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Field Weed Recognition Based on an Improved VGG With Inception Module

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ABSTRACT

The precision spraying of herbicides can significantly reduce herbicide use, and recognizing different field weeds is an important part of it. In order to enhance the efficiency and accuracy of field weed recognition, this article proposed a field weed recognition algorithm based on VGG model called VGG Inception (VGGI). In this article, three optimizations were made. First, the reduced number of convolution layers to reduce parameters of network. Then, the Inception structure was added, which can maintain the main features, and have better classification accuracy. Finally, data augmentation and transfer learning methods were used to prevent the problem of over-fitting, and further enhance the field weed recognition effect. The Kaggle Images dataset was used in the experiment. This work achieved greater than 98% precision in the detection of field weeds. In actual field, the accuracy could reach 80%. It indicated that the VGGI model has an outstanding identification performance for seedling, and has significant potential for actual field weed recognition.

KEYWORDS

Data Augmentation, Inception Structure, Transfer Learning, VGG Model, Weed Recognition

1. INTRODUCTION

Recognizing and removing weed is an important part of field management. Weeds secretions hinder the growth of seedlings and cause the yield reduction in the field (Su, 2017). In addition, weeds are main medium to spread diseases and insect pests (Zhao & Liu, 2019). Weeds compete for environmental resources such as nutrients, sunlight, and water (Hu, 2007). Manual weeding (Xie et al., 2018) and biological weed control (Shabbir et al., 2018) are primitive and traditional methods for weeds control in China (Lv, Dong, Sun, & Li, 2018). On the one hand, the cost for the research work and development of biological weed control is very high (Chen & Qiang, 2015), on the other hand, chemical weeding (Wen, Ying, & Libai, 2007) pollutes the environment (Liu, Wang, & Guan, 2005). There is an urgent need to improve the efficiency of weeds recognition and removing.

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The versatility of computer vision has made it a fit tool used in many fields, including precision agriculture (Andrea, Daniel, & Misael, 2017). Machine vision technology was first incorporated into crop detection algorithms to identify crop rows and to segment plants and weeds (Brivot & Marchant, 1996). Researchers developed an automated crop spraying system, and analysised the green histogram of plants images and performed crop and weed segmentation with unspecified classifiers (Aitkenhead et al., 2003). Cao, Wang, Mao, and Zhang (2007) developed a method to identify weeds in field by using position and texture features of drill crops, the method could achieve 93% accuracy. Qiao, He, Zhao, and Tang (2013) developed and tested a method of weed recognition based on multi-spectral images and SVM classifier, this method spent less time than traditional SVM classifier. However, this method had a limitation that the accuracy needs to be improved. Wang and Li (2016) proposed an algorithm to extract the height feature of the image and then fuse it with the texture to identify and obtain a higher recognition rate, the algorithm had an effectiveness of 98.33%. However, the plant detection algorithm presented a limitation that the method pent extremely large computing time. Yan (2018) proposed a method to identify weeds by removing shape and color of images, the goal of which was to prepare for intelligent inter-tillage in fields. In order to improve accuracy of crop and weed identification, a fast field weed identification method was proposed based on the deep convolution network and binary code, the method could achieve 92.7% accuracy (Jiang et al., 2018). However, the effectiveness of the approach was not guaranteed in some production crop scenarios.

In recent years, with the development of computer technology, the application of machine vision recognition method in the identification of weeds and crops is also very extensive. Machine vision technology can provide important tools for real-time image processing and weed detection. The convolution neural network (CNN) (Lecun and Bengio, 1998) have been widely used in various fields and also have achieved remarkable results in the field of image recognition. One of the major advantages is that the original image can be used as an input and the automatic training feature, and further reduce the manual pre-processing. Especially, LeNet, VGG16 (Ke et al., 2018; Zhang et al., 2018; Zhuo et al., 2018), GoogLeNet (Szegedy et al., 2014; Zhai et al., 2019; Xie et al., 2018), ResNet (Gu et al., 2019) and other classical neural network, they all have achieved excellent results in image classification and recognition. Here, an VGG Inception (VGGI) model was proposed to identify and detect field seedlings and weeds. In this paper, three optimizations were made. First, the reduced number of convolution layers to reduce parameters of network. Then, the Inception module was added and dropout operations, which can maintain the main features, have better classification accuracy and are more robust. Finally, data augmentation and transfer learning methods were used to prevent the problem of over-fitting, and further enhance the field weed recognition effect. Moreover, the VGGI model applied to the actual images, the algorithm preformed a good effectiveness.

2. MATERIALS AND METHODS

In this section, we describe the characteristics of the dataset in detail, introduce the model in this paper and related model.

2.1. Dataset

In this paper, the weeds and crops image datasets of Kaggle competition were used to train and test the network model. According to Xu (2011), the dataset includes six kinds of weeds, Black-grass, Charlock, Cleavers, Common Chickweed, Fat Hen, Loose Silky-bent and six kinds of crops, Common wheat, Maize, Scentless Mayweed, Shepherds Purse, Small-flowered Cranesbill, Sugar beet. The total of 4750 field weed samples of 12 categories were depicted in Table 1.

All the images are patched of 224×224 pixels by Matlab. The number of images were randomly divided into two groups: 80% of images as the training data and 20% of images as testing data. As shown in Figure 1, which is the example of field plants.

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