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REVIEW ARTICLE

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IOT IN SMART AGRICULTURE: A SYSTEMATIC REVIEW AND CLASSIFICATION OF TECHNIQUES AND GAPS

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ABSTRACT: IoT technologies are reshaping agricultural practices by supporting real-time data analysis and intelligent automation. This paper presents a systematic review and classification of recent IoT-based techniques in smart agriculture, focusing on applications such as smart irrigation, disease detection, and environmental monitoring.

Ten research papers published between 2019 and 2025 are analysed to identify common architectures, core technologies, and implementation strategies. The review highlights the role of sensors, microcontrollers, wireless protocols, and mobile/cloud platforms in building intelligent farming systems. It also explores emerging trends like edge AI and predictive analytics.
The paper concludes by discussing key challenges including energy inefficiency, interoperability issues, and low adoption rates, and outlines future directions for building robust, secure, and scalable IoT ecosystems tailored to agricultural needs.

KEYWORDS: internet of things (iot), smart agriculture; precision farming, wireless sensor networks (wsn), edge computing, machine learning, smart irrigation

I. INTRODUCTION

In recent years, IoT has evolved into a key enabler for intelligent and automated solutions in agriculture, enabling real-time monitoring [1], data-driven decision-making, and improved resource utilization. This survey paper explores recent developments in IoT applications within agriculture, with a focus on techniques such as smart drip irrigation, polyhouse automation, and precision farming systems. It also highlights the integration of emerging technologies like Artificial Intelligence (AI), which significantly enhance productivity and predictive capabilities. In addition to reviewing current systems and architectures, this paper identifies key challenges, including increased power consumption, technical complexity, and the need for farmer training, and outlines potential future directions for advancing smart farming solutions.

II. LITERATURE REVIEW

The literature review in this paper is presented in the form of a classification table that summarizes ten selected research papers on IoT-based smart agriculture. The table categorizes each work based on year, technologies used (e.g., sensors, microcontrollers, communication modules), key contributions, and identified limitations. This classification provides a clear comparative view of how different studies have approached IoT integration in smart farming and highlights the diversity in implementation techniques as well as the existing gaps. Readers can refer to Section 8 for the full classification table.

Iot Architecture in Smart Agriculture

The architecture of IoT-based smart agriculture systems typically follows a layered model comprising sensing, network, and application layers [1] as shown in Figure 1. At the sensing layer, various sensors such as soil moisture, temperature, humidity, and pH sensors alongside advanced modules such as NPK, acoustic, and color sensors as discussed in [10] are deployed to collect real-time environmental data from the field, often organized into Wireless Sensor Networks (WSNs) for efficient data aggregation [5]. These sensors are connected to microcontrollers like Arduino, WEMOS Mini D1, or Raspberry Pi, which act as edge devices to preprocess and transmit data.
The network layer ensures communication between edge devices and cloud servers or fog gateways. Commonly used communication technologies include Wi-Fi, ZigBee, LoRa, Bluetooth, GSM, GPRS, and 6LoWPAN. Some systems implement fog computing or edge AI to reduce latency and enable real-time decision-making locally [3].
At the application layer, cloud platforms aggregate and analyse sensor data using machine learning or decision-support systems to automate irrigation, fertilization, and pest management. The architecture may also include a user interface for farmers via mobile apps or dashboards, enabling remote monitoring and control of field activities.
This layered structure enables efficient data collection, transmission, processing, and decision-making, forming the backbone of smart agricultural systems.

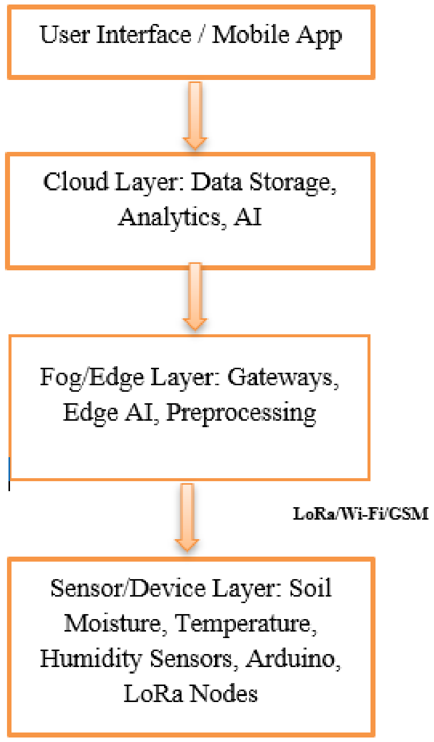

Fig. 1. Layered IoT Architecture for Smart Agriculture

Smart Irrigation Systems

Smart irrigation is one of the most impactful applications of IoT in agriculture, aiming to optimize water usage based on real-time soil and climate data [1]. These systems integrate soil moisture sensors, temperature sensors, weather APIs, and actuators to monitor field conditions and automate irrigation schedules [4]. The data collected from sensor nodes is transmitted via LoRa, Wi-Fi, ZigBee, or GSM modules to cloud or edge platforms, where it is analysed to make timely irrigation decisions [3].

Various studies have implemented platforms using Arduino, Raspberry Pi, and WEMOS boards for controlling valves and pumps based on soil moisture thresholds. Some advanced systems incorporate machine learning algorithms to predict irrigation needs based on historical and environmental data. The integration of mobile apps allows farmers to monitor and override irrigation remotely.

While these systems significantly reduce water wastage and improve crop yields, challenges remain, including high initial setup cost, energy consumption in remote areas, and inconsistent network coverage in rural regions.

Table 1. Comparison of Smart Irrigation Systems in IoT-based Agriculture

Paper Title	Sensors Used	Controller	Connectivity	Smart Feature	Limitation
A Review on IoT Applications in Smart Agriculture	Soil moisture, temperature	Arduino	Cloud, GSM	Remote monitoring and water-saving	High cost, power consumption
Smart Farming: The Role of AI and IoT in Modern Agriculture	Multiple: moisture, temperature, pest-related	AI-enabled controllers, drones	Mixed (ZigBee, LoRa, Wi-Fi)	AI-driven irrigation and fertilization	High investment, complexity, training needed
IoT-Based Smart Irrigation Systems: An Overview	Soil moisture, humidity, rain	Arduino UNO, WEMOS Mini D1, Raspberry Pi	Wi-Fi, ZigBee, GSM, LoRa	Sensor-triggered irrigation control, cloud reporting	No standardization, rural connectivity issues

As shown in Table 1, most smart irrigation systems employ a range of environmental sensors combined with microcontrollers like Arduino or Raspberry Pi. Connectivity varies depending on geographic context, with LoRa and GSM more suited for remote locations. While all systems aim to minimize water usage, common limitations include lack of infrastructure, energy dependency, and integration complexity.

Crop Monitoring and Disease Detection

Crop monitoring in smart agriculture relies on real-time data collected through a variety of sensors and imaging systems to assess crop growth, soil condition, and detect potential diseases. IoT systems equipped with **temperature, humidity, soil nutrient sensors**, and **multispectral or RGB cameras** mounted on **drones or ground units** can capture critical data across large field areas.

As demonstrated by Kokardekar et al. [8] and Kumar et al. [2], these systems use **machine learning algorithms** to detect early signs of diseases such as leaf discoloration, wilting, or fungal infections. Data is processed either on the cloud or at the edge, enabling real-time feedback and alerts. Advanced setups also integrate **weather forecasting APIs** to anticipate disease outbreaks based on environmental conditions.

While IoT-enabled monitoring enhances yield and reduces losses, major challenges include **sensor calibration**, **image interpretation errors**, and **limited affordability** for small-scale farmers. Moreover, most systems require significant internet or mobile network infrastructure to function effectively in rural regions.

III. CHALLENGES AND LIMITATIONS

While IoT brings notable improvements to agriculture, multiple barriers continue to limit its scalability and sustainable deployment.

- ***Energy and Power Constraints***
  One of the major concerns is energy consumption, especially in remote areas where frequent battery replacements or lack of renewable sources can disrupt continuous monitoring [5].
- ***Connectivity and Coverage Gaps***
  Network connectivity remains a bottleneck in rural and mountainous regions, limiting the reliability of real-time data transmission.
- ***Data Security and Privacy***
  Security and privacy of data continue to be key issues in smart farming applications.
  As IoT systems collect sensitive information related to soil fertility, crop cycles, and even farmer identities, they become targets for unauthorized access or tampering. As explored by Gupta et al. [6], many existing systems lack proper encryption, authentication, and intrusion detection mechanisms.
- ***Technical Complexity and Training***
  Another barrier is the high initial setup cost and technical complexity. Small and marginal farmers often find it challenging to understand, maintain, or troubleshoot IoT setups.
- ***Lack of Standardization***
  lack of standardization in hardware and communication protocols, leading to integration issues across vendors and platforms.
- ***Data Storage and Processing***
  Data management and scalability are growing concerns. With increasing deployment of sensors and AI-driven platforms, there is a pressing need for efficient data storage, real-time analytics, and intelligent decision-making without overburdening the system or the end-user.

IV. OPEN RESEARCH GAPS

Although numerous IoT-based solutions have been proposed for smart agriculture, several open research gaps remain unaddressed. One major gap is the **lack of standardization** across sensors, platforms, and communication protocols. Most systems are designed as standalone solutions with limited interoperability, making large-scale integration difficult [4].

Another significant gap lies in **energy-efficient system design**. Many existing solutions use high-power sensors and microcontrollers that are not optimized for long-term field deployment, especially in rural areas with limited power infrastructure.

In the domain of **crop disease detection**, current image-based approaches using machine learning often suffer from **dataset limitations** and poor generalization across different crops, climates, and disease types. Similarly, **edge-based AI solutions** are still underexplored due to hardware and processing constraints in real-world environments.

Additionally, **data security and privacy** issues are not adequately addressed in most reviewed systems. With the increasing use of cloud and mobile applications, the risk of unauthorized access to sensitive farm data is rising [6], yet few solutions incorporate encryption or authentication mechanisms.

Finally, there is a visible **gap in farmer training and adoption**. Even highly effective systems remain unused due to lack of awareness, complexity of operation, and absence of localized support, especially in developing regions.

Classification Of Techniques

Table 2. Classification Table

SL.No	Paper Title	Year	Application Area	Technology Used	Contribution	Limitation
1.	A Review on IoT Applications in Smart Agriculture	2023	Improve crop yields	Sensors, Cloud	Less wastage of water, remote monitoring is achieved	Increased power consumption, highly expensive
2.	Smart Farming: The Role of AI and IoT in Modern Agriculture	2025	Optimize irrigation, fertilization, pest control	Sensors, drones, AI algorithms	Productivity, environmental sustainability, cost reduction, climate resilience	High initial investment, technical complexity and training needs, data privacy and security concerns, connectivity and interoperability issues

3.	Edge AI in Smart Farming IoT: CNNs at the Edge and Fog Computing with LoRa	2019	Moving data analytics and compression near end devices	LoRa, edge gateway, repeater, fog gateway, cloud	Multiplies the options of IoT deployments, enables real-time processing	Infrastructure gaps, resistance to change, limited data rate
4.	IoT-Based Smart Irrigation Systems: An Overview on the Recent Trends on Sensors and IoT Systems for Irrigation in Precision Agriculture	2020	Smart irrigation systems, sensor deployment	WEMOS Mini D1, Arduino Mega/UNO, Raspberry Pi 2, GSM, Wi-Fi, ZigBee, Bluetooth, LoRa, GPRS, MQTT, 4G, 6LoWPAN, IEEE 802.15.4	Identified the most monitored parameters and most frequently used wireless and sensing nodes in precision irrigation	Lacks discussion on integration strategies, energy optimization, and large-scale implementation
5.	Applicability of Wireless Sensor Networks in Precision Agriculture: A Review	2019	Precision agriculture using WSN	ZigBee, Bluetooth, Wi-Fi, GPRS/GSM, WiMAX, Sensors	Highlights the role and comparative impact of different WSN technologies in smart farming	Limited focus on energy efficiency and field-level deployment challenges
6.	Security and Privacy in Smart Farming: Challenges and Opportunities	2020	Security and privacy in precision agriculture	Sensor networks, cloud, edge computing, encryption techniques	Highlights specific vulnerabilities like spoofing, data tampering, and insecure transmission in smart farming systems	Lack of robust authentication, privacy leakage, limited implementation of proposed solutions
7.	Precision Irrigation: An IoT-Enabled Wireless Sensor Network for Smart Irrigation Systems	2020	Wireless technologies in smart irrigation	BLE, ZigBee, Wi-Fi, GSM/GPRS, LoRaWAN, MQTT, DS18B20 sensors, Arduino, Raspberry Pi, NodeMCU	Saves water, reduces manpower, time, and cost	Power consumption, protocol interoperability, scalability limitations in large deployments, and dependence on network reliability
8.	Plant Disease Detection Using Image Processing and Machine Learning Algorithm	2022	Image-based plant disease detection using pre-processing and recognition techniques	Image improvement, segmentation, k-means clustering, convolutional neural networks (CNN), Gray Level Co-occurrence Matrix (GLCM)	Proposes an accurate disease detection system using ML and image analysis techniques	Accuracy depends on image quality, requires large datasets for training, model generalization issues for different crops or diseases
9.	Deep Learning for Plant Disease Detection	2025	Image-based disease detection using deep learning in agriculture	CNNs, TensorFlow, drone-based imaging, mobile applications	Addresses scalability issues, improves model interpretability, enhances precision in disease detection	Data scarcity, poor generalization to unseen conditions, high computational demand, inaccurate labeling in datasets

10.	Review on IoT-Based Smart Agriculture Monitoring System	2024	Multi-parameter crop monitoring and environment sensing	NPK, soil moisture, pH, temperature, humidity, color, acoustic, PIR, thermal sensors; Raspberry Pi B+, NodeMCU, Arduino UNO, ATmega, GSM, ZigBee, Pi Camera; THINGSPEAK, PLANTONE, STM32 Nucleo	Provides a comprehensive review of advanced sensor-based monitoring systems integrated with cloud/mobile platforms and machine learning for crop health analytics	High hardware complexity, high cost of implementation, sensor calibration requirements, limited large-scale deployment evidence

V. FUTURE DIRECTIONS

The evolution of IoT in smart agriculture presents numerous opportunities for further innovation. One promising direction is the development of energy-harvesting and ultra-low-power sensor nodes, which can enable long-term deployments in remote agricultural regions without the need for frequent battery replacements.

Another critical area is the integration of edge AI to reduce dependency on cloud connectivity. Real-time decision-making at the field level using lightweight machine learning models will significantly improve responsiveness and reliability in smart farming operations [2], [3], [9].

Additionally, future systems should prioritize open, interoperable IoT frameworks to ease integration across devices and platforms. Future systems should adopt open communication protocols and scalable designs to facilitate broader adoption, especially in multi-vendor environments.

Security and data privacy must also be given higher priority in upcoming research. Techniques like blockchain, end-to-end encryption, and federated learning can be explored to enhance data trust and system resilience [2], [6].

Finally, future solutions must be designed with farmer inclusivity in mind—through affordable systems, multilingual mobile apps, and local support networks— to align IoT capabilities with on-ground agricultural adoption and effectiveness.

VI. CONCLUSION

IoT integration in agriculture has modernized traditional practices through real-time sensing, data-driven insights, and optimized resource management. This survey has reviewed recent advancements in IoT-based systems for irrigation, crop monitoring, disease detection, and architectural frameworks. Through the classification and analysis of 10 research papers, we identified the core technologies, implementation strategies, and the challenges that persist in real-world adoption.

While significant progress has been made, despite advancements, unresolved issues persist, including high energy use, fragmented standards, and difficulties in scaling solutions. **Studies like [7] demonstrate practical WSN-based irrigation architectures that highlight both the potential and the constraints of current systems.** Addressing these gaps will require interdisciplinary collaboration, deployment of low-power and intelligent edge solutions, and a strong focus on usability for farmers in resource-constrained environments.

Future research should aim to develop inclusive, robust, and secure IoT ecosystems that are scalable and adaptable across diverse agricultural settings. By doing so, smart agriculture can move closer to becoming a sustainable and widely accessible solution to global food production challenges.

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