrating expert systems with data-driven methods to improve environmental adaptability while maintaining decision interpretability.

Overall, the proposed architecture and validation results provide a field-based example of AIoT-enabled smart agriculture deployment. Future studies may further incorporate larger-scale validation, quantitative performance analysis, and alternative decision-making mechanisms to strengthen practical applicability and system scalability.

6. Conclusions

This study developed and validated an intelligent management architecture integrating AIoT with a rule-based expert system for smart agriculture deployment. A desktop-scale aquaponics prototype was implemented as a highly coupled empirical testbed to evaluate deployability feasibility and operational performance under real agricultural environments. The main conclusions are summarized as follows:

(1) Demonstration of system-level deployability: the layered architecture integrating endpoint sensing, edge processing, cloud-based governance, and rule-based inference established a functional closed-loop mechanism linking sensing, decision-making, and actuation.

(2) Verification of real-time responsiveness and decision consistency: the system achieved real-time responses and consistent rule execution under repeated conditions, supported by event logs and rule-trigger observations.

(3) Confirmation of long-term operational stability: multi-day continuous operation demonstrated stable system performance without frequent manual intervention, providing traceable records of performance in a highly coupled environment.

(4) Enhancement of explainable rule-based integration: the expert-rule framework supports decision traceability, reproducibility, and cross-site knowledge transfer while reducing reliance on operator experience.

By emphasizing deployability rather than isolated algorithmic performance, this study provides a practical reference for implementing AIoT-enabled smart agriculture systems in complex operational environments. The validation results demonstrate that the proposed architecture can maintain stable sensing, decision-making, and control behavior under repeated operational conditions. These characteristics are important for smart agriculture systems that require long-term operation, system coordination, and management consistency.

Conflicts of Interest

The authors declare no conflict of interest.

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