Pest YOLO: An Effective Insect Target Detection Algorithm for Small Targets

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Abstract: This paper proposes three distinct strategies to enhance the performance of the You Only Look Once version 5 (YOLOv5) model in object detection tasks. The enhancements encompass the integration of a BiFormer attention mechanism, the addition of an Adaptive Feature Pyramid Network (AFPN), and the replacement of the Spatial Pyramid Pooling Module (SPPF) with the Multi-Task Spatial Pyramid Pooling (MTSPPF). The BiFormer attention mechanism aims to enhance the model's focus on target regions, leading to improved detection accuracy by capturing long-range dependencies and enhancing the understanding of spatial relationships within images. Integrating AFPN into the YOLOv5 model optimizes the feature pyramid network, enabling adaptive adjustments of feature representations across various scales, which improves the detection of objects with different sizes and complexities. Additionally, the replacement of SPPF with MTSPPF facilitates more effective aggregation of spatial information from multiple scales, thereby enhancing performance while reducing both parameter count and computational complexity. Experimental evaluations on standard datasets indicate significant improvements in object detection performance for all three approaches. Collectively, these enhancements tackle challenges related to complex scenes and varying object scales, providing a comprehensive solution for improving the YOLOv5 model's effectiveness in object detection tasks.

1 INTRODUCTION

As people's quality of life continues to improve, agriculture remains a vital component of human livelihood. However, the agricultural sector encounters challenges like pest and disease outbreaks, which can severely affect crop yields and quality (Donatelli, Magarey, Bregaglio, et al., 2017). This situation creates an increasing demand for efficient and accurate methods for detecting pests and diseases in crops. Timely detection is essential for ensuring food security and promoting sustainable agricultural development.

The process of pest and disease detection in crops involves various steps, including identification, monitoring, and management. Traditionally, manual inspection by agricultural experts has been the primary method for pest and disease detection. Hothe paperver, manual inspection is labor-intensive, time-consuming, and may not always be accurate, especially when dealing with large agricultural areas (Wen, Chen, et al., 2022). Detection algorithms utilizing machine vision have proven to be a promising method for identifying pests and diseases in agricultural settings (Khalid, Oqaibi, et al., 2023). For example, Mukhopadhyay (Mukhopadhyay, Paul, Pal, et al., 2023) proposed an image-based automatic detection method for identifying crop diseases. Yang (Yang, Yuan, et al., 2019) developed a computer vision algorithm using infrared thermal imaging technology to detect crop disease areas and estimate disease severity. Karunasena (Karunasena, Priyankara, 2022) introduced a novel approach for pest detection in crops, utilizing a cascade classifier that effectively integrates a histogram of oriented gradient features with support vector machine techniques. This innovative method enhances the accuracy of pest identification by leveraging the strengths of both feature extraction and machine learning classification, thereby providing a more reliable solution for agricultural pest management. Additionally, an improved feature extraction method

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based on the Shi-Tomasi algorithm was proposed by Zhang (Zhang, Zou, et al., 2021) to enhance pest detection in crops.

Recently, there has been a marked increase in the application of deep learning-based object detection algorithms within the agricultural sector. These algorithms, such as You Only Look Once (YOLO) and Faster R-CNN (Region-based Convolutional Neural Network), have shown promising results in detecting pests and diseases in crops (Tang, Lu, et al., 2023). Lawal (Lawal, Zhao, et al., 2021) proposed an improved YOLOv3 model for detecting pests and diseases in crops, achieving superior performance compared to other methods. Roy (Roy, Bose, et al.,2022) Roy developed a high-performance framework designed for real-time object detection, specifically aimed at identifying diseases in crops. This innovative approach enhances the efficiency of disease detection processes, allowing for timely interventions in agricultural practices, showcasing impressive accuracy and efficiency, the paper attempts to improve the YOLOv5 model using three novel approaches in an effort to achieve better detection performance.

2 RELATED WORKS

2.1 YOLOv5 Algorithm

The YOLOv5 algorithm represents an advancement within the YOLO series of object detection models, recognized for its remarkable speed and precision. By building on the achievements of earlier versions, YOLOv5 introduces several enhancements in areas such as model architecture, training methodologies, and inference efficiency (Liu, Xu, et al., 2021). These improvements aim to optimize performance, making YOLOv5 a more effective tool for real-time object detection tasks.

The YOLOv5 algorithm adopts a one-stage object detection approach, allowing for real-time processing of images with high accuracy. Its architecture comprises three key components—the backbone, neck, and detection head—each essential for the model's effectiveness in various detection tasks.

The backbone network acts as a feature extractor, capturing semantic information from the input image. YOLOv5 employs a variant of CSPDarknet53 as a lightweight and efficient extractor. Positioned between the backbone and detection head, the neck network fuses feature across different scales to improve detection accuracy. Finally, the detection head of YOLOv5 outputs bounding box predictions and class probabilities, making it highly suitable for diverse applications, especially in agricultural object detection (Wang, Zheng, et al., 2021).

Recently, researchers have explored several modifications and extensions to the YOLOv5 algorithm to better address specific agricultural challenges, particularly in pest and disease detection in crops. These adaptations aim to enhance the algorithm's effectiveness in these applications. YOLOv5 retains the core components that define the YOLO architecture series, with its network structure illustrated in Figure 1.

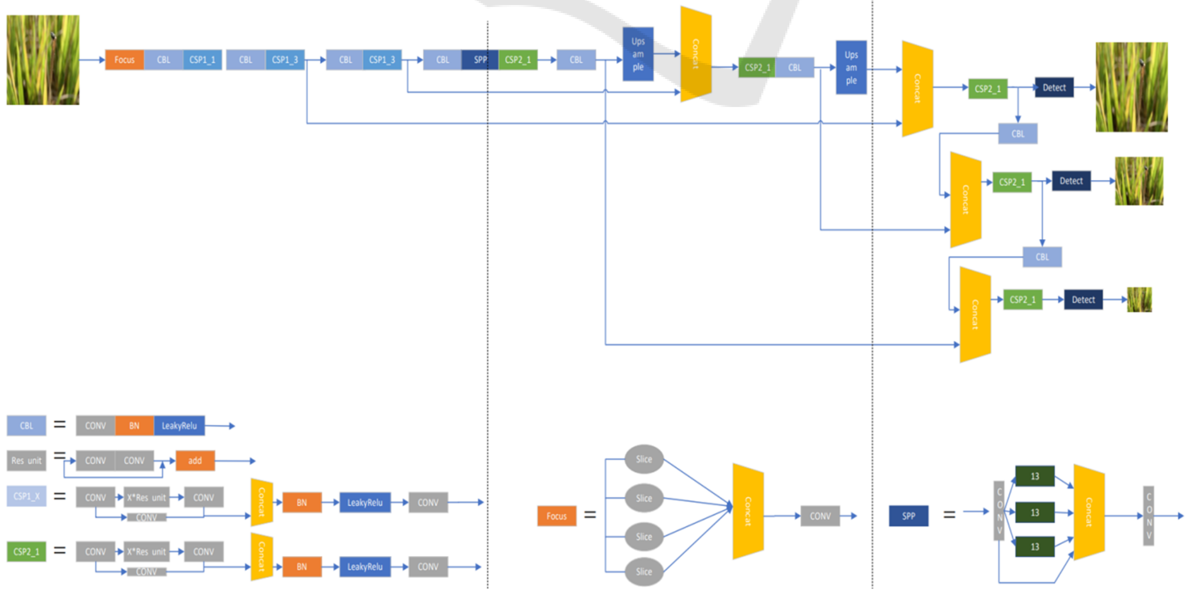


Figure 1: YOLOv5 network structure diagram. (Photo/Picture credit: Original)

2.2 Algorithm Optimization

2.2.1 Replacement of YOLOv5 C2f Layer

The standard architecture of the original YOLOv5 model may not sufficiently meet the specific needs for accurately detecting small defects related to crop diseases and pests. The small target recognition layer is designed to improve the detection of minor defects in crops caused by diseases or pests. By integrating this layer into the YOLOv5 architecture, this paper aims to enhance the model's sensitivity to subtle features and overall performance in agricultural inspection tasks. By doing so, the research aims to enhance the model's ability to accurately detect and analyze critical details in agricultural contexts. To implement the proposed modification, the C3 layer in the YOLOv5 backbone is replaced with the newly introduced C2f layer, which is essential for improving the model's capacity to detect small defects related to crop diseases and pests.

In the YOLOv5 architecture, the third convolutional layer, known as the C3 layer, is crucial for feature extraction from the input image. Its design significantly contributes to the model's ability to identify and interpret important characteristics, enhancing overall detection performance. It performs convolution operations on the feature maps obtained from earlier layers, capturing hierarchical representations of the input image. The output of the C3 layer serves as the input to subsequent layers, facilitating object detection and localization tasks.

In the context of detecting small targets, such as pests or diseases on crops, the traditional C3 layer may not adequately capture spatial information essential for accurate detection. To address this limitation, the paper proposes replacing the C3 layer with a novel C2f (Convolutional to Fusion) layer. The C2f layer not only performs convolutional operations similar to the C3 layer but also incorporates fusion mechanisms to aggregate features from multiple scales effectively.

The C2f layer effectively merges features from the second layer of the backbone network (C2 layer) with outputs from the preceding layer, allowing for a richer representation of the input data. By replacing the C3 layer with the C2f layer, this paper seeks to significantly enhance the model's capacity to detect small targets in agricultural images. This strategic modification aims to enhance the model's performance and reliability in agricultural inspection tasks, ultimately leading to more accurate assessments of crop health. Figure 2 shows the YOLOv5 C2f layer.

2.2.2 MTSPPF Replacement

The proposed method enhances feature fusion in the backbone network by improving convolutional operations, enabling the capture of detailed target information while minimizing irrelevant data. This paper suggests substituting the SPP layer with the Multi-scale Spatial Pyramid Pooling Fusion (MTSPPF) mechanism, as outlined by Dong (Dong, Sun, et al., 2024). The purpose of this replacement is to enhance the model's capability to effectively process multi-scale features, which is expected to result in improved overall performance. By optimizing this aspect, the model can better adapt to varying object sizes, ultimately leading to more accurate detections.

This process facilitates the compression of the feature space, allowing for the extraction of critical information from each channel in a more efficient manner. Following this, the Excitation operation plays a crucial role by adjusting the significance of the features from each channel based on their relevance to the target of interest. This modulation enables the model to focus on the most salient features, effectively amplifying those that contribute

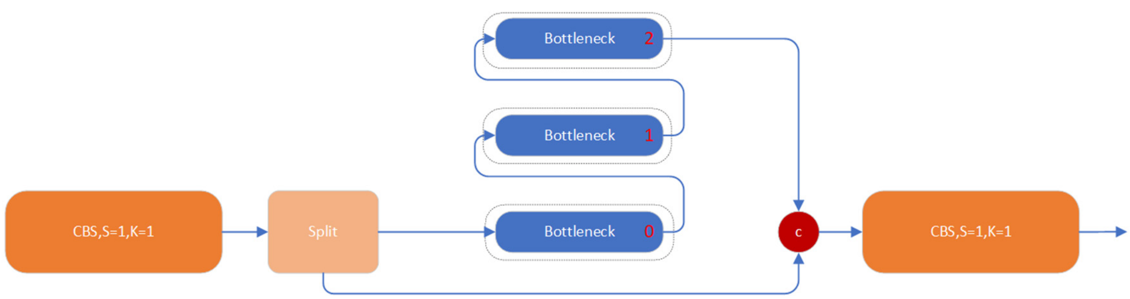


Figure 2: YOLOv5 C2f Layer (Photo/Picture credit: Original)

to accurate detection while suppressing irrelevant information. As a result, the overall performance of the model in detection tasks is significantly enhanced, leading to improved accuracy and reliability in identifying key elements within the data.

2.2.3 BiFormer

BiFormer is a visual Transformer model that incorporates Bi-level Routing Attention (Zhu, Wang, et al., 2023), centered around the concept of dual-level routing attention mechanisms. In this model, each image patch is assigned to a positional router that directs it to either upper-level or lower-level routers based on specific criteria. While the upper-level routers are designed to capture global contextual information, the lower-level routers concentrate on detailed aspects within local regions. In the BiFormer architecture, the upper-level routers utilize global self-attention mechanisms to engage with all image patches, effectively generating a comprehensive global representation of the input. In contrast, the lower-level routers implement local self-attention mechanisms, allowing them to concentrate on neighboring patches and create more localized representations. This dual approach enhances the model's ability to capture both broad context and fine details. The structure of BiFormer is illustrated in the Figure 3.

In the i-th stage, overlapping patch embedding is utilized when i=1, whereas patch merging is employed when i=2,3……to reduce input spatial resolution while increasing channel count. Following this, N_i-connected BiFormer blocks are utilized to perform transformer operations on the input features. By integrating the BiFormer structure into the YOLOv5 architecture, the model's feature representation capabilities are significantly enhanced. This integration improves the model's ability to capture intricate spatial relationships within the input image, thereby allowing for more nuanced understanding and detection of objects.

2.2.4 AFPN

The AFPN module is designed to address the challenge of feature resolution discrepancy across different levels of the feature pyramid. It achieves this by incorporating attention mechanisms to adaptively recalibrate feature maps at each pyramid level, ensuring that features from different scales are appropriately utilized for object detection. Meanwhile, the attention fusion mechanism selectively combines features from different pyramid levels based on their importance, leveraging attention mechanisms to assign higher the paperweights to more informative features.

The integration of the AFPN module into the YOLOv5 architecture is intended to strengthen the model's resilience to scale variations and improve its ability to detect objects of different sizes. AFPN facilitates adaptive feature recalibration, allowing for the effective use of multi-scale information, which leads to more accurate and reliable object detection in various scenarios. The Generalized IoU (GIoU) Loss function for bounding box regression is defined as follows:

$$L_{GIoU} = 1 - IoU + \frac{|C - B \cup B^{gt}|}{|C|} \tag{1}$$

When the predicted box perfectly overlaps with the ground-truth box and their dimensions are identical, distinguishing the relative positions of these two boxes becomes difficult. To tackle this challenge, the Complete IoU (CIoU) Loss is utilized instead of the Generalized IoU (GIoU) Loss. The CIoU Loss enhances the GIoU Loss by considering not only the

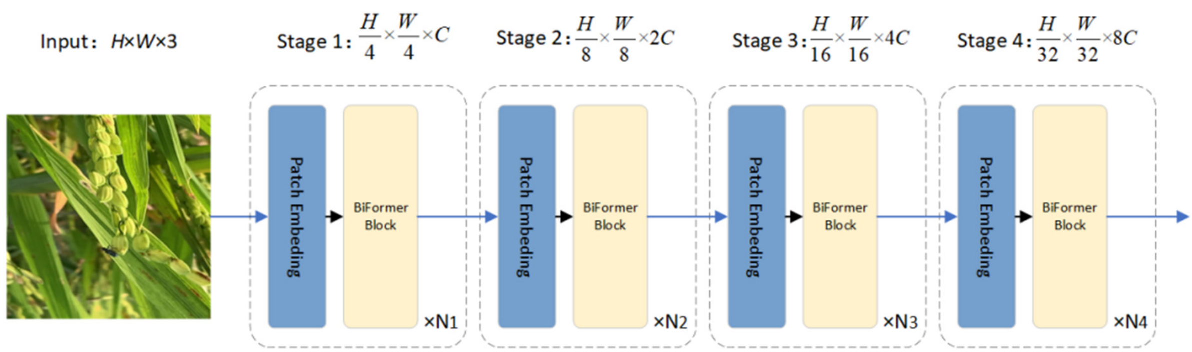


Figure 3: The structure of BiFormer (Photo/Picture credit: Original)

area of overlap but also the distance between the centers of the predicted and ground-truth boxes. Additionally, it accounts for the consistency of the aspect ratios of the bounding boxes. The formulation of the loss function can be defined as follows:

$$R_{CIoU} = \frac{\rho^2(b, b^{gt})}{c^2} + \alpha v \quad (2)$$

$$v = \frac{4}{\pi^2}\left(arctan\frac{w^{gt}}{h^{gt}} - arctan\frac{w}{h}\right)^2 \quad (3)$$

$$L_{CIoU} = 1 - IoU + R_{CIoU} \quad (4)$$

The penalty term is established by minimizing the normalized distance between the centers of the two bounding boxes (BBoxes). In this context, 'd' signifies the Euclidean distance between the predicted and ground-truth box centers, while 'c' represents the diagonal length of the smallest enclosing box that encompasses both bounding boxes. Additionally, 'alpha' serves as a positive balancing parameter to evaluate aspect ratio consistency, defined as follows:

$$\alpha = \frac{v}{(1 - IoU) + v} \quad (5)$$

2.3 Experimental Setup

2.3.1 Dataset Production and Preprocessing

From September 2021 to December 2021, a dataset of pests and diseases was randomly collected at Kunming Second Farm. Different types of pests and diseases exhibit variations in shape and size. To ensure effective training and enhance sample diversity, the collected image data underthe papernt screening prior to training. The image annotation software used for labeling was Labeling.

Ultimately, the paper obtained 3033 images, stored at a resolution of 640 pixels × 640 pixels. Of these images, a total of 3,033 were assigned to the training set, while 127 images were designated for the validation set, and 124 images were reserved for the test set. The dataset was labeled as nc=1 for pest detection. Additionally, the paper incorporated the COCO 2018 dataset into the study for further evaluation and comparison. The dataset is shown in Figure 4:

Figure 4：A test case (Photo/Picture credit: Original)

The paper devised two models in total, each leveraging multiple modules. The initial model integrates the previously discussed attention mechanism and transfigures the network backbone's C3 layer into C2f, while the SPP layer is transformed into MTSPPF. The second model incorporates APFN alongside other modifications. Both models under the papernt training and validation using the dataset outlined in the preceding section

2.3.2 Experimental platform

The experiment was carried out utilizing the PyTorch framework, which provides a flexible and efficient environment for deep learning tasks. The specific software and hardware configuration parameters used in this study are detailed in Table 1, outlining the essential components that contributed to the experimental setup.

Table 1. Software and hardware platform configuration parameters

Configuration	Parameter
(CPU)	Intel i9-13900kf
(GPU)	NVIDIA GTX4090
Operation system	Windows11
CUDA	10.2
Opencv	3.2.2

2.3.3 Model Evaluation Indicators

This paper details the evaluation metrics used to assess the performance of the Kiwi flaw detection model, with a primary emphasis on precision (P) alongside recall (R) and mean average precision (mAP). These metrics are crucial for gaining a comprehensive insight into the model's effectiveness in detecting flaws. The formulas for calculating precision and recall are provided below:

$$P = \frac{TP}{TP + FP} \tag{6}$$

$$R = \frac{TP}{TP + FN} \tag{7}$$

True positives (TP), false positives (FP), and false negatives (FN) are essential for evaluating model performance. True positives are correctly identified instances, while false positives are incorrectly labeled as positive, and false negatives are actual positives misclassified as negative. To measure model effectiveness, average precision (AP) is calculated by integrating precision values over their corresponding recall values, effectively determining the area under the precision-recall curve. This provides a comprehensive assessment of the model's ability to balance precision and recall across various thresholds.

Mean average precision (mAP) is derived by averaging the average precision (AP) values across all categories, providing an overall precision measure. Mean Average Precision at IoU threshold 0.50 (mAP50) is calculated by averaging the AP values for each class at the specified IoU threshold. The metrics are defined as follows:

$$AP = \sum_{K=i}^{N} P(k)\, \Delta R(k) \tag{8}$$

$$mAP = \frac{1}{C}\sum_{c=i}^{C} AP(c) \tag{9}$$

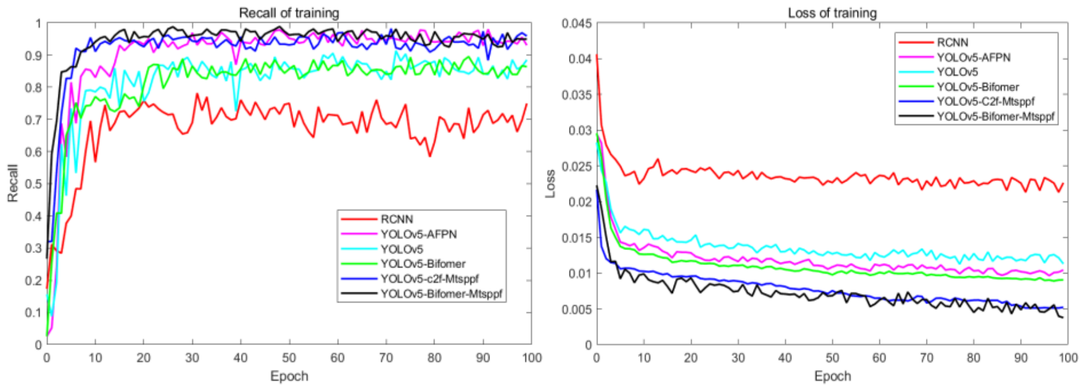
Additionally, the size of the weights file (measured in megabytes, MB) plays a significant role in the practical deployment of the model. A larger weights size often indicates a more complex model with a greater number of parameters, which can impact both storage requirements and inference speed.

3 RESULTS AND DISCUSSION

The loss function curve offers a visual representation of the model's convergence during the training process, highlighting enhancements in stability as the number of iterations increases. Conversely, mean Average Precision (mAP) is a critical indicator of the defect detection model's efficacy; higher mAP values signify a greater average detection accuracy and enhanced overall performance. By analyzing these metrics, the paper can gain deeper insights into the model's strengths and areas for improvement. The results of the recognition process are shown in Figure 5.

The enhanced method is evaluated against the original YOLOv5 model and other prominent deep learning-based object detection algorithms. This comparison assesses the performance improvements resulting from the proposed modifications, providing a thorough evaluation of its effectiveness in various detection tasks. Specifically, the study contrasts the YOLOv5 variant integrating C2f with MTSPPF, the version optimized with FPN for the detection head, and the one enhanced by the attention mechanism with the original YOLOv5 and RCNN. Training was conducted using the pest dataset collected from Yunnan Farm. The results are shown in Figure 6.

Figure 5: Identification diagram. (Photo/Picture credit: Original)



(a) loss curve (b) recall curve

Figure 6: Loss curves and recall curves. (Photo/Picture credit: Original)

To ensure a robust and reliable validation process, this study implemented additional training using the COCO 2017 dataset while following the previously outlined methodologies. This strategic decision significantly enriched the training experience, enabling a more thorough evaluation of the enhanced detection model's performance across various datasets and scenarios. The research sought to improve the model's adaptability and generalization by capturing a wide range of object characteristics through the use of diverse training data. This comprehensive approach not only assesses the model's effectiveness in different contexts but also enhances its resilience to variations in object appearance and environmental conditions, ultimately leading to better real-world applicability.

The results of this extensive evaluation are visually represented in Figure 7. A noteworthy aspect of the COCO 2017 dataset is that approximately 40% of its content consists of small objects, which are often challenging for detection algorithms. Addressing this challenge is crucial, as small objects significantly impact various real-world applications, especially in agriculture. By focusing on such a diverse dataset, the training regimen was designed to better accommodate the complexities of real-world scenarios, particularly in recognizing small-scale features that are vital for tasks such as crop health monitoring.

Additionally, this approach provided a deeper insight into the model's capabilities, helping researchers pinpoint its strengths and areas needing improvement. The results shown in Figure 7 not only demonstrate the effectiveness of the proposed enhancements but also highlight the model's robustness in managing various object sizes and types. This ultimately underscores its potential for practical applications in crop inspection and pest detection.

In the analysis of the agricultural pest dataset, the paper observed that the loss function tends to converge around the 100-epoch mark, indicating a stabilization in the model's learning process. This early convergence suggests that the model effectively captures the essential patterns and features present in this dataset, allowing it to adapt quickly to the underlying data distribution. Notably, the recall rate shows a quicker convergence, achieving stability after approximately 30 epochs. The swift enhancement in recall suggests that the model excels at early identification of true positives during the training process. This capability is especially advantageous in real-world applications, where timely detection of pests is crucial for effective management and intervention. Conversely, when examining the COCO 2017 dataset, the paper found that the loss function requires nearly 200 epochs for convergence, signifying a more complex learning landscape. The extended training duration reflects the dataset's intricate diversity and the challenge of accurately detecting objects across various scales and contexts. Moreover, the recall rate for this dataset begins to exhibit a converging trend only after 450 epochs, underscoring the need for prolonged training to achieve reliable performance. This significant disparity between the two datasets highlights not only the varying complexities inherent in each but also the different responses of the models to these challenges. Such findings emphasize the importance of tailored training strategies that consider the unique characteristics of each dataset to optimize model performance.

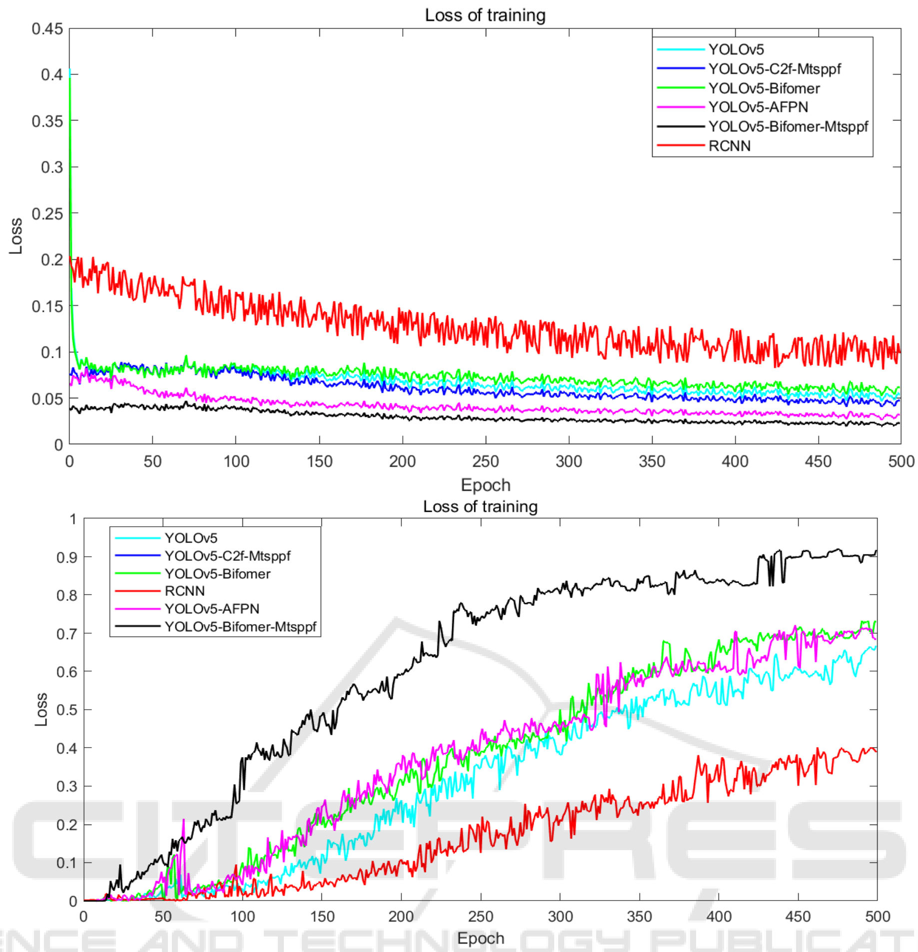


Figure 7: Loss curves and recall curves of Coco. (Photo/Picture credit: Original)

Through thorough analysis, the paper discovered that YOLOv5, particularly when augmented by the integration of the MTSPPF module and the BiFormer attention module, demonstrates a markedly faster convergence rate along with enhanced detection performance. The addition of these advanced modules appears to optimize the model's architecture, allowing it to more effectively utilize additional features and contextual information. This optimization not only improves the model's overall efficiency but also its ability to accurately identify objects in diverse scenarios. This suggests that the modifications not only expedite the training process but also enhance the model's overall efficiency in accurately identifying pests in agricultural settings. The faster convergence indicates that the model can learn the relevant patterns more quickly, leading to improved performance in a shorter amount of time. Furthermore, the detailed data comparisons supporting these findings are presented in Table 2, which provides a comprehensive view of the model's performance across different scenarios. This table highlights the effectiveness of the enhancements and offers valuable insights into how these modifications contribute to superior detection outcomes.

Based on the provided Table 3 and Table 4, YOLOv5_BiFormer_MTSPPF stands out as the top-performing model, achieving the highest mean Average Precision (mAP) along with exceptional precision and recall rates. This robust performance highlights its effectiveness in accurately detecting objects across various scenarios, making it particularly suitable for applications that require high reliability. Following closely is YOLOv5_C2F_MTSPPF, which excels in both mAP and recall, demonstrating a strong capability to capture essential features while effectively minimizing false negatives. Both YOLOv5_AFPN and YOLOv5_BiFormer also deliver competitive results, though they lag slightly behind

Table 2: Comparative experimental test results of tiny insect

Algorithm	P(%)	R(%)	mAP50(%)	the weights size (MB)
RCNN	75.34	68.61	65.32	6
YOLOv5	82.48	86.61	80.36	13
YOLOv5_C2f_Mtsppf	88.12	91.46	93.42	48
YOLOv5_AFPN	87.84	90.42	92.89	32
YOLOv5_Bifomer	82.33	87.01	91.32	64
YOLOv5_Bifomer_Mtsppf	88.50	90.22	93.22	84

Table 3: Comparative experimental test results of Coco2017

Algorithm	P(%)	R(%)	mAP50(%)	the weights size (MB)
RCNN	66.1	70.74	67.88	8
YOLOv5	72.84	62.31	79.24	17
YOLOv5_C2f_Mtsppf	88.12	91.46	88.33	52
YOLOv5_AFPN	81.76	84.42	84.33	49
YOLOv5_Bifomer	80.74	68.65	72.61	63
YOLOv5_Bifomer_Mtsppf	86.67	90.48	95.67	135

YOLOv5_BiFormer_MTSPPF. In comparisons with the RCNN model, YOLOv5 consistently outperforms RCNN across nearly all metrics, with the exception of precision, where RCNN shows relatively better results. Notably, RCNN exhibits the lowest mAP and recall rates among the evaluated models, underscoring the advancements achieved by the YOLOv5 variants in the domain of object detection.

Table 4: Comparison results before and after adding different modules.

Algorithm	C2f	mtsppf	Bif	P(%)	Time(s)
YOLOv5	√			72.2	0.031
	√	√		77.3	0.054
	√	√	√	65.3	0.067
		√	√	85.7	0.074

4 CONCLUSIONS

The study improved the YOLOv5 model for real-time detection of small-scale crop defects and pests by integrating modules such as C2f, MTSPPF, and BiFormer attention mechanisms. Among the enhanced models, YOLOv5_BiFormer_MTSPPF demonstrated the best performance, achieving the highest mean Average Precision (mAP), precision, and recall rates across various datasets. This indicates that the combination of BiFormer and MTSPPF effectively optimizes the model’s feature extraction and fusion capabilities, making it highly suitable for real-time agricultural applications.

Although the improvements in detection performance were not universally significant compared to the original YOLOv5, the YOLOv5_BiFormer_MTSPPF model consistently outperformed other versions and traditional object detection methods such as RCNN in key metrics. However, the model's larger size and higher computational requirements suggest the need for hardware optimization in practical implementations.

Future research will focus on enhancing the model’s efficiency, including potential pruning strategies and extending its application to more crop types. These advancements are essential for improving real-time agricultural monitoring systems, offering farmers more accurate and timely insights into crop health and pest management.

REFERENCES

Donatelli, M., Magarey, R.D., Bregaglio, S., Willocquet, L., Whish, J.P.M., Savary, S. 2017. Modelling the Impacts of Pests and Diseases on Agricultural Systems. Agricultural Systems, 155, pp. 213-224. Elsevier.

Dong, Q., Sun, L., Han, T., Cai, M., Gao, C. 2024. PestLite: A Novel YOLO-Based Deep Learning Technique for Crop Pest Detection. Agriculture, 14(2), 228. MDPI.

Khalid, S., Oqaibi, H.M., Aqib, M., Hafeez, Y. 2023. Small Pests Detection in Field Crops Using Deep Learning Object Detection. Sustainability, 15(8), 6815. MDPI.

Karunasena, G.M.K.B., Priyankara, H.D.N.S. 2020. Tea Bud Leaf Identification by Using Machine Learning and Image Processing Techniques. International Journal of Scientific & Engineering Research, 11(8), pp. 624-628.

Lawal, O.M., Zhao, H. 2021. YOLOFig Detection Model Development Using Deep Learning. IET Image Processing, 15(13), pp. 3071 - 3079. Wiley Online Library.

Liu, H., Xu, K. 2021. Densely End Face Detection Network for Counting Bundled Steel Bars Based on YoloV5. In: Pattern Recognition and Computer Vision: 4th Chinese Conference, PRCV 2021, Beijing, China, October 29- November 1, 2021, Proceedings, Part I 4, pp. 293-303. Springer.

Mukhopadhyay, S., Paul, M., Pal, R., De, D. 2021. Tea Leaf Disease Detection Using Multi-objective Image Segmentation. Multimedia Tools and Applications, 80, pp. 753-771. Springer.

Roy, A.M., Bose, R., Bhaduri, J. 2022. A Fast Accurate Fine-Grain Object Detection Model Based on YOLOv4 Deep Neural Network. Neural Computing and Applications, 34(5), pp. 3895-3921. Springer.

Tang, Z., Lu, J., Chen, Z., Qi, F., Zhang, L. 2023. Improved Pest-YOLO: Real-time Pest Detection Based on Efficient Channel Attention Mechanism and Transformer Encoder. Ecological Informatics, 78, 102340. Elsevier.

Wang, Z., Zheng, Y., Li, X., Jiang, X., Yuan, Z., Li, L., Zhang, L. 2021. DP-YOLOv5: Computer Vision-Based Risk Behavior Detection in Pothe paperr Grids. In: 4th Chinese Conference on Pattern Recognition and Computer Vision, PRCV 2021, Proceedings, Part I, Beijing, China, October 29-November 1, pp. 318-328. Springer, Heidelberg.

Wen, C., Chen, H., Ma, Z., Zhang, T., Yang, C., Su, H., Chen, H. 2022. Pest-YOLO: A Model for Large-Scale Multi-Class Dense and Tiny Pest Detection and Counting. Frontiers in Plant Science, 13, 973985. Frontiers Media SA.

Yang, N., Yuan, M., Wang, P., Zhang, R., Sun, J., Mao, H. 2019. Tea Diseases Detection Based on Fast Infrared Thermal Image Processing Technology. Journal of the Science of Food and Agriculture, 99(7), pp. 3459-3466. Wiley Online Library.

Zhang, L., Zou, L., Wu, C., Chen, J., Chen, H. 2021. Locating Famous Tea's Picking Point Based on Shi-Tomasi Algorithm. Computers, Materials & Continua, 69(1).

Zhu, L., Wang, X., Ke, Z., Zhang, W., Lau, R.W.H. 2023. Biformer: Vision Transformer with Bi-level Routing Attention. In: Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pp. 10323-10333. IEEE.