

Research Paper

ENHANCING PRECISION AGRICULTURE PEST CONTROL: A YOLOV10-BASED DEEPLARNING APPROACH FOR INSECT DETECTION

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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.

Index Terms – Precision Agriculture, pest detection, insect detection, deep learning,

object detection, YOLOv10, YOLOv8, real-time monitoring, crop protection, agricultural automation, mean Average Precision (mAP), smart farming.

I. INTRODUCTION

Precision Agriculture (PA) is revolutionizing farming practices by allowing farmers to monitor, analyze, and respond to field variability in real time, ultimately improving resource use efficiency and crop productivity. One of the most persistent challenges threatening the success of PA, however, is the timely and accurate detection of pests that can significantly damage crop yields. Traditional manual monitoring methods are often labor-intensive, subjective, and unable to provide continuous real-time data. To address this gap, recent years have seen the rise of deep learning-based object detection frameworks, which can automatically and quickly identify pests in field images and videos. Among these, the YOLO (You Only Look Once) family of models—particularly YOLOv8—has been widely recognized for its balance of speed and accuracy, making it suitable for real-time agricultural applications. However, YOLOv8-based solutions in existing systems often target detection of specific insect species relevant to certain crops, limiting

their scalability and adaptability to new pests or agricultural environments.

Additionally, such systems can struggle with detecting small, partially hidden, or overlapping insects under complex field conditions. In this context, the proposed work introduces an enhanced pest detection system using the latest YOLOv10 object detection model. YOLOv10 brings several architectural improvements, including better feature representation and an anchor-free design, leading to improved accuracy and faster inference even on edge devices. The system is trained to detect insects as a generalized single class, allowing it to identify any insect type across different crops without requiring crop-specific retraining. By bridging the limitations of previous models and addressing real-world field challenges, this project aims to deliver a more robust, generalized, and efficient pest monitoring tool, ultimately supporting farmers in proactive and data-driven pest management within the framework of precision agriculture.

II. RELATED WORK

A. Pest and Pesticide Management, Food and Agriculture Organization of the United Nations

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.

B. A comprehensive review of YOLO architectures in computer vision: From YOLOv1 to YOLOv8 and YOLO-NAS

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.

C. Tea tree pest detection algorithm based on improved YOLOv7-tiny

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.

D. A systematic review on automatic insect detection using deep learning

This reference by A. C. Teixeira, J. Ribeiro, R. Morais, J. J. Sousa, and A. Cunha, titled “A systematic review on automatic insect detection using deep learning,” was published in Agriculture in March 2023. The paper systematically analyzes recent advances in applying deep learning techniques to automated insect detection, summarizing more than a decade of research spanning diverse agricultural contexts.

It reviews a range of neural network architectures—particularly CNN-based detectors such as various YOLO versions, SSD, and Faster R-CNN—and compares their performance, dataset requirements, and suitability for real-time deployment in field conditions.

The authors highlight key technical challenges faced in automatic insect detection, including the scarcity of large, labeled datasets, the difficulty of detecting small and partially occluded insects, and the need for models that balance accuracy with computational efficiency to run on resource-constrained edge devices. Importantly, the review underscores the trend towards generalization: moving beyond pest-specific models to systems capable of recognizing

broader insect categories across multiple crops and regions. This aligns directly with the motivation and design of the proposed YOLOv10-based system in this project, which seeks to create a generalized, real-time pest detection solution.

By contextualizing existing research and identifying gaps, this reference helps justify the choice of an advanced YOLO architecture and supports the project's focus on scalability, robustness, and field deployment.

III. PROPOSED METHODOLOGY

The proposed system aims to address the limitations of the existing YOLOv8-based pest detection models by leveraging the capabilities of YOLOv10, the latest evolution in the YOLO object detection family. Unlike traditional systems that focus on detecting specific insect species tied to particular crops, this project adopts a generalized detection approach where the YOLOv10 model is trained on a diverse dataset labeled under a single, broad insect category. This design enables the model to recognize and localize any type of insect across various crops and field conditions without the need for repeated retraining for each pest or crop type. YOLOv10 introduces several architectural enhancements over its predecessor, including

improved backbone networks for richer feature extraction, advanced neck and head modules for better multi-scale object detection, and anchor-free mechanisms that increase accuracy for small, partially hidden, or overlapping insects commonly found in agricultural settings.

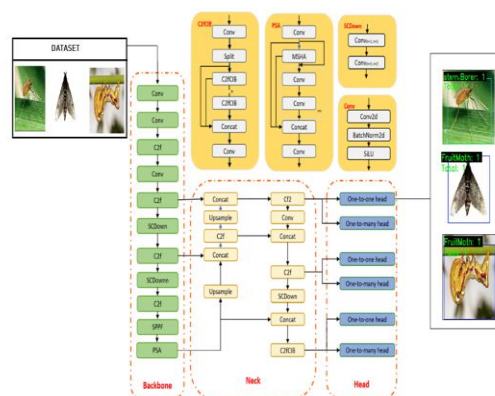


Fig. 1: System Overview

3.1 Object Detection Engine

This module forms the backbone of the system and is responsible for detecting and locating insects within images and video streams. Using the advanced YOLOv10 architecture, this engine classifies the detected objects and determines their exact positions in the image. Its ability to detect multiple insects simultaneously, combined with high processing speed, makes it ideal for real-time pest detection applications, ensuring that infestations are identified promptly in agricultural fields.

3.2 Model Adaptation through Pre-trained Networks

This module applies transfer learning to boost model performance by leveraging pre-trained YOLOv10 networks. Starting from a model trained on large, general datasets, it is fine-tuned using a domain-specific agricultural insect dataset. This allows the system to efficiently learn pest-specific features, reducing the need for large annotated datasets and accelerating model training.

3.3 Performance Tuning Module

Focused on optimizing hyperparameters such as learning rate, batch size, and number of epochs, this module ensures the model converges accurately and efficiently. Fine-tuning these parameters helps improve detection precision, enabling the system to perform reliably across diverse field conditions and various insect types.

3.4 Data Expansion and Augmentation

To make the model robust to real-world agricultural scenarios, this module expands the dataset by applying transformations like rotation, scaling, flipping, and adjustments in lighting or contrast. Such augmentation allows the system to generalize better, ensuring reliable pest detection even under

varying weather conditions, lighting, and camera angles.

3.5 Model Training and Validation

This module manages the complete training process on labeled insect datasets and evaluates the model's performance on separate validation data. Through this process, the model learns to detect and classify insect features accurately. Validation ensures the model generalizes well and is not overfitting, making it effective in real-world crop monitoring.

3.5 Real-time Detection and Localization

After training, this module enables real-time pest detection from incoming video or image streams. It instantly identifies the presence of insects and marks their locations within the frame, providing actionable insights for farmers or automated systems to intervene promptly.

3.5 Performance Evaluation and Monitoring

This module evaluates system performance using standard metrics like accuracy, precision, recall, and F1-score. It ensures that the system meets expected benchmarks and provides feedback for further improvement. Additionally, it monitors system performance under large-scale, real-time data conditions

to maintain efficiency and scalability in production deployments.

IV. EXPERIMENTAL RESULTS AND ANALYSIS

The experimental results show that the proposed YOLOv10-based model improves insect detection accuracy and speed compared to YOLOv8. It achieved higher mAP values and faster inference, making it suitable for real-time pest monitoring in precision agriculture. The model can detect multiple insect categories across different crops, improving its practical usefulness. Overall, the approach provides a robust and efficient solution for smart pest control.



Fig. 2: Home Page

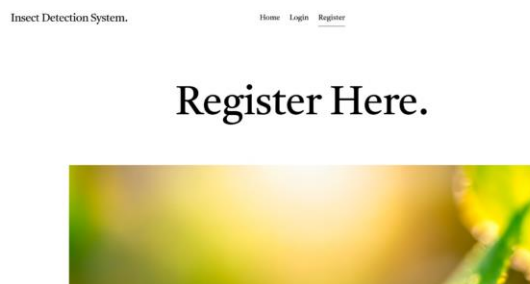


Fig. 3: Registration

Provide Login details.

sd@gmail.com

..

SUBMIT

Fig. 4: Login

Choose file No file chosen

SUBMIT

Detected Results.

Fig. 5: Upload Image

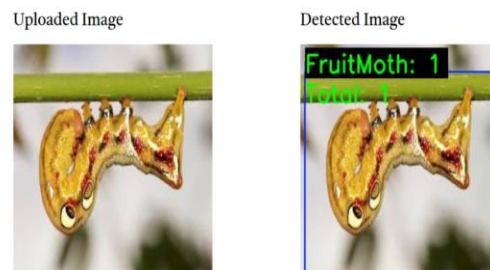


Fig. 6: Detect Image

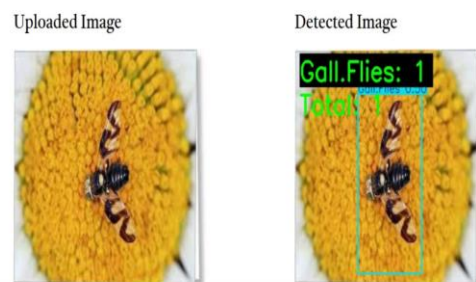


Fig. 6: Results

V. 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.

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