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SMART AGRICULTURE: A REVIEW

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Agriculture is regarded as one of the most crucial sectors in guaranteeing food security. However, as the world's population grows, so do agri-food demands, necessitating a shift from traditional agricultural practices to smart agriculture practices, often known as agriculture 4.0. It is critical to recognize and handle the problems and challenges related with agriculture 4.0 in order to fully profit from its promise. As a result, the goal of this research is to contribute to the development of agriculture 4.0 by looking into the growing trends of digital technologies in the field of agriculture. A literature review is done to examine the scientific literature pertaining to crop farming published in the previous decade for this goal. This thorough examination yielded significant information on the existing state of digital technology in agriculture, as well as potential future opportunities.

Keywords: *Smart Agriculture; Artificial Intelligence; Machine Learning; IOT; Edge Computing; Fog Computing*

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1. Introduction

1.1. A worldwide dilemma of food security

Food security is a multifaceted notion that aims to eliminate hunger by assuring a steady supply of nutritious food. It is defined by a four-pillar paradigm, each of which is necessary to provide food security [1]. Food security is becoming a severe global concern as a result of anthropogenic factors such as rapid population expansion, urbanization, industrialization, farmland loss, freshwater scarcity, and environmental degradation. This is due to the fact that these factors have a direct impact on the agricultural industry, which is the world's principal source of agri-food production. By 2050, it is expected that the global population will rise from 7.7 billion to 9.2 billion, urban population will rise by 66 percent, arable land will decline by approximately 50 million hectares, global GHG emissions (source of CO 2 – promote crop disease and pest growth) will rise by 50 percent, agri-food production will decline by 20%, and food demand will rise by 59 to 98 percent, posing an imminent threat. To meet rising food demands, agricultural practitioners around the world will need to increase crop and livestock production to maximize agricultural output. The emphasis of this review paper is crop farming, which includes the production of both food and cash crops.

A typical agri-food value chain displaying three key stages in the production of agricultural products: pre-field (pre-plantation stage), in-field (plantation and harvesting stage), and post-field (post-harvesting stage). All of the stages are important in the value chain, but in this examination, we will focus on the second stage, in-field, which includes numerous crop-growing operations such as ploughing, sowing, spraying, and harvesting, among others. Traditional agricultural approaches are now used in these procedures, which are labor-intensive, require arable land, time, and a significant quantity of water (for irrigation), and make it difficult to produce enough food [5]. A part of the problem is also due to the improper application of pesticides and herbicides, as well as the misuse of available technologies, both of which hurt crops and ultimately result in agricultural waste [6]. These problems can be solved by combining advanced technologies and computer-based applications that ensure higher crop yields, less water use, better pesticide/herbicide use, and improved crop quality. This is where the concept of smart agriculture comes into play.

1.2. Smart Agriculture

Every industry is being revolutionized and reshaped by Industry 4.0. It's a strategic initiative that combines emerging disruptive digital technologies like the 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 systems (CPS), digital twin (DT), and additive manufacturing (AM) to enable the digitization of the industry [7].

Agriculture 4.0, also known as smart agriculture, smart farming or digital farming [7], is the next phase of industrial agriculture, fueled by the integration of these technologies in agriculture. Farmers can use smart agriculture to address a variety of agricultural food production concerns such as farm productivity, environmental impact, food security, crop losses, and sustainability. Farmers, for example, can connect to farms remotely, regardless of location or time, using IoT-enabled equipment based on WSNs to monitor and control farm operations. Drones outfitted with hyper spectral cameras can collect data from a variety of sources on farmlands, while autonomous robots can assist or complete repetitive chores on farms. Data analytics techniques can be used to examine the obtained data, and computer programs can be utilized to help farmers make decisions.

Similarly, smart agriculture can monitor and analyze a wide range of parameters related to environmental factors, weed control, crop production status, water management, soil conditions, irrigation scheduling, herbicides and pesticides, and controlled environment agriculture to increase crop yields, reduce costs, improve product quality, and maintain process inputs through the use of modern systems [8].

1.3. Research Motivation and Contribution

The reason for writing this assessment is that digital technologies in agricultural systems provide new strategic solutions for increasing farm output efficiency and effectiveness. Furthermore, digital transformation paves the door for modern farming technologies like vertical farming (hydroponics, aquaponics, and aeroponics) to be used, which has the potential to solve food security issues. However, there are a number of issues and restrictions connected with this change from a technological, socioeconomic, and management perspective that must be overcome in order to fully realise the potential of agricultural 4.0 [9].A number of publications [9–18] have examined developing trends in the development of agriculture 4.0 by offering concise information on essential uses, benefits, and research problems of smart farming. These studies' research focuses on either explaining more general technical aspects while focusing on only one or a few digital technologies, or improving agricultural supply chain performance, or developing an agriculture 4.0 definition, or achieving sustainable agronomy through precision agriculture, or proposing a smart farming framework. Nonetheless, these studies do not include an explicit discussion of the tools and techniques utilized to construct various systems, as well as their maturity level. There are also few studies that look at the consequences of digital technology in modern soilless farms including hydroponics, aquaponics, and aeroponics (indoor/outdoor). As a result, in order to promote conversation in this field, it is necessary to examine the emergence of agriculture 4.0 from many angles. This research seeks to provide a comprehensive overview of digital technologies used in the second stage of the agricultural production value chain (in-field) for various farm types as described in section 1.1. The study's key theoretical contribution is the analysis and dissemination of the tools and techniques used, as well as the farm type, maturity level of produced systems, and potential obstacles or inhibiting factors in agriculture 4.0 development. Researchers and agricultural practitioners will benefit from the review's insights in future study on agriculture 4.0.

1.4. Paper organization

The following is the structure of the paper after the introduction:

Section 2 discusses the methodology used to collect relevant literature; Section 3 then presents the statistical results obtained after a general analysis of the selected research studies; Section 4 then provides a detailed overview of the core technologies used in agricultural digitization; Section 5 then highlights the technical and socio-economic roadblocks to digital integration in agriculture; and finally, Section 6 outlines a discussion of the research questions.

2. Research Methodology

A systematic literature review (SLR) is a technique for organizing and identifying research related to a specific topic [19]. SLR is used in this study to look into the state of Industry 4.0 technologies in the agricultural industry. Cases where the phrase 'agricultural' occurred in the title, abstract, or keywords of an article with any of the 'Industry 4.0 technologies' described in section 1.2 are specifically sought. A review procedure is established prior to conducting the SLR to ensure a transparent and high-quality research process, which are the features that distinguish a systematic literature review [20]. By conducting thorough literature searches, the review methodology also helps to reduce bias. The creation of the research questions, the defining of the search method, and the specification of inclusion and exclusion criteria are all part of this process.

To conduct SLR, this paper uses a recommended reporting item for systematic reviews and meta-analysis (PRISMA) approach. PRISMA is a minimum collection of items based on evidence that is used to guide the construction of systematic literature reviews and other meta-analyses [19].

2.1. Review Protocol

Before doing the bibliographic analysis, a review methodology is established to identify, analyze, and interpret data that are relevant to the research focus. To begin, research questions are developed in order to provide insight into the study of published studies in the research area of interest from many perspectives. These are the questions that must be addressed in the research. The search strategy is then created, which aids in the identification of appropriate keywords later in the search equation, as well as the identification of relevant information sources, such as academic databases and search engines that allow access to vast amounts of digital documentation. Science Direct, Scopus, and IEEE Xplore are three online research archives that are utilized to find relevant studies. Finally, boundaries are created by predefining inclusion and exclusion criteria for further inquiry and content assessments of selected articles in order to narrow the search results of each database.

2.2. Evaluation Process

Identification, screening, eligibility, and inclusion are the four stages of the literature search process that are evaluated. Consolidation is done for the removal of duplicate items in the identification step after initial metadata filtering by the use of search expressions. After this phase, the number of publications is reduced. The titles and abstracts of the papers are reviewed during the screening stage, and the most relevant publications are chosen for integral reading. In the third stage, full-text screening of these papers is done to ensure that they are eligible for this paper's goal.

2.3. Threats to Validity

(i) SLR replication: Because the current search is confined to only three online repositories, the provided SLR is vulnerable to risks to validity.

Additional sources could potentially lead to the discovery of more publications. Validity can be regarded satisfactorily addressed because the SLR process is clearly defined in sub-sections 2.1 and 2.2. However, it is possible that slightly different publications will be found if this SLR is replicated. This variation could be due to various personal choices made throughout the PRISMA screening and eligibility phases, but it's highly improbable that the overall results would alter.

(ii)The search string used to discover the relevant papers covers the entire spectrum of SLR; however it's possible that some important studies were overlooked. More research may be found if more keywords and synonyms in the search are included.

3. Digitization Trends in Agriculture

Although the agriculture business is making significant progress in terms of digital technology adoption, it is still lagging behind other industries such as healthcare, manufacturing, mining, automotive, energy, and others [15]. The crop farming method considered while designing an application or framework is referred to as the farm type. The farming method, for example, can be soil-based or soilless. Open-air fields (conventional outdoor agricultural farms) and greenhouse farms are included in the soil-based farming category (indoor). The soilless farming category, on the other hand, includes modern farming techniques such as aquaponics, aeroponics, and hydroponics (mostly indoor). In the recent decade, autonomous robotics systems (including unmanned guided vehicles and unmanned aerial vehicles (drones)), the internet of things, and machine learning appear to be the most commonly used technology in agriculture. Agriculture's growing sectors include big data, wireless sensor networks, cyber-physical systems, and digital twins. Furthermore, in contrast to indoor farms, open air farms are the most usually examined in research investigations. Few publications exist for soilless farming systems (aquaponics, aeroponics, and hydroponics), implying that these modern farming practices are still in their infancy. Similarly, each use case's services are identified and classified into nine service categories: I crop management, CM (estimation/harvesting period and seed plantation/prediction of crop yield/ growth rate/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 environmental management, WEM (monitoring and control of flow rate, water level, water quality (nutrients), temperature, humidity, CO2, and weather forecasts, among other things); 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 decision-making);

PDM (pest and disease management) is a term used to describe the management of pests and diseases (pest identification and disease detection) SM (Soil Management) vii) (moisture content, soil nutrients, fertilizer needs and application) WUVM (weed/unknown vegetation mapping, classification, and pesticide application) viii) weed and unwanted vegetation management FDC (fruit detection and counting), and ix)

The role of various digital technologies in smart farming is depicted in these categories. Crop management characteristics such as crop yield prediction, growth rate estimation, and harvesting period evaluation are the most 4.0 in the previous decade, whereas soil management, fruit identification and counting, and crop quality management receive very less attention. The European Union's TRL scale, which divides system maturity into three generic categories [21], is used to assess the technology readiness level (TRL) of all use cases. The first level is conceptual, which corresponds to European TRL 1–2 (use case is in concept phase), the second level is prototype, which corresponds to European TRL 3–6 (use case is functional even without all planned features), and the third level is deployed, which corresponds to European TRL 7–9. (Use case is mature with all the possible functions). Each use case's TRL was produced in a few experiments. It has been noticed that smart agricultural systems have made little progress from the concept and prototype stages to the commercial stage. The majority of use cases, for example, are still in the prototype stage.

4. Agriculture 4.0 enabling technologies

4.1. Internet of Things driven agricultural systems

The Internet of Things (IoT) is a network of interconnected computing devices, sensors, appliances, and machines that are all connected to the internet and have their own unique identities and capacities for remote sensing and monitoring [21]. Network layer (communication), perception layer (hardware devices), , middleware layer (device management and interoperability), service layer (cloud computing), application layer (data integration and analytics), and end-user layer are the six layers of the IoT reference architecture (user-interface). IoT devices on the physical layer in the agricultural domain collect data on environmental and crop characteristics such as temperature, humidity, pH value, water level, leaf colour, fresh leaf weight, and so on. The network layer is responsible for transmitting this information, and its architecture is determined by the field size, farm location, and type of farming method. ZigBee, LoRa, and Sigfox, for example, are widely utilized and employed in outdoor fields because they are less expensive, have low energy consumption, and have a long transmission range [22, 23]. Bluetooth, despite being a secure technology, is only employed in indoor farms due to its limited transmission range [22]. Due to its high costs and high energy consumption, Wi-Fi is not a promising technology for agricultural applications [22]. On the other hand, RFID (radio frequency identification) and NFC (near field communication) technologies are increasingly being used in agricultural systems for product tracking [24]. For periodic monitoring of environmental and soil characteristics, GPRS or mobile communication technology (2G, 3G, and 4G) is utilized. Furthermore, HTTP, WWW, and SMTP are the most commonly utilized communication protocols in agricultural contexts. Similarly, middleware HYDRA and SMEPP are commonly used in agricultural systems to enable interoperability and system security for their context-aware functionalities [25].

Cloud computing approaches are used in the service layer to store data. This information is then used on the application layer to create smart apps that farmers, agriculture experts, and supply chain professionals can use to improve farm monitoring and productivity. The use of IoT in agriculture is intended to provide farmers with decision-making tools and automation technologies that allow them to seamlessly integrate knowledge, products, and services in order to increase production, quality, and profit. A slew of research have been conducted and presented on the incubation of IoT concepts in the agricultural industry. The development of IoT-based agricultural systems has addressed a variety of technological and architectural concerns. However, most of these technologies are now in the conceptual stage or in prototype form (not commercial). Farm management, irrigation control, crop development, health monitoring, and disease detection are all priorities.

Some of these studies also explained how IoT is being used in current agricultural systems like vertical farming (soilless farming - aquaponics, hydroponics, and aeroponics) and greenhouse farming (soil-based). Furthermore, the majority of studies have been focused on a single issue.

4.2. Wireless sensor networks in agriculture

A wireless sensor network (WSN) is a technology that is utilized in an Internet of Things (IoT) system. It is defined as a collection of spatially distributed sensors for monitoring environmental physical conditions, temporarily storing obtained data, and transferring the information to a central point [22]. A wireless sensor network (WSN) for smart farming is made up of multiple sensor nodes connected by a wireless connection module. These nodes have a variety of skills that allow them to self-organize, self-configure, and self-diagnose (for example, processing, trans- mission, and feeling). There are various varieties of WSNs, which are classified based on the environment in which they are used. TWSNs (terrestrial wireless sensor networks), WUSNs (wireless underground sensor networks), UWSNs (underwater wireless sensor networks), WMSNs (wireless multimedia sensor networks), and MWSNs (mobile wireless sensor networks) are a few examples [26]. TWSN and UWSN are commonly utilized in agricultural applications. TWSN nodes are sensors that collect data from the environment and are located above ground. The second type of WSN is WUSNs, which are WSNs with sensor nodes embedded in the soil. Lower frequencies easily enter the soil in this environment, whereas higher frequencies are severely attenuated [27]. Because of the limited communication radius, the network requires a larger number of nodes to cover a big area. Many research publications on the use of WSN for various outdoor and indoor farm applications, such as irrigation management, water quality testing, and environmental monitoring, are accessible in the literature. The goal of these experiments was to create WSN architectures that were simple, low-cost, energy-efficient, and scalable. However, several aspects of WSNs, such as minimum maintenance, robust and fault-tolerant architecture, and interoperability, require more study.

4.3. Cloud computing in agriculture

Cloud computing (CC) is defined as a model for enabling convenient, ubiquitous, 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, according to the National Institute of Standards and Technologies (NIST) [28]. The datacenter (hardware), infrastructure, platform, and application layers make up the primary architecture of CC [29]. Each of these layers corresponds to one of three cloud service models: SaaS (software as a service), PaaS (platform as a service), and IaaS (infrastructure as a service) (IaaS). In the agriculture sector, cloud computing has gotten a lot of attention in the last decade because it provides: 1) low-cost storage for data collected from various domains via WSNs and other preconfigured IoT devices, 2) large-scale computer systems to make intelligent decisions by converting raw data into usable knowledge, and 3) a secure platform for developing agricultural based IoT applications [30].

CC is used to develop various agricultural applications in conjunction with IoT and WSN. CC technology is also utilized to develop operational farm management systems (FMSs) that help farmers and farm managers monitor farm activities more efficiently. The traceability of agri-product quality is another area of interest that is being investigated in global research [31]. However, only preliminary research has been done to see if traceability complies with food safety and quality criteria. The usage of cloud-based agricultural systems has the potential to address issues such as rising food demand, pollution from pesticides and fertilizers, and the safety of agricultural products. These FMSs, on the other hand, lack the flexibility to offer run-time customization in response to specific farmer needs. Furthermore, because most farm data is fragmented and distributed, recording farm operations accurately in existing FMSs systems is problematic [32].

4.4. Edge/fog computing in agriculture

The rapid expansion of IoT has resulted in an explosion of sensors and smart devices, creating massive amounts of data. The processing and analysis of such a large volume of data in real time is difficult since it puts a strain on the cloud server and slows response times. When dealing with such a massive data set, a cloud server alone will not be able to offer real-time responses. Furthermore, because IoT applications require a constant exchange of information between devices and the cloud, they are susceptible to network latency, making CC unsuitable for these applications [23]. The introduction of the edge computing idea has the potential to overcome the CC issues. This novel computing architecture places computational and storage resources (such as cloudlets or fog nodes) closer to data sources like mobile devices and sensors at the network's edge. This allows for real-time analytics while maintaining data security on the device [23]. Although edge computing has exciting potential for smart agriculture, its applications in agricultural systems are still in their infancy. As a result, there are limited research studies in this field. The majority of the edge computing-based agricultural systems covered in these papers are prototypes that solve a small number of challenges across a variety of agricultural disciplines. Interoperability and scalability issues haven't gotten enough attention so yet. Agricultural robots combine emerging technologies such as computer vision; wireless sensor networks (WSNs), satellite navigation systems (GPS), artificial intelligence (AI), cloud computing (CC), and the Internet of Things (IoT) to help farmers improve productivity and quality of agricultural products. AARS in smart farming can be mobile or fixed [33]. Mobile AARS can move around the working field. Unmanned ground vehicles (UGVs) and unidentified aerial vehicles (UAVs) are the two types of mobile AARSs, as discussed in the following sections.

4.5.1. Unmanned ground vehicles in agriculture

Unmanned ground vehicles (UGVs) are agricultural robots that work without the use of a human operator on the ground. A platform for locomotive apparatus and manipulator, navigation sensors, a supervisory control system, an interface for the control system, communication links for information exchange between devices, and system architecture for integration between hardware and software agents are the main components of UGVs [34]. The control architecture of a UGV can be remote-operated (controlled via an interface by a human operator) or totally autonomous (operated without the use of a human controller using artificial intelligence technology) [34]. Locomotive systems, likewise, can be based on wheels, tracks, or legs [34]. Legged robots are uncommon in agriculture, despite their great terrain flexibility, inherent Omni directionality, and soil protection. These robots, however, offer a disruptive locomotion mechanism for smart farms when paired with wheels (wheel-legged robots). UGVs should meet specific requirements, such as small size, maneuverability, resilience, efficiency, human-friendly interface, and safety, in addition to the necessary features for infield operations, in order to improve crop yields and farm productivity. A 4WD locomotive system is used in the majority of agricultural robotic systems due to its ease of manufacture and control.

The disadvantage of 4WD is that terrains with stone elements and/or voids have a significant impact on the wheels [34]. As a result, other mechanisms, such as legged or wheel-legged locomotive systems, should be investigated. Although some robots include computer vision systems, most of these robots are designed with a low-cost computer vision system, such as traditional RGB cameras, due to the difficulties of establishing an accurate and dependable system that can replace manual labour. Furthermore, the majority of the systems mentioned above are still in the research phase, with no large-scale commercial application.

4.5.2. Unmanned aerial vehicles in agriculture

Unmanned aerial vehicles (UAVs), sometimes known as aerial robots, are planes that do not have a human pilot on board. There are many different types of UAVs [35] depending on the technology used to fly (wing structure) and the level of autonomy. Fixed-wing (planes), single-rotor (helicopter), hybrid system (vertical takeoff and landing), and multi-rotor UAVs are examples of wing types (drone). Drones (multi-rotor technology), which are raised and driven by four (quad-rotor) or six (hex-rotor) rotors, have grown in popularity in the agriculture sector because to their mechanical simplicity in comparison to helicopters, which rely on a much more complex plate control mechanism [36]. Similarly, UAVs can be tele-operated or tele-commanded, depending on their autonomy level, with the pilot providing references to each actuator of the aircraft to control it in the same way that an onboard pilot would, or tele-commanded with the aircraft relying on an automatic controller on board to maintain a stable flight [35]. Agricultural UAVs with the right sensors (vision, infrared, multispectral, and hyper spectral cameras, for example) can collect data (vegetation, leaf area, and reflectance indexes) from their fields to monitor dynamic changes in crops that aren't visible from the ground [37]. Farmers can deduce information about crop illnesses, nutrient deficits, water level, and other agricultural growth characteristics using this data. Farmers might plan possible cures using this knowledge (irrigation, fertilization, weed control, etc.).

The majority of the systems mentioned above are still in the research stage, with no large-scale commercial use. Other issues with these UAVs include battery life and flight time [35]. Lithium-ion batteries are currently in use because their capacity exceeds that of conventional batteries.

However, increasing the battery capacity increases the weight of the drone, and research is currently underway to overcome this issue.

Furthermore, existing UAVs have complicated user interfaces that can only be used by experts to accomplish agricultural chores. People who are elderly or unfamiliar with UAV technology will be able to control it more readily if the user interface is improved and made more human-centered with multimodal feedback.

4.6. Big data and analytics in agriculture

Rapid advancements in IoT and CC technologies have massively expanded the amount of data available. Textual content (structured, semi-structured, and unstructured) and multimedia content (e.g., videos, photos, and audio) are included in this data, also known as Big Data (BD) [38]. Big data analytics is the practice of analyzing large amounts of data to find hidden patterns, unknown relationships, market trends, client preferences, and other important information (BDA). Big data is usually classified into five dimensions, each of which is represented by a V.

The concept of BD-driven smart agriculture is very new, but its trend is good because it has the potential to make a dramatic change in the food supply chain and boost food security through higher productivity. Agricultural big data is typically generated from a variety of sources in agriculture, including ground sensors, aerial vehicles, and ground vehicles equipped with special cameras and sensors; governmental bodies in the form of reports and regulations; private organizations through online web services; farmers in the form of knowledge gained through surveys; and social media [39]. Depending on the agricultural domain, the data can be environmental (weather, climate, moisture level, etc.), biological (plant disease), or geospatial, and it comes in a variety of volumes, speeds, and formats [40]. The information is acquired and stored in a computer database, where it is analyzed using computer algorithms for seed characteristics, weather patterns, soil attributes (such as pH or nutrient content), marketing and trade management, consumer behaviour, and inventory management. In agriculture, a range of strategies and tools are used to examine large data. The most often employed techniques include machine learning, cloud-based platforms, and modelling and simulation. Machine learning technologies are used to solve problems like prediction, clustering, and classification, while cloud platforms are utilized for large-scale data storage, preprocessing, and visualization. There are still numerous potential areas where BDA can be used to address various agricultural concerns that are not well covered in existing literature. For example, 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 help farmers design indoor vertical farms, and scientific models for policymakers to help them make decisions about the physical ecosystem's sustainability. Finally, the majority of systems are still in the prototype stage.

4.7. Artificial intelligence in agriculture

Artificial intelligence (AI) is the study of theories and computer systems that can perform activities that need human intelligence, such as sensory perception and decision-making [41]. AI, particularly in the areas of machine learning (ML) and deep learning (DL), is seen as one of the primary forces driving the digitization of agriculture when combined with CC, IoT, and big data. These technologies have the potential to increase crop production, harvesting, processing, and marketing in real time [42]. ML and DL algorithms are being used to determine various parameters such as weed detection, yield prediction, and disease identification in a number of intelligent agricultural systems. The following two sub-sections go through these systems.

4.7.1. Machine learning in agriculture

supervised learning (linear regression, regression trees, non-linear regression, Bayesian linear regression, polynomial regression, and support vector regression), and unsupervised learning (hierarchal clustering, k-means clustering, neural networks (NN) anomaly detection, principal component analysis, independent component analysis, a-priori algorithm, and singular value decomposition (SVD)). Weed detection, Crop yield prediction, disease and weather prediction (rainfall), soil properties estimation (moisture content, type, pH, temperature, etc.), water management, fertilizer amount determination, and livestock production and management all use machine learning techniques and algorithms [2, 43]. According to the study of these publications, “crop yield prediction” is an extensively researched area, with the most widely utilized ML approaches to allow smart farming being linear regression [4], neural network (NN), random forest (RF), and support vector machine (SVM) [2].

The presented use cases are still in the research phase, and no commercial use has been recorded as of yet. Furthermore, AI and machine learning approaches are found to be underutilized in greenhouse and indoor vertical farming systems, particularly hydroponics, aquaponics, and aeroponics. There are only a handful publications that use machine learning techniques. To enable digital farming, new methodologies such as federated learning and privacy preserving methods are being developed in light of the digital transformation’s cyber-security and data privacy problems [44]. These methods create machine learning models from local parameters rather than sharing private data samples, reducing security concerns.

4.7.2. Deep learning in agriculture

Deep learning (DL) is an extension of classical machine learning (ML) because extra “depth” (complexity) is added to the model, it can accomplish difficult tasks (predictions and classification) extraordinarily well and quickly. DL's main benefit is feature learning, which includes extracting features (high-level information) from big datasets automatically [45]. Long short term memory (LSTM) networks, convolutional neural networks (CNNs), 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 are examples of deep learning algorithms Various sites [46] provide a full overview of these methods, popular architectures, and training systems. DL algorithms are commonly used in agriculture to solve problems related to computer vision applications that aim to predict key parameters such as crop yields, soil moisture content, weather conditions, and crop growth conditions; detect diseases, pests, and weeds; and identify leaf or plant species [47]. Computer vision is an interdisciplinary field that has exploded in popularity in recent years thanks to the rise of CNNs. It provides methods and techniques for accurately processing digital images and allowing computers to analyze and comprehend the visual world [48]. CNNs, generally is known as Convet and its derivatives, are the most widely used deep learning algorithms in agricultural applications. Region-based CNNs (RCNN), Fast-RCNN, Faster-RCNN, YOLO, and Mask-RCNN are some of the CNN variants, with the first four being the most typically used to address object detection issues. On the other side, Mask-RCNN is utilized to overcome instance segmentation issues. The reader can find a thorough explanation of these algorithms and their applications in the existing bibliography [47]. Other DL approaches have been employed in a few research. When it comes to datasets, the majority of deep learning models are trained on photographs, with only a few trained on sensor data collected in the field. This demonstrates that DL can be used on a wide range of datasets. It's also worth noting that the majority of the research is focused on outdoor farms, with next-generation farms (environment-controlled) receiving less attention. Though digital farming has the potential to be enabled by DL, most systems are still in the prototype stage. Furthermore, the additional obstacles created by cyber-security and privacy concerns necessitate the improvement of current deep learning and computer vision technologies.

4.8. Agricultural decision support systems

A decision support system (DSS) is a smart system that assists stakeholders and potential users in making decisions in response to specific needs and challenges by offering operational responses based on meaningful information retrieved from raw data, documents, personal knowledge, and/or models [49]. Data-driven, model-driven, communication-driven, document-driven, and knowledge-driven DSS are all possibilities. The following source [50] lists the key features of these DSSs. The volume of farming data has exploded as a result of the advent of agriculture 4.0. Platforms like agricultural decision support systems (ADSS) are necessary to convert this heterogeneous data into practical knowledge in order to make evidence-based and precise judgments about farm management and facility layout [51]. ADSSs have gotten a lot of interest in the agriculture industry over the last few years. A variety of agricultural concerns, such as farm management, water management, and environmental management, have been addressed by a number of ADSSs. Most ADSSs have been found to ignore expert knowledge, which is extremely useful since it enables for the construction of systems that are tailored to the demands of the users. Complex GUIs, insufficient re-planning components, a lack of prediction and forecasting abilities, and a lack of ability to adjust to unpredictable and dynamic elements are some of the other identified faults with some of these ADDSs. It's also worth noting that all of the ADSSs are for outside agriculture systems and are still in development. In comparison, the use of ADSS in indoor soilless agriculture is currently underutilized.

4.9. Agricultural cyber-physical systems

A cyber-physical system (CPS) is an automated distributed system that integrates physical processes with communication networks and computing infrastructures [52], and it is one of the key technologies of Industry 4.0. There are three standard CPS reference architecture models: 5C, RAMI 4.0, and IIRA, which may be found in full at the following source [53]. Among these, the 5C is a well-known and widely used reference model. CPS takes advantage of a number of existing technologies, including agent systems, IoT, CC, augmented reality, big data, and machine learning (ML) [54]. Scalability, flexibility, autonomy, reliability, resilience, safety, and security are all improved as a result of its adoption.

One of the most difficult domains that can benefit from CPS technology is agriculture. Agricultural cyber-physical systems (ACPSs) combine advanced electronic technology with agricultural infrastructure to create integrated farm management systems that interact with the physical environment to keep crops growing at their best [55]. ACPSs collect high-accuracy data regarding climate, soil, and crops and utilize it to manage watering, humidity, and plant health, among other things. For the management of various services, a range of ACPSs have been created; however, most of these systems are still in the prototype and conceptual stages. Furthermore, the majority of studies are for outdoor farms, with only a few publications published on soil-based greenhouse systems. There has been no research on indoor soilless agricultural methods. Since of its prospective applications in a variety of fields, ACPSs have sparked a lot of academic interest; nevertheless, deploying CPS models in real-world applications is still a difficulty because it requires the right hardware and software [56]. When designing ACPSs, special emphasis should be paid to autonomy, robustness, and resilience in order to deal with the unpredictable nature of the environment and the unknown characteristics of agricultural facilities. ACPSs are influenced by a variety of factors, including humans, sensors, robots, crops, and data.. ACPSs must be properly and extensively developed to provide a seamless operation while avoiding conflicts, errors, and disturbances.

4.10. Digital twins in agriculture

A digital twin (DT) is a dynamic virtual replica of a real-life (physical) object that mimics its behaviours and states across multiple stages of the object's lifecycle by combining real-world data, simulation, and machine learning models with data analytics to enable understanding, learning, and reasoning [57]. The physical and virtual entities, the physical and virtual environments, the metrology, and realization modules that perform the physical to virtual and virtual to physical connection or twinning, the twinning and twinning rate, and the physical and virtual processes are all required for a complete description of the DT concept for any physical system [58]. Because of advancements in technology such as the Internet of Things, big data, wireless sensor networks, and cloud computing, the DT concept has gained traction. This is due to the fact that these technologies enable real-time monitoring of physical twins at high spatial resolutions using both small devices and distant sensing, which generate ever-increasing data streams [21]. In comparison to other fields, the notion of DT in agricultural applications is relatively new, with the first references appearing in 2017; as a result, its added value has not yet been thoroughly studied [21]. Because of its reliance on natural circumstances (temperature, soil, humidity), as well as the presence of living and non-living physical twins (plants and animals), framing is a very complex and dynamic realm (indoor farm buildings, grow beds, outdoor agricultural fields, agricultural machinery).

Non-living physical twins interact directly or indirectly with plants and animals (living physical twins), posing more obstacles for DT in agriculture, whereas non-living physical twins are the focus of DT in other domains such as manufacturing. The majority of research has been on open-air agricultural systems. There is just one study that proposes DT for a soil-based vertical farming system and one study that implements DT for a soilless vertical farming system (aquaponics). This could be due to the difficulty of designing and managing modern farming systems. Furthermore, the majority of DTs are still in the research phase, with no commercial deployment planned. Cost savings, disaster prevention, clearer decision making, and efficient management operations are all reported benefits of DT applications in agriculture, which can be applied to a variety of agricultural subfields such as plant and animal breeding, aquaponics, vertical farming, cropping systems, and livestock farming. While DT technology offers a lot of promise, achieving synchronization between the real and digital worlds is difficult. Due to the quirks of living physical twins, the intricacy of this procedure is magnified in agricultural settings. As a result, agricultural DT should begin with micro-farms, which can then be gradually upgraded to a more intelligent and autonomous form by adding more components.

4.11. Roadblocks in digitization of agriculture industry

This section outlines a series of interconnected hurdles to a wider adoption of digital technologies in agriculture. Following a review of the literature, 21 barriers were found, which were divided into technical and socioeconomic categories.

4.12. Technical roadblocks

•Interoperability: Data is regarded as a critical component in the success of smart systems. Agricultural data is typically gathered from a variety of sources, including thousands of individual farmlands, animal industries, and business applications. Data can be in a variety of formats, making data integration difficult. As a result, after systematic data collection, storage, processing, and knowledge mining, data interoperability is critical to increasing the value of this widely distributed data [59]. Interconnected and interoperable devices are also required for successful communication between heterogeneous devices. The system's interoperability can be improved through cross-technology communication [60].

•Standardization: Standardization of devices is required to fully use digital technologies for smart farming applications. Differences in output can occur as a result of misinterpretation and changes over time. Device, application, and system interoperability concerns can also be overcome by standardization [25].

•Data quality: Data quality, as well as data security, storage, and openness, are essential for producing meaningful outcomes. Another impediment to the adoption of smart farming technologies is the lack of decentralized data management systems [9]. Multiple actors' willingness to exchange farm data is being harmed as a result of this problem.

•Hardware implementation: It is incredibly difficult to establish a smart agricultural setup in large-scale open areas. This is due to the fact that all hardware, including IoT devices, wireless sensor networks, sensor nodes, machinery, and equipment, is directly exposed to harsh environmental conditions such as heavy rainfall, extreme temperatures, extreme humidity, high wind speeds, and a variety of other dangers that can destroy electronic circuits or disrupt their normal functionality [61]. A possible answer is to construct a sturdy and lasting casing for all of the expensive devices that can withstand real-world conditions [62].

•Adequate power sources: Typically, wireless gadgets used on farms function for an extended period of time and have a limited battery life.

Because replacing a battery in the event of a failure is difficult, especially in open-air farms where devices are strategically located with limited access [61], a proper energy-saving system is required. Low-power sensors and proper communication management are two viable strategies for reducing energy consumption [24, 63]. Other intriguing technologies to eliminate the need for battery renewal by recharging batteries using electromagnetic waves include wireless power transfer and self-supporting wireless systems. In most agricultural applications, however, long-distance wireless charging is required [9]. Another potential alternative is to capture ambient energy from rivers, fluid flow, vehicle movement, and the ground surface using sensor nodes; however the converted electrical energy is currently restricted, necessitating the need to enhance power conversion efficiency [64].

•Reliability: The dependability of devices, as well as the software applications that run on them, is critical. This is due to the fact that IoT devices must collect and transmit data from which judgments are made utilizing a variety of software packages. Unreliable sensing, processing, and transmission can result in erroneous monitoring data reports, significant delays, and even data loss, all of which can have a negative impact on agricultural system performance [25].

•Adaptability: Agriculture is a complicated, dynamic, and continuously changing environment. As a result, when building a system, it is critical for devices and applications to react proactively with other entities in the face of unknown and dynamic elements in order to provide the required performance [65].

•Robust wireless architectures: Low-cost, wide-area coverage, enough networking flexibility, and high scalability are all advantages of wireless networks and communication technologies. However, in a dynamic agriculture environment, such as temperature swings, the movement of live objects, and the existence of impediments, dependable wireless connection is a major difficulty. For example, multipath propagation effects cause signal strength oscillations, resulting in unstable connectivity and insufficient data transmission [66]. These elements have an impact on the agricultural system's performance. As a result, robust and fault-tolerant wireless architectures with proper sensor node placement, antenna height, network topology, and communication protocols are required, as well as low-maintenance wireless systems [11].

•Interference: Because of the extensive deployment of IoT devices and wireless sensor networks, another difficulty is wireless interference and quality of service degradation. Effective channel scheduling between heterogeneous sensing devices, cognitive radio-assisted WSNs, and upcoming networking primitives like concurrent transmission [67] can all help to solve these problems. Because agriculture equipment are dispersed in indoor greenhouses, outdoor farmlands, underground locations, and even aquatic areas, cross-media communication between underground, underwater, and air is also necessary for full integration of smart technologies [68].

•Security and privacy: Because smart agricultural systems are dispersed, they are vulnerable to cyber-attacks such as eavesdropping, data integrity, denial-of-service assaults, and other sorts of disruptions that could jeopardize the system's privacy, integrity, and availability [69]. With various privacy-preserving techniques and federated learning approaches, cyber-security is a fundamental concern that needs to be addressed in the context of smart farming [44].

•Compatibility: in order to meet the fragmentation and scalability standards, the models or software applications developed must be adaptable and able to run on any equipment in the agricultural system [13].

•Resource optimization: To boost farm profitability, farmers need a resource optimization procedure to determine the ideal number of IoT devices and gateways, cloud storage size, and volume of transmitted data. Resource optimization is difficult since farms vary in size and require different types of sensors to assess different variables [70]. Second, most farm management systems do not support run-time changes to match the demands of individual farmers. To estimate adequate resource allocation, complicated mathematical models and algorithms are necessary [32].

•Scalability: Due to technological improvements, the number of gadgets, gear, and sensors put on farms is continually expanding.

Gateways, network applications, and back-end databases should all be dependable and scalable in order to serve these entities [71].

•Human-centered user interfaces: Existing agricultural software and gadgets have complicated user interfaces, which are limiting smart farming methods. The majority of graphical user interfaces are constructed in such a way that only specialists can use them to accomplish agricultural activities. By making the user interface more human-centered and providing multimodal feedback, a bigger group of individuals will be able to use it to complete various agricultural tasks [35].

4.13. Socio-economic roadblocks

•Gap between farmers and researchers: Farmers' engagement is critical to the success of the agriculture industry's digitization. Agricultural specialists are frequently unaware of the concerns that farmers encounter during the agri-food production process, which smart technologies could solve [16]. Furthermore, it is critical to completely comprehend the nature of problems in order to create an appropriate smart solution.

As a result, bridging the gap between farmers, agricultural professionals, and AI researchers is critical.

•Expenses connected with smart systems: the costs associated with adopting smart technology and systems are a major impediment to the agriculture sector's digitization. These expenses typically include deployment, operation, and maintenance. Smart system deployment costs are typically significant since they include: I hardware installation, such as autonomous robots and drones, WSNs, gateways, and base station infrastructure, and ii) paying trained labour to do particular agricultural tasks [72]. Similarly, subscriptions to centralized networks and software packages are necessary to support data processing, control of IoT devices and equipment, and knowledge exchange, which eventually raises operating expenses [73]. Even if service providers occasionally provide free subscription packages with limited capabilities, storage capacity is limited. Periodic maintenance is essential to ensure the proper operation of the smart system, which adds to the total costs.

Environmental, ethical, and societal costs may also be connected with the adoption of smart devices. Initiatives focusing on cooperative farming are needed to overcome cost-related roadblocks by providing: I support services for better cost management and needed investments, and ii) hardware solutions to transform conventional equipment into smart farm-ready machinery to reduce high initial costs [73].

•Digital division: a lack of awareness of digital technology and their applications is another problem limiting the digitalization of the agriculture sector. The majority of farmers have no understanding what digital technologies are, how to install and utilize them, or which technology is appropriate for their farm and matches their needs [14]. As a result, farmers must be educated on current farming technologies and processes.

Furthermore, various tactics are required to develop tools that use natural language and are easily understood by farmers with low levels of education [74].

•Return on investment: In agriculture, like in other industries, the profit margin is critical. When it comes to implementing modern technologies, farmers are concerned about the time it will take to recoup their investment and the difficulty in assessing the benefits [12].

•Building faith in the effectiveness of smart technology in agriculture is difficult, unlike in other disciplines, because many decisions influence systems that involve both living and non-living elements, and the results can be difficult to reverse [16]. In addition, the lack of verification of the influence of digital tools on farm productivity exacerbates the current difficulties.

•Legal frameworks: different regions and nations have distinct legal frameworks that influence the deployment of digital technologies in agriculture, particularly in monitoring and agri-food supply [31]. Similarly, laws governing resource allocation (spectrum for wireless devices), data privacy, and security differ from country to country [31].

•Connectivity infrastructure: In most developing nations, connectivity infrastructure is poor, limiting access to advanced digital technologies that could help turn data from disparate sources into useful and actionable insights [10].

4.14. Discussion

The goal of this study was to describe the new digital technologies that are being used in the agricultural industry in order to predict the future trajectories of agriculture 4.0. Big data and analytics, wireless sensor networks, cyber-physical systems, and digital twins are among the technologies that have yet to be fully explored in agriculture. This disparity could be due to the fact that installing advanced technologies with more complex processes can be costly, at least in the early stages of their acceptance. The agricultural industry's development of these technologies is expected to speed up in the next years. The findings of SLR also reveal that IoT is widely used in farms. This is owing to the IoT's diverse capabilities, which include monitoring, tracking, and tracing, agricultural machinery, and precision agriculture [21]. One of the key research aims within the farm 4.0 techniques can be regarded to be IoT. Nonetheless, when building an intelligent agricultural system, only a few researches have examined data security and dependability, scalability, and interoperability. The outcomes of the study also revealed that the majority of use cases are still in the prototype stage. The reason for this could be that most agricultural activities involve live subjects, such as animals and plants, or perishable products, and establishing systems for living subjects is more difficult than developing systems for non-living human-made systems. Another explanation could be that, due to the trans-disciplinary character of agriculture, it is a late adopter of technology. As a result, in order to construct intelligent systems, the agricultural community must become conversant with all digital technologies. Finally, differences in plant/

crop species and growth conditions complicate agricultural system digitalization [55]. In contrast to indoor farms, the majority of the technologies created by SLR are for open-air soil-based farms (soilless and soil-based). This is owing to the complicated design and maintenance of indoor farms, particularly soilless farms, where the parameters and elements to be maintained are numerous (pH, air temperature, humidity, etc.) [5]. However, by incorporating digital technology and data-driven computer applications into indoor farms, a more reliable control of the process can be attained. Furthermore, SLR reveals that insufficient research is undertaken in three of the nine service areas described in section 3 (soil management, fruit detection and counting, and crop quality management). This supports the notion that significant research and development is required in some areas to ensure the successful digitization of the agriculture business in both developed and developing countries. The agriculture ecosystem's complexity creates a set of interrelated hurdles that prevent full integration of digital technology for agriculture 4.0 implementation. As a result, identifying possible bottlenecks is critical in order to devise strategic strategies to overcome them. This research aims to figure out what these stumbling barriers are. Following the investigation, 21 barriers were found and characterized on both a technical and socioeconomic level. These impediments are addressed in section 5, which outlines what needs to be done on a bigger scale to digitize the agricultural economy. However, it is still unknown how much removing or mitigating these hurdles aids in the successful integration of digital technologies.

4.16. Added value of agricultural digitization

Several benefits that can inspire framers and other actors to assist agriculture industry digitization have been discovered and outlined based on analysis. The benefits described here have the potential to increase farm productivity and improve product quality, but they should not be viewed as a cure for the problems that come with smart agriculture [73].

•Improved agility: Farm operations can now be more agile thanks to digital technologies. Farmers and agricultural professionals can quickly respond to any anticipated changes in environmental and water conditions using real-time surveillance and forecasting technologies to save crops [72].

•Green process: By lowering the use of in-field fuel, nitrogen fertilizers, pesticides, and herbicides, digital technologies make farming more ecologically friendly and climate-resilient [75].

•Resource efficiency: By increasing the quantity and quality of agricultural output while reducing the use of water, energy, fertilizers, and pesticides, digital platforms can improve resource efficiency [3].

•Time and cost savings: By automating various tasks such as harvesting, sowing, or irrigation, managing the application of fertilizers or pesticides, and scheduling irrigation, digital technologies provide significant time and cost savings [76].

•Asset management: digital technologies enable real-time observation of farm holdings and equipment, allowing for theft prevention, component replacement, and routine maintenance [10].

•Product safety: By eliminating fraud [17, 18] linked to adulteration, counterfeiting, and artificial enhancement, digital technologies maintain appropriate farm output and ensure a safe and nutritious supply of agri-food products [69].

4.17. Considerations and future prospects

The agricultural industry would see major benefits as a result of the planned measures. However, the impediments identified in section 5 must be solved first in order to make things sustainable for small and medium-scale growers. Some of the above hurdles can be mitigated by awareness campaigns emphasizing the importance of smart agriculture at every level of the agricultural value chain and encouraging novel techniques (such as gamification) to encourage stakeholders to take an active role in the digital transformation [9]. Initiatives at the federal level, grants and endowments, public-private collaborations, data transparency, and regional research efforts can all help overcome potential hurdles. Finally, when constructing a smart agriculture system, a roadmap can be used, starting with a basic architecture with few components and simpler functionality and gradually adding components and functionality to develop a sophisticated system with full digitization potential [21]. These issues can pave the road for agriculture 4.0's successful adoption. The use of explainable artificial intelligence to monitor crop development, estimate crop biomass, evaluate crop health, and control pests and diseases is one of the future prospects of digital technologies in smart agriculture. Explainable AI eliminates the old black-box approach of machine learning and allows for a better understanding of the reasoning behind any given decision [15]. The use of common semantics and ontologies to describe big data, as well as the adoption of open standards, has the potential to accelerate research and development in the field of smart farming. Similarly, 5G technology must be thoroughly investigated in order to enable improved connectivity and live streaming of crop data [6]. By executing precise crop inspections remotely, 5G technology will reduce internet costs and enhance the entire user experience of farm management and food safety [77]. It would also help to close the gap between stakeholders by keeping them informed about crop availability. Finally, blockchain can be used in conjunction with IoT and other technologies to address data privacy and security concerns [78].

4.18. Transition to Agriculture 5.0

The agriculture sector has traditionally had a breakthrough during industrial revolutions. Agriculture 4.0 offers significant potential to offset rising food demands and prepare for the future by reinforcing agricultural systems with WSN, IoT, AI, and other technologies, as formally mentioned in preceding sections. While agricultural 4.0 is still being implemented, agriculture 5.0 is already being discussed.

Agriculture 5.0 builds on agriculture 4.0 by incorporating industry 5.0 principles to provide healthy, affordable food while also ensuring that the environments on which life depends are not degraded [79]. Industry 4.0 focuses less on the original principles of social fairness and sustainability and more on digitalization and AI-driven technologies for increasing efficiency and flexibility, the European Commission formally called for the Fifth Industrial Revolution (industry 5.0) in 2021 [80]. Industry 5.0 adds to and expands on the industry 4.0 concepts by emphasizing human-centricity, sustainability, and resiliency [81]. It entails improving human-machine collaboration, decreasing environmental effect through the circular economy, and designing systems with a high degree of robustness to reach an ideal balance of efficiency and productivity. Among the enabling technologies of industry are cobots (collaborative robots), smart materials with embedded bio-inspired sensors, digital twins, AI, energy efficient and secure data management, renewable energy sources, and others 5.0[80].

Farm production efficiency and crop quality can be improved in agriculture 5.0 settings by delegating repetitive and boring activities to machines and those that need critical thinking to humans. For this reason, agricultural cyber physical cognitive systems (CPCS) that observe/study the environment and conduct appropriate actions, comparable to those established for the manufacturing sector, should be developed. This might include collaborative farm robots that work in the fields to aid crop growers with time-consuming operations like seed sowing and harvesting. Similarly, digital twins in agriculture 5.0 can add substantial value by recognizing technical difficulties in agricultural systems and resolving them more quickly, detecting crop illnesses, and producing more accurate crop output estimates. This demonstrates that agriculture 5.0 has the potential to pave the way for climate-smart, sustainable, and resilient agriculture, but it is still in its infancy.

5. Conclusions

Concerns about global food security have heightened the demand for next-generation industrial farms and agricultural intensive production systems. Digital technologies, such as those given by the Industry 4.0 programme, are at the vanguard of this modern agricultural period, providing a wide range of innovative solutions. Disruptive technologies are being integrated into traditional agriculture systems by scientists and researchers in order to boost crop yields, cut costs, reduce waste, and sustain process inputs. This report includes an SLR that discusses the current state of various technologies in the agriculture sector. Several findings are drawn, including the fact that big data and analytics integration, wireless sensor networks, cyber-physical systems, and digital twins in agriculture are still in their infancy, with the majority of use cases still in the prototype stage. Similarly, 21 technological and socioeconomic impediments are found and categorized. These impediments must be identified and addressed if the agriculture industry is to be digitalized. The report also identifies and presents the additional value of digital technology in the agriculture industry. Overall, this research contributes to the ongoing research on agricultural 4.0. The review's principal restriction is twofold: first, only three online repositories (Scopus, IEEE, and Science Direct) are considered for literature searches, and second, new keywords and synonyms may return more papers. The main conclusions are highly unlikely to alter in either scenario. Additional research databases and areas can be considered for future study in order to provide a complete overview of the agriculture industry in terms of digitization. In addition, papers focusing on agriculture 5.0 in general will be featured.

References

1. F Schierhorn, M. Elferink, Global Demand for Food Is Rising. Can We Meet It? *Harv Bus Rev,* 2016, 7 (2017). https://hbr.org/2016/04/global-demand-for-food-is-rising-can-we-meet-it
2. Singh, G. Machine Learning Models in Stock Market Prediction. *International Journal of Innovative Technology and Exploring Engineering*, 2022, vol. 11, no. 3, pp. 18-28. https://doi.org/10.35940/ijitee.C9733.0111322
3. WK Mok, YX Tan, WN. Chen, Technology innovations for food security in Singapore: A case study of future food systems for an increasingly natural resource-scarce world, *Trends Food Sci Technol,* 2020, vol. 102, pp. 155–168, https://doi.org/10.1016/j.tifs.2020.06.013
4. Nagar, P., & Issar, G. S. Detection of outliers in stock market using regression analysis. *International Journal of Emerging Technologies in Computational and Applied Science*, 2013. https://doi.org/10.5281/zenodo.6047417
5. R Abbasi, P Martinez, R. Ahmad, An ontology model to represent aquaponics 4.0 system's knowledge, *Inf Process Agric,* 2021. https://doi.org/10.1016/J.INPA.2021.12.001

6. R Abbasi, P Martinez, R. Ahmad, An ontology model to support the automated design of aquaponic grow beds, *Procedia CIRP,* 2021, vol. 100, pp. 55–60, https://doi.org/10.1016/j.procir.2021.05.009
7. G Aceto, V Persico, A. Pescapé, A Survey on Information and Communication Tech- nologies for Industry 4.0: State-of-the-Art, Taxonomies, Perspectives, and Challenges, *IEEE Commun Surv Tutorials,* 2019. https://doi.org/10.1109/COMST.2019.2938259
8. B. Ozdogan, A. Gacar, H. Aktas. Digital agriculture practices in the context of agriculture 4.0. *Journal of Economics, Finance and Accounting (JEFA),* 2017, vol. 4, iss. 2, pp. 184-191. https://doi.org/10.17261/pressacademia.2017.448
9. Y Liu, X Ma, L Shu, GP Hancke, AM. Abu-Mahfouz, From Industry 4.0 to Agriculture 4.0: Current Status, Enabling Technologies, and Research Challenges, *IEEE Trans Ind Informatics,* 2021, vol. 17, no. 6, pp. 4322-4334. https://doi.org/10.1109/TII.2020.3003910
10. F da Silveira, FH Lermen, FG. Amaral, An overview of agriculture 4.0 development: Systematic review of descriptions, technologies, barriers, advantages, and disadvantages, *Comput Electron Agric* 189 (2021) 106405, https://doi.org/10.1016/J.COMPAG.2021.106405
11. G Idoje, T Dagiuklas, M. Iqbal, Survey for smart farming technologies: Challenges and issues, *Comput Electr Eng,* 2021, vol. 92, 107104. https://doi.org/10.1016/J.COMPELECENG.2021.107104
12. J Miranda, P Ponce, A Molina, P. Wright, Sensing, smart and sustain- able technologies for Agri-Food 4.0, *Comput Ind,* 2019, vol. 108, pp. 21–36. https://doi.org/10.1016/J.COMPIND.2019.02.002
13. M Lezoche, H Panetto, J Kacprzyk, JE Hernandez, Alemany Díaz MME. Agri-food 4.0: A survey of the supply chains and technologies for the future agriculture, *Comput Ind,* 2020, vol. 117, 103187. https://doi.org/10.1016/J.COMPIND.2020.103187
14. Bhakta I, Phadikar S, Majumder K. State-of-the-art technologies in precision agriculture: a systematic review. *Journal of the Science of Food and Agriculture*, 2019, vol. 99, no. 11. pp. 4878-4888. https://doi.org/10.1002/jsfa.9693
15. SO Araújo, RS Peres, J Barata, F Lidon, JC. Ramalho, Characterising the Agriculture 4.0 Landscape — Emerging Trends, Challenges and Opportunities, *Agron,* 2021, vol. 11, no. 4, 667. https://doi.org/10.3390/AGRONOMY11040667
16. M Bacco, P Barsocchi, E Ferro, A Gotta, M. Ruggeri, The Digitisation of Agriculture: a Survey of Research Activities on Smart Farming, *Array*, 2019, 3–4, 100009. https://doi.org/10.1016/j.array.2019.100009

17. Singh, G., & Nager, P. A case Study on Nutek India Limited Regarding Deep Falling in Share Price. *Researchers World - Journal of Arts, Science & Commerce*, 2012, vol. 3(2), 3.
18. Nager, P., & Singh, G. An Analysis of Outliers For Fraud Detection in Indian Stock Market. *Researchers World - Journal of Arts, Science & Commerce*, 2012, vol. 3(4), 4.
19. MJ Page, JE McKenzie, PM Bossuyt, I Boutron, TC Hoffmann, CD Mulrow, et al., The PRISMA 2020 statement: An updated guideline for reporting systematic reviews, *BMJ,* 2021, 372. https://doi.org/10.1136/BMJ.N71
20. Ahmed MA, Ahsan I, Abbas M. Systematic Literature Review: Ingenious Software Project Management while narrowing the impact aspect. *RACS '16: Proceedings of the International Conference on Research in Adaptive and Convergent Systems*, 2016, pp. 165–168. https://doi.org/10.1145/2987386.2987422
21. C Pylianidis, S Osinga, IN. Athanasiadis, Introducing digital twins to agriculture, Comput Electron Agric 184 (2021) 105942, https://doi.org/10.1016/J.COMPAG.2020.105942
22. Shaikh ZA Aqeel-ur-Rehman, NA Shaikh, N Islam, An integrated framework to de- velop context aware sensor grid for agriculture, Aust J Basic Appl Sci, 2010.
23. W Shi, J Cao, Q Zhang, Y Li, L. Xu, Edge Computing: Vision and Challenges, IEEE Internet Things J 3, 2016, 637–646, https://doi.org/10.1109/JIOT.2016.2579198
24. A Tzounis, N Katsoulas, T Bartzanas, C. Kittas, Internet of Things in agriculture, recent advances and future challenges, Biosyst Eng, 164, 2017, 31–48, https://doi.org/10.1016/J.BIOSYSTEMSENG.2017.09.007
25. VP Kour, S. Arora, Recent Developments of the Internet of Things in Agri- culture: A Survey, IEEE Access 8, 2020, 129924–129957, https://doi.org/10.1109/AC- CESS.2020.3009298
26. MU Aftab, O Ashraf, M Irfan, M Majid, A Nisar, MA. Habib, A Review Study of Wireless Sensor Networks and Its Security, Commun Netw, 7, 2015, 172–179, https://doi.org/10.4236/cn.2015.74016
27. X Yu, P Wu, W Han, Z. Zhang, A survey on wireless sensor network infrastructure for agriculture, Comput Stand Interfaces, 1, 2013, 59–64, https://doi.org/10.1016/J.CSI.2012.05.001
28. Mell PM, Grance T. The NIST definition of cloud computing, 2011. https://doi.org/10.6028/NIST.SP.800-145
29. Alwada'n T. Cloud computing and multi-agent system: monitoring and services. 2018.

30. X Shi, X An, Q Zhao, H Liu, L Xia, X Sun, et al., State-of-the-art inter- net of things in protected agriculture, Sensors (Switzerland), 19, 2019, 1833, https://doi.org/10.3390/s19081833
31. J Wang, H Yue, Z. Zhou, An improved traceability system for food quality assurance and evaluation based on fuzzy classification and neural network, Food Control, 79, 2017, 363–370, https://doi.org/10.1016/J.FOODCONT.2017.04.013
32. S Fountas, G Carli, CG Sørensen, Z Tsiropoulos, C Cavalaris, A Vatsanidou, et al., Farm management information systems: Current situation and future perspectives, Comput Electron Agric, 115, 2015, 40–50, https://doi.org/10.1016/J.COMPAG.2015.05.011
33. A Bechar, C. Vigneault, Agricultural robots for field operations: Concepts and components, Biosyst Eng, 149, 2016, 94–111, https://doi.org/10.1016/J.BIOSYSTEMSENG.2016.06.014
34. Gonzalez-De-Santos P, Fernández R, Sepúlveda D, Navas E, Armada M. Unmanned Ground Vehicles for Smart Farms. Agron - Clim Chang Food Secur, 2020. https://doi.org/10.5772/INTECHOPEN.90683
35. J del Cerro, CC Ulloa, A Barrientos, L. Rivas J de, Unmanned Aerial Vehicles in Agri- culture: A Survey, Agron, 11, 2021, 203, https://doi.org/10.3390/AGRONOMY11020203
36. Patel PN, Patel M, Faldu RM, Dave YR. Quadcopter for Agricultural Surveillance, 2013.
37. Sylvester G, Food and Agriculture Organization of the United Nations., International Telecommunication Union. E-agriculture in action: drones for agriculture n.d.:112.
38. U Sivarajah, MM Kamal, Z Irani, V. Weerakkody, Critical analysis of Big Data challenges and analytical methods, J Bus Res, 70, 2017, 263–286, https://doi.org/10.1016/J.JBUSRES.2016.08.001
39. M Chi, A Plaza, JA Benediktsson, Z Sun, J Shen, Y. Zhu, Big Data for Remote Sensing: Challenges and Opportunities, Proc IEEE, 104, 2016, 2207–2219, https://doi.org/10.1109/JPROC.2016.2598228
40. K Tesfaye, K Sonder, J Caims, C Magorokosho, A Tarekegn, GT Kassie, et al. Target- ing drought-tolerant maize varieties in southern Africa: a geospatial crop modeling approach using big data, Int Food Agribus Manag Rev, 19, 2016.
41. R Sharma, SS Kamble, A Gunasekaran, V Kumar, A. Kumar, A system- atic literature review on machine learning applications for sustainable agri- culture supply chain performance, Comput Oper Res, 119, 2020, 104926, https://doi.org/10.1016/J.COR.2020.104926
42. T Talaviya, D Shah, N Patel, H Yagnik, M. Shah, Implementation of artificial intelli- gence in agriculture for optimisation of irrigation and application

of pesticides and herbicides, Artif Intell Agric, 4, 2020, 58–73, https://doi.org/10.1016/J.AIIA.2020.04.002
43. KG Liakos, P Busato, D Moshou, S Pearson, D. Bochtis, Machine Learn- ing in Agriculture: A Review, Sensors, 18, 2018, 2674, https://doi.org/10.3390/S18082674
44. G Xu, H Li, S Liu, K Yang, X. Lin, VerifyNet: Secure and Verifiable Federated Learning, IEEE Trans Inf Forensics Secur, 15, 2020, 911–926, https://doi.org/10.1109/TIFS.2019.2929409
45. J. Schmidhuber, Deep Learning in Neural Networks: An Overview, Neural Networks, 61, 2014, 85–117, https://doi.org/10.1016/j.neunet.2014.09.003
46. Canziani A, Paszke A, Culurciello E. An Analysis of Deep Neural Network Models for Practical Applications, 2016.
47. A Kamilaris, FX. Prenafeta-Boldu, Deep learning in agriculture: A survey, Comput Electron Agric, 147, 2018, 70–90, https://doi.org/10.1016/j.compag.2018.02.016
48. V Kakani, VH Nguyen, BP Kumar, H Kim, VR. Pasupuleti, A critical review on computer vision and artificial intelligence in food industry, J Agric Food Res, 2, 2020, https://doi.org/10.1016/J.JAFR.2020.100033
49. F Terribile, A Agrillo, A Bonfante, G Buscemi, M Colandrea, A D'Antonio, et al., A Web-based spatial decision supporting system for land management and soil conservation, Solid Earth 6 (2015) 903–928, https://doi.org/10.5194/SE-6-903-2015
50. A Felsberger, B Oberegger, G. Reiner, A Review of Decision Support Systems for Manufacturing Systems, Undefined, 2016.
51. P Taechatanasat, L. Armstrong, Decision Support System Data for Farmer Decision Making, ECU Publ Post (2013) 2014 .
52. L Wang, M Törngren, M. Onori, Current status and advancement of cyber- physical systems in manufacturing, J Manuf Syst, 37, 2015), 517–527, https://doi.org/10.1016/J.JMSY.2015.04.008
53. DGS Pivoto, LFF de Almeida, R da Rosa Righi, JJPC Rodrigues, AB Lugli, AM. Al- berti, Cyber-physical systems architectures for industrial internet of things appli- cations in Industry 4.0: A literature review, J Manuf Syst, 58, 2021, 176–192, https://doi.org/10.1016/J.JMSY.2020.11.017
54. AF Jimenez, PF Cardenas, F Jimenez, A Canales, A. López, A cyber-physical intelli- gent agent for irrigation scheduling in horticultural crops, Comput Electron Agric, 178, 2020, 105777, https://doi.org/10.1016/J.COMPAG.2020.105777
55. A Selmani, H Oubehar, M Outanoute, A Ed-Dahhak, M Guerbaoui, A Lach- hab, et al., Agricultural cyber-physical system enabled for remote management of solar-powered precision irrigation, Biosyst Eng, 177, 2019, 18–30, https://doi.org/10.1016/J.BIOSYSTEMSENG.2018.06.007

56. A Nayak, RR Levalle, S Lee, SY. Nof, Resource sharing in cyber-physical systems: modelling framework and case studies, 54, 2016, 6969–6983, https://doi.org/10.1080/00207543.2016.1146419
57. C Verdouw, B Tekinerdogan, A Beulens, S. Wolfert, Digital twins in smart farming, Agric Syst, 189, 2021, 103046, https://doi.org/10.1016/J.AGSY.2020.103046
58. D Jones, C Snider, A Nassehi, J Yon, B Hicks, Characterising the Digital Twin: A systematic literature review, CIRP J Manuf Sci Technol, 29, 2020, 36–52, https://doi.org/10.1016/J.CIRPJ.2020.02.002
59. S Aydin, MN. Aydin, Semantic and syntactic interoperability for agricultural open- data platforms in the context of IoT using crop-specific trait ontologies, Appl Sci, 10, 2020, https://doi.org/10.3390/app10134460
60. Y He, J Guo, X. Zheng, From Surveillance to Digital Twin: Challenges and Recent Advances of Signal Processing for Industrial Internet of Things, IEEE Signal Process Mag, 35, 2018, 120–129, https://doi.org/10.1109/MSP.2018.2842228
61. MS Farooq, S Riaz, A Abid, K Abid, MA. Naeem, A Survey on the Role of IoT in Agriculture for the Implementation of Smart Farming, IEEE Access, 7, 2019, 156237–156271, https://doi.org/10.1109/ACCESS.2019.2949703
62. A Villa-Henriksen, GTC Edwards, LA Pesonen, O Green, CAG. Sørensen, Internet of Things in arable farming: Implementation, applications, challenges and potential, Biosyst Eng, 191, 2020, 60–84, https://doi.org/10.1016/J.BIOSYSTEMSENG.2019.12.013
63. HM Jawad, R Nordin, SK Gharghan, AM Jawad, M. Ismail, Energy-efficient wire- less sensor networks for precision agriculture: A review, Sensors (Switzerland), 17, 2017, 1781, https://doi.org/10.3390/s17081781
64. L Sigrist, N Stricker, D Bernath, J Beutel, L. Thiele, Thermoelectric Energy Harvesting from Gradients in the Earth Surface, IEEE Trans Ind Electron, 67, 2020, 9460–9470, https://doi.org/10.1109/TIE.2019.2952796
65. AR Yanes, P Martinez, R. Ahmad, Towards automated aquaponics: A review on monitoring, IoT, and smart systems, J Clean Prod, 2020, https://doi.org/10.1016/j.jclepro.2020.121571
66. N Brinis, LA. Saidane, Context Aware Wireless Sensor Network Suitable for Preci- sion Agriculture, Wirel Sens Netw, 2016, https://doi.org/10.4236/wsn.2016.81001
67. M Zimmerling, L Mottola, S. Santini, Synchronous Transmissions in Low-Power Wireless: A Survey of Communication Protocols and Network Services, ACM Comput Surv, 53 2021, https://doi.org/10.1145/3410159
68. F Tonolini, F. Adib, Networking across boundaries: Enabling wireless communica- tion through the water-air interface, SIGCOMM 2018 - Proc 2018

Conf ACM Spec Interes Gr Data Commun, 2018, 117–131, https://doi.org/10.1145/3230543.3230580
69. L Chen, S Thombre, K Jarvinen, ES Lohan, A Alen-Savikko, H Leppakoski, et al., Robustness, Security and Privacy in Location-Based Services for Future IoT: A Survey, IEEE Access, 5, 2017, 8956–8977, https://doi.org/10.1109/ACCESS.2017.2695525
70. Y Njah, M. Cheriet, Parallel Route Optimization and Service Assurance in Energy- Efficient Software-Defined Industrial IoT Networks, IEEE Access, 9, 2021, 24682–24696, https://doi.org/10.1109/ACCESS.2021.3056931
71. A Rajput, VB. Kumaravelu, Scalable and sustainable wireless sensor networks for agricultural application of Internet of things using fuzzy c-means algorithm, Sustain Comput Informatics Syst, 22, 2019, 62–74, https://doi.org/10.1016/J.SUSCOM.2019.02.003
72. BB Sinha, R. Dhanalakshmi, Recent advancements and challenges of Internet of Things in smart agriculture: A survey, Futur Gener Comput Syst, 126, 2022, 169–184, https://doi.org/10.1016/J.FUTURE.2021.08.006
73. F Caffaro, E. Cavallo, The effects of individual variables, farming system character- istics and perceived barriers on actual use of smart farming technologies: Evidence from the piedmont region, northwestern Italy, Agric, 9, 2019, https://doi.org/10.3390/AGRI- CULTURE9050111
74. Mohit Jain, Pratyush Kumar, Ishita Bhansali, Q. Vera Liao, Khai Truong, Shwetak Patel. FarmChat: A Conversational Agent to Answer Farmer Queries. Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies, 2018, vol. 2, issue 4, article 170, pp 1–22. https://doi.org/10.1145/3287048
75. Mclaughlan B, Brandli J, Smith F. Toward Sustainable High-Yield Agriculture via Intelligent Control Systems, 2015.
76. RK Kodali, S Soratkal, L. Boppana, IOT based control of appliances, in: Proceeding - IEEE Int Conf Comput Commun Autom ICCCA 2016, 2017, pp. 1293–1297, https://doi.org/10.1109/CCAA.2016.7813918
77. Abbasi R, Reyes A, Martinez E, Ahmad R. Real-time implementation of digital twin for robot based production line n.d.:4–6.
78. O Bermeo-Almeida, M Cardenas-Rodriguez, T Samaniego-Cobo, E Ferruzola- Gómez, R Cabezas-Cabezas, W. Bazán-Vera, Blockchain in Agriculture: A Systematic Literature Review, Commun Comput Inf Sci, 883, 2018, 44–56, https://doi.org/10.1007/978-3-030-00940-3_4
79. V Saiz-Rubio, F. Rovira-Más, From Smart Farming towards Agriculture 5.0: A Review on Crop Data Management, Agron, 10, 2020, 207, https://doi.org/10.3390/AGRONOMY10020207

80. X Xu, Y Lu, B Vogel-Heuser, L. Wang, Industry 4.0 and Industry 5.0 – Inception, conception and perception, J Manuf Syst, 61, 2021, 530–535, https://doi.org/10.1016/J.JMSY.2021.10.006
81. PKR Maddikunta, Q-V Pham, P B, N Deepa, K Dev, TR Gadekallu, et al., Industry 5.0: A survey on enabling technologies and potential applications, J Ind Inf Integr, 2021, 100257, https://doi.org/10.1016/J.JII.2021.100257

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