Exploring the Integration of Artificial Intelligence with IoT in Smart Farming: A Systematic Review

Menjelajahi Integrasi Kecerdasan Buatan dengan IoT dalam Pertanian Cerdas: Tinjauan Sistematis

Aswin Rosadi[1,2*], Mokh. Sholihul Hadi[1]

[1]Department of Electrical Engineering and Informatics, Faculty of Engineering, Universitas Negeri Malang, Indonesia

[2]Department of Computer Science, Faculty of Engineering, Universitas Muhammadiyah Surabaya, Indonesia

*Coresponding author

E-mail addresses: aswin.rosadi.2405349@students.um.ac.id, mokh.sholihul.ft@um.ac.id

Abstract – *This study examines the integration of artificial intelligence (AI) and the Internet of Things (IoT) in smart farming through a systematic literature review. This research focuses on the application of AI, the AIoT architecture, the datasets used, and the problems solved by this technology. The main problems faced are the complexity of technology integration and the limitations of infrastructure in implementation in the field. The purpose of the research is to provide a comprehensive understanding of the advancements and challenges of AIoT technology in the agricultural sector. The method used follows the guidance of Kitchenham (2007) by reviewing the latest relevant literature. The results show that AIoT has great potential in improving the efficiency and sustainability of the agricultural sector through efficient data management and data- driven decision-making. However, the success of the implementation of this technology is highly dependent on the availability of quality datasets and the adaptability of the technology at scale. This research provides practical recommendations for the development and application of AIoT in various smart agriculture scenarios in the future.*

Keywords*: Artificial intelligence, IoT, smart farming, AIoT, systematic literature review, agricultural sustainability*

INTRODUCTION

Agriculture is an important sector in supporting global food security. In recent decades, pressure on the sector has increased due to population growth, climate change, and limited natural resources. Artificial intelligence (AI)-based technologies and the Internet of Things (IoT) offer innovative solutions to address these challenges. Both enable data- driven agricultural management with high efficiency and better accuracy. According to a study by [1] the integration of AI in agricultural systems can increase crop yields by up to 30%. Meanwhile, IoT supports real-time data collection that can improve decision-making [2], [3]

In the context of smart farming, the integration between AI and IoT (AIoT) is the main focus of research because of its potential in optimizing resource management and increasing productivity. AIoT enables the use of sensors to collect environmental data that can be processed by intelligent algorithms to provide data-driven recommendations. For example, CNNs have been used to detect plant diseases with up to 95% accuracy [4], [5]. In addition, the use of multi-layer architectures in AIoT, such as edge-fog-cloud, demonstrates the ability to efficiently manage data [6], [7].

Although a lot of research has been conducted, there is still a knowledge gap regarding how AIoT can be integrated holistically in smart agriculture systems. For example, many solutions have not taken into account the limitations of infrastructure in rural areas. In addition, challenges such as device interoperability and data security are also concerns that have not been fully answered [8]. This gap suggests that more research is needed to explore the full potential of AIoT in the sector.

This study aims to answer this gap by conducting a systematic literature review on the application of AIoT in smart farming. This approach follows the guidance from Kitchenham (2007) and Elbasi (2023) which ensures that research is carried out in a structured and comprehensive manner [8], [9]. By analyzing more than 60 scientific articles, this study evaluates the application of AI, the AIoT architecture, the datasets used, as well as the problems that can be solved by this technology [10], [11]

This research makes an important contribution in answering the challenges of AIoT integration in smart farming. The findings show that AIoT is not only able to improve operational efficiency but also offers solutions to sustainability problems in the agricultural sector. Thus, this research not only provides academic insights but also supports the development of more modern and technology-based agricultural practices [12], [13].

METHODS

This research was conducted using a systematic literature review (SLR) approach based on guidance from Kitchenham (2007) and a method developed by Ersin Elbasi (2023) [8], [9], [14]. This approach ensures a systematic and structured analysis, following key stages that include planning, execution, and reporting. The focus of this study is to explore the application of Artificial Intelligence of Things (AIoT) technology in the smart farming sector to answer research questions. We can see the flowchart of SLR method in Figure 1.

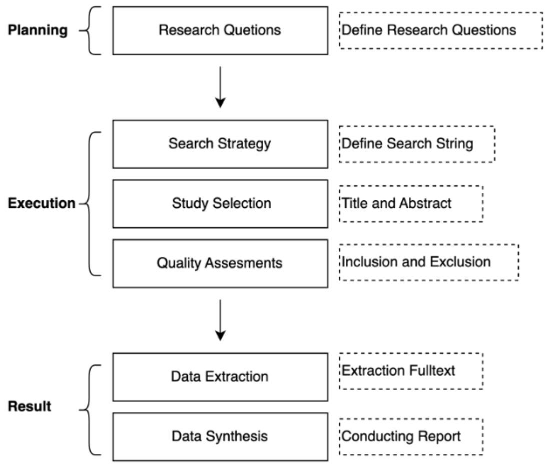

Figure 1. Flowchart of SLR

A. *Define Research Questions*

To guide the research process, we used the PICOC (Population, Intervention, Comparison, Outcome, and Context) framework. The framework is designed to provide a clear structure in formulating a research approach. "Population" refers to research related to smart farming that utilizes AIoT technology, while "Intervention" focuses on the implementation of AI, IoT, or a combination of both. No specific comparisons were made in this framework, so the "Comparison" component was declared irrelevant for this study. The expected outcome or "Outcome" is an in-depth understanding of the application of AI and AIoT, including the challenges and solutions faced. Finally, "Context" narrows the scope of research on publications in the last five years (2018-2023) in the agricultural sector. Using this framework, we can ensure that the research has a focused focus and high relevance to the topic discussed. Table 1 is a breakdown of the PICOC framework used.

This SLR process is designed to answer the following questions based on the previously formulated PICOC framework. The relationship between PICOC and this research question helps ensure that each RQ not only has a relevant focus but can also produce significant findings. For example, the "Population" related to smart farming is the basis for understanding how the application of AI (RQ1) and AIoT architecture (RQ2) is impacting the sector. Similarly, "Outcome" provides direction to RQ3 and RQ4 to identify the datasets and the key challenges addressed by these technologies. The motivation behind each RQ reflects the need to delve into the key aspects of smart farming, which can support sustainability and operational efficiency [15]. Table 2 is the details of the research questions designed. *Architecture*", "*Datasets in Agriculture*", and "*AIoT Challenges in Smart Farming*". Boolean operators *("AND", "OR")* are implemented to ensure broad yet still relevant coverage of results. We can see the Summary of PICOC in Table 1.

Table 1. Summary of PICOC

PICOC	Detail
Population	Research related to smart farming using AIoT technology
Intervention	Implementation of AI, IoT, or a combination of both technologies in smart farming
Comparison	No specific comparisons were made

Understanding of the application of *Architecture*", "*Datasets in Agriculture*", and "*AIoT Challenges in Smart Farming*". Boolean operators *("AND", "OR")* are implemented to ensure broad yet still relevant coverage of results. This search protocol is limited to publications published in the last five years (2020-2024) to ensure relevance to the latest technology trends. Studies that did not speak English or did not provide full-text access were excluded from further analysis.

B. Search Strategy

Each article found through a literature search is systematically evaluated using strict inclusion and exclusion criteria to ensure the relevance and quality of the findings. The inclusion criteria include articles that explicitly discuss the implementation of AI or AIoT in the agricultural sector, analyze the design of AIoT solutions faced in smart farming. In contrast exclusion criteria include articles that are opinions only, irrelevant to the research topic, or do not include validiable experimental data [16].

Table 2. Detail of RQ

RQ	Detail Motivation	Motivation
RQ1	How is AI applied in smart farming?	To understand the role of AI in optimizing agricultural efficiency and sustainability
RQ2	How is the AIoT architecture applied in smart farming?	To explore the technical design and relevant AIoT framework in smart farming.
RQ3	What datasets are used in smart farming research?	To identify datasets that support the development of AI/AIoT models in agriculture
RQ4	What problems d oes AIoT solve in the context of smart farming?	To find out the main challenges that can be solved with AIoT solutions.

C. *Study Selection*

This selection process is carried out in three successive stages to improve accuracy: first, screening by title to eliminate articles that are clearly inappropriate; second, abstract review to evaluate the summary of the content of the article; and third, full-text analysis to ensure that the article meets all inclusion criteria. Articles that pass this stage are then further analyzed to identify key data relevant to the research question.

D. Quality Assessment

The quality assessment stage is carried out to ensure that only articles with a strong methodology and high relevance are included in the final analysis. This process involves three main steps to improve the accuracy. The stages of the search strategy are carried out to identify relevant articles from various leading academic databases. The literature search strategy is carried out using reputable academic databases, such as IEEE Xplore, Scopus, and Web of Science. The keywords used include a combination of the following terms: "*AI in Smart Farming*", "*AIoT* efficiency of selection [15], [17].

Figure 2 explains that the first step is an initial evaluation through filtering by title, where articles that are clearly irrelevant to the focus of the research are omitted. Of the 964 initial articles obtained from databases such as MDPI, IEEE Explore, ScienceDirect, Springer, and Scopus, only 437 articles are eligible for the next stage.

The second step is an abstract review, where a summary of the content of each article is analyzed to assess its suitability with the research question and inclusion criteria that have been set. This process further distills articles into 251 which are considered relevant for in-depth analysis.

The final step is full-text analysis, which includes a comprehensive examination of the content of the article to ensure that all inclusion criteria are met. The criteria assessed include clarity of research objectives, methodological suitability, and relevance of the data presented. Of the 251 articles, 149 were further processed in the quality assessment stage, resulting in 67 articles that were finally selected for in-depth analysis.

This process not only ensures that the selected articles are of high relevance but also meet the quality standards necessary to support the overall research objectives [7]. With this approach, research can produce accurate and trustworthy findings. The process of assessing the quality of articles is carried out with a systematic approach to ensure that only studies with high relevance and a strong methodology are included in the final analysis. Each article is evaluated based on three main criteria, namely clarity of research objectives, suitability of methodology to research questions, and quality of data and analysis presented [16], [18].

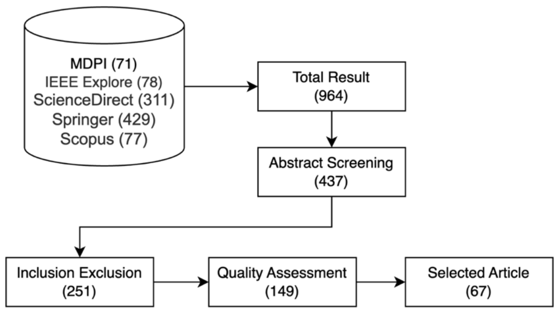

Figure 2. Search and Quality Assesment

E. Data Extraction

The data extraction stage is carried out after a selection process and quality assessment to identify relevant information from the selected articles. This process is systematically designed to ensure that all extracted data supports the effort to answer Research Questions (RQs). A total of 67 articles that passed the quality assessment stage became the main source in this process. The extracted data includes key elements, such as AI application (RQ1): AI techniques, algorithms, or methods used in smart farming, AIoT Architecture

(RQ2): Design and framework of applied AIoT technologies, Datasets (RQ3): Types, sizes, and sources of datasets used in the study, Problems Solved (RQ4): Specific challenges overcome by AIoT in the agricultural sector.

F. Data Synthesis

The results of the extracted data were thoroughly analyzed using thematic synthesis and data visualization approaches to identify key patterns and trends in the literature. Quantitative data, such as the distribution of publications per year, are studied using graphs to reveal temporal trends that show the development of research in the field of AI- and AIoT-based smart farming. This visualization helps in providing a clearer picture of the increase in academic interest and contribution over time [19].

Meanwhile, qualitative data is summarized based on the main themes related to the research question (RQ). For example, the AI techniques and algorithms used (RQ1) are analyzed to find common patterns in their implementation, while the AIoT architectural design (RQ2) is synthesized to evaluate dominant technical innovations and frameworks. The dataset used in the study (RQ3) was mapped to understand the resources that support the development of this technology. Finally, the challenges overcome by AIoT (RQ4) are analyzed to identify technological solutions to the problems faced in smart farming.

Through this analysis, the research contributes to the development of a deeper understanding of how AI and AIoT technologies can be optimized to support efficiency, sustainability, and adaptability in the agricultural sector. The findings also provide relevant guidance for future research by describing innovation opportunities and areas that require further exploration.

AI with CNN : [32], [33], [34], [35], [36], [37], [38], [39]
IoT-based Fuzzy Logic : [16], [17], [18], [40], [41], [42], [43], [44], [45], [46], [47], [48], [49], [50], [51], [52], [53]
Edge-Fog- Cloud Architecture : [54], [55], [56], [57], [58], [59], [60], [61], [62], [63], [64], [65], [66]
Precision Farming : [67], [68], [69], [70], [71], [72], [73], [74], [75], [76]
High- accuracy detection of plant diseases Optimal water management and irrigation Energy efficiency and data management Improving crop yields through a data-driven approach : [15], [77], [78], [79], [80], [81], [82]

RESULTS AND DISCUSSION

A. *RQ1: How is AI applied in smart farming?*

The results of the study show that the application of AI technology in smart farming makes a significant contribution to the sustainability and efficiency of the agricultural sector as shown in table 3. This technology not only allows for improved accuracy of crop yield prediction and plant disease detection, but also supports more economical and optimal management of resources.

The analyzed article shows that AI-based algorithms, such as Machine Learning (ML), Convolutional Neural Networks (CNNs), and evolution-based techniques, play a crucial role in automating agricultural processes and providing data-driven insights [5], [6]. For example, the implementation of CNNs for plant disease detection using image analysis has achieved up to 95% accuracy, while regression-based algorithms have helped. reduce water use by up to 30%. This combination demonstrates the potential of AI technology in driving the transformation of traditional agriculture towards more precise and technology-based practices.

Table 3. AI applied in smart farming

Category	Function	Reference
ZigBee, WiFi, and LoRaWAN integration	Digital Twin Integration	[20], [21], [22], [23], [24], [25], [26], [27], [28], [29], [30], [31],
Blockchain implementation for data authentication and supply chain monitoring	IoT Communication Protocol	[60], [62], [63], [64] [12], [13], [20], [21],
CNN-BiLSTM-based object detection for agricultural environmental classification	Blockchain-IoT Framework	[22], [23], [24], [25], [26], [27], [83], [85], [86], [87], [88]

In Figure 3, IoT technology dominates with the largest proportion (30%), showing its significant role as the backbone in real-time resource management and communication of agricultural devices. IoT enables efficient environmental monitoring and data collection, thus supporting fast and accurate decision- making. Furthermore, AI-based algorithms such as Machine Learning and Convolutional Neural Networks (CNNs) contribute 25% in smart farming applications [83], [84]. The technology is widely used for crop disease detection and crop yield prediction, with the ability to provide deep data-driven insights.

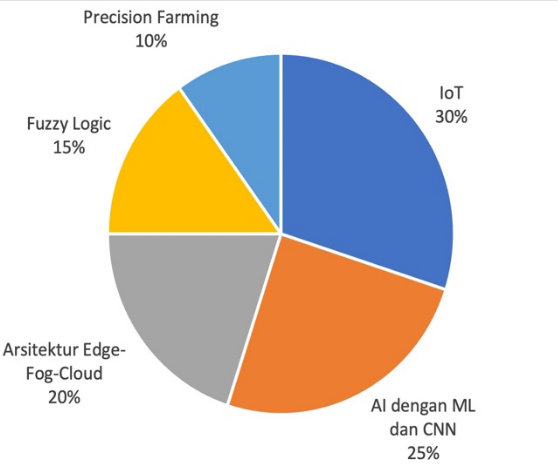

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Figure 3. Proportion of Technologies Used

As many as 20% of the applications analyzed utilize the Edge-Fog-Cloud architecture, which enables efficient data management with low latency. This approach is particularly relevant for scenarios that require real-time response, such as irrigation management or detection of environmental conditions. Fuzzy Logic, which accounts for 15% of the total application, is used to maximize water and energy use efficiency through an uncertain logic-based management system [85], [86]. Finally, precision farming with a contribution of 10% shows great potential in utilizing Big Data and AI-based analytics to optimize the use of fertilizers, pesticides, and other resources, thereby supporting the sustainability of the agricultural sector. IoT with LoRaWAN Real-time monitoring and waste reduction : [20], [21], [22], [23], [24], [25], [26], [27], [28], [29], [30], [31].

B. RQ2: How is the AIoT architecture applied in smart farming?

The results of the analysis show that the application of AIoT architecture in smart farming integrates various technologies to create a more adaptive, responsive, and efficient system in data management and real-time decision-making [29], [30]. Frequently used approaches include multi-layer architectures, which manage data at the edge, fog, and cloud levels, allowing for faster and localized data processing as shown in Table 4.

Table 4. AIoT applied in smart farming

Category	Function	Reference
ZigBee, WiFi, and LoRaWAN integration	Digital Twin Integration	[60], [62], [63], [64]

Blockchain implementation for data authentication and supply chain monitoring	IoT Communication Protocol	[12], [13], [20], [21], [22], [23], [24], [25], [26], [27], [83], [85], [86], [87], [88]
CNN-BiLSTM-based object detection for agricultural environmental classification	Blockchain-IoT Framework	[1], [2], [3], [4], [5], [6], [7], [8], [10], [11], [12], [13], [83], [84], [89], [90], [91]
		[31], [32], [33], [34],[35], [36], [37], [38], [39], [40], [92]
AI-IoT Hybrid System	Application of IoT-based digital twin to monitor pH, temperature, and humidity parameters	[20], [21],[22], [23], [24], [26], [85], [86], [88]

Digital twins provide a dynamic virtual representation of the agricultural environment, allowing for more accurate monitoring and prediction of agricultural conditions such as soil moisture, temperature, and nutrient levels. Communication protocols such as LoRaWAN, ZigBee, and MQTT play a crucial role in guaranteeing reliable and efficient connectivity between IoT devices [24], [25]. Additionally, blockchain-IoT strengthens data transparency and security, providing solutions for authentication of data collected in the agricultural sector. This combination of technologies is designed to address key challenges such as low latency, information security, and the need for distributed data management in the modern agricultural sector as we can see it in Figure 4.

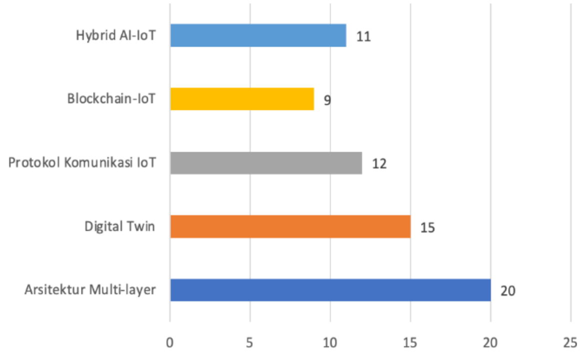

Figure 4. Architectural Proportions Used

In Figure 4, Multi-layer Architecture has the highest frequency with 20 studies, demonstrating the dominance of this approach in supporting structured data management at the edge, fog, and cloud levels. This approach allows for faster and more efficient data processing, supporting real-time data-driven decision-making [29]. The Digital Twin, with 15 studies, plays a crucial role in modeling the farming environment virtually. This technology provides the ability to accurately monitor and predict conditions such as soil moisture, temperature, and nutrient levels.

Table 5. Architecture smart farming

Category	Function	Reference
Multi-layer Architecture	Simulation Data	[14], [16], [17], [18], [48], [49], [50], [51], [52], [53], [54], [55], [56], [57], [58], [59]
Data Blockchain-IoT	Rust, Rice Leaf Disease Dataset Proteus Design Suite, ThingSpeak, Ganache	[20], [21], [22], [23], [24], [25], [26], [85], [86], [87], [88], [89], [90], [91]
ToN-IoT, Edge-IIoTset		[1], [2], [3], [4], [5], [6], [7], [8], [10], [11], [12], [13]

IoT Communication Protocols, recorded in 12 studies, highlight the role of protocols such as ZigBee, LoRaWAN, and MQTT in supporting efficient connectivity between IoT devices.

Blockchain-IoT, used in 9 studies, provides a solution for data security and transparency, which is increasingly relevant to the needs of authentication and data security in modern agriculture. Meanwhile, Hybrid AI- IoT, with 11 studies, shows the potential of integrating AI technology with IoT to support object detection, machine learning-based data analysis, and agricultural environmental classification [39], [40]. The combination of these various approaches forms a strong foundation for optimizing AIoT systems in the agricultural sector.

C. *RQ3: What datasets were used in the Smart Farming research?*

The results of the analysis show that research in smart farming uses various types of datasets, which reflects the diversity of technology and application needs in this sector. The dataset includes environmental sensor data, such as soil moisture, temperature, and air humidity, collected through IoT devices to support data-driven decisions [37], [38]. In addition, high-resolution satellite data and drone imagery play an important role in monitoring plant health and early detection of diseases at scale. Public datasets, such as FAOSTAT and plant disease datasets, are used for the training of more general and applicative analytical models. Other research also utilizes simulation data to test the effectiveness of IoT prototypes and smart agriculture network systems before implementation in the field. Details about the dataset are in Table 6.

Table 6. Smart Farming Dataset Category

Category	Function	Reference
Environmental Sensor Data	IoT sensors (soil moisture, temperature, air humidity)	[16], [17], [18], [43], [44], [45], [46], [47], [48], [49], [50], [51], [52], [53], [54], [55], [56]
Satellite Data and Drone Imagery	MODIS satellite, UAV with multispectral and thermal imagery FAOSTAT, Wheat Leaf	[16], [18], [46], [47], [48], [49], [50], [59], [60], [61], [62], [63], [64]
Public Datasets		[26], [27], [28], [29], [30], [31], 32], [33], [34], [35], [92]

On the other hand, blockchain-IoT- based datasets, such as ToN-IoT and Edge- IIoTset, make a unique contribution in ensuring data security, transparency, and reliability throughout the agricultural supply chain [46], [47]. This diversity shows that the datasets used not only serve as a source of information, but also as a foundation for technological innovations that support precision agriculture and sustainability, and we can see in Figure 5.

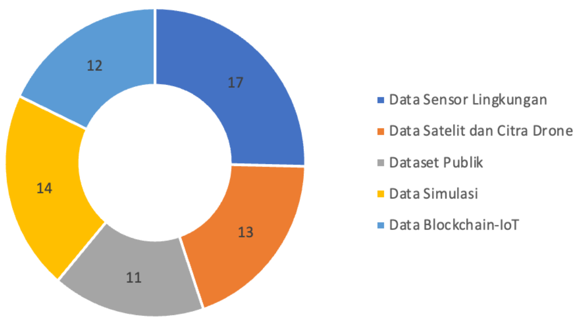

Figure 5. Dataset used

The diagram in Figure 5 provides an overview of the distribution of the use of various types of datasets in smart farming research. Based on this diagram, environmental sensor data occupies the largest portion with 17 studies, reflecting the importance of this data to support data-driven decisions in the field, such as irrigation management and soil condition monitoring. Satellite data and drone imagery, used in 13 studies, have a significant role at scale, including plant health monitoring and disease detection [45], [46]. Public datasets, such as FAOSTAT and the leaf disease dataset, were used in 11 studies to train more general and applicative analytical models.

Simulation data, with 14 studies, is often used for the validation of technology prototypes, such as IoT network simulations and smart farming systems, which provide reliability before implementation in the field. Finally, blockchain-IoT-based data, used in 12 studies, focuses on securing data as well as ensuring transparency and integrity in agricultural IoT networks.

C. *RQ4: What problems does AIoT solve in the context of smart farming?*

The results of the analysis show that AIoT in the context of smart farming solves various problems that focus on resource efficiency, land management, and sustainability [53], [54]. Some of the main challenges that have been successfully overcome include irrigation optimization, early detection of plant diseases, improved data security, and reduction of energy consumption as presented in Table 6. These issues have a direct impact on the successful implementation of smart technologies in the agricultural sector.

AIoT is also used to address the fragmentation of agricultural processes by providing real-time data-driven solutions. For example, AIoT enables more accurate prediction of crop yields based on historical data, automated nutrient management for hydroponics, and improved interoperability of IoT devices in complex networks[61]. By utilizing a combination of AI and IoT technologies, the system provides higher operational efficiency while reducing reliance on traditional methods. Use of standard protocols such as LoRaWAN and ZigBee for communication between devices successful implementation of smart technologies in the agricultural sector. We can see this problems in Table 7.

Table 7. Problems with Smart Farming

Key Issues	AIoT Solutions	Reference
Environmental Sensor Data	IoT sensors (soil moisture, temperature, air humidity)	[1], [2], [3], [4], [5], [6], [7], [10]
Irrigation Optimization	IoT-based irrigation system with soil moisture sensor	[8], [11], [12], [13], [83], [84]
Plant Disease Detection	Machine learning algorithms for plant image analysis	[20], [84], [85], [86], [87], [88], [89], [90], [91]

AIoT is also used to address the fragmentation of agricultural processes by providing real-time data-driven solutions. For example, AIoT enables more accurate prediction of crop yields based on historical data, automated nutrient management for hydroponics, and improved interoperability of IoT devices in complex networks[61]. By utilizing a combination of AI and IoT technologies, the system provides higher operational efficiency while reducing reliance on traditional methods. We can see in Figure 6.

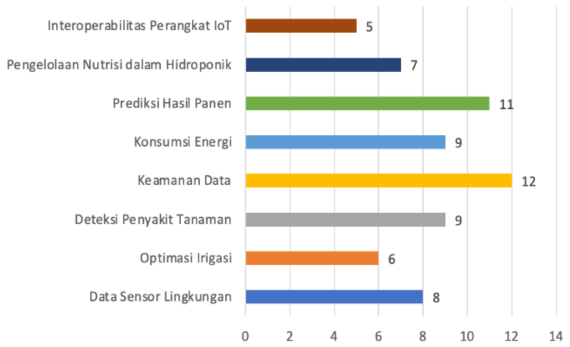

Figure 6. Problems faced

Crop yield prediction has a frequency of 11, indicating the important role of AIoT in providing accurate insights into land productivity based on historical and environmental data [62]. Energy consumption and plant disease detection each recorded a frequency of 9, highlighting the need for better energy efficiency and early identification of diseases to prevent crop losses. Nutrient management in hydroponics with frequency 7 shows how AIoT supports sustainable agriculture through automated systems that optimize nutrient delivery. Meanwhile, irrigation optimization, with a frequency of 6, reflects the importance of more efficient water management to support resource sustainability [60], [61]. The interoperability of IoT devices, despite having a frequency of 5, remains a critical aspect in ensuring that various devices can work harmoniously in complex networks. We can see in Table 8

Table 8. Frequency of Irrigation optimation

Key Issues	AIoT Solutions	Reference
Data Security	Blockchain-IoT for data authentication and protection	[22], [23], [24], [25], [26], [27], [28], [29],[30], [31], [32], [92]
Energy Consumption	Neuro-fuzzy-based	[[33], [34], [35], [36],

CONCLUSION

This study has explored the integration of Artificial Intelligence (AI) and Internet of Things (IoT) technology in the context of smart farming through the Systematic Literature Review (SLR) approach. Using research protocols adopted from Kitchenham (2007) and Elbasi (2023), this study succeeded in identifying four main aspects, namely the application of AI in smart farming, the AIoT architecture, the type of dataset used, and the problems solved by AIoT in this sector.

The results of the study show that the application of AI in smart farming contributes significantly to the optimization of agricultural processes, ranging from crop yield prediction to early detection of plant diseases. Frequently implemented AIoT architectures include multi-layer approaches, digital twins, and communication protocols such as LoRaWAN, which enable efficient and real-time data management. The study also found that the datasets used vary, ranging from environmental sensor data, drone imagery, to blockchain-based datasets designed for data security and transparency. In addition, AIoT has proven to be able to address a variety of key challenges, such as energy efficiency, data security, IoT device interoperability, and more sustainable resource management.

Although this research has provided comprehensive insights, there are several opportunities for further study. One of them is further exploration regarding the integration of AIoT technology with a cloud-edge computing- based approach to improve scalability and operational efficiency. In addition, future research can be focused on developing more representative public datasets to support the generalization of AI models in various agricultural scenarios. The data security aspect also requires more attention, especially with the increasing cyber threats in complex IoT networks.

Overall, this study confirms that the integration of AI and IoT in smart farming has great potential to revolutionize the agricultural sector. With the continued development of technology and the need for sustainable solutions, AIoT can be a key driver in achieving agricultural efficiency and sustainability in the future.

REFERENCES

[1] N. Abdullah *et al.*, “Towards Smart Agriculture Monitoring Using Fuzzy Systems,” *IEEE Access*, vol. 9, pp. 4097–4111, 2021, doi: 10.1109/ACCESS.2020.3041597.

[2] Z. Raza, I. U. Haq, and M. Muneeb, “Agri-4-All: A Framework for Blockchain Based Agricultural Food Supply Chains in the Era of Fourth Industrial Revolution,” *IEEE Access*, vol. 11, pp. 29851–29867, 2023, doi: 10.1109/ACCESS.2023.3259962.

[3] M. Gupta, M. Abdelsalam, S. Khorsandroo, and S. Mittal, “Security and Privacy in Smart Farming: Challenges and Opportunities,” *IEEE Access*, vol. 8, pp. 34564–34584, 2020, doi: 10.1109/ACCESS.2020.2975142.

[4] M. S. M. Shah, Y. B. Leau, Z. Yan, and M. Anbar, “Hierarchical Naming Scheme in Named Data Networking for Internet of Things: A Review and Future Security Challenges,” 2022, *Institute of Electrical and Electronics Engineers Inc.* doi: 10.1109/ACCESS.2022.3151864.

[5] H. A. Alharbi and M. Aldossary, “Energy-Efficient Edge-Fog-Cloud Architecture for IoT-Based Smart Agriculture Environment,” *IEEE Access*, vol. 9, pp. 110480–110492, 2021, doi: 10.1109/ACCESS.2021.3101397.

[6] A. U. H. Hashmi *et al.*, “Effects of IoT Communication Protocols for Precision Agriculture in Outdoor Environments,” *IEEE Access*, vol. 12, pp. 46410–46421, 2024, doi: 10.1109/ACCESS.2024.3381522.

[7] S. Qazi, B. A. Khawaja, and Q. U. Farooq, “IoT-Equipped and AI- Enabled Next Generation Smart Agriculture: A Critical Review, Current Challenges and Future Trends,” 2022, *Institute of Electrical and Electronics Engineers Inc.* doi: 10.1109/ACCESS.2022.3152544.

[8] E. Elbasi *et al.*, “Artificial Intelligence Technology in the Agricultural Sector: A Systematic Literature Review,” 2023, *Institute of Electrical and Electronics Engineers Inc.* doi: 10.1109/ACCESS.2022.3232485.

[9] B. Kitchenham and S. Charters, “Guidelines for Performing Systematic Literature Reviews in Software Engineering,” 2007. doi: 10.1541/ieejias.126.589.

[10] I. Ali, I. Ahmedy, A. Gani, M. U. Munir, and M. H. Anisi, “Data Collection in Studies on Internet of Things (IoT), Wireless Sensor Networks (WSNs), and Sensor Cloud (SC): Similarities and Differences,” *IEEE Access*, vol. 10, pp. 33909–33931, 2022, doi: 10.1109/ACCESS.2022.3161929.

[11] D. Javeed, T. Gao, M. S. Saeed, and P. Kumar, “An Intrusion Detection System for Edge-Envisioned Smart Agriculture in Extreme Environment,” *IEEE Internet Things J*, vol. 11, no. 16, pp. 26866–26876, 2024, doi: 10.1109/JIOT.2023.3288544.

[12] A. Saputhanthri, C. De Alwis, and M. Liyanage, “Survey on Blockchain- Based IoT Payment and Marketplaces,” *IEEE Access*, vol. 10, pp. 103411–103437, 2022, doi: 10.1109/ACCESS.2022.3208688.

[13] P. V. Astillo, J. Kim, V. Sharma, and I. You, “SGF-MD: Behavior rule specification-baseddistributed misbehavior detection of embedded iot devices in a closed-loop smart greenhouse farming system,” *IEEE Access*, vol. 8, pp. 196235–196252, 2020, doi: 10.1109/ACCESS.2020.3034096.

[14] E. Elbasi, N. Mostafa, C. Zaki, Z. AlArnaout, A. E. Topcu, and L. Saker, “Optimizing Agricultural Data Analysis Techniques through AI- Powered Decision-Making Processes,” *Applied Sciences (Switzerland)*, vol. 14, no. 17, Dec. 2024, doi:

10.3390/app14178018.

[15] V. Kumar, K. V. Sharma, N. Kedam, A. Patel, T. R. Kate, and U. Rathnayake, “A comprehensive review on smart and sustainable agriculture using IoT technologies,” *Smart Agricultural Technology*, vol. 8, Dec. 2024, doi: 10.1016/j.atech.2024.100487.

[16] G. Singh and S. Sharma, “A comprehensive review on the Internet of Things in precision agriculture,” *Multimed Tools Appl*, 2024, doi: 10.1007/s11042-024-19656-0.

[17] M. Anila and O. Daramola, “Applications, technologies, and evaluation methods in smart aquaponics: a systematic literature review,” *Artif Intell Rev*, vol. 58, no. 1, Dec. 2025, doi: 10.1007/s10462-024- 11003-x.

[18] I. A. Ali, W. A. Bukhari, M. Adnan, M. I. Kashif, A. Danish, and A. Sikander, “Security and privacy in IoT-based Smart Farming: a review,” *Multimed Tools Appl*, 2024, doi: 10.1007/s11042- 024-19653-3.

[19] B. Maroua, A. A. Rachida, and M. Abdelaziz, “Smart farming architectures based on IoT review: comparative study,” in *Procedia Computer Science*, Elsevier B.V., 2022, pp. 783–788. doi: 10.1016/j.procs.2022.07.117.

[20] K. Chicaiza, R. Paredes, I. M. Sarzosa, S. G. Yoo, and N. Zang, “Smart Farming Technologies: A Methodological Overview and Analysis,” *IEEE Access*, 2024, doi: 10.1109/ACCESS.2024.3487497.

[21] P. D. Rosero-Montalvo, C. A. Gordillo-Gordillo, and W. Hernandez, “Smart Farming Robot for Detecting Environmental Conditions in a Greenhouse,” *IEEE Access*, vol. 11, pp. 57843–57853, 2023, doi:10.1109/ACCESS.2023.3283986.

[22] A. Ahmed, I. Parveen, S. Abdullah, I. Ahmad, N. Alturki, and L. Jamel, “Optimized Data Fusion With Scheduled Rest Periods for Enhanced Smart Agriculture via Blockchain Integration,” *IEEE Access*, vol. 12, pp. 15171–15193, 2024, doi: 10.1109/ACCESS.2024.3357538.

[23] A. A. Alzubi and K. Galyna, “Artificial Intelligence and Internet of Things for Sustainable Farming and Smart Agriculture,” *IEEE Access*, vol. 11, pp. 78686–78692, 2023, doi: 10.1109/ACCESS.2023.3298215.

[24] S. Ghosh, “Neuro-Fuzzy-Based IoT Assisted Power Monitoring System for Smart Grid,” *IEEE Access*, vol. 9, pp. 168587–168599, 2021, doi: 10.1109/ACCESS.2021.3137812.

[25] M. Abdurohman, A. G. Putrada, and M. M. Deris, “A Robust Internet of Things- Based Aquarium Control System Using Decision Tree Regression Algorithm,” *IEEE Access*, vol. 10, pp. 56937–56951, 2022, doi:10.1109/ACCESS.2022.3177225.

[26] F. Kaçar *et al.*, “Editorial Board Editor in Chief Associate Editors Assistant Editor Advisory Board.” [Online]. Available: https://electricajournal.org/en/instructi ons-to-authors-1013.

[27] A. Hamadani and N. A. Ganai, “Development of a multi-use decision support system for scientific management and breeding of sheep,” *Sci Rep*, vol. 12, no. 1, Dec. 2022, doi: 10.1038/s41598-022-24091-y.

[28] T. Rathod *et al.*, “Blockchain-Driven Intelligent Scheme for IoT-Based Public Safety System beyond 5G Networks,” *Sensors*, vol. 23, no. 2, Dec. 2023, doi: 10.3390/s23020969.

[29] N. N. Thilakarathne, M. S. A. Bakar, P.Abas, and H. Yassin, “A Cloud Enabled Crop Recommendation Platform for Machine Learning-Driven Precision Farming,” *Sensors*, vol. 22, no. 16, Dec. 2022, doi:

10.3390/s22166299.

[30] K. S. Balamurugan, C. K. Pradhan, A. N. Venkateswarlu, G. Harini, and P. Geetha, "An internet of things based smart agriculture monitoring system using convolution neural network algorithm," *EAI Endorsed Transactions on Internet of Things*, vol. 10, 2024, doi: 10.4108/eetiot.5105.

[31] K. Ragazou, A. Garefalakis, E. Zafeiriou, and I. Passas, "Agriculture 5.0: A New Strategic Management Mode for a Cut Cost and an Energy Efficient Agriculture Sector," *Energies (Basel)*, vol. 15, no. 9, Dec. 2022, doi: 10.3390/en15093113.

[32] S. Yonbawi *et al.*, "Modeling of Sensor Enabled Irrigation Management for Intelligent Agriculture Using Hybrid Deep Belief Network," *Computer Systems Science and Engineering*, vol. 46, no. 2, pp. 2319–2335, 2023, doi: 10.32604/csse.2023.036721.

[33] E. M. Raouhi, M. Lachgar, H. Hrimech, A. Kartit, and E. Jadida, "Unmanned Aerial Vehicle based Applications in Smart Farming: A Systematic Review." [Online]. Available: www.ijacsa.thesai.org

[34] N. J. Lemphane, B. Kotze, and R. B. Kuriakose, "Developing a Digital Twin Model for Improved Pasture Management at Sheep Farm to Mitigate the Impact of Climate Change," 2024. [Online]. Available: www.ijacsa.thesai.org

[35] V. Balaska, Z. Adamidou, Z. Vryzas, and A. Gasteratos, "Sustainable Crop Protection via Robotics and Artificial Intelligence Solutions," *Machines*, vol. 11, no. 8, Dec. 2023, doi: 10.3390/machines11080774.

[36] J. Kim, I. Do Ha, S. Kwon, I. Jang, and M. H. Na, "A Smart Farm DNN Survival Model Considering Tomato Farm Effect," *Agriculture (Switzerland)*, vol. 13, no. 9, Dec. 2023, doi: 10.3390/agriculture13091782.

[37] N. Zelisko, N. Raiter, N. Markovych, H. Matskiv, and O. Vasylyna, "Improving business processes in the agricultural sector considering economic security, digitalization, risks, and artificial intelligence," *Ekonomika APK*, vol. 31, no. 3, pp. 10–21, Dec. 2024, doi: 10.32317/2221-1055.2024030.10.

[38] J. Mehare and A. Gaikwad, "Secured Framework for Smart Farming in Hydroponics with Intelligent and Precise Management based on IoT with Blockchain Technology," *International Journal on Recent and Innovation Trends in Computing and Communication*, vol. 11, pp. 244–254, 2023, doi: 10.17762/ijritcc.v11i9s.7418.

[39] B. Edwin *et al.*, "Smart agriculture monitoring system for outdoor and hydroponic environments," *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 25, no. 3, pp. 1679–1687, Dec. 2022, doi: 10.11591/ijeecs.v25.i3.pp1679-1687.

[40] M. Nawaz and M. I. K. Babar, "IoT and AI: a panacea for climate change- resilient smart agriculture," *Discover Applied Sciences*, vol. 6, no. 10, Dec. 2024, doi: 10.1007/s42452-024-06228-y.

[41] A. R. Yanes, R. Abbasi, P. Martinez, and R. Ahmad, "Digital Twinning of Hydroponic Grow Beds in Intelligent Aquaponic Systems," *Sensors*, vol. 22, no. 19, Dec. 2022, doi: 10.3390/s22197393.

[42] O. H. Abdelkader, H. Bouzebiba, D. Pena, and A. P. Aguiar, "Energy- Efficient IoT-Based Light Control System in Smart Indoor Agriculture," *Sensors*, vol. 23, no. 18, Dec. 2023, doi: 10.3390/s23187670.

[43] J. Popp, J. Oláh, M. Neményi, and A. Nyéki, "Global challenges and the 'farm to fork'

strategies of the European Green Deal: Blessing or curse," *Progress in Agricultural Engineering Sciences*, 2024, doi: 10.1556/446.2024.00113.

[44] A. Sarkar, M. M. Singh, and H. S. Sharma, "Artificial recurrent neural network coordinated secured transmission towards safeguarding confidentiality in smart Industrial Internet of Things," *International Journal of Machine Learning and Cybernetics*, 2024, doi: 10.1007/s13042-024-02310-4.

[45] D. Sharma, R. Kumar, and K. H. Jung, "A Bibliometric Analysis of Convergence of Artificial Intelligence and Blockchain for Edge of Things," *J Grid Comput*, vol. 21, no. 4, Dec. 2023, doi: 10.1007/s10723-023-09716-4.

[46] R. Manikandan, G. Ranganathan, and Bindhu, "Deep Learning Based IoT Module for Smart Farming in Different Environmental Conditions," *Wirel Pers Commun*, vol. 128, no. 3, pp. 1715–1732, Dec. 2023, doi: 10.1007/s11277-022-10016-5.

[47] F. A. Almalki and M. C. Angelides, "A synthesis of machine learning and internet of things in developing autonomous fleets of heterogeneous unmanned aerial vehicles for enhancing the regenerative farming cycle," *Computing*, Dec. 2024, doi: 10.1007/s00607-024-01347-1.

[48] S. J. Soheli, N. Jahan, M. B. Hossain, A. Adhikary, A. R. Khan, and M. Wahiduzzaman, "Smart Greenhouse Monitoring System Using Internet of Things and Artificial Intelligence," *Wirel Pers Commun*, vol. 124, no. 4, pp. 3603–3634, Dec. 2022, doi: 10.1007/s11277-022-09528-x.

[49] K. Kethineni and G. Pradeepini, "Intrusion detection in internet of things-based smart farming using hybrid deep learning framework," *Cluster Comput*, vol. 27, no. 2, pp. 1719–1732, Dec. 2024, doi:10.1007/s10586-023-04052-4.

[50] H. Y. Riskiawan *et al.*, "Artificial Intelligence Enabled Smart Monitoring and Controlling of IoT-Green House," *Arab J Sci Eng*, vol. 49, no. 3, pp. 3043–3061, Dec. 2024, doi: 10.1007/s13369-023-07887-6.

[51] M. Mohy-eddine, A. Guezzaz, S. Benkirane, and M. Azrour, "Malicious detection model with artificial neural network in IoT-based smart farming security," *Cluster Comput*, vol. 27, no. 6, pp. 7307–7322, Dec. 2024, doi:10.1007/s10586-024-04334-5.

[52] Y. Al Mashhadany, H. R. Alsanad, M. A. Al-Askari, S. Algburi, and B. A. Taha, "Irrigation intelligence— enabling a cloud-based Internet of Things approach for enhanced water management in agriculture," *Environ Monit Assess*, vol. 196, no. 5, Dec. 2024, doi: 10.1007/s10661-024-12606-1.

[53] X. Wang and V. Jannesari, "Towards a crop pest control system based on the Internet of Things and fuzzy logic," *Telecommun Syst*, vol. 85, no. 4, pp. 665–677, Dec. 2024, doi: 10.1007/s11235-024-01106-9.

[54] N. G. Rezk, E. E. D. Hemdan, A. F. Attia, A. El-Sayed, and M. A. El- Rashidy, "An efficient IoT based framework for detecting rice disease in smart farming system," *Multimed Tools Appl*, vol. 82, no. 29, pp. 45259–45292, Dec. 2023, doi: 10.1007/s11042-023- 15470-2.

[55] E. Shakeripour and M. H. Ronaghi, "Proposing an artificial intelligence maturity model to illustrate a road map for cleaner animal farming management," *Operations Management Research*, Dec. 2024, doi: 10.1007/s12063-024-00502-3.

[56] A. Dahane, R. Benameur, and B. Kechar, "An IoT Low-Cost Smart Farming for Enhancing Irrigation Efficiency of Smallholders Farmers," *Wirel Pers Commun*, vol. 127, no. 4, pp. 3173–3210, Dec. 2022, doi: 10.1007/s11277-022-09915-4.

[57] S. Babu, S. Madhusudanan, M. Sathiyanarayanan, M. Z. Mortka, J. Szymański, and R. Rahul, "Soil mapping for farming productivity: internet of things (IoT) based sustainable agriculture," *Microsystem Technologies*, 2024, doi: 10.1007/s00542-024-05608-z.

[58] S. Zyoud and A. H. Zyoud, "Internet of things supporting sustainable solid waste management: global insights, hotspots, and research trends," *International Journal of Environmental Science and Technology*, 2024, doi: 10.1007/s13762-024-06146-x.

[59] A. C. R, A. K. Pani, and P. Kumar, "Blockchain-enabled Smart Contracts and the Internet of Things: Advancing the research agenda through a narrative review," *Multimed Tools Appl*, 2024, doi: 10.1007/s11042-024-18931-4.

[60] M. Gao, A. Souri, M. Zaker, W. Zhai, X. Guo, and Q. Li, "A comprehensive analysis for crowd counting methodologies and algorithms in Internet of Things," *Cluster Comput*, vol. 27, no. 1, pp. 859–873, Dec. 2024, doi: 10.1007/s10586-023-03987-y.

[61] C. S. kumar and R. V. Anand, "A Review of Energy-Efficient Secured Routing Algorithm for IoT-Enabled Smart Agricultural Systems," *Journal of Biosystems Engineering*, vol. 48, no. 3, pp. 339–354, Dec. 2023, doi: 10.1007/s42853-023-00192-y.

[62] M. Rahaman, C. Y. Lin, P. Pappachan, B. B. Gupta, and C. H. Hsu, "Privacy- Centric AI and IoT Solutions for Smart Rural Farm Monitoring and Control," *Sensors*, vol. 24, no. 13, Dec. 2024, doi: 10.3390/s24134157.

[63] W. Li, W. Dong, X. Zhang, and J. Zhang, "A New Remote Sensing Service Mode for Agricultural Production and Management Based on Satellite–Air–Ground Spatiotemporal Monitoring," *Agriculture (Switzerland)*, vol. 13, no. 11, Dec. 2023, doi: 10.3390/agriculture13112063.

[64] R. Benameur, A. Dahane, B. Kechar, and A. E. H. Benyamina, "An Innovative Smart and Sustainable Low- Cost Irrigation System for Anomaly Detection Using Deep Learning," *Sensors*, vol. 24, no. 4, Dec. 2024, doi: 10.3390/s24041162.

[65] P. Indira, I. S. Arafat, R. Karthikeyan, S. Selvarajan, and P. K. Balachandran, "Fabrication and investigation of agricultural monitoring system with IoT & AI," *SN Appl Sci*, vol. 5, no. 12, Dec. 2023, doi: 10.1007/s42452-023- 05526-1.

[66] Y. W. Lin, Y. B. Lin, T. C. Y. Chang, and B. X. Lu, "An Edge Transfer Learning Approach for Calibrating Soil Electrical Conductivity Sensors," *Sensors (Basel)*, vol. 23, no. 21, Dec. 2023, doi: 10.3390/s23218710.

[67] P. Majumdar, S. Mitra, D. Bhattacharya, and B. Bhushan, "Enhancing sustainable 5G powered agriculture 4.0 : Summary of low power connectivity, internet of UAV things, AI solutions and research trends," *Multimed Tools Appl*, 2024, doi: 10.1007/s11042-024-19728-1.

[68] O. H. Abdelkader, H. Bouzebiba, D. Pena, and A. P. Aguiar, "Energy- Efficient IoT-Based Light Control System in Smart Indoor Agriculture," *Sensors*, vol. 23, no. 18, Dec. 2023, doi: 10.3390/s23187670.

[69] A. Siddique, J. Sun, K. J. Hou, M. I. Vai, S. H.

Pun, and M. A. Iqbal, "SpikoPoniC: A Low-Cost Spiking Neuromorphic Computer for Smart Aquaponics," *Agriculture (Switzerland)*, vol. 13, no. 11, Dec. 2023, doi:10.3390/agriculture13112057.

[70] D. Kalfas, S. Kalogiannidis, O. Papaevangelou, K. Melfou, and F. Chatzitheodoridis, "Integration of Technology in Agricultural Practices towards Agricultural Sustainability: A Case Study of Greece," *Sustainability (Switzerland)* , vol. 16, no. 7, Dec. 2024, doi: 10.3390/su16072664.

[71] M. Bhattacharyya *et al.*, "Designing optimal middle-mile network architecture for smart farming applications in rural areas," *Innov Syst Softw Eng*, 2024, doi: 10.1007/s11334- 024-00574-1.

[72] N. J. Lemphane, B. Kotze, and R. B. Kuriakose, "Developing a Digital Twin Model for Improved Pasture Management at Sheep Farm to Mitigate the Impact of Climate Change," 2024. [Online]. Available: www.ijacsa.thesai.org

[73] I. K. Gandhi, "AIoT-Driven Edge Computing for Rural Small-Scale Poultry Farming: Smart Environmental Monitoring and Anomaly Detection for Enhanced Productivity," *International Journal on Recent and Innovation Trends in Computing and Communication*, vol. 11, no. 8, pp. 44–52, Dec. 2023, doi: 10.17762/ijritcc.v11i8.7923.

[74] Z. A. Pampori and A. A. Sheikh, "Technology driven livestock farming for food security and sustainability," *Environ Conserv J*, vol. 24, no. 4, pp. 355–366, Dec. 2023, doi: 10.36953/ECJ.15072477.

[75] J. Zhang *et al.*, "Achieving the Rewards of Smart Agriculture," *Agronomy*, vol. 14, no. 3, Dec. 2024, doi: 10.3390/agronomy14030452.

[76] M. H. Widianto, Y. D. Setiawan, B. Ghilchrist, and G. Giovan, "Smart farming based on IoT to predict conditions using machine learning," *International Journal of Reconfigurable and Embedded Systems*, vol. 13, no. 3, pp. 595–603, Dec. 2024, doi: 10.11591/ijres.v13.i3.pp595 603.

[77] N. Ghavipanje, M. H. F. Nasri, and E. Vargas-Bello-Pérez, "Trends and future directions of artificial intelligence applications in Iranian livestock production systems," *Annals of Animal Science*, 2024, doi: 10.2478/aoas-2024-0098.

[78] G. Gebresenbet *et al.*, "A concept for application of integrated digital technologies to enhance future smart agricultural systems," *Smart Agricultural Technology*, vol. 5, Dec. 2023, doi: 10.1016/j.atech.2023.100255.

[79] A. Morchid, R. El Alami, A. A. Raezah, and Y. Sabbar, "Applications of internet of things (IoT) and sensors technology to increase food security and agricultural Sustainability: Benefits and challenges," *Ain Shams Engineering Journal*, vol. 15, no. 3, Dec. 2024, doi: 10.1016/j.asej.2023.102509.

[80] P. Rajak, A. Ganguly, S. Adhikary, and S. Bhattacharya, "Internet of Things and smart sensors in agriculture: Scopes and challenges," *J Agric Food Res*, vol. 14, Dec. 2023, doi: 10.1016/j.jafr.2023.100776.

[81] B. Fasciolo, A. Awouda, G. Bruno, and E. Lombardi, "A smart aeroponic system for sustainable indoor farming," in *Procedia CIRP*, Elsevier B.V., 2023, pp. 636–641. doi: 10.1016/j.procir.2023.02.107.

[82] M. G. S. Wicaksono, E. Suryani, and R. Hendrawan, "Increasing productivity of rice plants based on IoT (Internet of Things) to realize Smart Agriculture using System

Thinking approach," in *Procedia Computer Science*, Elsevier B.V., 2021, pp. 607–616. doi: 10.1016/j.procs.2021.12.179.

[83] H. Liang, W. Gao, J. H. Nguyen, M. F. Orpilla, and W. Yu, "Internet of Things Data Collection Using Unmanned Aerial Vehicles in Infrastructure Free Environments," *IEEE Access*, vol. 8,pp. 3932–3944, 2020, doi: 10.1109/ACCESS.2019.2962323.

[84] V. P. Kour and S. Arora, "Recent Developments of the Internet of Things in Agriculture: A Survey," 2020, *Institute of of Electrical and Electronics Engineers Inc.* doi: 10.1109/ACCESS.2020.3009298.

[85] R. Y. Aburasain, "Enhanced Black Widow Optimization With Hybrid Deep Learning Enabled Intrusion Detection in Internet of Things-Based Smart Farming," *IEEE Access*, vol. 12, pp. 16621–16631, 2024, doi: 10.1109/ACCESS.2024.3359043.

[86] M. N. Mowla, N. Mowla, A. F. M. S. Shah, K. M. Rabie, and T. Shongwe, "Internet of Things and Wireless Sensor Networks for Smart Agriculture Applications: A Survey," *IEEE Access*, vol. 11, pp. 145813–145852, 2023, doi: 10.1109/ACCESS.2023.3346299.

[87] M. F. Alumfareh, M. Humayun, Z. Ahmad, and A. Khan, "An Intelligent LoRaWAN-based IoT Device for Monitoring and Control Solutions in Smart Farming through anomaly detection integrated with unsupervised machine learning," *IEEE Access*, 2024, doi: 10.1109/ACCESS.2024.3450587.

[88] K. Huang *et al.*, "Photovoltaic agricultural internet of things towards realizing the next generation of smart farming," *IEEE Access*, vol. 8, pp. 76300–76312, 2020, doi: 10.1109/ACCESS.2020.2988663.

[89] M. S. Farooq, S. Riaz, M. A. Helou, F. S. Khan, A. Abid, and A. Alvi, "Internet of Things in Greenhouse Agriculture: A Survey on Enabling Technologies, Applications, and Protocols," *IEEE Access*, vol. 10, pp. 53374–53397, 2022, doi: 10.1109/ACCESS.2022.3166634.

[90] R. Alfred, J. H. Obit, C. P. Y. Chin, H. Haviluddin, and Y. Lim, "Towards paddy rice smart farming: A review on big data, machine learning, and rice production tasks," 2021, *Institute of Electrical and Electronics Engineers Inc.* doi: 10.1109/ACCESS.2021.3069449.

[91] A. Pagano, D. Croce, I. Tinnirello, and Vitale, "A Survey on LoRa for Smart Agriculture: Current Trends and Future Perspectives," *IEEE Internet Things J*, vol. 10, no. 4, pp. 3664–3679, Dec. 2023, doi: 10.1109/JIOT.2022.3230505.

[92] A. Massaoudi, A. Berguiga, A. Harchay, M. Ben Ayed, and H. Belmabrouk, "Spectral and Energy Efficiency Trade-Off in UAV-Based Olive Irrigation Systems," *Applied Sciences (Switzerland)*, vol. 13, no. 19, Dec. 2023, doi: 10.3390/app131910739.