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Internet of Things Applications in Precision Agriculture: A Review

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***Abstract*—The goal of this paper is to review the implementation of an Internet of Things (IoT)-based system in the precision agriculture sector. Each year, farmers suffer enormous losses as a result of insect infestations and a lack of equipment to manage the farm effectively. The selected article summarises the recommended systematic equipment and approach for implementing an IoT in smart farming. This review's purpose is to identify and discuss the significant devices, cloud platforms, communication protocols, and data processing methodologies. This review highlights an updated technology for agricultural smart management by revising every area, such as crop field data and application utilization. By customizing their technology spending decisions, agriculture stakeholders can better protect the environment and increase food production in a way that meets future global demand. Last but not least, the contribution of this research is that the use of IoT in the agricultural sector helps to improve sensing and monitoring of production, including farm resource usage, animal behavior, crop growth, and food processing. Also, it provides a better understanding of the individual agricultural circumstances, such as environmental and weather conditions, the growth of weeds, pests, and diseases.**

***Keywords*—component; Internet of Things; Precision agriculture; Data management; Crop monitoring; Smart farming**

I. Introduction

The agriculture sector contributes to a large share of emerging countries' Gross Domestic Product (GDP) [1]. The ability of this industry to keep up with the ever-increasing population and the demands of emerging technologies is in jeopardy due to the ever-increasing population. By 2030, the population of the planet will have topped 8 billion, and nearly 10 billion by 2050. In terms of population size, China and India are the most populous countries in the world, with more than 1 billion inhabitants each, accounting for 19 percent and 18 percent of the world's total population, respectively. By 2022, China is expected to overtake India in population by 2022. Agricultural production is critical to the economies of both countries in order to ensure a steady supply of livelihoods for their growing populations.

The Internet of Things (IoT) is a modern developing mechanism that has taken over networked cloud applications, ranging from electrical to digital systems, mechanical, as well as individuals with unique IDs. By far the most important consideration of the IoT is the potential to transmit data without the need for a human transmission interface. Attributed to the reason that the field is stretched across a large region of farmland for agricultural or animal gazing, the application of Wireless Sensor Nodes (WSN) is the best way to solve the problem. The actuator modules are interconnected to the Personal Area Network (PAN) as they consume a huge amount of power which is not as numerous as the sensor nodes. This comprehensive framework can be integrated into an IoT-based system by utilizing existing Local Area Network (LAN) and Internet infrastructure.

Agricultural digitization is advancing in the majority of emerging countries. In Japan, computerised crop breeding, insect utilisation, agricultural management, and the preparation of meteorological reports are all common. Farmers in the United States (US) have access to large data cloud systems, as well as government databases for agriculture, research institutes, and libraries. Farmers can use the database to acquire up-to-date market prices, crop improvement, and growing skills and technology in the agriculture sector. Computers can assist farmers in determining the best crops to plant, the best seasons to grow them, and the best farming mode to use, resulting in farms with the maximum yields and benefits. Well-known financial management information system (FMIS) providers, such as Wisu 10 and Agrineuvos, offer plug-in or comparable solutions for a variety of agricultural management specialties.

Acknowledging appropriate and available information is essential for agricultural production education. An agriculture management information system (AMIS) is built on the foundation of agricultural information. The management of agricultural data is greatly influenced by the quality of agricultural data collection and processing. Because the farming ecosystem is a relatively complicated ecological framework with numerous elements ranging from the environment to the human, from ecology to economics, and from geography to culture, data collection often incurs significant expenditures and technologies.

In conclusion, this study has made a significant contribution in that the application of IoT in the agricultural sector may enhance sensing and monitoring of production, including farm resource utilisation, animal behaviour, crop development, and food processing [93, 95]. In addition, it helps farmers better understand specific agricultural situations, such as how the environment and weather affect the growth of weeds, pests, and diseases, as well as other things [95, 96].

II. Data Management In Agriculture

Smart agriculture, also known as automated farming, is the most recent paradigm based on agricultural data to emerge. It was made possible by advancements in telecommunications and data processing, which were combined with the previously existing concept of precision agriculture to improve operational accuracy. In this sense, smart agriculture is founded on the same principles, with farmers implementing this technology that collects data from agricultural fields, which would then be analyzed in order to draw suitable managerial and operational conclusions. Traditionally, farmers had to personally visit the ground farm to inspect the state of the plots and to review decisions that were made without their prior knowledge. A multitude of factors have rendered this method ineffective, including the fact that many sectors are too broad to be adequately addressed within the framework of legal standards. In the context of smart agriculture, cutting-edge management tools are providing practical applications. Aside from that, although some farmers have long-term expertise gathered via a variety of experiences, technology can provide an automated way to find unpredictable defects that are difficult to notice through eyesight assessment on a periodic basis. Younger farmers are more likely to use new agricultural technologies than older farmers, as they will employ smart devices or instruments to enhance their limited knowledge. Even so, the average age of farmers has risen rapidly in recent decades: 63 in Japan, 60 in Africa, and 58 in the US and Europe [2]. Fortunately, various policies are being revised and expanded in Europe to help generational transformation by increasing access to initial capital, loans, market counsel, and coaching. Generational regeneration goes beyond merely decreasing rural farmer's retirement age. In addition, it involves encouraging the most educated and active young farmers to use technology to promote viable agri-business practices. In order to attain sustainable food security and food chain competitiveness, young farmers must convert their current land into more sustainable and efficient farms.

A. *Data Acquisition Using an IoT*

The correlation of IoT with agriculture has always been defined as the use of sensing devices and other instruments to convert any part of farming activities into data. Over 10% of US farmers are anticipated to use IoT devices on their plantations, which cover more than 2400 million acres. The Internet of Things is at the heart of so-called "agricultural 4.0". Indeed, IoT technology has become a catalyst in agriculture businesses because it enables the generation of such a vast volume of relevant knowledge, and improvements in these technological advancements are expected to have a significant impact on the farming sector. By 2050, it is predicted that the IoT will be able to boost agricultural output by over 70% using existing techniques. This is a positive development, as Myklevy et al. claimed that the planet's food supply must expand by 60% by 2050 to accommodate the world's growing population of nearly 900 million people. The main benefits of the Iot systems are better harvests and lower prices. A typical farming business that uses IoT can improve yield by up to 2% and minimize energy use by up to 8%.

B. *Analytics of Big Data*

In order to generate organisational big data, a new form of automation technique is required due to the enormous amounts of data streams accessible for farm management. Even so, the volumes of information retrieved from either the majority of industrial or agricultural subject areas are unlikely to meet the criteria for classification as big data. It can be classified into three perspectives when it comes to big data: the volume, velocity, and variety of organisms. Veracity and valorization, resulting in the following:

a) Volume: Volume linked with databases that are too large to be captured, archived, handled, and analyzed using conventional methods. It provides an estimate of the size of a database required to be considered huge, which varies by respected field, based on commonly available computing resources and standard dataset sizes, which often begin in the terabyte range.

b) Velocity: The term "velocity" describes the capability of learning, comprehending, and experiencing events as they occur. When it comes to agriculture, these systems operate in real-time, such as information extraction in the area to implement different amounts of chemicals in equipment fitted with variable-rate delivery mechanisms, among other applications.

c) Variety: The phrase "variety" alludes to the various information formats (text, videos, and audio) and levels of sophistication. Soil or temperature sensors and images are just two examples of the kinds of data that are employed in agriculture when dealing with ever-changing circumstances.

d) Veracity: The word "veracity" relates to the consistency, reliability, and authenticity of the information.

e) Valorization: It is called valorization when one wants to share awareness, respect, and creativity with other people.

In terms of agricultural management, big data is significant in agriculture only in particular circumstances, relying on the plantation and the pace of technological acceptance. There were 34 surveys that talked about how information systems could be utilised in farming [3], and research on how big data could be used in modern agriculture was conducted by Wolfert et al. [4]. To keep up, the Organization of Global Agricultural Research Centers launched the Agriculture Big Data Platform, which promises to address agricultural growth concerns more rapidly, more affordably, and more effectively than the existing approaches.

C. *Using Artificial Intelligence (AI) and Robotics to Aid Humanity in Agriculture 5.0*

Through transformative technology, large engineering problems frequently lead to significant solutions, and Agriculture 5.0 is most certainly one for the early half of the twenty-first millennium. Agriculture 5.0 is a concept that describes farmlands that employ Precision Agriculture standards and technology, such as autonomous operational processes and automated decision support tools. As a matter of fact, Agriculture 5.0 incorporates various forms of AI and robotics. Historically, farms have relied heavily on seasonal labour to work the fields and increase profitability. However, the culture has changed from an agrarian community with many people residing in fields to one that has more people living in towns, which has led to a shortage of workers on farms. According to a Forbes report, agricultural robots help humans by harvesting crops faster and more efficiently. Whilst robots are still extremely slow than individuals in so many elements, agriculture is currently improving technology tools to assist farmers with repetitive tasks, driving agricultural systems into the modern paradigm of Agriculture 5.0. Based on Reddy et al. [5], agricultural robotics has increased efficiency and decreased farm operating expenses in a number of nations. Robotic technologies for agriculture are developing at a quick speed [6], offering exciting potential for smart farming in the face of staff shortages and long-term diminishing profit growth; but, just like other breakthroughs, major restrictions must be addressed in the current early phases. Since small individual farms are less profitable due to scale economics, these technologies remain outrageously expensive for the majority of farmers, including those with small farms. Furthermore, as technology becomes more affordable, agricultural robotics will undoubtedly be used in the future as a means of increasing production. Farming and crop production around the world slowed down in 2015. Agricultural robots were designed to address these concerns and fulfill an increasing necessity for better returns. According to a Verified Market Intelligence analysis, agricultural robotics would be able to accomplish field chores more efficiently than farmers, improving the worldwide agriculture and crop production market.

Over $800 million has been raised by agricultural technology startups within the last five years. In 2014, start-ups that use automatons and the use of machine learning to tackle agricultural challenges have expanded. This coincided with a big rise in the popularity of AI. For the last five years, there has been a significant increase in venture funding for AI [7]. The United Nations Food and Agriculture Organization (FAO) says there will be more than 9 billion people worldwide on Earth by 2050. This new form of agriculture gives the pretence of accomplishing something for less. In agriculture, the use of high-tech sensing technologies will help solve the problem. These technologies will provide accurate information regarding soil and crops as well as the environment, which will enable the practical implementation of phytosanitary goods that will drastically reduce herbicides and pesticides, enhance water utilization reliability, and raise agricultural production.

III. Review On Implementing IoT Based Agriculture In The Current Market

Pesticide or fertilizer management, plant health, disease prevention, irrigated agricultural monitoring, soil conservation, distribution network traceability, automotive and machine and equipment control, are some of the most often used applications for IoT solutions in modern agriculture. Table 1 lists the articles that were reviewed, which are organized by climate of farmlands and the utilisation of the IoT approach. In particular, it is vital to keep in mind that some of the IoT systems strategies presented in the examined papers could be applied in a range of settings. Agricultural crop monitoring, as illustrated in Table 1, is the most widely utilised IoT system for smart farming. Furthermore, these solutions have been created for usage in a number of agricultural contexts, including arable fields, orchards, and greenhouses, among others. Crop surveillance is critical for farmers, which explains why this sort of technology is so popular in agriculture. IoT solutions for crop monitoring were made with the goal of getting environmental data from plantations, like temperature, humidity, luminosity, and so on, from the field. Farmers can utilise this data to gain a more comprehensive view of their plantations. Similar data, for example, has been used to evaluate the vigour of price [8, 9], alfalfa [10], and maize [11] crops, as well as to regulate greenhouse environmental conditions [12, 13, 14].

TABLE I. THE APPLICATION AND THE ENVIRONMENT OF SMART AGRICULTURE

Application	**Orchard**	**Arable Land**	**Greenhouse**	**Generic**
Monitoring of Crop	[14-17]	[18-21]	[22-24]	[25, 26]
Chemical control	[27]	[28, 29]	[30]	[31]
Disease		[32, 33]	[34]	[35]
Control of Irrigation	[36, 37]	[38]	[39, 40]	[41, 42]
Supply chain traceability			[43]	[44]
Soil management	[45]	[46]		[47]
Other	[48]	[49]		[50]

Similarly, as demonstrated in Table 1, IoT automated irrigation systems have been created for a variety of agricultural situations. To enhance agricultural water use, numerous IoT systems are intended to use sensors to detect soil moisture and monitor irrigation sources. Alternatively, in a more simplified manner, by integrating weather and humidity data to ascertain the amount of accessible water when watering the crops [36]. IoT disease control approaches are designed to detect and avoid diseases on plantations. These IoT solutions obtained a range of environmental and plantation data for this purpose, including plant photos [33], sounds, temperature, humidity, and so on. This data is analyzed using various methods. For example, image processing and AI. For instance, the Internet of Things driving innovation in [51], analyses shots of a sugarcane plant and discovers infections of pesticides on the plant's green leaves. In comparison, [52] established an Internet-of-Things-enabled device for recording the sounds emitted by larvae within trees. Table 1 summarizes IoT technologies for chemical control that aid in optimizing fertilizer and pesticide application on plantations. As a result, these technological solutions gather information from crops (such as nitrogen, salinity, or PH). These IoT technologies can distinguish crop zones that may require fertilizer or pesticide application results derived. The nitrogen content in a large plantation, for example, can be evaluated using aerial pictures of crops [53]. These pictures may be used to locate the precise field that needs fertilizer. Furthermore, [30] created an autonomous robot that optimizes pesticide distribution in greenhouse growing areas. The industrial IoT soil science platforms seek to describe a variety of soil characteristics that may be implemented for planting. As an example, such systems are used to determine soil water content [54], analyze water consumption patterns [55], identify soil nutrients [56], and as weather station with air quality measurement [57].

The IoT technologies for automobile and machinery management are primarily focused on collecting and analysing data from agricultural plants and facilities such as trucks, harvesters, and tractors. As a result, IoT solutions have to handle unique features of agricultural gear, such as mobility. Sensors receive inputs from the equipment itself, such as the state of the implement, engine performance, or rpm, in order to optimise their maintenance period. Further, as agricultural equipment has become more mobile, opportunistic computing has been used to collect data from remote crop fields via tractors equipped with sensors [62, 63]. Each agricultural condition in Table 1 poses unique challenges for production, along with the environment's influence on sensor information exchange, which can be caused by sensor node distance [59], a breakdown in communication in farmlands [63], or even the effect of vegetation on signal transmission. Additionally, meteorological variables such as snow, fog, or solar irradiance have an impact on both the sensor network and the planting. Approximately 96% of the papers surveyed used electronic sensors to cover these situations. This descriptive approach is validated by the fact that such sensor nodes are certified, affordable, and available, as well as meeting the essential monitoring criterion for IoT technology for smart agriculture. As indicated by Table 2, such sensors are utilised to gather real-time data on various agricultural parameters, including meteorological variables, substrate characteristics, luminance, CO2 concentration, and pictures. Additionally, certain publications (4%) focused on the development of customised sensors for the purpose of keeping track of specific agricultural parameters, using approaches like soil mineral elements (e.g., nitrate 56]) and plant leaf evaporation to calculate hydric pressure in tobacco crops [65].

As shown in Table 2, a wide range of sensors were implemented in IoT approaches for modern farming to glean knowledge about farming from a variety of sources, including the environment, agricultural productivity, and substrates. As shown in Table 2, electronic detectors are being applied in IoT solutions to acquire parameters. For example, humidity, temperature, and luminosity [14, 23, 58]. Besides that, electronic sensor nodes were implemented to acquire information from the soil surface (e.g., water and soil) for substrate supervision, including moisture, temperature, and nitrogen. Similarly, pH sensors are often applied in hydroponics cultivation practices to test the alkalinity or acidity of the water. Multispectral sensor systems and cameras were used to take pictures of crops so that they could be tracked. UAVs may be employed in multiple ways to take aerial photos of huge plantations [8, 9, 11] or robots are being implemented to get a very detailed picture of a plant leaf [73]. The choice of equipment is an important part of the development of an IoT application because it affects the expenses as well as the technological advances for use. Among the publications, 60% reviewed the components applied to facilitate the IoT application.

Moreover, SBCs were described in 40% of the studies surveyed. The usage of SBCs is justified by their low cost and scalability [21], which enables the production of customised IoT systems. Certain SBCs, such as Arduino, includes a built-in development environment (IDE). It allows for the advancement of customised applications that may be employed in order to run as software on the microcontroller. Moreover, the Raspberry Pi runs on a multitude of platforms, such as Ubuntu Core, Raspbian, and Mozilla Web Things. It is possible to modify the source code of several of these operating systems. Additionally, these operating capabilities enable the execution of programmes developed in programming languages like Python [74]. Moreover, the functions of SBCs can be enhanced by incorporating other elements such as sensing devices or transceivers. Due to this feature, SBCs can operate as gateways or core networks in IoT approaches. The application of ESP boards (including ESP12, ESP32, and ESP8266), Arduino, and Raspberry Pi was mentioned in 82% of the publications that covered SBCs. The following table depicts how integrated machine platforms and UAVs are used in modern agriculture.

TABLE II. NUMEROUS VARIETY OF DETECTORS AND THEIR FUNCTIONS IN FARMING

Purpose of Implementation	**Examples of detectors**	**Application of sensing devices**	**References**
Management of Crop	DSC-QX100 Cyber-shot, Parrot Sequoia	Growth	[11]
	FLIR Blackfly 23S6C	Pest detection	[35]
Substrate monitoring	DS18B20, VH400	Moisture and temperature of soil	[57]
	SEN0244	Chemical elements such as nitrate, nitrogen	[58]
Environment monitoring	DHT11, DHT22	Humidity and temperature of air	[23]
	SQ-110	Solar radiation	[59]
	MG-811, MQ135	CO_2 concentration	[14]
	YF-S402, YL-83, Helsinki, SE-WS700D	Rain	[60]
	WS-3000, SEN08942	Wind speed and direction	[57, 59]
	MPL3115A2	Atmospheric pressure	[21]
	BH1750, TSL2561	Luminosity	[61]

Table 3 shows how IoT-enabled computers are employed in a variety of IoT systems for modern agriculture. SBCs can be used as sensors and channels. Table 3 discloses that Arduino has been a widely used platform for integrated systems among the articles checked. As an open-access platform that can be implemented to build a variety of devices, Arduino is a popular choice for hobbyists and professionals alike. Table 3 further shows that crop monitoring IoT applications are placing greater emphasis on intelligent sensor platforms. As sensor nodes, sensors like rain sensors, solar radiation detectors, and soil humidity sensors are connected via a USB cable to an Arduino Uno in order to collect environmental data. The microcontroller board is then used to evaluate a vineyard's health. Similar to [75], to measure the temperature of a greenhouse, a Raspberry Pi is utilised. Long-distance communication protocols can be used to establish a brief connection of WSNs to the internet via IoT devices acting as gateways. A WSN using three independent protocols (Wi-Fi, ZigBee, and Bluetooth) was linked to a distant server using 3G via a gateway. The LoRaWAN gateway implemented in [49] obtains data from the sensors via LoRa and retransmits it via 4G to a cloud-hosted platform. Cellular network technologies such as 3G and 4G allow users to connect over long distances and transfer lots of data quickly.

TABLE III. PLATFORMS FOR INTEGRATED SYSTEMS AND UAVS IN AGRICULTURE

Application	Raspberry	UAV	ESP	Arduino
Disease prevention	[66]	[51]	[51, 66]	[33]
Waste management	[67]			
Chemical control		[28]		
Monitoring of Crop	[23]	[18]	[68, 69]	[70]
Management of Soil	[46]			[45]
Machinery and Vehicles control	[63]			
Control of Irrigation	[38, 41]		[71, 72]	[41, 36]

The utilisation of UAVs in IoT systems for crop management, disease prevention, and biological control is shown in Table 3. Attributed to their ability to monitor big crops quickly and cheaply, UAVs are increasingly being implemented for crop surveillance. For this specific purpose, UAV systems equipped with multispectral sensing devices and cameras are implemented to take airborne photos of enormous fields of crops. In order to measure agricultural factors like the leaf area index, the IoT solution employs these photographs (LAI). The LAI is a metric that is deployed to ascertain how much vegetation is present in a given region. To measure and discover the level of nitrogen in rice production [9], compute the vigour of rice as well as maize crops [8, 11], and determine the presence of pests in sugarcane crops [51], LAI can be implemented in conjunction with other indicators. In addition, [67] uses UAV systems to optimise pesticide and fertiliser applications in agricultural production. Acquired data is often transferred beyond a wired or wireless network to an endpoint such as an IoT-based, database, or webserver.

The set of rules for networks utilized in the IoT strategy were addressed in 60% of the articles reviewed. Among the communication protocols mentioned, Ethernet and CAN were the most frequently employed for wired networks. Similarly, for long-distance wireless connections, LoRaWAN and wireless network configurations are by far the most widely used. For example, 3G, GPRS, and etc. Similarly, Bluetooth, ZigBee, and Wi-Fi are the most often used mechanisms for short-to medium-range wireless channels. The network protocols implemented in the examined articles for IoT solutions are presented in Table 4. Numerous network protocols, as indicated in Table 4, are employed to enable connectivity between smart devices such as routers and motes in selected agricultural contexts (e.g., greenhouse, orchard, arable land). This collection of data structures allows the construction of both short-range and long-range networks.

TABLE IV. MODERN FARMING EMPLOYS NETWORK PROTOCOLS IN A VARIETY OF AGRICULTURAL APPLICATIONS

Network	Protocols	Farm land	Generic	Green house	Orchard
Wired	Ethernet		[67]	[76]	[27]
	CAN		[32, 77]	[78]	
Short-range	Bluetooth	[79]	[72]	[75]	[62]
	LoRa	[54]	[80]	[8]	[28]
	RFID		[44]		
	ZigBee	[81]	[82]	[84]	[45]
Middle range	(RF-ISM)	[62]	[82, 84]	[13]	[16]
	Wi-Fi	[46, 61, 69]	[25, 71, 78]	[24, 59, 68]	
Long-range	LoRaWAN		[52, 64]	[23, 34]	
	Cellular	[21, 61, 85]	[52, 80]	[58, 75]	[37]
	Sigfox				[36]

As shown in Table 4, different devices were utilised for middle-range and short-range networking in the IoT implementations that were assessed, including Wi-Fi, ZigBee, and Bluetooth. Table 4 further shows that Wi-Fi has been a frequently selected mechanism for connectivity in the papers that were reviewed. This widespread need for Wi-Fi may be highlighted regardless of the fact that Wi-Fi is a pervasive facility that is relatively simple to build. In spite of this, energy-efficient technological advances, for instance, Bluetooth and ZigBee continue to be frequently employed as a result of the high energy demand of Wi-Fi. The ZigBee protocol, for example, was used to transfer information from a farm to an unreachable server, and established a Bluetooth-enabled node to monitor data straight from a field to a smart device. As indicated in Table 4, long-distance networks such as cellular networks, Sigfox, and LoRaWAN were used in the studied articles on IoT implementations. Smart farming solutions that rely on cellular networks are becoming widely attractive. Cellular networks, which enable IoT devices to be connected over vast distances and at faster speeds, might be used to support this argument. Communication data using cellular network obtained from humidity sensing devices to an IoT platform, and operate a watering system. LoRaWAN and Sigfox, on the other hand, enable the transmission of data over extremely long distances while consuming minimal energy. LoRaWAN and Sigfox, which are based on these characteristics, have been applied for long-distance connections, giving another option to wireless networks or in places where cell service coverage is poor or absent. A plantation irrigation management solution based on Sigfox is described in [36] as a network protocol for the IoT. Additionally, in [34], data from many sensors placed throughout the greenhouse is transmitted via LoRaWAN to a cloud-based service. Apart from the range between sensor devices, gateways, as well as other network equipment, vegetation itself may operate as an obstruction to sensor contact, as demonstrated by [62], who evaluated the impact of 2.4 GHz and 433 MHz signal transmission in large estates as well as an orchard. Another drawback with greenhouses is the amount of detectors, which might result in wireless signal interruption due to their close proximity [59]. To address this issue, Ethernet [78] and CAN [76] are two examples of wired connections that can be utilized. As illustrated in Table 4, these systems are being employed more extensively in plants, since this pattern of farming setting lends itself well to demonstrating access points.

The topology of a network is another important consideration when implementing an IoT strategy. According to [90], sensor networks can be either star, mesh-based, or tree-based (also known as a cluster). The topology of the network has an effect on both the amount of nodes in the WSN and the length between sensor devices and the destination [91]. For instance, networks of stars are made up of a central unit and a large number of end nodes. In this design, data is sent from peripheral nodes to the center node [59]. In this case, the physical layer communication standard limits how far the peripheral nodes can be from the main node. In comparison, mesh networks include routing capabilities built into each node, allowing for multi-hop communication to extend network coverage. Depending on the specifications of the IoT strategy and the task overview, 61 percent of the reviewed publications employed the same topology. Using the LoRa protocol, [36] interconnect sensors to a central point using star topology. Irrigation systems can be monitored via Sigfox through this central point, which serves as a channel for cloud-based software. The star topology is also utilised to integrate various sensors inside a conservatory via wireless communication. To stay updated on a greenhouse, [59] used this topology. Cluster networks, which are also called tree networks, are made up of a lot of star networks that connect to each other. Cluster networks were used by both [90] and [50] to manage crops. Sensor nodes in [90] gather and transmit data from a harvesting station to a router point.

This router acts as a network interface, retransmitting messages to the network's central router node. Multiple router nodes are installed around the crop to maximize the energy consumption of sensor nodes. Table 5 tabulated the cloud-based IoT platform for processing data and each technique such as computer vision and big data. In the other/not identified column, stated the categories that have either used a cloud platform to do data processing or have not clearly stated the method of data processing. According to Table 5, the most often encountered cloud computing in the checked articles are Mobius, ThingSpeak, Google, Azure IoT, Thinger.io, and AWS IoT. ThingSpeak has become the most widely used cloud-based framework in all surveyed articles, referring to its open-source nature and low technology requirements [36]. Furthermore, Table 5 tabulated the use of AWS IoT for a greater variety of information processing methods. Only some of the cloud-based platform providers have an identical range of features and capabilities, but they all facilitate information management in general [10, 13, 33, 79], modelling [68], processing and farm-level action management. Moreover, despite the fact that various cloud-based frameworks exist, several of the examined articles establish personal cloud-based systems for the IoT solution, as demonstrated in Table 5. By using cloud computing for both data processing and storage, cloud-based platforms offer connectivity for IoT projects. Some of the IoT platforms, like Thinger.io [25], are completely based on infrastructural suppliers such as Amazon AWS and Microsoft Azure. Such services often feature data processing elements with visuals and panels that acquired data or the design of personalised components from the aggregation of different data sets as time progresses.

TABLE V. THE DATA PROCESSING TECHNOLOGIES AND IOT PLATFORMS THAT APPLIED IN SMART FARMING

Platform	Big Data	Artificial Intelligence	Computer Vision	Machine Learning
AgroCloud	[86]			
AWS	[87]	[46]		[46,87]
Azure IoT Hub	[88]			
Google				[73]
Mobius		[89]		
Rural IoT	[10]			[10]
Self-developed	[26]			[38]
Thinger.io	[25]			
ThingSpeak			[33]	

Because of the scalability offered with these channels, the vast volumes of information produced by the detectors are processed in database systems to create big data, where an unorganised source of data is utilised to obtain crop details. Technology is needed to minimise reaction time owing to the large amount of data. A parallel computer system known as Hadoop provides big data applications; it has been shown to be more successful at analysing the rainfall benchmark data from numerous weather stations. IoT solutions analyse data in a number of ways and use a range of technologies [92]. Table 6 shows the most widely used technology for each application as described in the reviewed articles. It also shows that the most common applications to process data are big data, deep learning, and artificial intelligence. These technologies are capable of handling high volumes of data in a very short period of time. Furthermore, IoT technology is the most common technology in crop monitoring using data processing technology. In addition, crop control is the mode of application that requires the widest range of data processing tools. This is understandable given that most IoT solutions for crop monitoring gather a large amount of information through deep learning and big data analytics to process it. Table 6 shows that big data was applied to many IoT solutions like fertiliser control and soil management systems. For example, the data on soil moisture was collected by using sensors were connected to cloud datasets [55, 87] such as the Prediction of Worldwide Energy Resources (POWER) of NASA, which includes datasets such as the market trading price of crops, feedback from users to optimise the irrigation performance, and assists farmers at the stage of acquisition of material such as seed and fertiliser. Big data is also applied in [27] to monitor irrigation systems and provide irrigation advice to farmers based on the intelligent basis developed and data collected from sensing devices such as temperature and moisture detectors in soil.

TABLE VI. APPLICATION AND TECHNOLOGIES IN AGRICULTURE SECTOR

Application	Artificial Intelligence	Big Data	Computer Vision	Machine Learning
Disease prevention	[34]		[33, 51]	[80, 34]
Supply-chain traceability		[44]		
Chemical control	[27]		[31]	[27, 31]
Crop monitoring	[17, 20]	[10, 25, 88]	[9, 81]	[18, 24, 73]
Soil management	[46, 47, 55]	[47, 55]		[46, 47]
Irrigation control		[87]		[38]

Furthermore, the modification of numerous parameters is required for IoT-based automated management. Initially, basic monitoring of soil moisture, as described by [72], can be utilised to drive irrigation or cooling systems. However, greenhouse upkeep might be more demanding. As demonstrated in [14], greenhouse characteristics, including humidity and temperature, are strongly connected, and modifying one would have a domino impact on the others. Table 6 summarises how computer vision is applied in IoT solutions to achieve image processing like pest and disease detection. Based on the reviewed paper, computer vision is also possible to clarify and manage the objects in the image acquired from the camera, such as applying computer vision to clarify types of fruit in an orchard and [31, 51, 80] applying computer vision to achieve pest and disease detection. Similarly, computer vision was applied in [98] as a monitoring equipment to achieve diseases detection on olive groves and [31] applied same technology to analyse the diseases that may cause morphological deformation on crops. Additionally, computer vision is also applied in crop management systems, such as attaching a camera and other physical sensors on the robot to make it capable to acquire visuals of vegetation and, through image processing, detect and eliminate weeds in farmland, while [73] applying computer vision to a robot in order to clarify the crops and interact with the farm when necessary.

IV. CONCLUSION

Precision agriculture is a kind of farming that makes use of data sensors, linked devices, remote control tools, and other modern technology to provide farmers with more control over their fields and teams [97]. Precision agriculture is becoming increasingly popular [98]. This article conducts an in-depth survey of current Internet of Things (IoT) applications in farming. This research demonstrated that while the majority of agriculture work was focused on simple data processing and decision making a few years ago, the trend toward systematic management systems, for instance, cloud technology and big data is used to analyze enormous amounts of information has lately gained traction. Additionally, artificial intelligence and computer vision have become new trends in agriculture, with the goal of improving farm management. According to the numerous initiatives covered in this paper, the major portion of IoT smart farming technologies were utilized to monitor crop data. Numerous applications discussed in this article utilized multiple types of network protocols concurrently to improve the performance of their IoT solutions. Furthermore, this article compared several forms of communication networks, with wired network systems being applied to indoor farming, such as greenhouses, and wireless network systems being applied to outdoor farming, such as arable lands and plantations. The assessment in this paper demonstrated that IoT applications in smart farming are growing in insignificance. A farmer will get a comprehensive evaluation of all aspects of his or her operation, including crop and livestock management, weather conditions, soil quality, and the performance of his or her employees [93, 99, 100]. The site's history and evolution will be shown in a unified manner by storing all of this data together and making it readily accessible [94]. This article would serve as a reference for future work on project cost estimation and equipment selection for IoT systems. Building better distribution plans and outlining prospective income streams are both made possible by precisely forecasting the yield levels that will be gathered in each field [95, 96].

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