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The digitization of agricultural industry – a systematic literature review on agriculture 4.0

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ABSTRACT

Agriculture is considered one of the most important sectors that play a strategic role in ensuring food security. However, with the increasing world's population, agri-food demands are growing — posing the need to switch from traditional agricultural methods to smart agriculture practices, also known as agriculture 4.0. To fully benefit from the potential of agriculture 4.0, it is significant to understand and address the problems and challenges associated with it. This study, therefore, aims to contribute to the development of agriculture 4.0 by investigating the emerging trends of digital technologies in the agricultural industry. For this purpose, a systematic literature review based on Protocol of Preferred Reporting Items for Systematic Reviews and Meta-Analyses is conducted to analyse the scientific literature related to crop farming published in the last decade. After applying the protocol, 148 papers were selected and the extent of digital technologies adoption in agriculture was examined in the context of service type, technology readiness level, and farm type. The results have shown that digital technologies such as autonomous robotic systems, internet of things, and machine learning are significantly explored and open-air farms are frequently considered in research studies (69%), contrary to indoor farms (31%). Moreover, it is observed that most use cases are still in the prototypical phase. Finally, potential roadblocks to the digitization of the agriculture sector were identified and classified at technical and socio-economic levels. This comprehensive review results in providing useful information on the current status of digital technologies in agriculture along with prospective future opportunities.

1. Introduction

1.1. A global food security problem

Food security is a multidimensional concept that alleviates hunger by ensuring a sustainable, nutritious food supply. It is characterized by a four-pillar model shown in Fig. 1, with each pillar intrinsic to ensure food security [1].

Due to several anthropogenic factors, such as rapid population growth, urbanization, industrialization, farmland loss, freshwater scarcity, and environmental degradation, food security is becoming a serious global issue. This is because these factors are also directly impacting agricultural industry which is a primary source of agri-food production around the world. It is anticipated that by 2050 global population will be increased from the current 7.7 billion to 9.2 billion, urban population will be rise by 66%, arable land will be declined by approximately 50 million hectares, global GHG emissions (source of CO_2 – promote crop disease and pest growth) will be increased by 50%, agri-food production will be declined by 20%, and eventually, food demand will be increased by 59 to 98% – posing an imminent threat to food security and adequate food availability [2–4]. To satisfy the increasing food demands, agricultural practitioners worldwide will need to maximise the agricultural productivity involving crop and livestock farming. In this review paper, the focus is on *crop farming* that involves cultivation of both food and cash crops. A typical agri-food value chain depicting three primary stages, namely pre-field (pre-plantation stage), in-field (plantation and harvesting stage), and post-field (post-harvesting stage) involved in the production of agricultural products is shown in Fig. 2. All the stages play a vital role in the value chain but, in this review, the second stage ˝in-field˝ will be considered that involves several crop growing processes such as plowing, sowing, spraying, and harvesting, etc. These processes currently employ traditional agricultural practices that are labor-intensive, require arable land, time, and a substantial amount of water (for irrigation) – making it a challenge to produce enough agri-food [5]. A part of problem is also related to irregular use of pesticides and herbicides and misuse of available technology which cause harm to crop and eventually resulting in agricultural wastes [6]. These issues can be addressed by integrating sophisticated technologies and computer-based applications that ensure high crop yield, less water consumption,

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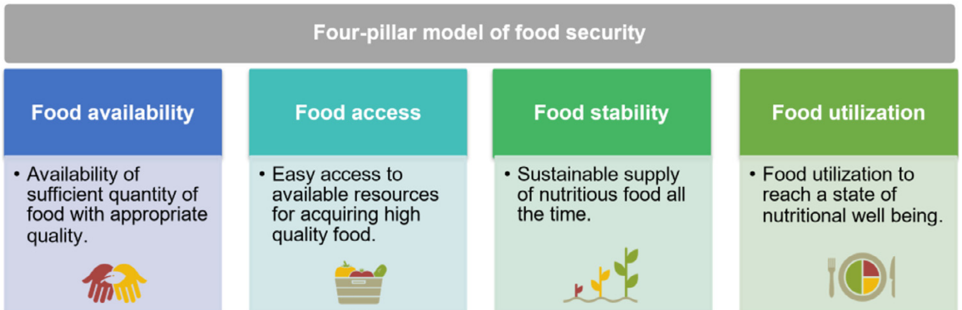

Fig. 1. Four-pillar model of food security by Food and Agriculture Organization of the United Nations.

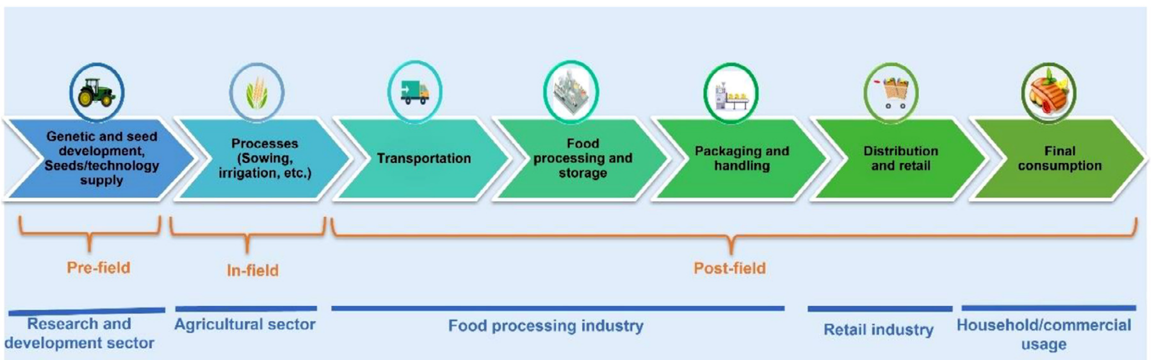

Fig. 2. Agriculture value chain: stages and main functions.

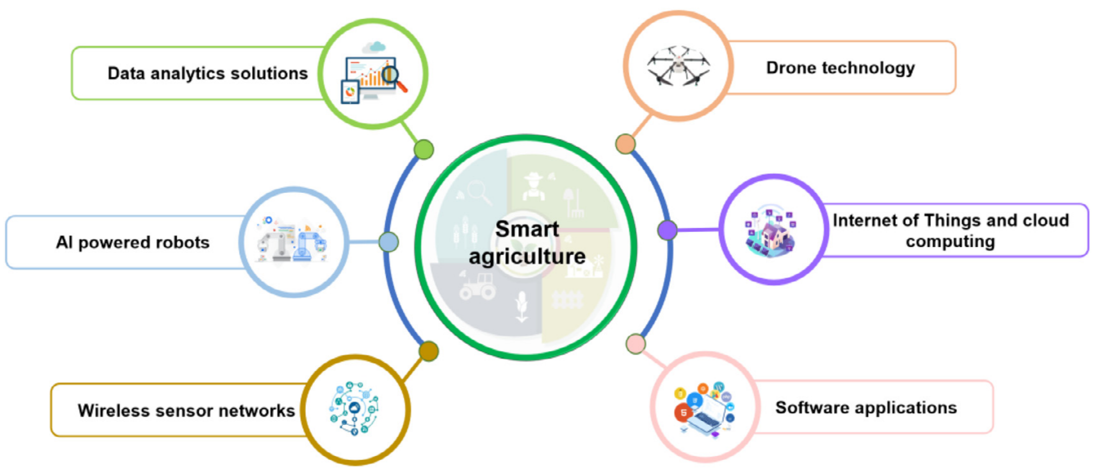

Fig. 3. The concept of "Smart Agriculture".

optimised pesticide/herbicide utilization, and enhanced crop quality. This is where the *smart agriculture* concept comes in.

1.2. Smart agriculture

Industry 4.0, also known as the fourth industrial revolution, is revolutionizing, and reshaping every industry. It is a strategic initiative characterized by a fusion of emerging disruptive digital technologies such as Internet of Things (IoT), big data and analytics (BDA), system integration (SI), cloud computing (CC), simulation, autonomous robotic systems (ARS), augmented reality (AR), artificial intelligence (AI), wireless sensor networks (WSN), cyber-physical system (CPS), digital twin (DT), and additive manufacturing (AM) to enable the digitization of the industry [7]. The integration of these technologies in agriculture is sparking the next generation industrial agriculture, namely, *agriculture 4.0* – also termed *smart agriculture, smart farming*, or *digital farming* [7].

Smart agriculture provides farmers with a diverse set of tools (shown in Fig. 3) to address several agricultural food production challenges associated with farm productivity, environmental impact, food security, crop losses, and sustainability. For instance, with IoT-enabled systems consisting of WSNs, farmers can connect to farms remotely irrespective of place and time to monitor and control farm operations. Drones equipped with hyperspectral cameras can be used to collect data from heterogeneous sources on farmlands and autonomous robots can be used to support or accomplish repetitive tasks at farms. Data analytics techniques can be employed to analyze the gathered data with computer applications can be used to assist farmers in decision-making process. Likewise, a wide variety of parameters related to environmental factors, weed control, crop production status, water management, soil conditions, irrigation scheduling, herbicides, and pesticides, and controlled environment agriculture can be monitored and analyzed in smart agriculture to increase crop yields, minimize costs, enhance product quality, and maintain process inputs through the use of modern systems [8].

1.3. Research motivation and contribution

The motivation for preparing this review stems from the fact that digital technologies in agricultural systems offer new strategic solutions for enhancing the efficiency and effectiveness of farms' production. Moreover, digital transformation provides a way forward to implement modern farming practices such as vertical farming (hydroponics, aquaponics and aeroponics), which has the potential to overcome food security problems. But there is a set of problems and limitations associated with this transformation from the technical, socio-economic, and management standpoint that must be death to fully exploit the potential of agriculture 4.0 [9]. There are number of studies that have discussed emerging trends in the development of agriculture 4.0 by providing succinct information on key applications, advantages, and corresponding research challenges of smart farming [9–18]. The research focus of these studies is limited to either explaining more generic technical aspects while paying attention to only one or few digital technologies, and/or enhancing agricultural supply chain performance, and/or developing agriculture 4.0 definition, and/or achieving sustainable agronomy through precision agriculture, and/or proposing a smart farming framework. Nevertheless, these studies do not involve explicit discussion on the tools and techniques used to develop different systems and maturity level of these systems. There is also a lack of studies considering modern soilless farms such as hydroponics, aquaponics and aeroponics (indoor/outdoor) and implications of digital technologies in these farms. Hence, it is necessary to analyse the evolution of agriculture 4.0 from different perspectives to stimulate the discussion in the area. This study aims to present a holistic overview of digital technologies implemented in second stage of agricultural production value chain (in-field) for different types of farms as mentioned in section 1.1. The main theoretical contribution of the study involves analysis and dissemination of the tools and techniques employed, the farm type, the maturity level of the developed systems, along with potential roadblocks or inhibiting factors in development of agriculture 4.0. The reflections presented in the review will support researchers and agricultural practitioner in future research on agriculture 4.0.

1.4. Paper organization

Following the introduction, the paper is structured as follows: Section 2 discusses the approach used to gather the relevant literature; then, Section 3 presents the statistical results obtained after a general analysis of the selected research studies; next, Section 4 provides a detailed overview of the core technologies used in the digitization of agriculture; after, Section 5 highlights the technical and socio-economic roadblocks to digital integration in agriculture; next, Section 6 outlines a discussion about the research questions followed by added value, considerations and future prospects related to agricultural digitization, and transition to agriculture 5.0; and lastly, Section 8 concludes the review.

2. Research methodology

A systematic literature review (SLR) is a tool used to manage the diverse knowledge and identify research related to a predetermined topic [19]. In this study, SLR is conducted to investigate the status of Industry 4.0 technologies in agricultural industry. Particularly, cases are searched where the term 'agriculture' appeared concurrently in the title, abstract, or keywords of an article with any of the 'Industry 4.0 technologies" mentioned in section 1.2. Before conducting the SLR, a review protocol is defined to ensure a transparent and high-quality research process, which are the characteristics that make a literature review systematic [20]. The review protocol also helps to minimize bias by conducting exhaustive literature searches. This includes three steps: the formulation of the research questions, the definition of the search strategy, and the specification of inclusion and exclusion criteria. This paper uses a preferred reporting item for systematic reviews and meta-analysis (PRISMA) approach to conduct SLR. PRISMA is an evidence-based minimum set of items that are used to guide the development process of systematic literature reviews and other meta-analyses [19].

2.1. Review protocol

A review protocol (in Table 1) is defined before conducting the bibliographic analysis to identify, evaluate, and interpret results relevant to the research scope. First, research questions are formulated to provide insight into the analysis of published studies in the research area of interest from different dimensions. These questions need to be answered in the study. Next, the search strategy is defined, which helps identify appropriate keywords later in the search equation to identify the relevant information sources, such as academic databases and search engines that provide access to a massive amount of digital documentation. Three online research repositories are used to retrieve relevant studies: ScienceDirect[1], Scopus[2], and IEEE Xplore[3]. Finally, to refine the search results of each database, boundaries are set by predefining inclusion and exclusion criteria for further investigation and content assessments of selected publications. It involves, for instance, defining the time interval for the research process from 2011 to 2021 to limit the studies to those published in English, disregarding chapters of books and grey literature, such as reports and summaries of events and seminars. These last two steps of the review protocol allow the preliminary filtering of metadata sources and narrow down the scope of research.

2.2. Evaluation process

The evaluation of the literature search process is done in four stages: identification, screening, eligibility, and inclusion, as detailed by the PRISMA flow diagram shown in Fig. 4. After initial metadata filtering through the application of search expression, a total of 3165 records are found (1690 from Scopus, 926 from ScienceDirect, and 549 from IEEE Xplore), which are then consolidated for the removal of duplicate items in the identification stage. The number of publications after this step is reduced to 2876. In the screening stage, the titles and abstracts of the papers are analyzed, and only 498 papers are selected for integral reading. In the third stage, full-text screening of these articles is performed to verify their eligibility in relation to the objective of this paper, which is to answer the research questions mentioned in Table 1. Of the 498 papers, 137 are found to be relevant for this review. Another 11 are added through a cross-referencing approach, adding up to 148 papers selected in the final stage for further analysis.

2.3. Threats to validity

i SLR replication: The presented SLR is susceptible to threats to validity because the current search is limited to only three online repositories. More publications could potentially be found if additional sources were explored. The process of SLR is described clearly in sub-sections 2.1 and 2.2, and hence, validity can be considered well addressed. However, in the case of replication of this SLR, it is possible that one can find slightly different publications. This difference would result from different personal choices during the screening and eligibility steps of PRISMA, but it is highly unlikely that the overall findings would change.

ii Search string: the search string used to find the relevant studies cover the whole scope of SLR, but there is a possibility that valuable studies might have been missed. Additional keywords and synonyms with a broader search might return more studies.

[1] www.sciencedirect.com
[2] www.scopus.com
[3] ieeexplore.ieee.org

Table 1
Review protocol for systematic literature review.

Review questions	RQ1: Which Industry 4.0 technologies have been used in the literature for digitization of agriculture? RQ2: How and to what extent have these technologies been applied in the context of service type, tools and techniques used, system's maturity level, and farm type? RQ3: What are the primary roadblocks in implementation of Industry 4.0 technologies for smart farming?
Study selection criteria	Inclusion criteria: • Peer-reviewed journal articles and conference papers. • Studies published during the period between 2011 and 2021. • Studies should provide answers to the research questions. • The article must include the title, year, source, abstract, and DOI. • Literature focussing on application of Industry 4.0 technologies in crop plantation and harvesting activities particularly in-field processes. Exclusion criteria: • Summaries of events and seminars, book review, and editorial. • Literature focusing on application of Industry 4.0 technologies in livestock farming; pre-field processes such as genetic development, seed development and seed supplying; post-field stages such as crop distribution, food processing and consumption; and agri-food supply chain. • Studies published before 2011. • The publication is not available in full text. • The publication is not in English.
Literature search	Sources: Scopus, ScienceDirect, and IEEE Xplore for academic literature, citations in identified literature Search equation: (("agriculture*") AND ("Industry 4.0" OR "Digital Farming" OR "Intelligent Farming" OR "Smart Agriculture" OR "Agriculture 4.0" OR "Smart Farming" OR "Internet of Things" OR "IoT" OR "Cloud Computing" OR "Edge Computing" OR "Wireless Sensor Networks*" OR "Artificial Intelligence*" OR "Big Data*" OR "Data Analytics*" OR "Data Science*" OR "Cyber Physical System*" OR "Robotics*" OR "Computer Vision*" OR "Machine Learning*" OR "Deep Learning*" OR "Data Integration*"))

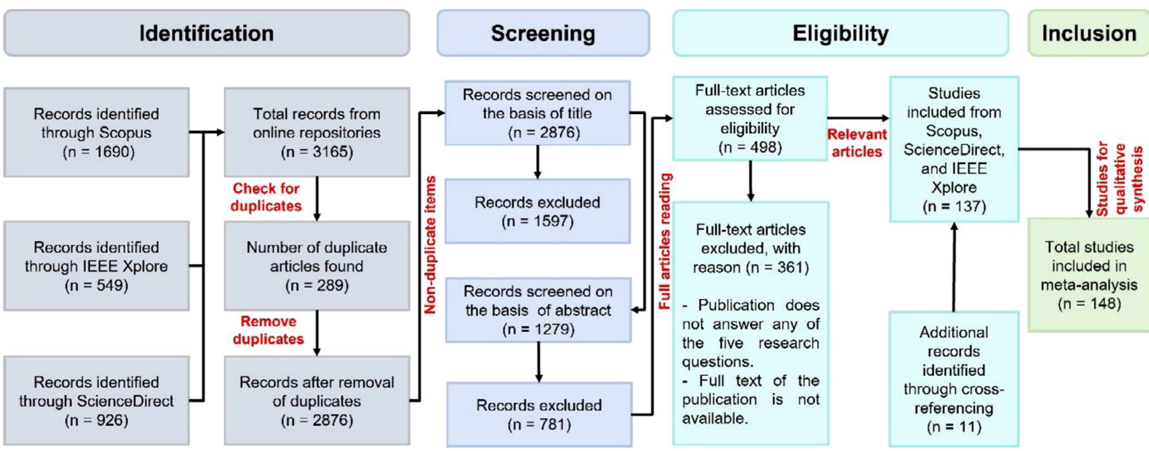

Fig. 4. Four-step evaluation of literature search process (PRISMA).

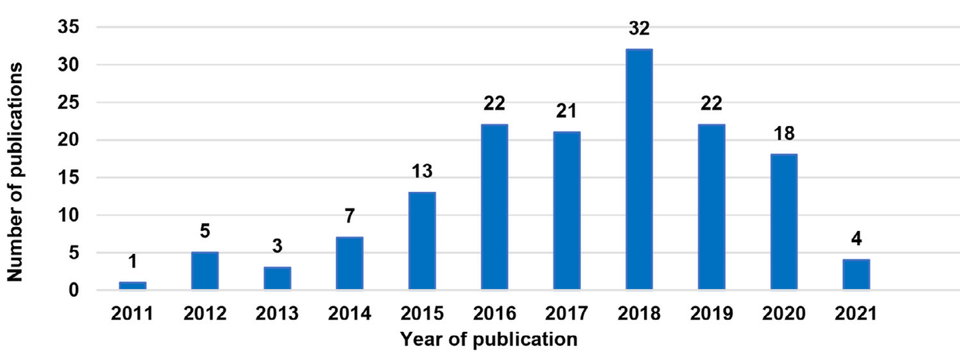

Fig. 5. Year-wise distribution of selected research studies from 2011 to 2021.

3. Digitization trends in agriculture

The year-wise distribution of the 148 articles from 2011 to 2021 is represented in Fig. 5. Around 22% of the scientific publications in the last ten years were published in 2018. This reflects that the agricultural industry is making considerable progress in the context of the implementation of digital technologies, but the pace is still slow as compared to other domains such as healthcare, manufacturing, mining, automotive, energy, etc.,[15].

The breakdown of these publications with respect to digital technologies (mentioned in sub-section 1.2) and targeted farm types is represented in Fig. 6.

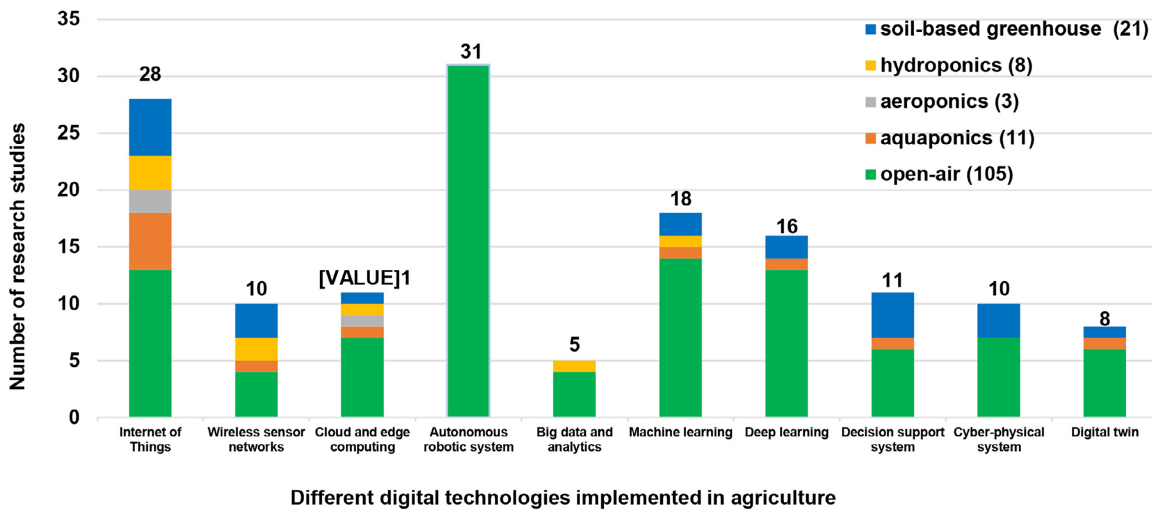

Fig. 6. Technology-wise distribution of the 148 selected research studies.

The farm type refers to the crop farming method considered while developing an application or framework. For instance, the farming method can be soil-based or soilless. The soil-based farming category involves open-air fields (traditional outdoor agricultural farms) and greenhouse farms (indoor). On the other hand, the soilless farming category involves modern farming practices such as aquaponics, aeroponics, and hydroponics (mostly indoor). The numbers at the top of the stacked column in Fig. 6 indicate the total number of studies that have used the particular technology to develop a smart agriculture system, whereas different colors of columns indicate the respective farm types. Use cases are from these publications are analysed, and conclusions are drawn. For instance, it is found that *autonomous robotics systems* (including unmanned guided vehicles and unmanned aerial vehicles (drones)), *internet of things*, and *machine learning* appear to be the widely applied technologies in the agricultural domain in the last decade. The same illustration suggests that *big data, wireless sensor networks, cyber-physical systems*, and *digital twins* are the emerging areas in agriculture. Moreover, *open-air* farms are the most frequently considered in research studies (69%), contrary to indoor farms (31%). For soilless farming systems (*aquaponics, aeroponics, and hydroponics*), only 22 publications are found, which insinuates that these modern farming practices are still in their infancy.

Likewise, services of each use case are identified and are classified under nine different service categories, namely: i) crop management, CM (Estimation/ prediction of crop yield/ growth rate/ harvesting period and seed plantation/ harvesting/ pollination/ spraying (fertilizer/ pesticide)); ii) crop quality management, CQM (fresh weight, green biomass, height, length, width, leaf density, piment content (chlorophyll) and phytochemical composition); iii) water and environment management, WEM (monitoring and control of flow rate, water level, water quality (nutrients), temperature, humidity, CO2, and weather forecast etc.); iv) irrigation management, IM (water stress detection and scheduling); v) farm management, FM (monitoring of farm operations, tracking and counting products, determining production efficiency, financial analysis, energy consumption analysis, technology integration and decisions implementation); vi) pest and disease management, PDM (pest identification and disease detection); vii) soil management, SM (moisture content, soil nutrients, fertilizer needs and application); viii) weed and unwanted vegetation management, WUVM (weed/unknown vegetation mapping, classification, and herbicides application); and ix) fruit detection and counting, FDC — as shown in Fig. 7. These categories illustrate the role of different digital technologies in smart farming. Upon analysis, it is found that crop management parameters, such as crop yield prediction, growth rate estimation, or evaluation of harvesting period are the most frequently researched areas for agriculture 4.0 in the last decade (29%), whereas very little heed is paid towards soil management (2%), fruit detection and counting (2%), and crop quality management (3%).

The technology readiness level (TRL) of all the use cases is examined using European Union's TRL scale that partitions system's maturity level into three generic levels [21]. The first level is c*onceptual*, that represents European TRL 1–2 (use case is in conceptual phase), the second level is the *prototype*, which means European TRL 3–6 (use case is working even without the complete planned functionality), and the third level is *deployed*, that includes European TRL 7–9 (use case is mature with all the possible functions). Fig. 8 depicts the TRL of each use case developed in selected studies. It is observed that little progress has been made in advancing smart agricultural systems beyond the concept and prototype levels to the commercial level. For instance, most use cases (129) are at the *prototype* level.

4. Agriculture 4.0 enabling technologies

This section provides critical insights towards answering RQ1 and RQ2 from Table 1.

4.1. Internet of Things driven agricultural systems

Internet of things (IoT) refers to a cosmos of interrelated computing devices, sensors, appliances, and machines connected with the internet, each having unique identities and capabilities for performing remote sensing and monitoring [21]. The reference architecture of IoT with six layers, namely perception layer (hardware devices), network layer (communication), middleware layer (device management and interoperability), service layer (cloud computing), application layer (data integration and analytics), and end-user layer (user-interface), is shown in Fig.9. In the agricultural domain, IoT devices in the physical layer gather data related to environmental and crop parameters such as temperature, humidity, pH value, water level, leaf color, fresh leaf weight, etc. The transmission of this data takes place in the network layer, the design of which depends on the selection of suitable communication technologies relevant to the field size, farm location, and type of farming method. For instance, ZigBee, LoRa, and Sigfox are widely used and employed in outdoor fields because they are cheaper and have low energy consumption and a good transmission range [22,23]. Despite being a secure technology, Bluetooth is only used in indoor farms as it offers a short transmission range [22]. Wi-Fi is not a promising technology for agricultural applications due to its high costs and high energy consumption [22]. RFID (radio frequency identification) and NFC (near field

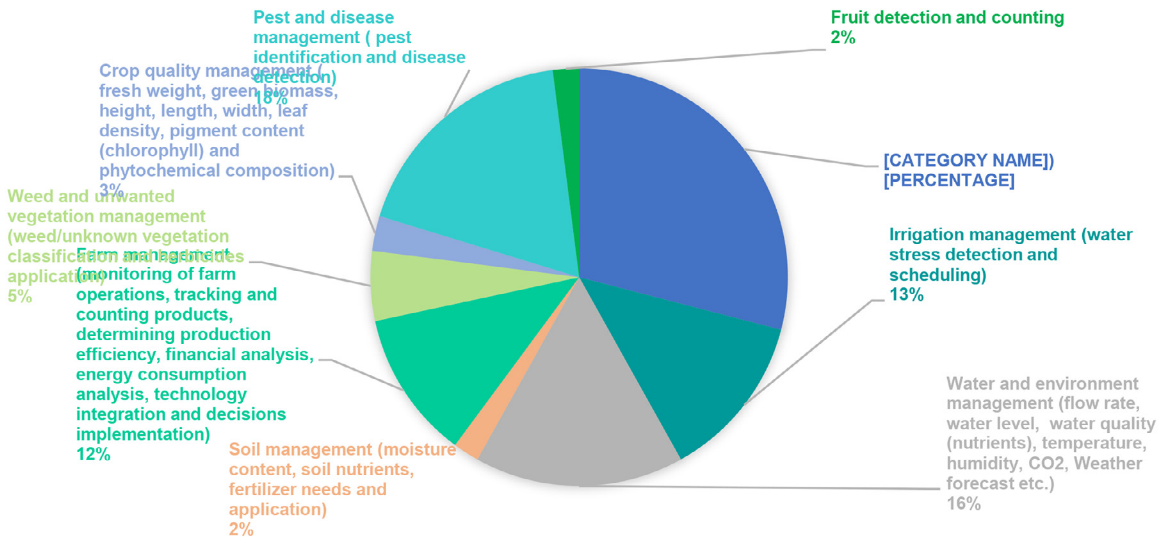

Fig. 7. Service-wise distribution of selected research studies:

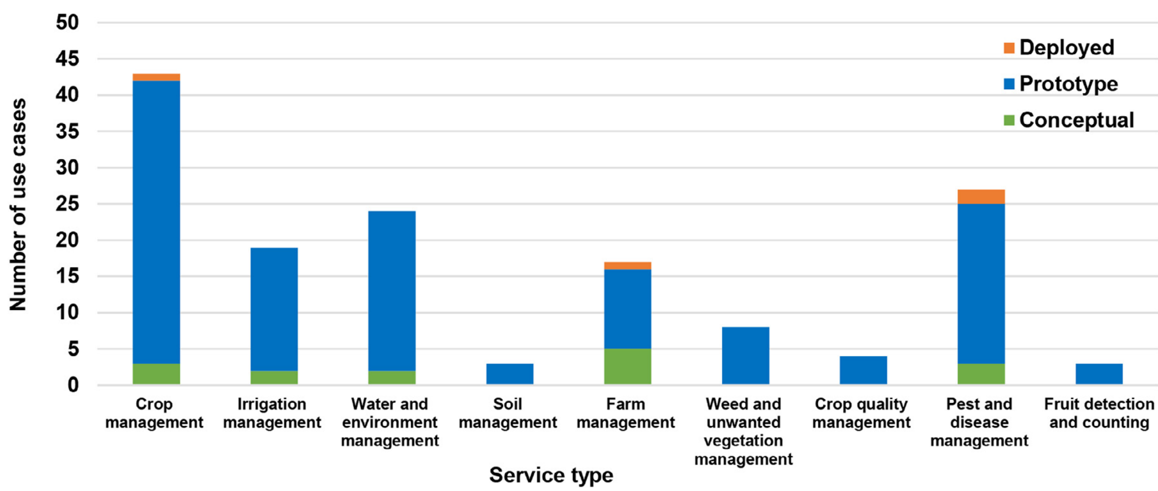

Fig. 8. Distribution of studies based on the service category and system's maturity level.

communication) technologies, on the other hand, are increasingly being implemented in agricultural systems for tracking agricultural products [24]. GPRS or mobile communication technology (2G, 3G, and 4G) are used for periodic monitoring of environmental and soil parameters. In addition, communication protocols mostly used in the agricultural scenarios are HTTP, WWW, and SMTP. Likewise, to ensure interoperability and system security to their context-aware functionalities, middleware HYDRA and SMEPP are mostly employed in agricultural systems [25]. To store data, cloud computing techniques are employed in the service layer. This data is then used in the application layer to build smart applications used by farmers, agriculture experts, and supply chain professionals to enhance farm monitoring capacity and productivity.

The integration of IoT in agriculture is meant to empower farmers with the decision tools and automation technologies that seamlessly integrate knowledge, products, and services to achieve high productivity, quality, and profit. A multitude of studies is performed and put forward concerning the incubation of the IoT concepts in the agricultural sector. The main findings of some of the studies are presented in Table 2. Multiple technological issues and architectural problems have been addressed through the development of IoT-based agricultural systems. But most of these systems are either in a conceptual stage or in a prototype form (not commercial) at the moment. Focus is mainly laid on-farm management, irrigation control, crop growth, health monitoring, and disease detection. Some of these studies have also explained IoT implementation in modern agricultural systems such as vertical farming (soilless farming - aquaponics, hydroponics, and aeroponics) and greenhouse farming (soil-based). Moreover, most studies have focused on addressing a specific problem.

4.2. Wireless sensor networks in agriculture

Wireless sensor network (WSN) is regarded as a technology that is used within an IoT system. It can be defined as a group of spatially distributed sensors for monitoring the physical conditions of the environment, temporarily storing the collected data, and transmitting the gathered information at a central location [22]. The general architecture of WSN is shown in Fig. 10. A WSN for smart farming is made up of numerous sensor nodes connected through a wireless connection module. These nodes have a variety of abilities (e.g., processing, transmission, and sensation) that allow them to self-organize, self-configure, and self-diagnose. There are different types of WSNs, which are categorized depending on the environment where they are deployed. These include terrestrial wireless sensor networks (TWSNs), wireless underground sensor networks (WUSNs), underwater wireless sensor networks (UWSNs), wireless multimedia sensor networks (WMSNs), and mobile wireless sensor networks (MWSNs) [55]. In agricultural applications,

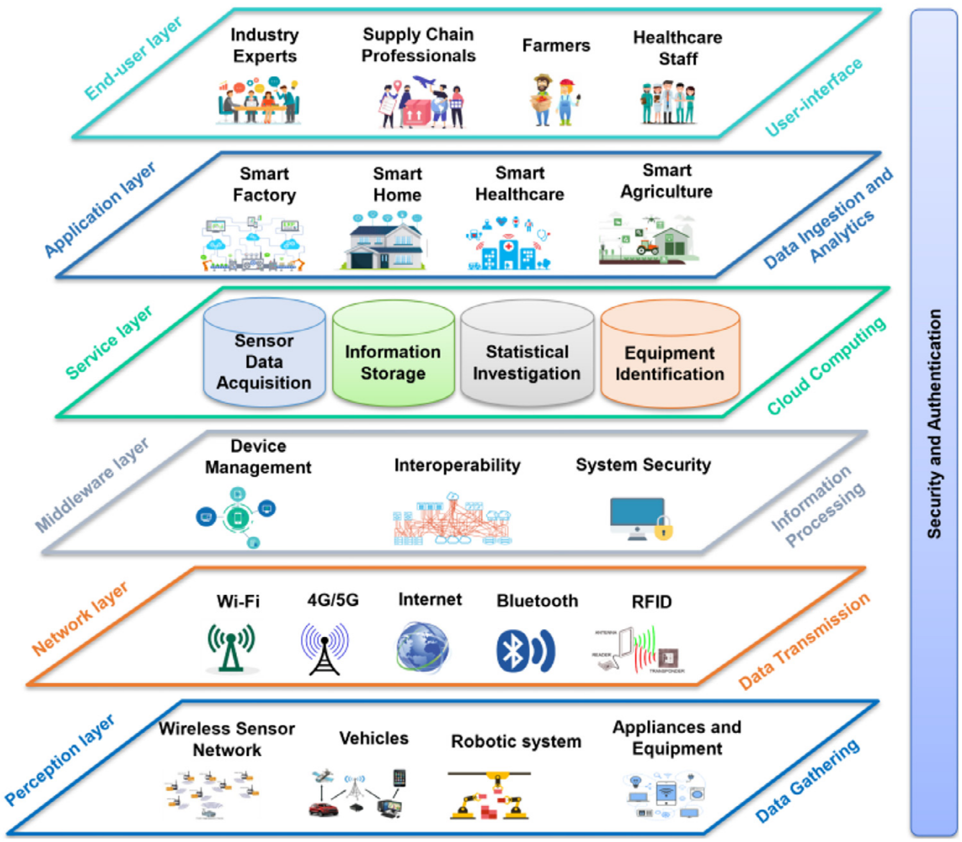

Fig. 9. Six-layered architecture of Internet of Things (IoT), (adapted) [26].

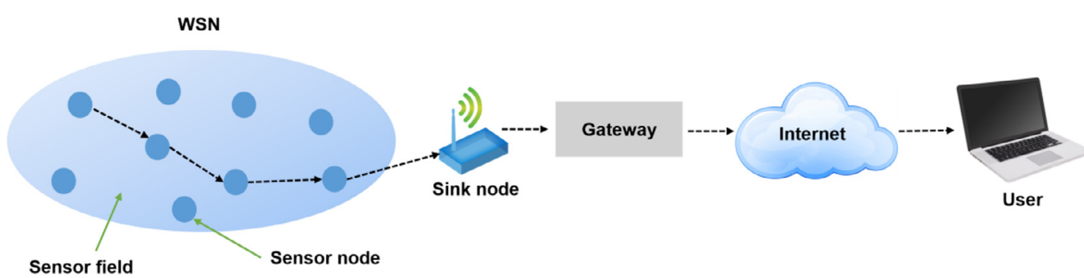

Fig. 10. General architecture wireless sensor network (WSN).

TWSN and UWSN are widely used. In TWSNs, the nodes are deployed above the ground surface, consisting of sensors for gathering the surrounding data. The second variant of WSNs is its underground counterpart – WUSNs, where sensor nodes are planted inside the soil. In this setting, lower frequencies easily penetrate through the soil, whereas higher frequencies suffer severe attenuation [56]. Therefore, the network requires a higher number of nodes to cover a large area because of the limited communication radius. Many research articles are available in the literature that discusses the use of WSN for different outdoor and indoor farms' applications such as irrigation management, water quality assessment, and environmental monitoring. A summary of some of these articles is given in Table 3. These studies have focused on developing WSNs architectures that are simplified, low cost, energy-efficient and scalable. Yet, various factors associated with WSNs need further attention, such as minimum maintenance, robust and fault-tolerant architecture, and interoperability.

4.3. Cloud computing in agriculture

According to the National Institute of Standard and Technologies (NIST), cloud computing (CC) is defined as a model for enabling ubiquitous, convenient, on-demand network access to a shared pool of configurable computing resources (e.g., networks, servers, storage, applications, and services) that can be rapidly provisioned and released with minimal management effort or service provider interaction [67]. The main architecture of CC shown in Fig. 11 is comprised of four layers: datacenter (hardware), infrastructure, platform, and application [68]. Each of these layers is linked with specific cloud service models, which are classified as software as a service (SaaS), platform as a service (PaaS), and infrastructure as a service (IaaS). Cloud computing has gained great attention over the past decade in the agriculture sector because it provides: 1) inexpensive storage services for data gathered from different domains through WSNs and other preconfigured IoT devices, 2) large-scale computing systems to perform intelligent decision-making by transforming this raw data into useful knowledge, and 3) a secure platform to develop agricultural IoT applications [69]. In combination with IoT and WSN, CC is employed to develop different agricultural applications, most of which are presented in Tables 2 and 3. CC technology is also used to create operational farm management systems (FMSs) to support farmers and farm managers in efficient monitoring of farm operations Table 4. presents the salient features of some of these FMSs. Another topic of interest that is being explored in global research is

Table 2
IoT-driven agricultural systems.

Use case No.	Service category	Tools and techniques	Farm type	Maturity level	Citations
1.	CM	WSN, CC, and reinforcement learning	Greenhouse (soil-based)	Deployed	[27]
2.		Sensors, actuators, and controllers	Open-air	Prototype	[28]
3.		Sensors, controllers, and mobile app	Greenhouse (soil-based)	Prototype	[29]
4.		Sensors, CC, BD analysis, and ML	Greenhouse (soil-based)	Prototype	[30]
5.		Sensors, and CC	Aeroponics	Prototype	[31]
6.		Sensors, actuators, and control system	Aeroponics	Prototype	[32]
7.		Weather boxes, sensors, and camera	Open-air	Prototype	[33]
8.	CQM	IoT devices, LED lights, and software application	Hydroponics	Prototype	[34]
9.	WEM	Sensors, and CC	Aquaponics	Conceptual	[35]
10.		Sensors, Arduino board, and database	Open-air	Prototype	[36]
11.		Sensors, Arduino board, and database	Greenhouse (soil-based)	Prototype	[37]
12.		Sensors, CPS, edge, and cloud computing	Hydroponics	Prototype	[38]
13.		Sensors, electronic components, and network	Aquaponics	Prototype	[39]
14.		Sensors, Arduino, Raspberry Pi3, and deep neural network	Hydroponics	Prototype	[40]
15.		Sensors, and database	Aquaponics	Prototype	[41]
16.		Sensors, actuators, and CC	Aquaponics	Prototype	[42]
17.		Sensors, controllers, and mobile app	Aquaponics	Prototype	[43]
18.	IM	WSN, fuzzy logic and neural network	Open-air	Prototype	[44]
19.		Sensor information unit, MQTT, HTTP, and neural network	Greenhouse (soil-based)	Prototype	[45]
20.	FM	Sensors, controllers, web interface, and CC	Open-air	Conceptual	[46]
21.		Sensors, controllers, cloud, and Android application	Open-air	Prototype	[47]
22.		Sensors, IEEE, and GSM protocols	Open-air	Prototype	[48]
23.	PDM	Sensors, controllers, and image processing	Open-air	Prototype	[49]
24.		Cloud, camera, controllers, and K-mean clustering	Open-air	Prototype	[50]
25.		WSN, controller, and cloud	Open-air	Prototype	[51]
26.		WSN, cloud storage, and agricultural knowledge base	Open-air	Prototype	[52]
27.		WSN, Hidden Markov Model, and SMS module	Open-air	Deployed	[53]
28.		Sensors, Image processing, k-mean clustering, and support vector machine	Open-air	Prototype	[54]

Table 3
Use of WSNs in agricultural systems.

Use case No.	Service category	Tools and techniques used	Farm type	Maturity level	Citation
29.	IM	Soil-moisture and temperature sensors, web application, and photovoltaic panels	Open-air	Prototype	[57]
30.		Electronic board, sensor board and GPRS board.	Open-air	Prototype	[58]
31.		Wireless sensor nodes, and Zigbee	Open-air	Conceptual	[59]
32.		Moisture sensors, actuators, and GUI	Greenhouse (soil-based)	Prototype	[60]
33.	WEM	Wireless communication, temperature, and humidity sensors	Greenhouse (soil-based)	Prototype	[61]
34.		Sensor nodes, gateway unit, database, ordinary kriging spatial interpolation (OKSI) algorithm	Hydroponics	Prototype	[62]
35.		Microcontrollers, wireless radio frequency and sensor nodes	Greenhouse (soil-based)	Prototype	[63]
36.		Wireless sensor nodes, communication network, and mobile application	Aquaponics	Prototype	[64]
37.		Arduino, wireless module with temperature, relative humidity, luminosity, and air pressure sensors	Any farm	Prototype	[65]
38.		Zigbee, Wi-fi and sensors	Hydroponics	Prototype	[66]

Table 4
Cloud computing-based farm management systems.

Use case No.	Service category	Tools used	Farm type	Maturity level	Citation
39.	FM	Fuzzy logic, Java, HTML, Apache Karaf, etc.;	Greenhouse (soil-based)	Conceptual	[71]
40.		RFID, and mobile app	Open-air	Deployed	[72]
41.		MySQL, financial analysis tool and mobile app	Open-air	Conceptual	[73]
42.		Self-leveling scale, control box, LCD display, and RFID tags	Open-air	Conceptual	[74]

related to the traceability of agri-product quality [70]. But only preliminary research has been attempted to explore traceability compliance with standards of food safety and quality.

The cloud-based agricultural systems have the potential to solve problems of increasing food demands, environmental pollution caused by excessive use of pesticides and fertilizers, and the safety of agricultural products. These FMSs, however, do not have the capability to support run-time customization in relation to distinct requirements of farmers. Moreover, because most farm data is usually fragmented and dispersed, it is difficult to record farm activities properly in current FMSs applications [75].

4.4. Edge/fog computing in agriculture

The rapid development of IoT has led to the explosive growth of sensors and smart devices, generating large volumes of data. The pro-

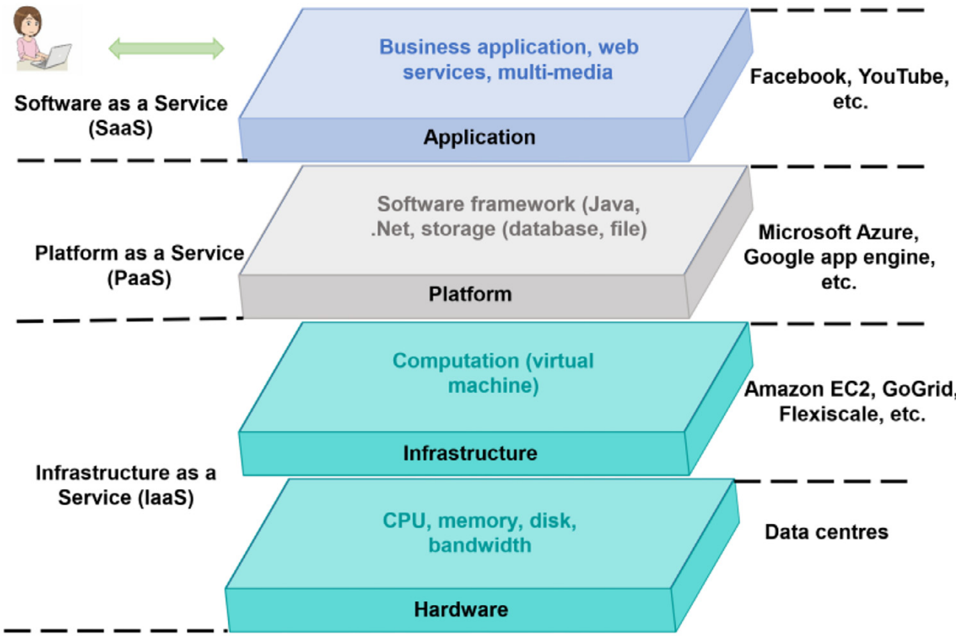

Fig. 11. Architecture of cloud computing, adapted from [68].

Table 5
Edge computing-based agricultural systems.

Use case No.	Service category	Edge computing techniques used	Farm type	Maturity level	Citation
43.	FM	Computation offloading	Aeroponics	Prototype	[76]
44.		Computation offloading (automated control)	Hydroponics	Prototype	[77]
45.		Computation offloading (alert generation)	Any farm	Prototype	[78]
46.	PDM	Computation offloading	Open-air	Prototype	[79]
47.	WEM	Latency reduction	Any farm	Prototype	[80]
48.		Computation offloading	Aquaponics	Prototype	[81]
49.	SM	Computation offloading (data analysis)	Open-air	Prototype	[82]

cessing and analysis of such an enormous amount of data in real-time are challenging because it increases the load on the cloud server and also reduces the response speed. Simply using a cloud server is not able to provide real-time response while handling such a large data set. Additionally, IoT applications are sensitive to network latency because they require a constant exchange of information between devices and the cloud, making CC unfeasible to handle these applications [23]. The emergence of the edge computing concept can resolve the problems associated with CC. This new computing model deploys computing and storage resources (such as cloudlets or fog nodes) at the edge of the network closer to data sources such as mobile devices or sensors. This way, it can facilitate real-time analytics while keeping data secure on the device [23]. Edge computing offers intriguing possibilities for smart agriculture, but the applications of this technology are only in their infancy in agricultural systems. Hence, few research studies are available in this area; see Table 5. Most of the edge computing-based agricultural systems discussed in these studies are prototypical and address a limited selection of problems in various agricultural domains. So far, interoperability and scalability issues have not received sufficient consideration.

4.5. Autonomous robot systems in agriculture

Autonomous robot systems (ARS) are intelligent machines capable of performing tasks, making decisions, and acting in real-time, with a high degree of autonomy (without external influence or without explicit human intervention) [83]. Interest in agricultural ARS (AARS) has grown significantly in recent years because of their ability to automate some practices in outdoor and indoor farms - including seeding, watering, fertilizing, spraying, plant monitoring and phenotyping, environmental monitoring, disease detection, weed and pest controlling, and harvesting [15]. The agricultural robots use a combination of emerging technologies such as computer vision, WSNs, satellite navigation systems (GPS), AI, CC, and IoT, thereby facilitating the farmers to enhance productivity and quality of agricultural products. AARS in smart farming can be *mobile* AARS, which can move throughout the working field, or *fixed* AARS [84]. Mobile AARSs are further classified into unmanned ground vehicles (UGVs) and 2) unnamed aerial vehicles (UAVs), which are explained in the following sections.

4.5.1. Unmanned ground vehicles in agriculture

Unmanned ground vehicles (UGVs) are agricultural robots that operate on the ground without a human operator. The main components of UGVs generally include; a platform for locomotive apparatus and manipulator, sensors for navigation, a supervisory control system, an interface for the control system, the communication links for information exchange between devices, and a system architecture for integration between hardware and software agents [85]. The control architecture of UGV can be remote-operated (controlled by a human operator via the interface) or fully autonomous (operated without the need for a human controller based on artificial intelligence technologies) [85]. Likewise, locomotive systems can be based on wheels, tracks, or legs [85]. Despite high ground adaptability, intrinsic omnidirectionality and soil protection of legged robots, they are uncommon in agriculture. However, when combined with wheels (wheel-legged robots), these robots offer a disruptive locomotion system for smart farms. In addition to their needed characteristics for infield operations, UGV should fulfill certain requirements such as small size, maneuverability, resilience, efficiency, human-friendly interface, and safety – to enhance crop yields and farm productivity. Table 6 summarizes the diverse range of UGVs designed for agricultural operations.

Table 6
Different types of UGVs designed for performing agricultural tasks.

Use case No.	Service category	Primary function	Tools and techniques used	Locomotion system	Farm type	Maturity level	Citation
50.	WUVM	Weed control	Modules (Vision, spray, mechanical weeding), and classification algorithms	Four-wheel-steering system (4WS).	Open-air	Prototype	[86]
51.			Vision system with Kinect v2 sensor, and random sample consensus algorithm	Four-wheel-drive (4WD)	Open-air	Prototype	[87]
52.	PDM	Pesticides spraying	RGB camera, HMI, and LiDAR	Four-wheel-drive (4WD)	Open-air	Prototype	[88]
53.			RGB camera, and laser	Four-wheel-drive (4WD)	Open-air	Prototype	[89]
54.		Crop treatment	Hyperspectral cameras, thermal and infrared detecting systems.	Four-wheel steering system (4WS)	Open-air	Prototype	[90]
55.	CM	Seed sowing	Ultrasonic sensor, and PI controller	Caterpillar treads	Open-air	Prototype	[91]
56.			Ultrasonic sensor, GSM module and actuators.	Four-wheel-drive (4WD)	Open-air	Prototype	[92]
57.		Artificial pollination	Sensing module, pollinator system, RGB camera and odometry.	Four-wheel-drive (4WD)	Open-air	Prototype	[93]
58.		Harvesting	RGB-D camera and RCNN	Four-wheel-steering system (4WS).	Open-air	Prototype	[94]
59.			RGB camera and RCNN	Four-wheel-drive (4WD).	Open-air	Prototype	[95]

Most of the agricultural robotic systems presented above have a 4WD locomotive system because it offers ease of construction and control. The drawback of 4WD is that the wheels are strongly affected by terrains containing stone elements and/or cavities [85]. Hence, it is significant to explore other mechanisms, such as legged or wheel-legged locomotive systems. Some robots have computer vision systems, but due to the difficulty of developing an accurate and reliable system that replaces manual labor, most of these robots are built with a low-cost computer vision system, that is, using conventional RGB cameras. Moreover, most of the systems mentioned above are still in the research phase, with no commercial use on a large scale.

4.5.2. Unmanned aerial vehicles in agriculture

Unmanned aerial vehicles (UAVs) or aerial robots are aircrafts with no human pilot on board. Depending on the type of technology incorporated to fly (wing structure) and autonomy level, there is a wide variety of UAVs [96]. For instance, according to wing type, UAVs can be fixed-wing (planes), single-rotor (helicopter), hybrid system (vertical takeoff and landing), and multirotor (drone). Among these, drones (multi-rotor technology) which are lifted and propelled by four (quadrotor) or six (hex-rotor) rotors, have become increasingly popular in the agriculture sector due to their mechanical simplicity in comparison to helicopters, which rely on a much more sophisticated plate control mechanism [97]. Similarly, according to autonomy level, UAVs can be either teleoperated in which the pilot provides references to each actuator of the aircraft so as to control it, in the same manner, an onboard pilot would, or telecommanded in which the aircraft relies on an automatic controller on board that is in charge of maintaining a stable flight [96]. Equipped with the appropriate sensors (vision, infrared, multispectral, and hyperspectral cameras, etc.), agricultural UAVs allow farmers to obtain data (vegetation, leaf area, and reflectance indexes) from their fields to study dynamic changes in crops that cannot be detected by scouting the ground [98]. This data permits farmers to infer information related to crop diseases, nutrient deficiencies, water level, and other crop growth parameters. With this information, farmers can plan possible remedies (irrigation, fertilization, weed control, etc.). Table 7 reviews some of the UAV-based systems used for different agricultural operations.

Most of the systems mentioned above are still in the research phase, with no commercial use on a large scale. Other problems with these UAVs are associated with battery and flight time [96]. At the moment, lithium-ion batteries are being used because their capacity is larger than that of conventional batteries. But an increase in battery capacity increases the drone weight, and now research is undergoing to address this issue. In addition, the existing UAVs have complex user interfaces, and only experts can use them to perform agricultural tasks. By improving the user interface making it human-centered with multimodal feedback will allow people who are older or unfamiliar with UAV technology to control it more easily.

4.6. Big data and analytics in agriculture

Rapid developments in IoT and CC technologies have increased the magnitude of data immeasurably. This data, also referred to as Big Data (BD), includes textual content (i.e., structured, semi-structured, and unstructured), and multimedia content (e.g., videos, images, audio) [119]. The process of examining this data to uncover hidden patterns, unknown correlations, market trends, customer preferences, and other useful information is referred to as big data analytics (BDA). Big data is typically characterized according to five dimensions defined by five Vs, which are displayed in Fig. 12 [120]. The paradigm of BD-driven smart agriculture is comparatively new, but the trend of this application is positive as it has the capacity to bring a revolutionary change in the food supply chain and food security through increased production. Agricultural big data is usually generated from various sectors and stages in agriculture, which can be collected either from agricultural fields through ground sensors, aerial vehicles, and ground vehicles using special cameras and sensors; from governmental bodies in the form of reports and regulations; from private organizations through online web services; from farmers in the form of knowledge through surveys; or from social media [120]. The data can be environmental (weather, climate, moisture level, etc.), biological (plant disease), or geo-spatial depending on the agricultural domain and differs in volume, velocity, and formats [121]. The gathered data is stored in a computer database and processed by computer algorithms for analyzing seed characteristics, weather patterns, soil properties (like pH or nutrient content), marketing and trade management, consumers' behavior, and inventory management. A variety of techniques and tools are employed to analyze big data in agriculture. A summary of some of the studies is given in Table 8. Machine learning, cloud-based platforms, and modeling and simulation are the most commonly used techniques. Particularly, machine learning tools are used in prediction, clustering, and classification problems. Whereas cloud platforms are used for large-scale data storing, preprocessing, and visualization. There are still many potential areas that are not adequately covered in existing literature, where BDA can be applied to address various agricultural issues. For instance, these include data-intensive greenhouses and indoor vertical farming systems, quality control and health monitoring of crops in outdoor and indoor farms, genetic engineering, decision support platforms to assist farmers in the design of indoor vertical farms, and scientific models for policymakers to assist them in decision-making regarding the sustainability of the physical ecosystem. Lastly, most systems are still in the prototypical stage.

Table 7
Different UAV based systems developed for performing different agricultural operations.

Use case No.	Service category	Primary function	UAV type	Cameras/ sensors	Flight altitude (m)	Farm type	Maturity level	Citation
60.	CQM	Vegetation monitoring	Hexacopter	Hyper-spectral camera	30	Open-air	Prototype	[99]
61.		Biomass monitoring	Octocopter	RGB-sensor	50	Open-air	Prototype	[100]
62.	CM	Real-time growth monitoring	Quadcopter	Digital camera	100	Open-air	Prototype	[101]
63.		Photosynthetic active radiation mapping	Fixed wing	Multi-spectral camera	150	Open-air	Prototype	[102]
64.		Remote sensing	Helicopter	Multi-spectral camera	15-70	Open-air	Prototype	[103]
65.		Remote sensing and mapping	RC plane	Digital camera	100-400	Open-air	Prototype	[104]
66.		Rice pollination	Helicopter	Wind speed sensor	1.15, 1.23, 1.33	Open-air	Prototype	[18]
67.		Droplet distribution estimation	Quadcopter	Digital canopy imager	3.5, 4, 4.5	Open-air	Prototype	[105]
68.		UREA spraying	Quadcopter	Multi and hyper spectral cameras	Few meters	Open-air	Prototype	[106]
69.		Pesticide spraying	Quadcopter	RF module	5, 10, 20	Open-air	Prototype	[107]
70.		Pesticide spray application	Helicopter	Digital camera	3-4	Open-air	Prototype	[108]
71.		Automatic spray control system	Helicopter	Image transmitter	5, 7, 9	Open-air	Prototype	[109]
72.	WUVM	Multi-temporal mapping of weed	Quadcopter	Digital camera	30, 60	Open-air	Prototype	[110]
73.		Weed mapping and control		Digital camera	30	Open-air	Prototype	[111]
74.	IM	Water status assessment	Fixed wing	Multi-spectral camera	200	Open-air	Prototype	[112]
75.		Water stress detection	Fixed wing	Micro-hyper spectral camera	575	Open-air	Prototype	[113]
76.		Water stress investigation	Fixed wing	Digital camera	90	Open-air	Prototype	[114]
77.		Assessing the effects of saline reclaimed waters and deficit irrigation on Citrus physiology	Fixed wing	Digital camera	100	Open-air	Prototype	[115]
78.		Water status and irrigation assessment	Quadcopter	Multi-spectral camera	30	Open-air	Prototype	[116]
79.	PDM	Phylloxera disease detection	Hexacopter	RGB and multi-spectral cameras	60, 100	Open-air	Prototype	[117]
80.		Citrus greening disease detection	Hexacopter	Multi-spectral camera	100	Open-air	Prototype	[118]

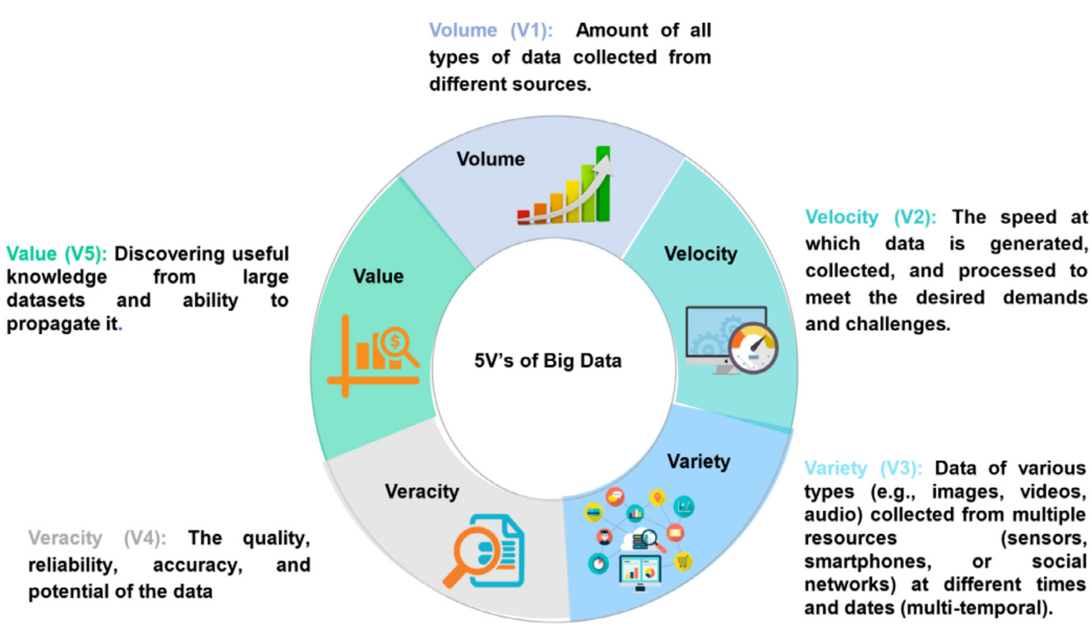

Fig. 12. Five dimensions of "Big Data".

Table 8
Big data tools and services in agriculture.

Use case No.	Service category	Tools and techniques used	Big data source	Farm type	Maturity level	Citation
81.	WEM	Crop modelling and simulation, geospatial analysis	Weather station, historical databases	Open-air	Conceptual	[121]
82.	CM	Clustering, prediction, and classification	Sensor, historical, and farmer data	Open-air	Conceptual	[122]
83.		Support vector machine	Sensor data	Open-air	Conceptual	[123]
84.	IM	Cloud-based application.	Sensor data	Hydroponics	Prototype	[124]
85.		Cloud-based platform, and web services	Sensor data, industry standards	Open-air	Conceptual	[125]

4.7. *Artificial intelligence in agriculture*

Artificial intelligence (AI) involves the development of theory and computer systems capable of performing tasks requiring human intelligence, such as sensorial perception and decision-making [126]. Combined with CC, IoT, and big data, AI, particularly in the facet of machine learning (ML) and deep learning (DL), is regarded as one of the key drivers behind the digitization of agriculture. These technologies have the potential to enhance crop production and improve real-time monitoring, harvesting, processing, and marketing [127]. Several intelligent agricultural systems are developed that use ML and DL algorithms to determine various parameters like weed detection, yield prediction, or disease identification. These systems are discussed in the next two sub-sections.

4.7.1. *Machine learning in agriculture*

Machine learning (ML) techniques are broadly classified into three categories: 1) supervised learning (linear regression, regression trees, non-linear regression, Bayesian linear regression, polynomial regression, and support vector regression), 2) unsupervised learning (k-means clustering, hierarchal clustering, anomaly detection, neural networks (NN), principal component analysis, independent component analysis, a-priori algorithm and singular value decomposition (SVD)); and 3) reinforcement learning (Markov decision process (MDP) and Q learning) [128]. ML techniques and algorithms are implemented in the agriculture sector for crop yield prediction, disease, and weed detection, weather prediction (rainfall), soil properties estimation (type, moisture content, pH, temperature, etc.), water management, determination of the optimal amount of fertilizer, and livestock production and management [129] Table 9. presents a list of publications where different ML algorithms are utilized for various agricultural applications. From the analysis of these articles, “crop yield prediction” is a widely explored area, and linear regression, neural network (NN), random forest (RF), and support vector machine (SVM) is the most used ML techniques to enable smart farming. The presented use cases are still in the research phase with no reported commercial usage at the moment. Moreover, it is also found that AI and ML techniques are sparsely explored in the greenhouse and indoor vertical farming systems, particularly hydroponics, aquaponics, and aeroponics. There are only a few publications available summarized in the same table where ML techniques are employed. Considering the digital transformation’s cyber-security and data privacy challenges, new approaches such as federated learning and privacy-preserving methods are being developed to enable digital farming [130]. These approaches build ML models from local parameters without sharing private data samples, thus mitigating security issues.

4.7.2. *Deep learning in agriculture*

Deep learning (DL) represents the extension of classical ML that can solve complex problems (predictions and classification) particularly well and fast because more “depth” (complexity) is added into the model. The primary advantage of DL is feature learning which involves automatic extraction of features (high-level information) from large datasets [149]. Different DL algorithms are convolutional neural networks (CNNs), long short term memory (LSTM) networks, recurrent neural (RNN) networks, generative adversarial networks (GANs), radial basis function networks (RBFNs), multilayer perceptron (MLPs), feed-forward artificial neural network (ANN), self-organizing maps (SOMs), deep belief networks (DBNs), restricted Boltzmann machines (RBMs), and autoencoders. A detailed description of these algorithms, popular architectures, and training platforms is available at various sources [150]. Fig. 13 illustrates an example of DL architecture of CNN [151]. In the agriculture sector, DL algorithms are mostly used to solve problems associated with computer vision applications that target the prediction of key parameters, such as crop yields, soil moisture content, weather conditions, and crop growth conditions; the detection of diseases, pests, and weed; and the identification of leaf or plant species [152]. Computer vision is an interdisciplinary field that has been gaining huge amounts of traction in recent years due to the surge in CNNs. It offers methods and techniques that allow the processing of digital images accurately and enables computers to interpret and understand the visual world [153]. A summary of agricultural applications using DL and computer vision techniques is given in Table 10. Among all the DL algorithms, CNNs or Convet and its variants are the most used algorithms in agricultural applications. The variants of CNN are region-based CNNs (RCNN), Fast-RCNN, Faster-RCNN, YOLO, and Mask-RCNN, among which the first four are mostly used to solve object detection problems. Mask-RCNN, on the other hand, is used to solve instance segmentation problems. The reader could refer to the existing bibliography for a detailed description of these algorithms and their applications [152]. Few studies have also used other DL techniques. Talking about datasets, most DL models are trained using images, and few models are trained using sensor data gathered from fields. This shows that DL can be applied to a wide variety of datasets. It is also observed that most of the work is done on outdoor farms, whereas next-generation farms (environment-controlled) are not extensively explored. Though DL has the potential to enable digital farming, most systems are still in the prototype phase. Additionally, the new challenges imposed by cyber-security and privacy issues require optimization of current DL and computer vision approaches.

4.8. *Agricultural decision support systems*

A decision support system (DSS) can be defined as a smart system that supports decision-making to specific demands and problems by providing operational answers to stakeholders and potential users based on useful information extracted from raw data, documents, personal knowledge, and/or models [170]. DSS can be data-driven, model-driven, communication-driven, document-driven, and knowledge-driven. The salient features of these DSSs are available at following source [171]. Fig. 14 presents the general architecture of a DSS, consisting of four fundamental components, each having its specific purpose.

Due to the evolution of agriculture 4.0, the amount of farming data has increased immensely. To transfer this heterogenous data into practical knowledge, platforms like agricultural decision support systems (ADSS) are required to make evidence-based and precise decisions re-

Table 9
Machine learning-based agricultural systems.

Use case No.	Service category	Data sources	Algorithms used	Farm type	Maturity level	Citation
86.	CM	Yield maps, climate, and temporal data.	SVM with radial basis functions	Open-air	Prototype	[131]
87.		Vegetation dataset from Landsat 8 OLI.	Boosted regression tree, RF regression, support vector regression, and Gaussian process regression	Open-air	Prototype	[132]
88.		Historical soil and rainfall data	Recurrent neural network	Open-air	Prototype	[133]
89.		Plot-scale wheat data	Multiple linear regression and RF	Open-air	Prototype	[134]
90.		Temperature and rainfall records	Artificial neural network	Open-air	Prototype	[135]
91.		Soil data, and satellite imagery	Counter-propagation artificial neural networks	Open-air	Prototype	[136]
92.		Rainfall records	RF	Open-air	Prototype	[137]
93.		Field survey data of 64 farms	SVM, RF, decision tree	Open-air	Prototype	[138]
94.		Tap water samples	RF	Hydroponics	Prototype	[139]
95.	PDM	Images from a strawberry greenhouse	SVM	Greenhouse (soil-based)	Prototype	[140]
96.		Sensor data	Least squares SVM	Open-air	Prototype	[141]
97.		Sensor data	Decision trees	Aquaponics	Prototype	[142]
98.	WUVM	Image data	RF	Open-air	Prototype	[143]
99.		Images from a university farm.	SVM	Open-air	Prototype	[144]
100.	SM	140 soil samples from top layer	Least squares support vector machines	Open-air	Prototype	[145]
101.		Humidity data from Radarsat-2	Extreme learning machine-based regression	Open-air	Prototype	[146]
102.	WEM	Rainfall data	Bayesian linear regression, boosted decision tree and decision forest regression, neural network regression	Open-air	Prototype	[147]
103.		Air temperature, wind speed, and solar radiation data	Artificial neural network and SVM	Greenhouse (soil-based)	Prototype	[148]

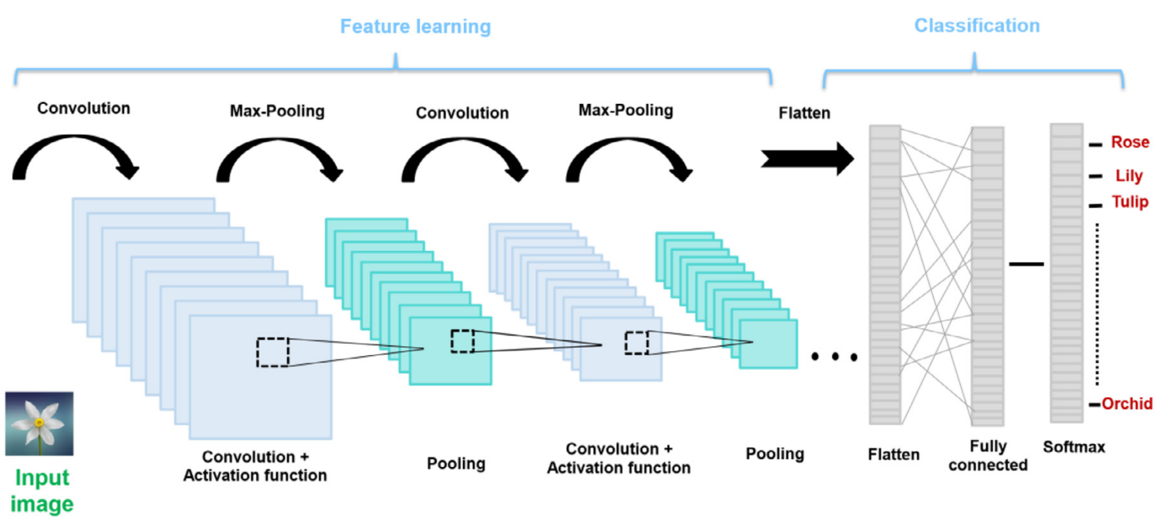

Fig. 13. Example of CNN architecture.

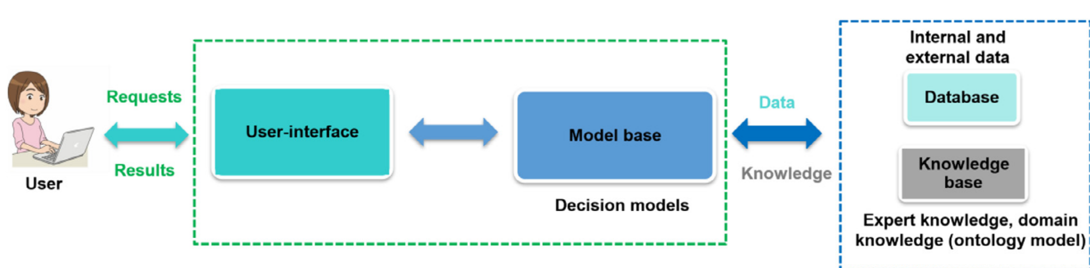

Fig. 14. The general architecture of decision support system.

Table 10
Deep learning-based agricultural systems.

Use case No.	Service category	Data sources	Algorithms used	Farm type	Maturity level	Citation
104.	CM	Satellite and weather data	LSTM network	Open-air	Prototype	[154]
105.		Rice yield data, meteorology, and area data (81 counties).	Back-Propagation neural networks and RNN	Open-air	Prototype	[155]
106.		Commercial fields' images	CNN	Open-air	Prototype	[156]
107.		Aerial orthoimages	Faster RCNN	Open-air	Prototype	[157]
108.		Historical yields and greenhouse environmental parameters.	Temporal CNN and RNN.	Greenhouse (soil-based)	Prototype	[158]
109.		Lettuce images from farm.	CNN	Greenhouse (soil-based)	Prototype	[159]
110.	WEM	Soil moisture data, and daily meteorological data	RBMs	Open-air	Prototype	[160]
111.	CQM	Images from the farm and Google search engine	Mask-RCNN	Aquaponics	Prototype	[161]
112.	WUVM	Weed and crop species images from 6 different datasets.	CNN	Open-air	Prototype	[162]
113.	PDM	Images collected from Internet.	CNN	Open-air	Prototype	[163]
114.		Public dataset	Deep CNN	Open-air	Prototype	[164]
115.		Images from camera.	Faster R-CNN, and single shot multibox detector	Open-air	Prototype	[165]
116.		Dataset with images of Walnut leaves	CNN	Open-air	Prototype	[166]
117.	FDC	RGB and multi-modal images	Faster R-CNN	Open-air	Prototype	[167]
118.		Images of oranges and green apples	CNN	Open-air	Prototype	[168]
119.		Images of ripe young and expanding apples.	YOLO-V3	Open-air	Prototype	[169]

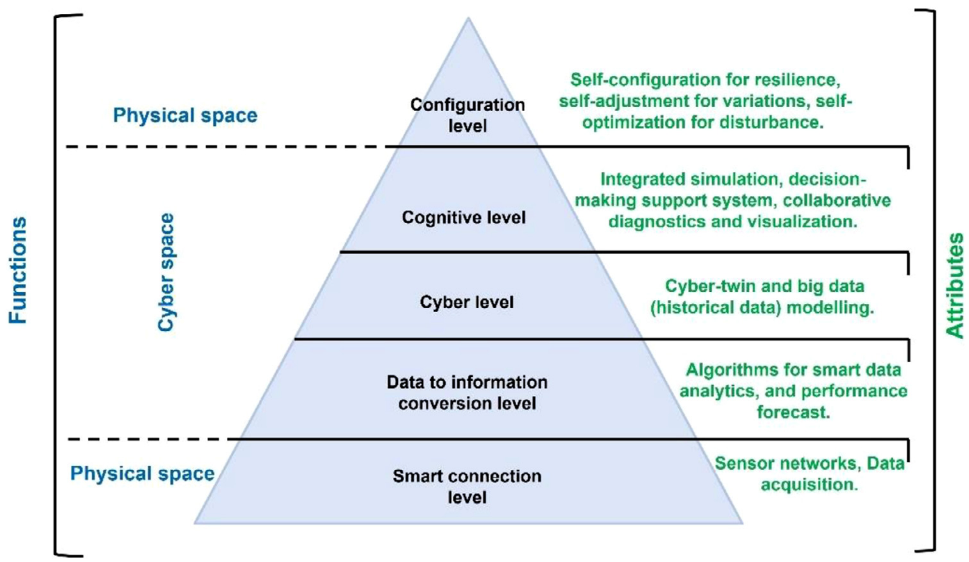

Fig. 15. 5C architecture for cyber-physical systems, (adapted) [187].

garding farm operation and facility layout [172]. Over the past few years, ADSSs are gaining much attention in the agriculture sector. A number of ADSSs have been developed that focus on a variety of agricultural aspects, such as farm management, water management, and environmental management. Table 11 presents a summary of the ADSSs found in the literature. From this analysis, most ADSSs have been found to not consider expert knowledge, which is highly valuable as it allows to development of systems as per user's needs. The other reported issues with some of these ADDSs are complex GUIs, inadequate re-planning components, a lack of prediction and forecast abilities, and a lack of ability to adapt to uncertain and dynamic factors. It is also worth noting that all the ADSSs are for outdoor agricultural systems and are in the research phase. In comparison, the application of ADSS in indoor soilless farming is still very much unexploited.

4.9. Agricultural cyber-physical systems

As one of the main technologies of Industry 4.0, a cyber-physical system (CPS) refers to an automated distributed system that integrates physical processes with communication networks and computing infrastructures [184]. There are three standard CPS reference architecture models: namely, 5C, RAMI 4.0, and IIRA, and their detailed description is available at following source [185]. Among these, the 5C is a well-known reference model with widespread usage. The architecture of 5C consists of five levels which are represented in Fig. 15. CPS benefits from a variety of existing technologies such as agent systems, IoT, CC, augmented reality, big data, and ML [186]. Its implementation ensures scalability, adaptability, autonomy, reliability, resilience, safety, and security improvements.

Table 11
Agricultural decision support systems.

Use case No.	Service category	Data sources	Tools and techniques used	Maturity level	Farm type	Citation
120.	IM	Environmental and crop data	Partial least squares regression and adaptive neuro fuzzy inference system	Prototype	Open-air	[173]
121.		Crop and site data	Fuzzy C-means algorithm	Prototype	Open-air	[174]
122.	WEM	Meteorological and crop data	Geographical information system (GIS)	Prototype	Open-air	[175]
123.		Environmental, economic, and crop data	VEGPER, ONTO, SVAT-CN, EROSION, GLPROD	Prototype	Open-air	[176]
124.	FM	Environmental and crop-related data	B-patterns optimization algorithm	Prototype	Open-air	[177]
125.		Environmental and crop data	Agent-based modeling, SVM and decision trees	Prototype	Aquaponics	[178]
126.		Environmental and crop data	Object-oriented methodology	Prototype	Greenhouse (soil-based)	[179]
127.	PDM	Crop data	Excel based algorithm	Prototype	Greenhouse (soil-based)	[180]
128.		Environmental data	Rule-based approach	Conceptual	Greenhouse (soil-based)	[181]
129.		Environmental data	Rule-based approach	Prototype	Greenhouse (soil-based)	[182]
130.	WUVM	10 years weather data and a set of vegetation index.	Rule-based application	Prototype	Open-air	[183]

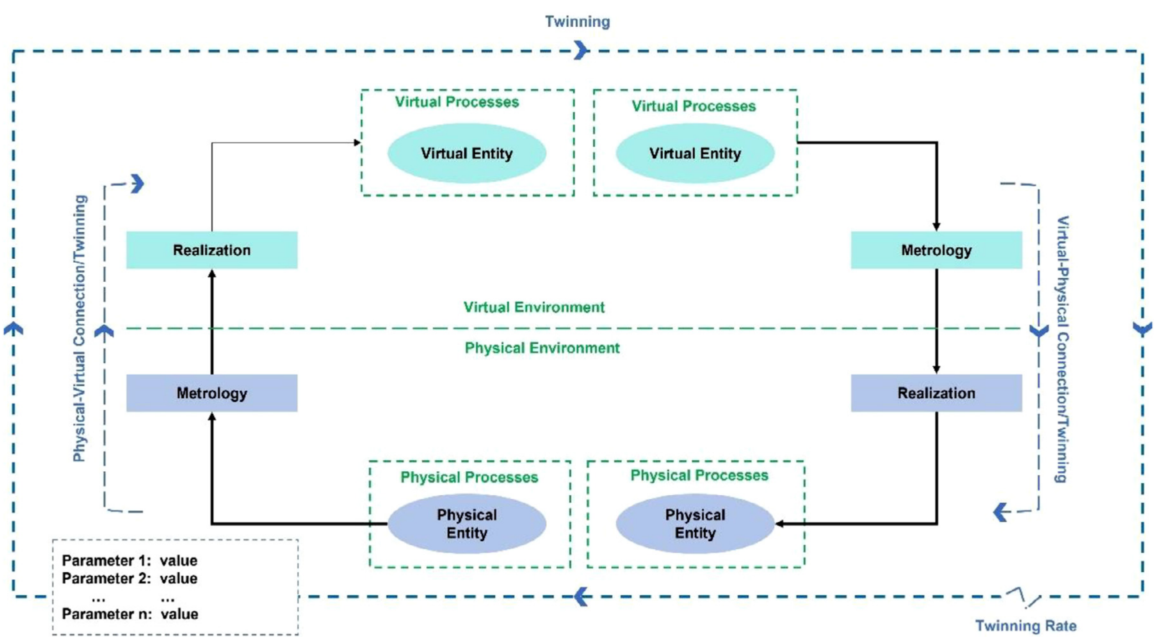

Fig. 16. Schematic of a digital twinning process, (adapted) [199].

Agricultural field is regarded as one of the complex domains that can benefit from CPS technology. Agricultural cyber-physical systems (ACPSs) use advanced electronic technologies and agricultural facilities to build integrated farm management systems that interact with the physical environment to maintain an optimal growth environment for crops [188]. ACPSs collect the essential and appropriate data about climate, soil, and crops, with high accuracy and use it to manage watering, humidity, and plant health, etc. A variety of ACPSs has been developed for the management of different services, and their summary is given in Table 12. Looking at these ACPSs, most systems are still at the prototype and conceptual level. Moreover, most studies are conducted for outdoor farms, with only a few works published related to soil-based greenhouse systems. No study is found that is relevant to indoor soilless farming systems. ACPSs has attracted significant research interest because of their promising applications across different domains; deploying CPS models in real-life applications is still a challenge as it requires proper hardware and software [189]. Moreover, particular attention should be given to autonomy, robustness, and resilience while engineering ACPSs in order to handle the unpredictability of the environment and the uncertainty of the characteristics of agricultural facilities. There are multiple factors

Table 12
Agricultural cyber-physical systems.

Use case No.	Service category	Tools and techniques used	Maturity level	Farm type	Citation
131.	IM	Integrated open geospatial web service	Prototype	Open-air	[190]
132.		Moisture sensors, and solenoid valves	Prototype	Greenhouse (soil-based)	[191]
133.		Sensor and sink nodes, network, and control centre	Prototype	Greenhouse (soil-based)	[188]
134.		Transceiver modules, multi-sensor array and weather forecasting system	Prototype	Open-air	[186]
135.	PDM	ToxTrac and NS2 simulator	Conceptual	Open-air	[192]
136.		Sensors and cameras	Prototype	Greenhouse (soil-based)	[193]
137.		Unmanned aircraft system	Conceptual	Open-air	[194]
138.	CM	Multispectral terrestrial mobile and autonomous aerial mobile mechatronic systems, and GIS	Conceptual	Open-air	[195]
139.		Edge and cloud computing	Prototype	Open-air	[196]
140.		Sensors, actuators, Arduino, and Raspberry Pi	Prototype	Any farm	[197]

(humans, sensors, robots, crops, and data, among others) that impact ACPSs. To ensure a smooth operation while avoiding conflicts, errors, and disruptions, ACPSs need to be designed carefully and comprehensively.

4.10. Digital twins in agriculture

Digital twin (DT) is a dynamic virtual replica of a real-life (physical) object of which it mirrors its behaviors and states over multiple stages of object's lifecycle by using real-world data, simulation, and machine learning models, combined with data analytics to enable understanding, learning, and reasoning [198]. A complete description of the DT concept for any physical system requires consolidation and formalization of various characteristics, including the physical and virtual entities, the physical and virtual environments, the metrology, and realization modules that perform the physical to virtual and the virtual to physical connection or twinning, the twinning and twinning rate, and the physical and virtual processes [199]. The schematic showing the mapping of these characteristics is shown in Fig. 16. The DT concept has gained prominence due to the advances in the technologies such as the Internet of Things, big data, wireless sensor networks, and cloud computing. This is because these technologies allow real-time monitoring of physical twins at high spatial resolutions through both miniature devices and remote sensing that produce ever-increasing data streams [21].

The concept of DT in agricultural applications is rather immature as compared to other disciplines with its first references occurred in 2017; hence its added value has not yet been discussed extensively [21]. This is because framing is a highly complex and dynamic domain because of its dependence on natural conditions (climate, soil, humidity) and presence of living physical twins (plants and animals) and non-living physical twins (indoor farm buildings, grow beds, outdoor agricultural fields, agricultural machinery). The non-living physical twins interact directly or indirectly with plants and animals (living physical twins), thereby introducing more challenges for DT in agriculture. Whereas in other domains such as manufacturing DTs are mostly concerned with non-living physical twins. Table 13 summarises the agricultural DTs developed in the last 10 years.

The analysis shows that most studies have focused on open-air farming systems. Only one study is found that has proposed DT for soil-based vertical farming system and one study that implemented DT for soilless farming system (aquaponics). This might be because the design and management of modern farming systems are challenging. Moreover, most DTs are in the research phase with no commercial deployment at the moment. The reported benefits of the DT applications in agriculture are cost reductions, catastrophe prevention, clearer decision making, and efficient management operations, which can be applied to several agricultural subfields like plant and animal breeding, aquaponics, vertical farming, cropping systems, and livestock farming. While DT technology has great potential, achieving the synchronization between the physical entity and its digital counterpart is challenging. The complexity of this process is further amplified in agricultural systems due to the idiosyncrasies of living physical twins. Hence, implementation of agricultural DT should start with micro-farms, which can then be gradually enhanced to an intelligent and autonomous version by incorporating more components.

4.11. Roadblocks in digitization of agriculture industry

This section provides an answer to RQ3 by listing a series of interconnected roadblocks hampering a larger adoption of digital technologies in the agriculture sector. After analysing 148 articles, 21 roadblocks are identified which can be categorized at technical and socio-economic levels.

4.12. Technical roadblocks

- Interoperability: data is considered a cornerstone for the success of smart systems. Agricultural data usually comes from multiple heterogeneous sources such as thousands of individual farmlands, animal factories, and enterprise applications. This data can have diverse formats, making data integration complex. Hence, data interoperability is essential to enhance the value of this massively dispersed data after systematic data collection, storage, processing, and knowledge mining [208]. Likewise, for establishing effective communication between heterogeneous devices, they need to be interconnected and interoperable. With cross-technology communication, interoperability of the system can be improved [209].
- Standardization: to fully exploit the digital technologies for smart farming applications, standardization of the devices is essential. Output differences can occur because of misinterpretation and alterations from time to time. With standardization, the interoperability issues of the devices, applications, and systems can also be resolved [25].
- Dataquality: to produce meaningful results, data quality is also crucial along with data security, storage, and openness. The lack of decentralized data management systems is another roadblock hindering the adoption of smart farming practices [9]. This issue decreases the willingness of multiple actors to share agriculture data.
- Hardwareimplementation: the deployment of a smart agricultural setup in large-scale open fields is extremely challenging. This is be-

Table 13
Digital twins in agriculture

Use case No.	Service category	Physical twin	Tools and techniques used	Maturity level	Farm type	Citation
141.	WEM	Aquaponics system and building	IoT sensor system, and MQQT broker	Prototype	Aquaponics	[200]
142.	CM	Agricultural product	Sensor, network, and computational units	Prototype	Open-air	[201]
143.	FM	Agricultural machinery	ROS platform, Gazebo 3D and Open Street Maps	Prototype	Open-air	[202]
144.		Farmland	Sensor, network, and computational units	Prototype	Open-air	[203]
145.		Agricultural farm/landscape	Sensors, and PLCs	Conceptual	Open-air	[204]
146.		Agricultural building	Sensors, GUI, and control centre	Prototype	Greenhouse (soil-based)	[205]
147.	PDM	Crops (plants)/ Trees	Mobile application and computational unit	Deployed	Open-air	[206]
148.		Trees planted on orchard	IoT sensors, network, and computational units	Prototype	Open-air	[207]

cause all the hardware consisting of IoT devices, wireless sensor networks, sensor nodes, machinery, and equipment directly exposed to harsh environmental conditions such as heavy rainfall, high/low-temperature levels, extreme humidity, strong wind speeds and many other possible dangers which can destroy electronic circuits or disrupt their normal functionality [210]. A possible solution is to build an adequate casing for all the costly devices that is robust and durable enough to endure real field conditions [211].

- Adequatepower sources: typically, the wireless devices deployed at farms consistently operate for a long time and have limited battery life. A suitable energy saving scheme is necessary because, in case of any failure, instant battery replacement is complicated, especially in open-air farms where devices are strategically placed with minimum access [210]. The possible solutions to optimize energy consumption are usage of low power sensors and, proper management of communication [24,212]. Wireless power transfer and self-supporting wireless system are other promising solutions to eliminate the need for battery replacement by recharging the batteries through electromagnetic waves. However, long-distance wireless charging is needed in most agricultural applications [9]. Ambient energy harvesting from rivers, fluid flow, movement of vehicles and, ground surface using sensor nodes offers another viable solution, but the converted electrical energy is limited at present – posing the need to improve power conversion efficiency [213].
- Reliability: The reliability of devices, as well as corresponding software applications, is crucial. This is because IoT devices need to gather and transfer the data based on which decisions are made using several software packages. Unreliable sensing, processing, and transmission can cause false monitoring data reports, long delays, and even data loss – eventually impacting the performance of agricultural system [25].
- Adaptability: agricultural environments are complex, dynamic, and rapidly changing. Hence, when designing a system, it is pertinent for the devices and applications to proactively adapt with the other entities under uncertain and dynamic factors - offering the needed performance [214].
- Robust wirelessarchitectures: wireless networks and communication technologies offer several benefits in terms of low cost, wide-area coverage, adequate networking flexibility, and high scalability. But dynamic agriculture environments such as temperature variations, living objects' movements, and the presence of obstacles pose severe challenges to reliable wireless communication. For instance, fluctuations in the signal intensity occur due to the multipath propagation effects – causing unstable connectivity and inadequate data transmission [215]. These factors impact the performance of the agricultural system. Hence, there is a need for robust and fault-tolerant wireless architectures with appropriate location of sensor nodes, antenna height, network topology, and communication protocols that also require minimum maintenance [11].
- Interference: another challenge is wireless interference and degradation of the quality of service because of the dense deployment of IoT devices and wireless sensor networks. These issues can be mitigated with efficient channel scheduling between heterogeneous sensing devices, cognitive radio-assisted WSNs, and emerging networking primitives such as concurrent transmission [216]. Since agriculture devices are distributed at indoor greenhouses, outdoor farmlands, underground areas, or even water areas, cross-media communication between underground, underwater, and air is also required for the complete incorporation of smart technologies [217].
- Security and privacy: the distributed nature of smart agricultural systems brings potential vulnerabilities to cyber-attacks such as eavesdropping, data integrity, denial-of-service attacks, or other types of disruptions that may risk privacy, integrity, and availability of the system [218]. Cyber-security is a major challenge that needs to be addressed within the context of smart farming, with diverse privacy-preserving mechanisms and federated learning approaches [130].
- Compatibility: to achieve the standards of fragmentation and scalability, the models or software applications developed should be flexible and run on any machine installed in the agricultural system [13].
- Resource optimization: farmers require a resource optimization process to estimate the optimal number of IoT devices and gateways, cloud storage size, and amount of transmitted data to improve farm profitability. Since farms have different sizes and need distinct types of sensors to measure different variables, resource optimization is challenging [219]. Secondly, most of the farm management systems do not offer run-time customization in relation to the distinct requirements of farmers. Hence, complex mathematical models and algorithms are required to estimate adequate resource allocation [75].
- Scalability: the number of devices, machinery, and sensors installed at farms is increasing gradually due to advancements in technologies. To support these entities, gateways, network applications, and back-end databases should be reliable and scalable [220].
- Human-centereduserinterfaces: complex user interfaces of existing agricultural applications and devices are impeding smart farming practices. Most GUI is designed in a way that only experts can use to perform agricultural tasks. Improving the user interface by making it human-centered with multimodal feedback will allow a larger group of people to use it to perform different agricultural operations [96].

4.13. Socio-economic roadblocks

- Gap between farmers and researchers: the participation of farmers is a key factor toward the success of the digitization of the agricultural industry. Farmers face a lot of problems during the agri-food production process, which smart technologies could fix, but agricultural experts are not usually aware of these issues [16]. Moreover, to devise an adequate smart solution, first, it is important to fully understand the nature of problems. Hence, it is essential to bridge the gap between farmers, agricultural professionals, and AI researchers.

- Costs associated with smart systems: the costs associated with the adoption of smart technologies and systems are the major deterrent in the digitization of the agricultural sector. These costs usually involve deployment, operating, and maintenance costs. The deployment costs of smart systems are usually very high as they involve; i) hardware installation such as autonomous robots and drones, WSNs, gateways, and base station infrastructure, etc., to perform certain farm operations, and ii) hiring the skilled labour [221]. Likewise, to facilitate data processing, management of IoT devices and equipment, and knowledge exchange, subscription of centralized networks and software packages is required, which ultimately increases the operating costs [222]. Though sometimes service providers offer free subscription packages with restricted features, the amount of storage capacity is limited. To ensure the adequate operations of the smart system, occasional maintenance is required, which then also adds up to total costs. Other types of costs associated with smart systems deployment could be environmental, ethical, and social costs. To overcome cost related roadblocks, initiatives focusing on cooperative farming are needed that provide; i) support services for better handling of costs and needed investments, and ii) hardware solutions to transform conventional equipment into smart farm-ready machinery to reduce high initial costs [222].
- Digital division: another factor that is slowing the digitization of the agricultural sector is the lack of knowledge of digital technologies and their applications. The majority of farmers have no idea about the significance of digital technologies, how to implement and use them, and which technology is suitable for their farm and meets their requirements [14]. Hence, it is essential to educate farmers about modern farming technologies and systems. Moreover, different strategies are needed to build tools using natural language that farmers with low education levels can easily understand [223].
- Return on investment: in agriculture, the profit margin is very important like other sectors. When it comes to the implementation of advanced technologies, farmers have concerns related to the time to recover the investment and to the difficulties in evaluating the advantages [12].
- Trust building: unlike in other disciplines, building trust regarding the effectiveness of smart technologies in agriculture is difficult because many decisions affect systems that involve living and non-living entities, and consequences can be hard to reverse [16]. Additionally, insufficient proof of the impact of digital tools on-farm productivity further intensifies the current challenges.
- Laws and regulations: different regions and countries have different legal frameworks which impact the implementation of digital technologies in the agriculture sector, particularly in monitoring and agri-food supply [70]. Likewise, regulations related to resource allocation (spectrum for wireless devices), data privacy, and security also vary from one country to another [70].
- Connectivity infrastructure: most less-developed countries usually have insufficient connectivity infrastructure that limits access to advanced digital tools that would help to turn data from heterogenous sources into valuable and actionable insights [10].

4.14. Discussion

This section discusses the main conclusions of RQ1, RQ2, and RQ3. In addition, added value, considerations, and future directions are also presented to ensure higher accuracy and great advancements in agricultural industry.

4.15. RQ1, RQ2 and RQ3

The present study tried to articulate the emerging digital technologies being implemented in agricultural industry to anticipate the future trajectories of agriculture 4.0. By looking at Tables 2-13 in section 4, it can be seen some technologies such as big data and analytics, wireless sensor networks, cyber-physical systems, and digital twins are not significantly explored in agriculture. A reason for this gap could be that implementing advanced technologies with more complex operations can be expensive, at least in the early experimental phase of their adoption. Hence, the development of these technologies in agricultural industry should increase in the coming years. The results of SLR also show that IoT is significantly implemented in farms. This is due to the broad functionality of IoT such as in the monitoring, tracking and tracing, agriculture machinery, and precision agriculture [21]. It can be said that IoT is one of the main research objectives within the agriculture 4.0 approaches. Nevertheless, only few studies have considered data security and reliability, scalability, and interoperability while developing an intelligent agricultural system.

The research findings also demonstrated that most use cases are still in the prototype phase. The possible reason could be because most agricultural operations have to do with living subjects, like animals and plants or perishable products, and developing systems is harder than non-living human-made systems. Another reason might be that agriculture is a slow adopter of technology because of transdisciplinary nature of this field, and hence to develop intelligent systems, the agricultural community must become familiar will all the digital technologies. Lastly, variations in plant/crops' species, and growth conditions also make digitization of agricultural systems complex [188]. The SLR findings also show that most of the systems are developed for open-air soil-based farms contrary to indoor farms (soilless and soil-based). This is due to complex design and management of indoor farms particularly soilless farms where parameters and factors (pH, air temperature, humidity, etc.) to be controlled are diverse [5]. But with introduction of digital technologies and data-driven computer applications in indoor farms, a more robust control of the process can be achieved. Furthermore, it is also revealed from SLR that limited research is conducted in three (soil management, fruit detection and counting and crop quality management) out of nine different service categories mentioned in section 3. This corroborates that substantial research and development is needed in some areas to ensure successful digitization of agriculture industry in developed countries as well as in developing countries.

The complexity of agriculture ecosystem presents a series of interconnected roadblocks that hinder the full integration of digital technologies for agriculture 4.0 realization. Hence, it is essential to identify potential roadblocks in order to come up with strategic solutions to overcome them. This study is an attempt to explore what these roadblocks are. Based on analysis, 21 roadblocks were identified and classified at technical and socio-economic levels. These roadblocks are listed in section 5, which suggests what needs to be done for digitization of agricultural industry on larger scale. But it is still not known, to what extent elimination or mitigation of these roadblocks assist in successful integration of digital technologies.

4.16. Added value of agricultural digitization

Based on analysis, several benefits that can motivate framers and other actors to support digitization of agricultural industry are identified and summarised below. The presented benefits have potential to maximise the farm's productivity and enhance product quality, but they should not be considered a panacea for challenges associated with smart agriculture [222].

- Improved agility: digital technologies improve the agility of farm operations. Through real-time surveillance and forecast systems, farmers or agricultural experts can rapidly react to any potential fluctuations in environmental and water conditions to save crops [221].

- Green process: digital technologies make the farming process more environmentally friendly and climate-resilient by significantly reducing the usage of in-field fuel, nitrogen fertilizers, pesticides, and herbicides [224].
- Resource use efficiency: digital platforms can improve resource use efficiency by enhancing the quantity and quality of agricultural output and limiting the usage of water, energy, fertilizers, and pesticides [3].
- Time and cost savings: digital technologies enable significant time and cost savings by automating different operations, such as harvesting, sowing, or irrigation, controlling the application of fertilizers or pesticides, and scheduling the irrigation [225].
- Asset management: digital technologies allow real-time surveillance of farm properties and equipment to prevent theft, expedite component replacement and perform routine maintenance [10].
- Product safety: digital technologies ensure adequate farm productivity and guarantee a safe and nutritious supply of agri-food products by preventing fraud related to adulteration, counterfeit, and artificial enhancement [218].

4.17. Considerations and future prospects

The upcoming initiatives would result in significant improvements in the agricultural sector. But in order to make things sustainable for small and medium-scale growers, roadblocks mentioned in section 5 need to be addressed first. Awareness campaigns highlighting the significance of smart agriculture at every level of the agricultural value chain and promoting innovative ways (such as gamification) to encourage stakeholders to take on an active role in the digital revolution can mitigate some of the mentioned roadblocks [9]. Government level initiatives, grants and endowments, public-private partnerships, the openness of data, and regional basis research work can also assist in coping with potential roadblocks. Lastly, a roadmap can be adopted while developing a smart agriculture system, starting from basic architecture with few components and simpler functionality, gradually adding components and functionality to develop a complex system with the full potential of digitization [21]. These considerations can pave the way for successful implementation of agriculture 4.0.

The future prospects of digital technologies in smart agriculture involve using explainable artificial intelligence to monitor crop growth, estimate crop biomass, evaluate crop health, and control pests and diseases. Explainable AI fades away the traditional black-box concept of machine learning and enables understanding the reasons behind any specific decision [15]. Description of big data through common semantics and ontologies and the adoption of open standards have great potential to boost research and development towards smart farming . Similarly, to ensure enhanced connectivity and live streaming of crop data, 5G technology need to be extensively explored [6]. 5G technology will minimize internet costs and augment the overall user experience of farm management and food safety by performing accurate crop inspections remotely [226]. Furthermore, it will significantly bridge the gap between stakeholders by keeping them well informed on produce availability. Lastly, blockchain in combination with IoT and other technologies can be implemented to address the challenges related to data privacy and security [227].

4.18. Transition to Agriculture 5.0

The industrial revolutions have always brought a breakthrough in the agricultural sector. As formally discussed in previous sections, agriculture 4.0 has great potential to counterbalance the growing food demands and prepare for future by reinforcing agricultural systems with WSN, IoT, AI, etc. While the realization of agriculture 4.0 is still underway, there is already a talk about agriculture 5.0. Agriculture 5.0 extends agriculture 4.0 with inclusion of industry 5.0 principles to produce healthy and affordable food while ensuring to prevent degradation of the ecosystems on which life depends [228]. The European Commission formally called for the *Fifth Industrial Revolution* (industry 5.0) in 2021 after observing that industry 4.0 focuses less on the original principles of social fairness and sustainability but more on digitalization and AI-driven technologies for increasing the efficiency and flexibility [229]. Industry 5.0 complements and extends industry 4.0 concept to recognize the human-centricity, sustainability, and resilience [230]. It involves refining the collaborative interactions between humans and machines, reducing environmental impact through circular economy, and developing high degree of robustness in systems to achieve optimal balance between efficiency and productivity. The enabling technologies of industry 5.0 are Cobots (collaborative robots), smart materials with embedded bio-inspired sensors, digital twins, AI, energy efficient and secure data management, renewable energy sources, etc [229].. In agriculture 5.0 settings, farm's production efficiency and crop quality can be enhanced by assigning repetitive and monotonous tasks to the machines and the tasks which need critical thinking to the humans. For this purpose, similar to manufacturing sector cyber physical cognitive systems (CPCS) that observe/study the environment and take actions accordingly should be developed for agricultural sector. This may include collaborative farm robots which will work in the fields and assist crop producers in tedious tasks such as seed sowing and harvesting etc. Likewise, digital twins in agriculture 5.0 can also offer significant value by identifying technical issues in agricultural systems and overcoming them at a faster speed, detecting crop diseases, and making crop yield predictions at a higher accuracy rate. This shows that agriculture 5.0 has potential to pave a way for climate smart, sustainable and resilient agriculture but as of now, it is in the developing phase.

5. Conclusions

Increased concerns about global food security have accelerated the need for next-generation industrial farms and intensive production methods in agriculture. At the forefront of this modern agricultural era, digital technologies offered by Industry 4.0 initiative are suggesting a myriad of creative solutions. The scientific community and researchers integrate disruptive technologies in conventional agriculture systems to increase crop yields, minimize costs, reduce wastes, and maintain process inputs. An SLR discussing the prevailing state of these technologies in the agriculture sector is presented in this study. After applying SLR protocol, 148 articles were considered from the time frame of the year 2011 to 2021. Various research questions pertaining to i) current and continuing research trends, ii) functionality, maturity level, farm type and tools and techniques used, iii) primary roadblocks, and iv) added value of digital technologies; were put forward and answered. Several conclusions are drawn such as integration of big data and analytics, wireless sensor networks, cyber-physical systems, and digital twins in agriculture is only in its infancy, and most use cases are in the prototype phase. Likewise, 21 roadblocks are identified and classified at technical and socioeconomic levels. To ensure the digitization of agricultural industry, these roadblocks must be analyzed and overcome. The added value of digital technologies in agriculture industry are also identified and presented in the study. Overall, this study contributes to the research being carried around agriculture 4.0. The primary limitation of this review is twofold: firstly, only three online repositories are considered for literature search (Scopus, IEEE and Science Direct), and secondly additional keywords and synonyms might return more studies. In both scenarios, it is highly unlikely that the overall findings would change. For the future work, additional research databases and aspects can be considered to provide holistic overview of agricultural industry in terms of digitization. Moreover, studies targeting agriculture 5.0 in general will also be included.

Declaration of Competing Interest

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

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