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RESEARCH ON IDENTIFICATION OF CROP LEAF PESTS AND DISEASES BASED ON FEW-SHOT LEARNING

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KEYWORDS

crop leaf pests and diseases, few-shot learning, siamese network.

ABSTRACT

The yield of crops has a significant impact on economic and social development. It is significant to ensure the healthy growth of crops. Leaves can represent the growth of crops. Crop health can be monitored by analyzing a sufficient number of leaf images. But advanced farming techniques make leaves less susceptible to pests and diseases. Therefore, it is difficult to collect enough leaves with pests and diseases for image analysis. To solve this problem, this research proposed a method based on few-shot learning to identify crop leaf images and judge crop health status. The main structure of the method is a siamese network. The structure of its two subnetworks is the convolution neural network with an attention module. Each subnetwork outputs a feature vector. Measuring the distance of two feature vectors in the feature space, the similarity is calculated. Then the categories of leaf pests and diseases are judged. The experiments in this research were carried out on apple and potato leaves. The accuracy of identifying their pests and diseases reached 98.03% and 97.34% respectively. The experiment proved that when the sample size is small. The method proposed can effectively identify crop leaf pests and diseases.

INTRODUCTION

There is a close relationship between crop production and social development. Ensuring crop yield and quality is of great significance to economic development (Masahiko & Hirohisa, 2016). Crop leaves can represent the content of nutrients and chlorophyll. They reflect the health of the crop (Shreyas et al., 2022). As artificial intelligence technology is promoted, researchers have proposed analyzing images of leaves to monitor crop health. Its core is to use neural networks to learn the features of leaf images (Grinblat et al., 2016). The neural network has the characteristic of nonlinear activation. Neural networks have powerful perception capabilities and can identify the categories of leaf pests and diseases. The process of this approach is shown in Fig. 1.

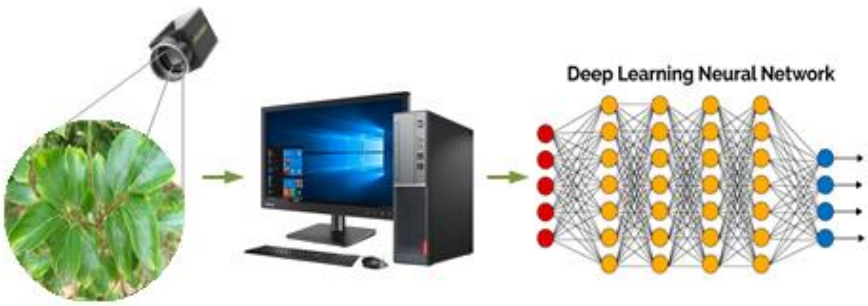

FIGURE 1. Flow chart of image recognition by neural network.

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It outlines three main steps. First, an industrial camera is used to capture a large number of leaf images and transfer the data to the computer. It may consume a lot of manpower and time. Then, the neural network model for analyzing the data is constructed and trained. This step requires as much computational method and power as possible. Finally, the performance of the model is verified and the results are visualized (Goldblatt et al., 2018). Some evaluation indicators will be used. The accuracy of this method is very high. But models need enough samples for learning. When the sample is not enough, it is difficult to meet the training of the model.

RELATED WORK

Traditional machine learning methods have been maturely used in image processing technology. S Yang designed a tipcap identification algorithm based on Harris corner detector. This method got overall accuracy of 95.6% for tipcap of kernels (Yang et al., 2011). JA Kolmer explored whether genetically differentiated groups of Puccinia triticina are present in Europe. It indicated there was a significant correlation between the SSR genotypes and virulence phenotypes of the isolates (Kolmer et al., 2013). F Galindo evaluated the effect of forms of application and doses of boron in irrigated wheat grain yield. It ensured profitability from production of irrigated wheat (Galindo et al., 2018). In the next year, Y Sun proposed an algorithm combining SLIC (Simple Linear Iterative Cluster) with SVM (Support Vector Machine) to identify tea plant leaf disease. The accuracy of the method was 96.8% (Sun et al., 2019). These methods needed manual feature extraction and could not explore the deep semantic information of images automatically. The accuracy of recognition was difficult to improve.

In recent years, deep learning have also been widely used in agriculture. In 2019, K Zhang tried to fine tuning the AlexNet network using transfer learning. The recognition effect of this method was better than traditional methods (Zhang et al., 2019). In 2020, S Lee used an improved convolution neural network to analyze tea leaves. The accuracy reached 77.5% on a dataset with a small number of samples (Sheng et al., 2020). In 2022, Gopinath Siddan proposed concept follows feature extraction and transfer learning based classification. Experimental results proved that deeper networks have better recognition ability (Siddan & Palraj, 2022). SA Rashwan used MobileNetV2 model to identify crop leaf pests and diseases. It maintained accuracy and also had faster analysis speed (Rashwan & Elteir, 2022). These methods have higher recognition accuracy when they were fully trained. But in the current production background, especially when the samples are not enough, they can not show good recognition effect. Therefore, this research proposed a method to identify the pests and diseases of crop leaves from the perspective of few-shot learning (Su et al., 2022).

MATERIAL AND METHODS

The leaves of apple and potato were analyzed in this research. There are 4 kinds of pests and diseases on apple leaves. They are healthy, browned, withered and spotted. As shown in Fig. 2(a). Their numbers are 672, 204, 240 and 104. There are 5 kinds of pests and diseases on potato leaves. They are healthy, browned, withered, perforated and spotted. As shown in Fig. 2(b). Their numbers are 748, 1032, 252, 884 and 848.

FIGURE 2. Image of apple and potato leaves.

In the process of image acquisition, the camera will be affected by the properties of the sensor material and the environment. There may be some pulse noise in the original image and it interferes with the observable information. Median filtering is carried out in the data preprocessing (Chervyakov et al., 2018). After filtering, the noise of the image is suppressed and the image becomes smoother. Fig. 3 shows original image, filtered image and the corresponding three-dimensional spectral graphs (Ran, 2019). It can represent the distribution of image information. Comparing the two spectral graphs, the influence of noise is obviously reduced and signal strength increase after median filtering. The information of the image is presented more clearly. In the experiment, the size of all figures was adjusted to 64×64. The input image contains three color channels R, G, and B. Some categories of leaves have a small number of samples. At the same time, consider the background of current agricultural production. In this research, a few-shot learning method was used to learn the image features and identify the pests and diseases of the leaves.

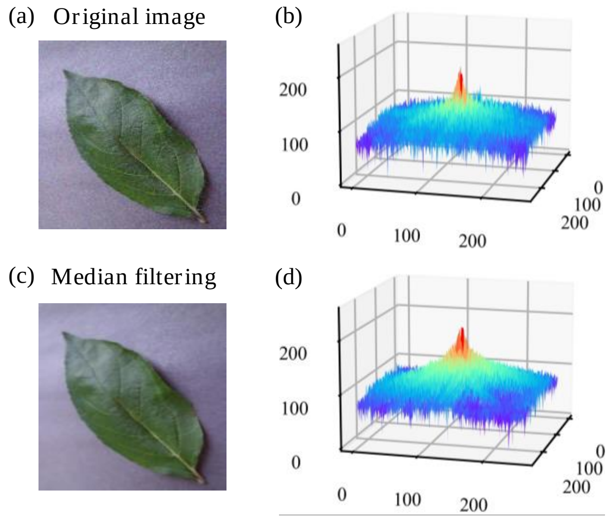

FIGURE 3. (a) is the original image. (b) is the three-dimensional spectral graphs of the original image. (c) is the filtered image. (d) is the three-dimensional spectral graphs of the filtered image.

This research adopts the idea of few-shot learning. Metric learning is a typical methods (Wang et al., 2023). Its principle is to calculate the distance of a pair of samples in the feature space. Calculating the similarity score and determine the category of the sample according to the score. Therefore, a siamese network which can handle a pair of samples is proposed (Luo et al., 2022). Its two subnetworks extract and obtain the feature vectors of the two samples respectively. The distance of two feature vectors in feature space is calculated based on the Manhattan distance (Kenchappa & Karibasappa, 2021). Mapping the distance to a score that represents similarity. The score of similar samples is higher. The score of different samples is lower. The score is used as the basis for determining the category. The training and testing process of the proposed method is shown in Fig. 4.

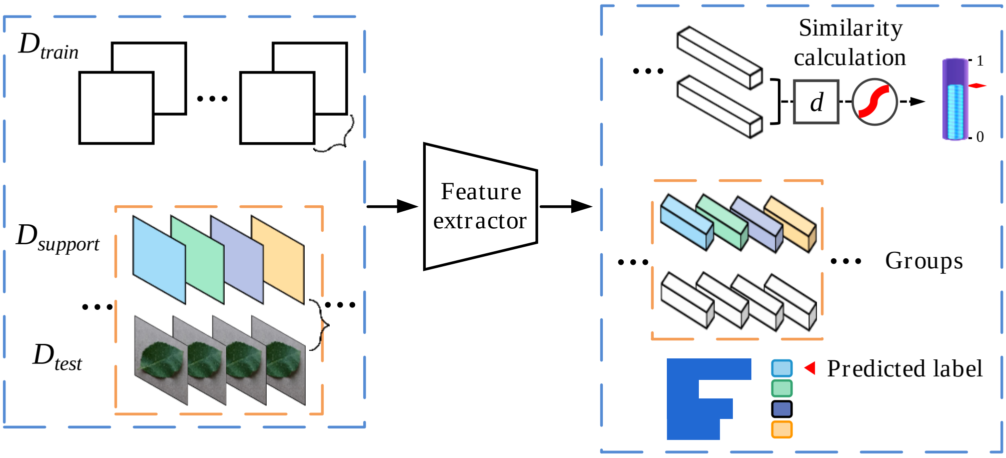

FIGURE 4. The flowchart of the proposed method.

Take the Apple dataset as an example. D_{train} is the train set that contains a certain number of sample pairs. The samples were selected randomly. Two samples in each pair are either homogeneous (The label is 1) or inhomogeneous (The label is 0). They remained balanced. $D_{support}$ is the support set, which consists of four samples. Each sample is randomly drawn from different categories of the test set. Their categories are explicit. D_{test} is a test set, in which each sample is copied 4 times to form 4 pairs of samples with the support set. The structure of Feature extractor is a siamese network. It is used to extract the feature information of sample pairs and output a pair of vectors. Manhattan distance is used to measure the distance of two feature vectors in feature space. As shown in formula (1).

$$d(v_1, v_2) = \| v_1 - v_2 \| \tag{1}$$

Where:

v_1 and v_2 represent two feature vectors respectively.

The Sigmoid function is used to map the distance to a score in the range (0, 1). As shown in formula (2). This score represents the similarity of two vectors. During the training stage, the model will learn how similar the features are. The binary cross entropy loss function was used to update the weight of the parameters (Li et al., 2021). As shown in formula (3).

$$score = \frac{1}{1 + e^{-d(v_1, v_2)}} \tag{2}$$

$$L(score, t) = t\log(score) + (1-t)\log(1-score) \tag{3}$$

In formula (3), t indicates whether two random inputs belong to the same class. If they belong to the same class, t=1. Otherwise t=0. After model calculation, the score between samples of the same class will approach 1. The score between samples of different classes will approach 0. In the test stage, the score is used as the basis to judge the category. The support set sample corresponding to the maximum score in each group is considered to be in the same category as the test sample.

The main structure of the proposed method is a siamese network. It is also a feature extractor. Its two subnetworks have the same structure and share parameters. Two of the sample pairs are fed into two subnetworks. In the subnetwork, the convolution layer is used to extract the feature information of the sample image (Taresh et al., 2021). The batch normalization layer speeds up the iterative convergence of the network (Du et al., 2022). The maxpooling layer is used to compress the size of feature map. This speeds up the calculation. The role of the dropout layer is to prevent the model from overfitting. At the end of the subnetwork is a fully connected layer. It outputs a feature vector so that representation of the sample feature information can be obtained (Barbhuiya et al., 2022). The overall framework of the model is shown in Fig. 5.

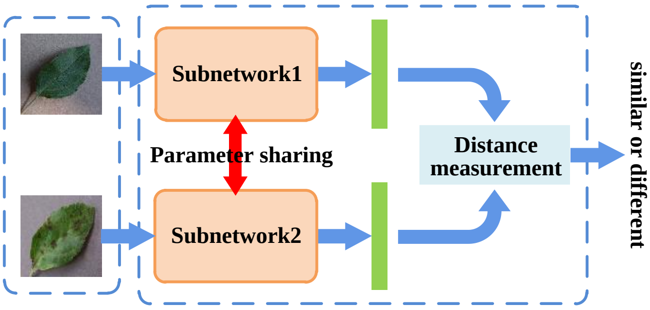

FIGURE 5. The frame diagram of the model.

Calculate the Manhattan distance in feature space for the outputs of two subnetworks. The similarity is obtained to determine whether the two samples have the same category. The higher the similarity, the more likely it is that two samples belong to the same category. The structure of the subnetwork is shown in Fig. 6.

The first layer of the subnetwork is a convolution layer with 32 filters. The second layer is a convolution layer with 64 filters. Each convolution layer is followed by a batch normalization layer and a maxpooling layer. Each pooling reduces the length and width of the feature map to a quarter of its original size. Subsequently, the feature map was mapped to a fully connected layer containing 64 neurons. Create an attention module on the basis of the fully connected layer. The attention module is used to adjust the information data of the neurons in the fully connected layer.

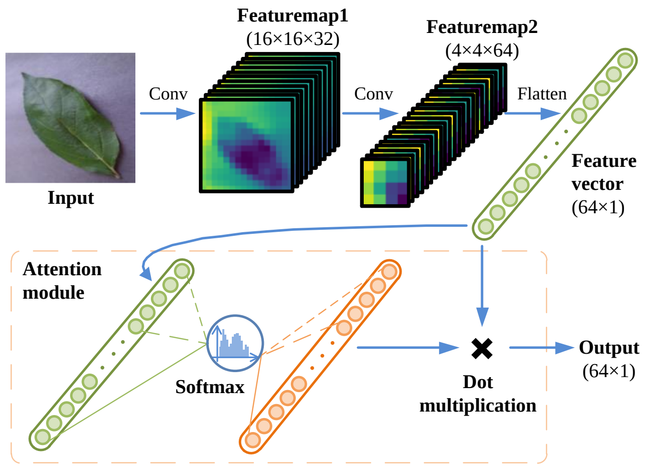

FIGURE 6. The structure diagram of the subnetwork.

Specifically, the weight of neurons in the fully connected layer is changed through Softmax function in another branch (Guo et al., 2020), then the dot multiplication operation is performed with the original fully connected layer. The Softmax function is shown in formula (4). It represents a probability distribution of weights.

$$Soft\max(z_i) = \frac{e^{z_i}}{\sum_{c=1}^{C} e^{z_c}} \tag{4}$$

In formula (4), z_i is the value of the i_{th} neuron and C is the number of neurons. The Dropout layer is also added after the convolution layer and the fully connected layer. It causes some neurons to stop working during forward propagation (Zhangirov et al., 2020). The model will generalize better. Finally, the subnetwork outputs feature vector. At this point, the extraction of image features is completed. Then calculate the Manhattan distance between the two vectors in the feature space and the similarity score will be obtained by sigmoid function. This is also the basis for determining the categories of leaf pests and diseases.

RESULTS AND DISCUSSION

The operating system used in this research is Windows10. The processor is the Inter(R) Core(TM)i5-10400M. The computing architecture is CUDA10.1. The deep learning framework is Pytorch1.8.0. Table 1 shows the main layers and parameters of the subnetwork. The network model designed in this research has a small number of parameters. It computes faster than large networks. The recognition results can be obtained in real time (Zhu et al., 2022).

TABLE 1. The structure table of the subnetwork.

Layer name	Kernel size	Stride	Kernels	Output size	Parameters
Input	—	—	—	64×64×3	—
Conv1	3×3	(1.1)	3	64×64×32	896
BN1	—	—	—	64×64×32	128
Pool1	4×4	(4.4)	32	16×16×32	0
Conv2	3×3	(1.1)	32	16×16×64	18496
BN2	—	—	—	16×16×64	256
Pool2	4×4	(4.4)	64	4×4×64	0
Flatten	—	—	1024	1024	0
Output	—	—	64	64	65600

In the experiment, the train set and the test set were divided according to the ratio of 3:1. To verify the effect of the proposed method. Multiple experiments with different sample size were carried out. And the method proposed in this research is compared with the existing methods. The accuracy of different sample size is shown in Table 2 Fig. 7 is the corresponding line chart.

TABLE 2. Table of accuracy in each group.

Dataset of apple leaf (%)								
Sample size	Number of training samples							
	60	90	120	180	240	300	600	900
Random Forest	59.02	65.25	68.52	72.13	73.11	75.41	78.36	80.33
SVM	65.57	68.52	70.16	71.8	76.39	83.61	87.21	88.2
ResNet	78.36	80.98	82.3	84.59	90.82	92.79	96.07	97.38
AlexNet	79.67	87.21	93.11	95.08	95.74	96.39	97.38	97.7
VGG	82.3	86.56	91.8	93.77	94.1	96.72	97.7	98.03
Proposed method	86.23	92.13	96.07	97.05	97.7	98.03	98.03	98.03
Dataset of potato leaf (%)								
Sample size	Number of training samples							
	60	90	120	200	500	1000	2000	2800
Random Forest	66.63	68.33	70.67	74.07	76.62	82.46	85.12	86.29
SVM	61.64	64.93	69.08	71.41	78.21	81.4	83.32	84.91
ResNet	79.38	83.53	86.4	89.27	91.6	92.77	93.41	93.52
AlexNet	80.55	82.78	87.57	91.39	93.3	94.05	95.21	95.75
VGG	82.04	87.46	90.22	92.03	95.01	96.28	96.92	97.02
Proposed method	84.27	91.29	94.26	96.07	96.71	97.13	97.34	97.34

In Table 2, the accuracy of method proposed in this research reached 98.03% and 97.34% respectively. In Fig. 7, when the sample size is same, the method proposed in this research has the highest accuracy.

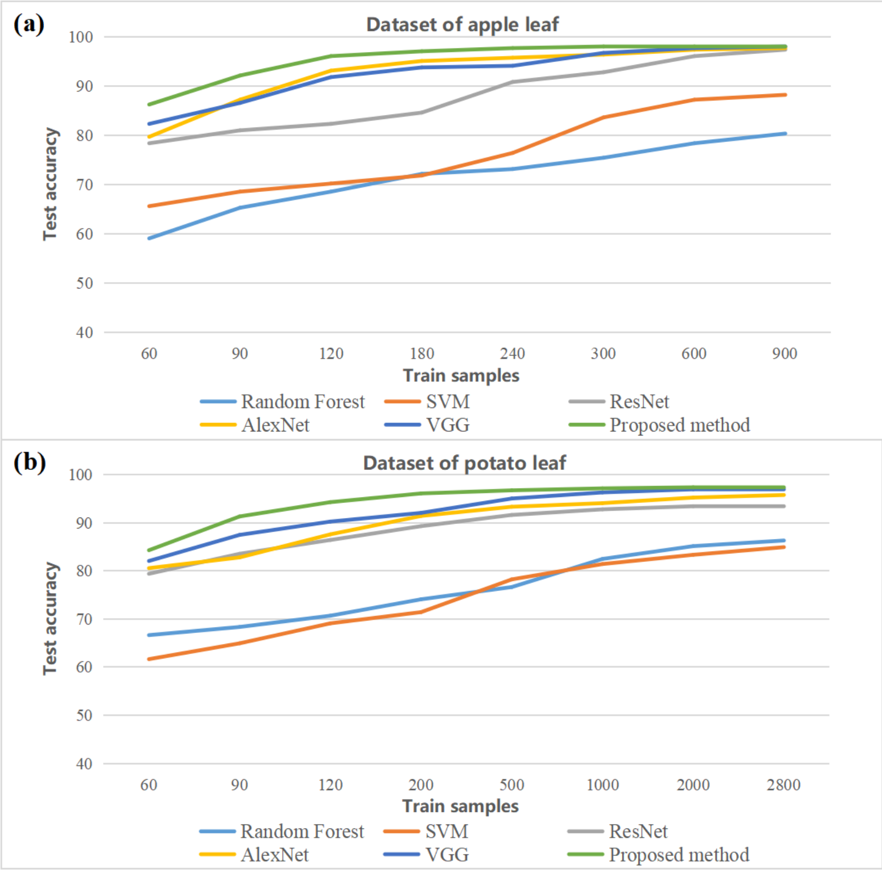

FIGURE 7. Line chart of accuracy with the different sample size.

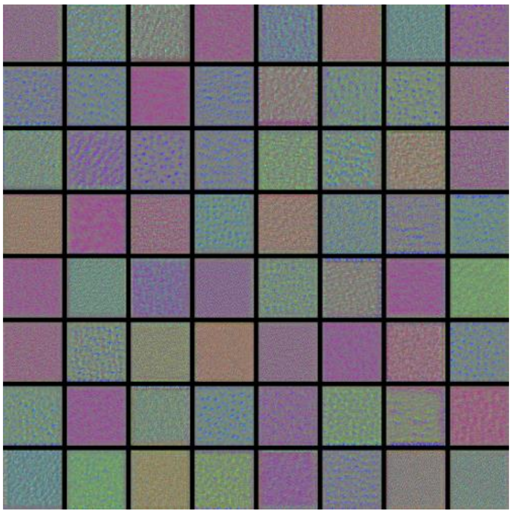

FIGURE 8. Visualization of deep convolution filters.

And in the case of only 90 samples, both accuracy rates are more than 91%. The leaf pests and diseases can be analyzed effectively by the proposed method when the number of samples is small. With the increase of the number of samples, the proposed method can quickly approach the optimal state (Pereira et al., 2021). Fig. 8 visualizes the deep convolution filters. Each convolution filter has a unique pattern of detail feature extraction. They can sense and discover subtle features distributed across images. In the experiment, the characteristic regions that the model was interested in were visualized in images of leaves infected with pests and diseases. This is shown in Fig. 9.

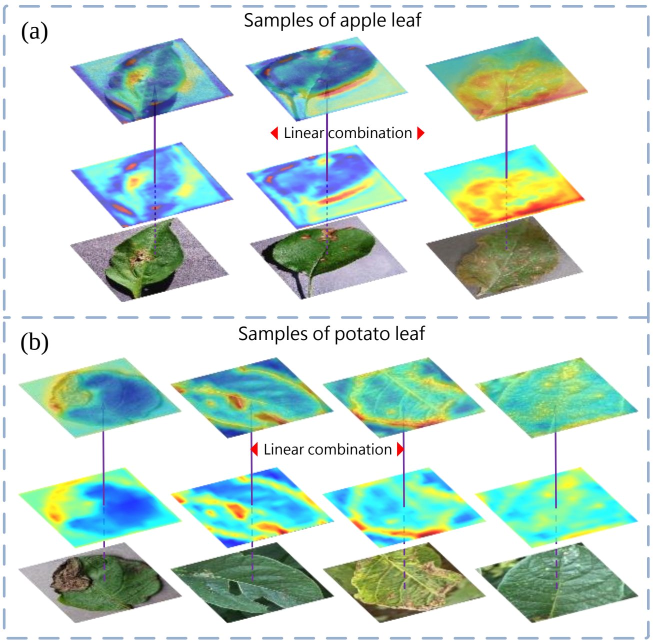

FIGURE 9. Visualization of image feature area.

Fig. 9(a) corresponds to apple leaves infected with pests and diseases. Fig. 9(b) corresponds to potato leaves infected with pests and diseases. Among them, the preprocessed images are at the bottom. The feature maps of the images are in the middle. The linear combination images are at the top (Schnlein, 2022). It can be seen that the method proposed in this research can effectively extract the main features of the images. Areas of the leaves infected with pests and diseases can be correctly identified. It helps to properly cultivate crops and eliminate pests and diseases. In the experiment, the confusion matrix is used to show the recognition rate of the test set samples (Zhao et al., 2022). After extracting features from subnetworks, the T-SNE method is used to visualize the distribution of samples in the two-dimensional plane (Ardali et al., 2022). As shown in Fig. 10.

From Fig. 10(a) and Fig. 10(b), it can be seen that the model can correctly identify the vast majority of samples of these two crops. The accuracy of the proposed method to identify some pests and diseases reached 100%. It shows that after iterative training, the model can accurately extract the features of the samples and analyze the degree of similarity between the features. Fig. 10(c) and Fig. 10(d) show the distribution of samples in the two-dimensional feature plane. In particular, all the output vectors of the fully connected layer are compressed into two-dimensional vectors. Their positions are represented by scatter points on the plane. The distribution of each category of samples can be clearly seen from the figure. It proves that the proposed method can extract the main and similar features of each type of samples.

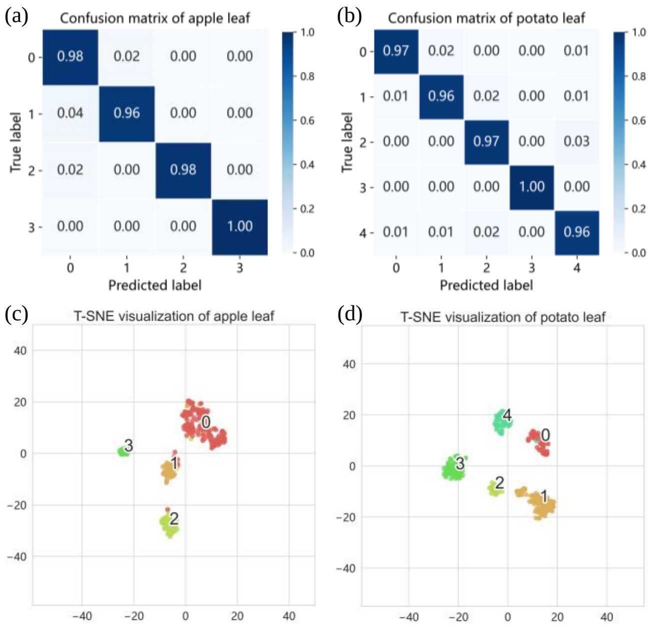

FIGURE 10. Confusion matrix and T-SNE visualization diagram.

The experiment also explores the ability of the model to recognize new categories. In the training stage, all samples of some categories are randomly excluded. Only the remaining categories are offered to the model for learning. The average accuracy of the model identification across all categories is verified during the test stage (Pimenta et al., 2022). Table III shows the effect of the model on the recognition of new categories of two crops.

TABLE 3. Accuracy of recognition new categories.

Train samples	3 new categories	2 new categories	1 new categories
60 (apple leaf)	—	77.05	82.3
60 (potato leaf)	63.34	72.58	78.85
90 (apple leaf)	—	81.64	86.23
90 (potato leaf)	66.21	76.09	83.32
120 (apple leaf)	—	84.26	89.51
120 (potato leaf)	68.54	79.17	84.91

■ apple leaf ■ potato leaf

It can be seen from Table III that the model is capable of identifying new categories of samples. With fewer new categories, experience-constrained model can learn more knowledge. The model extracts the characteristics of similar samples. This helps in the judgment of new categories of samples. Accuracy is improved even with very small training sample size.

CONCLUSIONS

This research considers that in the background of advanced agricultural technology will reduce crop infection with pests and diseases. And manually collecting data will be difficult. For solving the problem of small sample size, this research proposed a few-shot learning method to identify crop leaf pests and diseases. The main structure of the method is a siamese network. It extracts and outputs a pair of feature vectors. Calculate the Manhattan distance between the vectors to evaluate the similarity. It is used as a basis to judge the categories of leaf pests and diseases. The experiment proves that the method proposed in this research has better recognition effect when the sample size is small. As the sample increases, the model rapidly approaches the optimal. The results of this research are applicable to current agricultural production field. It has good practical significance for crop cultivation and pest prevention. In addition, the model structure can be modified flexibly. It can provide ideas for other industrial production fields.

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