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Recognition Method of No-seedling Grids of Trays based on Deep Convolutional Neural Network

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Abstract: In the process of replanting, it is necessary to recognize that whether the tray grids are short of seedlings. In the seedling cultivating process, the phenomenon of seedling leaves intruding the adjacent grids due to various reasons make it difficult to identifying the tray grid that if it is lacking seedlings. The traditional image processing methods face the problems of poor human selection features and complex feature extraction process. In this paper, the recognition method of no-seedlings grids of tray based on deep convolutional neural network (GoogLeNet model) is proposed, which uses 9 Inception-V3 modules to construct deep convolutional neural network. Inception-V3 modules use selective multi-scale convolution kernels to extract grid seedlings features, use the convolution kernels factorization to reduce the operation parameters and use Batch Normalization algorithm to improve the model training speed to build the predictive recognition model of tray no-seedlings grids. To verify the effectiveness of this method, this research designed an images acquisition device, collected 3400 pepper tray grids image samples, label the samples by manual. Adjust the model parameters, Build the optimal deep convolution network recognition model when the learning rate is 0.01, Batch size is 100, iteration is 6000, the recognition average accuracy was 94.5%. By using this deep convolutional neural network model, test the samples with and without a leaf or several leaves intrusion individually. The test accuracy of samples without intrusion was 100%. The average accuracy of seedling identification with intrusion conditions was 81.5%. Compared with the traditional image processing method, the average accuracy of recognition with this method was increased by 16%. The results of this research prove that this deep convolutional neural network recognition method is very accurate when there is no intrusion, and the accuracy is relatively high when there is a leaf or several leaves intrusion. This research provide a new theoretical solution for the recognition of no-seedlings grids of tray.

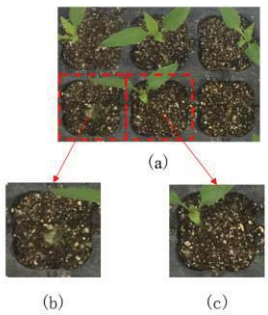
Key Words: Image processing, Deep convolutional neural network, GoogLeNet, Tray No-seedling Grids Recognition

1 Introduction

In the early stage of seedling cultivation in facility agriculture, it is necessary to replant the cultivated tray grids without seedlings growing. In this process, it is important to use the corresponding technical means to identify the tray grids with or without seedlings and it is a key issue to improve the efficiency and intelligence of replanting machine. At present, this work in China is mainly based on manual sorting, which is high intensity work and low efficiency. There are already relatively mature greenhouse automatic transplanting machines in several countries [1], such as the Pic-O-Mat series transplanting machine produced by Visser in the Netherlands.

In the replant process, the no-seedling grids recognition faces these problems: due to the high density of the seedlings in the tray (⩾72 grids/tray), the errors during the sowing operation that seedlings are not growing in the center of the grid, and the seedlings grow obliquely due to uneven illumination, the seedling leaves in the tray may invade the adjacent grids, or the no-seedling grids are invaded by the adjacent seedling leaves. It can be known from the literature [2-4] that when these situations occur, the accuracy of the identification of no-seedlings of trays is greatly affected, and the intrusion is more serious as the replanting time is later.

For example, Fig. 1(a) is a partial image of a tray containing 6 grids, in which the two grids in the lower left corner with the red square have the phenomenon that the seedlings invade the adjacent grids, and it is easy to cause misjudgment. There are two kinds of misjudgments: one is that the seedling leaves of the adjacent grids invade into the no-seedling grids, and the grids are judged to have seedlings, as shown in Fig. 1(b); the other is the leaves of the seedlings invade the adjacent grids, and the grids with seedlings are judged to have no seedlings, as shown in Fig. 1(c).



(a) Local image of tray (b) No seedling in grid, nearby seedling intrude into the grid. (c) Seedling in grid, the seedling intrude into nearby grid.

Fig.1 Images of seedlings in tray

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In view of the problem of the identification no-seedlings grids of tray in the greenhouse replanting machine, there have been related identification methods researches based on image processing. The machine vision system designed by Ryu[2] compares the leaf surface information of the seedlings with the pixel values represented by the pre-designed seedling leaves to identify the lack of seedlings. Jiang Huanyu[3] used tomato seedlings as test samples, using morphological watershed algorithm to complete leaf edge segmentation, extracting leaf area and leaf circumference of seedlings in each grid to identify seedlings, and the recognition accuracy reached 98%. Wang Xiaochan used the color component difference (2g-r-b) to divide the seedlings and the background of the trays, and then extracted the leaf area and leaf color of the seedlings in the grids to identify the seedlings. Feng Qingchun[4] used structured light and industrial camera methods to identify seedlings by detecting seedling leaf area and stem height, and the recognition accuracy was above 90%. Tong Junhua[5] used a decision-making method that combines the center information of the leaf area and the improved watershed method to segment the seedlings, and then calculate the leaf area of the seedlings to realize the seedling identification judgment and the recognition accuracy was more than 95%. The traditional image processing recognition method has strong recognition ability in the case of no intrusion or few intrusion, but the recognition effect is not good when the intrusion leaf area is large.

In the traditional image processing, the use of features for the depiction of information will be lost more or less in the image process, the artificial extraction of certain feature algorithms is complex, and the recognition accuracy depends largely on the judgment of the selected features. Convolutional neural networks (CNN) is a neural network with convolutional structure. The convolution structure can reduce the amount of memory occupied by deep networks, the number of parameters of the network and the over-fitting problem with the model [6-7]. This advantage is more obvious when the input of the network is multi-dimensional images. The image can be directly used as the input of the network, avoiding the complicated feature extraction and data reconstruction process in the traditional recognition algorithm. Currently, convolutional neural networks are widely used in agriculture [8-18]. In 2012, the Alex convolutional network model designed by Krizhevsky[19] won the championship in the ILSVRC(ImageNet Large Scale Visual Recognition Copetition)-2012 competition. In 2014, the GoogLeNet convolutional network model designed by Szegedy[20-23] extended the convolutional network to 27 layers, increasing the depth of the convolutional network. This model uses lower parameters than Alex while ensuring better accuracy. The model won the ILSVRC-2014 championship. It can be seen that the deep convolutional neural network has strong image classification ability.

This paper proposes a method based on deep convolutional neural network (GoogLeNet) to identify the no-seedlings grids of tray. In this research, an image acquisition device was designed, and the pepper seedlings were taken as an example for test for this method. The device was used to collect a large number of samples of the seedlings of pepper seedlings, and a model based on deep convolutional neural network was established, and the samples were used for experimental verification. The results show that this method has good recognition ability for the no-seedlings grids of tray with or without intrusion. This method has certain theoretical significance for the recognition of fruit, vegetable and flower seedlings trays in replanting work.

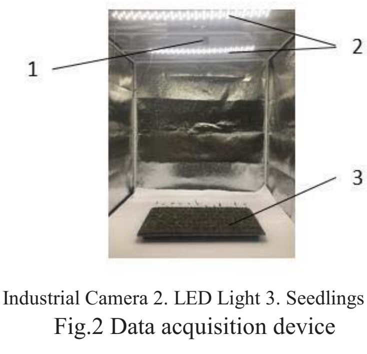
2 Materials and Methods

2.1 Materials

According to the factory seedling cultivating process, the pepper seedlings should be replanted during the two-leaf and one-heart period, and the replanting time is about 15~20 days. If the replanting is too early, some seedlings are not yet fully grown. If the replanting is too late, the lack of seedlings grids will occupy the resources of the trays, which will affect the subsequent cultivation. During the period of 15 to 20 days of pepper seedling cultivation, there were already cases where pepper seedlings invaded the adjacent cells in the tray, and the later the intrusion ratio was greater. Because of the intrusion into the adjacent grids in the trays in the formal replanting period, the number of samples is small, there are more samples in the trays in the later transplanting period, which is effective to verify the recognition ability of this method on intrusion situation. This study selected the 20 days pepper tray as test samples. The test time was May 2018, and the cultivation company was Beijing Zhongnong Futong Co., Ltd. The size of the plug is 540mm ×280mm, with a total of 6×12=72 grids. The matrix component: light matrix soilless material such as peat, vermiculite or perlite.

2.2 Image Acquisition Devices

In order to prevent the interference of uncertain factors such as natural light, the light box is used to collect images of the tray seedlings. In the image acquisition device designed in this study, the industrial camera (1) is installed in the middle of the top of the light box, and the seedlings (3) are taken overhead view, and the industrial camera lens is 860 mm from the tray, as shown in Fig. 2. The industrial camera adopts the Mercury series developed by Daheng Image Co., Ltd., model MER-500-7UM/UC, 5 million pixels, resolution 2592 pixels ×1944 pixels, lens focal length 8mm, aperture 2.4. The device uses two LED (2) symmetrically distributed on the side of the top industrial camera to provide illumination for image acquisition.



1. Industrial Camera 2. LED Light 3. Seedlings Tray

Fig.2 Data acquisition device

2.3 Image Preprocessing

The experiment collected 48 images of pepper tray seedlings images, as shown in Figure 3. Using Matlab2014a to segment it by the grid. Obtain a sample of each grid image. Each grid image size is 186 pixels $\times$186 pixels, which is normalized to 128 pixels $\times$128 pixels, as shown in Figure 4.

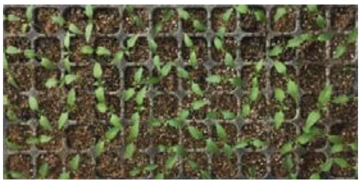


Fig.3 Image of tray sample

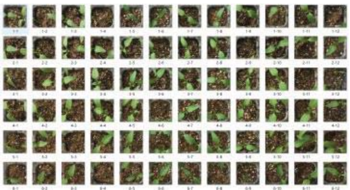


Fig.4 Image of tray grid sample

2.4 Construction of Deep Convolutional Neural Network Model

The deep convolutional neural network GoogLeNet model consists of 22 layers with parameters[20] (if there are 27 layers in the pooled layer). It includes the convolutional layer, the pooling layer, the Inception-V3 module, the fully connected layer, and the Softmax layer. The network structure is shown in Figure 5.

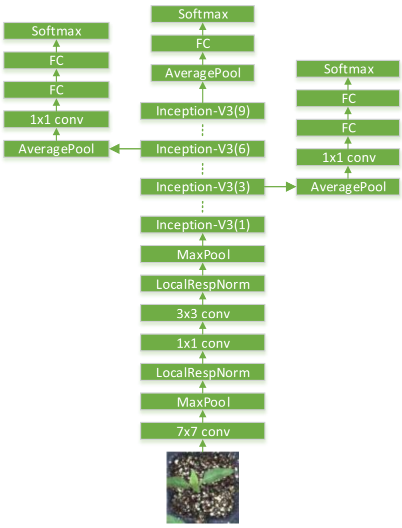


Fig.5 GoogLeNet(Inception-V3) network structure

The network model contains nine Inception-V3 modules. The structure of each Inception-V3 module[22] is shown in Figure 6. The module optimizes the network model by decomposing the large convolution kernel into small convolution kernels and decomposing the convolution kernel into asymmetric convolution kernels. For example, a 5×5 convolution kernel is decomposed into two 3×3 Convolution kernel, or a 3×3 convolution kernel is split into a 1×3 and a 3×1 convolution, as shown in Figures 7 and 8. This method saves a lot of parameters, accelerates the operation and reduces the over-fitting, and increases the expression ability of a non-linear extended model.

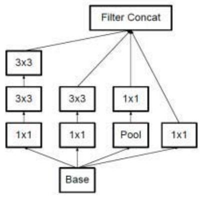


Fig.6 Inception-V3 module structure

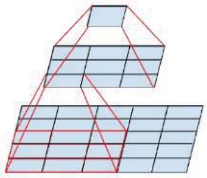


Fig.7 a 5×5 convolution kernel factor into two 3×3 convolution kernels

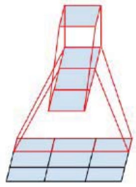


Fig.8 a 3×3 convolution kernel factor into a 3×1 convolution kernel and a 1×3 convolution kernel

Using cross entropy as the loss function, calculated as formula (1).

$$L(Y,P(Y\mid X))=-\log P(Y\mid X)=-\frac{1}{N}\sum_{i=1}^{N}\sum_{j=1}^{M}y_{ij}\log(P_{ij}) \quad (1)$$

2.5 Batch Normalization

Each layer of the model is optimized by Batch Normalization[21] algorithm, which can greatly improve the speed of model training and allow the model to use a large learning rate for model training. The algorithm calculation steps are:

Calculate the mean of the batch as formula (2).

$$\mu_B=\frac{1}{m}\sum_{i=1}^{m}x_i \quad (2)$$

Calculate the variance of the batch as formula (3).

$$\sigma_B^2=\frac{1}{m}\sum_{i=1}^{m}\left(x_i-\mu_B\right)^2 \quad (3)$$

Normalization x as formula (4).

$$\hat{x}_i=\frac{x_i-\mu_B}{\sqrt{\sigma_B^2+\epsilon}} \quad (4)$$

Calculate output after the normalization of the batch as formula (5).

$$y_i=\gamma\hat{x}_i+\beta\equiv \mathrm{BN}_{\gamma,\beta}\left(x_i\right) \quad (5)$$

3 Test and Analysis

The experimental software environment is Ubuntu 16.04 LTS 64-bit system, using tensorflow deep learning open source framework, using Python as a programming language. The computer has 16 GB of memory and is equipped with an Intel® Xeon(R) CPU E5-2603 v4@1.7GHz 12 processor and accelerated image processing with the NVIDIA GeForce GTX 1080/PCle/SSE2 graphics card.

A total of 3400 image samples were used in the test, including 2476 seedling samples and 924 no-seedling samples.

From this 3400 images, 400 samples were selected as model recognition effect verification test samples, and the remaining 3000 were used as model training, verification and test samples.

The model recognition effect verification test samples (Total 400): 200 test samples without intrusion in the test sample, which were divided into 100 samples with seedlings and 100 samples without seedlings. There are 200 intrusion test samples, divided into four cases, 50 each case.

Model training, validation and test samples (Total 3000): 10% (300) random samples as model test samples, 10% (300) random samples were used as model validation samples, and the remaining 80% (2400) samples were used as model training samples.

3.1 Model training, Verification and Testing

Using the GoogLeNet (Inception-V3) deep convolutional neural network model, to enhance the generalization ability of the model, adjust the input training image sample cropping transformation ratio to 10%, the size conversion ratio to 10%, the brightness conversion ratio to 10%, and increase the image flip and transform.

Based on the data batch regularization process, the deep convolutional neural network model used in this study can use a large learning rate for model training. This experiment uses three different learning rates of 0.001, 0.01, and 0.1 for model training. Batch is set to 100 and the number of iterations is set to 6000 steps. After the parameters are adjusted, the model built in this paper is trained, verified and tested. The test results are shown in Table 1.

Table 1 Deep Convolutional Neural Network Test Result

Network	Learning Rate	Test Accuracy
GoogLeNet （Inception-V3）	0.001	93.7%
GoogLeNet （Inception-V3）	0.01	94.5%
GoogLeNet （Inception-V3）	0.1	93.1%

The test results show that the accuracy of model recognition varies with different learning rate parameters, but they are all maintained above 93%. When the learning rate is 0.01, the Batch is 100, and the number of iterations is 6000, the GoogLeNet(Inception-V3) recognition model established in this paper can achieve the optimal effect, and the test accuracy is 94.5%.

The training accuracy rate of the model is changed with the number of iterations as shown in Fig. 9. The training cross entropy changes with the number of iterations as shown in Fig. 10.

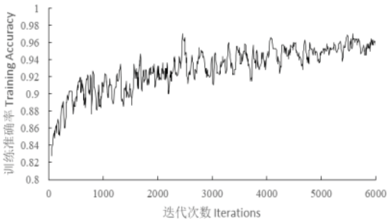


Fig.9 Diagram of training accuracy by iterations

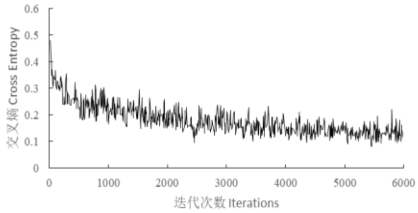


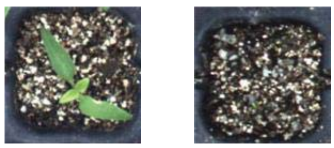
Fig.10 Diagram of cross entropy by iterations

3.2 Model Recognition Effect Verification

In order to further verify the identification effect of the research method on seedlings, 400 specific test samples were used, which were divided into no-intrusion samples and intrusion samples.

- Samples test without intrusion

No-intrusion samples refer to: (a) the seedlings themselves have seedlings, and the seedlings of the grids do not invade other nearby grids; (b) the cells themselves have no seedlings, and no other adjacent seedlings invade the grids. For example: samples without intrusion is shown in Figure 11.



(a) Grid with seedling (b) Grid without seedling

Fig.11 Examples of grids without intrusion

Using the trained deep neural network model, 100 samples with seedlings and 100 cells without seedlings and no intrusion conditions were tested. The test data is shown in Table 2.

Table 2 Test Result of Samples without Intrusion

Number	Different Situations	Number of sample	Correct Number	Accuracy
1	Grid with seedling	100	100	100%
2	Grid without seedling	100	100	100%
Total		200	200	100%

It can be seen from the test results that the deep convolutional neural network model established in this paper can accurately identify whether there are seedlings or no seedlings in the no-intrusion grids, and the recognition accuracy is 100%.

- Samples test with intrusion

In view of the phenomenon that the seedling leaves in the grids invade the adjacent grids, the situation is divided into four cases, namely, Case 1: There is no seedling in the grid, a single leaf invade into this grid from adjacent seedling (invasive leaf area < 1/2 invasive seedling total leaf area) ; Case 2: There is no seedling in the grid, a single adjacent seedling leaf invading (invasive leaf area ⩾ 1/2 invasive seedling total leaf area) or multiple adjacent seedling leaves invading into it; Case 3: There is a seedling in the grid, and seedling leaves invade adjacent the grid (invasive leaf area < 1/2 the total leaf area of the seedling); Case 4: There is a seedling in the grid, and the seedling leaves invade the adjacent grids (invasive leaf area ⩾ 1/2 of the total leaf area of the seedlings). Four different intrusion test sample cases are shown in Figure 12.

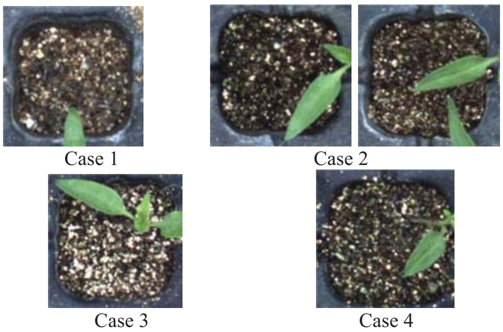


Fig.12 Examples of 4 different cases

Using the deep convolutional neural network model method and the traditional image processing method [3-5] (firstly, the seedlings in the cell image are segmented from background imaged, then binarize the images; secondly, the leaf area is calculated by the pixel ratio; finally leaf area was taken threshold to determine whether the grid is lacking seedling.) do the test. The samples of the above four cases were tested separately. The test data is shown in Table 3.

Table 3 Test Result of Samples with Intrusion

No.	Different cases	Sample number	Traditional method correct number	This paper method correct number	Traditional method accuracy	This paper method accuracy	Increase Percentage
1	Case 1	50	41	46	82%	92%	10%
2	Case 2	50	23	38	46%	76%	30%
3	Case 3	50	40	43	80%	86%	6%
4	Case 4	50	27	36	54%	72%	18%
Total		200	131	163	65.5%	81.5%	16%

It can be seen from Table 5 that when the invasive leaf area of the adjacent seedling leaves is small (Case 1 and Case 3), the recognition accuracy of the method is still high. The recognition accuracy of Case 1 is 92%, and the recognition accuracy of Case 3 is 86%. When the leaf invading leaf area of the seedling seedlings is close (case 2 and case 4), the recognition accuracy of the method is decreased, but it remains above 70%. The recognition accuracy of Case 2 is 76%, and the recognition accuracy of Case 4 is 72%. In the case of intrusion, the average accuracy of identification using this method is 81.5%. Compared with the traditional image processing method, the recognition accuracy of this method is improved when the area of the invading adjacent leaf area is small (case 1 and case 3). When the invading leaf area of the seedlings is large (case 2 and case 4), the method in this paper is obviously superior to the traditional image recognition method. It can be seen from the experimental data that the average accuracy of the recognition of this method is 16% higher than that of the traditional identification method in the case of intrusion.

By using the deep convolutional neural network model to identify the test samples with misjudgment in the experiment, the main reason for the misjudgment is that there are relatively few training samples with intrusive conditions, especially the number of training samples in case 2 and case 4. With limited training samples, the recognition model could not learn more recognized features, which leads to a lower accuracy of recognition.

4 Conclusion

Aiming at the demand of replanting work in the process of greenhouse nursery, a recognition method of no-seedlings girds of tray based on deep convolutional neural network was proposed. This method directly takes the cultivated seedlings images as the input, uses a large number of samples to train the model, and the model learns the effective features of the grids with or without seedlings itself, avoiding the complicated feature extraction process in the traditional recognition algorithm. To make up for the shortcomings of selected features and feature extraction by manual.

In this paper, the image acquisition device was designed and take the pepper seedlings as an example for test this method. 3400 test samples were collected by this device. The prediction model based on the deep convolutional neural network (GoogLeNet) was established, and the model parameters were adjusted. When the learning rate was 0.01, the Batch was 100, and the number of iterations was 6000, the optimal recognition model was obtained. The accuracy of the seedling identification was 94.5%. This job requirements for greenhouse planting operations.

In order to verify the recognition ability of this method in the case of the grids invaded by adjacent seedlings, the seedling samples of non-intrusion and intrusion were tested separately. The test accuracy of samples without intrusion was 100%. The average accuracy of seedling identification with intrusion conditions was 81.5%. Compared with the traditional image processing method, the average accuracy of recognition with this method was increased by 16%. The results of this research prove that this deep convolutional neural network recognition method is very accurate when there is no intrusion, and the accuracy is relatively high when there is a leaf or several leaves intrusion. This research provide a new theoretical solution for the recognition of no-seedlings grids of tray.

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