A deep learning-based algorithm for crop Disease identification positioning using computer vision

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Abstract: ***Food security is fundamental to a country. As the main risk factors, pests and diseases seriously restrict the normal growth of crops and the quality and safety of agricultural products. With the intensification of climate change and the continuous adjustment of farming methods, crop diseases and pests have become more frequent in recent years. Therefore, the agricultural production mode has gradually moved from family production to large-scale agricultural planting, and the production equipment has become more automated and intelligent. Agricultural intelligent robots can reduce labor costs in the process of agricultural production and improve the standardization of agricultural production. The application of computer vision in agriculture is rapidly becoming an important aspect of modern agricultural technology, especially in crop positioning and management. Through the use of advanced image processing algorithms and pattern recognition technology, computer vision systems are able to accurately identify and locate various crops in the field, enabling automated and precise management. This technology shows great potential for crop health monitoring, pest identification, and maturity assessment. For example, by analyzing images of plants, computer vision systems can spot signs of lesions or nutrient deficiencies in time and guide farmers to treat them accordingly. In addition, this technology can also be used to guide automated agricultural machinery, such as driverless tractors and harvesters, to improve the efficiency of crop harvesting and reduce labor costs. In general, the combination of computer vision and crops provides new technical means for the development of modern precision agriculture, which helps to improve the efficiency and sustainability of agricultural production.***

Keywords: Computer vision positioning; Crop damage; Deep learning; Intelligent pest control

1. INTRODUCTION

In the early stage, the identification of crop diseases and pests is carried out by artificial field identification. Farmers and professional agricultural technicians analyze the causes of diseases and pests by visual inspection or sending plant samples to the laboratory for testing. Due to the wide coverage and variety of pests and diseases, it is necessary to rely on professional knowledge or planting experience to diagnose them. However, the characteristics of some diseases and pests are similar, and it is difficult to distinguish them. The artificial identification method has some outstanding problems such as strong subjectivity, heavy workload and low detection rate, and it is easy to delay the best time for the treatment of diseased crops. With the rise of computer network technology, the use of machine learning to identify pests and diseases has been further developed. Machine learning labels and classifies the features of external crop images, and reveals the correlation information between the data through data analysis, data mining and other technologies, so as to automatically detect the damage situation and improve the recognition efficiency and accuracy to a greater extent. Traditional machine learning algorithms include least square method, support vector machine K-means clustering algorithm, principal component analysis, etc[1]. Different models and algorithms present specific advantages for different problems.

At present, big data promotes the rapid development of smart agriculture, digital transformation has become an inevitable choice for agricultural modernization, and the use of deep learning technology to analyze crop diseases and pests has become a new research hotspot. Compared with traditional machine learning algorithms, deep learning is completely data-driven without manual intervention, so it can maximize the use of the information contained in the data itself for target detection[2]. Its deep network structure can accommodate rich semantic information, and can quickly and accurately complete target location and image classification tasks even in complex application scenarios, and show good recognition performance in pest image analysis.

2. RELATED WORK

2.1 Traditional crop feature extraction

The method of identification by the characteristics unique to the target in the image, such as color, texture, histogram, shape, etc., which are obviously different from the background is usually suitable for the picking scene with obvious features. A crop with red, round ripe fruit, such as tomatoes and apples.

(1) Value segmentation algorithm

The reading segmentation method is to convert the image into gray image for recognition, generally combined with other feature extraction methods, and can also be used in the scene where the color feature distinction is more obvious[3]. The commonly used stop value selection method OTSU algorithm can automatically select the threshold according to the number of gray pixels in the image, and transform the image into a binary image to achieve the purpose of recognition. Secondly, the gray level histogram of the image is analyzed, and the appropriate reading value is selected through statistical theory to segment the image into binary images. In addition, the gray level histogram can be extended to the RGB channel of the image, and the histogram information of a certain color channel can be counted separately for binary segmentation of the image, which is often used to identify the situation where the color of the target is different from that of the background.

(2) Edge feature detection

Through the convolution calculation of various operators, the texture and gradient features of the image can be obtained, and then the edge information of the object in the image can be obtained by further judgment. Canny edge detection[4].As the most widely used edge detection algorithm, edge information is extracted one pixel by one pixel in a recursive way, and the identification results are clear and clear. The commonly used operators of Canny include Sobel operator, Prewitt operator, etc.

$$Sobel_X = \begin{bmatrix} 1 \\ 0 \\ -1 \end{bmatrix} * \begin{bmatrix} 1 & 2 & 1 \end{bmatrix} = \begin{bmatrix} 1 & 2 & 1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{bmatrix} \tag{1}$$

Generally, the soble operator is used, so is OpenCV, which uses the soble horizontal and vertical operators to convolve with the input image to calculate dx and dy.

(3) Clustering detection algorithm

The clustering algorithm maps the RGB three-channel into the three-dimensional space, and classifies the pixels by the position and distance relation of each pixel space, so as to achieve the purpose of image segmentation. Common Clustering detection algorithms include K-means clustering algorithm and Simple Linear Iterative Clustering (SLIC) algorithm.

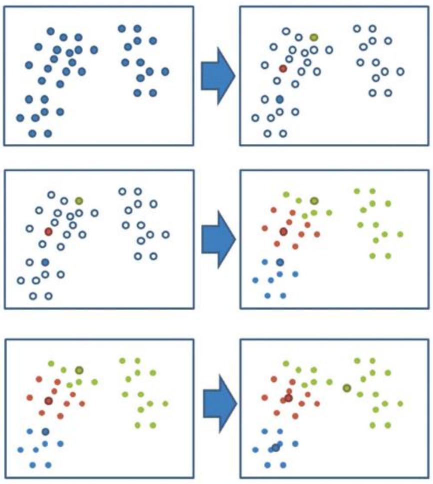

Figure 1: Traditional clustering algorithm implementation steps

Randomly set K points in the feature space as the initial clustering center; For each other point, the distance to K centers is calculated, and the nearest cluster center point is chosen as the marking category for the unknown point. Then, the new center point (mean value) of each cluster is recalculated against the marked cluster center[5]. If the calculated new center point is the same as the original center point (the center of mass no longer moves), then the end, otherwise repeat the second step.

2.2 Key links of crop identification and positioning

Deep learning model identification of crop pests and diseases includes four steps: data preprocessing, data enhancement, deep network framework selection and model optimization:

(1) Data preprocessing is the first step to build a model. High-quality, large-scale and highly labeled data sets are of great help to train deep neural networks. In order to make open data sets or images obtained by self-shooting more suitable for network computation, targeted preprocessing of input data is taken, including size adjustment, image segmentation, normalization and graying.

(2) Data enhancement is to create different variants of the same data by means of geometric transformation, spatial change, color transformation, random generation, etc., without substantially increasing the data, it can make up for the problems of small total dataset and single structure, improve the number of samples and model performance, and reduce the risk of overfitting.

(3) The selection of the final frame of the deep network is related to the system response speed and target recognition accuracy, and the focus of establishing a high-performance model is to design an appropriate feature extractor. It is usually a complex network structure composed of multiple convolutional layers and pooling layers, which needs to design a reasonable network depth and hierarchy according to specific task objectives and network model characteristics.

(4) To improve the time and space efficiency of the network model. The integration of multiple optimization strategies in deep learning is a hot research direction at present. Wan Weixiang[6] Used decision tree for preliminary classification according to the attribute characteristics of pest such as color, shape and gray level, and then constructed TensorFlow deep learning model to analyze the original disease image. Through Booting algorithm, the two types of discriminators were linearly combined according to different weights to output the final results.] Experiments show that the fusion model performs better than the single model in recognition tasks. Wei Chao et al. conducted initialization training and transfer training for six kinds of deep network models, and the loss function adopted was composed of cross entropy and regularization terms. In general, under the framework of VGGNet16 deep network, the accurate identification network model of wheat pests and diseases is built by using gradual learning rate and transfer learning, and the average recognition accuracy is as high as 95%.

3. METHODOLOGY

In the visual positioning and detection of crop seedlings, in the field of target detection, after years of development of neural networks, many classical neural network models have emerged, which can be divided into two-stage model and one-stage model according to the model implementation principle and steps, among which the two-stage model is Faster-RCNN.

3.1 Faster-RCNN model

The model proposed by Ren et al. in 2015 improved on the basis of Fast-RCNN. The RPN layer was used to select candidate frames, and the feature graph structure was used to realize weight sharing, and the repeated feature extraction operations in some areas of the image were omitted, thus improving the computing speed of the network. Faster-RCNN is mainly divided into two parts[7]: the RPN structure is used to extract the region of interest, and the Roihead is used to classify and identify the region of interest and to correct the location and size of the detection frame.

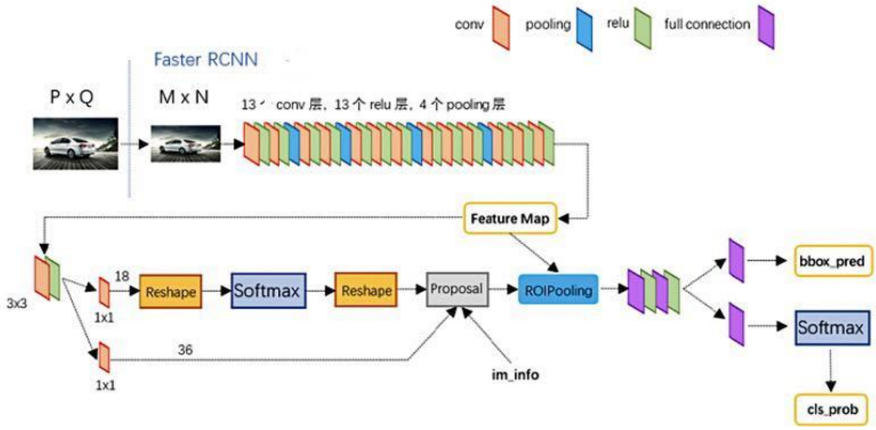

Figure 2: Network structure of faster_rcnn_test.pt in VGG16 model

In the visual detection of crop seedlings, faster-RCNN (Faster Region-Based Convolutional Neural Network) plays a key role. As an efficient deep learning algorithm, Faster-RCNN effectively realizes fast and accurate identification of crop seedlings through its convolutional neural network (CNN) and regional proposal network (RPN). The implementation process mainly includes: first, image features are extracted by convolutional layer; RPN then generates regional proposals on these features, which identify areas of the image that may contain seedlings; These regions are then analyzed more deeply through the fully connected layer of the network to determine the exact location and category of seedlings[8]. In addition, Faster-RCNN also includes refinement steps for these regions, further improving the accuracy of detection. This method is very useful in the agricultural sector and can be used to automate seedling monitoring during the planting process to optimize crop management and increase yields. With this technology, agricultural producers are able to quickly identify and respond to problems in seedling growth, such as disease or malnutrition, thereby improving overall crop quality and yield.

3.2 Crop Openpose key point detection

Openpose is a convolutional neural network used for key point detection. It adopts a bottom-up recognition method and mainly consists of two parts for key point detection, namely, Part Confidence Map (PCM) and Part AffinityFields (PAF). The PCM module is responsible for predicting all the key points, and in the human pose estimation, the PCM predicts all the joint information of different people in the way of Gaussian heat map. The PAF pairs all the key points in the way of affinity, identifying the key points that belong to a target.

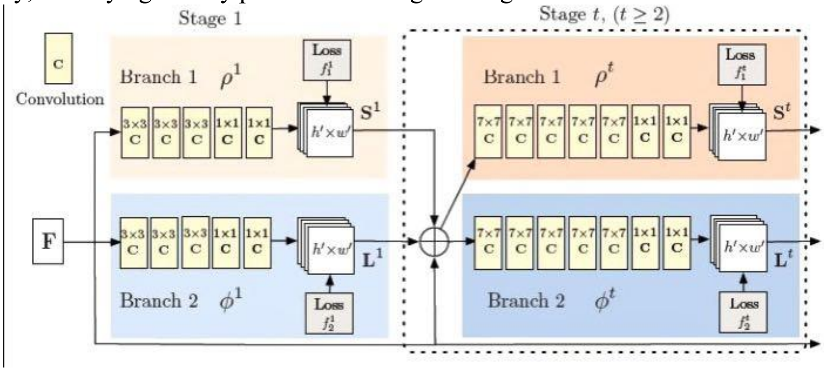

Figure 3: Openpose structure

Firstly, the feature map of the target is obtained through the backbone network, as shown in Figure 3. In step 1, the thermal map and affinity relationship of the key points are obtained through the feature map. In this process, all the key points cannot be identified due to the obscured points in the image. Therefore, in Openpose, a new feature map is obtained after the recognition results of step 1 are added and fused with the feature map. The new feature map is used as the input of step 2 for re-prediction, and the final thermal map PCM and PAF of the target will be obtained after the prediction of multiple steps.

$$\begin{cases} f_S^t = \sum_{j=1}^{J}\sum_{P} W(p)\cdot S_j^t(p) - S_j^*(p)_2^2 \\ f_L^t = \sum_{c=1}^{C}\sum_{P} W(p)\cdot L_c^t(p) - S_c^*(p)_2^2 \end{cases} \tag{2}$$

For crop localization, Openpose needs to monitor all the steps, and the output of each step is similar, including heat maps and affinity representations. The loss function of a single step is the sum of the two. Taking step t as an example, the formula of the loss function is (2).

3.3 PCM thermal map detection and positioning

In Openpose, PCM heat map is used to represent the position of key points in the image. Taking daylily as an example in this paper, four key points are set. Gauss heat map indicates that the marked position of each key point is distributed around Gauss algorithm, which is because there is more than one pixel belonging to a point in the image and there are annotation errors. If Gaussian distribution is not used, there will be a contradiction in training, that is, the feature of a key point is almost the same as the feature of its neighboring points, but only one point belongs to the required key point in the annotation of the real key point. After using Gaussian graph, a competitive relationship is formed between two points, and probability is used to represent the possibility of two points as a certain key point[9], so as to avoid the occurrence of contradictory events with the same characteristics but different categories in the training process.

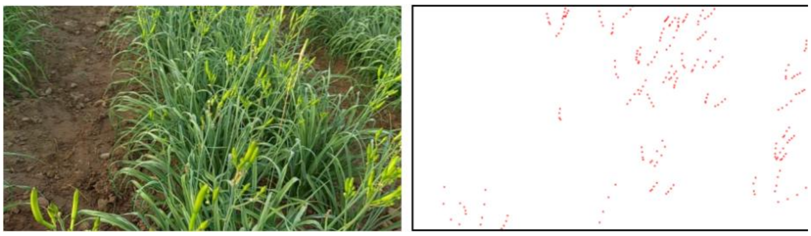

Figure 4: Thermal map location detection original and detection diagram

Methods The principles and functions of convolutional layer, pooling layer and activation function in convolutional neural networks are briefly described. Then, the object detection network structure of Faster-RCNN and openpose is described, and the principle of the existing object detection algorithm is expounded. Among them, openpose will be used as the basic model to improve the detection of key points. Finally, the principle of FCM thermal map to predict key points is introduced, and the related concepts of key point detection are introduced.

4. CONCLUSION

This study discusses the application of deep learning algorithms in the visual localization of crop seedlings in detail, and emphasizes the important role of two advanced deep learning models, Faster-RCNN and Openpose, in the field of agriculture. In this paper, the traditional methods of crop pest identification and their limitations are summarized, and then the key steps of deep learning model in crop pest identification and localization are introduced in detail, including data preprocessing, data enhancement, network framework selection and model optimization. Of particular note is the in-depth analysis of the function of the Faster-RCNN model in extracting regions of interest, and the explanation of how the model effectively achieves fast and accurate identification of crop seedlings through CNN and RPN[10-12]. At the same time, the application of Openpose model in critical point detection is also discussed in detail.

To sum up, deep learning technology has significant advantages in the field of crop visual localization. The application of the two models, Faster-RCNN and Openpose, not only improves the accuracy and efficiency of crop pest identification, but also provides effective technical support for precision agriculture management. The application of this technology will greatly improve the health monitoring and pest control of crops[13], thereby improving the quality and efficiency of agricultural production. In the future, with the continuous improvement and optimization of deep learning technology, we can foresee that its application in the agricultural field will be more extensive, not only limited to the identification and positioning of pests and diseases, but also may expand to crop growth monitoring, yield forecasting and other aspects[14-15]. This will provide strong technical support for the realization of a more intelligent and automated modern agricultural production mode.

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