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Perspective

From Smart Farming towards Unmanned Farms: A New Mode of Agricultural Production

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Abstract: Agriculture is the most important industry for human survival and solving the hunger problem worldwide. With the growth of the global population, the demand for food is increasing, which needs more agriculture labor. However, the number of people willing to engage in agricultural work is decreasing, causing a severe shortage of agricultural labor. Therefore, it is necessary to study the mode of agricultural production without labor force participation. With the rapid development of the Internet of Things, Big Data, artificial intelligence, robotics and fifth-generation (5G) communication technology, robots can replace humans in agricultural operations, thus enabling the establishment of unmanned farms in the near future. In this review, we have defined unmanned farms, introduced the framework of unmanned farms, analyzed the current state of the technology and how these technologies can be used in unmanned farms, and finally discuss all the technical challenges. We believe that this review will provide guidance for the development of unmanned farms and provide ideas for further investigation of these farms.

Keywords: unmanned farm; accurate perception; intelligent decision; auto-work

Citation: Wang, T.; Xu, X.; Wang, C.; Li, Z.; Li, D. From Smart Farming towards Unmanned Farms: A New Mode of Agricultural Production. *Agriculture* **2021**, *11*, 145. https://doi.org/10.3390/agriculture11020145

Received: 1 January 2021
Accepted: 6 February 2021
Published: 10 February 2021

1. Introduction

Agriculture is the most important industry in the world, as it ensures survival of the global human population [1]. Agricultural production needs more agricultural labor to cope with the rising global population [2]. However, in past few decades, the average age of farmers has increased dramatically: around 58 years old in the USA and Europe, 63 in Japan [3]. Moreover, the number of people willing to work as agricultural labor is declining, especially in the United States, Japan, Germany and Russia [4]. The data show that in 2017, the proportion of the labor force involved in agriculture in the United States, Japan, Germany and Russia is 1.66%, 1.28%, 3.49% and 6.70% respectively [5], and it is still a downward trend, which causes the agricultural labor force will be increasingly lower in the future. Therefore, the current agricultural research mainly focuses on developing strategies for improving agricultural production with less labor.

An agricultural factory develops agriculture from a traditional small-scale farm to a large-scale enterprise, which has a high resource utilization rate, small land occupation and high yield and is not limited by climate and region [6]. However, the agricultural factory needs more human resources. Sudden situations lead to the shortage of agricultural labor, which will have a huge impact on an agricultural factory [7,8]. Therefore, it is necessary to study the mode of agriculture in which no one enters the agricultural work site.

Recently developed technologies, such as the Internet of Things (IoT) [9,10], robotics [11], Big Data [12] and artificial intelligence (AI) [13,14], have been used to guide agricultural production, which greatly reduces the use of the labor force and enhances efficient utilization of resources, thus facilitating the development of sustainable agriculture [15]. The development of these technologies has made it possible to construct unmanned farms [16].

As early as 2017, Harper Adams University (Newport, UK) collaborated with Precision Decision company on the Hands Free Hectare project, and realized automatic work through the transformation of traditional tractors, exploration vehicles and harvesters and the use of unmanned aerial vehicles (UAVs) for drawing paths and for positioning [17]. However, this required manual participation in UAV operation and background monitoring. Techno Farm Keihanna opened in November 2018 and is the first factory to use Techno Farm™. It is one of the largest automated vertical farms in the world, leveraging cutting-edge technologies such as robotics and the IoT, where planting, management and harvesting are controlled by robots. Intelligent environmental control and advanced water circulation technology have greatly improved the efficiency of vertical planting, achieving the goal of 98% water resources will be recycled and producing 30,000 lettuce stably every day. Production could be raised by 25% and labor costs halved. Moreover, light-emitting diodes (LEDs) are used to simulate sunshine, achieving 1/3 energy saving [18]. In August 2020, academician Luo Xiwen harvested rice grown in an unmanned farm in Zengcheng, a teaching and research base of South China Agricultural University, using intelligent agricultural machinery to achieve full coverage of farming, management and production. At this unmanned farm, the theoretical yield of rice per acre was 3390.7 kg, as determined by the five-point sampling method [19]. Jingdong agriculture and animal husbandry company announced the establishment of and researched an intelligent pig breeding system. The system can automatically adjust the fan, water curtain, heating and other equipment to ensure that the air, temperature and humidity of the pig farm are maintained in the best state suitable for the healthy growth of pigs. Combined with AI technology, they have developed modern equipment suitable for a pig farm environment, such as an intelligent camera, pig feeding robot, inspection robot, telescopic semi-limited pig pen and so on. The goal is to realize the whole process of unmanned, non-intervention and non-contact breeding. It is estimated that the company can reduce the labor cost of pig breeding by 30–50%, reduce the feed consumption by 8–10%, and shorten the average slaughter time by 5–8 days, which can reduce the cost of 50 billion yuan a year [20].

To date, many agricultural operations have been unmanned, and many countries have been involved in the construction of unmanned farms; however, there has been no formal introduction of unmanned farms in scientific literature. In this paper, we presented an overview of the unmanned farm shown in Figure 1, and divide unmanned farms into basic layer–decision layer–application layer. The main contributions of this paper are:

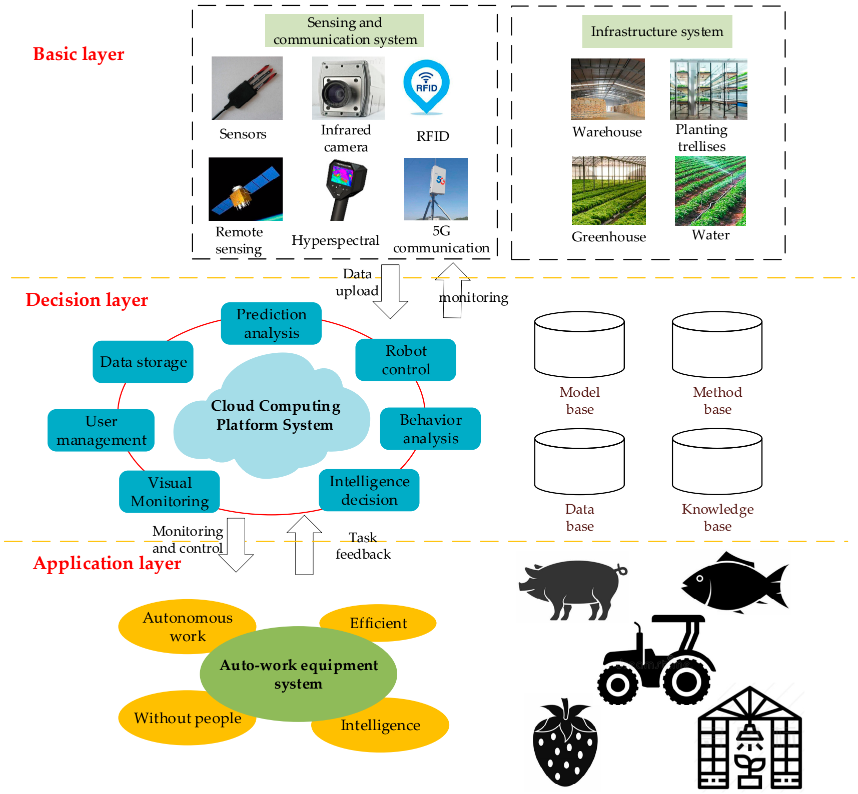


Figure 1. Conceptual unmanned farm system architecture showcasing various elements and interactions.

- We proposed a new agriculture production mode, namely unmanned farm, and describe different interactions between the components.
- We introduced the application of related technologies in recent years, and discussed how to apply these technologies in unmanned farm and the existing challenges.
- We analyzed the problems that will exist in the unmanned farm, including the current technical problems, as well as the social impact, data privacy, transparency etc.
- We put forward our own suggestions and views on the development of unmanned farms.

In Section 2, we define the unmanned farm and describe its system composition, operation principle and the important of each part. In Section 3 we introduce the crucial technologies of each system, and min reviewed recent research about the application of these technologies, discussion the problem of these technologies' application in unmanned farms. We discuss the benefits in Section 4 and problems in Section 5 that unmanned farms bring to farmers and society. Finally, we conclude the paper in Section 6. We believe that this article provides guidance for the development of unmanned farms and ideas for further investigation of the unmanned farms in the future.

2. Unmanned Farms

2.1. Definition

An unmanned farm is a new production mode, which does not require labor force but adopts diverse novel technologies such as IoT, Big Data, AI, fifth-generation (5G) technology and robots, for performing all farm production operations through remote control, whole-process automatic control of facilities, equipment and machinery or autonomous control by robots. The unmanned farm is the ultimate form of intelligent agriculture and the highest standard of agricultural production.

Unmanned farm uses modern sensing technology for monitoring the environment, growth status of agricultural animals and plants and the working status of various operating equipment, and for transmitting data to the cloud using a low-delay and high-reliability communication technology. A cloud platform can analyze and process data through Big Data and AI technology, independently generate production and operation decisions and then transmit decision information to the robot. The robot completes the decision-making information of the cloud platform through path planning and navigation, target recognition and flexible machinery and other technologies, and this process does not require human participation.

In an unmanned farm, every link of production and management can be automatically planned and decided by the cloud platform and then performed by machinery, independent of people's participation, 24 h a day from the beginning to the end of planting or breeding. An unmanned farm realizes precise management, self-decision making, unmanned operation, precise investment and personalized service during the whole process of agricultural production and management, and then realizes the sustainable development goals of agricultural production. In the future, unmanned vehicles, unmanned boats, UAVs and all kinds of agricultural intelligent machinery will be able to independently complete mobile operations without human intervention and realize the seamless docking of fixed equipment and mobile equipment.

2.2. System Composition

The architecture of an unmanned farm consists of basic layer, decision layer, and application services layer together, and the role and components is described as follows:

The basic layer consists of sensing and communication system and infrastructure system. Infrastructure system includes basic conditions such as factory building, roads, utilities, garages, network equipment and intelligent terminals, which provides basic working conditions and environment for the unmanned farm system through the IoT technology. The sensing and communication system aiming at getting the information of the farm mainly about environment, the growth state of breeding objects and the operation state of equipment, which is obtained by sensors, space information equipment, camera equipment, positioning/navigation equipment and a wireless transmission module deployed at the farm. The basic layer is to convert various farm information to digital data, provide the work environment for other work equipment, and the high-speed communication between various items of equipment.

The decision layer is an intelligent decision cloud platform for unmanned farm, which hosts that analysis, processing and storage of massive data resources of unmanned farm. It is the nerve center of the unmanned farm that makes data-based intelligent decisions for the unmanned farm. Intelligent decisions include model base, method base, database and knowledge base and, with the help of cloud computing, Big Data and AI technologies, it can perform tasks such as animal and plant welfare monitoring, environmental data analysis, remote robot control, equipment fault diagnosis and farm intelligent production and operation. The decision layer instead of humans is for thinking about agricultural production, to produce a more scientific and reasonable proposal.

The application layer is the auto-work equipment system, which is the core component of the unmanned farm that utilizes the technology of intelligent agricultural equipment and IoT. The operation and equipment system include fixed and mobile equipment. Fixed equipment mainly applied in unmanned livestock farming, fishery or glasshouse, and can perform independent tasks, such as feeding and aeration, without moving. On the other hand, mobile equipment refers to equipment, such as a seeder and unmanned ground vehicle (UGV), which are dependent on movement for completing farm operations. Moreover, mobile equipment can realize unmanned transport mission and can serve as a platform for carrying. The application layer in unmanned farm is to replace humans to complete the agricultural work, especially in the harsh conditions.

The three layers of components of the unmanned farm play different roles: the basic layers' infrastructure system is necessary for supporting the operation of other systems; the basic layers' sensing and communication system is responsible for data collection and transmission; the decision layer performs data management and makes production and operation related decisions; the application layer use machines, instead of people, to conduct farm operations. These three layers cooperate with each other to realize safe and reliable operation of the unmanned farm.

2.3. The Development Stage of the Unmanned Farm

Remote-controlled farm: remote control is the primary stage of unmanned farm, which is used to realize the unmanned operation of the farm through the remote control of facilities, equipment, machinery, etc. The characteristic of this stage is that it only realizes the replacement of labor by machines, and it also requires people to carry out remote operation, participate in decision-making and control, but it does not require people to participate in work on site, which liberates people from heavy physical labor. Therefore, it can also be called hands-free farm.

Unattended farm: unattended is the intermediate stage of the unmanned farm, in which there is no need for people to remotely operate farm equipment in the remote monitoring room 24 h a day. The system can cruise independently, but it still needs people's participation, mainly for the issuance of agricultural operation instructions and decision-making of production management. In this stage, the time of participating in the production process of the farm is greatly shortened, and there is no need to be on duty all the time. When necessary, it can participate in the decision-making management.

Autonomous farm: the autonomous operation is the advanced stage of the unmanned farm that does not need human participation. All farm operations and management have cloud management and control platforms for independent planning, decision-making and operation, and all farm businesses are completed by equipment independently, especially business docking link, which is completed by equipment through communication and identification. Human participation is not required in the whole production management process. It is a completely unmanned autonomous farm and the ultimate form of farm development.

3. Unmanned Farm System

3.1. Infrastructure System

The infrastructure system in the foundation layer is to provide basic working conditions for the whole unmanned farm intelligence, involving the transformation, layout and design of infrastructure. The layout and construction of the infrastructure system is determined according to the production object and scale as well as the intelligent equipment. For example, the small and scattered land should be effectively integrated, and the water supply network, road network, power grid and communication signal must be constructed in compliance with certain conditions. Therefore, the infrastructure of the unmanned farm needs to be laid out and built according to certain principles, namely, practicability and cost. Practicability implies that every workshop, warehouse, road, etc. should play a specific role in the unmanned farm and should be sufficient to support the normal operation of the unmanned farm. The second principle of cost implies that the construction of infrastructure should be cost-effective, given the low value of agricultural products, and the future operation and maintenance costs of agricultural production should be considered.

In addition, infrastructure digitization is very necessary. Consistent use of digital methods from the start of a project provides a basis for the definition of the intended construction state [21]. Building information modeling (BIM) technology can be shared and transferred throughout project planning, operation and maintenance via the integration of building data and information model [22]. This ensures that engineering and technical personnel develop a correct understanding of building-related information, three-dimensional (3D) visualization and automatic layout, thus reducing design time and improving project coordination. This technology shows great potential for planning the infrastructure system of an unmanned farm and consequently improving the reliability of the farm.

The design of the infrastructure system is particularly important, as it provides operation support for the whole unmanned farm. Following the principles of practicability and cost can be more easily accepted by farmers and, with the help of BIM technology, can improve the reliability of unmanned farms. At present, we can use various tools to help people build infrastructure. In addition to the principle of practicality and low cost, the infrastructure of unmanned farm also needs to be digitized. People are required to participate in the process of design and construction, and the management of infrastructure only needs a remote-control robot to complete it.

3.2. Sensing and Communication System

The sensing and communication system is the foundation that realizes the interconnection of everything, based on the IoT and information and communication technology (ICT). In the agricultural environment, IoT refers to the use of sensors and other devices, which transform each element and action involved in agriculture into data. IoT and ICT have been applied in intelligent agriculture for tasks, such as crop or livestock management, resource management and animal, plant and environment monitoring, which can help improve the quality and quantity of agricultural products [23]. Information acquisition in an unmanned farm is similar to smart agriculture, which relies on IoT for building the sensing and communication frameworks. Sensing and communication system is the basis of the digitalization of the unmanned farm. A complete information transmission system can obtain the various information parameters of the farm without human participation, and the information is processed by the intelligent decision cloud platform and then make the decision.

3.2.1. Sensing: Intelligent Perception of Unmanned Farm

In traditional agriculture, farm management relies on the experience of the farmer; however, there are many uncertainties and errors. To build an unmanned farm, it is important to eliminate these uncertainties for accurate management, which requires sensitive and fast sensors. A sensor is a device that perceives and transmits the environmental information and provides a foundation for the digitization of agricultural information. In an unmanned farm, sensors obtain agricultural information, including the growth environment, physiological status of animals and plants and information about the equipment or robot status [24]. This information is transmitted to the cloud platform through the processing network, thus providing data support for decision control.

Agricultural sensors have been widely used for collecting information on environmental factors such as temperature, humidity, light, dissolved oxygen (DO) and heart rate. Research shows that the wireless sensor network built with various types of sensor, such as information acquisition terminals, enable intelligent monitoring and intelligent control [25,26]. This system usually uses sensors to build wireless sensor networks and sends data to servers or terminals through telecommunication technologies (such as 4G) to help farmers make better decisions and accomplish the goal of accurate management. In some ways, sensor networks are essential for implementing intelligent agricultural systems, the same will be true on an unmanned farm. However, unmanned farm have more stringent requirements for the accuracy and timeliness of information acquisition because it is a completely unmanned production process.

Over the past few years, sensor research has become more miniaturized and intelligent, and new sensors have been developed using novel materials, which have advantages in detection sensitivity. These sensors provide reliable data support for more precise unmanned management but are not popular because of the high cost. Advances in material science and processing technology will help solve these problems. In recent years, the image-processing technology, based on the neural network, has led to widespread application of the image sensor. The machine vision method has replaced the traditional information acquisition method in some aspects. For example, the pig face recognition method has started replacing the traditional radio frequency identification (RFID) method [27], as it offers more advantages in management and convenience. Breakthroughs in sensor performance and changes in information acquisition methods help optimize the sensing system and increase the possibilities for unmanned farm. In addition, remote-sensing technology is an important tool for spatial information acquisition in an unmanned farm. Remote-sensing technology offers many advantages such as synchronous and non-destructive observations in a large area, strong timeliness and objective response to ground object change. This technology has been widely used for monitoring farm crop growth and drought and freezing injury and for controlling disease and insect pest populations [28–30].

An unmanned farm is a completely unmanned production process. Therefore, all equipment and systems must work on the basis of agricultural data, which are collected using sensing equipment. However, the sensors may not be reliable or stable for long-term use, and special agricultural sensors are not comprehensive. In addition, the explosive growth of equipment and data consumes a lot of network and cloud resources because of unified upload and centralized processing. Moreover, data processing is not timely, and the network is unstable, which reduce the stability and availability of the sensor system. Edge computing can meet the key requirements of network capacity constraints, data timeliness, resource constraints, security and privacy challenges. Each edge of the IoT has data collection, analysis and calculation, communication and intelligent processing capabilities, and can process, filter and analyze nearby data [31].

3.2.2. Transmission: High-Speed and Efficient Communication Promotes the Unmanned Farm

The transmission of information on an unmanned farm is performed through a network. The network efficiently, stably, safely and in a timely way transmits data obtained from the "end" layer of agricultural IoTs and processed data to the "cloud" layer of agricultural IoTs, which as a link between the "cloud" layer and the "end" layer. Information transmission is the fundamental guarantee for the normal operation of agricultural IoTs, with more emphasis on reliability and security.

Information transmission may include both wired and wireless communication, depending on the transmission medium. Wired communication refers to the technology that transmits information through a twisted pair, coaxial cable, optical fiber and other tangible media, which are mostly Ethernet and fieldbus [32]. Wireless communication is a communication technology that uses electromagnetic wave signals to transmit information directly in space for information exchange; examples of wireless communication technologies include RFID, near-field communication (NFC), infrared data association (IrDA), Zigbee, Wi-Fi, long range (LoRa), Bluetooth, narrowband IoT (NB-IoT), 3G and 4G [33,34]. Wireless communication technologies connect various elements of agriculture and simplify the information interaction among various fixed agricultural equipment, robots, sensors and machine vision and remote-sensing monitoring platforms in an unmanned farm is an efficient and intelligent manner.

Wireless sensor networks (WSNs) have created novel research opportunities, leading to tremendous improvements in agricultural application systems such as those used for groundwater quality monitoring, irrigation management, fertilizer control, planting monitoring, crop quality monitoring, pest and disease control, agricultural product tracking, environmental gas monitoring and animal movement monitoring [35]. WSNs collect data from different types of sensor and send them to the primary server via a transmission system. This makes standardized planting or breeding management smart. Farmers can achieve accurate management by monitoring farm crops from any location using soil moisture sensors, temperature and humidity sensors, light sensors and automated irrigation systems [36]. Wang and colleagues designed an automatic monitoring system for greenhouse crop survival, based on a WSN [37]. This system can effectively control and maintain optimal microclimate conditions in the greenhouse. Similarly, Mahale et al. implemented intelligent monitoring of chicken farms using mobile phones and smart devices [38], while Goud et al. completed the control and remote monitoring of environmental parameters in the chicken farm using a WSN and mobile system network [39]. Research shows that IoT-based intelligent monitoring systems will help farms grow crops or livestock in a scientific and balanced manner.

Nowadays, the 5G communication technology is being employed for wireless communication. For example, in China, the Daoji Agriculture company has started to operate smart farms based on 5G. The 5G networks are expected to provide 1000–5000 times more capacity than 3G and 4G networks and will consist of cellular networks with peak rates of 10–100 Gb, which will take 1–10 milliseconds to transmit data from one specified point to another. The 5G Intelligent Internet of Things (5G I-IoT) proposed by Wang et al. can help realize the intelligent processing of Big Data and facilitate the optimization of communication channels [40], thus providing the possibility for fast, real-time and high-throughput demand of unmanned farm.

3.3. *Intelligent Decision Cloud Platform*

The intelligent decision cloud platform is the brain of unmanned farm, which performs data processing, intelligent decision-making and remote monitoring on an unmanned farm. The workflow and application of the intelligent decision cloud platform are shown in Figure 2. The operation of the intelligent decision cloud platform is mainly supported by three technologies: Big Data, AI algorithm and cloud computing. Big Data technology can analyze and process the data uploaded to the cloud platform and extract effective information; the AI technology, together with Big Data, analyzes various data to make scientific production-based decisions; cloud computing technology provides technical support for the reliability of Big Data and AI processing of massive data. These technologies work together to ensure the intelligence and effectiveness of the cloud platform.

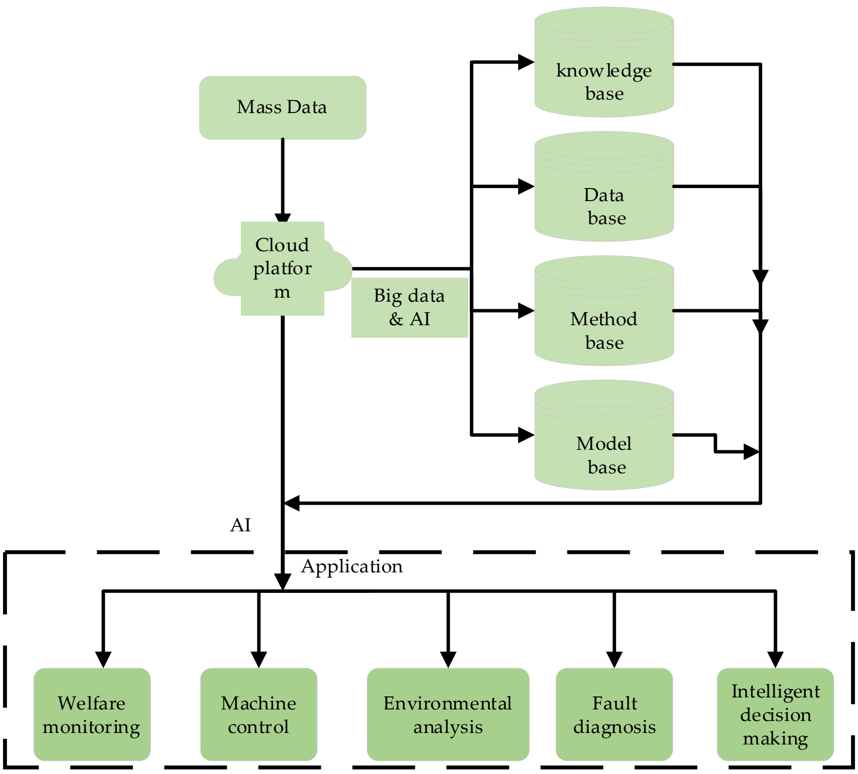


Figure 2. Workflow and application of the intelligent decision cloud platform.

3.3.1. Big Data: Data-Driven Unmanned Farm

In unmanned farming, various types of data, including digital, sound, image and video, are produced during the process of agricultural production and management. Because of the different sources and forms of data and interaction between many elements, it is difficult to process, analyze and store the data within a specific time period. Therefore, mining effective information from multidimensional heterogeneous data obtained from diverse sources is difficult.

Big Data technology provides a solution for effective data mining. Big Data refers to the technology of analyzing, processing and storing data, which is s very important technology of mass data processing [41]. Data mining is one aspect of Big Data application, and can be divided into 4 steps: data pre-processing, data reduction, data modeling and solution analysis [42]. Data storage also can be solved by Big Data technologies and cloud computing [43].

Big Data is still in its infancy in agriculture, but it has been proposed as a tool for guiding farm-based decisions [44]. Australia uses the Big Data technology to analyze dairy production, lactation and reproduction data in dairy farms, and studies the importance of Big Data in agricultural decision-making [45]. Through mining and analysis the data of climate, soil conditions, crop growth and pest and disease, Li obtained the optimal conditions of high quality and high yield of crops, and then intelligent planting was realized by guides the regulation of agricultural varieties and production environment [46].

To date, a number of studies have been conducted on the application of Big Data in the field of agriculture. Kamilaris et al. reported 34 studies on the use of Big Data in agricultural applications [12]. Wolfert et al. summarized the application of Big Data in smart farming [47]. Several studies have also been conducted in the construction of an agricultural Big Data platform [48]. The Consortium of International Agricultural Research Centers (CGIAR; Montpellier, France) has created an agricultural Big Data platform, aiming to solve the problems of agricultural development faster, better and on a larger scale using Big Data. In China, numerous provinces have set up agricultural Big Data platforms to guide and improve agricultural production and increase farmer income.

Application of the Big Data technology needs tremendous data, and this requires farms to use numerous pieces of data acquisition equipment [49]. Unmanned farms have sufficient data to meet the needs of Big Data. Therefore, Big Data technology will also play an important role in unmanned farms, which is mainly reflected in four aspects: (1) Big Data technology enables the processing of multi-source for unmanned farm, and uses data processing methods such as removing false data, storing true data and classifying data; (2) Big Data can mine, analyze and discover knowledge from numerous data, and form a regular farm management knowledge base; (3) Big Data can effectively store all kinds of data to form historical data for learning and invocation of unmanned farm could platform; (4) Big Data, together with cloud computing and edge computing technology, forms an efficient computing system that ensures rapid, precise and independent operation.

Big Data plays an important role in the massive data processing and storage, which provides technical and reliable data support for intelligent decision-making in the unmanned farm. Given the complexity of agricultural operations and the diversity, heterogeneity and accuracy of data, more research is needed to verify the reliability of Big Data in agriculture.

3.3.2. Artificial Intelligence (AI): Make Unmanned Farms Think Like People

Big Data provides data processing and storage technology, but AI technology plays the thinking and decision-making roles [50]. AI allows the machine or system to exhibit independent, but rational, thinking and behavior, similar to human beings [51,52]. With classification, logistic regression, correlation analysis and decision-making capabilities, AI has been widely used in agricultural decision support systems (ADSS), agricultural prediction analysis, visual monitoring systems, robot control [14,53,54].

Agricultural Decision Support Systems

An ADSS is a human-computer system which utilizes data from various sources, aiming at providing farmers with a list of advice for supporting their decision-making under different circumstances by AI [54]. The ADSS does not give direct instructions or commands to farmers, it provides advice to farmers, farmers make the final decisions. The ADSS has been used in feeding decision-making [55], smart irrigation decision support systems [56], and crop nutrient management [57]. For example, Zhou et al. proposed the near infrared computer vision and neuro-fuzzy model-based feeding decision system for fish in aquaculture, which can conversion rate can be reduced by 10.77% and water pollution can also be reduced [55]. It shows ADSS is very helpful for assisting farmers in performing various agricultural activities.

However, there are also some questions to be answered if ADSS is to be widely used, such as the incomplete functionality, insufficient consideration, inadequate requirement analysis and bad graphical user interfaces (GUIs) [58]. For an unmanned farm, ADDS need do more performing analysis on historical information to enhance the quality of decision supports. It also should consider provide more adequate decision supports and re-planning mechanisms, the more important is to do the agricultural prediction analysis.

Agricultural Prediction Analysis

Predictive analysis uses data, statistical algorithms and machine learning techniques to determine the possibility of future results based on historical data. AI has shown great potential in agricultural prediction analysis, such as dissolved oxygen prediction [59,60], agricultural product price forecasting [61], greenhouse gas emissions prediction [62] and agricultural yield prediction [63,64]. For example, Liu et al. [59] study the effectiveness of attention-based recurrent neural network (RNN) methods in the short-term and long-term prediction of dissolved oxygen, achieve the good results in the prediction of almost all time steps.

However, some of the more accurate forecasting models require longer working time. In an unmanned farm, it is necessary to further to combining data-driven machine learning (ML) and biophysical based approaches, and optimizing their configuration and parameters in an ensemble learning approach [62].

Agricultural Computer Vision

Computer vision is an important technology, which studies how to use a computer to understand the information contained in a digital image or video at a high level [65]. Machine vision technology is often combined with an AI algorithm, which has been widely used in the field of agriculture, such as species classification [66], crop disease recognition [67], behavior analysis [68,69] etc. Chen et al. [70] proposed neural network and long short-term memory for recognition of aggressive episodes of pigs with an accuracy of 97.2%. These show that AI has great application potential in agricultural machine vision

Among some review conclusions [65,71], the deep learning algorithm has the most potential, it has good nonlinear simulation performance, as well as the ability to apply in more complex environments. However, most of the methods proposed in the literature are only used in the laboratory, and there are still some problems in practical application, especially for an unmanned farm. It is necessary to study how to use artificial intelligence to improve the recognition accuracy in complex scenes.

Agricultural Robot Control

Robots can work autonomously because artificial intelligence replaces human thinking. For example, the multi-robot task system [72] aims at performing tasks automatically by control aerial and ground vehicles. The robot path planning [73] needs the help of AI technology to plan the optimal path, such as Ayushman et al. [74] used the method of "chase the rabbit" to plan the path of the lemniscate shape, and the real underwater experiment by an autonomous underwater vehicle (AUV) showed that the algorithm has faster calculation speed.

These studies demonstrate that AI plays an important role in smart farming. However, the application of AI in agriculture is in its infancy [75], and many difficulties, such as data sets, need to be resolved for the establishment of deep learning in agriculture.

Similarly, the intelligent decision cloud platform of an unmanned farm also needs AI technology, which is mainly reflected in four aspects. First, the utilization of machine vision technology, in combination with AI technology, for the analysis of the physiological characteristics of animals and plants can provide more accurate data. Second, the agricultural robot equipped with AI can enhance the autonomous walking and workability of the robot. Third, Big Data and AI can analyze the current data and historical database, and predict the trend of data at the next stage, so that decisions can be made at the next stage without delay. Fourth, AI technology can provide the intelligent decision cloud platform the ability to think like a human and realize intelligent decision-making and control.

AI is the core of the intelligent decision-making cloud platform and also the basis for the realization of the unmanned farm. Although a large amount of research has been conducted on the application of AI technology in the field of agriculture, there is still a long way to go before it can be applied in an unmanned farm. Moreover, we need to increase not only the investment in agriculture to obtain more data but also the number of scholars engaged in agricultural AI research.

3.3.3. Cloud Computing: Stable and High-Speed Data Storage and Computing

An intelligent decision cloud platform uses Big Data technology to discover effective information and rules from massive data processing, and then makes production decisions using the AI technology. However, because of the relatively large amount of data, using only a local computer for data calculation will greatly increase the cost and processing time [76]. The emergence of cloud computing effectively solves the problem of massive data operation and rapid data processing [77].

Cloud computing is a form of distributed computing, i.e., the huge data computing processing program is decomposed into numerous small programs through the cloud network. Cloud computing provides flexible, convenient and on-demand network access to many configured computing resources, which greatly improves the computing efficiency. Therefore, this system has been widely used for Big Data processing. Chen proved that cloud computing is effective for optimizing cold chain logistics vehicle routing [78]. Zhou et al. demonstrated an effective solution for monitoring soil moisture in precision agriculture by integrating cloud computing and information infrastructure supporting web services [79]. Liu et al. designed a modern agricultural IoT monitoring system based on cloud computing to reduce the development cost of the system and ensure its reliability and security [80]. Zamora et al. constructed a smart agriculture system based on cloud computing, edge computing and IoT, and used this system in a real greenhouse in Southeast Spain, saving more than 30% water and 80% of some nutrients [81].

Given the huge amount of data generated during the production and operation of an unmanned farm, combining the cloud computing technology with Big Data technology is necessary to process and store data. To date, many enterprises such as Amazon, Microsoft, Alibaba and Google have developed cloud computing businesses and promoted the rapid development of cloud computing. However, no cloud computing platform has been specifically designed for the agricultural field, and more research is needed on information security of the cloud computing platform.

3.4. Auto-Work Equipment System

Artificial phenotypic tasks are labor-intensive, destructive and error prone [82], and auto-work equipment can overcome problems in manual operations. Relying on intelligent equipment and robots to complete work that would have been done manually in traditional agriculture is the key to realizing the complete replacement of artificial labor in an unmanned farm. Based on the sensor and transmission system, operational equipment interconnects different pieces of equipment and connects equipment with the cloud platform. The rational management and control of Big Data, AI and the cloud platform will help achieve effective docking and cooperative operation between devices, increase the environmental adaptability and working efficiency of unmanned automatic operating equipment, and improve the intelligence level of the unmanned farm. The auto-work equipment has an information processing system, which provides reliable hardware support for edge computing. Reliance on edge computing technology can help realize the terminal processing of equipment information and terminal control of autonomous operation.

3.4.1. Intelligent Fixed Equipment

Intelligent fixed equipment can complete the autonomous work tasks of the unmanned farm without moving can be independently regulated and combined with other equipment and agricultural robots to carry out systematic operation control. In addition to relying on its own intelligent control system, autonomous intelligent fixed equipment also needs to rely on the IoTs to achieve information exchange and intelligent decision cloud platform to achieve information processing and decision-making.

Sprinkler or drip irrigation equipment is important for crop cultivation, especially in low-crown or orchard environments. Intelligent management of fresh water and fertilizer for precise irrigation is critical for increasing crop yield and reducing the input cost [83], while contributing to environmental sustainability. Based on the IoTs, automatic irrigation equipment can help farmers achieve remote management [84,85]. Additionally, with the help of the cloud platform, automatic irrigation equipment can be used in an automated manner without the need for farmer interference. In the future, in unmanned management, autonomous operation will be achieved by combining sensing, transmission and cloud platform systems, and the decision control of these devices will be more scientific and intelligent.

Unlike plant management equipment, the animal control equipment is more diverse and complex, which requires higher technical support. Animal control equipment is designed to manage the growth of a single animal through the automatic, continuous and non-invasive real-time monitoring of environmental factors, animal health and welfare, production, reproduction, thus adding value to the product without causing any additional stress to the animal [86]. Given the large size of animals and considerable variation among them, animals need to be managed on an individual level. Smart collars (wearable devices) are designed to track the health of an individual animal, and can be used to monitor cows or sheep [87,88]. For example, these collars monitor the fertility of a cow by tracking its movements during the fertile period, and alert farmers by sending messages to a laptop or smartphone when the cow is ready to mate (Figure 3). Furthermore, the collar can detect early signs of disease by monitoring the average time spent by each cow on eating and regurgitating.

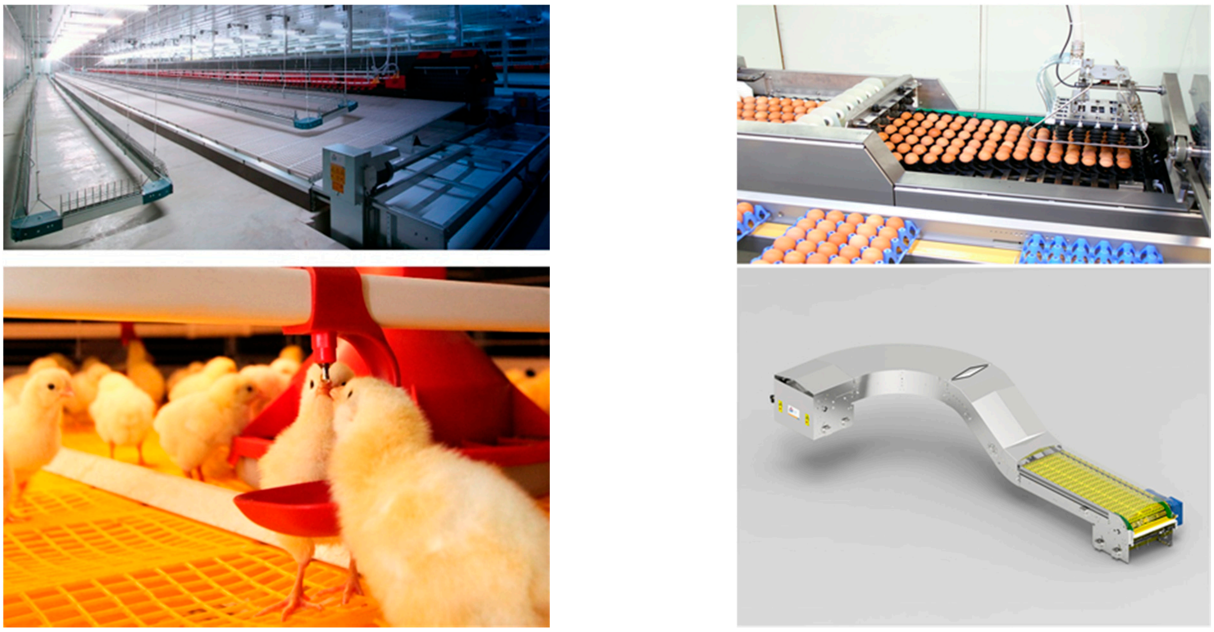
Figure 3. Smart collars (Source: DAIRYMASTER).

Feeding equipment occupies an important position in farms, especially in pig, chicken and cattle farms. Conveyor belt or guide rail feeding equipment developed by LELY Industries N.V. can achieve precise target feeding using the guideway, and can control the size of the outlet to achieve more accurate feeding, which has more advantages in precision feeding. The intelligent control system of feeding equipment can be connected with the cloud computing platform through a wireless network, and the cloud can provide reliable decision-related information to achieve intelligent feeding. In the field of aquaculture, some developed countries, such as Norway, Japan and USA, the automatic feeding system has been applied. The net cage automatic feeding system developed by the Norwegian fishery equipment enterprise Fishery Equipment Enterprise is composed of a management system, online monitoring system and feeding module. The online monitoring system can simultaneously monitor the pH, dissolved oxygen (DO) level, temperature and other parameters of aquaculture water in real time, and transmit the data to the management system to enable the automatic feeding of bait.

Automatic milk equipment has been used in many modern cattle farms. For example, the fully automatic milking machine (Figure 4) developed by LELY Industries N.V. provides accurate teat-position information, independent of light or background, thus providing a comfortable milking experience by quickly, consistently and accurately connecting nipple cups. Additionally, the automatic milking machine enables accurate health management through individual identification and milk quality detection, and provides nutrition management and disease treatment by adjusting the feed ratio. Precise management requires more accurate target recognition. Electronic device tags or collars can be used to classify individuals, but tags still need to be artificially worn, and it is a difficult work for small animals. Recognition based on a visualization-based technology is non-invasive and contact-free, it can not only overcome these problems but also allow for fast recognition [27].

Figure 4. Automatic milking equipment (Source: LELY Industries N.V.).

In chicken houses, advanced technologies such as automatic feeding and water supply are commonly used (Figure 5a). In recent years, extensive research has been carried out to improve poultry production and comprehensive benefits [89]. Because of the structural configuration of the cage production system, a variety of automated equipment has become a functional component of this system. A good example is the highly automated machine used to collect and sort egg layers (Figure 5b). Nonetheless, checking the health and welfare of chickens and optimizing the overall management of the hen house requires human intervention [90]. Currently, large chicken farms are equipped with the cloud-based data management system (CDMS), which can share real-time visual data on the performance and feeding conditions of chicken flocks in a given chicken farm with a number of different chicken farms. This is conducive to the realization of scientific management [91]. An unmanned farm is committed to intelligent management, where intelligent equipment can be used to replace repetitive and frequent manual operations, such as assessing animal status, eliminating dead chickens, maintaining indoor environmental conditions (dry cleaning, wet washing, fertilizer removal, ventilation and sanitary treatment), inoculation, trade-offs, selection of floor eggs, sorting and packaging [92,93]. A cloud platform can be established as the core of the system to achieve unmanned management.



(a) (b)

Figure 5. Chicken house equipment. (**a**) is the chain feeding systems (Source: Jansen Poultry Equipment). (**b**) is the egg collection systems (Source: Jansen Poultry Equipment).

As a part of an auto-work equipment system, intelligent fixed equipment plays an important role in accurate management and control, especially intelligent monitoring equipment. Intelligent fixed equipment can replace the repeated and tired work of human beings, but the management of intelligent equipment still needs human participation. The setting and adjustment of parameters and the planning of tasks are mostly dependent on human thinking, and computers can only assist human thinking, which is the goal of a smart farm. The final stage of the unmanned farm is to achieve complete operation without human participation, and all decisions and thinking will be made by the intelligent decision cloud platform.

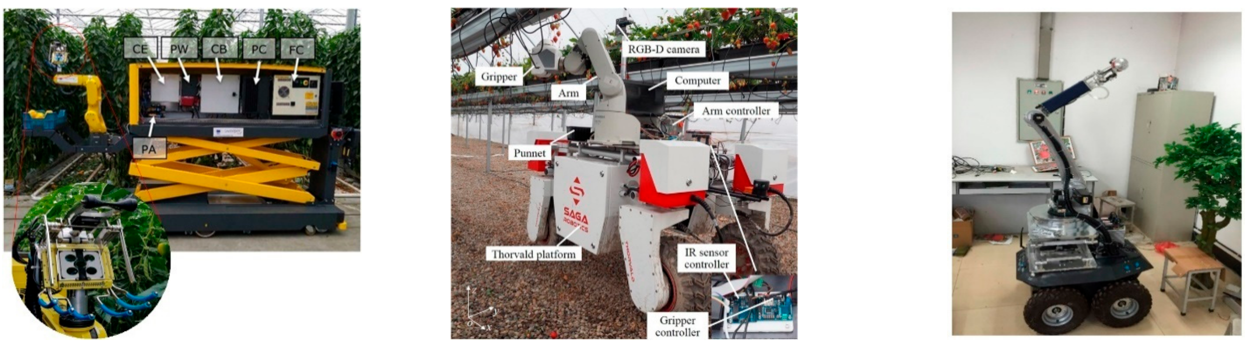
3.4.2. Agricultural Robots: Replace Farmers

Agricultural robots are mobile and autonomous operating equipment in an unmanned farm; examples of agricultural robots include field farm ploughing and sowing machinery, harvesting machinery, plant protection machinery and other operating machinery. Unmanned vehicles, unmanned surface vessels (USVs) and UAVs are the most important mobile equipment on an unmanned farm. These agricultural robots not only enable unmanned transport missions but also serve as a platform for carrying other intelligent equipment. Mobile equipment also includes a variety of mobile robot equipment. Mobile equipment and fixed equipment execute farm operations on an unmanned farm. Effective docking and cooperation between these equipment increase the environmental adaptability and work efficiency of intelligent equipment and robots on an unmanned farm, improve the intelligence level of the unmanned farm and help realize the replacement of manual operations by machines.

Agricultural robots are used in diverse applications, including automatic seeding and harvesting (with mobile platforms and robots), point spraying, plant health testing and point pruning. Field robots play an important role in improving operational reliability, environmental health and crop productivity. Agricultural field robots and manipulators have become an important part of the intelligent agricultural system [13,47]. Unmanned driving technology forms the basis of free movement of field robots. Although operator-free driving technology shows good performance in industry, it is still at the development stage in agriculture. Because of the complexity of the agricultural working environment, unmanned driving cannot develop as rapidly in agriculture as in industry. In the field environment, unmanned driving has been used for automatic sowing, cultivation and harvesting, and these processes can be monitored in real time using the data platform [94,95]. Because the environment of a cultivated land system is relatively simple and maneuverable, unmanned cultivation shows a great potential for realization.

Automatic harvesting platforms are one of the important achievements in the field of agricultural robotics, and there has been very good verification in fruit and vegetable picking. For example, Panasonic (Japan) has developed a tomato harvesting robot, equipped with its own image sensors, which can harvest tomatoes unattended. It uses image sensors to detect ripe red tomatoes and then pinpoints their shape and location. At harvesting, the robot pulls on the stem without damaging the fruit. When the harvest basket is full, wireless communication technology informs the robot to automatically replace the empty basket. In addition, the yield and quality of tomatoes are recorded by data management, and the harvest can be planned. Arad et al. analyzed the greenhouse sweet pepper harvesting robot (Figure 6a), and showed that the robot can run automatically on pipe rails and concrete floors and in an end-user environment [96]. Xiong et al. evaluated a strawberry picking robot (Figure 6b) used in greenhouses, which was able to pick individual strawberries with a near-perfect success rate of 96.8% [97]. As for agricultural robots, Shamshiri et al. have made a detail summary, especially those used for automatic weed control, field reconnaissance and harvesting [11].

The robotics system is designed to replace simple manual labor. In the future, agricultural robots will act as the “hand” and “foot” on an unmanned farm and provide technical support for planting, cultivation, harvesting and plant protection. The agricultural robotics technology is developing rapidly, but the lack of stable recognition and accurate picking ability hinder the commercial application of harvesting robots extensively. Machine vision technology plays an important role in alleviating such problems. Birrell and colleagues used visual technology to locate, classify and harvest iceberg lettuce in a complex environment [98]. Visual control technology provides important technical support to the fruit and vegetable harvesting robots, and the research on picking robots in recognition, positioning, all-weather operation mode and intelligent computing indicates the possibility of robot application driven by information technology [99]. An unmanned farm relies on the application of these robots, but autonomous operating platforms are currently less efficient than mobile operating platforms with human participation. Smooth mechanical control is the key to improving efficiency. The traditional PID algorithm shows high complexity and low adaptability, while an intelligent algorithm (e.g., neural network algorithm) can reduce the complexity of parameter adjustment to a certain extent and improve the control accuracy, as shown in apple picking (Figure 6c) [100].



(**a**) (**b**) (**c**)

Figure 6. Harvesting robot. (**a**) is the sweet pepper harvesting robot [96]. (**b**) is the strawberry picking robot [97]. (**c**) is the apple-picking robot [100].

In fish pond or lake farming, the premise of scientific farming is to obtain key water related parameters, such as temperature, pH, DO level, oxidation-reduction potentiometer and electron conduction, quickly and in real time. At present, the development of robotic fish (for water quality monitoring/early warning; Figure 7) [101–103], USV (for fish density estimation and water quality monitoring; Figure 8) [104], and robots (for integrating feeding and water quality monitoring [105] has been initiated. The underwater mobile robot is a good equipment for fishing and observing underwater plants and animals. For example, robots used for sea cucumber fishing enable visual observation and capture based on underwater images [106] and are expected to operate autonomously [107]. In addition, the inspection robot can detect the position of dead fish, based on deep learning, computer vision and positioning technology. When combined with optical and acoustic systems and an automatic manipulator, the underwater detection robot can be used for picking dead fish. A biomimetic robotic fish is a flexible underwater machine which can perform self-inspection, underwater positioning, automatic obstacle avoidance, breeding target tracking, biomass estimation and 3D monitoring of underwater aquaculture by carrying sensor equipment. To performs tasks on the water surface, USVs are urgently needed. The USV can effectively reduce the sensor layout requirements in large areas or deep water, and can be used for water sampling at any designated location as well as real-time online monitoring through the combination of dynamic nodes and static monitoring nodes. Moreover, the data can be uploaded to the cloud platform, which provides the robot with instructions for the next action through calculation and decision making. USVs can carry underwater monitoring sonar for tracking fish stocks and estimating the biomass. USVs can also be used as a carrier platform for other breeding equipment, such as an aerator, bait machine and harvesting equipment, especially as the launching platform of UAV and bionic unmanned fish. However, taking into account the demands of an unmanned farm, the current techniques are not mature enough. Some problems have been resolved, such as the bit rate problem of communication via remote Wi-Fi communication satellite [108], path planning, autonomous obstacle avoidance and visual tracking in autonomous navigation [109–111]. However, further investigation of unattended autonomous operations and fishing or feeding operations is needed. It will not be long before the autonomous robots replace humans in fishing or feeding on the surface of the water, just as USVs replaced humans in water-quality monitoring.

Figure 7. Bio-inspired fish robot [103].

Figure 8. ESM30 autonomous water sampling and monitoring boat (Source: YUNZHOU TECH).

In livestock and poultry breeding farms, livestock and poultry robots can replace a large number of manual activities. For example, fully automatic self-walking feeding robots, cleaning robots, feeding system by automated guided vehicle [112] and egg picking robot can complete the work efficiently, independent of human intervention, after receiving the necessary instructions. Researchers at the Georgia Tech Research Institute (Atlanta, GA, USA) have developed a robot that can autonomously navigate, perform inspections and pick-up eggs from the floor among a flock of live chickens, with a success rate of 91.6% [113], which has met the work needs. TRIOLIET Feeding Technology, LELY Industries N.V. and other companies have provided smart farming support programs. However, these programs can only help farmers to better manage the livestock but cannot be used for unattended farming, as the latter requires cloud computing (for enabling unmanned decision-making) and a more intelligent robot or a device (for performing complex and difficult tasks such as disease diagnosis, treatment, breeding and nursing).

On an unmanned farm, UAVs are indispensable. Unmanned farm require joint supervision of air and land, especially in large farming or growing areas such as fields, lakes or open sea, where the dependence on UAVs is extremely high. UAV-based monitoring systems show high spatial and temporal range and are widely used in precision agriculture and intelligent farming. To date, UAV-based monitoring systems have mainly been used for monitoring crops [114,115], environment [116], and animal behavior [117]. Multispectral remote sensing based on a UAV shows great potential for precise crop management [118]. UAVs provide accurate terrain surface and height information through images and accurate surface information for unmanned vehicles or unmanned ships. For example, Comba et al. used a UAV to obtain vineyard row spacing and terrain slope information to better manage the path and operation of unmanned vehicles [119]. SZ DJI Technology Co., Ltd. (DJI) developed a UAV-based platform for plant protection, pest detection and data management. The T20 plant protection UAV, equipped with a reliable omni-directional digital radar (Figure 9), can perform the full autonomous operation of sowing and fertilizing in fields, terraces, orchards and other operation scenes. UAV PHANTOM 4 Multispectral can quickly obtain the indexes of each growth stage of crops, conduct real-time monitoring of crop growth, help users quickly find diseases, pests and weeds, take targeted plant protection measures and perform precise management. The DJI Agricultural Data Platform, which is for the comprehensive demand of agricultural Big Data and IoT, and can perform statistical analysis on data records of any node. On an unmanned fishing ground, a UAV can be used for water exploration and patrol, fish fry delivery, bait delivery, fish swarm monitoring and other operations. Because UAVs are fast, convenient and demonstrate high precision and easy interconnection, they show great potential on unmanned farm.

Figure 9. DJI T20 plant protection unmanned aerial vehicle (UAV) (Source: DJI).

Different agricultural production objects and environments (cultivated land, greenhouse, livestock, poultry and aquaculture) require different types of robots (examples as Figure 10), and these robots are the key to achieving unmanned production. Supported by modern information technologies such as comprehensive perception, intelligent processing, intelligent navigation and accurate operation, and combined with traditional equipment, robots can perform unmanned production, information monitoring, optimal control and accurate independent operation.

(**a**) (**b**) (**c**)

Figure 10. Different types of robot. (**a**) is feeding robot (Source: TRIOLIET Feeding Technology). (**b**) is floor cleaning robot (Source: LELY Industries N.V.). (**c**) is procleaner robot (Source: WASHPOWER).

Intelligent robots and UAVs will likely play an important role in an unmanned farm. Influenced by the working environment, there are differences in the degree of intelligence of robots. Robots in livestock and poultry farms have been capable of working autonomously, while in the greenhouse environment, picking is still a challenge, and human participation in picking is essential [120]. In general, agricultural robots currently require human involvement, such as task decision-making, planning and supervision. In the future, an unmanned farm, which involves human participation, will eventually be replaced by autonomous robots and computers, and humans only need to view them remotely.

4. Prospect

Obviously, unmanned farms can improve agricultural production and product quality. Intelligent decision cloud platforms can make farm production more scientific and efficient, causes fewer losses of fertilizer and pesticides to the environment, reduced water consumption, and reduced greenhouse gas emissions, which is conducive to reduce the problem of environmental pollution [121]. With the application of auto-work equipment, it is conducive to more professional agricultural operations, and can effectively avoid the problem of rising labor costs and labor shortage [122].

According to international research predictions, the global intelligent agriculture market value is expected to have a revenue of US$23.14 billion in 2022 [123] with opportunities for technology providers, agricultural equipment and machinery providers, producers and others involved in this business. An unmanned farm uses more new information technologies and products, involving the IoT, Big Data, AI, robotics, 5G and others, which will provide the market for the development of these technologies.

At present, the unmanned farm is only in the tentative stage. With the development of science and technology, intelligent equipment and information industry, we predict that there will be unmanned farm with independent planning, decision-making and management capabilities from 2050 to 2070. In all agricultural sectors, crop production would be the first to realize unmanned farming. This is because the land where crops grow is easy to manage, and it is easier to sow, cultivate, manage and harvest crops than other types of produce. The hardest aspect of animal husbandry is that animals have uncontrollable factors. Other agricultural sectors also have weaknesses (Table 1), for example, the accuracy of fruit picking robots in an actual farm is not high [97]. High-speed transmission (5G) technology can be implemented in the farm, other technologies have some challenges shown in Table 1.

Table 1. The convenient areas for implementation of technologies through unmanned farm in agri sectors.

Level	Agri Sectors		Technologies	
Easiest	**Crop**	• Crop production system has low complexity and is easy to implement. • Fully automatic machines for ploughing, sowing, plant protection and harvesting are already available.	**Sensing and Communication**	• Available of high-speed, high-bandwidth transmission technology. • Micromachining technology and microsensor technology offer more possibilities • Special sensors need further development (etc. animal physiology, disease).
	Floricultural greenhouses	• Floricultural greenhouse is easy to be intensive, and the cultivation machine can run autonomously • The flower classification packaging needs intelligent machine.		
to	**Poultry industry**	• Poultry (etc. chickens and ducks) are easy to raise and manage. • The intelligent equipment of poultry farm feeding and harvesting is already available. • Diagnosis and management of the disease are needed	**Big Data**	• The quantity of agricultural information data is insufficient and the technology is not mature enough. • There are still many problems with big data (data security, privacy protection, transparency...).

Table 1. *Cont.*

Level	Agri Sectors		Technologies	
	Aquaculture	• Aquaculture in deep-sea cages and factory facilities can be operated autonomously. • Lack of stable sensing, accurate and efficient surface and underwater robots.	**AI**	• AI algorithm efficiency cannot adapt to the actual needs. • Instability in a complex environment presents great challenges. • Inadequate hardware base for computing.
Hardest	**Fruit and vegetables**	• Vegetables and fruits planting, management equipment can be partially automated. • Efficient and precise picking robots still need to be researched.		
	Animal husbandry	• The automatic feeding and cleaning equipment in animal husbandry has been able to operate autonomously. • More research is needed on reproductive facilities/machines.	**Robots**	• Intelligent machines in some environments are available, but machines in complex environments operate inefficiently. • Robots for breeding need to be developed • Intelligent robots rely on AI training

5. Challenges

It is true that an unmanned farm can assist farmers and enhance food production, but, at the same time, there are many issues that need to be solved.

Whether the technology is compatible with unmanned farm is the first question (Table 1). An unmanned farm requires all information to be digitized, and the data acquisition is real-time, continuous and highly reliable. However, the special real-time online sensors for agriculture are not comprehensive, and some sensors have insufficient long-term stability and reliability under complex conditions. Some intelligent agricultural robots can be used in agriculture, but an agricultural picking robot shows low work efficiency and crop recognition error, and its flexible arm technology is not as good as manual picking [124]. The data obtained in agriculture is not enough for Big Data analysis, and AI technology cannot replace human beings to make correct decisions. Therefore, for now, these technologies are not compatible with driverless farms, and more research is needed. But these technologies are already compatible with smart farms [125], and their applications in an unmanned farm need to be further studied in the future.

The second problem is that there are still many problems in the application of big data technology in unmanned farms [126]. First, who owns the data? Farmers don't know how to use and obtain big data. Although farmers have contributed to the development of tools, they don't have right about data collection, analysis and use [127]. Secondly, big data may lead to the disclosure of their privacy [128,129]. Then, the transparency of data use is not clear, and farmers are not willing to share their data [130] unless they understand what people are doing with it [131]. Finally, how to distribute the benefits brought by big data is a problem. Although farmers contribute to the data, they do not have ability to control over the income distribution generated by the data. These problems also exist in an unmanned farm, such as data privacy leakage, opaque data use and fair distribution of big data revenue. It is essential for the government to establish an intermediate regulatory mechanism, which is responsible for data sharing and storage, data transparent use, data revenue distribution and other tasks

Third, how to make the transition to an unmanned farm is also an important question [132]. Unmanned farm will lead to a large number of people's unemployment, such as the reduction of production of fertilizer, feed, pesticides and other manufacturers, resulting in layoffs, and the surplus of labor force caused by farmers not having to farm land to participate in other industries. There are three stages of transition in the research of unmanned farms, namely remote-control farm, unattended farm and autonomous farm. There is some work that humans need to complete in these three stages, but the number of farmers will increasingly decline, which is a slowly changing process. In this process, the government needs to increase the training of farmers, so that farmers learn more skills.

Finally, a lot of advanced equipment is used in an unmanned farm, even for the larger farms, and the cost of this equipment is high, especially for developing countries [133,134]. This requires the joint efforts of researchers and the state, which needs to increase subsidies for these equipment and research funds for experts, and experts need to conduct in-depth research to reduce the cost of these machines. Similarly, farmers can use much-needed equipment first, such as unmanned harvesters.

The problems described above limit the practical application of an unmanned farm. In the future, it is important to study how to solve these problems for an unmanned farm, which requires the join efforts of the government, researchers, farmers and enterprises in this direction.

6. Conclusions

In this paper, we introduce a new agricultural production mode, i.e., an unmanned farm, which does not require people to enter the farm, and uses modern information technology and intelligent equipment to replace manual labor with machines for the production and management of the farm. Here, we defined the unmanned farm, explained its operation principle and characteristics, and introduced the system architecture of the unmanned farm system. We also analyzed the technology needed for system operation, and described the current application of these technologies. Finally, we summarized the challenges that unmanned farm faces.

Through the analysis of literature, it can be concluded that unmanned farm is feasible. We will gradually realize unmanned farm in the next 50 years, which will play a role in reducing the number of environmental problems, solving the shortage of agricultural labor and bringing economic benefits. But at the same time, we need to solve some problems, such as unstable sensors, inefficient robots, AI applications in complex environments, privacy and management problems brought by Big Data, and how to transition to unmanned farm.

We believe that solving these problems of unmanned farms requires joint efforts of the government, enterprises and research institutes. The government should give policy support, such as agricultural subsidies, data security legislation and so on. Enterprises increase production, reduce the production costs of various agricultural machinery, and improve the utilization rate of agricultural machinery. The research institute should study agricultural robots and systems with high precision, fast response and stability in depth.

Author Contributions: Conceptualization, T.W. and X.X.; validation, Z.L., C.W. and D.L.; writing—original draft preparation, T.W.; writing—review and editing, X.X. and T.W.; supervision, D.L.; All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by Major Science and Technology Innovation Project of Shandong Province (Grant no: 2019JZZY010703) and National Key R&D Program "Advancing digital precision aquaculture in China (ADPAC)" (Grant no.2017YFE0122100).

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Acknowledgments: The author thanks Charlesworth Author Services Team and Professor Lin Zhu of Penn State University for providing English language editing of this paper. We also thank the reviewers for their comments which helped improve this article.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. FAO. *The State of Food Security and Nutrition in the World 2020*; FAO: Rome, Italy, 2020.
2. Hunter, M.C.; Smith, R.G.; Schipanski, M.E.; Atwood, L.W.; Mortensen, D.A. Agriculture in 2050: Recalibrating Targets for Sustainable Intensification. *BioScience* **2017**, *67*, 385–390. [CrossRef]
3. European Commission. *Generational Renewal in EU Agriculture: Statistical Background*; DG Agriculture & Rural Development, Economic Analysis of EU Agriculture Unit: Brussels, Belgium, 2012; pp. 1–10.
4. Unay-Gailhard, I.; Bavorova, M.; Bednarikova, Z.; Ponkina, E.V. "I don't want to work in agriculture!" The transition from agricultural education to the labor market in Rural Russia. *Rural Sociol.* **2019**, *84*, 315–349. [CrossRef]
5. Share of the Labor Force Employed in Agriculture. Available online: https://ourworldindata.org/employment-in-agriculture#all-charts-preview (accessed on 4 February 2021).
6. Stevant, P.; Rebours, C.; Chapman, A. Seaweed aquaculture in Norway: Recent industrial developments and future perspectives. *Aquac. Int.* **2017**, *25*, 1373–1390. [CrossRef]
7. Phan, L.T.; Nguyen, T.V.; Luong, Q.C. Importation and human-to-human transmission of a Novel Coronavirus in Vietnam. *N. Engl. J. Med.* **2020**, *382*, 872–874. [CrossRef]
8. Wang, C.; Horby, P.W.; Hayden, F.G.; Gao, G.F. A novel coronavirus outbreak of global health concern. *Lancet* **2020**, *395*, 470–473. [CrossRef]
9. Akbar, M.O.; Shahbaz Khan, M.S.; Ali, M.J.; Hussain, A.; Qaiser, G.; Pasha, M.; Pasha, U.; Missen, M.S.; Akhtar, N. IoT for development of smart dairy farming. *J. Food Qual.* **2020**, *2020*, 1–8. [CrossRef]
10. Ramli, M.R.; Daely, P.T.; Kim, D.; Lee, J.M. IoT-based adaptive network mechanism for reliable smart farm system. *Comput. Electron. Agric.* **2020**, *170*, 105287. [CrossRef]
11. Shamshiri, R.R.; Weltzien, C.; Hameed, I.A.; Yule, I.J.; Grift, T.E.; Balasundram, S.K.; Pitonakova, L.; Ahmad, D.; Chowdhary, G. Research and development in agricultural robotics: A perspective of digital farming. *Int. J. Agric. Biol. Eng.* **2018**, *11*, 1–14. [CrossRef]
12. Kamilaris, A.; Kartakoullis, A.; Prenafeta-Boldu, F.X. A review on the practice of big data analysis in agriculture. *Comput. Electron. Agric.* **2017**, *143*, 23–37. [CrossRef]
13. Chlingaryan, A.; Sukkarieh, S.; Whelan, B. Machine learning approaches for crop yield prediction and nitrogen status estimation in precision agriculture: A review. *Comput. Electron. Agric.* **2018**, *151*, 61–69. [CrossRef]
14. Liakos, K.G.; Busato, P.; Moshou, D.; Pearson, S.; Bochtis, D. Machine learning in agriculture: A review. *Sensors* **2018**, *18*, 2674. [CrossRef]
15. Walter, A.; Finger, R.; Huber, R.; Buchmann, N. Opinion: Smart farming is key to developing sustainable agriculture. *Proc. Natl. Acad. Sci. USA* **2017**, *114*, 6148–6150. [CrossRef]
16. Daoliang, L.I.; Zhen, L.I. System Analysis and Development Prospect of Unmanned Farming. *Trans. Chin. Soc. Agric. Mach.* **2020**, *51*, 1–12. [CrossRef]
17. Hands Free Hectare Project Set to Become World's First Fully Automated Crop Cycle. Available online: https://www.fdfworld.com/food/hands-free-hectare-project-set-become-worlds-first-fully-automated-crop-cycle (accessed on 20 November 2020).
18. Unprecedented Productivity through Advanced Robotics. Available online: https://technofarm.com/en/innovation/ (accessed on 4 February 2021).
19. Unmanned Agricultural Machinery Completes Rice "Farming Management". Available online: http://digitalpaper.stdaily.com/http_www.kjrb.com/kjrb/html/2020-09/07/content_453125.htm?div=-1 (accessed on 10 October 2020).
20. Jingdong Liu Qiangdong Announced: Pig Raising! Available online: https://www.sohu.com/a/366309070_488608 (accessed on 4 February 2021).
21. Goger, G.; Bisenberger, T. Digitalisierung im Infrastrukturbau—Baubetriebliche Entwicklungen. *Geomech. Tunn.* **2020**, *13*, 165–177. [CrossRef]
22. Gamayunova, O.; Vatin, N. BIM-technology in architectural design. *Adv. Mater. Res.* **2015**, *1065–1069*, 2611–2614. [CrossRef]
23. Dagar, R.; Som, S.; Khatri, S.K. Smart Farming—IoT in Agriculture. In Proceedings of the 2018 International Conference on Inventive Research in Computing Applications (ICIRCA), Coimbatore, India, 11–12 July 2018. [CrossRef]
24. Jaiganesh, S.; Gunaseelan, K.; Ellappan, V. IOT agriculture to improve food and farming technology. In Proceedings of the 2017 Conference on Emerging Devices and Smart Systems (ICEDSS), Tiruchengode, India, 3–4 March 2017; pp. 260–266. [CrossRef]
25. Thakur, D.; Kumar, Y.; Kumar, A.; Singh, P.K. Applicability of Wireless Sensor Networks in Precision Agriculture: A Review. *Wirel. Pers. Commun.* **2019**, *107*, 471–512. [CrossRef]
26. Aygun, S.; Gunes, E.O.; Subasi, M.A.; Alkan, S. Sensor Fusion for IoT-based Intelligent Agriculture System. In Proceedings of the 2019 8th International Conference on Agro-Geoinformatics (Agro-Geoinformatics), Istanbul, Turkey, 16–19 July 2019; pp. 1–5. [CrossRef]

27. Hansen, M.F.; Smith, M.L.; Smith, L.N.; Salter, M.G.; Baxter, E.M.; Farish, M.; Grieve, B. Towards on-farm pig face recognition using convolutional neural networks. *Comput. Ind.* **2018**, *98*, 145–152. [CrossRef]
28. Zhang, J.; Huang, Y.; Pu, R.; Gonzalez-Moreno, P.; Yuan, L.; Wu, K.; Huang, W. Monitoring plant diseases and pests through remote sensing technology: A review. *Comput. Electron. Agric.* **2019**, *165*, 104943. [CrossRef]
29. Zhao, L.; Li, Q.; Zhang, Y.; Wang, H.; Du, X. Normalized NDVI valley area index (NNVAI)-based framework for quantitative and timely monitoring of winter wheat frost damage on the Huang-Huai-Hai Plain, China. *Agric. Ecosyst. Environ.* **2020**, *292*, 106793. [CrossRef]
30. Weiss, M.; Jacob, F.; Duveiller, G. Remote sensing for agricultural applications: A meta-review. *Remote Sens. Environ.* **2020**, *236*, 111402. [CrossRef]
31. O'Grady, M.J.; Langton, D.; O'Hare, G.M.P. Edge computing: A tractable model for smart agriculture? *Artif. Intell. Agric.* **2019**, *3*, 42–51. [CrossRef]
32. The Truth about IoT Implementations—Wireless vs. Wired. Available online: https://blog.senseware.co/2017/10/10/iot-implementations-wireless-vs-wired (accessed on 30 December 2020).
33. Lounis, K.; Zulkernine, M. Attacks and Defenses in Short-Range Wireless Technologies for IoT. *IEEE Access* **2020**, *8*, 88892–88932. [CrossRef]
34. Poursafar, N.; Alahi, M.E.E.; Mukhopadhyay, S. Long-range wireless technologies for IoT applications: A review. In Proceedings of the 2017 Eleventh International Conference on Sensing Technology (ICST), Sydney, Australia, 4–6 December 2018.
35. Ojha, T.; Misra, S.; Raghuwanshi, N.S. Wireless sensor networks for agriculture: The state-of-the-art in practice and future challenges. *Comput. Electron. Agric.* **2015**, *118*, 66–84. [CrossRef]
36. Rajalakshmi, P.; Mahalakshmi, S.D. IOT based crop-field monitoring and irrigation automation. In Proceedings of the 2016 10th International Conference on Intelligent Systems and Control (ISCO), Coimbatore, India, 7–8 January 2016.
37. Wang, L.; Wang, B. Greenhouse microclimate environment adaptive control based on a wireless sensor network. *Int. J. Agric. Biol. Eng.* **2020**, *13*, 64–69. [CrossRef]
38. Mahale, R.B.; Sonavane, S.S. Smart Poultry Farm Monitoring Using IOT and Wireless Sensor Networks. *Int. J. Adv. Res. Comput. Sci.* **2016**, *7*, 187–190.
39. Goud, K.S.; Sudharson, A. Internet based Smart Poultry Farm. *Indian J. Sci. Technol.* **2015**, *8*. [CrossRef]
40. Wang, D.; Chen, D.; Song, B.; Guizani, N.; Yu, X.; Du, X. From IoT to 5G I-IoT: The Next Generation IoT-Based Intelligent Algorithms and 5G Technologies. *IEEE Commun. Mag.* **2018**, *56*, 114–120. [CrossRef]
41. Maya, G.P.S.; Chintala, B.R. Big data challenges and opportunities in agriculture. *Int. J. Agric. Environ. Inf. Syst.* **2020**, *11*, 48–66. [CrossRef]
42. Muangprathub, J.; Boonnam, N.; Kajornkasirat, S.; Lekbangpong, N.; Wanichsombat, A.; Nillaor, P. IoT and agriculture data analysis for smart farm. *Comput. Electron. Agric.* **2019**, *156*, 467–474. [CrossRef]
43. Li, C.; Niu, B. Design of smart agriculture based on big data and Internet of things. *Int. J. Distrib. Sens. Netw.* **2020**, *16*, 812444474. [CrossRef]
44. Wang, F. Applied research on agricultural big data. *J. Phys. Conf. Ser.* **2020**, *1533*, 42051. [CrossRef]
45. Newton, J.E.; Nettle, R.; Pryce, J.E. Farming smarter with big data: Insights from the case of Australia's national dairy herd milk recording scheme. *Agric. Syst.* **2020**, *181*, 102811. [CrossRef]
46. Li, Y. Research on precision planting management system based on agricultural big data. *J. Phys. Conf. Ser.* **2020**, *1544*, 12174–12176. [CrossRef]
47. Wolfert, S.; Ge, L.; Verdouw, C.; Bogaardt, M. Big data in smart farming—A review. *Agric. Syst.* **2017**, *153*, 69–80. [CrossRef]
48. Huang, J.; Zhang, L. The big data processing platform for intelligent agriculture. In *AIP Conference Proceedings*; Liu, L., Xiao, J., Ke, J., Eds.; American Institute of Physics: College Park, MD, USA, 2017.
49. Weersink, A.; Fraser, E.; Pannell, D.; Duncan, E.; Rotz, S. Opportunities and challenges for big data in agricultural and environmental analysis. In *Annual Review of Resource Economics*; Rausser, G.C., Zilberman, D., Eds.; Annual Reviews: Palo Alto, CA, USA, 2018.
50. Zhang, Q.; Yang, L.T.; Chen, Z.; Li, P. A survey on deep learning for big data. *Inf. Fusion* **2018**, *42*, 146–157. [CrossRef]
51. Sudduth, K.A.; Woodward-Greene, M.J.; Penning, B.W.; Locke, M.A.; Rivers, A.R.; Veum, K.S. AI down on the farm. *IT Prof.* **2020**, *22*, 22–26. [CrossRef]
52. Smith, M.J. Getting value from artificial intelligence in agriculture. *Anim. Prod. Sci.* **2020**, *60*, 46. [CrossRef]
53. Yang, X.; Zhang, S.; Liu, J.; Gao, Q.; Dong, S.; Zhou, C. Deep learning for smart fish farming: Applications, opportunities and challenges. *Rev. Aquac.* **2021**, *13*, 66–90. [CrossRef]
54. Zhai, Z.; Martínez, J.F.; Beltran, V.; Martínez, N.L. Decision support systems for agriculture 4.0: Survey and challenges. *Comput. Electron. Agric.* **2020**, *170*, 105256. [CrossRef]
55. Zhou, C.; Lin, K.; Xu, D.; Chen, L.; Guo, Q.; Sun, C.; Yang, X. Near infrared computer vision and neuro-fuzzy model-based feeding decision system for fish in aquaculture. *Comput. Electron. Agric.* **2018**, *146*, 114–124. [CrossRef]
56. Navarro-Hellín, H.; Martínez-Del-Rincon, J.; Domingo-Miguel, R.; Soto-Valles, F.; Torres-Sánchez, R. A decision support system for managing irrigation in agriculture. *Comput. Electron. Agric.* **2016**, *124*, 121–131. [CrossRef]

57. Qin, Z.; Myers, D.B.; Ransom, C.J.; Kitchen, N.R.; Liang, S.; Camberato, J.J.; Carter, P.R.; Ferguson, R.; Fernandez, F.G.; Franzen, D.W.; et al. Application of Machine Learning Methodologies for Predicting Corn Economic Optimal Nitrogen Rate. *Agron. J.* **2018**, *110*, 2596–2607. [CrossRef]
58. Jan, T.; Vaclav, V. The current state of the issue of information needs and dispositions among small Czech farms. *Agric. Econ. (Zemědělská Ekon.)* **2017**, *63*, 164–174. [CrossRef]
59. Liu, Y.; Zhang, Q.; Song, L.; Chen, Y. Attention-based recurrent neural networks for accurate short-term and long-term dissolved oxygen prediction. *Comput. Electron. Agric.* **2019**, *165*, 104964. [CrossRef]
60. Chen, Y.; Xu, J.; Yu, H.; Zhen, Z.; Li, D. Three-dimensional short-term prediction model of dissolved oxygen content based on pso-bpann algorithm coupled with kriging interpolation. *Math. Probl. Eng.* **2016**, *2016*, 6564202. [CrossRef]
61. Wang, L.; Feng, J.; Sui, X.; Chu, X.; Mu, W. Agricultural product price forecasting methods: Research advances and trend. *Brit. Food J.* **2020**, *122*, 2121–2138. [CrossRef]
62. Hamrani, A.; Akbarzadeh, A.; Madramootoo, C.A. Machine learning for predicting greenhouse gas emissions from agricultural soils. *Sci. Total Environ.* **2020**, *741*, 140338. [CrossRef]
63. Saranya, C.P.; Nagarajan, N. Efficient agricultural yield prediction using metaheuristic optimized artificial neural network using Hadoop framework. *Soft Comput.* **2020**, *24*, 12659–12669. [CrossRef]
64. Mostafaeipour, A.; Fakhrzad, M.B.; Gharaat, S.; Jahangiri, M.; Dhanraj, J.A.; Shamshirband, S.; Issakhov, A.; Mosavi, A. Machine Learning for Prediction of Energy in Wheat Production. *Agriculture* **2020**, *10*, 517. [CrossRef]
65. Yang, L.; Liu, Y.; Yu, H.; Fang, X.; Song, L.; Li, D.; He, L. Computer Vision Models in Intelligent Aquaculture with Emphasis on Fish Detection and Behavior Analysis: A Review. *Arch. Comput. Methods E* **2020**. [CrossRef]
66. Li, Y.; Chao, X. ANN-Based Continual Classification in Agriculture. *Agriculture* **2020**, *10*, 178. [CrossRef]
67. Castro-Maldonado, J.J.; Patiño-Murillo, J.A.; Florian-Villa, A.E.; Guadrón-Guerrero, O.E. Application of computer vision and low-cost artificial intelligence for the identification of phytopathogenic factors in the agro-industry sector. *J. Phys. Conf. Ser.* **2018**, *1126*, 12022. [CrossRef]
68. Li, D.; Wang, Z.; Wu, S.; Miao, Z.; Du, L.; Duan, Y. Automatic recognition methods of fish feeding behavior in aquaculture: A review. *Aquaculture* **2020**, *528*, 735508. [CrossRef]
69. Zhao, J.; Bao, W.; Zhang, F.; Zhu, S.; Liu, Y.; Lu, H.; Shen, M.; Ye, Z. Modified motion influence map and recurrent neural network-based monitoring of the local unusual behaviors for fish school in intensive aquaculture. *Aquaculture* **2018**, *493*, 165–175. [CrossRef]
70. Chen, C.; Zhu, W.; Steibel, J.; Siegford, J.; Wurtz, K.; Han, J.; Norton, T. Recognition of aggressive episodes of pigs based on convolutional neural network and long short-term memory. *Comput. Electron. Agric.* **2020**, *169*, 105166. [CrossRef]
71. Yang, Q.; Xiao, D. A review of video-based pig behavior recognition. *Appl. Anim. Behav. Sci.* **2020**, *233*, 105146. [CrossRef]
72. Conesa-Muñoz, J.; Valente, J.; Del Cerro, J.; Barrientos, A.; Ribeiro, A. A Multi-Robot Sense-Act Approach to Lead to a Proper Acting in Environmental Incidents. *Sensors* **2016**, *16*, 1269. [CrossRef]
73. Li, D.; Wang, P.; Du, L. Path Planning Technologies for Autonomous Underwater Vehicles-A Review. *IEEE Access* **2019**, *7*, 9745–9768. [CrossRef]
74. Barua, A.; Kalwa, J.; Shardt, Y.; Glotzbach, T. Path planning for an identification mission of an Autonomous Underwater Vehicle in a lemniscate form. *IFAC Pap.* **2018**, *51*, 323–328. [CrossRef]
75. Zhang, Q.; Liu, Y.; Gong, C.; Chen, Y.; Yu, H. Applications of deep learning for dense scenes analysis in agriculture: A review. *Sensors* **2020**, *20*, 1520. [CrossRef]
76. Chen, J.; Cao, X.; Hu, H.; Anthony, L. Agricultural product monitoring system supported by cloud computing. *Clust. Comput.* **2019**, *22*, 8929–8938. [CrossRef]
77. Mokarram, M.; Khosravi, M.R. A cloud computing framework for analysis of agricultural big data based on Dempster—Shafer theory. *J. Supercomput.* **2020**. [CrossRef]
78. Chen, Y. Intelligent algorithms for cold chain logistics distribution optimization based on big data cloud computing analysis. *J. Cloud Comput.* **2020**, *9*. [CrossRef]
79. Zhou, L.; Chen, N.; Chen, Z. A cloud computing-enabled spatio-temporal cyber-physical information infrastructure for efficient soil moisture monitoring. *ISPRS Int. J. Geo-Inf.* **2016**, *5*, 81. [CrossRef]
80. Liu, S.; Guo, L.; Webb, H.; Ya, X.; Chang, X. Internet of things monitoring system of modern eco-agriculture based on cloud computing. *IEEE Access* **2019**, *7*, 37050–37058. [CrossRef]
81. Zamora-Izquierdo, M.A.; Santa, J.; Martínez, J.A.; Martínez, V.; Skarmeta, A.F. Smart farming IoT platform based on edge and cloud computing. *Biosyst. Eng.* **2019**, *177*, 4–17. [CrossRef]
82. Xiang, L.; Bao, Y.; Tang, L.; Ortiz, D.; Salas-Fernandez, M.G. Automated morphological traits extraction for sorghum plants via 3D point cloud data analysis. *Comput. Electron. Agric.* **2019**, *162*, 951–961. [CrossRef]
83. Kamienski, C.; Orcid, J.S.; Taumberger, M.; Dantas, R.; Toscano, A.; Cinotti, T.S.; Maia, R.F.; Neto, A.T. Smart Water Management Platform: IoT-Based Precision Irrigation for Agriculture. *Sensors* **2019**, *19*, 276. [CrossRef]
84. Sharma, S.; Borse, R. *Automatic Agriculture Spraying Robot with Smart Decision Making*; Corchado Rodriguez, J.M., Mitra, S., Thampi, S.M., El-Alfy, E., Eds.; Springer International Publishing: Cham, Switzerland, 2016; pp. 743–758. [CrossRef]

85. Singh, P.; Saikia, S. Arduino-based smart irrigation using water flow sensor, soil moisture sensor, temperature sensor and ESP8266 WiFi module. In Proceedings of the 2016 IEEE Region 10 Humanitarian Technology Conference (R10-HTC), Agra, India, 21–23 December 2016; pp. 1–4. [CrossRef]
86. Berckmans, D. General introduction to precision livestock farming. *Anim. Front.* **2017**, *7*, 6–11. [CrossRef]
87. Saravanan, K.; Saraniya, S. Cloud IOT based novel livestock monitoring and identification system using UID. *Sens. Rev.* **2017**, *38*, 21–33. [CrossRef]
88. Nóbrega, L.; Gonçalves, P.; Antunes, M.; Corujo, D. Assessing sheep behavior through low-power microcontrollers in smart agriculture scenarios. *Comput. Electron. Agric.* **2020**, *173*, 105444. [CrossRef]
89. Yang, Y.; Yu, Y.; Pan, J.; Ying, Y.; Zhou, H. A new method to manipulate broiler chicken growth and metabolism: Response to mixed LED light system. *Sci. Rep.* **2016**, *6*, 25972. [CrossRef] [PubMed]
90. Oliveira, J.L.; Xin, H.; Chai, L.; Millman, S.T. Effects of litter floor access and inclusion of experienced hens in aviary housing on floor eggs, litter condition, air quality, and hen welfare. *Poult. Sci.* **2018**, *98*, 1664–1677. [CrossRef] [PubMed]
91. Chen, H.Q.; Xin, H.W.; Teng, G.H.; Meng, C.Y.; Wang, C. Cloud-based data management system for automatic real-time data acquisition from large-scale laying-hen farms. *Int. J. Agric. Biol. Eng.* **2016**, *9*, 106–115. [CrossRef]
92. Vroegindeweij, B.A.; Blaauw, S.K.; Ijsselmuiden, J.M.M.; Van, H.E.J. Evaluation of the performance of PoultryBot, an autonomous mobile robotic platform for poultry houses. *Biosyst. Eng.* **2018**, *174*, 295–315. [CrossRef]
93. Vroegindeweij, B.A.; van Hell, S.; Ijsselmuiden, J.M.M.; van Henten, E.J. Object discrimination in poultry housing using spectral reflectivity. *Biosyst. Eng.* **2018**, *167*, 99–113. [CrossRef]
94. Bonadies, S.; Lefcourt, A.; Gadsden, S.A. A survey of unmanned ground vehicles with applications to agricultural and environmental sensing. In Proceedings of the SPIE Commercial + Scientific Sensing and Imaging, Baltimore, MD, USA, 17–21 April 2016.
95. Gonzalez-De-Santos, P.; Fernández, R.; Sepúlveda, D.; Navas, E.; Armada, M. Unmanned Ground Vehicles for Smart Farms. In *Agronomy—Climate Change and Food Security*; IntechOpen: London, UK, 2020. [CrossRef]
96. Arad, B.; Balendonck, J.; Barth, R.; Hahar, O.B.; Tuijl, B. Development of a sweet pepper harvesting robot. *J. Field Robot.* **2020**, *37*, 1027–1039. [CrossRef]
97. Xiong, Y.; Peng, C.; Grimstad, L.; From, P.J.; Isler, V. Development and field evaluation of a strawberry harvesting robot with a cable-driven gripper. *Comput. Electron. Agric.* **2019**, *157*, 392–402. [CrossRef]
98. Birrell, S.; Hughes, J.; Cai, J.Y.; Iida, F. A field-tested robotic harvesting system for iceberg lettuce. *J. Field Robot.* **2019**, *37*. [CrossRef]
99. Jia, W.; Zhang, Y.; Lian, J.; Zheng, Y.; Li, C. Apple harvesting robot under information technology: A review. *Int. J. Adv. Robot. Syst.* **2020**, *17*, 255688461. [CrossRef]
100. Chen, W.; Xu, T.; Liu, J.; Wang, M.; Zhao, D. Picking Robot Visual Servo Control Based on Modified Fuzzy Neural Network Sliding Mode Algorithms. *Electronics* **2019**, *8*, 605. [CrossRef]
101. Ravalli, A.; Rossi, C.; Marrazza, G. Bio-inspired fish robot based on chemical sensors. *Sens. Actuators B Chem.* **2017**, *239*, 325–329. [CrossRef]
102. Marrazza, G.; Ravalli, A.; Rossi, C. Fish Robot Based on Chemical Sensors for Water Monitoring. In Proceedings of the AISEM Annual Conference on Sensors and Microsystems, Lecce, Italy, 21–23 February 2017.
103. Ryuh, Y.; Yang, G.; Liu, J.; Hu, H. A School of Robotic Fish for Mariculture Monitoring in the Sea Coast. *J. Bionic Eng.* **2015**, *12*, 37–46. [CrossRef]
104. Koprowski, R.; Wróbel, Z.; Kleszcz, A.; Wilczyński, S.; Woźnica, A.; Łozowski, B.; Pilarczyk, M.; Karczewski, K.J.; Migula, P. Mobile sailing robot for automatic estimation of fish density and monitoring water quality. *Biomed. Eng. Online* **2013**. [CrossRef]
105. Von Borstel, F.D.; Suárez, J.; De La Rosa, E.; Gutiérrez, J. Feeding and water monitoring robot in aquaculture greenhouse. *Ind. Robot.* **2013**, *40*, 10–19. [CrossRef]
106. Design and Motion Analysis of ROV Robot for Catching Sea Cucumber. *Int. J. Simul. Syst.* **2016**, *17*, 31–38. [CrossRef]
107. Qiao, X.; Bao, J.; Zhang, H.; Zeng, L.; Li, D. Underwater image quality enhancement of sea cucumbers based on improved histogram equalization and wavelet transform. *Inf. Process. Agric.* **2017**, *4*, 206–213. [CrossRef]
108. Takahata, K.; Shimizu, E.; Umeda, A.; Oode, T.; Tsuchiya, T.; Tamura, Y. Development of remotely operated unmanned boat with long-range Wi-Fi. *Artif. Life Robot.* **2016**, *21*, 365–370. [CrossRef]
109. Tong, X.; Zhang, H.; Chen, W.; Zhao, P.; Leng, Z.; Cheng, K. A research on intelligent obstacle avoidance for unmanned surface vehicles. In Proceedings of the 2018 Chinese Automation Congress (CAC), Xi'an, China, 30 November–2 December 2018; pp. 1431–1435. [CrossRef]
110. Zeng, B.; Song, Y.; Liu, C. Design and implementation of an unmanned boat visual target tracking system. In Proceedings of the 2020 Chinese Control and Decision Conference (CCDC), Hefei, China, 22–24 August 2020; pp. 5225–5230. [CrossRef]
111. Chen, H.; Wu, Z.; Zheng, R.; Zhang, S. Design of Autonomous Obstacle Avoidance Unmanned Boat System for Wetland Monitoring. *J. Phys. Conf. Ser.* **2020**, *1486*, 72033. [CrossRef]
112. Ahn, S.; Lee, Y.; Yoo, J.; Lee, Y. Development and Verification of the Automated Cow-Feeding System Driven by AGV. *Korea Acad. Ind. Coop. Soc.* **2017**, *18*, 232–241. [CrossRef]
113. Joffe, B.P.; Usher, C.T. Autonomous robotic system for picking up floor eggs in poultry houses. In Proceedings of the 2017 ASABE Annual International Meeting, Spokane, WA, USA, 16–19 July 2017.

114. Tsouros, D.C.; Bibi, S.; Sarigiannidis, P.G. A Review on UAV-Based Applications for Precision Agriculture. *Information* **2019**, *10*, 349. [CrossRef]
115. Yang, S.; Yang, X.; Mo, J. The application of unmanned aircraft systems to plant protection in China. *Precis. Agric.* **2017**, *19*, 278–292. [CrossRef]
116. Manfreda, S.; Mccabe, M.F.; Miller, P.E.; Lucas, R.; Madrigal, V.P.; Mallinis, G.; Ben-Dor, E.; Helman, D.; Estes, L.; Ciraolo, G.; et al. On the use of unmanned aerial systems for environmental monitoring. *Remote Sens.* **2018**, *10*, 641. [CrossRef]
117. Nyamuryekung, E.S.; Cibils, A.F.; Estell, R.E.; Gonzalez, A.L. Use of an Unmanned Aerial Vehicle−Mounted Video Camera to Assess Feeding Behavior of Raramuri Criollo Cows. *Rangel. Ecol. Manag.* **2016**, *69*, 386–389. [CrossRef]
118. Deng, L.; Mao, Z.; Li, X.; Hu, Z.; Duan, F.; Yan, Y. UAV-based multispectral remote sensing for precision agriculture: A comparison between different cameras. *ISPRS J. Photogramm.* **2018**, *146*, 124–136. [CrossRef]
119. Comba, L.; Biglia, A.; Ricauda Aimonino, D.; Gay, P. Unsupervised detection of vineyards by 3D point-cloud UAV photogrammetry for precision agriculture. *Comput. Electron. Agric.* **2018**, *155*, 84–95. [CrossRef]
120. Amer, G.; Mudassir, S.M.M.; Malik, M.A. Design and operation of Wi-Fi agribot integrated system. In Proceedings of the 2015 International Conference on Industrial Instrumentation and Control (ICIC), Pune, India, 28–30 May 2015; pp. 207–212. [CrossRef]
121. Balafoutis, A.; Beck, B.; Fountas, S.; Vangeyte, J.; Wal, T.; Soto, I.; Gómez-Barbero, M.; Barnes, A.; Eory, V. Precision Agriculture Technologies Positively Contributing to GHG Emissions Mitigation, Farm Productivity and Economics. *Sustainability* **2017**, *9*, 1339. [CrossRef]
122. Pivoto, D.; Barham, B.; Waquil, P.D.; Foguesatto, C.R.; Corte, V.F.D.; Zhang, D.; Talamini, E. Factors influencing the adoption of smart farming by Brazilian grain farmers. *Int. Food Agribus. Manag. Rev.* **2019**, *22*, 571–588. [CrossRef]
123. Forecast Market Value of Smart Agriculture Worldwide in 2017 and 2022. Available online: https://www.statista.com/statistics/720062/market-value-smart-agriculture-worldwide/ (accessed on 15 November 2020).
124. Hajjaj, S.S.H.; Sahari, K.S.M. Review of agriculture robotics: Practicality and feasibility. In Proceedings of the 2016 IEEE International Symposium on Robotics and Intelligent Sensors (IRIS), Tokyo, Japan, 17–20 December 2016; pp. 194–198. [CrossRef]
125. Lioutas, E.D.; Charatsari, C. Smart farming and short food supply chains: Are they compatible? *Land Use Policy* **2020**, *94*, 104541. [CrossRef]
126. Lioutas, E.D.; Charatsari, C.; La Rocca, G.; De Rosa, M. Key questions on the use of big data in farming: An activity theory approach. *NJAS—Wagening. J. Life Sci.* **2019**, *90–91*, 100297. [CrossRef]
127. Bronson, K.; Knezevic, I. Big Data in food and agriculture. *Big Data Soc.* **2016**, *3*, 1245635505. [CrossRef]
128. Shepherd, M.; Turner, J.A.; Small, B.; Wheeler, D. Priorities for science to overcome hurdles thwarting the full promise of the 'digital agriculture' revolution. *J. Sci. Food Agric.* **2020**, *100*, 5083–5092. [CrossRef] [PubMed]
129. Fielke, S.; Taylor, B.; Jakku, E. Digitalisation of agricultural knowledge and advice networks: A state-of-the-art review. *Agric. Syst* **2020**, *180*, 102763. [CrossRef]
130. Wiseman, L.; Sanderson, J.; Zhang, A.; Jakku, E. Farmers and their data: An examination of farmers' reluctance to share their data through the lens of the laws impacting smart farming. *NJAS—Wagening. J. Life Sci* **2019**, *90–91*, 100301. [CrossRef]
131. Jakku, E.; Taylor, B.; Fleming, A.; Mason, C.; Fielke, S.; Sounness, C.; Thorburn, P. "If they don't tell us what they do with it, why would we trust them?" Trust, transparency and benefit-sharing in Smart Farming. *NJAS—Wagening. J. Life Sci.* **2019**, *90–91*, 100285. [CrossRef]
132. Scholz, R. Sustainable Digital Environments: What Major Challenges Is Humankind Facing? *Sustainability* **2016**, *8*, 726. [CrossRef]
133. Kendall, H.; Naughton, P.; Clark, B.; Taylor, J.; Li, Z.; Zhao, C.; Yang, G.; Chen, J.; Frewer, L.J. Precision Agriculture in China: Exploring Awareness, Understanding, Attitudes and Perceptions of Agricultural Experts and End-Users in China. *Adv. Anim. Biosci.* **2017**, *8*, 703–707. [CrossRef]
134. Şekerli, Y.E.; Say, S.M.; Keskin, M.; Şehri, M.; Dündar, M.Ş.; Şişman, A. Adoption of precision agriculture technologies in developed and developing countries. *J. Sci. Technol.* **2018**, *8*, 7–15.