Internet of Things for the Future of Smart Agriculture: A Comprehensive Survey of Emerging Technologies

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***Abstract*—This paper presents a comprehensive review of emerging technologies for the internet of things (IoT)-based smart agriculture. We begin by summarizing the existing surveys and describing emergent technologies for the agricultural IoT, such as unmanned aerial vehicles, wireless technologies, open-source IoT platforms, software defined networking (SDN), network function virtualization (NFV) technologies, cloud/fog computing, and middleware platforms. We also provide a classification of IoT applications for smart agriculture into seven categories: including smart monitoring, smart water management, agrochemicals applications, disease management, smart harvesting, supply chain management, and smart agricultural practices. Moreover, we provide a taxonomy and a side-by-side comparison of the state-of-the-art methods toward supply chain management based on the blockchain technology for agricultural IoTs. Furthermore, we present real projects that use most of the aforementioned technologies, which demonstrate their great performance in the field of smart agriculture. Finally, we highlight open research challenges and discuss possible future research directions for agricultural IoTs.**

***Index Terms*—Agricultural internet of things (IoT), internet of things (IoT), smart agriculture, smart farming, sustainable agriculture.**

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I. Introduction

AGRICULTURE is the largest source of food in the world. It has been paramount to the development of civilizations throughout history. The United Nations (UN) estimates that by 2050, the world's population will increase by 2 billion people from the current 7.8 billion, meaning the planet will need to support about 11 billion people by the end of the century [1]. As a result, the global demand for food and water will continue to increase. Agriculture is the world's largest consumer of water, where it is used to support a wide range of activities such as irrigation, watering, and cleaning of livestock and aquaculture; using about 70% of the world's annual water consumption [2]. These applications pollute water with high amounts of nutrients, pesticides, and other pollutants. It would appear that global food production has to increase to satisfy the world's population growth. However, the Food and Agriculture Organization of the United Nations (FAO) believes that the challenges of hunger elimination and food security do not necessarily require an increase in agricultural production, even by 50% [3], if agricultural production systems become more sustainable [4]. Technology, research, and development must be used to the fullest extent possible, to realize the principles of sustainable agriculture.

Throughout the history of agricultural development as shown in Fig. 1, there were four distinct revolutions, namely, 1) age of traditional agriculture featured by human and animal power, 2) age of mechanized agriculture featured by rumbling sounds, 3) age of automated agriculture featured by high-speed development, 4) age of smart agriculture featured by emerging technologies, as discussed by Liu *et al.* in [18], and Huang *et al.* in [19]. Therefore, smart farming offers a path to sustainability through the use of technology. It involves the use of information and communication technologies (ICTs) in the cyber-physical cycle of farm management, with technologies such as the IoT and cloud computing, robotics, and artificial intelligence (AI) [20]–[24]. Precision Agriculture is a smart farming approach that improves the accuracy of operations by giving each plant or animal precisely what it needs to grow in the best possible way, optimizing overall performance while reducing waste, inputs, and pollution. While precision agriculture is a very sophisticated technology, it only takes into account variables related to field conditions. On the other hand, smart farming goes further by making management duties based not only on geographical location

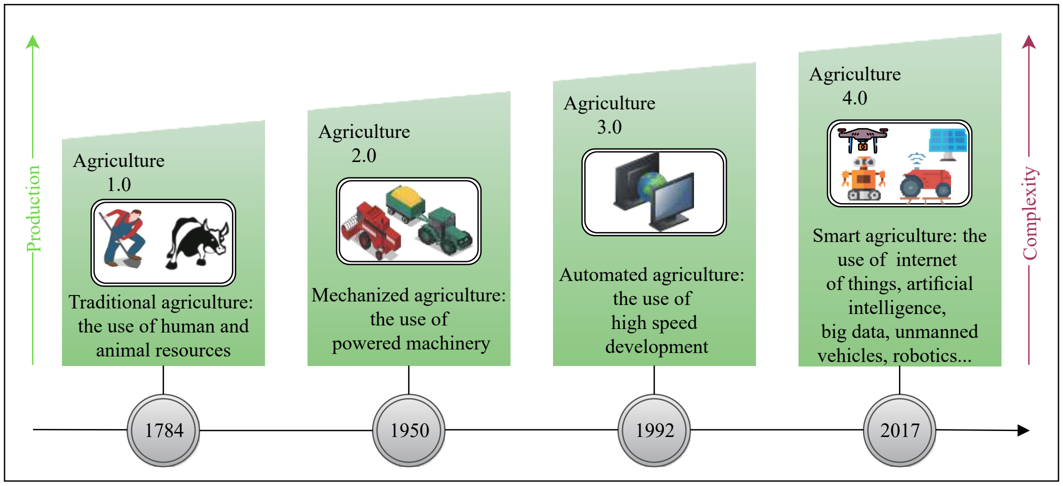


Fig. 1. The four agricultural revolutions.

but also on data, which are enforced by context and situational awareness and driven by real-time events [25]. In these early years, smart farming benefited from the advancement of new technologies such as IoT, low-cost and improved sensors, actuators and microprocessors, high-bandwidth wireless technologies, cloud-based ICT systems, big data analysis, AI, and robotics. Farm equipment is no longer the only source of data; new services are available which turn data into usable information. The application of IoT in agriculture aims to provide farmers with the appropriate tools to support them in their decision making and automation activities by offering products, knowledge, and services for better productivity, quality, and profit. IoT is considered part of the internet of the future, and will contain billions of intelligent communication "things". Different authors have defined it in many different ways [26]–[28]. Although the definition of "things" has changed with the advancement of technology, the primary objective of making sense of computer information without human intervention remains the same. There is no single universal architecture of the IoT applications, and different researchers have proposed various architectures [26], [28]. The same is true for agricultural IoT-based applications [5]–[7], [10].

Fig. 2 provides a comprehensive overview of the entire paper, highlighting sections, sub-sections, and their relationships in a visual representation. The red dashed board entitled IoT architecture for smart farming applications contains the principal layers that form the core of the paper. To better understand this architecture, Fig. 3 demonstrates an example of a smart farm, where IoT and other technologies covered in this survey are presented. The system structure is based on a layered architecture composed of five main layers: physical, networking, middleware, service, and application. The physical layer includes different types of sensors, actuators, wireless sensor network (WSN), agricultural robots, driverless tractors, radio frequency identification (RFID), unmanned aerial vehicles (UAVs) to perform sensing, and control actions. Devices can be powered by batteries, which can be recharged from some source of renewable energy like solar panels and wind turbines. The data sent and the commands received by this layer pass throw the networking layer. It consists of field gateways based either on Ethernet, mobile networks (2G/3G/4G/5G), field devices transceivers using ZigBee, long range network protocol (LoRA), NB-IoT, Sigfox, Bluetooth, near field communication (NFC), or WiFi. The middleware layer encapsulates the hardware and software complexities to simplify the use and development of IoT applications and services. The service layer provides several technologies, such as cloud computing, fog computing, AI, and big data for the application layer. The application layer utilizes the services provided by the previous layers, and various IoT-based messaging protocols, such as constrained application protocol (CoAP), message queue telemetry transport (MQTT), extensible messaging and presence protocol (XMPP), advanced message queuing protocol (AMQP), to perform a wide range of agricultural activities, with minimal human interaction.

A. Related Surveys

In the literature, some surveys have covered different aspects of agricultural IoT. In Table I, we classify the IoT-based agriculture surveys according to the following criteria:

1) Physical Layer: It states whether the survey outlined the physical layer technologies for IoT-based agriculture, including UAVs and/or other technologies.

2) Network Layer: It specifies whether the survey described the network layer communication technologies like 5G and/or others for IoT-based agriculture.

3) Middleware Layer: It clarifies whether the survey introduced the middleware layer, and highlighted some middleware platforms for IoT-based agriculture.

4) Service Layer: It details whether the survey took into account the use of emerging service technologies, with emphasis on fog computing and SDN/NFV, and/or other services in the service layer for IoT-based agriculture.

5) Application Layer: It specifies whether the survey took into account emerging techniques like blockchain, agrivoltaic applications, application layer protocols, and/or other newest developments in the application layer, for IoT-based agriculture.

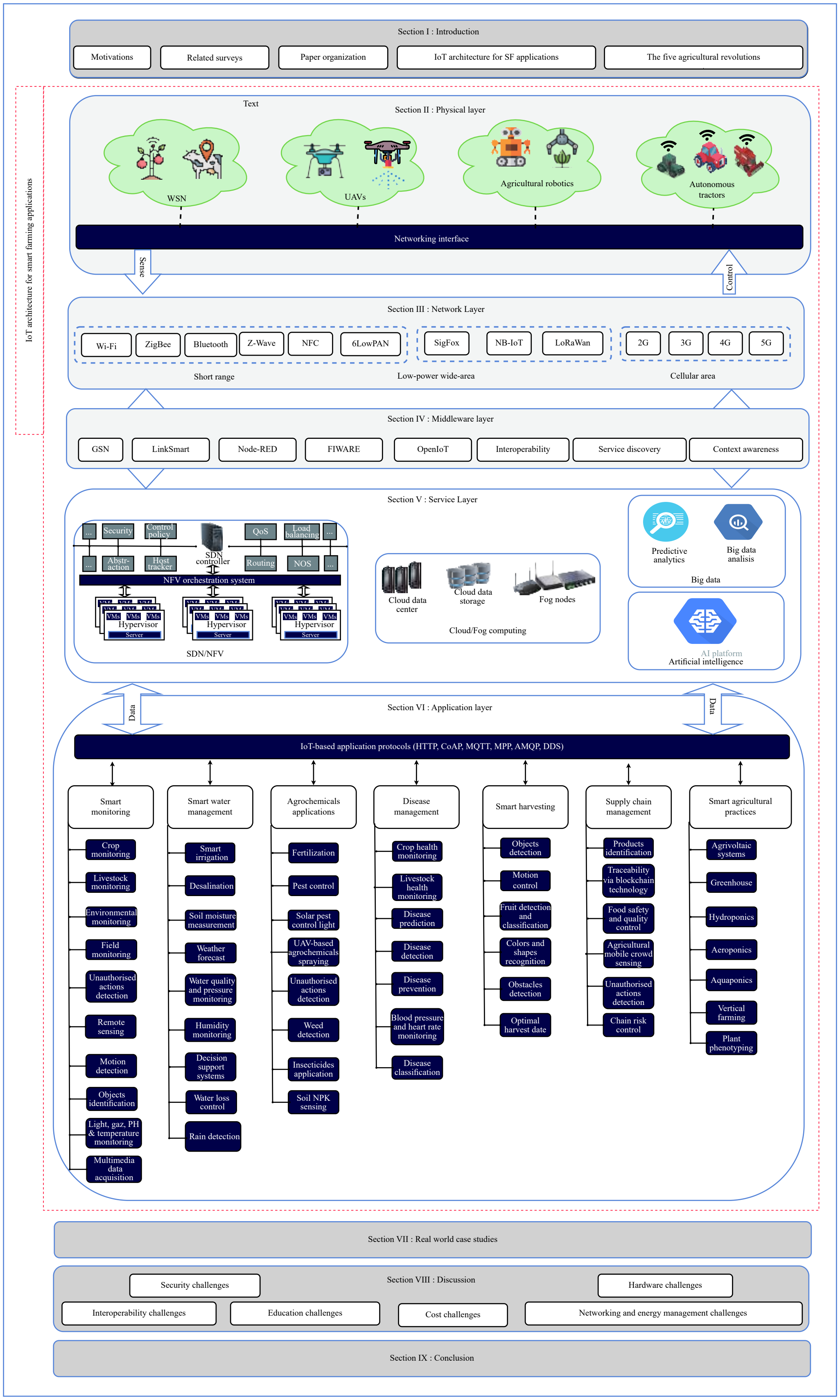


Fig. 2. Survey structure.

Talavera *et al.* [5] reviewed IoT-based agro-industrial and environmental applications, and grouped the selected sources into four application areas, namely monitoring, control, logistics, and prediction. The authors neither reviewed the

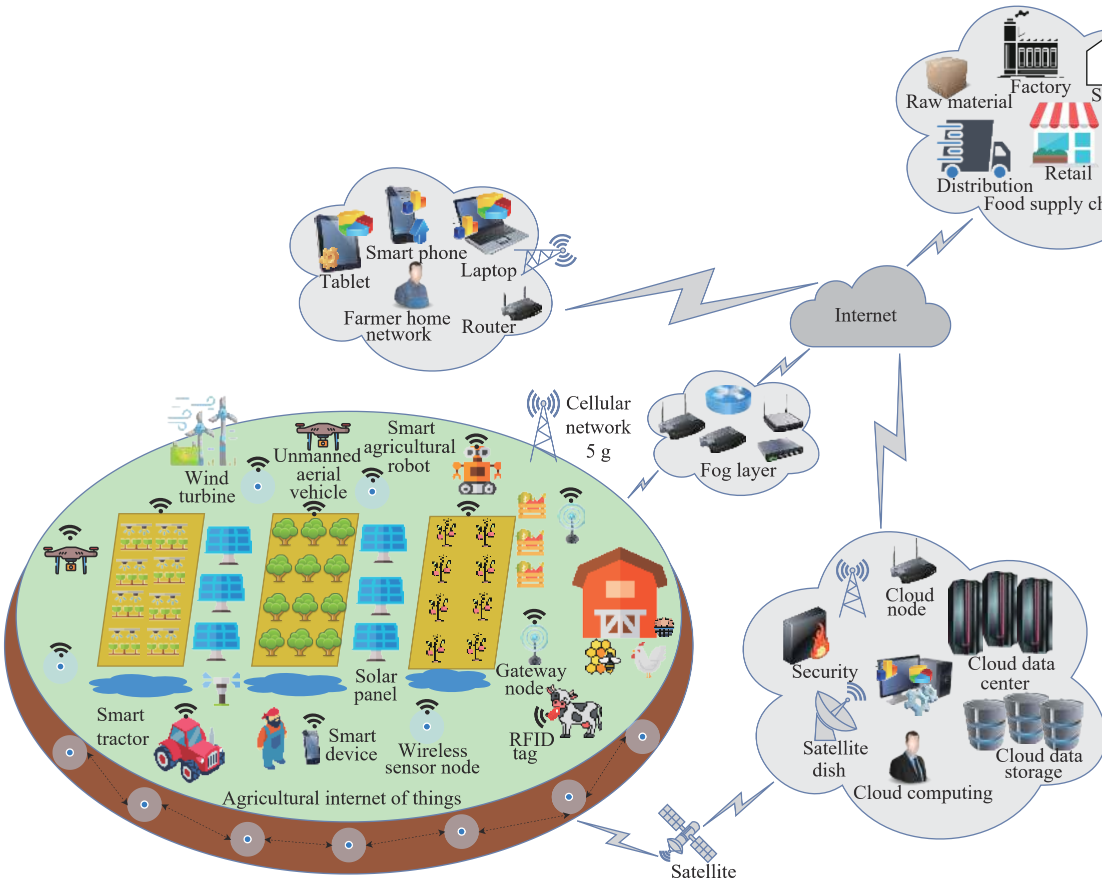


Fig. 3. IoT-connected smart agriculture sensors enable the IoT.

emerging technologies used in the physical layer, nor did they thoroughly detail the underlying smart farming applications. Ray [6] reviewed various applications of IoT-based smart agriculture. The author also highlighted the requirements of IoT-associated wireless communication technologies and devices. Many case studies were provided, and specific challenges and issues related to the deployment of IoT for agriculture was also addressed. However, the review did not consider many essential IoT-based intelligent agriculture applications and services from the current literature, such as blockchain technology, fog computing, etc. Tzounis *et al.* [7] presented IoT technologies and their utility in agriculture, as well as their value to future farmers, and the challenges that face the IoT-based agriculture. However, the review did not include up-to-date coverage of current developments in the sector, including 5G networks, SDN/NFV, blockchain, and others. Elijah *et al.* [8] examined the IoT eco-system for agriculture with four main components, namely IoT devices, communication technologies, data storage, and processing. The authors also discussed advantages, issues, challenges, future trends, and opportunities in the agi-IoT eco-system. But agricultural IoT-based services such as SDN/NFV and fog computing were missing, and emerging applications such as agrivoltaic systems and blockchain-based applications were not provided.

Khanna and Kaur [9] reviewed the various communication techniques used in IoT for smart farming. Although the authors highlighted the limitations and challenges facing the agricultural sector, they did not examine in depth the evolving technologies and applications used in the literature. Shi *et al.* [10] examined the applications of IoT in protected agriculture and proposed a system framework with core technologies. The selected references are grouped into three areas of the application corresponding to plant management, animal husbandry, and traceability of food/agricultural supplies. Nevertheless there was no thorough examination of the physical layer. Liu *et al.* [18] examined both the current state of industrial agriculture and the experiences of industrialized agroproduction models. The authors also discussed the trends in technologies towards Agriculture 4.0, but missed some of the emerging ones, such as fog and SDN. Ruan *et al.* [11] conducted a literature review of intelligent agriculture. The authors highlight emerging trends in both applied IoT techniques and issues of concern to agriculture. However, the review omitted the middleware layer and some key applications in the sector. Feng *et al.* [12] reviewed wireless communication technologies for precision agriculture, namely NB-IoT, LoRa, and ZigBee, by analyzing agricultural application scenarios and experimental tests. The authors did not examine IoT-based smart agriculture application protocols such as CoAP and MQTT. Shafi *et al.* [13] reviewed wireless communication technologies, sensors and wireless nodes, platforms for spectral imaging of crops, standard vegetation indices used to analyze spectral images, and applications of

TABLE I
RELATED SURVEYS ON AGRICULTURAL IOT

	Physical L.			Network L.			Middleware L.		Service L.				Application L.					Year
Survey	M	UAVs	O	M	5G	O	M	Platforms	M	Fog	SDN/NFV	O	M	Blockchain	Agrivoltaic	Protocols	O	
Talavera *et al.* [5]	×	×	×	√	×	◑	×	×	√	◑	×	×	√	×	×	×	√	2017
Ray [6]	√	◑	√	√	×	√	√	◑	√	×	×	√	√	×	×	×	√	2017
Tzounis *et al.* [7]	√	◑	√	√	×	√	√	√	√	◑	×	◑	√	×	×	×	√	2017
Elijah *et al.* [8]	√	◑	√	√	×	√	√	◑	√	×	×	◑	√	×	×	×	√	2018
Khanna and Kaur [9]	×	×	×	√	√	√	×	×	√	×	√	×	√	×	×	×	√	2019
Shi *et al.* [10]	√	×	√	√	◑	√	√	◑	√	√	×	√	√	◑	×	×	√	2019
Ruan *et al.* [11]	√	◑	◑	√	◑	×	×	×	×	×	×	×	√	×	×	×	√	2019
Feng *et al.* [12]	√	×	◑	√	×	√	×	×	√	×	×	√	√	×	×	×	√	2019
Shafi *et al.* [13]	√	√	√	√	√	√	×	×	√	◑	×	√	√	×	×	×	√	2019
Ayaz *et al.* [14]	√	√	√	√	◑	√	×	×	√	◑	×	√	√	×	×	×	√	2019
Farooq *et al.* [15]	√	√	√	√	×	√	×	×	√	×	×	√	√	×	×	×	√	2019
Radoglou-Grammatikis *et al.* [16]	√	√	◑	×	×	×	×	×	×	×	×	×	√	×	×	×	√	2020
Ferrag *et al.* [17]	√	◑	◑	√	√	×	×	×	√	√	√	◑	√	√	×	×	√	2020
Liu *et al.* [18]	√	×	◑	√	◑	◑	√	×	√	×	×	√	√	√	√	×	√	2020
Our survey	√	√	√	√	√	√	√	√	√	√	√	√	√	√	√	√	√	/

(√): Supported; (◑): Partially supported; (×): unsupported. Layer (L.); Mentioned (M); Others (O);

WSN in agriculture. The authors skipped some IoT-based agricultural enabling technologies such as middleware platforms, SDNs, fog computing, and blockchains.

Ayaz *et al.* [14] stressed the potentials of WSN and IoT in agriculture, as well as the IoT devices, and the related networking protocols. The authors also discussed the challenges that should be addressed when integrating this technology into traditional agricultural practices. However, there was a lack of technical details on intelligent agricultural technologies. Farooq *et al.* [15] reviewed key components of IoT-based Intelligent Agriculture, including network technologies, cloud computing, big data storage, analysis, and security issues were also highlighted. Middleware layers platforms and technologies were not provided. Radoglou-Grammatikis *et al.* [16] provided an overview of precision farming, by outlining its different aspects and technologies and analyzing the different types of UAVs according to their specifications and payload. Neither the network technologies nor the services layer techniques were discussed by the authors. Ferrag *et al.* [17] discussed security and privacy issues and the challenges in IoT-based green agriculture. To address these issues, the authors proposed a classification of threat models under five categories, including attacks on privacy, authentication, confidentiality, availability, and integrity properties. The authors also investigate privacy-focused blockchain solutions and their suitability for IoT-based green agriculture. Other aspects such as middleware platforms and IoT-based agricultural applications were not discussed.

B. Contributions

Although there are many studies on IoT-based smart agriculture, most of them only address some specific aspects of the topic. In this study, we highlight the constituent elements of the domain, along with the most emerging technologies used in it, in a comprehensive manner. Our contributions in this work are:

1) We provide a list of emerging technologies for agricultural IoTs, including unmanned aerial vehicles, wireless technologies, open-source IoT platforms, SDN and NFV technologies, cloud/edge computing, and middleware platforms.

2) We present IoT applications for smart agriculture and provide a classification into seven categories: smart monitoring, smart water management, agrochemicals applications, disease management, smart harvesting, supply chain management, and smart agricultural practices.

3) We emphasize open research challenges and discuss possible future research directions for agricultural IoTs.

The rest of this paper is organized as follows. Section II presents the physical layer for IoT-based agriculture. Section III introduces the network layer, where an overview of some of the communication technologies for smart farming are highlighted, and a brief description of each one is provided. In Section IV we present the middleware layer for IoT-based agriculture. In Section V introduces the service layer, where we discuss various services for smart farming. Section VI discusses the application layer, where we provide a classification of IoT applications for smart agriculture into seven categories. Besides, we provide a taxonomy and a comparison of cutting-edge methods in supply chain management based on blockchain technology for agricultural IoTs. Section VII provides real-world case studies that incorporate most of the technologies discussed in this survey. Then, we discuss the challenges and future research directions in Section VIII. Finally, Section IX presents conclusions. To help readers understand this paper, acronyms found in this paper are shown in Table II.

TABLE II
ACRONYMS USED IN THIS SURVEY

Acronym	Description
FAO	Food and Agriculture Organization of the United Nations
ICT	Information and communication technology
IoT	Internet of things
AI	Artificial intelligence
WSN	Wireless sensor network
RFID	Radio frequency identification
NFC	Near field communication
UAV	Unmanned aerial vehicle
SDN	Software defined networking
NFV	Network function virtualization
LoRa	Long range network protocol
5G	Fifth generation communication
LPWAN	Low-power wide-area network technologies
3GPP	3rd generation partnership project
GSM	Global standard for mobile communication
WCDMA	Wide-band code division multiple access
LTE	Long-term evolution
CPS	Cyber physical system
M2M	Machine to machine
QoE	Quality of experience
QoS	Quality of service
CoAP	Constrained application protocol
AMQP	Advanced message queuing protocol
XMPP	Extensible messaging and presence protocol
MQTT	Message queue telemetry transport
HTTP	Hypertext transfer protocol
GPS	Global positioning system

II. PHYSICAL LAYER

Also known as the perception layer, the physical layer includes different types of sensors, actuators, WSN, RFID tags, and readers. Its main tasks are to link objects in IoT networks, and to monitor, gather, and process status information related to these objects via deployed intelligent devices, and to forward the processed data to the upper layer [29]. It also receives control commands from the application layer so that the related equipment, such as agricultural machinery, take corresponding actions.

A. Sensor Nodes

Fig. 4 illustrates the architecture of a typical sensor node. The basic components of each sensor node are networking, sensing, processing, and power units [30]. Also, as required by the application, other sub-units may exist, such as power generator, display, mobilizer, and others. Analog to digital converter (ADC) converts the analog signals provided by the sensors from the monitored event into digital signals and sends them to the processing unit, allowing the sensor node to cooperate with other nodes to perform the affected tasks [30].

1) Radio Frequency Identification Technology (RFID): RFID enables remote identification. Unlike bar code technology, it can identify multiple tags situated within the same zone without the need of human presence [31]. There are many uses for RFID in agriculture, including livestock identification and tracking [32], and food chain traceability [33].

2) Wireless Sensor Networks: WSN has many important applications in several fields; agriculture and the food industry are no exception. It consists of several components called "nodes", a set of intelligent devices that are used to collect the data needed for applications. There are three basic functions of a sensor network: detection, communication, and calculation using hardware and software [30]. Distributed nodes that collect data are known as source nodes, while the node that collects data from all source nodes are known as a gateway node [34]. There are many variants of WSNs used in agricultural applications which include: wireless sensor and actuator network (WSAN) [35], terrestrial wireless sensor networks (TWSN) [36], wireless underground sensor networks (WUSN) [37], underwater wireless sensor networks (UWSN) [38], multi-media WSN [39], and mobile WSN [40].

B. Hardware Boards

Hardware boards are typically used to control equipment and devices automatically. Numerous projects have used such devices in smart farming research [49]–[51], some of which are well known:

1) Arduino: is an open-source electronic platform for hardware and software, which develops and manufactures single-board microcontrollers kits. It receives inputs from many sensors, as well as controlling actuators [52].

- *Arduino UNO:* is an open-source microcontroller board based on the ATmega328P microcontroller. It features a set of digital and analog input/output (I/O) pins that can be connected to various expansion boards and other circuits. Shirsath *et al.* [53] used Arduino UNO to implement a greenhouse monitoring and controlling system, with multiple sensors and actuators, including soil moisture sensor, humidity sensor, and temperature sensor.

2) Raspberry Pi: is a low cost, tiny, and single-board computer developed by the Raspberry Pi Foundation. It is a low-cost computer operating under Linux that provides a set

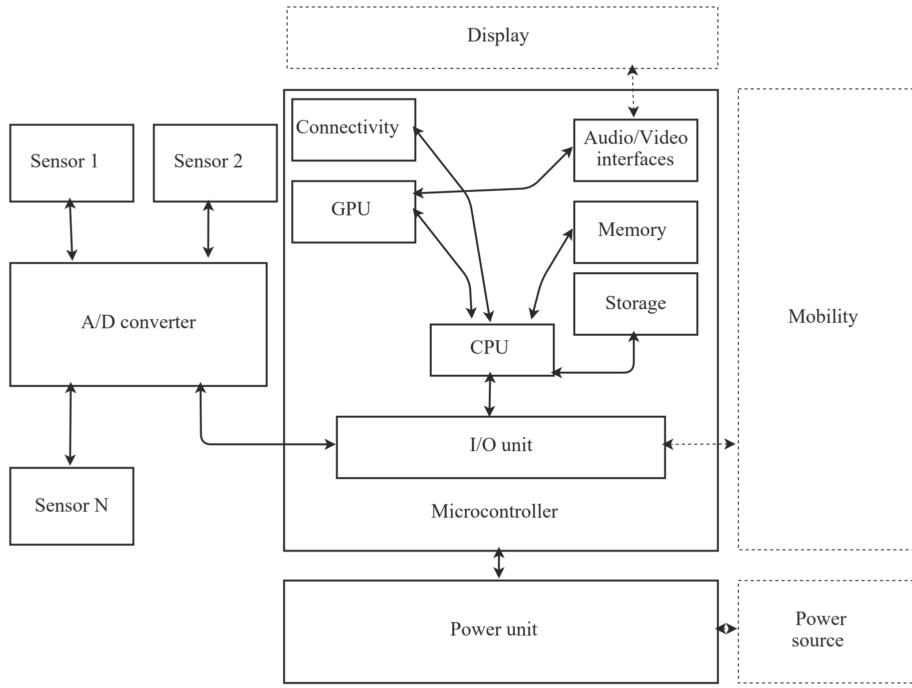


Fig. 4. The architecture of a typical IoT sensor node.

of general-purpose input/output (GPIO) pins, allowing the control of electronic components and the exploration of IoT [54]. Mehra *et al.* [55] developed an intelligent IoT based hydroponic system. A case study for tomato plant growth was designed using Arduino and Raspberry Pi3.

3) Espressif: is a semiconductor company focused on developing WiFi and Bluetooth low-power IoT solutions [56].

• *ESP8266:* is a very flexible WiFi module manufactured by Espressif Systems, easily adaptable to the Arduino platform, for easy integration into a wide array of projects Khoa *et al.* [49] used the ESP8266 module for connecting low-cost and effective smart agriculture system components for controlling environmental factors in agriculture.

• *ESP32:* is a series of low-cost, low-power systems on a chip microcontroller, with integrated Wi-Fi and Bluetooth communication technologies. It is a successor to the ESP8266 microcontroller. Biswas and Iqbal [50] presented a low cost automated solar water pumping system for smart irrigation. The sensor detected parameters are sent to the ESP32 microcontroller, which sent it to the cloud, and use it to control the water pump motor.

4) Intel Edison: is a tiny sized compute module for wearable and IoT devices. It features I/O pins compatible with Arduino UNO, and is capable of running light-weight Linux distributions [57]. Bhowmick *et al.* [51] developed a sensor network capable of monitoring the environmental variables of vertical agricultural warehouses which is based on the Intel Edison wireless module.

5) BeagleBone: is a small, low-power, open-source, and system-on-a-chip computer produced by Texas Instruments [58]. The Beagle family revs as high as 1 GHz. Ali *et al.* [59] implemented a real-time green internet of things monitoring system, using BeagleBone Black Rev C model. It also acts as a decision support system to help water resources management and mitigates the impact of agrochemicals.

C. Unmanned Aerial Systems

Remote sensing applications in agriculture are usually grouped by sensor platform type, including satellite, aerial and land-based platforms [60]. Unmanned aerial system (UAS) refers to the unmanned aircraft-unmanned aerial vehicle (UAV) and its associated remote control equipment. Compared to satellite imagery, images acquired by the UAS generally have a higher temporal and spatial resolutions [61]. The use of these systems is growing rapidly across many civil application domains, including agriculture. Its application in agriculture include, but are not limited to, fertilizer management [62], hyper-spectral imaging [63], yield prediction and crop monitoring [64], weed detection [65], and data collection from various sensor types [66]. Table III presents a selection of different UAVs used for a wide range of agricultural tasks. While there are different types and shapes, the three major types are: Fixed Wing [42], [45], Hybrid Fixed-Wing [41], [47], and Multi-Rotor [43], [44], [46], [48]. The main two missions for these UAVs are aerial imagery for obtaining field data [41], [42], [44], [45], [47], and liquids spraying for irrigation and chemicals spraying actions [46], [48]. One of the most important characteristics used for UAVs evaluation is the wingspan of the winged UAVs; the payload, which is the weight each UAV can carry; The endurance, to know how long the UAV can fly; the coverage area, to make sure it can cover the whole field; the maximum speed; and finally, the cost.

D. Agricultural Robotics

The use of agricultural machinery in farming increased investment and research thanks to the use of robotic technology in the development of machines and the execution

TABLE III
A BRIEF COMPARISON OF SOME UAVS THAT IS USED IN SMART AGRICULTURE

Project	Type	WingSpan	Payload	Endurance	Coverage	Max. Speed	Main Applications	Cost
ALTI Reach [41]	Hybrid Fixed-Wing	6 meters	7 Kg	20 hours	1800 Km	90 Km/h	Aerial imagery	$295K or $9.5/h
AgEagle RX-60 [42]	Fixed-Wing	1.37 meters	N/A	60 minutes	400 acres	42 m/h	Aerial imagery	$12K
M600 Pro [43]	Multi-Rotor	N/A	6 Kg	35 minutes	5 km	65 km/h	Aerial Imaging	$5,7K
Omni Ag [44]	Multi-Rotor	N/A	2 Kg	25 minutes	1.60 km	15 m/s	Aerial imagery	$17K
eBee SQ [45]	Fixed-Wing	1.10 meters	N/A	55 minutes	41 km	110 km/h	Aerial imagery	$25K
THEA 140 Pro [46]	Multi-Rotor	N/A	5 kg	5 hours	2 km	14 m/s	Liquids Spraying	$7.5K
ALTI Ascend [47]	Hybrid Fixed-Wing	2 meters	600 g	6 hours	450 Km	75 Km/h	Aerial imagery	$35K or $3/h
Agras T16 [48]	Multi-Rotor	N/A	16 kg	18 minutes	0.1 km	7 m/s	Liquids Spraying	$16K or $3/h

TABLE IV
WIRELESS TECHNOLOGIES FOR AGRICULTURAL IOT

Range	Technology	Standard	Frequency	Data rate	Power	Max. range	Security
Short range	NFC	ISO/IEC 13157	13.56 MHz	106 kbps–424kbps	1–2 mW	0.1 m	N/A
	RFID	Numerous standards	13.56 MHz	423 Kbps	1 mW	1 m	N/A
	Zigbee	IEEE 802.15.4	2.4 GHz	250 Kbps	1 mW	20 m	AES-128 Bit
	Z-Wave	Z-Wave	908.42 MHz	100 Kbps	1 mW	30 m	Security 2 (S2)
	Wi-Fi	IEEE802.11 a/c/b/d/g/n	2.4 GHz–60 GHz	1.2 Mbps–6.75 Gbps	1 W	100 m	WEP/WPA/WPA2
	Bluetooth	802.15.1	2.45 GHz	1–3 Mbps	1 W	100 m	AES 56/128 bit
	Bluetooth LE	Bluetooth smart	2.4 GHz	1 Mbps	10–500 mW	100 m	AES-128 bit
	6LowPAN	IEEE 802.15.4	908.42 MHz–2.4 GHz	20 Kbps–250 Kbps	1 mW	100 m	AES-128 Bit
Long range	LoRaWAN	LoRaWAN	Many	0.3–50 Kbps	Very low	10 Km	AES-128 bit
	SigFox	SigFox	908.42 MHz	10–1000 bps	Very low	50 Km	AES-128 bit
	NB-loT	3GPP	180 KHz	200 Kb/s	Very low	15 Km	LTE encryption
Cellular area	2G	GSM	850–1900 MHz	171–384 Kbps	1 W–3 W	26 Km	GEA2,3,4/A5/3,4
	3G	UMTS	850–1900 MHz	40 0.73–56 Mbps	1 W–4 W	26 Km	USIM
	4G	LTE	700–2600 MHz	0.1–1 Gbps	1 W–5 W	28 Km	SNOW 3G
	5G	ITU IMT-2020	700 MHz–72 GHz	20 Gbps	1 W–5 W	28 Km	256-bit

of tasks. Numerous agricultural land-based robots are available to perform farming operations and to replace or extend human capabilities in certain tasks [67]. Such vehicles have four main capabilities when performing agricultural tasks: detection, guidance, mapping, and action [68]. Agricultural robotics research covers a wide range of applications, from automated harvesting [69], weed management and control [70], autonomous spraying for pest control [71], environmental conditions monitoring, and animals health [72], helping improve operational reliability while enhancing soil health and productivity.

1) Autonomous Tractors: Tractors are machines used to carry out farming operations and to support other agricultural machinery. Self-driving tractor technology can meet the growing concern of work-labor force shortages, and will also improve performance and efficiency without requiring a human. This technology will permit real 24/7 operations, where a farmer will be able to control the farm from anywhere, with just a smart device and internet access.

III. NETWORK LAYER

In this layer, the processed data from the physical layer is received and forwarded to the upper layer. It also passes control commands from the application layer to the perception layer. This layer includes relevant communication technologies from different transmission ranges, such as ZigBee, Bluetooth, Wi-Fi, and NFC for short-range; LoRaWan, SigFox, and NB-IoT for long-range; and 2G, 3G, 4G, and 5G for cellular. Table IV presents a summary of some wireless technologies classified by transmission ranges. A brief description of each communication technology is given below.

1) Wi-Fi: is one of the most popular radio access technologies that we can find in almost all handheld devices with networking capabilities. It is a collection of wireless local area network (WLAN) IEEE 802.11 standards, operates in various frequencies from 2.4 GHz to 60GHz, and provides data rates from 1 Mb/s to 6.75 Gb/s. WiFi provides a communication range up to 100 m [73].

2) ZigBee: is an IEEE 802.15.4 standard-based specification used to create wireless personal area networks with low-power, low-bandwidth requirements, designed for applications in limited sized projects. It provides communication ranges up to 20 m [73].

3) Z-Wave: is a short-range wireless communication technology with the following advantages: low cost, low battery consumption, and high reliability. Its primary focus is to ensure transmission reliability. It is suitable for limited network bandwidths and provides data rates up to 100 kbit/s [74].

4) Bluetooth: is an IEEE 802.15.1 compliant standard, that provides a cost-effective and low-power wireless communication technology adapted to the transmission of data over a short distance. The extremely energy-efficient and cost-effective version of this standard is called bluetooth low energy (BLE or Bluetooth Smart). BLE joined with Bluetooth v4.0 [75].

5) 6LowPAN: is a shorthand for IPv6 over low power wireless personal area networks (6LoWPAN) [76]. It is based on the IEEE 802.15.4 standard and developed by the internet engineering task force (IETF). 6LoWPAN allows devices with limited resources to send data over IPv6.

6) NFC: Near-field communication is a near-range wireless technology that uses RFID tags and readers [77]. It operates at 13.56 MHz with data rates ranging from 106 to 424 kbps. A separation of 10 cm or less is required. It uses low power consumption.

7) Cellular Technologies: 3rd generation partnership project (3GPP) is wide area network (WAN) technologies from global standard for mobile communication (GSM), Wide-band code division multiple access (WCDMA), long-term evolution (LTE) to 5G. It runs on a licensed frequency and focuses mainly on high-quality cellular services. IoT devices based on these technologies can connect across mobile networks [78].

- *5G technology:* is expected to provide high data rates, reliability for errors, delay reduction, higher energy efficiency, and lower latency, essential features for smart agricultural applications. With enhanced mobile broad-band (eMBB) functionality, for enhancing mobile data rate providing up to 20 Gbps of data throughput, machine-type communications (MTC) for long-range, low data rate capabilities, and ultra-reliable low latency communication (URLLC) for ultra-reactive connections offering air interface latency of less than 1 ms [79], and many other benefits that smart agriculture will take advantages from, including the motivation for a new design of agricultural devices and machinery since data gathering and network bandwidth are no longer problem. This will, for instance, will completely free the robots from manual or in-field control, allowing them to support innovative farming techniques.

A. Low-Power Wide-Area Network Technologies (LPWAN)

The success of LPWAN communications technologies resides in their capacity to provide a low power connection between a large group of devices over large geographical areas at a very low cost.

1) SigFox: is an LPWAN network operator that provides a complete IoT connectivity solution based on its proprietary technologies [80]. Using an IP network, Sigfox deploys and connects its exclusive base stations to end devices. Sigfox makes efficient use of the bandwidth and operates at minimal noise levels, resulting in ultra-low battery power usage, high receptor sensitivity, and cheap hardware devices [81].

2) LoRaWan: Low Power Wide Area Networks is a long-range communication protocol developed by LoRa™ [82]. Its main objective is to ensure interoperability between different operators and to enable IoT. It provides long-distance transmissions over 10 km in rural areas with low energy usage.

3) NB-IoT: Narrowband Internet of Things is a 3GPP cellular technology. It meets the significant needs of IoT, such as wide geographical coverage, scalability, low-cost, support for a large number of devices, and long battery life while offering up to 10 years of life-time [81].

IV. Middleware Layer

The middleware layer abstracts system or hardware complexities to facilitate the development of numerous IoT applications and services [83]. It is generally regarded as a software system built to serve as an interface between IoT devices and applications [84]. Many designs approach for middleware solutions exists [83], including application-specific, event-driven, tuple-spaces, cloud-based, agent-driven, virtual machine-based, database-oriented, service-oriented, and others. Symeonaki *et al.* [85] simplified the process of managing, manipulating, and exchanging the large amount of diverse data generated in many different precision agriculture systems by implementing a cloud-based and contextual middleware as a framework for an embedded, reactive, scalable, and service-oriented IoT system. According to the authors, context-based middleware is one of the leading research targets under the Agriculture 4.0 approach. The framework introduced in their paper, which is based on the integration of WSANs into IoT, offers the advantage of being easily adaptable, modifiable, and extensible for any application in any precision agriculture system environment, regardless of its complexity. Fortino *et al.* [20] developed an IoT project that provides an effective model for agent design and programming, as well as efficient tools for the construction of an effective IoT system based on a multi-agent system. The proposed agent-based approach is specifically based on the agent-based cooperating smart object (ACOSO) methodology, and the corresponding middleware. Dobrescu *et al.* [86] developed a context-aware IoT-based smart platform for agricultural monitoring and control. It can be considered as middleware support, which allows the transfer of environmental information and commands from field to cloud for interpretation and decision.

A. IoT-Based Middleware Platforms for Agricultural Applications

Different IoT middleware platforms are used for the development of agricultural applications, in which the separate middleware solutions focus on particular parts of the IoT such as service discovery, security, scalability, interoperability, portability, and context awareness, as shown in Table V.

1) LinkSmart: Previously known as HYDRA, is a funded European Union project to develop service-oriented middleware for IoT and Embedded systems [92]. Its primary focus involved the integration and management of heterogeneous hardware devices into applications in a distributed architecture, regardless of their network technologies [84]. Furdik

TABLE V
MIDDLEWARE PLATFORMS FOR SMART AGRICULTURE

Middleware	Type	SD	S/P	S	I	P	CA	OS	UL
LinkSmart	Service-based	√	√	◑	◑	√	√	√	[87]
GSN	Service-based	√	√	◑	×	√	×	√	[88]
Node-RED	Actor-based	√	√	√	◑	√	√	√	[89]
FIWARE	Service-based	√	√	√	√	√	√	√	[90]
OpenIoT	Cloud-based	√	√	√	√	√	√	√	[91]

(√): Supported; (◑): Partially supported; (×): Unsupported. Service discovery (SD); Security/Privacy (S/P); Scalability (S); Inter-operability (I); Portability (P); Context aware (CA); Open source (OS); Used in literature (UL)

et al. presented an IoT-enabled meat traceability prototype, implemented using the LinkSmart middleware. It gathers real-world data from selected farms in Denmark [87].

2) Global Sensor Networks (GSN): is an open-source sensor middleware platform designed to facilitate the deployment and programming of sensor networks [93]. It provides a scalable framework for integrating heterogeneous and distributed sensor network technologies using a few powerful abstractions. Gaire *et al.* [88] illustrated how GSN could be used to extend and enable the integration of IoT with external data, and to provide monitoring conditions and measurements to implement a smart farm prototype of 269-hectare livestock property located in Armidale.

3) Node-RED: is an open-source IoT-based middleware platform developed by IBM. It is based on node.js, a server-side javascript platform [94]. Node-RED uses a visual tool that simplifies the job of representing IoT devices for abstraction purposes [84]. Kousiouris *et al.* presented the architecture and implementation of a micro-service system for supply chain management and its dependencies. The authors used Node-RED to permit smooth coordination between various and complex systems, enabling the adaptability of information and the creation of workflows for the necessary sequences of actions [89].

4) FIWARE: is an open-source platform for context data management that ease the development of solutions such as smart agriculture [95]. It provides Advanced Middleware that allows smooth, effective, expandable, and secure inter-communication between distributed applications and the FIWARE platform. Muñoz *et al.* [90] developed and tested a smart water management system based on the FIWARE middleware. The system showed good results in saving operating costs.

5) OpenIoT: is an open-source cloud-based, middleware platform that enables the semantic interoperability of IoT services [96]. Data from many heterogeneous sources can be shared across the domain. Jayaraman *et al.* [91] proposed a solution based on OpenIoT to address the data processing needs of smart agriculture in Australia and demonstrates how agriculture can benefit from IoT.

V. SERVICE LAYER

In this layer, various services such as cloud computing, fog computing, AI, SDN/NFV, and big data are provided for the application layer, which enable agricultural applications to perform a wide range of smart management actions. Table VI presents a comparison of different open-source, IoT-based platforms that are used in intelligent agricultural applications.

A. Cloud Computing

IoT can take advantage of the benefits of the cloud features and resources to overcome its limitations such as storage, processing, and communication [97]. Using cloud and IoT together will facilitate the implementation of a high-speed information system, between the surveillance entity and the sensors/actuators deployed in the area [97]. IoT along with cloud computing, has become a technology of the future, and their applications have been used in many sectors, including agriculture. Ghahramani *et al.* [21] reviewed and categorized cloud QoS technical details, resulting in better insights into the different aspects of QoS frameworks. CLAY-MIST [98] is a cloud-based solution that can effectively monitor comfort levels of specific crops that could be an extremely exact and efficient decision support tool for farmers, with a declared precision of 94%. Agri-Info [99] is a system that offers information about agriculture as a service, using cloud computing and IoT. It processes various types of agricultural data gathered from multiple users through IoT devices based on different areas. Also, the system provides the necessary information to users, and automatically establishes a diagnosis of the agricultural situation. The authors developed a web and mobile application. Results indicated a reduction of 12.46% in cost, 15.52% on network bandwidth, 10.18% in execution time, and 13.32% in latency.

B. Fog/Edge Computing

Fog/Edge is a high virtualization platform that provides traditional cloud computing services between end devices and cloud computing data centers, usually located on the edge of the network [100]. That means, instead of performing all processing at the cloud center, fog computing can complete a part of it at the edge of the network with any device with storage, computing, and network connectivity, which collect data from the IoT devices related to the IoT application [29], as shown in Fig. 5. Because of its characteristics, such as proximity, location awareness, geographical spread, and hierarchical organizations, it is a perfect platform to support low-energy WSNs [100]. In recent years, cloud-based applications for intelligent irrigation have been widely used. However, there are challenges related to network traffic, security, and legal challenges. Zamora-Izquierdo *et al.* built a flexible edge-based IoT platform for supporting the needs of

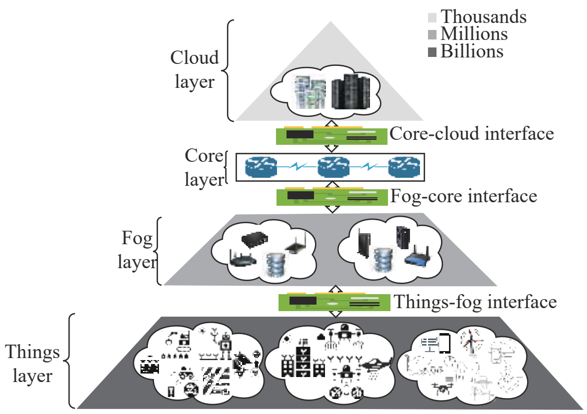


Fig. 5. Fog computing-based agricultural IoT.

soil-less culture greenhouses, with low-cost hardware. The whole system is implemented in a real greenhouse located in Spain. The project is a three-layer edge-based system [101]. Chen presented an intelligent cyber physical system approach to food traceability, using a fog computing architecture. Results showed that the system is effective [102].

C. Big Data

Since the IoT connects all types of objects and devices in both agriculture and the supply chain, huge amounts of data is collected from a wide range of sources including sensors, UAVs, agricultural mobile crowd sensing (AMCS) [40], etc. These data can be processed, analyzed, and used for decision making in real-time [8]. Data analysis is a critical enabler for successfully creating value from these data, and addressing issues such as food security and sustainability [25]. Chen *et al.* used big data through an IoT framework for the effective functioning of the agro-economic farm model. It was used to analyze a sample of data from ten different sensor nodes on yield production, with the shortest possible computation time and the maximum accuracy. Results indicated a nearly 34% reduction in memory utilization [103].

1) Big Data Analytics: is the complex process of analyzing big data sets to reveal useful information that can help to make informed decisions. Muangprathub *et al.* [36] introduced a system for monitoring environmental parameters in crop fields. The system is designed to connect to any agricultural field, and to receive information from the IoT, and to manipulate crop data details and field information. Data from the IoT are stored and used in data analysis by applying data mining to find useful information about the impacts of the environment. Findings showed that vegetables cultivated in the country had a temperature adapted to high productivity, ranging from 29°C to 32°C. Also, suitable humidity for the high productivity of lemons was between 72% and 81%. Tseng *et al.* [104] introduced and Intelligent Agriculture IoT system for surveillance of environmental factors on a farm. The data collected was analyzed in 3D cluster analysis. The results validate that the system is feasible. Lambrinos [105] developed a decision support system for intelligent agriculture that uses data from several sensors obtained via a LoRaWAN network, as well as meteorological data and crop information, to make informed decisions.

2) Predictive Analysis: is a branch of data analysis that aims to provide predictions about future outcomes using historical data and analytical techniques, such as statistical modeling and AI. AgriPrediction [106] is a framework based on both LoRa IoT technology and a prediction engine that anticipates potential crop malfunctions proactively to inform the farmer of potential solutions as quickly as possible. Gains of 17.94% were achieved in terms of leaf development and 14.29% in terms of weight compared to a standard cultivation procedure. In [107], the authors proposed a granular AI-based predictor for agricultural cyber physical system (CPSs) with large-scale data. Results showed that computation efficiency is significantly reduced while maintaining an equivalent prediction accuracy. Diedrichs *et al.* [108] established a prediction engine as part of an IoT-compatible frost prediction system that gathers environmental data to predict frost events. The authors' evaluation of their algorithm involved training regression and classification patterns, using multiple machine learning algorithms.

3) Visualization: is an essential aid in gaining an overview of research data-sets. The analysis of numerical data, in many cases, provides too little information. Visualization offers an excellent first impression of the results, enabling the user to study exciting trends in the data, verify the correctness of the results, and display them in an intelligible manner.

D. Artificial Intelligence

AI technology assists different sectors to improve their efficiency and profitability, including agriculture. There are problem areas in agriculture, such as crop diseases, poor storage control, pesticide management, weed problems, and water management, all of which can be addressed by AI [109]. Garibaldi introduced a framework of indistinguishable concepts to be used as the main element in the assessment of automated decision-support systems [22]. Ghahramani *et al.* [23] provided a detailed analysis of intelligent semiconductor manufacturing based on computational scalability, and neural network algorithms. The authors proposed a dynamic algorithm to get valuable information on semiconductor manufacturing processes and to address a variety of challenges. Rajput and Kumaravelu [110] proposed a fuzzy logic-based distributed clustering protocol for wireless intelligent sensor networks (WSSNs) that is used in agricultural monitoring systems. Their main goal is to improve the energy efficiency of WSSNs while maximizing the coverage area. The results indicated that the proposed protocol balances energy use between nodes in an efficient manner.

1) Deep Learning (DL): has shown great potential and promising results, and as it is successfully applied in various fields, it is also used in agriculture [121]. PestNet [122] is a deep learning approach for the discovery and categorization of widespread and multi-class pests. It has been evaluated on a set of pest image data collected by task-specific image acquisition equipment. Experimental results showed a 75.46% mean average precision (mAP). Bu and Wang [123] presented a smart farming system based on deep reinforcement learning, to make intelligent decisions such as smart water management

TABLE VI
A BRIEF COMPARISON OF SOME OPEN-SOURCE IOT PLATFORMS FOR SMART AGRICULTURE

	Device-related		Service-related				Error-related		Application-related		
Frameworks	Device management	Scalability	Fog	AI	Analytics	Visualization	Error management	Fault tolerance	WorkFlow	Events processing	Business rules
FIWARE [95]	√	√	√	√	√	√	√	√	√	√	√
ThingsBoard [131]	√	√	√	√	√	√	√	√	√	√	√
Thinger.io [132]	√	√	×	√	√	√	◑	×	√	√	◑
Murano [133]	√	√	×	√	√	√	√	◑	√	√	√
ThingSpeak [134]	√	√	×	√	√	√	◑	×	√	√	×
MainFlux [135]	√	√	√	√	√	√	◑	◑	√	√	×
Iotivity [136]	√	√	×	×	◑	◑	◑	◑	√	√	×
KAA [137]	√	×	√	×	√	√	√	√	√	√	◑
WSO2 [138]	√	√	√	√	√	√	◑	◑	√	√	√
SiteWhere [139]	√	√	×	√	√	√	◑	◑	√	√	√
DeviceHive [140]	√	√	×	√	√	√	◑	◑	√	√	◑

(√): Supported; (◑): Partially supported; (×): Unsupported.

and to adjust the environment for crop growth. Vincent *et al.* [124] proposed an expert system to assist farmers in evaluating agricultural land for cultivation, based on the integration of data collected by the various sensors, with AI systems such as neural networks and multilayer perceptron (MLP), for the evaluation of the suitability of agricultural land. The study presented a model which is reported to be as accurate as 99%. Jiang *et al.* [125] proposed the real-time detection of apple leaf diseases, based on improved convolutional neural networks (CNNs), a deep learning approach. The experimental results showed that the proposed model realizes a detection performance of 78.80% mAP. Ashqar *et al.* presented a plant seedling classification approach based on CNN, with a dataset containing about 5000 images with 960 unique plants belonging to 12 species. The model achieved an accuracy of 99.48% [126].

E. SDN and NFV Technologies

The rapid growth of smartphones, virtualization, and widespread use of cloud computing services are some of the key drivers behind new trends in the networking business, which is pushing conventional network architectures to be reconsidered. SDN attempts to decouple the network control functionality (the control plane), from the transmission functionality (the data plane) of the network [127]. On the other hand, NFV aims to abstract network transfer and related network function from the hardware on which it operates, and it creates a virtual network overlay using software that performs similar path control functions of SDN [128]. SDN and NFV are closely related and highly complementary to each other and both rely extensively on virtualization technology, to allow the network design and structure to be abstracted into software and subsequently implemented by underlying software on hardware platforms and devices [128]. It is also possible to combine both SDN and NFV to provide the benefits of both architectures to improve infrastructure flexibility, facilitating the design, delivery, and operation of network services dynamically and adaptively, which is necessary for IoT services. Huang *et al.* [129] proposed an architecture of vehicle sensor networks based on SDN, as a means of reducing the impact of controller failure and improving the stability and the operability of vehicle sensor networks in agriculture. They showed that the recovery time in case of loss of controller connection is less than 100 ms, with rule updates in real-time and at a constant throughput rate. In [130], the authors proposed an approach based on an Open vSwitch extension, for multi-domain SDNs for agricultural WSNs. The results showed that each sensor switches having a short failure recovery time, less than 300 ms, with low packet loss.

Different SDN/NFV frameworks are compared in Table VII. Framework type indicates whether the platform support SDN only [114]–[119], NFV only [112], [120] or both [111], [113]. 5G connectivity, quality of experience (QoE) / quality of service (QoS), and load balancing support are of great importance these days, especially for real-time, massive-data IoT-based applications since they deliver better services to the networking module. While some platforms support those metrics [111]–[114], others do not [115], [117]. Scalability, elasticity, and stability metrics are used to evaluate the ability of dynamic and continuous adaptability of these platforms, facing different scenarios. The security metric indicates whether the platform can deliver security policies (CIA): confidentiality, integrity, and availability. According to our compression, ONOS [111], Open NFV [112], Open Day Light [113], and Tungsten [114] are from the best available SDN/NFV frameworks.

1) SDN/NFV Architecture for Smart Agriculture: The IoT-based SDN/NFV system for agricultural applications is illustrated in Fig. 6. In this figure, we can visualize four layers with different services. The first layer consists of the perception layer which is composed of various agricultural IoT-based networks. The data plane is made up of network components such as switches and routers dedicated to the routing of packets. Yet, unlike conventional networks, they are merely routing components without integrated intelligence

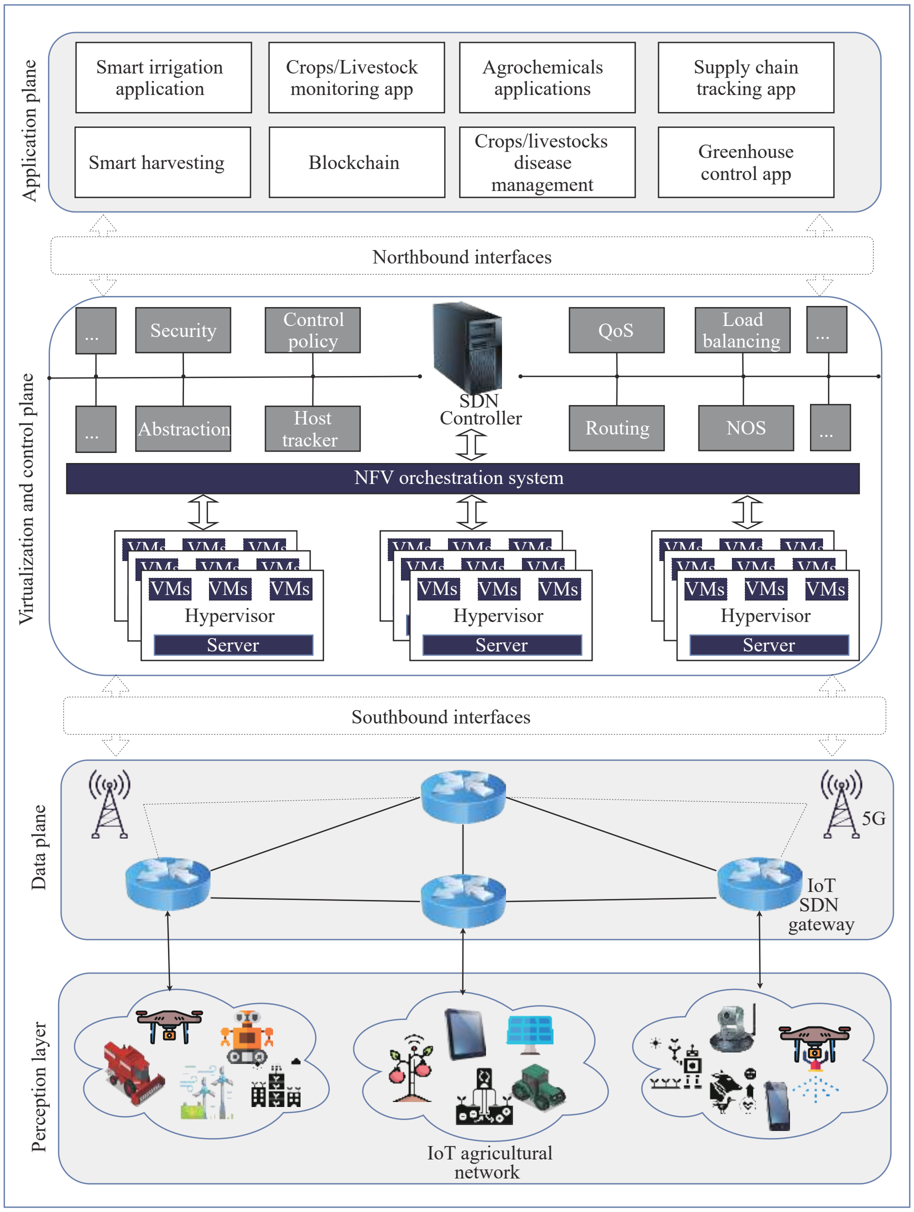


Fig. 6. SDN/NFV architecture for smart agriculture.

for autonomous decision making [141]. The packet forwarding logic is defined by the SDN controller and is enforced in the forwarding devices through transmission tables [128]. The southbound interface is among the most important components of an SDN/NFV system, providing a connector between the forwarding devices and the SDN controller. Currently, OpenFlow is the most widely accepted standard [141]. The NFV platform relies on backbone servers to implement low-cost networking functions. Servers have hypervisors running to support virtual machines that implement network functions. It allows programmable and personalized data processing functions that run as software in VMS, where NFs are shipped to operators just as software [128]. The SDN controller, together with the NFV orchestration system, forms the logic control module. Being the core of the SDN, it consists of a centrally located controller, that logically manages the network, takes application layer requests, and manages the network devices via standard protocols [128]. SDN controller produces network configurations according to the policies specified by the network administrator. The northbound interface offers a shared interface for application development [141]. The application layer covers an array of applications for agricultural services, and they are mainly software applications communicating with the control layer.

F. Open Source Platforms

As a cluster of technologies, IoT platform provides the essential elements for IoT-based applications development [95]. It offers the foundations for creating specific features of your solution [131]. In Table VI we compare a selection of open-source IoT platforms for smart agricultural applications based on four criteria: device-related, service-related, error-related, and application-related. For the first criteria, device management provides centralized management and real-time status reports for all existing physical/virtual devices [132],

TABLE VII
A BRIEF COMPARISON OF SOME SDN/NFV FRAMEWORKS FOR SMART AGRICULTURE

	Type	Networking			Adaptability			Security			OpenFlow	Programming L.
Frameworks		QoS/QoE	5G	Load balancing	Scalability	Elasticity	Stability	C	I	A		
ONOS [111]	SDN/NFV	√	√	√	√	√	√	√	√	√	√	Java
Open NFV [112]	NFV	√	√	√	√	√	√	√	√	√	√	Java, Python
Open-Daylight [113]	SDN/NFV	√	√	√	√	√	√	√	√	√	√	Java
Tungsten Fabric [114]	SDN	√	√	√	√	√	√	√	√	√	√	Python
NOX/POX [115]	SDN	◑	×	×	×	◑	◑	◑	◑	◑	√	Python, C
RYU [116]	SDN	√	√	×	√	◑	◑	◑	◑	◑	√	Python
Floodlight [117]	SDN	◑	×	×	◑	◑	◑	√	√	√	√	Java
lighty.io [118]	SDN	◑	√	×	√	◑	◑	◑	◑	◑	√	Java, Python, Go
Cherry [119]	SDN	◑	×	×	◑	×	×	×	×	×	√	Go
Open Baton [120]	NFV	√	√	×	√	√	◑	√	√	√	√	Java, Python, Go

(√): Supported; (◑): Partially supported; (×): Unsupported; Confidentiality (C); Integrity (I); Availability (A).

[133]. Scalability is the key feature that allows a platform to support a growing amount of tasks [135], [136]. Service-Related features includes service layer technologies, like fog [137], [138], AI [139], [140], analytics [133], [134], and visualization [95], [131]. Error-related features report the ability of the platform for handling errors, which is evaluated by error management and fault tolerance metrics. Application-Related is the services that a platform can provide to IoT-based applications, including workflow, event processing, and business rules [95], [138], [139]. From the previous comparison we conclude that FIWARE [95] and ThinsBoard [131] are among the best open-source IoT platforms for smart agriculture.

VI. APPLICATION LAYER

Numerous applications have been developed in this layer to monitor and control plants and animals, to warn of and manage diseases and pests, and to track the food supply chain, which can improve productivity, reduce waste and pollution of primary resources, and also save time and money. Table VIII summarizes critical technologies used in each layer for various selected projects, as well as the contribution, results, and limitations. The classification of IoT-based applications, together with their sub-classes, is graphically illustrated in Fig. 7. This classification is supported by an extensive review of IoT solutions, currently available for smart agriculture. A detailed discussion is given below.

A. Application Protocols

IoT-based agricultural applications use several protocols for the exchange of data. The most common types of application protocols are HTTP, CoAP, MQTT, XMPP, AMQP, and DDS.

1) Hypertext Transfer Protocol (HTTP): is the foundation of data communication for the world wide web (WWW). It is the most commonly used application layer protocol when developing web applications due to its relevance in serving hypermedia resources that satisfies the most essential needs on the internet.

2) Constrained Application Protocol (CoAP): is an IoT-based application layer protocol created by the IETF constrained restful environments (CoRE) working group [230]. It provides a representational state transfer (REST) based web transfer protocol in addition to the HTTP functionalities. The CoAP uses UDP, which makes it more efficient for IoT applications. It alters some HTTP features to suit IoT demands and deals with lost and noisy links. It enables tiny and low-powered devices with computing and communicate capabilities to benefits from the RESTful interactions [28].

3) Message Queue Telemetry Transport (MQTT): is a light and very simple publish/subscribe messaging protocol developed for unreliable networks with higher latency or low bandwidth. It is designed to ensure that network bandwidth and device resource requirements are minimized, while trying to guarantee reliability and a degree of assurance in the delivery. These principles make the protocol perfect for machine to machine (M2M) or IoT connected devices, as well as for mobile applications, that require high bandwidth and battery power [28].

4) Extensible Messaging and Presence Protocol (XMPP): is an application layer protocol based on the extensible markup language (XML), which allows the exchange of real-time data between network entities, in a structured but extensible way. XMPP permits instant communication between multiple users over the internet, while ensuring end-to-end encryption [28].

5) Advanced Message Queuing Protocol (AMQP): is an open standard IoT-based application layer protocol for message-oriented applications. AMQP standardizes messaging using producers, brokers, consumers, and messaging. AMQP uses TCP to exchange messages. Two main components that handle communications are: exchanges and message queues.

TABLE VIII
IoT APPLICATIONS FOR SMART AGRICULTURE

Year	Work	Main contribution	Phy. layer	Net. layer	Mid. layer	Serv. layer	App. layer	Performance (+) Limitation (–)
2020	Popescu *et al.* [157]	Advanced UAV–WSN system for intelligent agricultural monitoring	- Soil and Weather related sensors - Satellite	- 6LoWPAN, ZigBee - LoRaWAN, GSM - BLE, Wi-Fi	N/A	- Edge/Fog computing - Cloud computing	- User server for data interpretation	(+) Design of optimized trajectories that allows efficient use of limited ground sensor network resources (–) Increased complexity for multilevel data processing
2020	Hang *et al.* [207]	Blockchain-based fish farm platform	- Temperature, water level, O2 sensor, PH - Water pump, pond heater, fish feeder	- LoRaWAN, ZigBee, Z-Wave, Bluetooth, Wi-Fi	N/A	- Cloud computing - Fog computing	- Blockchain - HTTP - Web application	(+) Scalability, high throughput, off-chain storage, and privacy (–) Application too complex for ordinary farmers
2020	Zhao *et al.* [190]	Automatic crop disease recognition system	- Weather related sensors - Cameras	- N/A	- N/A	- AI - Big data analytics	- Application for the visualization of crop disease identified	(+) Identification accuracy of 97.5% (–) Unbalanced data structure has not been well solved
2020	Muñoz *et al.* [90]	IoT architecture for water resource management in agro-industrial environments	- Variety of sensor and actuator technologies for soil, plant, and weather activities	- 2G, 3G	FIWARE middleware	- Cloud computing	- CoAP & MQTT - HTTP - Web-based application.	(+) 75% of the operational cost could be saved. (–) The speed of computing and latency could be better on edge computing approach
2019	Kamienski *et al.* [165]	IoT-based smart water management platform	- Variety of commercial sensor and actuator technologies for soil, plant, and weather - UAV	- LoRaWan - Wi-Fi - 2G, 3G, 4G	FIWARE middleware	- Cloud computing - Fog computing - Big data analytics - AI	- MQTT - Web application	(+) Real-time responses for adapting irrigation (–) Savings in consumption are not analyzed compared to Zamora-Izquierdo *et al.* [101]
2019	Zamora-Izquierdo *et al.* [101]	Smart farming platform	- Sensors: light, humidity, temperature, CO2, PH. - Actuators: soil and water nutrition pumps, valves	- 6LowPAN - Serial/direct digital/ analogue I/O connections	FIWARE middleware	- Cloud computing - Fog computing - Big data analytics	- MQTT, CoAP - Greenhouse control Web service	(+) Savings of more than 30% in water consumption and up to 80% in some nutrients (–) Real-time responses are not considered
2019	Kousiouris *et al.* [89]	Smart microservice IoT-based supply chain management system	- N/A	- N/A	Node-RED	- AI	- HTTP - Web-based microservice	(+) Reduced overall spin-up time (–) Did not discuss security and privacy
2020	Alonso *et al.* [150]	Smart edge-IoT based platform for livestock and crops monitoring	- RFID - Sensors: weather, soil, livestock, and transport sensors	- SigFox, LoRa, ZigBee, Bluetooth, Wi-Fi, 3G, and others	FIWARE middleware	- Edge computing - Cloud computin - AI - Big data analytics	- Blockchain - Web application	(+) The introduction of edge nodes improves the reliability of communications and reduced the costs (–) Consumers cannot access and analyze all the data in the system
2018	Goap *et al.* [170]	IoT based smart irrigation management system	- WSN - Sensors: soil moisture and temperature, precipitation, air temperature, light radiation, humidity - Actuators: water pump	- Wi-Fi, ZigBee - Mobile data connection	N/A	- Cloud computing -AI	- Web-based interface for real-time monitoring - HTTP REST API	(+) The system is cost effective, as it is based on the open standard technologies (–) Water saving analysis is not provided
2018	Rao and Sridhar [171]	Crop-field monitoring and automation irrigation system	- Sensors: soil moisture, temperature - Actuators: relay, beeper	- 4G	N/A	- Cloud computing	- Web-based application	(+) Low-cost implementation (–) Very basic compared to Kamienski *et al.* [165]
2018	Yoon *et al.* [227]	Smart farming system	- Sensors: temperature, humidity, and CO2	- LPWAN, Bluetooth - RS-485	N/A	N/A	- MQTT - MQTT broker server	(+) Data can be trans-received at 500 m (–) Service layer (Cloud, AI, etc.) is not present

Table VIII (Continued)

Year	Work	Main contribution	Phy. layer	Net. layer	Mid. layer	Serv. layer	App. layer	Performance (+) Limitation (–)
2017	Cambra *et al.* [228]	Smart IoT irrigation system	- Sensors: moisture, PH - Actuators: irrigation and fertilization controller - UAV	- LoRaWAN, SigFox - Wi-Fi - 3G, 4G	Network administration middleware	- Cloud computing	Web application	(+) 868 MHz mesh networks is the best solution for data acquisition in farming systems (–) The flexibility of system applications is not provided
2017	Suma *et al.* [229]	IoT-based smart agriculture monitoring system	- GPS - Sensors: soil moisture, temperature, PIR - Actuator: buzzer, relay	- GSM - Wi-Fi	N/A	N/A	- Android application for monitoring and control	(+) Sensors and microcontroller interfaced successfully (–) Service layer (Cloud, AI, etc.) is not present
2016	Furdik *et al.* [87]	Food traceability chain management	RFID, WSN	GPRS, Wi-Fi	LinkSmart	Cloud computing	Mobile application	(+) Provides context-awareness (–) Did not discuss security and privacy
2015	Jayaraman *et al.* [91]	Enabling high resolution precision agriculture driven by IoT	- WSN - Soil sensor - Temperature sensor	- N/A	OpenIoT	- Cloud computing - Data analytics	- CoAP - HTTP - Visualization application	(+) Dynamically select sensors in order to meet the service request demand (–) The flexibility of system applications is not provided
2015	Liu *et al.* [142]	Agriculture greenhouse environment monitoring and control system	- Sensors: temperature, pressure, CO2, light, humidity - Actuator: fan controler, curtain controler, sprinkler	- ZigBee - 2G - ADSL, Ethernet	N/A	- Cloud computing	CGI and GUI control application application	(+) Improving operational efficiency while maintaining the flexibility of system applications (–) The study of data acquisition is not provided compared to work [228].
2013	Gaire *et al.* [88]	SAchitecture design of a smart farm	- GPS - Weather and soil related sensors - Livstock tracking devices	- N/A	GSN	- Cloud computing	- Application server - Web application for visualisation	(+) Fast query capability (–) The study of data acquisition is not provided compared to work [150]
2012	Mendez *et al.* [153]	Smart WSN for an agricultural environment monitoring	Temp, moist, humid, light, pressure, water level	- Wi-Fi - Ethernet	N/A	N/A	- Plotting application	(+) The system is scalable (–) Service layer (Cloud, AI, etc.) is not present

It and also support the publish/subscribe communications model [28].

6) Data Distribution Service (DDS): was developed by the object management group (OMG) for real-time M2M communications using a publish/subscribe approach. It is built on a broker-less infrastructure, and utilizes multi-casting to provide excellent QoS with reliability. In contrast to other publish-subscribe protocols, it is ideally suited to meet the real-time needs of IoT and M2M communications [28].

B. Smart Monitoring

Smart IoT-based monitoring systems help maintain optimal conditions to ensure better Agricultural Products quality. The past few years have witnessed an increase in the development of monitoring systems.

1) Crop Monitoring: crop growth and production performance monitoring, throughout the stages of development, is an essential aspect of farm management. Triantafyllou *et al.* [143] provided structural components of an intelligent agricultural monitoring system, building on IoT communication technologies and WSN features in cooperation with energy-saving protocols. The project is illustrated by a practical application for monitoring saffron agriculture in Kozani, Greece. The mySense environment is designed to provide a systematic approach to data acquisition processes [144]. It is built on a 4-layer technological structure, including sensor nodes, networks, cloud services, and support for end-user software applications. It allows the use of inexpensive, quickly deployable, seamless, and integrated technologies to enhance the adoption of crop monitoring applications. AR-IoT [145] is an application of augmented reality (AR) in crop monitoring, which supports IoT data visualization by using a color scale to represent the crop parameters. It enables agricultural data acquisition, with IoT-based multi-cameras, to provide 3D visual serving in the physical world. Results showed that AR-IoT could be applied to monitor crops simply and effectively. Daskalakis *et al.* [146] proposed a low-power leaf sensing system for temperature and water stress measurements on plants. The system used solar energy as a power source. The sensor node can be used as a part of a low-cost, low-power IoT-based agricultural monitoring system.

2) Livestock Monitoring: IoT helps the farmer in monitoring and raising livestock. Using IoT devices, the farmer can monitor them remotely. Zgank [147] suggested an IoT-based

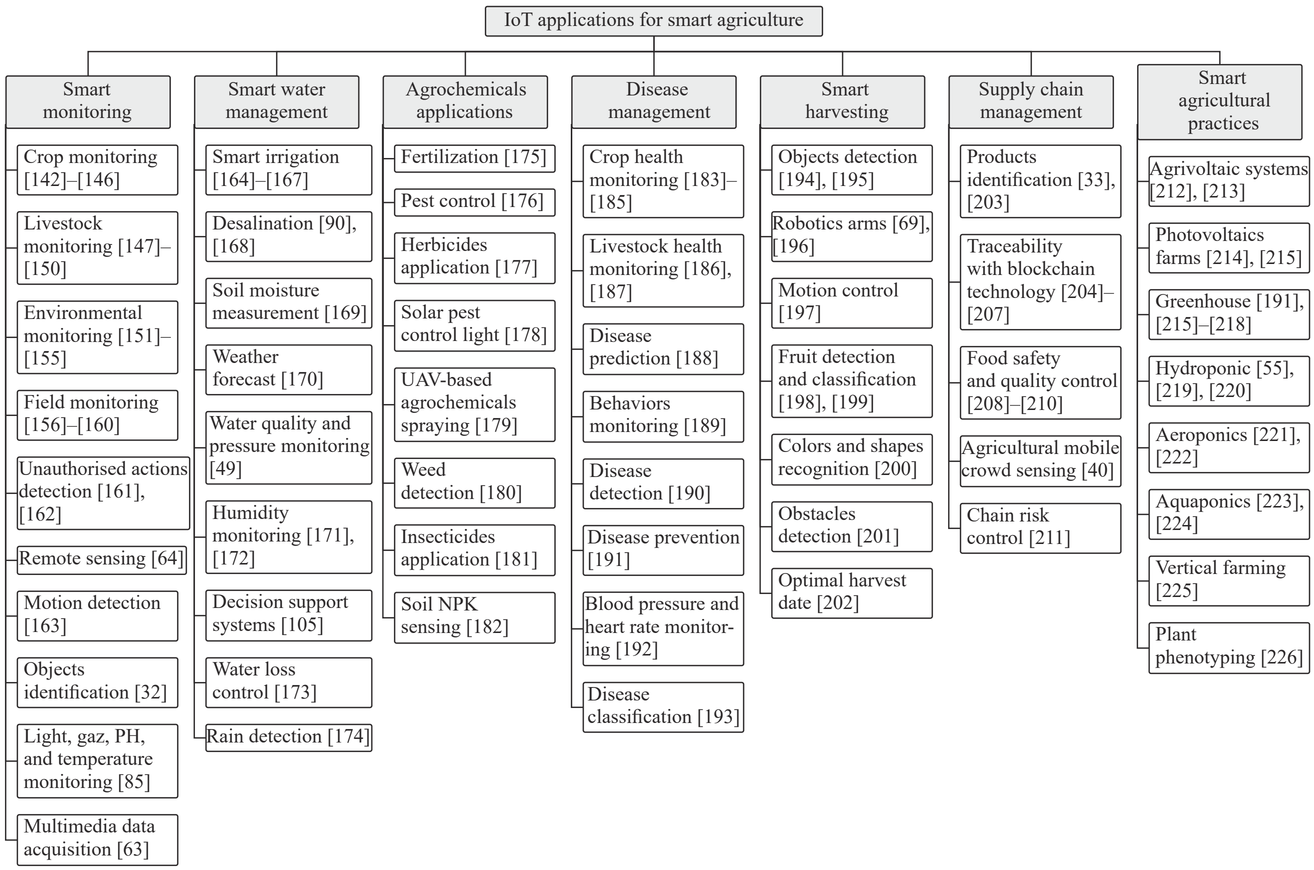


Fig. 7. Classification of IoT applications for smart agriculture.

swarm monitoring system concept, based on the input audio signal picked up in a beehive and classified audio signal with deep learning. Maroto-Molina *et al.* [148] developed a low-cost IoT-based livestock monitoring system using GPS collars, Sigfox network, and Bluetooth tags. It was tested in two commercial farms that are based on global edge computing architecture [149]. Alonso *et al.* [150] presented a dedicated platform for the application of IoT, edge computing, AI, and blockchain technologies in intelligent agriculture. The platform was developed for real-time monitoring of dairy cattle and crops conditions. It is also ensured the tracking and the sustainability of all processes, associated with the production chain.

3) Environmental Monitoring: IoT technology has a critical role in understanding the physical world through real-time data on air, soil, and water. Harun *et al.* [151] developed a method for manipulating the growth of Brassica Chinensis in a controlled environment using LEDs by varying the light parameters. The authors also studied the correlation between light, environment, and the morphology of the plant through IoT platform. Treatment at different light intensities also had a positive impact on plant yield. Lazarescu [152] presented the functional design and implementation of a cost-effective, comprehensive, multi-sensor, quickly deployable, long life, low maintenance, and high quality of service WSN platform that can be used for a range of long-term IoT environmental monitoring applications. Mendez *et al.* [153] designed and developed a smart WSN for monitoring agricultural environments, suitable for various factors such as temperature and humidity. Hirsch *et al.* [154] presented a low-power, upgradeable, IoT-based architecture for farmers in the field and for scientists to monitor the environmental impact on plant development by monitoring soil moisture and temperature. Lai *et al.* [155] proposed an air quality monitoring and real-time prediction system using low-cost hardware based on IoT and edge computing. The authors used the Kalman filter (KF) algorithm. Results showed an accuracy of 27% on the edge side, and errors were decreased by 68.3%.

4) Field Monitoring: sensors in the field collect data and transmit them to the processing center, which uses the corresponding software applications to analyze the operating data. Gondchawar and Kawitkar [156] developed a GPS-controlled robot system for remote monitoring and control of field data and field activities. Popescu *et al.* [157] introduce a cooperative hierarchical system structure between IoT, WSN, and UAVs for agricultural field monitoring applications. The system proved both robustness and efficiency and showed an increase in performance. Baseca *et al.* [158] implemented a smart real-time decision support system prototype. The system automatically learns decision rules from various types of data, including irrigation events and selected parameters from field and weather conditions. The platform can be controlled remotely and provides an open network of intelligent agriculture data with common layers of restriction for the exchange of information. Chen *et al.* [159] offered a reliable delivery protocol, Multi-Packet LoRa, for the delivery of voluminous messages, such as images, in LoRa networks. In point-to-point experiments with a single pair, this protocol decreased image transfer time by an average of 24%. Ahmed *et al.* [160] introduced the WiLD network, an WSN-based solution based on fog computing architecture for smart agricultural monitoring. The main objective is to cover a more extended range with lesser network delays.

5) Unauthorised Actions Detection: plays a crucial role in the protection of the farm. Muminov *et al.* [161] established the concept of virtual fencing, an intelligent collar device, where an animal is given a stimulus based on its posture on one or more fence lines. It has been used to control goats without visible physical fencing, and to monitor their status. The 20% probability that the goat would receive an electrical stimulus, is used only if the goat neither turned, nor stopped on the warning zone. Potamitis *et al.* [162] established an automated insect surveillance accelerometer-based sensor device at a global scale for Tree monitoring. The device transmits short vibration clips stemming from an internal part of the tree to a remote server. The proposed device can be used in different application scenarios, including detection of wood-boring insects in trees and illegal cutting or unauthorized tree movement detection.

6) Remote Sensing: is based on the interaction of electromagnetic radiation with the ground or the plant. Remote sensing usually implies the monitoring of reflected radiation, instead of emitted or absorbed radiation [60]. In [64], the authors used a UAV to provide height estimates of a cornfield, using 3D photogrammetry technology, for corn crop monitoring.

7) Motion Detection: applications in this sub-class usually use a passive infrared detector (PIR sensor) to detect movement in monitored areas. Liu *et al.* [163] developed and constructed an agricultural IoT monitoring system using open-source hardware. The authors developed an intelligent, scalable, and inexpensive IoT gateway with built-in motion detection. The gateway is used to collect data as well as control equipment remotely.

8) Objects Identification: is common in a different agricultural application that needs to identify and recognize products or objects for various purposes. In [32], the authors investigated the potential of data from RFID technology in remote scale to monitor cattle visit times and time intervals between cattle visits to water points.

9) Light, Gaz, PH, and Temperature Monitoring: is essential in determining the ideal conditions for controlled environments. In [85], the proposed system framework for farm management incorporated monitoring and control of properties related to the crop, the soil, and environment such as temperature, O2, CO2, PH level, and nutrient concentration.

10) Multimedia Data Acquisition: is the process of collecting multimedia data, such as images and videos, where the physical conditions of the real world are measured, and then processed to extract useful information. In [63]. The authors presented the technical details and functionality of the UAV-based hyper-spectral imaging system. They also discussed the image processing needed to acquire a high quality hyper-spectral imaging dataset.

C. Smart Water Management

IoT can be used to improve water resource management and achieve efficient and optimal results. The wise use of water resources in agriculture is essential to increase crop yields and reduce costs, while at the same time being a necessary step towards sustainability.

1) Smart Irrigation: An efficient irrigation system must provide water to the entire field in a uniform manner, or else the quality of the crop produced will be reduced [164]. Smart agriculture can improve water distribution on the farm to increase product quality and reduce wastage. The smart water management platform (SWAMP) project [165] provides an intelligent IoT-based water management platform for high precision irrigation in agriculture with a practical approach based on four pilots across Europe and Brazil. The management of agricultural water is divided into three phases: water supply, distribution, and consumption. SWAMP provides tools for the use of various applications of IoT for irrigation management according to the crops and soil moisture. Data collection, processing, and synchronization services can be customized by users for multiple plants, weather conditions, and countries. Findings indicated that SWAMP can reach satisfactorily results. Nawandar and Satpute [166] developed a low-cost neural network-based intelligent irrigation scheduling system for efficient irrigation. The system uses MQTT and HTTP to inform the user about the current crop situation at any time, no matter how remote the location. Fernández-Ahumada *et al.* [167] developed an intelligent, automatic, cloud-based, and low-cost irrigation system design. SIGFOX is used for internet connectivity. By focusing on reducing energy consumption, the nodes became self-sufficient for more than five years.

2) Desalination: is a process for treating sea or salty water in desalination plants to obtain fresh water. It is beneficial, particularly for the agricultural industry, because it provides sustainable freshwater in areas where there is no other source of water. Muñoz *et al.* [90] proposed and tested an IoT infrastructure for water resources management in agro-industrial environments. This work focused on areas with desalination plants, public utility grid connections, and various consumer entities. This structure features highly efficient management methods using a predictive model control approach, designed to minimize operating costs. The study results showed that approximately 75% of total operating costs can be saved. Yaqub *et al.* [168] has established a hybrid desalination plant based on wind and solar energy. The goal for this work is concrete conceptual proof of concept for the application of an industrial control system (ICS), in the IoT framework.

3) Soil Moisture Measurement: Being aware of soil moisture status ensures highly efficient irrigation, providing water as required, and avoiding wasted water when irrigation is not. Angelopoulos *et al.* [169] designed, implemented, and validated an intelligent decentralized irrigation solution for strawberry greenhouses, which was tested in Greece. Each pot uses a corresponding soil moisture sensors and mote-driven electro-valve. The authors concluded that the intelligent irrigation approach greatly surpasses the traditional method in terms of water consumption, costs, and benefits.

4) Weather Forecast: is essential for irrigation scheduling, i.e., the coordination of time and amount of water used to irrigate crops to maximize profits. Goap *et al.* [170] proposed an intelligent system for predicting irrigation needs based on data from several sensors, including current soil moisture. The system also uses data from weather forecasts to predict soil moisture for the coming days. The prototype system is based on open standard technologies.

5) Water Quality and Pressure Monitoring: is an important step in understanding the chemical and physical composition of water, as well as identifying and detecting leaks and breaks in irrigation systems. In [49]. The authors designed and implemented a solution for the real-time monitoring of water management, including water quality measurement, with the aim of power consumption optimization.

6) Humidity Monitoring: A humidity sensor measures and detects both the humidity and temperature of the air. Rao and Sridhar designed a system that uses humidity, soil temperature, and light information from many sensors to calculate the amount of water needed for irrigation [171]. In [172], the authors proposed an irrigation control scheme using an IoT-driven WSN system; many sensors used included soil moisture and temperature, environmental temperature and humidity, CO2 sensor, and daylight intensity sensor, to acquire real-time farm information. The framework utilizes structural similarity (SSIM)-based water valve management mechanism and a fuzzy logic weather model. Control orders for irrigation valves are generated successfully in nearly all weather situations.

7) Decision Support Systems: is the component with responsibility for making the final decisions on irrigation actions. In [105], authors developed a decision support system for smart agriculture that uses data from several sensors obtained via a LoRaWAN network, as well as meteorological data and crop information, to make informed decisions.

8) Water Loss Control: is the action of preventing water leakage or unnecessary irrigation using IoT technologies. Campos *et al.* [173] proposed a smart and green framework to offer intelligent irrigation services, such as monitoring of data, pre-treatment, storage, and control of irrigation enriched by soil moisture prediction. On average, between 56.4% and 90% of irrigation water can be saved.

9) Rain Detection: is accomplished by a rain sensor to detect unpredictable rainfall management. Severino *et al.* [174] presented a framework for intelligent irrigation in agricultural applications. It consists of an autonomous network of sensors that collect data on soil moisture and the concentration of dissolved contaminants. The framework incorporates all this data, together with predicted precipitation, into predictive models of soil moisture and contaminant migration dynamics. It uses these models to optimize irrigation management strategies and to reduce environmental impact.

D. Agrochemicals Applications

Annual agricultural losses caused by insects, weeds, and diseases are estimated by FAO to be between 20 and 40 percent of total production. While pesticides are essential in reducing crop losses, if misused, they can have harmful effects on human health and the environment. IoT can help farmers to minimize waste and increase crop yields. Wireless sensors detect nitrogen, phosphate, and potassium (NPK) levels in the soil. Agrochemicals are agricultural chemicals, commonly referred to as pesticides and fertilizers, which are used in agriculture to control insects and weeds and prevent disease and promote plant growth. Examples of agrochemicals include pesticides, herbicides, insecticides, and fungicides.

1) Fertilization: The most commonly used fertilizers in agriculture contain the three primary plant nutrients: nitrogen, phosphorus, and potassium. Lavanya *et al.* [175] developed a smart fertilization system based on IoT and AI. The designed NPK sensor integrates the colorimetric mechanism by using light dependent resistor (LDR) and light emitting diodes (LEDs). The authors also developed a fuzzy rule-based system to analyze measured data and to determine proportions of N, P, and K in the soil.

2) Pest Control: Sensors can collect data automatically, such as the presence of a pest, or a trap trigger that indicates that a pest has been captured. Yue *et al.* [176] proposed an intelligent high-resolution model for pest detection. Results showed that the proposed method greatly improved the recall rate, reaching 202.06%.

3) Herbicides Application: The most popular technique for weed control is herbicide spraying. In [177], a system based on IoT, image processing, and machine learning to identify weeds and to selectively spray the right amount of herbicides.

4) Solar Pest Control Light: is a green pest control method with solar insecticidal lamps (SILs) [178]. It is a low-voltage power supply system that does not only reduce pesticide residues, but also significantly increases the value of agricultural products. It acts as a trap that kills pests, while avoiding the need to reduce pesticide residues. It is also safer for humans and animals.

5) UAV-Based Agrochemicals Spraying: significantly reduces the time and cost of manual spraying and sprayer rental. Faiçal *et al.* presented a demonstration of a UAV-based architecture that can be used to implement a control loop for smart farming applications, where UAVs are tasked with spraying chemicals on crops [179]. The authors proposed and evaluated an algorithm that automatically adapt the UAV's route according to changes in wind intensity and the direction. The algorithm input is the WSN feedback deployed in the field. Results showed that this system could significantly reduce pesticide and fertilizer wastage.

6) Weed Detection: Weeds can be a significant factor affecting crop yields. Machine learning, combined with image processing techniques, has become a promising tool for accurate, real-time detection of weeds and crops in the field. Lottes *et al.* [180] presented a visually based approach to weed classification that operates on image sequences. It carries out a semantic segmentation of images according to pixels, into soils, crops, and weeds. Potena *et al.* [231] implemented a real-time, accurate weed classification based on a summarised training set, using a multi-spectral camera mounted on a ground agricultural robot. Experimental results showed a high-precision classification.

7) Insecticides Application: in agriculture is used to kill insects; however, it can also harm crops. Therefore, IoT can help decrease the use of unnecessary use of chemicals. Lee *et al.* [181] developed an IoT system for reducing the use of insecticides in fruit trees and to predict when pests appear according to temperature and humidity.

8) Soil NPK Sensing: is one of the keys required in soil analysis for fertilization is to determine the level of soil nutrients in the soil, followed by nutrient requirement and site-specific fertilization recommendations. Ramane *et al.* [182] developed a fiber optic sensor to detect N, P, and K nutrient levels in the soil. It is based on the colorimetric principle, where light absorption by a solution causes a variation in the output of the sensor.

E. Disease Management

Diseases damage plants and animals, as well as affect market availability and agricultural production. Disease management using IoT and emerging technologies is the practice of minimizing crop and livestock diseases to increase yields and prevent losses.

1) Crop Health Monitoring: The regular surveillance of crop health conditions on a continuous basis will help farmers to increase their productivity on a large scale with a minimum of effort. Pantazi *et al.* developed an automated method for identifying crop diseases on various leaf samples of different species [183]. It was trained to identify four different health conditions. A 95% total success rate was achieved for all 46 combinations of plant conditions that was tested. Furthermore, the application can determine the health conditions mentioned above in plant varieties other than the ones previously tested, and to classify them in new categories. Uddin *et al.* [184] deployed a crop health monitoring system using IoT and UAVs. The system can withstand harsh climatic conditions and can integrate heterogeneous sensors to collect the necessary data. Kim *et al.* [185] proposed a farm as a service (FaaS) integrated system, that can process the collection, analysis, and forecasting of information on the agricultural environment on the cloud, and supports sophisticated application services by running and supervising farms as well as handling the corresponding devices, data, and models. The authors developed an infection prediction model specialized for strawberry diseases.

2) Livestock Health Monitoring: The identification of livestock diseases can be managed through regular monitoring and recording of animal feeding and daily behavior. Kumar and Hancke [186] presented a prototype for an animal health monitoring system. It was tested to monitor real-time livestock physiological and environmental parameters. In the developed sensor module, the energy consumption is low. The sensor module is miniaturized, smart, user-friendly, low-cost, and is high-quality. The results showed a high degree of accuracy. Edwards-Murphy *et al.* [187] developed a heterogeneous WSN-based smart health monitoring beehive network. The collected data include pollutant gases, weather data, O2, and others that provides an analysis dimension. The decision tree-based classification algorithm for describing the beehive reached a 95.38% accuracy, and short term local forecasts for environmental monitoring achieved 95.4% accuracy.

3) Disease Prediction: is used to predict the occurrence of diseases in crops and livestock. Khattab *et al.* [188] developed an IoT-based monitoring system for multiple plant disease control. Environmental monitoring services are available to keep the conditions in which crops grow optimal, and predict the occurrence of disease epidemics rapidly. The proposed system mimics the decision-making skills of an expert on diseases.

4) Behaviors Monitoring: using wearable sensors to monitor animal behaviors is becoming an essential option for farm management. Başçiftçi and Gündüz [189] designed an IoT-based circuit to be placed in the rumen part of cattle, which can be useful in diagnosing acidosis disease. The developed system record nutrition parameters and behaviors of animals.

5) Disease Detection: Rapid and accurate detection and diagnosis of diseases play a crucial role in agricultural production, and in minimizing both qualitative and quantitative losses. Zhao *et al.* introduce an effective IoT-based agricultural system for automatic crop disease recognition in the wild, based on a deep learning system using a multi-context fusion network (MCFN) approach, and visual features from over 50 000 in-field crop disease samples. Experimental results on 77 common crop diseases achieved a good identification accuracy of 97.5% [190].

6) Disease Prevention: Controlled environments based on IoT help prevent and control diseases affecting agricultural goods. In [191], the authors designed and implemented a WSN-based greenhouse automatic dew condensation control system to prevent the phenomenon of dew condensation on the leaf surface of crops, which is considered to be a factor in plant disease development. The results proved that the proposed system could predict and prevent dew condensation, by controlling the conditions of dewdrop formation in the greenhouse environment.

7) Blood Pressure and Heart Rate Monitoring: The use of IoT devices and sensors ensures continuous monitoring of livestock blood pressure and heart rate. It is an essential factor in determining animal agitation and stress [15].

8) Disease Classification: Many reviewed projects have carried out classification using deep learning models to help in the identification of livestock, plant leaf diseases. In [193], the authors proposed an intelligent IoT-based agriculture decision support system, applied to large biomedical datasets, such as plant disease datasets, as well as real-time applications, which improved the accuracy of classification by 9.52% and 5.71%, and reducing characteristics by 58.50% and 72.73%, respectively.

F. Smart Harvesting

A wide variety of smart harvesting systems were developed for intelligent agriculture [240]. These systems can reduce the harvesting cost by about 35–45% [241].

1) Objects Detection: is based on image processing, which involves detecting instances of a specific class of objects in images or videos. In [194], the authors proposed a vision-based fruit detection system, by performing a supervised machine learning task, that trains a model of the object of interest. Lin *et al.* [195] presented a framework for detecting a wide array of fruit types. The algorithm was evaluated on image datasets of 450 images captured in the natural environment.

2) Robotic Arms: The harvesting stage is one of the main areas of robot application in agriculture. Thangavel and Murthi [196] suggested a system that would automatically harvest the tea leaves by a robotic arm that would pull them off according to the applied quality, using key image extraction and optical flow. Barnett *et al.* [69] investigated the division of harvesting tasks so that several robot arms can harvest, in the shortest possible time, kiwifruit.

3) Motion Control: Harvesting robots can, at any time, receive direct commands from the farmer for controlling their movements, which makes the harvesting task more efficient. Megalingam *et al.* [197] presented the design of an inexpensive robotic arm capable of pruning and harvesting tree fruits. A mobile application developed to control the motion of the robotic arm via Bluetooth.

4) Fruit Detection and Classification: Successful detection of fruit in the tree is one of the most important requirements of a fruit harvesting system. Kang and Chen [198] developed a DL-based framework of a fruit detection in apple harvesting. It comprises a smart and real-time fruit detector named "LedNet" from 800 images collection. Experimental results showed achievement of 0.821 and 0.853 on recall and accuracy on apple detection, and an average computational time of 28 ms. Reference [199] proposed and improved a faster region-based convolutional neural network (R-CNN) for multi-class fruit recognize of different sizes. Results showed more than 91% mAP for apples, mango, and orange.

5) Colors and Shapes Recognition: Lin *et al.* [200] has proposed an algorithm to guide harvesting robots to automatically pick up fruits based on three different criteria: color, depth, and shape. The results showed that the algorithm applies to agricultural harvesting robots equipped with an inexpensive RGB-D sensor, but was quite time-consuming.

6) Obstacles Detection: A collision with a greenhouse construction element can cause damage to the greenhouse construction or the harvesting robot. Thus, an obstacle detection mechanism should be implemented to avoid this type of injury. In [201], the authors focused on the development of an obstacle mapping system for pepper harvesting to plan a collision-free movement for a harvesting robot. The authors separated hard and soft obstacles, as the dense obstacle map requires the robot manipulator to push some obstacles sideways, to reach the target.

7) Optimal Harvest Date: Yield loss occurs if harvesting is carried out earlier or if it is delayed, both are undesirable. Xu *et al.* [202] proposed a method for predicting the optimal harvest date of corn in the field using multi-spectral remote sensing imagery. The technique also reduced requirements for field data collection, which is critical for vast area crops.

G. Supply Chain Management

It is the process of managing the flow of goods and services, from the raw materials to the finished products. The escalating demand of the final consumer for safe and healthy food, imposes strict obligations for a well-structured traceability system [33]. ICT technologies, including IoT, provide significant changes in the agricultural supply chain and deliver critical technologies, to establish a smooth flow of the supply chain information from farm to fork. Table IX provides a compilation of selected projects, including a brief description of the work focus, the supply chain mechanism employed, and whether the work takes into account network latency, energy management, storage, and security.

1) Products Identification: RFID tags can be extensively used to categorize, identify, and manage the flow of products in an industrial context. To track Chinese agri-food supplies, Tian [33] presented a traceability system using RFID and blockchain. Leng *et al.* [203] explored the application of RFID in the Identification process of agricultural products and testing the efficiency of the system.

2) Traceability via Blockchain Technology: Blockchain technology is a distributed data structure that is mirrored and shared among network members, and it can be applied in many fields and different areas where IoT applications are involved [242], [243]. Machine learning approaches can be combined with blockchain technology for secure smart agriculture [244]–[246]. Therefore, the blockchain technology promises future secure and transparent system for the exchange of supply chain and logistics information across supply networks. AgriBlockIoT [204] is a decentralized traceability solution, based on blockchain for agri-food supply chain management. It is capable of smoothly integrating IoT devices in the food supply chain for a transparent, fault-tolerance, immutable, and auditable records, using two different blockchain implementations: Ethereum and Hyperledger Sawtooth. Casado-Vara *et al.* [205] proposed a blockchain approach to improve the current agricultural supply chain. The researchers focused on a multi-agent system to solve real-time problems in the supply chain sector. The principal goal of the proposed approach was to secure shared information. BRUSCHETTA [206] is a blockchain-based system for tracking the entire process of production of Extra Virgin Olive Oil by allowing customers to access a copy of the full immutable product history. The authors also suggested and tested a dynamic auto-tuning mechanism for the parameters of the blockchain, to guarantee the timely publication of information in the system. Hang *et al.* [207] proposes a blockchain-based fish farm platform. The designed platform aims to provide fish farmers with scalability, high throughput, off-chain storage, and privacy. A proof of concept that integrates a legacy fish farm system with the Hyperledger Fabric blockchain is implemented on top of the proposed architecture.

3) Food Safety and Quality Control: The use of IoT in the food supply chain will improve food safety and quality through monitoring and surveillance of food conditions along

TABLE IX
RESEARCH WORKS ON SUPPLY CHAIN MANAGEMENT FOR AGRICULTURAL IOT

Research work	Supply chain mechanism	Latency	Energy	Storage	Security	Focus of this work
Makhdoom *et al.* (2020) [232]	Blockchain	√	√	√	√	Privacy preserving and secure data sharing framework
Wang *et al.* (2020) [233]	Decentralized Stackelberg and a Nash bargaining cost sharing models	×	√	√	×	Green fresh product supply chain optimization
Arena *et al.* (2019) [206]	Blockchain	×	×	×	√	Traceability and certification of extra virgin olive oil
Leng *et al.* (2019) [203]	RFID	√	√	√	×	Identification of agricultural products in the supply chain
Caro *et al.* (2018) [204]	Blockchain	√	×	√	√	Blockchain-based traceability solution for Agri-Food supply chain management
Gupta and Rakesh (2018) [208]	Smart device	×	×	×	√	Food adulteration detection system can be used to detect the presence of adulterants in the food product
Casado-Vara *et al.* (2018) [205]	Blockchain	×	×	√	√	Multi-agent system uses smart contract, to manage the entire Blockchain-based alimentary supply chain
El Maouchi *et al.* (2018) [234]	Blockchain	×	×	×	√	A fully transparent, decentralized traceability system for the supply chain
Rajakumar *et al.* (2018) [209]	Smart device	√	√	×	×	IoT system for food fraud, which concentrates on the detection of adulterants in milk
Leng *et al.* (2018) [235]	Blockchain	×	√	√	√	Agricultural business resource Blockchain, based on double-chain structure
Davcev *et al.* (2018) [236]	Blockchain	√	√	√	√	Food on demand cognitive model with a high level of trust and quality control system for the food supply chain
Nirenjena and collegues (2018) [210]	Smart device	√	√	×	×	Monitor and control food quality, authors used the system to monitor and analyse the quality of meat and seafood products throughout the supply chain as a case study
Lucena *et al.* (2018) [237]	Blockchain	×	×	√	√	Discuss and stress the benefits achieved through the application of the Blockchain platform in the agricultural context
Tian (2017) [238]	Hazard analysis and critical control points (HACCP) and blockchain	√	×	√	√	Real-time food tracing system for food supply chain
Wang and Yue (2016) [211]	RFID, AI (Apriori algorithm)	×	×	×	√	Develop an early warning system to assist managers of food producing companies to detect food safety risks in advance
Tian (2016) [33]	Blockchain & RFID	√	×	√	√	Agri-food supply chain products identification and traceability system
Zhang *et al.* (2013) [239]	Self-adaptive dynamic partition sampling (SDPS) strategy	×	×	√	√	Tracing contamination sources in large IoT systems for complicated food supply chains Chain

(√): Supported; (×): Unsupported.

the food supply chain, and sharing the data obtained with consumers and supervisors. In [208], the authors developed a system to detect adulterants in food products. This system can be used by different actors, including farmers and consumers, to catch food adulteration. Various sensors are included in the system. Rajakumar *et al.* [209] developed an IoT system for food fraud, which focuses on the detection of adulterants in milk using several sensors such as gas sensor, temperature sensor, and RFID readers. In [210], the authors developed an IoT system to control food quality, the system monitor, and analyze the quality of meat and seafood products during the supply chain. Several sensors have been used to detect food spoilage, such as temperature and humidity sensors.

4) Agricultural Mobile Crowd Sensing: Mobile crowd sensing (MCS) is a strategy in which large-scale and complex detection tasks are performed by a wide range of individuals with mobile detection and computing devices by collectively measuring and sharing valuable information [40]. Farmers with smart devices will have a higher likelihood of obtaining agricultural data in the field, making it possible to apply MCS in agriculture. MCS is a critical way to improve the existing agricultural data collection system.

5) Chain Risk Control: The ability to identify risks immediately at any point in the food supply chain ensures a much higher level of safety for the consumer and the manufacturer. Wang and Yue [211] proposed a food safety system that tracks all relevant data detected throughout the supply chain, and automatically alerts food manufacturing managers if any food safety risk is identified. The system can effectively identify safety risks and accurately determine whether a warning should be issued based on expert assessment. When the system detects a problem, it provides some useful decision-support information to maintain the quality and the safety of food products. A case study was carried out in dairy farms.

H. Smart Agricultural Practices

1) Agrivoltaic Systems: The concept of Agrivoltaics (a.k.a. agrophotovoltaic (APV)) was initially proposed in the year 1982, by Goetzberger and Zastrow. APV systems combine solar panels and crops at the same time, and on the same land area, leading to a potential growth in the overall productivity up to 73% [247], and 30% more economic value of farms over traditional agriculture [248]. Various scientific and commercial APV projects have been implemented over the past few years [249] in many application modes [250], including greenhouses, breeding, and fisheries. It is considered the next generation of smart farming [19], [251]. Agrovoltaico system is a type of APV technology [212]. The system produces renewable energy on-farm without negatively affecting land productivity [214]. For maize crops, it showed a yield increase of 4.3% [212]. Valecce *et al.* [213] presented the Solarfertigation system, an IoT based smart fertilization and irrigation system with low power network protocol architecture and a photovoltaic plant for energy self-sustainability to power it. The system can make decisions based on environmental data that drive automated actions, such as irrigation or fertilization. Sharma *et al.* [252] proposed a solution to address the limited energy availability problem by using solar energy harvesting technologies to charge the batteries of the WSN nodes. Results of simulations showed that the life of the WSN has increased from 5.75 days to 115.75 days. Besides, the throughput of the network has also increased from 100 Kbit/s to 160 Kbit/s.

2) Greenhouse: is the main form of growing plants in a controlled agricultural environment. Kang *et al.* [215] presented an agricultural cyber-physical-social system (CPSS) for the management of farming production, featuring solar greenhouse as a practical case study. Social and physical sensors are used as system inputs, and data is used for real-time monitoring and prediction. The decision support mechanism is based on the ACP method, which is composed of artificial societies for modeling, computational experiments for analysis, and parallel execution for control [216], leading to a smart control facility for the greenhouse. Ferrández-Pastor *et al.* [217] proposed architecture for intelligent IoT-based agricultural monitoring and control system based on two levels of communication and processing, edge, and fog nodes. Fog nodes are used to carry out the machine learning processes, store data, and communicate with the cloud. González-Amarillo *et al.* [218] developed a traceability model for tracking seedlings and other agricultural products in greenhouses. Variables control is performed using proportional, integral, and derivative (PID) analog techniques. Results showed that humidity levels over 80% relative humidity are a favorable environment for pathogens, while below 60% levels cause water stress and low photosynthesis rates. The proposed model reduces water and energy consumption. Authors designed a web-based system that can be used by farmers to access information about seedlings or observe the harvest of the products in the greenhouse.

3) Hydroponics: is the process of growing plants without soil. The roots of the crop are exposed to the mineral solution. Lakshmiprabha and Govindaraju [219] proposed an intelligent monitoring and control system for the hydroponic environment, data such as water flow-rate, temperature and humidity were recorded with their respective times in the ThingSpeak IoT platform. Mehra *et al.* [55] developed an intelligent IoT-based hydroponics system. The system delivers the proper control action for the hydroponic environment based on the multiple input parameters collected. The control action provided for real-time data has reached an accuracy of 88%. Cambra *et al.* [220] designed a self-calibrating PH sensor that can detect and adjust nutrient pH level imbalances used in hydroponic agriculture. The collected data is presented through a user-friendly web portal, for easy management and visualization.

4) Aeroponics: is one of the techniques of soilless culture. The process involves growing plants in an air or mist environment without the use of soil or an aggregate medium, where plants grow suspended in the air, and the roots are sprayed with water. Compared to other soilless systems, aeroponic reduce water usage through continuous water circulation [222]. Francis *et al.* [221] proposed an IoT-based aeroponics system, sensed data, including temperature, humidity, PH value of water, and the light are measured and uploaded to the cloud. Multiple LED strip lighting was used to compensate for the ambient light.

5) Aquaponics: refers to any system that combines the production of aquatic organisms with plant production [223]. IoT-based aquaponics helps to monitor the growth conditions of both marine creatures and hydroponic plants. Water is used both for plant growth and to breed fish or other water cultures. In [224], the authors presented a monitoring system for aquaponics based on IoT and cloud computing. The system measures water temperature, water depth, dissolved oxygen, PH, and fish activity.

6) Vertical Farming: is the practice of growing products in layers that are stacked vertically. It can use soil, hydroponic, or aeroponic methods of farming. Vertical farming seeks to produce food in some challenging environments, for example, when there is little or no available arable land. Haris *et al.* [225] proposed an of an indoor vertical farming prototype, based on fog-cloud computing, and provided by CPS/IoT ecosystem and Arrowhead IoT framework. The system is built using service-oriented architecture. The network contains two types of sensor nodes: the environmental and the soil-based measurement nodes.

7) Plant Phenotyping: refers to a description of the anatomical, ontogenetic, physiological, and biochemical quantitative characteristics of the plant [253]. All plant-related sciences, from the molecular to the field scale, must be integrated to develop strategies for a sustainable plant. Selvaraj *et al.* [226] developed an aeroponic system to examine cassava root architecture during the early differentiation of storage roots, as well as being able to perform reliable high-throughput, and non-destructive phenotyping. The results obtained from this research had

(a) (b)

Fig. 8. Greenhouse system [101].

significant implications for the genetic improvement of cassava, and its durable intensification.

VII. Real-World Case Studies

In this section, we look at a few fresh real-world cases, that were briefly cited above, which use most of the technologies examined in this study, and that have achieved excellent results in improving the value of quality in IoT-based smart farming.

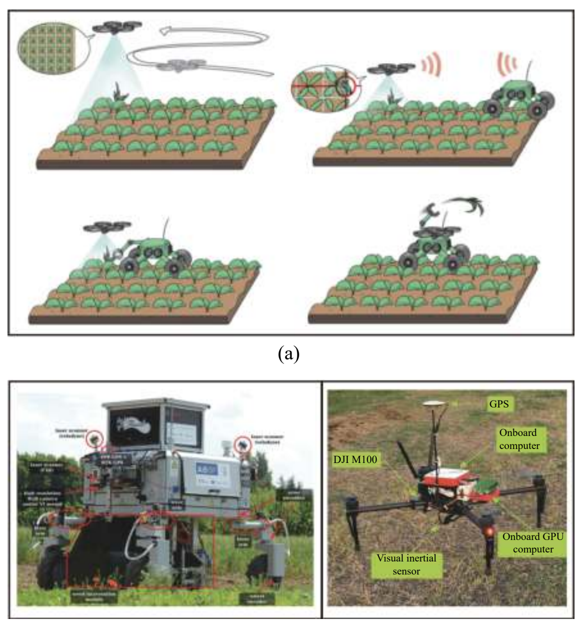
A. Case Study 1: Greenhouse System

A greenhouse system that can accommodate the requirements of the soil-less greenhouse using low-salinity water, was implemented in a frame of south-east Spain, as a part of the EU DrainUse project [101]. The real-life deployment of the system is shown in Fig. 8(a), while the architecture is illustrated in Fig. 8(b). The project is composed of three layers. The first layer is a local CPS, that interact with IoT sensors and actuators, to gather data and carry out tasks in real-time, and linked to greenhouse installations.

The second layer is the edge computing layer, where data collection and task offloading takes place. This layer is also responsible for controlling virtualized nodes with NFV technology, and improving the reliability of the system in case of network access failure. The last layer is the cloud computing layer, where complex calculations and data analysis are performed for better decision management. The last two layers are implemented using the FIWARE platform [95]. 6LowPAN is used to connect with IoT sensors and actuators, while protocols as MQTT and CoAP, are used to connect the CPS. The project was tested with two cycles of the tomato crop, and showed that over 30% water conservation has been achieved, and up to 80% for certain nutrients.

B. Case Study 2: Aerial-Ground Robotics

The flourish research project focused on building an adaptable robotic solution for precision agriculture, that integrates the aerial surveying capabilities of UAV, with a general-purpose unmanned ground vehicle (UGV) [67]. The overall concept of the system is shown in Fig. 9(a). The UAV monitors a field by collecting crop and weed data by mapping wide zones, while meeting the requirements of the batteries, then sharing the information with a UGV, that is used for specific data evaluation and actions, with secure navigation in a cultivated area, including accurate location and crop row detection. Aggregated information is then passed on to high computation operators for better analytics and decision-making.



(a)

(b) (c)

Fig. 9. Aerial-ground robotics system [67].

The UGV system is the BoniRob Bosch's Deepfield Robotics system as shown in Fig. 9(b), which is a research platform for agricultural robotics. The UGV is equipped with a diverse range of sensors, including GPS, RTK-GPS, lidars, RGB and hyperspectral cameras, wheel odometer, and others. The UGV features intervention modules for weed classification, multi-modal actuation systems, and their associated

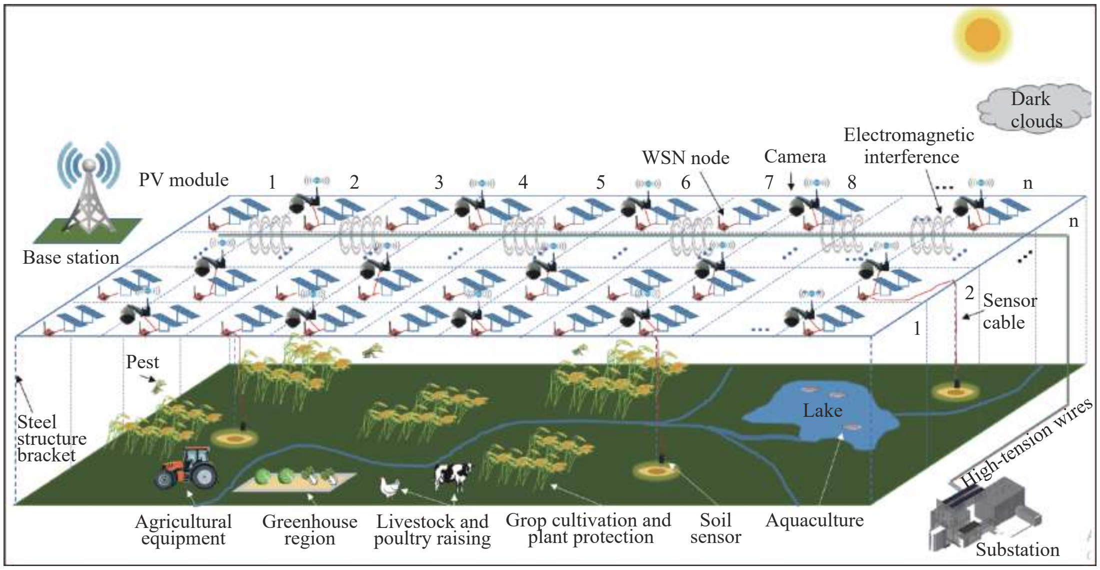


Fig. 10. Photovoltaic agri-IoT schematic diagram [251].

(a) (b)

Fig. 11. Smart dairy farming system [254].

support aggregates. The UAV system is a DJI Matrice 100 multi-rotor shown in Fig. 9(c) that integrated various sensors for real-time weed detection, GPS positioning, visual-inertial, and egomotion estimation. The project implemented multi-spectral perception algorithms for aerial and terrestrial systems to effectively track and to accurately classify crop and weeds, and calculate the plant sanitary indicators. The project also implements modules for selective crop spraying, mechanical treatment, and the removal of weeds. A field task integrating the previous modules was successfully carried out in a rough and flat environment.

C. Case Study 3: Photovoltaic Agricultural IoT

A novel IoT-based agricultural paradigm is proposed for the first time in [251], it is called the photovoltaic agricultural IoT (PAIoT). Fig. 10 illustrates a model of the concept, where IoT-based devices located in the physical layer could use photovoltaic solar electricity via wireless energy transfer and could communicate using active transmission, wireless, and wired backscatter techniques. With the advantage of sufficient and permanent power, it is possible to process and analyze data locally to provide continuous feedback and to perform real-time actions.

The research group investigating the key questions that concern the feasibility of PAIoT and identified some issues [19], including the efficient use of water resources for cleaning panels together with agricultural activities, cost-effective deployment of nodes, optimization of data transmission in the agricultural environment, environmental climate impact, and troubleshooting of the photovoltaic module. By doing this, the research group recognized a better understanding of how to implement the PAIoT, thereby enhancing the level of smart farming.

D. Case Study 4: Smart Dairy Farming

MooCare is and IoT-based smart dairy farm model used in a dairy farm located in the south of Brazil [254], which is illustrated in Fig. 11(a). It was developed to help dairy cattle producers achieve better productivity rates by analyzing their milk production and providing automatic and individualized nutrition to the animals. The data collected from IoT devices allows the provision of milk production forecasts based on individual cows. This way, breeders can be well informed in advance, and thereby better reacting in terms of developing a better nutritional plan from which each cow can benefit from a personalized diet. The model also supports a procedure for the valuation and notification of non-conformities. MooCare is composed of two essential modules MooField and MooServer, as shown in Fig. 11(b). The MooField module is handling data collection for food production and supply, animal identification, and feeding. This module incorporates multiple IoT technologies including RFID tags, milk production sensors, feed actuators, and a system controller.

The MooServer module is a centrally located controller designed for collecting, visualizing, and storing data. It also incorporates prediction engine, feeding, and notification services. The communication between the two modules is done through HTTP. The prediction engine auto-regressive moving average (ARIMA) showed better results against artificial neural networks (ANN), and random forest (RF) prediction algorithms. The forecasting accuracy of the MooCare model was 94.3%, which indicates that it can adequately predict milk production.

E. Case Study 5: Solar Insecticidal Lamp

A group of researchers from Nanjing Agricultural University in China have proposed the concept of IoT-based solar insecticidal lamps (SIL-IoTs), presented in Fig. 12(a), which is based on the integration of wireless radio-frequency modules into existing SILs that emits a high-voltage pulse when contact is made with the wire mesh by migratory insects with phototaxic [178], [255]. The implementation, as shown in the Fig. 12(b), is composed of four main modules: a ZigBee-based module, an information collection module that uses the Raspberry Pi 4B model, a discharge simulation module, and a SIL. The concept allows the communication and the coordination between them, to provide accurate information on ecological data needed for automatically predicting insect disasters, and better management of insect migration. The implementation results indicated that when the discharge simulator module is running, it causes interference during discharge with the ZigBee-based device, which forces the device to restart in case of insects are killed, indicating a more severe interference. The results provided very valuable insights, in particular the prohibition of deploying such devices near the IoT nodes without protection, as it can be used to attack them, leading to an abnormal working state of the whole IoT network [256].

A major challenge for SIL deployment is the complicated geography of agricultural land and its associated features, including random edges and obstacles, an example of which is provided by the authors and illustrated in Fig. 12(c), showing a real agricultural land located in the city of Babaiqiao, Nanjing, China, together with its map diagram in Fig. 12(d). The SIL deployment problem (SILDP), which is the duplication rate optimization through deploying of as few SILs as possible while maintaining full coverage, has been addressed in [257]. The authors have proposed two genetic algorithm-based methods, namely Independent boundary based deployment method (IBDM) and separate partition based deployment method (SPDM). The two methods share the same optimization objectives but differ in the deployment sequence. The experimental studies showed that these methods offer superior performance on deployment cost (Fig. 12(e)) with 32 SIL nodes, compared to other peer algorithms (Fig. 12(f)) with 37 SIL nodes.

VIII. Discussion

IoT technology promises a broad scope of possibilities for optimizing production in agriculture. The integration of middleware, fog/cloud computing, big data analysis, SDN/NFV, and AI can be seen in recent years, as these technologies are essential for extending the functionalities. The IoT has widely influenced agriculture, but despite its advantages, several challenges need to be addressed.

A. Hardware Challenges

The perception layer is directly affected by rough environmental conditions like intense sunlight, humidity, strong winds, and others which can destroy devices. Equipment must remain active and reliable for long periods while relying on low battery power resources. Also, building IoT systems in open fields plantations requires a lot more sensors to monitor the wild environment, as well as the growing crops; to ensure efficiency, mobile sensors and UAVs have great potential for data collection in the agricultural field. The fabrication, delivery, and use of IoT resources is usually accompanied by higher volumes of both solid and toxic waste. G-IoT is a sustainable and more energy-efficient model for the creation of products and services [85].

B. Interoperability Challenges

This type of challenge can be viewed from different points of view, such as hardware, network protocols, syntax, semantics, and platforms heterogeneity. To communicate and exchange data efficiently between different infrastructures, gateways, virtual networks, networking technologies, open application programming interfaces (APIs), service oriented architecture (SOA), semantic web technologies, and open standards can be used based on their interoperability handling techniques. Standards must be tailored to handle a wide range of implementations that satisfy the basic specifications for IoT-related applications. Thus, one of the challenges that should attract more attention in the future is providing global standardization frameworks for IoT-based agriculture.

C. Networking and Energy Management Challenges

Wireless networks have low cost, flexible networking, and high scalability compared to wired networks. Still, due to field changes as plants grow, background noise is produced, reducing the reliability of the data transmission. When a node is responsible for routing the communication tasks of many devices, and this node is disconnected from the network, it can cause a partial or even total network shutdown. Improving power management to increase the resilience of IoT devices will increase the durability of applications, as one of the main

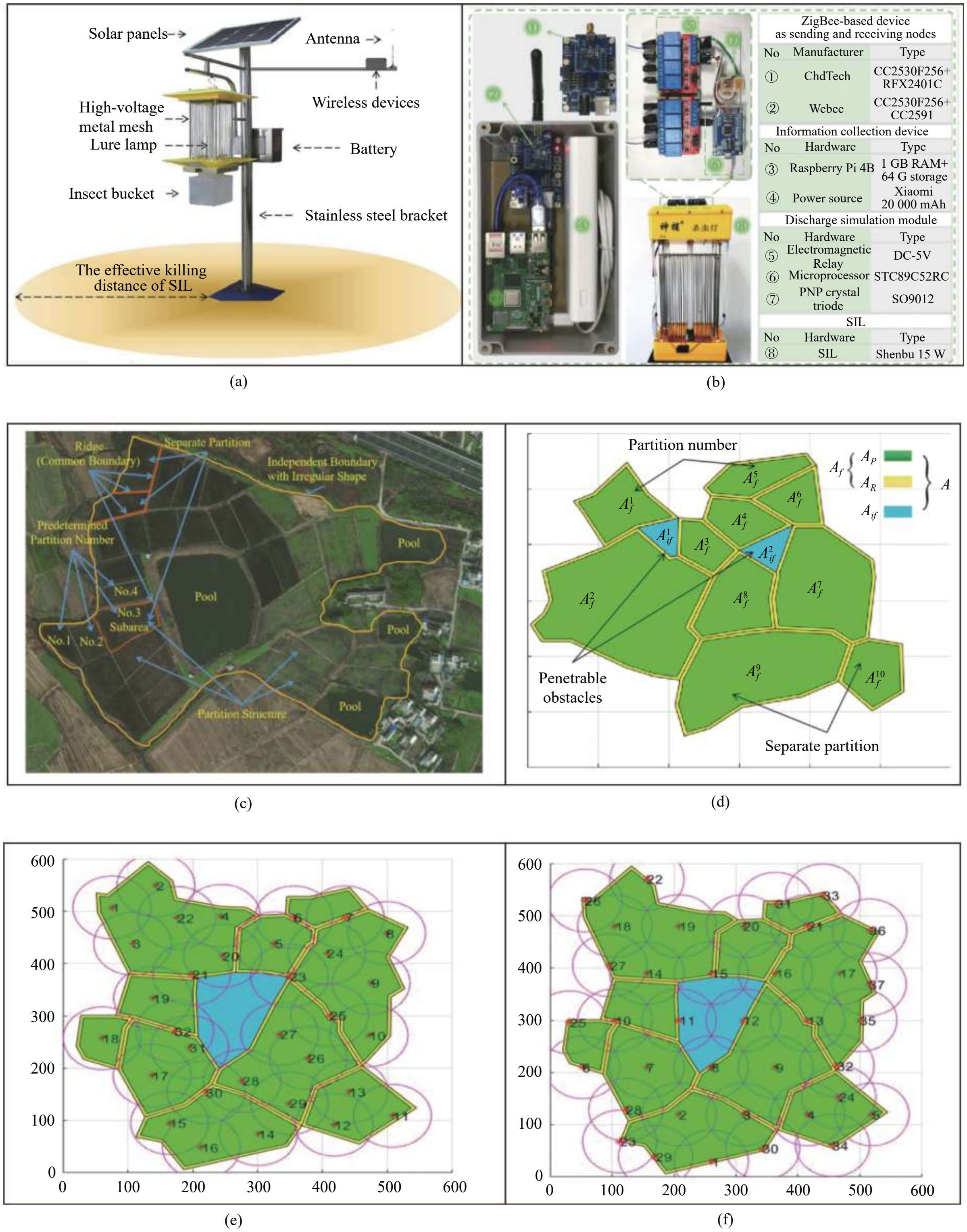


Fig. 12. IoT-based solar insecticidal lamp [256], [257].

factors limiting the lifetime of IoT installations is power drain. Renewable sources of energy harvesting solutions, such as solar power and wind, could also be used in IoT-based smart agriculture systems. Area coverage problems is among the most critical issues in IoT based systems. LPWAN technologies can solve such problems thanks to their long communication range. However, the installation cost of LPWAN base stations remains high. Metaheuristic algorithms have been widely used for addressing the coverage problems. Therefore, the question we ask here is: how do we choose the right algorithm among different types? We believe that a comparative study of area coverage optimization algorithms for IoT-based agriculture is needed.

D. Security and Privacy Challenges

Security and privacy issues are seen as critical challenges in agriculture because of potential losses. Smart agriculture not only has the same security problems as IoT security, privacy, authentication, and access control, but also has its specific issues such as information storage and management problems. Frequent security issues in the physical layer include data collection security and the physical security of the equipment. While fog computing brings a lot of benefits, many new security and privacy threats are emerging that did not exist before. For example, it is more challenging to control users' privacy in a decentralized manner, since for nodes are dispersed across broad surfaces.

Blockchain technology brings significant potential for real improvements in supply chains, including transparency, security, and, above all else, trust. But it has its proper limitations such as scalability and energy-efficient mining issues [17]. Big agricultural data is passed to the application layer, including agricultural material consumption, information on fruit and vegetable supply, and location of field machinery. Data security and confidentiality must be taken into account. Encryption algorithms, intrusion detection systems (IDS), key distribution [258], and security routing policies have to be deployed with consideration of IoT end devices characteristics of weak computing power, small storage space, and short battery lifetime.

E. Hardware and Software Costs Challenges

Efforts to lower hardware and software costs in IoT implementations, together with maximizing system performance, is a major objective of researchers around the world. Even though the costs of IoT platforms have reduced remarkably, the prices of top-quality sensors and actuators are still high. Costs need to be reduced more, and an optimization model of minimum service costs needs to be implemented.

F. Education Challenges

Farmers in developing countries are often located in rural areas where most of them are uneducated. The inability of information utilization by such farmers could be a major obstacle for the integration of IoT and other technologies in agriculture. A possible research direction in this topic could be related to developing smart farming education service for IoT-based agriculture environment to ensure that farmers receive ongoing training in order to keep up to date with the rapid changes in technology that affect farm operations from farm to fork.

IX. Conclusion

In this paper, we surveyed the emerging technologies for the internet of things-based smart agriculture. We provided a list of emerging technologies for agricultural IoTs, including unmanned aerial vehicles, wireless technologies, open-source IoT platforms, SDN and NFV technologies, cloud and fog computing, and middleware platforms. Through extensive research and analysis that was conducted, we were able to classify the IoT applications for smart agriculture into seven categories, including smart monitoring, smart water management, agrochemicals applications, disease management, smart harvesting, supply chain management, and smart agricultural practices. Also, we analyzed supply chain management solutions for agricultural IoTs based on blockchain. In addition, we provided real-life smart farming projects that utilize several of the above mentioned technologies. There still exist several challenging research areas, such as hardware boards, interoperability of systems, networking and energy management, security and privacy threats, hardware and software costs, and education challenges, which should be further investigated in the near future.

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