# RESEARCH ON DRIED DAYLILY GRADING BASED ON SSD DETAIL DETECTION WITH FEATURE FUSION

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# *基于特征融合细节检测 SSD 的干制黄花菜分级研究*

**Xueli ZHANG[1,2], Haiyan SONG*[1,2], Decong ZHENG[1,2], Renjie CHANG[1,2], Chenfei LI[1,2], Yile SUN[1,2], Zonglin LIU[1,2]**

[1] College of Agricultural Engineering, Shanxi Agricultural University, Taigu 030801/ China;

[2] Dryland Farm Machinery Key Technology and Equipment Key Laboratory of Shanxi Province, Taigu 030801/ China

*Tel: +86 13994576078.; E-mail: yybbao@sxau.edu.cn*

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## ABSTRACT

*Daylily is widely used in medicine and diet therapy. In order to prolong the preservation period of daylily and make better use of its edible value, most of the daylily on the market are dried vegetables. Aiming at the problems of small size of dried daylily, similar color and texture between dried daylily, and difficulty in grading, this study proposes a method for grading dried daylily based on SSD. In the backbone feature extraction stage, the original backbone network VGG16 is replaced with the residual network model ResNet50 to realize the feature extraction of dried daylily. ResNet50 can deepen the network better and is more suitable for dried daylily feature extraction. Secondly, a feature fusion layer is added to improve the problem of insufficient utilization of shallow features in SSD network, which is more suitable for detail detection and improves the accuracy of dried daylily grading. Finally, the input image size is selected [512,512] to increase the image pixels, so that the network can capture more details of the dried daylily to improve the detection accuracy. The results show that the grading precision of the improved SSD algorithm is significantly improved compared with the traditional SSD, and the mean average precision is increased by 4.17%. At the same time, the same data set was used to test on the YOLOv5 model. Compared with YOLOv5s, YOLOv5s-CA and YOLOv5s-CBAM, the mean average precision was increased by 18.32%, 21.82% and 22.02% respectively, which further verified the precision and feasibility of the method and provided effective technical support for the grading of dried daylily.*

## 摘要

*黄花菜营养成分丰富，具有很高的食用和药用价值。鲜黄花菜因含有多种生物碱不宜多食，为了更好地利用其食用价值以及延长黄花菜的保存期，市面上的黄花菜大多是干菜。针对干制黄花菜体积小，黄花菜之间颜色和纹理相似，分级困难等问题，该研究提出了一种基于 SSD 的干制黄花菜等级分级的方法。该方法以 SSD 算法为基础，在主干特征提取阶段，将原主干网络 VGG16 替换为残差网络模型 ResNet50，实现对干制黄花菜的特征提取。ResNet50 可以更好地深化网络，更适合于干制黄花菜细节特征提取。其次，添加了特征融合层，改善了 SSD 网络中浅层特征利用不足的问题，更适合细节检测，提高了干制黄花菜分级的精度。最后，输入图像尺寸选取[512,512]，提高图像像素，使网络可以更好地捕捉干制黄花菜的细节信息，以提升检测精度。结果表明，改进后的 SSD 算法与传统 SSD 对比，分类精确度有明显的提升，平均精确度达到 97.52%，对比原 SSD 算法提高了 4.17%。同时，利用相同数据集在 YOLOv5 模型上进行试验，对比 YOLOv5s、YOLOv5s-CA、YOLOv5s-CBAM，平均精确度分别提升 18.32%、21.82%、22.02%，进一步验证了该方法的准确性和可行性，可以为干制黄花菜分级提供有效的技术支持。*

## INTRODUCTION

Daylily (*Hemerocallis citrina Baroni*) is an edible angiosperm of *Hemerocallis in Asphodelaceae*, which is a Chinese specialty. Daylily is rich in nutritional value, rich in protein, fat, sugar, etc. Daylily has high medicinal value. It has good functions of promoting diuresis and cooling blood, tranquilizing mind and improving acuity of vision, strengthening brain, anti-aging, and can significantly reduce serum cholesterol content. Because daylily contains a variety of alkaloids, which will cause diarrhea and other poisoning phenomena, its fresh flowers cannot be eaten too much. Therefore, it needs to be processed before eating. The main processing object of daylily is its flower bud; it is processed into dried vegetables by steaming (*Xu, 2004*), and then graded according to different quality, finally packaged for sale.

In recent years, the market demand for daylily has gradually increased. The grading of dried daylily has an important impact on the sales. Now, the sorting of dried daylily is still completely manual operation, as shown in Figure 1. The cost of the manual operation is high, the classification accuracy and the efficiency are low. Furthermore, the workers are in direct contact with daylily, which has certain food safety hazards. The grading problem restricts the development of daylily industry to a certain extent. With the expansion of the scale of the daylily industry, using automated grading equipment instead of manual labor to complete high-quality daylily external quality detection and grading will be of great significance for the realization of production automation and refinement in the daylily industry (*Ma et al., 2022*), and also has a great impact on the price and sales of daylily.

**Fig. 1 - Artificial classification workshop site of daylily**

Image recognition based on machine learning is of great significance to the classification and identification of agricultural products. It has a wide range of applications in agriculture. There are many application objects in the field of agricultural product sorting, such as corn (*Sun et al., 2021*), walnut (*Zhang et al., 2022*), apple (*Chen et al., 2024*) and so on. Because of the special shape and complex grading standards of daylily, the existing sorting machines on the market cannot be well applied. It is necessary to propose a proprietary sorting method for daylily.

Using deep learning to realize the classification and identification of agricultural products is an important direction of current research at home and abroad. *Yin Chuan et al., (2023),* built a green tea quality detection algorithm based on YOLOv5s, and the mAP value reached 91.9%, which was 3.8% higher than the average accuracy of the basic YOLOv5s. *Gui Zhiyong et al., (2023),* proposed a lightweight deep learning model for tea bud recognition based on YOLOv5. Compared with the original YOLOv5 model, the mAP value of the modified model increased by 9.66 %. *Cao Shuo et al., (2020),* built an underwater live crab detection algorithm based on SSD, fused the feature pyramid with SSD to propose Faster MSSDLite, with an average accuracy of 99.01%. *Sun Henan et al., (2021),* used SSD combined with MEAN module and Apple-Inception module to build a new apple leaf disease detection model, with an average accuracy of 83.12%.

Through the above literature research, it can be found that the mainstream deep learning model algorithm has high accuracy and has been applied in agriculture-related fields to a certain extent. However, there are still few studies on the classification of small agricultural products such as daylily. In this paper, aiming at the characteristics of dried daylily in the actual detection process, such as similar color texture and small size, a grade classification algorithm based on improved SSD is proposed. The algorithm replaces the VGG16 network in the traditional SSD with Resnet50, and adds a feature fusion layer to the network, which improves the accuracy of the algorithm. The commonly used input image size of SSD is increased from [300,300] to [512,512] to better detect small targets. The experimental results show that the proposed method can significantly improve the precision of dried daylily grading.

## MATERIALS AND METHODS

### Image data acquisition and preprocessing of dried daylily

Daylily of Yunzhou District, Datong City, Shanxi Province, China was selected as the detection target of this paper. According to the “National Standard of Daylily” and “Quality grading standard of dried daylily products in Datong”, through the comparison of color, shape and the degree of flowering crack at the top of daylily, daylily was divided into three grades: A-grade, B-grade and C-grade. The color of the A-grade daylily is uniform and shiny, it is golden or light yellow, the shape is symmetrical, and the head of the daylily does not bloom.

The B-grade daylily also has uniform color, golden or light yellow, the color may be slightly uneven but the shape is well, and the flowering degree of daylily's head is low. The C-grade daylily's color is uneven, the shape is irregular, and the head of daylily has a greater degree of flowering. Pictures of different grades of dried daylily are shown in Figure 2.

The images were captured in Agricultural Engineering College, Shanxi Agricultural University, using Hikvision CA060-10GC industrial camera. When collecting images, the background is single and the illumination is stable. A total of 860 images of daylily were collected. In order to avoid overfitting problems, the image data is enhanced by vertical flipping, 90° rotation, blurring processing and adding salt and pepper noise, so that the image data is increased by 8 times, that is, 6880 images. The target annotation tool LabelImg was used for data annotation, and the daylily image dataset was constructed. They were randomly divided into training set and test set according to the ratio of 8:1. The final quantity of daylily at all levels is shown in Table 1.


**(a)A-grade**


**(b)B-grade**


**(c)C-grade**

**Fig. 2 - Examples of pictures of different grades of dried daylily**

**Table 1**

**The dried daylily dataset**

| Dataset | Number | Number of each grade of Daylily | | |
|---|---|---|---|---|
| | | A-grade | B-grade | C-grade |
| **Training set** | 6117 | 1565 | 2176 | 2376 |
| **Test set** | 763 | 195 | 272 | 296 |

## SSD algorithm

Single Shot MultiBox Detector (SSD) algorithm is a fast and accurate target detection algorithm, which realizes the efficient detection of multi-scale targets by simultaneously detecting targets at different scales (*Liu et al., 2016*). The SSD algorithm mainly includes three parts: feature extraction network, prediction network and loss function. In the feature extraction network, the features of the image are extracted by convolution and pooling. In the prediction network, the location and category of the target are predicted by a multi-scale convolutional layer; in the loss function, the model parameters are optimized by calculating the loss function between the predicted results and the real labels.

The main design idea of SSD is multi-scale aspect ratio dense anchor point design and feature pyramid. The network structure of SSD is shown in Figure 3. SSD is based on a feedforward convolutional network, which generates a fixed-size bounding box set and the corresponding score of the target category in the box, and generates the final detection result according to the non-maximum suppression. SSD uses VGG16 as the base layer (*Simonyan et al., 2014*). The VGG16 network structure is shown in Figure 4. The Conv4_3 is selected as the first feature layer for target detection. In addition, SSD adds several additional feature layers for target detection. The FC7 (Fully Connected Layer7) in VGG16 is replaced by the convolutional layer Conv7, and several feature layers of Conv8, Conv9, Conv10, and Conv11 are added to perform target detection on multiple scales to improve detection accuracy. The idea of feature pyramid is realized. At the same time, SSD designs a large number of dense prior boxes to detect the entire image.

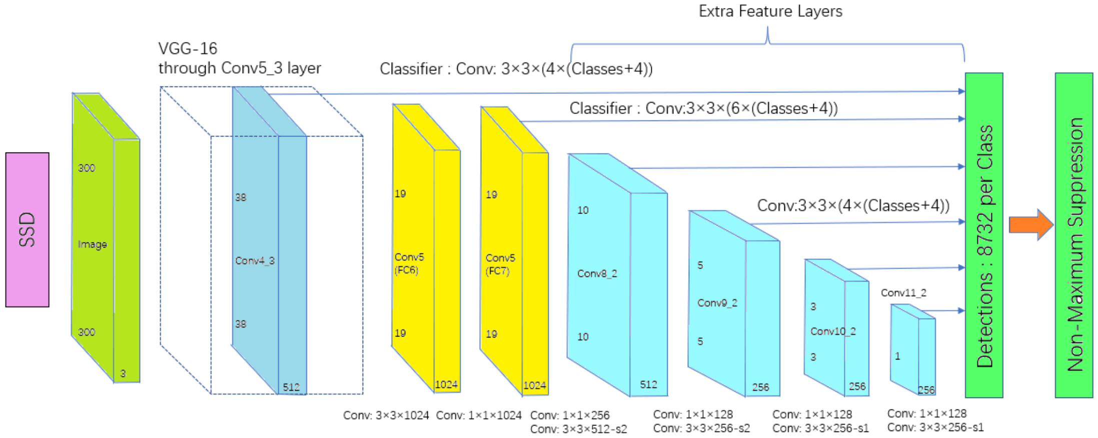


**Fig. 3 - Network structure of SSD**

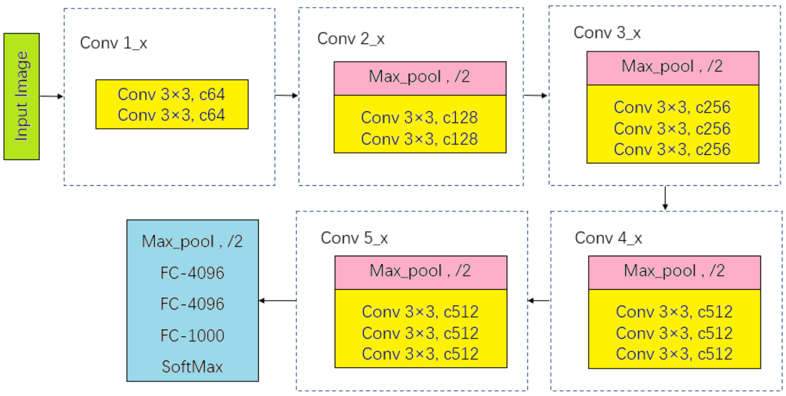


**Fig. 4 - Network structure of VGG16**

### Improved SSD algorithm

In order to further improve the grading accuracy of dried daylily, the SSD algorithm was improved. The improved SSD network structure is shown in Figure 5. By replacing the original VGG16 with Resnet50 (*He et al. 2016*), the residual network can build a deeper network structure for detail detection, and improve the accuracy of daylily grading results. At the same time, the feature fusion layer is added. The small targets tend to rely more on shallow features. The feature fusion of SSD shallow information can enhance the characterization ability of features (*Li et al., 2017*), improve the model's understanding and expression ability of input data, and thus enhance the model's recognition ability of details (*Tian et al., 2022*). The image size is selected [512,512]. Improving the image pixels can provide more detailed information of daylily to the network (*Tan et al., 2020*), thereby improving the accuracy of grading. The network structure of the backbone network Resnet50 is shown in Figure 6. The improved SSD removes Conv5 and subsequent networks, and selects three feature maps generated by Conv2_3, Conv3_4, and Conv4_6 for feature fusion. Then the fusion results are sent to a series of additional feature layers to obtain multi-scale features, which are sent to the detector for detection. Finally, the prediction results are output by Non-Maximum Suppression.

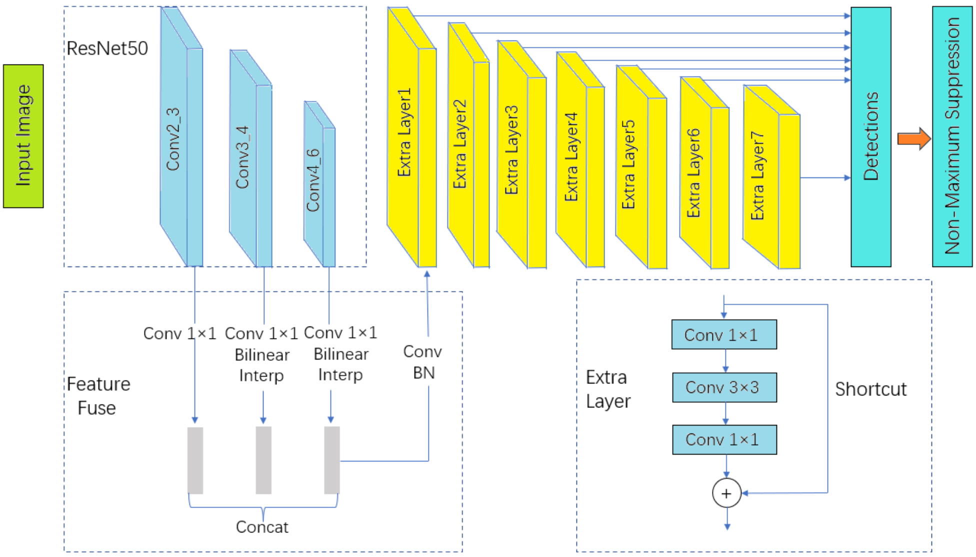


**Fig. 5 - Network structure of the improved SSD**

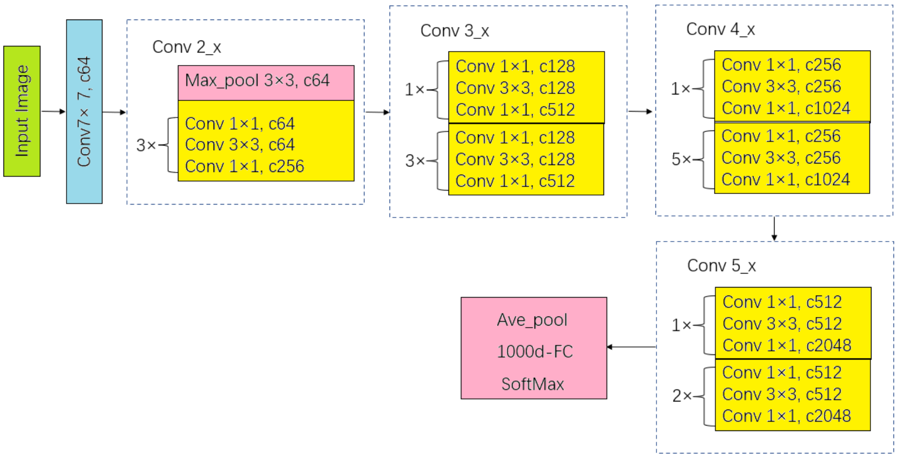


**Fig. 6 - Network structure of ResNet50**

Residual Network (ResNet) is one of the most commonly used convolutional neural network architectures. In deep learning training, with the deepening of the network, it is likely to appear the problem of gradient disappearance and gradient explosion. Using data initialization and normalization layer (BN) can solve the gradient problem, but the deepening of the network will also bring the problem of network degradation, that is, with the deepening of the network depth, the network performance will decrease instead. ResNet can be used to solve the degradation problem, and at the same time alleviate the problems of gradient disappearing and gradient explosion to a certain extent, and improve the performance of the network. Compared with the VGG network, Resnet can construct a deeper network structure. When the VGG network has a deeper network structure, the number of parameters is relatively large, which is prone to over-fitting. The number of Resnet parameters is relatively small, which reduces the risk of over-fitting. When training the deep network, Resnet is more stable, and the training and reasoning speed is relatively fast. The classical network structures of ResNet are: ResNet-18, ResNet-34, ResNet-50, ResNet-101, ResNet-152. In this paper, Resnet50 is selected as the backbone network.

Feature Fusion refers to the use of complementarity between features to fuse the advantages of features when features of different attributes are given, so as to improve the performance of the model. Although the SSD algorithm predicts features from different layers, SSD regards them as the same layer and predicts them directly, which cannot make full use of local detail features and global semantic features. Through feature fusion, shallow detail features and high-level semantic features can be combined to improve the prediction effect of the network. As shown in Figure 7 (a), SSD predicts directly on the feature of each layer, and there is no connection between each layer. After adding feature fusion, as shown in Figure 7 (b), the features of each layer are fused, and then the feature pyramid is generated from the fusion feature.

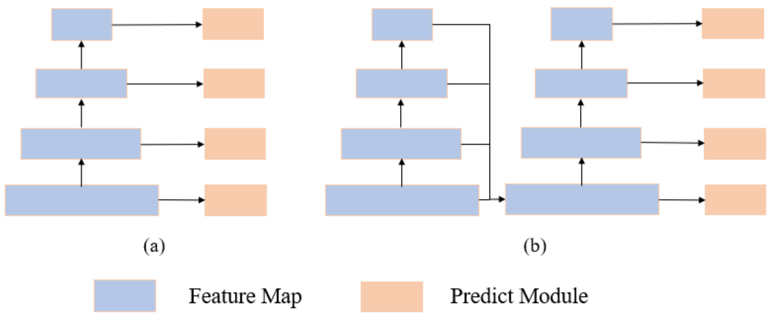


**Fig. 7 - Feature information processing**

## RESULTS

In this paper, the Precision (P) and Mean Average Precision (mAP) are selected as the evaluation criteria of the algorithm. The Precision refers to the proportion of samples that are truly positive in all samples predicted by the classifier. The mAP provides a comprehensive measure to compare and evaluate the performance of different algorithms. The formulas are as follows.

$$P = \frac{TP}{TP+FP} \tag{1}$$

$$R = \frac{TP}{TP+FN} \tag{2}$$

$$AP = \int_0^1 P(R)dR \tag{3}$$

$$mAP = \frac{1}{K}\sum_{i=1}^{K} AP(i) \tag{4}$$

where:

$P$ and $R$ denote Precision and Recall. $TP$, $FP$ and $FN$ mean true positive, false positive and false negative, respectively. $K$ is the number of detection classes.

### The results of SSD

In this paper, the SSD algorithm and the improved SSD algorithm are used to classify the dried daylily. The experimental results are shown in Table 2. The results show that the improved SSD algorithm can effectively grade dried daylily. The $mAP$ of the SSD512 reaches 97.52 %, which is 4.17 % higher than that of the traditional SSD algorithm. The examples of the grading results are shown in Figure 8.

**Table 2**

**Experimental results of SSD and improved SSD**

| architecture | backbone | P (%) | | | mAP (%) | FPS |
|---|---|---|---|---|---|---|
| | | AL | BL | CL | | |
| **SSD** | **VGG16** | 90.78 | 92.71 | 96.56 | 93.35 | 44 |
| **SSD300 r50** | **ResNet50** | 92.42 | 91.09 | 96.85 | 93.46 | 40 |
| **SSD512 r50** | **ResNet50** | 96.92 | 96.64 | 98.99 | 97.52 | 40 |


**Fig. 8 - The examples of the grading results of SSD512**

**Comparison with YOLOv5 processing results**

YOLOv5 is one of the YOLO (*Redmon et al., 2016*) series algorithms. It regards the target detection task as a regression problem, and directly predicts the bounding box and category probability through the convolutional neural network. YOLOv5 is mainly composed of four parts: Input, Backbone, Neck, and Head. The network structure of YOLOv5s is shown in Figure 9. In this paper, YOLOv5s algorithm is used for dried daylily grading.

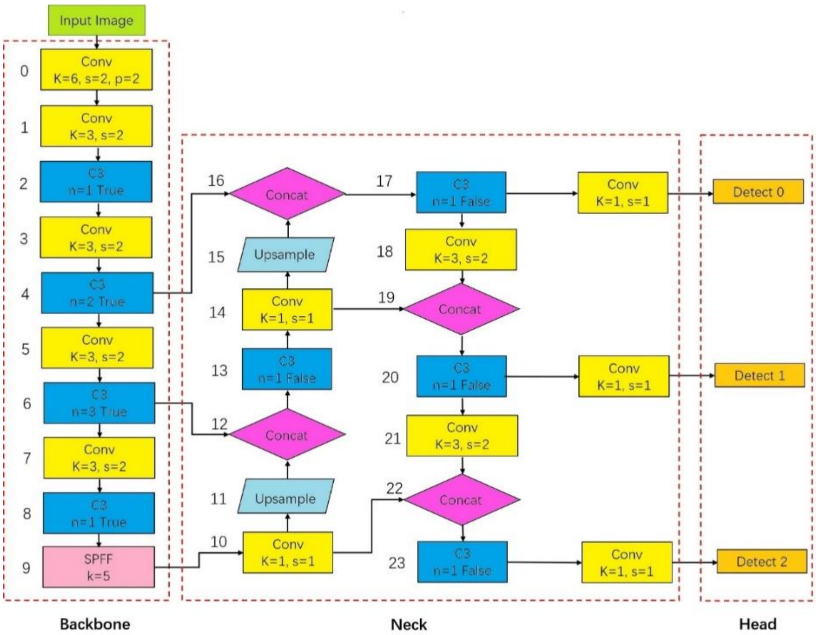


**Fig. 9 - Network structure of YOLOv5s**

In order to grade dried daylily better, the YOLOv5s network was improved by adding attention mechanism to the model *(Wang et al., 2022)*. The attention mechanism is a computer science principle that imitates the human attention mechanism, which is mainly used to improve the performance of neural networks in processing sequence data (*Xia et al., 2023*). This paper selects two attention mechanisms: CBAM (Convolutional Block Attention Module) (*Woo et al., 2018*) and CA (Coordinate attention) (*Hou et al., 2021*). YOLOv5s-CA (*Du et al., 2024*) and YOLOv5s-CBAM (*Dai et al., 2024*) are used to process dried daylily data, respectively.

The processing results are shown in Table 3. The $P$ value of each grade are not very high, and the $mAP$ is lower than 80 %. Because the YOLO algorithm does not perform regional sampling directly, it extracts information through full-image detection. Therefore, YOLO has a good performance on global information, but a poor performance on small-scale information. The grading of dried daylily focuses on detailed information, so the precision of YOLOv5 is not high. After adding CBAM attention mechanism and CA attention mechanism to YOLOv5s, the two attention mechanisms have significantly improved the precision of A-grade, but the grading effect on B-grade is poor, resulting in a decrease in mAP value instead of an increase.

**Table 3**

**Experimental results of YOLOv5s and improved YOLOv5s**

| architecture | $P$ (%) | | | $mAP$ (%) |
|---|---|---|---|---|
| | AL | BL | CL | |
| YOLOv5s | 78.5 | 75.2 | 83.9 | 79.2 |
| YOLOv5s-CA | 80.4 | 63.5 | 83.9 | 75.9 |
| YOLOv5s-CBAM | 80.2 | 62.5 | 83.6 | 75.5 |

The comparison of the results of the SSD series algorithm and the YOLOv5 series algorithm is shown in Figure 10. For the problem of dried daylily grading, the classification effect of YOLOv5 algorithm is limited. The detail detection algorithm based on SSD proposed in this paper has obvious advantages in classification accuracy.

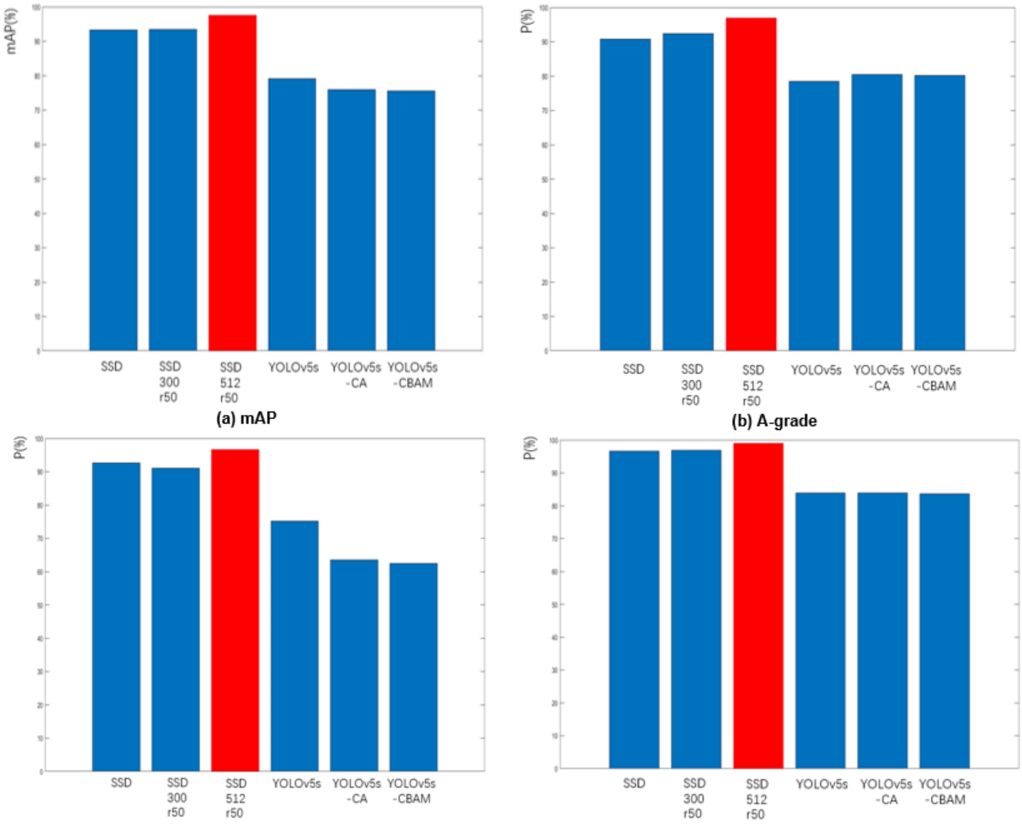


**Fig. 10 - The comparison results of each algorithm**

## CONCLUSIONS

Daylily is small in size and similar in color and texture. The grading of dried daylily is extremely dependent on the ability to identify details. The manual sorting lacks specific quantitative criteria, the classification efficiency is low and the results are inaccurate. In terms of automatic grading, the requirement for the detail recognition ability of the algorithm is very high. The existing machine vision algorithm is mainly aimed at relatively large targets in the field of agricultural product recognition, and the ability of detail recognition is limited. This paper studies the grading algorithm of dried daylily based on deep learning, improves the detail recognition ability of the algorithm, establishes an efficient grading model, and realizes the automatic classification of daylily. The experimental results show that for dried daylily grading, the grading effect of YOLOv5 is relatively limited, while the SSD algorithm uses multi-scale feature extraction, that is, using multiple feature maps of different scales for target detection, which can effectively detect targets of various sizes, and the detection of small targets is more accurate. At the same time, SSD uses Default Boxes of different proportions and aspect ratios, which can better adapt to the target of various shapes. Therefore, this paper finally selects SSD algorithm as the grading algorithm of daylily. The improved SSD algorithm can effectively grad daylily with high precision. Compared with the original SSD algorithm, the precision is significantly improved, and the mAP is increased by 4.17%. At the same time, compared with YOLOv5s, YOLOv5s-CA and YOLOv5s-CBAM, the mAP increased by 18.32%, 21.82% and 22.02%, respectively. The improved SSD algorithm has good stability and reliability, and has a good application prospect, which can provide better technical support for the development of daylily industry.

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## REFERENCES

[1] Cao, S., Zhao, D., Liu, X. Y., & Sun, Y. P. (2020). Real-time robust detector for underwater live crabs based on deep learning. *Computers and Electronics in Agriculture*, Vol. 172: 105339.

[2] Chen, Y. P., Niu, Y., Cheng, W. D., Zheng. L. N., & Sun, D. C. (2024). Apple detection method in the natural environment based on improved YOLOv5. *INMATEH - Agricultural Engineering*, 72(1), pp. 183-192. DOI: https://doi.org/10.35633/inmateh-72-17

[3] Dai, J. X., Luo, Y. F., Shi, S. Y., Yang, D. T., & Zhao, Z. X. (2024). Design and experimental evaluation of an intelligent sugarcane stem node recognition system based on enhanced yolov5s. *Multimedia Systems*, 30(6), pp. 1-16.

[4] Du, Y. H., Gao, A, Song, Y. P., Guo, J., Ma, W. & Ren, L. L. (2024). Young apple fruits detection method based on improved yolov5. *INMATEH - Agricultural Engineering*, 73(2), pp. 84-93. DOI: https://doi.org/10.35633/inmateh-73-07

[5] Gui, Z. Y., Chen, J. N., Li, Y., Chen, Z. W., Wu, C. Y., & Dong, C. W. (2023). A lightweight tea bud detection model based on Yolov5. *Computers and Electronics in Agriculture*, Vol. 205: 107636.

[6] He, K. M., Zhang, X. Y., Ren, S. Q., & Sun, J. (2016). Deep residual learning for image recognition. *Proceedings of the 2016 IEEE/CVF conference on Computer Vision and Pattern Recognition*. 770-778.

[7] Hou, Q. B., Zhou, D. Q., & Feng, J. S. (2021). Coordinate attention for efficient mobile network design. *Proceedings of the 2021 IEEE/CVF conference on Computer Vision and Pattern Recognition*. pp.13713-13722.

[8] Li, Z. X., & Zhou, F. Q. (2017). FSSD: feature fusion single shot multibox detector. *Computer Science. arXiv preprint arXiv: 1712.00960*.

[9] Liu, W., Anguelov, D., Erhan, D., Szegedy, C., Reed, S., Fu, C. Y., & Berg, A.C. (2016). SSD: Single Shot MultiBox Detector. *Proceedings of the Computer Vision – ECCV 2016.* pp. 21-37.

[10] Ma, C., & Chen, X. D. (2022). Dried daylily sorting method based on machine vision (基于机器视觉的黄花菜干菜分选方法研究). *Ningxia Journal of Agri. And Fores. Sci. &Tech*, 63(4), 61-65.

[11] Redmon, J., Divvala, S., Girshick, R., & Farhadi, A. (2016). You Only Look Once: Unified, Real-Time Object Detection. *Proceedings of the 2016 IEEE conference on Computer Vision and Pattern Recognition*. pp.779-788.

[12] Simonyan, K., & Zisserman, A. (2014). Very deep convolutional networks for large-scale image recognition. *Computer Science. arXiv preprint arXiv: 1409.1556.*

[13] Sun, H., Qiao, J. B., Li, S., Li, M.Z., Song, D., & Qiao, L. (2021). Recognition of the maize canopy at the jointing stage based on deep learning(基于深度学习的玉米拔节期冠层识别). *Transactions of the Chinese Society of Agricultural Engineering (Trans. of the CSAE)*, 37(21), 53-61.

[14] Sun, H. N., Xu, H. W., Liu, B., He, D. J., He, J. R., Zhang, H. X., & Geng, N. (2021). MEAN-SSD: A novel real-time detector for apple leaf diseases using improved light-weight convolutional neural networks. *Computers and Electronics in Agriculture*, Vol. 189: 106379.

[15] Tan, L., & Gao, A. (2020). SSD object detection algorithm with feature enhancement of receptive field(感受野特征增强 SSD 目标检测算法). *Computer Systems & Applications*, 29(9), 149−155.

[16] Tian, P. Y. (2022). FFSSD: feature fusion SSD algorithm with SE on traffic sign detection. *Procedia Computer Science*, Vol. 208, pp. 338-346.

[17] Wang, Q. F., Cheng, M., Huang, S., Cai, Z. J., Zhang, J. L., & Yuan, H. B. (2022). A deep learning approach incorporating YOLO v5 and attention mechanisms for field real-time detection of the invasive weed Solanum rostratum Dunal seedlings. *Computers and Electronics in Agriculture*, Vol. 199: 107194.

[18] Woo, S., Park, J., Lee, JY., & Kweon, I.S. (2018). CBAM: Convolutional Block Attention Module. *Proceedings of the Computer Vision – ECCV 2018*. pp. 3-19.

[19] Xia, Y., Lei, X. H., Herbst, A., & Lyu, X. L. (2023). Research on pear inflorescence recognition based on fusion attention mechanism with YOLOv5. *INMATEH - Agricultural Engineering*, 69(1), pp.11-20. DOI: https://doi.org/10.35633/inmateh-69-01

[20] Xu, X. D. (2004). Drying processing of daylily(黄花菜的干制加工). *Agricultural product processing*, 0(8), 31-31.

[21] Yin, C., Su, Y. H., Pan, M., & Duan, J. S. (2023). Detection of the quality of famous green tea based on improved YOLOv5s(基于改进 YOLOv5s 的名优绿茶品质检测). *Transactions of the Chinese Society of Agricultural Engineering (Trans. of the CSAE)*, 39(8), 179-187.

[22] Zhang, S. L., Zhang, L. P., Zheng, W. Q., Guo, Z., & Fu, Z. Q. (2022). Identification and localization of walnut varieties based on YOLOv5(基于 YOLOv5 的核桃品种识别与定位). *Journal of Chinese Agricultural Mechanization*, 43(7) ,167-172.