Turkish Journal of Agriculture and Forestry

http://journals.tubitak.gov.tr/agriculture/

Review Article

Turk J Agric For
(2022) 46: 642-661
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doi:10.55730/1300-011X.3033

Artificial intelligence and digital twins in sustainable agriculture and forestry: a survey

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Received: 29.05.2022 • **Accepted/Published Online:** 06.08.2022 • **Final Version:** 03.10.2022

Abstract: Affected by global economic pressure and epidemics, sustainable agriculture has received widespread attention from farmers and agricultural engineers. Throughout history, agricultural technology has closely followed the pace of scientific and technological development and has followed the footsteps of mechanization, automation, and intelligence to progress continuously. At this stage, artificial intelligence (AI) is dominating the field of agriculture and advancing the progress of sustainable agriculture. However, the large amount of data required by AI technology and the high cost of data have ensued, while the rapid development of virtualization technology has made people gradually begin to consider the application of digital twins (DT) in agriculture. This paper examines the application of artificial intelligence technology and digital twin technology in smart agriculture in recent years and discusses and analyzes the challenges they face and the future directions of development. We find that digital twins have great potential for success in sustainable agriculture, which is of great significance to advancing smart agricultural solutions that achieve low cost and high precision to meet the growing demand for high-yield production from farmers around the world.

Key words: Smart agriculture, artificial intelligence, digital twins, sustainable agriculture

1. Introduction

In the postepidemic era, agriculture, as the most basic source of material security for human life, has received great attention from various countries. In recent years, the pace of agricultural modernization and technological development has accelerated, and people have gradually combined agriculture with various types of high-tech and intelligent algorithms, and the concepts such as “smart agriculture”, “precision agriculture”, “digital agriculture”, “decision agriculture”, and “agriculture 4.0” have emerged. These developments are inseparable from the help and promotion of artificial intelligence (AI) technology. Looking at the current agricultural production process, artificial intelligence is everywhere. However, most AI applications are based on large amounts of data, and the data and time cost problems they bring have gradually become new challenges for farmers. In response to these challenges, digital twins have come to the forefront of agricultural researchers’ minds. Digital twin technology aims to build mirror models of information in the hyper-real world, using computerized virtual reality. For example, a model of a plant can be constructed in which its physical characteristics are transformed into digital information, and this digital information can be used to make it grow naturally in the virtual space beyond reality. This makes it easier to develop and test new agricultural technologies in virtual reality. This means that issues such as data and time costs are no longer a barrier to progress. Therefore, digital twins have become an important research direction in the field of agriculture in the future. This paper introduces the typical application of artificial intelligence in agriculture and the development of digital twin technology in agriculture.

This paper will outline and answer the following research question:

· What is the current state of development of artificial intelligence technologies in agriculture? In the whole process of agricultural production, what are the main technologies and applications of artificial intelligence technology for different agricultural tasks in the preproduction, midproduction, and postproduction stages?

· What is the “digital twins”? What are the basic characteristics and attributes of the architecture based on digital twins? What are the main technologies and application directions of the digital twins?

· How to integrate digital twin technology with agriculture? What is the impact of the introduction of the digital twins on the agricultural sector? What are the scenarios in which digital twin technology can be applied in the agricultural sector and truly benefit from it?

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· What are the opportunities and challenges in the application of artificial intelligence technology and digital twin technology in agriculture at this stage? What are the possible future evolution and development trends?

The remainder of the paper is organized as follows. In Section 2, starting from the three links of the preproduction, midproduction, and postproduction stages of the agricultural production process, the research and application status of artificial intelligence in the agricultural field are introduced. An overview of the digital twins is given in Section 3, followed by a description and analysis of its current state of the art in agriculture. The challenges and possible future directions of AI and DT in agriculture are discussed in Section 4. Finally, a brief conclusion is given in Section 5.

2. Artificial intelligence in agriculture

At present, artificial intelligence agriculture dominates the development direction of modern agriculture, and researchers are committed to applying artificial intelligence technology to the whole process of agricultural production. The agricultural production process can be divided into three stages: preproduction, midproduction, and postproduction. Figure 1 shows the agricultural production process after division. The application of artificial intelligence technology in the preproduction, midproduction, and postproduction stages of agricultural production is briefly introduced to provide a reference for the rapid and effective transformation and improvement of intelligent agricultural technology and the promotion of agricultural industrialization and modernization.

2.1. Preproduction stage of agricultural production

In the preproduction stage of agriculture, "what are we going to grow?" is the question that people need to consider. The application of artificial intelligence technology to the preproduction stage is aimed at helping agricultural workers to grasp the prerequisites in the agricultural scene. At this stage, we focus on soil fertilizer quality testing, irrigation scheme design, seed quality testing, and crop yield and quality forecast to briefly introduce the application of AI in agriculture in the past five years.

2.1.1. Soil fertilizer quality testing

At the preproduction stage of the agricultural process, the quality of soil fertilizer plays a decisive role in the growth of crops. The determination of the content of minerals, nutrients, and other elements in the soil is an important indicator to judge whether the soil is polluted (Jia et al., 2021), and whether it is suitable for planting a particular plant (Chen et al., 2019; Wilhelm et al., 2022), and whether it meets the nutrients required by crops (Kulkarni et al., 2019). Therefore, it is vital to systematically test and evaluate soils and fertilizers before planting. There are many substances in the soil that affect crop growth. This paper simply divides them into "human-eye distinguishable" and "human-eye indistinguishable", which are introduced in the following contents respectively. Among them, the "human-eye distinguishable" substances in the soil are mainly the residues from the previous cropping cycle while the "human-eye indistinguishable" substances in the soil refer to the physical, chemical, and biological indicators that are hardly observable by human beings alone and require the help of some professional detection tools, such as the content of some trace elements, minerals, and the activity of some microorganisms.

Firstly, the detection of "human-eye distinguishable" substances in the soil is focused on plant residues that have a major protective effect on the soil. Not only do they reduce soil erosion and consolidate soil quality, but also bring nutrients and improve soil structure for recultivation. However, the workload of manually determining the types of residues and the coverage rate of residues on large areas of land is undoubtedly huge and extremely time-consuming, and it is subjective and uneven, and the error of the results is uncertain with the experience of different observers. In this regard, with the help of machine vision, image processing and other technologies, people have proposed a series of reliable, consistent, and automated methods. For example, Tao et al. (2021) developed a deep learning method MSCU-net + C, which was used to draw the residual coverage area of maize on high spatial resolution satellite remote sensing images, and classify different coverage rates and measure the classification accuracy index. The results showed that the average value of IoU increased from 0.8604 to 0.908, and the average value of Kappa increased from 0.8864 to 0.9258. Another example is the crop residue level estimation using machine learning methods for RGB images of three different ground image resolutions (GSD) by Upadhyay's team (2022). The RFE-SVM feature selection method was used to obtain cross-validation scores up to 10 times better than other methods, as well as residual cover estimation by location for classified images using a Bayesian-based classification model.

Secondly, the most familiar part of the "human-eye indistinguishable" substances in the soil is the detection of soil salinity, followed by the detection of nitrogen (N), phosphorus (P), potassium (K), and carbon (C), which are the main nutrients provided by the soil for crop growth. Soil salinization is closely related to the sustainable development of agriculture and is a phenomenon of soil degradation. Therefore, it is of great significance to accurately monitor soil salinization. Recently, the popular way of predicting soil salinity is "Internet of things + machine learning", such as Wang et al. (2021) and Wei et al. (2020) both used the way combination of "multispectral

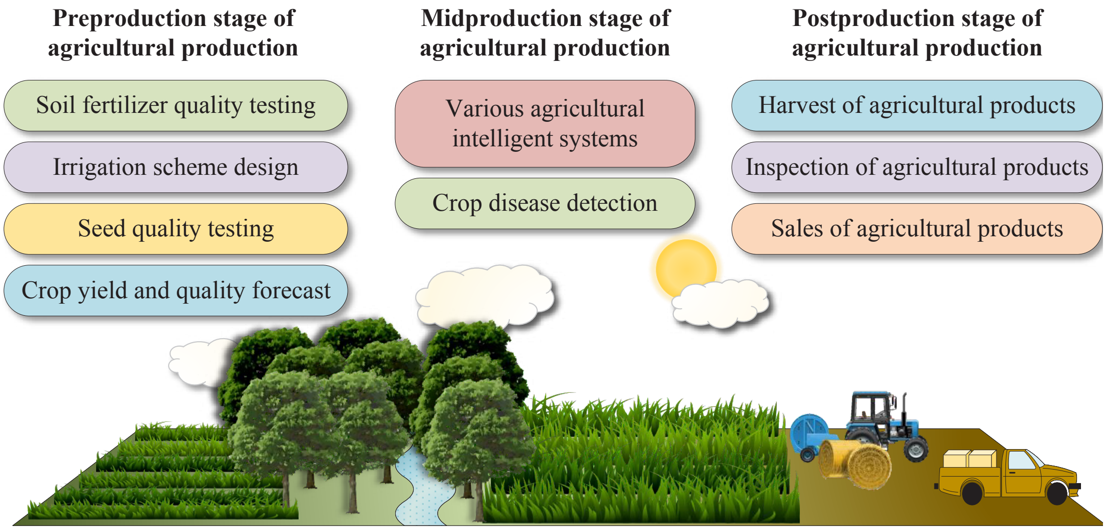

Figure 1. Three links in the agricultural production process.

image acquisition + machine learning prediction model" to predict soil salinity. Analyzing the nutrient levels of elements in the soil and adjusting fertilizer planning to crop needs can not only mitigate the general environmental degradation, climatic disasters, and economic losses caused by over-fertilization, but also increase crop yields and productivity. Some typical examples of combining machine learning with soil chemical element prediction in the last 5 years are presented in Table 1.

After testing the elemental content of the soil, scientific fertilization planning based on soil nutrient status is the basis for high-quality and high-yielding crops (Chen et al., 2018; Nie et al., 2021). Uneven distribution and low utilization of fertilizer will be caused by blind, mechanical application of fertilizer, which can even cause adverse consequences such as soil pollution and excess crop nutrients. Researchers have conducted research on this problem. Chaganti et al. (2019) used technologies such as machine learning, image processing, and the Internet of things to optimize fertilizer use decisions on farms. Escalante et al. (2019) used machine learning to determine the optimal fertilizer dose for specific barley varieties. In an application program developed by Goyal et al. (2021), the fertilizer calculator function provides the user with the number of DAPs, MOPs, and kilograms of urea needed for the crop after entering the "crop type" and "number of hectares". These efforts have promoted the progress of fertilization methods in a more reasonable and accurate direction, all of which are of great significance to the sustainable development of agriculture and the successful implementation of precision agriculture.

2.1.2. Irrigation scheme design

Besides soil, water is another decisive factor restricting agricultural production. In the preproduction stage of agriculture, proper irrigation planning is the basis for sustainable agricultural production (García-Tejero et al., 2011). The introduction of several artificial intelligence technologies has made intelligent and automatic irrigation possible, while irrigation management and decision making are continuously optimized, thus advancing the development of fine agriculture and sustainable agriculture. A typical AI-based intelligent irrigation system is shown in Figure 2.

The typical intelligent irrigation system shown in Figure 2 is mainly composed of terminal monitoring part, gateway module, cloud service module, expert decision system, and user terminal. The expert decision system is a key part whose main function is to process, calculate, predict, and analyze the historical or real-time data in the cloud system through a series of artificial intelligence algorithms to obtain the best irrigation decision. As can be seen from the figure, the data affecting the decision-making are mainly irrigation water quality, soil condition, reference evapotranspiration (ETo), precipitation, crop factor and other.

Agriculture is inseparable from water, and the primary concern in the irrigation process is the quality of irrigation water. Traditional methods of irrigation water quality assessment are cumbersome and costly, which increases the burden of farmers. Therefore, the use of artificial intelligence technology to predict and manage the quality of groundwater is a valuable research direction at present. Zhao et al. (2020) compared the CAR-RR model and the advanced CAR-SVR model they developed for depth modeling of the groundwater table with the support vector regression (SVR) model and multiple linear regression (MLR) model, and they validated them in the Hetao Irrigation Area in northwest China; Chen et al. (2020b)

Table 1. Some cases of detection of elemental content in soil based on machine learning.

Reference	Material sources	Soil testing methods	Detection elements	Data/image acquisition	Models	Performance indicators
(Sirsat et al., 2018)	Marathwada District, Maharashtra, India	——	OC; P_2O_5; Fe; Mn; Zn	——	76 regressors which belong to 20 families	RMSE; R^2
(Li et al., 2019)	Lishui, Zhejiang, China	Kjeldahl method	TN	Near infrared (hyperspectral imaging) HSI system	PLS; ELM	rc; rp; RPD; RMSEC; RMSEP
(Guo et al., 2020)	Center of Jianghan Plain, Hubei, China	CHNS combustion gas analyzer	SOC	UAV + Multispectral Camera	STR; PLSR; SVM; BPNN; ELM	R^2; RMSE; RPIQ
(Patel et al., 2020)	Roorkee, Uttarakhand, India	Transformation factors and their molecular mass determination; Ion Chromatography Technology	N (Urea)	Portable spectroradiometer	DL network based on DASU	R^2
(Hossen et al., 2021)	Sturgis, South Dakota, USA	Laser-induced breakdown spectroscopy (LIBS)	N	UAV + Multispectral Camera; UAV + Sentera high precision NDVI single sensor	MLP-R; SVR	RMSE
(Jaihuni et al., 2021)	Sacheon City, Republic of Korea	Inductively coupled plasma-optical emission spectrometry (ICP-OES)	NPKC	UAV + Multispectral Camera	CNN regression	RMSE; R^2; MAPE
(Haritha et al., 2022)	Erode, India	Homemade samples	N (Urea)	Midinfrared spectroscopy	PLSR; SVM	RMSE; R^2

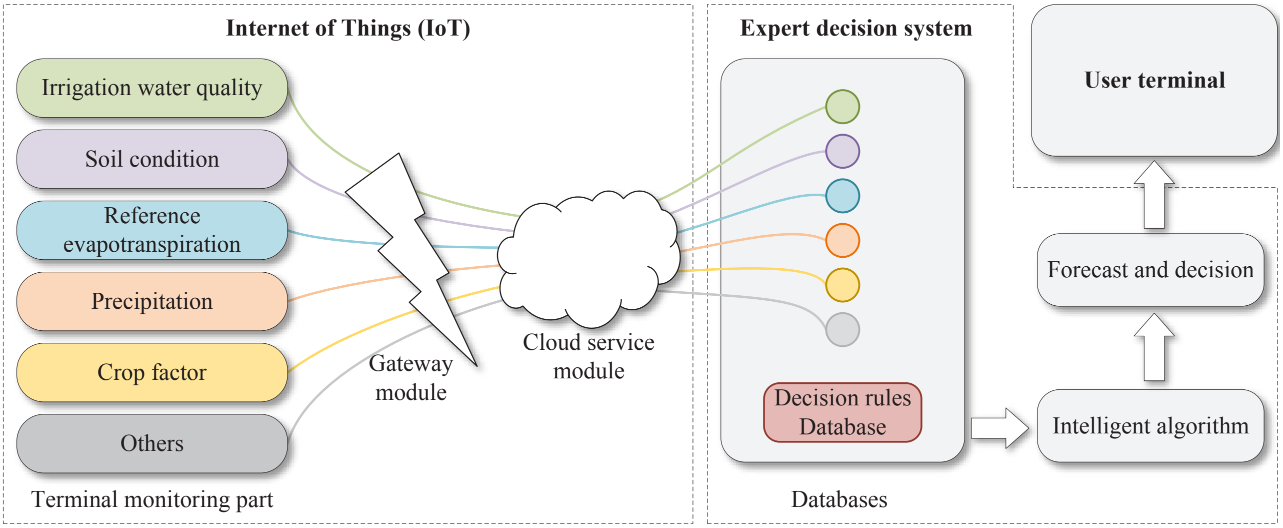

Figure 2. A typical intelligent irrigation system based on artificial intelligence.

designed an improved near-infrared CNN calibration model that can be used for quantitative determination of water pollution levels; Band et al. (2020) predicted groundwater nitrate concentrations in Iran's Marvdasht watershed based on support vector machine (SVM), Cubist, random forest (RF), and Bayesian artificial neural network (Baysia-ANN) models. El Bilali et al. (2021) developed and evaluated Adaboost, random forests (RF), artificial neural networks (ANNs), and support vector regression (SVR) models that predict the Berrechid aquifer in Morocco, promising in low-cost and real-time prediction of groundwater quality.

Soil conditions are mainly the determination and prediction of soil temperature, salt content, and water content. The daily soil temperature (DST) model proposed by Zeynoddin et al. (2019), the method for determining soil salinity levels and environmental conditions based on machine learning proposed by Bashir et al. (2020), and the ResBiLSTM model for detecting soil water content (SWC) proposed by Yu et al. (2020a), all provide important information for irrigation demand forecasting. Soil salinity prediction has been briefly outlined in Section 2.1.1 and will not be repeated here. For soil moisture content, the mode of "Internet of things + machine learning" is also the most widely used mode at present. Thus, Tseng et al. (2018) used drones to collect images and compared seven different prediction methods based on deep learning; Singh et al. (2019) assembled data collected from sensors deployed in the field and weather forecast data from the Internet, to analyze and compare multiple ML techniques to predict future soil moisture.

Reference evapotranspiration (ETo) reflects the impact of weather on crop water requirements. Using machine learning model, people can not only estimate the past and current ETo more accurately, but also predict the future ETo value. With the continuous development and progress of technology, people compare a variety of models to find the best method to predict ETo. For example, Huang et al. (2019) evaluated CatBoost, RF, and SVM models, of which CatBoost is a machine learning method based on gradient-boosted decision trees; Ferreira and da Cunha (2020) evaluated long-term short-term memory (LSTM), one-dimensional convolutional neural networks (1D CNN), CNN-LSTM in deep learning models, as well as artificial neural network (ANN) and random forest (RF) in traditional machine learning models; Ponraj and Vigneswaran (2020) trained, validated, and tested datasets using multiple linear regression, random forest (RF), and gradient augmented regression (GBR) algorithms; Mohammadi and Mehdizadeh (2020) compared PL-SVR, RF-SVR, PCA-SVR, and COR-SVR models and coupled the whale optimization algorithm (WOA) with the best-performing RF-SVR to form a new hybrid called RF-SVR-WOA model. In addition, researchers have also worked to find ways to use less information while obtaining more accurate results. Nagappan et al. (2020) reduced the input variable dimensions from six to three when modeling based on deep learning neural networks (DLNN).

2.1.3. Seed quality testing

Seed quality testing mainly includes purity analysis, variety determination, germination test, viability determination, and health determination. Inspection and determination of seeds by scientific and reliable methods, and thus evaluation of seeds, are important tools for ensuring seed quality, calculating appropriate sowing amounts, selecting suitable seed batches, and making rational tillage decisions. However, old quality testing equipment, insufficient number of professional testers, and insufficient knowledge reserve of testers have restricted the results of seed quality testing, and have made the results lack accuracy and less scientific. At present, the seed quality testing methods are also mostly combined with "IoT + ML" and generally use the Internet of things technology to collect image and other source information, mainly spectroscopy, hyperspectral imaging (Zhang et al., 2021), electronic nose, thermal imaging technology, and X-ray imaging technology; then the algorithms of machine learning, especially of deep learning, are introduced to assist model construction.

For example, Larios and his colleagues (2020) used infrared spectroscopy (FTIR) and machine learning algorithms to distinguish soybean seed vigor, and in their cross-validation tests, high and low vigor soybean seeds were discriminated with 100% accuracy. Another example, Tigabu et al. (2020) studied the potential of near-infrared spectroscopy in the rapid and nondestructive determination of Chinese fir seed viability, and the average classification accuracy of the test was 99% and above. In addition, Zeng's team (2019) worked on identifying and classifying the maturity stages of cucumber seeds in a nondestructive, accurate, fast, and inexpensive manner. The single-core near-infrared spectroscopy (SK-NIRS) technique they proposed, successfully distinguished five categories of cucumber seeds with different maturity levels in a nondestructive state, and obtained an accuracy of 99.69%. These research results show the high adaptability and mutual achievement of artificial intelligence and seed quality detection.

2.1.4. Crop yield and quality forecast

Crop yield and quality forecasting is one of the challenging issues in precision agriculture and an important task for agricultural decision makers. Accurate crop yield forecasting models can help farmers decide what to plant and when to plant it, as well as help governments develop timely food policies, market prices, import/export policies and proper storage. Crop yield forecasting is not an easy task as crop yields depend on many different factors such as climate, weather, soil, fertilizer use and seed variety (Xu et al., 2019). The mainstream method in recent years is to apply artificial intelligence technologies (Paudel et al., 2021) such as machine learning and machine vision to forecast crop yield.

Prior to this, researchers have conducted extensive systematic literature review (SLR) work: Vaidya et al. (2022) focused on precision agriculture and examined related work using hyperspectral remote sensing for crop yield prediction and estimation; Klompenburg et al. (2020) conducted an extensive study of the literature on yield forecasting and summarized and analyzed it from three perspectives: prediction feature selection, machine learning algorithm selection, and evaluation parameter selection. The results show that the most commonly used methods are CNN, LSTM, and DNN; Koirala et al. (2019) reviewed methods for fruit detection and yield estimation using deep learning, and also recommended methods such as CNN, LSTM, and deep regression.

2.2. Midproduction stage of agricultural production

In the midproduction stage of agricultural production, "How are we going to grow?" is the core issue that people need to consider. At this stage, farmers expect high yields and high-quality returns through newer and better farming techniques. Around this core goal, various agricultural intelligent systems have been developed, and various disease detection and control methods have been proposed to better answer the question of "how to grow".

2.2.1. Various agricultural intelligent systems

Agricultural expert system is an intelligent computer program system, which integrates the knowledge and experience of agricultural experts and can deal with the problems in the process of agricultural production from the perspective of experts (McKinion and Lemmon, 1985). It is well known that when solving agricultural problems, agricultural experts are usually required to have considerable experience accumulation and research basis, and have high requirements for talents. However, the help of agricultural experts is not always available when farmers need it. In order to solve the above problems, agricultural expert system uses big data technology to integrate relevant data into database, and establishes mathematical model through machine learning, so as to carry out heuristic reasoning, which can effectively solve the problems encountered by farmers and scientifically guide planting. For example, Khalil's apple tree knowledge system designed by CLIPS with Delphi can help farmers get the correct diagnosis and treatment of more than a dozen apple diseases (Khalil et al., 2019).

In addition, some systems support users to access them through the Internet and enter questions to obtain expert-level answers. For example, Galala developed a system for early date coconut disease diagnosis consulting (Galala, 2019); Adi and Isnanto (2020) developed a rice management expert system based on positive chain and deterministic factor method, including seed selection consultation and pest detection consultation. Such Expert Question Answering System can answer users' questions in natural language with accurate and concise natural language, which is a research direction that has attracted much attention and has broad development prospects in the field of artificial intelligence and natural language processing (Hu, 2006). The emergence of Expert Question Answering System combines knowledge map with question-and-answer system, simulates experts to answer farmers ' questions one to one, and provides farmers with fast, convenient, and accurate query services and knowledge decision-making.

Recording, monitoring, and controlling environmental conditions in agricultural production is particularly important. Internet of things equipment, wireless sensor networks, suitable sensors, and cloud services embedded with the capabilities of artificial intelligence and machine learning are the pillars of smart environmental monitoring (SEM). Intelligent environment detection system plays an important role in intelligent or green agriculture (Nayyar and Puri, 2016; Shahzadi et al., 2016; Sushanth and Sujatha, 2018; Pathak et al., 2019). It can help people obtain soil health, water analysis, water pollution level, water level and other factors data, and intelligent analysis is very important to obtain the sustainable productivity of the agricultural sector. In addition, agricultural intelligent system includes weed identification system (Sabzi et al., 2018; Espejo-Garcia et al., 2020; Yang et al., 2022b), agricultural decision support system (Hafezalkotob et al., 2018; Asher and Brosh, 2022), geographic information system (Manuel et al., 2020), portable agricultural information system (Keerthana et al., 2018; Akhter et al., 2021), etc.

2.2.2. Crop disease detection and control

Plant diseases cause great losses to the production, economy, quality and quantity of agricultural products. Therefore, it is necessary to monitor the disease of crops from the first stage of crop life cycle to before harvest. The traditional method is a visual observation, which is not only time-consuming and labor-intensive, but also requires supervisors to have a lot of professional knowledge. To solve these problems, researchers have proposed a series of automated and intelligent disease detection methods. Table 2 lists some typical cases of crop pest detection using artificial intelligence technology in recent years.

It is not difficult to see from Table 2 that the main implementation methods of disease recognition are gradually moving from traditional deep learning to few-shot learning. This is primarily because the algorithms based on Deep Learning typically rely heavily on large amounts of data. Deep Learning driven by big data faces the challenges of the high cost of data acquisition, high cost of high-end hardware and high consumption of power resources (Li and Chao, 2021b), which is not conducive to the sustainable development of agriculture. In order to conform to the sustainable development of agriculture, researchers should focus on the trade-off between data quality and quantity. For the data quality in the agricultural field, Li et al. (Li and Chao, 2021a; Li et al., 2021; Li et al., 2022b) believed that limited good data can defeat a large number of bad data. For the problem of data quantity, Yang et al. (2022a) examines the application of few-shot learning in smart agriculture, and Nie et al. (2022) investigated sustainable computing in intelligent agriculture. The results show that using small sample in some agricultural tasks can achieve a better model algorithm with less sample data.

2.3. Postproduction stages of agricultural production

In the postproduction stage of agricultural production, it is necessary to consider the harvesting of agricultural products, that is, to achieve the transformation of agricultural product output to efficiency. The review of the postproduction stage of agriculture mainly focuses on the harvesting, inspection, and marketing of agricultural products. Among them, the general trend of agricultural product harvesting work lies in automation and robotization, while the current state of harvesting technology for different types of crops has a different focus; agricultural product inspection work mainly includes maturity grading, quality inspection and appearance classification, and its mainstream technology lies in computer vision technology; every part of agricultural product marketing work relies heavily on the application of information technology.

2.3.1. Harvest of agricultural products

Crop harvesting activities include harvesting, stacking, handling, threshing, cleaning, and hauling. These jobs are usually tedious and require large labor and high repeatability. Under the influence of increasing demand for agricultural products and labor shortage, the harvest of agricultural products needs to improve the level of agricultural automation and roboticization.

For cereal crops, such as wheat and corn, which mature evenly in the field, large machines can be used to harvest the crop efficiently and on a large scale. For melon and fruit crops, different fruits have different growth environment, spatial location, geometry shape, size, color, hardness, and maturity, so it is not suitable for uniform harvesting. At the same time, factors such as rugged orchard terrain and obstacle interference also increase the difficulty of harvesting melon and fruit crops. The smaller harvesting robots capable of sensing and adapting to different crop types or environmental changes are therefore required for harvesting (Zhao et al., 2016; Silwal et al., 2017). At present, fruit harvesting robots can already use visual perception to perceive and learn crop information, which can complete camera calibration (Wang et al., 2019), target recognition and localization (Yu et al., 2020b), target background recognition (Feng et al., 2019), 3D reconstruction (Kusumam et al., 2017; Blok et al., 2019; Onishi et al., 2019), robot behavior planning based on visual positioning (Gongal et al., 2015; Wibowo et al., 2016), and avoid complex factors interference localization (Xiong et al., 2018) and other tasks. The object recognition methods for these harvesting robots are mainly single-feature vision methods, multifeature fusion methods, and deep learning algorithms. In addition, the study found that for sweet potato, potato, yam, taro, and other root

Table 2. Cases of crop disease and insect pest detection based on artificial intelligence technology.

Reference	Detection object	Data/image acquisition	Size of dataset	Detection method	Method classification	Accuracy
(Brahimi et al., 2017)	Tomato	PlantVillage dataset	14828 leaf Images	AlexNet; GoogleNet	Deep learning	98.660% 99.185%
(Sahu et al., 2018)	Rice	Digital camera; Smart phone	——	CNN	Deep learning	90.9%
(Li and Yang, 2020)	Cotton	NBAIR; natural scenes dataset	50 classes with 10 images per class	CNN; FPGA	Few-shot learning	95.4% 96.2%
(Li et al., 2020)	Maize	PlantVillage dataset	4 classes with 500 images per class	SCNN-KSVM; SCNN-RF	Deep learning	94% 94%
(Li and Chao, 2020)	20 classes	crop pest dataset; plant leaf dataset	200 images per dataset	ANN-based continual classification	Deep learning	Almost 100%
(Chen et al., 2020a)	*Tessaratoma papillosa*	UAV; Smart phone	687 images of adult *Tessaratoma papillosa*	YOLOv3 based on CNN	Deep learning	About 90%
(Li and Chao, 2021c)	38 classes	PlantVillage dataset	1000 images per category	Semisupervised few-shot learning	Few-shot learning	92.6%
(Zeng et al., 2021)	Grape	PlantVillage dataset	10 of Esca; 10 of Leaf blight; 300 of Black rot; 300 of Healthy	CycleGAN; LFMGAN	Deep learning	90.91% 92.44%
(Li and Yang, 2021)	20 classes	PlantVillage dataset	6000 images	CNN	Few-shot learning	90.4%
(Mukhtar et al., 2021)	wheat	CGIAR Crop Disease dataset; Google images	440 images	MobileNetv3	Few-shot learning	More than 92%
(Yasmeen et al., 2021)	Citrus	Hybrid Citrus; Citrus Leaves; Citrus Fruits	3988 + 2184 + 1328 images	Resnet18; Inception V3	Deep learning	99.5% 94% 97.7%

crops (also known as potato crops) growing in the soil, the harvesting technology mostly stays in the way of manual mining, or semiman and semimechanical harvesting at present. There are few intelligent automatic harvesting technologies for this kind of crop, and most of them remain in the development of mechanical institutions (Bahadirov et al., 2020; Matmurodov et al., 2020) and the optimization stage of the automatic control system, which need to be broken through and improved.

2.3.2. Inspection of agricultural products

With the support of various intelligent algorithms, microelectronic systems, nanotechnology, sensors, on-site rapid detection technology, and remote data transmission and processing technology, the agricultural product inspection, and detection system tend to be miniaturized and intelligent. This paper mainly introduces the inspection of agricultural products under the influence of artificial intelligence from three aspects of maturity classification, quality inspection, and appearance classification.

2.3.2.a. Maturity classification

Firstly, judging the maturity of agricultural products and choosing appropriate preservation methods are the prerequisites for consumers to obtain fresh agricultural products. The ripening process of fruit is usually accompanied by changes in color, aroma, texture, and pattern. These changes are usually gradual, subtle, and inappropriate for human judgment. Using artificial intelligence can quickly and accurately grasp these changes that are not obvious in the eyes of people, so as to judge the immaturity, maturity, and decay of agricultural products. Using artificial intelligence, researchers have proposed various detection methods of fruit ripeness based on sound, light, color, and taste, and combined them with intelligent algorithms (Balbin et al., 2018; Gutierrez et al., 2019; Zhang et al., 2020). The method of fruit ripeness detection using acoustic vibration (Fadchar et al., 2020) is a typical example of the abovementioned sound-based methods; the light-based detection methods mainly include spectral technology and hyperspectral imaging technology (Pu et al., 2019; Garillos-Manliguez et al., 2021); the color-based fruit ripening detection methods use color feature extraction technology (Alfatni et al., 2020; Zhong et al., 2021); and there is no doubt that methods using the electronic nose (Jia et al., 2019; Guo et al., 2021) exemplify taste-based approach. At this stage, spectral technology and hyperspectral imaging technology are still the mainstream. However, the expensive equipment limits their large-scale application and development, and low-cost photodiode-based fruit maturity estimation (Giovenzana et al., 2015; Bhatnagar et al., 2019) may become a more popular direction in the future.

2.3.2.b. Quality inspection

The quality and safety of agricultural products is directly related to people's health, and its quality testing is mainly divided into two aspects: component content testing and damage testing. Firstly, for ingredient content detection, the easiest way is of course to cut it open and conduct chemical inspection. However, due to the consideration of food protection and sustainable agriculture, in recent years, people have been striving for physical nondestructive testing. Taking fruit sweetness analysis as an example, Tran et al. (2021) used a simple spectroscopic system with a classifier based on machine learning they developed and trained to detect apple sweetness, with a maximum accuracy of 91.5%; Nguyen et al. realized the precise sweetness classification of mango by using low cost visible near infrared (VIS-NIR) multispectral sensors and random forest (RF) classifier. Secondly, the nondestructive damage detection of fruits is of great significance for screening bad fruits and fruit grading. The damage of agricultural products is divided into internal damage and surface damage. Here, the surface damage can be classified as appearance classification of agricultural products, so internal damage is mainly introduced here. Traditional physical methods include magnetic resonance imaging (Thybo et al., 2004), acoustic localization (Yoshida et al., 2018), computer tomography (Meberg et al., 2001) and so on. However, these methods are either complicated to operate, expensive, or not compatible with different fruits, so they are not suitable for large-scale production practice. Therefore, researchers have proposed to apply the deep learning algorithm. Only by determining the internal damage of a small number of samples to train the classifier model, the machine can quickly and reliably predict the situation of a large number of fruits. In the nondestructive detection of withered kernels in shelled walnuts, Zhai et al. (2020) used walnut images and weight information to fuse the training of the machine learning algorithm, and achieved 97% classification accuracy with only 0.001 average cost calculation time.

2.3.2.c. Appearance classification

The classification of agricultural products according to their appearance characteristics, such as size, shape, color and so on, is also an important step before their sales work. However, the efficiency of manual operation is low and the influence of subjectivity is large, and the accuracy rate of pure mechanical operation is low. That is why people want to apply artificial intelligence to the classification of agricultural products. After the introduction of a very reliable inspection tool-machine vision technology, the fruit can be accurately and efficiently identified and classified according to the color, texture, shape, disease defects, and other characteristics, which is helpful to increase yield, reduce production time and improve quality control (Ayyub and Manjramkar, 2019). Such methods have been relatively mature at this stage, so the problems to be considered have gradually shifted from the method itself to how to put them into practical application.

2.3.3. Sales of agricultural products

The final work of the postproduction stages of agricultural is the sale of agricultural products, which needs to be processed, packaged, transported, and sold. In the transportation process, most agricultural products are perishable, which inevitably leads to certain losses. People will be based on the Internet of things radio frequency identification technology is applied to this, through the dynamic way to obtain product information, so that managers can monitor the whole circulation process, real-time tracking. In this way, it can effectively plan the quantity of product storage and transportation, reduce operating costs and prevent transportation losses. In the sales process, artificial intelligence technology can be applied to collect data on production, consumption, storage, and circulation, and in-depth analysis of the whole market. It can effectively understand the current level of agricultural development, prevent sharp rise or fall, and promote more stable product transactions. In addition, the online marketing of mobile or PC-side e-commerce platforms built by artificial intelligence and Internet technology can maximize the use of online integration advantages to effectively integrate information resources, reduce production costs, and improve the relationship between suppliers and consumers. At the same time, based on the Internet of things and mobile network technology (Zhou and Zhou, 2012), the information management of agricultural production and circulation process, the traceability management of agricultural product quality (Yang et al., 2018), the management of agricultural product production archives (origin environment, production process, and quality detection), and the establishment of agricultural product quality and safety traceability system based on website and mobile phone short message platform (Tian, 2017; Zheng et al., 2021) can realize the traceability of the whole quality and service of agricultural product quality and safety, improve the brand effect of traceability agricultural products, and ensure the quality and safety of agricultural products.

3. Digital twins in agriculture

3.1. Overview of digital twins

3.1.1. General definition of digital twins

Review history, the prototype of digital twins, "mirror space model", was first conceived by Michael Grieves in 2003 (Githens, 2007). In 2010, the National Aeronautics and Space Administration (NASA) adopted two identical aircrafts, one was the native and the other one was the twin, to realize the comprehensive diagnosis and prediction function of the flight system, which led to the concept of "digital twins" (Piascik et al., 2010). In 2014, Michael Grieves provided another detailed definition of digital twins. He proposed that the basic framework of the digital twins system should include the physical space, the virtual space, and the flow of information and data connecting the two spaces (Grieves, 2014). With the development of related technologies, the definition of the term "digital twins" has been more widely discussed by different researchers and institutions. For example, Mayani et al. (2018) saw the digital twins as a bridge between the physical and digital worlds; Wanasinghe (2020) regarded it as an immersive data analysis technique; Poddar (2018) and Sharma et al. (2018) regarded it as a virtual and simulated model or a realistic replica of a physical asset. Although these definitions differ somewhat from each other, none of them has ever departed from the basic framework of the digital twins.

A general definition of digital twins is that it refers to the establishment and simulation of a physical entity, process, or system in the information platform. By integrating physical feedback data, assisted by artificial intelligence, machine learning and software analysis, a digital simulation is established in the information platform, and this simulation will automatically make corresponding changes with the change of physical entities according to feedback. Ideally, digital twins can self-learn according to multiple feedback source data, and present the real situation of physical entities in the digital world almost in real time. In other words, with the help of digital twins, the state of physical entities can be understood on the information platform, and the predefined interface components in physical entities can be controlled (Schleich et al., 2017; Vatn, 2018; Liu et al., 2019).

3.1.2. Basic architecture of digital twins

The most typical and widely accepted DT framework still consists of three main components: "physical space", "virtual space", and "connections between these spaces" (Grieves, 2014). Among them, the physical space contains physical assets, sensors, and actuators; the virtual space includes multiphysics, multiscale, probabilistic simulation models; and the connection between the physical space and the virtual space ensures seamless data and drive command exchange between these two spaces. With the continuous expansion and upgrading of application demands, DT faces more service demands from different fields, different levels of users, and different services (Qi et al., 2021). At the same time, the interconnection of all things provides conditions for realizing the information physical interaction and data integration of DT. To facilitate further applications of DT in more domains, researchers have extended the three-component DT framework. Tao and Zhang added “DT data fusion” and “service system” modules to the original framework which have only “physical space” and “virtual space”, and the connection between them was also expanded accordingly. The six-component framework proposed by Parrott and Warshaw consists of five enabling components and a six-step process. Their work embodies “physical space” and “virtual space”: “sensors” and “actuators” in enabling components, and “act”, “create”, and “communicate” in processes belong to physical space; while the enabling components “data” and “analytics”, as well as the “aggregate”, “analyze”, and “insight” processes belong to the virtual space; in addition, the role of “integration” is to connect the physical and virtual worlds.

3.1.3. Key technologies and typical applications of digital twins

The digital twins exists in virtual form, which can not only reflect the characteristics, behavior process and performance of physical objects in a highly realistic way, but also realize real-time monitoring, evaluation, and management in a surreal form. Its ability to present a surreal mirror image of the target physical entity object relies on the support of the following technologies: high-performance computing, advanced sensing acquisition, digital simulation, high-fidelity modeling, intelligent data analysis, VR presentation, etc. By constructing digital twins, not only the health state of the target entity can be described perfectly and meticulously, but also the deep, multiscale, and probabilistic dynamic state assessment, life prediction, and task completion rate analysis can be realized through the integration of data and physics.

Through the integration with artificial intelligence, mobile Internet, cloud computing, big data analysis, and other technologies, DT has potential application value in many fields involving physical and virtual space mapping, fusion, and collaborative evolution. DT can be applied in different fields such as smart city, construction, medical treatment, agriculture, freight, drilling platform, automobile, aerospace, manufacturing, electric power, and other fields.

3.2. The applications of digital twins in agriculture

With the current global expectations for the agricultural field, scientific and technological achievements such as agricultural artificial intelligence technology, agricultural Internet of things technology, agricultural data model analysis system, and agricultural intelligent equipment continue to emerge. Agriculture has basically realized digitalization and networking, is moving towards the stage of intelligence and virtualization. The emergence of the agricultural digital twins system will realize the organic integration of the physical entity of agricultural production and the digital cyberspace, so as to realize the integration of “connection-perception-decision-control”. This will support the better realization of accurate, efficient, and sustainable smart agriculture, and provide new momentum for the digital transformation and upgrading of agriculture.

Agricultural digital twins are mainly based on the elements of the agricultural production process (physical entities) as the object, focus on the digital solidification of agricultural knowledge based on various types of production models, system rules, and data collections. Agricultural digital twins are dedicated to constructing multidimensional, multiscale, multidisciplinary, and multiphysical quantity dynamic virtual models to portray the attributes, behaviors, and laws of each element in the agricultural production process to replace some complex experiments in real environments. Figure 3 shows a typical schematic diagram of an agricultural digital twins system. In the figure, the virtual model is constructed based on agricultural entities and iteratively interacts and optimizes with them in the agricultural production process. Through the data and information interaction between the twin data fed back to the 3D model and the physical world, the integrity of the digital world is continuously improved, and then precise control over agricultural entities can be achieved. The agricultural digital twin system realizes the simulation, monitoring, diagnosis, prediction and control of agricultural objects by constructing real-time and accurate digital mapping of physical objects—animals, plants, and motion trajectories—in virtual space. According to the state of agricultural entities in the physical world and application requirements, quantitative prediction, and decision feedback are carried out.

Digital twins have been used less in agriculture in recent years. Our examination of it reveals its main applications as follows.

Agricultural product model was established to monitor crop growth or determine crop quality parameters. Li et al. (2022a) proposed a single-view leaf reconstruction method of plant growth digital twins system based on deep learning ResNet, which provided important ideas and methods for single-view leaf reconstruction in plant growth digital twins system. Evers et al. (2020) are committed to developing digital twins of greenhouse tomato crops, updating the 3D simulation model through real-time input of sensor information from real greenhouses, so as to simulate the interaction between crop quality, environmental factors, and crop management. Pattanaik and Jenamani (2020) created digital twins of three different mango varieties, Alphonso, Totapuri, and Kesar, and accurately simulated the cooling behavior of real mangoes according to the airflow rate and temperature, so as to analyze and grasp the cooling heterogeneity and quality attenuation in the process of mango export. Kampker et al. (2019) established a plastic “potato digital twin” as a substitute for

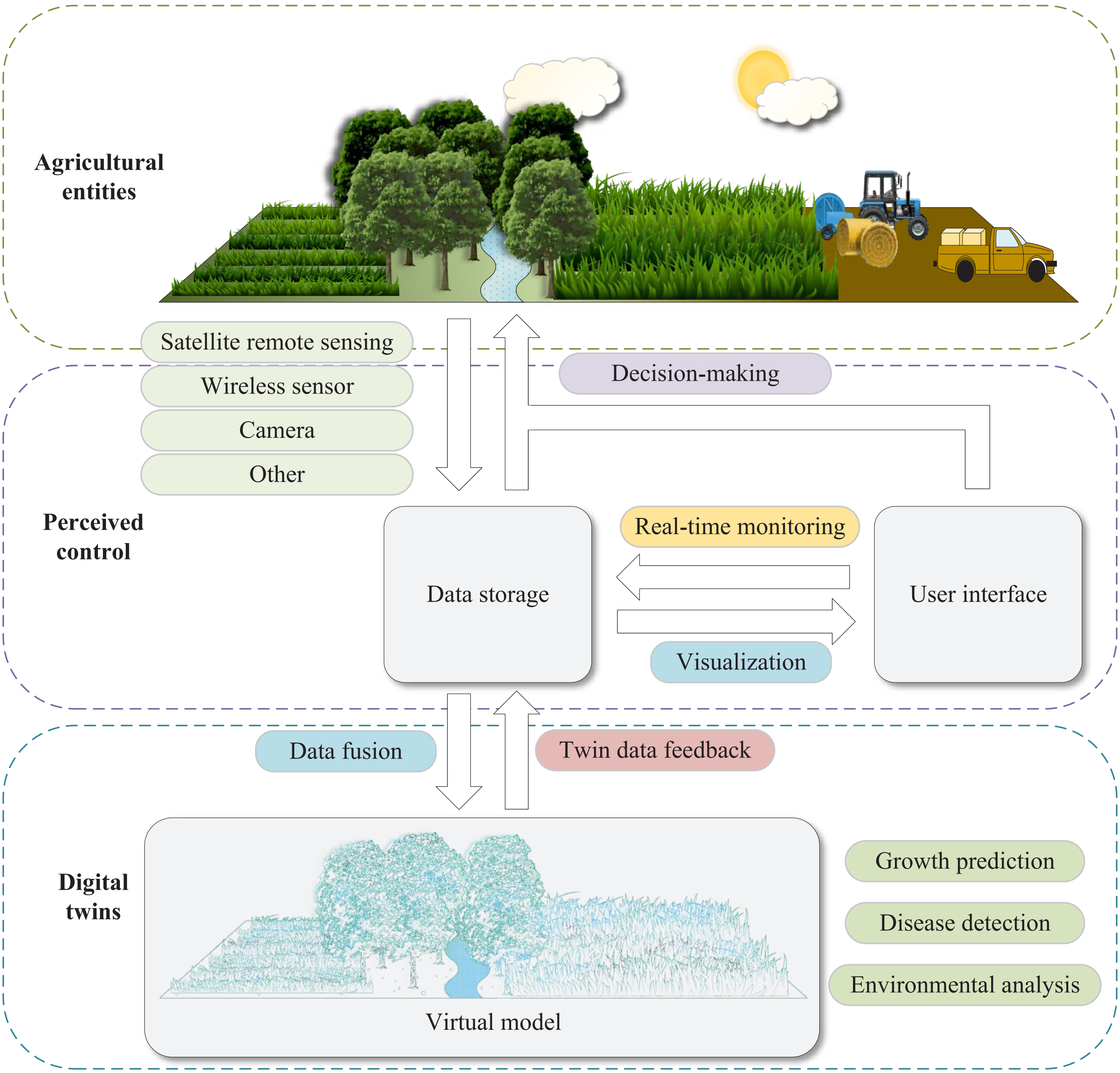

Figure 3. Typical schematic diagram of agricultural digital twin system.

real potatoes to detect the impact and rotation of potatoes during harvest.

The environment model is established to obtain decision support. The farm management simulation tool AgROS developed by Tsolakis et al. (2019) allows the introduction of static object layout characteristics such as actual fields and trees, so as to carry out field tests of agricultural robots or autonomous unmanned ground vehicles (UGV) in quasireal environment. Jo et al. (2018) proposed an intelligent pig farm based on digital twins to improve animal welfare, and conducted a feasibility study on it. Alves et al. (2019) established a digital twins intelligent farm using sensing data from soil detectors, weather stations, irrigation systems, and equipment to obtain visual return and decision-making suggestions. Moghadam et al. (2020) developed an automatic dynamic crown monitoring system, AgScan3D +, which is now used in mango, macadamia, avocado, and vine orchards and generates digital twins of 15,000 trees. It uses a rotating 3D camera to create a digital twin model for each tree in the orchard, and monitors the health, structure, pressure, fruit quality, and other indicators of each tree to predict pressure, disease, and crop loss, and provide real-time farm decision support for farmers. Cor Verdouw et al. proposed a conceptual framework for the design and implementation of digital twins, which has been applied and verified in five intelligent agricultural cases (field zoning management, cow welfare, greenhouse tomato production, weed monitoring and pig farm management) of the European IoF2020 project.

4. Discussion

This chapter focuses on "AI in agriculture" and "DT in agriculture", and discusses and analyzes the challenges and future development trends of these two technologies in agriculture at this stage. In Subsections 4.1 and 4.2, the challenges and development trends of AI in agriculture are discussed respectively, while the corresponding contents of digital twin are discussed in Subsections 4.3 and 4.4.

4.1. Challenges of artificial intelligence

The survey shows that the abovementioned AI technologies are cutting-edge agricultural science research hotspots, and their applications run through the preproduction, midproduction, and postproduction stages of the agricultural production process. They have helped to achieve intelligent management and precise control, improve production efficiency and product quality, and reduce environmental pollution and energy waste. They have shown excellent performance and great application potential and have undoubtedly played a role in promoting work related to agricultural sustainability. At the same time, we find that AI in agriculture, especially in the field of agricultural sustainability, still faces many challenges:

· Various artificial intelligence technologies have not been integrated and implemented with intelligent equipment widely and on a large scale, and the intelligent agricultural system still needs to be improved. On the one hand, different types and growth cycles of crops have different growth states, which makes the agricultural analysis model not have a universal; on the other hand, the high cost or lack of key technologies and equipment makes it impossible for various intelligent algorithms to be put into agricultural production on a large scale. Therefore, most of the research on it is still in the process of algorithm development, which fails to enable farmers to truly enjoy the convenience of artificial intelligence algorithms.

· The application of AI in various fields of agriculture lacks in-depth analysis with relevance. The factors involved in agricultural production are complex. Regions, seasons, types of crops, production environments, and operating methods all affect the application effect of various intelligent technologies. At the present stage, most of the studies only stay on the acquisition and surface analysis of agricultural data. They fail to start from the excavation of agricultural production laws and lack the deep analysis of error laws with the correlation between theory and practice.

· The global level of agricultural automation and intensification is uneven, and there is a technological gap between developing and developed countries. The main manifestation is that developing countries are prone to form shortcomings in basic theory, core algorithms, key equipment, high-end chips, and major systems and software of agricultural artificial intelligence.

· Artificial intelligence technology in agriculture is inseparable from the support of a large amount of data, and how to obtain high-quality data information is one of the challenges in the future. Big data mining in agriculture is the process of extracting potentially useful agricultural information and crop growth laws from a large number of incomplete, noisy, fuzzy, and random agricultural data. At present, the segmentation and data mining of agricultural Internet of Things data resources are still in the initial stage, and the intelligent algorithm models and practical databases in various agricultural fields are in urgent need of expansion. With the continuous updating and expansion of intelligent algorithms, at this stage, the amount of data required and data costs are both increasing. At the same time, agricultural data obtained in the real world is limited by the crop growth cycle, and the problems of complex acquisition methods and long acquisition periods are also a big challenge for researchers.

· Restricted by factors such as the shrinking global economy, limited scientific and cultural exchanges, sluggish high-tech development, lack of talents, and inadequate infrastructure, the infrastructure, policies and regulations, investment in agricultural scientific research, and talent pools in related fields adapted to the development of smart agriculture gradually fail to meet the growing demand for agricultural pressure. It is also a great challenge to balance the impact of unfavorable factors on the highly intelligent development of sustainable agriculture.

4.2. Future directions of artificial intelligence

Artificial intelligence technology, which has a broad application space in agriculture, is a pillar to promote smart agriculture. Faced with the above challenges, the following suggestions for the possible development of artificial intelligence technology in agriculture are put forward as follows:

· Attention should be paid to the improvement of the computing force and technology implementation of agricultural AI. The computing force is one of the important efficiency indicators of agricultural AI. Conventional AI algorithms are too computationally intensive to be directly integrated and applied to traditional IoT systems. The lightweight and efficient algorithm models, such as Few-shot Learning and so on, are easy to embed in IoT devices and compute at the edge of the devices, thereby realizing AI applications on the IoT devices.

· Research and development of more universal agricultural artificial intelligence equipment, strengthening standardization and standardized management, and improving the level of agricultural intelligence on a large scale and without threshold are necessary. Artificial intelligence equipment is an important part of artificial intelligence technology, among which the core technologies such as artificial intelligence chips and intelligent sensors need to be developed and optimized. In order to meet the different performance requirements of agricultural application scenarios, it is necessary to carry out continuous and in-depth research, formulate relevant standards around the integration of AI technology and agricultural IoT, agricultural machinery equipment and agricultural big data, and develop agricultural artificial intelligence terminal equipment with lower cost and higher robustness.

· People should focus on the fact that technology development and information security go hand in hand, focus on agricultural data security, and build a green data-sharing model. The development of agricultural AI technology relies on data. Agricultural data have the characteristics of large volume, various types, and wide sources. It is necessary to ensure the security of agricultural data and information systems to ensure the safe production, accurate management, and intelligent decision-making of agriculture. At the same time, establishing a safe, efficient, and mature agricultural data open sharing mode can promote not only the rapid development of intelligent agriculture, but also the inevitable trend of the environment.

· The cross-integration of different fields should be promoted to lead to the transformation of the modern agricultural development mode. In order to meet the increasingly diversified agricultural production tasks, it is necessary to promote the integrated development of agricultural AI in different fields. For example, integrating the real-world agricultural process with the virtual-world agricultural model can reduce the cost and time cycle of agricultural data acquisition and accelerate AI technology iteration in the real world.

4.3. Challenges of digital twins

As a cutting-edge technology, the digital twin technology has received widespread attention from industries that it will revolutionize. Driven by technological updates and historical experience, the digital twins can almost reflect all aspects of products, processes, or services. However, the study found that the current potential of the digital twins in agriculture is far from being realized, and there are still many challenges in the development of agricultural digital twin technology:

· It is easy to see that digital twin technology is still in its infancy and rising stage in the agricultural field, and the technology and tools need to be developed. Researchers have to collect and merge various types of data to model all the different parts of an agricultural object or system from scratch, which will be a complex and lengthy process.

· How to form and design cognitive digital twins? At this stage, although some low-level operations can be implemented autonomously without human intervention, many decision-making activities still need to be maintained by manual operations based on human interaction. How to enable spontaneous and intervention-free simulation free from human control and seamless interaction among multiple models is also a major challenge in the research process.

· DT offers real-time simulation possibilities for the product lifecycle and can even help integrate the entire supply chain through all stages of its lifecycle. However, connecting data information collected, aggregated, and exchanged between different suppliers, manufacturers, and customers in a virtual space, or fusing digital twin models developed using different DT architectures, technologies, interfaces, communication protocols, models, and data, can pose interoperability issues. Therefore, the development of standard-based interoperability for digital twin applications is undoubtedly another major challenge for digital twin technology.

4.4. Future directions of digital twins

Since its inception, the digital twin has shown great promise in many aspects. With the further development of its technology and the increasing maturity of agricultural virtualization technology, everything in the physical world may be replicated in digital space by digital twin technology in the future. The following are some outlooks on future applications of the digital twin in agriculture:

· Digital twin technology will become the best practice in various agricultural sectors. DT supports manufacturing and controlling the entire life cycle of a product or process and therefore can model complex links in agricultural production processes from physical to virtual in order to obtain agricultural information. For example, by constructing the plant model, the crop life cycle and environmental changes can be accelerated in the virtual space, so that the data of each stage can be easily obtained. By constructing virtual workshops and previewing robot motion planning schemes to simulate the real-world agricultural product processing, and then mapping the virtual data information to the real robot, the fully automated processing and production can be realized to reduce the production cost of agricultural products. By constructing the virtual farm breeding environment, the accurate simulation of animals from organs, tissues, and systems to the whole can be realized, so as to obtain the knowledge database of animal living environment, animal nutrition needs, and variety breeding.

· Industry standardization will allow different models, different systems, and even different domains to interact and respond to each other. While different physical objects can interact with each other naturally and without barriers, the problem of interaction in virtual spaces requires the creation of application-specific interfaces and functions. Industry specifications and interface standardization of digital twin technology will enable the models to have programmability, interoperability, etc. so that they can be interoperated between different production systems and application areas in the virtual space. For example, an apple tree model constructed by one person using DT can be planted accessibly in a pear tree population model constructed by another person, and a series of feedback information on growth conditions can be obtained.

5. Conclusion

In this paper, we focus on artificial intelligence and digital twin technology in sustainable agriculture, review and summarize the application of artificial intelligence technology in each stage of the agricultural production process in the past few years, briefly outline what digital twin is, and review the current status of digital twin technology in agriculture. The results of the inquiry are as follows:

(1) Application: A range of AI technologies run through the whole process of agricultural production and are applied to all aspects of the production process. In contrast, compared with the application of AI in agriculture, the application of DT in agriculture appears to be stretched.

(2) Challenges: There is still a lot of work that can be done to improve the field of agricultural artificial intelligence, especially in terms of computing power improvement, large-scale implementation, and multifield integration. Due to the specificity and complexity of agricultural production, the challenges faced by digital twin technology in this application are greater than those in any other industry, and it will take time to achieve a real breakthrough in all aspects.

(3) Future development: The research on digital twin technology in agriculture is still in its infancy, and there are still many problems that need to be solved urgently. In the era of big data, the origins and development of artificial intelligence and digital twin cannot be separated from the database, so their development should be complementary to each other.

Acknowledgment

This work was supported by the National Natural Science Foundation of China (31860333) and the National Natural Science Foundation of China (32101612).

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