IoT solutions for smart farming: A comprehensive review on the current trends, challenges and future prospects for sustainable agriculture

Chu Duc Ha[1], Le Duc Chien[1], Phung Truong Trinh[1], Tran Van Tien[2], Pham Phuong Thu[3], Le Tien Dung[4], Pham Minh Trien[1*]
[1]*University of Engineering and Technology*
[2]*National Academy of Public Administration*
[3]*Hanoi Pedagogical University 2*
[4]*Nguyen Tat Thanh University*

Giải pháp IoT trong canh tác thông minh: Bài tổng quan về xu hướng, thách thức và định hướng tương lai cho nông nghiệp bền vững

Chu Đức Hà[1], Lê Đức Chiến[1], Phùng Trường Trinh[1], Trần Văn Tiến[2], Phạm Phương Thu[3], Lê Tiến Dũng[4], Phạm Minh Triển[1*]
[1]*Trường Đại học Công nghệ*
[2]*Học viện Hành chính Quốc gia*
[3]*Trường Đại học Sư phạm Hà Nội 2*
[4]*Trường Đại học Nguyễn Tất Thành*
[*]*Corresponding author: trienpm@vnu.edu.vn*

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ABSTRACT

Agriculture is the most resource-intensive human activity. The goal to reduce agricultural input while producing more has been a primary driver of agricultural technology advancement since its inception. With recent advancements in supporting technologies, the usage of Internet-of-things (IoT) has become a trend in farming practice for agriculture management that use information technology to ensure that soil and plants receive their requirements for optimum health and productivity. It could be significant to summarize the trends and challenges of the application of IoT-based solutions in precision agriculture, more specifically smart crop production. Thus, the current review sought to give a complete overview of the use of IoT technology in smart farming. By surveying recent high-quality publications, IoT-based solutions applied to smart farming, with four basic layers, including data collection (perception), data transmission (transport), data processing, and application layers were summarized. The use of IoT solutions allows for resolving several issues in smart farming, such as the optimization of input resources, saving irrigation water, reducing the amount of fertilizer and pesticides, and optimizing energy resources. Accordingly, we discussed some notes about sensors, microcontroller systems, communication methods, and cloud platforms. In particular, a list of low-cost sensors and several typical single-board computers was provided. The IoT communication was discussed to get insight into the essential considerations. Since then, several key points have been noted for further directions of the application of IoT-based solutions for smart farming. Taken together, our mini-review could provide solid information for further construction and development of smart models of farming.

Từ khóa:
cảm biến, canh tác thông minh, dẫn truyền dữ liệu, Internet vạn vật, thu thập dữ liệu, ứng dụng, xử lý dữ liệu.

TÓM TẮT

Nông nghiệp là lĩnh vực đòi hỏi sử dụng nhiều tài nguyên. Ứng dụng công nghệ vào nông nghiệp đảm bảo mục tiêu giảm thiểu yếu tố đầu vào trong khi tạo ra nhiều sản phẩm hơn. Với sự phát triển của công nghệ phụ trợ, Internet vạn vật (IoT) trở thành xu hướng trong canh tác thông qua sử dụng công nghệ thông tin nhằm tối ưu hóa sản lượng cũng như sức khỏe cây trồng. Do vậy, tóm lược xu hướng và thách thức trong ứng dụng giải pháp IoT vào nông nghiệp chính xác, đặc biệt trong canh tác là cần thiết. Bài tổng quan được thực hiện nhằm cung cấp cái nhìn toàn diện về công nghệ IoT trong mô hình canh tác thông minh hiện nay. Thông qua việc tóm lược các công trình nghiên cứu, giải pháp IoT trong canh tác thông minh thường chia làm bốn lớp, bao gồm thu thập, truyền tải, xử lý dữ liệu và giải quyết bài toán. Sử dụng công cụ IoT cho phép xử lý nhiều bài toán trong canh tác, như tối ưu tài nguyên, tiết kiệm nước tưới, giảm lượng phân bón và thuốc trừ sâu, hợp lý hóa năng lượng. Cụ thể, bài tổng quan đã chỉ ra các điểm lưu ý trong sử dụng cảm biến, bộ vi điều khiển, phương thức truyền thông và nền tảng đám mây. Danh sách các cảm biến giá thành rẻ và hệ thống vi điều khiển phổ biến đã được đề xuất, trong khi phương thức truyền thông được đưa ra thảo luận nhằm cung cấp thông số kỹ thuật cần thiết khi lắp đặt. Từ đó, một vài điểm chính đã đặt ra để định hướng cho việc ứng dụng công cụ IoT trong canh tác thông minh. Bài tổng quan này có thể cung cấp những kiến thức căn bản cho xây dựng và phát triển mô hình canh tác nông nghiệp thông minh.

1. INTRODUCTION

The resource-intensive nature of food production in the twenty-first century is becoming an increasingly relevant theme as population growth continues to rise year after year. It is anticipated that by 2050, the world will have 9.4 to 10.1 billion people who rely on biodiversity to survive, increasing the necessity for specialized food production regions [1]. Human-caused environmental changes may result in conditions that make the cultivation of new crops impossible. Similarly, expanding urbanization diminishes manpower in areas normally involved in food production [2], raising costs and reducing the sector's productive potential [3]. To deal with this issue, precision agriculture, particularly smart farming has been regarded as a new farm management concept that employs techniques and technologies at various levels and scales of agricultural production [4, 5], allowing to overcome obstacles in food production demands and workforce reduction [6, 7]. Smart farming, for example, may employ many types of sensors to gather environmental data, like temperature, humidity, light, soil features and plant characteristics [5, 8-10], communication networks to send and receive data, which is then managed and analyzed by data analysis solutions [5, 11, 12]. Consequently, by using these advanced approaches, the main purpose of smart farming is to enhance the efficiency, productivity and sustainability of crop production, and to optimize field-level management [5]. In this case, Internet-of-Things (IoT) refers to a network of physical items integrated with sensors, software, and other technologies for connecting and exchanging data with other devices and systems via the Internet. The utilization of data produced by smart farming aids in increasing output and reducing waste by allowing critical actions to be carried out at the proper time, quantity, and location. Furthermore, current technological advancements in IoT-related sectors enhance the adoption and usage of smart farming with IoT. Network connectivity, hardware size reduction, power consumption optimization, and device cost reduction are examples of such technological advancements.

The aim of this current review was to provide a comprehensive survey of the application of IoT solutions in smart farming. We first reported the trends of using IoT solutions in precision agriculture, particularly smart farming. Next, all issues related to three basic layers in IoT architectures, including perception, transport, processing and application were comprehensively summarized. Finally, we provided several prospects for the application of IoT solutions in smart farming.

2. TREND OF APPLICATION OF IoT SOLUTIONS IN SMART FARMING

The use of IoT solutions in smart farming has increased in recent years, particularly since roughly five years ago [5]. IoT tools, in particular, are used to solve problems related to farming in the field and farming in greenhouse systems [13], which can be categorized into five major groups, including smart irrigation [14, 15], plant health monitoring [8], pest and disease control [16], supply chain traceability [9], and automated machinery operation dynamic [17].

Crop health monitoring is the most prominent application of IoT in field and greenhouse farming [5, 8]. Particularly, physical data, such as temperature, humidity, and light features are monitored and gathered to aid in the assessment of plant growth, development, and yield prediction (Figure 1) [18, 19]. Several models have been successfully utilized to analyze crop biomass and estimate yields on a variety of essential crops grown in the field or greenhouse [20, 21]. In comparison to conventional farming practices, the use of IoT solutions allows for the optimization of farming resources, such as saving irrigation water [14, 15], reducing the quantity of fertilizer and pesticides used [16], optimizing energy resources [11], and lowering human resource expenditures [5, 17].

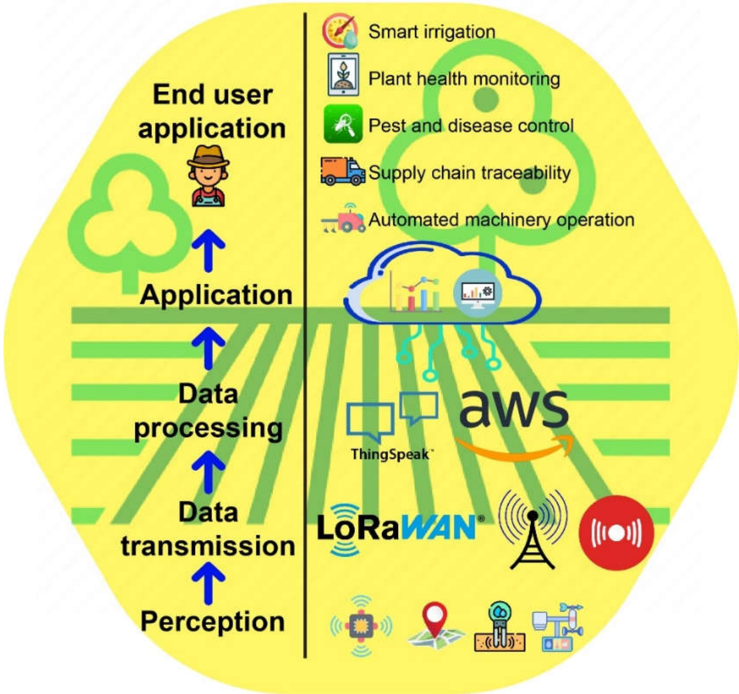

Figure 1. Potential applications of IoT in smart farming

In a typical IoT model, data gathering (perception), data transfer (transport), information processing (processing), and application of processed information to issues (application) are four common layers in IoT architectures. Data collection, in particular, is the process of collecting data from the surrounding environment (such as temperature, humidity, light, and localization) utilizing sensors and recognition devices (Figure 1) [22]. Devices can transform many types of data into digital signals, allowing electronic data to be transmitted to a server or database via communication protocols. Finally, the processed data can be used to aid decision-making, take action, or display outcomes through a user interface, with the goal of resolving four challenges for farmers [8, 9, 14, 16, 17]. Many issues remain in the problem of data gathering, data transfer, and information processing in smart farming.

3. PERCEPTION ISSUES IN SMART FARMING

In conventional farming practices, data collecting is frequently relied on farmers' direct experience and observation, which leads to inconsistency and inaccuracy in problem-solving [23, 24]. One of the major issues of conventional farming practices is the lack of ability to detect environmental factors concurrently. To deal with this gap, IoT systems can be utilized in smart farming to collect extensive environmental data in real-time, giving a modern, accurate, and automated approach for better at observing and reacting to environmental elements and crop conditions, allowing for early detection and decision-making [14, 22, 25].

Sensors are currently being developed to estimate indicators of crop growth, soil and atmospheric parameters, and monitor a variety of other indicators (Table 1). The most frequent types of sensors, in particular, are incorporated directly in the field, on greenhouse farming systems (hydroponics, aeroponics), or integrated into smart weather stations. Cameras and multispectral sensors can be installed on unmanned aerial vehicles (UAV) and unmanned ground vehicles (UGV) to obtain aerial photographs of fields [26, 27] and leaf and fruit images [28], respectively (Figure 1). Most farming models in greenhouses and fields only collected data on 3 - 4 indicators related to soil and atmosphere features and vegetation indices [10, 22]. Among them, vegetation indices are thought to be mainly associated with yield and yield-related characteristics and to evaluate the canopy normalized difference vegetation index (NDVI) [29-31]. For example, NDVI measured by a multispectral sensor mounted in a UAV was used to compare the growth and development of wheat (*Triticum* *aestivum*) cultivars under limited irrigation and full irrigation treatments [31]. It has been demonstrated that the NDVI is significantly correlated with biomass and several yield-compounding traits of wheat plants [31]. Recently, a concept of the monitoring system for a greenhouse system has been constructed by using three simple IoT-based sensors [13]. More specifically, DHT11 (Adafruit Industries, USA) and DHT22 sensors (Adafruit Industries, USA) were selected to measure temperature (ranging from 0 - 50 ± 2ºC) and humidity (ranging from 20 - 90 ± 4% RH), while BH1750 sensor (ROHM Apollo Co., Ltd., Japan) was used to estimate the light density (ranging from 0 - 27306 lx) [13].

Table 1. Introduction of sensors used in smart farming

Issues in smart farming	Parameters	Plots	Common models	Origin
Plant health monitoring	Plant growth	1	Cyber-shot DSC-QX100	Sony Electronics Inc., Japan
		2	Parrot Sequoia	MicaSense Inc., USA
	Pest and disease detection	3	FLIR Blackfly 23S6C	FLIR Systems, USA
	Active canopy	4	ACS-430, ACS-470	Holland Scientific Inc., USA
Soil monitoring	Soil temperature, soil moisture	5	DS18B20	Maxim Integrated, USA
	Soil pH	8	E-201	Shanghai REX Sensor Technology Co, China
	Chemical components (nitrate, nitrogen)	9	SEN0244	DFROBOTS, China
Atmosphere monitoring	Air temperature, air humidity	10	DHT11, DHT22	AM2302, Aosong Electronics Co. Ltd., China
	Solar radiation	11	SQ-110	Apogee Instruments, Inc., USA
	Rain content	12	YF-S402	Graylogix, India
		13	YL-83	Vaisala Corp., Finland
		14	SE-WS700D	Lufft Inc., Germnay
	Light density	15	BH1750	Rohm Semiconductor, Japan
		16	TSL2561	Adafruit Industries, USA
	Atmosphere pressure	17	MPL3115A2	NXP Semiconductors, Netherlands
	Wind direction and speed	18	WS-3000	Ambient Weather, USA
		19	SEN08942	SparkFun Electronics, USA
	CO_2 concentration	20	MG-811	Zhengzhou Winsen Electronics Technology Co., Ltd., China
		21	MQ135	Waveshare Electronics, China
Others	Tracking	22	Mifare Ultralight NFC tag	NXP Semiconductors, Netherlands
	Localization	23	Blueberry RFID reader	Tertium Technology, India
		24	UM220-III	Unicore Communication Inc., China

Hardware selection is thought as a significant component in deciding the success of IoT projects used in agriculture [9, 32]. These single-board computers (SBCs) are regarded as nodes or devices capable of gathering data from sensors and/or operating devices. Up till now, Arduino, Raspberry Pi, BeagleBone, and NVIDIA Jetson Nano are among popular SBCs in agricultural IoT projects [5, 10, 22, 32]. Specifically, Arduino, including variations of Arduino UNO, Arduino Nano, and Arduino Mega, is an open-source hardware platform that runs C/C++ programming language written by users and is based on the use of a microprocessor board. For example, a low-cost platform for monitoring and controlling CO2 has been designed by using Arduino-based microcontrollers to access the data logging of CO2 concentrations [33]. Meanwhile, Raspberry Pi and BeagleBone are mini SBCs that have more robust performance and processing capabilities than Arduino and run versions of the Linux operating system that allow for linguistic customization of their source code (Python, C/C++, JavaScript, Node.js, Java, and Shell scripting). Finally, the NVIDIA Jetson Nano is a form of SBC optimized for graphics processing that can be trained for image recognition, making it frequently used in detecting difficulties, such as weeds, pests, and detecting ripe fruit. Recently, the ESP microcontroller system (created by Espressif Systems) was developed and widely used in small-scale agricultural IoT projects, with two models including ESP8266 (compact, integrated WiFi) and ESP32 (upgraded version of ESP8266 with extra Bluetooth). In smart farming, a total of five most popular hardware modules for irrigation control was Arduino UNO, Node MCU-ESP8266, Arduino Mega, Raspberry Pi 2 Model B, and Raspberry Pi 3 Model B+ [5, 10, 15].

4. DATA TRANSMISSION ISSUES IN SMART FARMING

IoT communication is critical for linking agricultural equipment and machines. Data collected by sensor nodes is often transmitted to a data processor over a wired or wireless network. Distance, bandwidth, performance, dependability and security, compatibility and cost are all essential considerations when choosing a communication channel for agricultural IoT applications. The most often used protocols for wired networks in smart farming are controller area networks and Ethernet. Additionally, Long Range Wireless Area Network (LoRaWAN), cellular network protocols (like general packet radio service and 3G/4G/5G) and Sigfox are the most commonly used protocols for long-range wireless networks, whereas ZigBee, Wi-Fi and Bluetooth are the most commonly used protocols for short- and medium-range wireless networks.

Wi-Fi has a high bandwidth (54 Mbps or more with Wi-Fi 4, and up to 3.5 Gbps with Wi-Fi 6), allowing for fast data transfer; nevertheless, Wi-Fi consumes a large amount of power and has a restricted operating range (a few hundred meters). Bluetooth, an open standard technology developed by the Bluetooth Special Interest Group, exhibits a low bandwidth (with Bluetooth 5.0, the highest data transfer rate is 3 Mbps), requires little power and has a limited range (100 meters). LoRa is a wireless technology for mesh networks with low bandwidth, low power consumption, and long range (up to 15 km in rural regions). It is also a reliable communication technique in peripheral locations and distributed IoT applications. NB-IoT (Narrowband IoT) offers a very narrow frequency band, typically 200 kHz, low power consumption, and a wide range, much like LoRa. Because NB-IoT is built on top of the current mobile network infrastructure, it has very high dependability and coverage. Meanwhile, Zigbee provides low bandwidth, low power consumption, and works well in household contexts by employing a mesh network concept that allows devices to send data across other devices to extend range and reliability [5]. Recently, (i) mobile networks, such as 3G (data upload speed reaches 7.2 Mbps, download speed reaches 2 Mbps), 4G/LTE (data upload speed reaches 150 Mbps, download speed reaches 50 Mbps) and 5G, (ii) Bluetooth radio, including IEEE 802.15.1-Bluetooth (frequency range 2,400 - 2,483.5 MHz, maximum data transfer rate up to 3 Mbps) and BLE (frequency range 2,400 - 2,483.5 GHz, maximum data transfer rate up to 2 Mbps), (iii) Zigbee (maximum data transfer rate up to 250 kbps), (iv) Wi-Fi radio, including IEEE 802.11a (frequency range 5,725 - 5,875 MHz, maximum data transfer rate up to 54 Mbps), IEEE 802.11b (frequency range 2,400 - 2,500 MHz, maximum data transfer rate up to 11 Mbps), IEEE 802.11g (frequency range 2,400 - 2,500 MHz, maximum data transfer rate up to 54 Mbps), IEEE 802.11n (maximum data transfer rate up to 600 Mbps), IEEE 802.1ac (maximum data transfer rate maximum data rate up to 3.46 Gbps) and IEEE 802.11ah (maximum data transfer rate up to 40 Mbps), (v) NB-IoT radio (maximum data transfer rate up to 200 kbps), (vi) Sigfox (maximum data transmission rate up to 600 bps) and (vii) LoRaWAN wave (maximum data transmission rate from 0.3 - 50 kbps) were used to send data collected from sensors into a cloud-based platform to control irrigation systems [10, 15]. For example, a simple LoRa-based platform for remote monitoring of agriculture farms in Chile has been constructed to enable continuous data collection from many IoT-based devices [34]. Particularly, two types of calculations, like ambient parameters (temperature, humidity, ultraviolet and vibration) and soil parameters (soil temperature and moisture) were explored for the design [34]. The data transmission was built based on a low power wide area network (LPWAN) using LoRaWAN to adapt to the large scale [34].

5. DATA PROCESSING ISSUES IN SMART FARMING

Previously, the usage of IoT solutions in agriculture was frequently focused on gathering and storing data from sensor nodes. However, in recent years, an increasing number of IoT solutions for agriculture have shifted to cloud-based data processing, machine learning, artificial intelligence, and big data [5]. The capacity of data obtained from IoT-based sensors in smart farming models is enormous and grows seasonally. Data capacity in agricultural models has been determined by the amounts of sensors, the frequency with which data is collected, and the type of data collected [25]. Thus, an issue has been raised on how platforms process and store data collected from IoT sensors in smart cultivation. To deal with this problem, cloud-based platforms can help IoT systems scale by storing, processing, and visualizing data acquired from sensor nodes, allowing end users to control operations. Up till now, ThinkgSpeak, FIWARE, Ubidots, SmartFarmNet, AWS IoT, and Thinger.io were among the most prominent cloud systems used in smart cultivation [5, 25]. Particularly, ThingSpeak is the most common cloud-based platform in smart farming since it is open source and has modest infrastructure requirements, making it suited for simple data from environmental sensors. Meanwhile, Thinger.io is wholly based on infrastructure services supplied by cloud providers, such as Amazon AWS and Microsoft Azure, and thus always has application programming interfaces for real-time monitoring and analyzing data [5].

However, the cost of adopting cloud platform services are frequently prohibitively expensive when compared to the requirements of smart farming models. Self-development of simple data analysis and processing tools is frequently used to handle huge amounts of information in a short period of time. The majority of smart farming application processing technologies is related to six core keywords, including artificial intelligence [22], big data, computer vision [17], machine learning [25], blockchain, and fuzzy logic [15]. The majority of these technologies is aimed at monitoring plant health and irrigation system control issues [10].

The automation of management in smart farming models using IoT solutions is dependent on the manipulation of numerous variables. For example, soil moisture and temperature monitoring were commonly utilized to activate irrigation systems in a simple closed-loop control method [13-15]. Water management and crop monitoring in greenhouse farming, on the other hand, can be more complicated, needing more climate parameters and crop characteristics. Because it allows calculations based on imprecise and uncertain information, which is frequently encountered in cultivation practice, the data processing approaches based on fuzzy logic have been successfully employed in irrigation system control [15]. An irrigation system based on fuzzy logic, for example, can use data, such as air temperature, soil moisture, time since last watering, and crop type to calculate when and how much water should be applied. These parameters can be represented as fuzzy variables, like "high temperature", "average humidity", "recently watered", and so on, and fuzzy rules can be used to make irrigation management decisions [5, 10, 14].

For example, an automated irrigation system has been constructed based on RTC-DS1302 water pump and Arduino Mega-2560. A timing sensor was explored to manage the water volume for farming in coastal Java Island, Indonesia [35]. Particularly, the microcontroller is set up for automatic drip irrigation and sprinkler irrigation systems for the cultivation of onions (Allium cepa) and cabbage (Brassica oleracea) [35]. The timer system is created with a real-time clock and an Arduino SBC to irrigate at three periods within 15 minutes, including 07:00, 11:00, and 17:00

[35]. Controlled watering systems with timers and humidity sensors have previously been designed for lettuce (Lactuca sativa) cultivation [36]. The results show that using a timed irrigation system with two formulas, $\Theta = 0.3$ (volumetric water content reaches 0.3 m^3 water/m^3 soil) and 0.4 (volumetric water content reaches 0.4 m^3 water/m^3 soil), saved 17 and 42% of irrigation solution, respectively [35].

6. FUTURE DIRECTION FOR THE APPLICATION OF IoT SOLUTIONS IN SMART FARMING

IoT solutions for smart farming take advantage of the cloud-based computing platform and scalability to store a huge amount of environmental data obtained by sensors. These big data sets could be utilized by using machine-learning to enhance the management capacity of smart farming. For example, the processing of big data may be used to get insight into the growth and development of crops, optimize resources (energy, fertilizer, water and pesticide) and increase crop quality and productivity. Thus, using SBCs and UAVs or UGVs together with IoT-based sensors to collect data in indoor (greenhouse) or outdoor environments (field) were highly recommended for crop monitoring solutions [31, 37-39].

Next, computer vision is indeed a significant application of IoT in precision agriculture. Computer vision combined with IoT technologies helps in monitoring and managing crops, assessing plant health, and making data-driven decisions for enhancing agricultural productivity. The most significant advantage of using computer imaging IoT-based devices is that they eliminate human labor. This can assist farmers in properly managing acres of land. These sensors can also tell them what type of finite natural resources to use and when to use them. They also offer crop monitoring and soil quality tracking to farmers. Farmers can alter their production based on information such as soil quality and weather conditions. Furthermore, these IoT-based smart sensors and other gadgets can reduce crop losses and optimize yields on the same area of land.

Various kinds of network connections, like wired and wireless connections have been explored to interact between IoT-based devices. It is strongly believed that two typical wired networks, such as CAN and Ethernet are often applied for indoor agriculture, like greenhouse conditions because the physical components of these wired networks are thought to be less susceptible to climatic agent impacts. Meanwhile, wireless connections, including Wi-Fi, ZigBee and LoRa were used both in greenhouse and field conditions. Wi-Fi exhibited several serious issues, like power consumption and signal range, whereas ZigBee and LoRa were energy-efficient protocols for communication in wireless networks [34, 40]. Thus, improvement in algorithms for the reduction of power consumption in data transfering has been still needed.

7. CONCLUSIONS

In this mini-review, we provided a systematic survey of the state-of-the-art of IoT-based solutions in smart farming. By collecting all high-quality publications related to smart farming, the application of IoT-based solutions could be classified into five main aspects, including smart irrigation, plant health monitoring, pest and disease control, supply chain traceability, and automated machinery operation dynamic. Among them, three issues related to the layers of IoT architectures, including perception, data transport and data processing were intensively discussed. Further studies may extend this current review by including other relevant publications and complementary analysis of other issues of the IoT architecture in smart farming.

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