DETECTION OF CUCURBITS' FRUITS BASED ON DEEP LEARNING
/
基于深度学习检测葫芦科果实

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ABSTRACT
Cucurbitaceae is widely planted and its fruits have great economic value. Object detection is one of the key aspects of cucurbit harvesting. In this paper, four models, YOLOv3, YOLOv4, YOLOv5s and improved Resnet_YOLO, were used to detect mixed bitter melon, cucumber, white melon, and "Boyang 9" melon fruits. Fruit images of bitter melon, cucumber, white melon and "Boyang 9" melon were collected under different natural conditions for model training. The results showed that "Boyang 9" melon had the best overall detection results among the four cucurbit species, with the highest AP and F1, 0.99 and 0.94 respectively. The YOLOv5s model performed best among the four models: the best weights size was the smallest at 14 MB; the better mAP value of 0.971 for all classes of cucurbits; and the fastest detection speed with fps of 90.9. This paper shows that four types of cucurbit fruit images, bitter melon, cucumber, white melon, and "Boyang 9" melon, can be detected based on deep learning methods for hybrid detection.

摘要
葫芦科种植面积广泛，其果实具有巨大的经济价值。目标检测是葫芦科采摘的关键环节之一。本人采用 YOLOv3、YOLOv4、YOLOv5s 和改进的 Resnet_YOLO 四种模型对苦瓜、黄瓜、白皮甜瓜、"博洋 9"甜瓜果实进行混合检测。采集不同自然情况下的苦瓜、黄瓜、白皮甜瓜、"博洋 9"甜瓜的果实图像进行模型训练。结果表明，在 YOLOv3、YOLOv4、YOLO5、Resnet_YOLO 四种模型检测苦瓜、黄瓜、白皮香瓜和"博洋 9 号"甜瓜时，"博洋 9 号"甜瓜检测结果整体最优，AP 和 F1 最高，分别为 0.99、0.94；YOLOv5 模型表现最优：最佳权重内存最小，为 14MB； 具有很好的 mAP 值，达到了 0.971；检测速度最快，fps 为 90.9 。此方法表明苦瓜、黄瓜、白皮香瓜、"博洋 9"甜瓜四类葫芦科果实图像可进行混合检测。

INTRODUCTION
Fruits provide people with a rich source of minerals, vitamins and dietary fibre. However, fruit picking is not an easy task. Fruit picking is an important part of cucurbit fruit production that is labour intensive and highly seasonal. An example is the cucurbit fruit. Cucurbitaceae is widely cultivated with about 113 genera and 800 species (*Tzortzakis N. et al., 2018*). Among them there are 32 general and 154 species in China (*Ren Chunmei et al., 2014)*. Cucurbitaceae fruits include important vegetables and melons such as bitter melon, cucumber, melon, and sweet gourd. Bitter melon has medicinal values such as being purgative and low in sugar (*Huang H. et al., 2019*). Cucumber is rich in protein and various vitamins and has diuretic, sore throat relief and weight loss properties (*Wang Chen et al., 2020*). Melon contains nutrients such as sugar, aromatic substances, and proteins (*Sánchez E. et al., 2021*). However, cucurbit fruit picking is also difficult.

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The reason is that some cucurbit fruits are similar in shape and some cucurbit fruits are similar in colour, which makes it difficult to distinguish and locate them when the machine performs object detection.

Cucumber Bitter melon White melon "Boyang 9" melon

Fig. 1 - Different cucurbit fruits

In recent years, with the rise of artificial intelligence, deep learning has developed rapidly, and great breakthroughs have been made in target detection algorithms. The more popular algorithms can be divided into two categories. One category is the two-stage algorithm based on the R-CNN system of Region Proposal, which divides the target detection task into two steps, target category and target region (*Li Z et al., 2017; Wimmer G et al., 2021; Ren S et al., 2017*), and the other category is the one-stage algorithm such as YOLO and SSD, which directly predicts the category and location of different targets. As the first class of algorithms, R-CNN and Faster RCNN methods have high target detection accuracy, but convolutional neural networks are very computationally large and slow. And as one of the two-stage second class algorithms, YOLO (You Only Look Once) algorithm was proposed by *Redmon et al. (2016),* which guarantees the detection speed and the target detection accuracy (*Redmon J et al., 2016*). This algorithm has been widely used in the field of target detection and has undergone v1-v5 development (*Redmon J et al., 2017; Bochkovskiy A et al., 2020*).

YOLOv1 takes the whole image as the network input and regresses the position and category of the bounding box directly in the output layer. Its disadvantages are: the output layer is a fully connected layer, the YOLOv1 training model only supports the same input resolution as the training image; each cell can only predict one object, and the prediction of small objects is poor. The YOLOv2 network model was adopted from Darkent_19 (*Xiong Juntao et al., 2018*). And the YOLOv3 model is more complex than the YOLOv1 and YOLOv2 models and can predict small targets (*Redmon J et al., 2018; He K, Zhang X et al., 2016*). YOLOv4 improves various parts of YOLOv3 to make the AP value rise, for example, mosaic data enhancement on the input, CSPDarknet53 on the backbone, Mish activation function, etc (*Qingshu W et al., 2021*). There are four versions of YOLOv5s, YOLOv5m, YOLOv5l, and YOLOv5x models in the YOLOv5 target detection network, and the YOLOv5s network model is the smallest, the fastest, and the AP accuracy is not low.

Shilei Lu used YOLOv3-LITE lightweight neural network for citrus recognition with 91.13% AP and 87.32% average IoU for the whole test set (*Lü Shilei et al., 2019*). *Lawal O.M.* developed a YOLO fig detection model based on deep learning, with an average accuracy and speed of 89.3% and 96.8 fps for the optimal model (*Lawal O.M.,2021*). *Juntao Xiong* used UAV vision to detect green mangoes on trees in a natural environment, and the average time to detect one image was 0.08 s, and the correct recognition rate of the test set was 90.64% (*Xiong Juntao et al., 2018*). *Xiaoyang Liu et al.* performed instance segmentation, based greenhouse cucumber detection with an improved mask RCNN F1 of 89.47% and a running time of 0.3461 s (*Liu X et al., 2019*). *Anna Kuznetsova et al.* used YOLO3 combined with pre-processing and post-processing for apple detection by fruit harvesting robot (*Kuznetsova A. et al., 2020*).

The above-mentioned scholars have conducted different fruit detection studies based on deep learning, but the studies on the differentiation and identification of the fruits of Cucurbitaceae plants have not been reported. To solve different cucurbit classification and recognition problems, this paper uses YOLO deep learning algorithms for cucurbit fruit image classification and recognition.

MATERIALS AND METHODS

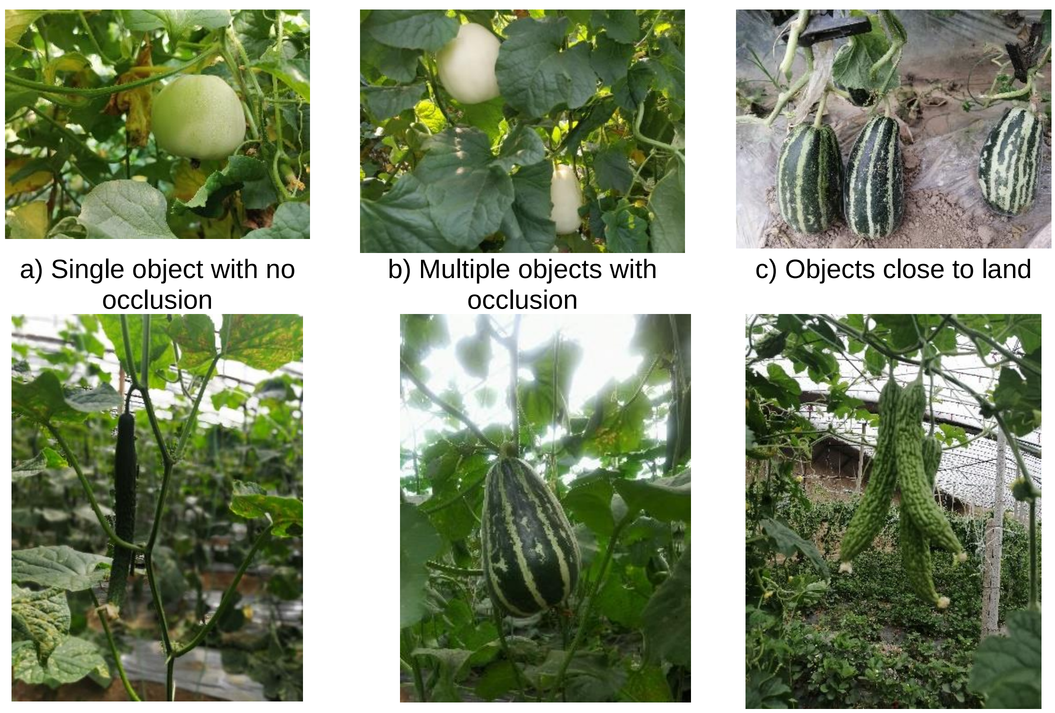
Image Acquisition

The datasets used in this research work were collected from the bitter melon, cucumber, white melon, and "Boyang 9" melon greenhouses at the Juxin Venture Park in Taigu County, Jinzhong City, Shanxi Province, China. The images were taken using a smartphone with 2340X1080-pixel resolution, RGB colour space and JPG storage format. Images were captured in a natural light environment, including the complexity of the growing environment: light changes, shading and overlap. A total of 2469 pictures were collected. Among them, 665 pictures of bitter melon, 664 pictures of cucumber, 404 pictures of white melon and 736 pictures of "Boyang 9" melon. The four species were randomly divided into an 80% training set and a 20% test set, respectively (Table 1). Randomly, the captured images included a single target without shading, a single target with stem and leaf shading, multiple targets without shading, multiple targets with stem and leaf shading, and targets near the land, among others. The images in different environments are shown in Figure 2.

Table 1

Number of pictures of different Cucurbitaceae fruits

Class	Training set	Validation set	Total number
Bitter melon	532	133	665
Cucumber	532	132	664
White melon	324	80	404
“Boyang 9” melon	588	148	736



a) Single object with no occlusion   b) Multiple objects with occlusion   c) Objects close to land

d) Shading conditions   e) Illumination variation   f) Cluster objects

Fig. 2 - Cucurbits samples under different growing environments

Data Annotation

Before the YOLO detection model is trained, the data needs to be labelled, i.e., category labels and detection target locations. The open source tool Labelling is used to manually label all the data, and the label file is saved in txt format with the name corresponding to the image one by one. The bounding boxes are as small as possible while being able to cover the target, which helps to reduce the chance of human error (*Lawal M.O., 2021*). For shaded fruits, the shape is marked according to what the person thinks it is.

YOLO Algorithm

(1) YOLOv3

The backbone of YOLOv3 is Darknet-53, YOLOv3 adds a residual networks every two layers based on YOLOv2, i.e. short cut layer, which can solve the problem of gradient disappearance or gradient explosion. The number of residual blocks is 1, 2, 8, 8, 4. YOLOv3 uses the K-means clustering approach with 9 anchor frames. Each size of feature map uses 3 anchor frames with multi-scale prediction for small targets. Neck of YOLOv3 uses FPN (Feature Pyramid Network). FPN is fast like Single feature map and Pyramidal feature hierarchy, but it is more accurate. In the whole YOLOv3 network, there is only convolutional layer, no pooling layer. The size of the output feature map is controlled by adjusting the convolutional step, so there is no limitation on the image input size.

(2) YOLOv4

YOLOv4 splits the target detection framework into: input, backbone, neck, head. YOLOv4=CSPDarknet53+spp+PAN+YOLOv3. YOLOv4 is an efficient and powerful target detection model with the goal of finding the optimal balance between the network input resolution, the number of convolutional layers, the number of parameters and the number of layer outputs optimal balance.

(3) YOLOv5s

The network structure of YOLOv5s mainly consists of Backbone, Neck, and Head, where Backbone mainly uses CSPdarknet + SPP structure, Neck uses PANet junction, and Head uses YOLOv3 head. The weight of YOLOv5s is much smaller than that of YOLOv4, and the speed is very fast, while the accuracy is comparable to that of YOLOv4. In this paper, YOLOv5s is used, and the network structure is shown in Figure 3.

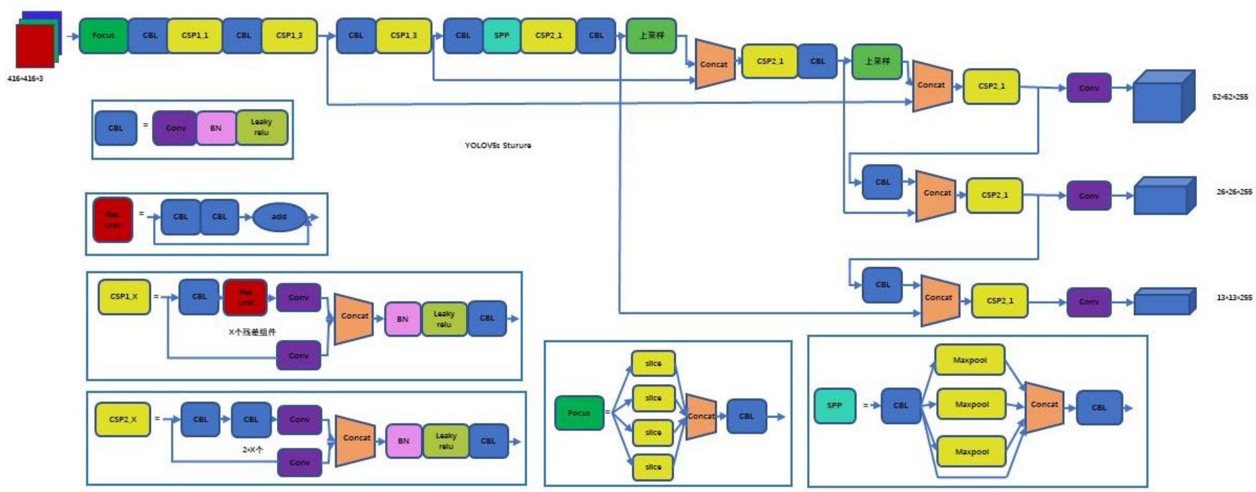


Fig. 3 - YOLOv5s model

(4) Resnet_YOLO

The backbone network of the Resnet_YOLO model is composed of ResNet43, which replaces DarkeNet53. Using ResNet43, the network depth is deeper and gradient disappearance does not occur; the classification accuracy is deepened due to the use of a deeper network; and the problem of deep network degradation is solved. The number of residual blocks of ResNet43 is 2,3,4,3,2, as shown in Fig.4(a).

The structure of residual blocks used by Resnet43 is shown in Fig. 4(b). Each layer of ResNet43 uses the Leaky activation function. The fruit detection optimization is performed by adding SPPNet as part of the Resnet_YOLO model to the ResNet43 backbone network. SPPNet is a feature enhancement network that simultaneously extracts global features of multiple dimensions and local features of the same detection stage. The application of SPPNet helps to avoid missed and inaccurate detection of the extracted fuzzy feature maps. The three scales of Resnet_YOLO are provided through 13×13, 26×26 and 52×52 feature vectors, as shown in Figure 4(a).

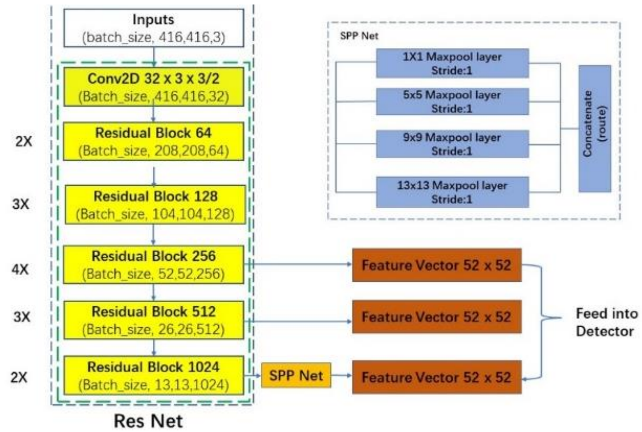


Fig. 4(a) - ResNet structure

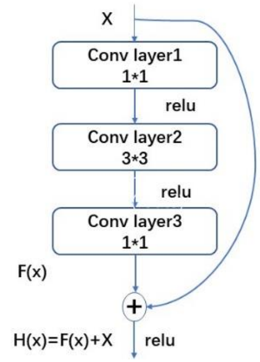


Fig.4 (b) - Resnet_YOLO model

Resnet_YOLO model uses DIoU-NMS (The non-maximum suppression) algorithm to remove the redundant detection of multiple bounding boxes and find the best matching bounding box from multiple overlapping entities. DIoU-NMS considers not only the IOU but also the distance between the centre points of two boxes to avoid missing detection. In the Resnet_YOLO model, the original 6 layers of the YOLOv3 head are cropped to 4 layers in order to improve the detection speed using FPN (Feature Pyramid Networks). As the neck, FPN is a feature pyramid network that upsamples the top-level features and fuses them with the bottom-level features to obtain high-resolution, strongly semantic features. FPN can handle the multi-scale variation of object detection with a very small increase in computational effort. Finally, the Resnnet_YOLO model uses a full IOU (CIoU) loss function with fast convergence and good performance.

Model training and testing

Experimental platform

The experimental platform for this study is built as follows: Computer: Lenovo Legion R90000P 2021H, Operation system: Windows 10 (Professional edition), CPU: AMD Ryzen 7 5800H 3.2GHz, GPU:RTX3060 , RAM:16GB, CUDA v11.1, cuDNN v8.0.4, OpenCV v4.2.0.

Image training

Before training and testing, it is necessary to find out the most likely size of the anchor box from the dataset instead of using the default anchor box provided by YOLOv, which can reduce the convergence time of the model and improve the accuracy of the generated coordinate boxes. In this paper, The K-mean clustering algorithm was used to generate 9 clusters at 416 × 416 pixels according to 3 scales of detection layer.

The input image size of the model is 416X416 pixels. the number of samples per batch for the model hyper hyperparameters is 64, the momentum factor is 0.949, the initial learning rate is 0.001, the learning rate decreases by 10 times after every 8000 iterations of training, and the model saves the weights once every 1000 training sessions.

Model Evaluation

In order to verify the merits of the four models YOLOv3, YOLOv4, YOLOv5s and Resnet_YOLO, using Precision, Recall, F1score, AP value (average precision),mAP(mean Average Precision) as evaluation parameters, the formulas were calculated as follows.

$$P = \frac{TP}{TP + FP}$$

$$R = \frac{TP}{TP + FN}$$

$$F1 = \frac{2PR}{P + R}$$

$$AP = \int_0^1 P(R)\mathrm{d}R$$

$$mAP = \frac{\sum AP}{C}$$

where:

P is the accuracy rate, R is the recall rate;
TP is the number of true positive samples;
FP is the number of false positive samples;
FN is the number of false negative samples,
mAP is the average precision mean;
C is the total number of target species.

RESULTS AND ANALYSIS

Analysis of the results of different models

In order to verify the performance of target detection of bitter melon, cucumber, white melon and melon "Boyang 9" in this paper, four models, YOLOv3, YOLOv4, YOLOv5s and Resnet_YOLO, were used for target detection, comparing the advantages and disadvantages of the models, focusing on the accuracy and detection speed of the models. The F1 score is a trade-off between balanced precision P and recall R. The AP value is a more comprehensive measure between precision and recall. YOLOv3, YOLOv4, YOLOv5s, and Resnet_YOLO four model detection results are shown in Tables 2, 3, 4, and 5, respectively.

Table 2

YOLOv3 detection model results

Class	Precision	Recall	F1	AP
Bitter melon	0.91	0.85	0.89	0.91
Cucumber	0.77	0.88	0.82	0.90
White melon	0.95	0.81	0.87	0.88
“Boyang 9” Melon	0.88	0.94	0.91	0.98

In the YOLOv3 model, white melon had the highest P of 0.95; “Boyang 9” melon had the highest Recall, F1 score and AP value of 0.94, 0.91 and 0.98, respectively; while cucumber and white melon did not perform well in the detection results.

Table 3

YOLOv4 detection model results

Class	Precision	Recall	F1	AP
Bitter melon	0.90	0.88	0.89	0.97
Cucumber	0.82	0.89	0.85	0.95
White melon	0.91	0.90	0.90	0.98
“Boyang 9” Melon	0.92	0.96	0.94	0.99

In the YOLOv4 model, P, Recall, F1, and AP of "Boyang 9" melon were the highest in the four fruit types tested, at 0.92,0.96, 0.94, and 0.99, respectively; The P, F1, and AP of cucumber were the lowest in all four fruit types. The recall of bitter melon was the lowest in all four fruit types.

Table 4

YOLOv5s detection model results

Class	Precision	Recall	F1	AP
Bitter melon	0.91	0.87	0.89	0.98
Cucumber	0.68	0.92	0.78	0.94
White melon	0.92	0.87	0.89	0.97
“Boyang 9” Melon	0.91	0.97	0.94	0.99

In the YOLOv5s model, Recall, F1, and AP of "Boyang 9" melon were the highest among the four fruit types detected, with 0.97, 0.94, and 0.99, respectively; "Boyang 9" melon had the highest P value, as did Bitter melon, at 0.91. P, F1, and AP of cucumber were the lowest. The best detection results were obtained for the “Boyang 9” melon, followed by the bitter melon.

Table 5

Resnet_YOLO detection model results

Class	Precision	Recall	F1	AP
Bitter melon	0.89	0.90	0.90	0.94
Cucumber	0.72	0.91	0.80	0.93
White melon	0.87	0.91	0.89	0.94
“Boyang 9” Melon	0.84	0.97	0.90	0.98

In the Resnet_YOLO model, bitter melon had the highest P, reaching 0.89; "Boyang 9" melon had the highest Recall and AP values, 0.97 and 0.98; bitter melon and “Boyang 9” melon had similar F1 value of 0.90; cucumber had the lowest P, F1, and AP. In short, “Boyang 9” melon had the best general detection results and cucumber had the worst detection results.

Among the four models, "Boyang 9" melon had the best overall detection results, with the highest AP and F1 values of 0.99 and 0.94, respectively.

Comparison of the results of different models

The IoU threshold is set to 50% in the four modes of YOLOv3, YOLOv4, YOLOv5s, and Resnet_YOLO. The P-R curves of the above four models are shown in Figure 5, and the comparison of the best weights size, mAP, speed for the four models are shown in Table 5.

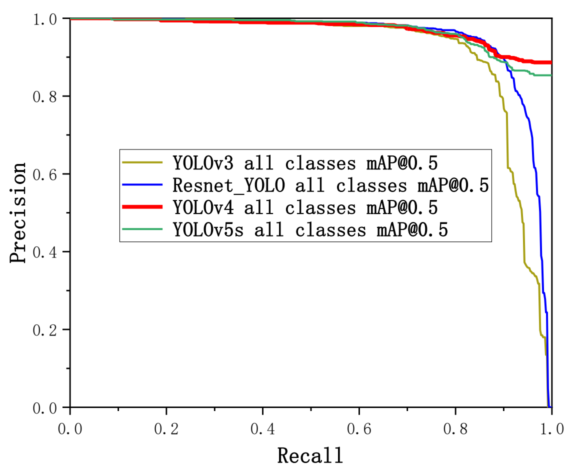


Fig. 5 - P-R curves for different modifications of cucurbits detection model

Table 5

Comparison of results of different models

Methods	Best Weights size (MB)	All classes mAP	fps
YOLOv3	234	0.92	31.9
YOLOv4	115	0.973	55.6
YOLOv5s	14	0.971	90.9
Resnet_YOLO	98	0.95	32.0

In terms of best weights size, the YOLOv5s model has the smallest best weights size of 14 MB. The best weights size for Resnet_YOLO is 98 MB and for YOLOv4 is 115 MB. YOLOv3 has the largest best weights size at 234 MB.

In terms of accuracy, YOLOv3 has the lowest mAP but also reaches 0.92. Resnet_YOLO has a higher mAP than YOLOv3 but lower than YOLOv4 and YOLOv5s, with a mAP of 0.95. YOLOv5s has an mAP of 0.971, while YOLOv4 has the highest mAP at 0.973. Correspondingly, the P-R curves of the YOLOv4 models perform better because it has the largest area under curve (area under curve, AUC).

In terms of speed, the fps values of the YOLOv3 and Resnet_YOLO models are close to each other, around 30. The fps of YOLOv4 is 55.6. The fps value of YOLOv5s reaches 90.9, which is a very fast detection speed.

The mAP of YOLOv5s is not the highest, but the speed and the best weights size are optimal. In a combined comparison, YOLOv5s is best among the four types of models: YOLOv3, YOLOv4, YOLOv5s, and Resnet_YOLO.

The images of bitter melon, cucumber, white melon and "Boyang 9" melon were combined into one image and detected by YOLOv3, YOLOv4, YOLOv5s and Resnet_YOLO models respectively, and the results are shown in Figure 6. The results indicate that the YOLOv4 and YOLOv5s models have the better detection results, but YOLOv5s is the fastest.

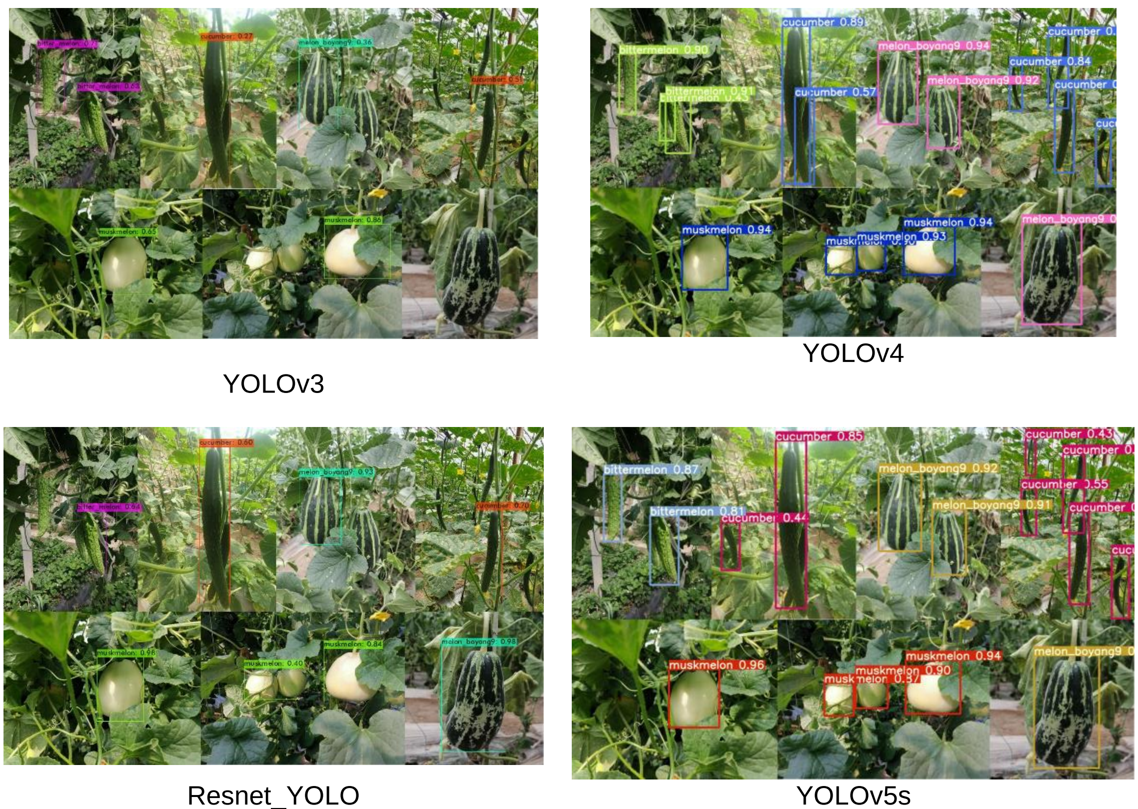


Fig. 6 - Four model image test results

CONCLUSIONS

In the paper, four models, YOLOv3, YOLOv4, YOLO5s and Resnet_YOLO, were used to detect cucurbits, including bitter melon, cucumber, white melon and "Boyang 9" melon varieties.

(1) In the four models of YOLOv3, YOLOv4, YOLO5s and Resnet_YOLO for bitter melon, cucumber, white melon and "Boyang 9" melon, the overall best results were obtained for "Boyang 9" melon, with the highest AP and F1 was the highest, with 0.99 and 0.94, respectively.

(2) YOLOv3, YOLOv4, YOLO5s and Resnet_YOLO models detect bitter melon, cucumber, white melon and "Boyang 9" melon, among them, YOLOv5s model has the best performance: the best weights have the smallest size, 14MB; the better mAP value, 0.971; the fastest detection speed with fps of 90.9.

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