Location of Mulberry Leaf Picking Points Based on Improved Mask RCNN

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Abstract. In response to the current situation of high labor cost and low efficiency in mulberry leaf picking in China, and the lack of information on the location of mulberry leaf picking points in the intelligent development process of mulberry leaf picking, a mulberry leaf picking point positioning method based on improved Mask RCNN is proposed. Firstly, we make the following improvements to Mask RCNN: 1) replace the ResNet network in the original Mask RCNN with ResNeXt network; 2) Add a bottom-up fusion path to the FPN network and propose a multi-scale region recommendation network; 3) design convolutional kernels of different sizes for different feature layers. Then we used the improved Mask RCNN to segment the node area of mulberry leaf, and used a thinning algorithm to skeleton the node area and located the corresponding points as picking points. The results showed that the average accuracy and F1 index of the proposed method for identifying mulberry leaf node areas are 89.1% and 75.7%, respectively, which are 2.8 and 3.5 percentage points higher than the original Mask RCNN network, which providing a theoretical basis for intelligent mulberry leaf picking machines.

Keywords: Picking points · Mask RCNN · Path enhancement · Mulberry leaf node area · Skeletonization

1 Introduction

China is a major country in the world of silkworm breeding, with a history of over 5000 years [1, 2]. In recent years, the silkworm industry has gradually shifted to the western region, and Guangxi has consistently ranked first in silkworm production in the country for over a decade, making a significant contribution to the local economy [3, 4]. However, currently, due to the transfer of a large number of rural labor to coastal cities, the shortage of mulberry planting and sericulture workers in the western silkworm breeding area has become a problem that needs to be solved. Therefore, many domestic scholars have developed and designed some mechanized and semi-automatic equipment for the mulberry leaf picking process in silkworm production. Li Jian et al. developed a small mulberry leaf picking machine, which is simple to operate and improves the efficiency of mulberry leaf picking [5]. The research group led by Hu Yingchun has designed

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multiple types of mulberry leaf picking equipment, such as reciprocating mulberry leaf picking machines, spiral mulberry leaf picking machines, and semi-automatic mulberry leaf picking machines, greatly promoting the traditional mulberry sericulture industry to move towards mechanization and semi-automatic processes [6–8]. Xu Bo [9] et al. designed a multi degree of freedom mulberry leaf picking machine, which can complete the picking of mulberry leaves at different heights by adjusting the height of the mulberry leaf cutting mechanism, making it convenient for mulberry farmers to carry out mulberry picking operations. Although these equipments have to some extent reduced the labor intensity of mulberry farmers and improved the efficiency of picking mulberry leaves, they still have not escaped manual operation.

In order to achieve intelligent mulberry leaf picking, the first task is to obtain the location of picking points [10, 11]. Therefore, this paper took mulberry trees in mulberry gardens as the research object, and firstly identified and segmented the mulberry leaf node area by the improved Mask RCNN algorithm, and divided them into "Y" and "moment" types according to the shape, then used the refinement algorithm for skeletonization, located the corresponding points as picking points, which provides visual information for intelligent mulberry leaf picking, and also provides reference for the research of locating other plant leaf picking points.

2 Methods and Results

This study first constructed a Mask-RCNN model to identify mulberry leaf node areas, and then improved the model to improve recognition accuracy. Finally, a method was designed to obtain the picking points of mulberry leaf node areas.

2.1 Mask RCNN Model

2.1.1 Mask RCNN Structure

Mask RCNN is an advanced instance segmentation method, using ROI Align instead of ROI Pooling and adding a mask segmentation branch to form a three-branch network with the generation of detection frame branch and classification branch. In Mask RCNN, ResNet is used as the backbone network, and five feature layers of different sizes are obtained by feature extraction of the input image, and then these feature layers are input into the feature pyramid network FPN for fusion to obtain effective feature layers. Input the effective feature layer into the region recommendation network, which then performs target and background binary classification, extracts regions that may contain targets, and generates candidate boxes. Then use ROI Align to adjust the candidate regions of different sizes to the same size in the feature map, and input the three branch network. The first and second branches complete the prediction of target categories and the regression of detection boxes after passing through two fully connected layers; The third branch is operated by a fully convolutional network to classify each pixel in the image and obtain the mask of the target.

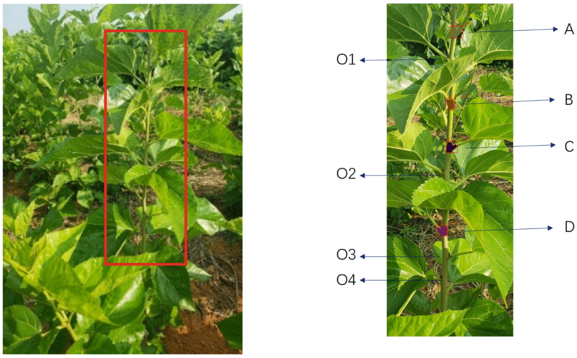
2.1.2 Node Recognition Using Original Mask RCNN

By taking a dataset of mulberry trees and using labelme software to create labels for the node areas of mulberry leaves, it was found that they can be divided into two parts based on their shape: one type is the “Y” shaped node area of mulberry leaves, which contains forks and has a shape similar to the “Y” shape; Another type is the circular “rectangular” mulberry leaf node area. As shown in Fig. 1.

(a) "Y" type mulberry leaf node area (b) "rectangle " mulberry leaf node area

Fig. 1. Type of mulberry leaf node area

Then, the Mask RCNN algorithm is used to train the labels to obtain the original Mask RCNN model, which is used to detect the node areas of mulberry leaves. The results are shown in Fig. 2(b). It can be found that in the result graph, except for the nodes at points A, B, C, and D, the four nodes O1 to O4 were correctly identified, but the missed detection phenomenon is relatively serious.



(a) Original image (b) recognition in the way of Mask RCNN model

Fig. 2. Recognition results of Original Mask RCNN

2.2 Improve Mask RCNN Model

Due to the small area of mulberry leaf nodes, the recognition accuracy of the original Mask-RCNN model is not high, and there are many missed detections. Therefore, this study aims to improve the following aspects:

1) The backbone network in the Mask RCNN is the ResNet network, which was replaced by the ResNeXt network in this study;
2) We Added a bottom-up fusion path to the FPN network in the model;
3) In the RPN of Mask RCNN, we proposed a multi-scale regional suggestion network, and designed convolution kerns of different sizes for different feature layers.

2.2.1 ResNeXt Network

ResNet is replaced as the backbone network by a more concise and modular ResNeXt network. In essence, ResNeXt is a packet convolution, which replaces the residual block of three-layer convolution of the original ResNet network with a topology structure of parallel stacking of the same modules [10]. It also uses the segmentation - transformation - fusion structure of Inception network for reference to improve the scalability and performance of the model. Reduce the number of overparameters and improve the ability of the model to extract features of mulberry leaf node area.

2.2.2 Adding a Path Enhancement

In order to improve the detection ability of mulberry leaf node area, a bottom-up path is introduced laterally after feature layer fusion in the feature pyramid, as shown in Fig. 3. Since the information in shallow C2 needs to pass through dozens or even hundreds of network layers to the top P5, it is easy to lose information after such multiple layers of transmission. Moreover, a large number of features including edge shapes in shallow feature layer are very important for instance segmentation. Therefore, an enhancement path is introduced to transfer the shallow feature information of C2 feature layer to N5 along this path. The number of layers passing through is significantly reduced, and the underlying information is better preserved.

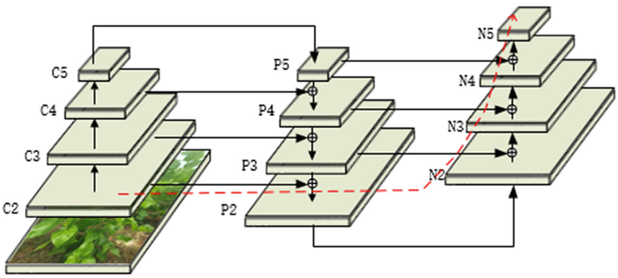


Fig. 3. Path enhanced structure

2.2.3 Multi-scale Regional Suggestion Network

When acquiring mulberry leaf images, the pixel area of the nodal area of mulberry leaves is generally small. Increasing the receptive field is the key to many vision tasks [11], so for the detection problem of targets with small size, the performance of detecting targets can be improved by increasing the size of the receptive field to obtain more contextual information. To expand the perceptual field of each effective feature layer obtained after the path enhancement network, a multi-scale region proposal network is designed with different sizes and numbers of convolution kernels for different sizes of effective feature layers, as shown in Fig. 4. The input image is superimposed with different sizes of convolutional kernels for N3, N4 and N5: (i) N3: 1*1, 1*3 and 3*1 kernels; (ii) N4: 1*1, 1*3 and 3*1 kernels; and (iii) N4: 1*1, 1*3 and 3*1 kernels. (ii) N4: superimposed with 1*1, 1*3, 3*1, 1*5 and 5*1 convolutional kernels; (iii) N5: superimposed with 1*1, 1*5, 5*1, 1*7 and 7*1 convolutional kernels.

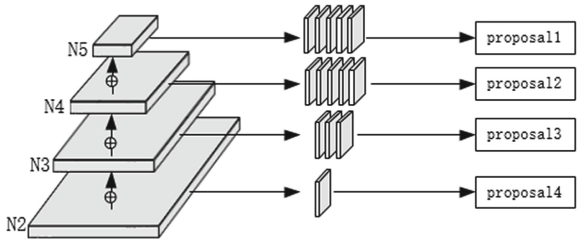


Fig. 4. Multi-scale regional proposal network

2.2.4 Improved Mask RCNN Recognition Results

To verify the effectiveness of the model improvement, an improved Mask RCNN model was used to identify the mulberry leaf node area, as shown in Fig. 5. By comparing the recognition results of the original Mask RCNN in Fig. 2(b), we can find that the improved model has identified a total of six mulberry leaf node areas A' ~ F', which can identify the node areas at O1 and O2 points that were not recognized before the improvement, improve the situation of missed detection. And it has better segmentation details, closer to the real area of mulberry leaf nodes.

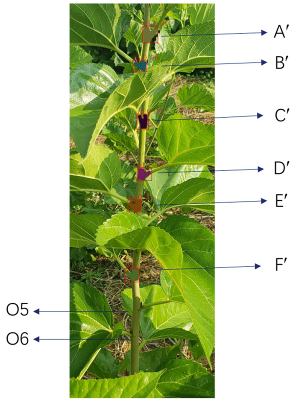
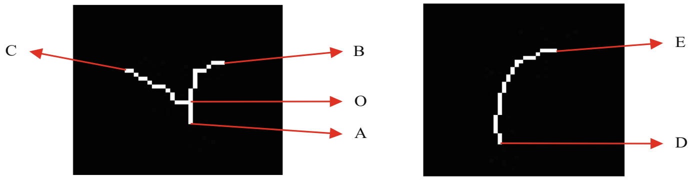


Fig. 5. Recognition results of Improved Mask RCNN

2.3 Positioning Picking Points

We designed different picking point positioning methods for these two types of node areas. For the "Y" type node area, We searched for endpoints A, B, and C based on the size of the vertical pixel coordinates, and then obtained point O based on the number of pixel points in its eight neighboring areas. Finally, by comparing the angle formed by line segments OC, OB, and OA, we determined OC as the petiole bone and take its midpoint as the picking point. For "rectangular" node area, We extracted the center point of the bone as the harvesting point. as shown in Fig. 6.



(a) Bones in the "Y" node area (b) Bones in the "rectangular" node area

Fig. 6. Bones in the mulberry node area

To verify the effectiveness of the model improvement, the Mask RCNN model and the improved Mask RCNN model are evaluated using the precision rate P, recall rate R, average precision AP and F1 index metrics, the results are shown in Table 1.

Table 1. Evaluation results of the model before and after improvement

model	P/%	R/%	AP/%	F1/%
Mask RCNN	84.2	63.2	86.3	72.2
Improved Mask RCNN	86.7	67.1	89.1	75.7

It can be found that the improved Mask RCNN has improved in the AP and F1 index by 2.8% and 3.5%, which verifies the effectiveness of the model and the improved Mask RCNN has better recognition performance for the mulberry node area.

Finally, we used the picking point positioning method to locate the mulberry leaf picking points, and the positioning results are shown in Fig. 7. It can be found that the final positioned picking points are all located within the optimal picking area (black box), verifying the effectiveness of the picking point positioning method mentioned above.

(a) Node area recognition (b) Picking point positioning

Fig. 7. Picking point positioning results

3 Conclusion

Identifying the mulberry leaf node area and locating it with higher accuracy is the key to smart picking of mulberry leaves. Therefore, in this paper, we build a detection model based on Msak RCNN for the research object of mulberry tree, and by improving its backbone network as well as RPN network, the average accuracy of the final detection is 89.1% and the F1 index is 75.7%, which are 2.8% and 3.5% improved respectively compared with the model before improvement. At the same time the segmented obtained mulberry leaf node area, the method of this study can basically locate its picking point accurately, which can provide theoretical reference for the intelligent development of mulberry leaf picking.

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