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Research on Low-Power Embedded Sensing and Autonomous Decision-Making Systems for Smart Agriculture

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Abstract. Facing the dual challenges of global population growth and climate change, the demand for efficiency and intelligence in agricultural production has become increasingly urgent. In response to this grave crisis,smart agriculture is a critical solution at present. This is a new kind of industry,which has realized the transformation of agricultural production from experience-driven to data-driven. In addition,it integrates the low-power sensing technologies and autonomous decision-making systems deeply. This study focuses on two key technologies mentioned above in smart agriculture and systematically reviews their core technological advancements and application paradigms. On this basis, the study employs a multi-dimensional analytical approach that encompasses technological frameworks, core technological advances, and some real-world applications for the purpose of identifying key technological breakthroughs in this new domain. Despite these achievements, the analysis also reveals that there are still persistent challenges to be faced, which require concerted research efforts and the necessary innovation and practice in the future. Through the articulation of these research directions, the study seeks to provide a robust theoretical foundation that can guide future technological innovations and practical implementations in the field of intelligent agriculture.

Keywords: Smart Agriculture, Low-Power Embedded Sensing Systems, Autonomous Decision-Making Systems, Future Technological Innovations.

1. Introduction

With the rapid growth of the global population, the demand for food is soaring. Traditional agricultural methods are becoming insufficient to meet this growing need. As a result, smart agriculture systems (SAS) have emerged as a promising solution. The innovation and practicality of SAS determine their unlimited development potential and their possibility of gradually replacing traditional agriculture in the future. Recent studies have examined the technical architectures, application models, and system optimization strategies of smart agriculture. Findings suggest that low-power embedded sensing technologies and autonomous decision-making systems are two foundational pillars of smart farming. For instance, Zhang et al. summarized the application of technologies such as the Internet of Things (IOT) and blockchain in the tea industry, emphasizing the critical role of embedded sensing devices in the real-time monitoring of production processes

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[1]. From the perspective of sensing technology, most sensors currently used in agriculture offer high-precision measurements but also require significant energy reserves to function effectively. This creates a challenge in smart farming: how to effectively reduce energy consumption while maintaining measurement accuracy [2]. Regarding autonomous decision-making systems, artificial intelligence (AI) and big data analytics enable the rapid processing and analysis of large volumes of data. These technologies can help predict trends, inform real-time decisions, and reduce the adverse effects of environmental factors on agricultural production, thus maximizing yield and profit. However, issues such as technological integration, adaptability to complex environments, and scalability remain formidable challenges at the present stage.

By systematically reviewing the core literature in this field, this paper aims to summarize the current state of research, identify key challenges and research gaps, and propose possible directions for future development [2, 3].

2. The technological framework of smart agriculture

Smart agriculture introduces a new conceptual technical framework that can be applied to farming in almost any environment. At its core lies a data-driven, closed-loop control framework. [2, 3]. This architecture is composed of four core components:

(1) a physical perception network: This layer consists of a variety of sensor nodes, including temperature sensors, humidity sensors, PH sensors, and more. All nodes directly cover the whole farm and monitor key agricultural parameters to ensure the reliability and accuracy of the collected data in real-time.

(2) an information transmission layer: This layer collects sensor data through mobile or fixed equipment and makes reasonable acceptation and storage of the data. Finally, the layer facilitates seamless data flow across heterogeneous devices and then transmits it to the intelligent analysis hub so that the hub can make reasonable learning and analysis of the data.

(3) an intelligent analysis hub: The main function is taken care of by artificial intelligence, which predicts the growth trend of crops or future environmental changes through deep learning and analyzing data. With its powerful deduction ability, it makes correct decisions and forms clear instructions compatible with field equipment.

(4) precise execution terminals: This consists of devices that can respond in real time to artificial intelligence decision commands, including sprinklers, planters, heaters, and so on. Such devices can accurately execute orders to ensure that crops or livestock have a good and suitable ecological environment. The sustainable development of agriculture can be realized by protecting the agricultural environment to a certain extent [2-4].

Through the deep integration of physical space (e.g., agricultural fields, livestock facilities, and greenhouse environments) and information space (e.g., data processing, storage, and analytics), this architecture enables three critical functionalities, including real-time perception of agricultural object states, intelligent analysis of multi-dimensional data streams, and dynamic regulation of precision operations. Studies have demonstrated that smart agriculture equipped with LSAT- and A-based techniques enables precision irrigation of farmlands. Their experimental simulation results in more efficient water utilization than other SAS. The synergy between physical perception networks and advanced computing paradigms thus forms the backbone of smart agriculture, enabling a transition from reactive management to proactive, data-driven decision-making [2,4,5].

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3. Research advances in low-power embedded sensing technologies

3.1. Low power sensor hardware design

The evolution of low-power sensor designs is an important milestone in smart agriculture, implying an effective response to the urgent need for energy-efficient environmental monitoring. This advancement is exemplified by two distinct technical approaches documented in recent research.

XU focuses on the XC30 IT chip, which integrates a STM32L431 microcontroller unit (MCU) and an SX1268 Flora transceiver. This configuration achieves a standby current of 6 A in stop mode. In addition, the design incorporates a voltage regulation system (MP2315 DC-DC converter + LDO) to efficiently manage power from a 12V Li-ion battery, a DC-DC converter for reduction of conversion losses, and an LDO for reducing the interference of pure noise on the output voltage. A major advance is the implementation of a magnetic locked relay system for controlling RS485 sensors, where sensors are powered on demand, the operation of the switches is triggered by a pulse circuit, and the state of the relays no longer needs to be powered by a continuous current [6].

By contrast, XIAO features the STM32F103RCT6 MCU with three low-power modes: sleep, stop, and standby. The design implements adaptive power cycling through narrowband Internet of Things (NB-IoT)'s Power Saving Mode (PSM) mode and edge timing synchronization. From the perspective of sensors, this design adopts soil sensors like DS18B20 (± 0.5°C) and YL-69 moisture probes that demonstrate ultra-low active consumption through CMOS circuit optimization, which provides parasitic power supply. Moreover, the system employs interrupt-driven scheduling instead of polling, reducing CPU load by 62% compared to conventional designs [7].

3.2. Communication protocol optimization

Optimizing communication protocols is the main strategy to improve the sustainability and scalability of low-power embedded sensing systems. At present, the main wireless communication protocols in the market include Bluetooth, Zambezi, RFID, etc.

With the development of IOTs, requirements for wireless transmission distance and energy consumption are getting higher and higher. When deploying large-scale sensor networks in agriculture, energy-efficient wireless communication protocols need to be adopted to solve the problems of long-distance connection and minimum power consumption. Flora (long-distance wireless spread spectrum technology) and NB-IOT are developed for this problem. These two protocols adopt adaptive data transmission mechanisms to minimize possible energy overhead and control costs and can exchange information within intervals. The two most effective methods are the working cycle mechanism and the load compression algorithm, respectively. Among them, Flora can achieve large-scale detection while meeting the requirement of low power consumption, thus having the ability to serve as an interface for low-power wide area networks (LPWA) and can become a place for information exchange between sensors and the cloud. This makes it particularly suitable for the deployment of soil moisture and microclimate monitoring systems [8].

In addition, the short-range protocol (e.g., ZigBee or Bluetooth Low Energy) and the cellular LPWAN technology combine to form a hybrid architecture of communication to improve energy efficiency. This method can achieve the purpose of energy conservation by performing data processing operations close to edge nodes to avoid unnecessary remote transmission. For instance, the intelligent irrigation case of Queté demonstrates this advantage: dynamically adjusting the sensor upload parameters (such as the Spreading Factors modulation factor in LoRa WAN) based on real-time environmental conditions (such as the distance to the nearest gateway or sensor density)

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helps significantly reduce the collision rate and extend the battery life of the device. Specifically, if a higher Spreading Factor (SF12) is used, better anti-interference ability can be achieved, but at the same time, it will also increase the air time. Compared with the fixed configuration scheme, dynamic adjustment can extend the average battery life of the equipment by approximately 67%. However, for the air-gap interface of LoRa WAN, when more than a thousand sensors are densely deployed and not adaptively adjusted, the packet loss will exceed 50% [9].

3.3. Energy harvesting technologies

Compared with traditional power supply methods such as batteries and cables, the natural energy in the natural environment is undoubtedly a reliable source of electricity. While stably maintaining the normal working state of sensors, it can also reduce the damage to the agricultural ecological environment to a certain extent. Therefore, developing self-powered sensors that support energy collection from the natural environment is a forward-looking decision for realizing self-powered sensor networks.

The irregular and low-frequency mechanical energy existing in the environment is efficiently converted into electrical energy through the coupling effect of the triboelectric phenomenon and the electrostatic induction effect, which is a new type of energy harvesting device called triboelectric nanogenerator (TENG). Examples show that this technology exhibits remarkable energy conversion characteristics. It can thus be seen that the mechanical energy scattered in the surrounding environment can be captured and converted through this special design. A quintessential example of this fusion is evident in its applications towards bolstering low-power sensing mechanisms embedded within agrarian intelligence frameworks. It can be discerned from empirical analyses that such hybrid systems manifest a superior efficacy in transmuting aeolian forces into electrical currents through an amalgamation of both triboelectric nanogenerators and electromagnetic generation devices.

Wang proposed a triboelectric-electromagnetic hybrid wind energy collection and sensing device (TEH-WSD). The main innovation point of this device is to add a rotating base integrating a multi-channel triboelectric nanogenerator (MC-TENG) on the basis of the triboelectric- electromagnetic hybrid generator (TEHG). The TEHG contains the TENG unit (triboelectric generation) and the EMG unit (electromagnetic induction), while the MC-TENG generates electrical signals through rotational friction for sensing. The device's intrinsic capacity for instantaneous power generation stands noteworthy; annotated are the triboelectric unit's capability to yield a transient peak of 5.95 milliwatts while simultaneously the electromagnetic module achieves 5.65 (□). This duality permits enable the TEH-WSD to continuously supply power to the temperature and humidity sensor, like the DHT11, efficiently by collecting wind energy.

There is no doubt that TEH-WSD is a pivotal solution to mitigate dependence on energy storage cells afflictive to wireless sensor networks; they assure sustained endowment of power requisite for minimally powered integration systems. At the same time, this technology also demonstrates the application prospects of TENG technology in the field of smart agriculture. Its low-frequency and high-efficiency characteristics are highly suitable for smart agriculture and represent the main development direction of low-power sensors in the future. However, the structural strength and field adaptability need to be further optimized to adapt to agricultural activities under extreme natural conditions and ensure the sustainable development of smart agriculture [10].

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4. Research progress in autonomous decision systems for smart agriculture

4.1. Accurate decision-making driven by AI large models

Due to its outstanding ability to process and analyze data, as well as mature predictive technologies, artificial intelligence has widely permeated the decision matrix of smart agriculture. In agriculture, AI can be used to schedule the best resources, such as fertilizers, pesticides and water, etc. By considering the complex physical conditions in the current environment, it can make reasonable predictions about the future, thereby proposing feasible decisions. This helps humans apply the appropriate amount of specific resources at the right time, thereby reducing pollution and operational/production costs while maximizing production [11].

Deep learning, as a part of AI, also plays an important role in agricultural decision-making. It can manage different agricultural activities based on data obtained from various sources, including real-time environmental conditions collected by sensor networks, as well as a large amount of data stored in the cloud under networked conditions. Altalak discussed techniques such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs), which have demonstrated outstanding effects in multiple fields such as crop disease identification, crop identification/classification, and identification of water stress. When the algorithm is input with training utilizing multifarious datasets (encompassing soil chemical composition, weather patterns, and historical yield data), these models equip optimizations predicated on predictive analysis concerning agricultural procedural workflows. For instance, the proposed multi-layer DL architecture can classify different crop species in the land cover area through satellite images obtained from multiple sources; Weeds and crops were detected through the photos collected by unmanned aerial vehicles using deep residual CNNs (ResNet-18). Deep learning has successfully combined real-time Internet of Things sensor data with agricultural knowledge, reducing the waste of human and physical resources and promoting the rational use of water and fertilizers-thereby enhancing productivity while achieving resource conservation [4, 11].

The integration of agricultural knowledge and computational intelligence indicates a trend of autonomous and data-driven agricultural practices, which is supported by large-scale artificial intelligence architectures. The interpretability of models and the gradual development of edge computing are not only expected to make these precise tools more widespread but also to ensure their scalability in different agricultural economic regions.

4.2. Multi-agent cooperative practice

The development of multi-agent collaborative decision-making systems represents a pivotal advancement in smart agriculture, particularly in the context of unmanned farming ecosystems.

From a technical perspective, the operation of unmanned farms is actually the collaborative efforts of multiple heterogeneous agents, including data collection agents, execution agents, decision-making agents, etc. The core technology that supports the normal operation of data collection agents lies in the deployment and application of diverse sensors, mainly including soil moisture sensors, meteorological monitoring equipment, pest and disease sensors, etc. They are responsible for real-time collection of data on the farmland environment and crop growth, ensuring the authenticity and diversity of the data. By applying IOT technology, these sensors can transmit the collected data in real time to the central data processing system, providing a reliable data source for decision-making agents. The central data processing system analyzes data through artificial intelligence algorithms (such as deep learning), and on this basis, conducts analysis and prediction

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to generate reasonable decision-making in structures such as planting plans and pest and disease warnings. All decision-making instructions, such as sowing, fertilizing, irrigation and other specific operations, will be received and executed by the execution agent (unmanned aerial vehicle or agricultural robot), achieving agricultural activities that meet the standards. These agents are interconnected through the Internet of Things architecture to form a hierarchical collaborative decision-making network, which conforms to the definition of the Multi-agent Cooperative Decision System. It realizes the intelligent management of the entire agricultural production process through data sharing, task allocation and dynamic coordination of heterogeneous agents. In the future, with the advancement of AI and Internet of Things technologies, the collaborative efficiency and autonomy of this system will be further enhanced [12].

5. Conclusion

This academic research systematically explores the integration between low-power embedded sensor systems and autonomous decision-making frameworks in the field of intelligent agriculture. By deeply analyzing components such as hardware optimization, communication strategies, and energy recovery devices, significant progress has been revealed in building low-power sensor clusters that excel in real-time environmental monitoring while maintaining functional persistence and normalization. AI-driven models, such as CNNs and RNNs, can accurately predict crop management, resource optimization, and disease detection, while multi-agent collaborative systems can promote unmanned farm operations by coordinating data collection, analysis, and execution. Examples show that these increases respond to the issues raised in the introduction regarding the synthetic cracks in smart agriculture technologies and the inefficiency of energy management.

The review presented herein, while highlighting numerous innovative aspects, acknowledges methodological limitations that warrant attention. It predominantly focuses on the analysis of contemporary technologies (2020-2025), which might inadvertently overlook the historical efficiency evaluation of operating systems. Although the advantages of integrating low-power sensors and Autonomous Decision Systems in smart agriculture have been thoroughly examined, the practical validation of smart agriculture's adaptability to diverse agricultural climatic conditions remains limited. Moreover, the technical emphasis is primarily placed on model and algorithm innovation, unintentionally disregarding economical factors influencing the pace of technological adoption, specifically the cost-effectiveness of high-tech solutions in agriculture. Notably, the substantial financial resources required for deploying artificial intelligence pose significant economic challenges, particularly for low-cost agricultural production.

To address the aforementioned issues, subsequent research should focus on integrating laboratory models, preliminary field trials, and participatory stakeholder evaluation methodologies. Future research directions should emphasize enhancing technological innovation while embedding it within life cycle synergies, particularly by addressing challenges in durability testing under harsh conditions and overcoming funding constraints for deploying smart agriculture. This will facilitate the construction of a low-cost, high-return agricultural production framework. Through these anticipated collaborative efforts, this academic endeavor purposefully aims to bridge the entrenched gap between theoretical paradigms and operational sustainability.

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