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**International Journal of Recent Advances in Engineering and Technology**

ISSN: 2347-2812
Volume 14 Issue 1s, 2025

# AI-Powered Pest Management System

Prof. A. P. Bangar[1], S. B. Bhosale[2], Sukanya Gitaram Varpe[3], Savitra Shivaji Giri[4], Rohan Rajendra Gadekar[5]

*[1,2,3,4,5]Dept. of Computer Engineering Jaihind College of Engineering, Kuran, India wc.abhibangar@gmail.com[1], ssachinbhosale@gmail.com[2]sukanyavarpe10@gmail.com[3],savitragiri12@gmail.com[4], rohangadekar07@gmail.com[5]*

**Peer Review Information**

*Submission: 20 Jan 2025*
*Revision: 24 Feb 2025*
*Acceptance: 27 March 2025*

**Keywords**

*Pest Detection*
*Agriculture*
*Robot*
*YOLOv10*
*IP102*

**Abstract**

This study develops an autonomous robotic system designed to improve pest monitoring and control in agricultural settings. Conventional approaches, such as manual sticky traps, are often time-consuming and expensive. Our robot utilizes high-resolution cameras and multispectral imaging to monitor crops, collecting pest-related data that is processed using computer vision algorithms. The system relies on the IP102 dataset and the YOLOv10 model to detect harmful insects, distinguishing between stationary and flying species. Targeted pest control measures are then deployed: stationary pests are treated with precise organic or chemical sprays based on the extent of crop damage, while flying insects are eradicated with laser technology—using multi-diode lasers for groups and single-diode lasers for individuals. GPS ensures the robot stays within field boundaries, and a GSM module sends alerts to the farmer. This innovation seeks to reduce pesticide usage, contributing to more sustainable and efficient agricultural practices.

## INTRODUCTION

Insects present a significant threat to both agricultural productivity and public health, as many species are not only crop pests but also vectors for diseases that can impact both human and animal populations. These pests damage crops, reduce yields, and contribute to the depletion of food supplies globally. Traditional pest management methods, including the use of sticky traps and manual inspections, are not only labor-intensive and costly but often involve the use of broad-spectrum pesticides that can harm ecosystems and the environment. With the growing need for more efficient and sustainable agricultural practices, there is an urgent demand for innovative pest control solutions that are more targeted, cost-effective, and environmentally responsible.

This project seeks to address these challenges by designing and developing an autonomous robotic system capable of performing real-time pest identification and providing targeted pest control interventions. The goal is to enhance agricultural productivity while promoting environmental sustainability by reducing pesticide dependency. The motivation behind this work lies in the potential of emerging technologies such as computer vision, machine learning, and robotics to revolutionize pest management. By incorporating advanced imaging systems and AI-powered algorithms, such as YOLOv10, the robot can accurately identify harmful insects, distinguish between different species, and categorize them as either stationary or flying.
This detailed analysis allows for the application

of tailored responses. For instance, the robot can deploy precise amounts of organic or chemical sprays based on an assessment of crop damage. Additionally, flying pests can be eliminated using advanced laser technology, offering an innovative pest control method. The robot is further equipped with GPS for accurate field navigation, ensuring it operates efficiently within the designated crop areas. A GSM module is integrated to notify the farmer about the robot's actions, offering real-time communication and situational awareness. Overall, this solution provides a promising, cost-effective alternative to traditional pest control practices, combining automation with sustainability to improve agricultural practices while reducing the environmental footprint.

**LITERATURE SURVEY**

Vilar-Andreu et al. "Enhancing Precision Agriculture Pest Control: A Generalized Deep Learning Approach With YOLOv8-Based Insect Detection",[4] The paper explores transforming the IP102 dataset into a single "insect" class using methodologies such as Dataset Analysis, Data Augmentation, and Evaluation Metrics with YOLOv8. The images are labeled in YOLO format, and YOLOv8 employs block architecture for data augmentation, performing adjustments to hue, saturation, and value. While the model shows good performance in certain situations, it struggles with low confidence in detection, inefficiencies when insects move, challenges in detecting insects at greater distances, and issues with light variations.

Subhashini et al. "Insect Identification in Field Crops Using CNN",[7] This paper proposes the use of CNN to assist farmers in identifying and managing pests, thereby improving crop yield. The approach involves image preprocessing, segmentation, and feature extraction, with the model evaluated using metrics such as precision, recall, F1 score, and accuracy based on an independent dataset. Deployed in a real-world environment with a microcontroller, GSM module, and Relay, the system achieves an accuracy of 90.7%. The system alerts farmers and triggers pesticide spraying. However, the accuracy is heavily reliant on the quality of the dataset, and the use of pesticides may negatively affect the quality of the produce.

Satpute et al. "Dangerous Farm Insects Detection Using Transfer Learning and CNN",[3] This paper investigates the use of machine learning and transfer learning for detecting dangerous farm insects by utilizing the Dangerous Farm Insects Image Dataset. The study focuses on identifying the most effective network architecture for insect classification. Among various models tested, the Xception model showed the highest accuracy, emphasizing the role of hyperparameter tuning in improving performance. However, the dataset's limited classes and the model's reliance on a specific dataset may hinder its ability to generalize across different insect species. Extending the dataset could potentially lead to performance issues.

Kumaran et al. "Crop Pest Control using IoT Real-Time Monitoring and Intervention",[11] This study proposes an IoT-based system for real-time agricultural pest control, integrating sensors that monitor temperature, humidity, soil moisture, light, and wind speed. The system utilizes machine learning algorithms for pest detection and employs a real- time decision support system for immediate intervention. The application of biopesticides through the system is shown to improve agricultural yield. However, the model must be durable, energy-efficient, and compatible with agricultural equipment. Data security and potential data loss are significant concerns that need to be addressed.

Kasinathan et al. "Insect Classification and Detection in Field Crops Using Modern Machine Learning Techniques,"

[8] This research introduces a machine learning model for insect classification using the Wang and Xie dataset. The model utilizes image preprocessing, augmentation methods, and shape feature extraction alongside algorithms like ANN, SVM, KNN, and NB. The study compares these models with CNN. However, the focus is on fully grown insects, neglecting larvae stages. Additionally, detection accuracy is hindered by challenges such as shadows, leaves, dirt, branches, and flower buds in the images.

Wu et al. "IP102: A Large-Scale Benchmark Dataset for Insect Pest Recognition,"[9] This paper evaluates state-of- the-art recognition methods using the IP102 dataset, which is processed through stages like taxonomic system establishment, image collection, data filtering, and annotation. Pre-trained networks on ImageNet are fine-tuned for SVM and KNN classifiers, with ResNet performing the best in terms of metrics. However, the paper highlights challenges such as inter and intra-class variance, difficulty in identifying fine-grained visual images, and class imbalance issues, which affect the accuracy of pest recognition.

**Problem Statement**

Identify the harmful insects in the field and eradicate them using laser beam technology or spraying precise pesticides.

**METHODOLOGY**

This section outlines the systematic approach for developing the robotic pest monitoring system, designed to improve pest detection and management in precision agriculture. The methodology is divided into the following key stages: data collection, image preprocessing, model development, pest detection, real- time monitoring. Each stage builds upon the previous to create a fully integrated, autonomous system for efficient pest management.

**Data Collection:**

*Dataset Compilation:* The first step involves compiling a comprehensive dataset of pest images for training the detection model. This includes using the IP102 dataset, which provides a large collection of labeled pest species examples. The dataset serves as a solid foundation for training the model to recognize various pest species commonly found in agricultural settings.

*Real-time Image Capture:* To supplement the dataset and improve the model's accuracy, real-time, high-resolution images are captured using multispectral imaging systems mounted on the robotic platform. These systems allow for detailed monitoring of crops under various lighting and environmental conditions, ensuring a robust dataset that reflects the diversity of real-world pest appearances.

**Image Preprocessing:**

*Noise Reduction:* Preprocessing begins with the application of noise reduction techniques to minimize irrelevant data and improve the quality of the images. This ensures the model focuses on important visual features.

*Normalization and Resizing:* Images are normalized to standardize pixel values across the dataset, and resized to uniform dimensions to reduce computational load during model training. Normalization improves the model's ability to generalize across varied image types, while resizing ensures faster and more efficient processing by the neural network.

*Image Augmentation:* Additional preprocessing steps include image augmentation techniques such as rotation, flipping, and color adjustments, which increase the variability of the dataset and improve the model's robustness to different orientations and lighting conditions.

**Model Development:**

*YOLOv10 Algorithm Implementation:* The core of the pest detection system relies on the YOLOv10 (You Only Look Once) algorithm, a state-of-the-art deep learning model known for its speed and accuracy in object detection tasks. YOLOv10 is specifically chosen for its efficiency in processing images and its ability to detect multiple objects in a single pass, making it ideal for real- time pest detection in agricultural environments.

*Architecture:* YOLOv10 builds on previous YOLO versions, with improvements in network depth, performance optimization, and better handling of small object detection. It incorporates advanced techniques such as multi-scale feature maps and sparse convolution to detect pests at various sizes and distances with high accuracy.

*Training:* The model is trained on the compiled pest image dataset. During training, the system learns to identify distinctive features of pests such as color patterns, shapes, and movement behaviors.

*Fine-tuning:* To improve accuracy, the YOLOv10 model undergoes fine-tuning based on the pest dataset. Hyperparameters such as learning rate, batch size, and number of epochs are optimized to ensure the best possible performance. Fine-tuning also helps the model adapt to real-world conditions and minimize false positives/negatives.

**Pest Detection:**

*Real-time Pest Detection:* After training, the YOLOv10 model is deployed on the robotic platform, where it processes real-time images captured by the multispectral camera. The trained model is tasked with detecting and classifying pests in the field as they appear, based on their unique characteristics such as size, shape, and color.

*Classifying Pests:* The model categorizes pests into two main types: static and flying. Static pests are those that remain in one place, while flying pests are those that move across the field. This classification is based on the observed behavioral patterns of pests, enabling more efficient control strategies.

*Threat Level Analysis:* The system also assigns a threat level to the detected pests, ranging from low to high, depending on the species' potential to cause damage to the crops. This allows farmers to prioritize pest management efforts based on the severity of the infestation.

**Real-time Monitoring and Notification:**

Continuous Monitoring: A key feature of the robotic pest monitoring system is its ability to continuously monitor crops in real-time. The system automatically analyzes images from the

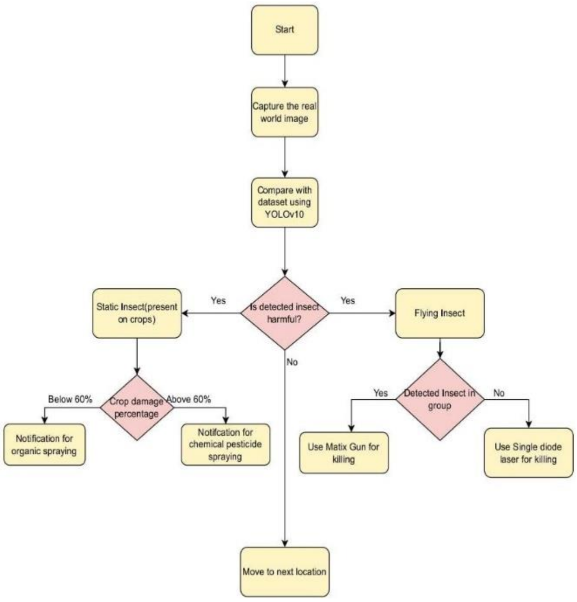


*Fig. 1. Workflow of System*

robotic platform's camera, scanning for pests as the robot navigates through the fields. *Farmer Notifications:* When a pest is detected, the system immediately sends a notification to the farmer's mobile device or central control system.

## SYSTEM ARCHITECTURE

### Master Robot Controller

ROS (Robot Operating System): Acts as the central framework enabling communication, data processing, and coordination between components.

Interfaces with several external sensors:

- *Stereo Cameras:* Two stereo cameras for visual perception, providing depth information and 3D mapping capabilities.
- *IMUs (Inertial Measurement Units):* Two IMUs for measuring orientation, velocity, and acceleration, aiding in the robot's navigation and stability.
- *GPS Receiver:* Provides geolocation data, enabling outdoor navigation.

### Rover Controller

Responsible for controlling the rover's movement and mobility.
*Actuation and Sensing:* Manages actuation of wheels and other motion-related sensors.
*Wheel Actuators:* Control the rotation and movement of the rover's wheels.
*Rotary Encoders:* Provide feedback on wheel rotation, helping to measure distance travelled.
*Steering Actuator:* Controls the direction in which the rover moves, enabling steering adjustments.

### Arm Controller

Manages the robotic arm's motion and positioning.
*Actuation and Sensing:* Controls the arm's movements and sensors for feedback.
*Stepper Motors:* Drive the arm's movements with precision, allowing it to perform tasks like picking up objects.
*Rotary Encoders:* Monitor the arm's movement, providing accurate position feedback for control.

### Laser Controller

Controls the robot's laser module, likely used for object detection, measurement, or scanning.
*Actuation:* Drives the movement of the laser and servo mechanisms.
*Laser Module:* Emits laser beams for sensing or scanning purposes.
*Servos:* Adjust the position of the laser module, providing precise control over its direction.
Each controller communicates with the Master Robot Controller via ROS, enabling synchronized operations and data sharing across the robot's subsystems"compliment", "discreet" and "discrete", "principal" and "principle".

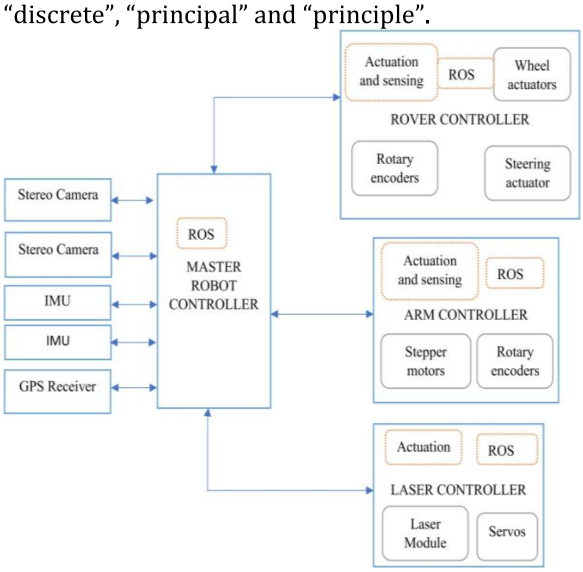


*Fig. 2. Proposed System Architecture*

## EXPERIMENTAL VALIDATION AND FINDINGS

The proposed system utilizes a laser-based insect eradication method.
Key experimental findings from the study are as follows:

**Optimal Laser Parameters:**
Target Area: Middle abdomen of the insect
Irradiation Area: 6.189 $mm^2$
Laser Opening Time: 1.177 seconds

### YOLOv10 Detection Accuracy and Performance

*Mean Average Precision (mAP):* YOLOv10 improves on previous versions with better objectdetection precision.
*Precision and Recall:* It balances high recall

(correctly identifying insects) and low false positive rates (avoiding misclassification).
*Detection Performance:* Suitable for small object detection, making it effective for agricultural pest monitoring.

**CONCLUSION**
The development of the automatic harmful insect detection and management system is progressing well, with core modules like data collection, image preprocessing, and YOLOv10-based pest detection successfully implemented.
Real-time monitoring and notification features are integrated, and field testing is ongoing for optimization. This system enhances agricultural efficiency by reducing labor costs, operating continuously, and minimizing pesticide use, promoting a more sustainable farming approach. While some refinements in performance and reporting remain, the project is advancing steadily toward completion.

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