Maize leaf disease identification using deep transfer convolutional neural networks

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Abstract: Gray leaf spot, common rust, and northern leaf blight are three common maize leaf diseases that cause great economic losses to the worldwide maize industry. Timely and accurate disease identification can reduce economic losses, pesticide usage, and ensure maize yield and food security. Deep learning methods, represented by convolutional neural networks (CNNs), provide accurate, effective, and automatic diagnosis on server platforms when enormous training data is available. Restricted by dataset scale and application scenarios, CNNs are difficult to identify small-scale data sets on mobile terminals, while the lightweight networks, designed for the mobile terminal, achieve a better balance between efficiency and accuracy. This paper proposes a two-staged deep-transfer learning method to identify maize leaf diseases in the field. During the deep learning period, 8 deep and 4 lightweight CNN models were trained and compared on the Plant Village dataset, and ResNet and MobileNet achieved test accuracy of 99.48% and 98.69% respectively, which were then migrated onto the field maize leave disease dataset collected on mobile phones. By using layer-freezing and fine-tuning strategies on ResNet and MobileNet, fine-tuned MobileNet achieved the best accuracy of 99.11%. Results confirmed that disease identification performance from lightweight CNNs was not inferior to that of deep CNNs and transfer learning training efficiency was higher when lacking training samples. Besides, the smaller gaps between source and target domains, the better the identification performance for transfer learning. This study provides an application example for maize disease identification in the field using deep-transfer learning and provides a theoretical basis for intelligent maize leaf disease identification from images captured with mobile devices.

Keywords: maize leaf disease, deep learning, transfer learning, convolutional neural networks

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1 Introduction

Maize is an important food crop and industrial raw material globally, and ensuring maize yield stability is of great importance to food security, agricultural development, and the national economy. Over ten kinds of common maize diseases directly affect maize yield and quality, including in the leaves, ears, and roots. Although gray leaf spots, common rust, and northern leaf blight in the leaves can severely reduce maize yield, timely identification and disposal lead to minimum harm caused by the disease. Traditional identification requires agricultural or forestry experts to diagnose in the field or from a distance, which is quite subjective, time-consuming, laborious, and inefficient. Therefore, realizing an intelligent, rapid, and accurate automatic identification method is of great significance.

Deep learning methods can be applied in hyperspectral images[1] and RGB images. Identifying crop phenotypic diseases with deep learning methods has become a strong research focus in precision agriculture[2], especially by using Convolution Neural Networks (CNN). CNN has diverse structures and offers outstanding capabilities as a consequence of gradual optimization, contributing to being the prevailing disease identification classifier for large- or small-scale tasks. Inchoate researchers considered CNNs as feature extractors, followed by machine learning classifiers (mostly SVM)[3,4]. After CNNs were gradually used for classification directly, small dataset size problem came into view. In practice, low disease incidence and high cost of acquisition result in only a few training data collected, which limits the application of deep learning methods in identification[5]. Therefore, most studies in plant disease identification and detection are based on the prevailing public dataset Plant Village[6], which contains 38 categories by species and disease, adding up to 54 303 images. Jaiswal et al.[7] sampled 5 diseases of every species in Plant Village to carry out their research, which focused on the hyperparameters' effect on GoogLeNet model performance.

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Sravan et al[8] utilized 20 639 images from Plant Village on ResNet50 model, which achieved 99.26% classification accuracy, and Agarwal et al[9] selected 10 kinds of tomato diseases with image preprocessing and brightness enhancement, reaching an accuracy of 98.7% on the proposed simplified CNN model. Besides, it is common to reassemble dataset with Plant Village and real field images on specific species, with data amplification, synthesis and generation followed. Liu et al.[10] used 4023 field images and 3646 Plant Village images to generate 107 366 grape leaf images for training the proposed DICNN model, with an overall accuracy of 97.22%. Furthermore, investigated approaches like structure modification, module enhancement and data preprocessing (augmentation, segmentation or background removal) have been validated to enhance the performances[11-14], which can be seen as the solution to dataset size problem.

Although deep learning method mitigates manual misjudgments, reliance on expert experience, and reduces workforce and material resource requirements, the performances of CNN models are based on intensive image computing processing, which indicates a large amount of manual labeling work. Besides, recent researches[15-17] showed that CNN methods lack robustness to environmental conditions. Training datasets are mostly collected under controlled conditions like laboratory background or public datasets, which causes problems with generalization, adaptability, and anti-interference capability[18]. Another application issue of CNN in disease identification is the limited amount of existing data for specific species, bringing about unstable training processes and overfitting models. Therefore, transfer learning methods are introduced to solve the above challenges. Transfer learning leverages knowledge from the source domain to offer solutions to the target domain, and stronger similarity between source and target domains improves accuracy, indicating better transferability[19]. The heavy workload of manual annotation is reduced greatly on account of source domain training, denoting high resource utilization. And the overfitting problem caused by limited existing data is solved simultaneously, since a fully trained CNN model on source dataset provides good feature extraction capacity which satisfies requirements on smaller targeted datasets. Xu et al.[20] adopted transfer learning to solve overfitting as well as a replacement of fully-connected layer into global pooling layer, which achieved 93.28% accuracy on a maize disease identification dataset, superior to four previous states of the art models.

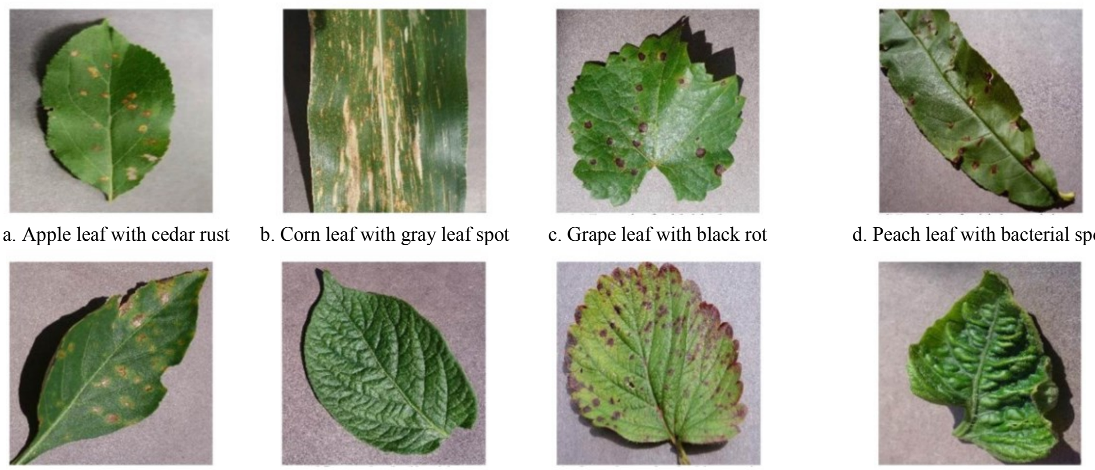
Pre-trained CNN models based on the ImageNet dataset are commonly employed in transfer learning, making full use of their feature extracting or fine-tuning in follow-up processing on another public or local disease dataset. Chen et al.[21] selected a CNN model pre-trained on ImageNet with initialized weights to achieve at least 91.83% validation accuracy on a public dataset. Average accuracy reached 92.00% on rice plant images with complex backgrounds. Yin et al.[22] extracted deep features for pepper disease and insect pest dataset using 8 CNN models pre-trained on ImageNet for identification, achieving 85.6% and 93.62% accuracy for disease and insect pest identification, respectively, using ResNet depth features. However, still unresolved are the lacking robustness to environmental conditions, which is more of dataset problem, and the less similarity between domains, indicating a more similar source dataset. Besides, high CNN model accuracy depends on computing power supported by high-performance hardware, whereas the general trend is toward lightweight and mobile agricultural equipment. Several recent studies have imported lightweight CNNs, such as MobileNet[23,24] and EfficientNet[25], for crop disease identification. Concessions must be made by accuracy against the network scale.

Therefore, a more feasible deep-transfer learning method is proposed in this paper. By training and comparing deep and lightweight CNNs on the Plant Village public dataset, optimal pre-trained models are transferred onto a maize leaf diseases dataset collected in a real field and optimized by fine-tuning, which solves the challenges mentioned above: manual annotation, model robustness, small dataset, domain similarity, and mobile simulation. In summary, this study provides an application example for maize disease identification under complex (field) background with deep transfer learning, which provides a theoretical basis for intelligent in-field identification using mobile terminal devices.

2 Materials and methods

2.1 Dataset

This experiment was divided into two parts: training on the Plant Village public dataset and transfer learning on the local maize leaf diseases dataset using pre-trained models in part one. The Plant Village dataset contains 39 classes which are composed of 38 kinds of diseases and 1 background. The 38 diseases may occur in 14 different crops and all categories contain 61 486 images in sum. Each category is stored in an independent folder, representing the label. Images were augmented by image flipping, gamma correction, noise injection, PCA color enhancement, rotation, and scaling. Figure 1 shows some sample images of Plant Village.



a. Apple leaf with cedar rust b. Corn leaf with gray leaf spot c. Grape leaf with black rot d. Peach leaf with bacterial spot

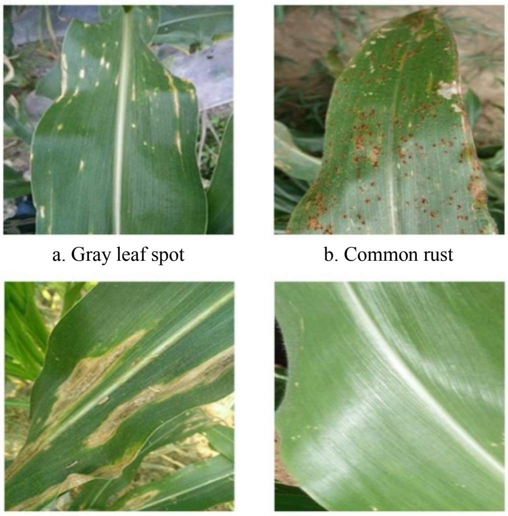
e. Pepper leaf with bacterial spot f. Potato leaf of health g. Strawberry leaf with scorch h. Tomato leaf with yellow leaf curl virus

Figure 1 Augmented Plant Village dataset sample images

The local maize disease dataset was collected from a maize test field in Zhaodong City, Heilongjiang Province, China. Image capture was achieved using iPhone 7 Plus rear camera with 3024×4032 pixel resolution, and shooting times included morning, noon, and afternoon. The camera supported 2× optical zoom, 10× digital zoom at most, and optical image stabilization. Since a couple of leaves with several diseases may appear in one photograph, a 300×300 pixels clipping frame was predefined for separating the principal part of each leaf. Pictures saved as JPG formats were manually clipped into 300×300 pixels images, and actual complex backgrounds (from the field) were retained wherever possible. The dataset contained maize leaf health status and other three diseases of gray leaf spot, common rust, and northern leaf blight, comprising 4 categories and 1189 images in total, while approximately 10% of images were acquired from search engines to enlarge the dataset. Table 1 lists the local maize dataset details and Figure 2 shows sample images.

Table 1 Local maize dataset details

No.	Name	Train	Test	Total
1	Gray leaf spot	233	58	291
2	Common rust	331	83	414
3	Northern leaf blight	229	57	286
4	Health	158	40	198
Total	4 categories	951	238	1189



a. Gray leaf spot b. Common rust

c. Northern leaf blight d. Health

Figure 2 Local maize dataset sample images

Each dataset was split training and test sets (ratio 4:1 respectively)[26]. Training set image resolution was adopted as the network entry size (224×224 pixels) or (299×299 pixels) in the following entrance of CNNs. Training images were enhanced online through numerical normalization, rotation (20° or 40° randomly), translation (horizontal or vertical), scaling, flipping (up and down, left and right), and cross-cutting, which can make the model more generalizable and robust.

2.2 Convolutional neural networks

Convolutional neural networks are pipeline multi-processing layer network models, comprising multiple convolutions (C), pooling (P), and fully connected (FC) layers generally. Deeper CNN architectures tend to extract better features, reduce loss levels, and improve fit, which also require more training data and computing resources. 12 different CNN models were trained on the Plant Village dataset and their performances for disease identification were compared. VGG16 and VGG19[27], ResNet[28], InceptionV3[29], InceptionResNetV2[30], DenseNet121, DenseNet169, and DenseNet201[31] were divided into a set of deep CNNs; whereas Xception[32], MobileNet[33], MobileNetV2[34], and ShuffleNet[35] were divided into a set of lightweight CNNs.

2.2.1 Dropout

Complex feedforward neural networks can cause overfitting when trained on small datasets. Dropout[36] helps prevent overfitting by reducing joint feature detector actions, improving overall CNN performance. In this study, dropout parameter = 0.5, i.e., each training batch ignores 50% of the feature detectors (we set 50% hidden layer node value=0), reducing interdependence between feature detectors (hidden layer nodes) to ensure local feature independence and enhance generalization.

2.2.2 Hyperparameters

The experiment was accomplished in 2 sections: deep learning on Plant Village and transfer learning on maize dataset, thus hyperparameters were introduced respectively.

In both sections, “Callback” functions were applied to enhance the efficiency of training, namely “Early Stopping” and “Learning Rate Scheduler”. The training began with a relatively big learning rate (LR) at first, and a metric (the accuracy or the loss value) was monitored at every step of every epoch. If the training proceeded rationally and smoothly, the LR would keep its value. Otherwise, a decay rate would minish the LR, and change the pace of training to reach convergence efficiently. However, the mechanism would not run endlessly. If the training hadn’t improved over a patience number of epochs even if the LR reached its least value, the training would be faced with a risk of overfitting and fluctuation. Then the training would be stopped and the best model weights would be saved.

In the first section, all CNNs trained on the Plant Village dataset shared the same hyperparameters: Learning rate (LR)= 0.001 with 0.000001 threshold. LR decay was set within 5 epoch patience, then LR would become half of the original when cross-entropy loss reduced slowly. Early stopping was implemented, and the epoch where loss converged to the minimum was recorded (Epoch convergent). Maximum epochs = 100 epochs. Preliminary trials determined maximum batch size for a single training = 32. Therefore, one epoch was completed after 1538 steps if all 49 193 images in the training set were included. The training process in every batch is not used as a reference, but the recording of accuracy and loss value after each round of epoch. We used the RMSprop optimizer.

In the second section, LR would begin at a smaller value, that is 0.0001 with 0.000001 threshold. LR decay was set within 3 epoch patience, other parameters remained unchanged. Therefore, one epoch was completed after 30 steps if all 951 images in the training set were included.

2.3 Transfer learning

A two-staged model-based transfer learning approach was applied in this study. Conventional transfer learning trains the CNN in the source domain and fine-tunes it in the target domain, solving overfitting and instability due to insufficient training data. In this paper, a closer source domain to the target domain was applied to obtain better performance. Challenges lay in that the source domain dataset was collected under lab conditions while the target domain dataset was shot in the field, indicating an impact on performance. Besides, in order not to destroy the ability of the previous layers of the network to extract features, pre-trained models needed to be fine-tuned temperately. And the target domain was a small-scale dataset thus overfitting could easily occur. Therefore, the transfer learning employed two training strategies: layer-freezing (LF), freezing all layers' parameters and initializing the classifier layer randomly; or fine-tuning (FT), defrosting part of the intermediate layer close to the classifier layer gradually and initializing them all. Moreover, training set images in the self-built maize disease dataset were enhanced online. The current applied both strategies to verify identification efficiency and accuracy. Figure 3 shows the proposed process.

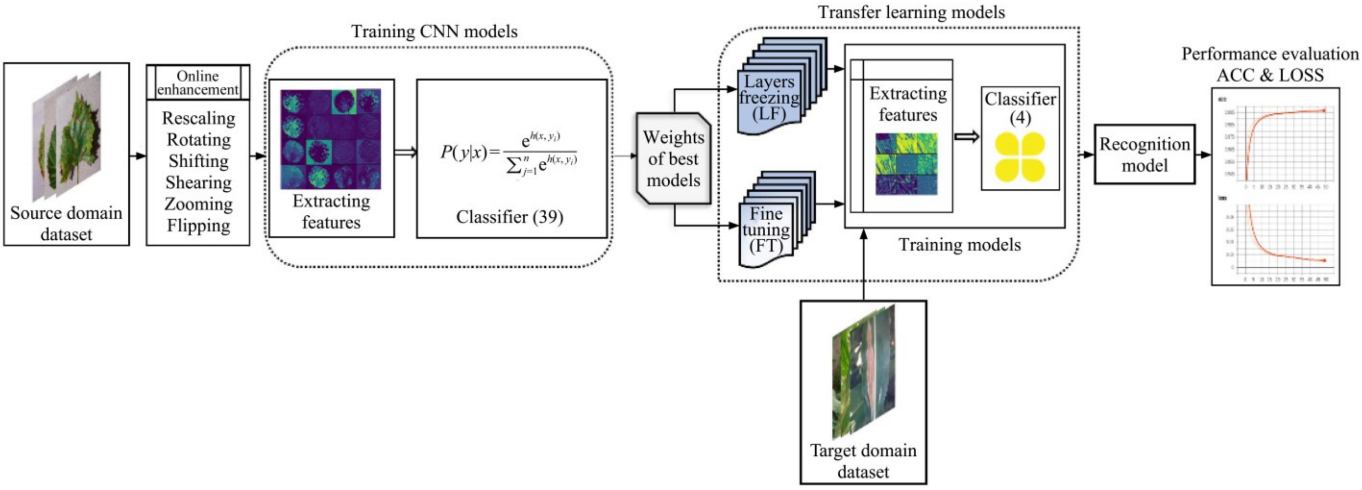


Figure 3 Leaf disease identification process

2.4 Hardware and software

The platform employed for this study was a deep learning workstation equipped with Intel® Core™ i9-9900K 16 CPU @ 3.6 GHz processor, RTX 3090 24G memory graphics card, 32 GB RAM, 2.5 TB HDD, graphics card driver version 455.45.01, CUDA version 11.1, and CUDNN version 8005. The operating system was 64 bit Ubuntu 20.04 LTS, and programming was implemented using Python 3.7.9 and Keras 2.4.3 under the TensorFlow-GPU framework.

3 Results and discussion

3.1 Pre-trained model performances

Table 3 shows pre-trained model performances. ResNet and InceptionResNetV2 test accuracy was superior to other models, achieving 99.48% and 99.31% respectively; whereas InceptionV3, MobileNet, and MobileNetV2 achieved 98.82%, 98.69%, and 98.00% respectively, and the remaining rest networks ranged from 96% to 98%.

Table 3 Baseline CNN model performances

Network	Epoch (Convergent)	Training		Test	
		Loss	Accuracy	Loss	Accuracy
VGG16	33	0.1666	95.79%	0.1767	96.76%
VGG19	41	0.0798	97.79%	0.1147	97.04%
ResNet	47	0.0076	99.82%	0.0183	99.48%
DenseNet121	27	0.0628	98.27%	0.1253	97.47%
DenseNet169	23	0.0662	98.37%	0.1391	97.67%
DenseNet201	34	0.0486	98.59%	0.1024	97.99%
InceptionV3	18	0.0515	98.42%	0.1524	98.82%
InceptionResNetV2	24	0.0151	99.63%	0.2096	99.31%
Xception	10	0.0452	98.90%	0.1863	96.81%
MobileNet	32	0.0178	99.44%	0.0493	98.69%
MobileNetV2	36	0.0297	99.04%	0.0814	98.04%
ShuffleNet	24	0.0352	98.82%	0.1473	96.08%

ResNet, MobileNet, and MobileNetV2 losses were also smaller, achieving 0.0183, 0.0492, and 0.0814, respectively, whereas the other considered other networks were between 0.1 and 0.21. All model test accuracies exceeded 96%, indicating the excellent CNN performance on a sufficient training dataset. Ferentinos et al.[37] trained CNN models on a large self-constructed dataset, including 25 plants, 58 categories, and 87 848 images in total, achieving the highest accuracy for classic CNN = 99.53%. Therefore, sufficient training data is critical for optimal performance. More complex networks can theoretically extract features better[38] but require more training data, hence DenseNet achieved the best accuracy in contrast to the present study[37].

In this study, the Test accuracy for the proposed deep CNN ranged from 96.76% to 99.48% and convergence occurred within 30 epochs on average; whereas test accuracy for lightweight CNNs=96.08% to 98.69% and convergence<25 iterations. This small test accuracy difference will ensure the lightweight network is easier to train.

Table 4 shows the model scales and related parameters. Under the premise that the accuracy is higher than 98% or the loss value is not greater than 0.1, MobileNet and MobileNetV2 employed relatively small parameter values=28.9 and 34.4, respectively, whereas ResNet, InceptionV3, and InceptionResNetV2 employed 12.5, 88.9, and 104.7, respectively. ResNet and MobileNet network models were relatively small, 144 and 208 MB, respectively, outperforming all other models. Figure 4 shows training accuracy and loss changes for ResNet and MobileNet during training.

Table 4 ResNet and MobileNet training accuracy and loss

Network	No. parameters (million)	Model size/MB	Input size (pixel)
VGG16	27.6	210	224×224
VGG19	32.8	251	224×224
ResNet	12.5	144	224×224
DenseNet121	49.5	223	224×224
DenseNet169	54.4	367	224×224
DenseNet201	66.5	438	224×224
InceptionV3	88.9	679	299×299
InceptionResNetV2	104.7	400	299×299
Xception	125.7	959	299×299
MobileNet	28.9	208	224×224
MobileNetV2	34.4	262	224×224
ShuffleNet	1.9	17.3	224×224

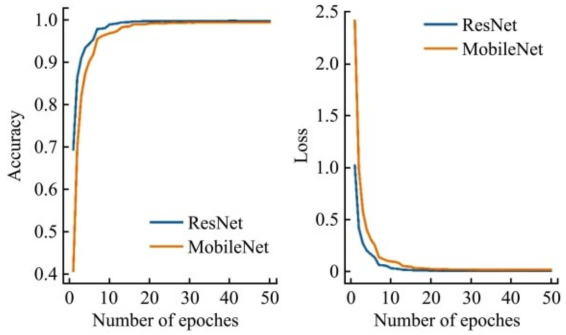


Figure 4 ResNet and MobileNet training processes

Consequently, ResNet and MobileNet have relatively small parameters and model sizes while providing high identification performances, and hence are more suitable to be mounted on mobile agricultural equipment. Therefore, after removing the bottom FC layer, these pre-trained models were retained for transfer learning in the next stage.

3.2 Feature extraction

Transfer learning requires a new FC layer for pre-trained models. Figures 5 and 6 show MobileNet and ResNet network structure diagrams for transfer learning training, respectively, with the numbers at the bottom in the shape format of the output for each layer. All convolutional layers included batch normalization (BN) and ReLU activation layers.

MobileNet and ResNet features were extracted before the second stage of transfer learning. Feature maps from the intermediate layer output can be obtained by importing three different disease images from the local maize disease dataset into the network. Figure 7 shows feature samples for gray leaf spots, northern leaf blight, and common rust in MobileNet. The number of channels selected = 10, 11, 12, 18, 19, and 20.

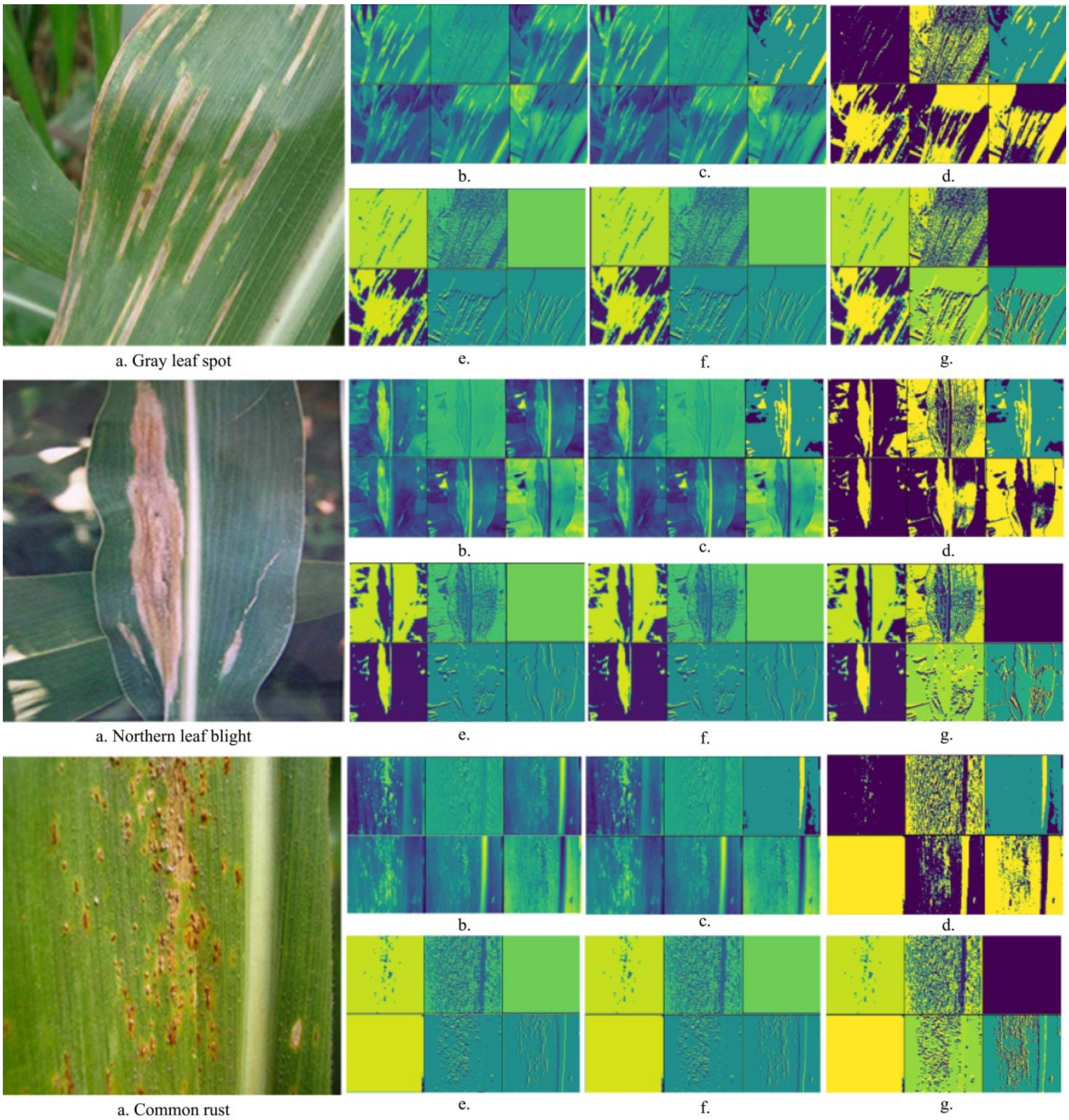


Figure 5 MobileNet internal layer features (a) original image; feature images from (b) convolution, (c) BN, and (d) ReLU6 layers; feature images from (e) depthwise convolution, (f) BN, and (g) ReLU6 layers

Figure 6 shows feature graphs from the 23rd channel within block 1. Comparing the original image with the feature image, the 23rd feature image can not only resist influence from complex backgrounds but can also classify lesion areas more accurately. Ahmad et al.[39] concluded performance on laboratory data was superior to field data regardless of network type, and complex backgrounds can reduce identification accuracy. Chen et al.[40] confirmed these conclusions for maize disease identification. Therefore, removing background interference will have significant impact on identification accuracy.

Figure 7 shows feature maps from the same three images as above in ResNet. The feature maps show sensitivity towards northern leaf blight and common rust, and the highlighted area indicates the lesion area. Most blade texture differences are also noted. However, edge outlines and considerable background remains in the feature map, which will impact disease identification.

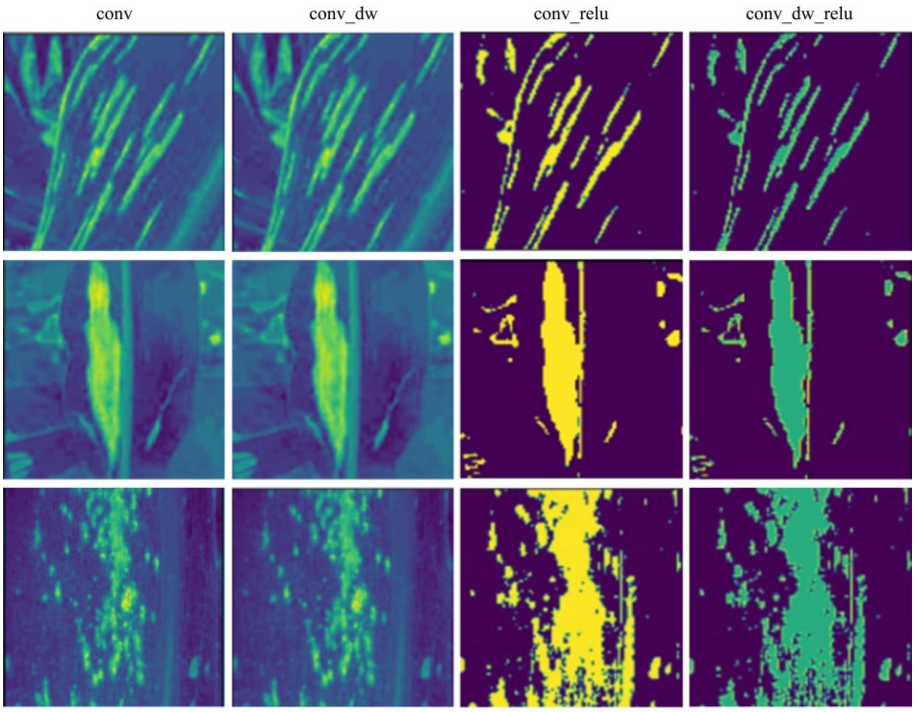
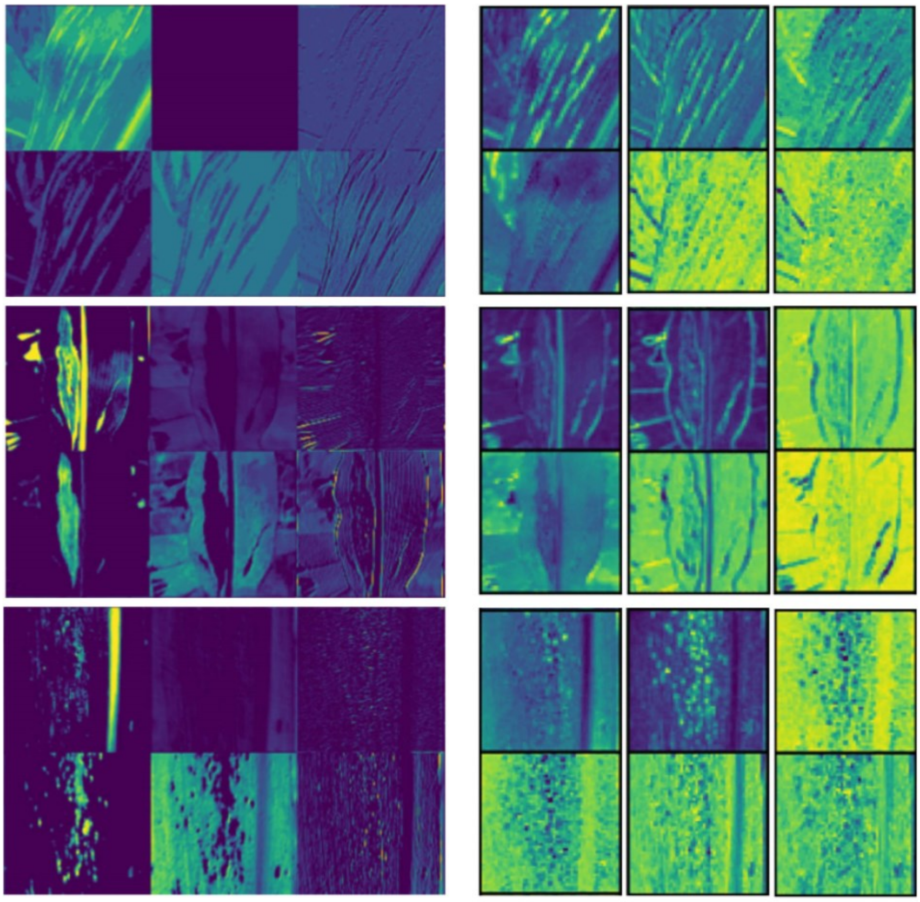


Figure 6 Features from Channel No.23 MobileNet Block 1



a. Features in Block0_cnv1 layer b. Features in Block0_res_module layer

Figure 7 ResNet internal layer feature maps

3.3 Transfer learning model performances

The pre-trained ResNet and MobileNet weights were loaded and performed transfer learning training on the local maize disease dataset. Four new models were derived depending on the different training strategies, layer-freezing (LF) or fine-tuning (FT): R-LF, R-FT, M-LF, and M-FT. Figure 8 compares accuracy and loss for these four models, and Table 5 lists training and test set performances, including early accuracy and loss after the first training epoch.

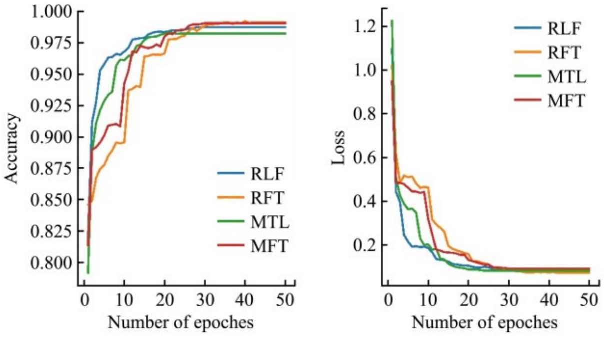


Figure 8 Training process for ResNet and MobileNet models with layer-freezing (LF) and fine-tuning (FT) training strategies: R-LF, R-FT, M-LF, and M-FT

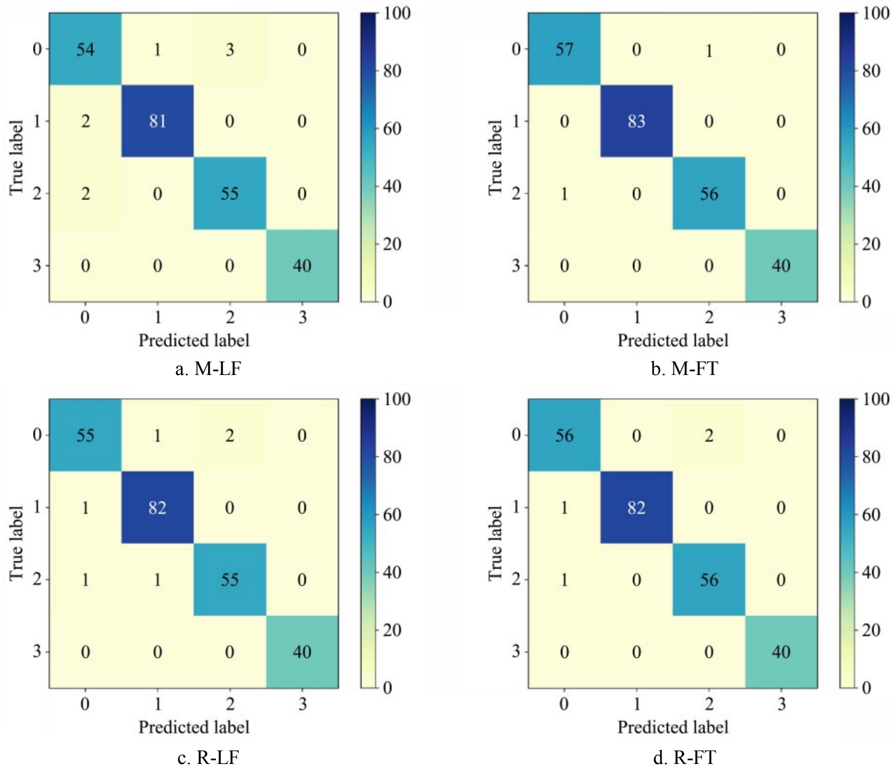
Table 5 ResNet and MobileNet transfer learning performance

Strategy	Epoch	Early		Training		Test	
		Loss	Accuracy	Loss	Accuracy	Loss	Accuracy
R-LF	28	1.0976	81.91%	0.0904	98.74%	0.1266	97.82%
R-FT	41	1.0197	84.61%	0.0722	99.23%	0.1368	98.77%
M-LF	24	1.2255	79.18%	0.0823	98.30%	0.1987	96.92%
M-FT	30	0.9486	81.38%	0.0918	99.05%	0.109	99.11%

All transfer models achieved test accuracy ≥96%. Fine-tuning strategy models performed better than LF models with 0.95% and 2.19% improvement for ResNet and MobileNet, respectively. Fine-tuning models also reduced losses by 0.0098 and 0.0893 compared with LF models. M-LF achieved the best test accuracy=99.11%. Thus, transfer learning provided good identification performance. The general outcome is consistent with Too et al.[41], who migrated pre-trained ImageNet models onto the Plant Village dataset, achieving accuracy >90% for all models except VGG16, whereas DenseNet and ResNet performed better and converged more easily. In contrast, the present study used the Plant Village dataset as the source rather than target domain. Plant Village is smaller capacity than ImageNet (1.28 million images tagged training sets, 1 thousand categories), hence deep-CNN fails to show significantly better performance, and Plant Village was more similar to the local maize disease dataset, hence improving accuracy.

On the other hand, LF effectively reduced training epochs at the expense of accuracy, reducing overall hardware resource requirements compared with FT. Transfer learning accuracy ≥79% and loss ≤1.3 after the first epoch, with FT achieving better initial accuracy and loss than LF. Thus, transfer learning training required less initial learning rate and patience with greater decay rate, hence improving training efficiency compared with training from scratch.

Figure 9 shows confusion matrices for the four model's disease identification performances. Gray leaf spot and northern leaf blight slightly misidentify each other, and common rust may be misidentified as gray spot, but gray spot does not tend to be misclassified as rust. ResNet and MobileNet were the superior pre-trained models on Plant Village, and also achieved outstanding performance on the local maize leaf disease dataset collected in the field. MobileNet achieved the best performance after FT (M-FT), with test accuracy = 99.11%, 2.19% higher than the original model. In contrast, R-FT test accuracy = 98.77%, 0.95% improvement.



Note: Label 0 to 3 refers to gray leaf spot, common rust, northern leaf blight and healthy leaves respectively; Test set predictions made by models are in the 4×4 grid and larger values are assigned darker colors.

Figure 9 Confusion matrices for R-LF, R-FT, M-LF, and M-FT models

Table 6 lists the comparison with current state-of-the-art methods of recent researches on plant disease identification, where P.V. is short for "Plant Village" dataset and TL is short for "Transfer Learning".

Along with the shrinking scale of dataset, more training strategies and innovative modifications to models are applied, and transfer learning becomes a common practice. Large scale dataset with conventional deep CNNs promises an extra high accuracy, which indicates sufficient samples are of the essence when networks have the capacity to extract deep features. Among the studies listed above, this paper proves the effectiveness of transfer learning from Plant Village with its high accuracy and supplies the solution to the dataset size problem. Moreover, fine-tuned MobileNet is guaranteed to be deployed on mobile terminal devices in real field scenario tasks, which is expected to be a direction of future development.

Table 6 Comparison with current state-of-the-art methods of diseases identification

Research	Dataset	Strategy	Model	Accuracy
a[37] (2018)	Expanded P.V. (87848)	Training from scratch	VGG	99.53%
b[41] (2018)	P.V.	TL (ImageNet)	DenseNets	99.75%
c[42] (2019)	Local (46135)	Background removal; Dataset expansion	GoogLeNet	94%-96%
d[21] (2020)	Maize (3852, P.V.); Local (rice&maize, 500 &466 each)	TL (ImageNet); Augmentation	INC-VGGN	92.00%
e[43] (2020)	Local (maize, 466)	TL (Plant Village); Attention mechanism	Mobile-DANet	95.86%
f [44] (2021)	Local (coconut, 1564)	TL (ImageNet); Segmentation	InceptionResNetV2, MobileNet	81.48%, 82.10%
g	Local (maize, 1192)	TL (Plant Village); Augmentation	MobileNet	99.11%

In this section, transfer learning was an efficient method and provided high-precision outcomes. MobileNet was more robust to interference from complex backgrounds than ResNet, which may explain why MobileNet achieved better identification performance on the local dataset.

4 Conclusions

Deep-transfer learning method was validly effective especially when the dataset was on small scale, and transfer learning improved initial model performance and training efficiency, illustrated by fine-tuned MobileNet achieving the best performance. This study provides a theoretical foundation for mobile collection terminal maize disease identification with deep-transfer learning method, which establishes the foundation for further practical development of models and enrichment of data set.

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