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Review

The Path to Smart Farming: Innovations and Opportunities in Precision Agriculture

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Abstract: Precision agriculture employs cutting-edge technologies to increase agricultural productivity while reducing adverse impacts on the environment. Precision agriculture is a farming approach that uses advanced technology and data analysis to maximize crop yields, cut waste, and increase productivity. It is a potential strategy for tackling some of the major issues confronting contemporary agriculture, such as feeding a growing world population while reducing environmental effects. This review article examines some of the latest recent advances in precision agriculture, including the Internet of Things (IoT) and how to make use of big data. This review article aims to provide an overview of the recent innovations, challenges, and future prospects of precision agriculture and smart farming. It presents an analysis of the current state of precision agriculture, including the most recent innovations in technology, such as drones, sensors, and machine learning. The article also discusses some of the main challenges faced by precision agriculture, including data management, technology adoption, and cost-effectiveness.

Keywords: precision farming; smart farming; agricultural technology; Internet of Things (IoT); big data analytics; machine learning; artificial intelligence (AI)

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1. Introduction

Precision agriculture (PA) is a management strategy for addressing geographical and temporal variabilities in agricultural fields [1–3] that involves data and contemporary technologies. With a forecasted human population of between 9 and 10 billion by 2050 [3–5], precision agriculture is becoming more and more important to contemporary agricultural research. By 2050, the amount of food produced worldwide must grow by at least 70% [1,5–7]. This is a difficult endeavor [4] because it puts further strain on already-scarce resources and the environment [1–3]. Therefore, precision agriculture is essential to maximize output while using fewer inputs of all sorts in more effective ways, reducing adverse impacts on the environment, and assuring sustainability [2,3]. Precision farming was born with the introduction of GPSs (global positioning systems), GISs (geographic information systems), yield monitors, and other data generators in all three crucial phases of agricultural operations in the 1990s [2,8,9]. In precision agriculture, motorized equipment was only used for performing agricultural processes [2,10], and the problem-recognizing and decision-making steps were authorized by humans. The technological advancement during the Third Industrial Revolution, known as Industry 3.0 [8], led precision agriculture to digitalization by integrating information technologies and improved automation capabilities in precision farming. As a result of this digitalization, "farm practices" with manual tools moved to "agriculture" from animal traction, then to motorized mechanization, and now to digital equipment [2].

Precision agriculture so far mainly consists of variable rate technologies (VRTs), electronic maps, yield monitors, and guidance farming systems [2,8]. Variable rate applications were firstly demonstrated in northern Germany and Denmark in 1988 after global positioning systems (GPSs) were available for civil services [11]. GPS services were opened for general use in U.S. farms in 1983 [2]. In the next decade, GPS technology facilitated farmers to precisely locate and map their fields [10,12], empowering them to manage their farmlands according to site-specific conditions and field variabilities. At the beginning of the second millennium, yield monitors were developed, enabling farmers to monitor crop yield in real-time via best matching [13]. Advancement of remote-sensing technology, such as satellites, drones, ground-based sensors, and crews, authorized farmers to collect high-resolution data on their fields, allowing them to make informed decisions about crop management [3]. Precision agriculture is not only focused on crop farming but also on other agricultural production systems: agronomics, livestock farming, aquaculture, and agroforestry [2,3,9,14].

In the current status of precision agriculture, there are several issues, such as unsustainable resource utilization, long-term monoculture, intensive animal farming [8], environmental compromises, uneven distribution of digitization [15], food safety issues, inefficient agri-food supply chain [13,16], and lack of awareness of and inertia toward novel changes. These issues prevent achieving efficiency, productivity, and sustainability from agricultural production and escalate unintended impacts on ecosystems [17]. The fourth industrial revolution, which is known as Industry 4.0, occurred in 2011 with the Internet of Things (IoT), big data, artificial intelligence (AI), robotics, and blockchain technology [8,18]. In 2017, these advanced technologies were integrated into agriculture in order to overcome the above-mentioned issues, transforming precision agriculture to Agriculture 4.0, or smart farming [8,16]. With this transition, there is a growing focus on sustainability in agriculture, with many farmers adopting precision agricultural technologies to reduce the environmental impacts of farming and promote long-term sustainability. As a result, agricultural-manufacturing processes and supply chains have become more autonomous and intelligent [18], including the automation of various tasks such as planting, seeding, harvesting, and soil sampling. This is making farming more efficient while reducing labor costs.

Smart agriculture is an evolving field that leverages technological innovations to transform traditional farming practices. The integration of digital technologies into agriculture has opened up new opportunities and possibilities, revolutionizing the way farmers manage their crops, resources, and operations. It is a rapidly evolving field that encompasses a wide array of approaches, applications, and impacts. The broader objective of this review is to delve into the essential aspects of precision agriculture, exploring its key components and highlighting its potential for sustainable farming practices. One of the critical aspects of precision agriculture is data collection and acquisition planning, which plays a fundamental role in optimizing farm management decisions. Through efficient data gathering, farmers can make informed choices regarding crop health, resource allocation, and yield optimization. Decision making and execution are also vital components of precision agriculture, where the integration of cutting-edge technologies is pivotal. Leveraging machine vision technology, the Internet of Things (IoT), and artificial intelligence (AI) can lead to enhanced precision and efficiency in agricultural processes, benefiting both farmers and the environment. Throughout this review, successful precision agriculture proposals and real-world implementations are analyzed to gain insights into their achievements and challenges. By identifying future developments required in precision agriculture, we aim to provide a comprehensive understanding of how this field can continually evolve to support sustainable farming practices and address global food security challenges. The amalgamation of scientific research and technological innovations holds great promise for the future of precision agriculture and its positive impact on agriculture and society as a whole.

2. Precision Agriculture Approaches, Applications, and Impacts

Precision agriculture involves data-driven management decisions that improve resource use efficiency, resulting in reduced agricultural costs while lowering the environmental impacts from agriculture [19]. Hence, data and data collection systems, decision support tools, and data-driven equipment and input adjustments are major components of precision agriculture [2], engaging in three key agricultural steps: diagnosis, decision making, and performing [20], respectively. Before the integration of smart technologies, ICT (information and communication technology) was incorporated into agricultural devices and machinery to capture real data. Here, remote sensing, automated hardware and software, telematics, drones, autonomous vehicles, GPSs, and robotic technologies were incorporated into agricultural practices. As an example, the agro-tech company John Deere introduced GPSs for tractors, expecting increased yield and decreased input wastage [19]. The previous status of precision agriculture before smart farming can be summarized as follows.

2.1. Data Collection and Acquisition

Data, data collection, and decision support tools are important for the identification and diagnosis of various aspects in agriculture. In precision agriculture, data on individual fields and crops are gathered by observing, measuring, and sensing with different kinds of sensors, yield and soil monitors, and remote-sensing tools, such as imaging from drones, crews, aircraft, or satellites [1–3,13]. Thus, “sensing” is a fundamental management tool of precision agriculture [3,13], which is observing detailed information and providing data on climate conditions, soil conditions, fertilizer requirements, water availability, pest and disease stresses, and other field parameters [3]. A range of sensors are used in precision agriculture. Biomass parameters are important in making decisions to monitor the fertilization and caring for crops. Sensors for mass flow and moisture content are components of yield monitors, together with a differential global positioning system (DGPS) receiver. Properly calibrated yield monitors can generate accurate real-time information for decision making, such as underperforming areas leading to site-specific crop fertilization designs [13]. Precision livestock farming uses sensors and monitoring technology to collect data on animal health and welfare, enabling farmers to make informed decisions about feed, waste, and other inputs with improved efficiency and productivity. Colter position sensors combined with ultrasonic soil surface sensors are employed in dynamic Colter depth control systems [3].

Remote-sensing technologies, such as drones, crews, aircraft, satellites, and other ground-based sensors, are used to collect data on crops and soil conditions [2,3]. Remote sensing supports the identification of spatial patterns of signatures of plants that are coincidental with soil characteristics, as well as pest or disease stresses [11]. Imagery is one kind of remote-sensing data that can reveal ground truthing [2,3,11]. Previously, aircraft have been used not only for many farming imagery operations that generate data, but also chemical- or fertilizer-spraying activities. Moreover, satellite images have been available for farm management for many years. As an example, the US-LANDSAT satellites were available for this purpose in 1970 [2]. Unmanned aerial vehicles (UAVs) equipped with global navigation satellite system (GNSS) technology have been recently employed for mapping, gathering imagery data, land surveying, crop spraying, and livestock monitoring [2,3]. Geocoded sampling is a requisite component of precision agriculture and ground truthing when spatial images are used for decision making [11]. Real-time and cost-effective remote sensing, such as LASSIE (low-altitude stationary surveillance instrumental equipment), are crucial in precision agriculture, as it enables continuous and automatic recoding of real-time images of crops and soil with GIS reference [11]. This information can be used to make informed decisions about crop management resource allocation [3].

Sensor data and other data associated with geospatial coordinates from a global navigation satellite system (GNSS) provide information to create maps, especially yield maps and soil maps for site-specific management decisions [2,3]. Yield maps are used to characterize field production quantitatively and qualitatively [21], which is crucial to make management decisions. Analyzing variabilities depicted on maps enables the identification of factors that influence productivity, facilitating the implementation of site-specific field management strategies [3]. Soil maps offer valuable insights into the spatial distribution of the physical and chemical properties within a given field [21], serving as indispensable decision-making tools in precision agriculture [13]. This significance stems from the fact that soil's physical and chemical characteristics, such as water availability, nutrient-holding capacity, bulk density, porosity, nutrient availability, and topography, typically exert an influence on crop yield [21]. Weather and climate trends can also be predicted using sensor data, which are important in all farming practices. Harvesting time is an affecting factor of grain loss in paddy rice farming, which is also able to be monitored with data observation [1].

2.2. Planning, Decision Making, and Execution

After creating decisions by analyzing gathered information, actions are performed according to the decisions created using data-driven equipment. Most fields are not homogenous in terms of soil and climate properties, as well as diseases [22]. Conventional agriculture did not take this into account; therefore, rigorous use of limited resources and excess use of chemicals and synthetic fertilizers resulted in unsustainable conventional agricultural practices. This also drove lots of wastage, even in the amounts of resource inputs and yield. Nonetheless, precision agriculture itself has proved that the application of technologies to manage the spatial and temporal variabilities in agricultural fields is possible to improve performance and environmental quality [9]. Variable rate technologies in precision agriculture involve applying inputs such as fertilizers, water and seeds, and crop protection chemicals (pesticides and weedicides) at varying rates, depending on the specific needs of each area of a field [23]. In this approach, residual issues of chemicals, as well as wastage of input resources, can be reduced. Also, net profit can be improved with increased crop yield and reduced input costs, as farmers can use resources according to the field requirements rather than full-coverage application in fields at uniform rates [2,24,25].

According to the identified heterogeneity of a field, amounts of water, fertilizer, herbicides, pesticides, and liming can be determined and applied. When considering the irrigation practices in precision agriculture, technology-driven, more sustainable smart irrigation systems are there to apply precise amounts of water at precise times. When soil moisture sensor data give an estimation of a required amount of water, irrigation systems can be diverted into variable rate irrigation to apply irrigation water until moisture content returns to the ideal level [26]. Most of the time, these effective and efficient water management systems are automatically controlled, increasing irrigation water use efficiency (IWUE). Monteiro et al. in 2021 described the use of satellite LANDSAT data and remote-sensing data to develop a feasible operational irrigation water model [3]. Likewise, tillage depth can be determined via matching with variabilities of soil physical properties [27]. Chemical spraying and seeding are also performed according to variable rate approaches. Previously, agricultural aircraft were used for chemical spraying, where a pilot controlled the spray [23]. In the present, aircraft are employed with an auto-adjusting ability for the application rate of chemicals based on a prescription map, whilst UAVs are also used as fertilizer spreaders [3]. Precision seeding can control sowing depth, densities, and distances effectively while saving seeds, time, and labor costs. Studies estimated that precision seeding based on variable rate technologies was 10% to 30% more efficient than conventional practices [3].

This site-specific management increases the number of correct decisions per unit area per unit time related to net benefits [9] while supporting the conservation of agricultural inputs and reducing costs together with environmental impacts [2,13,24]. Another management tool, grid sampling, also involves the division of fields into a grid and collecting data at each intersection of the grid. This approach provides representative information of the entire variation within a field [11], where such data are able to be used for site-specific management to optimize management practices precisely [7]. For small-scale variabilities of soil and crop features, a local resource management (LRM) system was developed with computer-aided farming (CAF), which translated information into variable rate applications [11].

Thus far, humans have used digital tools to enhance diagnosis and decision making while adding automated machines for precise performing [14]. The accelerating changes of Industry 4.0 plus these digital technologies have granted the gradual automation of the diagnosis and decision-making steps, limiting human involvement to only monitoring (Figure 1) [6]. This revolution mostly targets optimal farming and variability management in order to enhance production. However, fulfilling the food demand should not rely solely on "more production". At the same time, it should be consider "less wastage" of both the inputs and outputs of agricultural production [3].

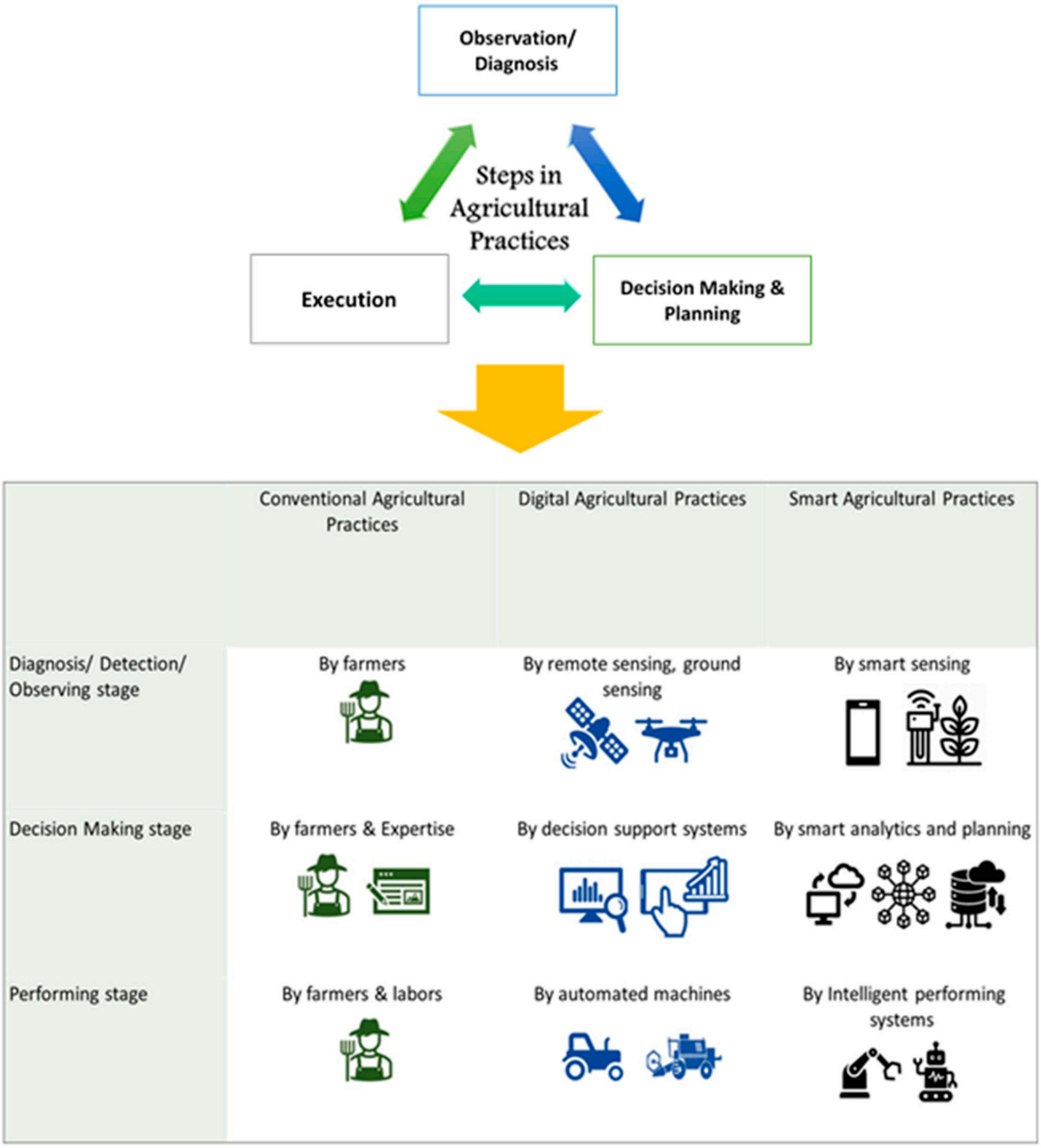

Figure 1. Three-phase cycle of an automation system and the evolution of automation of those phases in agriculture with emerging advanced technologies.

3. Precision Agriculture: The Next Frontier for Sustainable Farming

In the present, we are in the early stage of a new agricultural revolution with data-intensive approaches [2,6,16], which deploy machines at each and every step in agriculture (Figure 1), namely diagnosis, decision making, and performing. Human power is only involved in monitoring and maintaining [20]. Apart from the gradual modification of agricultural practices by the three previous industrial revolutions, the ongoing fourth industrial revolution is shaping the current status of agriculture, leading to Agriculture 4.0. This new discipline is characterized by data-driven management; new tool-based production, sustainability, professionalization; and the reduced environmental footprint of farming with modern smart technologies [24], such as robot technology (including drones), big data, artificial intelligence, computer vision, 5G, cloud computing, the Internet of Things, and blockchain technology [4,5,8,16]. This makes agricultural production systems more autonomous and intelligent [18,28]. Therefore, the following involvements can be identified as new trends and precision agriculture (Figure 2), where new capabilities are introduced to smart farming.

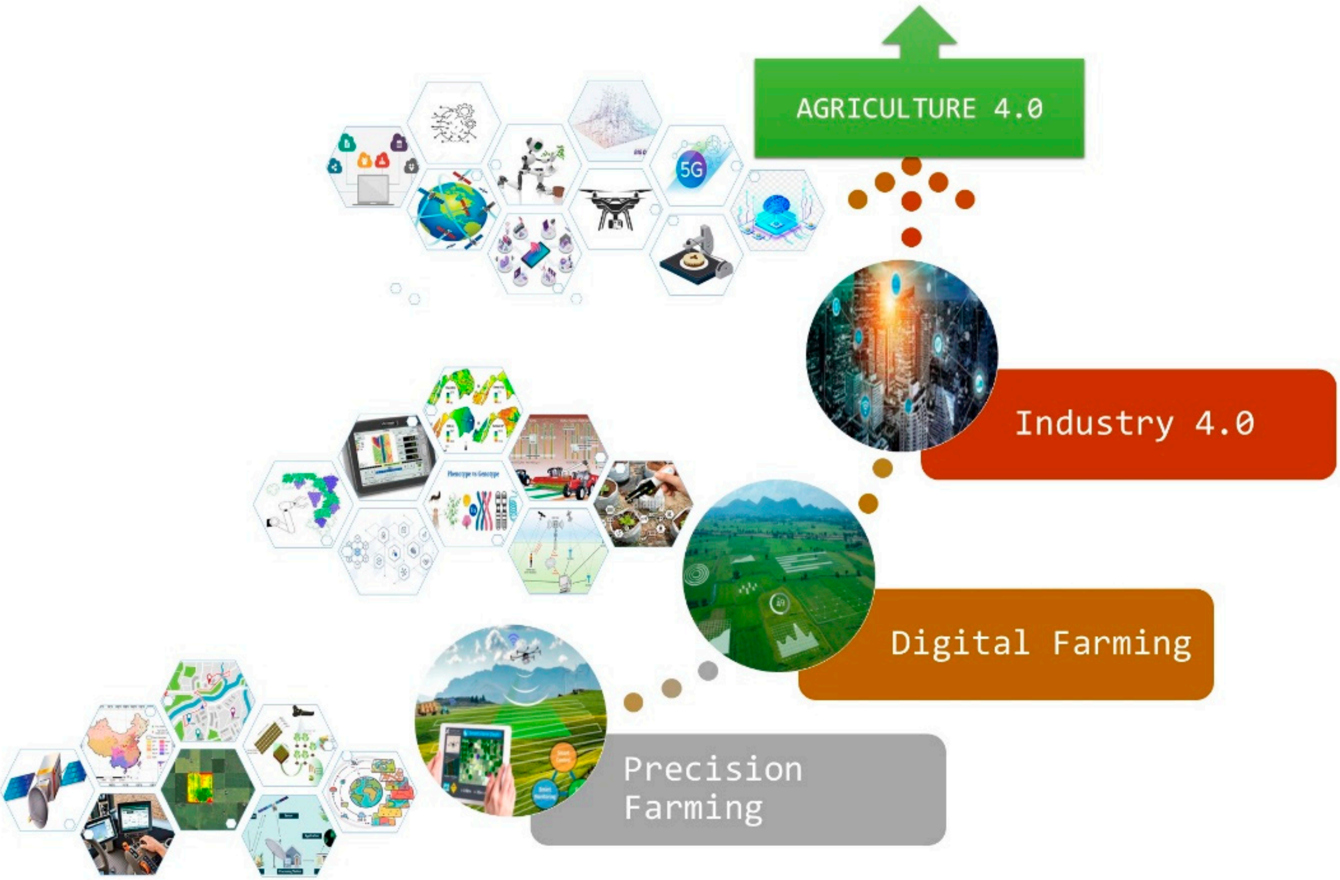

Figure 2. Different integrated technological contexts to form the fourth agricultural revolution: novel trends in precision agriculture.

3.1. Big Data

Precision agriculture systems are highly related to data and information [5]. Generally, unstructured and vast amounts of data are used by big business industries, like social-networking sites, to learn or predict customer behaviors accurately [4]. Similarly, in precision agriculture, big data analytics are applied to understand data-intensive agricultural processes for decision making [6], where analytic tools operate enormous data sets [4]. These analytic tools consist of data mining, statistics, AI, predictive analytics, neural language processing, etc. [4]. Big data science usually functions either with ML, cloud computing, image processing, modeling and simulation, statistical analysis, NDVI vegetation indices, or GIS. These conjugations can discover correlations, patterns, and trends from large quantities of data via capturing, storing, exchanging, analyzing, and marketing features of this high-performance informatics technology [6]. These predictions and recommendations assist farmers with handling the upcoming outcomes, risks, and challenges in the agricultural industry [4]. Combining the data in agricultural production processes creates traceability of product while increasing product quality, including safety and taste. As customers are now aware of the ecological footprint of agri-products, the above combination supports the increase in the demand for agricultural commodities [29], adding high market value. Recent advancements of high-resolution remote sensing and intelligent information and communication technologies, including social media (Facebook, Twitter, Amazon, Instagram, etc.), have contributed to big data analytics in many sectors, as well as in many stages in farming, including decision making, weather forecasting, weather management, disaster management, smart management of resources, disease and pest interruption, and harvesting time predictions [4,6,30]. Moreover, big data analytics aid in implementing real-time forecasting in precision agriculture [4]. However, data updating, device security, correctness of data, accuracy of data, availability of data, and security elements, such as encryption, are still barriers when combining big data with smart farming [31]. Invalid data can lead farmers to make costly, disruptive decisions and actions [5].

3.2. Machine Vision Technology

Precise and accurate data and information are the driving components of precision agriculture. Recently, image analysis has become a more reliable data source than manual, labor-intensive, costly data-collecting methods [22,32]. Here, machines can read and understand the real world through pixel images and produce accurate site-specific information [31]. Machines with 'eyes' in agricultural activities are called machine vision (MV). This, also known as agro-vision or the 'eyes' of robots, provides non-destructive, robust, rapid, and steady methods to monitor cultivation processes. MV systems give machines their vision and judgement capabilities in image processing and data extraction [10]. Although MV technologies have already been applied successfully for crop species identification, crop stress detection, crop seed quality assessment, weed detection, disease detection, etc., they are still at the prototype stage. Currently, emerging deep-learning (DL) techniques in growing machine-learning (ML) technologies are integrated with MV applications in order to develop intelligent robots for multispectral imagery analysis and real-time analysis in field variable rate applications [10,25]. Commercial smartphones, which are ubiquitous among the human population, are able to be used in monitoring crop health and stress based on MV systems [33].

3.3. Internet of Things (IoT)

The IoT refers to a network of interconnected items and technologies [16]. The IoT is one of the most important technological advancements in precision agriculture and smart farming [5]. IoT architecture for agriculture, such as agricultural sensors with ICT and UAV, collects data for precision agriculture [31]. Also, the burgeoning IoT and mobile data are the core of the fourth industrial revolution [10]. Meanwhile, advancements in communication technologies and wireless networks (5G, LoRaWAN, NB-IoT, Sigfox, ZigBee, and Wi-Fi) have broadened the application of the IoT in diverse fields, such as real-time remote control and high-throughput phenotyping, while giving better coverage, bandwidth, connection density, and end-to-end latency (Table 1) [8]. When it consolidates in agriculture together with cloud computing, it results in smart farming [6] for various scopes of livestock monitoring, smart greenhouses, fishery management, and weather tracking [8]. The IoT can be widely used in all areas of precision agriculture with the development of sensors with independent intellectual property rights and the development of smart devices, such as intelligent tractors, UAVs, and robots that can replace high levels of manual labor input, performing high-quality operations while adjusting to challenging working conditions [31].

Table 1. Main specifications of prominent wireless technologies of fifth-generation communication paradigm: [34–38].

	Sigfox	LoRaWAN	NB-IoT	Zigbee	Wi-Fi	5G
Bandwidth	Low bandwidth	Low to moderate bandwidth	Low to moderate bandwidth	Low to moderate bandwidth	High bandwidth	Very high bandwidth
Maximum Data Rate	Up to 100 bps	Up to 27 kbps	Up to 250 kbps	Up to 250 kbps	From a few Mbps to several Gbps (varies based on the version)	High data rates from several hundred Mbps to multi-Gbps
Payload Length	Limited to 12 bytes per message (140 messages per day)	Up to 51 bytes per message (varies depending on the region)	Up to 1600 bytes per message (varies depending on the network operator)	Up to 128 bytes per message (varies depending on the network layer)	Up to several kilobytes per message (varies based on the version)	Supports large payload sizes ranging from several kilobytes to several megabytes
Coverage	Several kilometers in rural areas and up to a few hundred meters in urban areas from a Sigfox base station	Varies from a few kilometers in urban area and tens of kilometers in rural areas depending on antenna height and line of sight	Wide area of coverage up to several kilometers or more from a base station by leveraging existing cellular infrastructure (similar to 2G/3G cellular networks)	Up to tens of meters (can be extended by utilizing mesh networking, allowing devices)	Limited to indoor around 30–50 m or local area environments (can be extended)	A few hundred meters to several kilometers from a base station (varies depending on the frequency band and deployment strategy)
Cost	Relatively low cost due to its simple infrastructure requirements	Cost-effective due to shared infrastructure and low-power devices	Affordable due to utilizing existing cellular infrastructure	Reasonably priced, especially for small-scale deployments	Cost-effective for local area networks, but infrastructure costs can vary	Higher infrastructure costs compared to other technologies
Advantages	Low power consumption, long-range coverage, low-cost infrastructure	Long-range coverage, low power consumption, low-cost infrastructure	Wide network coverage, secure, supports voice and mobility	Low power consumption, mesh networking, supports large networks	High bandwidth, widespread availability, support for various applications	Very high bandwidth, ultra-low latency, massive device connectivity, high reliability
Disadvantages	Limited bandwidth, low data rate	Limited bandwidth, shared spectrum, higher latency	Higher power consumption compared to other LPWAN technologies	Limited range, interference from other devices, complex network setup	High power consumption, shorter range, limited scalability	Higher infrastructure cost, limited coverage in some areas, higher power consumption

Different IoT sensors for temperature, humidity, light intensity, pressure, CO_2 levels, insect infestations, foliage, sunlight intensities, and wind speed are there to collect and receive data, which are then uploaded to cloud information support systems to manage [4,13,16,28]. Those sensors can directly combine with agricultural robots, autonomous platforms, machines, and weather stations for real-time monitoring [4]. With the IoT, UAVs can respond promptly, leading to high-quality, high-resolution, and exceptionally reliable observations through high-throughput 3D monitoring at different geographical areas. At the same time, various kinds of agricultural sensor nodes, autonomous farm vehicles, and mobile crowd sensing have been put forward based on the IoT for ground and undersurface cognition [8]. Most IoT sensors in precision agriculture are in wireless frameworks [13] or low-power wide-area networks [8] and, hence, can be used for on-site analysis [3], as well as mass data transfer, without any interruptions [29,31]. Still, there are cost, operational, technical, and data management difficulties in implementing the IoT in agricultural operations [13]. Designing low-cost, energy-efficient, wireless IoT technologies in autonomous applications is affected by the following dependencies: data latency on power consumption, data scalability on storage and processing cost, and data interoperability on cloud compatibility to store and process various kinds of data [13].

Different IoT devices are coalesced as networks to achieve high-speed data exchanging [4,30]. Therefore, the development of an IoT framework can also solve problems with big data [31]. With more advancements, agricultural operations like protecting, controlling, monitoring, and detecting can be extended using smart phones with the IoT [25]. As an example, time-consuming cattle status monitoring has also benefited from the IoT, allowing farmers to monitor the health and welfare of animals. Also, weed detection through MV primarily consists of deep learning (DL) and image processing [16].

Edge computing enables affordable real-time data transmission in IoT precision agriculture, reducing data package size and alleviating strain on centralized cloud resources. Internet and communication companies leverage their expertise to extend cloud service capabilities to edge networks, shaping the edge computing landscape. Pioneers like Cisco and Huawei have developed comprehensive frameworks and lightweight computing systems. The IoT connects objects through smart technologies, while research explores aerial edge–IoT systems for improved convergence speed and task completion rates [39–42].

3.4. Artificial Intelligence (AI), Machine Learning (ML), and Deep Learning (DL)

AI has a key role in robotics and autonomous systems (RASs). The development of AI in the IoT has contributed continuous data streams [31]. To make agricultural data into meaningful information in decision-making data, mining techniques are required. Various environmental data and farming historical records in big data are analyzed using AI, which finds patterns that are hidden in big data [29]. These discoveries are important in the pest identification, disease detection, yield prediction, and fertilizing plans [25,31] included in agricultural decision support systems. AI has noteworthy potential to accommodate the reduction of food wastage, the improvement of production hygiene, and the monitoring of machines in many stages of agriculture, such as supply chain, agricultural production pattern, and agricultural production process including soil, crop, and water management, as well as disease and pest control [4,8]. Then, AI has the potential to overcome problems in conventional farming [31].

Both ML and DL are subconcepts of AI (Figure 3) [10]. With ML, a computer learns independently to improve the performance of AI, which goes through explicit feature extraction [6]. ML focuses on the theory, performance, and properties of learning systems and algorithms, as it is a high-performance informatics technology for quantifying and understanding data-intensive farming processes [6]. On the other hand, DL can solve problems with combinations of layers and nonlinear functions [10]. To address limitations in the practical implementation of robots, mobile terminals, and intelligent devices in modern agriculture, the integration of machine-learning algorithms has had significant improvement. With machine-learning models, integration into mobile detection algorithms has paved the way for innovative and more precise detection methods, overcoming certain limitations faced by technology adaptation in plant factories, such as limited computer power, insufficient storage capacity, complexities within the plant factory environment, and precision issues related to small target detection [25,43]. Furthermore, machine-learning techniques can mitigate the need for large network sizes and improve the operational speeds of these systems [43]. This advancement has wide-ranging applications, including accurate fruit and pest detection, as well as the optimization and prediction of complex conditions in plant tissue cultures and breeding processes [25,28,44]. Notably, a study (referenced as study 13) successfully applied machine-learning models and artificial neural multilayer regression models to enhance the in vitro regeneration of soybeans by tracking simple, observable traits, such as shoot regeneration frequency and shoot length.

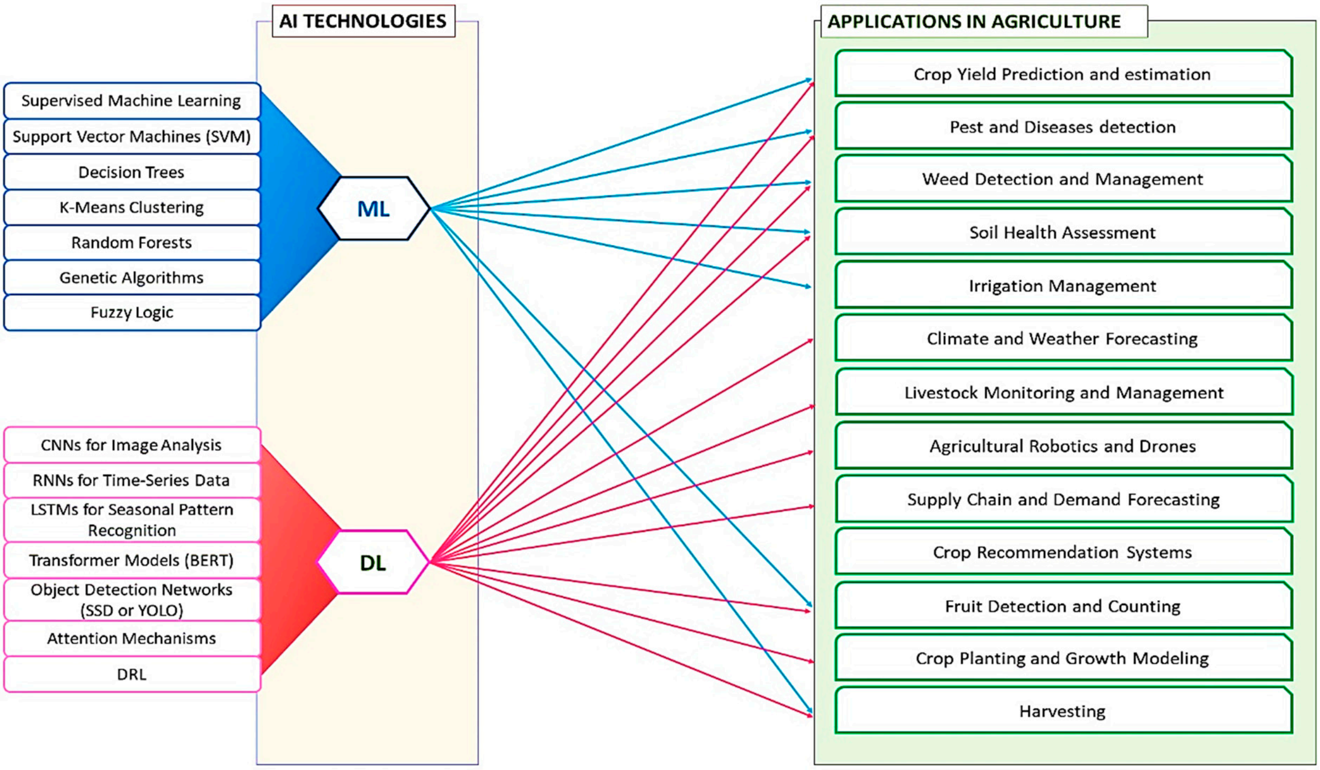

Figure 3. Major AI applications in different practices in precision agriculture.

Also, machine-learning algorithms are employed for data validation, enabling a deeper understanding of dynamic agricultural conditions through data collected from various elements of modern agriculture [6,44]. Despite these advancements, challenges remain in terms of processing speed and the development of efficient information visualization systems for farmers when dealing with big data [6]. Nonetheless, continued research in the fields of big data, the IoT, machine learning, and deep learning holds great potential in overcoming these roadblocks and providing accurate predictions of the dynamic nature of agriculture while identifying new opportunities [1]. Supervised machine-learning techniques, such as support vector machines, decision trees, k-means, random forests, genetic algorithms, deep learning, and fuzzy logic, are several categories of machine-learning models (Figure 3) that play a vital role in agricultural automation, augmenting the intelligence of other technologies, such as smartphones, unmanned aerial vehicles, unmanned ground vehicles, satellite systems, automated machines, agricultural robots, and big data analytics [1,28,31].

Mobile applications have significantly diverted from these AI, ML, DL, and MV technologies [10]. ML algorithms in big data are also critically essential because this integration can learn from data to create decisions, data-based prospects, and predictions. Due to the intricate input data requirements of machine learning (ML) and deep learning (DL), the initial stage of adopting ML models in precision agriculture may encounter significant obstacles in terms of the time and cost involved in gathering the necessary data from commercial farms [1,6,30]. However, with the continuous advancement of IoT sensors, AI-based autonomous machines or robots together with cloud computing, edge computing, and blockchain can support overcoming this difficulty during the transforming, storing, and processing of data in the creation of ML models [27,36,41]. Accordingly, ML is able to be used to solve diverse issues in agriculture related to yield prediction, crop quality, disease detection, weed detection, species identification, animal welfare, livestock production, water management, and soil management [6,45]. Common principles of ML techniques are clustering, decision trees, instance-based models, regression, artificial and deep neural networks, ensemble learning, support vector machines, and Bayesian models [6]. A study proved that ML was a powerful tool for analyzing data to monitor inputs and outputs aiming to optimize plant tissue culture protocols [44].

Smart farming is technology that relies on its implementation with the use of AI and the IoT in cyber-physical farm management [28]. According to current applications, AI has been involved in soil management, crop management, disease management, weed control, etc. Examples are the fuzzy-logic-based soil risk characterization decision support system (SRCDSS), management-oriented modeling (MOM), artificial neural networks (ANNs), CALEX, PROLOG, computer vision systems, ANN-GIS, invasive weed optimization (IWO), and support vector machines [4]. One key application of AI is a mobile expert system where farmers can use their smartphones for disease diagnosis, species identification, and soil health analysis with the help of mobile apps. In addition, AI is a real-time analyzer of satellite images when the progress of farming is tracked with satellite imagery [24]. With AI applications, precision agriculture now has a scientific background, which helps to make precision agriculture more formalized to perform optimal agriculture outputs [29]. In the future, AI may be improved to deal with the dynamic nature of agricultural microclimates, as it is now facing difficulties finding a single standard solution for that heterogeneity. The existing experience gap between AI researchers and farmers hinders the complete understanding of agricultural problems and solutions. To eliminate this obstacle, the knowledge of farmers, agricultural professionals, and AI researchers should be linked. In spite of this, accessibility and privacy protection problems when working with huge amounts of data should be addressed to deliver more skillful AI [8,16].

3.5. Guidance Systems

Guidance systems use GPS (global positioning system) technology to provide farmers with real-time information about their equipment locations and herd-grazing locations, enabling them to optimize field operations such as planting, harvesting, and herding [1,12]. The limited number of satellites, poor signal strengths, and lack of reliable connectivity were overcome by introducing a GNSS (global navigation satellite system), which then replaced labor-intensive, time-consuming farm operations with more effective methods, such as VRA [11,31]. Previously, agricultural inputs were performed manually, and during Agriculture 3.0, they were performed mechanically using digitalized machines [2]. With rapid commercialization, agricultural machinery services have emerged that require efficient management to prevent overuse or underuse issues. For the understanding of agricultural machinery, GNSS plays a crucial role in optimizing effectivity and efficiency [46]. The new trend of GNSS-enabled devices in the fully automated steering of tractions is saving time, labor costs, and money [2]. Precision agricultural robots require high-resolution navigation solutions [47]. Similarly, agricultural rovers and robots are effective only when precisely guided in their actions [45]. Some studies introduced DL propagation models in GNSS fused with inertial navigation data sets for precision agriculture [47]. One example is electric seeders with optical fiber detection technology that were developed and tested successfully [3]. The new development of software-based farm management solutions for GIS encourage the automation of data collection and analysis of supervising, storing, decision making, and farm management.

3.6. Blockchain Technology

Blockchain is defined as a decentralized, distributed database that maintains a continuously growing list of ordered records or blocks, which was first used in cryptocurrency [15,48]. Blockchain offers data transparency, immutability, and reliability, which improve the mutual trust between various parties in the supply chain [15]. As this technology eliminates the obstacles of corporations, this was introduced to precision agriculture, increasing the easiness of the integration of digital technologies into agriculture. This step provides solutions to some technical challenges in smart farming, furnishing the remote monitoring and controlling of farm equipment through the "IoT applied Greenhouse Monitoring System" [15,48]. One such challenge is an insufficient and insecure infrastructure for data sharing. Another challenge is the delay of remote-sensing satellites in detecting the variability of croplands. Therefore, as a solution for the above decentralization, anonymity, and security problems in the IoT in smart farming, blockchain has been proposed, expecting lightweight, distributed, decentralized, and transparent security and privacy [5,48]. Blockchain can assist with having a reliable, faster, and secure platform to monitor farm operations, although it is still in its early stages of maturity [15,48]. As information can be communicated securely in a distributed network [48], with the help of blockchain this can improve the planning of schedules for various agricultural processes, such as irrigation water sharing, energy consumption, the incorporation of machines and labors, and tasks for robot coalitions and autonomous UAVs [15,28]. Especially in the food supply chain, this is a crucial point because of food safety issues, as well as asymmetric and fragmented information occurring related to the insufficient supply chain [1,8,10].

3.7. Robotics and Autonomous Systems

Most recently, autonomous farming has involved a high degree of the use of robotics, sensors, drones, and remote sensing to perform various agricultural tasks, such as planting, spraying, harvesting, and weeding, while reducing labor costs and improving efficient decision making [3,45]. RASs are a combination of emerging modern technologies that have key applications in both agricultural production processes and production patterns. Mobile robots equipped with various sensors, actuators, and ML algorithms are key enablers to automatically handle variability and uncertainty in farming practices [47]. Key applications of RAS in agricultural patterns are in plant factories, 3D food printing, and biodiverse farming, whereas autonomous farming, aerial monitoring, and automated husbandry have become new applications in agricultural production processes [8]. However, agricultural RASs are required to be improved to fulfill efficient work with accurate guidance, autonomous navigation, and accurate detection of dynamic agricultural environments (changing appearances, growth stages, weather conditions, object overlapping, etc.). Intelligent actions, such as robot-assisted plant phenotyping, fruit counting, fruit harvesting, fruit counting, leaf peeling, selective spraying, and 3D mapping, are demonstrated and currently employed applications of RASs [8]. Auto-steered agricultural vehicles are also used in many field operations [3], such as tilling, planting, chemical applications, and harvesting. These machines, like harvesters, sprayers, tractors, planters, and mechanical weed controls, use guidance systems either with light bars [13] or a GNSS [2,20]. These guidance systems visualize the positions of equipment to prevent skips and overlaps, which is important in variable rate applications.

3.8. Artificial Satellites, Unmanned Aerial Vehicles (UAVs), and Unmanned Ground Vehicles (UGVs)

Artificial satellites, such as American Landsat satellites, the European Sentinel-2 System, the RapidEye constellation satellite system, the GeoEye-1 system, and WorldView-3, for remote sensing help to generate remotely accessible data in multispectral forms [8]. The establishment of these intelligent remote-sensing satellites has provided full coverage for collecting agricultural information [8,31,49]. More recently, ubiquitous and affordable technologies such as drones, crews, and aircraft have allowed images to be captured closer to the ground and at a higher frequency, increasing detail and functionality [45]. UGVs acquire high-resolution data for weed identification and control, selective pesticide spraying, soil analysis, and crop scouting, while scouting robots accomplish specific targets [49] such as mechanical weeding (Oz robot), spraying (GUSS autonomous sprayer), fertilizing, mapping, and seeding (RowBot system), as well as vineyard management (VineRobots) [4,50]. Information, including imagery data generated by satellites, UAVs, and UGVs, is the paramount thing in precision agriculture, as it supports vegetation patch identification, weed recognition, pest attack detection, observation of environmental stresses, and accurate classification in VRT [18,45]. Not only that, in other agricultural disciplines, such as aquaculture, agroforestry, and forestry, imagery data play a considerable role because they can cover large areas when gathering information, and these data are reproducible [20]. Data from satellites, UAVs, and UGVs are supported by detailed ground survey data processed with ML and DL algorithms in order to make them usable and meaningful information [18].

For example, in forestry, determining forest densities is labor-intensive and time-consuming, although it is an important parameter when combatting climate change. Recently, data of tree type distribution could be achieved over a wide area of forest with the help of hyperspectral images and NDVI and RGB images from UAVs such as Sentinel-2 [13,16]. Likewise, in remote sensing satellites and drones play a big role in monitoring deforestation and obtaining accurate coverage of vegetative types and classification of tree species and are more effective than other UAV or LiDAR data [14,34]. Although there are limitations, drone and remotely piloted aircraft usage is dramatically increasing while providing precise information for precision agriculture through hyperspectral sensors, multispectral cameras, and other novel technologies [14]. This is a cost-effective, promising method for monitoring large-scale farms or crop lands [4], as well as forest areas [14].

3.9. High-throughput Phenotyping

High-throughput phenotyping has emerged as a promising approach to enhance precision agriculture by allowing the rapid and accurate measurement of plant traits [51] quantitatively and qualitatively [22,52]. Accurate and high-throughput plant phenotyping is important for accelerating crop breeding [52]. This technique uses advanced technologies such as remote sensing [40,42], spectral imaging [41], and robotics [53] to collect large amounts of data on plant characteristics, such as growth rate, yield, disease resistance, and morphology [51,54,55]. By collecting and analyzing these data, farmers can gain insights into how their crops are performing and make more informed decisions about things like fertilization, irrigation, harvesting, and pest management [22,54]. High-throughput phenotyping can also help breeders to develop new crop varieties that are better adapted to local growing conditions and can produce higher yields (Figure 4) [51]. A full range of visible and near-infrared hyperspectral data enables ML techniques such as LSR (least squares regression) to predict specific biochemical and physicochemical traits beyond simple vegetative indices [56]. ML-based precision agriculture systems have AI background [52,54], and therefore, when detecting diseases, pests, nutrient deficiency, and weeds, stressed responses are detected using high-quality images generated with UGV or UAV remote sensing, hyperspectral imaging, and satellite imaging to support high-throughput phenotyping [57]. Ultimately, high-throughput phenotyping has the potential to revolutionize agriculture by enabling more the precise, real-time, and efficient monitoring of farming practices that can improve crop productivity, reduce environmental impacts, and increase food security [54].

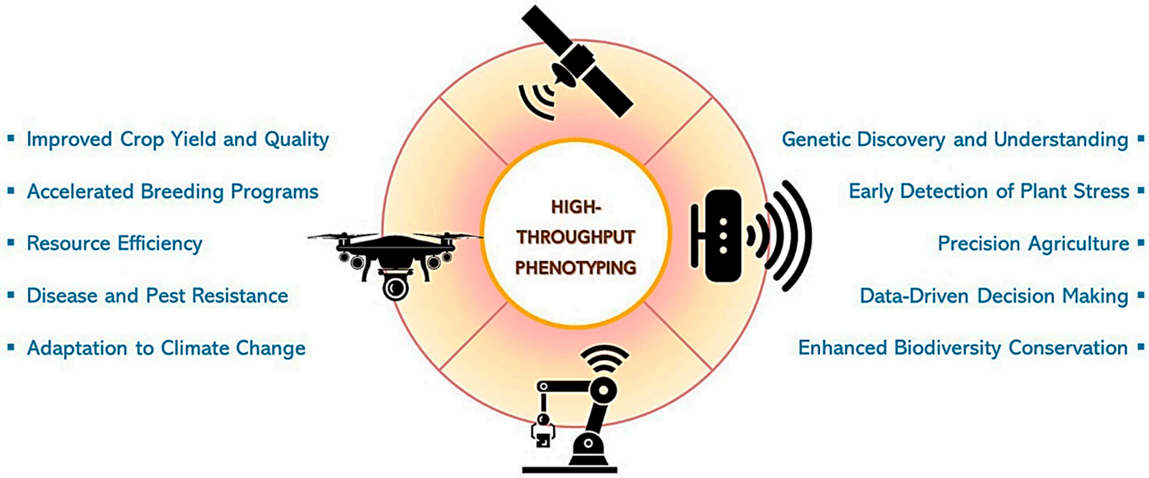

Figure 4. Importance of high-throughput phenotyping in agriculture.

The traditional methods of plant breeding have limitations in terms of time, cost, and accuracy. HTP, on the other hand, uses nondestructive and rapid methods to gather data on a large number of plants, allowing breeders to identify traits of interest more efficiently [58]. A study by Yang et al. (2017) [59] described using high-throughput phenotyping (HTP) and quantitative trait locus (QTL) mapping to investigate the genetic architecture of maize plant growth. The authors collected data on various traits related to plant growth, such as plant height, leaf area, and biomass, using HTP techniques, such as imaging and spectroscopy [59]. Unmanned aerial systems (UASs) have brought about a revolutionary change in field high-throughput phenotyping by providing a platform for different sensors to collect remote-sensing data in field-scale trials. These sensors include regular RGB cameras, multispectral-imaging cameras, hyperspectral-imaging cameras, thermal-imaging sensors, and light detection and ranging (LiDAR) sensors that enable the nondestructive estimation of plant traits, such as yield, biomass, height, and leaf area index. This is a significant advancement in agriculture, allowing for the high-throughput phenotyping of crops. In comparison to ground-based sensors, UASs increase the frequency and throughput for phenotyping, while being cost-effective and providing high-resolution images as compared to satellite-based techniques. The phenotypic traits can be used to select crops with high yield and strong stress resistance, such as disease and salt resistance, ultimately leading to improved production [60].

As technology advances, the future of high-throughput phenotyping (HTP) appears promising. Multiple HTP technologies, such as drones, sensors, and artificial intelligence, can be integrated to facilitate more efficient and accurate phenotyping, which can aid breeders in identifying desirable traits and making better selections. HTP can also be used for precision agriculture, where farmers can leverage data generated using HTP technologies to make informed decisions on inputs such as fertilizers, pesticides, and water to increase efficiency, reduce waste, and improve yield. HTP can also play a crucial role in climate change research by identifying crop varieties that can better adapt to changing climate conditions, thereby ensuring food security. Lastly, HTP can be used in developing countries to enhance food security and improve crop productivity, but it requires the development of affordable and accessible HTP technologies that can be easily adopted by farmers in those countries [56,58,59].

3.10. Telematics

Broadband connectivity is required when addressing challenges in the adoption, cost, and environment of smart technologies. Inadequate connectivity leads to inefficiencies, impacting machine downtime, human error, and real-time information availability. Limited connectivity not only affects profitability but also hampers the adoption of real-time-reliant precision agriculture. Producers with adequate connectivity are expected to be more efficient, highlighting the importance of connectivity in agriculture [61]. The transformative potential of 5G and beyond mobile networks in driving business and societal change is being recognized. Considering environmental concerns and climate change, the role of mobile networks in fostering sustainability and innovation is questioned. Sectors like smart agriculture, forestry, biodiversity monitoring, and water management are crucial for sustainable resource utilization. Evaluating the capabilities of 5G and 6G networks, including current and future support, is essential for identifying use cases and the requirements in these domains [34]. As an example, a study in Thailand designed telematics-equipped tractors to assist farmers in efficiently managing their machinery, optimizing performance and enhancing overall productivity. In addition to improved management capabilities, these tractors offered features such as theft prevention, effective maintenance monitoring, and machine operation tracking [62].

4. Studies of Successful Precision Agriculture Proposals and Implementations

The article [63] reviewed advancements in automated fruit-harvesting robots for sweet peppers and apples, highlighting the successful implementation of a sweet-pepper-harvesting robot called 'Harvey', which effectively addressed detection, grasp selection, and manipulation challenges. Similarly, the apple-harvesting robot utilized a picking manipulator and a catching manipulator, along with machine vision and prioritization algorithms, for efficient harvesting. The article emphasized interdisciplinary collaboration for further advancements in automated harvesting systems and the importance of intelligent systems like deep learning and crop management software for enhancing productivity and sustainability in modern agriculture. Field trials were conducted with Harvey for sweet peppers in Australia, while robotic picking systems for apples were tested in a Washington orchard in the U.S. [64,65]. Israel has successfully implemented autonomous robotic technology in their crop fields, paving the way for the commercial use of AI harvesters. Tevel Aerobotics Technologies developed an autonomous fruit-picking system that utilized flying robots tethered to an autonomous vehicle, enabling accurate fruit picking, extended work hours, and additional tasks like tree thinning and pruning. This system addressed labor shortages, reduced fruit production costs by approximately 30%, provided real-time updates to farmers via a mobile app, and aimed to tackle challenges faced by the agriculture industry. Tevel plans to introduce its innovative solution to the global market, catering to fruit farmers worldwide and contributing to the growing agricultural robotics sector [66].

Senapathy et al. introduced the IoTSNA-CR model from their study, which leveraged IoT technology to classify soil nutrients and provide crop recommendations, aiming to optimize fertilizer usage and maximize productivity for farmers. The implementation of AI harvesters in Israel showcases the potential of artificial intelligence, machine learning, cloud services, sensors, and automation for delivering real-time information and support to farmers. The proposed IoTSNA-CR model incorporated IoT sensors, cloud storage, machine-learning techniques, and an optimized algorithm (MSVM-DAG-FFO) to achieve high accuracy in soil analysis. The model allowed farmers to maintain soil information in the cloud, reducing costs and improving productivity. Experimental validation confirmed the effectiveness of the model for crop prediction and soil health maintenance, emphasizing the importance of real-time data collection and expanding data sets and regular application use for informed decision making and soil quality enhancement [49]. The use of unmanned aerial systems (UASs) and unmanned ground vehicles (UGVs) in precision agriculture for inspecting insect traps in olive groves was proposed by [49], with a cooperative robot architecture using UAS and UGV systems evaluating vision-based navigation algorithms and augmented reality tags for return and landing. The results demonstrated the feasibility of the architecture for automating inspections and improving pest control policies. Challenges remain in addressing real-world conditions and optimizing image capture. Future work includes real-world scenarios and long-term mission capabilities of UAS vehicles [49].

Two studies from University Tenaga National, Malaysia, present autonomous and robotic machineries to deal with fertilizer and pesticide spraying. The authors of [67] presented a low-cost agricultural robot for fertilizer and pesticide spraying, crop monitoring, and pest detection. The prototype system operated autonomously, reducing labor costs, although productivity slightly lagged behind human workers. An autonomous organic fertilizer mixer was developed in [68] based on IoT technology to reduce labor costs and enhance efficiency. The improved mixer allowed remote monitoring, updates, and alerts, aiming to further streamline the organic fertilizer-mixing process. A harvesting robot system for cherry tomatoes in greenhouses was developed by the Beijing Research Center of Intelligent Equipment for Agriculture. This new harvesting robot system for cherry tomatoes was designed featuring a railed-type vehicle, a visual servo unit, a manipulator, and picking end-effectors. Field tests demonstrated an average picking time of 12 s per bunch of tomatoes with a success rate of 83% [69]. Also, X. Jin et al. [70] designed a small-sized vegetable seed electric seeder with power drive and optical fiber detection technology, providing high efficiency and precision by monitoring sowing conditions in real-time for different seed sizes (Table 2).

The Cooperative Heterogeneous Robots for Autonomous Insects Trap Monitoring System experiment in Portugal proposed a cooperative UAS and UGV system for olive grove inspection that verified the feasibility and robustness of the multiple-cooperative robot architecture in an olive inspection scenario [49]. Russian researchers Filipe et al. [7] proposed an approach for dynamic robot coalition that combined fuzzy coalition games and smart contracts to form a dynamic and trusted coalition. It enabled the collection and dissemination of information from robot sensors in a shared space. Integration of the IoT with blockchain allows the continuous tracking of food in precision agriculture tasks, ensuring transparency and verification at each stage. Precision agriculture is a strategy that uses advanced technologies, like sensors, remote sensing, and data analytics, to improve agricultural management decisions and increase productivity, profitability, and sustainability. Machine-learning models have been integrated with IoT sensors to develop intelligent sensors for generating of big amount of data. In the study of Smolka et al. [71], a microchip capillary electrophoresis sensor was used for soil nutrient analysis, demonstrating its general sensitivity to ions in liquids, particularly NO3, NH4, K, and PO4. The sensor exhibited strong linearity and detected important plant nutrients, which could contribute to future developments in digital agriculture. Insufficient power infrastructure is one obstacle in adapting novel technologies in agricultural fields. Researchers successfully developed an IoT-based solar-energy-powered smart farm irrigation system in the United Arab Emirates that harvested renewable energy for smart farm irrigation [72]. This study outcome paved the way to developing three operation modes that are available for farmers' use.

VRT is a major constituent in precision agriculture that deploys field maps, GPSs, and GNSSs to establish the precision of input applications. A study of a data fusion method for yield and soil sensor maps [21] evaluated fusion results on fields, highlighting their usefulness in decision support for drainage, irrigation, and variable yield goals. It uncovered hidden areas of lost yield potential using soil sensing, EC, pH, organic matter, and topography data fusion. Researchers in Beijing, China, developed a new method using image segmentation and pixel-level visual features to accurately classify field and road areas in GNSS recordings of agricultural machinery, surpassing existing methods and demonstrating a superior performance for high-frequency GNSS trajectories [46]. A multisensor data fusion approach was used by Whattoff et al. for creating variable depth tillage zones [27]. Variable depth tillage (VDT) reduced costs, labor, and fuel consumption. A multisensor data fusion approach was developed to map soil properties for VDT implementation, showing the depth of tillage needed in different areas. This approach proved useful in guiding VDT operations for efficient soil management.

One study in Germany integrated computer-aided farming, an IoT-based pH sensor, and VRT for effective VR liming, and the lime requirement was successfully determined in situ by establishing a buffer curve [11]. A field evaluation of a VR aerial application was conducted in the study of Martin and Yang [23] utilizing prescription maps for aerial glyphosate applications with variable rate nozzles. Accurate spray deposition within 20 feet of the target was confirmed using multispectral imagery, boosting confidence in variable rate application and encouraging adoption. Italian authors Corbari et al. [73] explored the integration of a satellite-driven soil–water balance model and meteorological forecasts to enable precision smart irrigation. It discussed model performance and emphasized the importance of using consistent data for the calibration and validation of soil hydrological parameters [73]. The short communication of Jang et al. [22], "Spatial Dependence Analysis as a Tool to Detect the Hidden Heterogeneity in a Kenaf Field", presented high-throughput phenotyping as having potential in precision agriculture. This study demonstrated its application for revealing field heterogeneity and suggested its use for better analysis and management in plant breeding and precision agriculture. In [57], Kim et al. emphasized the importance of evaluating drought effects during the vegetative stages of soybean, indicating the potential of using phenotypic traits as selection indicators for breeding drought-resistant soybean cultivars, especially considering the escalating crop damage caused by drought and global warming.

Another study asserted precision agricultural applications in agroforestry. Tree species identification and classification is important when combatting climate change, as well as monitoring ecosystem health 17. Researchers used images from SENTINEL-2 to propose methods to determine tree type distribution in a wide forest area using UAV images [14,17]. They effectively distinguished evergreen, deciduous trees, and grassland areas, aiding in forest planning and preparing for climate change impacts. Ma et al. [14] used a random forest classifier with satellite images to improve texture feature separation among tree species. The overall classification achieved 86.49% accuracy and a 0.83 Kappa coefficient, although altitude, slope, and aspect influenced tree distribution. These outcomes were important in species classification and biodiversity monitoring, as well as in informing inventory estimation [14].

An evaluation of soybean wildfire prediction via hyperspectral transmission imaging was performed with Python, which detected bacterial wildfire in soybean leaves where different varieties exhibited distinct spectral signatures. This allowed the precise detection and differentiation of healthy and diseased plants effectively with high accuracy (97.19% and 95.69%) in early disease detection, confirming its usefulness in soybean plant monitoring [32].

Aasim et al. [44] focused on establishing the efficient and reproducible in vitro regeneration of common beans through a combined approach of in vitro regeneration and machine-learning algorithms. ML models, particularly ANN algorithms, were used for prediction and optimization. The ML and ANN models demonstrated superior performances, proving their efficacy in analyzing and optimizing complex conditions in plant tissue culture protocols for breeding purposes.

A computer vision and deep-learning-enabled weed detection model for precision agriculture was proposed in [25] integrating computer vision, DL, the IoT and a smartphone. The proposed CVDL-WDC technique combined multiscale object detection and ELM-based weed classification. The results showed improved outcomes over recent approaches, and future extensions included integration with IoT and smartphones.

At the same time, a novel procedure involving machine learning and UAV-based imagery was developed to accurately identify crops and weeds, offering potential integration into autonomous weed management systems and contributing to improved precision agriculture practices with reduced resource consumption [45].

At Sairam Institute of Technology in India, a flood detection system based on the IoT, big data, and a convolutional deep neural network (CDNN) was developed [30]. The CDNN algorithm demonstrated superior accuracy, achieving an impressive accuracy of 93.23%, a sensitivity of 91.43%, a specificity of 91.56%, a precision of 92.23%, a recall of 90.36%, and an F-score of 91.28% with a data set of 500. The flood detection system outperformed existing methods and holds potential for further enhancement through the integration of IoT devices and advanced algorithms, ensuring improved flood detection capabilities.

In order to alleviate the strain on agri-food production, the introduction of alternative nutrient sources can be explored, particularly through the utilization of cultured meat and 3D-printed meat as substitutes for traditional animal meats, thus reducing the demand on animal husbandry. In China, the production of lab-grown meat using muscle stem cells necessitated edible 3D scaffolds created through electrohydrodynamic (EHD) printing, showcasing the significant potential of prolamin scaffolds for cultivating cultured meat [74]. Similarly, the construction of 3D-printed meat analogs from plant-based proteins has been conducted, improving the printing performance of soy protein- and gluten-based pastes facilitated by rice protein. This study examined the rheological properties and printing performances of edible inks made from soy protein isolate (SPI), wheat gluten (WG), and rice protein (RP). Increasing the proportion of rice protein improved the 3D-printing performance, holding potential for the 3D printing of plant-based foods and constructing meat analogs simulating real meat properties [75].

Several studies have shown why the adaption rate of these studies is slow, and one case study conducted in Chumphon Province, Thailand, by Kasetsart University examined the adoption of smart farming technology among durian farmers, highlighting that factors such as age, occupation, access to extension services, and farm size influenced technology adoption, with younger farmers having larger farms being more inclined to adopt technology, resulting in decreased labor and fertilizer expenses, which emphasized the importance of providing continuous training and promoting extension services for sustainable adoption [76].

Table 2. Studies of successful precision agriculture proposals and implementations.

Exploration	Location	Technology Used	References
Usage of Smart Contracts with FCG for Dynamic Robot Coalition Formation in Precision Farming	St. Petersburg, Russia	IoT, agricultural robotics, blockchain technology with hyperledger fabric platform	[7]
A mobile lab-on-a-chip device for on-site soil nutrient analysis	Vienna University of Technology, Vienna, Austria	Micro-chip capillary electrophoresis sensor device	[71]
Development and test of an electric precision seeder for small-sized vegetable seeds	Henan University of Science and Technology, Luoyang, China	Optical fiber detection technology	[70]
Smart irrigation forecast using satellite LANDSAT data and meteo-hydrological modeling	Politecnico di Milano, Milan, Italy	IoT sensors	[73]
IoT solar-energy-powered smart farm irrigation system	American University of Sharjah, Sharjah, United Arab Emirates	Chip controller with built-in WiFi connectivity, IoT	[77]
Autonomous fertilizer mixer through the Internet of Things (IoT)	University Tenaga Nasional, Selangor Darul Ehsan, Malaysia	IoT	[68]
Design and development of a robot for spraying fertilizers and pesticides for agriculture	University Tenaga Nasional, Selangor Darul Ehsan, Malaysia	Agricultural robots	[67]
25 years of Precision Agriculture in Germany—A retrospective	Federal Research Institute for Cultivated Plants, Bundesallee, Braunschweig	Computer-aided farming, IoT-based pH sensor, VRT	[11]
Field Evaluation of a Variable Rate Aerial Application System	United States Department of Agriculture, Texas, USA	UAVs, VRT, high-resolution camera	[23]
A harvesting robot system for cherry tomatoes in greenhouses	Beijing Research Center of Intelligent Equipment for Agriculture, Beijing, China	Agricultural robots	[69]
Characterization of Tree Composition using Images from SENTINEL-2: A Case Study with Semiyang oreum	Republic of Korea	SENTINEL-2 satellite, image analysis, remote sensing,	[17]

Table 2. *Cont.*

Exploration	Location	Technology Used	References
Innovation in the Breeding of Common Beans Through a Combined Approach of in vitro Regeneration and Machine-Learning Algorithm Citation	Sivas, Turkey	ML and ANN models	[44]
3D-Printed Prolamin Scaffolds for Cell-Based Meat Cultures	Suzhou, Jiansu, China	3D-printing technology, high-precision microstructures for biomedical applications	[74]
Construction of 3D-printed meat analogs from plant-based proteins: Improving the printing performance of soy protein- and gluten-based pastes facilitated by rice protein	Nanchang, China	3D-printing technology	[75]
Tree Species Classification Based on Sentinel-2 Imagery and Random Forest Classifier in the Eastern Regions of the Qilian Mountains	Qilian Mountains, China	SENTINEL-2 images	[14]
Detection of flood disaster system based on IoT, big data, and convolutional deep neural network	Sairam Institute of Technology, India	CDNN classifier, ANN, DL, deep-learning neural network (DNN)	[30]
A multisensor data fusion approach for creating variable depth tillage zones	Newbury, UK	VRT	[27]
A Data Fusion Method for Yield and Soil Sensor Maps	Veris Technologies Inc., Kansas, USA	IoT, GPS, soil data maps, yield data maps	[21]
Computer Vision and Deep-learning-enabled Weed Detection Model for Precision Agriculture		Computer vision, DL, IoT, smartphone	[25]
Short Communication: Spatial Dependence Analysis as a Tool to Detect the Hidden Heterogeneity in a Kenaf Field	Jeju National University kenaf-breeding field, Jeju, Republic of Korea	LISA analysis	[22]
Evaluation of Soybean Wildfire Prediction via Hyperspectral Imaging	Kyungpook National University, Daegu, Republic of Korea	Hyperspectral transmission imagery, multispectral camera, Python	[32]
Field road classification for GNSS recordings of agricultural machinery using pixel-level visual features	Beijing, China	GNSS	[46]
A New Procedure for Combining UAV-Based Imagery and Machine Learning in Precision Agriculture	Alma Mater Studiorum University of Bologna, Bologna, Italy	UAV, GIS, ML	[45]
Cooperative Heterogeneous Robots for Autonomous Insects Trap Monitoring System in a Precision Agriculture Scenario	Campus de Santa Apolónia, Bragança, Portugal	UAV	[49]
Drought Stress Restoration Frequencies of Phenotypic Indicators in Early Vegetative Stages of Soybean (Glycine max L.)	Rural Development Administration, LemnaTec, Germany	RGB images, Python	[57]
Durian Farmer Adoption of Smart-Farming Technology: A Case Study of Chumphon Province	Kasetsart University, Bangkok, Thailand	IoT, UAV	[76]

5. Barriers to Adapting New Technologies in Precision Agriculture

High-tech technologies from the fourth industrial revolution have the potential to revolutionize the agriculture industry, enabling more efficient and sustainable practices while improving productivity and reducing resource wastage. The adaptation of these intelligent, advanced technologies in precision agriculture is still in its early stages, and as such, there exist several barriers (Table 3) that must be addressed to facilitate the transformation of precision agriculture. However, it is essential to carefully consider the specific requirements, challenges, and implementation considerations for each technology in the context of the agricultural operation at hand.

A lack of interdisciplinary skills is one of the major roadblocks, as big data engineers, data analysts, and data scientists do not have an agricultural background. On the other hand, farmers with long experience and practical knowledge are not educated enough to handle high technology like artificial intelligence [8]. The production and development costs of high-tech applications and the capital for establishing them in real-world agriculture are also high [78]. This high cost of the production and implementation of advanced technologies may render them inaccessible to small-scale farmers, who may lack the financial resources to invest in such technologies [79].

Furthermore, the unavailability of affordable technologies for small-scale farmers may create a digital divide, where only large-scale, educated farmers may be able to benefit from such technologies [20,80]. In the unequal distribution of resources in the world, it is difficult for certain groups to reach for such new technological inventions. The implementation of precision agriculture trends in many developing agricultural countries has become a difficult task due to lack of necessary funds, lack of confidence in the technologies, lack of proper infrastructure, lack of necessary resources, etc. [8,76,78,81]. Additionally, the lack of sufficient energy in rural areas hinders the use of new technologies, even as science strives to develop wireless power transfer methods and ambient or on-site energy-generating methods [8]. Furthermore, low digital literacy and unequal accessibility to digital technologies in rural areas, coupled with connectivity issues, pose significant challenges in establishing sustainable intelligent technologies in agricultural processes [20,79,82].

Limited computer power, storage capacity, and processing speed and high energy consumption by batteries are some technical obstacles in precision agricultural adaptations [43], especially when dealing with big data. In addition, collecting and analyzing data from agricultural operations may raise concerns about data privacy and security [4]. These data are heterogenous and, when transferring and storing vast amounts, software platforms from private companies are needed. This reveals some ownership controversies of data [78]. Blockchain interoperability, privacy problems, data leakage, cyber terrorism, and some nonrepudiation issues associated with big data are still difficulties in precision agriculture [5,8,78,83], thereby causing farmers to be reluctant to share their data with third-party service providers [4,16]. In many areas where agriculture is practiced, reliable internet connectivity, which is essential for collecting, transmitting, and analyzing data, may not be readily available [7] and, thus, may affect the absorption capacities of novel technologies [80].

The implementation of trending technologies requires technical expertise that may be unavailable in some regions, leading to job displacement and unemployment as new technologies increase the demand for highly skilled laborers while decreasing opportunities for nonskilled workers. This has implications for both small-scale and family commercial farmers [8,9,20,79]. To effectively use these technologies, farmers and service providers may need training. However, different technologies may not be compatible with each other or with existing agricultural machinery and equipment, which could limit the adoption of advanced technologies in precision agriculture [2,8,84]. Furthermore, the presence of bias and discrimination intertwined with information technology, education, risk-taking attitudes, and western power structures constitute formidable obstacles, hindering the equitable dissemination and advancement of smart-farming technologies, particularly within developing nations [80,85]. This highlights the need for policies on data sharing that cater to both the public and farming industries and are sufficient to ensure data security [20].

Table 3. Advantages, limitations, and main applications of advanced technologies in precision agriculture.

	Advantages	Limitations	Main Applications
Big Data	Data-driven insights Resource optimization Enhanced decision making [1,78]	Robust data management infrastructure Data privacy and security considerations Challenges in integrating heterogeneous data sources [8,78]	Crop yield forecasting Disease and pest management Precision agriculture Predictive analytics Farm management systems [1,6,8]
Machine Vision Technologies	Automated image capture and analysis Enhanced efficiency Reduction of reliance on manual labor Precise monitoring of plant health	Dependence on high-quality images Challenges in image interpretation under varying lighting and environmental conditions	Crop monitoring Disease detection Quality assessment Plant phenotyping Weed detection Yield estimation [8]
IoTs (Internet of Things)	Real-time monitoring Facilitation of data-driven decision making Optimization of resource usage Early detection of issues [78]	Requires reliable network infrastructure Data management and integration challenges Maintenance of hardware [8,16]	Precision agriculture Smart irrigation systems Livestock monitoring Environmental sensing Fishery management Remote farm management [8,13,16,78]
Artificial Intelligence (AI)	Automation and predictive analytics of decision support systems Enhancment of crop management, disease detection, and yield optimization [16,85]	Requires large data sets Computational resources Challenges in explainability and interpretability of AI models	Crop yield prediction Disease detection Pest management Image recognition Mobile expert systems Anomaly detection [8,85]
Machine Learning (ML)	Enables pattern recognition Predictive modeling Data analysis Assists in crop disease diagnosis, yield prediction, and recommendation systems [6,14]	Requires labeled training data, model training, and optimization Potential bias in algorithmic decision making [6,28]	Crop disease diagnosis Yield prediction Soil analysis Yield optimization Breeding optimization Farm management systems [6,28,44]
Deep Learning	Complex pattern recognition Analysis of large data sets Suitable for image and signal processing tasks, disease detection, and plant phenotyping [25,31]	Requires substantial computational resources Large labeled data sets Potential overfitting with limited data [31,86]	Plant disease detection Plant classification Object recognition Plant phenotyping Image-based analysis [25,31,86]
Guidance Systems	Precise navigation and operation of agricultural machinery Reduces overlaps and optimizes resource usage [47]	Requires accurate positioning systems Potential dependency on external signals Challenges in complex terrains [78]	Precision agriculture Automated field operations Autonomous machinery Variable rate application [34,47]
Blockchain Technologies	Provides transparency, traceability, and secure data sharing in the agricultural supply chain Enables trust, verification, and fair transactions	Scalability challenges Energy consumption Integration complexity	Supply chain management Food traceability Quality assurance Fair trade [8,16]
Robotics and Autonomous Systems	Enables automation, precision tasks, and labor reduction Assists in autonomous field operations, weeding, harvesting, and data collection [63,78]	Cost of implementation Limited adaptability to changing field conditions Detection accuracy and technical challenges in complex environments [8,63]	Automated harvesting Weeding Field monitoring Planting Labor-intensive operations [8,34,63]
UAVs (Unmanned Aerial Vehicles)	Remote sensing Aerial imaging Monitoring of large agricultural areas Provides timely data collection Improved field management Cost-effective crop assessment [34,78,86]	Restricted flight regulations Limited payload capacity Challenges in data analysis and interpretation Expensive and break easily [14,34]	Crop monitoring Mapping Aerial imaging Precision agriculture Disease detection [8,34,76]
Unmanned Ground Vehicles	Ground-level monitoring Data collection Field operations in various terrains Assists in precision spraying, mapping, and soil sampling	Limited mobility in challenging environments Dependence on stable terrain conditions	Precision spraying Soil sampling Field mapping Data collection [49,78,86]
High-Throughput Phenotyping	Facilitates rapid and non-destructive measurement of plant traits and characteristics Enhances breeding programs, genetic analysis, and crop improvement [56]	Cost of high-throughput phenotyping platforms Challenges in data interpretation Standardization of measurement protocols	Plant breeding Crop improvement Stress tolerance assessment Genetic analysis Trait selection [56,71]
Telematics	Enables real-time monitoring, tracking, and data collection from vehicles Enhances fleet management, route optimization, and driver safety	Requires reliable connectivity Potential data security concerns Challenges in integrating with existing vehicle systems	Fleet tracking Logistics management Fuel efficiency analysis Predictive maintenance Driver behavior monitoring [2]

6. Future Developments Required

In recent years, the agricultural sector has recognized the potential benefits of adopting new digital technologies. However, the slow rate of adaptation can be attributed to several roadblocks and uncertainties associated with these advancements. Despite the challenges, there is a growing demand for organic foods [78], leading to a shift from sustainable agriculture to smart organic farming. To capitalize on this emerging opportunity, certain steps need to be taken.

One crucial aspect is bridging the gap between expertise personnel and farmers. Providing better education, along with vocational training on novel technological applications, can empower farmers to make effective use of new technologies [20,78]. Governments can play a significant role by creating physical, economic, legal, and social infrastructure that supports the establishment of precision agriculture. Investments in energy infrastructure and communication infrastructure, internet connectivity, service markets, consultancy services, and credit markets can instill trust and willingness among farmers to embrace these technologies [2,20,81].

To further enhance precision agriculture, addressing the lack of professional agricultural sensors is paramount. The design of high-quality, high-resolution, and reliable sensors powered by the IoT that are specifically tailored for the agricultural production environment and the monitoring of plant and animal physiological signs is essential [8]. Moreover, integrating wireless power transfer options can eliminate the need for frequent battery replacements. However, special attention should be given to enabling underground or underwater transmission capabilities [8]. At the same time, on-site energy generation with renewable solar power or biogas energy can be considered comparatively to long distance energy transfer [77]. Although capital investment is high for establishment, it is more profitable than grid power.

Cross-technology communication is another crucial aspect that needs to be addressed. Machine vision for animal monitoring, the development of smart phone applications for the real-time tracking of spatial and temporal variations, and the utilization of 6G mobile networks are promising avenues for generating valuable data and informed decisions [34,83]. Additionally, the emergence of new agricultural systems such as smart hydroponics with the IoT and advancements in breeding technologies with DL and ML technologies contribute to the overall progress of precision agriculture.

Future advancements in precision agricultural technologies hold great promise for the agricultural sector. Overcoming the existing roadblocks and uncertainties is essential to unlocking the full potential of these technologies. By focusing on education, infrastructure development, sensor technology, communication systems, and novel agricultural approaches, we can pave the way for a more efficient, sustainable, and productive future in agriculture.

7. Conclusions

Precision agriculture, now part of Agriculture 4.0, harnesses the power of digitalization for improved farming management. The integration of Industry 4.0 technologies has led to notable trends, such as drones, GPS technology, data analytics, and artificial intelligence, enabling informed decision making in farming practices. Despite these advancements, achieving a fully integrated agricultural management system that comprehensively addresses the complexities of the field requires further studies and innovations. Crucially, the development of adaptive and predictive information systems that effectively integrate diverse data sources is essential for ensuring sustainable and intelligent precision agriculture. While precision agriculture offers numerous benefits, it also poses challenges for its widespread adoption. The initial investment in technology, concerns related to data privacy, and compatibility issues with existing farming systems can be significant barriers for small-scale farmers. Moreover, the scalability and adaptability of these technologies to different farming conditions may limit their applicability in certain regions. Overcoming these challenges necessitates the implementation of education and training programs to equip farmers with the necessary skills to leverage these technologies effectively.

This review paper serves as a valuable resource for farmers and companies seeking to adopt Industry 4.0 technologies in agriculture. By providing insights into IoT devices, automation systems, data analytics, and precision-farming techniques, this paper fosters awareness and understanding of the opportunities and challenges in smart farming. Armed with this knowledge, companies can make informed decisions regarding technology investments and strategic planning while promoting sustainable farming practices and collaboration within the industry. By embracing Industry 4.0 technologies, farmers and companies can enhance their agricultural operations, optimize resource utilization, and contribute to the collective progress toward smart farming's promising future.

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