STUDY ON RAPID DETECTION AND IDENTIFICATION OF MULTI CATEGORY APPLE LEAF DISEASE
/
多类别苹果叶病快速检测识别研究

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ABSTRACT
Apple planting process is often accompanied by the impact of a variety of diseases. A single apple leaf often presents the situation of multiple diseases occurring at the same time, which brings great challenges to fruit farmers' rapid diagnosis and correct control. In this paper, aiming at the rapid detection and recognition of multi-category apple leaf disease, a multi-target detection model is constructed to realize the rapid detection and recognition of single leaf and multi leaf, single disease and multi disease. Through the technical means of manual labeling, data enhancement and parameter optimization, Yolo v4, SSD and EfficientDet are selected to train and evaluate the apple leaf disease data set. The results show that the target detection model based on Yolo v4 achieves better training effect, and its mAP value is 83.34%. The model can meet the needs of rapid disease spot detection and recognition of single leaf single disease and multi leaf multi disease in natural environment.

摘要
苹果种植过程常伴随多种病害的影响，单一苹果叶片经常呈现多种病害同时发作的情形，为果农快速诊断和正确防治带来极大地挑战。本文以多类别苹果叶病快速检测与识别为目标，构建多种目标检测模型，实现了对单叶片和多叶片、单病害和多病害的快速检测识别。通过对病斑图像数据手工标注、数据增强、参数优化设置等技术手段，选用Yolo v4、SSD及Efficientdet三种目标检测预训练模型，对苹果叶病数据集进行训练评估。结果表明，基于Yolo v4的目标检测模型取得了更好的训练效果，其mAP值为83.34%，模型可以满足单叶片单病害和自然环境下多叶片多病害的快速病斑检测识别需求。

INTRODUCTION
According to the data released by the United Nations Food and Agriculture Organization, about 45% of the world's crops have been lost due to diseases and insect pests or different types of crop diseases. There are more than 1000 common diseases and insect pests on 48 deciduous and evergreen fruit trees in southern and Northern China. Apple is one of the most important deciduous fruit trees in China. In 2018, the total output of apple in China was 39.233 million tons, accounting for 45% of the world, ranking first in the world. Among the many factors restricting apple yield and quality, the influence of Apple disease is particularly important. Therefore, the detection and control of crop diseases is very important for the sustainable development of agriculture. In different stages of crop planting, the effective detection of various diseases plays a key role in crop disease control, pesticide application, and improving the yield and quality of agricultural products.

In the process of Apple planting, diseases occur from time to time, which are usually diagnosed by manual visual observation. This method is subjective, time-consuming and labor-consuming, and there is a risk of error. In order to solve this problem, using machines to realize automatic disease detection is an important content to be solved urgently. In recent years, target detection technology based on deep learning has been widely used in the detection of crop diseases and insect pests due to its unique target recognition and localization methods (*John et al., 2021*).

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The target detection technology based on deep learning has been widely used in the detection of crop diseases and pests with its unique target recognition and positioning method. In 2018, *Xiong et al. (2018)* used the Faster Region based Convolutional Neural Network (Faser R-CNN) algorithm to detect citrus in consideration of the impact of shooting conditions on target detection. This method achieved an average accuracy of 85.49%; In the same year, *Liu et al. (2018)* used the Faster R-CNN algorithm to locate grape leaves, generate leaf candidate areas, and then detect the leaves to reduce the number of samples and the interference of complex background, so that the method has good adaptability under natural environmental conditions. In 2019, *Jiang et al. (2019)* used the deep learning target detection Single Shot MultiBox Detector (SSD) algorithm to identify and detect three common apple leaf diseases and pests. The comprehensive detection performance of this method reached 79.63% mAP, providing a high-performance solution for the early diagnosis of apple leaf diseases[6]. In 2019, in order to realize the target detection of balsam pear leaf diseases in the natural environment, *Li et al. (2020)* proposed a target detection method based on improved Faster R-CNN, and took the residual structure convolution neural network Res Net-50 as the feature extraction network to obtain an average accuracy of 86.39%, which is 7.54% higher than the original model; In 2020, in order to realize rapid and effective automatic detection of apple leaf diseases, *Di et al. (2020)* applied Tiny-YOLO to apple leaf disease detection, reaching 99.86% mAP, which can effectively realize single disease detection of apple leaves.

MATERIALS AND METHODS

Image acquisition and data set division of apple leaf lesions

In this paper, three common diseases in single background and complex natural environment background in laboratory environment: Apple gray spot, apple scab, apple cedar rust and a healthy leaf image were selected, as shown in Figure 1. The open source apple leaf image data and the field collected apple leaf images are combined to form a new data set to obtain rich disease image samples. In order to describe the incidence rate of three apple leaf diseases comprehensively, we should ensure that each category is equal in quantity according to the classification of diseases.

Fig. 1 - Image Collection of Apple Leaf Disease Species

2425 apple leaf disease data images with single background in the laboratory were manually labeled for the learning of target detection model. Among them, 830 Apple gray spot, 807 Apple iron cedar rust and 788 apple scab. The number of various apple leaf disease images used for target detection is shown in Figure 2.

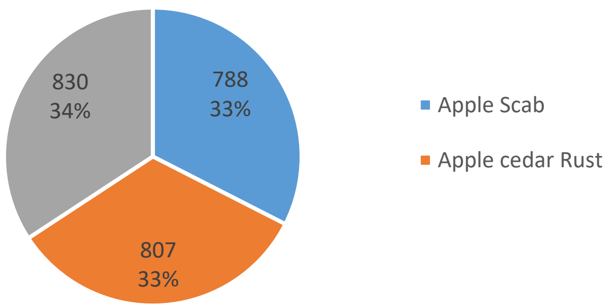


Fig. 2 - Distribution of Apple Disease Leaf Dataset

2425 images are divided according to the data when inputting the model. 90% of the images are divided into training set and 10% as verification set. In order to verify the generalization ability of the prediction model for apple leaf disease spot recognition in the natural environment, the test images include 2511 single background leaf images in the laboratory environment and 2617 complex background leaf images in the natural environment where there may be multiple leaves or multiple diseases.

Table 1 shows the number division of training set, verification set and test image used for target detection model.

Table 1

Division of target detection data set

Label	Name	Train Images	Validation Images	Test Images	
				Laboratory Environment	Natural Environment
n0	Apple Frogeye spot	747	83	576	562
n1	Apple Scab	710	78	511	578
n2	Apple cedar Rust	726	81	587	602
n3	Apple healthy	0	235	877	875

Method

Image preprocessing

Because different target detection models have different requirements for the size of the input image, the model will scale the image data when reading the input data. If the image size does not conform to the model definition, the coordinates of the marked blade lesion may be affected by scaling, resulting in coordinate deviation or target frame extrusion, which will affect the model's learning of lesion features. Therefore, when defining the size of the input image, it is particularly necessary to consider whether the image input size of the target detection model is suitable for the proportion specified by the target detection model, and adjust the image size according to the input size defined by the model.

In order to achieve multi angle feature fusion, improve the detection performance of leaf lesions, and ensure that the target frame will not be distorted in the process of model compression and automatic adjustment of input size, it is of great significance to standardize the image size. In this paper, the image size is uniformly defined by batch processing. The resolution of Efficientdet and Yolo v4 injected images is 512×512, fill in the blank part. SSD perfusion image pixel processing is 300×300, the spare part is filled in white. During the above image processing operations, ensure that the blade edge is not trimmed, and keep the edge characteristics of the blade from being affected by the image processing.

Image annotation

Manually labeling the target location is to obtain task related and task specific labels, which are used to define the location of the object in the image *(Gao et al., 2017)*. Annotation content usually includes text-based class labels and bounding boxes drawn on images. In this paper, 2425 apple leaf disease data images with a single background in the laboratory are manually labeled, with a total of more than 20000 a priori frames, which are used to learn the target detection model *(Song et al., 2017)*.

LabelImage software is used to manually label Apple disease spots. A rectangular bounding box is drawn around the disease spots and the category name is indicated. Each corresponding picture will automatically generate an xml format document. The document content includes the category of the marked target object and the x and y axis position coordinates of the standard frame. The marked image is the training set of the target detection model. In this paper, three kinds of disease spots, Frogeye spot (Apple gray spot), Scab (apple scab) and Rust (Apple cedar rust), are marked.

Taking an infected leaf as an example, the green box represents the infected area of the diseased apple leaf. The corresponding description of the marking target is shown at the bottom of the figure. The number of marking boxes in an image depends on the number of disease spots.

The image annotation box and the corresponding *.xml* file contents are shown in Figure 3:

(a) Apple gray spot (b) Apple cedar rust (c) Apple black spot

Fig. 3 - Image Annotation Diagram

Application of apple leaf spot detection model based on target detection

In this paper, the method of target detection is used to construct the apple leaf spot detection system. The selection of the model needs to consider the following aspects: the detection accuracy of the model for small targets, the number of parameters of the network model and the ability to detect multiple targets. In this paper, Yolo v4, SSD and Efficientdet three target detection pre training models in TF2.0 environment are selected to fine tune and train the model structure, so that the model can achieve better detection effect on apple leaf disease data set.

(1) Yolo v4 model

You Only Look Once（YOLO） series algorithm is a target detection algorithm based on direct regression *(Yang et al., 2021)*, which uses only one neural network to complete target detection. Yolo v4 is a relatively new target detection algorithm of Yolo series. Yolo v4 combines speed and accuracy well *(Bochkovskiy et al., 2020)*. In this paper, VGG16 was used as the backbone feature extraction network for the Yolo v4 network model, as shown in Figure 4.

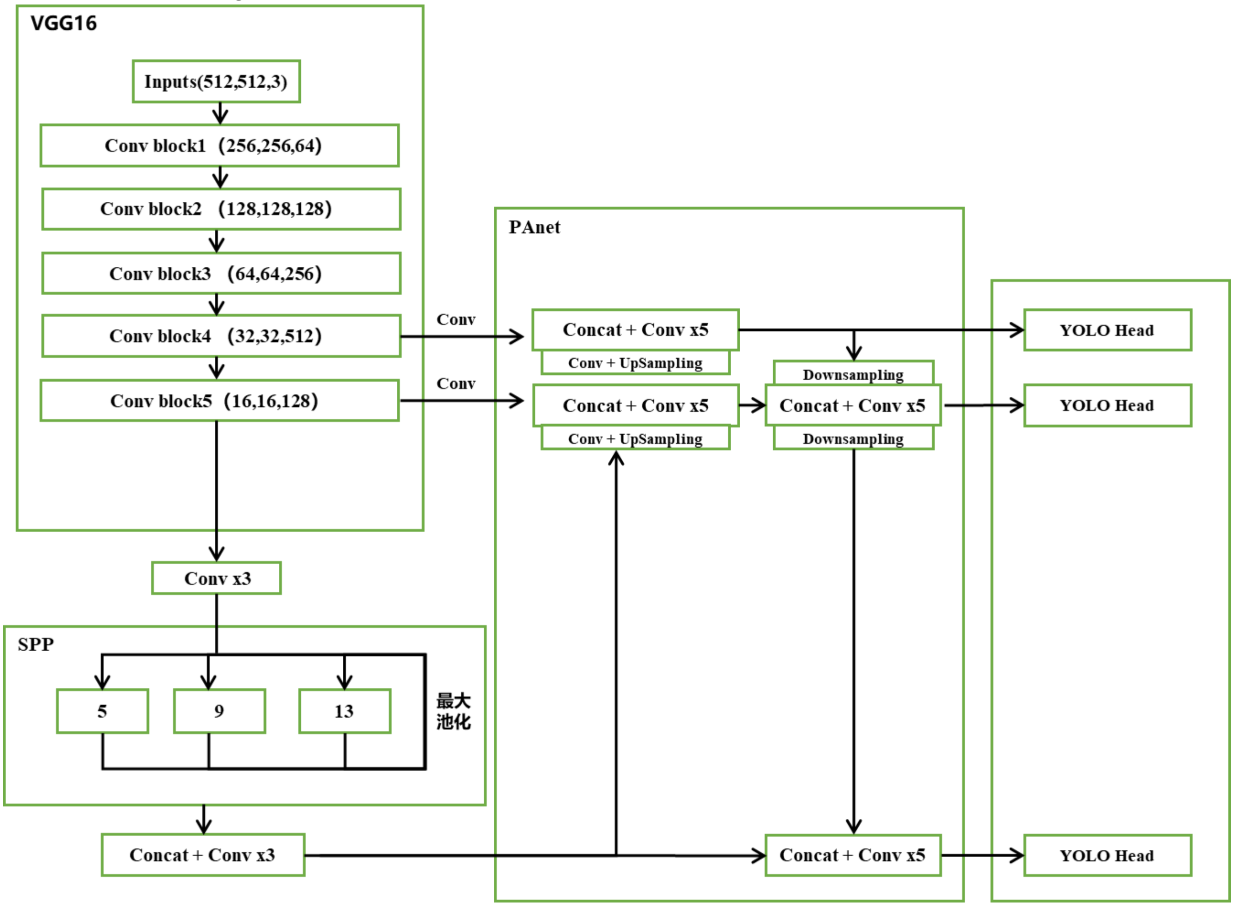


Fig. 4 - Network Structure of The YOLO Target Detection Algorithm

(2) SSD model

SSD is a target detection algorithm based on direct regression *(Wong et al., 2017)*. The SSD target detection algorithm adopts the backbone network VGG network as the basic feature extractor. The SSD detection algorithm adopts the multi-scale fusion method to fuse the detection information extracted from the convolution layer, layer by layer, which greatly improves the detection effect of small targets. Using this model, the detection speed reaches 59FPS and the mAP value reaches 74.3% on PASCAL VOC2007 data set, as shown in Figure 5.

As shown in the network structure of SSD target detection algorithm, SSD performs detection tasks on six FeatureMap with different scales. High-level FeatureMap predicts large-scale targets and low-level FeatureMap predicts small-scale targets *(Zhang et al., 2018)*.

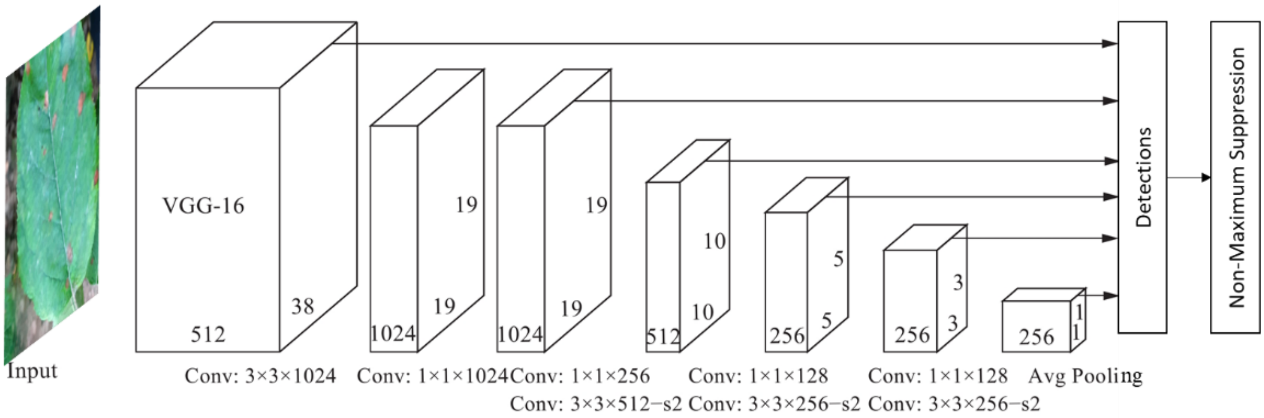


Fig. 5 - Network Structure of The SSD Target Detection Algorithm

(3) Efficientdet model

Efficientdet realizes two-way cross-scale connection and multi-scale feature fusion through weighted two-way feature pyramid network (BiFPN), follows the scaling method of composite feature pyramid network *(Atila et al., 2021; Lin et al., 2019)*, and uniformly scales the resolution, depth and width of all backbone, feature networks and box / class prediction networks *(Tan et al., 2019)*, so as to achieve more levels of feature extraction and obtain more features, realize an excellent network structure.

Description of experimental parameters

This topic selects Tensorflow 2 as the main deep learning framework, and the specific experimental environment is shown in Table 2:

Table 2

Experimental environment

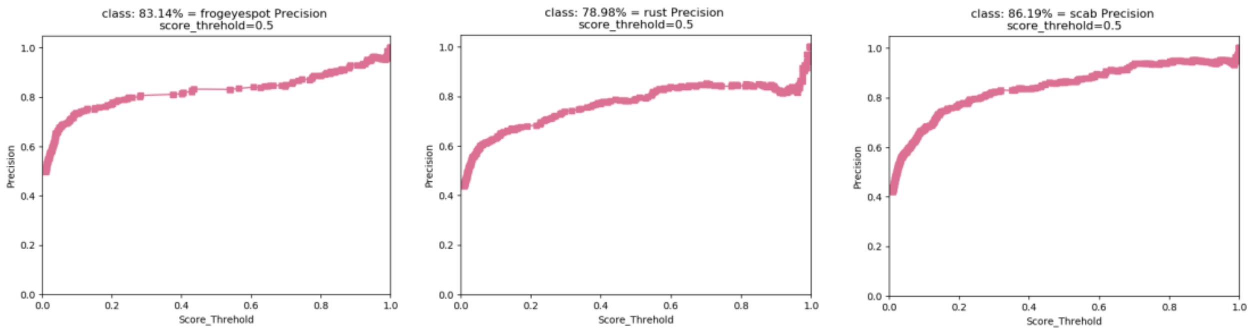
Hardware Environment	Software Environment
CPU：NVIDIA -SMI 44064.00	Operating system：Ubuntu 18.04
CUDA version：10.2	Development platform：Jupyter Notebook

RESULTS AND ANALYSIS

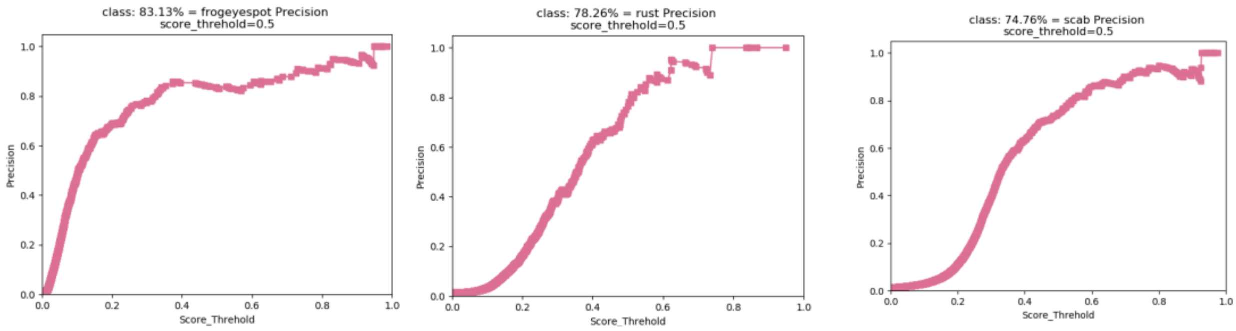
Comparison of training results

For better convergence, SGD algorithm is used to adjust the parameter learning step in model training. 16 images are learned in each batch, and the learning rate is 0.001. The loss rate of three rounds of training will not be reduced, and the learning rate will be reduced to half of the previous one; 10 rounds accuracy is no longer improved, stop training; the confidence threshold of the model is set to 0.5, and the prediction frames with a threshold less than 0.5 and those with high overlap are filtered out.

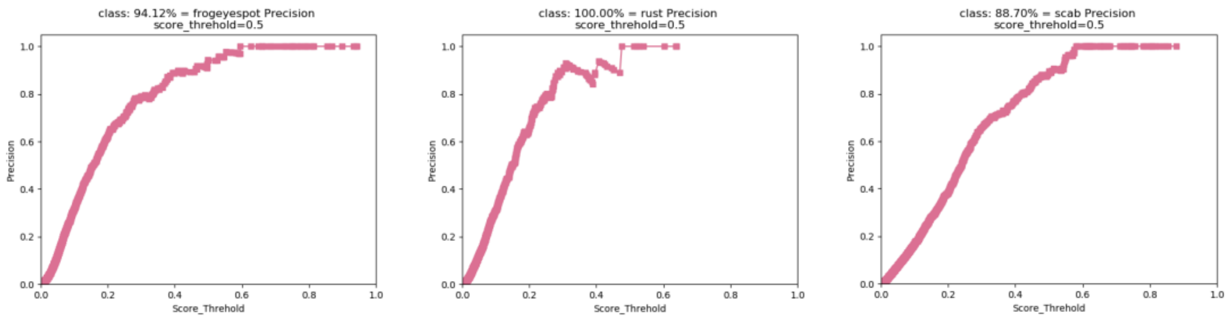
Figure 6 shows the AP values of Yolov4, SSD and Efficientdet models for the detection of three types of apple leaf lesions.



(a)



(b)



(c)

Fig. 6 – AP Values of The Model for 3 Types of Apple Leaf Spots:
(a)YOLO v4; (b) SSD; (c)Efficientdet

In order to better evaluate the model performance, this paper introduced multiple evaluation indicators to make a detailed comparison of the accuracy and mAP value of the three disease identification respectively. The average accuracy mAP value is the primary evaluation index of the comparison model. The experimental results showed that the Yolo v4 model was better than the other two models in all categories, and the mAP value reached 83.34%, as shown in Table 3.

Table 3

Comparison of the three model evaluation indicators

Category accuracy	Yolo v4	SSD	Efficientdet
AP（class=Frogeyespot）（%）	87.44	70.4	76.53
AP（class=Rust）（%）	76.88	62.95	71.87
AP（class=Scab）（%）	85.69	71.44	78.07
mAP（%）	83.34	58.26	75.49
Training duration (min / wheel)	14	8	10

Model prediction

In this paper, the trained target detection model is used to predict two kinds of apple leaf disease images in laboratory background and natural environment. The prediction results show that the model can not only meet the needs of single leaf with single background in the laboratory, but also meet the needs of single / multiple leaves with complex background in the natural environment, as well as the needs of disease spot detection of various types and multiple objects, and shows strong detection performance.

(1) The spot detection results of the same apple leaf disease image with a single background in the laboratory are shown in the Figure 7.

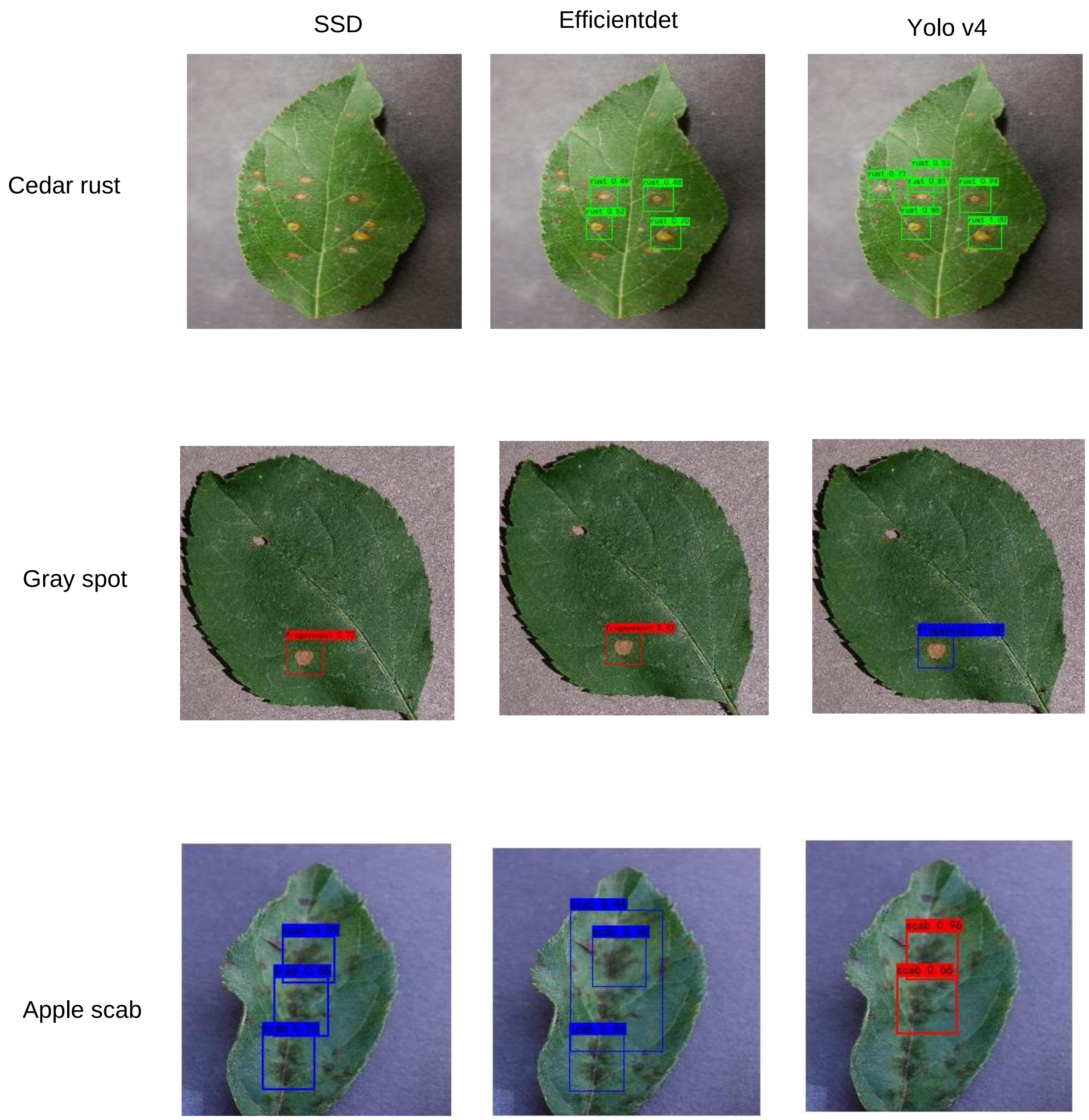


Fig. 7 - Comparison of Test Results of Three Models in Single Blade Test Samples

(2) Spot detection results of the same apple leaf disease image in multi leaf environment are shown in Figure 8.

The natural environment test data set meets two requirements: first, multiple diseases may occur simultaneously in the same leaf; second, most images contain complex backgrounds.

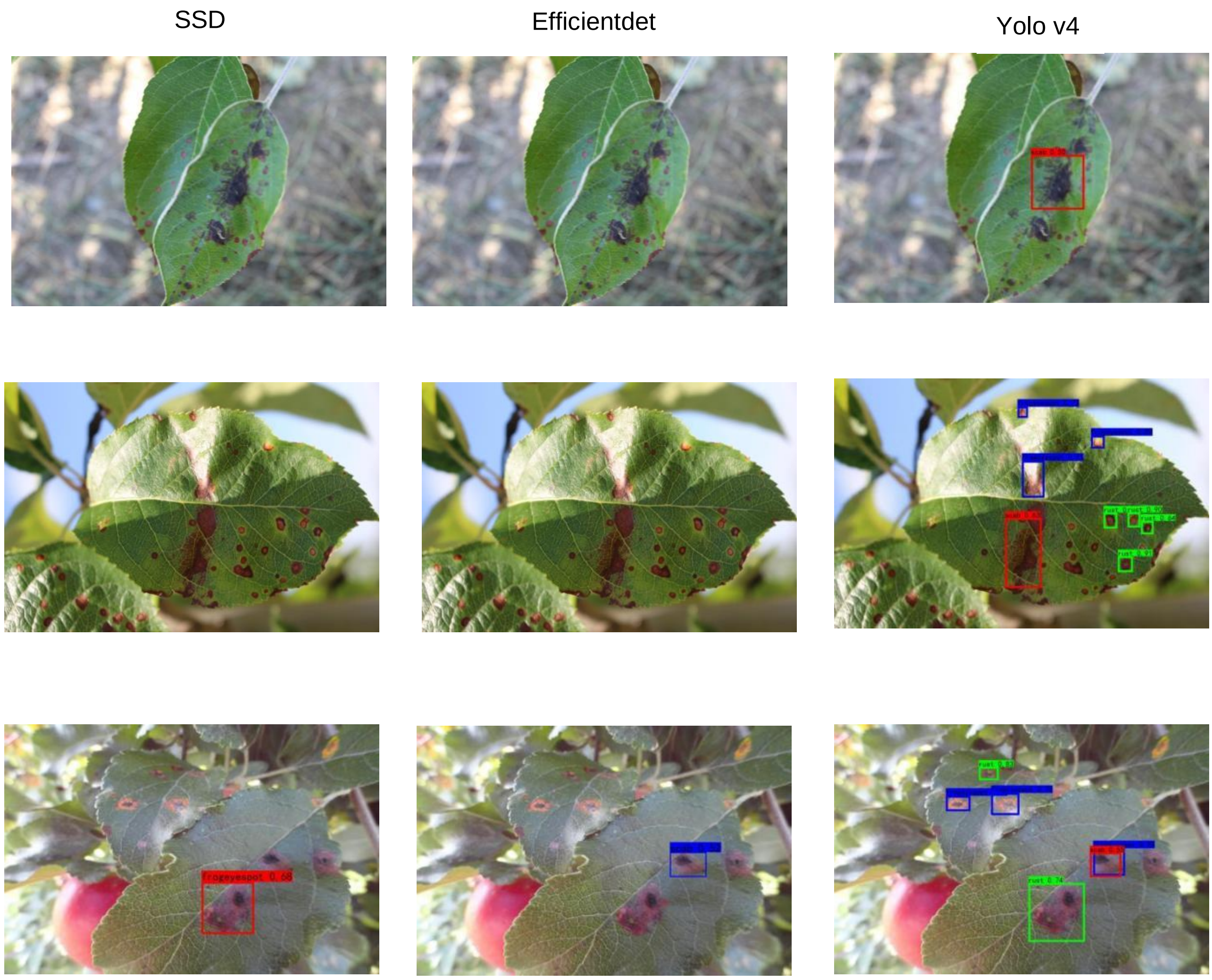


Fig. 8 - Comparison of Identification Results of Natural Environment Test Samples

(3) Detection visualization and error analysis

Although this method shows good adaptability in the detection of single background and complex background, due to many interferences in the natural environment, such as branch occlusion or chaotic background, it may interfere with the computer's judgment and cause false detection *(Chao et al., 2020)*.

As shown in Figure 9, a disease spot in Figure 9(a) is marked with gray spot and cedar rust at the same time. This is because there is a certain feature similarity in the shape and color of the disease spot at the initial stage of Apple cedar rust and Apple gray spot, so that in the natural environment image test, the initial Apple gray spot is easy to be confused with cedar rust.

Figure 9(b) because the background is dark, the background shadow is mistaken for apple scab by the detection algorithm. This is because the characteristics of apple scab spots are complex.

Some of the spots are black brown oval with obvious edges, and some of the spots are black. The texture extends all over the whole leaf with the vein, and the image annotation tolerance is large.

The black blur and irregular shadow of the background are very easy to be wrongly detected as the disease.

Figure 9(c) the whitish light spot is identified as gray spot disease, because the gray spot disease will become gray with the passage of time. Due to the influence of light, it is easy to be grayish white, and the detection algorithm mistakenly divides the parts with similar colors into the disease.

Figure 9(d) the lesion is small and not detected. If the leaf or diseased area accounts for only a small part of the image, it is not conducive to feature extraction and detection. Too small lesion is one of the factors leading to the increase of detection failure.

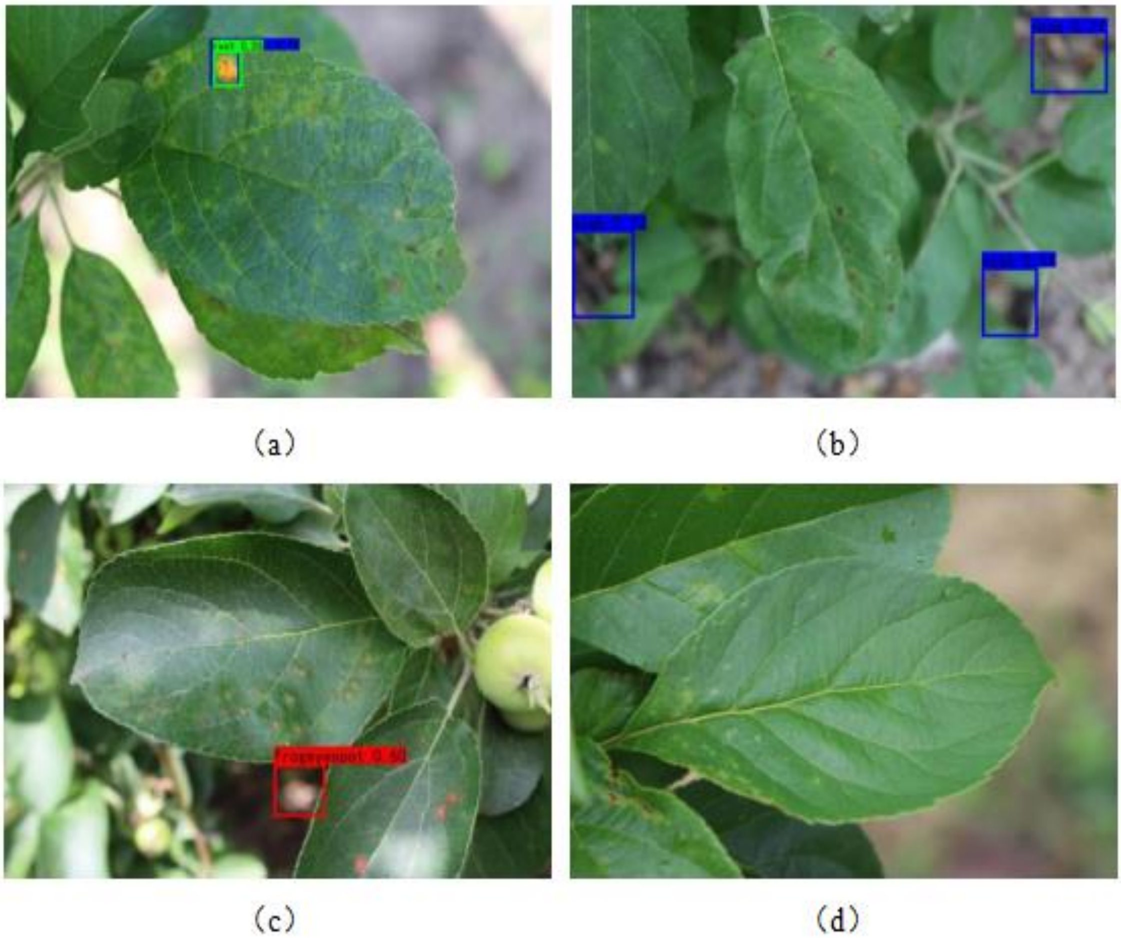


Fig. 9 - Detection of the Error Analysis

CONCLUSIONS AND OUTLOOK

Based on the target detection method, this paper studies the detection of single leaf disease and multiple leaf diseases and multiple spots of apple, compares and analyzes the prediction results of Yolo v4, SSD and Efficientdet target detection pre training models on the apple leaf disease data set, and uses the optimization training technologies such as super parameter adjustment, phased freezing parameters and dynamic adjustment of learning rate. A deep learning model based on Yolo v4 pre training model is proposed. Under the premise of confidence threshold of 0.5, the average prediction accuracy of the model is 83.34% in the natural environment with complex leaves and multiple diseases. The prediction accuracy of the three diseases is higher than that of SSD and Efficientdet pre training model. The results show that the multi category apple leaf disease rapid detection model based on Yolo v4 can be better competent for apple leaf disease detection under complex background in natural environment, and can help fruit growers quickly diagnose disease types and make correct control measures, so as to improve apple yield and quality.

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