Classification system study of soybean leaf disease based on deep learning

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三等奖

摘要

Accurate and automatic identification of leaf diseases can help farmers to formulate early response actions to reduce economic losses. A deep learning-based classification systemagainst soybean leaf disease wasproposed inthis paper. The dataset was derived from multi-blade real crop images taken directly by small UAVs at different time periods and under different illumination conditions. First, for the collected leaf images, SLIC method was used to segment the image of plant leaves by classification system. Then, fine-tuning and transfer learning strategies was adopted to expand training of deep neural networks,as wellas data enlargement andDropout techniques were used to avoid over-fitting. Finally, test results of real data sets are presented quantitatively and qualitatively by means of visualization.The results showed that the classification accuracy can be as high as 99.04% when using Inception-v3 combined with 75% fine-tune parameter strategy.

提出的方法

1. CLASSIFICATION SYSTEM

The classification system proposed in this paper can identify soybean diseases from images collected by UAVs. The system adopts the SLIC superpixel method to segment the plant leaves.

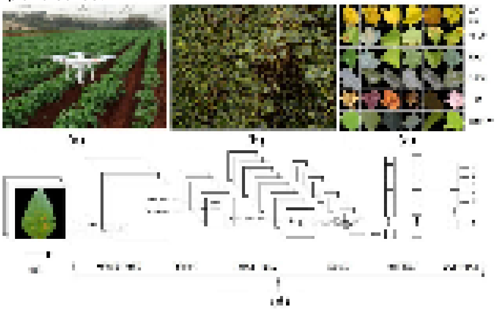

Fig. 1. structure diagram of soybean leaf disease classification system based on UAV image and deep learning

Figure 1 shows the schematic diagram of the system structure proposed in this paper. The system shown in Figure 1 consists of four steps :1) image acquisition; 2)SLIC segmentation; 3) image data sets; 4) classification of leaf diseases. Initially, the use of UAVs flight check through soybean fields to capture the image of the plantation [Figure 1(a)]. These images were segmented with SLIC superpixel method [figure 1(b)]. After image segmentation, visual analysis on leaf blades by experts to form a superpixel image dataset for training and testing systems, as shown in figure 1(c). In these circumstances, agronomists tagged each superpixel as a specific category on the basis of observation: Asian rust, Target_spot disease, Mildew , Powdery mildew,soil (bare land and straw) or samples of healthy leaves. Finally, And use these data to CNN for training, to extract visual resources from superpixel images. Eventually, soybean disease images were classified (See figure 1(d)). In the post-processing phase, this system will visualize the quantitative results of classification, so that the level of disease infection in each planting area can be calculated, thus more effective management of field pathogens.

2. Image acquisition

The paper captures images of soybean plants using Phantom 3 Professional UAVs equipped with a 1/2.3-inch Sony EXMOR sensor and 12.3 M pixel resolution. Where the camera and the ground into 90° angle (right angle), the photo shooting position is 2 metres above the plantation plants, digital photo format is DNG image.

3.UAV Height and Blade Segmentation

In order to identify the leaves of plants in the image, each implant image was segmented using a superpixel method Each image is 4000×3000 pixels in size, total 12,000,000 pixels. Segmentation parameter k defines 2000 regions, each individual soybean leaf images of about 6000 pixels in each region. In addition, owing to the higher incidence of disease in soybean growth cycles between phenology of R1 and R6. There was no significant change in blade size, We keep the parameter k and m values in the SLIC algorithm unchanged, segmenting all pictures with the same parameters. Finally, 3000 superpixel images were assigned in six categories, soybean disease, soil, and healthy leaves, and each category including 1000 images. Figure 1(c) escribes examples of each category.

4. Classification evaluation

The deep learning model for image classification is based on the tagged image training, to learn visual patterns and to identify and classify them. And we've implemented this system using open source algorithms with CNN, including Inception v3, VGG-19, ResNet-50 and Xception , which all are provided in Keras modules, and is validated on the ImageNet dataset. We use a supervised learning model, and divide the training and test set into 70% training sets, 30% for test set. This paper uses three indicators to evaluate the performance of each model: accuracy, duration of training and learning error. To analyze whether there are statistical differences in terms of the performance of the model, we used ANOVA hypothesis

To statistically evaluate the application potential of the model in soybean field in disease identification, we defined four different training strategies for our network using FT techniques, each derived from 25%-100% of the network parameters in the ImageNet, with a percentage step of 25%. Furthermore, we train the complete network using randomly initialized network weights (without transfer learning TL). And also use the weights obtained from ImageNet to a TL strategy from training.

实验

Table I shows the accuracy results obtained by the deep learning model. The Maximum accuracy values obtained for each model are highlighted in the table. Table 1 also shows the learning error and the total duration of training (in seconds) for constructing the classification model. The time results of table 1 refer to the hardware specifications presented in section III. The executing results in different machine configurations may show different.

TABLE I. EFFECTS OF DEEP LEARNING MODELS UNDER

Model	Strategy	Duration of training (s)	Accuracy	Learning error
Inception-v3	FT 100%	255891	98.87	0.0523
Inception-v3	FT 75%	202629	99.04	0.0490
Inception-v3	FT 50%	181223	97.22	0.1052
Inception-v3	FT 25%	160661	94.78	0.1645
Inception-v3	TL	147477	86.85	0.3869
Inception-v3	No TL	255897	95.75	0.1476
Resnet-50	FT 100%	304526	98.96	0.0414
Resnet-50	FT 75%	239265	99.02	0.0459
Resnet-50	FT 50%	200082	98.96	0.0421
Resnet-50	FT 25%	175921	98.79	0.0544
Resnet-50	TL	149396	96.95	0.1282
Resnet-50	No TL	304831	96.54	0.1106
VGG-19	FT 100%	392662	99.02	0.0476
VGG-19	FT 75%	330291	98.33	0.0569
VGG-19	FT 50%	253551	98.27	0.0703
VGG-19	FT 25%	194543	96.37	0.1236
VGG-19	TL	173697	77.53	0.6501
VGG-19	No TL	390494	69.59	0.6855
Xception	FT 100%	454838	98.56	0.0549
Xception	FT 75%	300902	97.98	0.0796
Xception	FT 50%	269355	94.53	0.2356
Xception	FT 25%	235287	92.63	0.2700
Xception	TL	200016	86.69	0.3922
Xception	No TL	437106	97.87	0.0796

It is obvious that Inception-v3FT 75% model obtained the highest accuracy value (99.04%), followed by Resnet- 50, VGG-19(99.02%) and Xception(98.56%). Inception-v3 has less duration of training, and then Resnet-50. VGG-19 and Xception. After ANOVA tests, we found that p value was 0.412, in the case of significant level of 5%, there was no statistical difference in the accuracy of the models. On the other hand, in selection of deep learning models and training strategies, VGG-19 models without TL training achieved 69.59% accuracy, while 99.02% accuracy was achieved using the FT 100%, and the difference was 29.43%. In addition, when compared with other training strategies, FT 100% shows a higher classification rate … use of these … ration of training was given.

结论

In this paper, we use the real image training depth neural network of crops at different stages captured by UAVs to identify the intelligent agricultural system of soybean leaf disease. First, SLIC superpixel algorithm is used for image segmentation in order to detect and segment plant leaves in the images. Amid steps in classification, four famous deep learning models were compared: Inception-v3, Resnet-50, VGG-19 and Xception. Experimental results show that the deep learning model does yield a higher classification rate, with accuracy rate of up to 99.04%. In addition, compared with other training strategies in our experiments, FT 100% and 75% strategies showed a higher classification performance. The system in this paper can provide users with qualitative and quantitative classification results of computer vision, and can be operated in real scenes under different illumination … tions.

主要参考文献

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