Journal of Computer Science and Electrical Engineering
Print ISSN: 2663-1938
Online ISSN: 2663-1946
DOI: https://doi.org/10.61784/jcsee3140

CROP PEST AND DISEASE IDENTIFICATION SYSTEM BASED ON MUTUAL LEARNING

HanQiu Shen*, Zhuo Xie, XiaoYu Guo, XinYing Liu
College of Information Science and Engineering, Hunan Institute of Engineering, Xiangtan 411104, Hunan, China.
**Corresponding Author: HanQiu Shen*

Abstract: As the fundamental industry supporting the national economy, agricultural production is seriously restricted by frequent occurrences of crop pests and diseases, which have been proven to cause enormous economic losses worldwide every year. Therefore, the rapid and accurate identification of crop pests and diseases is widely regarded as a crucial prerequisite for the sustainable development of green agriculture and high-quality agricultural production. Traditional pattern classification algorithms and representative deep learning models including VGG and ResNet have been gradually applied in the field of pest and disease identification, yet most deep networks are confronted with great challenges in real-world deployment on mobile and edge devices due to their excessively large number of parameters and high computational complexity. To effectively tackle this application bottleneck, a lightweight BMV3 network based on the mutual learning framework is proposed in this paper. After heterogeneous knowledge interaction and mutual learning with ResNet50, the identification accuracy of the proposed model is significantly improved by 2.6%, and the dual optimization of high identification accuracy and flexible terminal deployment is successfully realized.
Keywords: Crop disease; Deep learning; Mutual learning

1 INTRODUCTION

As the fundamental industry of the national economy, agriculture is of great significance, whose stable development is directly related to national food security and the well-being of society and people's livelihood. However, crop pests and diseases, which are regarded as the most major biological disasters in agricultural production, have long severely restricted the high-quality development of agriculture, leading to enormous economic losses and resource waste [1]. Therefore, the rapid and accurate identification of crop pests and diseases, which is a key measure to improve prevention and control efficiency, reduce losses, and promote the development of green agriculture, should be realized.

In the development process of crop pest and disease identification technologies, traditional classification algorithms have played an important role. Early identification methods, which mainly relied on manual observation, were highly subjective, inefficient, and dependent on professional experience, making it difficult for them to meet the needs of large -scale agricultural production [2]. With the rise of machine learning technology, traditional classification algorithms, such as decision trees, K-means clustering, support vector machines (SVM), and Bayesian algorithms, have been widely applied in the field of pest and disease identification [3]. Classification by these algorithms is realized through the extraction of shallow features, including color and texture, from pest and disease images, by which the identification efficiency has been improved to a certain extent.

With the rapid development of deep learning technology, convolutional neural networks (CNNs) have become the mainstream technology for crop pest and disease identification due to their powerful automatic feature extraction capability, among which the VGG and ResNet series algorithms are the most widely applied. The VGG series algorithms, which stack multiple convolutional layers and pooling layers to gradually extract deep image features, have shown excellent performance in identification tasks such as corn leaf diseases. By introducing a residual connection mechanism, the ResNet series algorithms can effectively solve the gradient vanishing problem during the training of deep networks, which enables them to extract more complex pest and disease features. These algorithms have demonstrated high accuracy and stability in the identification of various crop pests and diseases, providing solid technical support for the intelligent identification of pests and diseases [4]. However, such deep networks are characterized by large parameter quantities and high computational complexity, which makes it difficult for them to be deployed on mobile devices, and this limitation restricts their application in real-time field identification scenarios.

To address the difficulty in deploying deep networks, the application of lightweight models in the field of crop pest and disease identification has gradually attracted attention. Their core advantage lies in the simplification of the network structure and the reduction of the number of parameters, through which rapid model inference can be achieved to meet the demand for real-time mobile identification [5]. Among these lightweight models, the MobileNet series networks, which rely on the depthwise separable convolution structure, have significantly reduced the parameter quantity and computational complexity while retaining good identification performance, making them the preferred models for mobile pest and disease identification. Real-time identification in field scenarios can be realized by these models, and convenient diagnostic tools are provided for farmers and agricultural practitioners [6]. However, limited by the simplified network structure, the feature extraction capability of MobileNet networks is insufficient. Compared with deep networks such as VGG and ResNet, an obvious gap exists in their identification accuracy, and the space for

© By the Author(s) 2026, under the CC BY-NC-ND license (http://creativecommons.org/licenses/by-nc-nd/4.0).

accuracy improvement is limited, which has become a key bottleneck that restricts the further popularization and application of lightweight models in the field of pest and disease identification [7].

To solve the above problems, a mutual learning framework for the MobileNet model is proposed in this paper. Through information interaction and knowledge sharing between heterogeneous models, the collaborative improvement of model performance is achieved by the framework, which can effectively make up for the performance defects of a single model. Based on this, the advantages of the lightweight MobileNet network and the deep ResNet network are combined, through which the dual improvement of pest and disease identification accuracy and model deployment flexibility is realized.

2 RELATE WORK

2.1 Datasets

To verify the effectiveness of the mutual learning framework in improving the identification accuracy of lightweight models, a real-world crop pest and disease datasets was constructed for experimental validation. In this study, four typical crop pest and disease categories were selected as research objects, covering healthy samples and three common disease and pest types. A total of 3,181 valid samples were collected through field acquisition and standardized preprocessing, including 595 healthy crop samples, 1,208 leaf samples damaged by noctuid, 997 wilted leaf samples, and 381 leaf samples infected with leafhopper disease. The sample collection covered different lighting conditions, growth periods and damage degrees, which improved the diversity and generalization of the datasets. In the experimental setup, the complete dataset was divided into a training set and a validation set according to the ratio of 6:4. This division ratio ensures that the training set has sufficient data to support the knowledge transfer and interactive optimization process of the mutual learning framework, while the validation set can objectively evaluate the real performance of the model without overfitting. The detailed sample distribution of each category in the training set and validation set is presented in Table 1. On this basis, the lightweight network MobileNetV3 was optimized by using the mutual learning strategy, and the accuracy improvement effect was compared with that of the traditional residual network.

Table 1 The Precision Metrics of Different Models for Pest and Disease Recognition

Class	Healthy	Noctuid	Wilting	Leafhopper	Sum
Train	357	725	599	229	1910
Val	238	483	398	152	1271
Sum	595	1208	997	381	3181

2.2 Method

2.2.1 Mutual learning framework

The superiority of complementary information in heterogeneous networks is verified by the mutual learning framework. [8]. As shown in Figure 1, the BMV3 network framework (Boosted MobileNetV3) proposed in this paper is mainly divided into four parts: data augmentation, dual-branch feature extraction module, knowledge sharing, and loss optimization. Data augmentation expands the data scale and enriches data diversity through operations such as flipping, rotation, cropping, and scaling. The dual-branch feature extraction module means that ResNet50 and BMV3 respectively extract features from the input data images to obtain the detailed texture features of pests and diseases. Knowledge sharing refers to the information interaction between ResNet50 and BMV3, involving the intercommunication of pest and disease data, feature knowledge, and recognition experience of different crops, which makes up for the limitations of a single dataset. In loss optimization, the loss function of each branch network includes self-supervision loss and mutual learning loss, which jointly guide the training of each branch model to completion.

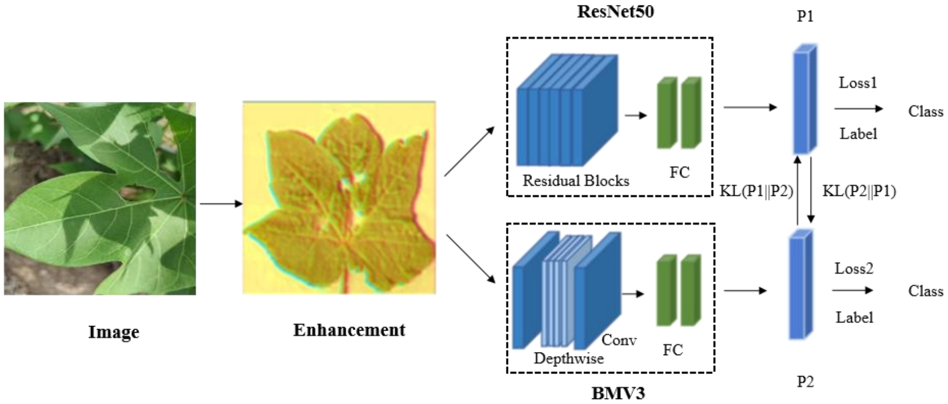

Figure 1 Mutual Learning Network Framework

2.2.2 Loss function

Kullback-Leibler (KL) divergence is an important tool employed to measure the similarity between two probability distributions, whose core significance lies in quantifying the degree of difference between the two distributions. When the KL divergence value is relatively high, it indicates that significant differences exist between the two distributions; conversely, a low KL divergence value implies that the two distributions are highly similar to a large extent. Therefore, the similarity or dissimilarity between probability distributions can be effectively quantified and evaluated through KL divergence. For the discrete form of KL divergence, its formula can be expressed as:

$$D_{KL}(P||Q)=\sum_{i=1}^{n}P_i log\frac{P_i}{Q_i} \tag{1}$$

To enable the transplantation of lightweight networks and fully utilize the heterogeneous information of different networks, the BMV3 framework can achieve knowledge complementarity between heterogeneous networks based on the introduced mutual learning idea. In the mutual learning framework, an additional mutual learning loss is introduced besides the supervised loss function to guide the network training. Therefore, in the process of mutual learning between ResNet50 and BMV3, their respective posterior probabilities are used to provide training experience, thereby promoting knowledge sharing and performance improvement. In terms of the training strategy, a simultaneous training method is adopted: the prediction results p_1 obtained from the training of ResNet50 are used to train BMV3, while the prediction results p_2 obtained from the training of BMV3. The KL divergence is employed to calculate the difference, and the mutual learning losses shown in Eqs. (1) and (2) are used to quantify the prediction matching degree between ResNet50 and BMV3.

$$D_{KL}(p_1||p_2)=\sum_{i=1}^{N}\sum_{m=1}^{M}P_1^m(x_i)log\frac{P_1^m(x_i)}{P_2^m(x_i)} \tag{2}$$

$$D_{KL}(p_2||p_1)=\sum_{i=1}^{N}\sum_{m=1}^{M}P_2^m(x_i)log\frac{P_2^m(x_i)}{P_1^m(x_i)} \tag{3}$$

The total loss function L_{Θ_1} obtained by the ResNet50 network consists of two components: the self-supervision loss L_{C_1} and $D_{KL}(p_2||p_1)$, Accordingly, the total loss function L_{Θ_2} for the BMV3 network comprises the self-supervision loss L_{C_2} and the Kullback-Leibler divergence $D_{KL}(p_1||p_2)$,as shown in Equations (4) and (5):

$$L_{\Theta_1}=L_{C_1}+D_{KL}(p_2 // p_1) \tag{4}$$

$$L_{\Theta_2}=L_{C_2}+D_{KL}(p_1 // p_2) \tag{5}$$

2.2.3 Accuracy metrics

Overall Accuracy, Precision, Recall, and F1-Score are widely used evaluation metrics for classification models. Overall Accuracy measures the proportion of correctly predicted samples across all classes, reflecting the global classification performance. Precision denotes the ratio of true positive samples among all predicted positive samples, while Recall represents the ratio of correctly identified positive samples to all actual positive samples; the two metrics usually exhibit a trade-off. As the harmonic mean of Precision and Recall, F1-Score provides a comprehensive assessment of model performance, especially on imbalanced datasets. as shown in Equations. (6)–(9):

$$OA=\frac{TP+TN}{TP+FP+TN+FN} \tag{6}$$

$$Precision=\frac{TP}{TP+FP} \tag{7}$$

$$Recall=\frac{TP}{TP+FN} \tag{8}$$

$$F1\_score=\frac{2*\ Precision*\ Recall}{Precision+Recall} \tag{9}$$

TP refers to correctly classified positive samples, FP refers to negative samples misidentified as positive，TN refers to correctly classified negative samples，FN refers to positive samples misidentified as negative.

3 EXPERIMENT

To explore the recognition results of different classification networks on pest and disease species, five precision evaluation metrics, namely OA, Precision, Recall, F1, and Kappa, were adopted to measure the models, and the results are shown in Table 2.

Table 2 The Precision Metrics of Different Models for Pest and Disease Recognition

Model	OA	Precision	Recall	F1	Kappa
VGG19	0.914	0.873	0.886	0.878	0.894
MobileNetV3	0.932	0.895	0.910	0.902	0.917
ResNet34	0.963	0.917	0.950	0.933	0.955
ResNet50	**0.971**	**0.928**	**0.965**	**0.941**	**0.966**

Since the accuracy of ResNet50 is the highest among the aforementioned classification networks, to verify the performance of the proposed BMV3 model, experiments were conducted based on individual classification networks, and mutual learning was performed between ResNet50 and each classification network, yielding the experimental results shown in Table 3. The accuracy improvements of BMV3 and VGG19 were obtained by referring to the results of the individual classification networks, where the accuracies of VGG19, ResNet34, ResNet50, and BMV3 were 0.935, 0.969, 0.973, and 0.958, respectively. It was found that the accuracy of all combined networks was improved, and the accuracy was significantly higher than that of the individual classification networks. Specifically, the accuracies of BMV3 and VGG19 were increased by 0.026 and 0.021, respectively, while ResNet34 and ResNet50 also achieved slight improvements of 0.006 and 0.002, respectively. In particular, when mutual learning was performed between heterogeneous networks, ResNet50 and BMV3 conducted mutual learning, and the results showed that BMV3 achieved a greater accuracy improvement compared with the individually trained network. With only 16.2M parameters, BMV3 achieved a relatively high accuracy under the constraint of parameter quantity, which is conducive to practical applications. Secondly, after mutual learning between ResNet50 and VGG19, the accuracy was significantly improved.

Table 3 Mutual Learning Results of ResNet50 with Different Classification Networks (OA)

Model	Single-class Accuracy	Mutual Learning Accuracy	Accuracy Improvement	Model Size
VGG19	0.914	0.935	0.021	532.1M
ResNet34	0.963	0.969	0.006	81.3M
ResNet50	**0.971**	**0.973**	0.002	90.0M
BMV3	0.932	0.958	**0.026**	**16.2M**

4 DISCUSSION AND CONCLUSION

Lightweight models exhibit significant advantages in the deployment for pest and disease identification on mobile devices [9]. Although residual networks deliver superior identification accuracy, their large number of parameters limits their portability [10]. In this study, a mutual learning strategy is adopted to improve the accuracy of BMV3 while preserving its lightweight structure and efficient inference characteristics, enabling the model to be directly deployed on mobile terminals and providing a feasible solution for field real-time pest and disease detection. The experimental results show that the improved model based on mutual learning not only narrows the accuracy gap with the deep residual network, but also maintains the operational efficiency suitable for mobile platforms, realizing the organic unity of high precision and high portability. This design breaks through the limitation that high-performance models are difficult to land on mobile terminals, and provides a feasible and effective technical scheme for real-time, portable and intelligent identification of plant diseases and pests. The research results can be directly integrated into agricultural mobile detection systems, which is helpful to promote the application of edge computing and artificial intelligence in field plant protection, and provide strong technical support for accurate disease and pest control, yield guarantee and intelligent upgrading of agricultural production.

COMPETING INTERESTS

The authors have no relevant financial or non-financial interests to disclose.

REFERENCES

[1] Zhang Yiyang, Liu Jie, Bian Yue, et al. Analysis of the Occurrence Trends and Causes of Major Crop Diseases and Pests in China in 2026. China Plant Protection Guide, 2026, 46(01): 45-49.

[2] Khan A I, Quadri S M K, Banday S, et al. Deep diagnosis: A real-time apple leaf disease detection system based on deep learning. Computers and Electronics in Agriculture, 2022, 198: 107093

[3] Fang Yingying, Pan Yanhong, Pan Xinling, et al. Design of a Crop Disease and Pest Identification System Based on Deep Learning. Smart Agriculture Guide, 2026, 6(03): 23-28. DOI: 10.20028/j.zhnydk.2026.03.006.

[4] Gao R, Wang R, Feng L, et al. Dual-branch, efficient, channel attention-based crop disease identification. Computers and Electronics in Agriculture, 2021, 190: 106410.

[5] Xu Yuchao, Wu Qian, Zhang Bingyuan, et al. Advances in the application of lightweight deep learning networks in crop target detection. Chinese Journal of Agricultural Mechanization, 2025, 46(03): 261-270. DOI: 10.13733/j.jcam.issn.2095-5553.2025.03.038.

[6] Karar M E, Alsunaydi F, Albusaymi S, et al. A new mobile application of agricultural pests recognition using deep learning in cloud computing system. Alexandria Engineering Journal, 2021, 60(5): 4423-4432.

[7] Boogaard F P, Rongen K S A H, Kootstra G W. Robust node detection and tracking in fruit-vegetable crops using deep learning and multi-view imaging. Biosystems Engineering, 2020, 192: 117-132.

[8] Zhang Y, Tao X, Hospedales T M, et al. Deep mutual learning. Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2018: 4320-4328.

[9] Yang Xiang, Duan Junming, Dong Minggang. Image recognition method for plant diseases for mobile devices and its application. Jiangsu Agricultural Sciences, 2023, 51(04): 191-197. DOI: 10.15889/j.issn.1002-1302.2023.04.028.

[10] Liu Bin, Jia Runchang, Zhu Xianyu, et al. A lightweight identification model for apple leaf diseases and pests for mobile devices. Transactions of the Chinese Society of Agricultural Engineering, 2022, 38(06): 130-139.