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Deep Learning Approaches for Precise Pest Identification in Agriculture

Asni Ansar[1], *Geetha Radhakrishnan*[2], *Santhoshkumar T*[3]
[1]*PG - Entomology, College of Agriculture, Vellayani, Kerala, India.*
[2]*Assistant Professor, Computer Science, College of Agriculture, Vellayani, Kerala, India.*
[3]*Assistant Professor, Entomology, College of Agriculture, Vellayani, Kerala, India.*
Emails: *asni2512@gmail.com*[1], *geetha.ramesh@kau.in*[2], *santhoshkumar.t@kau.in*[3]

Abstract
One of the most important pest management strategies in agriculture is the precise and accurate identification of pests, which significantly reduces the crop losses and improves yield through timely interventions. This research focuses on the development of a novel approach for identification of pod bug species, which is an important pest in cowpea using the YOLOv8 deep learning model. In this study, major focus was given to the classification of four major species of pod bug viz. Clavigralla horrens, Coptosoma cribraria, Nezara viridula, and Riptortus pedestris. For this, ten different sets of models were created by varying the image sizes, preprocessing steps, number of epochs and training/testing ratios to identify the most optimal model configuration. It was found that the most effective model achieved a mean Average Precision (mAP50) of 0.989 on the validation set with 276 epochs. The ability of developed models to accurately detect and classify the pests in a complex agricultural environment were validated through prediction graphs. The use of this model in crop protection practices imparts significant improvement in managing pests by providing real time insight to farmers. Further, the model developed through this study lays the groundwork for expansion, to include other pest species that could potentially enhance pest management strategies in agriculture.
Keywords: *Image detection; Pest identification; Pest management; YOLOv8*

1. Introduction
The accurate identification of pests is a critical component in the selection of effective management strategies for the protection of crops from insect pests. The mis-identification or late detection of pests in crops can lead to ineffective pest management, which will result in increased use of pesticides, reduce crop yield and culminate in significant economic losses. Traditionally, the pest identification relied on manual-human inspection, which is time consuming, labour intensive and were prone to human errors (Sankaran et al., 2010; Barbedo, 2014). The recent advancement in computer vision has developed deep learning algorithms which have revolutionized this domain, by providing an automated and precise solution for pest identification (Kamilaris and Prenafeta-Boldú, 2018). Deep learning models, especially use of Convolutional Neural Networks (CNNs), have demonstrated significant potential in image based pest identification tasks which outperform the traditional machine learning approaches (Ferentinos, 2018; Liu et al., 2020). However, the accuracy of these models is often limited by the quality, quantity and diversity of the training datasets, as well as the selection of model architectures (Chollet, 2017; Wang et al., 2021). Majority of the existing studies focused on general pest detection without addressing the unique characteristics of specific agricultural contexts, which is a crucial factor in the development of precise pest management strategies (Shao et al., 2021). This study aims to develop a deep learning model for the precise identification of major sucking pests of pulses, by focusing on the creation of a dataset that contains the four major species of pod bug. Using the YOLOv8 (You Only Look Once, version 8) architecture, ten different models were created by varying the key model parameters such as image size, preprocessing techniques, number of epochs, and

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training-to-testing ratios to optimize model performance. The proposed approach seeks the model to achieve high accuracy in pest identification and also aims to provide insights into the customization of deep learning models for specific needs. The research focuses on finding the best configuration for deep learning models to enhance their performance in identifying pests. This research addresses a gap in the literature concerning the development of specialized models for pest identification that can adapt to different agricultural environments. The originality of this work lies in its methodological approach to parameter tuning (Sun et al., 2022; Qiu et al., 2023). The findings from this study can significantly impact sustainable agricultural practices by reducing dependency on chemical pesticides and improving pest management efficiency through precise and early detection methods. [1-5]

2. Methods

For this study, a specialized dataset was created to identify pests affecting cowpea pulses. About 15,000 images of four pod bug species (Clavigralla horrens, Coptosoma cribraria, Nezara viridula, and Riptortus pedestris) were captured. The images were then annotated with precise bounding boxes for each species using Roboflow. The dataset was divided into training (80%), validation (10%), and testing (10%). To enhance dataset quality, preprocessing steps were applied using Roboflow. All images were resized to 640x640. Automatic orientation and contrast adjustment were done for the preprocessing of the dataset. These steps aimed to standardise the dataset, improving model performance and consistency during training and testing. Data augmentation techniques such as flipping, rotations, scaling, and brightness adjustments were employed to increase dataset diversity and improve model robustness. These augmentations simulated different environmental conditions. By enhancing variability, these methods aim to improve the capability of the model for pest identification in diverse agricultural environments. For the model development, YOLOv8 object detection framework was used in Google Colab with GPU. Ten models were created by varying parameters. The number of epochs ranged from 20 to 300 epochs to balance accuracy and computational efficiency. [6-10]

Table 1 Different Models Developed

MODEL NO.	EPOCH	PIC SIZE	TEST:TRAIN	PRE-PROCESSING
M1	20	640 X 640	80:20	With greyscaling
M2	50	640 X 640	80:20	With greyscaling
M3	100	640 X 640	80:20	With greyscaling
M4	200	640 X 640	80:20	With greyscaling
M5	300	640 X 640	80:20	With greyscaling
M6	20	640 X 640	75:25	With greyscaling
M7	50	640 X 640	75:25	With greyscaling
M8	100	640 X 640	75:25	With greyscaling
M9	200	640 X 640	75:25	With greyscaling
M10	300	640 X 640	75:25	With greyscaling

Each model was trained on an augmented dataset with two different data splits: training (80%), validation (10%), and testing (10%) and training (75%), validation (15%) and testing (10%). This variation helped assess model performance on unseen data. The details of these models are summarised in Table 1.

3. Results

Table 2 Results of Different Model

MODEL NO.	EPOCH	TRAINING TIME (HRS)	PRECISION	RECALL	mAP50	mAP 50-95
M1	20	4.189	0.832	0.848	0.909	0.619
M2	50	0.115	0.113	0.928	0.934	0.932
M3	100	0.252	0.9	0.958	0.941	0.768
M4	200	0.500	0.899	0.911	0.962	0.78
M5	300	0.745	0.967	0.921	0.989	0.785
M6	20	4.280	0.845	0.853	0.905	0.634
M7	50	0.112	0.91	0.873	0.907	0.685
M8	100	0.240	0.87	0.913	0.933	0.761
M9	200	0.471	0.98	0.953	0.979	0.723
M10	300	0.468	0.871	0.84	0.907	0.734

The results of training and evaluating the model for pest detection were assessed using metrics precision,

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recall, and mean Average Precision (mAP) at different Intersections over Union (IoU) thresholds. The YOLOv8 models showed varying performance based on the number of training epochs. The model trained for 20 epochs achieved an mAP50 of 0.909, which improved while increasing the epochs. At 50 and 100 epochs, the mAP50 reached 0.934. The 300 epoch model, with early stopping had an mAP50 of 0.989. Overall, the results suggest that the model trained for 300 epochs provided the best balance of precision and recall. The models trained beyond 200 epochs showed limited improvements, indicating that optimal training duration lies between 100 and 200 epochs to maximise performance without unnecessary computational cost. Results of the developed models are summarised in Table 2. (Refer Figure 1)

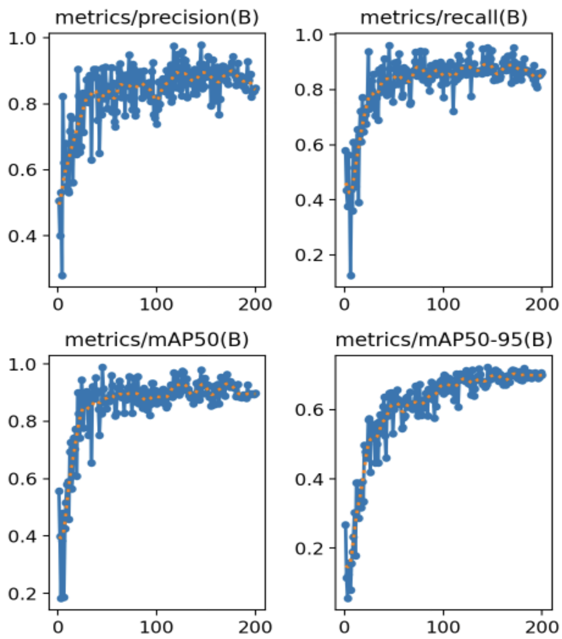

Figure 1 Precision, Recall and Map Graph of M4 Model

These results provide a comprehensive understanding of the strengths of the model and weaknesses in accurately identifying different pest species and managing object detection tasks. [11-14]

Conclusion

This study developed and evaluated YOLOv8-based models for identifying different species of pod bugs. The results showed that varying parameters like epochs and data splits significantly affected the performance of the model in terms of precision, recall, and mAP. Model M5 performed the best, with a precision of 0.967, recall of 0.921, and mAP50 of 0.989. In contrast, Model M1 had the lowest performance, highlighting the importance of optimal parameter settings for effective detection. These findings underscore the significance of model configurations for accurate pest identification. Future research could extend this approach to other pests, providing valuable insights for automated pest management strategies.

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