ISSN 1816-4528 (Print) ISSN 2949-0634 (Online)

Научная статья

УДК 62-5:004.5
DOI: 10.26730/1816-4528-2025-2-12-21

Ян Янь [1,2], Чичерин Иван Владимирович [1], Лицзюнь Чжао [2], Чанцзюань Лонг [1,2], Игнатьева Елена Александровна [1]

[1]Кузбасский государственный технический университет имени Т.Ф. Горбачева
[2]Школа интеллектуального производственного инжиниринга, Чунцинский университет искусств и наук

[*] для корреспонденции: chiv.iap@kuzstu.ru

РАЗРАБОТКА АЛГОРИТМОВ РАСПОЗНАВАНИЯ В СИСТЕМЕ УПРАВЛЕНИЯ ПРИВОДАМИ РОБОТА ДЛЯ СБОРА ЧАЙНЫХ ЛИСТЬЕВ

Аннотация.
Данное исследование посвящено распознаванию изображений чайных побегов с использованием алгоритма обнаружения объектов, основанного на технологии глубокого обучения. Разрабатываемые алгоритмы используются в системе управления приводами робота для сбора чая. Морфологические требования к чайным побегам таковы: один бутон с одним листом или один бутон с двумя листьями. В этой статье используется алгоритм обнаружения объектов YOLOv5 для создания модели распознавания чайных побегов. Надежность обученной модели оценивается с помощью четырех показателей обучения: точность, запоминание, оценка F1 (гармоническое среднее точности и запоминания) и средняя точность (mAP). Сначала выполняется улучшение изображения, включая преобразование изображений в оттенки серого, повышение резкости, устранение шумов и симметричное зеркальное отображение. Улучшенные изображения вручную помечаются с помощью инструмента "Маркировка" и экспортируются в формате YOLO в виде текстовых файлов, в результате чего создается папка, содержащая помеченные изображения. Во-вторых, обучение проводится в Pycharm с разделением обработанных изображений на пакеты и получением соответствующих показателей эффективности. Наконец, все подходящие блоки с достоверностью более 0,65 сохраняются без каких-либо пропущенных обнаружений, преобразование в оттенки серого делает эффект обработки более очевидным при извлечении карт объектов в процессе обучения YOLOv5, поскольку изображения в оттенках серого имеют только черно-белые градиенты. В конечном итоге это приводит к улучшению результатов обучения. Однако такие факторы, как скрученные листья, остаточные листья, цвет, освещение, условия съемки и угол наклона, которые в действительности характерны для чайных листьев, могут привести к снижению общих показателей оценки и, таким образом, в некоторой степени повлиять на результаты эксперимента.

Информация о статье
Поступила:
25 марта 2025 г.

Одобрена после рецензирования:
01 мая 2025 г.

Принята к печати:
05 мая 2025 г.

Опубликована:
05 июня 2025 г.

Ключевые слова:
***:** обнаружение объектов, алгоритмы распознавания, управление приводами, YOLOv5, чайные побеги*

Для цитирования: Ян Янь, Чичерин И.В., Лицзюнь Чжао, Чанцзюань Лонг, Игнатьева Е.А. Разработка алгоритмов распознавания в системе управления приводами робота для сбора чайных листьев // Горное оборудование и электромеханика. 2025. № 2 (178). С. 12-21. DOI: 10.26730/1816-4528-2025-2-12-21, EDN: GOLMOX

1. Introduction

Tea is one of the main economic crops for Chinese tea farmers[1]. In rural areas, many young people go to cities for work, resulting in a labor shortage. Hand-plucking has the advantage of ensuring that the morphology of tea shoots meets the standard of high-quality tea (eg. one bud with one or two leaves) and can distinguish between shoots and old leaves effectively, but it is time-consuming and labor-intensive[2]. Machines available on the market have reduced the labor to some extent and improved the efficiency of tea plucking. However, this method implements a "one size fits all" approach that lacks selectivity[3, 4], causing low-quality tea, as well as significant damage to the canopy of tea trees[5]. Hence, these machines cannot replace the traditional hand-plucking harvesting approach. It is necessary to study and develop a machine that can automatically pluck shoots from tea bushes. Tea shoot recognition is the primary and difficult task required for this[6, 7].

In the early stages, threshold segmentation color-space-based and machine learning were used for tea shoot recognition. Yang et al. [8] extracted the G-component color information from the RGB images of the tea tree canopy and used a double-threshold method to separate the shoots from the old leaves. They then combined the contour shape features of the shoots to achieve overall recognition. Wang [9]extracted the color and edge features of tea images and used region growing to segment the tea shoots. Wu et al. [10]collected tea shoot images taken at different distances in natural environments and compared the recognition effects of the K-means clustering algorithm and Otsu’s method in the Lab color model. It was found that the K-means clustering algorithm had higher accuracy in overall shoot recognition. Although presumably accurate, The collection of tea-shoot images is carried out indoors and in a structured environment[11]. However, A tea garden, has complex environments, including uncontrolled illumination conditions, high growth density and varied canopy structure of tea trees, in addition, the young and old leaves have similar colors (‘green-on-green’), and their shapes and texture can be very similar at the growth phase[12, 13]. In an image of a bushy background, detecting the targeted morphology of tea shoots is inherently a challenging problem[14]. In these conditions, the performance of the above algorithm may not be suitable.

With the rapid development of deep learning technology in the field of target detection, Currently, typical algorithms for object detection include the R-CNN algorithm and the YOLO algorithm[15, 16]. R-CNN algorithm greatly improves accuracy but has slower processing speed. Although researchers have proposed Fast R-CNN and Faster R-CNN algorithms [17], the processing speed still remains slow, until Joseph Redmond's Yolo algorithm made a significant breakthrough in processing speed [18]. Subsequently, researchers have proposed various improved versions of the Yolo algorithm. YOLOv5 stands out for its exceptional speed, efficiency, high accuracy, user-friendliness, versatility, robustness, and strong community support, making it a leading choice for object detection tasks[19, 20]. The study is based on the YOLOv5 model for the recognition of tea shoots.

2.Deep Learning Process

2.1 Training Tools

Since deep learning has become increasingly popular, many open-source or commercial deep learning tools have emerged. In field of young tea bud recognition and detection, Caffe, Keras, Tensorflow, Pytorch, and other open-source training tools are well-known. Pytorch is a scientific computing library based on Python. It utilizes tensors and automatic differentiation for deep learning. It primarily provides operations such as addition, subtraction, multiplication, division, convolution, pooling, matrix algorithms, etc., for building models[21]. This experiment is conducted using Pytorch.

2.2 Experimental environment

Table 1. Hardware

GPU	NVIDIA GeForce RTX3050Ti
CPU	12th Gen Intel(R) Core(TM) i7-12650H @ 2.30 GHz
RAM	16GB

Table 2. Software

Operating system	window 11
Programming languages	python 3.9
GPU driver	Cuda 12.1

Table 3. Python package configuration

Torch	1.12.0
Torchaudio	0.12.0
Torchvision	0.13.0
Numpy	1.20.3
Matplotlib	3.4.3
Scipy	1.7.1

(a)Top left-flip (b) top right -grayscale (c) bottom left -denoised (d) bottom right -sharpening
Fig.1. Data augmentation

2.3 Data acquisition and augmentation

Collecting a dataset of tea shoots images under natural conditions is a prerequisite for recognition. In order to ensure the effectiveness of the data, the images in the experiment were taken in the tea plantation of Chashan Zhuhai in Yongchuan District, Chongqing on March 20th and March 28th, 2023, using an iPhone 14 for the collection. Due to time constraints, the tea shoots images taken on-site also need to undergo data augmentation. The purpose is to expand the dataset for network training and improve the generalization ability of the detection model. Therefore, for the data collected in the experiment, the tea variety named Zhonghuang No. 1 tea shoot images were processed with left-right transformation using WPS, and at the same time, the images were converted to grayscale, denoised, and sharpened using Anaconda-Jupyter, as shown in Fig.2. After data augmentation, the total images were divided into training and test sets. The training set is used to train the network model, and the test set is used to evaluate the performance of the model after training.

3. Evaluation Metrics

In this experiment, the following evaluation metrics were used to assess the performance of the tea leaf region detection network: precision, recall, F1 score (harmonic mean of precision and recall), and mean average precision (mAP). In tea leaf recognition and detection, the size of the intersection of union (IOU) parameter is primarily determined, which analyzes the precision, recall, and overall detection performance mAP value.

IOU represents the intersection over union ratio between the detection box and the ground truth box, and it is commonly used in deep learning to measure the accuracy of object detection algorithms. The range of IOU values is from 0 to 1, where a larger value indicates a greater overlap between the two boxes, and thus a more accurate algorithm.

$$precision = \frac{TP}{TP + FP} \quad (3.1)$$

$$recall = \frac{TP}{TP + FN} \quad (3.2)$$

TP: true positive refers to correctly classifying a positive sample, also known as true positive.

FP: false positive refers to incorrectly classifying a negative sample as positive, also known as false positive.

FN: false negative refers to incorrectly classifying a positive sample as negative, also known as false negative.

TN: true negative refers to correctly classifying a negative sample, also known as true negative.

The calculation formula (3.1) for precision is the intersection area of the target box and the detection box divided by the area of the detection box.

The calculation formula for recall 3.2 is the intersection area of the target box and the detection box divided by the area of the target box.

Precision and recall are two evaluation metrics that are mutually exclusive. Increasing one metric will result in a decrease in the other, so in order to achieve good results, both metrics need to be at a high level simultaneously. The calculation formula (3.3) for F1 score is:

$$F1score = \frac{2 \times precision \times recall}{precision + recall} \quad (3.3)$$

This metric is primarily used to evaluate the overall ability of the model, avoiding a sole emphasis on accuracy or recall. mAP (mean Average Precision) measures the performance of the learned model across all categories, taking the average value of AP (Average Precision) for all categories. Therefore, here is the definition of AP.AP is used to assess the performance of

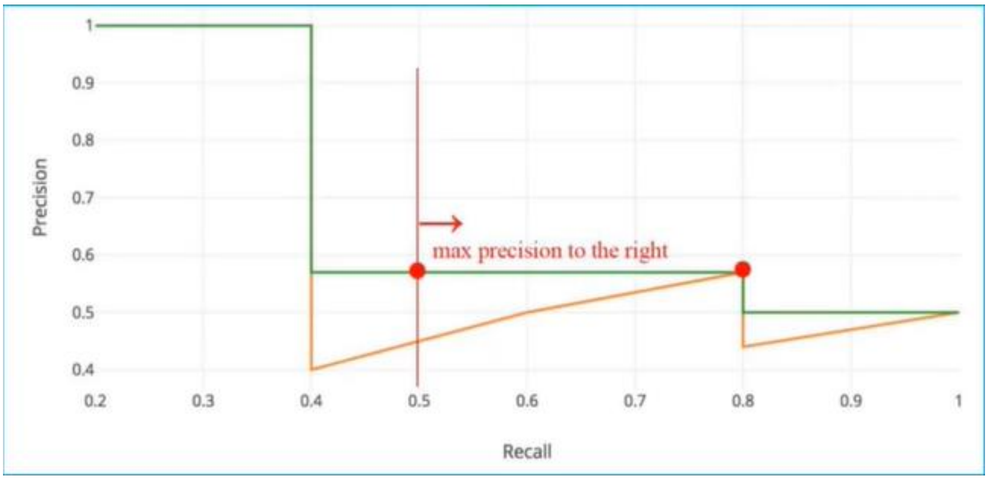


Fig. 2. P-R curve

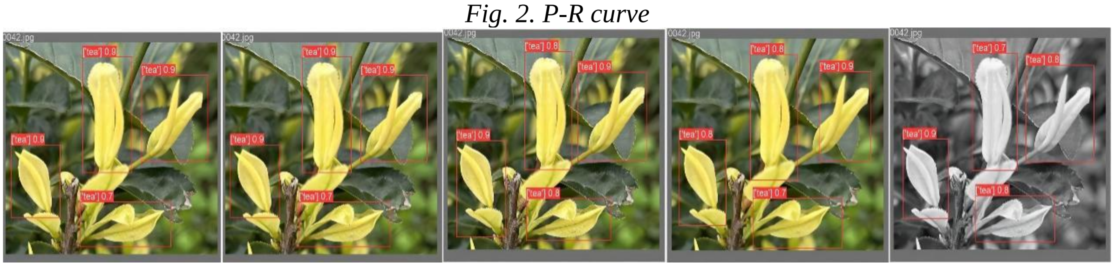


Fig.3. Training images

Table 4. Changing the acuuracy

Enhancement types	Precision(%)
Original	68.6
flip	67.1
sharpening	65.5
denoise	79.4
grayscale	80.7

the learned model in each category. The better the model, the higher its corresponding AP value. The calculation formulas (3.4) for AP and mAP(3.5) are as follows:

$$AP = \int_0^1 p(r)dr \quad (3.4)$$

$$mAP = \frac{1}{n}\sum_{i=1}^{n} AP \quad (3.5)$$

The symbol n represents the number of categories, and the mAP value ranges from 0 to 1. The mAP value can also be represented by the area under the P-R curve. As shown in Fig. 3, the area under the green curve is taken to approximate the area and calculate the mAP value. If there is only one category in the experiment, the AP value can be considered as the mAP value.

Based on the confidence threshold, calculate the metric. The confidence threshold refers to the likelihood of detecting the feature of tea leaves in a certain region within a candidate box in the input image. Filter out candidate boxes with confidence scores below the specified threshold. Obtain precision and recall values under this condition. (Precision and recall values range from 0 to 1).

4、Result and Discussion

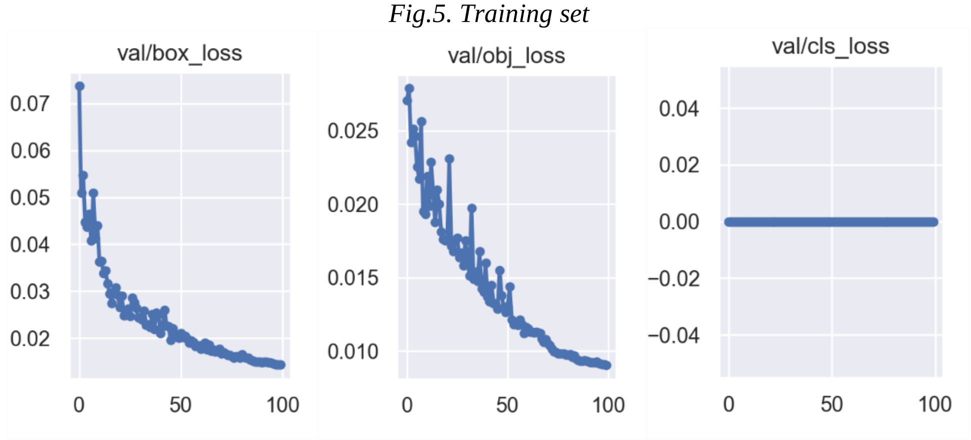
In order to use the detection results of Zhonghuang No.1 as an example, under the confidence threshold of 0.65, the image training situation after labeling with labelimg is shown in the figure. It can be seen that after training, all the candidate boxes with confidence greater than 0.65 are retained without any missed detections, indicating that the model training is effective, as shown in Fig.3

From Table 4, it can be seen that the precision effect trained by Zhonghuang No.1 tea after sharpening and folding is similar, while the precision has been significantly improved after image denoising and grayscale conversion. The reason for this may be that the pre-training weights are enriched by the original image, folding, and sharpening, resulting in better effects for the training of denoised images and grayscale images. Another reason may be that during the image acquisition stage, some images taken by the mobile phone camera may have blurring. Compared with denoising, folding and sharpening do not handle the problem of background blur or blurriness of the tested object very well. The grayscale conversion makes the processing effect more obvious when extracting feature maps during the YOLOv5 training process, because grayscale images only have black and white gradients. This ultimately leads to better training results.

In addition, the quality of a model is not solely determined by the above evaluation criteria, but also

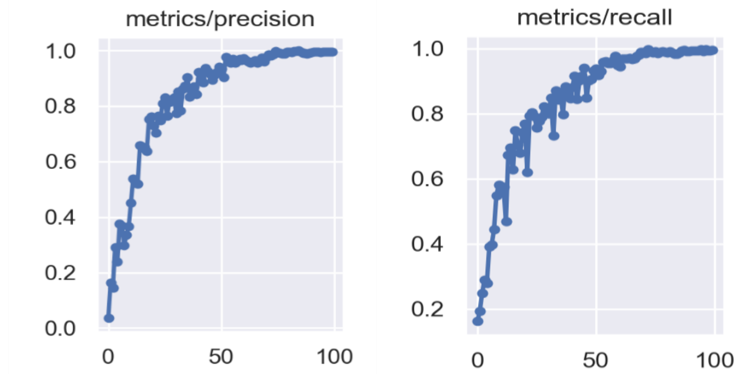
(a)localization loss (b)confidence loss (c)classification loss

Fig.5. Training set



(a)localization loss (b)confidence loss (c) classification loss

Fig.6. Validation set



(a)Precision (b)Recall

Fig.7. Training images

closely related to the convergence effect of its loss function. When the recognition accuracy of a model improves, its convergence effect can be better, resulting in an overall better performance of the model.

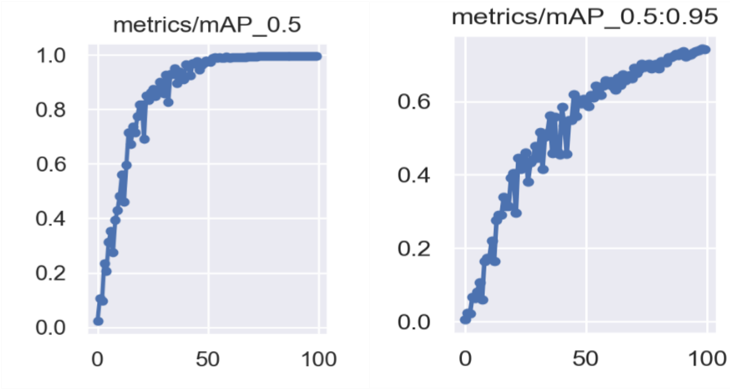
The types of loss functions include classification loss, localization loss (used to predict the error between the bounding box and the ground truth, referred to as box loss in this paper), and confidence loss (the object of the box, referred to as obj loss).

The overall loss function can be represented as formula (4.6):

$$total\ loss = cla_{loss} + box_{loss} + obj_{loss} \quad (4.6)$$

In this experiment, a total of 100 iterations were performed, and the final loss function image of YOLOv5 is shown in the figure. (Because this experiment is to detect tea buds, only one category 'tea' is set, so the cla_loss is 0)

As shown in Fig.5, from the detection indicators of Zhonghuang No.1-original image, it can be seen that both the localization loss and confidence loss in the training set had relatively high initial values, as shown in Fig.5(a and b). The localization loss in the first 50 iterations of the training set was high, and it gradually converged after about 80 iterations. In Fig.6(a and b,) the number of iterations in the validation set approached convergence after about 70 iterations. The reason for no classification loss is that in this experiment, only the tea category was labeled and there was no influence from.



(a)Precision (b)Recall

Fig.8. Validation set

Fig.9. Detection results

In addition, the precision curve and recall curve of the detection are plotted, as shown in Fig.7 and Fig.8.

From Fig.7(a and b), it can be seen that after approximately 80 iterations, the precision and recall rates begin to stabilize without significant changes. Figure 8(a) represents the curve of precision values of mAP at IOU=0.50, while Figure 8(b) represents the curve of precision values of mAP at IOU ranging from 0.50 to 0.95 with a step of 0.05. It is observed that as the IOU starts to increase, the mAP value decreases due to higher requirements. Clearly, the left graph shows a more stable mAP value around 60 iterations.

The reason for the relatively high mAP value of the Zhonghuang No.1 could be attributed to several factors. Firstly, the Chinese Yellow Tea dataset is rich, which contributes to better training results. Additionally, the color contrast between the tender shoots and the older leaves of Chinese Yellow Tea is noticeable, leading to better training outcomes.

In this experiment, the size of the input tea leaf bud images fed into YOLOv5 was adjusted to 640×640 pixel. The entire training process iterated 100 times in total, and the detection results are shown in Fig. 9.

From Fig.9, it can still be seen that, overall, YOLOv5 has performed well in complex environments. However, there are also a few issues. After the part labeled as "tea shoot" is trained with environmental training, some candidate boxes were missed due to the initial setting of a high IOU threshold during the debugging phase. Some occluded tea leaves may also be missed. Moreover, factors such as curled leaves, residual leaves, color, lighting, shooting environment, and shooting angle, which are characteristic of tea leaves in reality, can lead to decreased composite evaluation metrics and thereby affect the experimental results to some extent.

Acknowledgments

This study was supported by the Scientific and Technological Research Program of Chongqing Municipal Education Commission (Grant No. KJQN202101333).

СПИСОК ЛИТЕРАТУРЫ

1. K. Luo, Z. Wu, C. Cao, K. Qin, X. Zhang, and M. An, "Biomechanical Characterization of Bionic Mechanical Harvesting of Tea Buds," Agriculture, vol. 12, no. 9, 2022, doi: 10.3390/agriculture12091361.

2. T. Wang et al., "Tea picking point detection and location based on Mask-RCNN," Information Processing in Agriculture, vol. 10, no. 2, pp. 267-275, 2023, doi: 10.1016/j.inpa.2021.12.004.

3. T. Yiping, H. Wangming, H. Anguo, and W. Weiyang, "Design and Experiment of Intelligentized Tea-plucking Machine for Human Riding Based on

Machine Vision," Transactions of the Chinese Society for Agricultural Machinery, 2016.
4. B. Li, H. Zhu, L. Fang, Y. Zhu, and S. Fang, "Design and experimentation of crawler tea harvesting machine," Journal of the Chinese Institute of Engineers, vol. 47, no. 5, pp. 482-491, 2024, doi: 10.1080/02533839.2024.2346485.
5. Y. Han, H. Xiao, G. Qin, Z. Song, W. Ding, and S. Mei, "Developing Situations of Tea Plucking Machine," Engineering, vol. 06, no. 06, pp. 268-273, 2014, doi: 10.4236/eng.2014.66031.
6. Y. Wu et al., "An improved YOLOv7 network using RGB-D multi-modal feature fusion for tea shoots detection," Computers and Electronics in Agriculture, vol. 216, 2024, doi: 10.1016/j.compag.2023.108541.
7. Y. Wu, J. Chen, L. He, J. Gui, and J. Jia, "An RGB-D object detection model with high-generalization ability applied to tea harvesting robot for outdoor cross-variety tea shoots detection," Journal of Field Robotics, vol. 41, no. 4, pp. 1167-1186, 2024, doi: 10.1002/rob.22318.
8. F. Yang, L. Yang, Y. Tian, and Q. Yang, "Recognition of the tea sprout based on color and shape features," Nongye Jixie Xuebao/Transactions of the Chinese Society of Agricultural Machinery, vol. 40, pp. 119-123, 2009.
9. W. Jian, "Segmentation Algorithm of Tea Combined with the Color and Region Growing," Journal of Tea Science, 2011.
10. W. U. Xue-Mei, Z. Fu-Gui, and L. V. Jing-Tang, "Research on Recognition of Tea Tender Leaf Based on Image Color Information," journal of tea science, 2013.
11. Y.-T. Chen and S.-F. Chen, "Localizing plucking points of tea leaves using deep convolutional neural networks," Computers and Electronics in Agriculture, vol. 171, 2020, doi: 10.1016/j.compag.2020.105298.
12. X. Li et al., "An improved model based on YOLOX for detection of tea sprouts in natural environment," Evolving Systems, 2024, doi: 10.1007/s12530-024-09589-2.
13. Y. Li, L. He, J. Jia, J. Chen, J. Lyu, and C. Wu, "High-efficiency tea shoot detection method via a compressed deep learning model," International Journal of Agricultural and Biological Engineering, vol. 15, no. 3, pp. 159-166, 2022, doi: 10.25165/j.ijabe.20221503.6896.
14. H. Wang, J. Gu, and M. Wang, "A review on the application of computer vision and machine learning in the tea industry," Frontiers in Sustainable Food Systems, vol. 7, 2023, doi: 10.3389/fsufs.2023.1172543.
15. M. Shafiq and Z. Gu, "Deep Residual Learning for Image Recognition: A Survey," Applied Sciences, vol. 12, no. 18, 2022, doi: 10.3390/app12188972.
16. S. Ren, K. He, R. Girshick, and J. Sun, "Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks," IEEE Transactions on Pattern Analysis & Machine Intelligence, vol. 39, no. 6, pp. 1137-1149, 2017.
17. S. Ren, K. He, R. B. Girshick, and J. Sun, "Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks," IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 39, pp. 1137-1149, 2015.
18. J. Redmon, S. K. Divvala, R. B. Girshick, and A. Farhadi, "You Only Look Once: Unified, Real-Time Object Detection," 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), pp. 779-788, 2015.
19. M. Cao, H. Fu, J. Zhu, and C. Cai, "Lightweight tea bud recognition network integrating GhostNet and YOLOv5," Math Biosci Eng, vol. 19, no. 12, pp. 12897-12914, Sep 5 2022, doi: 10.3934/mbe.2022602.
20. Y. Li, R. Ma, R. Zhang, Y. Cheng, and C. Dong, "A Tea Buds Counting Method Based on YOLOv5 and Kalman Filter Tracking Algorithm," Plant Phenomics, vol. 5, p. 0030, 2023, doi: 10.34133/plantphenomics.0030.
21. P. Mishra, "Natural Language Processing Using PyTorch," in PyTorch Recipes, 2019, ch. Chapter 7, pp. 165-178.

Авторы заявляют об отсутствии конфликта интересов.

Об авторах:
Ян Янь, Кузбасский государственный технический университет имени Т.Ф. Горбачева, (650000, Россия, г. Кемерово, ул. Весенняя, 28), Школа интеллектуальной производственной инженерии, Чунцинский университет искусств и наук, (Чунцин, 402160, Китай)
Чичерин Иван Владимирович, Кузбасский государственный технический университет имени Т.Ф. Горбачева, (650000, Россия, г. Кемерово, ул. Весенняя, 28), e-mail: chiv.iap@kuzstu.ru
Лицзюнь Чжао, Школа интеллектуальной производственной инженерии, Чунцинский университет искусств и наук, (Чунцин, 402160, Китай)
Чанцзюань Лонг, Кузбасский государственный технический университет им. Т.Ф. Горбачева, (650000, Россия, г. Кемерово, ул. Весенняя, 28), Школа интеллектуальной производственной инженерии, Чунцинский университет искусств и наук, (Чунцин, 402160, Китай)
Игнатьева Елена Александровна, Кузбасский государственный технический университет имени Т.Ф. Горбачева, (650000, Российская Федерация, г. Кемерово, ул. Весенняя, д. 28), e-mail: iea.iap@kuzstu.ru

Заявленный вклад авторов:
Ян Ян – постановка исследовательской задачи; научное руководство; обзор соответствующей литературы; концептуализация исследования; написание текста, сбор данных; анализ данных; обзор соответствующей литературы; формулирование выводов; написание текста.
Иван Чичерин – постановка исследовательской задачи; научное руководство; обзор соответствующей литературы; концептуализация исследования; написание текста, сбор данных; анализ данных; обзор соответствующей литературы; формулирование выводов; написание текста.
Лицзюнь Чжао – постановка исследовательской задачи; научное руководство; обзор соответствующей литературы; концептуализация исследования; написание текста, сбор данных; анализ данных; обзор соответствующей литературы; составление выводов; написание текста.
Чаньцзюань Лонг – постановка проблемы исследования; научное руководство; обзор соответствующей литературы; концептуализация исследования; написание текста, сбор данных; анализ данных; обзор соответствующей литературы; формулирование выводов; написание текста.
Игнатьева Елена – сбор и анализ данных, ознакомление с соответствующей литературой.

Все авторы прочитали и одобрили окончательный вариант рукописи.

Original article

DOI: 10.26730/1816-4528-2025-2-12-21

Yan Yang [1,2], Ivan V. Chicherin[1], Lijun Zhao[2], Chanjuan Long [1,2], Elena A. Ignatieva[1]

[1]T.F. Gorbachev Kuzbass State Technical University
[2]School of Intelligent Manufacturing Engineering, Chongqing University of Arts and Sciences

***** for correspondence: chiv.iap@kuzstu.ru

DEVELOPMENT OF RECOGNITION ALGORITHMS IN THE CONTROL SYSTEM OF ROBOT DRIVES FOR PLUCKING TEA

Abstract.
This study focuses on image recognition of tea Shoots using an object detection algorithm based on a deep learning framework. The developed algorithms are used in the control system of the robot's drives for collecting tea. The morphological requirements for tea shoots are one bud with one leaf or one bud with two leaves. This paper uses the YOLOv5 object detection algorithm to establish a recognition model for tea shoots. The reliability of the trained model is evaluated using four training indicators: precision, recall, F1 score (harmonic mean of precision and recall), and mean average precision (mAP). Firstly, image enhancement is performed, including converting the images to grayscale, sharpening, denoising, and symmetric mirroring. The enhanced images are manually annotated using the Labeling tool and exported in YOLO format as .txt files, resulting in a folder containing the labeled images. Secondly, The training is conducted in Pycharm with the processed images divided into batches, and the respective performance indicators are obtained. Finally, all the candidate boxes with confidence greater than 0.65 are retained without any missed detections, The grayscale conversion makes the processing effect more obvious when extracting feature maps during the YOLOv5 training process, because grayscale images only have black and white gradients. This ultimately leads to better training results. However, factors such as curled leaves, residual leaves, color, lighting, shooting environment, and shooting angle, which are characteristic of tea leaves in reality, can lead to decreased composite evaluation metrics and thereby affect the experimental results to some extent.

Article info
Received:
25 March 2025

Accepted for publication:
01 May 2025

Accepted:
05 May 2025

Published:
05 June 2025

Keywords: *object detection, recognition algorithms, drive control, YOLOv5, tea shoots.*

For citation: Yan Yang, Chicherin I.V., Lijun Zhao, Chanjuan Long, Ignatieva E.A. Development of recognition algorithms in the control system of robot drives for plucking tea. Mining Equipment and Electromechanics, 2025; 2(178):12-21 (In Russ., abstract in Eng.). DOI: 10.26730/1816-4528-2025-2-12-21, EDN: GOLMOX

REFERENCES

1. K. Luo, Z. Wu, C. Cao, K. Qin, X. Zhang, and M. An, "Biomechanical Characterization of Bionic Mechanical Harvesting of Tea Buds," Agriculture, vol. 12, no. 9, 2022, doi: 10.3390/agriculture12091361.
2. T. Wang et al., "Tea picking point detection and location based on Mask-RCNN," Information Processing in Agriculture, vol. 10, no. 2, pp. 267-275, 2023, doi: 10.1016/j.inpa.2021.12.004.
3. T. Yiping, H. Wangming, H. Anguo, and W. Weiyang, "Design and Experiment of Intelligentized Tea-plucking Machine for Human Riding Based on Machine Vision," Transactions of the Chinese Society for Agricultural Machinery, 2016.
4. B. Li, H. Zhu, L. Fang, Y. Zhu, and S. Fang, "Design and experimentation of crawler tea harvesting machine," Journal of the Chinese Institute of Engineers, vol. 47, no. 5, pp. 482-491, 2024, doi: 10.1080/02533839.2024.2346485.
5. Y. Han, H. Xiao, G. Qin, Z. Song, W. Ding, and S. Mei, "Developing Situations of Tea Plucking Machine," Engineering, vol. 06, no. 06, pp. 268-273, 2014, doi: 10.4236/eng.2014.66031.
6. Y. Wu et al., "An improved YOLOv7 network using RGB-D multi-modal feature fusion for tea shoots detection," Computers and Electronics in Agriculture, vol. 216, 2024, doi: 10.1016/j.compag.2023.108541.
7. Y. Wu, J. Chen, L. He, J. Gui, and J. Jia, "An RGB-D object detection model with high-generalization ability applied to tea harvesting robot for outdoor cross-variety tea shoots detection," Journal of Field Robotics, vol. 41, no. 4, pp. 1167-1186, 2024, doi: 10.1002/rob.22318.
8. F. Yang, L. Yang, Y. Tian, and Q. Yang, "Recognition of the tea sprout based on color and shape features," Nongye Jixie Xuebao/Transactions of the Chinese Society of Agricultural Machinery, vol. 40, pp. 119-123, 2009.
9. W. Jian, "Segmentation Algorithm of Tea Combined with the Color and Region Growing," Journal of Tea Science, 2011.
10. W. U. Xue-Mei, Z. Fu-Gui, and L. V. Jing-Tang, "Research on Recognition of Tea Tender Leaf Based on Image Color Information," journal of tea science, 2013.
11. Y.-T. Chen and S.-F. Chen, "Localizing plucking points of tea leaves using deep convolutional neural networks," Computers and Electronics in Agriculture, vol. 171, 2020, doi: 10.1016/j.compag.2020.105298.
12. X. Li et al., "An improved model based on YOLOX for detection of tea sprouts in natural environment," Evolving Systems, 2024, doi: 10.1007/s12530-024-09589-2.
13. Y. Li, L. He, J. Jia, J. Chen, J. Lyu, and C. Wu, "High-efficiency tea shoot detection method via a compressed deep learning model," International Journal of Agricultural and Biological Engineering, vol. 15, no. 3, pp. 159-166, 2022, doi: 10.25165/j.ijabe.20221503.6896.
14. H. Wang, J. Gu, and M. Wang, "A review on the application of computer vision and machine learning in the tea industry," Frontiers in Sustainable Food Systems, vol. 7, 2023, doi: 10.3389/fsufs.2023.1172543.
15. M. Shafiq and Z. Gu, "Deep Residual Learning for Image Recognition: A Survey," Applied Sciences, vol. 12, no. 18, 2022, doi: 10.3390/app12188972.
16. S. Ren, K. He, R. Girshick, and J. Sun, "Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks," IEEE Transactions on Pattern Analysis & Machine Intelligence, vol. 39, no. 6, pp. 1137-1149, 2017.
17. S. Ren, K. He, R. B. Girshick, and J. Sun, "Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks," IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 39, pp. 1137-1149, 2015.
18. J. Redmon, S. K. Divvala, R. B. Girshick, and A. Farhadi, "You Only Look Once: Unified, Real-Time Object Detection," 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), pp. 779-788, 2015.
19. M. Cao, H. Fu, J. Zhu, and C. Cai, "Lightweight tea bud recognition network integrating GhostNet and YOLOv5," Math Biosci Eng, vol. 19, no. 12, pp. 12897-12914, Sep 5 2022, doi: 10.3934/mbe.2022602.
20. Y. Li, R. Ma, R. Zhang, Y. Cheng, and C. Dong, "A Tea Buds Counting Method Based on YOLOv5 and Kalman Filter Tracking Algorithm," Plant Phenomics, vol. 5, p. 0030, 2023, doi: 10.34133/plantphenomics.0030.
21. P. Mishra, "Natural Language Processing Using PyTorch," in PyTorch Recipes, 2019, ch. Chapter 7, pp. 165-178.

The authors declare no conflict of interest.

About the author:

Yan Yang, T.F. Gorbachev Kuzbass State Technical University, (28, Vesennyaya street, Kemerovo, 650000, Russian Federation), School of Intelligent Manufacturing Engineering, Chongqing University of Arts and Sciences, (Chongqing, 402160, China)

Ivan Chicherin, T.F. Gorbachev Kuzbass State Technical University, (28, Vesennyaya street, Kemerovo, 650000, Russian Federation), e-mail: chiv.iap@kuzstu.ru

Lijun Zhao, School of Intelligent Manufacturing Engineering, Chongqing University of Arts and Sciences, (Chongqing, 402160, China)

Chanjuan Long, T.F. Gorbachev Kuzbass State Technical University, (28, Vesennyaya street, Kemerovo, 650000, Russian Federation), School of Intelligent Manufacturing Engineering, Chongqing University of Arts and Sciences, (Chongqing, 402160, China)
Ignatieva Elena, T.F. Gorbachev Kuzbass State Technical University, (28, Vesennyaya street, Kemerovo, 650000, Russian Federation), e-mail: iea.iap@kuzstu.ru

Contribution of the authors:
Yan Yang – research problem statement; scientific management; reviewing the relevant literature; conceptualisation of research; writing the text, data collection; data analysis; reviewing the relevant literature; drawing the conclusions; writing the text.
Ivan Chicherin – research problem statement; scientific management; reviewing the relevant literature; conceptualisation of research; writing the text, data collection; data analysis; reviewing the relevant literature; drawing the conclusions; writing the text.
Lijun Zhao – research problem statement; scientific management; reviewing the relevant literature; conceptualisation of research; writing the text, data collection; data analysis; reviewing the relevant literature; drawing the conclusions; writing the text.
Chanjuan Long – research problem statement; scientific management; reviewing the relevant literature; conceptualisation of research; writing the text, data collection; data analysis; reviewing the relevant literature; drawing the conclusions; writing the text.
Ignatieva Elena – data collection and analysis; reviewing the relevant literature

The claimed contribution of the authors:

Authors have read and approved the final manuscript.