5. Моррисон К. CCNA Labs с использованием PacketTracer / Кевин Моррисон. – Москва, 2023. – 156 с.
6. Нельсон Б. Продвинутые техники работы в CiscoPacketTracer / Брайан Нельсон. – Санкт-Петербург, 2021. – 167 с.
7. О'Коннор Т. CiscoPacketTracer: от теории к практике / Тим О'Коннор. – Москва, 2022. – 142 с.
8. Тейлор Дж. Изучаем сети через CiscoPacketTracer / Джонатан Тейлор. – Москва, 2023. – 132 с.
9. Уокер Д. Практические сети в PacketTracer / Дерек Уокер. – Киев, 2022. – 154 с.
10. Харрис М. Сети Cisco: моделирование в PacketTracer / Марк Харрис. – Санкт-Петербург, 2023. – 165 с.
11. Шмидт К. Полное руководство по CiscoPacketTracer 8.0 / Карл Шмидт. – Москва, 2022. – 187 с.

Summary. The aim of the work is to develop, implement and automate a local computer network that meets the requirements of fault tolerance, security and ease of operation, meeting the requirements for IT services of information systems formed in accordance with the architectural approach to enterprise management. **Materials and methods:** they include designing the network topology, selecting hardware and software, configuring automated control systems, and testing the functionality of the created local network. **Result.** A model of a service-oriented architectural solution for IT process support is proposed and specific (industry-specific) requirements for IT services BI, ERP, MES and automated process management systems are described. Designing an enterprise's IT architecture based on services makes it possible to design an information flow management system that meets current business needs, including an automated system. When designing an IT architecture, it is important to pay special attention to production management systems (MES) and automated process control systems (APCS). When implementing such systems, IT solutions from developers specializing in enterprise automation are used in practice.

UDC 004.85:635.64

Minqiu Kuang[1,3], Bang Ji[1], Xu Li[1,2],
[1] College of Mechanical and Electrical Engineering, Hunan Agricultural University, Changsha 410128, China
[2] Hunan Provincial Key Laboratory of Intelligent Agricultural Machinery and Equipment, Changsha 410128, China
[3] Foshan-Zhongke Innovation Research Institute of Intelligent Agriculture and Robotics, Foshan, 528000, China

GCP-YOLO: HIGH-PRECISION DETECTION OF TINY CHILI FLOWERS IN COMPLEX GREENHOUSE SCENES

Abstract Precise detection of tiny chili flowers and buds is essential for intelligent greenhouse monitoring, robotic pollination, and early yield prediction. However, reliable visual detection remains challenging due to ultra-small target size, dense distribution, severe foliage occlusion, and dramatic illumination variations in greenhouse environments. Traditional lightweight YOLO models suffer from insufficient finegrained feature extraction and are vulnerable to background interference, resulting in high missed and false detection rates. To address these problems, this paper proposes GCP-YOLO based on YOLOv11n. Three core improvements are made: a generalized feature pyramid network (GFPN) for enhanced cross-scale feature fusion; a context-guided cascaded attention (C2CGA) module to suppress background noise and highlight floral morphological features; and extended P2-P6 multi-scale detection heads to improve the perception of tiny and occluded targets. Experimental results demonstrate that GCP-YOLO achieves 92.8% Precision, 83.7% Recall, 90.8% mAP50 and 72.2% mAP50-95. It outperforms YOLOv11n and other mainstream lightweight detectors. Deployed on NVIDIA Jetson AGX Orin, the model reaches an average inference speed of 97.9 FPS with only 6.29 M parameters, which fully meets the requirements of edge real-time detection in agricultural scenarios.

Keywords. Chili flower detection; Tiny object detection; YOLOv11n; GFPN; C2CGA; Edge deployment.

1. Introduction.

Chili is one of the most economically important vegetable crops worldwide. The flowering period directly determines fruit set and potential yield. Accurate detection of chili flowers is a prerequisite for intelligent greenhouse management, automatic pollination robots, and data-driven yield estimation. Nevertheless, chili flower detection faces prominent difficulties: flower buds are extremely small, densely distributed, and frequently sheltered by overlapping leaves. Meanwhile, greenhouse reflections, uneven light and complex backgrounds further degrade detection performance.

Current mainstream detectors such as YOLOv5-v11 and RT-DETR achieve promising results in common detection tasks, but they lack sufficient ability to extract subtle tiny-flower features. They are prone to feature dissipation in deep networks and cannot effectively suppress texture-similar background interference, leading to frequent missed and false detections. To solve the above limitations, this paper develops GCP-YOLO by optimizing feature fusion, attention mechanism and multi-scale detection structure, aiming to achieve high-precision and real-time detection of tiny chili flowers in complex greenhouse environments.

2. Miniature Object Perception Model (GCP-YOLO) Design

2.1 Dataset Construction

Image acquisition was conducted at the vegetable planting base of Hunan Agricultural University. Images were collected at different time periods, illumination conditions and shooting angles to ensure data diversity. A total of 1875 valid original images were screened. Multiple augmentation strategies including brightness adjustment, Gaussian noise addition, random occlusion, geometric transformation and contrast enhancement were adopted, expanding the dataset to 5399 samples. The dataset was divided into training set, validation set and test set at the ratio of 8:1:1.

2.2 Network Architecture of GCP-YOLO

The proposed GCP-YOLO is improved on the basis of YOLOv11n, with three core modules:

Generalized Feature Pyramid Network (GFPN)

Different from traditional FPN and PANet, GFPN adopts cross-scale skip connections and logarithmic layered transmission. It establishes efficient information interaction between shallow texture features and deep semantic features, which effectively alleviates the feature loss of ultra-small chili buds and enhances multi-scale feature fusion capability.

C2CGA Attention Module

The context-guided cascaded attention module splits features along the channel dimension and performs progressive feature refinement through cascaded multi-head self-attention. It adaptively strengthens floral edge contour features and suppresses background interference such as leaf reflection and canopy clutter, improving feature discrimination in complex scenes.

P2-P6 Multi-Scale Detection Heads

The detection head is extended to P2-P6 scale. The high-resolution P2 head enhances the perception of tiny buds; the deep P6 head enlarges the receptive field and provides global contextual information. The cooperative multi-scale structure effectively reduces missed detection under occlusion and false detection caused by background similarity.The entire technical roadmap for the proposed GCP-YOLO method is shown in Fig. 1.

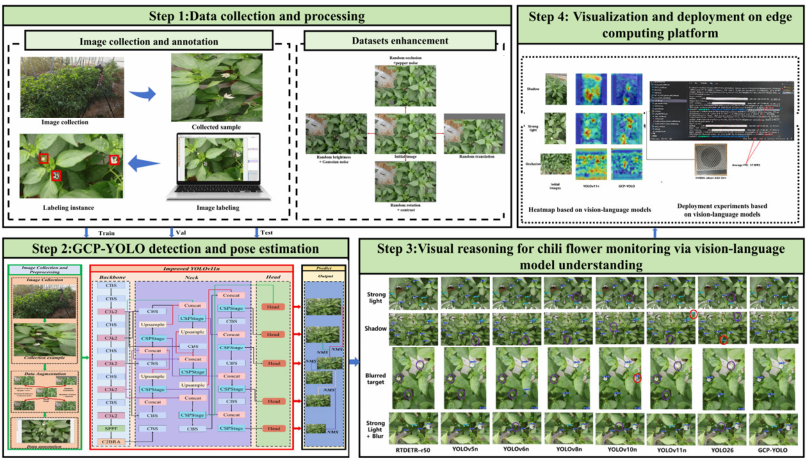

Fig. 1 – The technical roadmap of the proposed method

2.3 Experimental Settings

The hardware platform adopts Intel i5 processor and RTX 3060Ti GPU. The software environment is based on PyTorch framework. Precision, Recall, mAP50 and mAP50-95 are used as evaluation indicators. Model parameters, FLOPs and inference FPS are adopted to evaluate lightweight performance and deployment capability.

3. Experimental Results and Analysis

3.1 Ablation Experiment

Ablation results show that each improved module contributes positively to detection performance. GFPN improves cross-scale feature fusion; C2CGA increases recall and anti-interference ability; P2-P6 detection heads greatly improve mAP under complex occlusion. The combination of all modules achieves the optimal comprehensive performance.

3.2 Comparison with SOTA Methods

Comparative experiments with RTDETR-R50, YOLOv5n, YOLOv6n, YOLOv8n, YOLOv10n and YOLOv11n show that GCP-YOLO achieves the best comprehensive indexes: Precision 92.8%, Recall 83.7%, mAP50 90.8%, mAP50-95 72.2%. Compared with the baseline YOLOv11n, each index is improved by 2.1%, 1.3%, 3.9% and 6.6% respectively, showing superior detection accuracy and robustness.

Table 1 – Comparison with Representative Detection Models for Greenhouse Chili Monitoring (all values in %)

Detector	P	R	mAP50	mAP50-95
RTDETR-R50	91.8	82.3	86.6	61.2
YOLOv5n	93.4	81.9	87.2	66.6
YOLOv6n	93.7	82.9	87.2	67.2
YOLOv8n	92.9	83.1	87.4	68.6
YOLOv10n	**93.3**	80.2	86.1	67.8
YOLOv11n	90.7	82.4	86.9	65.6
YOLO26n	90.0	78.5	83.3	60.6
GCP-YOLO(Ours)	92.8	**83.7**	**90.8**	**72.7**

3.3 Visualization Analysis

Grad-CAM heatmap visualization indicates that the baseline model is easily disturbed by light and leaf background, with scattered attention areas. In contrast, GCP-YOLO can accurately focus on flower and bud targets, effectively filtering background noise, and has strong adaptability in strong light, shadow and heavy occlusion scenarios.

3.4 Edge Deployment Performance

Deployed on NVIDIA Jetson AGX Orin platform with FP16 mode, the inference speed of GCP-YOLO reaches 97.9 FPS. The model only has 6.29 M parameters and 12.8 G FLOPs, which is lightweight and meets the real-time working requirements of agricultural picking and pollination robots.

4. Conclusion and Future Work

This paper proposes GCP-YOLO for tiny chili flower detection in complex greenhouse environments. By designing GFPN feature fusion structure, C2CGA attention module and P2-P6 multi-scale detection heads, the proposed model effectively enhances small-target feature extraction and anti-interference ability. Comparative experiments and visualization results verify that GCP-YOLO achieves excellent detection accuracy and maintains lightweight characteristics. The model can be stably deployed on edge devices, providing an effective visual perception solution for intelligent greenhouse monitoring and robotic pollination systems.

References

1. Kuang M Q, Chen X, Li X, et al. Pepper disease and pest identification algorithm based on PDPI-YOLO[J]. Transactions of the Chinese Society for Agricultural Machinery, 2026, 57(10): 262-274.

2. Kuang M Q, Li X, Chen S, et al. Lightweight chili flower detection method based on improved YOLOv8n[J]. Transactions of the Chinese Society of Agricultural Engineering, 2025, 41: 198-207.

3. Kuang M Q, Li X, Wu B, et al. CF-Detr: A robust transformer-based framework for small-scale chili flower detection[J]. Frontiers in Plant Science, 2026, 17: 1824412.

4. Kuang M Q, Li X, Xie F, et. al. Advancements and prospects in key technologies for robotic pollination in greenhouse pepper breeding[J]. Frontiers in Plant Science, 2026, 17: 1778541.

5. Kuang M Q, Xie F, Liu D, et al. A refined yolov5n-based method for detecting pepper flower objects integrating transfer learning[J]. Applied Soft Computing, 2025.

6. Kuang M Q, Zou X, Xie F, et al. DDM-YOLO: A lightweight oriented detection model for mature daylily fruits in complex environments[J]. Journal of King Saud University – Computer and Information Sciences, 2026.

7. Aquino A, Millan B, Diago M, et al. Automated early yield prediction in vineyards[J]. Computers and Electronics in Agriculture, 2018, 144: 26-36.

8. Wu D, Lv S, Jiang M, et al. Using channel pruning-based YOLO algorithm for apple flower real-time detection[J]. Computers and Electronics in Agriculture, 2020, 178: 105742.

9. Xu J, Zhang X, Wang X, et al. ELSD-DETR: An efficient lightweight network for strawberry flower detection[J]. Computers and Electronics in Agriculture, 2026, 243: 111398.