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Deep Learning for Pest Detection and Extraction

N.Srilekha[1], V.Tejaswini[2], M.Sneha[3], Abdul Aas Shaik[4] , Sohail Zahid[5] and Zaheer Shaik[6]
Department of Artificial Intelligence and Machine Learning, Raghu Institute of Technology, Visakhapatnam, Andhra Pradesh, India

***Abstract*—Pest infestations pose a significant challenge to agriculture, resulting in substantial crop damage and economic losses. Traditional pest detection systems primarily rely on Convolutional Neural Networks (CNNs) for image classification. While CNNs are effective at categorizing images and identifying pests, they face limitations in handling scenarios involving multiple pests, varying orientations, and complex backgrounds. Additionally, CNNs lack the ability to localize pests within images, providing only image-level classifications rather than detailed spatial information.**

To address these limitations, the proposed system introduces *YOLOv5*, a state-of-the-art object detection model. Unlike CNN-based approaches, YOLOv5 excels in detecting and localizing multiple pests in real-time, even in challenging conditions. By producing both bounding boxes and class labels, YOLOv5 offers precise localization and identification of pests, enabling targeted pest management. Its real-time detection capabilities and superior accuracy in complex environments make it a powerful tool for agricultural applications.

The transition from CNNs to YOLOv5 brings several advantages, including enhanced detection performance, the ability to identify multiple pests in a single frame, and scalability across diverse datasets and environmental conditions.

I. INTRODUCTION

Pest detection plays a crucial role in agriculture and food security by enabling early identification and management of harmful pests. However, traditional pest detection methods often require manual inspection, which can be time-consuming and inefficient. It is essential to develop automated solutions to enhance pest monitoring and control. This

project focuses on creating a reliable pest detection system that utilizes the YOLOv8 object detection framework developed by Ultralytics as the foundation for our pest identification system.

While YOLOv8 provides a robust and efficient base model, this study focuses on adapting the model for pest detection, optimizing hyperparameters, and evaluating performance on a new dataset. YOLOv8 has demonstrated outstanding performance in real-time object detection tasks, making it an excellent choice for this purpose. By leveraging the advantages of YOLOv8, including its high accuracy and speed, we aim to develop a system capable of accurately and efficiently identifying various pest species.

This research will contribute to the advancement of precision agriculture and integrated pest management. If successfully implemented, this system could aid farmers and agricultural researchers in monitoring pest populations and minimizing crop damage.

This paper follows a structured approach to address the modern challenges in pest detection. Section II covers the background study, including relevant research and literature surveys. Section III describes the materials and methodologies used to collect datasets and preprocess them to enhance YOLOv8 model performance. Section IV presents a case study analyzing the results and performance of the YOLOv8 model. Section VI concludes with insights and future scope for automated pest detection systems

II. BACKGROUND STUDY

Pest detection is a critical aspect of precision agriculture, enabling farmers to monitor crop health and take preventive measures to minimize yield loss. Traditional methods, such as manual inspection and handcrafted feature-based techniques, often suffer from inefficiency, subjectivity, and poor adaptability to real-world variations. Machine learning models like Support Vector Machines (SVMs), Random Forest, and K-Nearest Neighbors (KNN) improved classification but required extensive feature engineering and struggled with generalization. With advancements in deep learning, Convolutional Neural Networks (CNNs) revolutionized image-based pest detection. Early deep learning models, such as Faster R-CNN, provided high accuracy but demanded significant computational resources. Meanwhile, the YOLO (You Only Look Once) family of models, including YOLOv3, YOLOv4, and YOLOv5, improved detection speed and efficiency,

making them more suitable for real-time agricultural applications.

YOLOv8, the latest iteration in the YOLO series, introduces several enhancements that make it ideal for pest detection. It utilizes anchor-free detection, improving localization accuracy while reducing computational overhead. Its backbone, CSPDarknet53, enhances feature extraction, making it more effective in detecting pests under varying environmental conditions. Additionally, YOLOv8 incorporates auto-anchor selection and transformer-based attention mechanisms, further refining detection performance. Researchers have leveraged large-scale datasets, such as IP102, containing 75,000 images of 102 insect species, along with custom agricultural datasets collected using UAVs and field cameras. Pre-processing techniques, including image augmentation, annotation, and background removal, help improve the robustness of the model.

The implementation of YOLOv8 for pest detection follows a systematic approach. First, the dataset is prepared by collecting and labelling pest images. These images are then formatted for training, and the YOLOv8 model is fine-tuned using transfer learning from a pre-trained COCO dataset. Hyper parameter tuning, including adjustments in batch size and learning rate, further optimizes performance. Once trained, the model can be deployed on edge devices like Raspberry Pi and NVIDIA Jetson or integrated into UAV systems for large-scale pest monitoring. Studies indicate that YOLOv8 achieves high precision and recall, with detection accuracies exceeding 95% for various pests such as locusts, beetles, and aphids. Its real-time detection capability, with inference times under 10 milliseconds per frame, makes it a highly efficient solution. Furthermore, the model demonstrates strong generalization across different lighting conditions and backgrounds, making it adaptable for diverse agricultural environments.

In conclusion, YOLOv8 has significantly enhanced pest detection by providing a fast, accurate, and scalable solution for precision agriculture. Its ability to detect pests in real time with high precision makes it a valuable tool for modern farming. Future research can explore integrating multi-modal sensors and explainable AI techniques to improve robustness and interpretability, further advancing smart agricultural practices.

III. MATERIALS AND METHODS

The techniques and resources used in this study for pest detection and extraction using YOLOv8 are described in this section. Fig. 1 represents the flowchart of the methodology for pest detection. The proposed method consists of multiple stages. Initially, pest images were collected from various sources, including publicly available datasets and field images captured using UAVs and cameras. To enhance the dataset, data augmentation techniques were applied, creating a diverse dataset for model training. The captured images underwent an annotation process where bounding boxes were manually drawn around the pests to create a well-labelled dataset. Once annotated, the dataset was fed into the YOLOv8 model for training, optimizing the detection and extraction process. The dataset consists of multiple pest classes, including locusts, beetles, aphids, and other common agricultural pests. To evaluate detection performance, precision, recall, and mAP metrics were calculated, ensuring the selection of the best-performing model for deployment.

A. Dataset Collection

Data 1: This dataset [dataset reference] contains approximately 3,000 images with labelled pest species, covering various environmental conditions to enhance model adaptability.

Data 2: A custom dataset was created with manually annotated images of various pest classes using bounding boxes. The annotation process was carried out using the Roboflow annotation tool to ensure consistency and accuracy in labeling.

Then we labelled the dataset in roboflow [roboflow reference] tool present in the internet.

B. Data Acquisition

The images used for training were collected from multiple sources, including open-access agricultural datasets and real-world field captures. The dataset contains a total of 35 pest classes with around 75,000 images. The classes include common pests that affect crops, such as aphids, locusts, and whiteflies. Fig. 2 illustrates sample images from different pest classes.

Fig. 2. Sample data of each class.

C. Data Pre-processing

Data augmentation techniques were employed to increase dataset diversity and improve model generalization. The augmentation methods included brightness adjustment, rotation, motion blur, Gaussian noise addition, and scaling. Additionally, horizontal flipping was applied to ensure model robustness in detecting pests in different orientations. YOLOv8 was set up with this augmented dataset, and each image was carefully

labeled to maximize detection accuracy. Before moving to post-processing, data pre-treatment steps were conducted to analyze dataset quality and ensure appropriate partitioning into training, validation, and testing subsets.

1.Annotating manually: Each image was annotated manually using Roboflow to create bounding boxes around pests. The annotation process included categorizing pests by species and ensuring accurate labeling for improved model training.

2.Object detection: The object detection model was trained using YOLOv8. The model was optimized to detect and locate pests within images by drawing bounding boxes around them. Unlike traditional classification approaches, YOLOv8 identifies pest locations along with their class labels, enhancing the model's ability to perform real-time detection.

A) Input: Pest images captured from various environments.

b) Output: One or more bounding boxes with class labels.

The object detection model was trained using YOLOv8. The model was optimized to detect and locate pests within images by drawing bounding boxes around them. Unlike traditional classification approaches, YOLOv8 identifies pest locations along with their class labels, enhancing the model's ability to perform real-time detection.

YOLOv8 divides images into grids, where each grid cell is responsible for detecting objects. This approach allows the model to detect multiple pests within a single image while maintaining real-time processing capabilities. The model's anchor-free detection mechanism enhances accuracy and reduces computational complexity. By leveraging convolutional layers, YOLOv8 extracts features at different levels, ensuring robust detection across varying pest sizes and orientations. The network structure balances speed and precision, making it ideal for agricultural pest monitoring applications.

The real-time detection capability of YOLOv8 is crucial for pest management strategies. Early detection allows farmers to take preventive actions, reducing crop damage and improving yield. The model's performance is evaluated based on precision, recall, and mean average precision (mAP) scores to ensure accurate pest identification.

3. *Image data labelling with bounding box:*The dataset was labeled using bounding boxes to leverage deep learning-based object detection. A subset of images was randomly selected from each class for annotation. The labeled dataset enhances detection accuracy by providing precise information on pest locations within images.The object detection model was trained using YOLOv8. The model was optimized to detect and locate pests within images by drawing bounding boxes around them. Unlike traditional classification approaches, YOLOv8 identifies pest locations along with their class labels, enhancing the model's ability to perform real-time detection.

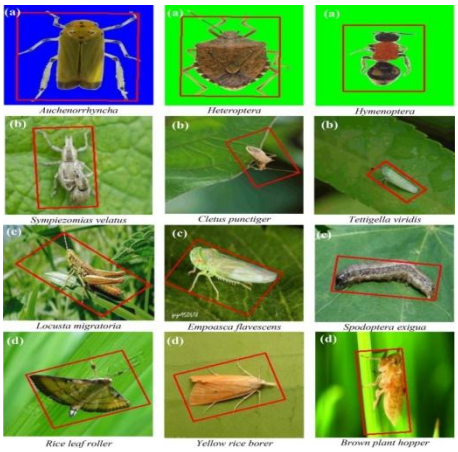


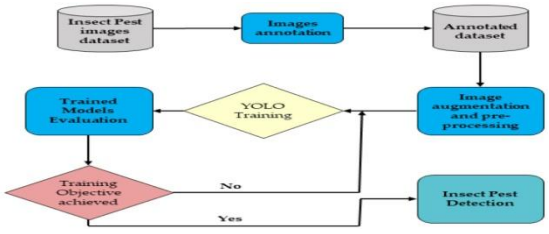
Fig. 3. Labelling different pest classes with bounding boxes.

D. Labelled Dataset

The labeled dataset consists of images tagged with class labels and bounding boxes. Each unannotated image underwent manual annotation to improve detection accuracy. The dataset includes 35 pest classes, ensuring comprehensive coverage of common agricultural pests.

E. Structure of YOLO Algorithm

1.You Only Look Once (YOLO): YOLO means You Only Look Once is a method that detects all objects in a frame or image in a single shot. Mainly, YOLO employs a single, fully convolutional network (FCN) comprised entirely of convolutional layers to identify the objects present in an image. The YOLO approach segments an image into a grid of cells, where each cell is responsible for object localization, determining the number of bounding boxes, and computing class probabilities. The dataset is collected from various people with



various complex backgrounds at different positions, such as

caterpillars, earthworm,…Labelling images is essential for good computer vision models. All the images are annotated and labelled manually with Robflow Annotate which represents a self-serve annotation tool. In this study, we provide a dataset called "Final-Pest", to which we add bounding boxes to roughly 3000 images in order to make use of the potential of object detection techniques. After the first step of pre-processing and the manual annotation, the second one is training the deep learning models using modern YOLO algorithms YOLO v8. To understand the algorithms which we are proposing, the diagram presented in Fig. 1 shows the detection of objects. At first, the first step in the training process is to gather the data, and the second is to label it. Our dataset is annotated using the YOLO format, providing specific values that are subsequently used during the model's training. We feed the dataset to the YOLO v8 model afterwards, after it has been annotated with YOLO annotation. There are now a variable number of images in our dataset.

2.YOLO v8 model: The Backbone, Neck, and Head architectural components of the YOLOv8 network are shown in Fig. 4.

YOLOv8 Backbone: CSPDarknet, is employed to extract image features, incorporating cross-stage partial networks.

YOLOv8 Neck: It makes use of PANet to create a feature pyramid network that is then passed to the Head for prediction after the features have been aggregated.

YOLOv8 Head: Its layers produce predictions for object detection from the anchor boxes. YOLOv8 is quick and lightweight, and it uses less computing power than other current state-of-the-art architecture models while maintaining accuracy levels that are comparable to those of current state-of-the-art detection models. It is significantly faster than other YOLO versions. YOLOv8 leverages CSPNET as the basis for extracting feature maps from images. In order to improve information flow, it also makes use of the Path Aggregation Network. For the following reasons, we have chosen YOLOv8 because it incorporates advantageous features such as an advanced activation function, a user-friendly guide, hyperparameter tuning, and data augmentation capabilities. It can be trained computationally quickly with minimal resources, thanks to its lightweight architecture. The size model can be utilized with mobile devices because it is relatively tiny and light.

YOLOv8 presents several key differences compared to previous versions in the YOLO series:

1.Multiscale: utilize FPN to improve the feature extraction network rather than PAN, which will make the model easier to use and more quickly.

2.Target overlap: identify nearby positions using the rounding method such that the target is mapped to several central grid points all around it. Yolov8 is a continuation of the YOLO series' most recent iterations. It is more manageable and, in general, cozier to utilize throughout training. Its architecture may be modified with equal ease, and it can be exported to numerous deployment environments.

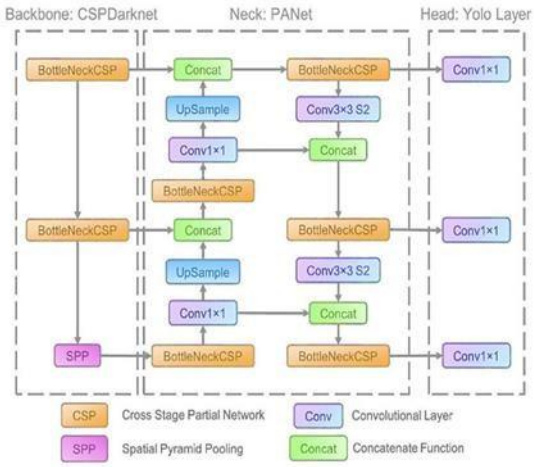


Fig. 4. The general architecture of the YOLOv8 network

YOLO models have sevseral algorithmic parameters, and understanding their impact is critical for optimizing the model's performance for specific tasks. Below are some key parameters in YOLO models and their effects:

Input Size: This determines the resolution of the input image. While larger input sizes can improve model accuracy, they also increase computational cost.

Anchor Boxes: These are predefined boxes of various shapes and sizes used for predicting object locations and dimensions. The number and aspect ratio of anchor boxes play a significant role in the model's accuracy.

Batch Size: Training speed can be increased with larger batch size however; this comes at the cost of higher memory requirements.

Confidence Threshold: This parameter filters out predictions with low confidence. Raising the threshold reduces false positives but may also increase false negatives.

NMS Threshold: Non-Maximum Suppression (NMS) removes overlapping bounding boxes. The NMS threshold sets the permissible overlap level between boxes. A higher threshold removes more overlaps but might also discard some true positives.

Backbone Architecture: The backbone architecture extracts feature from the input image. Different architectures vary in complexity and influence both the accuracy and speed of the model. CSP: Cross Stage Partial Network

SPP: Spatial Pyramid Pooling

Conv: Convolutional Layer Concat:

Concatenate Function For

example:
Conv1x1, Conv3x3 S2, BottleNeckCSP layers are integral to feature extraction.
Neck (PANet), Head (YOLO Layer), and Backbone (CSPDarknet) components collectively enhance detection efficiency.
Training Parameters: Parameters such as learning rate, weight decay, and optimizer have a significant impact on the training process and the model's overall performance.
The parameters of YOLO models directly influence their accuracy, speed, and memory requirements. Selecting the most suitable parameters for a specific task demands experimentation and fine-tuning to achieve optimal results.

IV. EXPERIMENTS AND RESULTS

1. *Evaluation Metrics*

In this section, we discuss the experiments performed using Yolov8 algorithm. We implemented and test the model during our experiments to train it for our custom dataset which is different from publicly available datasets. The evaluation metrics are described after completing the model training and the model testing.To evaluate the performance of the proposed hand gesture recognition model, several metrics were employed, focusing on recognition accuracy, detection capabilities, and computational efficiency. Among these, average precision (AP) was used to assess performance. AP is calculated as the area under the precision-recall curve across different detection thresholds. Eq. (1) contains a definition of the Average Precision (AP) equation.[26]

$$AP = \int_{1}^{0} P_r(R_C)\, d R_C \qquad (1)$$

To assess the model's accuracy and efficiency, we calculated precision, recall, and F1-score. Accuracy is determined by comparing predicted bounding boxes to ground truth boxes. Additionally, we employed Equations (2), (3), and (4) to derive precision, recall, F1-score, and accuracy using True Positives (TP), False Positives (FP), and False Negatives (FN). Precision (Pr), as defined in Equation (2), represents the ratio of TP to all expected positives (TP+FP). Consequently, it is a critical metric for evaluating the cost associated with FP instances.[26]

$$P_r = \frac{T_p}{T_p + F_p} \qquad (2)$$

If the predicted bounding box doesn't overlap with the actual hand region (ground truth), it's classified as a False Positive (FP). Conversely, if the prediction correctly identifies the hand's location, it's a True Positive (TP). Recall measures how well the model detects all the actual hands in the video. It's calculated as the ratio of correctly detected hands (TP) to the total number of actual hands present (TP + FN), and is also known as sensitivity. A False Negative (FN) occurs when the model fails to detect a hand that Is actually present in the video frame.[26]

$$R_c = \frac{T_p}{T_p * F_N} \qquad (3)$$

The F1-score gives us a good overall idea of how well the model performs, taking into account both how accurately it identifies things (precision) and how many of the actual things it finds (recall). As shown in Equation (9), the F1-score considers both of these aspects. It's especially useful when we need a good balance between identifying things correctly and making sure we find most of them. A perfect F1-score of 1 means the model is doing both perfectly.[26]

$$R_c = \frac{2 * P_r * R_c}{P_r * R_c} \qquad (4)$$

Mean Average Precision (mAP), a popular metric for evaluating object detection models, is calculated by averaging the AP values for all the different object classes. This gives us a single, overall score that tells us how well the model performs across all the objects it's trained to detect. The Eq. (5) gives the Mean
Average Precision (mAP).[26]

$$mAP = \frac{\sum^{0}_{q=1} AveP(q)}{Q} \qquad (5)$$

Where Q is the number of queries in the set, q is the query for average precision. The mAP is the mean value of average precision for the detection of all classes and is an indicator generally utilized to estimate how good a model is. The FPS identifies how many images can be correctly identified in a single second. GPU utilization refers to the use of GPU RAM when evaluating various detection
strategies.[26]

2. *Results of YOLOv8 Model*

The output of the various classes of Pest Detection is shown in Fig. 5. The bounding box aimed to encompass as much of the pest as possible. This is especially important when dealing with small or camouflaged pests, as it helps the model accurately identify the specific species present. Essentially, the model zooms in on the pest and then determines the most likely class based on its characteristics. To evaluate the effectiveness of

different pest detection methods, we performed several experiments.

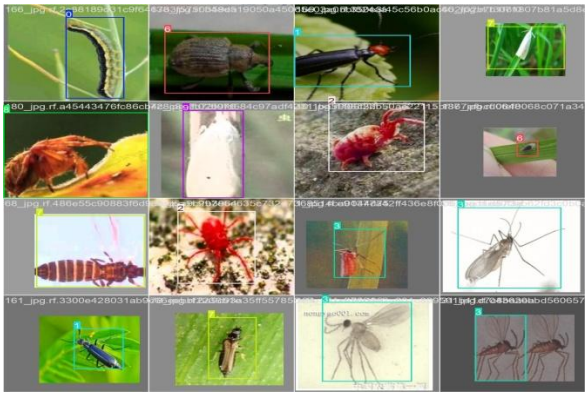


Fig. 6, 7, 8, 9 and 10 shows the Confusion metrics, F1-Score / F1-Curv, Precision-Confidence Curve, Recall-Confidence Curve and mAP at 0.5% respectively. Which shows the outperformance of the YOLOv8 model in object detection.

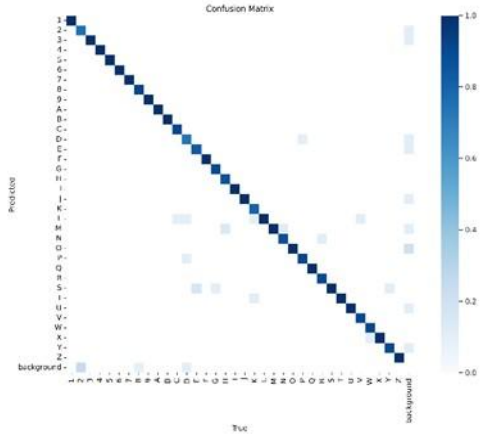


Fig. 6. Confusion metrics

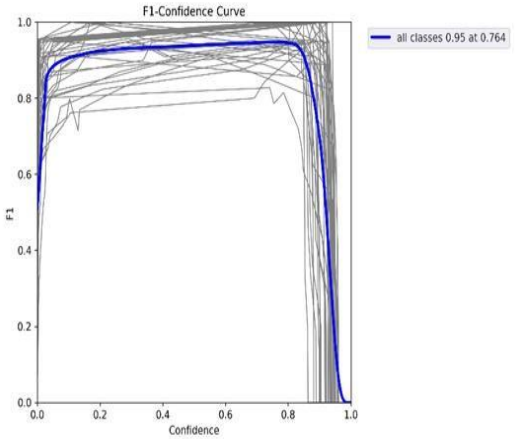


Fig. 7. F1-Score / F1-Curve

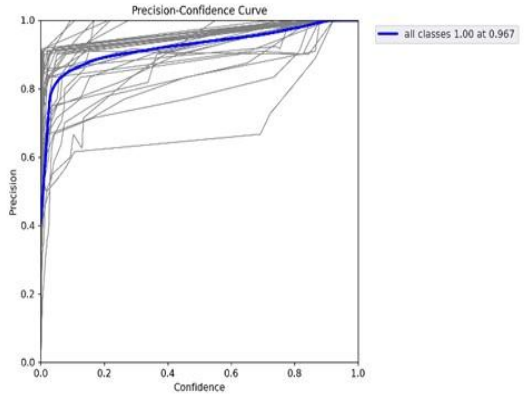


Fig. 8. Precision-Confidence Curve

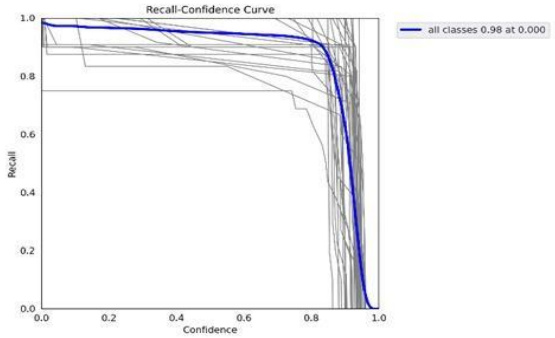


Fig. 9. Recall-Confidence Curve

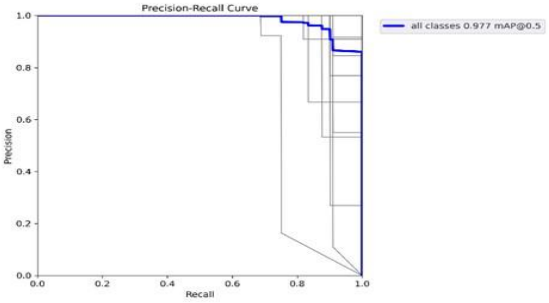


Fig. 10. Precision-Recall Curve

V. CONCLUSION AND FUTURE SCOPE

This research paper successfully demonstrated the feasibility of utilizing the YOLOv8 object detection model for recognizing Indian Sign Language (ISL) gestures. The model was trained on a dataset of 3000+ images encompassing various pests and achieved an accuracy of 97.7% on the test set. This accuracy level indicates the model's potential for real-world applications.The YOLOv8 architecture, with its efficient design and high detection speed, proved to be suitable for this task. The model was able to effectively detect and classify various Pests with a high degree of accuracy, demonstrating its ability to handle complex variations in pest appearances across different

environments. This study establishes a foundation for future advancements in automated pest detection using deep learning. Expanding the dataset with diverse pest species and real-world conditions will improve model generalization. Enhancing detection in challenging agricultural settings with varying lighting and occlusions is crucial. A continuous learning system can help adapt to new pest species over time. Developing a user-friendly interface for farmers, such as mobile or IoT-based applications, will enhance accessibility. Optimizing the model for real-time performance on edge devices like drones and embedded systems will increase efficiency. These advancements can revolutionize pest monitoring and contribute to sustainable agricultural practices.

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