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Deep Learning-Based Crop Weed Recognition

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ABSTRACT

To achieve accurate weed control, variable spraying of herbicides and accurate identification of weeds is a prerequisite. In this study, the research on weed recognition is carried out by using deep learning techniques with crop weed images obtained from complex backgrounds in the natural environment of crop production. Firstly, the original image is preprocessed to eliminate irrelevant information in the image, recover useful and real information, enhance the detectability of relevant information and maximally simplify the data; secondly, the crop weed recognition model based on VGG-16 convolutional neural network is constructed, and its convolutional layer is locally adjusted to optimize the main model parameters, so as to achieve the effective targeting of crop weed recognition. Finally, the techniques, methods and models used in this study can be applied to weed identification in complex backgrounds, which can provide technical support for crop herbicide targeting on the basis of weed species identification in this project, as well as provide references and reference for the research of species identification of companion weeds in other crops.

KEYWORDS

Convolutional neural network; VGG-16; Weed recognition

1. INTRODUCTION

Crops are subject to various biotic and abiotic stresses during growth, with biotic stresses consisting mainly of weeds, diseases and pests. Weeds will not only compete with crops for water and nutrients and growth space, but also provide a favourable environment for pests and diseases. How to achieve precise weed control is the key issue in the current weed management chain. In China, the majority of farmers in the field through a large area of spraying herbicides to remove weeds, so that the farmland soil and water environment is seriously contaminated, followed by food safety and agricultural products and agricultural products quality decline. With the rapid development of computer technology, weed control through intelligent equipment is the main direction of modern agriculture. You can use the camera sensor to collect images of farmland, and then through the computer to run the corresponding recognition algorithm to obtain weed-related data information, and finally analyse and process this information to control the mechanical mechanism to complete the precise removal of weeds. Using this approach can not only reduce the impact of weeds on the growth of crops in the farmland, but also enhance the total crop yield, and on this basis of weed removal does not cause environmental pollution, for people's healthy life, food safety, crop pollution and other issues proposed a new solution.

Currently weed recognition is mainly divided into two methods. One method is weed recognition based on traditional feature extraction. Wang et al. [1], provides a thorough summary of current developments in weed identification algorithms using deep learning. The writers investigate many methodologies that include both supervised and unsupervised learning as they look at the difficulties and opportunities in this field. The research also explores supervised, unsupervised, and transfer learning, as well as other deep learning methods used for weed detection. Etienne et al. [2], published " Deep Learning-Based Object Detection System for Identifying Weeds Using UAS Imagery: A technique for weed detection using deep learning and unmanned aerial vehicles has presented in research about the value and important of weed management in agriculture and difficulties faced with manual control. Yu, H.et al. [3], research article in the publication suggests a deep learning-based solution for weed detection in soybean fields. The authors discussed about weed management in soybean farming and the difficulties of manual weed control. The use of deep learning for weed detection is discussed. Mads et al. [4], Plant species classification using deep convolutional neural network An approach for classifying weed species using deep convolutional neural networks (CNNs) a method for application of deep learning for classifying weed species is then introduced.Nikita Genze et al. [5], The authors of the research provide a technique for deep learning-based crop and weed segmentation. Discussed about the value of weed management in agriculture and the difficulties of doing manual weed control. The application of deep learning for weed recognition and segmentation is then discussed.Andrea et al. [6], chose convolutional neural network to recognize maize and weeds and achieved 94.3% recognition rate.Adel et al. [7], trained datasets of weed images collected in Australia using ResNet-50 and incep-v3 models and achieved a recognition rate of 95.4%.From the above literature, it can be seen that deep learning has achieved certain results in the field of weed recognition, but the method requires a large number of data sets as a support, and it is difficult to collect large quantities of images of weeds in agricultural fields, while the deep learning method relies on high-performance computing equipment, which has a large cost.

To address the above problems, this paper uses a convolutional neural network model for recognition after pre-processing the datasets and expanding the samples, with a view to constructing an accurate, stable and applicable weed recognition model.

2. DATA PREPROCESSING

2.1. Data Sets

This paper examines the Deep-Weeds datasets, a publicly available datasets. The datasets contains 17,509 images that capture eight different weed species native to Australia and neighbouring flora. The weed species selected for this paper include: 'Chinese apple', 'snake-weed', 'horse-weed', 'prickly acacia", "Siamese grass", "white-flowered chrysanthemum", "rubber vine" and "Parkinson" totally 8403 images. The eight weed categories in the datasets are shown in Figure 1.

Figure 1. Deep-Weeds datasets

2.2. Data Pre-processing

Since raw data is not always suitable to be read directly into a deep learning model, after acquiring the datasets, pre-processing of the data read into the training and testing models is required, which helps the deep model to extract features more accurately and improves the generalization of the system.

2.2.1. Image Rotation and Flipping

To increase the diversity of the model, the datasets are expanded by performing rotation as well as flip transform operations on the Figure 2.

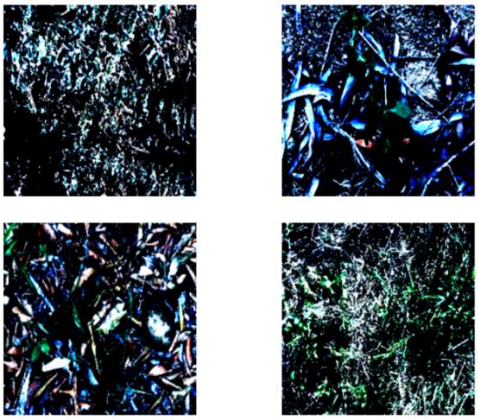

Figure 2. Image Rotation and Flipping

2.2.2. Picture Enhancement

During the data collection process, it may be affected by various factors, among which weather is one of the most significant influences. Among them, light is the most complicated one, which not only affects the brightness of the pictures, but also affects the gloss and texture of the leaves in many aspects. Therefore, in order to improve the generalization ability of the model, it is necessary to generate a new leaf image by adjusting the sharpness, saturation, contrast and brightness according to the original image of the datasets. This is shown in Figure 3.

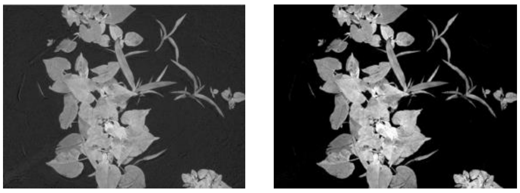

Figure 3. Picture Enhancement

3. RECOGNITION MODEL BUILDING

3.1. VGG-16 Network Model

VGG is a classical deep neural network model that explores the effect of neural network depth on its accuracy. Compared with the latest network structures, VGG is widely used because of its simplicity, lack of complex bottleneck structures, its regular design, concise stackable convolutional blocks, and its good performance on other datasets. The model contains only very small (3×3) convolutional filters, VGG16 has 13 convolutional layers, 4maximal pooling layers, 3 fully-connected layers, and activation functions, and the whole network has about 14728266 parameters, which makes the VGG16 network has a high fitting ability.

Table 1. VGG Parametric Model

ConvNet Configuration					
A	A-LRN	B	C	D	E
11 weight layers	11 weight layers	13 weight layers	16 weight layers	16 weight layers	19 weight layers
Input(224×224 RGB image)					
Conv3-64	Conv3-64 **LRN**	Conv3-64 **Conv3-64**	Conv3-64 Conv3-64	Conv3-64 Conv3-64	Conv3-64 Conv3-64
maxpool					
Conv3-128	Conv3-128	Conv3-128 **Conv3-128**	Conv3-128 Conv3-128	Conv3-128 Conv3-128	Conv3-128 Conv3-128
maxpool					
Conv3-256 Conv3-256	Conv3-256 Conv3-256	Conv3-256 Conv3-256	Conv3-256 Conv3-256 **Conv1-256**	Conv3-256 Conv3-256 **Conv3-256**	Conv3-256 Conv3-256 Conv3-256 **Conv3-256**
maxpool					
Conv3-512 Conv3-512	Conv3-512 Conv3-512	Conv3-512 Conv3-512	Conv3-512 Conv3-512 **Conv1-512**	Conv3-512 Conv3-512 **Conv3-512**	Conv3-512 Conv3-512 Conv3-512 **Conv3-512**
maxpool					
Conv3-512 Conv3-512	Conv3-512 Conv3-512	Conv3-512 Conv3-512	Conv3-512 Conv3-512 **Conv1-512**	Conv3-512 Conv3-512 **Conv3-512**	Conv3-512 Conv3-512 Conv3-512 **Conv3-512**
maxpool					
FC-4096					
FC-4096					
FC-1000					
Soft-max					

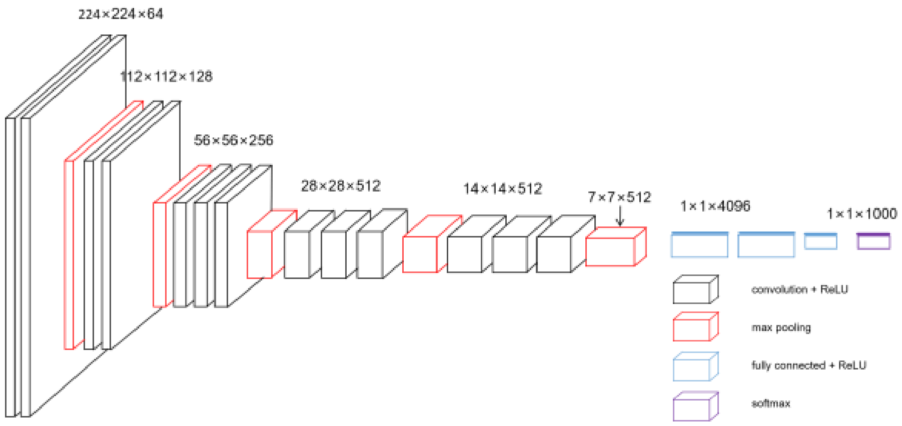

Figure 4. VGG-16 Network Structure

3.2. VGG-16 Network Model Improvement

3.2.1. Addition of BN layer

Since most of the image data are non-linearly related to each other, and the shape of the output distribution of the non-linear units will change during the training process, it is not possible to eliminate the variance bias, which causes the problem of gradient vanishing. Adding a BN layer to make the gradient larger in a certain way speeds up the training and convergence of the network and prevents over-fitting Language.

3.2.2. Improvement of the pooling layer

The pooling layer takes a down-sampling approach to continuously reduce the spatial size of the data, which serves to reduce over-fitting to some extent. However, the current maximum pooling layer removes about 75% of the activation function, resulting in the loss of spatial information, thus making it impossible to use information from the multi-layer activation function. Therefore, literature proposes in the conceptual framework of network models to change the maximum pooling layer in the structure of the VGG-16 model to a sort-pool2d structure, thus solving the problem in the maximum pooling layer.

The network structure after adding the BN layer and replacing the maximum pooling layer in the VGG-16 model is shown in Figure 5.

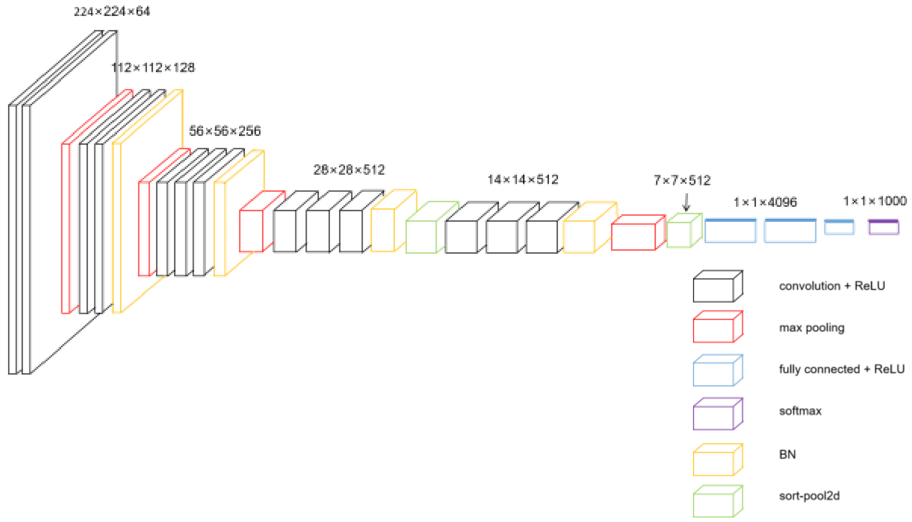

Figure 5. VGG-16 Network Model Improvement

4. RESULTS AND ANALYSES LITERATURE REFERENCES

4.1. Experimental Environment and Parameter Settings

In this paper, the experimental environment for Windows 11 64-bit operating system, and the use of NVIDIA GeForce GTX 1050Ti graphics card accelerated image processing, using the Python language, Pytorch framework for the construction, which Python version of Python 3.9, Pytorch for the 1.12.0 version.

4.2. Indicators for Model Assessment

Accuracy refers to the proportion of correctly classified samples to all samples in the classification process. In this paper, the classification accuracy (Accuracy) is used as the evaluation index of the experiment, the higher the model accuracy, the better the model classification effect. The formula of Accuracy is

$$A_{cc} = \frac{TP}{TP + FP}. \tag{1}$$

Where TP (True Positive) classifier predicts positive samples and is actually positive, i.e., the number of positive samples correctly identified. FP (False Positive) classifier predicts positive samples and is actually negative, i.e., the number of negative samples that are misreported.

4.3. Training Results

After training and testing the improved model in the dataset, the results show that the model has good classification ability and its accuracy reaches 96.32%. The original VGG-16 network and the improved VGG-16 network were subjected to the accuracy and the loss which is displayed as shown in Figures 5 and 6.

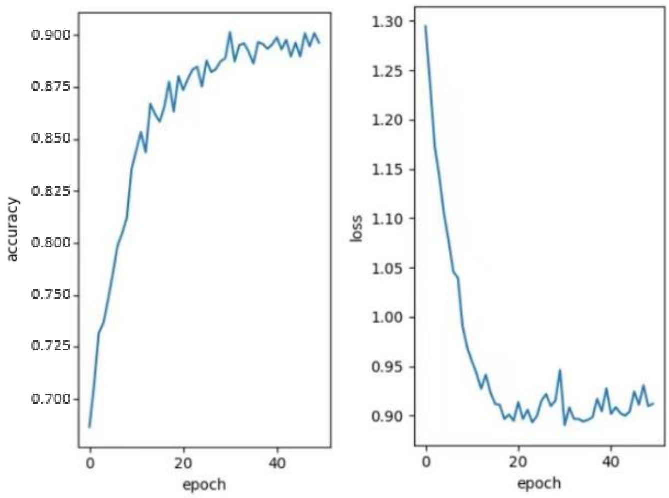

Figure 6.VGG-16 Network Training Results

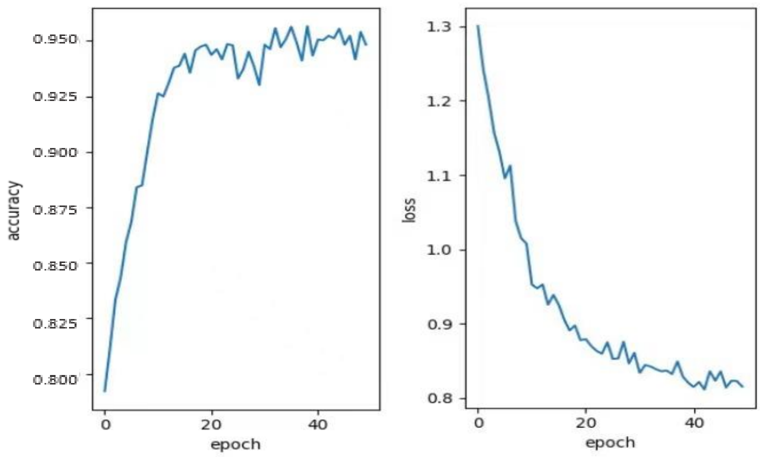

Figure 7. The Improved VGG-16 Network Training Results

As can be seen from the figure, the curve without adding the BN layer converges slower and stabilises only after 25 epochs, while the curve of the model with the BN layer converges faster and basically stabilises in 10 epochs. The experiments show that the improved model, which can make the parameters of the middle layer of the network obey the same distribution, speeds up the training and convergence of the model, thus preventing the gradient explosion and gradient disappearance and making the model more stable.

REFERENCES

[1] Wang, Y Liu, Wu Chen and Li, "Deep learning-based weed detection using a drone-carried camera", Computer and Electronic in Agriculture, vol. 165, pp. 104943, 2019, http://doi.org/10.1016/j.compag.2019.104943

[2] A. Etienne, A. Ahmad, V. Aggarwal and D. Saraswat, "Deep Learning-Based Object Detection System for Identifying Weeds Using UAS Imagery", Remote Sens, vol. 13, pp. 5182, 2021, https://doi.org/10.3390/rs13245182

[3] H. Yu, M. Che, H. Yu and J. Zhang, "Development of Weed Detection Method in Soybean Fields Utilizing Improved DeepLabv3+ Platform", Agronomy, vol. 12, pp. 2889, 2022, https://doi.org/10.3390/agronomy12112889

[4] Mads Dyrmann, Henrik Karstoft and Henrik Skov Midtiby, "Plant species classification using deep convolutional neural network", Biosystems Engineering, vol. 151, pp. 72-80, 2016.

[5] Nikita Genze, Raymond Ajekwe, Zeynep Güreli, Florian Haselbeck, Michael Grieb and Dominik G. Grimm, "Deep learning-based early weed segmentation using motion blurred UAV images of sorghum fields", Computers and Electronics in Agriculture, vol. 202, pp. 107388, 2022, https://doi.org/10.1016/j.compag.2022.107388

[6] Andrea C C, Daniel B B M, Misael J B J. “Precise weed and maize classification through convolutional neuronal networks”, IEEE Second Ecuador Technical Chapters Meeting.IEEE, 2017.

[7] Adel, Bakhshipour, Abdolabbas, et al. “Weed segmentation using texture features extracted from wavelet sub-images”. Biosystems Engineering, 2017.

[8] V. Maeda-Gutiérrez, C.E. Galván-Tejada, L.A. Zanella-Calzada, J.M. Celaya-Padilla, J.I. Galván-Tejada, H. Gamboa-Rosales, et al., "Comparison of Convolutional Neural Network Architectures for Classification of Tomato Plant Diseases", Applied Sciences, vol. 10, no. 4, pp. 1245, 2020.

[9] K. Zhang, Q. Wu, A. Liu and X. Meng, "Can deep learning identify tomato leaf disease?", Advances in Multimedia, 2018.