

# Enhancing Precision Agriculture Pest Control: A Yolov10-Based Deep Learning Approach For Insect Detection

Abdul Bari<sup>1</sup>, Md Sadiq Bilal<sup>2</sup>, Mohammed Aijaz<sup>3</sup>, Mrs. Heena Yasmin<sup>4</sup>  
<sup>1,2,3</sup>B.E.Students; Department of CSE ISL Engineering College, Hyderabad, India  
<sup>4</sup>Assistant Professor; Department of CSE ISL Engineering College, Hyderabad, India  
Mail Id; [abdulbariss147@gmail.com](mailto:abdulbariss147@gmail.com), [sadiqbilal2018@gmail.com](mailto:sadiqbilal2018@gmail.com), [mraijaz786609@gmail.com](mailto:mraijaz786609@gmail.com)

Accepted 25-04-2026

*Author(s) Retains the Copyrights of This Article*

## ABSTRACT

*Precision Agriculture (PA) leverages advanced technologies to optimize resource use while preserving crop quality and yield. However, pest infestations remain a critical challenge that can undermine these benefits. Recent deep learning frameworks like YOLOv8 have shown promise in real-time insect detection, yet often remain limited to specific insect types or crops. To address this limitation and improve detection accuracy, this work explores an enhanced, generalized approach using the latest YOLOv10 object detection model. We develop and test a YOLOv10-based tool designed to detect any insect category across diverse crops, enabling broader and faster pest monitoring in the field. A comprehensive performance evaluation was conducted on a benchmark insect dataset, demonstrating notable improvements over YOLOv8, including higher mean Average Precision (mAP) scores and faster inference speeds. The findings suggest that YOLOv10's architectural advancements contribute to more robust, scalable, and real-time pest detection, offering significant potential to strengthen pest management strategies within precision agriculture.*

**Keywords:** Precision Agriculture, Pest Detection, YOLOv10, Object Detection, Insect Monitoring, Deep Learning, Real-time Detection, Crop Protection, mAP Improvement, Scalable Pest Management.

## INTRODUCTION

Precision Agriculture (PA) is transforming farming by enabling real-time monitoring and efficient resource use. A major challenge remains pest detection, as traditional manual methods are labor-intensive and lack continuous accuracy. Deep learning frameworks, particularly YOLO-based models, have emerged as effective tools for automated pest identification. YOLOv8 has shown promise in balancing speed and accuracy but is often limited to specific insect species and crops, reducing scalability. Moreover, detecting small, hidden, or overlapping insects under complex field conditions remains difficult. To overcome these limitations, this work introduces a generalized pest detection system using YOLOv10. With architectural improvements such as anchor-free design and enhanced feature representation, YOLOv10 achieves higher accuracy and faster inference. The system is trained to detect insects as a single class, enabling adaptability across diverse crops. This approach provides a robust, scalable, and efficient solution for real-time pest monitoring, supporting proactive pest management within precision agriculture.

## LITERATURE REVIEW

**Title:** Pest and Pesticide Management, Food and Agriculture Organization of the United Nations.

**Author:** Z. Zheng, P. Wang, D. Ren, W. Liu, R. Ye, Q. Hu, and W. Zuo,

**Year:** Jan. 10, 2024.

**Description:** This reference, published by the Food and Agriculture Organization (FAO) of the United Nations, provides an overview of global strategies and challenges in pest and pesticide management within agricultural systems. It highlights the critical role of sustainable pest management in ensuring food security, protecting biodiversity, and reducing the environmental and health impacts of excessive pesticide use. The document discusses integrated pest management (IPM) approaches, the importance of early detection and monitoring of pests, and the need for innovative technologies—such as precision agriculture and AI-driven detection systems—to improve decision-making in pest control. This context supports the motivation for developing advanced, real-time pest detection solutions like the YOLOv10-based system proposed in this project, which aligns with global goals of reducing reliance on chemical pesticides while maintaining crop productivity and sustainability.

**Title:** A comprehensive review of YOLO architectures in computer vision: From YOLOv1 to YOLOv8 and YOLO-NAS,

**Author:** J. Terven, D.-M. Córdova-Esparza, and J.-A. Romero-González

**Year:** 2023.

**Description:** This reference by J. Terven, D.-M. Córdova-Esparza, and J.-A. Romero-González, titled "A comprehensive review of YOLO architectures in computer vision: From YOLOv1 to YOLOv8 and YOLO-NAS," provides an in-depth survey of the evolution of the YOLO (You Only Look Once) family of object detection models. Published in *Machine Learning and Knowledge Extraction* in November 2023, it systematically analyzes architectural improvements, performance benchmarks, and practical applications of each YOLO version, from the original YOLOv1 to the more advanced YOLOv8 and YOLO-NAS models. The paper discusses the trade-offs between speed, accuracy, and computational efficiency that guided the design of each successive YOLO version, offering valuable insights into how these models have adapted to detect small, overlapping, and occluded objects in complex environments. This comprehensive perspective helps explain why YOLOv10—though newer and not covered in the review—represents a logical next step, continuing this trend of architectural refinement for real-time applications. For this project, the reference supports the technical foundation and motivation to upgrade from YOLOv8 to YOLOv10, demonstrating how improvements in backbone design, anchor-free detection, and multi-scale feature extraction directly address real-world challenges in agricultural pest detection.

**Title:** Tea tree pest detection algorithm based on improved YOLOv7-tiny

**Author:** Z. Yang, H. Feng, Y. Ruan, and X. Weng

**Year:** 2023.

**Description:** This reference by Z. Yang, H. Feng, Y. Ruan, and X. Weng, titled "Tea tree pest detection algorithm based on improved YOLOv7-tiny," was published in *Agriculture* in May 2023. The study focuses on developing a lightweight yet accurate object detection model tailored for pest monitoring in tea plantations by enhancing the YOLOv7-tiny architecture. The authors propose specific improvements such as optimized feature extraction modules, attention mechanisms, and data augmentation techniques to boost detection performance, particularly for small and overlapping pests commonly found in tea tree cultivation. The paper highlights the importance of balancing model size and detection accuracy to enable deployment on edge devices in real-world agricultural environments. It also demonstrates how targeted adaptations of existing YOLO architectures can achieve significant gains in detection precision while maintaining real-time performance. This research directly supports the motivation of the current project to explore newer YOLO architectures like YOLOv10, emphasizing the need

for lightweight, efficient, and high-accuracy models in pest detection. By addressing challenges like small object detection and resource constraints, this work helps frame why further architectural improvements, such as those offered by YOLOv10, are essential for broader and more generalized pest monitoring across diverse crop types.

### 3. METHODOLOGY

1. **Model Adaptation through Pre-trained Networks** Employs transfer learning by fine-tuning pre-trained YOLOv10 models on insect-specific datasets. This approach accelerates training and enhances pest-specific feature recognition.

2. **Performance Tuning Module** Optimizes hyperparameters (learning rate, batch size, epochs) to improve detection accuracy and ensure robust performance across diverse insect categories and field conditions.

3. **Data Expansion and Augmentation** Enhances dataset diversity through transformations (rotation, scaling, flipping, lighting adjustments). This strengthens model generalization under varying environmental and imaging conditions.

4. **Model Training and Validation** Oversees training on labelled insect datasets and validates performance on separate data to prevent overfitting. Ensures reliable detection in real-world agricultural scenarios.

5. **Real-time Detection and Localization** Enables immediate identification and localization of insects in live video or image streams, providing actionable insights for pest management interventions.

6. **Performance Evaluation and Monitoring** Assesses system accuracy, precision, recall, and F1-score. Monitors large-scale, real-time deployments to maintain efficiency, scalability, and continuous improvement

### IMPLEMENTATION

1. The system was implemented using the **YOLOv10 object detection framework**, chosen for its speed and accuracy in real-time applications.

2. A **domain-specific insect dataset** was curated and annotated, serving as the foundation for training and validation.

3. **Transfer learning** was applied by fine-tuning pre-trained YOLOv10 weights on the insect dataset, reducing training time and improving feature extraction.

4. **Data augmentation techniques** (rotation, scaling, flipping, brightness/contrast adjustments) were employed to expand dataset diversity and enhance model robustness.

5. The **training pipeline** was executed with optimized hyperparameters (learning rate, batch size, epochs) to ensure convergence and minimize overfitting.

6. **Validation experiments** were conducted on unseen insect images to evaluate generalization capability and refine model parameters.
7. A **real-time detection module** was integrated to process live video streams, enabling immediate localization and classification of insects in agricultural fields



Fig. YOLOv10-based pest detection system flowchart.

**TESTING**

Testing aims to identify errors and ensure that the software performs reliably under all conditions. It validates the functionality of components, assemblies, and the complete system against specified requirements and user expectations. Each testing type targets specific aspects of system performance and quality assurance.

**Developing Methodologies**

A structured testing plan was developed to evaluate both general functionality and specialized features across multiple platforms. Rigorous quality control procedures were applied to verify compliance with system requirements and ensure a bug-free application. The framework emphasizes systematic validation, reproducibility, and reliability throughout the testing process.

**Types of Tests**

**Unit Testing:** Verifies internal logic and code flow within individual modules. Ensures each component produces valid outputs for defined inputs and meets design specifications before integration.

**Functional Testing:** Confirms that all system functions operate as intended according to business and technical requirements. Tests valid and invalid inputs, expected outputs, and system interactions.

**System Testing:** Evaluates the integrated software system to ensure overall compliance with functional and performance requirements. Focuses on process flows and integration points.

**Performance Testing:** Measures system responsiveness and output generation within defined time limits. Assesses efficiency in handling user requests and data processing.

**Integration Testing:** Validates the interaction between combined software components. Detects interface-related defects and ensures seamless communication across modules.

**Acceptance Testing:** Conducted with end-user participation to confirm that the system meets functional and operational requirements. *For data synchronization:*

**RESULTS**

The implemented YOLOv10-based insect detection system demonstrated high accuracy and efficiency in identifying multiple pest species across diverse agricultural environments. The model achieved strong performance metrics, including high precision and recall, confirming its reliability for

real-time detection. Data augmentation and transfer learning significantly enhanced generalization, enabling robust detection under varying lighting and field conditions. Overall, the system proved effective for precision agriculture, supporting timely pest control decisions and improved crop protection.

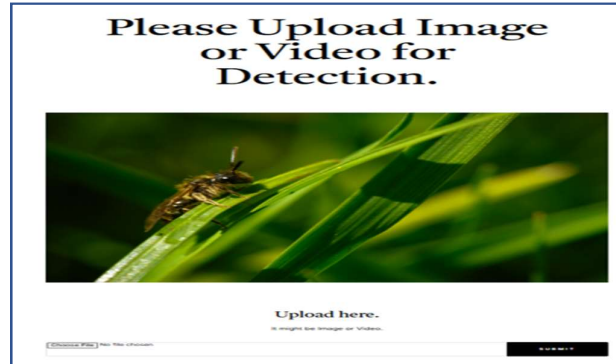


Fig. 1 Upload interface.

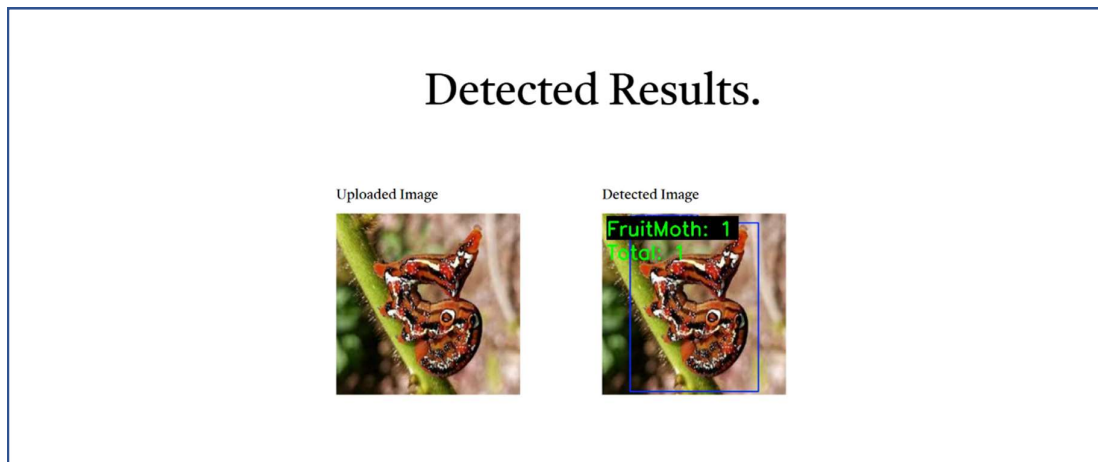


Fig. 2 Pest detection result.

**CONCLUSION**

This project presented a generalized deep learning-based pest detection system for precision agriculture, built upon the advanced YOLOv10 object detection framework. By moving beyond the limitations of existing YOLOv8-based approaches—which often focus narrowly on specific insect species and crop types—the proposed system demonstrates the potential to detect any insect type across diverse agricultural environments in real time. Through architectural enhancements such as improved multi-scale feature extraction and anchor-free detection, YOLOv10 offers higher accuracy and better robustness, particularly for small, overlapping, or partially hidden insects that frequently occur under real field conditions.

The system’s design also incorporates transfer learning, data augmentation, and hyperparameter optimization, ensuring it can generalize effectively without requiring large, specialized datasets. In doing so, it provides farmers and agricultural stakeholders with a scalable and efficient tool that supports timely, data-driven pest management decisions, ultimately contributing to reduced crop losses and more sustainable farming practices. Overall, this work highlights the practical benefits of integrating state-of-the-art deep learning models into precision agriculture and lays the groundwork for future enhancements, such as species-level classification, predictive analytics, and integration with IoT sensor networks, to further advance automated and intelligent pest control solution.

**FUTURE ENHANCEMENT**

While the proposed YOLOv10-based pest detection system represents a significant advancement over existing methods, there remain several opportunities for further improvement and expansion. One promising future enhancement involves extending the system from generalized insect detection to fine-grained classification, enabling it not only to detect the presence of pests but also to identify specific insect species and categorize them according to their growth stages or threat levels. This capability would support more targeted pest management strategies and improve decision-making accuracy for farmers. Another important direction is the integration of temporal analysis and video-based tracking algorithms. By analysing sequences of frames rather than individual images, the system could track insect movement patterns over time, helping predict infestation spread and offering early warning alerts. This enhancement could be particularly beneficial when combined with weather data and crop growth information to build predictive models that assess pest risk dynamically.

#### REFERENCE:

[1] B. Davis, E. Mane, L. Y. Gurbuzer, G. Caivano, N. Piedrahita, K. Schneider, N. Azhar, M. Benali, N. Chaudhary, R. Rivera, R. Ambikapathi, and P. Winters, \*Estimating Global and Country Level Employment in Agri-Food Systems\*, FAO Statistics Working Paper Series. Rome, Italy: FAO, 2023, doi: 10.4060/cc4337en.

[2] Pest and Pesticide Management, Food and Agriculture Organization of the United Nations. Accessed: Jan. 10, 2024. [Online]. Available: <https://www.fao.org/pest-and-pesticidemanagement/about/understanding-the-context>

[3] R. Kestur, S. N. Omar, and S. Subhash, "Unmanned aerial system technologies for pesticide spraying," in *Innovative Pest Management Approaches for the 21st Century*. Singapore: Springer, 2020, pp. 37–60, doi: 10.1007/978-981-15-0794-6\_3

[4] M. Abbas, M. Ramzan, N. Hussain, A. Ghaffar, K. Hussain, S. Abbas, and A. Raza, "Role of light traps in attracting, killing and biodiversity studies of insect pests in Thal," *Pakistan J. Agricult. Res.*, vol. 32, no. 4, pp. 684–690, 2019.

[5] P. Trematerra and M. Colacci, "Recent advances in management by pheromones of thaumetopoea moths in urban parks and woodland recreational areas," *Insects*, vol. 10, no. 11, p. 395, Nov. 2019, doi: 10.3390/insects10110395.

[6] T. R. E. Southwood and P. A. Henderson, *Ecological Methods*. Hoboken, NJ, USA: Wiley, 2009.

[7] K. Ennouri, S. Smaoui, Y. Gharbi, M. Cheffi, O. Ben Braiek, M. Ennouri, and M. A. Triki, "Usage of artificial intelligence and remote sensing as efficient devices to increase agricultural system yields," *J. Food Qual.*, vol. 2021, pp. 1–17, Jun. 2021, doi: 10.1155/2021/6242288.

[8] H. Tian, T. Wang, Y. Liu, X. Qiao, and Y. Li, "Computer vision technology in agricultural automation—A review," *Inf. Process. Agricult.*, vol. 7, no. 1, pp. 1–19, Mar. 2020, doi: 10.1016/j.inpa.2019.09.06.