Enhancing Precision Agriculture Pest Control: A YOLOv10 Based Deep Learning Approach for Insect Detection

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Publication History
Manuscript Reference No: IJIRIS/RS/Vol.12/Issue04/ISAP26.ISAP10084
Research Article | Open Access | Double-Blind Peer-Reviewed| ArticleID: IJIRAE/RS/Vol.12/Issue04/ISAP26.ISAP10084
Received:02,March 2026, Revised: 29, March 2026, Accepted: 10,April 2026,Published Online: 22, April 2026.
https://www.ijiris.com/volumes/Vol12/iss-04/05.ISAP26.ISAP10084.pdf

Article Citation:Ratnamala,Gumparlapati,Jerripothula,Kalwala(2026),Enhancing Precision Agriculture Pest Control: A YOLOv10 Based Deep Learning Approach for Insect Detection.IJIRIS: International Journal of Innovative Research in Information Security, Volume 12, Issue 04 of 2026 pages 287-295

Doi:> https://doi.org/10.26562/ijiris.2026.v1204.05 **BibTeX Key: Ratnamala@2026Enhancing**

IJIRIS papers should be cited as IJIRIS(International Journal of Innovative Research in Information Security, AM Publications, India 2026, ISSN 2349-7017, https://doi.org/10.26562/ijiris.2026.v1204.05 The journal's official abbreviation is IJIRIS. Orcid: https://orcid.org/0009-0004-9398-7488

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 (PA), YOLOv10, Insect Detection, Mean Average Precision (mAP), Convolutional Neural Networks (CNNs), Edge Deployment, Integrated Pest Management (IPM), Anchor-Free Detection, Data Augmentation, Performance Metrics, Sustainable Pest Control

I. INTRODUCTION

Precision Agriculture (PA) leverages advanced technologies to optimize resource use and improve crop productivity. Pest infestations, however, remain a major obstacle, often reducing yield and quality. Traditional monitoring methods are manual, labor-intensive, and lack real-time accuracy, limiting their effectiveness in large-scale farming.Deep learning frameworks, particularly the YOLO (You Only Look Once) family, have shown promise in automating pest detection. YOLOv8 achieved strong results but is restricted to crop-specific pests and struggles with small or overlapping insects. These limitations reduce scalability and adaptability in diverse agricultural environments. This study introduces a YOLOv10-based pest detection system designed for generalized insect identification across multiple crops. YOLOv10's anchor-free design and improved feature representation enable higher accuracy and faster inference. By training on a comprehensive insect dataset labeled under a single class, the system eliminates crop-specific retraining and enhances adaptability.The objective is to deliver a robust, real-time, and scalable pest monitoring tool that strengthens precision agriculture, reduces pesticide dependency, and supports sustainable crop protection.

II. LITERATURE SURVEY

Wenxia Yuan, Yuxuan Liu, Yifan Zhang, Yuxuan Wang, Yifan Liu (2025)

This paper introduces I-YOLOv10-SC, a customized YOLOv10 model enhanced with spatial-channel attention for pest detection in tea plantations. The approach improves recognition of tiny, camouflaged, and partially hidden pests under complex field conditions. A specialized dataset with diverse real-world images and data augmentation was used to train the model. Benchmarked against YOLOv5 and YOLOv8, it achieved superior precision, recall, and inference speed. Lightweight convolutional blocks and efficient attention modules reduce computational cost, enabling deployment on mobile devices, drones, and edge platforms. The study demonstrates I-YOLOv10-SC as a robust, scalable solution for smart agriculture.

Balaji Ganesh Rajagopal, S. S. Sruthi, S. S. Sreeja, S. S. Sreelakshmi (2025)

This paper compares YOLOv8, YOLOv9, YOLOv10, and YOLOv11 for pest detection in precision agriculture using the NBAIR dataset. Results show YOLOv9 achieving the highest accuracy (93%, mAP@0.5 = 0.959), while YOLOv10 offers the best balance of precision and efficiency, making it suitable for real-time deployment on mobile and edge devices. YOLOv11 demonstrates strong detection but requires high computational resources, limiting low-power use. The study emphasizes accuracy, speed, and hardware constraints as key factors in selecting models for smart farming applications.

Mario Vilar-Andrew, Laura Garcia, Antonia-Javier, Joan Garcia-Haro (2024)

This paper presents a deep learning framework for real-time insect detection in precision agriculture using the YOLOv8 model. By automating pest monitoring, the system addresses the limitations of manual methods and improves scalability. The model, trained on diverse agricultural datasets with data augmentation and transfer learning, achieves high mean Average Precision (mAP) and robust detection of small or overlapping insects. Its lightweight design supports deployment on drones and mobile devices, enabling real-time field monitoring. The study concludes that YOLOv8-based detection enhances sustainable agriculture by facilitating early pest identification, reducing pesticide reliance, and offering adaptability across crops and regions.

Sen Yang, Gang Zhou, Yuwei Feng, Jiang Zhang, Zhen Hong Jia (2024)

This paper introduces SRNet-YOLO, a hybrid model combining super-resolution reconstruction with YOLO to detect tiny pests in cotton fields. By enhancing low-quality images and applying multi-scale feature fusion with attention mechanisms, the model improves recognition of pests occupying only a few pixels. Trained on a custom cotton dataset, SRNet-YOLO outperforms YOLOv5 and Faster R-CNN in accuracy and recall. Its lightweight design enables deployment on mobile devices and UAVs, supporting real-time monitoring and sustainable pest management.

III. EXISTING SYSTEM

The existing system for automated pest detection in precision agriculture relies heavily on YOLOv8, a single-stage CNN-based object detector capable of real-time identification of pests through simultaneous bounding box and class prediction. Trained on crop-specific datasets, YOLOv8 achieves strong accuracy under controlled conditions and has proven effective for timely pest monitoring. However, its performance declines in diverse field environments where insects are small, occluded, clustered, or present against complex backgrounds with varying lighting and weather. Moreover, while faster than earlier models, YOLOv8 remains computationally demanding on low-power edge devices, limiting scalability. As a result, current YOLOv8-based systems, though advanced, remain specialized and insufficient for comprehensive, large-scale pest detection in precision agriculture.

Existing System Disadvantages

- Limited to specific insect species tied to certain crops
- Reduced accuracy when insects are small, hidden, or overlapping
- Requires retraining for every new pest or crop type
- Higher computational load limits real-time deployment on edge devices
- Performance drops under changing lighting and complex field backgrounds

Proposed System

The proposed system leverages YOLOv10 to overcome the limitations of YOLOv8-based pest detection by adopting a generalized approach, training on diverse datasets labeled under a single insect category to enable recognition across multiple crops and environments without retraining. YOLOv10 introduces architectural enhancements such as improved backbone networks, advanced neck and head modules, and anchor-free mechanisms, boosting accuracy for small, hidden, or overlapping pests. Alongside higher detection precision, the model offers efficient inference and lightweight scalability, making it suitable for real-time deployment on edge devices like drones, cameras, and mobile applications. Covering the full pipeline from preprocessing to visualization, the system enhances robustness against variable field conditions and supports faster, data-driven decisions, ultimately reducing crop losses and promoting sustainable pest management in precision agriculture.

Proposed System Advantages:

- Generalized detection of any insect type across multiple crops
- Improved accuracy for small, occluded, and clustered insects
- Lower computational requirements make it suitable for edge devices
- Greater robustness under diverse lighting and complex backgrounds

IV. SYSTEM ARCHITECTURE

The deep learning architecture for insect detection/classification consists of four stages: the Dataset, which provides raw insect images for training and testing; the Backbone, which extracts features using convolutional layers, residual blocks (C2f), down sampling (SC Down), spatial pyramid pooling (SPPF), and parallel split attention (PSA) to capture multi-scale and region-focused features; the Neck, which fuses multi-scale features through concatenation, up sampling, refinement blocks (C2f/C2fB), and additional down sampling to balance scales; and the Head, which generates final predictions using one-to-one and one-to-many heads, outputting bounding boxes and labels for detected pests. Specialized modules such as C2fCB, PSA with multi-scale head attention, and SC Down with BatchNorm2d and SLU further enhance feature learning, stability, and accuracy, enabling robust detection of tiny, occluded, or overlapping insects in complex agricultural environments.

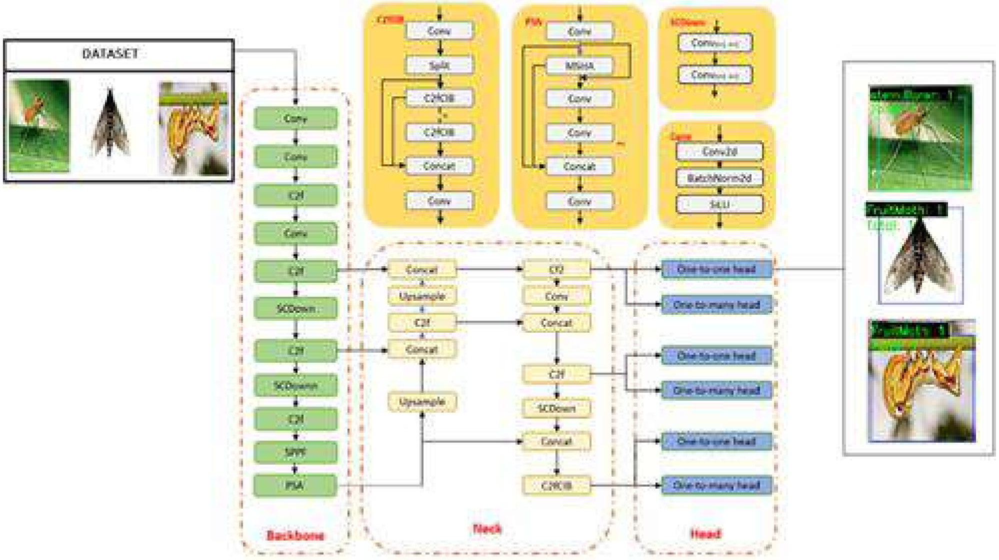


Fig 1.1 System Architecture

Methodology

Modules Name:

1. Object Detection Engine
2. Model Adaptation through Pre-trained Networks
3. Performance Tuning Module
4. Data Expansion and Augmentation
5. Model Training and Validation
6. Real-time Detection and Localization
7. Performance Evaluation and Monitoring

Object Detection Engine:

This module forms the backbone of the system and is responsible for detecting and locating insects within images. 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.

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.

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.

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.

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.

Real-time Detection and Localization:

After training, this module enables real-time pest detection from incoming 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.

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.

V. IMPLEMENTATION

The implementation phase converts the conceptual design of the YOLO10-Insect Detection system into a fully functional real-time detection application. This stage involved configuring the development environment, writing source code, preparing datasets, training models, and integrating visualization dashboards for performance evaluation. The architecture is modular, separating the machine learning backend from the interactive frontend, ensuring scalability and responsiveness.

Algorithm Used - Existing Algorithm

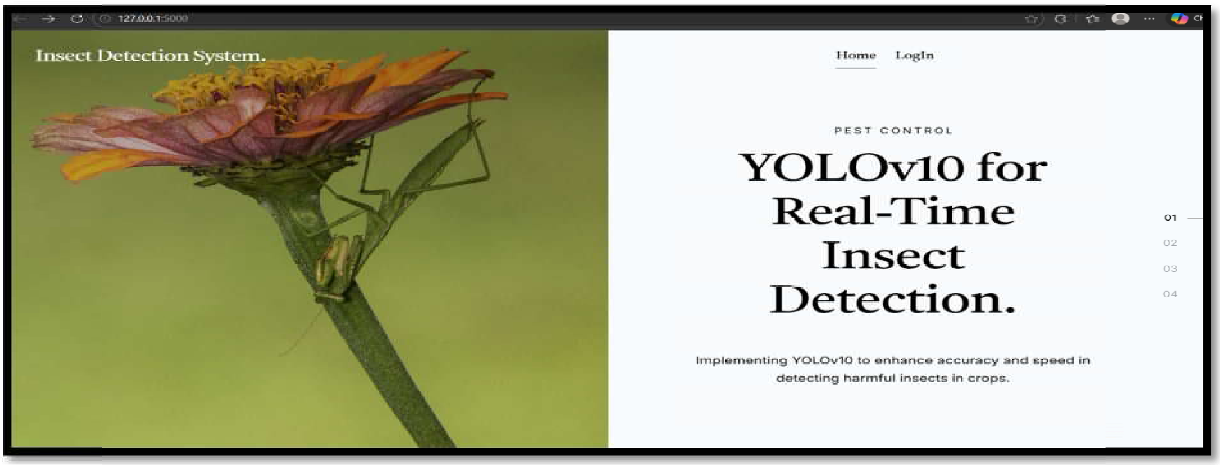
YOLOv8s, a lightweight single-stage object detector, is widely used in precision agriculture for real-time pest detection due to its balance of speed, accuracy, and efficiency. It processes entire images in one pass, predicting bounding boxes and class probabilities to detect multiple insects simultaneously. Architectural improvements like a decoupled head, enhanced feature fusion, and a stronger backbone yield higher mAP and faster training convergence compared to earlier YOLO versions. Trained on crop-specific annotated datasets, YOLOv8s achieves strong accuracy under controlled conditions but faces challenges in complex field environments with variable lighting, occlusion, or overlapping insects. Its reliance on species-specific data limits generalization to unknown pests, while deployment on edge devices can still strain resources. Moreover, adapting to new pests or crops typically requires retraining or fine-tuning, adding to data and computational costs.

Proposed Algorithm - YOLOv10:

The proposed pest detection system leverages YOLOv10, an advanced anchor-free object detection framework designed for complex agricultural environments with small, overlapping, and occluded insects. Its improved backbone and multi-scale feature aggregation enhance accuracy and robustness while maintaining real-time efficiency on edge devices like drones and field cameras. Unlike species-specific models, it generalizes by labeling all insects under a single class, enabling detection across crops and regions without retraining for each new pest. Transfer learning from large datasets, domain-specific fine-tuning, and data augmentation improve adaptability to diverse field conditions, while optimized hyperparameters ensure efficient convergence. Rigorous evaluation using accuracy, precision, recall, and F1-score validates its scalability, making YOLOv10 a more flexible, robust, and sustainable solution for precision-driven pest management.

VI. EXPERIMENTAL RESULTS

Home Page:



Insect Detection System.

PEST CONTROL

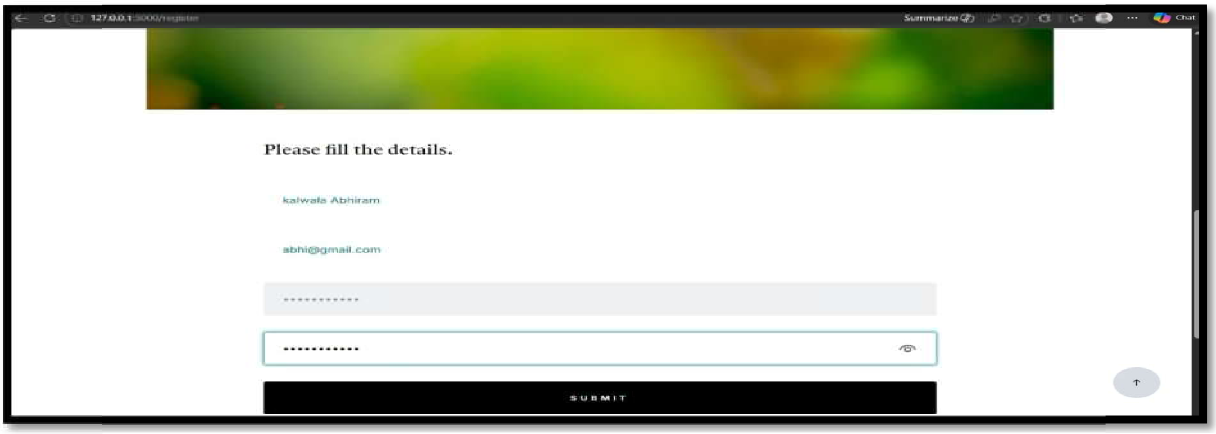
YOLOv10 for Real-Time Insect Detection.

Implementing YOLOv10 to enhance accuracy and speed in detecting harmful insects in crops.

Fig 2: Home Page

The interface serves as the entry point to the Insect Detection System, combining a clean design with an agricultural image to convey its purpose. A simple navigation bar provides access to Home and Login, while the main section emphasizes the project's goal—leveraging YOLOv10 for fast, accurate real-time pest detection in crops.

Registration Page:



Please fill the details.

kalwala Abhiram

abhi@gmail.com

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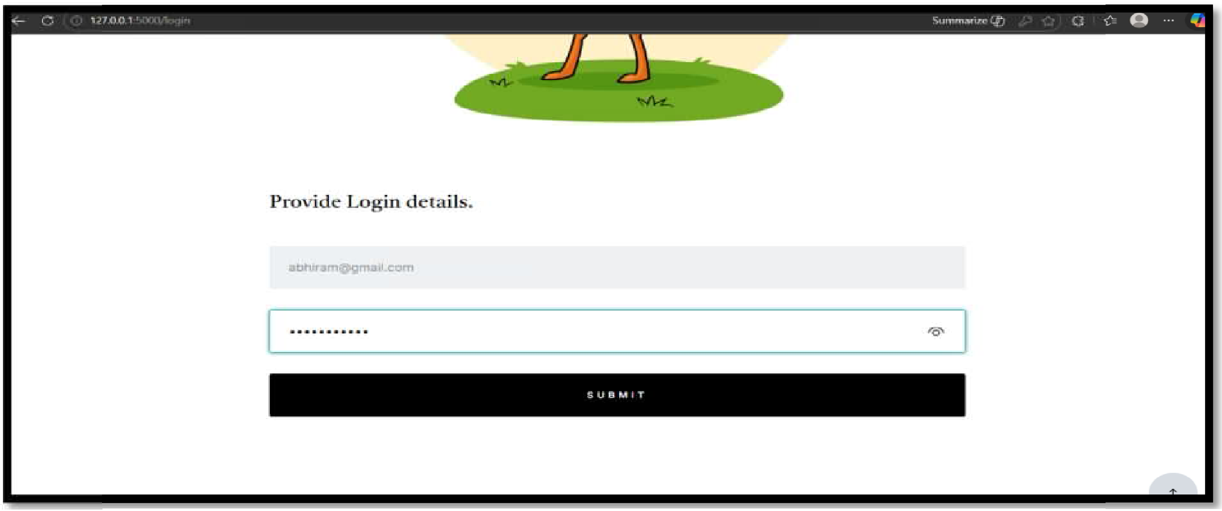
Fig 3: Registration Page

The registration interface follows a minimalist design with fields for name, email, and password plus a clear Submit button. It ensures quick, simple onboarding so farmers, researchers, and other users can easily create accounts and access the insect detection tools.

Login Page:



Provide Login details.

abhiram@gmail.com

Fig 4: Login Page

The login page acts as a secure gateway to the insect detection system, requiring email and password for straightforward authentication. Its minimalist design with clear input fields and a bold Submit button emphasizes privacy, usability, and trust, giving users access to core modules like image uploading, detection, and analysis once authenticated.

Dashboard Page:

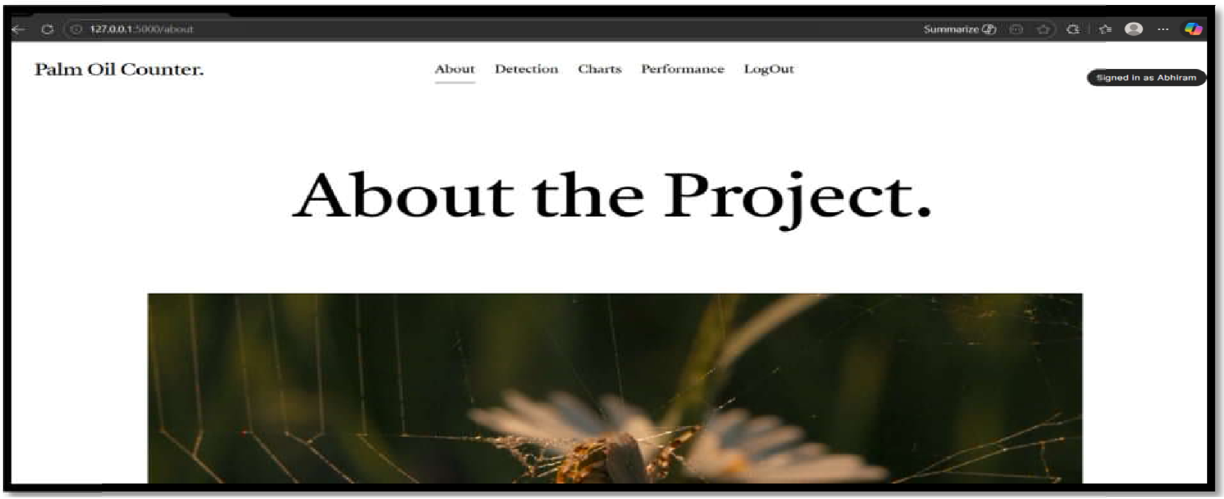


Fig 5: Dashboard Page

The dashboard provides a personalized hub after login, confirming the active session while offering modules like Detection, Charts, and Performance for core functionality. An About section adds project context, making the design clear, welcoming, and practical as the central navigation point for the insect detection system.

Detection Entry Point Page:

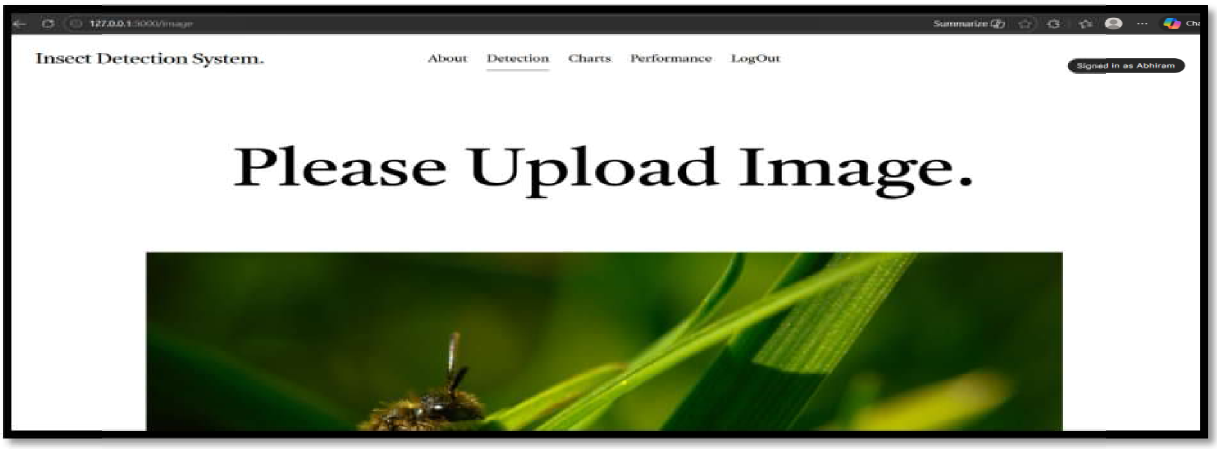
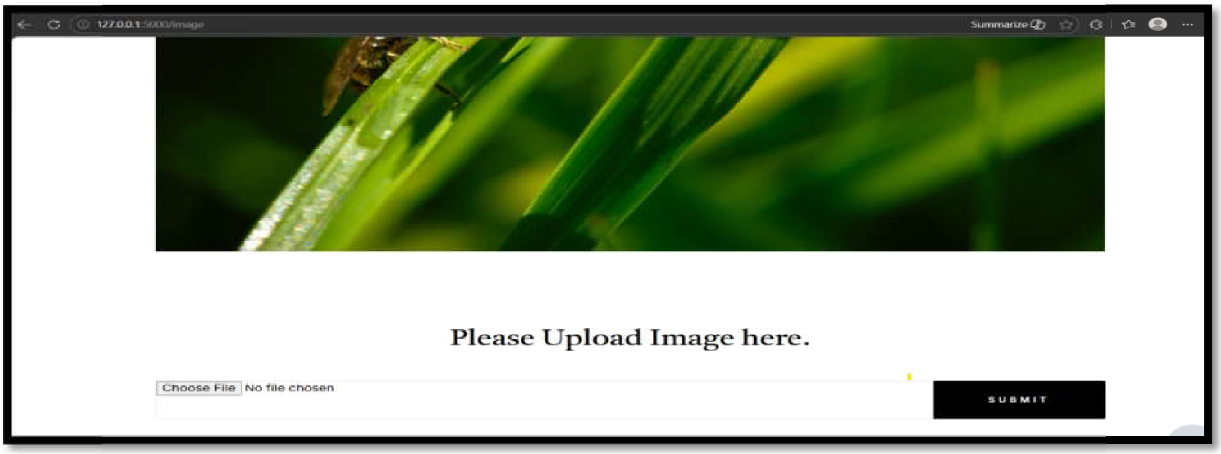


Fig 6: Detection Entry Point Page

This section guides users to upload an image for analysis, with a clear “Please Upload Image” prompt ensuring the next step is obvious. Once uploaded, the YOLOv10 model performs real-time insect detection with high accuracy, combining a simple interface with advanced technology to support practical pest control in agriculture.

File Upload Interface:



Please Upload Image here.

Fig 7: File Upload Interface

This page represents the data input stage, where users browse and select local image files for analysis. With a simple upload field and Submit button, it supports static formats and prepares data for YOLOv10 inference, making pest detection accessible and straightforward for farmers, researchers, and other users.

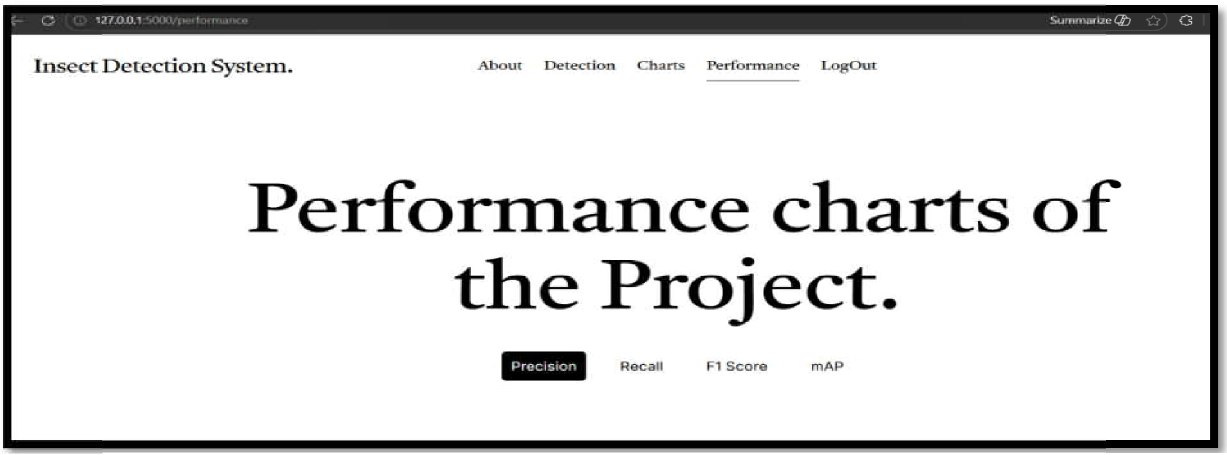
Real-Time Detection Results:

Detected Results.

Fig 8: Real-Time Detection Results

This page shows the detection output with a dual-view: the left side displays the original uploaded image, while the right side presents the YOLOv10-processed result. Bounding boxes and labels like “FruitMoth: 1” and “stem.Borer: 1” indicate insect types and counts, allowing users to directly compare input and output. This setup makes detection transparent, highlights accuracy, and demonstrates the system’s ability to classify multiple pests within a single image for effective monitoring.

Performance Metrics Overview Page:



Performance charts of the Project.

Fig 9: Performance Metrics

The Performance Evaluation and Monitoring module ensures the insect detection system meets benchmarks under real-world conditions using metrics like accuracy, precision, recall, F1-score, and mAP. It provides performance visualization, feedback loops for refinement, and monitors scalability, making it a central tool for reliability and long-term sustainability.

Precision-Confidence Evaluation Page:

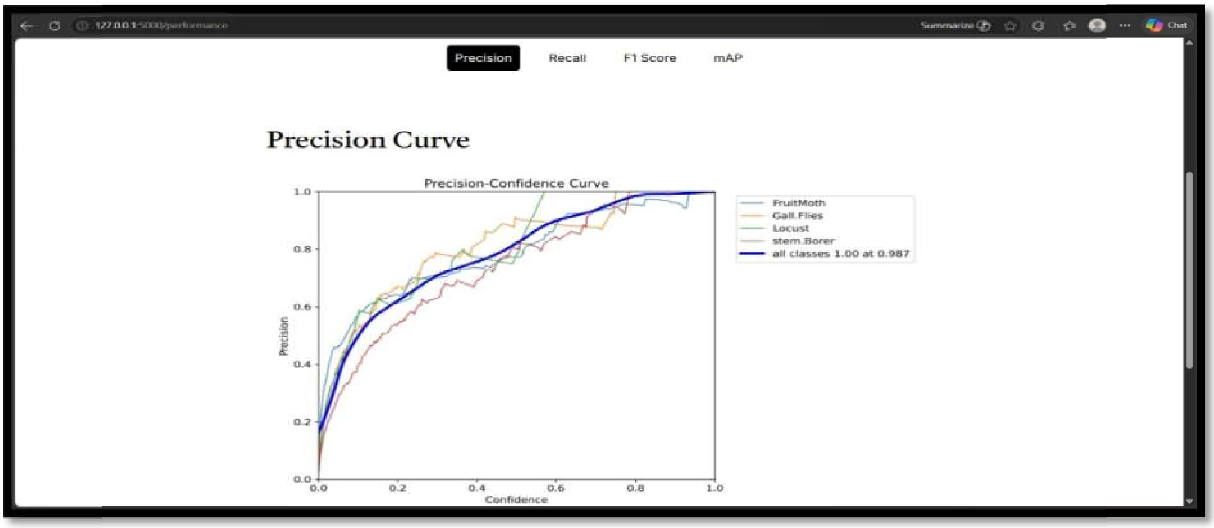


Fig 10: Precision-Confidence Evaluation Page

The Precision-Confidence Curve shows how precision varies with confidence thresholds. Each line represents an insect class, while the purple line indicates overall performance. Lower thresholds yield more detections but less precision, and higher thresholds improve precision. The near-perfect overall curve highlights the system's strong reliability in minimizing false alarms.

Recall-Confidence Evaluation Page:

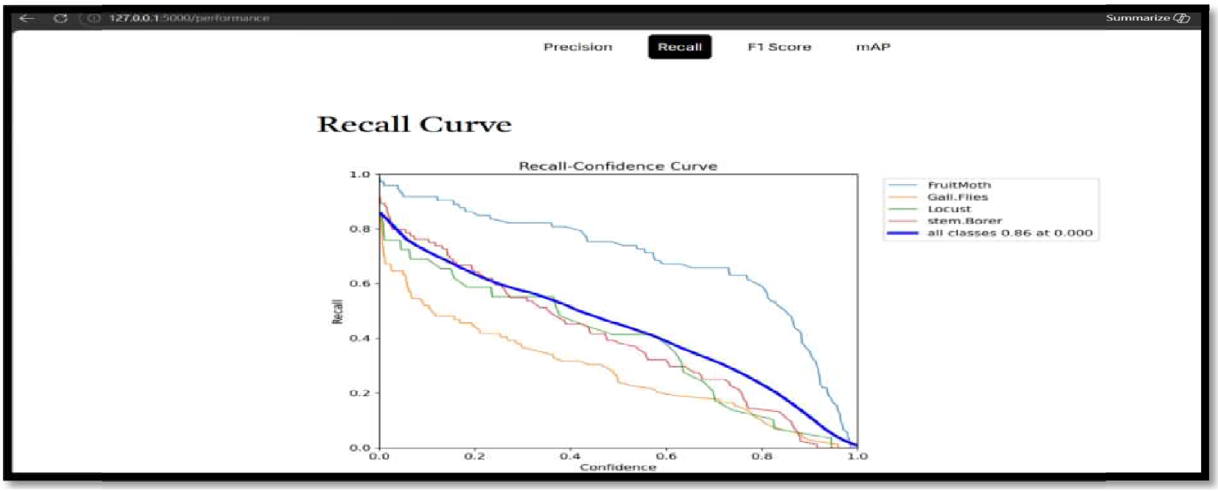


Fig 11: Recall-Confidence Evaluation Page

The Recall-Confidence Curve shows how recall changes with confidence thresholds. Each line represents an insect class, while the dark blue line indicates overall performance. At low thresholds, recall is high since more insects are detected, but as confidence increases, recall drops as the model becomes stricter. The overall curve highlights strong detection coverage at lower thresholds, balancing recall with the risk of false positives.

F1 Score Analysis:

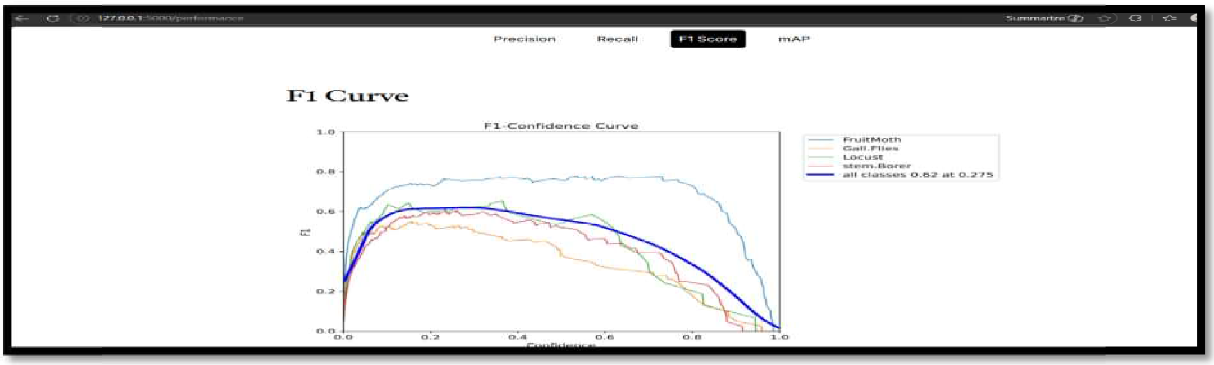


Fig 12:F1 Score Analysis

The F1-Confidence Curve shows how the F1 score changes with confidence thresholds. Each line represents an insect class, while the overall line peaks at 0.62 when the threshold is 0.275, marking the best balance between precision and recall. This highlights the model's optimal trade-off point and reveals class-specific performance differences across thresholds.

Mean Average Precision (mAP) Evaluation:

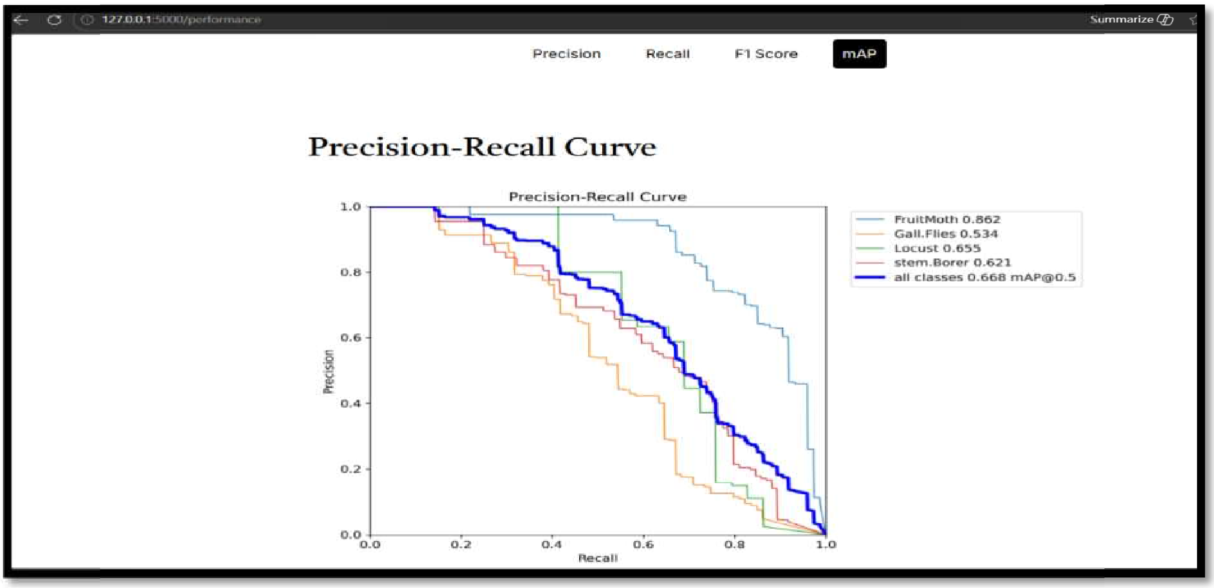


Fig 13: Mean Average Precision (mAP) Evaluation

The Precision-Recall Curve shows model performance across insect classes, with recall on the x-axis and precision on the y-axis. FruitMoth achieves the highest average precision (0.862) and GallFlies the lowest (0.534), while the overall mAP@0.5 is 0.668, summarizing effectiveness and the trade-off between detection coverage and false alarms.

VII. CONCLUSION

In conclusion, this project introduces a generalized pest detection system for precision agriculture using YOLOv10, moving beyond YOLOv8's species-specific limitations to detect any insect type across diverse crops in real time. With anchor-free detection, improved multi-scale feature extraction, transfer learning, data augmentation, and hyperparameter optimization, the system achieves higher accuracy and robustness, especially for small or overlapping pests in complex field conditions. It provides farmers with a scalable, efficient tool for timely, data-driven pest management, reducing crop losses and supporting sustainable farming, while laying the groundwork for future enhancements like species-level classification, predictive analytics, and IoT integration.

VIII. FUTURE ENHANCEMENT

Future research directions include the improvement of the algorithms to use other comprehensive features, thereby achieving better performance.

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