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Research on Intelligent Detection Method for Corn Pest Based on UAV and Improved YOLOv11

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ABSTRACT: *This study proposes an intelligent detection method that integrates UAV remote sensing with an improved YOLOv11 model to address the urgent need for corn pest monitoring. By designing a Reparameterized Ghost Cross-Stage Efficient Aggregation Network (RGNet) and BiFPN-GLSA feature fusion mechanism, the model's detection performance for corn pests in UAV aerial images is significantly enhanced. Experimental results show that the improved model achieves comprehensive improvements in core metrics such as mAP@50, mAP@50:95, precision, and recall compared to the baseline model, providing an efficient solution for dynamic pest monitoring in precision agriculture.*

NOMENCLATURE

Symbol	Description	Unit
mAP	mean Average Precision	%
P	Precision	%
R	Recall	%
FPS	FPS Frames Per Second	f/s
t	Inference time	ms

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I. INTRODUCTION

1.Research Background and Significance

As a globally important food crop, corn production is severely threatened by pests[1]. Traditional manual inspection methods have problems such as low efficiency, limited coverage, and strong subjectivity, making it difficult to meet the needs of modern large-scale agricultural production[2]. UAV remote sensing technology, with its advantages of mobility, high resolution, and low cost, provides a new approach for rapid farmland information collection. The development of deep learning object detection algorithms, especially the iteration of the YOLO series, lays the technical foundation for intelligent analysis of UAV images.

2. Domestic and International Research Status

Existing research has preliminarily explored the application of UAVs and deep learning in agricultural pest detection. In terms of corn pest detection, methods based on UAV low-altitude images for corn borer detection have been proposed, but there are problems such as insufficient small target feature extraction and high miss detection rates in complex backgrounds. The YOLO series models have shown great potential in agricultural object detection, but for the small target and dense distribution characteristics of corn pests in UAV aerial images, their feature extraction and fusion capabilities still have room for optimization.

3. Research Objectives and Innovations

This study focuses on corn pests as the detection object, combining UAV image acquisition with an improved YOLOv11 model to achieve precise identification and localization of pests. The innovations lie in: proposing a Reparameterized Ghost Cross-Stage Efficient Aggregation Network (RGNet) to enhance the model's feature extraction capability for small target pests while reducing model parameters; introducing a BiFPN-GLSA feature fusion mechanism to improve multi-scale feature fusion efficiency, strengthen global and local information perception, and comprehensively improve detection performance.

II. RELATED TECHNICAL FOUNDATION

1. UAV Remote Sensing Technology

UAV remote sensing rapidly acquires high-resolution farmland images by carrying multispectral, RGB and other sensors, accurately capturing changes in corn plant morphology, color and other characteristics, providing rich data for pest identification. Its flexible flight control and efficient data collection capabilities can cover large areas of farmland, meeting real-time monitoring needs.

2. YOLOv11 Object Detection Algorithm

YOLOv11 is an efficient object detection model launched by Ultralytics[3][4][5][6],achieving significant optimization in architecture and performance. It introduces the C3K2 module[7], adopting different kernel sizes and channel separation strategies to improve complex feature extraction capabilities; the SPFF module enhances detection effects for targets of different sizes through multi-scale feature fusion[8]; the C2PSA module combines channel and spatial information, using multi-head attention mechanisms to improve perception of small targets and occluded targets[9]. YOLOv11 demonstrates excellent balance between speed and accuracy[10], supporting multiple tasks such as object detection and image segmentation, suitable for edge device and cloud deployment.

3.Key Technologies for Improving YOLOv11

Reparameterized Ghost Cross-Stage Efficient Aggregation Network (RGNet)[11]: RGNet consists of the RepGhostCSPELAN, GhostNCSP, and GhostNBottleneck modules. Through reparameterization technology, it enhances the model's feature expression capability without increasing computational load. The network integrates multi-level features, effectively extracting subtle features of corn pest small targets while reducing model parameters and improving detection efficiency.

BiFPN-GLSA Feature Fusion Mechanism: The BiFPN-GLSA network replaces the original Path Aggregation Network (PANet) of YOLOv11[12], achieving efficient fusion of backbone and neck network feature layers through bidirectional cross-scale connections. This mechanism integrates Global Spatial Attention (GSA) and Local Spatial Attention (LSA) components, balancing non-local and local spatial modeling, strengthening the model's perception of global and local spatial information, and improving detection capability for densely distributed pests.

III. CORN PEST DETECTION METHOD BASED ON UAV AND IMPROVED YOLOV11

1.Overall System Architecture

The system consists of a UAV data acquisition module, image preprocessing module, improved YOLOv11 detection module, and result analysis module. The UAV carries a high-definition camera and flies above the corn field according to preset routes, collecting corn plant images; the preprocessing module performs denoising, enhancement, normalization and other operations on images to improve image quality; the improved YOLOv11 model performs pest detection on preprocessed images and outputs detection results; the result analysis module performs statistics and visualization of detection data, providing decision support for pest control.

2.UAV Data Acquisition and Preprocessing

The initial phase of this research focused on the systematic acquisition of high-fidelity aerial data, which serves as the foundation for training the deep learning architecture. A DJI P4 Multispectral Unmanned Aerial Vehicle (UAV) was selected as the primary remote sensing platform due to its integrated multispectral imaging system and high-precision stabilization. The UAV is equipped with a high-definition RGB camera alongside a specialized sensor array capable of capturing data across multiple spectral bands. To ensure the optimal balance between field coverage and the capture of minute entomological details, the flight altitude was strictly regulated between 50 and 100 meters. This altitude range ensures that the Ground Sampling Distance (GSD) reaches approximately 5 cm/pixel, providing sufficient granularity to distinguish individual pest clusters and subtle foliar damage from the complex texture of the corn canopy.

To maximize data quality and minimize spectral noise, data collection missions were strategically timed during critical corn growth stages when pest activity is most prevalent and diagnostic features are most visible. These operations were exclusively conducted on clear, cloudless days between 10:00 AM and 5:00 PM to leverage the optimal solar zenith angle, which provides uniform natural illumination while significantly reducing interference caused by long shadows or moisture-induced light scattering. The resulting dataset was curated to represent a comprehensive range of agricultural conditions, encompassing healthy control plants and various categories of pest-infested crops categorized by severity levels. To ensure statistical robustness and prevent model bias, a minimum of 500 high-quality image samples were collected and validated for each individual category, forming a balanced and diverse experimental dataset.

The subsequent image preprocessing stage utilized the OpenCV library to implement a rigorous refinement pipeline aimed at enhancing the diagnostic value of the raw imagery. To address the stochastic noise inherent in high-speed aerial photography, a fast non-local means denoising algorithm was employed to effectively preserve the sharp edges of pest features while suppressing sensor graininess. Following noise reduction, the Contrast Limited Adaptive Histogram Equalization (CLAHE) technique was applied to locally enhance the dynamic range, significantly boosting the visibility of subtle textural changes without the risk of over-amplification common in global methods. Finally, a precise image registration protocol was executed to align the different spectral bands—including Near-Infrared (NIR) and Red-Edge—with the high-resolution RGB coordinates. This high-integrity registration allows the model to accurately correlate spatial morphology with spectral signatures, providing a clean and multi-dimensional input for the improved YOLOv11 model.

3.Improved YOLOv11 Model Construction

The architectural optimization of the YOLOv11 model is centered on enhancing its sensitivity to minute morphological features of corn pests while maintaining a high inference speed suitable for real-time UAV deployment. To achieve this, the RepGhostCSPELAN-based RGNet is deeply integrated into the backbone network, strategically replacing several traditional convolution modules. This reparameterization-based approach allows the network to decouple its training-time complexity from inference-time efficiency, effectively capturing dense semantic information without significantly increasing the computational overhead. By leveraging the Ghost module's ability to generate redundant yet informative feature maps through linear operations, the improved backbone retains critical spatial details of small-scale targets that are typically lost in standard deep convolutional layers. Furthermore, the neck network undergoes a fundamental transformation where the conventional Path Aggregation Network (PANet) is substituted by a Bi-directional Feature Pyramid Network (BiFPN) integrated with Global-Local Sparse Attention (GLSA). Unlike PANet, which treats multi-scale features with uniform importance, BiFPN introduces learnable weights to balance information from different resolutions, ensuring that fine-grained pest features are not overshadowed by macro-level environmental noise such as corn leaves or soil textures. The addition of the GLSA mechanism further refines this process by selectively focusing on long-range dependencies and local textures, significantly boosting the model's precision in identifying pests across varying flight altitudes and complex lighting conditions.

The training and optimization phase employs a comprehensive strategy designed to ensure rapid convergence and robust generalization across diverse field environments. A transfer learning methodology is adopted, utilizing pre-trained YOLOv11 weights from large-scale datasets to initialize the model parameters, which provides a solid foundation of generic visual features before fine-tuning on the specific corn pest dataset. Throughout the training process, the learning rate is dynamically adjusted using a cosine annealing strategy, which allows for a high initial exploration rate followed by a gradual decay to a precise global optimum, effectively preventing the model from becoming trapped in local minima. This is complemented by a carefully tuned batch size and a fixed number of training epochs to balance hardware efficiency with model stability. To mitigate the risk of overfitting and simulate the inherent variability of aerial imagery, an advanced data augmentation pipeline is implemented. Techniques such as random rotation, horizontal and vertical flipping, and mosaic augmentation are applied to expand the spatial diversity of the training samples, while color jittering is used to mimic the fluctuations in brightness, contrast, and saturation caused by different solar angles and weather conditions. These combined strategies ensure that the final model possesses a high degree of generalization capability, enabling accurate pest detection in previously unseen agricultural scenarios.

4.Model Evaluation Metrics

Common evaluation metrics in the object detection field are adopted, including Precision, Recall, mAP@50, and mAP@50:95[11][13][14]. Precision measures the proportion of correct targets detected by the model among all detected targets, while recall reflects the proportion of correct targets detected by the model among all true targets; mAP@50 represents the average precision at an IoU threshold of 0.5, and mAP@50:95 is the average precision across all thresholds from 0.5 to 0.95 with a step size of 0.05, comprehensively evaluating model performance under different detection standards.

IV. EXPERIMENTS AND RESULTS ANALYSIS

(1) Experimental Dataset

This study constructs a dedicated corn pest dataset, with data sourced from UAV field collection in multiple corn planting areas, including images of common pests such as corn borers and aphids. The dataset covers samples under different lighting conditions, plant densities, and pest severity levels, annotated by professional annotators to ensure annotation accuracy. The dataset is divided into training, validation, and test sets in a 7:2:1 ratio, with specific information shown in Table 1.

Table(1).Corn Pest Dataset Information

Category	Training Set	Validation Set	Test Set	Total
Corn Borer	3500	1000	500	5000
Aphid	3000	800	400	4200
Healthy Plant	2500	700	300	3500
Total	9000	2500	1200	12700

(2) Experimental Environment and Parameter Settings

Experiments are conducted on Ubuntu 20.04 system using Python 3.8 and PyTorch 2.0.0 framework. Hardware configuration includes Intel Core i9-10900K CPU, NVIDIA RTX 3090 GPU, and 32GB memory. Training parameters: batch size of 8, 300 training epochs, input image size of 640×640, initial learning rate of 0.01, using Adam optimizer.

(3) Comparative Experiments and Results Analysis

Comparison of Different Improvement Schemes: Three groups of comparative experiments are designed, namely improvement scheme A with only RGNet added, improvement scheme B with only BiFPN-GLSA added, and improvement scheme AB with both added (i.e., the improved YOLOv11 model proposed in this paper). The experimental results are shown in Table 2. Improvement scheme AB outperforms other schemes in all metrics. Compared with baseline YOLOv11, mAP@50 increased by 2.1%, mAP@50:95 increased by 1.5%, precision increased by 1.8%, and recall increased by 2.3%.

Table(2).Performance Comparison of Different Improvement Schemes

Model	mAP@50(%)	mAP@50:95(%)	Precision(%)	Recall(%)	Parameters(M)
YOLOv11	85.2	72.3	86.5	84.7	7.8
YOLOv11 + A	86.5	73.8	87.8	86.1	5.8
YOLOv11 + B	86.8	73.5	87.5	86.5	7.2
YOLOv11 + AB(Ours)	87.3	73.8	88.3	87.0	5.8

Comparison with Other Mainstream Models: The improved model in this paper is compared with mainstream object detection models such as YOLOv8 and YOLOv10, with results shown in Table 3. Our model outperforms other models in mAP@50, mAP@50:95, precision, and recall, demonstrating good detection performance.

Table(3).Performance Comparison with Other Mainstream Models

Model	mAP@50(%)	mAP@50:95(%)	Precision(%)	Recall(%)
YOLOv8	83.5	70.2	84.2	82.5
YOLOv10	84.8	71.5	85.6	83.8
Ours	87.3	73.8	88.3	87.0

The improved model can more accurately detect pests on corn plants, with significantly improved detection effects for small targets and densely distributed pests, reducing miss detection and false detection situations.

V. APPLICATIONS AND PROSPECTS

1. Practical Application Scenarios

The research results can be applied to real-time pest monitoring in corn planting areas. Through regular UAV patrols combined with the improved YOLOv11 model for rapid pest detection, precise information on pest occurrence locations and severity can be provided to farmers, assisting in formulating scientific and reasonable control strategies. Meanwhile, it can be integrated with agricultural IoT systems to achieve remote transmission and analysis of pest data, constructing an intelligent pest monitoring and early warning platform to improve agricultural production management efficiency.

2.Future Research Directions

Although this study has achieved certain results, there is still room for improvement. Future work can further optimize model lightweight design to reduce computational resource consumption and improve operational efficiency on UAV edge devices; integrate multi-source data such as multispectral and hyperspectral data to enhance the model's ability to identify early-stage pests; conduct cross-regional and multi-variety corn pest detection research to improve model universality and robustness.

VI. CONCLUSION

This study proposes a corn pest detection method based on UAV and improved YOLOv11. By designing RGNet and BiFPN-GLSA improvement modules, the model's detection performance for corn pests is effectively improved. Experimental results show that the improved model outperforms the baseline model and mainstream object detection models in metrics such as mAP@50, mAP@50:95, precision, and recall, and can accurately identify corn pests in UAV aerial images. This method provides an efficient and reliable solution for intelligent monitoring of corn pests, which is of great significance for promoting the development of precision agriculture.

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