RESEARCH ON APPLE LEAF DISEASE SEGMENTATION AND CLASSIFICATION BASED ON SEMANTIC SEGMENTATION NETWORK
/
基于语义分割网络的苹果叶片病害分割与分级研究

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ABSTRACT
The key to diagnosing the types and degree of apple leaf diseases is to correctly segment apple leaf disease spots. Therefore, in order to effectively solve the problem of poor segmentation of leaves and diseased areas, the U2Net semantic segmentation network model was used in the research of apple leaf disease identification and disease diagnosis, and compared with the classic semantic segmentation network model DeepLabV3+ and UNet. In addition, the effects of different learning rates (0.01, 0.001, 0.0001) and optimizers (Adam, SGD) on the performance of U2Net network model were compared and analyzed. The experimental results showed that the learning rate is 0.001 and the optimizer is Adam, the average pixel accuracy (MPA) and mean intersection over union (MIoU) of the research model for lesion segmentation reach 98.87% and 84.43%, respectively. The results of this study were expected to provide the theoretical basis for the precise control of apple leaf disease.

摘要
诊断苹果叶病类型和程度的关键是正确分割苹果叶部病斑区域。因此，为有效解决叶片及病斑区域分割效果不佳的问题，提出将U2Net 语义分割网络模型用于苹果叶片病害识别及病害诊断的研究，并与经典语义分割网络模型DeepLabV3+和UNet进行对比分析。此外，比较和分析了不同学习率（0.01、0.001、0.0001）和优化器（Adam、SGD）对U2Net网络模型性能的影响。实验结果表明，学习率为0.001，优化器为Adam，U2Net网络模型的平均像素准确率（MPA）和平均交并比（MIoU）分别达到98.87%和84.43%。该研究结果以期为苹果叶片病害的精准化防治提供理论依据。

INTRODUCTION
In the process of apple growth, its leaves are extremely vulnerable to diseases (such as ring rot, rust, early leaf disease, scab, etc.). The occurrence of leaf diseases also easy to causes changes in leaf color, and in serious cases, leaves fall off, and even affect the resistance of fruit trees to diseases, resulting in reduced fruit yield or quality *(Wang et al., 2019)*. Therefore, the realization of intelligent, rapid, and accurate identification of apple leaf disease is of great significance for improving apple yield, quality, and safety, and promoting the sustainable development of the apple industry.

Deep learning has a higher recognition ability than traditional models in image classification, target detection, image segmentation, and other aspects. Therefore, more and more scholars have applied it to the disease identification of apple leaves *(Li et al., 2022)*. For example, *Ding et al. (2021)* improved the Internet model algorithm by introducing the CBAM attention mechanism and multi-scale feature fusion for apple leaf disease under complex background. *Li et al. (2022)* identified the types of corn diseases in the field environment by improving the RegNet model, with an average recognition accuracy of 95.33% for the three diseases. *Yu et al. (2022)* applied the MSO ResNet network model to the recognition of apple leaf disease images. Using the transfer learning method can improve the recognition rate of the model and provide a reference for the intelligent diagnosis of apple leaf disease. *Jiang et al. (2019)* used the target detection algorithm SSD to detect three common diseases of apple leaves. The results show that this model can automatically extract disease features and has high detection accuracy.

The deficiency of these studies is that the whole disease image is classified or the target is roughly framed by the bounding box, but the contour and shape information of the disease spot cannot be extracted.

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Therefore, it is of great significance to achieve accurate segmentation of leaf lesion area and leaf area to improve the diagnosis of disease degree. *(Li et al., 2021; Boulent et al., 2019; Sharma et al., 2020)*.

Some scholars also use deep learning models to complete semantic segmentation of plant leaf images and then use traditional image analysis methods to complete subsequent disease recognition, diagnosis, and other work *(Ganesh et al., 2019; Santos et al., 2020; Manso et al., 2019)*. It is proved that the deep learning semantic segmentation model based on plant disease spot image semantic segmentation performance is good. The image semantic segmentation model based on deep learning is used for semantic segmentation of the disease image, which realizes the classification of pixel level, and omits the tedious image preprocessing work, the design of the disease segmentation method, and the process of the disease feature extraction. It can directly calculate the proportion of the leaf spot area to the leaf area, and then evaluate the degree of disease according to the relevant standards.

However, to our knowledge, only the author Chao et al. (2021) proposed a semantic segmentation-based approach for segmenting apple leaf lesion areas, but the drawback is that the study did not include diagnostic work on disease severity.

In this study, it is proposed using semantic segmentation network models (U2Net, UNet, and DeepLabV3+) to segment apple leaf lesions and leaf areas, and based on this, calculate the area of the lesion and leaf areas, to estimate the degree of disease according to corresponding standards.

MATERIALS AND METHODS

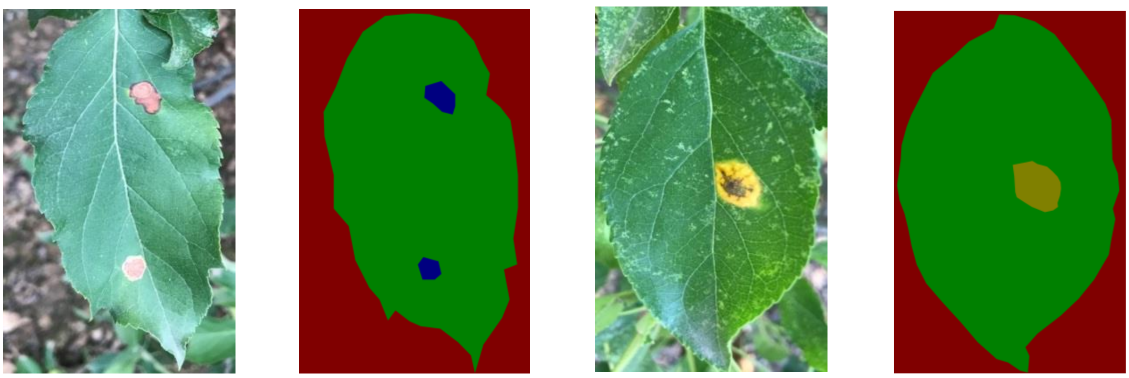
Sample Dataset

In order to identify apple leaf diseases, it is necessary to collect relevant images to establish an image dataset. The image data of apple leaf disease in this study was collected from the Fruit Tree Research Institute of Shanxi Agricultural University. A smartphone (iPhone 13) was used to capture 152 images of ring rot disease and 115 images of rust disease in a natural environment from multiple angles and periods, with an image resolution of 3024×4032, the image format is JPEG, and the color mode is RGB. An example image sample is shown in Fig. 1(a) and Fig.1(c).

Data Set Calibration

The convolutional neural network requires supervised training and learning, so the sprite marking assistant software was used to manually mark polygons in the area where the disease spots were located in the image, while also labeling the leaf area and background area. The method of horizontal, vertical, and rotation was used for data expansion. The original data set was expanded three times to improve the quantity and diversity of samples collected. The data set was divided into training sets (477), verification sets (162), and test sets (54) according to the ratio of 6:2:2. An example of marking the lesion area in the image was shown in Fig. 1.

When training a deep learning model, the more and more comprehensive the training data, the stronger its recognition ability. However, due to the difficulty in collecting disease samples, there is currently a lack of a large number of disease image datasets. Many researchers use a variety of data augmentation methods to expand the original image samples, reduce the over-fitting in the training stage and improve the generalization performance of the network model. The category and quantity of image data sets in this study were shown in Table 1.



a) Images of ring rot *b) Images of ring rot after labeling* *c) Images of rust* *d) Images of rust after labeling*

Fig. 1 - Examples of labeled disease images

Table 1

Distribution of experimental sample data

Classes	Original dataset	Training set	Validation set	Augmented training set	Augmented validation set	Test set
Ring rot	152	90	31	270	93	31
Rust	115	69	23	207	69	23
Total	267	159	54	477	162	54

Experimental Environment

The experiment was implemented based on Python 3.9.1, Pytorch 1.9.0, and Cuda 11.2 deep learning frameworks. Both training and testing are conducted on a PC with an R7-5800H CPU and a GeForce RTX 3070 8G GPU.

Semantic Segmentation Network Model

U2Net Network Model

The U2Net network model is a new network structure proposed by the author Qin et al *(2020)*. by adding a new module RSU (ReSidual U-blocks) based on the UNet network model. The network structure is shown in Fig. 2. It can be seen from the figure that each En_x in the U2Net network model uses an RSU module, and the structure of the RSU module is shown in Fig. 3(a). By using dilation convolution, U2Net can obtain a larger receptive field without increasing the amount of computation, and the whole network structure looks very deep, but the number of parameters does not increase significantly.

It can be easily seen from the RSU structure Fig. 3(a) that the so-called RSU is actually a simple UNet. The final mask is obtained by combining and merging the output results of multiple UNets. The function of the RSU module is to obtain multi-scale features of different stages (L refers to the number of layers in the encoder, C_{in} and C_{out} respectively refer to the number of input channels and output channels, and M represents the number of channels in the internal layer of RSU). The essence of the corresponding structure diagram of the module is shown in Fig. 3(b).

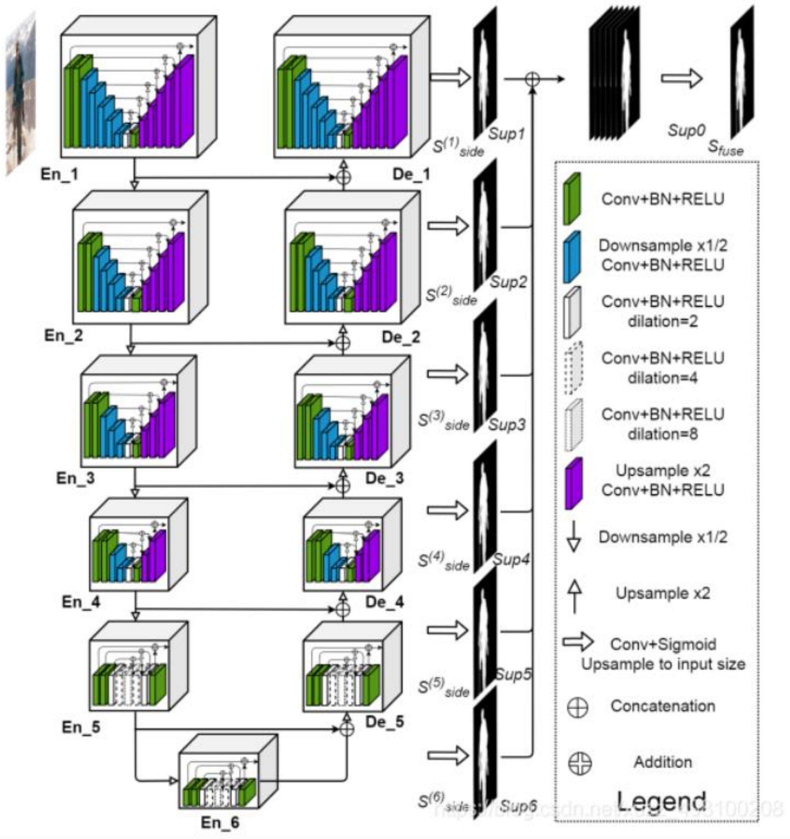
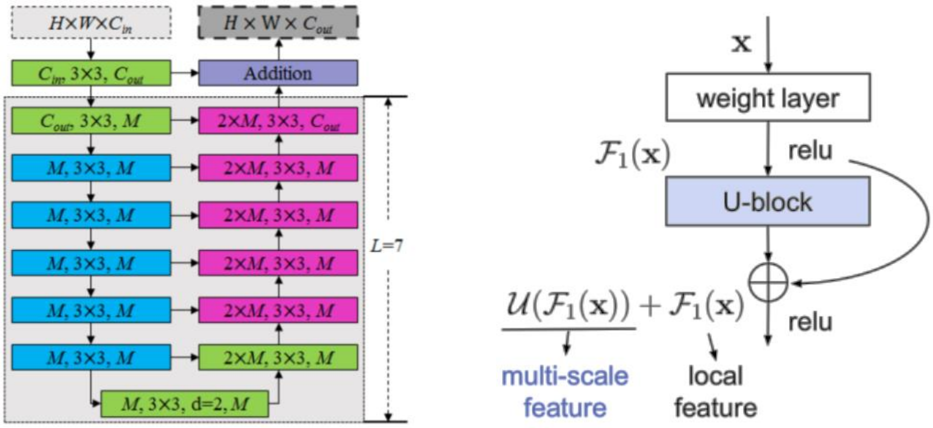


Fig. 2 - Schematic diagram of the overall structure of the U2Net model



a) RSU-L(Cin,M,Cout) b) ReSidual U-block(RSU)

Fig. 3 - Structure diagram of the RSU module

Since U2Net can be divided into multiple blocks, and each block outputs a loss, the loss of the whole model can be expressed as Equation (1).

$$L = \sum_{m=1}^{M} \omega_{side}^{(m)} I_{side}^{(m)} + \omega_{fuse} I_{fuse} \tag{1}$$

Where I_{side}^{m} (M=6, as the Sup1, Sup2, … Sup6 in Fig.2) in the loss of the side output saliency map $\omega_{side}^{(m)}$ and I_{fuse} (Sup 0 in Fig.2) is the loss of the final fusion output saliency map $\omega_{side}^{(m)} I_{fuse}$ and ω_{fuse} are the weights of each loss term. For each term L, the standard binary cross-entropy is used to calculate the loss:

$$L = -\sum_{(r,c)}^{(H,W)} \left[P_{G(r,c)} \log P_{S(r,c)} + (1 - P_{G(r,c)} \log(1 - P_{S(r,c)}) \right] \tag{2}$$

Where (r,c) are the pixel coordinates and (H,W) image size: height and width. $P_{G(r,c)}$ and $P_{S(r,c)}$ denote the pixel values of the ground truth and the predicted saliency probability map, respectively. The training process tries to minimize the overall loss L of Eq.(1). In the testing process, the fusion output I_{fuse} is chosen as the final saliency map.

Model Evaluation Indicators

In order to comprehensively evaluate the performance of the models, pixel accuracy (PA), Mean pixel accuracy (MPA), intersection over union (IoU), Mean intersection over union (MIoU), and model size were used to evaluate the model performance.

EXPERIMENTAL RESULTS AND ANALYSIS

Model performance comparison

In this study, the three models selected (U2Net, UNet, and DeepLabV3+) used the original network structure to complete the segmentation task of apple leaf disease data sets. The parameters of all models were set as follows: the optimizer selected Adam, the epoch was set to 50, the initial learning rate was 0.001, the batch size was 4, and the backbone network of UNet and DeepLabV3+ used ResNet50 *(He et al., 2016)*. The network training process includes two stages: freezing training and total training. In the first stage, freeze training is carried out to keep the parameters of the feature extraction stage unchanged and only train the decoder layer. In the training process, when the training loss remains low among the two epochs, the learning rate is adjusted to 1/2 of the original. The second stage is a comprehensive training, with all network parameters participating in the training. During the training process, when the training loss remains unchanged in one epoch, the learning rate is adjusted to half of the original rate, and the training is set to stop early. If the loss of the training set remains unchanged in 10 epochs, the training of the model will be ended.

By comparing the segmentation performance indicators MPA and MIoU of the three models in the test set, the segmentation performance of the model was analyzed. Table 2 list information on the hyperparameters, size of the model, MIoU, and MPA used by the models.

Table 2

Analysis of semantic segmentation performance of compared models

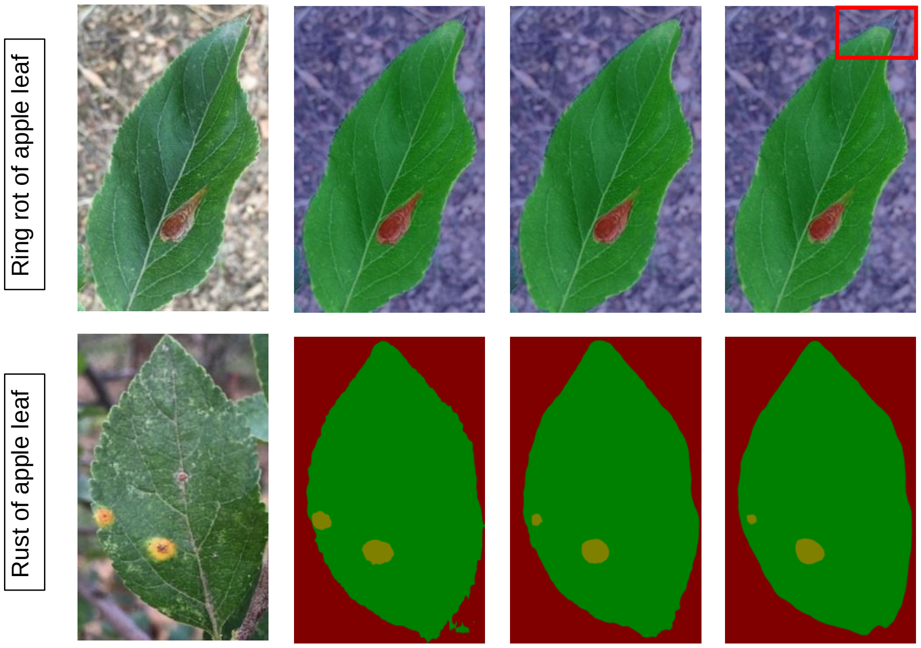
Model	Initial learning rate	Size (MB)	MPA (%)	MIoU (%)
DeepLabV3+	0.001	37.3	97.21	83.40
U2Net	0.001	176.3	98.87	84.43
UNet	0.001	7.76	93.31	81.51

As can be seen from Table 2 that the satisfactory segmentation of MPA and MIoU had been obtained in the apple leaf disease segmentation task for the three classical segmentation network models.

When the initial learning rate was set to 0.001, the MPA values of the three models were all above 93.00%, and the MIoU values were all above 80.00%. The U2Net network model had the best segmentation effect on apple leaf diseases (MPA=98.87%, MIoU=84.43%), followed by the DeepLabV3+ network model, and the UNet network model had the worst segmentation performance.

Considering the size of the models, U2Net had the biggest size (176.3MB), and the size is more than four times the size of the DeepLabV3+ network model (37.3MB). And the size of the UNet model was 7.76MB which was the least, this was one of the reasons leading to the worst model segmentation effect. While the MPA and MIoU indexes of the UNet network model are nearly 6 and 3 percentage points lower than the best network model respectively.

Based on the above analysis, the segmentation accuracy of the U2Net model was significantly improved compared to DeepLabV3+ and UNet models, indicating that the model had good segmentation performance for apple leaf diseases, and the model can be embedded in mobile devices in the future. Figure 4 shows the segmentation effects of two diseases on U2Net, DeepLabV3+, and UNet models.



a) Original image *b) U2Net* *c) DeepLabV3+* *d) UNet*

Fig. 4 - The segmentation effect of different models

As can be seen from Fig. 4, for apple rust, from the segmentation results of the three network models on the leaf area, it can be seen that U2Net had the best segmentation effect on the leaf area, and the segmentation results of the leaf area can be seen in Fig.4 showing that the segmentation of the leaf area was relatively complete and the blade edge burrs could be clearly seen. DeepLabV3+ occupied the second place in leaf area segmentation, and only slight burrs could be seen on the edge of the leaf. However, UNet had the worst segmentation effect, almost no burr could be seen and the segmented blade contour was poor. From the segmentation results of the three network models for the lesion area, it can be seen that the U2Net had the best segmentation effect also, and could segment the two lesions better.

However, DeepLabV3+ and UNet had a satisfactory segmentation effect for large lesions, but the segmentation effect for small lesions was not ideal.

For the ring rot disease, the U2Net network model was the best for the segmentation of leaves and diseased areas. DeepLabV3+network model had little difference in the segmentation of leaf area and U2Net, but the segmentation effect of the diseased area was worse than U2Net. The UNet had the worst segmentation effect on the leaf area and the diseased spot area (the part framed by the red line in the figure).

Comprehensive analysis showed that the segmentation effect of the U2Net network model was better than the other two models, DeepLabV3 and UNet.

Comparison of Segmentation on Different Disease Categories

To further compare and analyze the segmentation performance of three semantic segmentation network models, Table 3 lists the PA and IoU of the four categories in the dataset used for the three models (U2Net, UNet, and DeepLabV3+), where the ones highlighted in bold in the table are the best semantic segmentation network models among the current category and indicators.

Table 3

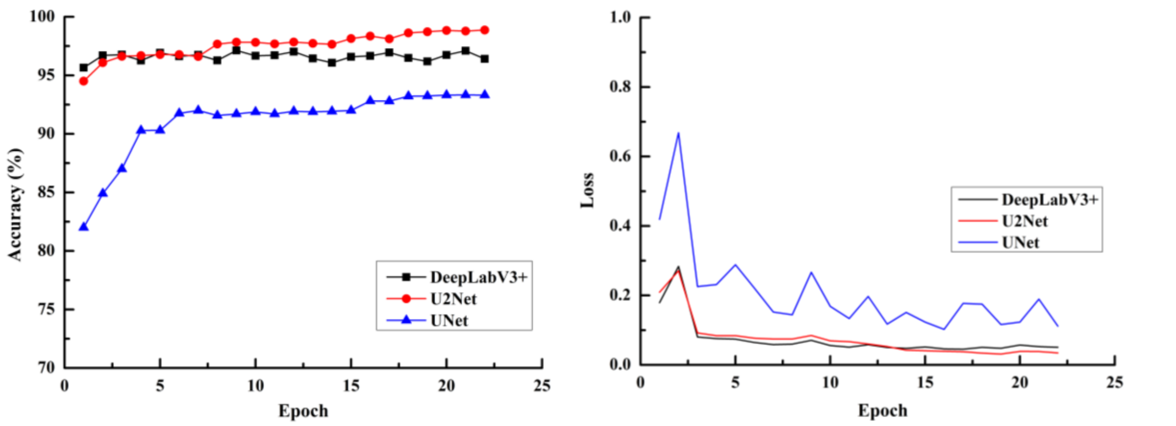
The PA and IOU of different models on different diseases

Evaluation indicators	Network model	Background (%)	Leaves (%)	Rust (%)	Ring rot (%)
IoU	DeepLabV3+	93.89	94.51	71.35	73.86
	U2Net	**95.21**	**94.62**	**74.92**	**73.90**
	UNet	83.24	80.13	78.43	70.96
PA	DeepLabV3+	**96.63**	97.28	89.2	84.67
	U2Net	96.59	**98.90**	**90.12**	**89.19**
	UNet	93.10	93.38	84.38	79.44

It can be seen from Table 3 that compared with the other two network models, the U2Net model had the highest IoU for the four categories, followed by the DeepLabV3+ network model, and the IoU index of the UNet network model was the lowest for the four categories. In addition to the background area, the PA index of the U2Net network model was the highest among the three semantic segmentation network models, and the PA for the background area was only 0.04 percentage points lower than the highest 96.63%. According to Tables 3 and 2, it can be seen that compared to other network models, the network model U2Net had the best comprehensive segmentation effect.

Comparison of Model Convergence Performance

By comparing the convergence performance of the three models (DeepLabV3+, U2Net, and UNet), Fig. 5 compared the convergence performance of three models in the validation set, showing the curves of PA accuracy and loss curves of the four models on the validation set as a function of the number of training rounds.



a) Variation of pixel accuracy with training rounds *b) Variation of validation set loss values with training rounds*

Fig. 5 - Convergence of different models

It can be seen from Fig. 5 that the models had high convergence starting points and fast convergence speed, for the reason that the weight parameters of the backbone network pre-trained on the ImageNet dataset were directly loaded into the model at the initial stage of training.

From the perspective of convergence point, the convergence point of DeepLabV3+ was the highest (95.65%), followed by the convergence point of the U2Net model (94.50%), and the convergence point of UNet model was the lowest (72.00%).

From the perspective of convergence speed and convergence stability, the U2Net network model had the best stability with the highest MPA of 98.87%, followed by the DeepLabV3+ network model with the highest accuracy of 96.4%, while the UNet network model had the worst convergence performance with the highest MPA of 93.30%. Comprehensive analysis showed that the U2Net model was the best model for the apple leaf disease segmentation task.

Hyperparameter Optimization of U2Net

The segmentation results of U2Net with different hyperparameter combinations (learning rates and optimizers) is shown in Table 4.

Table 4

Performance comparison of the U2Net

Model	Initial learning rate	Optimizer	MPA (%)	MIoU (%)
U2Net	0.01	Adam	97.30	83.81
	0.001		98.87	84.43
	0.0001		98.88	84.41
	0.01	SGD	96.16	83.19
	0.001		97.23	83.88
	0.0001		97.97	84.23

It can be seen from Table 4 that when the same Adam optimizer was used and the learning rate was 0.01, 0.001, and 0.0001, the MPA values obtained by the U2Net model on the test set were 97.30%, 98.87%, and 98.88%, and the MIoU values were 83.81%, 84.43%, and 84.41%, respectively.

On the whole, when the learning rate was 0.01, the segmentation performance of the U2Net model was the worst; When the learning rate was 0.001 and 0.0001, the difference in segmentation performance of the U2Net model was small and the same. When the learning rate was adjusted from 0.001 to 0.0001, the MPA value of the U2Net model was only increased by 0.01%, while the MIoU value was reduced by 0.02%, which leads to longer training time.

When the SGD optimizer was used and the learning rate was 0.01, the MPA and MioU of the U2Net model in the test set were the lowest, with values of 96.16% and 83.19% respectively. When the learning rate was adjusted from 0.01 to 0.001, the MPA value of the U2Net model increased by 1.07%, and the MIoU value only increased by 0.69%. When the initial learning rate was 0.0001, U2Net had the highest MPA and MIoU on the test set, which was 97.97% and 84.23%, respectively.

According to the above analysis, when the learning rate was 0.001 and the optimizer was Adam, the segmentation performance of the U2Net model was the best.

Diagnosis of Leaf Disease Degree

Generally speaking, the degree of apple leaf disease varies with the proportion of the diseased area to the entire leaf area. Therefore, according to the relevant standards of Air Assisted Orchard spray Operation Quality (NY/T 992-2006), which was issued by the Ministry of Agriculture and Rural Affairs of the People's Republic of China, list the classification standards for the disease degree of apple leaves, as shown in Table 5.

Table 5

Classification standard of apple leaf disease degree

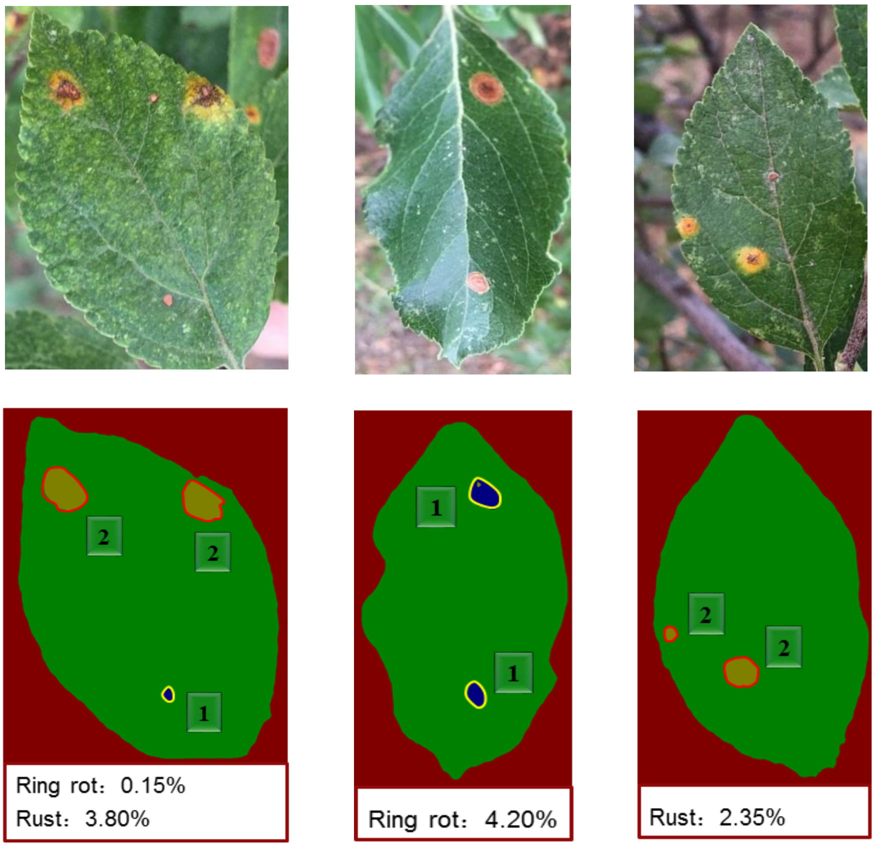
Grade	The proportion of lesion area to leaf area (%)
0	0
1	<=10
3	11~25
5	26~40
7	41~65
9	>=65

According to the segmentation results of the leaf area and lesion area of apple diseased leaves using semantic segmentation methods, the proportion of the total number of pixels in the lesion area to leaf area was calculated. Finally, the disease degree of apple leaves is inferred based on the disease degree classification criteria in Table 5. The calculation method is shown in Equation (3).

$$DD = \frac{S_d}{S_d + S_h} \tag{3}$$

where: DD is the disease degree of the apple diseased leaf, S_d is the number of pixels in the lesion area, S_h is the total number of pixels in the apple leaf area.

Fig. 6 shows the results of the semantic segmentation network model U2Net in symptom classification and severity estimation with ResNet50, Adam, and 0.001 as the backbone network, optimizer, and learning rate, respectively.



a) Ring rot and rust b) Ring rot c) Rust

Fig. 6 - Examples of the segmentation effect obtained by U2Net

Fig. 6 (a) showed the segmentation result of semantic segmentation network U2Net on apple leaf rust and ring rot, and it was calculated from the segmentation result that the lesion area ratio of rust and ring rot is 1.87% and 0.12%, respectively. Similarly, in Fig. 6 (b), the lesion area of ring rot was 1.98%, and in Fig. 6 (c), the lesion area of rust was 1.82%. Based on the above analysis, the proposed semantic segmentation network model has achieved satisfactory results. The disease grade of apple leaves was determined according to Table 5. The result showed that the method proposed in this study was effective for the segmentation of apple diseased leaves under complex field background.

CONCLUSIONS

In this paper, the classical semantic segmentation models (U2Net, UNet, and DeepLabV3+) were used for semantic segmentation of apple leaf area and diseased area, transfer learning was used for the reason of limited data set, and the U2Net network model was fine-tuned to select the most suitable combination of hyperparameter. Finally, the grading diagnosis of apple leaf disease was studied. The main research conclusions are as follows:

(1) By comparing MPA, MIoU, PA, IoU, average pixel accuracy curve, and loss function curve, the comprehensive performance of three semantic segmentation network models U2Net, UNet, and DeepLabV3+ (when using the learning rate of 0.001, the optimizer selected Adam) on apple leaves and diseased areas were analyzed. The research showed that the segmentation performance of the U2Net network model was superior to the other two segmentation network models (DeepLabV3+, UNet).

(2) The influence of three groups of different learning rates and two different optimizers on the performance of the U2Net network model was analyzed through experiments. The research showed that when the learning rate of the U2Net network model was set to 0.001 while the Adam optimizer was selected, the segmentation performance indicators MPA and MIoU of the model reached the highest, 98.87% and 84.43% respectively.

This study can achieve accurate segmentation of leaf area and lesion area, and provide a basis for the diagnosis of disease degree. At the same time, this study can provide more accurate information for subsequent disease prevention and early warning.

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