Identification of Maize Leaf Diseases based on Convolutional Neural Network

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ABSTRACT
The identification and diagnosis of crop leaf disease is of great significance to improve the quality of crop cultivation. Compared with the traditional manual diagnosis method, the automatic identification of crop leaf disease based on computer vision technology has high efficiency and no subjective judgment error. But the traditional image processing technology is affected by different illumination conditions, cross shading. The algorithm's robustness is affected. Because deep learning does not need to set learning features manually, which greatly improves the recognition efficiency. In this paper, the two-channel Convolutional Neural Network was constructed based on VGG and ResNet. Taking the maize leaf diseases as research objects, the maize leaf disease data set has been constructed and preprocessed. And the structure and characteristics of AlexNet, VGG and ResNet are introduced respectively. By adjusting the parameters of the two-channel Convolutional Neural Network, the accuracy of identifying the maize leaf disease type in the validation set can reach 98.33%, while the VGG model can reach 93.33%. The classification results on three types of maize leaf diseases show that the two-channel Convolutional Neural Network has a better performance than the single AlexNet model.

Three kinds of leaf disease data sets (big spot, gray leaf spot and rust) are downloaded from the “kaggle” platform.

1. Introduction
Crop disease protection is important for global food security, while the recognition of crop diseases at early stage is the key part of disease protection. The traditional identification and detection of crop leaf diseases is carried out by agricultural technicians, which leads to over investment of professionals and labor force, insufficient accuracy of identification.

With the development of computer vision and image processing technology, more accurate automatic detection methods of crop diseases have been developed to help identifying the early symptoms. Most of the crop diseases are on the leaves. Taking maize as an example, the common leaf diseases include leaf spot and rust. Based on the traditional image processing technology, such as support vector machine (SVM), K-means clustering algorithm, the shape, color, texture and other features of leaf images are extracted effectively. So the image processing method can carry out the recognition and classification of different disease types.

However, the traditional image analysis and processing methods are all based on feature engineering. And the feature extraction is often affected by lighting conditions, occlusion and other factors, and the algorithm is often not robust in practical application. Because the deep learning method does not need to set image features manually, which greatly improves the recognition efficiency. In
this paper, the two-channel Convolutional Neural Network was constructed based on VGG and ResNet. And the CNN model can work in a more realistic environment, including complicated background, insufficient sunlight, different angles of the leaf.

2. Material and methods

2.1 Dataset

Through reading the relevant literature, three kinds of maize leaf diseases were selected as the research objects in this paper. The 4205 images of maize leaves were analyzed and assigned as four class labels manually, such as healthy leaf, big spot leaf, gray spot leaf and rust leaf. There are about 4200 pieces of data of healthy leaves, big spot, gray spot and rust leaves. The corresponding relationship between label and disease type is as follows:

- Healthy: healthy leaf
- big: big spot leaf
- gray: gray spot leaf
- rust: rust leaf

Figure 1 shows some examples from the dataset. It indicates the disease of the maize leaf “big”, meaning corn spot, and 0 is its number in the sequence. The images we analyze are adjusted to 256 × 256 pixels.

![Sample Images from the Dataset](image1.png)

Figure 1: Sample Images from the Dataset

Table 1 shows all the diseases apart from healthy leaves to be recognized together with the number of images.
Table 1: Type of pictures in the training data set

| Type              | Number of original pictures |
|-------------------|-----------------------------|
| Healthy           | 1132                        |
| Big (corn spot)   | 955                         |
| Gray (gray spot)  | 956                         |
| Rust              | 1162                        |

2.2 Data Augmentation

The number of each type of leaf images varies, so the unbalanced distribution of different types of images may lead to the deviation of the model after training under different types. Data augmentation can balance the number of different image types, expand the training set, make images more realistic and restrain overfitting, which means the model becomes more sensitive to noises or subtle details rather than underlying relationships we want. In the field, the leaves block each other, and the images have various degrees sharpness and resolution. Uneven sunlight exposure also leads to random shadows and bright specks on the leaves. Thus we applied data augmentation to make the training more realistic and reduce overfitting during the training process.

The common methods include image transformation, fixed angle rotation and color jitter. In this paper, horizontal image transformation, image rotation, contrast change and brightness change are used for data augmentation. In order to avoid losing part of the image edge when rotating, we use the method of 90 degree and 180 degree rotation.

(1) Horizontal mirror transformation

If the position coordinate of the original image is, the coordinate of the new image after transformation is, and the image width is, then the horizontal image transformation formula is as follows:

\[
\begin{align*}
    x_2 &= w - x_1 \\
    y_2 &= y_1
\end{align*}
\]  

(2) Fixed angle rotation transformation

Rotation transformation refers to that the whole image is randomly rotated clockwise around a fixed point to change the angle of the image. Suppose the rotation angle is \( \theta \), the coordinates of the points in the original image are, and the coordinates of the new image after transformation are. The formula of rotation transformation can be expressed as follows:

\[
\begin{align*}
    x_2 &= y_1 \sin \theta + x_1 \cos \theta \\
    y_2 &= y_1 \cos \theta - x_1 \sin \theta
\end{align*}
\]

The rotation transformation results of fixed 90 degrees or 180 degrees are shown in Figure 3:
(3) Random change of brightness and contrast

The images’ brightness and contrast is adjusted to a random proportion from -10% to +10%. The formula of brightness adjustment is expressed as:

\[ R_{GB_2} = R_{GB_1} \times (1 + \alpha) \]

Where RGB represents the value of R, G, B channel respectively, \( \alpha \) varies from -0.1 to 0.1. The formula of contrast adjustment is expressed as:

\[ R_{GB_2} = \text{Average} + (R_{GB_1} - \text{Average}) \times (1 + \alpha) \]

Where Average is the average value of R, G, B channel of the whole image.

After data augmentation, the data scale of each type of leaves in simple background was expanded to about 2500. There were 10000 pictures of maize leaves in the data set. The python program was written to scramble the order of about 1200 pictures in each category folder, and randomly moved to the training data set folder and test data set folder according to the proportion of 5:1. Finally, there are 8500 images in the training set and 1500 in the test set. The proportion of each kind of picture is approximately the same, which ensures the data balance. The complex background data set was expanded to 10000 pieces, 8500 pieces were used to train semantic segmentation model, and 1500 pieces were divided into test data set.

2.3 Model Construction

2.3.1 Training Environment:
The training was applied on Ubuntu 16.04 LTS with 8GB memory, Intel® Core™ i7-6700hq, @
2.4GHz x8 CPU under the deep learning framework of Tensorflow 2.1.

2.3.2 Alexnet Model
The model includes 5 convolutional layers, 3 pooling layers and 2 fully connected layers. There is also a zero padding layer at the beginning, and a 0.2 dropout layer after the flattening layer and the first fully connected layer. The structure of the model is shown in Figure 5.

![Figure 5: Model of AlexNet](image)

2.3.3 VGG Model
In this paper, we use the convolutional and pooling layers of vgg19 model in keras, the pre-training weights for training on the Imagenet database is loaded to improve the initial state of training. Finally, we add a fully connected layer with 4 units as our output layer.

The total model has 5 blocks. The first block has 2 convolutional layers and a pooling layer. The second block has 2 convolutional layers and a pooling layer. The third block has 4 convolutional layers and a pooling layer. The fourth block has 4 convolutional layers and a pooling layer. The fifth block has 4 convolutional layers and a pooling layer. Finally there is a fully connected layer with “softmax” as activation function and 4 units. There are totally 20024384 parameters to be trained. The detailed structure of the vgg19 model is shown in Figure 6.
Figure 6: Model of VGG19

We first freeze the convolutional layers and train the fully connected layers on the dataset. Then we unfreeze the convolutional layers and adjust the parameters in the convolutional layers for the training dataset, and save the trained model.

2.3.4 ResNet Model

The resnet model we use is resnet50 in keras without the fully connected layers. The ResNet50 model includes 53 convolutional layers, 53 activation layers, 53 batch normalization layers, and 16 addition layers. The pre-training weights for training on the Imagenet database is loaded to improve the initial state of training. Finally, we add a fully connected layer with with “softmax” as activation function and 4 units as our output layer. There are totally 23587712 parameters to be trained.

In the same way as vgg19 model, we first freeze the convolutional layers and train the fully connected layers of the resnet50 model on the dataset. Then we unfreeze the convolutional layers and adjust the convolutional layers for the training dataset, and save the trained model.

2.3.5 Model of Two-channel CNN with VGG and ResNet:

After training by resnet50 and vgg19 models, we will need the trained convolutional layers of the two models saved to construct the two-channel model. We first load the trained model of vgg19 and resnet50 model without their final three fully connected layers. The two models without fully connected layers thus need not to be changed. The vgg19 models’ convolutional layers has an output of $8 \times 8 \times 512$, and resnet50 has an output of $8 \times 8 \times 2048$. We make a concat of them, which is a $8 \times 8 \times 2560$ feature map. Then we construct the fully connected layers. We flatten the feature map to get a $1 \times 163840$ vector and connect it with a 8-unit fully connected layer. Finally, we attach a softmax layer and classify the image by the output of the softmax layer. There are totally 1,310,728 trainable parameters and 43,612,096 untrainable parameters in the model. The structure of the model is shown in Figure 7.
Figure 7: Model of Two-channel CNN with VGG and ResNet Used in the Training

2.4 Validation Set:
Validation set consists of 30 pictures of corn leaves from each category “healthy”, “big”, “gray” and “rust” which are independent to the training set.

3. Results
In our method, we used the parameters mentioned in 2.3 to score the condition of ..... A total of 2000 experiments were conducted on 20 leaves, and 200 of the better results were selected for analysis. And we used the manually measuring results as a standard value for comparison. We let the program train for 15 epochs, the accuracy an loss function after each epoch is plotted in Figure 7 below:

Figure 8: Accuracy at each step
Figure 9: Loss at each step

The final validation accuracy is 98.33% and the test loss is 0.07628. Compared with VGG network trained in the same steps, whose validation accuracy is 93.33% and the loss 0.2385, and ResNet in the same conditions, whose validation accuracy is 97.75% and the loss 0.1276, the two-channel architecture obviously has a better performance. Various methods of optimization can be applied to increase the accuracy. We can enlarge the training set, expand the convolution and pooling sets or include pictures under a larger variety of circumstances.

4. Conclusion

In this paper, we constructed a 2-channel convolutional neural network based on ResNet and VGG.
model of the maize leaf disease image classification, built three data sets of maize leaf disease images as well as the healthy leaf images. We used the concat of the two models' feature extraction layers to improve the classification accuracy of maize leaf diseases, and trained the two-channel CNN model with the same data set as by single ResNet50, VGG19 and AlexNet model for contrast. The result verified the validity and superiority of this two-channel CNN model.

Our study has demonstrated the potential of using RGB camera for evaluation LEAVe condition of using measurements of leaves. This study used a RGB camera to obtain depth images of 20 ?? under outdoor condition at the Beijing Center. According to the ?? identification procedure, we can effectively evaluate the condition of leaves. Some parameters of leaves can be calculated. The average score of the calculated results is consistent with the standard value score. Our method could be used for solving problems associated with manual scores, such as high cost, extensive training, etc.

Specific conclusions are as follows:
Based on the characteristics of camera is erected at the appropriate position to extract the image of the leaves when the design algorithm automatically processes the data.
Through the extracted nodes, the relevant parameters are calculated, and the score results are fed back. However, we note that the data set used in this study included only the leaves from the same growth period. Further studies should include a broader assessment using a larger number of leaves obtained from over more than one growth period. In addition, a graphical interface should be designed to operate.

Acknowledgements
We are grateful to the http://, for their assistance in the experiments. We also thank to the reviewers for their helpful comments.

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