Research of Image Recognition of Plant Diseases and Pests Based on Deep Learning

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ABSTRACT

Deep learning has attracted more attention in speech recognition, visual recognition, and other fields. In the field of image processing, using deep learning methods can obtain a high recognition rate. In this paper, the convolution neural network is used as the basic model of deep learning. The shortcomings of the model are analyzed, and the DBN is used for the image recognition of diseases and insect pests. In the experiment, firstly, the authors select 10 kinds of disease and pest leaves and 50,000 normal leaves, each of which is used for the comparison of algorithm performance. In the judgment of disease and pest species, the algorithm proposed in this study can identify all kinds of diseases and insect pests to the maximum extent, but the corresponding software (openCV, Access) recognition accuracy will gradually reduce along with the increase of the types of diseases and insect pests. In this study, the algorithm proposed in the identification of diseases and insect pests has been kept at about 45%.

KEYWORDS

Convolution Neural Network, Deep Confidence Network, Deep Learning, Improved Depth Confidence Network

1. INTRODUCTION

China is a big agricultural country, and agriculture itself has the characteristics of ecological region and season complexity. Agricultural information can further promote the development of agriculture. Agricultural Internet of things is a major means to achieve information, using video sensor nodes to build a remote monitoring network to observe crop growth. However, the current crop monitor has the following problems(Wang, 2018) .There is no information record when the equipment is used to observe the occurrence of crop rot and weeds. The inaccurate identification of crop diseases and pests will lead to the blind use of fertilizers and pesticides, which will damage the environment and endanger food safety.

As a branch of machine learning, deep learning (Shi, 2015)can be regarded as a new type of artificial neural network. Deep learning has a very wide application in image processing. Bian Weixin and others used the depth Boltzmann machine (DBM) to recognize infrared face expression (Bian & Ding, 2019); He Pengcheng extracted operator to use DBM for types of vehicle recognition (He, 2016); Sun Mingshun studied the de-noising limited Boltzmann feature extraction algorithm (Sun, 2016), and the extracted features were used for target image recognition, and the error rate was only

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6.45%; CNN (Xu et al., 2012) has many applications in image target recognition. The target recognition algorithms represented by r-cnn (Li et al., 2018) include r-cnn, spp-net (Zhao et al., 2019), fast r-cnn (Zhao et al., 2017), faster r-cnn (Yao et al., 2017).

Based on the deep learning model, we mainly study the convolutional neural network, analyze the advantages and disadvantages of the model in image recognition. We make an acute improvement based on the deep confidence network (DBN) (Shao et al., 2019) in this paper. According to the problem of image recognition of crop diseases and insect pests, the performance of the algorithm proposed in this paper is tested from the algorithm level, and the algorithm is compared with the recognition software of pest image.

2. CONVOLUTION NEURAL NETWORK (CNN)

The deep learning model is a multi-layer mode constructed by integrating the convolution layer and the hidden layer. The common BP neurons are shown in Figure 1, and the corresponding functions are as follows (Aiqin et al., 2014):

$$R_{t,b}(a) = f(t^T a) = f(\sum_{i=1}^{3} t_i a_i + b) \tag{1}$$

In formula (1), f is the activation function, usually is a nonlinear function, such as sigmoid, ReLu, etc., and the neural network model is composed of multiple neurons. Figure 2 shows a three-layer BP neural network structure. Images can be represented in pixels, each pixel can represent one dimension, and the image of 100×100 is represented as 10000 dimensions correspondingly, and each dimension is represented as vector. If the dimensions of the input image set and the hidden image set were the same, the corresponding order of magnitude of the vector would be 10000^2. The order of magnitude is too large, and there is serious redundancy.

Figure 1. Basic model of neurons

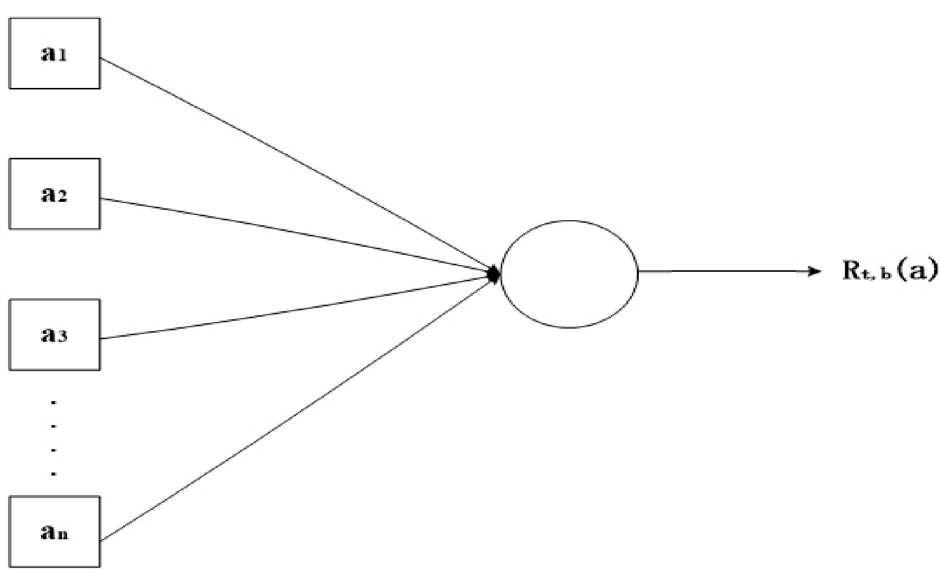
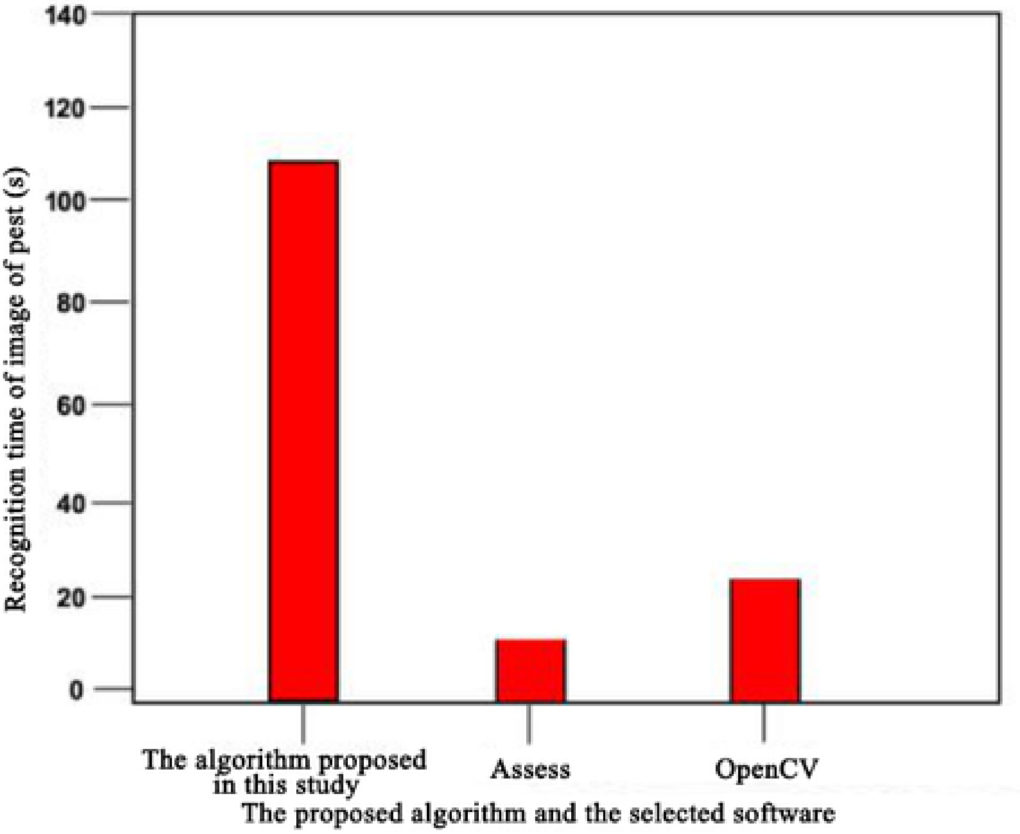


Figure 2. Three layer BP neural network structure

We use CNN to realize local visual field perception and the same weight in the same channel is used to reduce the order of magnitude of vector. The local visual field perception is based on the observation features of the human eye from the local to the overall. The hidden layer is only associated with the neuron set of the previous layer in the multi-layer neural network structure, so that the vector order of magnitude of the product will be greatly reduced, as shown in Figure 3 (Yang et al., 2014).

As the image of 100×100 is shown in CNN in Figure 3, assuming that each neuron in the hidden layer is associated with the 100 dimensions, the vector order of magnitude is reduced to 10^6, which are several orders of magnitude less than that of fully connected neural network. It is used the local sharing weights in CNN, that is, the features of the local image region are the same, and the convolution can be carried out between the vectors of the feature set and different vector of the partial region. The feature set of the corresponding region can be described as convolution kernel. When convolution kernel and image of the corresponding region are convoluted, convolution kernel can slide. Formula (2) shows the process of convolution of a 3×3 convolution kernel on 4×4 image.

Figure 3. Local visual field perception



$$\begin{bmatrix} 1 & 1 & 1 & 0 \\ 0 & 1 & 1 & 1 \\ 0 & 0 & 1 & 1 \\ 0 & 0 & 1 & 1 \end{bmatrix} \oplus \begin{bmatrix} 1 & 0 & 1 \\ 0 & 1 & 0 \\ 1 & 0 & 1 \end{bmatrix} = \begin{bmatrix} 4 & 3 \\ 2 & 4 \end{bmatrix} \tag{2}$$

As is shown in formula (2), the dimension of the corresponding region is obviously reduced after using CNN. The original image is of 4×4, and after convolution, it becomes the image of 2×2. After the feature is obtained by convolution, the classifier can be trained. However, there are still too many features after convolution, which leads to the large amount of computation, the regional feature fitting and image recognition distortion. In order to solve this problem, aggregate images of different local regions, and take the maximum or average value of different parts for local feature representation. This aggregation operation is also called pooling (Zhang, 2014).

3. SHORTCOMINGS AND IMPROVEMENT OF CONVOLUTION NEURAL NETWORK

In this paper, the deep learning method is used in the study of agricultural pest image recognition, convolution neural network is the research object, and we analyze the shortcomings of convolution neural network. The deep belief network is the model to be optimized, and we improve the model. The efficiency of learning is improved. Meanwhile, in order to improve the recognition accuracy, the deep belief network is used in the algorithm of wavelet block in color feature extraction to improve the recognition accuracy, the recognition efficiency is guaranteed and the recognition accuracy is improved.

3.1 Shortcomings of Convolution Neural Network Algorithm

Convolutional neural network (CNN) is adopted the insidious structure of human brain. The derivation of things is divvied into several stages. Each stage is implemented by convolution layer. After the derivation of each layer is completed, the current data need to be sampled for the next derivation. The process is realized by the down-sampling layer. The convolution layer can be used to enhance the original data and improved the recognition value of the data, that is, the data most in line with the feature requirements can be selected from the current data according to the selection requirements; get the down-sampling layer in the local image, and the image is regarded as a collection of several regions, and there are neighborhoods between regions, thus the amount of data calculation (Ren et al., 2015) is reduced in extracting important information.

Although convolution neural network has many advantages, its training time is too long. The training method is from the first layer of convolution layer to the last layer. Therefore, we study the deep belief network (DBN) in this paper, which can train the calculation of different layers in parallel, and the solution speed is greatly improved.

3.2 The Improved Deep Belief Network

There may be common features (Shang, 2016) in a group of images training used DBN. During the calculation, the corresponding data of the partial features can be removed from the data set. The data with common features are put into the restricted Boltzmann machine (RBM) for feature extraction, and the data sets with mixed data are trained in the non-shared layer RBM. It should be emphasized that the extraction of shared features is completed at the bottom layer, thus the corresponding improved depth belief network structure is shown in Figure 5.

In Figure 4, the shared RBM and unshared RBM are used as layers, and a feature recognition layer Er is is needed between them, that is, regression analysis method is used to obtain the common features from the shared data layer. These features are put in the Er layer, and the image data of RBM hidden layer is accepted as input. These data are filtered, and the features output in the shared layer also are into the unshared RBM layer. The shared RBM layers are used to extract common features, while the unshared RBM layer is used to further classify the data with other features.

By using shared / unshared RBM, much data with common characteristics can be eliminated when multiple non shared RBM layers are calculated at the same time. When multiple non shared RBM layers are calculated at the same time, a lot of data with common features can be removed to improve the calculation efficiency. In order to mine the main common features of image data set, the number of features should not be too much, that is, a small number of common features can represent this kind of image. Specifically, we need to consider whether the calculation amount of data can be reduced continuously. We can eliminate the supervised fine-tuning of the data nodes in the sharing layer, that is, we do not give the sharing layer label any more and remove it from the training data set.

In the improved deep belief network, unsupervised training is used for the shared RBM layer and supervised training is used for non-shared RBM layer. There is no interference between them, which is helpful to the parallel of layer to layer data training. The algorithm implementation process of the improved deep belief network is as follows:

In Figure 5, it can be seen that the whole improved deep belief network is realized in the parallel processing between layers. Meanwhile, after the introduction of the shared layer RBM the data sets that are not needed can continuously be eliminated in the process of calculation.

Figure 4. The improved structure of the deep belief network

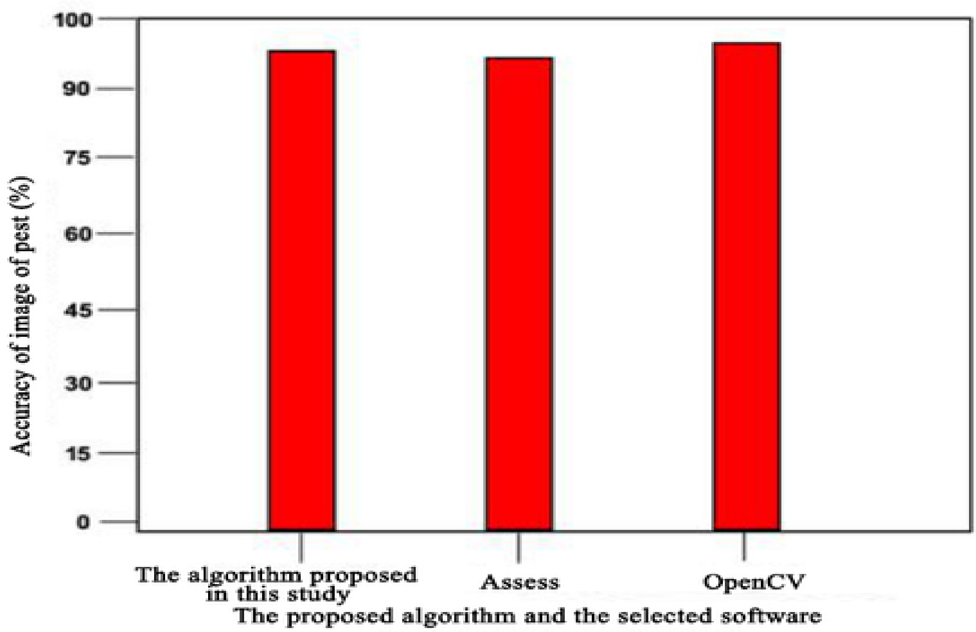
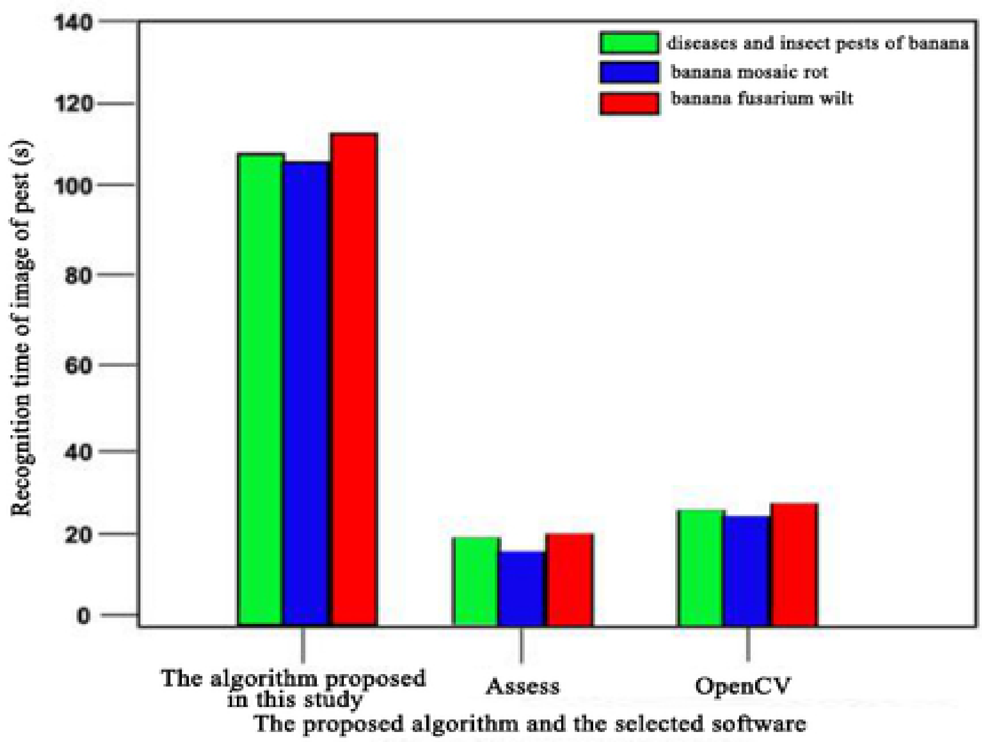


Figure 5. Implementation process of improved deep belief network algorithm



3.3 Wavelet Block Color Feature Extraction Algorithm Based on DBN

In order to improve the recognition accuracy of image recognition, it is necessary to optimize the feature extraction. Content based image retrieval (CBIR) is different from the traditional image retrieval method, it can realize the fuzzy recognition of the image. In the recognition process, the feature space is obtained from the image to identify other images. The features selected in CBIR can be color feature, texture feature and shape feature. The computational complexity of color feature is relatively low. Therefore, color feature is used to realize the image feature extraction.

The color features are regional in the image, and the information extraction of local area can be realized by the wavelet block. The Fourier transform is used to divide the different regions of the image according to the attention degree of the human eye. The different colors are regarded as the aggregation of vectors. A color pixel should include the feature vectors such as hue (H), brightness (I), color saturation (s), etc. The color feature set of the whole image can be obtained by the proportion of each color in the whole image.

The spatial distribution of the image is not adopted the global color histogram. It can be seen from the human visual characteristics, people will pay more attention to the center of the image, but not enough to the four horns around the image. Therefore, the image can be divided into eight blocks, that is, the image is divided into eight color regions, as shown in Figure 6.

According to previous, a color pixel can be represented by hue (H), brightness (I) and color saturation (s). In the color space of an image, the low-frequency part is retained most information of the image, and the medium and high-frequency parts are retained the details information of the image. In the calculation process, the corresponding features of each pixel are calculated by the average value, and the color region is divided according to the previous image division, which should contain different proportion coefficients. The following methods can be adopted in the calculation:

$$C_i = \sqrt{(x_i - x_0)^2 + (y_i - y_0)^2},\ i = 1,2,3..8 \tag{3}$$

$$S = | x_i - x_0 || y_i - y_0 | \tag{4}$$

$$\beta = \frac{S_i}{S_{total}},\ 0 < \beta < 1 \tag{5}$$

It will achieve good effect that DBN is used in color feature extraction, but after multiple transformation of feature of RBM, the image will lose its original feature information, that is, many image features will be lost after continuous unsupervised learning. Therefore, the color feature can be combined with the down sampling of DBN. The dimension of the filtered data can be reduced by the down sampling process, and then the color between image regions Feature can be preserved, and the partial connection between the image areas can be realized, as shown in Figure 7

After the introduction of the down sampling layer, the input layer is composed of $N_i \times N_i$ matrix. The hidden layer is contained k units and each group is contained $N_u \times N_u$ elements. Color features are included in these cells, and it is not suitable to select too many color features in actual calculation. Each unit of the k-group is associated with the filter of $n_g \times n_g$, and the characteristics of the filter within the group are shared. The down sampling layer is a step of the deep belief network, the local connection between the layers can be reached, and the weights of the model can be shared. The parameters trained in the previous layer can be retained, and the corresponding activation function

Figure 6. Image segmentation

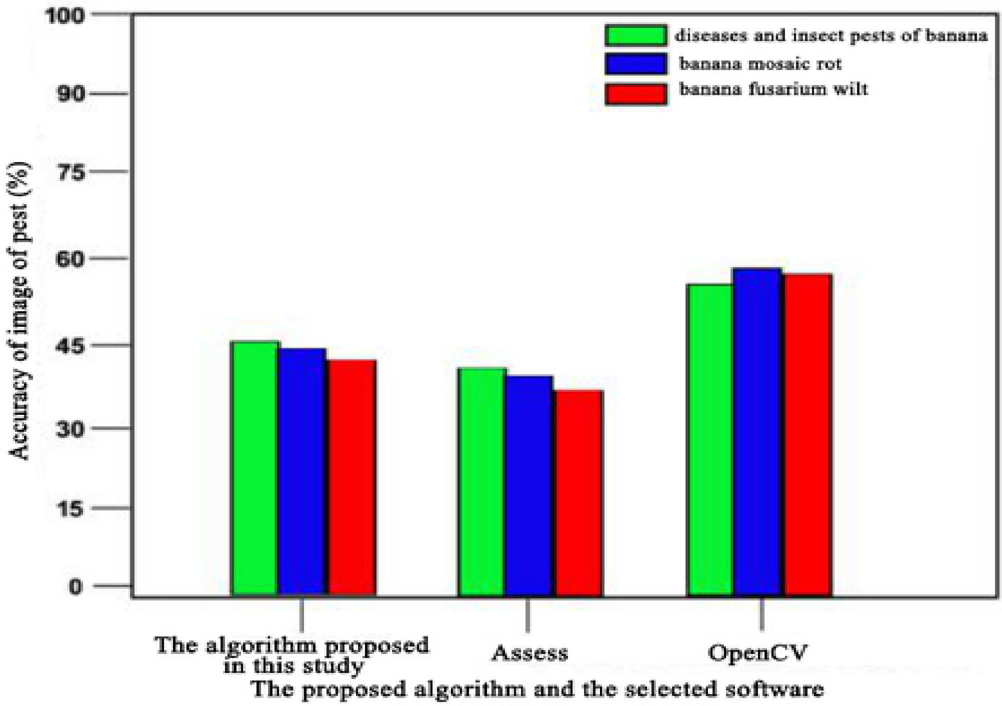
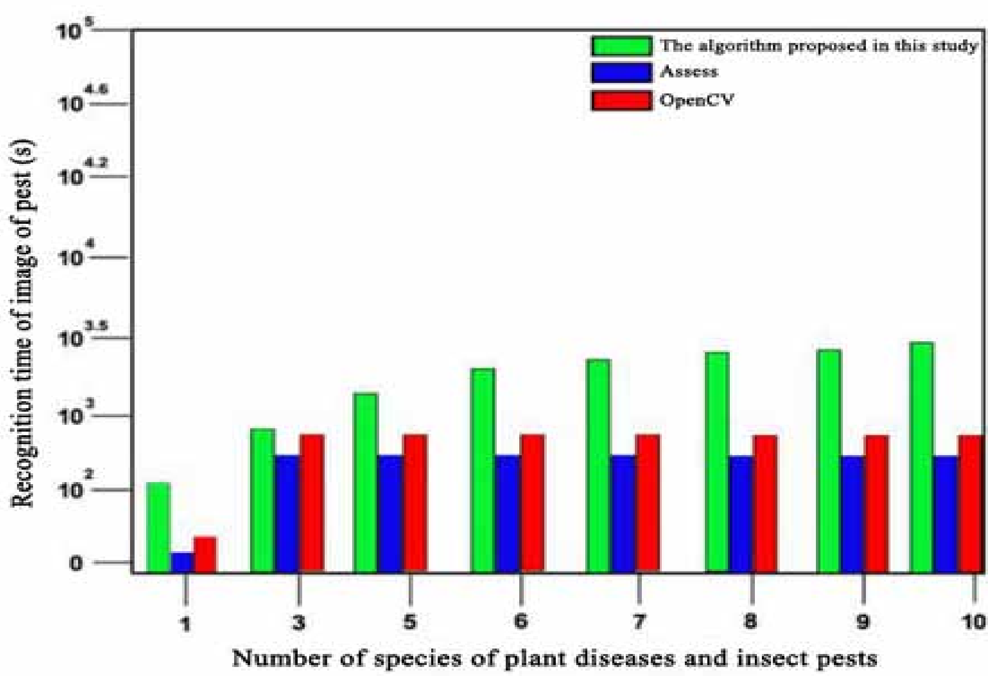


Figure 7. Color feature extraction in down sampling layer



value can be used as the input of the next layer. After the training of all layers is completed, the back-propagation algorithm is used to supervise the image learning and the weight is adjusted in the down sampling DBN layer.

In Figure 8, the wavelet non-uniform block is used to divide the image, and each color feature is obtained based on his. After the down sampling layer is introduced, the data is filtered and the dimension is reduced, so as to ensure that most of the feature information of the image can be retained, and then the main color features of the image are obtained in RBM.

4 EXPERIMENTAL PART

4.1 Experimental Environment

It is necessary to test the performance of the improved deep belief network algorithm that is the wavelet block color feature extraction algorithm is introduced in the experiment. The deep belief network is the main research model involved in this study. The hardware environment of the test is as follows in Table 1:

We need a distributed computing environment in the experiment. We use MySQL 7.5 and three HP hosts to build a virtual cluster for image data storage and feature calculation. The selected diseases and insect pests include gray mold, bacterial leaf blight, banana diseases and insect pests, banana mosaic heart rot, banana bunchy top disease, Banana Fusarium wilt, banana scab, banana leaf, brown edge gray spot disease and coal stripe disease. The above-mentioned plant samples for image analysis are from the plant disease epidemiology Laboratory of China Agricultural University. A digital camera with a pixel of no less than 20 million pixels is needed to take pictures. The image resolution is high, thus the processing time of the software is reduced and is helpful to image recognition and planting sample evaluation.

In addition to performance comparision of the algorithms, we will also compare the performance of the proposed algorithm with the image software. The image analysis software of plant diseases and insect pests commonly used in the market includes Assess,Sigma Scan Pro software,Visual C++,Matlab,Photoshop, free software / sharing software such as opencv, python, etc. these software can be used for image analysis of plant diseases.

The proposed image recognition algorithm is compared with OpenCV,Assess, and assess is an image processing algorithm application software for disease measurement, and it is not a multi-functional comprehensive software, but simple, cost-effective and highly professional software. The software is a professional software for agricultural disease evaluation, and a lot of fund for software is saved, and is widely used in the field of plant protection; OpenCV is an open source, computer vision library for cross platform, and it can run on Linux, windows and Mac OS operating systems, it supports C + + programming language, provides python, ruby and other language interfaces, and realizes the general algorithm of image and computer vision.

4.2 Experimental Data

The main programming language is python, which is with good interactivity and concise code writing. Numpy is a function extension library in Python, which provides rich functions and has strong data processing ability. We select leaves of many crops as data sources in the pest image database used in this algorithm, and the leaves are divided into normal and pest leaves according to the growth of leaves. These leaf images are collected and studied data, as shown in Figure 9 and Figure 10

In Figure 9 and Figure 10, the database contains 50000 normal leaf images and 50000 pest leaf images. In order to test conveniently, each image is adjusted to 256×256 pixel RGB image. It can be seen that the selected diseases and insect pests include gray mold, bacterial leaf spot, banana diseases and insect pests, banana leaf rot, banana bunchy top disease, banana fusarium wilt, banana scab and banana leaf spot disease, brown edge gray spot disease, coal grain disease. In order to test whether

Figure 8. The flow of color feature extraction algorithm with down sampling layer

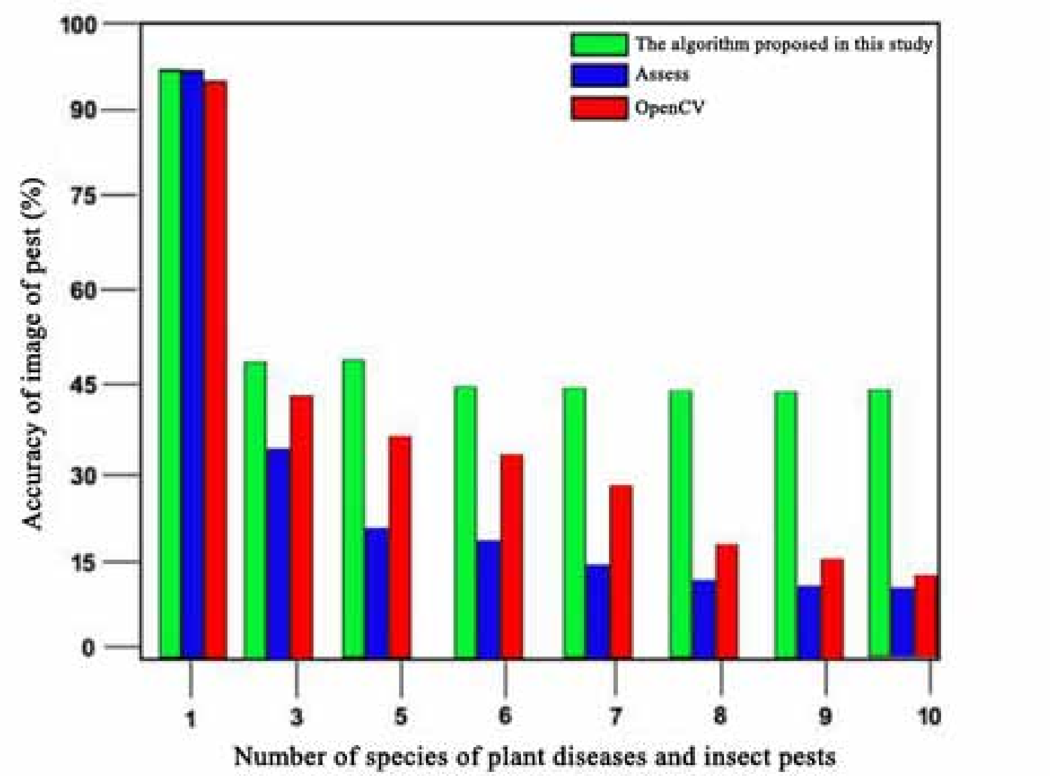


Table 1. Test hardware environment

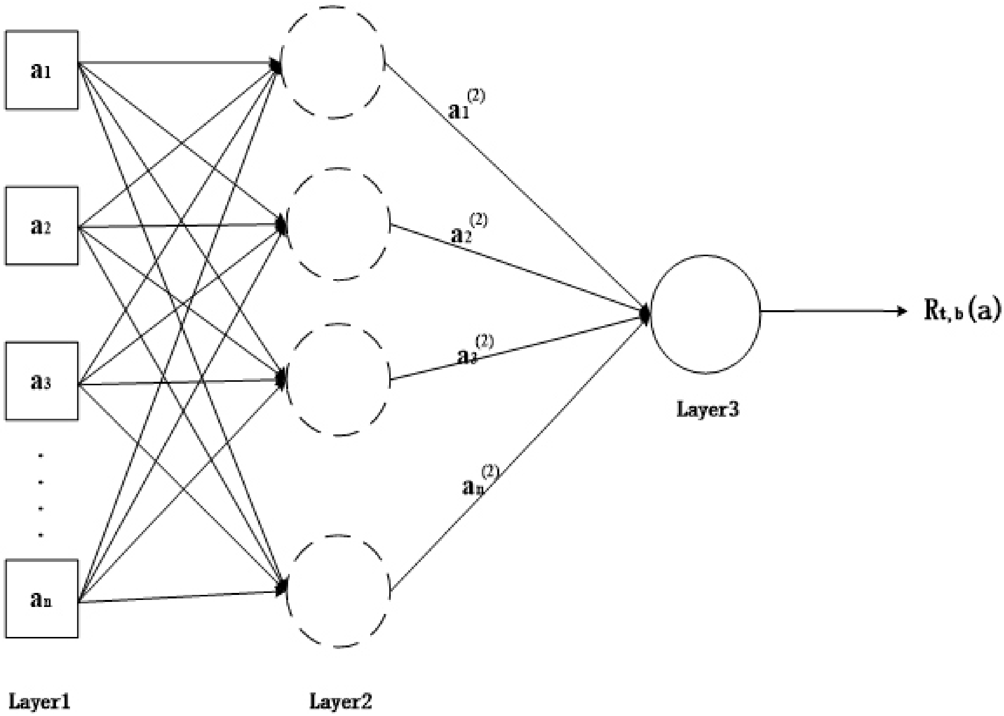
hardware	type
CPU	Intel i7 9700K+ MPG Z390
MEMORY	128G
GPU Video card	NVDIA GeForce GT 1080TI
OS	Supports 32-bit Ubuntu 10.04 (version 2.6.32)
DATA OPERATION	Matlab 2014b, python 2.7.8

the shared layer can be processed independently from the non shared layer, the number of layers of DBN model is set as 3 layers, and the number of nodes in each layer is set as 800. In order to grasp the main features of the image much better, and distinguish the normal part and the diseased part of the leaf much better, gray-scale processing is carried out on the image color.

4.3 Result Analysis of the Proposed Algorithm

First, we select 5000 images from normal leaf images and pest leaf images for training sessions of the shared layer. According to the previous analysis, the training of shared layer includes steps of supervised training and unsupervised training. The improved deep belief network algorithm is used

Figure 9. Collection of leaves of different kinds of diseases and insect pests



to identify the performance of the shared layer. Meanwhile, the training steps of the shared layer are adjusted during the testing process, and the recognition performance is as follows:

In Table 2, the recognition rate of different leaf images is about 40% in the improved deep belief network. The recognition accuracy is improved in the combination of unsupervised and supervised training. With the increase of iteration times, the recognition accuracy will be further improved.

In order to compare the recognition effect of the improved deep belief network model and the conventional deep belief network model, 5000 and 8000 images are selected from the normal leaf image and the pest leaf image respectively. The training results are shown in Table 3:

In Table 3, the efficiency of training is improved by introducing the sharing layer into the improved deep belief network. Compared with the training results of normal leaves before and after the improvement, the result is slightly improved in the improved deep belief network, we increase the number of training images, and the effect of the improved deep belief network algorithm is much better. The recognition error rate of pest leaves is reduced from 52.74% to 48.37%.

In the aspect of feature extraction, the deep belief network is introduced to obtain the improved wavelet block color feature extraction algorithm, and the color feature is selected as the main feature type. In the previous research, it is mentioned that a lot of characteristic information in the images will lost because of multiple use of RBM in conventional deep belief network, and the down sampling layer is introduced to realize the image dimension reduction, thus the feature information in images can be retained to the maximum extent. There are some errors in feature extraction used conventional deep belief network, and the number of features will also affect the error of feature extraction, as shown in Table 4:

The characteristic number and cumulative error is tested by using the conventional deep belief network, with the increase of calculation steps, the cumulative error will gradually decrease. At the

Figure 10. Collection of normal leaves

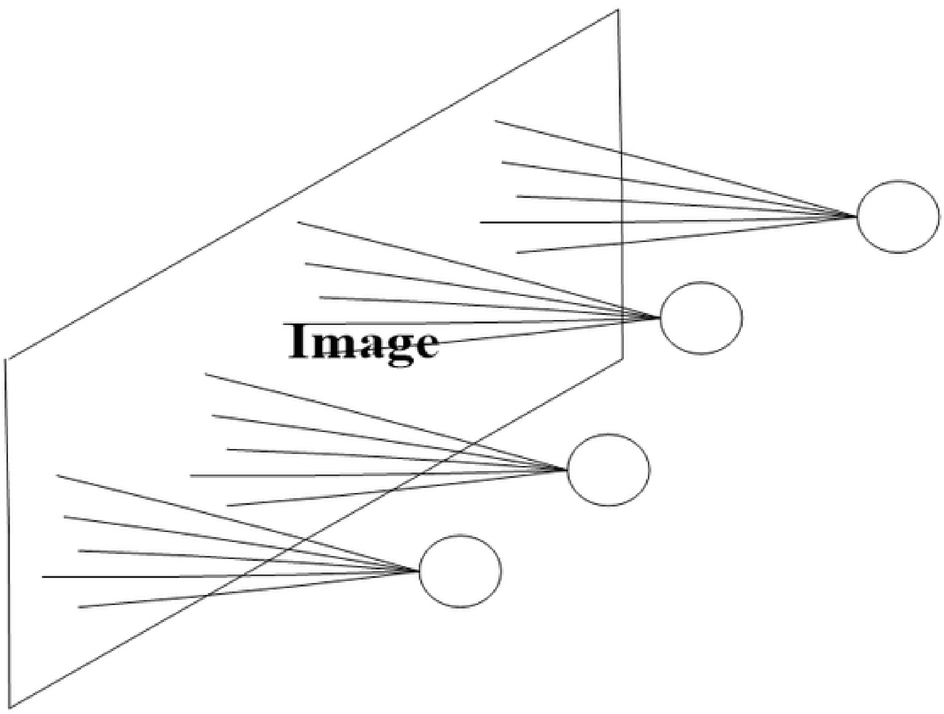


Table 2. recognition error rate of shared layer based on improved deep belief network and different training strategies

number of iterations	unsupervised training & supervised training	unsupervised training	supervised training	No (unsupervised training & supervised training)
2	64.25%	64.97%	58.77%	66.87%
10	63.87%	62.14%	57.29%	64.67%
15	61.88%	61.75%	56.78%	63.27%
30	61.25%	60.92%	55.34%	63.12%

Table 3. performance comparison before and after improvement of deep belief network model

	improved deep belief network		conventional deep belief network	
	normal leaves	leaves with pest	normal leaves	leaves with pest
error rate	42.657%	48.37%	48.95%	52.74%

Table 4. Characteristic error statistics after multiple iterations (unit: quart)

Steps Of Calculation	100 features	150 features	200 features	300 features
20	6.78	3.78	3.12	2.88
30	6.12	3.15	2.75	2.47
50	5.78	2.95	2.46	1.78
80	5.52	2.78	2.34	1.76
100	5.34	2.48	2.24	1.72

same time, the more features are selected, the less the cumulative error will be. Meanwhile, it can be seen that under the condition of certain feature number, as iteration times increase the effect of reducing the error become smaller and smaller. Therefore, it is necessary to select the appropriate number for feature extraction of crop.

We use wavelet block for color feature extraction in the optimized algorithm. Compared with the conventional color feature extraction, the improved algorithm reduces the selection of color features. Meanwhile, the main feature information of the image is retained by introducing the down sampling layer. We select 500 images from 10 kinds of leaves of diseases and insect pests respectively, and compare the algorithms of the color feature extraction used wavelet block before and after improvement, as shown in Table 5:

Table 5. comparison of image recognition accuracy before and after improvement of wavelet block for color feature extraction

color feature extraction algorithm based on wavelet block	**Graymold**	**bacterial leaf spot**	**diseases and insect pests of banana**	**banana mosaic rot**	**banana bunchy top disease**
	37.31%	**33.17%**	**35.7%**	**32.67%**	**35.75%**
	banana fusarium wilt	**banana scab**	**banana leaf spot**	**brown edge gray spot**	**coal stripe disease**
	40.67%	**38.75%**	**42.27%**	**35.64%**	**32.31%**
improved algorithm for color feature extraction based on wavelet block	**Graymold**	**bacterial leaf spot**	**diseases and insect pests of banana**	**banana mosaic rot**	**banana bunchy top disease**
	43.37%	38.67%	39.67%	36.69%	40.74%
	banana fusarium wilt	banana scab	banana leaf spot	brown edge gray spot	Coal stripe disease
	45.75%	43.75%	48.65%	40.74%	38.66%

As can be seen in Table 5, compared with the traditional wavelet block color feature extraction algorithm, the recognition accuracy rate of different insect pest images is improved in different degrees after the introduction of the down sampling layer in deep belief network. Further, it shows that the recognition accuracy of single sampling wavelet block color feature extraction will be greatly reduced due to the lack of image feature information, but the overall recognition accuracy rate is less than 50%.

4.4 Performance Comparison Between Proposed Algorithm and Image Software of Pest Image

Firstly, identify whether there are insect pests on the leaves. The experimental objects are the proposed algorithm, Assess and OpenCV in this study. We choose 12000 normal plant leaves and 12000 abnormal plant leaves with diseases and insect pests. Typical samples are shown in Table 6.

Table 6. Some samples of normal leaf and leaf with pest

	
normal plant leaves	abnormal plant leaves (diseases and pests of banana)
	
banana mosaic rot	banana fusarium wilt

In Table 6, it can be clearly observed that the normal leaves are mainly green with a little yellow on the edge, and the surface is relatively complete without holes. However, the surface of leaves is yellowing and there are dense holes on the leaves eroded by insects. The accuracy and efficiency of identification are shown in Figure 11 and Figure 12

As can be seen in Figure 11, the algorithm proposed in this study needs a lot of time to identify the normal and non pest leaves, and it is similar to opencv and assessment software in recognition accuracy.

In order to verify the proposed algorithm, opencv and assessment software, the leaf image of pest erosion, banana diseases and insect pests, banana leaf rot, banana fusarium wilt were selected for recognition. 3500 leaf images of each pest were selected, and some insect image samples were shown in Table 7

In Table 7, we can see that there are some differences in color and surface morphology of leaves eroded by different pests. Among them, a large number of holes can be seen in the leaves of banana diseases, and a large area of yellowing phenomenon appears on the edge of leaves. It appears large areas of dark parts on the surface of leaves with diseases of heart rot of banana, that is, the leaves have begun to rot. On the leaves of Banana Fusarium wilt, we can see that many leaves begin to shrink, that is, the size of leaves changes. Experiments are carried out on the samples with holes, black spots on the surface of leaves and changes in leaf shape. The identification efficiency and accuracy of damaged leaves by diseases and pets are shown in Figure 13 and Figure 14

It can be seen that the recognition efficiency of the leaves eroded by insects based on Assess softwareis still the highest, and the average time required is generally less than 20s, while the average time required by the improved algorithm proposed in this study is more than 100s, but the accuracy of Assess software is the lowest. The accuracy of pest image recognition of proposed algorithm in this study is higher than that of Assess software, but lower than that of OpenCV.

It should be pointed out that many leaves may suffer from more than one kind of insect pest mentioned above. The leaves can be damaged by 3 kinds or even 10 kinds of insect pest. Thus the proposed algorithm can be further compared with the pest image recognition software. Some images of leaves suffered from multiple insect pests are shown in Table 8.

In Table 8, we can see that many leaves damaged by insect may be eroded by a variety of pests. Take the sample at the bottom left of Table 8 as an example, the surface of the pest leaves has slightly shrunk, which is consistent with the characteristics of Banana Fusarium wilt. Meanwhile, it appears moldy on some patches, which conforms to the characteristics of bacterial leaf spot mildew. The leaf edge is yellowing, which conforms to the characteristics of diseases and insect pests of banana. Performance comparison of proposed algorithm and software is shown as follows:

It can be seen in Figure 15 and Figure 16, the recognition effect of conventional software gradually declines with the increase of leaf pest species. In fact, the conventional pest image recognition software can only run about 500s-600s when it is used to do calculation, which is subject to the overall running environment. The algorithm proposed in this study runs in a distributed environment. Although the recognition time is the longest, the insect species recognized are much stable, the more the number of pests is, the more obvious the advantages of the proposed algorithm are.

5. CONCLUSION

In this paper, we focus on the convolution neural network and improve the algorithm of deep confidence network in deep learning. The experimental process is divided into two parts, one part is to compare the performance of the algorithm itself, the other part is to compare the performance of the algorithm with that of the pest image software.

We can see that the overall efficiency of the algorithm proposed in this study is not high in the experiment. Compared with the conventional software, it usually takes much more time to identify the pests. However, the algorithm proposed in this study has certain advantages in multiple pest identification, and multiple pests can be identified on multiple pest leaves. It shows that the algorithm based on deep learning model has a certain application prospect in the recognition of complex features.

Figure 11. Comparison of recognition time of normal leaf images

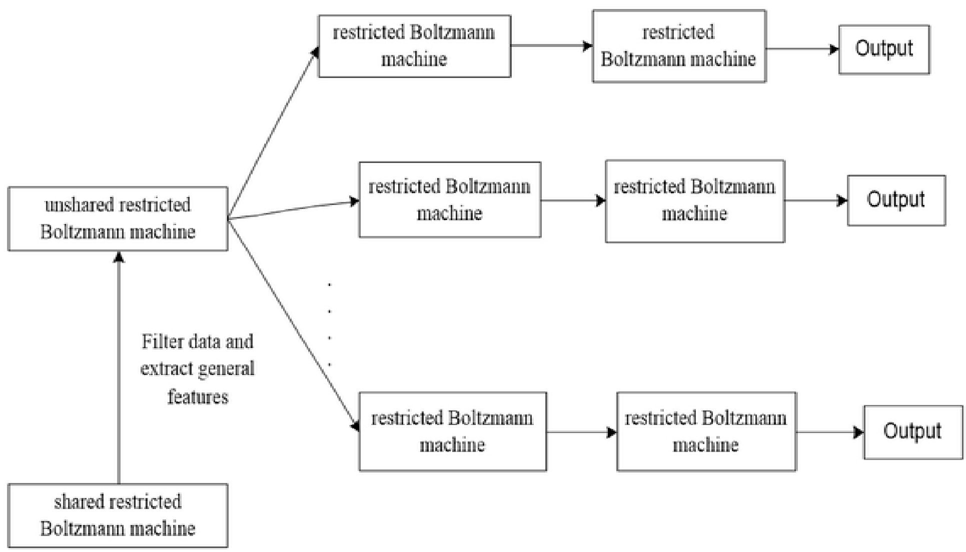


Figure 12. Comparison of recognition accuracy of normal leaf images

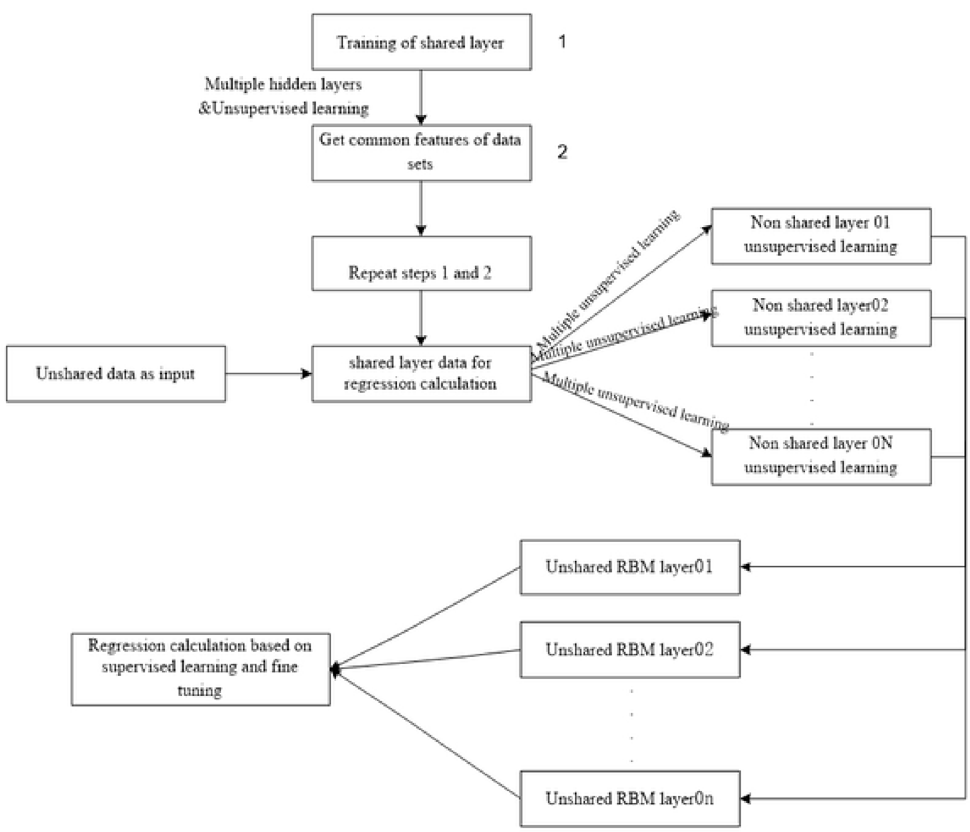


Table 7. Some images of pest samples

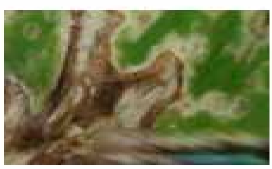
diseases and insect pests of banana	banana mosaic rot	banana fusarium wilt
		
		
		
		
		

Figure 13. Comparison of recognition time of image of leaf with pest

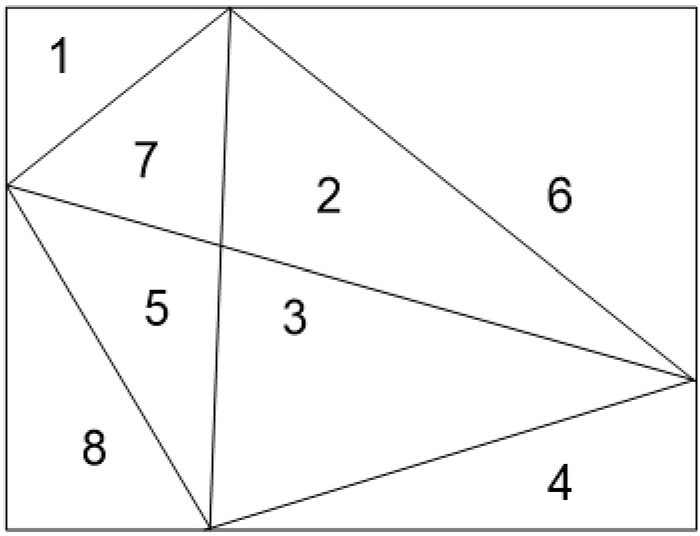


Figure 14. Comparison of recognition accuracy of image of leaf with pest

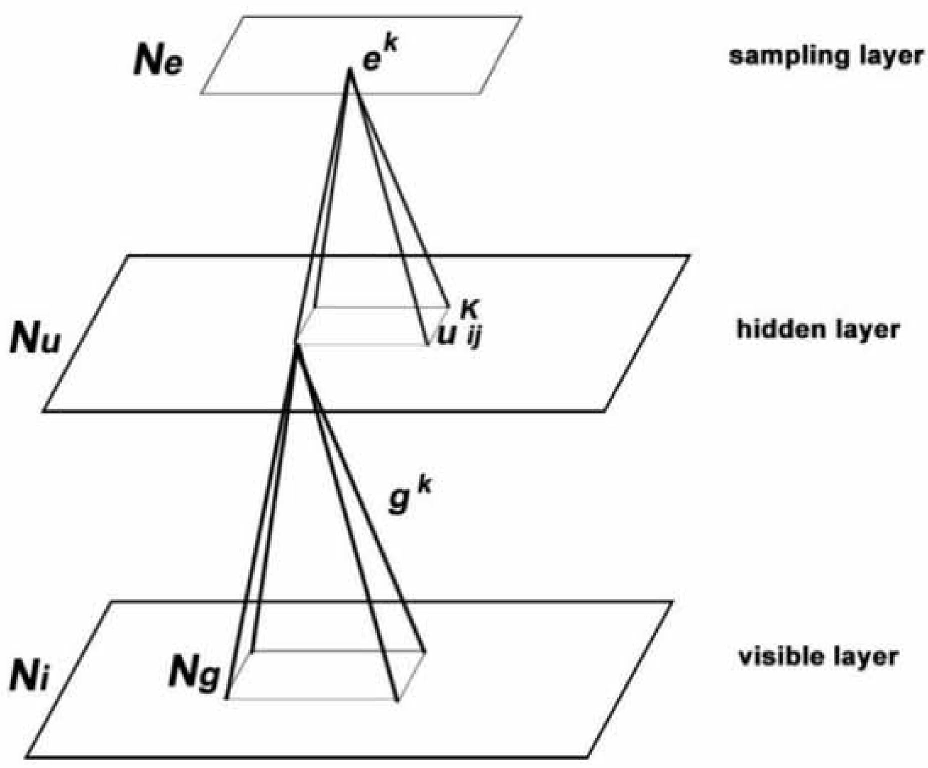
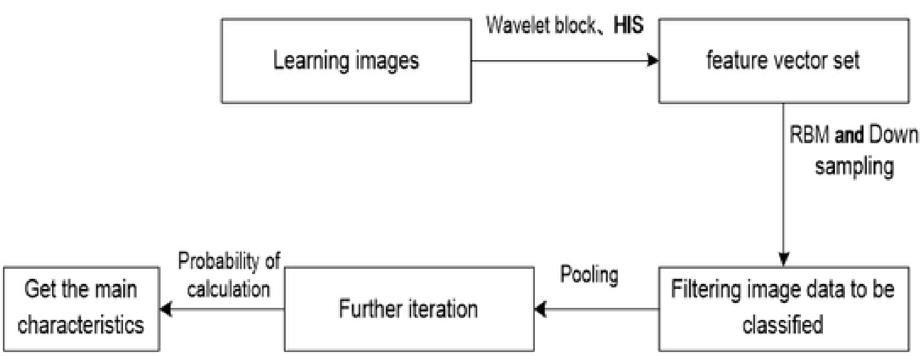


Table 8. image of leaf samples with multiple pests

 diseases and insect pests of banana、 Gray mold	 bacterial leaf spot、diseases and insect pests of banana、 banana leaf spot
 bacterial leaf spot、 banana fusarium wilt、 diseases and insect pests of banana	 banana scab、 banana leaf spot

Figure 16. Comparison of recognition accuracy of leaf images with multiple pest

Figure 15. Comparison of recognition time of leaf images with multiple pest



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