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A fast multi-source target recognition system for Dangshan pear based on lightweight "graph neural network - YOLOv5s"

Kaijie Zhang[1, 2][0000-0001-9018-8868] and Chao Wang[1, 2][0000-0003-1288-2621] and Xin Liu[3][0009-0000-5770-5923] and Xiaoyong Yu[2][0000-0002-5803-3441] and Yingying Wang[1] and Dejun Li[1] and Kangjian Zhang[1]

[1] School of Informatics and Engineering, Suzhou Aviation Vocational University, Anhui University, Suzhou 234122, China
[2] School of Informatics and Engineering, Suzhou University, Suzhou 234000, China
[3] School of Artificial Intelligence and Information Engineering, Jinken College of Technology, Nanjing 211156, China
szxycw@126.com

Abstract. China's Anhui Dangshan pear has a sweet and creamy taste and is a favorite product of consumers. However, it faces low economic added value and weak competitiveness, mainly due to the backwardness of post-production quality detection and grading and information management technology; to address the above problems, the project integrates graph neural networks and YOLOv5s to construct a multi-source image detection system for the fruit to be tested; combines graph neural networks to complete the comprehensive inversion of physicochemical properties, appearance and other physicochemical quality parameters; utilizes the characteristics of YOLOv5s, which occupies little memory and has a fast recognition rate, to accelerate the rapid identification of the target fruit. The characteristics of YOLOv5s, which occupies little memory and has a fast recognition rate, are utilized to accelerate the rapid recognition of target fruits. Experimental results show that in the process of batch picture recognition, the average recognition rate of a single picture is about 0.02 seconds, and the recognition accuracy reaches 99.32%. At the same time to ensure that the production line fast and robust operation, the establishment of Dangshan pear multi-source information recognition system research and development, and steadily promote the quality and value-added fruit industry, and promote the rapid development of the regional economy.

Keywords: Graph neural network, YOLOv5s, Rapid detection, Dangshan pear.

1 Introduction

China's fruit industry economic value-added low, weak competitiveness, the main reason is the fruit post-production grading and sorting technology is backward, the key link is the fruit quality testing; agricultural supply chain in the field of agriculture also exists in the supply chain management efficiency is low, the data quality is poor and non-transparent and the degree of informationization is low, etc. Anhui Suzhou Dangshan pear is also experiencing a similar predicament. Therefore, accurate and reliable detection of the comprehensive quality of Dangshan pears, simultaneous construction of planting, quality control and sales and other sources of information analysis and decision-making platform, is expected to realize the scientific planting of Dangshan pears, value-added enhancement and industrial risk management. Our proposed system model can efficiently and quickly solve the identification and detection of Dangshan pears in the pre-sale target, which is mainly aimed at providing assistance for the subsequent identification and screening of pear size, as well as the analysis of pests and diseases, and other aspects, so as to facilitate the provision of convenience in the region where visual observation is difficult. At the same time, due to the instability of production, fruit farmers in the transportation process, can not determine the number of qualified quality of the entire pear orchard, for the procurement of packaging tape is unknown, every year need to over-purchase, most of the unused paper bags can not be used in the following year because of environmental reasons. The system is based on this increase in the detection of the number of identification in the region, as far as possible to reduce unnecessary labor, to ensure that high-quality fresh Dangshan pear flow to the market. As a lightweight target detection algorithm, YOLOv5s is good at efficiently extracting local features and real-time localization through convolutional neural network (CNN), and its multi-scale prediction structure can adapt to the fast detection of different sizes of Dangshan pears; while GNN can capture the spatial topology of Dangshan pears in a complex scene through node relationship modeling, and improve the recognition robustness in the case of occlusion or dense arrangement. When the two are combined, YOLOv5s serves as the base detector to provide the initial target frame and features, while the GNN propagates the global context information through the graph structure to correct misdetections and omissions. This fusion retains the real-time performance of YOLOv5s and enhances the semantic understanding in complex agricultural scenarios through GNN, and the final system outperforms a single model in both accuracy and adaptability.

2 Related Work

2.1 State of the art in graph neural network research

Graph neural networks were born to deal with graph data and have made great development in the last few years [1,2]. Bruna et al. introduced the convolution operation in Euclidean data to graph data by utilizing the correspondence between the null domain and the frequency domain using the approximation operation in the frequency domain, but the computational complexity of this scheme was high, which was not conducive to the practical application [3]. Thereafter, Defferrard et al. simplified the convolution operation on graphs by using Chebyshev polynomials to approximate the convolution kernel [4], and Kipf et al. further simplified the previous work by applying the first-order approximation of the convolution kernel in the frequency domain, making the graph convolution operation truly usable, and this network is known as Graph Convolutional Network (GCN) [5]. Duvenaud et al. generalized the convolution operation to arbitrarily shaped graph structures by learning different parameters for nodes of different degrees [6]. Also generalizing the convolution operation over the null domain, Niepert et al. did so by taking a fixed number of neighboring nodes to the target node and ordering them [7]. In contrast, Gilmer et al. proposed a message passing mechanism where each node in the graph both sends messages to and receives messages from its neighboring nodes, from where the fusion of features is achieved [8]. In addition, Hamilton et al. proposed an inductive graph neural network framework called GraphSAGE, which expresses node features through sampling-aggregation [9]. Simonovsky et al. proposed an edge-conditional based convolution operation, where the weights of the convolution kernel depend on the edge labels and vary according to the input samples [10]. Velickovic et al. on the other hand introduced the attention mechanism into graph neural networks and proposed Graph Attention Network (GAT), which utilizes the attention mechanism to characterize the relationships between nodes [11].Xu et al. theoretically proved that the Weisfeiler-Lehman isomorphism algorithm [12] is the graph neural network upper limit of the accuracy that can be achieved, and accordingly proposed a graph heterogeneous network [13].Nguyen et al. introduced the Transformer structure into graph neural networks, which uses the Transformer mechanism to characterize the relationship between a target node and its neighboring nodes [14].

2.2 Research in the field of image recognition

In the field of image segmentation, X. F. Wang [15] proposed an efficient local Chan Vese model. This model improves the accuracy and efficiency of image segmentation by introducing local information. Z. Q. Zhao [17] explored a semi supervised method called collaborative training, which has been proven to improve each other only when two classifiers are relatively independent, to verify the complementarity between two opposite direction SRs. Finally, a collaborative kernel sparse representation (Co KSR) method for image annotation was established through the collaborative training of two SRs in the kernel space. In the field of facial recognition, B. Li [16] proposed a local linear discriminant embedding method. This method extracts effective features of facial images through local linear discriminant analysis, achieving efficient facial recognition. Z. Zhao [23] also explored multi feature based facial recognition methods, which fuse multiple features through the neural network committee mechanism to improve the robustness and accuracy of facial recognition. In terms of neural network models and their optimization, D.S. Huang [18-20] explored the systematic theory of neural network pattern recognition and the structural optimization and application of radial basis function probabilistic neural networks. By introducing probability theory and radial basis functions, this network model has achieved significant results in the field of pattern recognition. X. Wang [21] proposed a novel density clustering framework using the level set method. This method achieves density clustering of data by introducing the concept of level sets. L. Shang [22] used fast independent component analysis algorithm and radial basis function probability neural network for palm print recognition. In terms of finding roots of polynomials, D.S. Huang [24-28] involved using neural networks to solve polynomial roots. These studies have achieved accurate solution of polynomial roots by introducing strategies such as constraint learning and recursive solving. D. S. Huang [29] improved the performance of the radial basis function probabilistic neural network by using recursive orthogonal least squares to determine the center of the network. D. S. Huang [30-31] respectively explored the expansion method of polynomial roots and the application of generalized radial basis function networks in radar target recognition. In terms of learning algorithms for neural networks, D.S. Huang [32] studied the local minimum avoidance conditions of feedforward neural networks in externally supervised learning. D. S. Huang [33] proposed a unified adaptive learning algorithm for adjusting the connection weights and shape parameters of radial basis function networks, which improves the adaptability and generalization ability of the network. D. S. Huang [34] comprehensively analyzed linear and nonlinear feedforward neural network classifiers, providing a comprehensive understanding and guidance for the research of neural network classifiers.

3 Algorithmic core

3.1 Pixel-level hyperspectral transformation and Dangshan pear quality inversion using graph neural network

The data processing flowchart is shown in Figure 1, the hyperspectral instrument acquires the cube format data of the hyperspectral image, then processed into float format data by SRAnal710e software reads the float format data, and then selects three of the band images, fuses them into one image and then performs the image segmentation using the adaptive thresholding, basic global thresholding segmentation algorithm. The region of interest (ROI) is extracted from the segmented binarized image to find the average spectral reflectance of the region. The RGB image is used to select the appropriate region of interest by ENVI software, and after saving the image, the 3-channel or multi-channel response value data is calculated. Attempts are made to realize target and background segmentation using adaptive thresholding and basic global thresholding methods, and to integrate different alignment methods to realize pixel-level alignment.

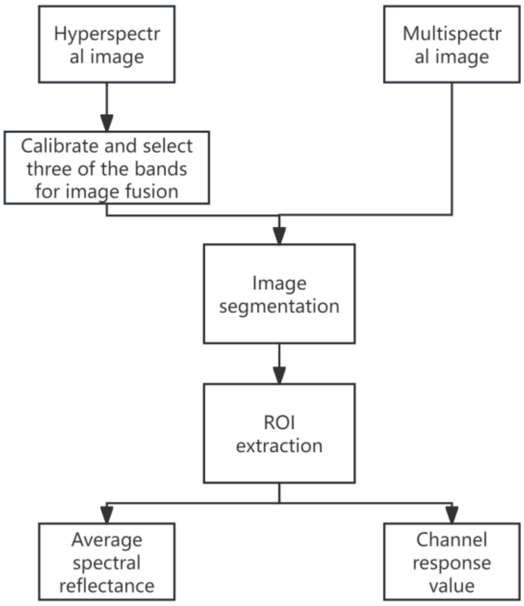

Fig. 1. Preprocessing flow of multispectral and hyperspectral images.

Based on the sorting and grading criteria, according to the nature of different kinds of apples and the responsivity of hyperspectral reflectance curves. By analyzing its spectral divisibility, the reflectance data of two bands or multiple bands are combined by adding, subtracting, multiplying, dividing, and linear or nonlinear operations, so as to downsize and compress the multi-dimensional hyperspectral information into a single channel, simplify the spectral information, and highlight the individual characteristics of fruit grading. Meanwhile, the adversarial network and deep convolutional network are fused to explore the establishment of its multivariate composite relationship with the appearance and internal biochemical indexes (sugar, acidity and VC content) of the measured fruits. Finally, the implementation of heat map visualization of fruit quality at pixel level is investigated to complete the high-quality inversion of fruit quality.

3.2 YOLOv5s network structure

YOLOv5 is an efficient target detection algorithm that uses Mosaic image enhancement to increase data diversity, adaptive anchor frame computation to improve detection accuracy, CSP and SPP structures to optimize feature extraction, and NMS to reduce repetitive detection. The model adapts to different scale targets by adaptive image scaling, combining FocalLoss and Mish activation function to improve performance, according to the network depth size and feature map width size is divided into Yolov5s, Yolov5m, Yolov5l, Yolov5, in this paper, yolov5s is adopted as the model to use, the structure of the model is shown in Fig. 2.

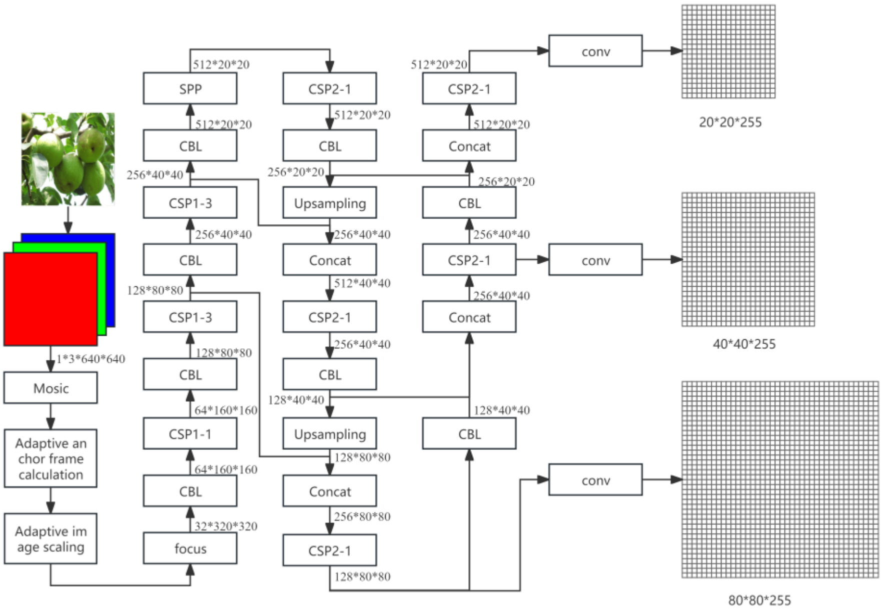

Fig. 2. YOLOv5s model structure.

YOLOv5 network structure is divided into two parts, respectively, the backbone network: the input end and the Backbone as proposed below, and the detection network: the Neck and the Prediction as proposed below. backbone backbone network, most of the time, refers to the network that extracts the features, and its role is to extract the information in the picture for the backbone network to use. backbone backbone network can directly load the parameters of the official trained model. The backbone network can be directly loaded with the official trained model parameters, in addition to the backbone network, add your own network, so that the custom model is more relevant to the actual use. neck is placed between the backbone and the head, to further utilize the features extracted by the backbone, and to improve the robustness of the model. head obtains the output of the network, head uses the features extracted before, and head uses the features extracted before, to improve the model's robustness. The head utilizes the previously extracted features to make predictions. The principle of the technique used in Focus comes from YOLOv2's pass-through, i.e., the pass-through layer consists of four slice-phase Concat and then a convolution that can change the 26×26×64 into a 13×13×256 structure, which makes the experimental results more accurate. Convolutional layer CBL is composed of Conv + BN + Leaky_relu activation function of the three components. CSP1_X in the principle of YOLO borrowed the CSPNet network structure, consists of three convolutional layers and X Res_unit module mutual Concate composition. Similarly, CSP2_X no longer uses Res_unit modules but changes to CBL, his fundamental principle is still based on the basic routing structure of YOLOv4 as well as YOLOv3. SPP, on the other hand, employs a maximum pooling of 1×1, 5×5, 9×9, and 13×13 for multi-scale fusion.

4 Experiments

4.1 Data set composition

In this paper, we make the Dangshan pear dataset into VOC format and name it as homemade me dataset. And the labeled data in PASCAL VOC format (XML file) is converted to labeled data in YOLO format (TXT file) in voc_label.py file, and the corresponding training, validation and test data list files are generated. Then a dataset is randomly divided into training, validation and test sets in the make-txt.py file, and their file names are written to the corresponding text files respectively. Specific division criteria:

1. The training and validation set (trainval.txt) accounts for 5% of the total dataset.
2. Training set (train.txt): further divided from the training and validation set, accounting for 95% of them.
3. Validation set (val.txt): the remaining 5%.
4. Test set (test.txt): 95% of the total data set.

4.2 Development environment and network parameters

The platform is developed based on python language, using PyCharm 2024.2.1 x64 and Anaconda3 2024.06 (Python 3.9 64-bit) as the development tools for the platform. The device for the experiment was an Asus laptop with Nvidia Geforce GTX1050 Ti (4 GB) graphics card and core i7-8750H CPU@2.20GHz 2.21GHz processor with win10 operating system. The training environment for this experiment is shown in Table 1, and the parameter settings during network training are shown in Table 2.

Table 1. Training environment.

CPU: i7-8750H	OS: Window10
GPU: Nvidia Geforce GTX1050 Ti	Torch: 2.0.1
Memory: 8G	CUDA: 10.1
Python: 3.9	Torch vision: 0.15.2
Compiler: Anaconda、PyCharm	Numpy: 1.18
onnx==1.14.0	onnxruntime==1.15.1
pycocotools==2.0.7	PyYAML==6.0.1
scipy==1.13.0	onnxsim==0.4.36
onnxruntime-gpu==1.18.0	gradio==4.31.5
opencv-python==4.9.0.80	psutil==5.9.8
py-cpuinfo==9.0.0	safetensors==0.4.3

Table 2. Network training parameters.

lr0: 0.01	fl_gamma: 0.0
lrf: 0.2	hsv_h: 0.015
momentum: 0.937	hsv_s: 0.7
weight_decay: 0.0005	hsv_v: 0.4
warmup_epochs: 3.0	degrees: 0.0
warmup_momentum: 0.8	translate: 0.1
warmup_bias_lr: 0.1	scale: 0.5
box: 0.05	shear: 0.0
anchor_t: 4.0	

4.3 Experimental results and analysis

yolov5 will generate an "expx" directory under the "runs" directory after each run (x represents the number of times the results are generated, the first time the training is completed, exp0 is generated, the second time exp1...... is generated, and so on). and so on). The "expx" directory stores the training files "weights" and "results.txt" and displays the results visually. The training result file contains the Precision-Recall curve, also known as the PR curve, which shows the trade-off relationship between precision and recall, and through this curve, we can evaluate the precision rate that the model can achieve under different recall levels, and the experiments show that it exhibits excellent recognition results in the Dangshan Pear detection and recognition dataset. The experimental results are shown in Figure 3.

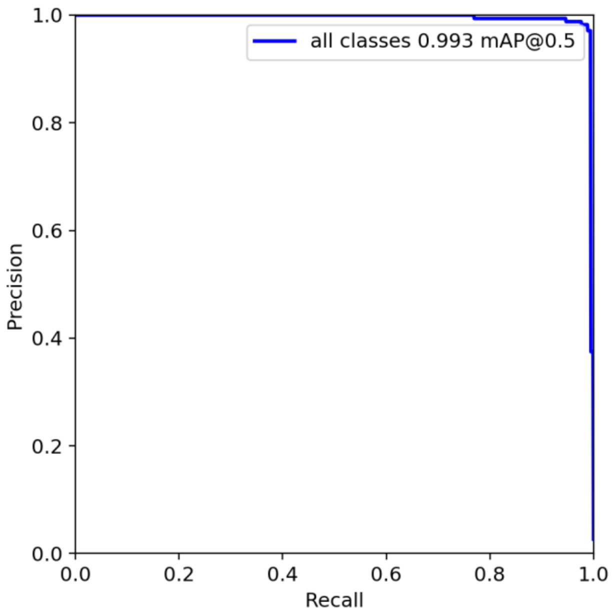

Fig. 3. Precision-Recall curve.

During the experiment we set 80 epochs for each training task, and the results of the sixth training session of the experiment (exp5) gradually converge to a stable value. exp5 training results are shown in Figure 4.

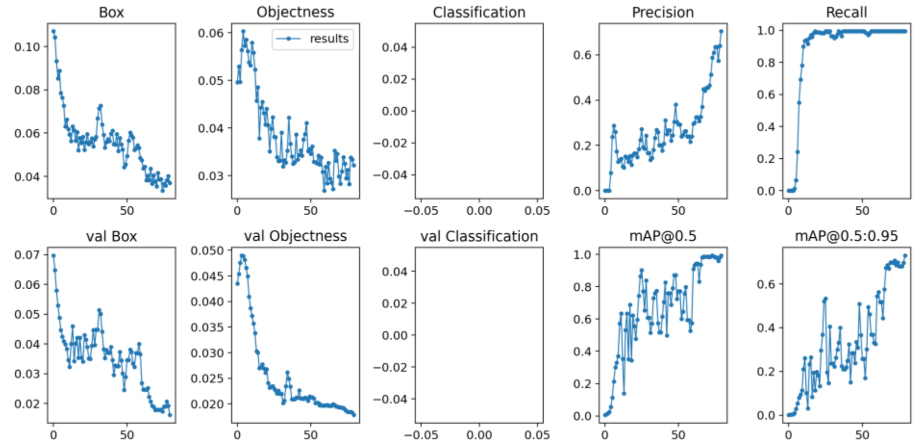

Fig. 4. Experimental visualization of resultant data curves.

In order to show the data of the experiment more clearly, we organize and analyze the results.txt file obtained from the sixth experiment, as shown in Table 3, the experiment counts the results of the last twenty experiments as well as the average experimental results and the optimal experimental results.

Table 3. Comparison of experimental data indicators for YOLOv5 Dangshan pear.

Indicator Comparison	Precision	Recall	mAP@0.5	mAP@0.5:0.95
Max	0.7039	0.9941	0.9932	0.7304
Average	0.2803	0.9496	0.7041	0.3591
Average of last 20	0.4706	0.9941	0.9636	0.6425

Through the iterative process of the experiment, we found that the average processing time of a single picture is only 0.02 seconds, and the experimental accuracy converges to 0.9932, and the extreme lightness of the model applies to GeForce GTX 1050 Ti, and it can also be run smoothly for computers with poorer performance calls. The results of the Anaconda Prompt test are shown below.

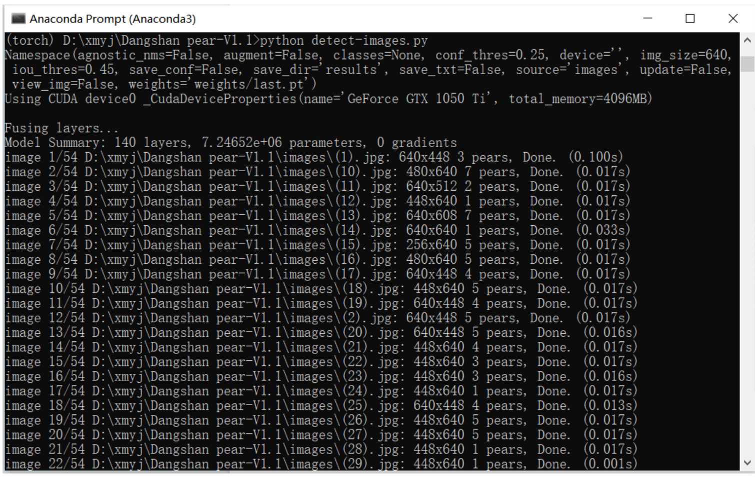

Fig. 5. Image recognition test results

5 Summary and Outlook

In this paper, we use the "graph neural network-YOLOv5s"-based Dangshan pear multi-source target rapid recognition system to successfully realize the tracking detection and recognition of Dangshan pear counting. By combining graph neural network and YOLOv5s model, the system makes a big change in the recognition rate and recognition rate compared with the previous research on single image classification, and the lightweight network can be easily run on most of the computers with poor performance, and the recognition accuracy rate reaches 99.32%. Subsequent work we will be based on the current recognition network for the details of pears whether there is damage, appearance, lesions and size and other aspects of control, to reduce the process of fruit and vegetable selection of a large number of labor waste, and thus obtain high-quality fruits, can be more quickly after picking and selection of fruits into the market to reduce the thought of the time to bring the loss of the product.

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