# Studies Advanced in Crop Disease Image Recognition

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**Abstract**. Crop diseases have an essential impact on food supply and agricultural productivity. Developing quick and automated technologies for crop disease diagnosis, therefore becomes crucial. Early identification of crop diseases mainly relied on field surveys by technicians, which was labor-intensive. Field agricultural disease detection has attracted a lot of scholarly interest owing to the rapid growth of technology for pattern recognition. Focusing on the above two categories of frameworks, this paper seeks to cover the most recent advances in crop disease image identification research. Specifically, representative methods are first introduced in detail, including the design ideas, key steps, advantages and disadvantages of these methods, etc. Second, the recognition accuracy of representative methods is compared to common datasets. Finally, the current hot topics in crop disease image detection are outlined, and discussion is had regarding the subject's potential future development.

**Keyword**: Crop disease recognition; Machine learning; Deep learning;

## 1 Introduction

Farming has propelled the global economy and grown to be a significant source of wealth for many nations over the past few decades. Agriculture has a considerable contribution to the worldwide economy. However, plant diseases can threaten food security by reducing agricultural production. For instance, the productivity of wheat, rice, maize, soybeans, and horse bell-flower, has decreased by 10% to 40% as a result of diseases and pests [1]. Therefore, crop disease represents one of the most significant challenges to be addressed and one crucial component of agricultural productivity. Currently, there are 2 main types of diagnosis: based on the cause of the disease and based on the manifestation of the crop disease. When a crop is diseased, morphological and biochemical changes occur, which vary from crop to crop, but mostly appear on the leaves first. Through the changes in various aspects of the



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diseased leaves, such as color and texture, the cause of the crop disease can be determined and the right medicine can be prescribed [2].

Early crop disease recognition mainly relied on manual work, where professionals realized the preliminary diagnosis of crop diseases through field inspection and visual observation. However, manual surveys cannot be carried out on a large scale due to the huge conflict between the limited number of technical personnel and the actual planting area. In addition, not all disease symptoms can be judged correctly and professionally because recognizing visual symptoms is a subjective approach. As technology advances, more and more businesses are using image processing and recognition, which opens up new possibilities for crop disease detection. The systems to detect agricultural diseases that are now available by using approaches centered around machine learning and methods relying on deep learning.

(1) Machine learning (ML) based methods. The common situation is that at most one or two layers of nonlinear feature transformation will exist in traditional structures, which means the data within them are in a shallow structure. Those methods use characteristics that were manually created, such as Principal Component Analysis (PCA). The machine learning algorithm takes a lot of time gathering data, sorting through the data, experimenting with various feature extraction methods, or combining a variety of characteristics to categorize and regress the data. Therefore, classical ML has a low degree of generalization.

(2) Deep learning (DL) based methods. Because DL can perform more complicated computations and produce quick, effective results. Deep learning and conventional approaches vary primarily in that features are extracted from enormous amounts of data using neural networks automatically, whereas classic machine learning requires manual feature construction. To get greater performance, researchers are currently looking into the idea of integrating typical methods and advanced methods. Region-CNN (RCNN) uses convolutional neural networks (CNN) to get features in order to generate a feature vector. Support vector machine (SVM) will then work with the vector to carry out the classification operation. After that, RCNN has undergone several revisions on top of it, including fast RCNN and faster RCNN.

Focusing on the aforementioned two frameworks, this paper introduces the advance in crop disease image recognition in recent years. Specifically, representative crop disease image recognition algorithms are first detailed in Section 2, including their design ideas, key steps, advantages, and disadvantages. Then, in Section 3, the commonly used crop disease image recognition datasets are introduced, followed by a quantitative comparison of various recognition algorithms. Finally, the problems and development directions are discussed in Section 4.

# 2 Method

## 2.1 ML-related crop disease identification

Conventional ML relies on manually designed features and faces some difficulties in recognizing some specific image features of a crop, such as low-level features. Traditional machine learning classification methods are unable to effectively and accurately identify the pest and disease targets in images because it is difficult to portray a specific range of characteristics or multiple features. Many factors will influence the outcome such as uneven target size of pictures, the regional spread of crop illness, and the various onset stages of diseases. It is challenging to represent a certain range of features or multiple features, some of which are even very similar to the leaf background color. In addition, these models are limited to leaf disease recognition of the same plant only. This makes segmentation-based classical image processing techniques very difficult to extract targets effectively and thus achieve good results.

To detect plant foliar diseases, Santosh et al. introduced a novel hybrid random forest multiclass support vector machine architecture (HRF-MCSVM). Before classification, spatially fuzzy c-mean segmentation and pre-processed picture features are used to increase computational accuracy. To assess the system's efficacy, performance measures including accuracy, f-value, specificity, sensitivity, and recall values were examined and it was contrasted with several already in use methods [3].

## 2.2 DL-related crop disease identification

**Data processing methods.** Ji et al. proposed a technique adding fuzzy logic for the severity judgment as well as automated diagnosis of grapevine black measles sickness [4]. The features, including regions of interest (ROI) and point of interest (POI), were recovered by the DeeplabV3+ semantic segmentation model, and a fuzzy rule-based disease hazard level prediction system was developed. Overall, 97.75% of the classifications were accurate. Saikawa et al. proposed an anti-overfitting preprocessing (AOP) method for detecting ROI in samples before training a disease classification network to remove the image background. The recognition accuracy of the model was improved by 12.2% on average after the introduction of AOP [5].

**Training strategies.** Some works boost the recognition accuracy by designing various training strategies. Jiang et al. claimed a novel model named INAR-SSD (SSD with Inception module and Rainbow concatenation), which can enhance the ability of deep neural networks to retrieve features [6]. Two designs are proposed to identify different infection kinds in tomato leaves by Karthik et al. [7]. The first design makes advantage of residual learning to discover the crucial properties required for categorization. The second design takes an attention mechanism into consideration. On a validation set with 5-fold cross-validation utilizing features the CNN acquired at various stages of processing, an overall accuracy of 98% was attained using the attention method. Gao et al. enhanced that the attention mechanism is a useful way for crop disease identification as well as residual neural network (ResNet). They also suggested an identification model inspired by channel attention and the optimized attention-based crop disease model was put to the test on three types of datasets and the illness diagnosis accuracy rates were 86.35%, 99.74%, and 98.54% [8].

**Transfer learning and lightweight.** To address the issue of the limited data volume of disease pictures obtained in the field environment, transfer learning is frequently utilized. Mohanty et al. trained a model utilizing the Google Convolutional Neural Network by transfer learning. 54306 images of leaves of 26 disease classes of 14 crops were analyzed to demonstrate that image data of multiple classes of crop pests and diseases can be identified simultaneously using a deep learning model [9].

Another inescapable issue in the use of crop disease diagnosis is lightweight. To identify apple leaf illnesses in the present, Sun et al. suggested a compact CNN model having the possibility to be employed on portable electronics. They put forth the MEAN (Mobile End AppleNet) block, a fundamental module for the Mobile End AppleNet architecture that reconstructs the common convolution. The results of the tests indicate that MEAN-SSD has the ability to recognize MAP (Mean Average Precision) at a good speed [10].

### 2.3 Combining ML and DL methods

The conjunction of ML and DL has been actively explored in academia, such as introducing the idea of a large margin in SVM into neural network training. This seems to be very intuitive, but it is not easy to implement, mainly because the nonlinearity of neural network layering makes us have no way to get the display expression of margin, and it is naturally difficult to introduce it into the training objective function like SVM. Li et al. suggested combining approaches related to SCNN (shallow CNN) by merging SVM and RF (Random Forest). By comparing the results of experiments, they found that the two methods named SCNN-KSVM and SCNN-RF surpass many pre-trained deep models with regard to common evaluation metrics [11].

# 3 Experiment

## 3.1 Dataset

PlantVillage dataset is the most commonly shared dataset, which has 54,303 health and disease images of 14 different plants, including more than 20 different diseases caused by different etiologies [12]. There are 50,000 images in The AI Challenger 2018 which is created on the basis of PlantVillage. Twenty-four of these diseases are subdivided into two levels of disease: general and severe, with a total of 61 different categories based on species, disease, and severity of occurrence.

Singh et al. published a dataset PlantDoc for real scenarios, containing a total of 13 plants and a database of 27 categories. It includes 17 diseases and 10 health types with a total of 2598 images [13].

## 3.2 Evaluation Metrics

Accuracy, precision, recall, and F1 Score are the major conventional model assessment measures for the crop disease picture detection job. The way how they are calculated is shown.

$$Accuracy = \frac{True\ positive + True\ negative}{True\ positive + True\ negative + False\ positive + False\ negative} \tag{1}$$

$$Precision = \frac{True\ positive}{True\ positive + False\ positive} \tag{2}$$

$$Recall = \frac{True\ positive}{True\ positive + False\ negative} \tag{3}$$

$$F_1 = \frac{2 \times Precision \times Recall}{Precision + Recall} \tag{4}$$

## 3.3 Performance Comparison and Analysis

The recognition accuracy of various methods for different crops can be observed in Table 1. The results show that HRF-MCSVM has the greatest overall accuracy of 0.989 on datasets for various types of crop categories. Generally speaking, Tiny_Xception behaves fairly evenly around 0.955 across datasets. Although the accuracy of SCNN-RF and SCNN-KSVM is 0.940, slightly mediocre compared with other methods, it has full possibilities in the future.

**Table 1.** The recognition accuracy of various methods on different datasets

| Method | Algorithm | Crop category | Accuracy |
|---|---|---|---|
| HRF-MCSVM [2] | ML | all 14 types in PlantVilliage | 0.989 |
| | | apple | 0.953 |
| | | corn | 0.951 |
| Tiny_Xception [14] | DL | potato | 0.946 |
| | | grape | 0.967 |
| | | tomato | 0.958 |
| Inception-V3 [15] | DL | apple | 0.800 |
| SCNN-RF [11] | ML+DL | apple, grape, maize | 0.940 |
| SCNN-KSVM [11] | ML+DL | maize | 0.940 |

# 4 Discussion

## 4.1 Problems

The dataset for training the model contains pest and disease samples from only a portion of the region, resulting in a model that does not effectively identify crop pests and diseases for each region. Moreover, when researchers select feature objects, feature samples are mainly collected manually and feature extraction mainly relies on manual intervention. This manual approach does not guarantee the accuracy of crop disease information and makes the sample size somewhat limited. In addition, the recognition of the model often has certain requirements on the standard of sample images captured. The robustness and accuracy of the CNN module are significantly impacted by images taken in actual surroundings, such as those with complicated or indistinguishable backgrounds, many leaves with damaged leaves, and tiny lesion locations. However, few researchers include genuine field leaf photographs in their research.

On the other hand, in nature and actual production, there are often multiple pathogens that co-breed and act on the plant, making the crop infected with 2 or more diseases at the same time, not limited to only one of them [2]. In many models, the object of study is generally set to one or several diseases on a specific crop, which lacks universality. If a recognition model can only recognize images of a single kind of crop disease, and the model encounters other kinds of diseases, it cannot accurately recognize the correct results. Moreover, the current research method with high accuracy is predicated on the diagnosis of a single disease, and the interaction of multiple diseases on crops needs to be further explored.

## 4.2 Future Directions

**A Richer and larger database.** Most of the current models are for static images of crops for detection and recognition, and the recognition performance is average in the more complex three-dimensional (3D) spatiotemporal information, such as video analysis tasks. Dynamic information recognition studies require processing in both temporal and spatial dimensions during feature extraction. 3D models theoretically have more parameters and a larger computational volume and also lack a massive training set like 2-dimensional image models.

Hyperspectral Imaging can simultaneously acquire images and spectral information of crops, thus reflecting various growth attributes and quality conditions of the target, and has gradually become an important tool for rapid nondestructive crop detection in recent years [2]. This kind of technology aids in the swift and precise classification of agricultural illnesses as well as the early identification and control of crop ailments in complex settings. By minimizing the effects of diseases on crops, crop yields are subsequently improved.

**Higher performance models.** By using attention mechanism and residual learning to optimize the existing deep learning models, a crop disease image recognition model with strong robustness and strong interference resistance is desired to be designed. The model is expected to be able to effectively solve the problems of complex sample backgrounds, obvious changes of light and darkness, and small areas of the disease area, and should also have generality and apply to the recognition of different crop species, different disease types, and different disease severity. The model network's simplicity is another important improvement area that must be taken into consideration. To further minimize parameter redundancy, cut computational complexity, and increase model efficiency, the model network should be further reduced to assure the model's correctness to accomplish real-time recognition's objective.

**Porting to mobile.** Popular deep-learning model techniques use many hardware resources and runtime when implemented on high-performance hardware. Although migration learning can reduce training time, it does not reduce the time required to load a significant amount of parameters and perform forward inference, especially when taking into account embedded or mobile devices. Embedded or mobile devices are a promising trend that is more suited for field applications in agriculture than high-performance computers or servers in terms of mobility, affordability, and practicality.

## 5 Conclusion

Focusing on the hot research topic of crop disease identification in the field since crop illnesses mostly appear from leaves, this paper introduces its latest research progress in detail from three aspects: machine learning, deep learning-based, and the integration of them. Representative crop disease identification methods are discussed in detail, including their design ideas and key steps such as changing structures and applying transfer learning. In addition, the recognition accuracy of representative methods is quantitatively analyzed and compared on common datasets to analyze their respective strengths and weaknesses. In general, deep learning is better suited for the computer vision domain than machine learning since it can automatically extract features, which is particularly helpful when working with vast amounts of data. The fusion of ML and DL extracts the gold from the dross, increasing the opportunities for image recognition in agriculture. Finally, this paper provides an overview of the field crop illnesses diagnosis research issues and talks about the future growth direction of this area from three angles: large-scale data set construction, high-quality algorithm design, and model lightweight application. Richer and larger databases and higher-performance models help to improve the ability to identify pests and diseases and portability allows the recognition technology to become more practical.

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