Recent Advances of Computer Vision-based Plant Disease Recognition Methods

Haochen Zhang*

School of computer science and technology, Huaibei Normal University, 235000 Huaibei City, China

Abstract. In the global agroecosystem, plant diseases, as important factors affecting crop yield, quality and ecological balance, have long been the focus of agricultural scientific research and practice. With climate change, the increase in international trade and the transformation of agricultural production methods, the frequency and distribution of plant diseases and the extent of their damage have shown a trend of increasing complexity and intensification. This not only poses a serious challenge to food security, but also poses a potential threat to sustainable agricultural development and biodiversity conservation. The aim of this paper is to provide an overview of current research advances and methods that can be applied to computer-based recognition of plant diseases and pests, as well as an outlook on future developments. The paper focuses on the recognition of plant diseases, categorizes the problem scenarios for recognition (single and multi-class) and in this way summarizes some informative methods (detection and tracking) and learning approaches for recognition.

1 Introduction

As an indispensable resource in human production and life, the demand for plant resources has increased significantly with the increasing population. While plants are inevitably affected by climate change, pests and diseases during the growth process, among which the economic and social losses caused by plant diseases cannot be ignored. Therefore, the traditional identification of plant diseases relies on manual identification by agricultural technicians, but the accuracy is affected by subjective factors such as human errors. In order to solve the above problems, researchers have turned their attention to other fields.

The continuous development and improvement of computer vision technology in recent years has brought more attention to its value, and it has also been more widely used and paid attention to in other fields, including agricultural production work. Among them, Convolutional Neural Networks (CNN), as one of the most famous and successful algorithms, has become the core algorithm for researchers in image classification work. To address the problem of low accuracy and high cost of plant disease identification in traditional methods, Diana Susan Joseph et al. used deep learning to develop grain datasets specifically for rice, wheat and corn and applied them to eight fine-tuned deep learning models with the same training hyperparameters [1]. Yuandong Bi et al. proposed a triple-streaming for small sample learning across domains Comparison Adaptive Network TsCANet [2]. Arunabha M

* Corresponding author: 20231202068@chnu.edu.cn

et al. proposed a deep learning object detection model for multiple types of plant diseases [3]. pushkar Gole et al. proposed a relatively lightweight and improved visual transformer network called "TrIncNet"[4]. poornima Singh Thakur et al. proposed a visual transformer network called "TrIncNet"[5]. Singh Thakur et al. proposed a hybrid model with a lightweight structure by combining visual transformers and convolutional networks to effectively recognize diseases of multiple crops. Aiming at the problem that traditional CNN have a high demand for resources in image recognition, Yang Xiang et al. proposed a lightweight CNN-based plant disease image recognition network, CSP-ShuffleNet V2, to reduce the cost of recognition [6] The network is based on a lightweight CNN to reduce the cost of recognition. These techniques provide more options and more effective technical support for plant disease detection and management.

Nowadays, plant disease identification has become a multidisciplinary and multidisciplinary research topic. In this paper, the problem of plant disease identification is divided into the identification of disease types and the methods of disease identification, the problem of plant disease identification is divided into two categories: single-type disease and multi-type disease, and the methods of disease identification are divided into two categories: target tracking and learning methods. Finally, the challenges of plant diseases are summarized and future research directions are outlined.

2 Classification of plant disease identification problems

2.1 Single-category disease identification

Monoculture plants are more common, and most of the virus identification is performed on specific plants. Siricharoen et al. performed dichotomous identification of wheat leaf rust with categories labeled as healthy and diseased. This approach is suitable for situations where the number of categories is small, the classification boundaries are linear, and the recognition model is relatively simple [7]. Recognizing only plants grown in a single room is not enough to meet the practical needs, so virus recognition of multiple classes of plants is needed.

2.2 Identification of multiple disease types

For disease identification of more diverse multi-class plants, researchers constantly try to optimize the previous research methods and push into new ones. Zhu Dongqin et al. used the γ coefficients in the Batch Normalization (BN) layer for channel pruning to realize the compression of Vgg16, ResNet164, and DenseNet40 networks, and then used the PlantVillage plant disease dataset as the research object to carry out model compression on the three networks [8]. The model compression of the three networks was then performed on the PlantVillage plant disease data set.

Where control is the model without compression, -70% indicates the model when the pruning rate is 70%, -80% indicates the model when the pruning rate is 80%, and 90% indicates the model when the pruning rate is 90%. The data from the table reflects the demand on device storage space and computation before and after model compression.

The results show that (as shown in Table 1), the average accuracy of the three compressed networks is higher than 97%, among which the DenseNet40 **-** 80% has the highest accuracy (99.68%), and the model's data of parameters is the lowest (0.27×106). The accuracy of Vgg16 **-** 80% and DenseNet40 **-** 80% after pruning was higher than the original model. It can be seen that the pruning-based plant disease recognition method can solve the over-parameterization problem of large-scale neural networks and reduce the computational cost, while exceeding the level of human eye recognition. Unlike disease recognition models that can only be run on computationally rich devices or deployed in the cloud, the pruning-based plant disease recognition method can be used in areas far away from well-connected areas, so that it can be easily deployed on resource-limited devices to realize automatic disease identification, real-time detection and timely control.

Table 1. Comparison of parameters before and after model compression

mould	accuracy	quantity of participants	Model size
Vgg16 (control)	96.76	14.74	118
Vgg16-70%	98.19	0.9	7.3
Vgg16-80%	97.46	0.32	2.6
ResNet 164 (control group)	99.55	1.72	14.1
ResNet164 -70%	99.28	0.51	4.4
ResNet164 -80%	99.12	0.37	3.3
DenseNet40 (control group)	99.62	1.08	8.8
DenseNet 40 - 70%	99.64	0.37	3.1
DenseNet 40 - 80%	99.68	0.27	2.3
DenseNet 40 - 90%	99.51	0.16	1.4

3 Plant disease identification methods

3.1 Target tracking

Three are presented here: vision-based target detection and tracking, Unmanned Aerial Vehicle (UAV) detection and tracking methods based on computer vision techniques, and feature recognition.

3.1.1 Vision-based target detection and tracking

A cross-sectional study utilizing many disciplines such as image processing, computer vision, and pattern recognition by Hongpeng Yin et al [9].

Target detection is the process of recognizing a moving target from a background of different complexity and separating the background for tracking, recognition and other effects. According to different needs can be divided into the following two main methods: target detection based on background modeling and target detection based on foreground target modeling, there are obvious differences between them (as shown in Table 2).

A. Target detection methods based on background modeling generally contain steps such as initialization of the background model, model maintenance and foreground detection and segmentation. The background models derived from this include Gaussian model and support vector model for dealing with dynamic background, subspace learning model for dealing with illumination change, fuzzy model for dealing with illumination change and dynamic background at the same time, and so on. Based on these models, researchers have developed new ones, which have greatly contributed to the development of experimental investigation.

B. Offline training and online detection are the two stages of target detection, which based on prospective target modeling. Sliding window scanning is done first in the online detection step, followed by the construction of the epistemic model and the classification using the classifier model that was learned offline.

Table 2. Main differences between different target detection methods

methodologies	The main difference
Context-based modeling	The scope of application is relatively narrow due to the limitations of the scene, and the detection results need to be re-segmented.
Based on prospective target modeling	It is not limited by the scene, the application range is relatively wide, and the detection results do not need to be re-segmented.

Target tracking consists of four parts: target state initialization, apparent modeling, motion estimation and target localization. Target tracking can be categorized into generative tracking and discriminative tracking according to the participation of detection process or not. Among them, the generative tracking method is based on the detection of the target, and then performs the surface modeling, and then estimates the optimal position of the tracked target. The discriminative tracking method, on the other hand, obtains the tracking target state by target detection for each frame, and the two have obvious differences (as shown in Table 3) and different usage scenarios.

Generative tracking methods:

Generative epistemic modeling can be categorized into the following three approaches: kernel-based, subspace-based, and sparse-based.

Discriminant tracking method:

Discriminative tracking methods can be categorized into the following four types of methods: online Boosting based, Support Vector Machine based, Stochastic Learning based, and Discriminative Analysis based.

Table 3. Main differences between different target tracking methods

methodologies	The main difference
Generative tracking methods	Both the tracking and detection processes follow a specific time sequence and are independent of one another.
Discriminant tracking method	The tracking process is linked to the detection process and the two are carried out simultaneously.

3.1.2 UAV computer vision-based detection and tracking technique

Liu Xinfeng et al. proposed a UAV detection and tracking method based on the target detection YOLOv5s algorithm and target tracking DeepSORT algorithm that can effectively solve the problems of UAVs that are difficult to detect due to small targets, slow detection speed, and difficult to track [10].

The technical route for UAV targets consists of five parts: dataset construction, target detection model implementation based on YOLOv5 algorithm, model pruning method based on BN layer, target tracking model implementation, and comparative validation, while constructing the dataset based on self-harvested dataset and public dataset.

3.1.3 Characterization

Chang Liu et al. designed a plant disease recognition model CLT by fusing Transformer and CNN for plant disease images in real scenarios.The model fuses the visual Transformer module and CNN module, and utilizes the convolution operation to enhance the local sensing ability of the Transformer module [11]. The model combines the visual Transformer module and CNN module, and utilizes the convolutional operation to enhance the local perception ability of the Transformer module.

Table 4. Average accuracy of InceptionV3, ResNet50, ViT, Swin Transformer and CLT

mould	Average accuracy
InceptionV3	62.06
ResNet50	70.3
ViT-base	64
Swin Transformer	73.7
CLT	77.91

InceptionV3, ResNet50, ViT and Swin Transformer were selected as the comparison models, which were trained on the expanded PlantDoc dataset and compared (as shown in Table 4). The above model CLT has achieved a better average accuracy than the other models after 50 iterations. Although the convergence speed of CLT is slightly slower than the other models, the improvement of the average accuracy and the ability to effectively express various features of plant diseases have proved that the fusion of the CNN and Transformer structure improves the generalization performance of the model, and it can better recognize the plant diseases in real scenes. The fusion of CNN and Transformer structure can better recognize plant diseases in real scenarios.

3.2 Learning styles

3.2.1 Identification of conventional plant diseases

Closed datasets satisfy the methods with sufficiently large training samples, training and test samples following independent homogeneous distributions and small sample requirements, and most of the closed datasets used satisfy the data independence (Manual feature-based plant disease identification methods).

3.2.2 Transfer learning

Carpel learning is the use of knowledge from an existing domain to accomplish a task in a new domain, i.e., to obtain relevant knowledge from one or more source domains.

The knowledge and experience of the target task can then be applied to another new target task. According to the difference of migration method,transfer learning can be categorized into the following four types: (1) Sample-based migration (2) Feature-based migration (3) Parameter-based migration (4) Relationship-based migration. Liu Chang et al. based on Transformer and CNN and the fusion of the two to produce the plant disease recognition model CLT, through the multi-stage hierarchical design, the initial feature extraction module to extract the shallow local features Conv Stem and Transformer module to learn the global features, the average accuracy of the real scenarios to reach the ideal value and the classification effect is better than the other models, to provide a reference for the identification of plant diseases in real scenarios [11]. The average accuracy is satisfactory and the classification effect is better than other models in real scenarios. The average accuracy is satisfactory and the classification effect is better than other models in real scenarios.

3.2.3 Small Sample Learning

Small sample learning aims to learn models with high generalization ability providing by a few samples. Small sample learning is characterized by the lack of labeled training samples. Ren Shengnan et al. propose a plant disease recognition method based on one-shot learning for the small sample problem of plant diseases [12]. The experimenters use eight types of plant disease images with small sample sizes in the dataset PlantVillage as the recognition objects, and train a relational network-based plant disease classifier using the focal loss function (FL) [8]. The results show that this method is more effective than the original method. The results show that the method improves the accuracy rate by 4.69 percentage points compared to the original relational network model, which is a significant improvement.

4 Challenges and Prospects

Computer vision has made considerable development in the field of disease recognition, showing good application prospects, but there are still problems and challenges, the access to data, the number of samples, the optimization of algorithms, and other problems still exist. Agriculture as an information-intensive industry, and most of the agricultural testing environment in the outdoor, so the storage space of the equipment has certain requirements. At the same time, computer vision algorithms require higher standard because of the variety of changes in the outdoor environment, researchers are required to figure out these problems or the application would mostly stay in the preliminary research and experimental validation stage, the number of methods that can be finally applied in practice is far from meeting the actual demand, and further optimization of technology is needed. At the same time, the development of agriculture can not be separated from the farmers as a group, due to the farmers generally have a lower degree of cognition and acceptance of the new technology (different from the traditional technology), but also to apply the computer vision in agriculture could make an impact.

In this regard, the paper would like to propose the following outlook for future development:

1) Integration of multidisciplinary and multifaceted knowledge and methods applied to the identification of plant pests and diseases. Single computer vision technology has been unable to meet the needs of actual production, so should maximize the use of computer applications in this field widely combined with other fields, on the one hand, can optimize the technical algorithms to better cope with the changing environment, on the one hand, can be the majority of the working people are familiar with, recognized, and applied, which in turn accelerates the speed of the research, but also more in the real demand.

2) Further development of lightweighting models. In this paper, it has mentioned the research on the lightweighting of CNN models, but they can only be applied to specific scenarios or are still in the experimental research stage. Therefore, further research is needed to lightweight more models to cope with a variety of needs, optimize and improve the existing lightweight model to make it out of the experimental stage, can be really put into practical use, such as CNN has not yet solved the efficiency problem is that it can not get out of the laboratory at all, reduce the amount of computation, reduce the number of parameters, reduce the actual running time, etc. can be a certain degree of improvement in the efficiency of the problem. Therefore, through improving optimizing the lightweight model can apply the technology efficiently.

5 Conclusion

As a large agricultural country, if people can realize high-speed and effective plant disease recognition, people can respond to and prevent the disease in time when the disease is flooding, and then reduce the loss while the output efficiency of agricultural products can be guaranteed. Unfortunately, heaven forbid there's a huge emergency, in the actual natural environment, plant disease recognition is faced with the dilemma of insufficient reference samples and messy classification. Similar to the traditional CNN model, classical image recognition methods can achieve better recognition results, but still have higher requirements for the equipment. Aiming at the above problems, this paper takes single- and multi-class disease recognition as the starting point, and then leads to the three plant disease recognition methods introduced below: vision-based target detection and tracking, UAV detection and tracking method based on computer vision technology, and feature recognition. The vision-based target detection and tracking refines target detection into target detection based on background modeling and target detection based on foreground target modeling, and target tracking into generative tracking and discriminative tracking; the UAV detection and tracking method based on computer vision technology combines the YOLOv5s algorithm for target detection and the DeepSORT algorithm for target tracking with the UAV, optimizing the traditional detection and tracking method. traditional UAV detection and tracking methods; feature recognition is the fusion of Transformer and CNN to produce a new plant disease recognition model CLT, this model has a more excellent generalization performance, and can better identify plant diseases in real scenes. Then the paper moves to the introduction of learning methods, taking the conventional plant disease recognition as the entry point, the paper introduces the migration learning and small sample learning, which have significant improvement over the traditional methods, and provide a reference for the plant disease recognition in real scenarios. It can be seen that computer vision has announced a significant advance in the field of disease recognition, although there are certain problems and challenges, but still has a worthy prospect of development.

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