

## Review

# IoT-Enabled Smart Agriculture: Architecture, Applications, and Challenges

Vu Khanh Quy <sup>1</sup>, Nguyen Van Hau <sup>1</sup>, Dang Van Anh <sup>1</sup>, Nguyen Minh Quy <sup>1</sup>, Nguyen Tien Ban <sup>2</sup>, Stefania Lanza <sup>3</sup>, Giovanni Randazzo <sup>4</sup> and Anselme Muzirafuti <sup>4,\*</sup>

- <sup>1</sup> Faculty of Information Technology, Hung Yen University of Technology and Education, Hung Yen 160000, Vietnam; quyvk@utehy.edu.vn (V.K.Q.); haunv@utehy.edu.vn (N.V.H.); dangvananh@utehy.edu.vn (D.V.A.); minhquy@utehy.edu.vn (N.M.Q.)
- <sup>2</sup> Faculty of Telecommunication 1, Posts and Telecommunications Institute of Technology, Hanoi 100000, Vietnam; bannt@ptit.edu.vn
- <sup>3</sup> GeoloGIS s.r.l., Dipartimento di Scienze Matematiche e Informatiche, Scienze Fisiche e Scienze della Terra, Università degli Studi di Messina, Via F. Stagno d'Alcontres, 31-98166 Messina, Italy; stefania.lanza@unime.it
- <sup>4</sup> Dipartimento di Scienze Matematiche e Informatiche, Scienze Fisiche e Scienze della Terra, Università degli Studi di Messina, Via F. Stagno d'Alcontres, 31-98166 Messina, Italy; giovanni.randazzo@unime.it
- \* Correspondence: anselme.muzirafuti@unime.it

**Abstract:** The growth of the global population coupled with a decline in natural resources, farmland, and the increase in unpredictable environmental conditions leads to food security is becoming a major concern for all nations worldwide. These problems are motivators that are driving the agricultural industry to transition to smart agriculture with the application of the Internet of Things (IoT) and big data solutions to improve operational efficiency and productivity. The IoT integrates a series of existing state-of-the-art solutions and technologies, such as wireless sensor networks, cognitive radio ad hoc networks, cloud computing, big data, and end-user applications. This study presents a survey of IoT solutions and demonstrates how IoT can be integrated into the smart agriculture sector. To achieve this objective, we discuss the vision of IoT-enabled smart agriculture ecosystems by evaluating their architecture (IoT devices, communication technologies, big data storage, and processing), their applications, and research timeline. In addition, we discuss trends and opportunities of IoT applications for smart agriculture and also indicate the open issues and challenges of IoT application in smart agriculture. We hope that the findings of this study will constitute important guidelines in research and promotion of IoT solutions aiming to improve the productivity and quality of the agriculture sector as well as facilitating the transition towards a future sustainable environment with an agroecological approach.

**Keywords:** sustainable agriculture; food security; green technologies; Internet of Things; natural resources; sustainable environment; IoT ecosystem



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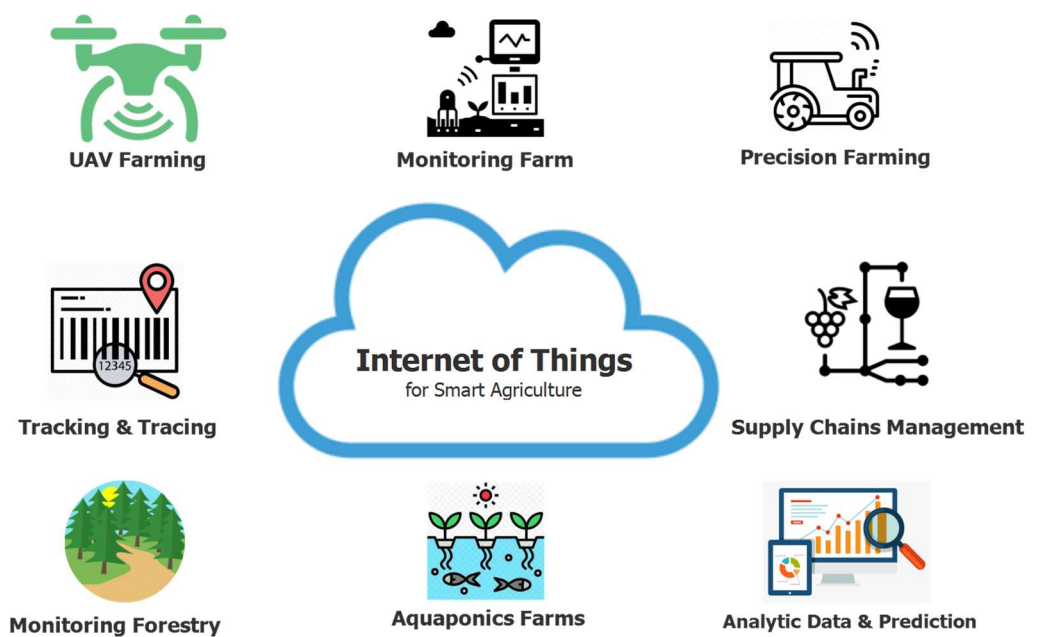
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## 1. Introduction

In order to meet the current global needs of humanity, new solutions and technologies are constantly being proposed and implemented. This has led to the advent of the Internet of Things (IoT) [1,2]. IoT is defined as the network of all objects that are embedded within devices, sensors, machines, software and people through the Internet environment to communicate, exchange information and interact in order to provide a comprehensive solution between the real world and the virtual world [3]. In recent years, IoT has been applied in a series of domains, such as smart homes [4,5], smart cities [6,7], smart energy [8,9], autonomous vehicles [10,11], smart agriculture [12–15], campus management [16,17], healthcare [18,19], and logistics [20,21]. Series of other IoT applications have been described by Shafique et al. [22]. An illustration of rich and diverse IoT applications for smart agriculture is provided in Figure 1.



**Figure 1.** An illustration of IoT applications for smart agriculture.

According to the United Nations' (UN 2019) statistics, the world population is estimated to grow to 10 billion by 2050 [23]. As a consequence, the requirements of agricultural products are continually increasing. However, farmlands are declining, natural resources are increasingly depleted, and the rise of unpredictable nature challenges, such as global warming, salinization, and flooding, make food security the most concerning problem for all nations worldwide.

In recent years, with the aim of increasing agricultural production, new solutions and technologies have been introduced in the agriculture sector [24]. An emerging trend is the application of the IoT and big data. A significant number of studies have been focused on research, experiments, and applications [25,26]. According to the Cisco forecast, over 500 billion IoT devices will be connected to the Internet by 2030 [27]. The use of IoT and big data will enable smart agriculture and is expected to enhance efficiency and productivity [28].

Over the years, wireless sensor networks (WSN) have been strongly applied in the agricultural sector, building the foundation for developing smart agriculture [29]. The unique characteristics of WSN, such as the ability to self-organize, self-configure, self-establish, and self-recover, make it suitable for smart agriculture [30]. The sensor device consists of a radio frequency (RF) transceiver, sensor, microcontroller, and battery power [31]. The WSN focuses on applications such as environmental monitoring, machine control automation, and traceability [32–35].

Along with the development of science and technology, the urgent requirement for breakthrough solutions and technologies aiming at improving productivity and efficiency in the agriculture sector has led to adoption of the IoT. The primary motivation for their applications is the breakthrough progress of smart agriculture and its inevitable role as the future of smart and sustainable environment management. IoT integrates a series of existing solutions and technologies, such as WSN, cognitive radio, ad hoc networks, cloud computing, and end-user applications [36]. In the smart agricultural sector, automation solutions and technologies, mechanical machines, knowledge, decision-making tools, services, and software are integrated seamlessly to help farmers improve productivity, product quality, and profitability [37].

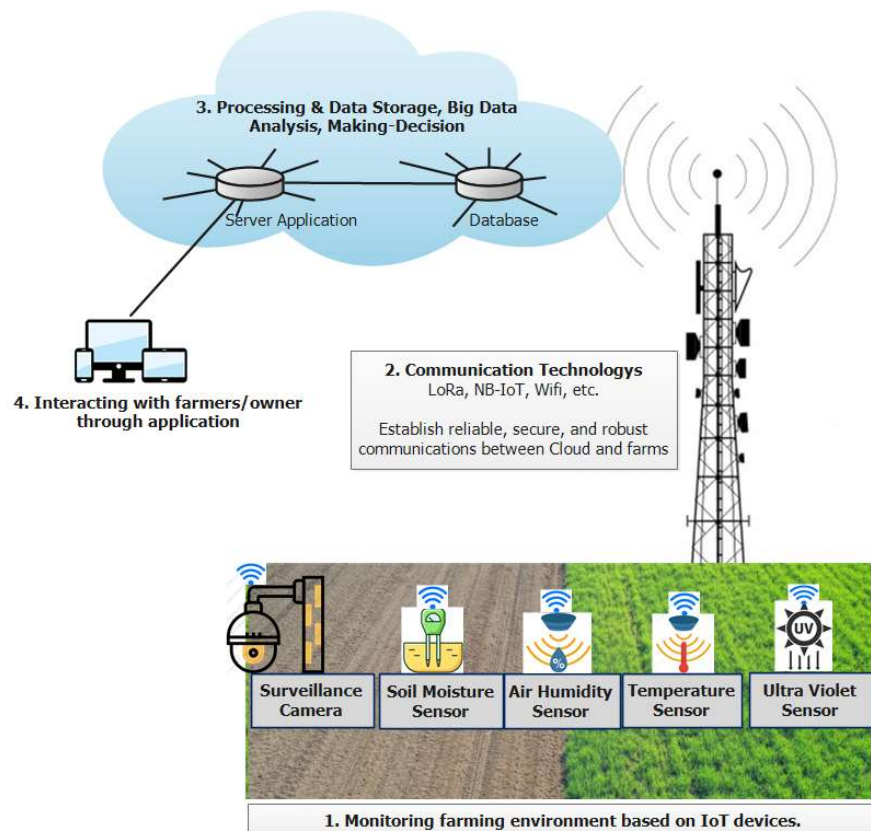
In this work, a comprehensive survey of IoT applications for smart agriculture is conducted. An analysis of 135 relevant works published between 2017 and 2022 was conducted. Firstly, relevant 550 papers published in the period of (2017–2022) were retrieved from major scientific databases, namely IEEE Xplore Digital Library, Science Direct, MDPI,

and Springer, by using keywords such as IoT-enabled smart agriculture, smart agriculture, Internet of Things, aquaponics, monitoring forestry based on IoT, tracking and tracing, smart precision farming, greenhouse production, Sigfox, LoRa, Wi-Fi, LoRaWAN, and IoT ecosystems. In the next step, we excluded papers that were published in low-repute conferences and journals, and then we conducted the content analysis for the obtained paper. Finally, 135 papers were selected for the preparation of the present work.

In addition, we analyzed and discussed the benefits and challenges, open issues, trends, and opportunities of IoT in the smart agriculture sector. This work is organized as follows: Section 1 introduces our work, and in Section 2, we present an IoT ecosystem architecture for smart agriculture that consists of three main components: IoT devices, communication technology, and data storage and big data processes. Section 3 presents the IoT applications in agriculture, including (1) monitoring, (2) tracking and traceability, (3) precision agriculture, and (4) greenhouses. Section 4 introduces some open issues and future research challenges of IoT for smart agriculture. Issues are discussed for two main directions: business and technology. In Section 5, we present the main conclusions of this work.

## 2. IoT Ecosystem Architecture for Smart Agriculture

In this section, we present a common framework of an IoT ecosystem for smart agriculture based on three main components, including (1) IoT devices, (2) communication technologies, and (3) data process and storage solutions. An illustration of the IoT ecosystem for smart agriculture is presented in Figure 2.

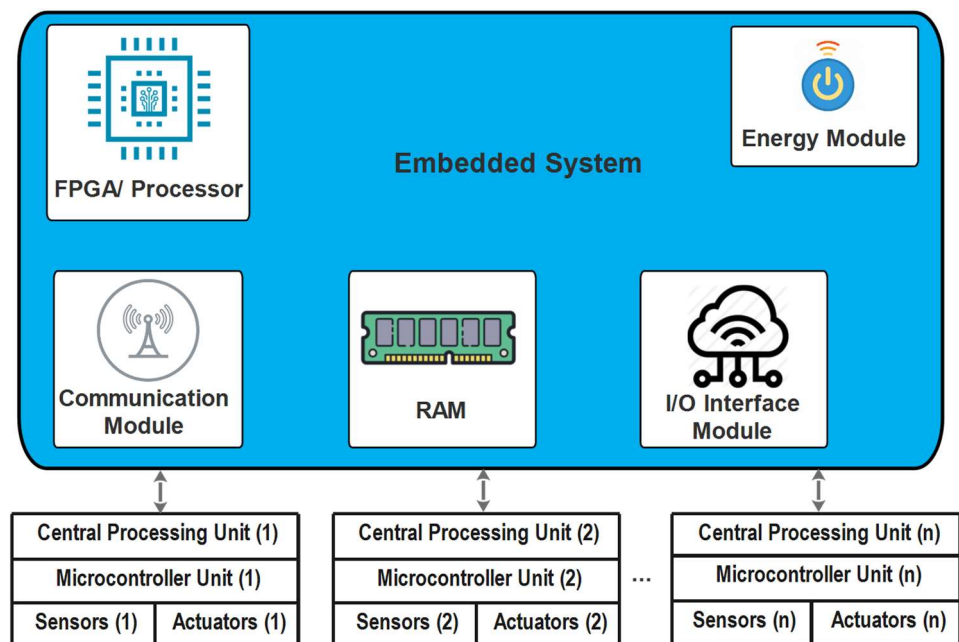


**Figure 2.** An illustration of IoT ecosystems' architecture for smart agriculture.

### 2.1. IoT Devices

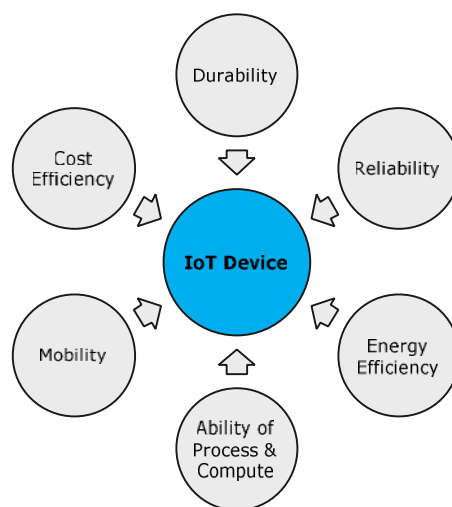
The common architecture of an IoT device consists of sensors to collect information from the environment, actuators based on wired or wireless connections, and an embedded system that has a processor, memory, communication modules, input–output interfaces,

and battery power [38,39]. The common architecture of a typical IoT device for smart agriculture is shown in Figure 3.



**Figure 3.** An illustration of the common architecture of an IoT device.

Embedded systems are programmable interactive modules, namely FPGAs (field programmable gate arrays). Sensor devices are specially designed to operate in open environments, in nature, in soil, water, and air to measure and collect environmental parameters that affect production, such as soil nutrients, humidity, temperature, etc. Smart farming solutions are agricultural operations that are often deployed on large farmlands, outdoors, so the devices that support solutions need some unique characteristics, such as the ability to withstand the effects of weather, humidity, and temperature instability throughout their service lifecycle. Some of their main features, as shown in Figure 4, make IoT devices suitable for smart agriculture solutions [40–42].



**Figure 4.** The main characteristics of IoT devices.

Depending on the required operation, there are several typical sensors applied in the smart agriculture sector. Sensors can be divided into several typical categories, such as (1) location sensor, (2) optical sensor, (3) mechanical sensor, (4) electrochemical sensor, and

(5) air flow sensor. These sensors are used to collect information such as air temperature, soil temperature, air humidity, soil moisture, leaf moisture, precipitation, wind speed, wind direction, and solar radiation, and barometric pressure [21,24,36].

## 2.2. Communication Technology

The survey of communication technologies for IoT [43,44] indicated that to integrate IoT into the smart agriculture sector, communication technologies must progressively improve the evolution of IoT devices. They play an important role in the development of IoT systems. The existing communication solutions can be classified as: protocol, spectrum, and topology.

Protocols: many wireless communication protocols have been proposed for the smart agriculture sector. Based on these protocols, devices in a smart agricultural system can interact, exchange information, and make decisions to monitor and control farming conditions and improve yields and production efficiency. The typical, low-power communication protocol numbers commonly used in smart agriculture can be divided into short-range and long-range categories based on the communication range.

- Short-range: NFMI (near-field magnetic induction) [45], Bluetooth [46], ZigBee [47], terahertz (Z-Wave) [48,49], and RFID [50].
- Long-range: LoRa [51], Sigfox [52], and NB-IoT (Narrowband IoT) [53].

Table 1 presents some typical communication technologies for the smart agriculture sector. The values in Table 1 indicate that short-range communication technologies have a transmission distance of less than 20 (m), high energy efficiency, and low data rate. These protocols are often employed in sensor networks, while long-range communication technologies have transmission distances of up to several tens of kilometres, consume more energy, and are installed for backhaul device-to-device communications. A diverse survey of low-power communication technologies for IoT that presents solutions, challenges, and some open issues is described by Sundaram et al. [54].

**Table 1.** Some typical communication technologies for smart agriculture.

Type	Spectrum	Transmission Distance	Type of Network	Frequency	Data Rate
802.11a/b/g/n/ac	Unlicensed	100 m	WLAN	2.4–5 GHz	2–700 Mbps
802.11ah	Unlicensed	1000 m	WLAN	Several Sub-GHz	78 Mbps
802.11p	Licensed	1 km	WLAN	5.9 GHz	3–27 Mbps
802.11af	Licensed	1 km	WLAN	54–790	25–550 Mbps
SigFox	Licensed	Rural: 50 km Urban: 10 km	LPWA	Zwave	100–600 bps
LoRaWAN	Licensed	20 km	LPWA	Several Sub-GHz	0.3–100 kbps
NB-IoT	Licensed	35 km	LPWA	Zwave	250 kbps
LTE-3GPP	Licensed	5 km	WWAN	1.4 MHz	200 kbps
EC-GPRS	Licensed	5 m	WWAN	GSM bands	240 kbps
WiMAX	Hybrid	50–80 km	WWAN	Several Sub-GHz	70 Mbps
Bluetooth	Unlicensed	100 m	WPAN	2.4 GHz	2–26 Mbps
ZigBee	Unlicensed	1 km	WHAN	2.4 GHz	250 kbps
Z-Wave	Unlicensed	100 m	WHAN	900 MHz	100 kbps
6LoWPAN	Unlicensed	30 m	WHAN	Zwave	250 kbps
NFC	Unlicensed	20 cm	D2D	13.56 MHz	424 kbps

Spectrum: Each radio device uses certain frequency bands for communication. The FCC (Federal Communications Commission) has defined unlicensed spectrum bands for unlicensed operations in scientific, industrial, and medical purposes [55]. These spectrum bands are often applied for low-power levels and short-range applications. Consequently, a series of common technologies for the smart agriculture sector, from wireless machine control and UAVs to communication technologies such as Wi-Fi and Bluetooth, use unlicensed



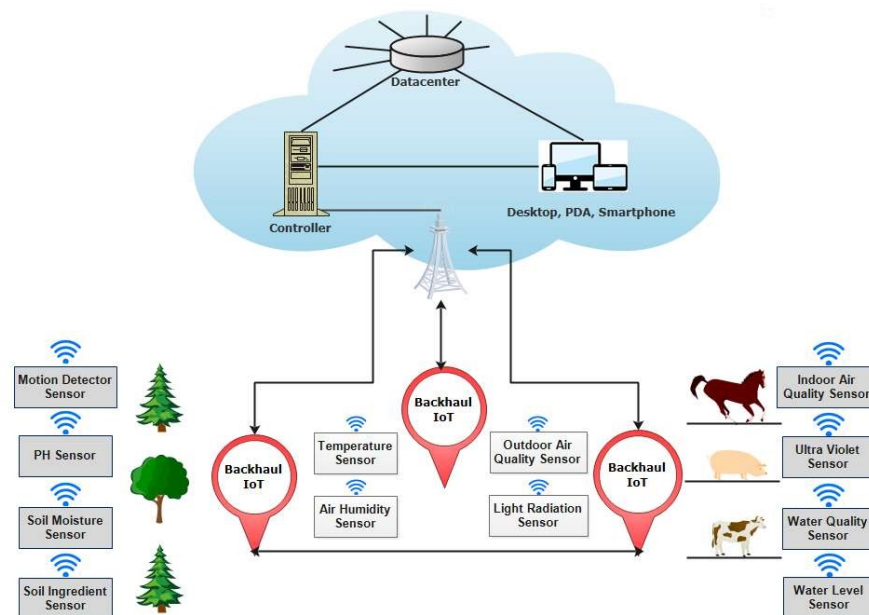
spectrum bands [56]. However, the use of unlicensed spectra faces several challenges, such as the quality of service guarantee, the cost of setting up the initial infrastructure, and the interference generated by the huge number of IoT devices [57,58].

A licensed spectrum usually is allocated to mobile networks. It provides more efficient network traffic, more reliability, enhances the quality of service (QoS), offers security, provides extensive coverage, and involves lower initialization infrastructure costs for users. However, the use of licensed spectrum bands has faced some limitations, such as high data transmission costs and the low energy efficiency of IoT devices [59].

Several recent studies have demonstrated the efficiency of unlicensed spectrum bands in the mm wave range. It uses extremely low power but provides large transmission distances and high data rates [60,61]. One limitation of the mm wave spectrum is that the data rate is strongly affected by weather conditions, especially rain [62].

**Topology:** The establishment of the communication spectrum band and operation protocol of IoT devices depends on the structure that deploys IoT devices for smart agriculture applications. Network structures for smart agriculture usually have two main types of nodes: sensor and backhaul nodes [63]. The common characteristics of IoT sensor nodes are short communication distance, low data rate, and high energy efficiency. In contrast, IoT backhaul nodes often require large transmission distances, high throughput, and data rates. Therefore, based on the role of each IoT network node, the sensor node or backhaul node selects and installs appropriate communication technologies [64]. Figure 5 presents a typical low-power network topology designed for measuring and monitoring factors in a smart farm. The system includes:

- (1) IoT sensor nodes collect information from the farming environment, such as soil moisture, air humidity, temperature, nutrient ingredients of soil, pest images, and water quality, then transmit collected data to IoT backhaul devices. Depending on the operation purpose and installation location, IoT sensor nodes can be installed as RFDs (reduced-function devices), which only communicate with FFDs (full-function devices). These nodes cannot communicate with the other RFDs, aiming to save energy and decrease investment costs.
- (2) IoT backhaul nodes, besides having the role of an IoT sensor node, also play a role as intermediate nodes to receive information from other IoT nodes and transmit it to the control centre. IoT backhaul nodes are often installed as an FFD device, which can connect to other FDD and RFD devices.



**Figure 5.** An illustration of the common IoT-based smart agriculture topology.

### 2.3. Data Analytics and Storage Solutions

In the smart agriculture domain, besides the main problems of sensing, collecting data, and controlling devices to respond to the real farming environment, data storage and processing are also important problems and face some challenges [26,28]. In reality, the number of collected data is huge, and traditional data storage, organization, and processing solutions are not feasible. Therefore, big data processing solutions need to be researched and applied for smart agriculture [65,66].

The complexity of data storage and processing is due to the unique characteristics of the smart agriculture field, including unstructured data and various formats, such as text, images, audio and video, economic figures, and market information. Recent solutions and technologies have introduced the use of cloud platforms for storage and data analytics, which are collected from farms [36,67]. In addition, cloud-assisted big data analytic solutions, such as edge computing [68] or fog computing [69], are also proposed to reduce latency and costs and support QoS.

The survey results demonstrate that, in recent years, many management information systems for smart agriculture have been proposed [70–72]. Nowadays, possible solutions have been developed and commercialized, providing solutions and services for farmers to manage farms and fields, aiming to increase productivity, reduce human labour, and enhance farming efficiency, as follows:

- *OnFarm* [73]: It is part of the SWIM family, which specializes in providing solutions and technology for smart agriculture. *OnFarm* is a technology platform that allows farmers to manage and use data in the simplest way. It is also a comprehensive solution for managing, using, and controlling water on smart farms.
- *Farmobile* [74]: It is a commercialized online platform to manage smart farms that allows farmers, traders, scientists, and insurance companies to operate and communicate centrally on an online platform.
- *Silent Herdsman Platform* [75]: It is a platform that allows monitoring of the activities of cow colonies and predicting their milk production.
- *CropX* [76]: It is a platform that will enable monitor and control nutrients of farming soil based on a sensor system and big data analytic solutions.
- *FarmX* [77]: It is an all-in-one platform for tree crops. *FarmX* provides a series of diverse farming management solutions, including irrigation, fertilizer, cropland management systems, environmental monitoring, and crop production forecasting.
- *Easyfarm* [78]: It is a platform that provides software to help farmers manage and account for figures of farms. *Easyfarm* provides visual figures, including input and output supplies management, production forecasting, and market connectivity, to help farmers fully manage their farms.
- *KAA* [79]: It is a cloud-based IoT platform that aims to provide comprehensive, end-to-end solutions for farmers, including: (1) connecting and managing IoT devices in farms or fields; and (2) monitoring and controlling behaviours of devices based on data analysis results.
- *Farmlogs* [80]: It is a platform that provides tools and solutions for: (1) automating the production cost calculation process; (2) managing the day-to-day activities of the farm in real-time; and (3) supporting marketing and increasing sales of products.

### 3. Typical Applications of IoT in Smart Agriculture

In recent years, a series of IoT applications for agriculture have been introduced. According to survey results, we divided these applications into categories based on their purpose, including monitoring, tracking and traceability, and greenhouse production. The detailed results are presented in the following subsection.

#### 3.1. Monitoring

In the agriculture sector, factors affecting the farming and production process can be monitored and collected, such as soil moisture, air humidity, temperature, pH level, etc.

These factors depend on the considered agricultural sector. Some smart agricultural sectors are applying the following monitoring solutions:

**Crop Farming:** In this sector, some vital factors that affect the farming process and production efficiency include air temperature, precipitation, air humidity, soil moisture, salinity, solar radiation, pest status, soil nutrient ingredients, etc. In [81], the authors designed an IoT device called FarmFox. This device allows real-time collection and analysis of the composition of the farming soil and transmits the information to farmers/owners via the Internet. The results demonstrate the health of the soil is monitored in real time to provide timely recommendations to farmers aiming to increase productivity and farming efficiency.

Furthermore, in [82], the authors proposed an IoT device to allow intelligent control of temperature and humidity factors, called a weather radar. This device will automatically turn on the warning mode using the light signal and send messages to the farmer when the temperature or humidity exceeds a pre-installed threshold. In [83], the authors introduced an IoT system based on Web GIS to monitor pest status and provide early warnings. In addition, this study also proposes a predictive model based on monitoring the habitat of pests and diseases. The efficiency of the proposed system was indicated, based on the predicted figures of the locust epidemic, to have a high accuracy rate (over 87%) in 2019 (China).

Monitoring information, such as soil condition, moisture, and temperature, and the prediction of natural factors, such as rainfall and weather, support the control of growing conditions of crops, helping farmers plan and make irrigation decisions to optimize production and reduce labour costs. In addition, the collected data, combined with big data processing technology, can provide recommendations for implementing preventive and remedial solutions against pests and diseases in farming.

**Aquaponics:** It is an integration of aquaculture and hydroponics. Aquaponics is a farming technique where fish waste becomes a source of nutrients needed by plants. One of the most important issues in such farms is constantly monitoring water quality, water level, temperature, salinity, pH, sunlight, etc. [84]. According to this research direction, in [85], the authors designed an IoT system to monitor the temperature and pH value of water for aquaponics farms. Moreover, this system is also equipped with a control system of water metrics to keep the fish habitat stable and an automatic fish feeding function to increase the productivity of the fish. The results show that the IoT system had stable operation and provided real-time monitoring parameters. The authors of [86] designed an aquaponics farm for households/urban areas based on IoT. This system recommends the proper ratio of fish and plants.

Consequently, the system decreases feed consumption as well as reduces carbon emissions into the environment. The primary purpose of this proposal aims to balance the self-sustaining ability of the aquaponics system. The experimental results demonstrate the number of fish decreases from 30 to 15, and the number of plants increases from 20 to 30, but the crop production will increase by more than 50%. A detailed and diverse survey of the IoT systems and devices for control and monitoring of aquaponics farms is introduced in [87]. Based on the obtained data, monitoring can improve the production of fish and plants through the control, supplementation, and regulation of nutritional ingredients in the water. The collected data were also used to automate the management of aquaponics farms to reduce labour costs.

**Forestry:** Humans depend on forests for survival. Moreover, forests play a vital role in the carbon cycle and provide a habitat for more than two-thirds of animal species in the world. Forests also have the effect of protecting watersheds, limiting floods, and mitigating climate change. The main factors that need to be monitored in a forest include soil ingredients, air temperature, humidity, and concentration of several different gases, such as oxygen, methane, ammonia, and hydrogen sulphide. A series of forest control systems and solutions are presented in [88,89] based on IoT and big data analytics.



In [90], the authors designed a peatland forest environmental monitoring system. This forest area plays a very vital role in the rainforest ecosystem of Brunei. However, the peatland forest type is very burnt. This work designed an IoT system to monitor environmental conditions, such as temperature, humidity, wind direction, barometric pressure, and manage possible disasters. For the purpose of enhancing feasibility, IoT devices use the solar-powered system and communicate with the monitoring centre based on the LoRa network. In [91], the authors proposed a solution to control forest changes and vitality by using high-resolution RapidEye satellite imagery. This solution has been deployed commercially in several states in Germany and has detected leaf diseases in a pine forest affected by pests. Survey results indicate that monitoring in forestry focuses on providing early warning systems against forest fires, pest control, or deforestation.

**Livestock Farming:** It is defined as the process of raising domesticated animals, such as cows, pigs, sheep, and goats, chickens, etc., in an agricultural environment to obtain traction, serve production, and obtain products such as meat, eggs, milk, fur, leather, etc. In this area, the factors to be monitored depend on the type and number of farming animals [92]. In [93], the authors designed a support system for the diagnosis, prevention, and treatment of diseases for livestock called VetLink. This system can provide recommendations for animal health for farmers in rural areas where it is difficult to access veterinary doctors immediately. In [94], the authors proposed a noncontact temperature measurement system and monitoring of animals to ensure early detection of diseases and animal health. This system can be used for remote monitoring of animal health and timely anomaly detection. In [95], the authors introduced a monitoring system for large-scale pig farms based on IoT. The specific solution is to attach an IC tag on each pig to monitor the behaviour of each pig, such as their period of feeding and resting and exercise. Data from sensors are collected and combined with data analytics solutions that can make recommendations for pig health.

The monitoring data of water, feed, and animal health for livestock in the farming process helps farmers set up livestock plans, reduce labour costs, and enhance production efficiency. While a series of solutions has been provided for monitoring large-scale farms, their application in small and medium-sized farms is very limited, especially in developing countries. This can be attributed to the high cost and the lack of knowledge needed to set up, manage, and operate IoT systems. Therefore, effective and low-cost solutions for agricultural IoT have much potential.

### 3.2. Tracking and Tracing

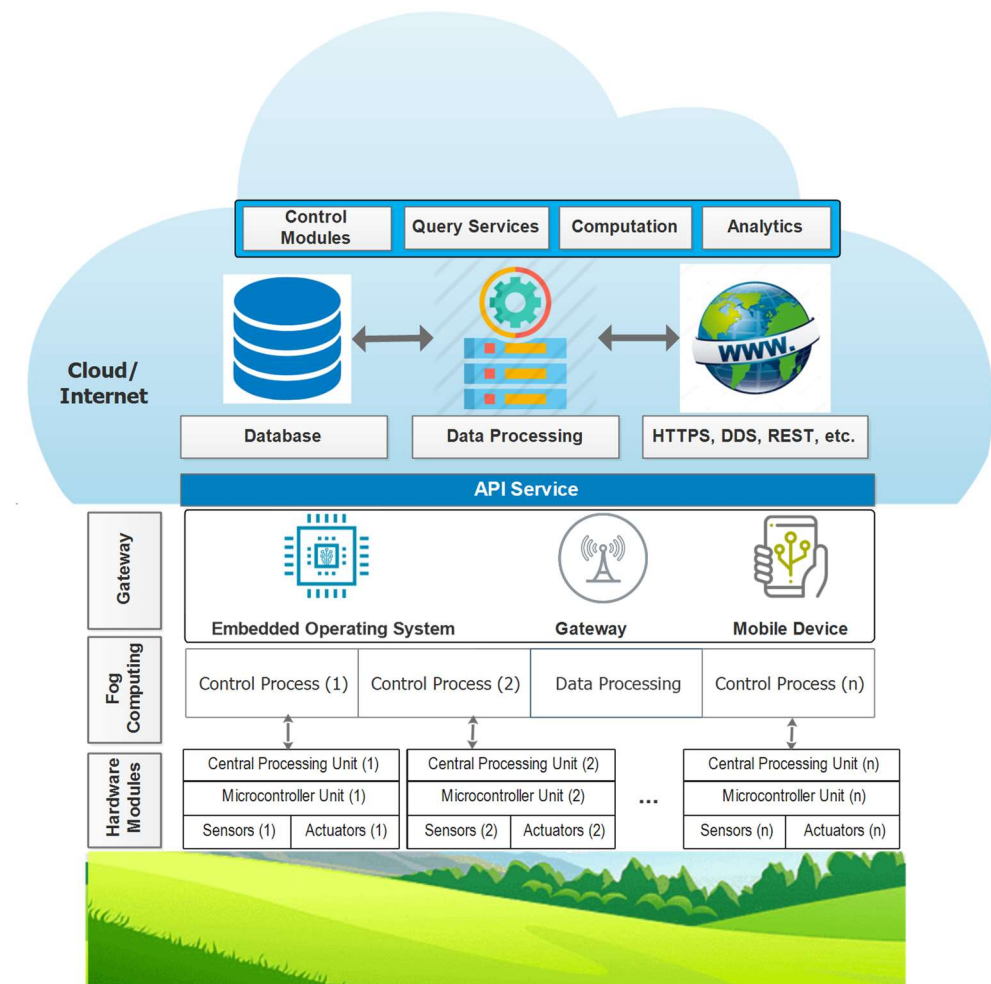
In order to meet the needs of consumers and increase profit value, in the future, farms need to demonstrate that products offered to the market are clean products and can be tracked and traced conveniently, thereby enhancing the trust of consumers in product safety and health-related issues. In order to solve this problem, a series of tracking- and tracing-based problems for the smart agricultural sector has been proposed, specifically as follows:

In [96], the authors designed an information system that allows tracking and tracing of agricultural products and foods such as dairy and vegetables, called SISTABENE. This system helps suppliers track the production process and errors arising in the supply chain, and helps end-users trace the origin of food. In [97], the authors proposed a food supply chain traceability system based on blockchain technology. It helps to track and trace agri-food supply chains' production process and trace the origin of agricultural products. This solution has been employed at Shanwei Lvfyngyuan Modern Agricultural Development Co., Ltd. (Shanwei, China). Although there are still limitations, the results demonstrate that this solution has successfully supported the tracing of food and agricultural products through QR codes, improving product quality and ensuring the clear traceability of products. In [98,99], the authors proposed smart agricultural solutions to tracking and tracing agricultural products, thereby allowing consumers to know the product's entire history. These solutions enable tracking and tracing some of the data collected along the

supply chain, ensuring that consumers and other stakeholders can identify products' origin, location, and history.

### 3.3. Smart Precision Farming

The advent of the GPS (global positioning system) has created breakthrough advances in many fields of science and technology. The GPS provides the most important parameters for locating a device, such as location and time. GPS systems have been successfully deployed in many fields, such as smartphones, vehicles, and IoT ecosystems. However, GPS is only good support for outdoor systems and the sky. Meanwhile, the demand for the locating and navigating systems in the home and on the streets of smart cities is growing rapidly. Aiming to solve this problem, an advanced global navigation satellite system (GNSS) is being deployed [100]. Based on GPS and GNSS systems, suitable farming maps have been established for fields and farms. As a result, agricultural machinery and equipment can be operated autonomously [101]. Figure 6 presents an illustration of the typical cloud-assisted, IoT-based precision agriculture platform.



**Figure 6.** Cloud-assisted IoT-based precision agriculture platform.

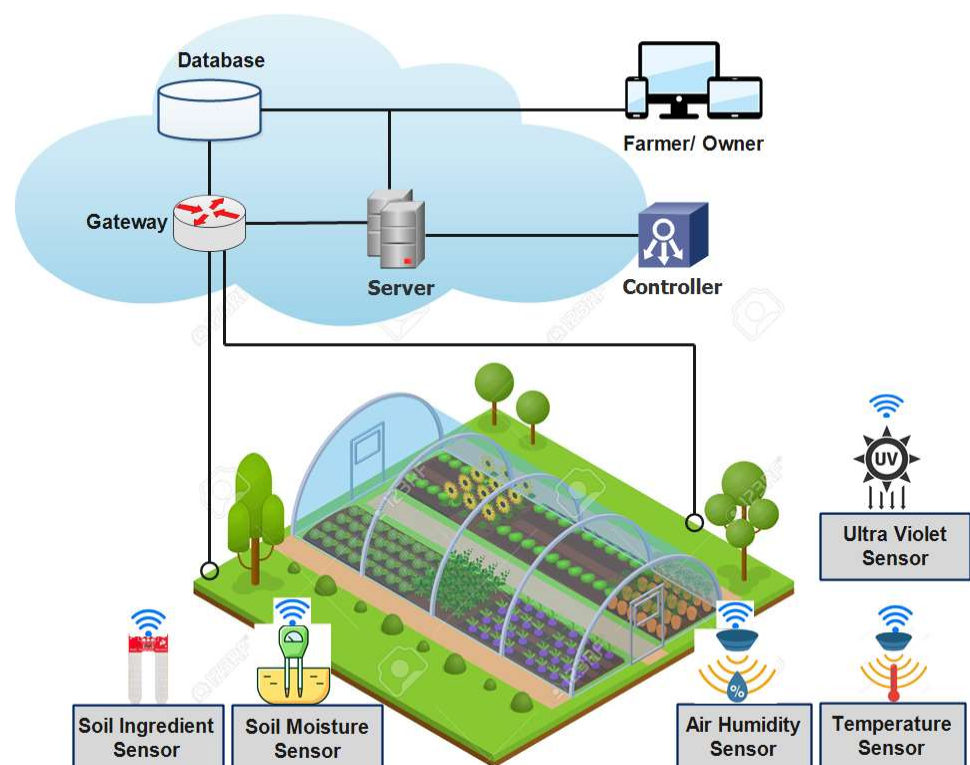
In smart precision farming, one of the most important applications is the use of drones in monitoring and farming activities. Some common farming tasks using UAVs include spraying pesticides, fertilizing, sowing seeds, evaluating and mapping, and monitoring crop growth. In [102], the authors presented a detailed survey of drone applications for smart agriculture, including applications, control technology, and future trends of the UAV application for smart agriculture. In [103], the authors designed an automatic agricultural product classification system based on camera systems, image processing algorithms, and

mechanical actuators. The experimental results for agriculture products such as oranges and tomatoes present a classification success rate of over 95%, and the sorting time for each product is less than 1(s). This solution can be adapted and applied to the classification of different agricultural products. In [104], the authors proposed a solution to estimate grape production. The proposed solution combines an RGB-D camera mounted on a mobile robot platform and size estimation algorithm for a bunch of grapes. The experimental results present an average error in the range of [2.8–3.5] (cm). The results demonstrate this solution is a feasible method for evaluating the productivity of large-scale grape farms.

The survey results show that smart precision agricultural equipment, such as irrigation systems, unmanned aerial vehicles (UAV), and smart agricultural equipment, etc., are configurable in an autonomous-control mode based on certain conditions or can be controlled remotely by the farmer via the Internet [105,106]. Smart precision farming helps to improve productivity and production efficiency and is suitable for large-scale farms. Nowadays, suppliers of precision agricultural equipment have IoT modules built into their machines, allowing machines to operate autonomously and remotely via the Internet [107].

### 3.4. Greenhouse Production

A greenhouse consists of walls and a roof, which are usually made from transparent materials, such as plastic or glass. In a greenhouse, plants are grown in a controlled environment, including controlling for moisture, nutrient ingredients of the soil, light, temperature, etc. Consequently, greenhouse technology makes it possible for humans to grow any plant, at any time, by providing suitable environmental conditions [108]. Figure 7 illustrates a smart agriculture IoT system for monitoring greenhouse farming factors based on IoT ecosystems.



**Figure 7.** An illustration of IoT application for monitoring farming conditions in a greenhouse.

In [109], the authors introduced an IoT-based greenhouse environmental monitoring system for multipoint monitoring in large greenhouses. Instead of using multiple sensors at different locations, this solution involves a drive system that allows the sensor system to move to different locations in the greenhouse. The experimental results show that the proposed system can effectively monitor multiple points in large greenhouses. In [110], the

authors introduced an energy-saving temperature control technology for smart greenhouses. This study proposed two intelligent control methods: active disturbance rejection control and fuzzy active disturbance rejection control. The experimental results demonstrate that the proposed technology saves over 15% of the total energy consumption of the greenhouse. In [111], the authors designed an intelligent IoT system to monitor and control greenhouse temperature for energy efficiency and improve crop productivity. The experimental results for the Kingdom of Saudi Arabia, where daytime temperatures can be above 50 °C, demonstrate the efficiency of the proposed solution, including saving energy and predicting the rate of plant growth.

Recent studies indicated that solutions integrating IoT, big data processing, and artificial intelligence could be applied in greenhouses to reduce labour and energy efficiency. Moreover, it also provides direct connections between the greenhouse farms and the customer [112–115].

#### 4. Challenges and Open Research Directions

The survey results indicate that IoT components for the smart agriculture sector, including hardware and software, have been focused on research and achieved many breakthrough results. Several IoT solutions have been deployed on large-scale farms/fields. However, the widespread deployment of IoT in the agricultural sector still presents some challenges. We have present two main problems: economic efficiency and technical problems. We consider these issues coupled with policies that will drive the integration of IoT technologies in agriculture.

##### 4.1. Economic Efficiency

In agricultural economics, one of the most important characteristics is a low rate of profit of an investment project, which presents many risks from natural conditions. The benefit–cost of a new technology seeking deployment in agriculture should be carefully calculated to ensure a trade-off between the cost of technology implementation and the profit potential. Therefore, we discuss the economic aspects related to IoT implementation in smart agriculture.

There are several types of costs related to the implementation of IoT in agriculture. We divided them into categories, including (1) the system initialization cost and (2) the system operating cost. The system initialization cost includes hardware purchases (IoT devices, gateways, base station infrastructure). The system operating cost includes service registration cost and the cost of labour to manage IoT devices. Furthermore, additional operating costs include incurred costs from energy consumption, maintenance, data exchange among IoT devices, gateways and cloud servers. According to the opinion of Turgut and Boloni [116], the successful deployment of the IoT technologies will only happen if the customer benefits (customers need to know the benefits and potential) that IoT systems provide exceed their physical value and privacy costs. The businesses participating in the IoT domain will profit and achieve success. We can describe this process using these two conditions, as follows:

$$\text{Success of IoT Applications} = \begin{cases} V_{\text{service}} > C_{\text{pri}} + C_h^{\text{user}} + C_{\text{pay}}, & \text{Farmer Benefits} \\ V_{\text{info}} + R_{\text{pay}} > C_h^{\text{business}}, & \text{Businesses Benefits} \end{cases} \quad (1)$$

where

$V_{\text{service}}$  is the expected value received by the IoT service users.

$C_{\text{pri}}$  is the cost of the loss of privacy.

$C_h^{\text{user}}$  is the equipment and hardware costs the user pays.

$C_{\text{pay}}$  is the payment for the service fee.

$V_{\text{info}}$  is the received information value.

$R_{\text{pay}}$  is the received direct payment.

$C_h^{\text{business}}$  is the share of the hardware and maintenance costs of the business.

According to the opinion of the service user (farmers or the owner of the farm), Equation (1) shows that the perceived value of the service for the user ( $V_{service}$ ) must be higher than the total of costs, including: the cost of the loss of privacy ( $C_{pri}$ ), the equipment and hardware costs the user pays ( $C_h^{user}$ ), and the payments for the service fee ( $C_{pay}$ ), while the opinion of the service provider, as shown in Equation (2), shows that the received information value ( $V_{info}$ ) and the received direct payments ( $R_{pay}$ ) must be higher than the share of the hardware and maintenance costs of the business ( $C_h^{business}$ ).

There is still a gap between service providers and service users (farmers or the owner of the farm), leading to the slow deployment of IoT applications in smart agriculture. In terms of the economic aspect, the analyzed results show that the need for a support policy from regulatory agencies and governments to allow service providers and service users to use IoT-based smart agriculture applications in their infancy can be met. As discussed in [117], to promote smart agriculture, the European Union has issued supportive economic policies, the so-called the European CAP (Common Agricultural Policy), whose annual budget amounts to approximately EUR 59 billion and is paid for by the nations of the EU.

In our view, to be able to apply IoT in the field of smart agriculture, service costs ( $C_{pay}$ ) and the operating and system initialization cost of IoT ( $C_h^{user}$ ) needs to constantly be improved and optimized to reduce the cost of the IoT services for farmers. In addition, IoT businesses (service providers) also need to maximize the value of information obtained ( $V_{info}$ ) to improve the profitability of the service providers.

In reality, service providers may commercially exploit the information received ( $V_{info}$ ) in the period of providing services for farms, aiming to encourage the deployment of IoT applications in smart agriculture. Nowadays, several IoT platform providers allow free registration and use of services with some limitation conditions regarding services' functionality and ability processing; the number of connected IoT devices; and the number of data stored while premium functions and services charge users a fee.

In addition, one of the significant factors slowing down IoT adoption in agriculture is farmers' knowledge and ability to use IoT devices. In developed countries, this issue can be easily solved due to the accessibility of new technologies of farmers. Otherwise, in developing countries, where the majority of farmers in rural areas have very limited access to advanced technologies, this issue is a significant challenge [118,119].

#### 4.2. Technical Problems

**Interference:** Deploying a huge number of IoT devices for smart agriculture can cause interference to different network systems, especially some IoT networks using short spectrum bands such as ZigBee, Wi-Fi, Sigfox, and LoRa (See Table 1). Interference can degrade system performance as well as reduce the reliability of IoT ecosystems. IoT networks that use cognitive technology to reuse unlicensed spectra increase the cost of the device. In our opinion, the advent of the 6G network [120] will allow a huge number of devices to connect to the Internet with an extremely high access speed and extremely large bandwidth. The full interference problem of IoT networks will be solved.

**Security and Privacy:** One of the most important problems of applying IoT in smart agriculture is the security problem, including the protection of data and systems from attacks on the Internet. In regard to system security, IoT devices' limited capacity and ability led to complex encryption algorithms that are impossible to implement on IoT devices. As a result, IoT systems can be attacked using the Internet to gain system control rights; IoT gateways are also attacked via denial of service [121–123]. In addition, cloud servers can be attacked by data spoofing to perform unauthorized tasks that affect the autonomous farming processes of farms. Cloud infrastructures can also be controlled by attackers [124,125]. Several issues of detailed IoT data privacy and security measures have been discussed in [126–128]. According to Neshenko et al., the IoT data security issue is one of the biggest problems slowing down IoT adoption in smart agriculture [129].

Regarding data security, the obtained information from IoT systems in farms is collected, processed, and commercially exploited by service providers to varying degrees.



Therefore, one of the most important problems of policies regards the validity and legal status of farm data [130]. In reality, these data are of great value when aggregated and analyzed for large-scale agricultural activities. Consequently, without policies, the data privacy and security of farms can affect the competitive advantage of farmers/farm owners. In our opinion, using cryptography coupled with access keys is a possible solution to solve this problem. Keys could be made available based on a regional user group and to those who contributed to the database. For further complex cases, secure multiparty computation can be used, where the homomorphic encryption method [131,132], or this method combined with the blockchain [133], can be applied for the purpose of balancing privacy and data utility.

In our opinion, the security problems of IoT systems will be an exciting research topic and garner attention for both academia and industry research. An in-depth survey of threats and solutions to improve robustness, trust, and privacy for future IoT systems is presented in [134].

**Reliability:** Most IoT devices are expected to be deployed outdoors (in fields and farms). Harsh work environments lead to the rapid degradation of IoT devices' quality and can lead to unexpected manufacturer failures. The mechanical safety of IoT devices and systems must be ensured so they can withstand extremes of weather, such as temperature, humidity, rainstorms, and floods [135]. In our opinion, new materials and technologies need to continue to be studied to improve the durability of devices.

The open problems and challenges discussed in this section indicate that for IoT to be widely deployed in the smart agriculture sector, there are still many issues to be solved. Service providers need to reduce the service costs, more effectively exploiting the information collected from the farm. On the other hand, farmers need to improve their skills to be able to apply IoT solutions on their farm to enhance productivity and farming efficiency. Researchers need to continually study and propose optimal solutions and technologies to ensure IoT systems' privacy and security and improve the durability of IoT devices. These are really major challenges and exciting research topics in the future so IoT can be widely applied in the smart agriculture sector.

## 5. Conclusions

In this study, we presented an overview of IoT and big data for the smart agriculture sector. Several issues related to promoting IoT deployment in the agriculture sector have been discussed in detail. Survey results indicate that many studies have been performed to apply IoT for smart agriculture, aiming to enhance productivity, reduce human labour, and improve production efficiency. The benefits of applying IoT and big data in agriculture were discussed. In addition, we also pointed out the challenges we need to overcome to be able to accelerate the deployment of IoT in smart agriculture. However, there are still some challenges that need to be addressed for IoT solutions to be affordable for the majority of farmers, including small- and medium-scale farm owners. In addition, security technologies need to be continuously improved, but in our opinion, the application of IoT solutions for smart agriculture is inevitable and will enhance productivity, provide clean and green foods, support food traceability, reduce human labour, and improve production efficiency. On the other hand, this survey also points out some interesting research directions for security and communication technologies for IoT. We think that these will be very exciting research directions in the future.

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