YOLOv8-Based Recognition of Wolfberry Pistil Assisted Pollination

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Abstract: In this paper, a pistil-assisted pollination recognition method based on improved YOLOv8 is proposed, aiming to improve the detection accuracy and efficiency in the pistil pollination process. Firstly, a weighted bidirectional feature pyramid network (BiFPN) is introduced to replace the PAN-FPN module in YOLOv8 to enhance the multi-scale feature fusion capability for the complex background and small target features of pistil images. Secondly, the Coordinate Attention (CA) mechanism is combined to further enhance the extraction ability of the model for stamen features. In addition, Ghost convolution is used to replace the traditional convolution, which effectively reduces the computational complexity and storage requirements of the model. The experimental results show that the improved YOLOv8 model achieves a mean average precision (mAP) of 90.5% on the self-constructed stamen dataset. The method provides an efficient and accurate solution for pistil-assisted pollination identification, which is suitable for real-time detection and low-match device deployment.

Keywords: Agricultural Decision Support; Mechanised Pollination; Image Classification; YOLOv8; Data Enhancement

1. Introduction

As a plant with important economic and medicinal values, the yield and quality of Lycium barbarum depend largely on an effective pollination process. The pollination efficiency of wolfberry stamens is not only affected by natural environmental factors, but also limited by the ability of artificial intervention. In modern agricultural production, the application of precise identification and assisted pollination technology is of great significance to improve the yield and quality of wolfberry[1]. In recent years, with the rapid development of computer vision technology, the application of target detection algorithms based on deep learning in the field of agriculture has gradually attracted attention. the YOLO (You Only Look Once) series of algorithms[2], as a highly efficient real-time target detection framework, has demonstrated a strong performance in a number of fields[3]. However, the recognition of wolfberry stamens faces many challenges, such as the tiny size and complex morphology of the stamens[4], and they are easily affected by factors such as light and background interference in the natural environment[5]. Overcoming in order to these difficulties, this study proposes an improved YOLOv8 algorithm specifically for assisted pollination recognition of wolfberry stamens[6]. By optimising the network structure, adjusting the hyperparameters and introducing data enhancement strategies, the improved algorithm is able to more accurately detect the position and state of wolfberry stamens, thus providing reliable information support for the automated pollination equipment, which is expected to significantly improve the pollination efficiency and accuracy of wolfberry stamens, and to promote the intelligent development of the wolfberry planting industry[7].

2. Related Research

Traditional pollination techniques mainly include hand pollination and insect pollination[8]. Artificial pollination is to transfer pollen from stamen to pistil by manual operation, this method can ensure the accuracy of pollination, but labour intensity, low efficiency, and requires a large amount of human input[9]. Deep learning techniques have made significant progress in the field of target detection, and many excellent algorithms have emerged, It has been successfully applied in several fields[10].

2.1 Deep Learning Target Detection Techniques

Deep learning object detection technology is an important branch in the field of computer vision and has made remarkable progress in recent years[11]. The YOLO (You Only Look Once) series of algorithms, as representatives of real-time object detection, have received extensive attention due to their high efficiency and accuracy[12]. As the latest version of this series, YOLOv8 has further optimized the network structure and introduced technologies such as attention mechanisms and dynamic convolutions, significantly improving the detection ability for small objects and complex scenes[13]. For example, YOLOv8 adopts the SPFF (Spatial Pyramid Fusion Fast) strategy and Task Aligned Assigner technology, which improve the multi-scale feature fusion ability and target alignment accuracy respectively [1].
In addition, YOLOv8 has demonstrated strong adaptability in practical applications. For instance, in blueberry fruit detection, by introducing the improved MPCA (Multiplexed Coordinated Attention) module and MultiSEAM (Multi-scale Separation and Occlusion - Aware Module), the detection accuracy and generalization ability of YOLOv8 have been significantly enhanced [2]. These improvements not only enhance the model's ability to detect small objects but also effectively solve problems such as object occlusion.

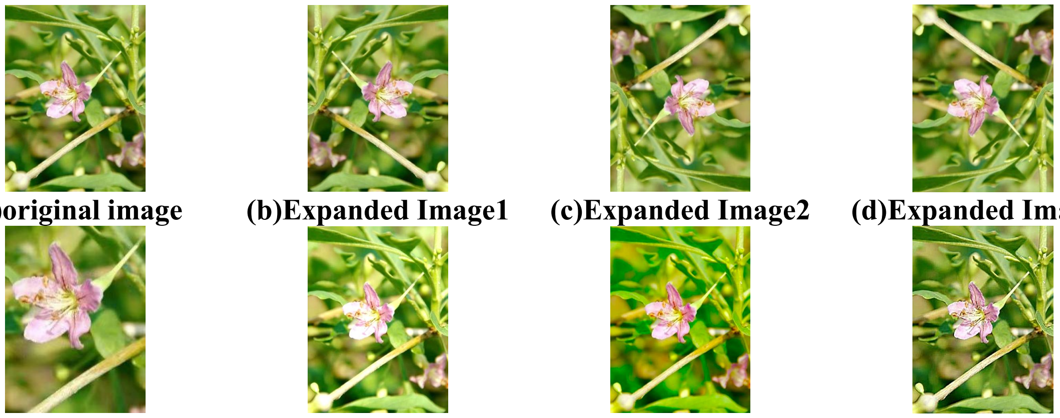
2.2 Deep Learning Target Detection Methods in Pistil-Assisted Pollination Recognition

In the agricultural field, the research on stamen recognition and assisted pollination technology has gradually become a hot topic. Traditional pollination methods are inefficient and have unstable effects, while the object detection technology based on deep learning provides a new solution for automated pollination. In recent years, the YOLO series of algorithms have been widely applied in stamen detection. For example, a flower stamen detection method based on the improved YOLOv8 significantly improves the detection accuracy of multiple targets and small stamens by introducing the Multi-Head Self-Attention Mechanism (MHSAM) and a small object detection layer[3].
Moreover, studies have also shown that data augmentation techniques (such as image cropping, translation, brightness adjustment, etc.) can further enhance the robustness of the model in complex scenarios. In the detection of goji stamen, the improved YOLOv8 model can more accurately identify the position and state of the stamen by optimizing the network structure and introducing the attention mechanism, providing reliable support for automated pollination devices[4].

3. Data Set and Methodological Design

3.1 Data Set Creation and Processing

In order to achieve accurate identification and assisted pollination of wolfberry stamens, this study constructed a specialised wolfberry stamen image dataset and enhanced the generalisation ability and robustness of the model through data enhancement techniques. The data collection was carried out in a wolfberry plantation, and a high-resolution camera was used to photograph wolfberry pistils from different angles, light conditions and time periods, covering samples of different maturity and growth stages. After the collection was completed, the stamens were accurately boxed and classified using manual annotation, followed by dividing the dataset into training, validation and testing sets, with proportions of 70%, 15% and 15%, respectively.
In the data processing stage, this study used a variety of data enhancement strategies, including random rotation, flipping, cropping, scaling, adding noise and colour adjustment. Random rotation and flipping simulate the different orientations and symmetries of stamens in the natural state; random cropping and scaling enhance the model's ability to adapt to the local features and size variations of the stamens; and adding noise and colour adjustment simulate the disturbances and light variations in the actual shooting to further improve the robustness of the model. Through these treatments, the diversity of the dataset is significantly increased, which provides high-quality inputs for the training of the improved YOLOv8 model, and lays a solid foundation for the realisation of accurate LBP pistil recognition and assisted pollination. The effect of data enhancement is shown in Figure 1.



(a)original image (b)Expanded Image1 (c)Expanded Image2 (d)Expanded Image3

(e)Expanded Image4 (f)Expanded Image5 (d)Expanded Image6 (h)Expanded Image7

Figure 1. Data Enhancement Effects

3.2 Overview of the YOLOv8 Algorithm

YOLOv8 is the latest version of the YOLO series of target detection algorithms, which inherits the high efficiency and real-time characteristics of the series, and significantly improves the detection accuracy and robustness through the optimisation of the network architecture, the introduction of the attention mechanism and the improvement of the data enhancement strategy. The algorithm introduces the Spatial Pyramid Pooling (SPP) module and task alignment allocator, which enhances the multi-scale target detection capability and target localisation accuracy; meanwhile, the Spatial Channel Cooperative Attention (SCCA) module is adopted, which improves the model's adaptability to complex backgrounds and small targets. In addition, YOLOv8 further improves the generalisation ability of the model by means of data enhancement such as random rotation, flipping, cropping, noise addition, etc., and optimises the training process by using Exponential Moving Average (EMA).Experiments on several publicly available datasets show that YOLOv8 outperforms its predecessor version in terms of both mean accuracy (mAP) and computational efficiency, as shown in Figure 2.

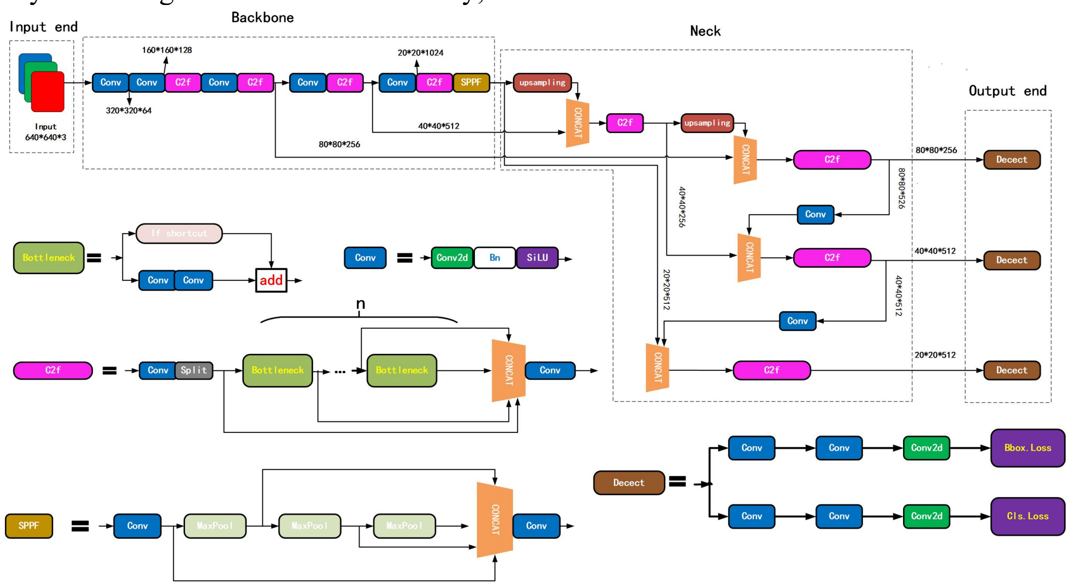


Figure 2. YOLOv5-LDPR Model Diagram

4. Experimental Results and Analysis

4.1 Model Training

The improved and comparison models in the experiments were trained and compared separately validated on Ubuntu 18.04.3 server. The server is equipped with Intel(R) Xeon(R) Gold6140 CPU @ 2.30 GHz processor and NVIDIA Tesla V100 SXM2 32 GB GPU.

The models covered in this paper were built using the deep learning framework PyTorch 1.7.1 and CUDA 10.1. The ablation experiments were performed using the Adam optimisation algorithm with a training time of 250 epoch. the input image resolution of the model was 640 × 640 pixels. The batch size is 32 and the initial learning rate is set to 0.01.

4.2 Model Training Results

This experiment trained 200 epochs, and after a long and detailed training process, the metrics/mAP reached 0.9. This excellent result fully demonstrates the strong learning ability and generalisation performance of the model.

In addition, the convergence of the model can be assessed by looking at the training process. If the curve flattens after a certain number of epochs and the metrics/mAP remain high, the model has converged to a good solution. On the contrary, if the curve continues to fluctuate or the metrics/mAP does not stabilise at a high value, further adjustments to the model structure, parameters or training strategy may be required.

4.3 Comparison Test

In this paper, we validate the model classification detection capability of YOLOv8 through model comparison experiments on the dataset by calculating the average precision of all categories. precision represents the precision, i.e., the probability that a sample predicted as a positive input sample is actually correct. recall represents the recall, i.e., the probability that a sample that is actually a positive input sample is predicted as correct. mAP_0.5 denotes the average precision of all categories in terms of IOU values. mAP_0.5 represents the average accuracy of all categories when the IOU value is set to 0.5. mAP_0.5:0.95 represents the average accuracy of all categories at different IOU values (from 0.5 to 0.95 in 0.05 steps).

4.4 Comparison Test

YOLOv8's shows great accuracy in all kinds of scenes, can closely fit the outline of the wolfberry stamen, whether in complex backgrounds or lighting changes, can accurately frame the stamen target, greatly improving the accuracy of recognition. It can clearly present a wealth of stamen features, whether it is the shape of the stamen, texture or differentiation from the surrounding environment, can be accurately reflected in the feature map, even if it is a small size or partially obscured stamen, it can be extracted to the significant features, which provides a solid foundation for accurate recognition, as shown in Figure 3.

Figure 3. Model Testing Effects

5. Conclusion

The purpose of this experiment is to investigate the performance of YOLOv8 in the task of wolfberry pistil-assisted pollination recognition and to compare it with other common models. The experimental results show that YOLOv8 exhibits excellent performance advantages.

Compared with the SSD model, YOLOv8 has a 5.135% higher accuracy, which means that YOLOv8 is able to judge the target more accurately and reduce misjudgments when identifying wolfberry stamens. In terms of recall, YOLOv8 is 11.036% higher than SSD, which indicates that it can detect the wolfberry pistil in the image more comprehensively to avoid omission. In the mAP_0.5 metric, YOLOv8 is 5.017% ahead of SSD, and in the mAP_0.5:0.95 metric, it is even 39.112%, which shows that YOLOv8 is much better than SSD in identifying the pistils of Lycium barbarum in different intersection and merging ratio thresholds.

Compared with YOLOv5, YOLOv8 has an advantage of 2.413% in accuracy, 7.865% in recall, 2.926% in mAP_0.5, and 34.998% in mAP_0.5:0.95. This indicates that YOLOv8 is better than YOLOv5s in detecting LBP stamens, both in terms of accuracy and ability to detect stamens at different scales and complex backgrounds.

Compared with YOLOv8, the other models have gaps in all indicators. In terms of accuracy, YOLOv8 is 2.813% higher than the comparison model, recall is 6.514% higher, mAP_0.5 is 1.755% higher, and mAP_0.5:0.95 is 32.904% higher. This further highlights the leading position of YOLOv8 in the LBP pistil recognition task.

YOLOv8 demonstrated high application value in the wolfberry pistil-assisted pollination recognition experiments by virtue of its significant advantages in accuracy, recall, and mean average precision, etc. It can provide reliable technical support for the intelligent recognition of wolfberry pistil-assisted pollination, and is expected to significantly improve the efficiency and quality of wolfberry pollination in actual agricultural production.

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