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CNN-Based Insect Detection Using YOLO for Resilient Agricultural Systems

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INTRODUCTION

Insect recognition, including categorization, identification, and classification, is a challenging task in entomology and agriculture. It plays a crucial role in ecosystems and is vital for food security and a stable agricultural economy [1], and requires expertise knowledge in agricultural fields.Insect pest identification differs significantly from standard object or animal classification tasks due to distinct characteristics.

Currently computer vision techniques play a crucial role in many fields of research such as entomological sciences, environment and agricultural engineering. The computer vision methods could be a feasible way to solve the problem of automated insect categorization and identification. Therefore, there is a need to find an efficient and fast technique for automatic classification and detection of harmful insects.

Deep learning (DL) has been extensively used for insect detection in recent years with features including image classification, and object detection. These DL models have shown remarkable results in object detection and classification tasks, making them a popular choice for insect detection. In such applications, CNNs are trained on large datasets of insect images to learn the features and patterns unique to different species. The trained model can then be used to classify new images of insects with high accuracy. The use of CNNs in insect detection has been effective in automating the process and reducing the time and effort required for manual identification and allows predicting and taking the decision.

METHOD

The dataset preparation and training process (Figure 1) begins with the IP102 dataset of ~19,000 XML-annotated pest images [2]. The data is cleaned, split into training, validation, and testing sets, and expanded using augmentation techniques such as rotation, flipping, scaling, and color jittering. These augmentations, applied via Roboflow, enhance dataset diversity and robustness.

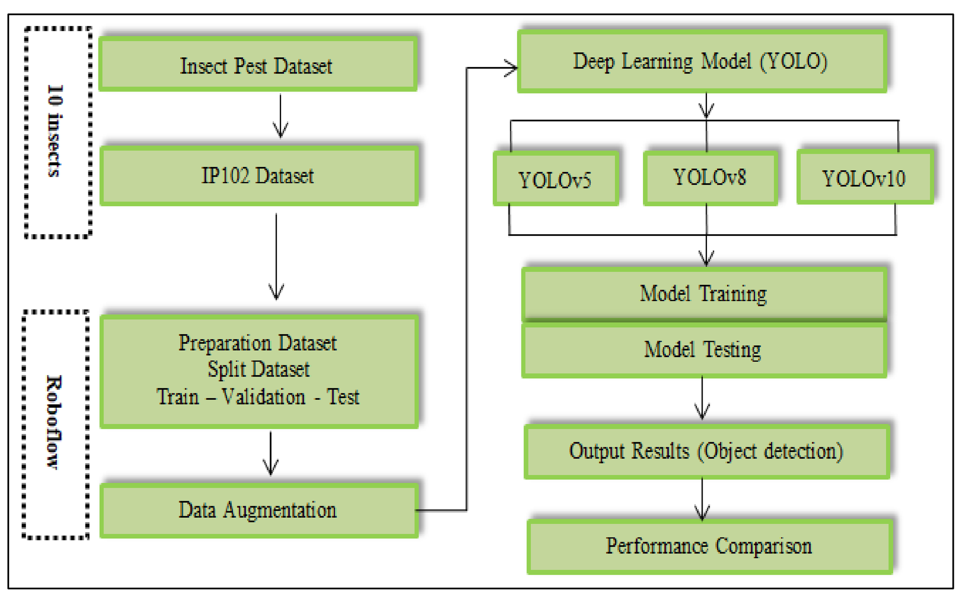

Figure 1. Work Flow

The proposed approach in our work builds upon the existing architecture of the single-stage object detector YOLO [3], and the study in the literature and research papers in the field of deep learning for image recognition and object detection, specifically insect detection.

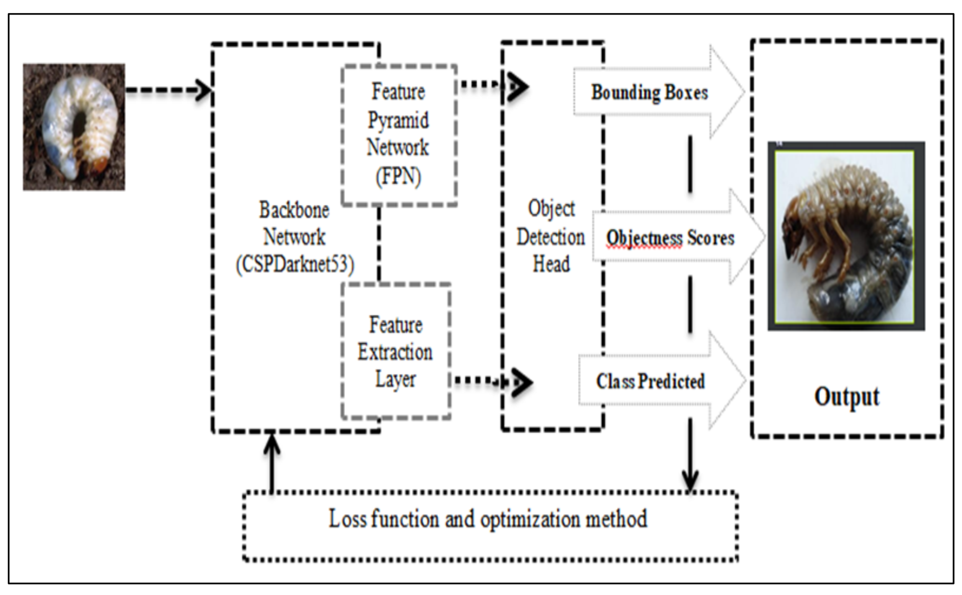

Figure 2. YOLO architecture

The YOLO model uses a CSPDarknet53 backbone with an FPN for multi-scale feature extraction, followed by a detection head that predicts bounding boxes, objectness scores, and class probabilities. Training optimizes these outputs against ground truth using a loss function. Known for real-time speed and accuracy, YOLO is implemented with Ultralytics, which streamlines pipeline setup by defining classes, feature extractor settings, augmentation methods, batch size, and learning rate.

RESULTS

Among the various multi-class metrics that have been studied, we selected the most representative to assess the model's performance. Precision (1) and recall (2) are two commonly used metric to judge the performance of model and the mean average precision (mAP) (3) .

$$Precision = \frac{TP}{(TP+FP)} \quad (1)$$

$$Recall = \frac{TP}{(TP+FN)} \quad (2)$$

$$mAP = \frac{\sum_{C=0}^{C} AP(c)}{C} \quad (3)$$

YOLOv5 showed strong accuracy for Black Cutworm (92%), though Red Spider suffered from misclassifications with other classes and background. YOLOv8 achieved 90% for Black Cutworm, 88% for Aphids, and 91% for Flea Beetle, but struggled with Red Spider and background separation. YOLOv10 outperformed the others, reaching 95% for Black Cutworm and 98% for Flea Beetle, though Red Spider remained problematic, with confusion involving both Aphids and background. Overall, while all models perform well on certain pests, challenges persist with Red Spider and background misclassifications.

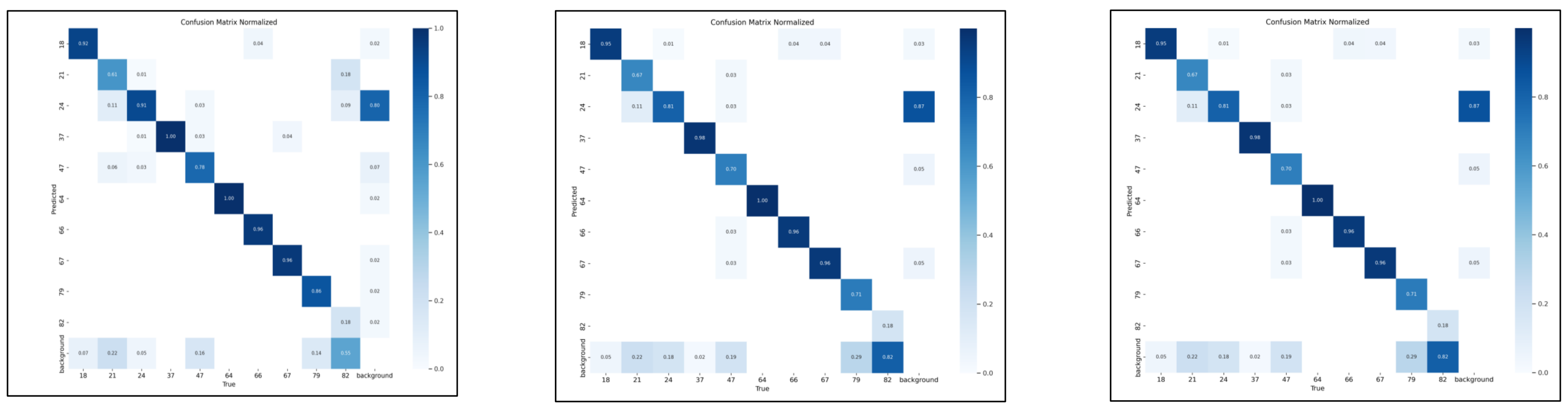

Figure 3 . Confusion Matrix for 10 Pest Classes.

Table 1 presents the results obtained during the training phase, showing that all three models achieved satisfactory performance with some differences. YOLOv8 proved to be the most effective, reaching the highest mAP@0.50 of 94.31% with a recall of 95.0% despite a slightly lower precision (80.0%). YOLOv5 followed with a mAP@0.50 of 92.88% based on a precision of 81.5% and recall of 93.6%, while YOLOv10 achieved comparable results with a mAP@0.50 of 92.17%, supported by a precision of 81.5% and a recall of 92.7%.

Table 2 presents the comparative evaluation of these models on a test set of 281 images (10% of the dataset). The analysis confirms the superiority of YOLOv8, followed closely by YOLOv5 and YOLOv10, with accuracy rates of 94.31%, 92.88%, and 92.17%, respectively.

Table 1. Performance of models during training phase

	YOLOv5	YOLOv8	YOLOv10
Precision (%)	80%	83%	86%
Recall (%)	79%	79%	76%
mAP@0.50 (%)	83%	83%	86%
Time	1 h and 21 min.	1 h and 38 min.	1 h and 35 min

Table 2. Models Comparative on Test Dataset

	YOLOv5	YOLOv8	YOLOv10
Non Detected	14	10	20
Incorrect Detected	6	6	2
Accuracy	92.88%	94.31%	92.17%

(a) (b) (c) (d)

Figure 4 . Examples of test images for correct detection. (A)Black Cutworm,(B) Red Spider, (C)Aphids , (D) Flea Beetle.

CONCLUSION

This work leverages YOLO-based CNN models for detecting 4 insect pests, achieving high accuracies with YOLOv5, YOLOv8, and YOLOv10. The system demonstrates potential for real-time pest identification, reducing pesticide use and preventing economic losses. Despite strong performance, challenges like misclassification and missed detections remain, highlighting areas for improvement.

FUTURE WORK / REFERENCES

Future work will focus on integrating automatic disease and pest detection into a unified smart farming system. Overall, this research contributes to sustainable agriculture by enabling timely interventions and efficient pest management.

[1] Faithpraise, F., et all. (2013). Automatic plant pest detection and recognition using k-means clustering algorithm and correspondence filters.
[2] Wu, J., et all. (2019). IP102: A large-scale benchmark dataset for insect pest recognition. Proceedings of the IEEE/CVF International Conference on Computer Vision (ICCV).
[3] Redmon, J., et all . (2016). You only look once: Unified, real-time object detection. IEEE Conference on Computer Vision and Pattern Recognition (CVPR).