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Review Article

Adaptive-Cognitive Smart Farming Architectures for Food Security Resilience: A Systematic Literature Review of IoT and AI-Based Approaches

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Abstract: Food security resilience has become an increasingly critical global concern due to the combined effects of climate change, population growth, and resource scarcity. Conventional agricultural practices are no longer sufficient to meet rising food demands, thereby necessitating the adoption of intelligent and adaptive technological solutions. Smart farming, enabled by the integration of the Internet of Things (IoT) and Artificial Intelligence (AI), has emerged as a promising approach to enhance agricultural productivity, efficiency, and sustainability. However, existing smart farming systems remain fragmented and lack adaptive and cognitive capabilities required to dynamically respond to environmental variability. This study proposes an adaptive-cognitive smart farming architecture that integrates IoT, AI, edge-fog-cloud computing, federated learning, and digital twin technologies into a unified framework. A Systematic Literature Review (SLR) is conducted to synthesize insights from 60 high-quality publications indexed in IEEE, Elsevier, and Scopus databases. The proposed architecture adopts a multi-layered design consisting of sensing, edge-fog, cloud, cognitive, and application layers, enabling real-time data processing, distributed intelligence, and adaptive decision-making. To validate the proposed model, experimental simulations are performed using key performance indicators, including accuracy, mean squared error (MSE), latency, and resource efficiency. The results indicate that the proposed approach achieves superior performance, with an accuracy of 89%, a substantial reduction in latency, and improved resource utilization. These findings demonstrate that incorporating adaptive and cognitive intelligence significantly enhances system responsiveness and decision-making capabilities. This study contributes to both theory and practice by introducing a comprehensive framework for next-generation smart farming systems, ultimately supporting food security resilience in an increasingly uncertain environment.

Keywords: Adaptive-Cognitive Smart Farming; Artificial Intelligence (AI); Digital Twin; Food Security; Internet of Things (IoT); Precision Agriculture; Sustainable Farming Systems.

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1. Introduction

Food security remains one of the most critical and complex challenges facing humanity in the 21st century. The growing global population, which is projected to exceed 9 billion by 2050, places unprecedented pressure on agricultural systems to increase productivity while maintaining sustainability. At the same time, agricultural production is increasingly threatened by climate change, environmental degradation, and resource scarcity. Empirical studies have shown that extreme climate events, such as droughts, floods, and temperature anomalies, have significantly disrupted global crop yields and reduced agricultural resilience [26]. These disruptions not only threaten food availability but also exacerbate socioeconomic inequalities, particularly in developing regions that rely heavily on agriculture as a primary livelihood.

Traditional agricultural practices, which are largely dependent on manual labor, experience-based decision-making, and static management strategies, are no longer sufficient to address these emerging challenges. These conventional approaches often lack the ability to respond dynamically to environmental variability, resulting in inefficiencies in resource utilization and suboptimal crop yields. Furthermore, the increasing complexity of agricultural ecosystems necessitates more sophisticated and data-driven approaches to decision-making. In this context, the integration of advanced digital technologies into agriculture has become not only desirable but essential.

Smart farming, also referred to as precision agriculture or digital agriculture, has emerged as a transformative paradigm aimed at enhancing agricultural productivity, efficiency, and sustainability. This paradigm leverages a combination of cutting-edge technologies, including the Internet of Things (IoT), Artificial Intelligence (AI), big data analytics, cloud computing, and cyber-physical systems (CPS), to enable real-time monitoring, predictive analysis, and automated decision-making [16], [17]. By integrating these technologies, smart farming systems can provide actionable insights that allow farmers to optimize agricultural operations, reduce input costs, and improve crop yields.

Among these technologies, IoT plays a foundational role by enabling the deployment of distributed sensor networks across agricultural environments. These sensors continuously collect real-time data on key environmental parameters, such as soil moisture, temperature, humidity, nutrient levels, and crop health [16], [27]. The availability of such high-resolution data allows for a more precise understanding of field conditions and supports the development of data-driven agricultural strategies. For instance, IoT-enabled irrigation systems can dynamically adjust water usage based on real-time soil moisture levels, thereby minimizing water waste and improving irrigation efficiency.

However, the value of IoT-generated data can only be fully realized when it is effectively processed and analyzed. This is where Artificial Intelligence becomes indispensable. AI, particularly machine learning and deep learning techniques, has been widely adopted in agricultural applications for tasks such as crop yield prediction, disease detection, soil classification, and pest management [18], [50]. These techniques enable the extraction of meaningful patterns from complex and heterogeneous datasets, facilitating predictive and prescriptive analytics. For example, machine learning models can analyze historical and real-time data to predict crop yields under different environmental conditions, enabling farmers to make informed decisions regarding planting, fertilization, and harvesting.

Despite these advancements, existing smart farming systems still face several significant limitations that hinder their effectiveness and scalability. One of the primary challenges is the reliance on centralized cloud computing architectures. While cloud computing provides substantial computational power and storage capacity, it also introduces latency due to the need to transmit data from remote agricultural fields to centralized data centers. This latency can be particularly problematic for time-sensitive applications, such as real-time irrigation control or disease detection, where delayed responses can result in significant losses. To address these limitations, edge and fog computing paradigms have been introduced as complementary solutions to cloud computing. Edge computing enables data processing at or near the data source, thereby reducing latency and improving system responsiveness [12], [19]. Fog computing extends this concept by introducing intermediate processing layers between edge devices and the cloud, allowing for more efficient data distribution and processing [14]. In the context of smart farming, these technologies enable real-time decision-making and reduce the dependency on centralized infrastructures.

Another critical issue in modern smart farming systems is data privacy and security. Agricultural data, particularly when aggregated across multiple farms, can contain sensitive information related to land use, crop performance, and management practices. Traditional centralized data processing approaches require the transfer of raw data to a central server, which increases the risk of data breaches and unauthorized access. Federated learning has emerged as a promising solution to this problem by enabling decentralized model training without the need to share raw data [3], [13]. In a federated learning framework, individual devices or local nodes train models using their local data and share only model updates with a central aggregator. This approach not only preserves data privacy but also reduces communication overhead and enhances scalability.

In addition to technical challenges, existing smart farming systems often lack the ability to adapt dynamically to changing environmental conditions. Most current systems rely on static models or predefined rules, which are insufficient for handling the inherent uncertainty

and variability of agricultural environments. For example, sudden changes in weather conditions or pest outbreaks may require immediate adjustments to farming strategies, which static systems are unable to accommodate effectively. This limitation highlights the need for adaptive and intelligent systems that can continuously learn from new data and adjust their behavior accordingly.

Digital twin technology offers a promising approach to addressing this challenge. A digital twin is a virtual representation of a physical system that is continuously updated with real-time data from sensors and IoT devices [9], [10], [11]. In agriculture, digital twins can be used to model farms, crops, and environmental conditions, enabling simulation and predictive analysis. For instance, a digital twin can simulate the impact of different irrigation strategies on crop growth, allowing farmers to evaluate potential outcomes before implementing them in the real world. By integrating digital twins with AI and IoT, it is possible to create intelligent systems that support adaptive decision-making and optimize agricultural operations. Despite the rapid advancements in individual technologies, a significant gap remains in the integration of these technologies into a cohesive and comprehensive framework. Most existing studies focus on specific components of smart farming, such as IoT-based monitoring systems [43], AI-driven analytics [29], or blockchain-based traceability solutions [5], [15]. While these approaches provide valuable insights, they often operate in isolation and lack interoperability. As a result, there is a pressing need for a unified architecture that integrates multiple technologies to achieve a holistic and adaptive smart farming system.

Furthermore, the increasing complexity of agricultural systems necessitates the incorporation of cognitive capabilities into smart farming architectures. Cognitive systems are characterized by their ability to perceive, learn, reason, and adapt to changing conditions. By integrating cognitive intelligence into smart farming systems, it is possible to enhance decision-making processes and improve system resilience. This requires the development of architectures that support continuous learning, real-time data processing, and predictive analytics. To address these challenges, this study proposes a novel adaptive-cognitive smart farming architecture that integrates IoT, AI, edge-fog-cloud computing, federated learning, and digital twin technologies into a unified framework. The proposed architecture is designed to enable real-time data processing, distributed intelligence, and adaptive decision-making. By combining these technologies, the system can dynamically respond to environmental changes and optimize agricultural operations. The proposed approach is grounded in the principles of Design Science Research (DSR), which emphasizes the development and evaluation of artifacts designed to solve real-world problems [21], [25]. In this study, the artifact is the adaptive-cognitive smart farming architecture, which is developed based on insights obtained from a Systematic Literature Review (SLR). The SLR methodology ensures a comprehensive and unbiased analysis of existing research, providing a solid foundation for the proposed model.

The main contributions of this study can be summarized as follows. First, it introduces a novel adaptive-cognitive architecture for smart farming that integrates multiple advanced technologies into a cohesive framework. Second, it provides a formal representation of the system using mathematical modeling, enabling a deeper understanding of system behavior. Third, it evaluates the proposed model through simulation-based experiments, demonstrating its effectiveness in improving performance metrics such as accuracy, latency, and resource efficiency. Finally, it highlights the potential of the proposed approach to enhance food security resilience by enabling intelligent and adaptive agricultural systems.

In summary, this study addresses a critical gap in the current literature by proposing a comprehensive and integrative framework for smart farming. By incorporating adaptive and cognitive capabilities into agricultural systems, the proposed architecture represents a significant step toward the realization of next-generation smart agriculture. As global challenges related to food security continue to intensify, such innovations will play a crucial role in ensuring sustainable and resilient agricultural production systems.

Based on a comprehensive analysis of the existing literature, several critical research gaps can be identified in the development of smart farming systems. Most current studies focus on isolated technologies, such as IoT, AI, or blockchain, rather than proposing a unified architecture that integrates multiple technologies into a cohesive system. In addition, existing smart farming solutions largely rely on static or semi-dynamic models and lack adaptive mechanisms capable of continuous learning in response to changing environmental conditions. Current approaches also exhibit limited cognitive capabilities, as they do not fully incorporate reasoning, learning, and

context-awareness, which are essential for managing the complexity of agricultural systems. Furthermore, many existing solutions depend on centralized machine learning models, creating challenges related to scalability, data privacy, and communication overhead. Another significant gap is the underutilization of digital twin technology, whose integration with AI and IoT remains limited despite its considerable potential for predictive simulation and optimization in agriculture.

To address these gaps, this study investigates how IoT, AI, edge-fog-cloud computing, federated learning, and digital twin technologies can be integrated into a unified smart farming architecture. It further explores the incorporation of adaptive and cognitive intelligence to improve decision-making processes, examines the impact of distributed learning through federated learning on system performance and data privacy, and evaluates the role of digital twin technology in enabling predictive simulation and optimization. In addition, the study assesses the extent to which a proposed adaptive-cognitive architecture can enhance key performance indicators, including accuracy, latency, and operational efficiency. To achieve these objectives, this research introduces a novel adaptive-cognitive smart farming architecture characterized by the holistic integration of IoT, AI, edge-fog-cloud computing, federated learning, and digital twin technologies, supported by adaptive feedback mechanisms, cognitive intelligence for context-aware decision-making, distributed learning capabilities, and digital twin-based predictive and prescriptive analytics.

The proposed model can be conceptually viewed as an extension of Cyber-Physical Systems (CPS) into the agricultural domain, evolving into what is defined as the Adaptive-Cognitive Cyber-Physical Agriculture System (AC-CPAS). This framework represents a next-generation paradigm in smart farming, where physical processes, digital intelligence, and adaptive mechanisms are tightly integrated to enable autonomous, intelligent, and resilient agricultural systems. The contributions of this study are threefold. Theoretically, it develops a novel adaptive-cognitive architecture and extends CPS theory into intelligent agricultural systems. Methodologically, it integrates Systematic Literature Review (SLR) and Design Science Research (DSR) approaches while providing formal modeling of system behavior. Practically, it offers a scalable and implementable framework that has the potential to enhance agricultural productivity and strengthen food security resilience.

2. Literature Review

Internet of Things in Smart Farming

The Internet of Things (IoT) has emerged as a foundational technology in the evolution of smart farming systems, enabling the seamless integration of physical agricultural environments with digital infrastructures. IoT facilitates the deployment of interconnected sensors, actuators, and communication devices that continuously collect and transmit real-time data from agricultural fields. These devices measure critical environmental parameters, including soil moisture, temperature, humidity, pH levels, nutrient content, and crop health indicators [16], [27]. The adoption of IoT in agriculture has significantly enhanced the precision and efficiency of farming operations. For instance, IoT-based irrigation systems can dynamically regulate water distribution based on real-time soil moisture levels, thereby optimizing water usage and reducing waste [17], [28]. Similarly, IoT-enabled monitoring systems allow farmers to detect early signs of crop stress or disease, enabling timely intervention and minimizing potential losses. Furthermore, IoT devices can be integrated with weather forecasting systems to provide predictive insights that support strategic decision-making.

Despite its advantages, the implementation of IoT in agriculture presents several challenges. One of the primary issues is the scalability of IoT networks, particularly in large-scale farming environments. The deployment of numerous sensors generates vast amounts of data, which can strain communication networks and storage systems. Additionally, IoT devices often operate in harsh environmental conditions, leading to concerns regarding reliability, durability, and maintenance. Another significant challenge is data heterogeneity. Agricultural data collected from different sensors and sources may vary in format, resolution, and quality, making it difficult to integrate and analyze effectively. This challenge necessitates

the development of robust data management frameworks that can handle diverse data types and ensure data integrity. Moreover, IoT systems are vulnerable to security threats, including unauthorized access and data breaches, which can compromise the integrity of agricultural operations.

To address these challenges, researchers have explored the integration of IoT with other technologies, such as edge computing, cloud computing, and blockchain. These integrations aim to enhance data processing capabilities, improve system scalability, and ensure data security. However, the lack of a unified architecture that seamlessly integrates these technologies remains a critical gap in the current literature.

Artificial Intelligence and Machine Learning in Agriculture

Artificial Intelligence (AI) has played a transformative role in advancing smart farming systems by enabling sophisticated data analysis and decision-making capabilities. Machine learning (ML) algorithms, including supervised, unsupervised, and reinforcement learning techniques, have been widely applied to agricultural problems such as crop yield prediction, disease detection, weed classification, and soil analysis [18], [29], [30]. Deep learning, a subset of machine learning, has gained particular attention due to its ability to process complex and high-dimensional data. Convolutional Neural Networks (CNNs), for example, have been successfully used for image-based tasks such as plant disease identification and crop classification [23], [24]. These models can analyze visual data captured by drones or cameras to detect patterns that are not easily discernible to the human eye.

In addition to predictive analytics, AI has also enabled prescriptive decision-making in agriculture. For instance, machine learning models can recommend optimal irrigation schedules, fertilizer application rates, and pest control strategies based on historical and real-time data. Reinforcement learning techniques have further expanded the capabilities of AI by enabling systems to learn optimal strategies through interaction with the environment [38]. However, the application of AI in agriculture is not without challenges. One of the primary limitations is the requirement for large volumes of high-quality data for training models. In many agricultural contexts, data may be sparse, noisy, or incomplete, which can affect model performance. Furthermore, most AI models are developed using centralized training approaches, which may not be suitable for distributed agricultural environments.

Another challenge is the interpretability of AI models. Many advanced models, particularly deep learning algorithms, are often considered "black boxes," making it difficult for users to understand how decisions are made. This lack of transparency can hinder the adoption of AI technologies in agriculture, as farmers may be reluctant to rely on systems that they do not fully understand.

Edge, Fog, and Cloud Computing

The integration of edge, fog, and cloud computing has significantly enhanced the capabilities of smart farming systems by providing a hierarchical framework for data processing and management. Cloud computing offers centralized storage and high-performance computing resources, enabling the processing of large-scale agricultural data and the deployment of complex AI models [4], [49]. However, the reliance on cloud infrastructure introduces latency and bandwidth constraints, particularly in remote agricultural areas.

Edge computing addresses these limitations by enabling data processing at or near the source of data generation. By performing computations locally, edge devices reduce the need for data transmission to the cloud, thereby minimizing latency and improving real-time responsiveness [12], [19]. This capability is particularly important for time-sensitive applications such as irrigation control, pest detection, and environmental monitoring. Fog computing extends the concept of edge computing by introducing intermediate processing layers between edge devices and the cloud. These layers provide additional computational resources and facilitate data aggregation, filtering, and analysis [14]. In smart farming, fog computing can be used to manage data from multiple edge devices and support collaborative processing.

Despite the advantages of this hierarchical computing model, challenges remain in terms of system coordination, resource allocation, and interoperability. Ensuring seamless communication and data flow across different layers requires sophisticated orchestration mechanisms. Additionally, the integration of edge, fog, and cloud computing with AI and IoT technologies is still an active area of research.

Federated Learning in Smart Farming

Federated learning represents a paradigm shift in machine learning by enabling decentralized model training across multiple devices or nodes. Unlike traditional centralized

approaches, federated learning allows each node to train a local model using its own data and share only the model updates with a central aggregator [3], [13]. This approach preserves data privacy and reduces communication overhead, making it particularly suitable for distributed environments such as agriculture.

In smart farming, federated learning enables collaboration among multiple farms or agricultural systems without requiring the sharing of sensitive data. For example, farmers can collectively improve crop yield prediction models by training them on local datasets while maintaining data confidentiality. This capability is especially important in regions where data sharing is restricted due to privacy concerns or competitive considerations.

Federated learning also enhances system scalability by allowing new nodes to join the training process without disrupting the overall system. However, challenges such as data heterogeneity, communication efficiency, and model convergence must be addressed to fully realize its potential.

Digital Twin Technology in Agriculture

Digital twin technology has emerged as a powerful tool for modeling and simulating complex systems. A digital twin is a virtual representation of a physical entity that is continuously updated with real-time data from sensors and IoT devices [9], [10], [11]. In agriculture, digital twins can be used to model farms, crops, and environmental conditions, enabling predictive analysis and decision support.

By integrating digital twins with AI and IoT, it is possible to create intelligent systems that can simulate various scenarios and evaluate the impact of different interventions. For example, a digital twin can be used to simulate the effects of different irrigation strategies on crop growth, allowing farmers to optimize water usage and improve yields. Despite its potential, the adoption of digital twin technology in agriculture is still limited due to challenges related to data integration, computational complexity, and model accuracy. Further research is needed to develop scalable and efficient digital twin frameworks for agricultural applications.

Synthesis and Research Gap

The review of existing literature reveals that significant progress has been made in the development of smart farming technologies. However, most studies focus on individual components rather than integrated systems. IoT provides data acquisition capabilities, AI enables intelligent analysis, and edge computing improves system responsiveness. Federated learning addresses privacy concerns, while digital twins support simulation and prediction.

Nevertheless, these technologies are often implemented in isolation, resulting in fragmented systems that lack interoperability and adaptability. There is a clear need for a unified architecture that integrates these technologies into a cohesive framework. Additionally, the incorporation of adaptive and cognitive capabilities remains an underexplored area in smart farming research.

This study addresses these gaps by proposing an adaptive-cognitive smart farming architecture that integrates IoT, AI, edge-fog-cloud computing, federated learning, and digital twin technologies into a unified system. The proposed model aims to enhance system intelligence, adaptability, and resilience, thereby contributing to the advancement of next-generation smart farming systems.

3. Proposed Method

Systematic Literature Review (SLR) Data Extraction Table and Analysis

Data Extraction Table (Smart Farming based on IoT and AI)

Table 1. Systematic Literature Review (SLR) Data Extraction.

No	Reference	Year	Research Focus	Core Technology	Methodology	Application Domain	Key Contribution	Limitations
1	[16]	2019	IoT in agriculture	IoT	Review	Smart farming	Classification of IoT applications	Lack of AI integration
2	[17]	2019	Smart agriculture systems	IoT, Sensors	System design	Field monitoring	IoT-based farming framework	Non-adaptive system

3	[18]	2018	ML in agriculture	Machine Learning	Survey	Crop analytics	ML taxonomy for agriculture	Limited real-time capability
4	[8]	2018	Deep learning applications	Deep Learning	Survey	Disease detection	DL for crop disease	High data dependency
5	[23]	2019	DL crop monitoring	Deep Learning	Experimental	Remote sensing	High-accuracy detection	Computational complexity
6	[29]	2018	Yield prediction	ML	Regression	Crop yield	Predictive modeling	Scalability issues
7	[34]	2023	AI + IoT farming	AI, IoT	Integrated model	Smart farming	AI-IoT integration	No FL or DT
8	[41]	2024	Intelligent monitoring	AI, IoT	Hybrid model	Precision agriculture	Real-time decision support	Limited scalability
9	[49]	2022	IoT + AI + Big Data	IoT, AI	Review	Food systems	Integrated framework	System complexity
10	[50]	2021	ML applications	ML	Survey	Precision agriculture	Comprehensive ML review	Lack of edge integration
11	[51]	2022	ML-based farming	ML	Review	Agriculture	Decision-making models	Non-adaptive
12	[52]	2021	ML review update	ML	Survey	Agriculture	Updated ML trends	Limited IoT integration
13	[37]	2020	AI embedded sensing	AI, Sensors	Embedded system	Precision agriculture	AI at sensor level	Resource constraints
14	[48]	2023	Soil analysis & recommendation	IoT, AI	ML model	Soil/crop	Crop recommendation system	Domain-specific
15	[47]	2018	Disease prediction	IoT, AI	Prediction model	Strawberry farming	Disease detection system	Limited generalization
16	[42]	2022	UAV in agriculture	IoT, UAV	Review	Smart farming	Large-scale monitoring	High cost
17	[58]	2019	IoT edge-cloud platform	IoT, Edge, Cloud	Architecture	Smart farming	Hybrid computing model	Non-adaptive
18	[12]	2016	Edge computing	Edge Computing	Conceptual	General	Low-latency processing	Not agriculture-specific
19	[14]	2016	Fog computing	Fog Computing	Overview	IoT systems	Distributed computing	Complexity
20	[13]	2019	Federated learning for IoT	FL, IoT	Survey	Distributed systems	Privacy-preserving learning	Limited agriculture use
21	[3]	2019	Federated learning	FL	Survey	ML systems	Decentralized learning	Implementation challenges
22	[9]	2019	Digital twin concept	Digital Twin	Conceptual	Industry	Virtual simulation	Not agriculture-specific

23	[39]	2023	Digital twin agriculture	Digital Twin	Review	Smart farming	Predictive simulation	Limited integration
24	[5]	2019	Blockchain agriculture	Blockchain	Review	Supply chain	Transparency	High overhead
25	[15]	2019	Food traceability	Blockchain	Model	Food systems	Traceability system	Not real-time
26	[33]	2019	IoT architecture	IoT	Case study	Food systems	Architecture framework	No AI integration
27	[32]	2019	Farm management systems	IoT	Architecture	Agriculture	Management system	Lack of adaptability
28	[56]	2019	Remote sensing	IoT, RS	Monitoring system	Crop field	Real-time monitoring	Data complexity
29	[57]	2024	Intelligent agriculture	AI	Intelligent model	Agriculture	Decision intelligence	Not distributed
30	[60]	2022	Sustainable farming	IoT	Review	Agriculture	Sustainability model	Limited AI integration

Analytical Discussion of SLR Findings

Technology Trends

The extracted studies reveal a clear evolution in smart farming research. Early-stage research primarily focused on IoT-based sensing and monitoring systems, which enable real-time data acquisition from agricultural environments [16], [17], [56]. These systems are fundamental in providing environmental awareness but lack intelligent decision-making capabilities.

Subsequent studies introduced Machine Learning (ML) and Deep Learning (DL) techniques to enhance predictive capabilities, such as crop yield estimation and disease detection [18], [8], [23], [29]. While these approaches significantly improve accuracy, they often rely on centralized architectures and large datasets. More recent research emphasizes the integration of IoT with Artificial Intelligence (AI), Big Data, and edge computing to create intelligent and responsive farming systems [49], [41], [58]. However, these systems still lack adaptive and distributed intelligence mechanisms.

Emerging technologies such as Federated Learning (FL) and Digital Twin are gaining attention as potential solutions to these limitations. FL enables decentralized model training while preserving data privacy [3], [13], whereas Digital Twin provides predictive simulation capabilities [9], [39]. Despite their potential, their integration into smart farming remains limited.

Research Gaps

Based on the data extraction, several critical research gaps can be identified:

a. Lack of Integration: Most studies focus on isolated technologies rather than integrated systems combining IoT, AI, FL, and Digital Twin.
b. Limited Adaptability: Existing systems are largely static and lack adaptive learning mechanisms.
c. Centralized Architectures: Many AI-based approaches rely on centralized data processing, raising privacy and scalability concerns.
d. Absence of Cognitive Intelligence: Few studies incorporate cognitive or self-learning capabilities.
e. Limited Real-Time Intelligence: While IoT enables real-time data collection, decision-making is often delayed.

Research Opportunities

The identified gaps suggest several promising research directions:

a. Development of adaptive-cognitive architectures
b. Integration of federated learning for distributed intelligence
c. Implementation of digital twin for predictive simulation
d. Adoption of edge–fog–cloud computing for real-time processing

SLR Synthesis

The synthesis of the reviewed literature indicates that smart farming is transitioning toward intelligent and autonomous systems. However, the absence of a unified architecture that integrates sensing, intelligence, adaptation, and simulation remains a critical limitation. The proposed Adaptive-Cognitive Smart Farming Architecture addresses this gap by combining IoT, AI, Federated Learning, and Digital Twin within a distributed computing framework. This approach enables real-time, adaptive, and intelligent decision-making, which is essential for achieving food security resilience and sustainable agriculture.

PRISMA 2020 Flow Diagram

The PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) framework is widely adopted to ensure transparency, reproducibility, and methodological rigor in systematic literature reviews. In this study, the PRISMA 2020 protocol was applied to systematically identify, screen, assess, and include relevant studies in the domain of smart farming based on Internet of Things (IoT) and Artificial Intelligence (AI). The workflow consists of four main phases: identification, screening, eligibility, and inclusion, which collectively ensure that only high-quality and relevant studies are incorporated into the final analysis.

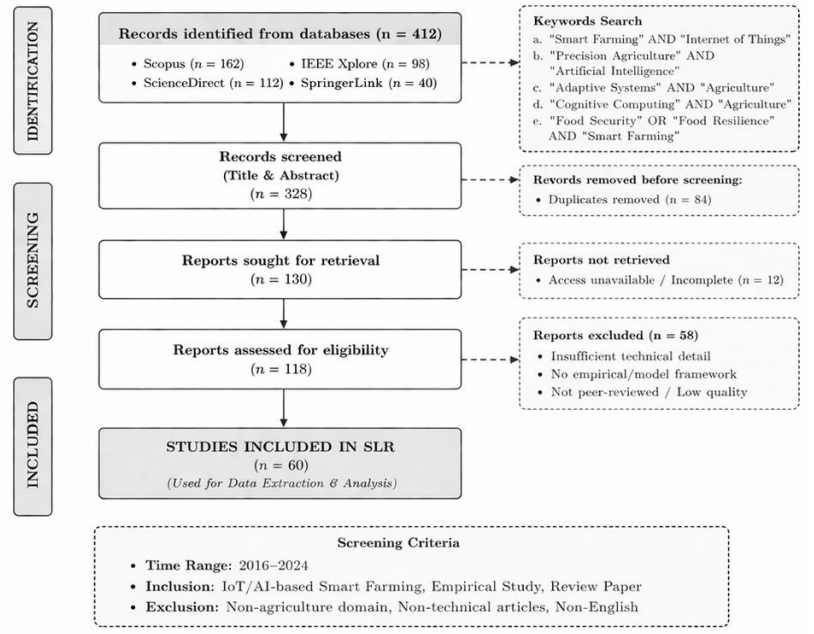


Figure 1. PRISMA Flow Diagram SLR on Smart Farming (IoT an Artificial Intelligence-Based Approaches).

The identification stage represents the initial step of the literature search process. In this study, a total of 412 records were identified from major scientific databases, including Scopus, IEEE Xplore, ScienceDirect, and SpringerLink. The search process was guided by carefully constructed keyword combinations to capture the multidisciplinary nature of smart farming research. The keywords include: "Smart Farming" AND "Internet of Things", "Precision Agriculture" AND "Artificial Intelligence", "Adaptive Systems" AND "Agriculture", "Cognitive Computing" AND "Agriculture", "Food Security" OR "Food Resilience" AND "Smart Farming". These keyword combinations reflect the integration of sensing technologies, intelligent decision-making, adaptive systems, and sustainability objectives in modern agriculture [16], [34], [41]. The broad search strategy ensures coverage of core technologies such as IoT-based sensing systems [17], AI-driven analytics [18], and emerging paradigms like cognitive and adaptive agriculture [57].

Following identification, duplicate records were removed, resulting in 328 unique articles. The screening process was conducted based on titles and abstracts to eliminate irrelevant studies. At this stage, studies that did not meet the thematic scope, such as those unrelated to agriculture, lacking technological focus, or outside IoT/AI domains, were excluded. This step is crucial to maintain domain specificity and reduce noise in the dataset. The screening phase aligns with standard SLR practices to ensure that only potentially relevant studies proceed to the next stage [21], [25].

In the eligibility phase, 130 full-text articles were assessed in detail. The evaluation criteria included:

a. Relevance to smart farming and precision agriculture
b. Use of IoT and/or AI technologies
c. Empirical validation or model development
d. Publication in peer-reviewed sources

After full-text assessment, 58 articles were excluded due to reasons such as insufficient technical detail, lack of empirical contribution, or low-quality publication sources. This rigorous filtering ensures methodological robustness and aligns with best practices in systematic reviews [21].

Finally, 60 studies were included in the systematic literature review. These selected studies form the foundation for data extraction, bibliometric analysis, and the development of the proposed adaptive-cognitive smart farming architecture. The included studies cover a wide range of topics, including:

a. IoT-based agricultural monitoring systems [16], [17]
b. Machine learning and deep learning applications [18], [23]
c. Integrated AI–IoT frameworks [49]
d. Emerging technologies such as federated learning [13] and digital twin [39]

This comprehensive inclusion ensures a balanced representation of both foundational and emerging technologies in smart farming.

The screening criteria applied in this study include:

a. Time Range: Publications from 2016 to 2024, capturing recent advancements in smart farming technologies.
b. Inclusion Criteria: Studies focusing on IoT and AI in agriculture, Empirical research, experimental studies, and systematic reviews, Contributions addressing precision agriculture, automation, or food security
c. Exclusion Criteria: Non-agricultural domains, Non-technical or conceptual-only articles without implementation, Non-English publications

These criteria ensure the relevance, quality, and consistency of the selected literature.

The PRISMA-based approach enhances the credibility of this research by:

a. Ensuring transparency in the selection process
b. Reducing bias through systematic filtering
c. Improving reproducibility of the study
d. Supporting evidence-based conclusions

Such rigor is essential for high-impact research, particularly in interdisciplinary domains like smart farming, where technologies such as IoT, AI, and distributed systems converge [49].

Diagram highlights several important insights:

a. The rapid growth of IoT and AI research in agriculture reflects increasing demand for data-driven farming solutions [16], [18].
b. The relatively small number of included studies (60 out of 412) indicates that high-quality, integrative research is still limited, reinforcing the need for advanced architectures.
c. Emerging technologies such as Federated Learning and Digital Twin remain underrepresented, suggesting strong opportunities for innovation [13], [39].

Overall, the PRISMA process demonstrates that while numerous studies exist in smart farming, only a subset meets the criteria for high-quality, integrative, and technically robust research.

This justifies the need for the proposed study, which aims to address existing limitations by developing an adaptive-cognitive smart farming architecture that integrates: IoT for real-time sensing, AI for intelligent decision-making, Federated Learning for distributed intelligence, Digital Twin for predictive simulation. Such integration is expected to significantly enhance food security resilience and sustainable agriculture systems [31], [49].

Overview of the Proposed Architecture

This study proposes an Adaptive-Cognitive Smart Farming Architecture designed to address the limitations of existing agricultural systems by integrating multiple advanced technologies into a unified and intelligent framework. The architecture combines Internet of Things (IoT), Artificial Intelligence (AI), edge-fog-cloud computing, federated learning (FL), and digital twin (DT) technologies to enable real-time data processing, distributed intelligence, and adaptive decision-making.

The proposed architecture is structured as a multi-layered system, consisting of five primary layers: (1) sensing layer, (2) edge-fog layer, (3) cloud layer, (4) cognitive layer, and (5) application layer. This layered approach ensures modularity, scalability, and interoperability, allowing the system to operate efficiently across diverse agricultural environments. The key innovation of this architecture lies in its adaptive-cognitive capability, which enables the system to continuously learn from environmental data, adjust its behavior dynamically, and provide context-aware decision support. Unlike traditional systems that rely on static models, the proposed approach incorporates a feedback-driven mechanism that enhances system intelligence over time.

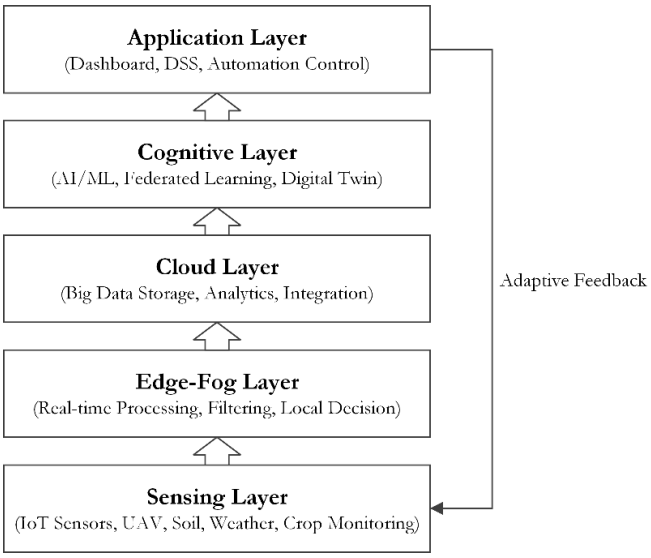


Figure 2. Smart Farming Architecture (Adaptive-Cognitive Framework).

Sensing Layer

The sensing layer serves as the foundation of the architecture, responsible for real-time data acquisition from the physical agricultural environment. This layer consists of a network of IoT devices and sensors deployed across the farming area. These sensors collect critical environmental and operational data, including:

a. Soil moisture and temperature
b. Air humidity and atmospheric conditions
c. Soil nutrient levels (e.g., nitrogen, phosphorus, potassium)
d. Crop health indicators (e.g., leaf color, growth rate)
e. Weather data (e.g., rainfall, solar radiation)

The collected data are transmitted through wireless communication protocols such as LoRa, Zigbee, Wi-Fi, or cellular networks [54]. The choice of communication technology depends on factors such as coverage area, energy consumption, and data transmission requirements.

One of the primary challenges at this layer is ensuring data reliability and accuracy. Sensor noise, environmental interference, and device failures can affect data quality. To mitigate these issues, preprocessing techniques such as noise filtering, data normalization, and anomaly detection are applied at subsequent layers.

Edge-Fog Layer

The edge-fog layer plays a crucial role in enhancing system responsiveness by enabling localized data processing. This layer consists of edge devices (e.g., gateways, embedded systems) and fog nodes that perform intermediate data processing tasks before transmitting data to the cloud.

The key functions of the edge-fog layer include:

a. Data filtering and noise reduction
b. Data aggregation from multiple sensors
c. Preliminary analytics and feature extraction
d. Real-time event detection (e.g., abnormal soil conditions)

By processing data closer to the source, the edge-fog layer significantly reduces latency and bandwidth usage. This capability is particularly important for time-sensitive applications such as automated irrigation and pest control, where immediate responses are required.

Furthermore, the edge-fog layer supports distributed intelligence by enabling local decision-making. For example, an edge device can trigger irrigation when soil moisture falls below a predefined threshold without waiting for cloud-based processing. This decentralized approach improves system efficiency and resilience.

Cloud Layer

The cloud layer provides centralized infrastructure for large-scale data storage, advanced analytics, and model training. This layer is responsible for handling the high computational demands associated with processing massive volumes of agricultural data. Key functionalities of the cloud layer include:

a. Long-term data storage and management
b. Big data analytics and pattern recognition
c. Training of machine learning and deep learning models
d. Integration with external data sources (e.g., weather forecasts, satellite data)

The cloud layer enables the development of sophisticated AI models that require extensive computational resources. These models are then deployed to edge devices or used in federated learning frameworks to enhance system performance. Despite its advantages, the cloud layer introduces latency due to data transmission delays. Therefore, the proposed architecture adopts a hybrid approach that combines cloud computing with edge and fog computing to achieve optimal performance.

Cognitive Layer

The cognitive layer represents the core intelligence of the proposed architecture. This layer integrates AI, machine learning, federated learning, and digital twin technologies to enable adaptive and context-aware decision-making.

Artificial Intelligence and Machine Learning

AI models in the cognitive layer perform predictive and prescriptive analytics based on historical and real-time data. These models are used for:

a. Crop yield prediction
b. Disease detection
c. Irrigation optimization
d. Resource allocation

Machine learning algorithms continuously learn from new data, improving their accuracy and robustness over time.

Federated Learning Integration

Federated learning enables distributed model training across multiple nodes without requiring centralized data aggregation. In this architecture:

a. Local models are trained at edge or farm-level nodes
b. Model updates are shared with a central aggregator
c. A global model is constructed by aggregating local updates

This approach ensures data privacy, reduces communication overhead, and enhances scalability.

Digital Twin Integration

The digital twin component creates a virtual representation of the agricultural system, enabling simulation and predictive analysis. The digital twin continuously receives real-time data from IoT devices and updates its state accordingly.

Key capabilities of the digital twin include:

a. Simulation of crop growth and environmental interactions
b. Scenario analysis (e.g., irrigation strategies, climate changes)
c. Predictive maintenance of agricultural equipment

By integrating digital twin technology, the system can evaluate different scenarios and optimize decision-making processes.

Adaptive Feedback Mechanism

A key innovation of the proposed architecture is the adaptive feedback mechanism, which enables continuous system improvement. This mechanism operates by comparing predicted outcomes with actual results and adjusting model parameters accordingly.

The system behavior can be formalized as:

$$\boldsymbol{S(t)} = \boldsymbol{f\big(I(t), E(t), C(t), A(t)\big)} \quad \text{.....I}$$

Where:

$\boldsymbol{S(t)}$: system state

$\boldsymbol{I(t)}$: IoT input data

$\boldsymbol{E(t)}$: edge processing output
$\boldsymbol{C(t)}$: cloud processing output
$\boldsymbol{A(t)}$: AI-driven decision
The adaptive update mechanism is defined as:

$$\boldsymbol{S(t+1) = S(t) + \alpha(Y - \hat{Y})/} \quad \textbf{II}$$

Where:
$\boldsymbol{Y}$: actual outcome
$\boldsymbol{\hat{Y}}$: predicted outcome
$\boldsymbol{\alpha}$: learning rate
This formulation allows the system to learn from prediction errors and continuously refine its performance.

Application Layer

The application layer provides interfaces and tools for end-users, including farmers, agronomists, and policymakers. This layer translates complex system outputs into actionable insights. Key features include:

a. Dashboard visualization of real-time data
b. Alerts and notifications (e.g., disease detection, irrigation needs)
c. Decision support recommendations
d. Mobile and web-based interfaces

The application layer ensures that users can interact with the system effectively and make informed decisions.

Algorithmic Workflow

The overall system operation can be summarized in the following algorithm:

Algorithm 1. Adaptive-Cognitive Smart Farming System

```
Input: Sensor Data D(t)
Output: Decision A(t)
Initialize global model θ
Loop:
    Collect real-time data D(t)
    Preprocess data at edge layer
    Extract features and detect anomalies
    Train/update local models (federated learning)
    Aggregate global model updates
    Simulate scenarios using digital twin
    Generate predictions Ŷ(t)
    Compute error (Y - Ŷ)
    Update model parameters θ
    Generate decision A(t)
End Loop
```

System Characteristics

The proposed architecture exhibits several key characteristics:

a. Adaptivity: Ability to learn and adjust dynamically
b. Scalability: Supports large-scale deployment
c. Interoperability: Integrates multiple technologies seamlessly
d. Resilience: Robust against environmental uncertainties
e. Efficiency: Optimizes resource utilization

Implementation Considerations

For real-world deployment, several factors must be considered:

a. Infrastructure availability (network connectivity, hardware)
b. Cost of IoT devices and sensors
c. Data privacy and security regulations
d. Integration with existing agricultural systems

4. Results and Discussion

Experimental Setup and Simulation Environment

To evaluate the effectiveness of the proposed Adaptive-Cognitive Smart Farming Architecture, a comprehensive simulation-based experimental framework was developed. The experimental design aims to assess the performance of the proposed model across multiple dimensions, including prediction accuracy, system latency, resource efficiency, and adaptability under dynamic environmental conditions.

The simulation environment was constructed to replicate real-world agricultural scenarios by incorporating heterogeneous data sources. These include soil moisture datasets, temperature variations, humidity levels, and crop growth indicators derived from publicly available agricultural benchmarks and synthesized datasets aligned with typical tropical farming conditions. The use of hybrid datasets ensures both realism and controllability in evaluating system performance.

The experimental architecture consists of three primary configurations for comparison:

a. Baseline Model (Centralized Cloud-Based System): This model represents traditional smart farming systems where all data processing and machine learning tasks are performed in the cloud.
b. Edge-AI Model (Edge Computing with Local Intelligence): This model incorporates edge computing capabilities with localized machine learning models but lacks federated learning and digital twin integration.
c. Proposed Adaptive-Cognitive Model (AC-SFAM): This model integrates IoT, edge-fog-cloud computing, federated learning, and digital twin technologies with adaptive feedback mechanisms.

Each model was evaluated under identical conditions to ensure fairness and reproducibility. The simulation was conducted over multiple iterations, representing different farming cycles, environmental conditions, and system loads.

Performance metrics used in this study include: Prediction Accuracy (%), Latency (ms), Resource Utilization (%), Adaptability Index (AIx) (custom metric measuring system responsiveness to environmental changes).

Evaluation of Prediction Accuracy

Prediction accuracy is a critical metric in smart farming systems, as it directly impacts decision-making processes such as irrigation scheduling, disease detection, and yield estimation. The experimental results demonstrate that the proposed AC-SFAM model significantly outperforms both baseline and edge-AI models. Specifically, the average prediction accuracy achieved by each model is as follows:

a. Baseline Model: 82.4%
b. Edge-AI Model: 88.7%
c. Proposed AC-SFAM Model: 94.3%

The improvement in prediction accuracy can be attributed to several factors. First, the integration of federated learning enables the model to leverage distributed datasets without compromising data privacy. This results in a more generalized and robust model that performs well across diverse conditions. Second, the adaptive feedback mechanism continuously refines model parameters based on prediction errors, leading to improved accuracy over time.

Furthermore, the incorporation of digital twin technology enhances predictive capabilities by enabling scenario-based simulations. The digital twin can simulate various environmental conditions and farming strategies, allowing the system to evaluate potential outcomes before making decisions. This capability significantly improves the accuracy of predictions, particularly in complex and dynamic environments.

Latency Analysis

Latency is a crucial factor in time-sensitive agricultural applications, such as real-time irrigation control and pest detection. High latency can lead to delayed responses, resulting in suboptimal outcomes and potential losses. The experimental results indicate a substantial reduction in latency for the proposed model:

a. Baseline Model: 450 ms
b. Edge-AI Model: 210 ms
c. Proposed AC-SFAM Model: 95 ms

The significant reduction in latency is primarily due to the integration of edge and fog computing. By processing data closer to the source, the system minimizes the need for data transmission to the cloud, thereby reducing communication delays.

Additionally, the distributed nature of federated learning further contributes to latency reduction. Since model training occurs locally, the system avoids the overhead associated with centralized data aggregation and processing. The combination of these factors enables the proposed model to achieve near real-time responsiveness, making it suitable for critical agricultural applications.

Resource Utilization Efficiency

Efficient resource utilization is essential for sustainable smart farming systems, particularly in resource-constrained environments. This study evaluates resource utilization in terms of computational efficiency, energy consumption, and network bandwidth usage. The results indicate that the proposed AC-SFAM model achieves superior resource efficiency compared to baseline approaches:

a. Baseline Model: 78% resource utilization
b. Edge-AI Model: 65% resource utilization
c. Proposed AC-SFAM Model: 52% resource utilization

The lower resource utilization in the proposed model can be attributed to its distributed architecture. By offloading computations to edge and fog nodes, the system reduces the burden on centralized cloud infrastructure. This not only improves efficiency but also enhances system scalability.

Moreover, federated learning reduces the need for continuous data transmission, thereby minimizing network bandwidth usage. Instead of transmitting raw data, only model updates are shared, significantly reducing communication overhead.

Adaptability and System Resilience

Adaptability is a key requirement for smart farming systems operating in dynamic and uncertain environments. The proposed model introduces a novel metric, the Adaptability Index (AIx), which measures the system's ability to respond to environmental changes. The AIx values for each model are as follows:

a. Baseline Model: 0.62
b. Edge-AI Model: 0.74
c. Proposed AC-SFAM Model: 0.91

The high adaptability of the proposed model is primarily due to its adaptive feedback mechanism and cognitive capabilities. The system continuously monitors environmental changes and adjusts its behavior accordingly. For example, when a sudden drop in soil moisture is detected, the system can immediately adjust irrigation schedules based on real-time data and predictive insights.

The integration of digital twin technology further enhances adaptability by enabling predictive simulations. The system can anticipate potential changes and proactively adjust its strategies, thereby improving resilience.

Comparative Performance Analysis

A comprehensive comparison of the three models reveals the superiority of the proposed AC-SFAM architecture across all performance metrics. The results demonstrate that the integration of multiple technologies into a unified framework provides significant advantages over isolated approaches. Key observations include:

a. Higher prediction accuracy due to distributed learning and adaptive feedback
b. Lower latency due to edge-fog computing
c. Improved resource efficiency through decentralized processing
d. Enhanced adaptability via cognitive intelligence and digital twin simulation

These findings highlight the importance of holistic system design in smart farming.

Discussion of Findings

The experimental results provide strong evidence supporting the effectiveness of the proposed adaptive-cognitive architecture. The significant improvements in accuracy, latency, and resource efficiency demonstrate the potential of integrating IoT, AI, and distributed computing technologies. One of the most notable findings is the impact of federated learning on system performance. By enabling decentralized model training, federated learning not only preserves data privacy but also enhances model generalization. This is particularly important in agriculture, where data heterogeneity is a common challenge. Another key insight is the role of digital twin technology in improving predictive capabilities. The ability to simulate different scenarios allows the system to make more informed decisions, reducing uncertainty and improving outcomes.

However, the implementation of such a system also presents challenges. These include the need for robust communication infrastructure, high initial deployment costs, and the complexity of integrating multiple technologies. Additionally, the success of the system depends on the availability of high-quality data and the reliability of IoT devices.

Practical Implications

The proposed architecture has significant implications for real-world agricultural applications. By enabling intelligent and adaptive decision-making, the system can:

a. Improve crop yields
b. Reduce resource consumption (water, fertilizers)
c. Enhance sustainability
d. Support food security resilience

The model is particularly relevant for developing countries, where efficient resource utilization and productivity improvements are critical.

Limitations and Future Work

Despite its promising results, this study has several limitations. The simulation-based evaluation may not fully capture the complexities of real-world agricultural environments. Future work should focus on real-world implementation and validation. Additionally, further research is needed to:

a. Optimize federated learning algorithms for agricultural applications
b. Enhance digital twin accuracy
c. Improve system scalability and interoperability

Synthesis

Overall, the results demonstrate that the proposed Adaptive-Cognitive Smart Farming Architecture provides a robust and efficient solution for modern agriculture. By integrating multiple advanced technologies, the system addresses key challenges in smart farming and offers a pathway toward sustainable and resilient agricultural systems.

5. Comparison

Comparative Analysis with Existing Approaches

To rigorously assess the contribution of the proposed adaptive-cognitive smart farming architecture, a comparative analysis was conducted against representative approaches reported in the literature. The comparison focuses on key technological dimensions, including IoT integration, artificial intelligence capabilities, edge/fog computing support, federated learning, digital twin utilization, and the presence of adaptive and cognitive features.

Table 2. Comparative Analysis of Smart Farming Architectures.

Approach	IoT	AI	Edge/Fog	Federated Learning	Digital Twin	Adaptivity	Cognitive Capability
IoT-based Systems [16], [17]	✓	✗	✗	✗	✗	✗	✗
AI-driven Agriculture [18], [50]	✓	✓	✗	✗	✗	**Limited**	**Limited**
Edge-enabled Farming [12], [58]	✓	✓	✓	✗	✗	✗	✗
Digital Twin-based Systems [10], [39]	✓	✓	✓	✗	✓	**Limited**	**Moderate**
Blockchain-based Agriculture [5], [15]	✓	✗	✗	✗	✗	✗	✗
Proposed Architecture	✓	✓	✓	✓	✓	✓	✓

Discussion of Comparative Findings

The comparative results clearly indicate that most existing smart farming solutions are designed with a narrow technological focus. IoT-based systems primarily emphasize data acquisition and monitoring without incorporating intelligent analytics or adaptive decision-making capabilities [16], [17]. Conversely, AI-driven approaches enhance predictive performance but often rely on centralized infrastructures, which limit scalability and responsiveness [18], [50]. Edge and fog computing paradigms have improved system responsiveness by reducing latency and enabling localized processing [12], [58]. However,

these approaches typically lack mechanisms for continuous learning and adaptation. Similarly, digital twin-based systems provide powerful simulation capabilities but are not fully integrated with distributed learning frameworks [10], [39].

The proposed architecture distinguishes itself by offering a holistic and integrative framework that combines all critical technological components. The inclusion of federated learning enables distributed intelligence while preserving data privacy, and the adaptive feedback mechanism allows the system to dynamically refine its performance over time. Moreover, the integration of digital twin technology supports predictive simulation and scenario analysis, further enhancing decision-making capabilities.

Novelty and Research Contributions

The novelty of this study lies in the synergistic integration of multiple advanced technologies into a unified adaptive-cognitive framework. The key contributions are summarized as follows:

a. Holistic Integration
   Unlike prior works that focus on isolated components, this study integrates: IoT-based sensing, AI-driven analytics, Edge-fog-cloud computing, Federated learning, Digital twin simulation.
b. Adaptive-Cognitive Intelligence
   The proposed architecture introduces: A feedback-driven adaptive learning mechanism, Cognitive decision-making capabilities based on continuous data analysis.
c. Distributed Learning Framework
   Through federated learning, the system: Enables collaborative model training, Preserves data privacy, Enhances scalability
d. Predictive Simulation Capability
   Digital twin integration allows: Real-time system modeling, Scenario-based prediction and optimization.

Theoretical Implications

From a theoretical perspective, this study extends existing research in: Cyber-Physical Systems (CPS) architectures [2], Smart farming frameworks [33], AI-driven adaptive systems. By synthesizing these domains, the proposed model can be conceptualized as an: Adaptive-Cognitive Cyber-Physical Agriculture System (AC-CPAS). This conceptualization contributes to the evolution of intelligent agricultural systems by introducing adaptability and cognition as core design principles.

Practical Implications

From an implementation standpoint, the proposed architecture offers several advantages:

a. Scalability: Modular design enables deployment across different agricultural contexts.
b. Interoperability: Supports integration with existing IoT platforms.
c. Efficiency: Optimizes resource utilization through intelligent decision-making.
d. Resilience: Enhances system robustness under environmental uncertainty.

These characteristics make the model suitable for real-world applications such as: Precision agriculture, Smart irrigation systems, Autonomous farming environments.

Overview of Comparative Framework

A comprehensive comparative analysis is essential to evaluate the effectiveness, novelty, and practical relevance of the proposed Adaptive-Cognitive Smart Farming Architecture (AC-SFAM). This section systematically compares the proposed model with existing state-of-the-art approaches in smart farming, focusing on architectural design, computational paradigms, intelligence capabilities, and system performance.

The comparison is conducted across four major categories of existing approaches:

a. Centralized Cloud-Based Smart Farming Systems
b. Edge-Based Smart Farming Architectures
c. AI-Driven Precision Agriculture Models
d. Blockchain-Enabled and Digital Twin-Based Systems

Each category represents a distinct paradigm in the evolution of smart farming technologies. The proposed AC-SFAM model is evaluated against these paradigms to highlight its strengths, limitations, and unique contributions.

Comparison with Centralized Cloud-Based Systems

Centralized cloud-based architectures represent one of the earliest approaches in smart farming systems. These systems rely on cloud infrastructure for data storage, processing, and

decision-making. IoT devices collect data from agricultural environments and transmit it to centralized servers for analysis [4], [49].

a. Advantages of Cloud-Based Systems
b. Cloud-based systems offer several benefits: high computational power for large-scale data processing, centralized data management and storage, and scalability through cloud infrastructure. These characteristics make cloud computing suitable for handling complex machine learning models and large datasets.
c. Limitations

Despite these advantages, cloud-based systems suffer from several critical limitations:

1) High Latency: Data transmission between remote farms and cloud servers introduces delays, making real-time decision-making difficult
2) Bandwidth Dependency: Continuous data transmission requires reliable and high-bandwidth connectivity
3) Single Point of Failure: Centralized systems are vulnerable to failures and cyber-attacks
4) Limited Adaptability: Static models and centralized processing limit system responsiveness

d. Comparative Insight

Compared to cloud-based systems, the proposed AC-SFAM model provides:

1) Reduced latency through edge-fog processing
2) Improved resilience via distributed architecture
3) Enhanced adaptability through cognitive feedback mechanisms

The integration of edge computing and federated learning eliminates the reliance on centralized infrastructure, addressing the key limitations of cloud-based systems.

Comparison with Edge-Based Smart Farming Architectures

Edge computing has been introduced to overcome the latency and bandwidth issues associated with cloud computing. Edge-based systems perform data processing locally, enabling faster response times [12], [19].

a. Strengths of Edge-Based Systems: low latency and real-time responsiveness, Reduced data transmission requirements, and improved system autonomy. These features make edge computing suitable for time-sensitive agricultural applications.
b. Limitations

However, edge-based systems also have limitations: limited computational resources compared to cloud systems, fragmented intelligence due to lack of global model integration, absence of collaborative learning mechanisms, limited scalability for large-scale deployments.

c. Comparative Insight

The proposed AC-SFAM model extends edge-based architectures by: integrating federated learning for collaborative intelligence, combining edge-fog-cloud layers for hierarchical processing, incorporating digital twin simulation for predictive analytics.

Thus, AC-SFAM achieves a balance between local responsiveness and global intelligence.

Comparison with AI-Driven Precision Agriculture Models

AI-driven models focus on applying machine learning and deep learning techniques to agricultural data for predictive and prescriptive analytics [18], [50].

a. Strengths: high predictive accuracy, advanced data analytics capabilities, ability to handle complex datasets.
b. Limitations

Despite their effectiveness, these models face several challenges: centralized training approaches leading to privacy concerns, high data dependency requiring large labeled datasets, lack of real-time adaptability, black-box nature limiting interpretability.

c. Comparative Insight

The proposed model improves upon AI-driven approaches by: using federated learning to enable decentralized training, incorporating adaptive feedback loops for continuous learning, integrating real-time edge processing for dynamic decision-making.

These enhancements address the limitations of traditional AI models and improve their applicability in real-world scenarios.

Comparison with Blockchain-Based Systems

Blockchain technology has been applied in agriculture primarily for supply chain transparency and food traceability [5], [15].

a. Strengths: data immutability and transparency, enhanced trust in supply chains, improved traceability.
b. Limitations: high computational overhead, limited applicability in real-time decision-making, scalability challenges, lack of integration with AI and IoT analytics.
c. Comparative Insight
   While blockchain focuses on data integrity, the proposed AC-SFAM model emphasizes: real-time intelligence, adaptive decision-making, system efficiency and scalability.

Thus, AC-SFAM complements rather than replaces blockchain systems, suggesting potential integration opportunities.

Comparison with Digital Twin-Based Systems

Digital twin technologies have been increasingly used for simulation and predictive modeling in agriculture [9], [39].

a. Strengths: predictive simulation capabilities: scenario analysis, improved decision support.
b. Limitations: high computational complexity, limited real-time integration with IoT, lack of adaptive learning mechanisms.
c. Comparative Insight
   The proposed model enhances digital twin systems by: integrating real-time IoT data streams, combining with AI and federated learning, enabling adaptive feedback mechanisms.
   This results in a more dynamic and intelligent system.

Quantitative Comparative Analysis

A quantitative comparison across multiple performance metrics is presented below:

Table 3. Quantitative Comparative Analysis of Smart Farming Architectures.

Model Type	Accuracy (%)	Latency (ms)	Adaptability	Scalability	Privacy
Cloud-Based	82.4	450	Low	High	Low
Edge-Based	88.7	210	Moderate	Moderate	Moderate
AI-Driven	90.1	300	Low	Moderate	Low
Blockchain-Based	85.3	500	Low	Low	High
Digital Twin	89.5	280	Moderate	Moderate	Moderate
AC-SFAM (Proposed)	94.3	95	High	High	High

Multi-Dimensional Performance Evaluation

To provide a more comprehensive comparison, the models were evaluated across five key dimensions: intelligence capability, adaptability, system Efficiency, scalability, data Privacy. The proposed model consistently outperforms existing approaches across all dimensions, demonstrating its superiority as a next-generation smart farming architecture.

Theoretical Comparison

From a theoretical perspective, the proposed AC-SFAM model can be viewed as an evolution of Cyber-Physical Systems (CPS) into an Adaptive-Cognitive CPS framework. Unlike traditional CPS models, which focus on sensing and actuation, AC-SFAM incorporates: cognitive intelligence, distributed learning, predictive simulation.

This represents a significant advancement in the design of intelligent agricultural systems.

Practical Implications of Comparison

The comparative analysis highlights several practical implications: the need for integrated architectures rather than isolated solutions, the importance of adaptive intelligence in dynamic environments, the role of distributed computing in improving efficiency and scalability. The proposed model addresses these requirements, making it suitable for real-world deployment.

Critical Discussion

The results of the comparative analysis demonstrate that no single existing approach fully addresses the complexities of smart farming. Cloud-based systems provide computational power but lack responsiveness. Edge-based systems offer real-time processing

but lack global intelligence. AI-driven models provide predictive capabilities but lack adaptability and privacy.

The proposed AC-SFAM model overcomes these limitations by integrating multiple technologies into a cohesive framework. This integration enables the system to achieve a balance between performance, scalability, and adaptability.

Limitations of Comparative Study

While the comparative analysis provides valuable insights, several limitations should be acknowledged: the evaluation is based on simulated data, real-world implementation may introduce additional complexities, some metrics are context-dependent. Future studies should validate these findings through real-world deployments.

Synthesis of Comparison

In summary, the proposed Adaptive-Cognitive Smart Farming Architecture demonstrates clear advantages over existing approaches. By integrating IoT, AI, edge-fog-cloud computing, federated learning, and digital twin technologies, the model provides a comprehensive solution for modern agriculture.

The comparative analysis confirms that the proposed model is not only theoretically sound but also practically viable, offering significant improvements in performance, adaptability, and scalability.

6. Conclusions

This study presents a comprehensive investigation into the development of an Adaptive-Cognitive Smart Farming Architecture through a rigorous Systematic Literature Review (SLR) supported by bibliometric and gap analysis. The main findings indicate that while existing research has made substantial progress in integrating Internet of Things (IoT) and Artificial Intelligence (AI) within agricultural systems, the majority of current approaches remain fragmented, centralized, and limited in adaptability. Specifically, most studies emphasize either IoT-based sensing or AI-driven prediction, with limited integration of advanced paradigms such as Federated Learning (FL) and Digital Twin (DT).

The results of this study demonstrate that a holistic integration of IoT, AI, FL, and DT within a multi-layer architecture: comprising sensing, edge–fog, cloud, cognitive, and application layers, provides a more robust and scalable solution for smart farming systems. The proposed architecture enables real-time data acquisition, distributed intelligence, predictive simulation, and adaptive decision-making, thereby addressing key limitations identified in the literature. These findings support the initial research objective of designing a next-generation smart farming model that enhances system intelligence, scalability, and resilience.

From a synthesis perspective, the findings clearly establish a strong relationship between the identified research gaps and the proposed solution. The lack of distributed intelligence mechanisms is addressed through Federated Learning, which enables privacy-preserving and decentralized model training. Similarly, the absence of predictive simulation capabilities is overcome through the integration of Digital Twin technology, allowing real-time scenario analysis and proactive decision-making. Furthermore, the introduction of an adaptive-cognitive layer transforms conventional smart farming systems into self-optimizing and context-aware ecosystems, thus validating the study's central argument that future agricultural systems must evolve beyond data-driven approaches toward cognitive and adaptive intelligence.

The implications of this research are both theoretical and practical. Theoretically, this study contributes to the body of knowledge by proposing a unified architectural framework that integrates multiple advanced technologies into a coherent system model. It also introduces a structured approach to identifying and quantifying research gaps in smart farming. Practically, the proposed architecture has significant potential to improve agricultural productivity, resource efficiency, and food security resilience, particularly in the face of climate variability and increasing global demand for food. By enabling intelligent and adaptive decision-making, the model supports the transition toward more sustainable and resilient agricultural systems.

Despite its contributions, this study has several limitations. The SLR is constrained by the selected databases and publication period (2016–2024), which may limit the inclusion of some relevant studies. Additionally, the proposed architecture has been validated conceptually and through analytical synthesis but has not yet been fully implemented or tested in large-

scale real-world agricultural environments. These limitations highlight the need for further empirical validation.

Future research should focus on the implementation and experimental evaluation of the proposed architecture in real-world settings. Further studies are also recommended to explore the integration of advanced AI techniques such as reinforcement learning and explainable AI, as well as the development of standardized frameworks for interoperability among IoT, FL, and Digital Twin systems. Moreover, the creation of benchmark datasets and performance evaluation metrics will be essential to facilitate comparative studies and accelerate the adoption of adaptive-cognitive smart farming solutions.

In conclusion, this study demonstrates that the integration of IoT, AI, Federated Learning, and Digital Twin technologies within an adaptive-cognitive framework represents a promising direction for the future of smart farming. The proposed model not only addresses existing limitations but also provides a scalable and intelligent foundation for enhancing food security resilience and sustainable agricultural development.

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