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Review article

Artificial Intelligence of Things (AIoT) for smart agriculture: A review of architectures, technologies and solutions

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A R T I C L E I N F O

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Smart agriculture
Internet of Things
Machine learning
Sensors

A B S T R A C T

The Artificial Intelligence of Things (AIoT), a combination of the Internet of Things (IoT) and Artificial Intelligence (AI), plays an increasingly important role in smart agriculture (SA). AIoT has been adopted in many applications including agriculture, such as crop yield estimation, soil and water conservation, pest and disease detection and supply chain management. While there are plenty of studies on AIoT applications in healthcare, smart cities, manufacturing, and transportation, SA still has a small share of the reported research. This paper presents a comprehensive review of the existing literature in AIoT and Federated Learning (FL) for SA. It identifies current and potential challenges and provides research direction for the future investment in both academia and industry.

1. Introduction

One of the main goals of the United Nations (UN) is to eradicate hunger by 2030 (Pathan et al., 2020). The growth of the global population, estimated to reach 9 billion by 2050 and 11 billion by 2100, emphasizes the critical need for a more sustainable and efficient food production system. At the same time, many challenges, such as climate change leading to high temperatures, water scarcity, soil degradation, land use change and environmental pollution (Durai and Shamili, 2022) will have a negative impact on the way food is produced worldwide. Global reduction in agricultural land mass, for cultivation and animal husbandry, due to rising water and desertification are already the cause of food shortages. As a result, one of the major issues facing the world today and in the future is a looming food crisis (Hu et al., 2022).

To meet the next decade's production challenges, Smart Agriculture (SA) has been proposed as a promising approach to improve agricultural yields and increase food production. SA solutions have been shown to improve farm management with soil, weather, crop, and temperature monitoring leading to water, harvest, energy and supply chain management (Katiyar and Farhana, 2021).

IoT and AI have already been successfully applied in healthcare, transport and energy management over the past years. And, increasingly, Artificial Intelligence of Things (AIoT), a combination of the Internet of Things (IoT) and Artificial Intelligence (AI), is providing solutions in SA that combine automatic decision-making with the classic IoT sensing and system controls.

Agriculture benefits from IoT devices' ability to sense, process, and transmit environmental data, such as vision, acoustic, and ambient data, including temperature, soil humidity, and nutrition, from usually vast distributed lands. AI, on the other hand, can be trained to analyze sensor data, improving crop and livestock wellness and management by making informed decisions about irrigation, fertilization, and pest and animal control (Alzuhair and Alghaihab, 2023).

While storing and analyzing data on a centralized cloud brings many benefits, including cost efficiency and high computing and storage capabilities, it also is ineffective or even infeasible for some applications that generate high volumes of data, require a high level of scalability, constant network connectivity, and, increasingly, data governance. Hence as will be seen in the paper, AIoT uses different combinations of edge, fog, and cloud computing to achieve its goals.

In particular, because of its requirements, SA may need dedicated AIoT architectures and technologies. SA requires a high number of devices to interconnect in real-time for decision-making. While connecting to the AI training is feasible, relying on a remote facility

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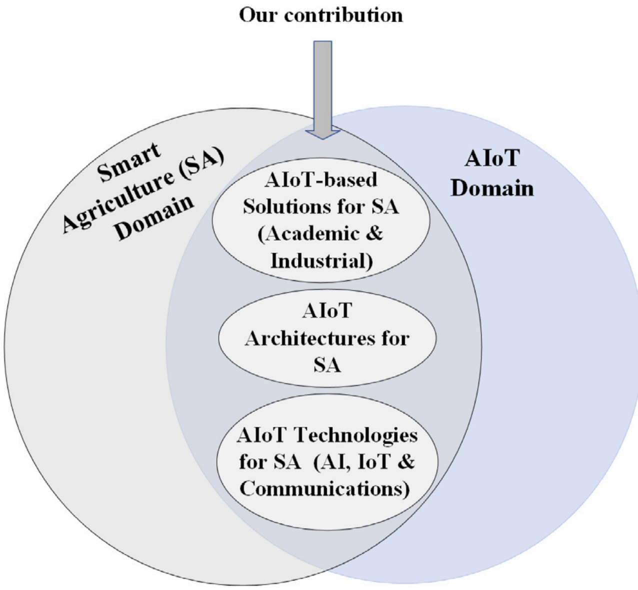

Fig. 1. Relation (overlap) between AIoT and SA.

for timely decision-making could be challenging outside of a main metropolitan area. In this case, using edge computing can overcome the limitations of the centralized cloud when it comes to the distributed data analytics and decision-making that are essential for SA.

In addition, because SA may need different farms to cooperate, emerging AI approaches such as Federated Learning (FL) are required. FL enables distributed devices to train a shared AI model collaboratively while keeping the training data stored locally for privacy and providing local automatic decision support (Ahvar et al., 2022). It is now widely believed that when included in the AIoT toolkit, FL can help to develop more efficient solutions for SA.

FL's benefits have been proved already in other domains such as healthcare (e.g., a study by Wassan et al. (2022)). Apart from FL, some new techniques and technologies such as Digital Twins and Extended Reality (XR) showed their future potential usage in SA.

In view of these recent developments, our paper main contributions are as follows:

- We first review AIoT applications, architectures and technologies.
- We collate, review and analyze the existing AIoT-based solutions for SA.
- We collate, review and analyze the existing architectures using AIoT for SA.
- We collate, review and analyze the AIoT technologies have been used for SA.
- We finally identify challenges of using AIoT for SA and provide research direction for the future.

To illustrate our contributions, the intersection of SA and AIoT is presented in Fig. 1.

The remainder of the paper is organized as follows: Section 2 reviews namely previous related or similar surveys. Section 3 presents the methodology, Section 4 presents some AIoT background, Section 5 surveys the AIoT landscape for SA and Section 6 defines challenges and future directions. Finally, Section 7 summarizes the salient contributions of the paper. The complete structure of the paper is available in Fig. 2.

2. Related work

In this section, we first review the existing surveys on AIoT. Because of the increasingly close relationship between AIoT and FL, we also

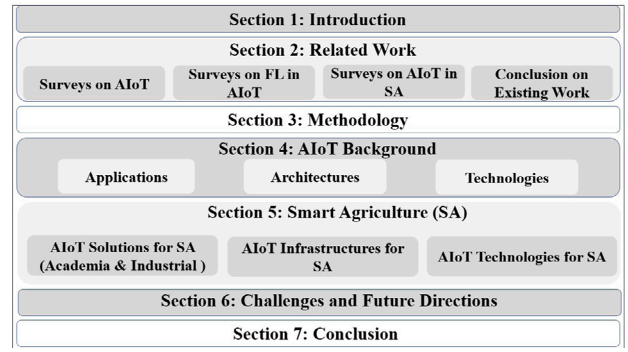

Fig. 2. Paper general structure.

present some of the existing studies on FL as they pertain to SA. Finally, we present the existing surveys in SA, especially those related to AIoT in their corresponding subsections.

2.1. Surveys on AIoT

There have been recent reviews of AIoT applications by researchers in the field. Table 2 presents the previous work from three perspectives: AI, IoT and communications. It can be noted that most of these do not consider all three aspects of AIoT technologies combined. Table 1 also shows that there are only a few that mention SA as a potential application.

2.2. Surveys on FL in AIoT

Looking at recent research, it can be seen that FL plays an increasingly important role in AIoT architectures and systems. A summary of some of the existing available reviews on FL is presented in Table 3. While there is some research on the role of FL in AIoT solutions in SA (Yin et al., 2022; Saha et al., 2020), at the time of writing, no survey paper focused on investigating this topic.

2.3. Survey on AIoT in SA

As mentioned above, after a comprehensive review of the literature, we found only a few AIoT surveys focusing on SA (i.e., Katiyar and Farhana (2021), Gupta et al. (2020), Mitra et al. (2022) and Yang et al. (2021)). The work reported in Katiyar and Farhana (2021) includes solutions and technologies, while (Mitra et al., 2022) briefly discussed architecture and networks as well as solutions and technologies. Authors in Gupta et al. (2020), Yang et al. (2021) focused on SA security and privacy. Adli et al. (2023) focused on a Systematic Literature Review (SLR) for highlighting the increasing trends of AIoT publication in SA. They summarized AIoT application and other AI/IoT enabling techniques and challenges of AIoT adoption. See Tables 1 and 4 for summarizing surveys in AIoT for all domains and specially in SA.

2.4. Research gaps

The results of our literature review can be summarized in Tables 1 and 4. It showed that there are only a few surveys on AIoT for SA. Non of them considered the whole spectrum of AIoT in SA (i.e., architecture, solutions and technologies). In addition, they did not consider details of networking and communication. Unlike the existing surveys on AIoT for SA, we provide a comprehensive survey on AIoT architectures, solutions and technologies for SA and dwell on the details of networking and communication technology aspects essential to create the underlying infrastructure. Also, we reviewed the related surveys in FL as it is considered as the technology used in training the distributed ML models in AIoT and similarly for SA which was not provided in related surveys.

Table 1
Existing AIoT surveys articles.

Refs.	Application	No. of Surveys
Pise et al. (2022), Chen et al. (2021), Pappakrishnan et al. (2021), Jain et al. (2021), Qian et al. (2021), Alshehri and Muhammad (2020), Alshamrani (2021), Amin and Hossain (2020), Chamola et al. (2020), Durga et al. (2019), Tunc et al. (2021), Ali et al. (2022) and Kakhi et al. (2022)	Smart Healthcare	14
Nozari et al. (2022), Salih et al. (2022), Pan and Zhang (2021) and Barton et al. (2022)	Smart Industries	4
Molokomme et al. (2022)	Smart Grids	1
Mitra et al. (2022), Katiyar and Farhana (2021), Gupta et al. (2020), Yang et al. (2021) and Adli et al. (2023)	Smart Agriculture	5
Huang et al. (2021), Wazid et al. (2021), Patel et al. (2022) and Sigov et al. (2022)	Smart (security) Management	4
Ghoreishi et al. (2022), Bronner et al. (2021)	Smart Business	2
Guo et al. (2022)	Smart Transportation	1
Seng et al. (2022), Kuguoglu et al. (2021), Wu et al. (2019), Dong et al. (2021) and Zhang et al. (2023)	Smart Cities	5

Table 2
Summary of AIoT surveys on technologies.

Ref.	AI	IoT	Communications
Wu et al. (2019)	✓	✓	
Zhao et al. (2020)			✓
Hao et al. (2021)			✓
Lin (2021)			✓
Pan and Zhang (2021)	✓	✓	
Altalak et al. (2022)	✓	✓	
Qazi et al. (2022)	✓		✓
Vyas et al. (2022)	✓	✓	
Hashni et al. (2022)	✓	✓	
Guo et al. (2022)			✓
Ahmed et al. (2022)			✓
Esenogho et al. (2022)	✓	✓	✓
Our survey	✓	✓	✓

AI: Artificial Intelligence; IoT: Internet of things.

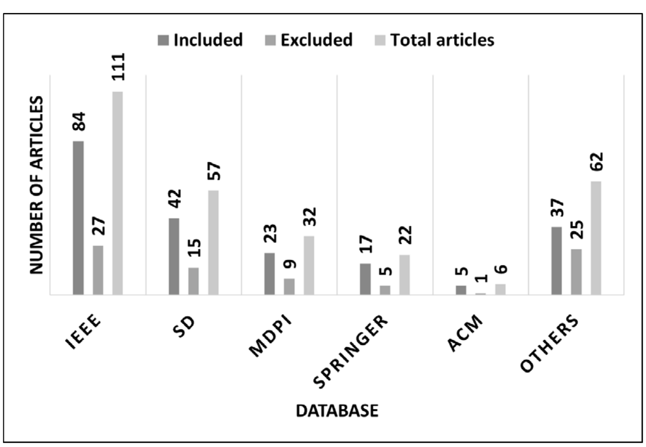

Fig. 3. Summary of the reviewed articles.

3. Methodology

This section explains the methodology used in this paper for investigating the related work including the used keywords, our research objective and questions and the selection and quality assessment criteria. This process was carried out in three major steps of planning, reviewing and reporting. In planning, research objectives and research questions were formulated, in the reviewing stage articles were selected based on our selection and quality assessment criteria. Lastly, we reported the findings of our research.

3.1. Research objectives

The major objective of this research is to investigate solutions and architectures as well as technologies and challenges of AIoT and FL for SA. To achieve this objective, we start by reviewing the AIoT and FL related surveys as presented in Section 2 to show the trends of the available surveys across AIoT application domains and briefly introduce the available existing literature. As we moved to SA in Section 5 which is the main targeted application of this research, we dwell into the existing AIoT solutions for SA both the academia and industry solutions, we considered architectures and technologies specialized for SA.

3.2. Research questions

This section explains the research as follows:

- Q1. What are the available AIoT-based solutions for SA (academia and industry)?
- Q2. What are the specialized AIoT-based architectures used in SA?
- Q3. What are the AIoT technologies used in SA?
- Q4. What are the current AIoT challenges in SA and what are the directions for the future?

3.3. Articles collection procedure

The articles used in this research were collected mostly from relevant and reputable databases such as Elsevier (ScienceDirect (SD)), IEEE Explorer, ACM Digital Library, MDPI, Springer published from 2018 to 2023. For finding the industrial solution, we relied on the list of companies presented.[1] To exhaust all the available search avenues, the following keywords were used “AIoT Surveys” “Artificial Intelligence of Things (AIoT) Applications”, “AIoT-based Solutions for Smart Agriculture”, “AIoT-based Architecture” “AIoT-based Architecture for SA”, “AIoT Technologies”, “AIoT Technologies for SA”, “Surveys on FL in AIoT ” and “FL for Smart Agriculture”. We used inclusion and exclusion criteria for article selection as presented in Table 5. Fig. 3 presents the statistics related to filtered articles. Similarly, a quality assessment is presented in Table 6.

[1] https://ausagritech.org/about/what-is-ausagritech/

Table 3
Existing surveys articles on FL applications.

Ref.	Application	No. of Surveys
Nguyen et al. (2022), Mahlool and Abed (2022), Pfitzner et al. (2021), Antunes et al. (2022) and Ali et al. (2022)	Smart Healthcare	5
Pham et al. (2021), Zhou et al. (2021), Aledhari et al. (2020)	Smart Industries	3
Briggs et al. (2021), Mothukuri et al. (2021), Campos et al. (2021), Li et al. (2021), Ghimire and Rawat (2022), Hou et al. (2021), Li et al. (2022a), Nguyen et al. (2021), Ali et al. (2021), Billah et al. (2022) and Campos et al. (2021)	Smart (security) Management	11
Du et al. (2020)	Smart Transport	1
Jiang et al. (2020), Zheng et al. (2022, 2021), Pandya et al. (2023) and Ramu et al. (2022)	Smart Cities	4

Table 4
Existing surveys articles on AIoT for SA.

Ref.	Title.	Year	Objective
Gupta et al. (2020)	Security and Privacy in Smart Farming: Challenges and Opportunities	2020	Studied the security and privacy in smart farming ecosystems and outline the multilayered architecture for precision farming and present the security and privacy issues in a dynamic/distributed cyber–physical environment. They also highlight potential cyberattack scenarios.
Yang et al. (2021)	A survey on SA: Development modes, technologies, and security and privacy challenges	2021	This paper surveyed the state-of-the-art work related to smart development modes, technologies, applications and privacy and security.
Katiyar and Farhana (2021)	SA: The Future of Agriculture using AI and IoT	2021	Present the research work for agriculture automation using sensors, agricultural robots and drones as well as AI-driven technologies to improve productivity.
Mitra et al. (2022)	Everything you wanted to know about SA	2022	Presents the solutions, technologies trends, available datasets, network options and deployment challenges.
Adli et al. (2023)	Recent Advancements and Challenges of AIoT Application in Smart Agriculture: A Review	2023	Presents AIoT concepts, IoT smart devices and AI techniques adoption, the trends in increasing publication in AIoT applications using SLR. Highlighted application of AIoT and other AI/IoT enabling techniques and challenges of AIoT adoption.
Our survey	Artificial Intelligence of Things (AIoT) for Smart Agriculture: A Review of Architectures, Technologies and Solutions	2023	A comprehensive survey of AIoT for SA considering AIoT architecture, solutions and technologies. Also, reviewed the related surveys in FL as it is considered as the technology used in training distributed ML models in AIoT and similarly highlighted the challenges and future directions of AIoT for SA.

Table 5
Inclusion/Exclusion method.

Inclusion	Criteria
1	Title with all keywords in search string published between 2018 to 2023
2	Title with AIoT plus any of its application domains in the search string
3	Focusing on AIoT-based architecture
4	Focusing on AIoT technologies
5	Focusing on AIoT for SA and any of its 6 solutions
Exclusion	Criteria
1	Title that does not include any of the AIoT application domains
2	Articles that are not within the context of the study domain
3	Articles published before 2018 or not peer review
4	Short articles or duplicated articles published by different journals

Table 6
Quality assessment.

ID	Question
Q1	Is the research objective defined clearly in line with the research problem?
Q2	Are the research questions answered accordingly?
Q3	Does the research focus on AIoT and any of its applications domains, architectures or technologies?
Q4	Does the research scope include FL for AIoT applications or SA solutions?
Q5	Is the research report well elaborated and the experiment is clearly explained?
Q6	Is the research findings valid and relevant to the study domain?

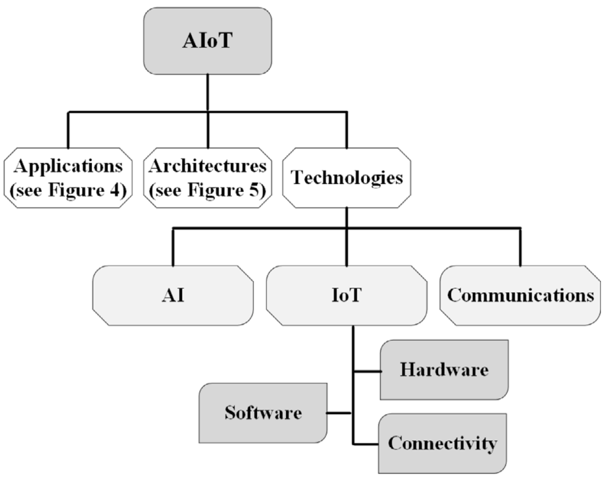

Fig. 4. AIoT background.

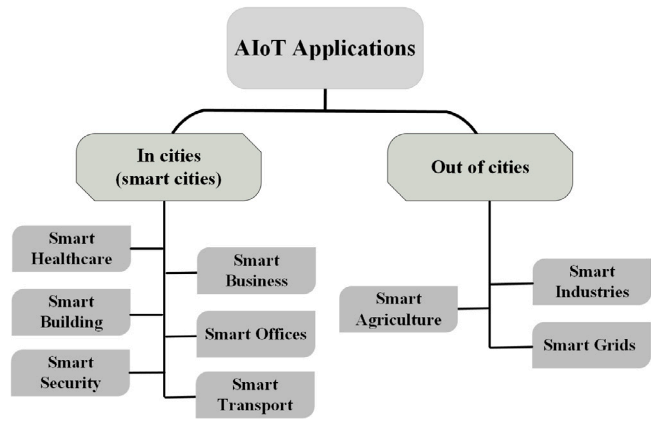

Fig. 5. General AIoT applications.

4. AIoT background

The combination of AI technologies with the IoT infrastructure refers to AIoT (Ahvar et al., 2022; Dia et al., 2022). We can consider two main forms for collaborating AI and IoT in AIoT systems: loosely coupled (i.e., AI for IoT) and tightly coupled (i.e., AI on IoT). In loosely coupled AIoT (e.g., a traditional combination/collaboration of IoT and AI), the data is generated in IoT devices and forwarded to a local or remote location (e.g., cloud facility) to be analyzed by an AI-based method such as neural networks. In tightly coupled AIoT (e.g., a modern combination/collaboration of IoT and AI), IoT devices are equipped with AI processing capabilities and AI algorithms are run on IoT devices partially or even completely. In other words, the IoT devices have AI processing capabilities in tightly coupled AIoT. The systems that use the loosely coupled form of collaborating AI and IoT are called loosely coupled AIoT systems and the ones that use the tightly coupled form are called tightly coupled AIoT systems (Ahvar et al., 2022).

Loosely coupled AIoT already is improving traditional farmers practices (e.g., smart dynamic irrigation patterns instead of fixed scheduling irrigation (Amatya et al., 2016)). Tightly coupled AIoT systems can bring some benefits in comparison to the loosely coupled AIoT systems. In traditional loosely coupled AIoT systems, data are generated by IoT devices and should be transmitted to a remote location (e.g., a cloud data center) for AI processing. In modern AIoT applications (e.g., many smart agriculture applications), because of a high volume of generated data, high scalability of networks and data privacy issues, it may not be possible to transfer data to a remote location.

A broad perspective of AIoT architectures, technologies, and applications is presented in this section and summarized in Fig. 4.

4.1. AIoT applications

To start our wide-ranging survey, we review existing AIoT applications and propose a taxonomy where AIoT applications are classified into two broad categories: city applications (i.e., smart cities) and non-city specific as presented in Fig. 5. In cities, AIoT applications target healthcare, buildings, offices, businesses, transportation, and government (safety and security). More broadly defined AIoT applications include smart manufacturing, smart grids, and SA. To mention examples, of each domain, a healthcare AIoT solution for identifying persons of interest (POI) in COVID-19 analysis was implemented based on far distance camera with low-resolution handling in Istiklal street of Istanbul in Turkey.[2] For transport example, we can refer to images from the autopilot camera which with the help of AI are used to automatically convert the wiper speed to the intensity of rain or snow in Tesla (Slama et al., 2023).

4.2. AIoT architectures

To functionally distribute the needs of AIoT, several layered architectures have been recently proposed that include some or all the following features: devices for data acquisition, an edge/fog layer that contains computing devices, for aggregation and pre-processing, and gateways for connectivity to the cloud layer for storage and analysis. In each architecture, the number of layers and the nature of the operations performed at each layer can vary based on the specific requirements of the targeted system. Because common need for data gathering and processing, three-layer and four-layer architectures are becoming almost standard.

[2] https://github.com/vahit19/4DeepAnalytics.com

4.2.1. Layered models

Generally, the device layer (also called the data acquisition layer) is where the sensing and measurement systems are located. This layer may host numerous devices responsible for the generation and collection of data based on the target application. Different devices including but not limited to sensors, actuators, and other embedded devices as well as drones, cameras, smartphones, and radio frequency identifiers (RFID) may be used as data sources in that layer. They are deployed in specific areas based on the application requirements for sensing, processing, and communicating the data amongst themselves and to the other layers.

The edge/fog layer refers to the next layer that receives the raw or processed data from the device layer performs aggregation and further processing, including security and then sends the results to the cloud layer using some form of communication interface. Although some of the existing architectures consider the edge/fog layer as one, others follow the OpenFog Consortium recommendations and make the distinction between fog and edge. While fog computing provides resources (e.g., computing, storage and networking) anywhere from the cloud to the end devices (the edge cloud continuum), edge computing may be limited to computing locally (OpenFogConsortium, 2017; Ramya, 2021). As was stated in Digiteum (2022), "As a layer in between clouds and edges, fog offers the advantages of both. It utilizes the cloud and communicates directly with it to distribute data that does not require immediate processing. Fog is also positioned nearer the edge at the same moment. It uses local processing and storage resources for real-time analytics and prompt event reaction. Fog is decentralized, with numerous nodes, just like the edge. Fog, in contrast to the edge, has a network architecture. Fog nodes are interconnected and can disperse computing and storage to complete specific tasks more effectively. Edge provides the lowest latency and fastest reaction to data because it is the closest to end devices. The structure in edge computing is typically more loosely coupled, with edge nodes handling data on their own".

Either part of the edge or fog layer or as a layer of its own, the connectivity layer relays the data between layers. As an independent layer, in some literature, it offers added services such as encryption, and service and data discovery.

Finally, the cloud layer receives the data from all preceding layers, performs data analysis and stores the data for future use. The cloud layer enables end-users to access the relevant data virtually for their specific tasks. Some architectures use the cloud as the uppermost layer, whereas others further separately use the application layer as an upper layer.

Examples of specific architecture illustrate the concept. The authors in Wazid et al. (2021) presented the architecture of AIoT as a blockchain-based secure framework consisting of three major components: IoT devices/users, gateways and cloud. In this study, in the second layer, the gateway nodes convert the huge amount of received data from the smart IoT devices into partial blocks and forward them to the cloud server. The cloud server converts the partial block into the full block and forwards it to the Peer-to-Peer Cloud Server (P2PCS) network for mining and incorporates it with the blockchain to secure the data. Another layered architecture with a different nomenclature is proposed in Yu et al. (2021). This architecture consists of the data layer, the security layer, the processing layer (with AI modules) and the application layer which focuses on securing the data from attacks and threats by malicious agents preventing their access. At the data layer, data is generated and transmitted to the processing layer through the security layer to prevent and recover from attacks.

Hence, after review, a common architecture emerges as is shown in Fig. 6. It consists of four layers. In the device layer, end devices are deployed for gathering data related to a particular application domain; the generated data is then sent to the edge/fog layer through the connectivity layer for further processing. Finally, the data is transmitted to the cloud for processing and storage.

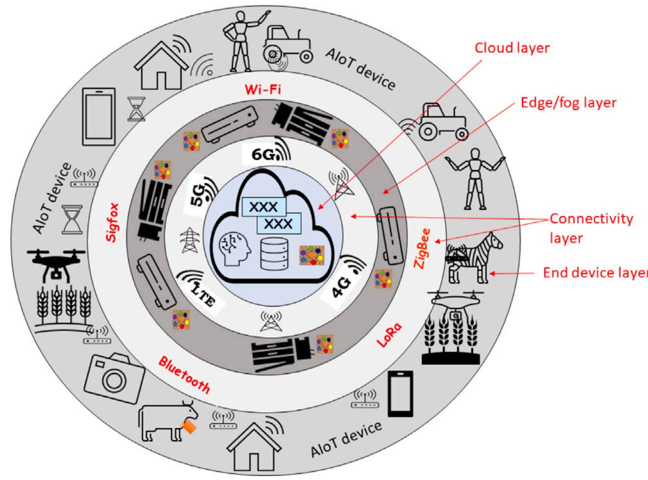

Fig. 6. AIoT common architecture.

Depending on the second layer choice, we define 4-layered architectures Fog–Cloud (F–C), Edge–Cloud (EC) and Edge/Fog–Cloud (E/F–C).

In addition, the AI mechanisms can be centralized or distributed in the network across every layer, as illustrated in Fig. 7. In a centralized deployment, AI processing occurs only in one of the layers of the architecture or even in only one device in the edge cloud continuum, as shown in Fig. 8. Whereas in a distributed deployment, AI inference can occur across the devices themselves, with support at the edge/fog and cloud layers in a vertically, horizontally or hybrid manner as shown in Fig. 9 (Ahvar et al., 2022).

It is in the distributed deployment that FL becomes an asset. In FL, ML algorithm training is performed across multiple decentralized edge devices or servers each holding local data samples. FL trains the model from the local data generated and sends the local model update to the server for global aggregation. This improves the model performance because the client nodes can use the global modeling results from many nodes received from the server to train their local model while reducing the network traffic sent to the central server. FL also provides improvements in data privacy and security by keeping the data at the source.

Similar, to FL, distributed learning is the process of training ML models using multiple computing resources that are interconnected. Rather than relying on a single machine, distributed learning harnesses the collective computational power of a network of machines or nodes. By dividing the workload and data across multiple nodes, distributed learning enables parallel processing, leading to faster and more efficient training of machine learning models (Gülen, 2023). However, in centralized learning (CL), environmental row data is required by the clients which are transmitted to the central server after initial pre-processing to perform respective model training tasks (heavy computation) (Drainakis et al., 2020a). There are some studies in different domains comparing central learning and FL from different aspects (Drainakis et al., 2020a,b).

Getting help from distributed learning and FL, and depending on applications and required performance, different layered AIoT architectures have been used in related work. A summary of the common AIoT architectures is presented in Table 7 with their corresponding application areas. Moreover, we identified the level of AI and IoT coupling in these architectures. The most common layered architecture studied in our survey is E–C architecture. This choice can be related to a lack of standard definition and support for the fog layer. Tightly coupled have been already proposed in most of the domains. SA AIoT architectures will be addressed separately in Section 5.

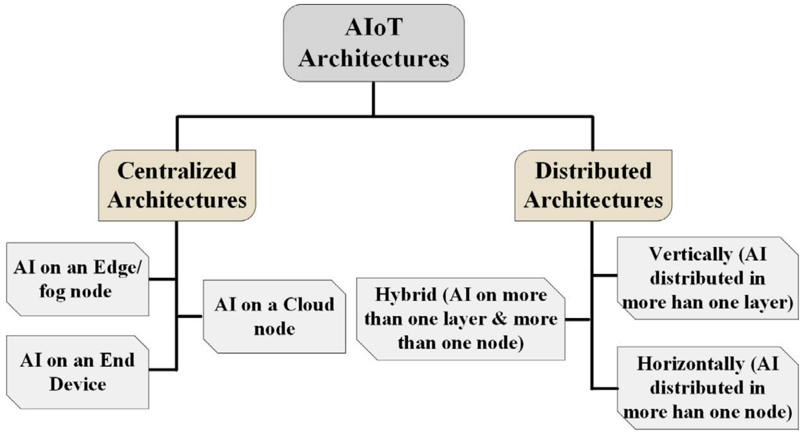

Fig. 7. AI deployment in AIoT architectures.

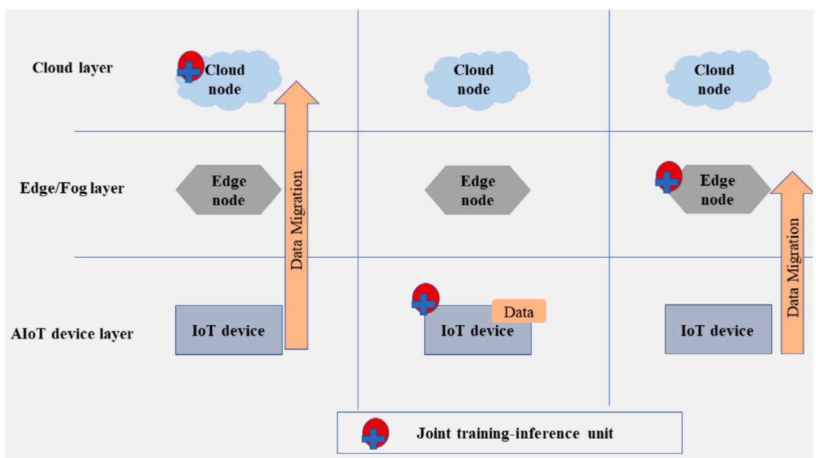

Fig. 8. Centralized AI deployments (Ahvar et al., 2022).

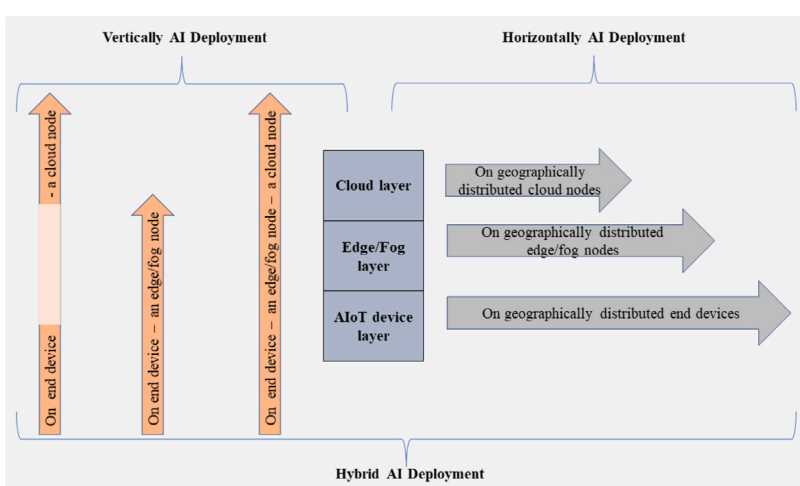

Fig. 9. Distributed AI deployment (Ahvar et al., 2022).

Table 7
General AIoT architectures and systems.

Ref.	Architecture				NL	AIoT Systems		Application
	E/F–C	E–C	F–C	C-B		Loosely	Tightly	
Zhang and Tao (2020)	✓				3		✓	General
Wazid et al. (2021)				✓	3	✓		Security
Liu et al. (2021)			✓		4		✓	Industry
Yu et al. (2021)		✓			4	✓		Security
Ning (2021)		✓			4	✓		Smart grid
Seng et al. (2022)		✓			3		✓	Smart Homes
Mitra et al. (2022)		✓			3	✓		Smart Agriculture

NL: Number of Layers; E/F–C: Edge/Fog–Cloud; E–C: Edge–Cloud; F–C: Fog–Cloud; C-B: Cloud-Based; Loosely: Loosely coupled; Tightly: Tightly coupled.

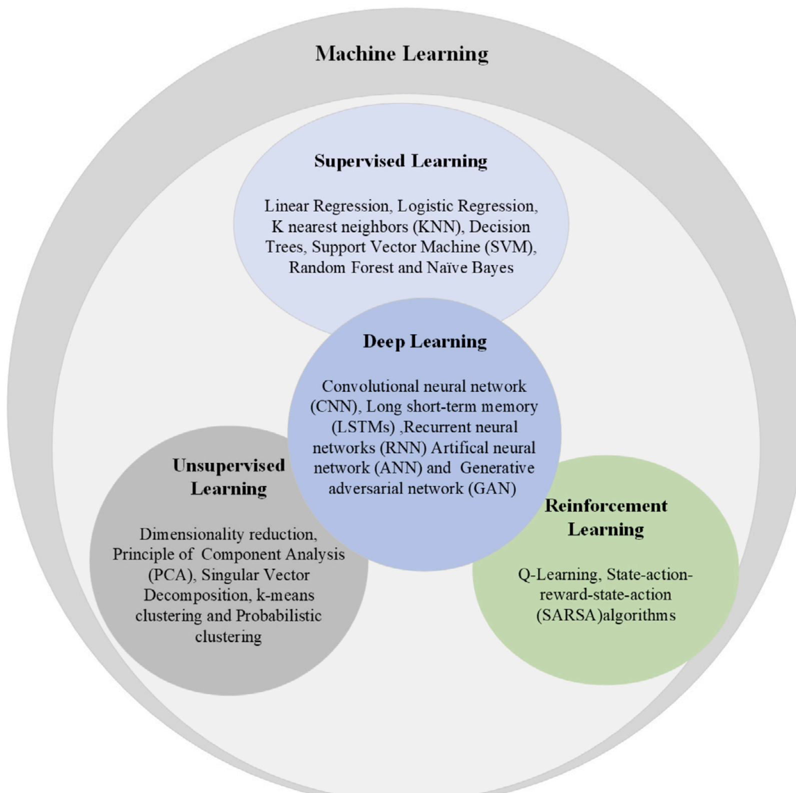

Fig. 10. Classification of AI/ML technologies (Wazid et al., 2021).

4.3. AIoT technologies

In this section, we divide AIoT technologies into AI, IoT and communications to present a comprehensive overview.

4.3.1. AI/ML technologies

AIoT uses extensive ML to implement model-based and data-centric decision-making. There are many classifications of AI/ML encompassing supervised, unsupervised and re-reinforcement learning. They include a wide variety of intelligent applications such as natural language processing, speech recognition, virtual agents, decision management, bio-metrics, robotic process automation technologies, etc. Fig. 10 proposed by Wazid et al. (2021) summarizes the different approaches.

As an application of distributed ML and as mentioned before, FL enables distributed devices to collaboratively train a shared AI model while keeping all the training data locally. With the development of FL and the increasing computing power of edge devices, FL is rapidly becoming an effective solution for data privacy-preserving in the AIoT domain. By locating the computation in edge devices and ensuring that the user's data does not leave the local area, FL protects user privacy against leakage (Zhang et al., 2020; Yin et al., 2022).

4.3.2. IoT technologies

IoT technologies are the backbone of AIoT applications as they enable data acquisition across different types of hardware devices (e.g., sensors, smart cameras, RFID, embedded systems, drones, smartphones, etc.) and provide the connectivity to enable the devices to communicate with each other and forward the data to a target destination for processing and storage (Chang et al., 2021).

An IoT devices classification model presented by Cvitić et al. (2021) for classifying traffic features generated by IoT devices and analyzed the possibilities of applying those features for classifying IoT devices.

IoT technologies can be further divided into three: hardware, software and networking technologies. IoT hardware collects the data. IoT software supports data normalization, analysis, manipulation and security as well as, when needed, AI model deployment. Various IoT software solutions are readily available (Knud, 2019; Satyajit, 2022). IoT connectivity includes the actual networking technologies to connect the devices to the gateways and the cloud. Different IoT hardware and software are used in AIoT and are presented in Fig. 11. Connectivity in IoT will be explained in the next section (Note that connectivity and communication are used in this paper interchangeably).

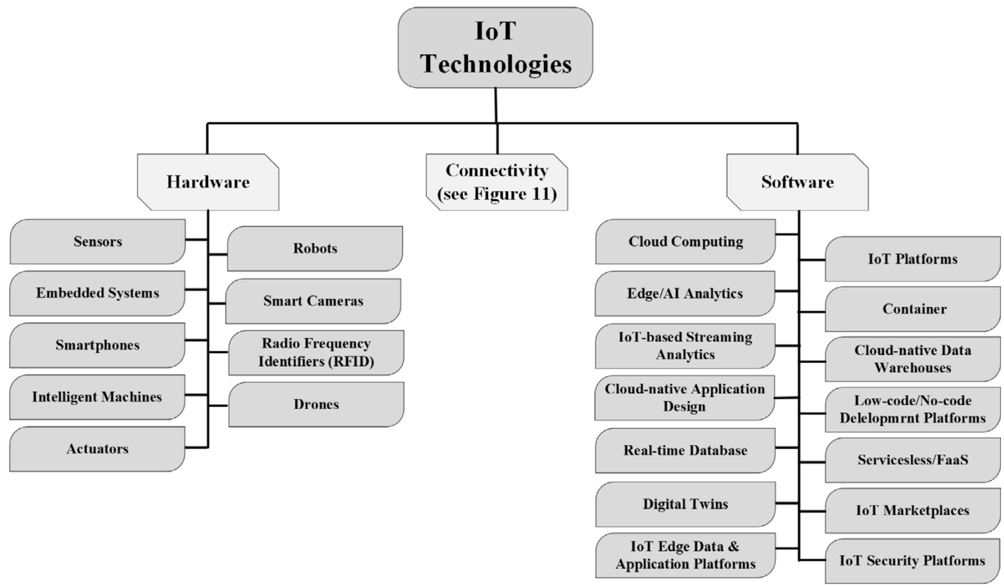

Fig. 11. Classification of IoT technologies.

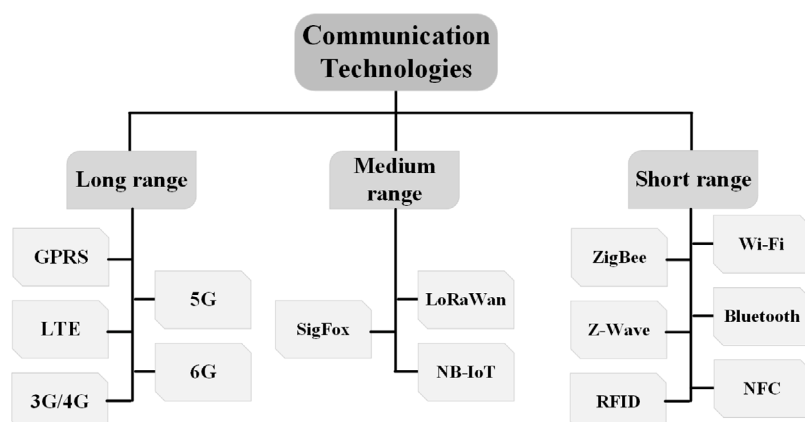

Fig. 12. Communications technologies.

4.3.3. Communications technologies

Different communications technologies are used to connect AIoT devices to each other, and to edge/fog or cloud nodes. These technologies can be further divided into three main short, medium and long-range groups as shown in Fig. 12. Table 8 also compares the communications technologies based on technology standards, data rate, frequency and range.

Long-range communications technologies including both wired and wireless, such as General Packet Radio Service (GPRS), Long-Term Evolution (LTE), Third Generation (3G), Fourth Generation (4G), Fifth Generation (5G) and soon Six Generation (6G) are mainly used for communications between the edge/fog and the cloud. For SA, 5G and 6G technologies will most likely predominate in the future because of high reliability, low latency, wide communications ranges and high data transmission capabilities (Qazi et al., 2022). However, deploying these technologies in rural areas is a major challenge due to installation costs (with small cells) and the lack of access to high-speed backhauls. In this case, private networks (e.g., private 5G) can already be used.[3] Experimental wireless and long-range optical platforms are also considered.[4]

For communications between the end-devices layer and edge/fog layer, medium-range solutions such as Narrowband Internet of Things (NB-IoT), Long Range Wide Area Networks (LoRaWAN) and SigFox, and short-range solutions such as Near Field Communication (NFC), RFID, Bluetooth, Z-Wave, Wireless Fidelity (WIFI), Building Automation and Control networks (BACnet) and ZigBee are used.

For the literature, the most commonly used communications technologies well-adapted for SA at the end-devices layer of SA are LoRaWAN, ZigBee and BACnet due to their low power consumption, small size, ease of implementation, simplicity, scalability, range (usually medium) and in the case of BACnet heritage from industrial automation. In addition, there are some studies to adapt WIFI for SA, such as “WIFI-based long distance (WiLD)” proposed by Ahmed et al. (2018) for monitoring and controlling smart farming in rural areas because of its low cost.

It is worth mentioning that an investigation and comparison of the performance of different wireless communications technologies (WIFI, LoRaWAN and ZigBee), in terms of energy consumption in agriculture monitoring, showed that LoRaWAN works well for SA when network lifetime and energy consumption are priorities (Ray, 2018; Sadowski and Spachos, 2020). There is also an increasing number of sensors that support LoRa and that should enable its penetration in SA.

[3] https://www.uctel.co.uk/blog/private-5g-and-agriculture-the-digital-age
[4] https://arawireless.org

Table 8
Comparison of communications technologies.

Tech	Stand	Range	Freq	Max.DR
ZigBee	ZigBee alliance, IEEE 802.15.4	less than 1 km	902–928 MHz, 2.4 GHz	250 Kbps
Z-wave	Z-wave	100 m	868 MHz	100 Kbps
WiFi	IEEE 802.11	100 m	2.4–60 GHz	10 Mbps
Bluetooth	IEEE 802.15.1	100 m	2.45 GHz	1–3 Mbps
RFID	Many standards	1 m	13.56 MHz	423 Mbps
NFC	ISO /IEC 13157	0.1 m	13.56 MHz	106 kbps–424 Kbps
BACnet	ANSI/ASHRAE Standard 135	1.2 km (RS-485)	Depends on physical layer used (Ethernet, RS-485)	10 Mbps to 100 Gbps (Ethernet), 9.6 kbps to 115.2 kbps (RS-485)
LoRa	LoRa alliance	15 km	915–928 MHz	50 Kbps
SigFox	SigFox Collaboration of ETSI	20+km	868 and 915–928 MHz	100 Kbps
NB-IoT	3GPP	1 km (urban), 10 km (rural)	700, 800, 900 MHz	200 Kbps
GPRS	3GPP	25 km/10 km	GSM 850, 1900 MHz	171 Kbps
LTE	3GPP	28 km/10 km	700–2600 MHz	0.1–1 Gbps
3G/4G	UMTS/LTE	26 km/28 km	GSM 850, 1900 MHz/700–2600 MHz	400.73 Mbps/0.1–1 Gbps
5G	IEEE 802.11ac/ITU IMT-2020	28 km	700 MHz–72 GHz	20 Gbps
6G	IEEE 802.11ax		10 THz	1 Tbps

Tech: Technologies; Stand: Standards; Freq: Frequency; Max.DR: Maximum data rate.

5. Smart agriculture (SA)

The agricultural evolution started with Agriculture 1.0, with indigenous tools for farming, then continued to Agriculture 2.0, with fertilizers and tractors then to Agriculture 3.0, where monitoring systems and decision systems were introduced, and finally to Agriculture 4.0, where smart farming (SA) is currently in use (Liu et al., 2020) with automation and embedded-decision systems. As mentioned before AI and IoT are inherently linked to SA. Specific technologies that can be included in agriculture 4.0 include robotics, blockchain and other cyber-security technologies, drones (Unmanned Aerial Vehicles or UAV), satellites and of course a wide variety of sensors including novel devices using nanotechnology (Mitra et al., 2022).

Traditional (conventional) farming of levels 2 and 3 in the evolution, in which traditional techniques are used for crop cultivation (Durai and Shamili, 2022) is still dominant in the industry. SA has special requirements such as sensing, processing and connectivity that are still not available everywhere. In addition, AIoT solutions designed for other non-SA use cases may not comply with SA requirements. However, we have seen that the technologies presented in Section 4.3 can be adapted to SA when they meet a wide range of requirements since SA targets open-field solutions (with drones for example) as well as greenhouses and vertical farms (Controlled Environment Agriculture (CEA)).

Some studies in SA compared the result of AIoT-based solutions with traditional solutions called farmer treatment (FMR), which is the normal practice of the local farmers (e.g., smart irrigation comparison in Amatya et al. (2016)).

While SA may or may not include AI, in this section, we focus on the AIoT architectures and solutions that have been adapted to SA.

5.1. AIoT solutions for smart agriculture (SA)

AIoT solutions in SA may need to support quite large-scale environments. A tomato farm which was referred in the study on Ambient IoT in 3GPP release 19 (AmbientIoT3GPP, 2023), is a good real case to show the scale of the problem in SA. This farm is using ambient power-enabled IoT devices, which are either battery-less or with limited energy storage capability (e.g. several hundred micro-watts) getting energy through the harvesting of radio waves, light, motion, heat or similar sources. The optimal scale considered for this greenhouse construction is 8 10 m span, 80 100 m length. A single greenhouse area reaches nearly 70,000 square meters, equivalent to ten standard football field sizes. A team of eight people controls this greenhouse in front of the computer and knows everything that is going on in the greenhouse. "For example, the temperature and humidity in each area of the 70,000 square meters greenhouse, the temperature of the underground heating tube, the concentration of carbon dioxide are how much, whether the fan is opened, and whether the nutrition is enough for each tomato" (AmbientIoT3GPP, 2023).

We can classify AIoT-based proposed SA solutions into academic and industrial and further categorize the academia solutions into six sub-classes as shown in Fig. 13 (Katiyar and Farhana, 2021; Mitra et al., 2022), crop, soil, water and disease management, enhanced harvesting techniques and supply chain management. These classes can inter-work to provide special use cases. In this section, we analyze each solution in terms of: type, features, ML model if appropriate and data sources. This is summarized in the form of specific tables in their corresponding subsections.

5.1.1. Academic solutions

The details of SA academic research are presented below.

Crop Management: Crop management is a set of agricultural practices to improve growth, development and yield. It begins with seedbed preparations, sowing and crop maintenance, including pest and disease detection, and it ends with harvest, processing, storage and distribution. Hence it includes end-to-end crop production activities that are under the responsibility of the producer.

Several crop management systems consider growth monitoring and yield prediction (Reddy and Kumar, 2021; Schwalbert et al., 2020; Kumar et al., 2019a) for different types of production such as wheat,

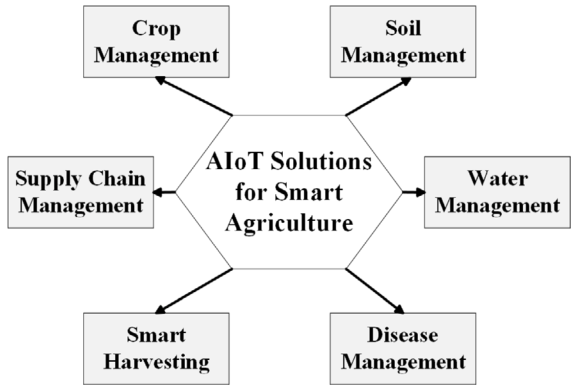

Fig. 13. AIoT solutions for SA.

maize, rice, coffee, tea, cherries, etc. Crop disease detection (scouting) and remediation is the focus of Jiang et al. (2019), Guo et al. (2020). Numerous crop recommendation approaches using different models are available in Kulkarni et al. (2018), Durai and Shamili (2022). Crop recommendations are also the focus of many other papers (Doshi et al., 2018; Kumar et al., 2019b; Suchithra and Pai, 2020; Pawar and Chillarge, 2018; Chougule et al., 2019; Patel and Patel, 2020; Kedlaya et al., 2021; Patil et al., 2021; Pande et al., 2021; Sadia et al., 2021).

More recently, a SA soybean crop yield prediction using FL was the topic of Manoj et al. (2022). In this paper, the researchers compared the performance of FL, Deep Learning (DL) and other more generic ML for the prediction of soybean yield. The result showed the overall performance of the comparison for the validation set metrics: FL using ResNet-16 Regression outperformed ML and DL but at the expense of added complexity. In addition, Durrant et al. (2022) proposed a data-sharing approach for improving production optimization through soybean yield prediction using a variety of ML approaches including FL, Convolutional Neural Networks (CNNs), rectified linear activation function (ReLU), recursive neural networks (RNN), long short-term memory (LSTM) and multi-layer-perceptron (MLP) on remote sensing images, weather and soil data. The results indicated that even simple approaches can give improved measurements compared to manual evaluation.

While AI shows promise across all research papers, factors that have been rarely considered in academic research are the costs of investments, the price of the targeted crops and the added revenue generated by the SA operation. Authors of Priyadharshini et al. (2021) used traditional linear regression (LR) and Neural Networks (NNs) to consider the combined effects of the cost of cultivation, crop price modeling, nutrient contents, rainfall and temperature data. They showed that data-driven and AI approaches in SA can improve revenues by better planning and forecasting.

Soil Management: There are different types of soil and many crops require specific soil types, fertilization and nutrients for optimum growth and production. There are several published use cases in soil management including soil type classification (Vincent et al., 2019), land recommendation focus (Patel and Patel, 2020), soil quality monitoring (Murugamani et al., 2022), moisture monitoring (Araya et al., 2020; Bhattacherjee et al., 2020), overall soil health monitoring (Jain et al., 2020), salinity estimation (Klibi et al., 2020), nutrient content analysis (Dong et al., 2018), and soil manure composition (Ather et al., 2022; Chang et al., 2019). As part of soil management, carbon farming is a new agricultural method by which sequestering atmospheric carbon in crop vegetation, soil and biomass reduces atmospheric greenhouse gas emissions. At the same time, the carbon sequestered in plant material and soil can improve farm productivity and increase soil health including aiding plant growth, building drought and flood resistance, increasing soil water retention capacity and decreasing the amount of fertilizers used in the farm. Due to some governmental policies for encouraging carbon farming, more and more farmers are engaging in using this practice (Moinet et al., 2023; Feng et al., 2023; Payen et al., 2023) as presented in Table 10.

Water Management: Water management in agriculture includes practices that cover both the quality and the quantity of water used. As an important component of SA, water management uses smart irrigation systems to properly control the use of water (Tomaszewski and Kołakowski, 2023). There are several known use cases in smart water management such as AIoT solutions for real-time water quality monitoring (Wang et al., 2021; Chiu et al., 2022; Alahi et al., 2018). In Abinaya et al. (2019), Miao et al. (2022), authors used water analysis to evaluate fish well-being in a fish-farm operation. Guillén-Navarro et al. (2020), focused on optimization of water consumption, using anti-frost sprinkler irrigation technique. A real-time soil wetness monitoring for water management in irrigation is the target of Nursyahid et al. (2019). A use case for managing hydroponic farming water management is developed in the paper of Mehra et al. (2018). The research presented in Mohammed et al. (2019), Dahane et al. (2020) focused on real-time smart irrigation, while Usmonov and Gregoretti (2017) proposes a drip irrigation control system for irrigation control. A flood observation and early warning system using AIoT (Sung et al., 2022) was presented to effectively forecast floods using a fuzzy algorithm. A special use case, presented in Manikandan et al. (2022), addressed paddy rice irrigation by considering the most important growth parameters in rice including the crop growth level. Evapotranspiration (ETo) evaluation was available in the papers of Antonopoulos and Antonopoulos (2017), Nema et al. (2017), Elbeltagi et al. (2020) and Elbeltagi et al. (2022) for requirements, estimation, calculation and prediction. ETo is an important derived parameter needed to evaluate how plants react to the irrigation and environmental humidity. The research focused on predicting ETo using different ML models. As presented in Table 11, most of the papers on water and irrigation considered soil moisture, humidity, temperature, oxygen, water level and pH as important parameters. However, Wang et al. (2021) also considered nitrates and phosphates concentration (Nitrate-Nitrogen (NO3-N), Phosphate (PO4), Nitrite-Nitrogen (NO2-N), Ammonia-Nitrogen (NH3-N)) and other parameters. For open field SA, Antonopoulos and Antonopoulos (2017), Nema et al. (2017), Elbeltagi et al. (2020) and Elbeltagi et al. (2022) considered weather, solar radiation, rain forecast, rain probability and wind speed also to have accurate models of water consumption.

In the AI realm, Fog-assisted FL (FogFL) (Saha et al., 2020) proposed a smart irrigation scheduling application where sensor nodes monitor weather and soil data and communicate the data to the edge devices for the local model update. The local model is forwarded to the fog node for local aggregation and after certain rounds, the cloud application selects an optimal fog node, based on a greedy heuristic approach, to do the global aggregation. The FogFL framework reduced the global aggregation rounds, communication latency and energy consumption of the resource-constrained edge devices and increased the reliability of

Table 9
Crop management solution.

Subsolution	Ref.	Features	ML model	Data source	Comments
crop monitoring	Kumar et al. (2019a)	images	OpenCV	private	growth prediction
	Torres-Sanchez et al. (2020)	temperature	MLR, MNLR	private	predict shelf life quality losses
	Mehra et al. (2018), Jung et al. (2020)	water level, pH, temperature, humidity, and light intensity	ANN, NARX and RNN-LSTM	private	action control prediction
crop recommendation	Reddy et al. (2019)	depth, texture, pH, soil color, water holding	CHAID, KNN, Naive Bayes	private	predicting crop to the farmers
	Setiadi et al. (2020)	weather, yields, selling prices	Naive Bayes	public (BMKG)	suggesting suitable crop to farmers
	Doshi et al. (2018)	temperature and rainfall	Naive Bayes, SVM, RF	public	selecting crop to farmers
	Kumar et al. (2019b)	soil color, pH, rainfall, temperature	SVM,DT, Logistic R	public	crop recommendation
	Patel and Patel (2020)	soil types, quality, crop, climate, water	KNN, SVM	private	predicting crop to the farmer
	Pande et al. (2021)	crop, year, season, soil type, area, region	SVM, KNN, ANN, RF, MLR	public	crop recommendation
	Durai and Shamili (2022)	pH, rainfall	Naıve-B, Logistic-R, SVM, DT, RF, KNN,	public (Kaggle)	predict crop, pesticides, weed and cost
	Priyadharshini et al. (2021)	rainfall, temperature, pH, soil type, NPK and location	NN and Linear-R	public (Kaggle)	profit analysis of crops based on the previous data
fertilizer recommendation	Haban et al. (2020)	NPK, season	Fuzzy	public	predict fertilizer
yield prediction	Manoj et al. (2022)	crop, soil,weather	FL,ResNet-16,ResNet-28	public	soybean yield prediction
	Durrant et al. (2022)	images, weather, soil	FL,CNN, ReLU, RNN, LSTM MLP	private	data sharing for soybean yield prediction
iron deficiency prediction	Yu et al. (2022)	images	FL	public	soybean iron deficiency chlorosis prediction

Table 10
Soil management solution.

Subsolution	Ref.	Features	ML model	Data source	Comments
soil type classification	Vincent et al. (2019)	soil texture, granular, water content, degree saturation, pH, salinity	ANN, MLP	private	land suitability assessment
land recommendation	Patel and Patel (2020)	soil types, soil quality, crop, climate, water demand	SVM, KNN	public	land recommendation
soil quality monitoring	Murugamani et al. (2022)	soil moisture, soil pH, humidity temperature	SVM	private	assessment of soil quality
soil moisture monitoring	Araya et al. (2020), Bhattacherjee et al. (2020)	images	SVR, RF, ANN, RVR, BRT	private	soil moisture prediction
soil health monitoring	Jain et al. (2020)	images	SVR, RF	private	soil health assessment
soil salinity monitoring	Klibi et al. (2020)	images	SVM,AE, KNN,DT	private	soil salinity prediction
phosphorous monitoring	Dong et al. (2018)	images	CNN	private	soil phosphorus prediction
soil manure composition	Ather et al. (2022)	soil pH, temperature, and NPK	ANN	public	manure prediction
carbon sequestering	Moinet et al. (2023), Feng et al. (2023) and Payen et al. (2023)	soil nutrient, retention	Nill	Nill	reduce atmospheric carbon

Table 11
Water management solution.

Subsolution	Ref.	Features	ML model	Data source	Comments
water quality monitoring	Wang et al. (2021)	NO3-N, PO4, NO2-N, NH3-N	GRNN, MPR	laboratory data	water quality
	Abinaya et al. (2019)	temperature, pH, dissolved oxygen, water level, foul smell, ammonia	Naive Bayes	private	aquaculture water quality monitoring and control
	Miao et al. (2022)	dissolved oxygen, pH, temperature	DL	private	water quality
	Chiu et al. (2022)	pH, temperature, dissolved oxygen, turbidity	ANN	private	fish fond water quality monitoring
anti-frost sprinkler	Guillén-Navarro et al. (2020)	temperature, humidity, wind speed	LSTM	public (SIAM)	accuracy to predict low temperature
soil wetness monitoring.	Nursyahid et al. (2019)	soil moisture	Linear regression	private	soil moisture monitoring
irrigation monitoring	Dahane et al. (2020)	soil moisture, air temperature, air humidity	LSTM, GRU	private	optimizing water resources
	Rahmouni et al. (2022a)	soil moisture, temperature, humidity, barometric pressure	not specify	private	Irrigation prediction
flood monitoring	Sung et al. (2022), Manikandan et al. (2022)	water level, rainfall intensity, water speed land slop	Fuzzy	private	flood prediction accuracy
irrigation scheduling	Alves et al. (2023)	weather, soil moisture, DAP, rain forecast	Penman Monteith, Fuzzy	private	water saving
	Souza et al. (2020)	soil moisture, weather, rain forecast, ET	fuzzy	private	water saving
	Granata (2019)	temperature, solar radiation, wind speed, humidity	ANN	public	evapotranspiration estimation
	Elbeltagi et al. (2020, 2022)	weather data	ANN	public	evapotranspiration prediction
	Başağaoğlu et al. (2021)	weather data	NGBoost-XGBoost, probability	public	evapotranspiration prediction
	Saha et al. (2020)	soil moisture, temperature, humidity	FL, MLP, ReLU	public	watering planning

the system by reducing dependency on a centralized entity. The water management solutions are summarized in Table 11.

Disease Management: Pests and diseases are major challenges that affect the quality and quantity of crop production. Crop growth is an important element in the optimization of adequate food production and is affected by disease and stress including, as seen previously, improper irrigation, biotic stress, diseases and soil salinization (sodium chloride (NaCl) which occur naturally or due to improper anthropogenic activities). Disease prediction, detection and remediation are thus major research areas in SA. Disease and stress identification and prediction can help in providing more food productivity (Udutalapally et al., 2020) by allowing us to determine the best approaches to remediation.

Plant stresses are either biotic (infectious) or abiotic (non-infectious). Biotic stresses are usually caused by infection causal agents such as fungi, bacteria, parasitic plants, viruses and nematodes. The non-infectious stress (abiotic) is caused by nutrient deficiencies, poor farm management, or unfavorable environmental conditions. These include too-low or too-high temperatures, inappropriate moisture levels, high winds or uneven wind speed, drought or flood, soil compaction, frequent and heavy rain, improper water management, deficiency or excess of nutrients and chemical injury caused by pesticides or salt.

There are several use cases in crop disease management (scouting) in the literature. They include disease detection and prediction, weed monitoring, disease classification, and pest monitoring, detection and classification. They are listed in Table 12. Disease management in these solutions are facilitated by the emergence of high-quality hyperspectral cameras and libraries of image processing algorithms.

One approach of particular interest is an FL-based method using UAVs imaging for disease identification and classification is presented in Khan et al. (2022). In this paper, UAVs on four different farms locations are used to detect pest occurrences. The proposed pest classification solution accurately classified the nine available pests in Kaggle pest datasets using FedAvg. In research conducted in Patros et al. (2022), another FL framework was developed for rural weed detection using hyper-spectral pasture images captured from three different sites.

Smart Harvesting: Smart harvesting can be performed with the help of autonomous harvesters and robots. Smart harvesting has used different types of sensors and imaging systems such as ultrasonic sensors, global navigation satellite systems (GNSS), depth cameras, single-shot multi-box detectors, RFID, Three-dimensional (3D) sensors and red, green and blue (RGB) cameras to guide the harvester and define optimal times for collecting the crops.

Several solutions have been published in smart harvesting. Object detection is the focus of Chen et al. (2020), Cheng and Zhang (2020), whereas the paper in Hsu et al. (2022) targeted fruit classification. Finally, the authors in Paul et al. (2021) used color recognition to determine the ripeness of crops and decide on the best harvesting times as presented in Table 13.

Supply Chain Management: Supply Chain Management (SCM) is the process of planning, implementing and controlling the operations of the supply chain to meet customer requirements as efficiently as

Table 12
Disease management solution.

Subsolution	Ref.	Features	ML model	Data source	Comments
disease monitoring	Jiang et al. (2019)	images	CNN GoogleNet inception, rainbow	public	apple leaf disease detection
	Pallagani et al. (2019), Udutalapally et al. (2020)	images	CNN	public	crop disease prediction
	Bhatia et al. (2021)	images	Tensoflow	public	crop disease prediction
	Li et al. (2022b)	images	InceptionV3, ViT, MobileNet	public	plant disease detection
	Chatterjee et al. (2021)	diseases symptoms, behavior changes	Fully-Connected NN(FCNN)	private	cow disease prediction
	Chen et al. (2019)	temperature, humidity, rainfall, barometric pressure	CNN	private	rice blast disease detection
	Antico et al. (2022)	images	FL, CNN,	public	maize disease prediction
	Saberi Anari (2022)	images	Multiple SVM	public	classifying images of crop disease
disease detection and control	Murugamani et al. (2022)	images	SVM	private	detect and control cotton leaf diseases
	Li et al. (2022d)	images	ViT	public	detect and control cotton leaf diseases
pests management	Liu et al. (2019)	images	CNN	public	pests detection and classification
	Chen et al. (2020)	images	YOLOv3, CNN, LSTM	private	pest identification
	Guo et al. (2020)	images	Chan–Vese, RPN	public	pest identification
	Khan et al. (2022)	images	FL, CNN,ResNet-101,ResNet50	public	pests management
	Patel and Patel (2020)	soil types, pH, electric conductivity	KNN, SVM	private	pesticide recommendation
weeds management	Partel et al. (2019)	images	YOLOv3 with CNN	private	weed detection, mapping, spraying
	Patros et al. (2022)	images	FL,ANN, ReLU,	private	unwanted weeds management

Table 13
Smart harvesting solution.

Subsolution	Ref.	Features	ML model	Data source	Comments
object detection	Cheng and Zhang (2020)	images	YOLOv4, CNN ResNet	public	flower detection and classification
fruit classification	Hsu et al. (2022)	images	CNN, YOLOv3-tiny	Private	dragonfruit ripeness prediction
color recognition	Paul et al. (2021)	images	Naive Bayes	private	cultivation prediction

possible. The use of AI in SCM is currently a major research area. AIoT can have an important impact on SCM in SA: SCM defines the requirements at each layer of food production that AIoT can meet. Supply chain management contributions in SA include (Ahamed and Vignesh, 2022; Nahr et al., 2021; Nozari et al., 2022; Liu et al., 2016) dedicated to ensuring a secure food supply chain and safe delivery of the food items (see Table 14). In addition, a technical solution based on FL was presented by Durrant et al. (2022) that used decentralized data to develop a cross-silo ML model. This solution facilitates data sharing across the supply chain for improving production optimization through soybean yield prediction. The authors also provided potential use cases in which such methods can assist in other problem settings.

5.1.2. Industrial solutions

There are an increasing number of industrial solutions presented by different companies helping farmers to make proper decisions in managing their farms. Some are presented in this section.

For example, there are SA solutions delivered by Nokia in several countries in the series of projects called real action (Nokia, 2023; Aero-Farms, 2021). In India, Nokia in collaboration with Vodafone started the pilot project across Indian states in 100 locations in which 50,000 farmers are expected to benefit from the proposed solution, SmartAgri, in improving their productivity and income. More than 400 sensors were installed as part of the project across over 100,000 hectares of farmland. This solution uses Nokia's Worldwide IoT Network Grid (WING). For crop management and includes smart pesticide control, smart irrigation, a platform for commodity exchange and proactive information sharing frameworks on weather and crops which offers weather forecasts and information on irrigation management and supports local languages (NS Agriculture Staff Writer, 2020). Also in 2019, Nokia piloted a Smart Agriculture-as-a-Service in Algeria.

Another existing solution is from Metos (by Pessl) in Austria for disease management which provides more than 80 disease management models for more than 40 different crops. The solutions are distributed

Table 14
Supply chain management solution.

Ref.	Features	ML model	Comment
Ahamed and Vignesh (2022)	autonomous vehicle, robot	DLT	food supply chain
Nahr et al. (2021)	food materials	Not specify	green supply chain
Nozari et al. (2022)	interviews, questionnaires	Fuzzy DEMATEL	supply chain
Aliahmadi et al. (2022)	consumers, producers, suppliers	Not specify	sustainable supply chain
Durrant et al. (2022)	images	FL	soft fruit production optimization and fresh food distribution

to Europe, Asia-Middle East, Asia, North America, Central America, South America, Africa, Australia and New Zealand (Metos, 2022).

MyEasyFarm and its global partners work with farmers every day to help them make the best choices and be more effective in maximizing competitiveness and profitability while protecting the environment (MyEasyFarm, 2023). MyEasyCarbon engaged in low-carbon projects by increasing carbon storage in the soil (carbon sequestering) to reduce carbon emissions using digital tools that support the agroecological transition.

Solutions provided by startups include Ferme d'Hiver (FH) in Canada.[5] FH is specialized in vertical agriculture. In FH's farm, strawberries are grown vertically in a closed controlled environment using LED illumination, advanced HVAC and automatic irrigation without chemicals. Intelligent controllers and AIoT are planned to be added to the product offering. FH intends to sell its technology to provide local production and reduce the need for foreign imports.

ISAGRI is a solution for grain growers that helps farmers to make the best choices for their farming operations. It includes regulatory safety as well as means to meet environmental challenges for better optimization of pig farming, dairy farm management, sucker cattle farming and small ruminant farming (ISAGRI, 2023).

ATIM monitors temperature in greenhouses and allows fast action via SMS alerts and for example ensures mist spraying in the vineyard to prevent damage due to frost (ATIM, 2023) until the temperature rises again. It has been deployed in the Burgundy wine-producing region in France.

Another solution for crop monitoring, cultivation and production was developed by Elzeard. It enables farmers to schedule their production activity for the entire season(s) using a planning module. It handles the end-to-end agricultural plans from the determination of the marketing requirements, the setting and production goals and the optimization of crop rotations. The cultivation module consists of the features required for crop monitoring, farm activity organization, and data collecting for operation traceability (Elzeard, 2023).

The Agribot Platform, a United Kingdom smart agriculture solution platform (Agribot Platform, 2023; Rai et al., 2022), enables farmers to make disease treatment decisions that are both environmentally and economically advantageous by giving them an understanding of crop health which can be received on their smartphone. Agribot can perform several tasks including AI-based disease diagnosis, crop health status, the detection of soil stress and the measurement of localized weather. The company also proposes an Agribot Edge solution to capture pictures that are then processed using image processing software and AI decision-making. When the application identifies an unhealthy crop or stress problem, it will deliver a message outlining the problem and can automatically perform the appropriate action depending on the situation.

[5] www.fermedhiver.com

LEMKEN provides SA solutions such as soil cultivation (i.e., ploughing, reconsolidation, seedbed preparation and stubble cultivation), sowing (drill seeding, precision seeding and intercrop seeding) and crop care (fertilization technology) across Europe, Asia, North America and Africa (LEMKEN, 2023).

Microsoft developed the FarmBeats system, recently transitioned to a product called Azure FarmBeats, the Microsoft cloud-based agriculture offering.[6] It is a complete digital agriculture solution. Microsoft works with its SA partners to prototype agricultural services for farmers. The system gathers a lot of information, spatial, historical and temporal, about every farm, from several data sources, such as drones, satellites, sensors, cameras, tractors and weather stations. The technology employs AI to combine this data and infer likely occurrences on the farm. Partners have access to the information via APIs and they may subsequently create agricultural insights for growers using their in-depth agricultural knowledge (Chandra et al., 2022; Ye, 2021).

Agro Smart lab is another solution that provides mathematical models for scouting using the weather data obtained from the weather station to predict diseases and monitor the appearance of pests (Smartlab, 2023).

Finally, Farms.io (farmsio, 2023) is an application for farm management, crop monitoring, carbon analysis, link to markets, production traceability, land use and land cover, post-harvest climate change monitoring and agriculture advisory. This is dedicated to helping a farmer in decision-making as presented in Table 15.

5.1.3. Discussion

To summarize the entire review, we conclude that research on crop and disease management has the highest number of published articles, followed by smart monitoring and water management, then soil management, smart harvesting and finally, the least cited topic, supply chain management. This shows where research has focused and opens ways for innovation.

Finally, regarding the datasets, there are some available datasets for individual plants but we could not find an open or standard dataset for agricultural and environmental parameters across different crops. One of the common websites providing public datasets is Kaggle.com used by several papers. However, the lack of data is a major challenge to the implementation of AIoT in SA.

5.2. AIoT infrastructure for SA

This section explains AIoT architecture and frameworks used in SA.

[6] https://www.microsoft.com/en-us/research/project/farmbeats-iot-agriculture/

Table 15
Industrial solutions.

Ref.	Company	Solutions					
		Crop-M	Soil-M	Water-M	Disease-M	Smart-H	Supply chain-M
Nokia (2023), AeroFarms (2021)	Nokia	✓	✓	✓	✓		
Metos (2022)	Metos (by Pessl)	✓	✓	✓	✓		
ISAGRI (2023)	ISAGRI	✓		✓	✓		
ATIM (2023)	ATIM	✓					
Elzeard (2023)	Elzeard	✓		✓		✓	
Agribot Platform (2023), Rai et al. (2022)	Agribot	✓			✓		
LEMKEN (2023)	LEMKEN	✓	✓				
MyEasyFarm (2023)	MyEasyFarm	✓	✓		✓		
Chandra et al. (2022), Ye (2021)	FarmBeats	✓	✓		✓		
Smartlab (2023)	AGRO SMART LAB	✓	✓		✓		
farmsio (2023)	Farmsio	✓	✓		✓	✓	✓

Crop-M: Crop management; Soil-M: Soil Management; Water-M: Water management; Disease-M: Disease Management; Smart-H: Smart Harvesting; Supply chain-M: Supply chain Management.

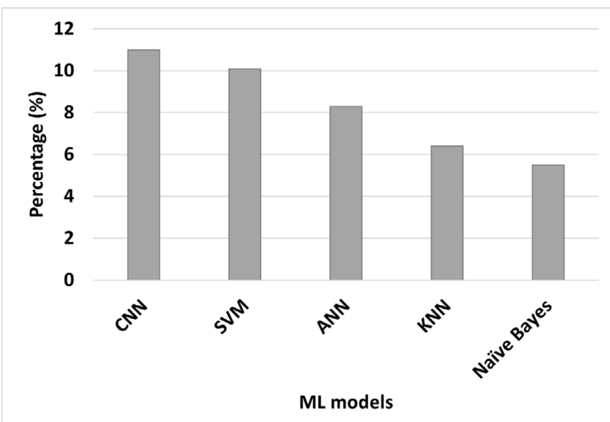

Fig. 14. Percentage of the 5 most popular ML models used in the articles reviewed in this survey. The percentage of every other remaining model (i.e., not mentioned in this figure) is under 5%.

5.2.1. SA architectures

While there is no standard AIoT infrastructure for SA, many similar architectures have been proposed. A common SA architecture comprises at the minimum an agricultural device layer, an edge/fog layer or data gateway and a cloud layer as shown in Fig. 6. Different IoT and AIoT devices can be deployed in the device layer for sensing, monitoring and tracking different activities of SA. Connectivity sublayers can be added consisting of the short-range and medium-range to long-range communications technologies. A connectivity layer 1 connects the AIoT devices layer with the edge/fog layer with short to medium-range technologies and connectivity layer 2 links the edge/fog layer with the cloud layer with long-range technologies. The edge/fog devices are responsible for the processing of the data generated at the device layer before transferring it to the cloud where it can be further processed and stored as illustrated in Fig. 6. As was mentioned previously, AI can be implemented horizontally and vertically at each layer.

A more succinct cloud-based (C-B) two-layer infrastructure was presented by Chen et al. (2020) where mobile devices and drones in the first layer were used to capture pest images in fruit trees. The collected data was then uploaded to a database in the cloud (cloud layer) for processing (e.g., recognition of the pests images and identification of the pests locations using deep learning algorithms). In addition, in the 1st layer, environmental sensors collect data to provide meta-data for the crop growth analysis. This solution uses devices (i.e., smartphones, drones, and sensors) without AI capabilities and the AI is solely cloud-based.

The architecture presented by Tomar and Kaur (2021) is also a two-layer C-B architecture consisting of a data collection layer and a cloud computing layer (cloud platform). The data collection layer includes many different sensors (temperature, humidity, and moisture) responsible for generating environmental data. The sensing devices used in this study are intelligent devices that can perform some basic AI-related inference tasks. The raw data can be sent to a gateway through short and medium-range communications technologies for example Bluetooth, WIFI, LORA, and SigFox and then to the cloud layer. Data analysis, processing and storage are performed in the cloud. Users can get access to the data and the analyzed results through the internet. Preliminary implementation results validated the approach.

In the architecture presented in Chen et al. (2020), Tomar and Kaur (2021), there is no specified layered architecture and each device is vertically integrated into the cloud. This can bring some concerns such as network traffic management and its impact on AI applications efficiency and real-time decision-making.

The architecture described in Mitra et al. (2022) is a good example of the three-layer Edge–Cloud (E–C) architecture for SA with an agriculture devices layer, an edge layer, and a cloud layer. In the device layer, sensors are deployed in various locations on the farm to acquire physical and environmental parameters: in the field, in the greenhouses, in animal paddocks, and on tractors. These end devices are not intelligent as they cannot perform in-device processing and would not be able to participate in AI decision-making: the intelligence is potentially in the edge and the cloud. As in other solutions, the raw data is transferred to the edge layer through WIFI, Bluetooth, and Z-Wave gateways. Edge devices are responsible for processing, filtering and encrypting the data before transmitting it to the cloud through high-speed cellular technologies. The cloud layer can process, analyze and save the massive data gathered on the farms.

The authors in Islam et al. (2021) also proposed a three-layer architecture consisting of perception, network and application layers. The perception layer consists of sensing devices, such as RFID tags, terminal devices and readers, used to collect data about pests, plant diseases, nutrient levels, humidity, wind speed and temperature. The collected data is transferred to the application layer via network connectivity. Users can remotely access the cloud applications for monitoring and controlling their farms.

Another three-layer C-B AIoT infrastructure is proposed in Guillén-Navarro et al. (2020) with the now familiar devices, connectivity and cloud layer. The devices layer of this system measures the environment and includes wind speed, humidity and temperature sensors. The sensed data is transmitted to the cloud layer where the LSTM analysis capabilities are located. The data and results are accessible from the cloud layer for monitoring and decision-making.

A more distributed infrastructure is available in Gupta et al. (2020). It introduces a four-layer E–C AIoT architecture with a physical layer, a network layer, edge layer and a cloud layer. Here again as in all SA infrastructures, the physical layer, the "IoT devices layer" includes sensors installed in a greenhouse or on farmlands, embedded in livestock, and added to autonomous tractors and drones (UAVs). Use cases for these devices include sensing and monitoring the environment and application-specific data and transmitting it to the edge layer through the communications layer. These are traditional sensors in the sense that they do not process the data or make decisions. The edge nodes are used to complement the sensing by processing the received data: real-time monitoring, visualization, and online ML model for detection, prediction, and diagnosis. The edge also transmits the data to the cloud for further processing: AI/ML, database clusters, data visualization, big data analytics and storage.

A four-layer Fog–cloud (F–C) infrastructure is presented by Muhammed et al. (2022). In addition, it introduced a user-friendly component for obtaining the data automatically without human intervention directly from devices using APIs. This system has the standard end-device layer with the edge/fog, connection and cloud layers. The end-devices layer provides the necessary information to provide the data and create user requests. The edge/fog layer includes a user request creator (URC), an inference and decision-making tools. The model training is done in the cloud to benefit from more powerful computing resources. Two connection layers are considered: the first is located between the end-devices and edge/fog layers to transfer raw data from end-devices to the edge/fog layer and the second is located between the edge/fog and cloud layers to transfer data between them.

Continuing the four-layer concepts, Ferrández-Pastor et al. (2016) also presented a four-layer E–C architecture consisting of a things layer, an edge layer, a communications layer and a cloud layer. An extension of this infrastructure, which is an E/F–C type is proposed in Ferrández-Pastor et al. (2018). This architecture added a fog layer between the edge and the cloud. The fog node aggregates the received data from the edge nodes and transfers them to the cloud through the communications layer. The cloud processes, analyzes and stores the data. Here, as in most currently proposed architectures, there is no AI processing at the IoT devices layer (things): all analysis and decision-making are done at the edge, fog, and cloud layer.

Finally, targeted system performance and type of application is an important factor to select among the mentioned architectures. Utilization of edge intelligence for lightweight applications (e.g., acoustic and ambient sensing in SA), will lead to an efficient system. However, more compute-intensive applications may need more edge–cloud collaboration (Alzuhair and Alghaihab, 2023) or edge-to-edge collaboration to provide accurate results and systems with high energy efficiency and optimized performance. Distributed learning and FL are two tools that make these collaborations possible. A comparison of central ML and FL performed for crop classification in a smart farm decentralized network was reported by Idoje et al. (2023). The research utilized climate data consisting of temperature, humidity, rainfall and pH for crop classification using a federated averaging model. The analysis of their result using the farm dataset showed that decentralized models achieved a faster convergence and higher accuracy than the centralized models (binary relevance Gaussian NB, Classifier chain Gaussian NB, and Label Powerset Gaussian NB).

A summary of the existing SA AIoT infrastructure with their strengths and weaknesses are presented in Table 16. As Table 16 shows tightly coupled architecture is rarely used in the related work. While the other domains as seen in Table 7 already started using tightly coupled architectures.

5.2.2. Frameworks/practical implementation of AIoT for SA

This section presents the available frameworks and practical implementation of AIoT for SA. Device management, model management, support of various AI techniques and edge device integration are the four main features of AIoT platforms mentioned by Panduman et al. (2024). These frameworks need a data model to be built on top of it. Most of these frameworks follow the FIWARE data model framework.[7] Considering AIoT frameworks, the research presented by Rahmouni et al. (2022b) illustrated an example of AIoT framework for precision agriculture which showcases how AIoT can impact modern agriculture by implementing data-driven solutions based on low-cost devices and open source technologies, empowered by Edge Intelligence.[8] Also, the research of Li et al. (2022c) designed an AIoT system for SA based on front and rear end separation and a Model View View Model (MVVM) framework for handling complex business logics and easy integration of AI algorithms. They constructed a web page for the front end using Vue.js and Element and the rear end business logic using the Python Django framework. The data interaction between the front and rear end was via Axios. They integrated basic application functions such as historical data query, real-time data monitoring, abnormal data alerting and data visualization. Similarly, integrated deep learning plant disease and pest detection algorithms. Another example for helping farmer in mitigating the effects of climate change and improving their farming practices to increase the quality of their crop yield and food production was presented.[9] In Amazon Web Services (AWS), a smart agriculture startup based in France called Sencrop created a solution that enhances prediction accuracy and gives farmers access to precise climate condition insights to support data-driven decision-making. They build a microclimate application on AWS using Amazon EMR (a cloud big data solution for ML, interactive analytics and petabyte-scale data processing). Almost 30,000 farmers improved the sustainability of SA by reducing the use of spray treatment chemicals, water use and the trips tractors and harvesters using Sencrop's across Europe.[10] The research in Slama et al. (2023) presented AIoT Solution design, which is a simple canvas to visualize the key functional elements of a solution, and AIoT use case mapping, which clarifies how AIoT can best support typical use cases. Additionally, it introduced the AIoT framework, which includes an overview of AIoT, technical execution, development life-cycle perspective, data strategy, and design viewpoints and templates. The AIoT framework addresses aspects such as the agile approach, DevOps, trust and security, reliability and resilience, functional safety, and quality management. There are some solutions in the AWS marketplace examples can be EOSDA Crop Monitoring an online satellite-based precision agriculture platform for field monitoring created by EOS Data Analytics (EOSDA). It is a global provider of AI-powered satellite imagery analytics. The platform is a one-stop solution that integrates multiple types of data (crop health, weather conditions, crop rotation, field activities, elevation, soil moisture, and a host of other types) all in one place. Cropin Apps is another example of a solution in the AWS marketplace that enables the digitization of complex processes and workflows that span the complete agri-food value chain, a seed from the farm to a warehouse, all the way up to the fork. These solutions help streamline farm data capture and management and other complex field operations involved during seed production, seeds strain tracking & trialling across generations, crop protection and nutrition development both on & off the field for row crops, horticulture and plantations.[11]

7 https://www.fiware.org/
8 https://github.com/nabs13/Smart-Farming-though-AI-and-IoT
9 https://github.com/IoT-Communications/Smart-Farming
10 https://aws.amazon.com/fr/solutions/case-studies/sencrop-case-study/
11 https://aws.amazon.com/fr/solutions/agriculture/data-analytics/

Table 16
AIoT architectures for SA.

Ref.	Architecture				NL	AIoT Systems		Limitation	
	E/F–C	E–C	F–C	C-B		Loosely	Tightly	NAIPED	NEFN
(Khattab et al., 2016)				✓	3	✓		✓	
Ferrández-Pastor et al. (2016)		✓			4	✓		✓	
Ferrández-Pastor et al. (2018)	✓				5	✓		✓	
Chen et al. (2020)				✓	2	✓		✓	✓
Gupta et al. (2020)		✓			4	✓		✓	
Guillén-Navarro et al. (2020)				✓	3	✓		✓	✓
Tomar and Kaur (2021)				✓	2		✓		✓
Islam et al. (2021)				✓	3	✓		✓	✓
Mitra et al. (2022)		✓			3	✓		✓	
Muhammed et al. (2022)			✓		4	✓		✓	

NL: Number of Layers; E/F–C: Edge/Fog–Cloud; E–C: Edge–Cloud; F–C: Fog–Cloud; C-B: Cloud-Based; Loosely: Loosely coupled; Tightly: Tightly coupled; NAIPED: No AI Processing at the End Devices; NEFN: No Edge or Fog Nodes to process the data generated by end-devices.

5.2.3. Discussion

To summarize this section, we analyzed layering patterns of the available architectures and it was gathered that three layers are the most commonly adopted architectures followed by four layers. However, the two layers and five layers are found in rear cases. Similarly, Most of the existing architectures are loosely AIoT systems and Cloud-based architectures as they do not perform AI processing at the end devices layer but send their data to the Cloud layer for AI processing. For AIoT frameworks in SA, the AWS marketplace provides several frameworks such as Sencrop, EOS Data Analytics (EOSDA) and Cropin Apps for practical implementation of AIoT for SA.

5.3. AIoT technologies for SA

This section presents the existing technologies in SA in terms of AI, IoT and communications technologies.

5.3.1. AI technologies/techniques in SA

In this section, we summarize the findings on the use of AI in SA. Based on our reviews, we have noted that in smart monitoring solutions, Convolutional Neural Networks (CNNs) are widely used because of their higher accuracy in object detection and image classification.

For environmental monitoring such as temperature and humidity, CNNs are widely complemented or replaced by more feed-forward artificial NN (ANN) as well as Recursive NN (RNN). For crop management, supervised learning, including k-nearest neighbors (KNN), Naive Bayes, support vector machines (SVM), Random Forest (RF), Decision Tree (DT) and logistic regression are the most adopted models. Crop recommendation also relies on ensemble learning as shown in Table 9. In soil management solutions, it is the SVM model that is mostly adopted, ANN, KNN, FR and SVR were also frequently mentioned as presented in Table 10. Similarly, for water management solutions, LSTM was the most often cited model with ANN, Naive Bayes and linear regression (Table 11).

For disease management solutions, our investigation reveals that CNN is again most often used for disease detection and prediction, and for pest detection and classification because of the robustness of CNN and good accuracy in image classification. However, SVM, YOLOv3 and ViT were also frequently used as they are widely available as presented in Table 12.

CNN is still the most commonly adopted model for smart harvesting which deals with object detection and classification properly. Other models that were used include You Only Look Once (YOLO) YOLOv3, YOLOv4 YOLO-tiny as presented in Table 13.

For supply chain management Fuzzy logic, blockchain and other decision algorithms derived from big data were used (Table 14).

Furthermore, we listed all ML models used in the articles reviewed in this survey. These models are RF, LSTM, ReLU, YOLOv3, ViT, SVR, MLP, Linear Reg., Logistic Reg., MLR, OpenCV, MNLR, NARX, RNN-LSTM, CHAID, ResNet 16, ResNet 28, RNN, RVR, BRT, AE, GRNN, MPR, GRU, DLT, NGBoost, XGBoost, GoogleNet, Inception, Rainbow, TensorFlow, Inception V3, MobileNet, FCNN, Chain Vese, RPN, ResNet 101, ResNet 50, ResNet, YOLOv4 and YOLOv3-Tiny.

We then calculate the percentage of using each ML model in the articles under review. Fig. 14 shows the percentage of the 5 most popular ML models. The percentage of every other remaining model (i.e., not mentioned in Fig. 14) is under 5%.

5.3.2. IoT technologies

IoT technologies collect data from the location or place where they are deployed and use communications technologies to transfer the data to the target layer for processing. These devices include but are not limited to sensors used for environmental monitoring such as temperature sensors, soil moisture sensors, humidity sensors and so on. Similarly, drones, satellites and other cameras are used for capturing images of soil, pests and weeds. In this case, lightweight thermal and RGB (red–green–blue) cameras are mounted on a UAV to capture images. One of the other types of sensors used is for examining the audio signals. One example can be the study which used this information for identifying Queenlessness in Honeybee Hives using ML. This identification can be used by beekeepers as a means of promptly alerting them if the queen had died in any of their hives (Ruvinga et al., 2023). Some other source of data is generated from agricultural machinery. Today's agricultural equipment can collect a lot of information about soil and plants and machine performance as they operate in the field. For example, nowadays, grain harvesting combines are equipped with a yield monitoring system. Yield monitors can quantify and generate a map that shows the yield variability throughout the field. At the same time, the information generated by the yield monitor can be used to calculate position, velocity, and time spent during the harvesting operations. This information provides the field manager with information about the field efficiency, lost time, and operator performance. It can also be used to determine the optimum size of the combine for the given field size. The gap in the current system includes the lack of sensors that collect all the needed information. For example, no suitable sensor is commercially available to measure and map the variability of soil nitrate in the field. The data collected manually through field sampling often does not have the resolution needed for site-specific data analysis. The sheer volume of data needed for the decision support system and developing accurate management decisions means that excellent metadata and good data management are needed. Currently, some of the metadata collected manually is not digitized or has data entry errors and is not dependable.

5.3.3. Communications technologies

In SA, machine-to-machine (M2M) communications using many network technologies and protocols are needed to collaborate and share data. In addition, user applications and dashboards can be used to communicate requirements and retrieve and illustrate analysis for decision-making. Since in SA, sensors may be of different types and, as was seen, many wireless and wired standards can be used, there is a need for many technologies to provide SA connectivity. As a result, it can be expensive to establish and maintain an SA network (Sahitya et al., 2016; Chandra et al., 2022). Connectivity is also a major issue in large rural areas due to the lack of access to reliable broadband access. This is cited as one challenge in the deployment of SA solutions. The lack of network infrastructure will affect SA operations. For example, disruptions in wireless communication channels will prevent SA devices from communicating to the cloud for data processing and decision making (Mitra et al., 2022; Tao et al., 2021). This provides an incentive to move a lot of the SA data management to the edge and fog outside well-deserved areas. Given these challenges, there is a need to provide secure and robust communication for SA and look at functional decomposition to use local and edge resources, not just the cloud. The stakes are high but investments are flowing in. The United States (US) announced an initiative to bring broadband everywhere and compared it to the electrification efforts of 100 years ago. Initiatives like ARA Wireless[12] in the US also plan to bring broadband wireless (including free space optics) to rural areas. The 5GS Ambient IoT service study item in 3GPP release 19 is another initiative that includes agriculture use cases also from communication and architecture point of view reported in AmbientIoT3GPP (2023).

5.3.4. Discussion

In this section, we presented a summary of our findings in AIoT technologies based on our reviews. We have noted that the three most widely adopted AI technologies are CNN because of their higher accuracy in object detection and image classification, SVM and ANN. Considering IoT technologies, the commonly adopted IoT devices are sensors that are used for monitoring activities. Similarly, drones, smart cameras, embedded systems, smartphones and RFID are also used for capturing field data. For communications technologies, the most commonly used communications technologies well-adapted for SA at the end-devices layer are LoRaWAN, ZigBee and BACnet due to their low power consumption, small size, ease of implementation, simplicity, scalability, range (usually medium) and in the case of BACnet heritage from industrial automation. In addition, there are some studies to adapt WIFI for SA, such as "WIFI-based long distance (WiLD)" proposed by Ahmed et al. (2018) for monitoring and controlling smart farming in rural areas because of its low cost.

6. Challenges and future directions

Recent advances in AIoT in SA including AI-based decision systems, robotics, sensors and their applications will positively impact food production and offer avenues for innovation. In order to address how to achieve the goals of the implementation of AIoT in SA, we present a list of the existing and potential challenges and offer future directions. It is important to highlight that these challenges are not only for SA but also for many other applications. However, the level of importance and priority of a challenge can be different from one application (e.g., SA) to another (e.g., healthcare).

[12] arawireless.org

6.1. Energy

Access to clean and affordable energy is a major challenge in SA, especially in greenhouses and CEA. In addition, the need for long-duration and sustainable power sources for sensors is needed to reduce the Operational Expenses (OPEX) related to batteries and maintenance. This is especially challenging for sensors that need to be placed in the soil at different depths, making them very hard to access individually. There are some efforts at the research stage to develop biodegradable batteries that will resolve some of the sustainability of sensing and hence SA which can be seen as one of the future directions related to the energy challenge in SA.

In addition, there are several efforts to address power consumption in SA suggesting using renewable energy solutions (Liu et al., 2018; Ram et al., 2020; Huang et al., 2020). Also, an efficient micro-grid architecture with renewable energy was presented by Ebrahimi et al. (2019) but it is a preliminary design. Hydroelectric power is currently used in countries where it is readily available.

Hydroelectric power can be part of a sustainable future. As many sensor nodes used in AIoT are equipped with small batteries, balancing and saving of energy consumption in the network of sensors is another energy-related issue. As a solution, Yu et al. (2022) proposed an energy-aware device scheduling solution for optimizing the device selection and assigning communication resources to the optimal edge node to reduce global loss. As a future direction, it is required to offer more intelligent solutions for scheduling and management of sensor motes (e.g., combining ML and heuristics methods).

Putting all the pieces together, in a nutshell, it is required to design more energy-efficient sensor motes, find cheaper and simpler solutions than existing solutions to recharge the batteries (e.g., new methods of using solar energy for recharging the batteries) and use more intelligent solutions for scheduling and management of sensor motes.

6.2. Hardware availability

Maintenance and replacement of equipment such as sensor motes, gateways, processing devices, and lights in greenhouses and CEA is another challenge. As a result of hardware CAPEX, many small farmers will avoid deploying SA or will only use simple solutions which in the end could affect their revenues. Good quality SA sensors can cost up to hundreds of dollars and drones with cameras cost thousands of dollars (Chandra et al., 2022).

Deciding the number of sensors needed to capture the soil and plant data is another CAPEX decision. For example, monitoring soil nitrate variations may require many sensors that could be very costly. In this regard, sharing data and virtual devices (e.g., virtual weather station) usage is going to be one of the future directions.

6.3. Privacy, security and ethical issues

Like all cloud-based infrastructures, SA is also exposed to server attacks (Rettore de Araujo Zanella et al., 2020). Securing the equipment as well as protecting the data from attacks and unauthorized access need to be considered when engineering an AIoT-based SA system. Some solutions have been proposed to tackle this latter issue (Gupta et al., 2020; Chakraborty and Bhunia, 2009; Bathalapalli et al., 2021). However, today's existing SA technologies are resource-limited, making security measures practice difficult. Thus, data security and privacy remain a serious challenge in SA as the security and privacy of sensitive spatial, temporal and spectral information of crops are a serious concern for farmers (Pham et al., 2021).

For this reason, blockchain tracing is starting to be used in SA. Authors in Jadav et al. (2023) proposed a framework that used AI and blockchain tracing to minimize the use of pesticides predicting crops with pesticides above the threshold. Research reported in Zheng et al. (2023), also presented an integration of blockchain in the SA for the analysis of the optimal traceability strategies for agricultural products to guarantee fraud-free and sustainable agricultural supply chains.

Finally, access to the facilities themselves needs protection. The equipment security breach can be caused by the farm animals destroying access systems, and by farm workers compromising the SA environment. Hence, cyber–physical security is needed across all layers of the SA infrastructure.

The ethical issues are another concern in using AIoT for SA. Intellectual property (including intellectual data and algorithms/ML models) is one of the main ethical concerns where SA data owners (e.g., farmers and stakeholders) should have control over the data generated by AIoT devices on the farms and the algorithm and ML model applied to them. The data owners should know (and permit) how and where their data is being used. They should have the right to consent or opt out. FL is considered as a promising technique that can also solve or, at least, reduce several ethical and privacy concerns in the future. Developing robust encryption, authentication and access control mechanisms to safeguard agricultural data can be future research direction for addressing privacy and Security SA.

6.4. Scalability and reliability

In SA, farm sizes vary from small individual farms to large commercial operations. We can see an example of a single greenhouse area with nearly 70,000 square meters, equivalent to ten standard football field sizes in AmbientIoT3GPP (2023). Hence, different quantities of sensing equipment (sensors and associated computing elements) are needed. Consequently, variable data traffic loads will be generated. And to allow SA growth, this technology needs to be scalable. The layered approaches described previously may provide this scalability and it explains that they are widely considered for SA deployment.

SA also needs to provide reliable solutions. Sensors in open fields can be exposed to harsh environments, humidity, extreme temperatures and heavy rainfall. In greenhouses and CEA they are also exposed to environmental variations. Malfunctions due to sensor damage will disrupt the operations. Inaccurate decisions due to a defective sensor also will have impacts on revenues. For example, in paddy rice farming if damaged sensors cannot report the correct soil water content, it will lead to serious consequences: damaging the crop, reducing yield, impacting the food supply chain and eventually causing a price increase. Hence, to reduce OPEX and minimize downtime in the SA operation, there is a need for reliable and fault-tolerant devices to reduce the need for or the number of redundant devices to respond to faults and equipment breakage (Chandra et al., 2022). In addition to reliable and fault-tolerant devices design, providing a mechanism that checks the functionality and remaining energy level (residual energy) of the sensor nodes with timely replacement of the batteries or other power sources will be an essential future work for SA in this type of production. Reliability is a key element.

6.5. Data access

The different systems that are part of the sensing layer need integration to implement AI decision-making. Data science and the advances in “big data” allow the creation and management of the large datasets needed for SA. As was discussed earlier in this survey, the supply chain end-to-end efficiency of SA systems can be improved and food security issues can be mitigated with predictive analysis and real-time decisions on large datasets (as an example, Kempenaar et al. (2016) uses the datasets in the milk industry). The SA data workflow starting with the collection to the analysis is presented in Wolfert et al. (2017), Bhat and Huang (2021). In addition, the use of big data analysis and data science in SA enables new business models (Wolfert et al., 2017).

However, a major challenge facing the real deployment of SA is the lack of integrated and open datasets for research and deployment. While there are existing commercially available integrated sensing and processing systems, they are often too expensive for small-scale farms. Also, many farmers will want to improve on their existing capabilities not just replace all equipment: hence multiple data acquisition systems need to inter-operate, something that they were not designed for. And while they could be co-located often one needs to get to the cloud to retrieve the data as was previously mentioned. As a result, the data will be heterogeneous in nature (different formats, time granularity and precision). Delays incurred in cloud access also with impact real-time operations.

Data normalization is another issue. Sensor nodes, including cameras, collect a lot of data, and correlation and bias need to be addressed when using that data for decision-making. Hence a challenge is to normalize and transform the raw data into usable information (a process called ETL or extract transform load) that can then be used for training, inference, decision-making or digital twinning. This normalization is even more important if federation across locations is wished for. In addition, for supervised learning, data labeling is essential. Services like Sagemaker from AWS can be used.[13] However, their use in SA has not been proven and data labeling may remain a time-intensive human task for the near future.

But data transformation is not all. The datasets need to be open for testing and training agriculture systems but also for validation. To complicate things, equipment suppliers and farm operations alike may be reluctant to open their data as it could reveal trade secrets. Hence a big challenge for SA system developers is creating their own datasets to gather enough data to be able to implement and test both new equipment and algorithms. Digital Twins can be used to generate synthetic data but they themselves need access to some real-time data so their use can be limited.

Hence, it is a fact that SA development and implementation outside the confines of a laboratory is limited by the access to open and accessible data. As this is now a problem identified across the industry, there will be more and more initiatives to standardize and open sensor and system data in the future. Developing techniques to effectively fuse and analyze diverse data types for more accurate and holistic insights can be a future research opportunity for data access.

6.6. Artificial Intelligence for AIoT

As seen in previous sections, over the last decade, new AIoT technologies/methods such as CNN and FL have been widely used and deployed in a variety of different use cases (e.g., in smart cities and smart healthcare). These technologies are in the early stage of deployment in SA. While AI is now considered essential in achieving cost-effective and efficient farming, there are many challenges before AI can become an agricultural mainstay:

- There is still very little interaction between AI research and the agricultural industry. As a consequence, the AI researchers are not well aware of the farming requirements and OPEX and CAPEX challenges, and the farmers often do not understand AI technologies and what they can bring to their operations. Therefore, there is a need for more interdisciplinary collaborations among all stakeholders and a better technology transfer of academic research into commercial deployment.
- There is a lack of well-established legal framework, policies and regulations, for the implementation of AI in SA. In academic settings, many legal aspects of operations are not addressed. For example, a majority of proposed AIoT solutions in SA are vertically integrated and cloud-based. Without security audits, this may make them vulnerable to data breaches, cyber-attacks and compromised privacy. This is one concern that is making farmers wary of AI technologies. The emergence of edge AI seems

[13] https://aws.amazon.com/sagemaker/data-labeling/

to slowly mitigate the problem as it provides higher data privacy and security, as well as lower latency and cost by processing the sensor data at the local farm premises even if it adds complexity and cost (Bhat and Huang, 2021).

- AI can only be a game changer in remote rural areas with the availability of broadband wireless networks. And because of the data volume, it may also need novel data, image and video compression (Gia et al., 2019) that sends the compressed data to the fog layer and then to the cloud using the broadband network but at lower rates.
- AI needs data. Many important data for SA cannot be easily collected and it was discussed previously that datasets are hard to come by.

FogFL for training the smart irrigation scheduling (Saha et al., 2020) was discussed in the previous section. But while FL can be a candidate to provide AI in SA using local datasets and information, FL for multi-farm scenarios is not yet an active area of research. One of the challenges may be a lack of trust in data: farmers may manipulate the sensors and the sensors may not provide correct information regarding their farms. However, the complexity of FL (and impacts on OPEX and CAPEX due to the local equipment need and its maintenance) versus centralized NN in the cloud has also an impact on its wider deployment. Therefore, FL applications in multi-farm scenarios can be explored more in the future. In addition, developing more sophisticated AI algorithms for robotic perception, control and decision-making in dynamic agricultural environments and also Optimizing the distribution of computational tasks between edge devices and the cloud, ensuring seamless communication and developing efficient edge-based AI models can be the focus for the future research in AI for AIoT.

6.7. Capital investment

In most rural areas and in particular in developing countries, agriculture earns a meager profit margin. Because of the initial investment necessary in SA for acquiring, installing and testing advanced technology SA faces an obstacle before mass-scale deployment can be considered. (Chandra et al., 2022). Traditional farm loans and other agricultural financial instruments are ill-suited for SA and AIoT. New funding policies are needed that recognize the importance of SA so that farmers can buy AIoT equipment along with traditional machinery and materials (seeds, fertilizers, pesticides, herbicides, etc.).

6.8. Lack of common standards

There are plenty of wired and wireless standards for communications in IoT and AIoT-based SA uses a large number of them. However, customized solutions lack common standards and interoperability is still provided by gateways with added costs, complexity and reliability impacts. The lack of standards also increases the price of the SA products. And as it was discussed before, there are no standards in data collection and datasets, which creates delays in SA design and implementation. Global uniform and harmonized standards in SA, at the device, network and data levels are needed to reduce the time to market and reduce the price of the products (Mitra et al., 2022). From the communications and architecture point of view, the efforts in 5GS Ambient IoT service study item in 3GPP including agriculture use cases also can be mentioned as 2024 activities (AmbientIoT3GPP, 2023). Exploring frameworks and policies for responsible AI deployment in agriculture, including issues related to data ownership, transparency and fairness can be a new research opportunity in standards.

6.9. User-centric design

The number of SA farms is still very low compared to the number of farmers engaged in traditional farming. For example, in Sub-Sahara Africa, only 13 percent of small farm operations register for digital services and not all of them are active (Chandra et al., 2022). Price is of course a major driver but user interaction with the technology also needs to be considered.

User acceptability will be essential for SA. User-centric design is now part of any innovation and a major element of system design. For users to accept innovation, they need to be directly involved in the design process and give their input in the requirements gathering and the end product design. In addition, designing the system is different from understanding it hence farmers and developers need to interact.

In SA, some of the existing technologies are not user-friendly: they were developed for large-scale operations and required specific knowledge and expertise. Most farmers in rural areas do not possess the operational and technical knowledge to integrate SA in their production. Providing user-friendly systems and educating the farmers can address this problem. For example, testbeds and “Living Lab” systems can directly show the farmers the advantages (e.g., increase in product, revenue, minimizing loss, etc.) the systems will provide.

The support of multiple languages is also important. There are now automatic translation modules in a large number of languages that can be integrated into an application to help the end-users to get an understanding of the proposed system (Muhammed et al., 2022) and to use it appropriately.

AI can help in this acceptability. It provides future directions on how to design more automatic and robust systems that need less input from farmers. The rise of Extended Reality (XR) in agriculture may also support workers and operators in their daily activities (Anastasiou et al., 2023). Designing cost-effective, user-friendly solutions that leverage local knowledge and resources to enhance agricultural productivity is a future research opportunity for user-centric design.

6.10. Simulators and digital twins

One way to test AIoT-based SA systems is to use simulators and increasingly Digital Twins. One of the successful simulators in the domain is the Agricultural Production Systems Simulator (APSIM) was proposed in 1990 and provides deterministic modeling of cropping and pasture systems (Holzworth et al., 2018, 2014). APSIM performance has been improved by the Agricultural Production Systems Research Unit in Australia recently (Holzworth et al., 2006; Vogeler et al., 2023).

In addition to the simulators, some platforms allow testing new agriculture-related solutions such as Fed4FIRE[14] and ARA Wireless.[15]

Moreover, Digital Twins are emerging in SA. A Digital Twin is the interaction between a physical and digital object which allows for real-time, two-way communications between digital and physical items (Alves et al., 2023; Verdouw et al., 2021; Alves et al., 2023) proposed a Digital Twin for smart irrigation where farmers can evaluate the behavior of an automated system before implementing it. Others are in development and part of large research programs such as the one in the Institute for Resilient Agriculture (AIIRA) based at Iowa State University.[16] Wageningen University and Research also has launched 3 Digital Twin projects in January 2020 including virtual tomato crops.[17] Ferme d’Hiver and the University of Montreal also worked on a Digital Twin prototype for strawberry growth in CEA (Istvan et al., 2023). However, there are not many (if any) mature Digital Twin models for

[14] https://www.fed4fire.eu/demo-stories/oc2/farmsens/
[15] https://arawireless.org/
[16] https://aiira.iastate.edu/
[17] https://www.wur.nl/en/research-results/research-programmes/research-investment-programmes/digital-twins.htm

any crops yet and this is a future direction for SA. In addition, effective decision-making requires consideration of the context features to which Digital Twins belongs. In order to facilitate data exchange, the reuse of ontologies and improve semantic interoperability, contextualized ontologies (Rico et al., 2023) and ontology quality evaluation design are needed (Tiwari and Garg, 2022).

7. Conclusion

Recently, there has been an increasing amount of carried research, development, and implementation of AIoT in SA. However, there is still lack of a comprehensive survey of AIoT from a smart agriculture perspective covering all important aspects. It was the goal of this paper to survey SA landscape covering AIoT architectures, solutions, and technologies as they apply to SA. In addition, the paper wanted to highlight the current challenges and future research directions including data, connectivity, DT and CNN, XR, and FL to trigger further work in this emerging field. SA will be essential for the sustainability of agricultural production and this paper showed the progress to date and opened paths for the future. In the future work, we will study different key values that SA solutions should satisfy such as social, economic and exclusiveness aspects as the right technology might be different for different countries and cultures.

CRediT authorship contribution statement

Dalhatu Muhammed: Investigation, Resources, Writing – original draft, Methodology. **Ehsan Ahvar:** Supervision, Writing – review & editing. **Shohreh Ahvar:** Supervision, Writing – review & editing. **Maria Trocan:** Supervision, Writing – review & editing. **Marie-José Montpetit:** Writing – review & editing. **Reza Ehsani:** Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

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