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JING NIE

YI WANG

YANG LI

XUEWEI CHAO

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Sustainable computing in smart agriculture: survey and challenges

Jing NIE[1,2], **Yi WANG**[1], **Yang LI**[1,*], **Xuewei CHAO**[1]

[1]College of Mechanical and Electrical Engineering, Shihezi University, Shihezi, China

[2]Key Laboratory of Modern Agricultural Machinery of Xinjiang Production and Construction Corps, Shihezi, China

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Abstract: Research on sustainable computing in agriculture has a great potential as an effective way to solve most agricultural technology bottlenecks, save resource costs, and drive sustainable agricultural development. This paper provides a systematic introduction to the data collection, data mining and evaluation, classification and application of sustainable algorithms involved in the field of sustainable computing in agriculture. At the same time, the paper provides an insightful discussion on its challenges and future trends. The purpose of this work is to help researchers review the current status and pressing issues of sustainable algorithms in agriculture, and to provide a referenceable direction for future research development.

Key words: Agriculture, sustainable algorithms, data collection, data mining

1. Introduction

Now, the recurring recurrence of negative challenges that humans must deal with, such as climate change, economic upheaval, and epidemic outbreaks, has pushed people to reevaluate the sustainable development of agriculture. In recent years, the emerging sustainable computing research has become an effective way and a new research hotspot to solve the technological drive of sustainable agricultural development. The continuous penetration of cloud computing, the Internet of Things, and artificial intelligence technologies (Klerkx and Rose, 2020), has brought opportunities for sustainable computing research in the field of modern agriculture. Simultaneously, it also brings new challenges to researchers in data collection and mining, problem complexity, computing efficiency, method scalability and other aspects. How to use emerging hardware and software technologies to achieve sustainable progress in the comprehensive performance of agricultural intelligent systems is a problem that researchers from all over the world are concerned about. Agricultural sustainable computing research focuses on the collection of various agricultural resource data, as well as data mining models and resource-saving intelligent algorithms based on these data. This paper will focus on the above aspects to investigate.

This research is important for several reasons. First, the traditional data collection has the shortcomings of single source and complex method, and the data mining effect is not satisfactory. More intelligent, convenient and efficient data collection, mining and evaluation methods ensure its high availability and scalability, which is conducive to sustainable development (Ciruela-Lorenzo et al., 2020; Fountas et al., 2020; Hrustek, 2020). Second, from the perspectives of resource efficiency and environmental quality, the introduction of sustainable and resource-saving intelligent algorithms in agriculture has brought certain positive effects (Velten et al., 2015; Lampridi et al., 2019). Not only does it effectively save human resources such as manual measurement, collection, and processing, as well as material resources such as input costs, machine computing time, and wastage, it is also of great benefit to the current global resource shortage problem. Third, there are currently few overviews of the overall development of sustainable computing in agriculture, and we believe that such surveys will be very valuable to the research community, given the significant progress made in this field and its important implications for future research directions for smart agriculture tasks.

This paper will outline and answer the following research questions.

- What is the current status of research on data collection and mining and evaluation in agriculture?
- What are the practical applications of some resource-saving intelligent algorithms (mainly algorithms based on few-shot learning) in agriculture in the context of sustainable agriculture?

* Correspondence: liyang328@shzu.edu.cn

- What are the challenges faced by these smart algorithms in data collection and implementation, including economic, environmental, and social dimensions?
- What are the possible future directions to address the issue of sustainability of data collection and mining in agriculture?

One of the objectives of this paper is to demonstrate the importance, and foresight, of sustainable agriculture in the era of smart agriculture. On the one hand, in the context of agriculture 4.0 and precision agriculture, various types of smart agricultural systems are constantly proposed as the main trend for future agricultural development; on the other hand, smart agriculture must focus on sustainability if it is to meet the requirements of ensuring sound economic, environmental and social development. The second objective of this paper is to demonstrate the current state of the art in the field of sustainable computing in agriculture by analysing the practical applications of some intelligent algorithms that can save resources in agriculture. Specifically, it is to summarize and show the results in the field of sustainable computing in agriculture in recent years by searching the relevant literature. The main aspects will be illustrated in the following aspects, including data sources, method classification, and application classification. Finally, the third objective of this paper is to summarise the challenges faced by the above algorithms and discuss the possibilities of future developments in the field of sustainable computing in agriculture.

The rest of the paper is organized as follows. The current state of research on data collection and data mining in agriculture is described in Section 2. In Section 3, the practical applications of resource-saving intelligent algorithms in agriculture will be sorted and analysed in terms of algorithm classification and application classification. The challenges and possible future directions of these intelligent algorithms in data collection and concrete implementation are discussed in Section 4. Finally, in Section 5, a brief conclusion is given.

2. Current status of data collection and mining in agriculture

In recent years, thanks to the rapid development of information technology and other fields, data information has exploded, and data collection and mining has emerged and gradually become an emerging research hotspot. Data collection is the collection of relevant data according to the system or user's target requirements, which can be structured, such as data in relational databases; or semistructured, such as text, graphics and image data; or even heterogeneous data distributed on the network. Data mining (DM), also known as knowledge discover in database (KDD), searches for more information hidden in the large amount of data collected through algorithms. It is based on artificial intelligence, machine learning, pattern recognition, statistics, database, and visualization techniques to achieve a high degree of automation in analysing, summarising, and organising data to help decision-makers adjust and optimize strategies and reduce risk loss.

The advent of the era of smart agriculture and the proposal of precision agriculture have promoted the deep integration of agricultural processes and information technology and accelerated the continuous transformation of agricultural processes into data (Wolfert et al., 2017). Nowadays, more and more research institutions and universities are conducting research on data collection and mining in agriculture, focusing on the integration of various discovery strategies and multidisciplinary technologies (Rao and Yuan, 2021), mainly in the direction of intelligent databases (Lal et al., 2013; Tubiello et al., 2013; Chiu et al., 2020; Iaksch et al., 2021; Li and Yang, 2021), machine learning (Ferentinos, 2018; Kamilaris and Prenafeta-Boldu, 2018; Liakos et al., 2018; Sharma et al., 2020; Van Klompenburg et al., 2020), statistics (Kaur et al., 2017; Vanitha et al., 2019; Vashisht and Soni, 2019), data visualization (Thakur et al., 2019; Jiang et al., 2020; Kang and Chen, 2020; Tanted et al., 2020), high-performance computing (Cai et al., 2019; Darwish et al., 2020) and other high-tech directions.

The current status of data collection, data mining and evaluation in the agricultural field will be discussed separately below.

2.1. Data collection in agricultural

As the primary work of all agricultural tasks based on intelligent algorithms, data collection in the agricultural field should meet the characteristics of high quality and large scale. However, preparing such a dataset is not an easy task due to the effort and cost required to collect, classify, annotate, and in some cases physicochemically measure crops for agricultural data , including but not limited to image data (Lu and Young, 2020). Therefore, data collection in the field of agriculture is not limited to actual inspection and collection. In addition, the required data can also be obtained from existing public data sets according to the requirements and limitations of specific mission objectives.

2.1.1. Public datasets

We first discuss the case of obtaining data resources from public datasets or databases. The main sources of agricultural open data are databases full of agricultural resources established by various countries, as well as data sets created by institutions or individuals. Agricultural databases can be divided into agricultural resource database, agricultural technology database, agricultural statistics database, agricultural production database, agricultural policies and regulations database and related industry information database according to project types; they can be divided into world-class, national-level, regional-level and farm-level according to geography. Internationally famous world-class agricultural database systems include CABI (http://www.cabi.org), AORICOLA (http://agricola.nal.usda.gov), IFIS (https://www.ifis.org), AGRIS (http://www.fao.org/Agris/), etc. These databases cover multiple agricultural subsectors and contain millions of records in multiple countries and regions around the world. The national agricultural databases constructed by various countries are more integrated with the country's own agricultural development trends and characteristics, such as the China Crop Germplasm Resources Information System (https://www.cgris.net/). In addition, there are many public datasets at the regional or farm level constructed by institutions or individuals.

Since the agricultural sustainability algorithms investigated in this paper are mainly based on cloud computing, Internet of Things, artificial intelligence and other technologies, and the agricultural data sets used are mostly image data sets. Thus, this paper focuses on the development and use of image data sets in the agricultural field. As shown in Figure 1, the 22 literatures that used public datasets were examined, and the frequency of the public datasets used. Obviously, among the reviewed literatures using public datasets, the most widely used public dataset is the PlantVillage dataset. The PlantVillage dataset is composed of tens of thousands of annotated plant leaf images of healthy and diseased plants, and contains 54,305 leaf images collected under controlled conditions. The images are grouped into 38 categories, including 14 crops and 26 diseases, and all images are resized to 256 × 256 pixels without any additional image preprocessing, such as Table 1 for the crops and disease types it contains.

The study presented by Amin et al. (2022) was evaluated on this dataset. During the study by Afifi et al. (2021) the PlantVillage dataset was randomly partitioned to form two datasets: a source domain with 32 classes and 48,775 images on one side for the purpose of developing baseline plant leaf classification algorithms separately, and a target domain with the remaining 6 classes and 5528 images on the other side for the development and evaluation of FSL algorithms. Due to the unequal number of samples in each category, Li and Chao (2021) randomly

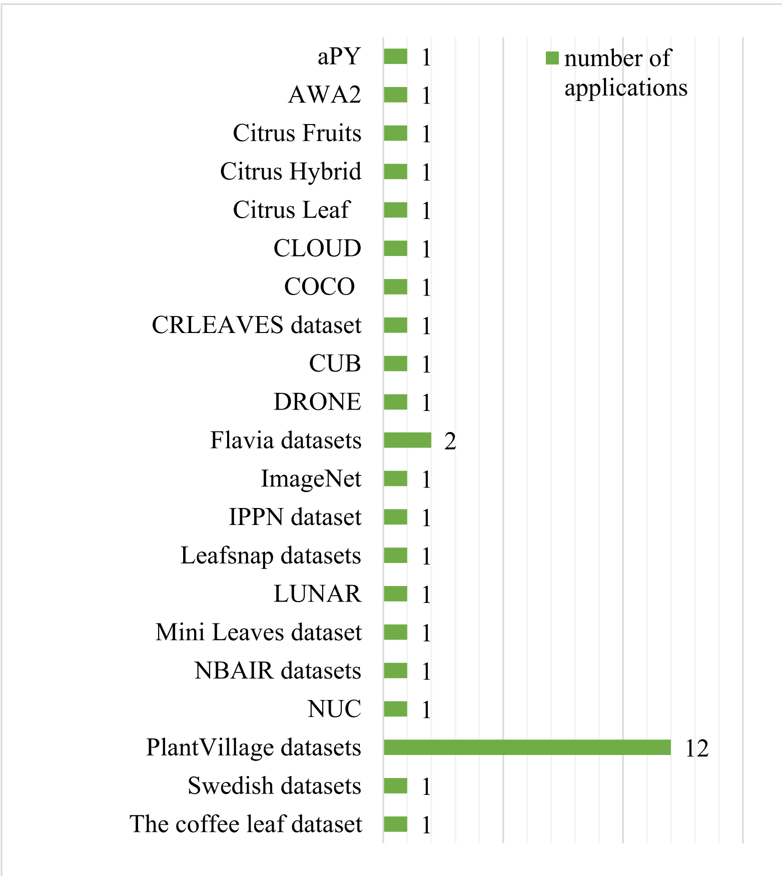

Figure 1. Use of public datasets in the literatures.

Table 1. PlantVillage dataset categories.

Category	Classes	Images	Category	Classes	Images
Apple	Apple scab	630		Healthy	1478
	Black rot	621	Potato	Early blight	1000
	Cedar apple rust	275		Late blight	1000
	Healthy	1645		Healthy	152
Blueberry	Healthy	1502	Raspberry	Healthy	371
Cherry	Powdery mildew	1052	Soybean	Healthy	5090
	Healthy	854	Squash	Powdery mildew	1835
Corn	Cercospora leaf spot & Gray leaf spot	513	Strawberry	Leaf scorch	1109
	Common rust	1192		Healthy	456
	Northern leaf blight	985	Tomato	Bacterial spot	2127
	Healthy	1162		Early blight	1000
Grape	Black rot	1180		Late blight	1909
	Esca (Black measles)	1383		Leaf mold	952
	Leaf blight (Isariopsis leaf spot)	1076		Septoria laef spot	1771
	Healthy	423		Two spotted spider mite	1676
Orange	Haunglongbing (Citrus greening)	5507		Target spot	1404
Peach	Bacterial spot	2297		Yellow leaf curl virus	5357
	Healthy	360		Mosaic virus	373
Pepper	Bacterial spot	997		Healthy	1591

selected 1000 images of each category to form a balanced dataset in order to avoid the influence of unbalanced data distribution.

Due to the large number of plant categories and huge information in the dataset, in some experiments, images of one or several categories of crops are only selected as experimental materials. Zeng et al. (2021) used the Esca, Leaf blight, Black rot, Healthy categories of grapes in the PlantVillage public dataset to create an unbalanced subset of a few grape diseases. Li et al. (2020) selected the Corn dataset, Apple dataset and Grape dataset in PlantVillage for generalization check. Zhao et al. (2021) used 8040 leaf images of three crops of tomato, apple, and grape in the PlantVillage public data set as training samples for the study of crop leaf disease transfer learning step-by-step identification method. At the same time, they performed pretraining tasks such as labelling, cropping, and dividing the training set and test set on the images.

It is worth mentioning that the original dataset obtained from AI challenger 2018 mentioned by Yang et al. and Zhou et al. is also the PlantVillage dataset. On the basis of the PlantVillage public dataset, the competition team redivided the types according to different disease degrees, and added some items appropriately. Yang et al. (2020) selected 1500 early images of grape leaf spot disease in three categories and constructed an annotated grape leaf spot image dataset by manually annotating the training images. Zhou et al. (2021) selected images containing five types of healthy corn, corn gray spot, corn rust, corn leaf spot, and corn dwarf mosaic virus disease, and performed data enhancement on them to form the Corn dataset.

In addition, we also briefly looked at some other databases. ImageNet database (http://www.image-net.org/) built on WordNet structural backbone, containing 21,841 synonym sets, and a total of more than 14 million images. It is much larger and more accurate than the vast majority of current image datasets. Although Figure 1 shows that the database was used only once, this is just for the specific experimental material. In fact, more than 3 of the papers we studied used transfer networks trained on the ImageNet database (Too et al., 2019; Chen et al., 2020; Valente et al., 2020). This shows that ImageNet's influence is far more than it seems.

The main purpose of the study by Wang Bin and Wang Dian (2019) is to solve the problem of leaf classification in the case of small samples, so the Flavia, Swedish and Leafsnap datasets were selected as training and test sets. Among them, Flavia datasets (http://flavia.sourceforge.net/) contains 33 categories with a total of 1912 leaf images (Wu et al., 2007), Swedish Leaf dataset contains leaf images from 15 tree classes (Söderkvist, 2001), and Leafsnap dataset (http://leafsnap.com/dataset/) contains 23,147 laboratory images as well as 7719 field images covering all 185 tree species from the northeastern United States (Kumar et al., 2012). Zhong et al. (2020) conducted experiments on the widely used CUB datasets, AwA2 dataset and aPY datasets. Among them, CUB datasets (http://www.vision.caltech.edu/datasets/cub_200_2011/) contains 200 categories of a total of 11,788 images, AwA2 consists of in total 37,322 images (Xian et al., 2019), and aPY (http://vision.cs.uiuc.edu/attributes/) contains two parts, aPascal and aYahoo, where the images are apparently collected from Pascal VOC 2008 and Yahoo, respectively (Farhadi et al., 2009). In addition to the published public datasets, people also obtained more public image resources through Internet retrieval (Mukhtar et al., 2021; Nuthalapati and Tunga, 2021). Furthermore, the dataset used by Li and Yang (2020), which they call Li's datasets, contains a total of 5629 images, most of which were crawled through web searches.

2.1.2. Self-collected data

It is true that the use of public datasets to obtain data resources greatly reduces the human and material consumption of manually creating datasets, which is beneficial to the development of sustainable agriculture. However, the scarcity of today's public datasets in certain domains persists, and a huge effort is still required to create new datasets. Therefore, in the survey, some people choose to make their own data sets, which is undoubtedly a way worthy of vigorous publicity and promotion.

There are two main types of datasets in agriculture, natural language datasets and image datasets. Since most of the NLP research at this stage is data-driven, or even dataset-driven, the construction of NLP datasets in agriculture is gradually becoming the focus. However, since the linguistic information surface in agriculture is too broad, complex and diverse, we only focus on image datasets here. In the process of making image datasets, we have to pay special attention to the problems that may arise in various links including image acquisition and prognosis processing, take into account the requirements of sustainable agriculture, and avoid these problems as much as possible.

In the process of image acquisition, it is necessary to consider lighting, angle, equipment and other environmental issues in the acquisition process, which are discussed here through some specific examples (Lu and Young, 2020). The first is the lighting issue. Crops exhibit different states under different environmental conditions, which may affect the experimental results to varying degrees. At the same time, pictures taken under different lighting conditions also increase the workload of prognosis processing, which wastes human and material resources to a certain extent. For the lighting problem when taking pictures, there are two ways to eliminate the interference of different lighting and different weather conditions on the experimental results. One way is to build a dark room dedicated to image acquisition, so that the lighting situation is controllable, for example, the self-made computer vision system of Sun et al. (2016). They placed samples of moldy unhulled rice on a black base and used two bar light sources as designated light sources for the vision system. In this way, the light source of the photos collected by the digital camera is stable and the background is uniform, which lays a good foundation for the follow-up work. Another way is to conduct classification control experiments based on images collected under different conditions. For example, Ren et al. (2019) took images in three different time periods of the day, morning, noon, and evening, and set up control experiments; the machine vision system for lentil grading built by Shahin and Symons (2001) captured images under three different lighting conditions: the room was illuminated, the room light was turned off, and the scanner excluded the room light.

The second is the shooting angle. The stability of the angle and distance of handheld shooting is not as good as that of fixed camera shooting. At the same time, the influence of the complex background on the subject of the image should also be considered. In the subsequent algorithm, if one wishes to simplify the algorithm even more, it is necessary to consciously avoid complex backgrounds during the image capture process. For example, Riou et al. (2020) set up a track on a row of cucumber ridges, a camera was installed on a trolley to travel along the track, and a lens with an adjustable angle was set at a distance of about 80 cm from the plants. At the same time, to avoid "motion blur", they always follow the principle of parking before shooting. Another example is when collecting rice disease images, Xiao et al. (2018) placed an A4 paper under the leaves in advance to avoid other complex background interference. Of course, in some experiments, we inevitably need images of the same object from different angles. For example, Beyaz and Öztürk (2016) took pictures of olives from 4 different angles front, handle hole, left side and tip side to test the effect of the algorithm system as realistically as possible when identifying olive varieties.

In addition, the selection of an appropriate imaging platform should also be considered. There are many options for imaging platforms, including ground platforms, handhelds, drones, etc., which need to be carefully selected according to the mission requirements. Under normal circumstances, the ground platform is mostly used, including the ground fixed platform and the moving platform. For datasets that need to shoot a single crop or even a part of the crop, close-up capture can be done by hand. An example is the cotton leaf image captured by Liang (2021) with Canon EOS 90D camera. And, in order to collect clearer images of rice diseases, Xiao et al. (2018) placed the Zen Z3 camera at a distance of 0.2 m from the leaves, and used the single focal length mode to shoot rice leaves. For some large-scale perspectives that need to be collected, drones are more suitable. For example, the experimental materials of Karami et al. (2020) were collected by flying at an altitude of 40 m. Contrast Kim et al. (2021) did not use drones to capture images of cultivated and noncultivated soil areas, which caused the buildings and sky in the upper half of the captured images to become interference, which required further processing. In addition, due to the angle problem, the lower left corner and the lower right corner of the image are not easy to identify, which increases the workload of prognostic processing.

During the preprocessing stage, data improvement, picture annotation, and subset splitting must be addressed with caution. Prior to increasing the picture data quality, it is critical to do a condition evaluation. Before filtering, we must first assess whether the captured pictures create the intended effect and include the necessary information. Here there are two mainstream approaches available for image annotation, one is to be constructed and written by human; the other is to acquire by remote supervision. Usually, it is necessary to divide the data into two data sets without intersection—training set and validation set, which are used to train the algorithm and evaluate the results, respectively. However, one of the most important and easily overlooked rules in the process of dataset production is "moderate preprocessing". The "moderate" here is not a fixed requirement, and needs to be adjusted according to the specific circumstances of the image. For example, in image cropping, for a series of photos taken with clear subjects and clean backgrounds, it is only necessary to precrop the images with uniform size; while for those images with subjects that are not prominent or contain complex backgrounds, it is necessary to use professional software for grayscale conversion, Gaussian filtering, and irregular cutting of complex backgrounds in order to highlight the image subjects. Following the principle of minimal preprocessing and performing only the necessary routine operations not only ensures the shareability of the dataset, but also is a way to avoid wasting resources in the process of extensive work.

2.2. Data mining and evaluation in agricultural

In the era of big data, the three basic indicators for judging data quality are capacity, type and speed. Capacity refers to the massive data generated per unit time, diversity refers to different formats and sources of data, and speed refers to data collection, storage, analysis and speed of distribution to end users. For agricultural big data, timeliness and regionality in the evaluation criteria are also particularly important (Wolfert et al., 2017; Morota et al., 2018) How to obtain more useful information from limited data, the importance of data mining in the agricultural field is self-evident. Figure 2 shows the general flow of data collection and mining.

The object of data mining can be any type of data source or database such as text, multimedia data, etc. The common techniques include: artificial neural networks, decision trees (Gao and Ren, 2009), genetic algorithms (Deng and Wang, 2016; Indu et al., 2021), nearest neighbour algorithms, rule derivation (Vignesh and Vinutha, 2019), etc. In the field of agriculture, the technology of data mining at this stage revolves around the continuous development of data collection technology. In order to solve the problems of poor timeliness and lack of information in the process of collecting and organizing agricultural raw data, people have been improving mining and statistical methods (Rao and Yuan, 2021) and developing more convenient data mining strategies (Bahlo and Dahlhaus, 2021). At the same time, high-dimensional spatial data mining (Hira and Deshpande, 2015; Si et al., 2020), the establishment of large repositories (D'arpa et al., 2011; Pykhtin and Gostev, 2018; Ngo et al., 2019), and agricultural data visualization (Russ et al., 2008) for the agricultural field have also been fruitful.

The current application of data mining in agricultural production mainly includes the following aspects. One is to predict the growth of crops. It can predict the yield of crops (Savla et al., 2015; Mishra et al., 2018), disease problems (Ayub et al., 2018; Das and Sengupta, 2020), and also predict the growing environment of crops such as soil condition and temperature condition (Anton et al., 2019; Avram et al., 2020). For example, Demir et al. (2018) applied data mining and adaptive neuro-fuzzy structure to predict the colour parameters of walnut; Demir et al. (2018) used physical properties and developed fairly accurate rules to predict the stem cavity of different apple varieties and the width and depth of the eye socket. The second is to mine crop growth rules from the database to guide scientific field production and improve product quality (Sun et al., 2017; Rao and Yuan, 2021). Thirdly, data mining can be used to improve the traditional agricultural expert system and solve the knowledge bottleneck problem of the traditional expert system (Gandhi and Armstrong, 2016). Fourth, the application of data mining in the field of plant disease identification has also matured in recent years, and the use of data mining techniques to create suitable prediction models is of great significance for crop disease avoidance and fruit protection efforts. For example, Ilic et al. (2018) applied data mining techniques to predict the likelihood of disease infection in cherry fruit by using different data mining techniques to build separate models and selected the best algorithm based on the final evaluation results.

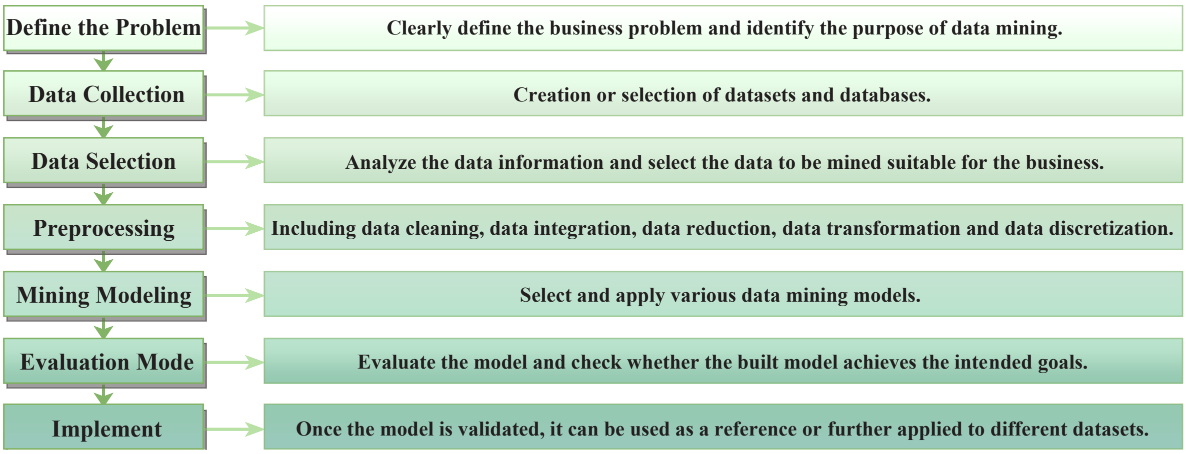

Figure 2. General process of data collection and mining.

As we all know, intelligent agriculture is inseparable from the collection and mining of data. The quality of these data inevitably affects the efficiency and cost issues of the subsequent work to be carried out. In the previous study, Li and Chao (2021) used an embedding range judgment (ERJ) method to conduct multiple sets of comparative experiments, and the results showed that limited good data can defeat a large number of bad data and obtain relatively ideal results. The use of large amounts of data directly into algorithms without evaluation has certain undesirable consequences: on the one hand, it increases the burden on the model, and the uneven data quality forces the algorithm to be more inclusive and its complexity will increase; on the other hand, due to the unreliability of bad data, one has to choose more quantity to offset the quality problem, thus creating the need for higher costs for The unsustainable pattern of data collection and mining efforts. For simple and effective data quality assessment methods in the agricultural field, Li Yang et al. have made active attempts, and their proposed perturbation entropy and effective distance entropy metrics can distinguish the good and bad image data in crop pest identification tasks from an information perspective (Li and Chao, 2022; Li et al., 2022). However, the assessment of data quality in the agricultural field has not attracted extensive attention and research at this stage; in other words, the research results for data assessment in the agricultural field are relatively few and need to be further explored.

3. Resource-saving intelligent algorithms in agriculture

Sustainable development is a very important topic, which is closely related to the survival and development of human beings. With the development and progress of science and technology, agricultural sustainability has gradually become the core premise for people to think about the development of related technologies. This chapter aims to summarise and display the achievements in the field of agricultural sustainable computing in recent years by analysing the practical application of some resource-saving intelligent algorithms in agriculture, starting from algorithm classification and application classification.

3.1. Algorithm classification

In recent years, a variety of economical algorithms in the agricultural field have been proposed, and these intelligent algorithms have achieved outstanding achievements in the fields of intelligent agriculture such as pest detection, plant identification, crop and weed detection and classification. They are currently classified differently. After investigation, the application of the proposed intelligent algorithm will definitely consume resource space, computing time, and raw data. Accordingly, this paper intends to divide the resource-saving intelligent algorithms in the agricultural field into the time-space-saving type and the raw-data-saving type. Among them, the time-space-saving algorithms mainly include two types: time-saving and space-saving. And the raw-data-saving algorithms is a type of algorithm that saves original data samples, which is typical of small sample learning.

3.1.1. The time-space-saving algorithms

As the name implies, the time-space-saving algorithms refers to an intelligent algorithm that significantly saves the utility time of the agricultural process or greatly reduces the algorithm space complexity. Among them, the algorithm based on machine learning saves time to a great extent, while the typical algorithm in saving space is mainly based on Cloud Computing architecture.

For some complex problems in the field of agriculture, using traditional solutions not only consumes a lot of manpower and material resources, but also the problem that computing time is too long has attracted people's attention. At this stage, most of the intelligent algorithms proposed by people have made more or less contributions in saving time. In comparison, machine learning undoubtedly saves manpower, material resources and timeliness issues to a greater extent. As a field with the most cutting-edge trends, the most human-like characteristics, and the most intelligent attributes in the field of artificial intelligence, machine learning is widely used in agriculture and has outstanding performance (Kamilaris and Prenafeta-Boldu, 2018; Liakos et al., 2018). For example, van Klompenburg et al. (2020) analysed and summarised 50 articles using machine learning to predict the direction of crop yield; Arjenaki et al. (2012) used machine vision to efficiently sort tomatoes online, and the accuracy of the entire system can reach 90%. Their studies have shown that the improved machine learning algorithm is superior to traditional commonly used algorithms, and the accuracy and efficiency of the results are greatly improved compared with traditional techniques. In addition, these algorithms help farmers decide which crops to plant for maximum yield by considering factors such as temperature, rainfall, area and more.

At the same time, the development of the agricultural informatization era has led to the explosive growth of agricultural big data. Cloud computing distributes tasks on a resource pool composed of a large number of computers, and users obtain computing power, storage space and information services as needed, which makes resource processing and application simple and efficient, and greatly saves local resource space. Cloud computing in the agricultural field has brought large-scale data storage capabilities and low-cost resource service methods to agricultural informatization. Its application focuses on the following aspects: saving local storage space for massive crop information on the cloud, saving machine computing space to process cloud data, using cloud services and cloud computing to plan new agricultural programs, etc. For example, the use of cloud computing technology can accurately monitor agricultural projects, use data analysis and processing to grasp the situation of crops, record the information of each link in the production process of agricultural products, etc., to promote the construction of agricultural informatization (Hori et al., 2010; Goraya and Kaur, 2015). At the same time, the combined role of cloud computing and the Internet of Things (IoT) cannot be ignored (Mekala and Viswanathan, 2017). Cloud computing technology is considered as the best infrastructure for IoT systems with its characteristics and unlimited services, and the existence of cloud-based intelligent applications and models promotes the development of informatization in the agricultural field. Tawalbeh et al. (2021) proposed a secure cloud IoT model with authorization and authentication technology using the Amazon Web Service platform, which introduces the edge computing concept between the physical and the cloud layers. Gill et al. (2017) proposed a cloud-based autonomous information system that collects user-side information through wireless sensor networks and the Internet of Things, and processes it in the cloud using big data analysis technology to add to agricultural information services.

3.1.2. The raw-data-saving algorithms

Deep learning (DL) is undoubtedly the highlight among existing agricultural sustainable algorithms; however, we found that deep learning models rely heavily on large amounts of training data. But in real-world scenarios, especially some specific agricultural scenarios, only a small amount of data or a small amount of labelled data is available. In this case, if you want to obtain enough training data, you need to not only label the original unlabelled data, but also recollect it. It has to be admitted that it will consume a lot of time and manpower. We cannot help but wonder, is there a more economical algorithm to choose from? In this context, the concept of few-shot learning (FSL) came into being. Few-shot learning is a subtopic of deep learning. On the basis of the advantages of DL, FSL can still complete most of the modelling tasks with few data samples, and has a wide range of research value and application space. Studying the application of FSL in the field of sustainable agricultural computing is of great relevance as it provides important references and research directions and stimulates new efforts in data collection preprocessing, algorithm development, and benchmarking in the field of sustainable agricultural computing.

Among the raw-data-saving algorithms examined, the vast majority are based on FSL. For few-shot learning, the current mainstream classification methods are based on data augmentation, based on model fine-tuning, and based on transfer learning (Zhao et al., 2021). Of which, few-shot learning method based on data augmentation mainly increases the training data set through prior knowledge, which can be to increase the characteristics of the samples in the data set, or to expand the data. The few-shot learning method based on model fine-tuning refers to fine-tuning the model through prior knowledge to limit the complexity of the model. The FSL method based on transfer learning is to transfer the knowledge that has been learned to a new field.

In the reviewed literature, few-shot learning methods based on model fine-tuning and data augmentation are rarely used. The plant detection and counting method based on the improved CentreNet proposed by Karami et al. (2020) belongs to the method based on model fine-tuning. Methods based on data augmentation include an image augmentation method for segmentation tasks proposed by Nesteruk et al. (2021), which transforms it with an image mask, providing the possibility to synthesize an infinite number of composite scenes. Riou et al. (2020)

proposed two data augmentation strategies: background replacement of base training images, and adding 'target background' as one of the base categories. In addition, Zeng et al. (2021) proposed a data generation model based on the recurrent generative adversarial network model in response to the lack of grape leaf dataset. The leaf foreground module (LFM) block is introduced into the model, which can generate high-quality grape leaf disease images, fill the gap of the lack of large-scale diseased leaf labelling datasets, and save a lot of manpower and material resources required to obtain professional datasets.

FSL methods based on transfer learning can be divided into based on metric learning, based on metalearning (Chen et al., 2021; Li and Yang, 2021; Wang and Wang, 2021), based on graph neural networks according to different learning frameworks. Among them, the methods based on metric learning determine the classification result by finding the neighbouring categories of the samples to be classified; the methods based on metalearning make the machine "learn how to learn"; the methods based on graph neural network model the graph information by connecting the sample vectors with the label vectors. Most of the FSL methods used in the reviewed literature are FSL methods based on metric learning. The general flow chart of the model is shown in Figure 3, and most of these methods are proposed based on CNN (Lu et al., 2021).

The basic CNN consists of three structures: convolution, activation, and pooling. The current mainstream convolutional neural networks, such as VGG and ResNet, are adjusted and combined by simple CNNs. Li and Yang (2020) directly used CNN to extract image feature vectors for training to distinguish different pest species. Li et al. (2020) considered whether shallow CNN can be used instead of deep CNN to complete tasks and save resources. In the experiment, only shallow CNN from the pretrained VGG-16 model (the first four convolutional layers and

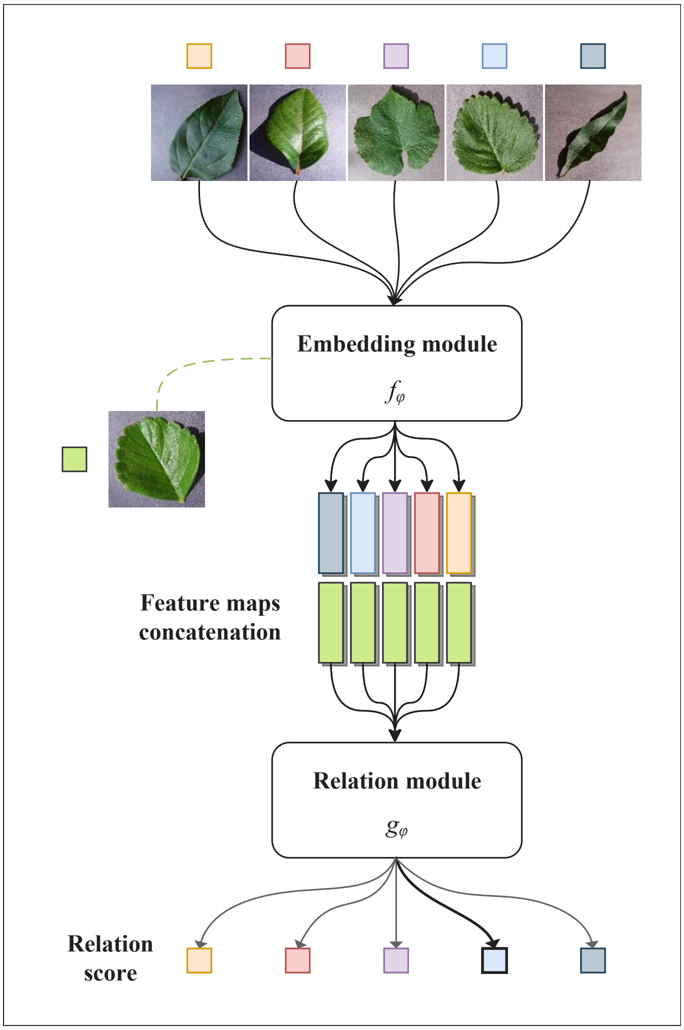

Figure 3. Generic flow chart of model based on metric learning.

two Pooling layer), select kernel SVM and random forest to classify the extracted features, and the obtained results are better than other deep learning models. Zhao et al. (2021) used ResNet as the original training model, and used the transfer learning approach to propose a stepwise recognition method on top of the original model, which improved the recognition accuracy by 20% and then by 8%. Yang et al. (2020) used CNN for comparative experiments. The experiments of them used AlexNet, GooleNet, Vgg16, RestNet34, MobileNetV2, and the migrated MobileNetV2 model as the comparison model.

There are some researchers completed the task with a new network model based on CNN architecture: Lu et al. (2021) proposed a spatiotemporal convolutional deep network model 3D-2D CNN with a mixture of 3D convolution and 2D convolution as building blocks for the identification of 13 crops in the study area. The experiments show that the model has lower model complexity. As well as high computational efficiency, and stability and applicability on small data sets. Li and Chao et al. (2020) combined convolutional neural network (CNN) and generative adversarial network (GAN) to propose an ANN-based continuous classification method with memorized storage and retrieval, which uses less data and has high flexibility.

3.2. Application classification

The practical application classification of the selected economical intelligent algorithms in agriculture is shown in Table 2, mainly including pest and disease identification, plant detection and classification, weed identification and other applications.

Plant diseases are one of the most fundamental problems that seriously affect agricultural production and quality. How to identify crop diseases and insect pests at high speed and effectively is a key task for sustainable agriculture. It can be seen from the above table that the research on the identification of crop pests and diseases is the most in the investigated literature, accounting for about 72.4% of the total. This also confirms the importance of crop pest and disease identification from the side. A wide variety of crop types and diseases are involved in our work. For example, Usra et al. (2022) proposed an algorithmic framework for citrus disease identification; the work of Zeng et al.(2021) improved the accuracy of grape disease identification task; to prevent and control cotton diseases and ensure cotton quality, Liang (2021) proposed a small learning framework that can be used for the task of cotton leaf disease spot classification. Some researchers have used the FSL to train models on a very small dataset so that the classification of new types of plant leaves and diseases (Argueso et al., 2020) and the identification of grape leaf spots under limited samples (Zhou et al., 2021) were realized. Jadon (2020) also proposed a method using SSM-

Table 2. Application classification.

Application classification	Number of documents
Pest identification	21
Plant detection and classification	3
Weed identification	2
Plant identification and counting	1
Crop residue division	1
Arable land area division	1

Net for plant disease identification in low data mode. And Li and Yang (2020) added a terminal to realize this work on the basis of proposing an intelligent algorithm, which is undoubtedly a positive attempt to combine software and hardware in the field of sustainable algorithmic agriculture. In addition, there are some algorithms that integrate multiple crop disease identification. Zhao et al. (2021) trained the transfer learning models of VGG16 and ResNet respectively, which were able to improve the recognition accuracy by 20% on the basis of the original model. On this basis, the step-by-step recognition method is introduced, and the accuracy of the VGG16 and ResNet models are again improved by 14% and 8%, respectively.

Of the literature reviewed, three focused on plant detection and classification. Wang Bin and Wang Dian (2019) proposed a few-shot learning method based on the Siamese network framework to solve the problem of leaf classification, which can achieve high classification accuracy when the training sample size is small. Mukhtar et al. (2021) used a convolutional Siamese network (CSN) to detect and classify plants. Figueroa et al. (2020) proposed a hybrid model 3D-2D CNN based on the CNN architecture, which identified 13 crops in the study area with a classification accuracy of 89.38%. The results show that the models under the above economic algorithm framework have low complexity and high computational efficiency, and have certain stability and applicability on small data sets. It greatly reduces the loss of human and material resources for plant detection and classification.

Weed identification is undoubtedly one of the important directions in agricultural applications. For example, Jabir et al. (2021) created and optimized a CNN model for high-accuracy detection and identification of weeds in sugar beet fields, using this model to control weed spread while promoting frugal use of herbicides. However, the inspection found that compared with deep learning, there are few weed identification technologies based on small sample learning. In evaluating the performance shown by 27 leading edge deep transfer learning (DTL) models on the weed identification task, Chen et al. (2021) also noted that these models did not perform as well as expected when identifying weed classes with a small number of samples. To address the problem of deep learning models requiring a large number of samples, Ronja et al. (2021) proposed a weed segmentation model called few-leaf learning, which allows a specific weed segmentation model to be trained on a small number of training data.

A number of other applications are covered in the literature examined. Karami et al. (2020) performed automatic plant counting and technology on corn images collected by drones, and the overall accuracy can reach more than 95%. Li et al. (2021) developed a Siamese domain transfer network (SDTN) architecture to achieve segmentation of corn residue. In the study of Kim et al.(2021), the field land was divided according to the cultivated land area and the noncultivated soil area to provide path guidance, so that the subsequent autonomous farming process can be carried out smoothly. The application technology is scalable and usable, not only providing relative differences in characteristics between arable and nonarable soil areas but also reducing the workforce required for dataset construction and annotation.

There is no doubt that few-shot learning is more conducive to deployment on portable terminal equipment because of the ability to learn problem-solving models from small samples. In the future, FSL will gradually become the focus of research on the application of economical algorithm in agriculture. The researchers if can better solve the contradiction between sample size and quality, the application scenario will cover the whole process of agricultural production.

4. Discussion

4.1. Challenges

Our survey analysis shows that the abovementioned frugal algorithms provide excellent performance in the vast majority of agricultural sustainability-related efforts. At the same time, we found that the current field of agricultural sustainability algorithms still faces many challenges.

(1) Looking back at the related work of our research, 26 of them, about 76% of the total number of papers, focused on the research direction of disease identification, which shows that the current application scenario of frugal intelligent algorithms in agriculture is relatively single and needs to be expanded. In agricultural production activities, we need to pay attention to various factors such as geographical conditions, climatic conditions, environmental conditions, pests and diseases, and biodiversity. All of these factors affect farming production, and artificial intelligence is created to replace human beings in the agricultural production process to regulate and avoid the negative effects of these factors. Why cannot we apply intelligent algorithms to the whole process of agricultural production? For example, before agricultural production, the design of irrigation systems, predictive analysis of plant growth (package live yield, quality, etc.); or in the production process, the management of crop pests and diseases, the construction of intelligent greenhouse systems, crop harvesting, environmental monitoring and prediction; and of course, after the production of agricultural products inspection, transportation, sales and other links.

(2) Among the sustainable algorithm applications examined, few of them are really integrated with various intelligent equipment and implemented on the ground. The era of agriculture 4.0 based on cloud computing, Internet of Things, and artificial intelligence has obvious integration characteristics, i.e. smart agriculture should be a high degree of integration of people, machines, and apparatus. However, this is not reflected in the study. On the one hand, it may be due to the lack of key technologies and equipment to put sustainable algorithms into the smart agriculture system and form a closed loop; on the other hand, it may be due to the fact that the smart agriculture system has not yet become a system and lacks promotion in the process of construction and application, so most of the research carried out for it still stays in the algorithm development link.

(3) At the present moment, the analysis of sample quality is still relatively small, and how to carry out high-quality data information collection, mining and pattern recognition is also one of the challenges in the future. At the same time, the segmentation and data mining of agricultural IoT data resources have not been carried out effectively, and various types of intelligent algorithm models and practical databases in agriculture are in urgent need of expansion. And the paradigms and standards of various sustainable algorithms are inconsistent at this stage, and different research work cannot be well carried out for horizontal comparison. In the future, data sets with complete information, standardized testing and high universality should be established as far as possible.

(4) While conducting large-scale research on various types of sustainable intelligent algorithms, attention should be paid to data security in smart farms. At this stage, there is a paucity of data security research in the field of sustainable agriculture algorithms. Especially for the 21st century when the Internet is developing rapidly, data security and privacy issues are facing great risks and challenges. How to effectively avoid data privacy and security risks in the process of algorithm development and model training is another key element of research at this stage.

(5) At present, the world is under the raging environment of the new crown pneumonia epidemic. The

shrinking global economy, limited scientific and cultural exchanges, sluggish development of high-tech, and sudden increase in employment pressure in various industries are all restricting the rapid and stable development of smart agriculture. How to balance the impact of the unfavourable factors in the current global sluggish development environment on the field of agricultural sustainable computing is also a huge challenge for researchers.

4.2. Future developments

The purpose of this paper is to provide insight into the current state of data collection and mining in agriculture, to demonstrate frugal algorithms with their applications, and hopefully to provide some reference for future research directions in sustainable computing in agriculture. However, the technology in this field is galloping forward at an alarming rate, and the state-of-the-art at this stage may soon become obsolete shortly after the publication of this paper. Therefore, to address the issue of sustainable development of data collection and mining in agriculture, the following possible future development directions are proposed.

4.2.1. Open sharing mode of agricultural data

We are living in such a big data era with rapid development of science and technology, and the development of agriculture is inseparable from digitalization and informatization. The production mode of precise fertilization, precise medicine application and precise irrigation based on various agricultural data has become the trend of agricultural development today. In this context, the importance of agricultural data is self-evident. Therefore, the establishment of a safe, efficient and mature open sharing mode of agricultural data will not only promote the more rapid development of intelligent agriculture development, but also the inevitable trend of the general environment.

4.2.2. Technology to promote industrial upgrading

The future smart agriculture will be the "ecological integration" of high-tech information technology and sustainable agriculture. In recent years, the rapid development of information technology around the world has provided the technical conditions for intelligent and sustainable agriculture. The growing maturity of modern information technology, such as the Internet of Things, the Internet, cloud computing, big data, machine learning, etc., will promote the transformation of agricultural information technology from a single algorithm application to a multialgorithm integration of integrated technology applications. With the promotion of technology, agricultural production can break through the multiple constraints of resources, markets and ecological environment, thus making it possible to upgrade the agricultural industrial structure and transform production methods.

4.2.3. Standardization of sustainable agriculture industry

One of the ultimate goals of agricultural development is sustainability, i.e. how to maximize land output rate, resource utilization rate and labour productivity under limited resource conditions. Therefore, whether or not to establish a standard for sustainable agricultural industry development and scientific management is of great significance to break through the various bottlenecks of resources, markets and ecology faced by agricultural development at this stage.

5. Conclusion

In this paper, we investigate the research work applied to the field of sustainable algorithms in agriculture, examining four aspects: data collection, data mining, technical algorithms, and application areas. The results of the investigation show that: data collection and mining in agriculture are mainly based on publicly available datasets, and the creation of datasets and the development of mining algorithms should be further enhanced in the future; in terms of resource efficiency and application performance, these resource-saving intelligent algorithms, especially those based on small-sample learning, show superior results compared with other existing technologies; it is worth noting that the application fields and directions shown by the examined resource-saving intelligent algorithms are relatively limited.

For future work, we discuss the current challenges in the field of sustainable algorithms for agriculture and the possibilities for future development. We hope that participants in sustainable agriculture will use our understanding to consider their own research in order to inspire more researchers to attempt to develop frugal agricultural intelligence algorithms. Applying resource-saving intelligent algorithms to solve a variety of agricultural problems and data analysis is a goal we have been pursuing. The future of sustainable agriculture research and implementation is an inevitable trend for society, as it can be further integrated with smarter, more accurate and safer agricultural production.

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