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Advanced agricultural disease image recognition technologies: A review

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ABSTRACT

Agricultural disease image recognition has an important role to play in the field of intelligent agriculture. Some advanced machine learning methods associated with the development of artificial intelligence technology in recent years, such as deep learning and transfer learning, have begun to be used for the recognition of agricultural diseases. However, the adoption of these methods continues to face a number of important challenges. This paper looks specifically at deep learning and transfer learning and discusses the recent progress in the use of these advanced technologies for agricultural disease image recognition. Analysis and comparison of these two methods reveals that current agricultural disease data resources make transfer learning the better option. The paper then examines the core issues that require further study for research in this domain to continue to progress, such as the construction of image datasets, the selection of big data auxiliary domains and the optimization of the transfer learning method. Creating image datasets obtained under actual cultivation conditions is found to be especially important for the development of practically viable agricultural disease image recognition systems.

Contents

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1. Introduction

A recent report by the Food and Agriculture Organization of the United Nations suggests that more than one third of the natural loss of agricultural production every year is caused by agricultural diseases and pests [1], making these the most important factors currently affecting agricultural production and food security [2]. Agricultural production is complex and there are numerous agricultural diseases and pests that need to be taken into account. Traditional approaches that rely on laboratory-based observations and experiments can easily lead to incorrect diagnoses. Alongside of this, a lack of professional agricultural technicians often makes it difficult to identify diseases and pests soon enough for adequate remedial action to be undertaken. In order to overcome these problems, a number of researchers have turned to using machine learning methods and computer vision technology for the identification of agricultural diseases and pests. In recent years, efforts have been made to support this by integrating existing knowledge about plant pathology and related matters into image recognition technology research. Generally, this first of all involves analyzing and processing image data relating to plant diseases and pests. After this, a machine learning model is built to obtain different levels relating to different image features. Finally, a classifier is used to enable the rapid and accurate recognition of different types of diseases and pests. All of the studies adopting this approach have the ultimate goal of providing technical guidance for the prevention and control of agricultural diseases and pests [3].

The image recognition of agricultural diseases is more challenging than the recognition of agricultural pests. A variety of machine learning methods have been addressed to this that date back to the 1980s. These include clustering method [4–6], SVM (Support Vector Machine) classifier [7–9], Bayesian classifier [10–12] and shallow neural network methods [13–15]. A lot of this work is ongoing. However, when traditional machine learning methods are adopted for the practical image recognition of agricultural diseases, they often have a number of shortcomings:

- First of all, they are highly dependent on the quality of the original disease images, so the requirements placed upon the image acquisition environment and acquisition methods are very strict.
- Secondly, the realization of these methods is typically very complex and involves a series of operations such as image preprocessing, image segmentation, feature extraction and classifier construction that themselves need further study to improve their effectiveness.
- Thirdly, if the number of training samples is large, the efficient construction of corresponding models can be difficult using these traditional machine learning methods.

The explosive growth in available Internet data that has happened alongside of the development of modern intelligent agriculture is making it ever-more important to use more advanced and intelligent machine learning methods to exploit the opportunities presented by this data to improve the effectiveness of agricultural disease image recognition [16].

Recent advances in machine learning methods, such as deep learning and transfer learning, have resulted in significant breakthroughs in a number of application fields and they have started to be adopted for the purposes of agricultural disease image recognition. Even here, however, numerous problems remain to be solved. Thus, explorations of how best to apply these new machine learning methods to agricultural disease image recognition have become an important focus of research in this domain. This paper reviews various new machine learning models and advanced intelligent image recognition technologies and their current application in the field of agriculture to assess and analyze the current state-of-the-art in agricultural disease image recognition. On the basis of this analysis, it also identifies the remaining challenges that existing methods are going to have to overcome. By undertaking this systematic review, we hope to provide a source of reference for further explorations of how best to make use of advanced machine learning methods and technologies for agricultural disease image recognition.

2. Overview of advanced image recognition technologies

Most traditional image recognition methods consist of a few key steps, such as image preprocessing, image segmentation, feature extraction, and classifier design [17]. Overall, this procedure is complicated and there are several issues that compound this problem. One such issue is that some of the key steps require further study to achieve better levels of accuracy. Another issue is that the feature parameters often need to be designed manually, which depends on significant amounts of prior knowledge. The number of manually designed feature parameters is also limited, so it is difficult to take advantage of large bodies of pre-existing data. Fortunately, some advanced image recognition technologies based on artificial intelligence and machine learning are able to overcome these problems. So, and for instance, end-to-end machine learning methods do not require as many complex steps. In the case of deep learning for image recognition, it is possible to extract image features automatically, thus reducing dependence on experts to inform the modeling process.

The deep learning approach was first proposed by Hinton et al. in 2006 [18]. Unlike traditional shallow machine learning, deep learning models are better able to express features and what is being learned. A key difference between deep learning and traditional methods is that the features in deep learning models can be automatically learned from big data rather than needing to be manually designed [19]. Theoretically, deep learning models can also contain thousands of parameters, making them more expressive. Introduction of deep learning methods significantly improves the efficiency and accuracy of image recognition. In 2012, deep learning made a particularly influential breakthrough in the field of computer vision. Hinton's research team won the ImageNet [20] image classification competition by explicitly drawing upon a deep learning method [21]. The accuracy rate produced by their approach was more than 10% higher than the second-placed technique. However, despite its notable advantages, as a supervised learning method, deep learning still has several shortcomings. For example, its modeling quality remains heavily dependent on large-scale labeled training samples [22].

Transfer learning is another advanced machine learning method. This was first proposed by Yang et al. [23] in 2005. In comparison to traditional machine learning methods and deep learning, the biggest advantage of transfer learning is that it can transfer trained model parameters or learned knowledge to the target domain to help the training of new models. As a result, target domains that lack large-scale labeled data can still be effectively modeled. This approach to using knowledge acquired in one field to assist with the learning of a task in a new field is closer to the human learning process. Transfer learning is considered to be the most effective new machine learning strategy in terms of reducing the cost of human supervision. By using current deep learning methods, large-scale labeled data can be used to learn the knowledge pertaining to a source domain and transfer learning can then be used to build a model in a different, target domain, significantly improving the resulting model. As a result, in recent years, transfer learning has attracted a growing amount of interest in the field of machine learning [24,25]. Since 2016, papers relating to transfer learning and its application have come to occupy an important position in some of the most prestigious international conferences in the field of artificial intelligence, such as AAAI, ICML, NIPS, etc. [26–28]. Over the past 5 years, more than 700 academic papers discussing different aspects of transfer learning have been published [29]. At present, in the international field of artificial intelligence, transfer learning is widely considered to be the next major breakthrough after deep learning. Thus, it is rapidly becoming one of the principal focuses of artificial intelligence and machine learning research [30].

3. Advanced image recognition technologies of agricultural diseases

3.1. *Methods based on deep learning*

3.1.1. *Deep learning models*

The concept of deep learning comes from artificial neural network research. It combines low-level features to form more abstract high-level representations of attribute categories or features, thereby producing a distributed feature representation of the data. If one assumes that there is a system, S, which has n layers $(S_1, \ldots, S_n)$ with I as the input and O as the output, the deep learning procedure can be expressed as follows:

$$I \Rightarrow S_1 \Rightarrow S_2 \Rightarrow \ldots \Rightarrow S_n \Rightarrow O$$

If the output O is equal to the input I, i.e., the input I does not change after passing through the system, no information is lost when the input, I, passes through each layer, S_i, or the lost information is redundant. In other words, the output of S_i at any layer is another form of input, I. So, the basic idea of deep learning is to obtain a hierarchical representation of the input information by superposing multiple layers, with the output of the previous layer being used as the input of the next layer. The parameters in the system can be adjusted to obtain a series of hierarchical features for each layer, S_i.

At present, the most commonly used deep learning network models include Convolutional Neural Networks (CNNs) [31], Recurrent Neural Network (RNN) [32] and Deep Belief Networks (DBN) [33]. CNNs are typical of these kinds of deep network models. They are feedforward neural networks with a deep structure and a convolution computation function [34]. They have the ability to represent learned features and can conduct shift-invariant classification of input information according to their hierarchical structure. Through convolution and pooling operations, CNNs can automatically learn the features of images at different levels. First, they learn color and brightness, then they obtain local details such as edges, corners and lines, before acquiring more complex information and structures such as texture and geometry. From these various features they are finally able to form the concept of whole objects. This learning process is consistent with the hierarchical abstraction process associated with how human beings recognize images. CNN architectures consist of three parts: the first part is an input layer; the second part is composed of a combination of n convolutional layers and a pooling layer; and the third part is a fully connected multi-layer perceptron classifier. Different CNNs can be constructed to cover specific situations, as long as the above principles are followed. Fig. 1 gives an example of CNN, which consists of different convolutional layers and pooling layers.

To ensure that the feature extraction is as accurate as possible, the network layers making up the second and third parts are usually combined together, according to the specific requirements of the task being undertaken. The formal representation of a CNN's general structure is as follows [35,36]:

$$INPUT \Rightarrow [[CONV] * n \Rightarrow POOL?] * m \Rightarrow [FC] * k,$$

where, $CONV$ denotes a convolutional layer that may overlap n times; and $POOL$ denotes an affixed pooling layer that is optional. The above structure can be repeated m times and then connected with a full connection layer FC, which can be iterated k times. According to this definition, the core of a CNN is composed of multiple convolutional layers, with each convolutional layer containing multiple convolution kernels. These can scan a whole image from left to right and from top to bottom to obtain the output data. This is called a feature map. The first convolutional layer in the network captures local detailed information about an image, with each

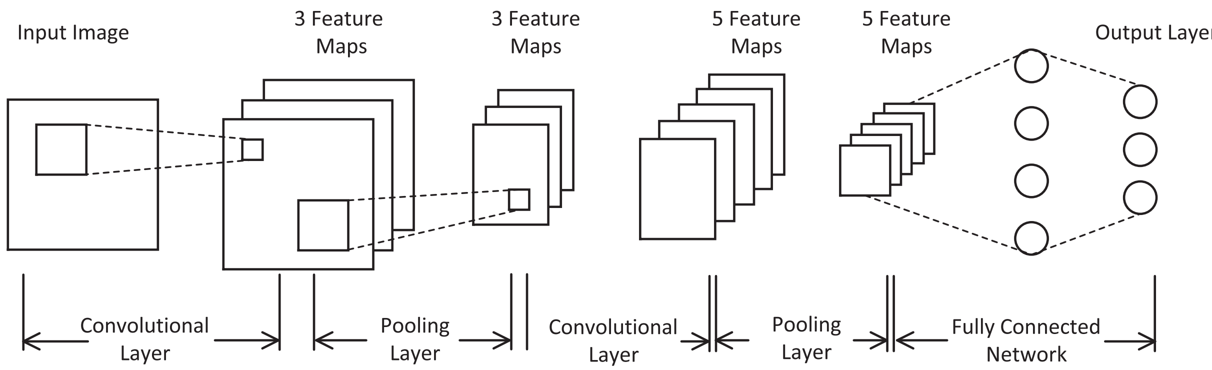

Fig. 1 – An example of convolutional neural network.

pixel of the output image only using a small amount of the information contained in the input image. The subsequent convolutional layers are used to capture more complex and abstract information. Once an image has passed through several convolutional layers, an abstract representation of it can be obtained at different levels. As a result of its powerful ability to extract and process image features, CNNs have become one of the most important methods in the field of image recognition.

3.1.2. *Works based on deep learning*

When traditional machine learning methods are used for agricultural disease image recognition, the feature parameters used to construct a model need to be designed manually, which is heavily dependent upon prior knowledge. This prior feature design is not necessary when using deep learning frameworks based on CNN. Instead, multi-level features in an image can be automatically extracted during the modeling process. The larger the training sample data, the more accurate the recognition results obtained. Over the past five years, an increasingly large number of researchers have adopted deep learning methods to carry out research in the field of agricultural disease image recognition.

For single-type crop disease image classification and recognition, most studies have focused on tomatoes, rice and cucumbers. In the case of tomato disease image recognition, Brahimi et al. (2017) [37] used a CNN model to classify their dataset, which contained 14,828 images of tomato leaves infected with nine diseases. This model achieved an accuracy of 99.18%. Fuentes et al. (2017) [38] investigated the effectiveness of a range of different deep learning networks for tomato disease classification. These included Faster R-CNN, R-FCN, and SSD. On the basis of this they were able to find a suitable architecture and method for local and global class annotation and data augmentation. This increased the accuracy of the results and reduced the number of false positives. Guo et al. (2019) [39] used a multi-scale AlexNet recognition model to implement a tomato leaf disease image recognition system on the Android mobile platform. This model managed to achieve a high average recognition accuracy for each disease in its early, middle and late stages. Fuentes et al. (2020) [40] have further proposed a practical deep meta-architecture-based method with a dedicated feature extractor to recognize plant diseases. This method was designed to be able to identify the location of diseases in any given image. It was verified on a tomato plant disease and pest dataset that they collected themselves in complex real-field scenarios and achieved good results.

When it comes to rice disease image recognition, Liang et al. (2019) [41] used CNN to construct an effective rice blast disease feature extraction and classification model and compared its performance against methods using LBPH and Haar-wavelet transforms. The results showed that the proposed model had a stronger recognition ability than the other methods and its classification accuracy exceeded 95%. Bhattacharya et al. (2019) [42] used a deep learning method to identify three kinds of disease in rice leaves, bacterial blight, blast, and brown mark. In this case, they achieved an accuracy of 78.44%. Liu et al. (2019) [43] used a CNN model to recognize rice sheath blight and compared its effectiveness with the performance of a traditional SVM method. The results showed that the recognition accuracy of CNN could reach 97%, while the best accuracy SVM could achieve was 95%.

Ma et al. (2018) [44] adopted a deep CNN for the purposes of cucumber disease image recognition. This study used augmented datasets containing 14,208 symptom images to construct a symptom-based recognition system that could identify four cucumber diseases, i.e., anthracnose, downy mildew, powdery mildew, and target leaf spots. This achieved a recognition accuracy of 93.4%. Lin et al. (2019) [45] proposed a semantic segmentation algorithm based on CNN that could segment the powdery mildew on cucumber leaf images at pixel level. This reached an average pixel accuracy of 96.08%, outperforming traditional segmentation methods such as K-means, Random forest, and GBDT (Gradient Boosting Decision Tree).

Some studies have focused on other plant disease image recognition. Tan et al. (2015) [46] centered their attention upon apple pathology image recognition and diagnosis, proposing an elastic momentum parameter-learning method based on CNN that obtained a recall rate of 98.4% by using error back propagation analysis of sampled elements. Zhang et al. (2018) [47] proposed a method for identifying citrus canker based on the AlexNet model, with an optimized network structure that could reduce the network parameters while maintaining the same degree of accuracy. Their results showed a recognition accuracy for both positive and negative samples that reached 98%. This was better than the performance of a number of traditional machine learning methods, such as decision trees, KNN, SVM and Adaboost. Amara et al. (2017) [48] applied a deep CNN based on the LeNet architecture to detect two well-known banana diseases in actual field images: banana leaf spot disease; and banana spot disease. This study was noteworthy because it also considered the influence of various challenging factors when undertaking the modeling, including different degrees of illumination, complex backgrounds and different resolutions, sizes and orientations.

Generally, disease image recognition research focused on multiple crops is more commonplace than research focused on single types of crops. Sladojevic et al. (2016) [49] proposed a deep neural network model that could recognize 13 different kinds of plant diseases out of a collection of images of both healthy and diseased leaves. The recognition accuracy of this model was between 91% and 98%. Soni et al. (2016) [50] used probabilistic neural networks to identify various crop leaf diseases and applied their model to the identification of different plant leaf diseases in images randomly collected from the Internet. By combining batch normalization with global pooling, Sun et al. (2017) [51] developed a recognition model for plant leaf diseases that could recognize 26 kinds of leaf diseases in 14 species of plants. Here, the average accuracy on an augmented test dataset was 99.56%, while the weighted average recall and accuracy score reached 99.41%. Park et al. (2017) [52] used a deep learning method to train a dataset and provided a mechanism for the dynamic analysis of disease images, with the goal of being able to achieve the diagnosis and prediction of diseases. Ferentinos et al. (2018) [53] used healthy and diseased leaf images from a variety of plants to train different CNN models to perform plant disease detection and diagnosis. In their results, VGGNet (Visual Geometry Group Network) achieved the best recognition accuracy, reaching 99.53% when classifying 17,548 images of plant leaves. Li et al. (2018) [54] adopted an unsupervised method to train a deep convolution generative adversarial network on 54,306 images from the public dataset, PlantVillage. This model was able to identify 14 species of crops and 26 kinds of diseases, with an accuracy of 89.83% on a dedicated test set. Barbedo et al. (2019) [55] used the GoogleNet architecture to train a CNN model on more than 40,000 images captured using different devices, such as smartphones and compact cameras. The accuracy ranged from 75% to 100% for different crops. Huang et al. (2019) [56] proposed a novel deep neural network structure consisting of two sub-models that was able to separate the leaves in an original image from the background. Various popular pretrained models were then used to extract features and classify diseases, achieving a disease image recognition accuracy of 87.45% in the AI Challenger competition in 2019. Aside from these various approaches, Cósta et al. (2019) [57] have proposed a hierarchical method to optimize standard deep learning models for the classification of apple, peach and tomato diseases.

There has been a general augmentation in the number of studies applying deep learning techniques to agricultural disease image recognition and classification over recent years. As artificial intelligence and big data technology continues to develop, deep learning looks set to have more and more impact on practical disease management applications in agricultural production.

3.1.3. Discussion

From the above, we can see that the introduction of deep learning into the field of agricultural disease image recognition has resulted in a number of valuable achievements. However, deep learning methods are heavily data-driven, making them subject to the following limitations:

- In the absence of large-scale labeled training sets, the training process is prone to over-fitting, making it difficult to build an ideal model;
- As the complexity of the models grows, the number of parameters increases exponentially, restricting their generalizability;
- For each new dataset and task, the models need to be trained from scratch, adding to the hardware performance requirements and computational cost and potentially limiting their practical applicability.

As a result, deep learning methods still require a good deal of research and development for them to be truly effective.

In the field of agriculture, the variety of crops and their diseases makes the factors affecting deep learning modeling especially complex [58]. A key problem is that there is an urgent need for more datasets for modeling to be constructed and for existing datasets to be expanded. When summarizing the status of deep learning in relation to field planting, Guo and Tai (2019) [59] pointed out that the main problem at present is the lack of labeled data. When it comes to image classification, data enhancement, fine-tuning and other machine learning technologies are needed to improve the quality of labeling. At present, there are few public agricultural disease image datasets, especially labeled ones, and it is time-consuming and expensive to label disease images manually. This lack of disease image datasets undermines the quality of deep learning models. Barbedo (2018) [60] investigated how the size and diversity of datasets can impact the effectiveness of different deep learning techniques when applied to plant pathology. The image database used in this investigation included a number of different types of plants, each of which had clearly distinct characteristics in terms of the number of samples, the number of diseases and changes in conditions. The results indicated that CNN was the most powerful method for dealing with problems of plant disease image recognition, but the recognition accuracy was still significantly limited by the size of the image dataset.

Unfortunately, the problem of dataset scarcity is difficult to solve in the short term. Some researchers have sought to address the problem by constructing agricultural disease image datasets. Hughes and Salathé (2015) [61], for instance, have released a dataset through the online platform PlantVillage that contains more than 50,000 images showing healthy and infected leaves of plants. Chen and Yuan (2018) [62] have constructed a dataset called the Image Database for Agricultural Diseases and Pests (IDADP) that contains nearly 50,000 high-quality disease and pest images collected in greenhouses or fields. Arsenovic et al. (2019) [63] have also recently introduced a dataset containing 79,265 images. Traditional augmentation methods and state-of-the-art generative adversarial networks were adopted to further expand the number of images in this dataset. Together, these datasets provide a good resource for research relating to agricultural disease image recognition, but there is still work to be done.

A second issue with existing deep learning approaches is that there are numerous technical problems that still need to be solved. One such problem is that deep learning classifiers are typically treated as black boxes by researchers because of their opacity. Thus, the classification mechanisms associated with deep learning need to be better understood and easier to interpret. Brahimi et al. (2018) [64] have made some effort in this direction by using saliency maps as a visualization method for some state-of-the-art CNN architectures focused on the identification of plant diseases. Parameter optimization in deep learning models is another area of concern. Darwish et al. (2020) [65] looked at hyper-parameter optimization in CNN models and adopted an orthogonal learning particle swarm optimization algorithm to optimize the number of hyper-parameters and identify their optimal values. With regard to the overall technical framework for deep learning, rather than seeking to undertake general object recognition tasks, Lee et al. (2020) [66] examined certain CNN-based methods in detail and proposed a more intuitive method for identifying diseases independent of specific crops. This may help to improve the current technical framework and make it easier to refine existing agricultural disease image recognition methods. In addition to these considerations, although deep learning is largely more effective than traditional methods, it is also important to look at ways in which deep learning and traditional methods might be integrated to build upon their complementary advantages [67].

Finally, there is an urgent practical need to combine the excellent benefits of deep learning with the increasingly popular range of smart mobile terminals to promote the diagnosis and control of agricultural diseases. In this vein, inspired by the work of Johannes et al. (2017) [68], Picón et al. (2019) [69] used different mobile devices to capture and analyze images of three different European endemic wheat diseases. In agricultural production, there is a need not only to identify the presence of diseases, but also to pay attention to their severity. Wang et al. (2017) [70] trained some deep CNN models to diagnose the severity of apple black rot, drawing upon images from the PlantVillage dataset that were further annotated by botanists according to four levels of severity. It should also be noted that, in view of the complexity of agricultural environments, apart from images of diseased leaves and other organs, there is also a need for associated data relating to external factors, such as temperature, humidity, and type of soil, when undertaking image recognition [71].

3.2. *Methods based on transfer learning*

3.2.1. *Transfer learning models*

As mentioned above, the quality of deep learning models is heavily dependent on large datasets. In the field of agriculture, the diversity of crop species and disease types often makes it hard to have enough target data to meet the modeling requirements of deep learning. Transfer learning offers a way of getting around this problem. It is especially effective in circumstances where there is insufficient training data when developing machine learning models [27]. The basic idea underlying this method is to transfer knowledge from a source domain to a target domain by relaxing the assumption that the training data and the test data must be independent and identically distributed. A comparison between traditional methods and transfer learning is shown in Fig. 2.

Formally speaking, there are two basic concepts in transfer learning: a domain; and a task [72]. A domain, D, consists of two factors: an edge probability distribution, $P(X)$; and a feature space, χ, where $X = \{x_1, x_2, \ldots, x_n\} \in \chi$ is the feature vector of a sample in the feature space, and $P(X)$ represents the edge probability of X in the feature space. There are two differences between a source domain and a target domain: one relates to the feature space; the other relates to the edge probability distribution, which can be different even when the feature spaces are the same. A task, T, contains two elements: one is the label space, Y; the other is the prediction function, f, which can be obtained by learning how to map the elements of the feature space to the label space, thereby providing a prediction label for each sample. The difference between two tasks refers to the difference in the label space between them or the difference in the prediction function, f, when the label spaces are the same.

Transfer learning can be defined formally as follows: Given an auxiliary domain, D_s, an auxiliary task, T_s, a target domain,

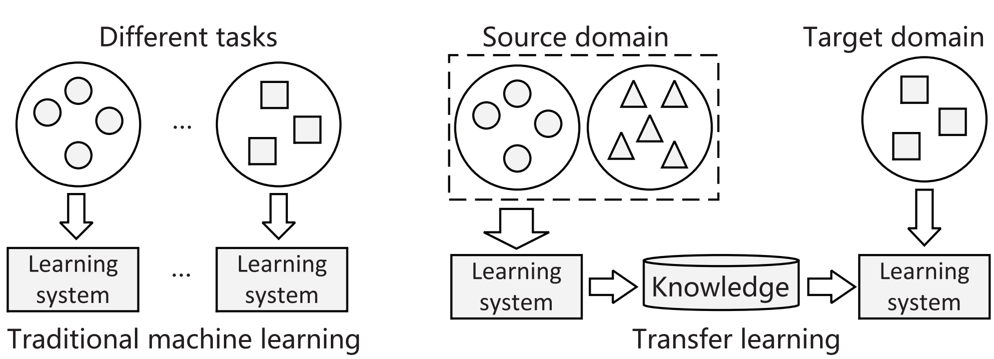

Fig. 2 – Different learning processes between traditional methods and transfer learning.

D_t, and a target task, T_t, a prediction function, f_t, can be established for the target task, T_t, in the target domain, D_t, with the help of knowledge learned from an auxiliary domain, D_s, and an auxiliary task, T_s.

According to the above definition, transfer learning can use existing well-constructed models or knowledge in a big data domain to solve the modeling problems associated with a small data domain. Given the current lack of disease image data resources, this method offers a potential way forward for intelligent agricultural disease image recognition.

3.2.2. *Works based on transfer learning*

According the types of transfer strategies adopted, transfer learning methods can basically be divided into homogeneous transfer learning and heterogeneous transfer learning [29]. The former is the kind of transfer learning most often used in the field of agricultural disease image recognition. It incorporates instance-based transfer learning and parameter-based transfer learning.

In instance-based transfer learning, the source domain and the target domain have numerous overlapping features and use the same or similar datasets. By means of re-weighting, part of the data in the source domain can be reused for modeling of the target domain. Inspired by this idea, Fang et al. (2017) [73] optimized the TrAdaBoost method to develop an instance-based transfer learning system that could solve the problem of insufficient labeled training samples in agricultural disease image recognition. Experimental results showed that this method offered significant improvements over methods based on KNN and SVM. Wang et al. (2018) [74] used 2,430 images from the IDADP dataset [75], including eight kinds of disease for two crop species, to train six kinds of CNNs with different depths as a way of exploring the potential efficiency gains provided by instance-based transfer learning. Their results demonstrated that a combination of CNN and transfer learning was effective for agricultural disease image classification with small-scale datasets. They obtained an accuracy of 90.84% when using a CNN model with five convolutional layers. Liu et al. (2018) [76] used a deep similarity network to learn the representative features in normal maize images, then used a transfer learning method to learn the features in diseased maize images. The results indicated that this method can identify ten kinds of common maize diseases with an accuracy of 90%.

In parameter-based transfer learning, the source domain and the target domain can share the model parameters. In other words, a model trained by a large amount of data in a source domain can be applied to a target domain for prediction. The advantage of parameter-based transfer learning is that it can make full use of the similarities between multiple models. Currently, a number of excellent deep learning models are making use of this method. Inspired by these models, a lot of studies have undertaken agricultural disease image recognition research based on parameter-based transfer learning. Drawing upon the VGGNet model, Jia et al. (2017) [77] adopted the transfer learning method to train a CNN model to detect tomato diseases and pests. This achieved an average classification accuracy of 89%. Zhang et al. (2018) [78] proposed an improved method based on the VGG16 model (VGGNet with 16 weight layers) for cotton disease image recognition. Here, the original Softmax layer was replaced by a six-tag Softmax classifier, so as to optimize the model's structure and parameters. Coulibaly et al. (2019) [79] also used the VGG16 model as the basis of an approach that combined transfer learning with feature extraction to build an identification system for mildew in pearl millet. This achieved an encouraging accuracy of 95%. Chai and Li (2019) [80] proposed a classification model where transfer learning was used to optimize the VGG19 model (VGGNet with 19 weight layers). The multi-layer structure of the trained CNN was used to gradually upgrade low-level features to higher-level abstract features, thus improving the model's feature learning ability. This produced good results when engaging in tomato disease image classification. Ding et al. (2018) [81] undertook transfer learning based on the AlexNet model and designed an eight-layer CNN model that was then used to train a network via transfer learning. When the learning rate was 0.001, the recognition accuracy for 12,836 images of common leaf diseases in five typical crops (i.e. rice, wheat, maize, cotton and soybean), taken from the PlantVillage dataset, was more than 95%. Long et al. (2018) [82] adopted the transfer learning method to transfer knowledge learned by applying the AlexNet model to the ImageNet dataset, to the recognition of diseased camellia leaves. Alongside of this, the powerful feature learning and feature expression abilities of a deep CNN were applied to automatically learn the features of the diseased camellia leaves. The resulting average recognition accuracy was 96.53%. Wang et al. (2019) [83] also used transfer learning based on the AlexNet model to realize a classification task for ten kinds of tomato disease images, including healthy leaves. Zhang et al. (2019) [84]undertook transfer learning to fine-tune a GoogleNet model pre-trained on the ImageNet dataset. They compared its performance with three traditional machine learning methods, SVM, KNN and BPNN (Back Propagation Neural Network), when evaluating a dataset containing 1,200 images collected by smart phones. The proposed method achieved the best accuracy 99.6% when identifying cherry leaf diseases. Yin et al. (2018) [85] used a pre-trained CaffeNet model as a prototype and used a fine-tuning method to construct an automatic identification system for cercospora leaf spot. Here, the root mean square error of the model reached 0.63 in experimental testing. To further improve the performance of neural networks under limited computing resources, the Inception model has been proposed. Tlhobogang et al. (2018) [86] used transfer learning to retrain the Inception model on 54,306 images from the PlantVillage dataset for the purposes of disease classification. Qiang et al. (2019) [87] integrated the InceptionV3 model with transfer learning and fine-tuning to identify leaf diseases in agricultural plants and achieved an accuracy of 95.8% on the PlantVillage dataset. Chen et al. (2019) [88] proposed an approach that combined data enhancement and transfer learning to optimize the InceptionV3 model for maize plant disease recognition, thereby achieving significant improvements in recognition accuracy. In parameter-based transfer learning, the choice of model is very important. A number of studies have therefore compared the effects of transfer learning on a variety of deep learning models. Yuan et al. (2018) [89] proposed a small sample crop disease image recognition method based on CNN parameter transfer learning. Using eight kinds of disease images from the IDADP dataset, they compared the outcome of fine-tuning two popular deep learning frameworks, AlexNet and VGGNet, and the traditional machine learning method, SVM. The results showed that the proposed method was better for small sample crop disease image recognition, achieving an average accuracy of 95.93%. Zhang et al. (2018) [90] explored using different deep learning frameworks, including AlexNet, GoogleNet, and ResNet, to find the best combination when they were fine-tuned by transfer learning. Experimental results showed that the best combined model could identify tomato leaf diseases with an accuracy of 97.28%. Kamal et al. (2019) [91] proposed a faster transfer learning-based technique for early plant disease detection and diagnosis drawing upon simple leaf images of healthy and diseased plants. By fine-tuning various deep learning models pre-trained on the ImageNet dataset, including VGG19, ResNet, InceptionV3, MobileNet, NasNet-Mobile, DenseNet121 and DenseNet169, the accuracy reached 99.74% when classifying 28 kinds of diseases in 15 different species of crops. Drawing upon the PlantVillage dataset, Too et al. (2019) [92] used transfer learning to fine-tune then evaluate several deep CNN models, including VGG16, InceptionV4, ResNet50, ResNe101, ResNe152 and DenseNets121. In experiments, the DenseNets121 model achieved the best recognition accuracy at 99.75%. Verma et al. (2020) [93] also used the PlantVillage dataset to develop a transfer learning approach that fine-tuned the model parameters in AlexNet and ResNet18 in order to assess the severity of diseases in grapevines.

3.2.3. *Discussion*

From the above, it can be seen that transfer learning is able to take models trained in a big data domain and relate them to a new domain, thereby delivering high-quality model learning and construction on the basis of small amounts of data. This method dispenses with the limitations associated with deep learning methods and their dependence upon large amounts of labeled training data. This makes transfer learning particularly suitable for agricultural disease image recognition when confronted with insufficient data resources. Most applications of transfer learning in the field of agricultural disease image recognition are based on parameter transfer, where a pre-trained model is fine-tuned by initializing the new network parameters with existing parameter files, thus transferring part of the pre-trained model to the target domain. This is an effective solution to the over-fitting problem typically associated with small-scale datasets, thus speeding up the model's training and saving time.

Transfer learning is becoming increasingly popular in the field of agricultural disease image recognition. However, the modeling quality of transfer learning can be affected by a number of different factors, such as the quality of the datasets, the selection of the prototypical models, negative transfer or excessive transfer, and so on. In each of these cases, the final result may not meet the desired requirements. Various issues in transfer learning therefore need further research. First of all, selecting the correct prototypical model is very important for parameter-based transfer learning. It would also seem that integrating and optimizing multiple models may further improve accuracy [94], so this merits further exploration. Secondly, most deep learning frameworks are complex and not conducive to transfer, so transfer learning based on lightweight models needs more attention. A number of studies have used lightweight models, such as SqueezeNet [95], InceptionV3 [96] and MobileNet [97], and it has been shown that this did not unduly affect their recognition accuracy. This method has notable potential for scenarios with limited computing resources, such as when using edge servers [98] or automatic recognition devices based on image acquisition [99]. Generally-speaking, for practical applications, it is necessary to find a balance between recognition accuracy, operating speed and network size when choosing the best framework.

3.3. *Summary*

In the above sections, we have reviewed advanced technologies that can be used for agricultural disease image recognition, focusing in particular upon deep learning and transfer learning. To facilitate a more intuitive comparison of these two methods, Table 1 summarizes their most important characteristics.

In general, because there are too many kinds of crop diseases and not enough datasets, fine-tuning models that have been pre-trained on large-scale public datasets, such as PlantVillage and ImageNet, so as to be able to undertake image recognition on the basis of relatively small samples, is preferable. The details of some relevant studies are given in Table 2, including the prototypical model, dataset and obtained accuracy.

It can be seen that, when based on large-scale open source datasets and pre-trained models, these methods are able to achieve high levels of accuracy when undertaking plant disease image recognition. However, when pursuing this investigation, it was found that both the scale of the plant disease

Table 1 – Comparison between deep learning and transfer learning.

	Deep learning	Transfer learning
training sample size	large	small
data distribution	same	different
data annotation	required	not necessary
model construction	training from scratch	fine-tuning existing model
model complexity	high	not high
modeling time	long	short
generalization	weak	strong

Table 2 – Prototypical models, datasets and accuracies of related works.

Reference	Prototype model	Dataset	Accuracy
Mohanty [100]	AlexNet, GoogleNet	PlantVillage	99.35%
Brahimi [37]	AlexNet, GoogleNet	PlantVillage	99%
Durmus [95]	AlexNet, SqueezeNet	PlantVillage	95.65%
Amara [48]	LeNet	PlantVillage(extended)	92–99%
Jia [77]	VGGNet	tomato(own)	89%
Yuan [89]	AlexNet, VGGNet	PlantVillage, IDADP	95.93%
Wang [74]	customized CNN	PlantVillage, IDADP	90.84%
Liu [76]	customized CNN	maize(own)	90%
Luna [99]	AlexNet	tomato(own)	91.67%
Ferentinos [53]	VGGNet, AlexNet	PlantVillage	99.53%
Ding [81]	AlexNet	PlantVillage	95%
Zhang [90]	AlexNet, ResNet	PlantVillage	97.28%
Zhang [84]	GoogleNet	ImageNet, cherry(own)	99.6%
Lin [45]	U-Net	cucumber(own)	96.08%
Barbedo [55]	GoogleNet	various plant(own)	75–100%
Liu [96]	InceptionV3, MobileNet	ImageNet, PlantVillage	95.62%
Liang [41]	customized CNN	rice(own)	95.83%
Selvaraj [97]	ResNet50, InceptionV2	banana(own)	90%
Qiang [87]	InceptionV3	PlantVillage	95.8%
Too [92]	DenseNets121	PlantVillage	99.75%
Wang [94]	InceptionV3, ResNet	PlantVillage, IDADP	96.61%
Verma [93]	AlexNet, ResNet18	PlantVillage	87.6%

image dataset used for modeling and the environment in which the images were acquired can have a great influence on the recognition accuracy. As most of the images in the PlantVillage dataset were collected with a simple background or in a laboratory environment with less interference, the recognition accuracy of systems constructed using the PlantVillage dataset is higher. Despite this apparent advantage, when these systems are applied to actual scenes, their recognition accuracy will inevitably decline because of the diverse character of the situations to which they are being applied [100]. This underscores the fact that image recognition is much more difficult and complex in the actual cultivation conditions than in laboratory conditions. In a study undertaken by Ferentinos et al. (2018) [53], images captured in the field were used to develop a model for the identification of images captured in a laboratory. This model was still able to perform effectively, with a recognition accuracy of up to 68%. When, by contrast, images captured in the laboratory were used train a model for the identification of images collected in the field, the accuracy fell to just 33%. Overall, this suggests that, for the construction of practical systems, more diverse training data is needed to improve the accuracy of the models. In particular, it is very important build image datasets where the images are collected under actual cultivation conditions. This is the best way to ensure that agricultural disease image recognition systems are able to achieve good results in practice.

4. Conclusion

This paper has reviewed the current state-of-the-art with regard to advanced technologies for agricultural disease image recognition, focusing in particular upon deep learning and transfer learning. Although this is a space that is attracting increasing attention, there remain problems with the practical application of these methods and technologies. The above discussion indicates that future work needs to be especially dedicated to the following concerns:

- First of all, in the case of both deep learning and transfer learning, there is an ongoing need for better disease image datasets containing images of actual cultivated crops in the field. This can serve as a cornerstone of future improvements in sample quantity and quality. We have already been involved in the construction of a dataset of agricultural disease images collected in actual field environments, IDADP (mentioned above). The image resolution in this dataset is very high, reaching 20 million pixels, and the number of images of each disease can be counted in the hundreds or even thousands, making it eminently suitable for training and modeling in machine learning research. The construction of this dataset is a sustained effort and it continues to grow, year on year.
- Secondly, the burgeoning use of intelligent mobile terminals suggests that the construction of lightweight models needs to form an important part of future research considerations. At present, a few studies focused on this concern have been undertaken, including MobileNet [101] and EfficientNet [102]. The lightweight character of these models makes them better able to meet the needs of mobile users or edge computing in practical applications, but there needs to be more studies of this kind.
- Finally, agricultural disease images have obvious inter-class similarities and intra-class differences. There are also numerous potential sources of interference during image acquisition, including complex backgrounds and changes in illumination. This presents transfer learning-

related research on agricultural disease image recognition with a number of significant challenges, especially with regard to auxiliary domain selection and the integration of transfer methods. Most existing large-scale image datasets, such as ImageNet and PlantVillage, are not dedicated solely to the provision of agricultural disease images in actual field settings, so any selection of auxiliary domains involves additional evaluation or restriction. Alongside of this, at present, transfer learning methods relating to agricultural disease image recognition research are all homogeneous in character. This makes it difficult for these methods to use large amounts of multi-modal data related to agricultural diseases on the Internet, such as text, images and videos, even though this data could indubitably help the progress of learning and modeling. Future research therefore needs to devote some effort to concerns such as the facilitation of multi-modal explanations by aligning two or more different information sources and enabling transfer learning over these heterogeneous sources for the purposes of prediction and modeling. In this way, it will be easier to ensure that knowledge present in data coming from different feature spaces, such as text, can be used to help with learning and modeling in the target domain. This has the potential to substantially improve the performance of agricultural disease image recognition systems based on transfer learning.

Declaration of Competing Interest

None.

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