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THE RAPID DEVELOPMENT OF A COMPUTER VISION MODEL FOR DETECTING CROP PESTS FOR INTEGRATED PEST MANAGEMENT: A CASE STUDY IN THE BLACK VINE WEEVIL.

Abstract
Black vine weevil poses a significant threat to global agriculture, causing substantial damage and economic losses. Traditional manual methods of pest monitoring are labor-intensive, time-consuming, and prone to human errors, limiting their scalability for large-scale applications. To address these challenges, this study proposes a rapid pest detection method utilizing YOLOv8-based computer vision models. The primary objective is to develop an efficient and accurate system capable of automatically identifying and localizing crop pests, facilitating integrated pest management practices. The YOLOv8 algorithm, is employed for real-time object detection and precise localization. A labeled dataset comprising images of the black vine weevil (BVW) and earwig pests is utilized for model training and evaluation. Through an extensive exploration of hyperparameters, including image size, batch size, and epochs, the study aims to optimize the model training process for superior performance. Results indicate that YOLOv8n and YOLOv8s models outperform other model sizes, achieving high precision, recall, and mean average precision (mAP) at varying intersection-over-union (IoU) thresholds. And finally, validated the best performing model in a real-time pest detection of weevil and earwig. The proposed methodology showcases the potential of computer vision technologies in revolutionizing pest management, offering promising implications for precision pest control and sustainable agriculture.

Introduction

Insect pests are a major cause of crop damage globally, resulting in significant losses in agriculture (Nanni, Maguolo and Pancino, 2020). Crop pests can interfere with metabolic processes and reduce yield output and quality(Muralidharan and Pasalu, 2006). Regular pesticide use is often habitual, which while sometimes effectively contributes to the accumulation of pest resistance and potentially negatively impacting non-pest species, while contributing to business costs(Hazarika, Bhuyan and Hazarika, 2009). Indeed, there is evidence routine pesticide use negatively impacts the ecological environment and leaves pesticide residues in agricultural products(Miller and Spoolman, 2014). Pest population information cannot be easily and accurately obtained, further contributing to the practice of pesticide overuse. On the other hand, if accurate pest population information were easily and efficiently accessible, Adequate pest control approaches, such as the careful use of insecticides, and proper prevention measures may be achievable(Zhang and Swinton, 2009). As a result, information on insect types and quantities is critical and essential. Because of the fast with the advancement of electronic picture technology, there's is a rising inclination towards adopting in the realm of agricultural research, technology for machine vision is being used to solve these difficulties with promising results.(Cho *et al.,* 2007).

Traditional manual methods of insect pest monitoring, relying on human experts, are labour-intensive, subjective, and unsuitable for large-scale applications (Ding and Taylor, 2016). Workers). Workers do this by comparing morphological features such as colour, texture, and other attributes. However, this often requires labour and expertise which are limiting and prone to mistakes (Cho *et al.,* 2007)(Ding and Taylor, 2016). A potential solution is to automate pest identification. This need has given rise to solutions using computer vision (Cho *et al.,* 2007).

Even though certain pertinent studies have achieved significant advancements, their study still mostly focuses on theoretical issues and pays little attention to real-world application scenarios for two key reasons: First, methods other than deep learning are frequently used to measure and identify insects, yet the precision varies (Wang *et al.,* 2012). Furthermore, most recent studies employ insect photos obtained in an ideal lab setting rather than in the field (Gassoumi, Prasad and Ellington, 2000) (Maharlooei *et al.,* 2017a); (Larios *et al.,* 2010)(Kang, Cho and Lee, 2014)Although only a few studies employ photos of insects taken in the wild, these high-resolution photographs must be transferred to a server where the counting and identification tasks are accomplished. To overcome the obstacles Real-time object identification is an important task in computer vision and is commonly used in computer vision systems. An object detector employs an object detection approach to estimate bounding boxes and class probabilities for each item in the input picture when conducting image recognition tasks.

In the context of comprehensive pest management (IPM), pest control that combines and integrates biological and chemical control is defined (Stern *et al.,* 1959). IPM tries to eliminate insect populations below the economic injury level which results in less effects on environment and human begins. The promise of computer vision models for automated, instantaneous detection of crop pests has gained significant attention. Such a model would facilitate the implementation of precision pest control measures, thereby reducing crop losses and remove the limitations of cost, time, and expertise. Among the pests Otiorhynchus sulcatus, sometimes known as the black vine weevil (BVW), is a significant pest of Horticultural crops, ornamentals used in landscaping. The black vine weevil harms host plants by marginally notching the leaves of broadleaved evergreens and other host plants. Adults prefer to consume plant leaves over culminating in subterranean tissues or fruits noticeable scratching with the leaf margin(Moorhouse, Charnley and Gillespie, 1992). Although it is well acknowledged that such notching has minimal influence Its presence has a negative impact on total crop health and can drastically impair the commercial value of attractive crops. that are less forgiving of aesthetic defects. (California Agriculture published descriptions of this univoltine species (having a single generation per year) in March–April 1984, January–February 1985, and May–June 1989.The overall aim of this project is to rapidly develop a computer vision model that accurately detects the black vine weevil.

Objectives

My specific objectives are: 1) Create a reproducible methodology to rapidly create a baseline dataset for training, testing and validation for pest insect classification; 2) create a reproducible baseline classification and detection model using a comparative framework (different model sizes in a recent YOLO model framework); 3) create and test a reproducible experiment methodology to rapidly train and tune pest detection models for accuracy and speed; and 4) validate an example model using real pest images in a biologically relevant scenario. I will discuss my results in the context of opportunities of computer vision applications for solving integrated pest management problems.

The background

This section provides a summary of the object identification model yolov8 and its five distinct models utilized to identify pest in this investigation.

Object detecting technique proposed.

YOLO (You Only Look Once) is a well-known object recognition system with excellent precision and efficiency. (Redmon, Joseph *et al.,* 2016) Initially announced YOLO in the publication "You only Look Once: Unified, Real-Time Object Detection," which is known as a single-stage detector since it accomplishes everything in a single step (Jiang *et al.,* 2022)YOLOv8, the most recent version of this framework developed by Ultralytics (Ultralytics, Maryland, USA), works by partitioning a picture into smaller sections and then predicting a bounding box and Probabilities of classes for each component in each zone. Darknet-53 (Redmon, J., 2018) is a convolutional neural network that serves as the foundation for the Yolo identification of object detection method. The Darknet-53 architecture is used by the YOLOv8 algorithm to increase feature extraction, resulting in more accurate object recognition. DarkNet-53 is a 53-layer convolutional neural network that can categorise photos into 1,000 item categories. This network is broken into smaller stages, which are then partially connected, allowing for greater feature reuse and gradient propagation. The YOLOv8 model was chosen for its ability to detect objects quickly while retaining high accuracy.

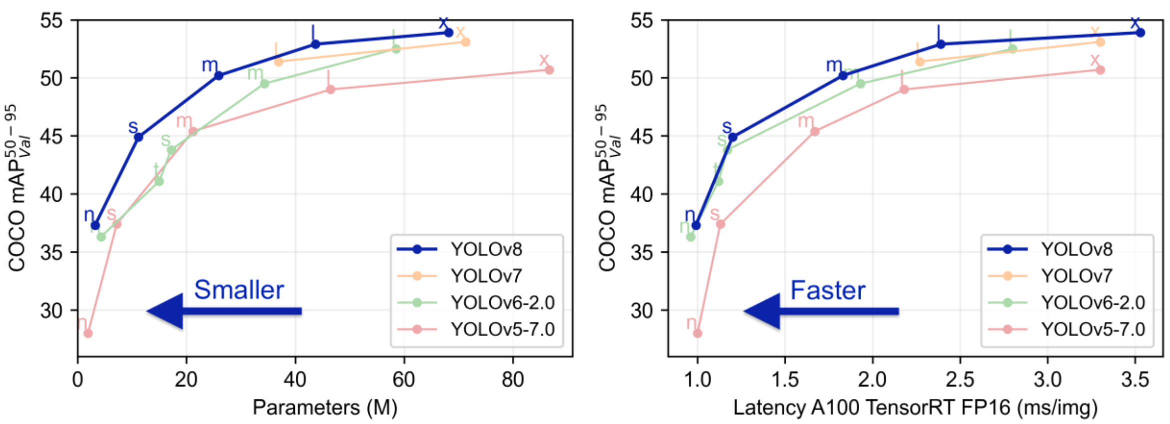


Figure 1: Schematic representation of YOLOV8 model (Ultralytics (Version 8.0.0) [Computer Software] https://github.com/ultralytics/ultralytics

To explore the model's sensitivity to parameter settings, training epoch number, batch size, and image size were adjusted iteratively. These hyperparameters were chosen to provide a balance of model accuracy and computational efficiency. There are five models (Figure 2) in yolov8 with different speed, accuracy, and size. YOLOv8 offers a spectrum of model sizes, ranging from YOLOv8n (smallest and fastest) to YOLOv8x (largest and most accurate). Each model size exhibits varying trade-offs between inference speed and accuracy. We have trained our dataset into twenty times to find out the best model for accuracy. While training we have adjusted many parameters specific to model for example image size 100 & 128 and batch size 8 & 16 and epochs 100 which is constant, likewise we have trained all the models into four times. Image size refers to the dimensions (width and height) of the input images fed into the YOLOv8 model during training and inference. We chose image size of 128 and 256 to train our model. Batch size denotes the number of input samples (images) that are processed together in one iteration during the training phase. For batch we have taken 8 and 16 batch size. An epoch represents one complete iteration through the entire training dataset. Training a model for a specified number of epochs allows it to learn from the data multiple times, updating its weights to minimize the loss. For epoch we have taken 100 which means our model trained into 100 times. Considering the interplay of image size, batch size, epochs, and other hyperparameters is crucial for optimizing the training process of YOLOv8. A comprehensive exploration of these parameters will provide valuable insights into achieving a well-performing model for diverse real-world applications, accounting for the delicate balance between accuracy and computational efficiency.

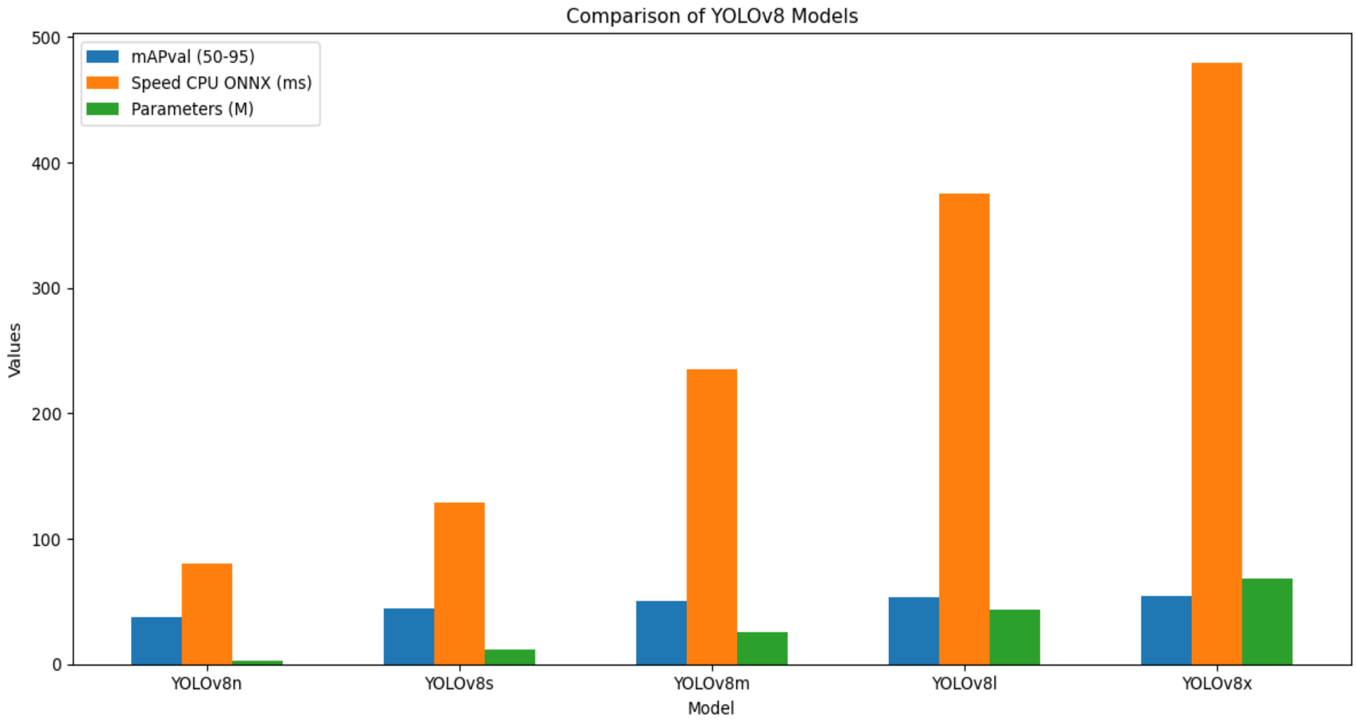


Figure 2: Yolov8 models comparison of MAP (50_90), speed and parameters.

The study of methodology

This section gives an overview of the approach, a description of the dataset information, and an explanation of the experimental setting.

Setup for the experiment

A summary of the pest detection technology used in this investigation.

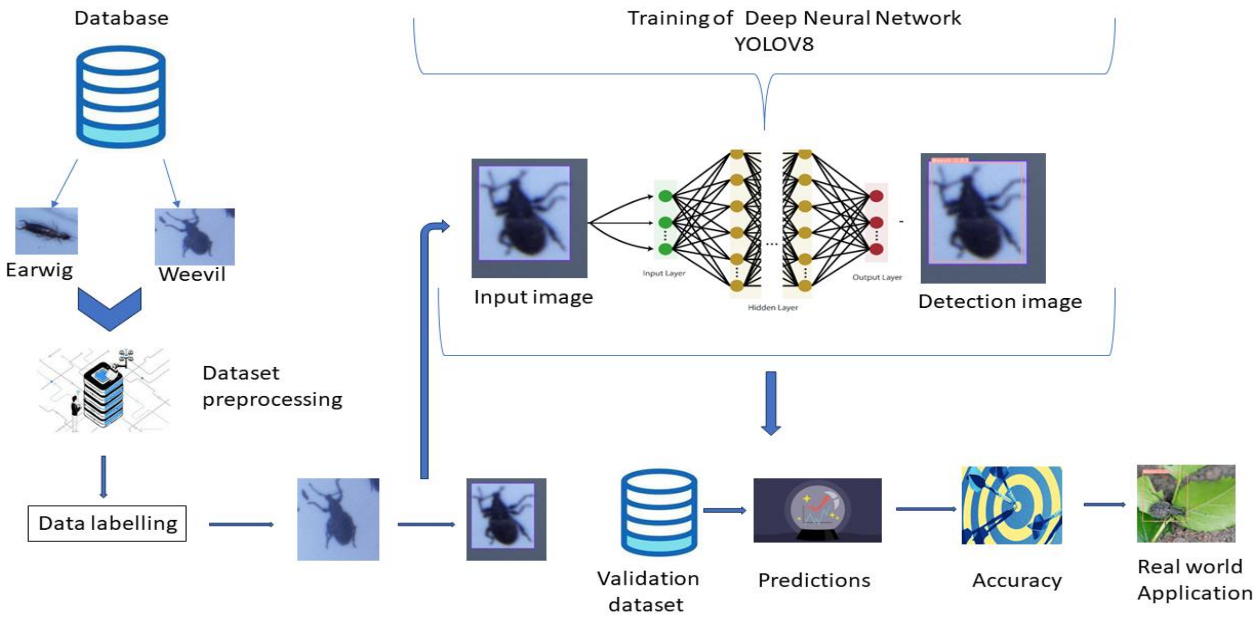


Figure 3: A concise summary of the suggested deep learning technique for this research.

Data set

Photographs of two distinct pests are included in the collection: black vine weevil and earwig. The photos are taken from a previously created database (https://github.com/onthesofa/weevil-watch). The photographs are subsequently processed to improve the collection, resulting in a blended database with two classes, each class contains 200 images and total 400 images of pests. The photographs in the collection are described in detail.

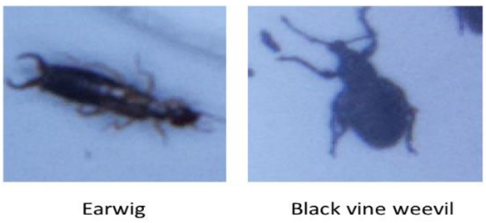
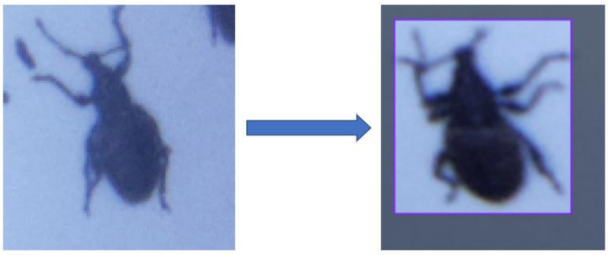


Figure 4: Two types of classes: Earwig and Weevil

Data labelling

Roboflow (Dwyer, Nelson and Solawetz, 2022) is used as an annotating tool for manually marking the position of each pest with the boundaries of the box in each image, starting with the pest dataset. The annotations are saved in the txt format as files of text. The purpose of the associated annotation technique is to identify the insect's type and position in the image.

By anticipating network outcomes during testing, this technique delivers the coordinates of variable size bounding boxes with their accompanying classes, which is quantified as intersection-over-union. Figure 5 shows the bounding box annotated to help understand things. The annotated pictures were divided into 8:1:1 group for training, validation, and testing.



Actual image

Image after labelling

Figure 5: Overview of Actual image vs Labelled image

Model Training

Yolov8 object detection models are constructed and trained on Earwig and Weevil photos. After the dataset has been labelled, training may begin. We utilised Google Colab to train the model. The Google colab interface is simple to use and executes the arbitrary Python code, making it ideal for Machine learning, Deep learning, and data analysis. Before commencing training, the model is setup in terms of dataset and GPU settings. The batch is set to 8 and 16 respectively. The picture width and height are adjusted to 128 × 128 and 256 x 256, respectively, and training is done using only 100 epochs.

Figure 6: Represents the Training images of the Earwig and weevil.

Results and Evaluation

Metrics of performance

Precision: Precision is the fraction of real positive predictions (objects properly recognised) out of all projected positive cases. Higher accuracy values suggest that the models have a low false positive rate, indicating that they are accurate in detecting the important items (Earwig and Weevil) in pest data.

$$P = \frac{True\ Positive}{(True\ Positive + False\ Positive)}$$

Recall: Recall, also known as sensitivity, is the fraction of genuine positive predictions in the dataset out of all real positive cases. Higher recall values indicate that the models effectively captured a considerable amount of the real Earwig and Weevil cases, lowering the frequency of false negatives.

$$R = \frac{True\ Positive}{(True\ Positive + False\ Negative)}$$

P and R numbers that are higher signify better detecting abilities. As opposed to this, the F-1 score is the P and R's arithmetic mean, which is expressed as:

$$F1 - SCORE = 2\left[\frac{Precision \times Recall}{Precision + Recall}\right]$$

mAP50: At 50%, the mean average precision is 50%. The Intersection over Union (IOU) criteria measures the average accuracy of the models when the projected bounding boxes and the ground truth overlap by at least 50%. A higher mAP50 score shows that the models are effective in reliably localising the commodities, especially when there is reasonable overlap with the ground truth.

mAP50-90: Mean Average Precision from 50% to 90%Intersection over union threshold evaluates the models' performance across a broader range of Intersection over union thresholds. A higher mAP50-90 score indicates that the models can retain consistent accuracy in localising Weevil and Earwig objects even as the overlap gets stricter (Intersection over union rises).

$$Intersection\ over\ union = \frac{Area\ of\ overlap}{Area\ of\ union}$$

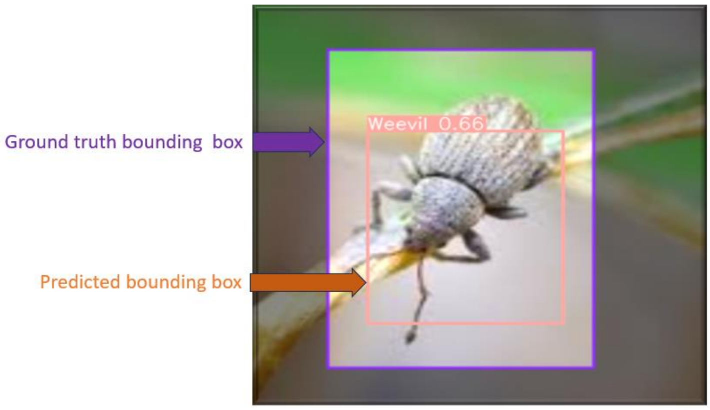


Figure 7: Ground truth bounding box vs predicted bounding box.

Detection Results

Figure 8 shows instances of Weevil and Earwig recognition produced with the YOLOv8-based model. These findings indicate the model's ability to effectively recognise and delineate the pest detection within the photos.

Validation Images

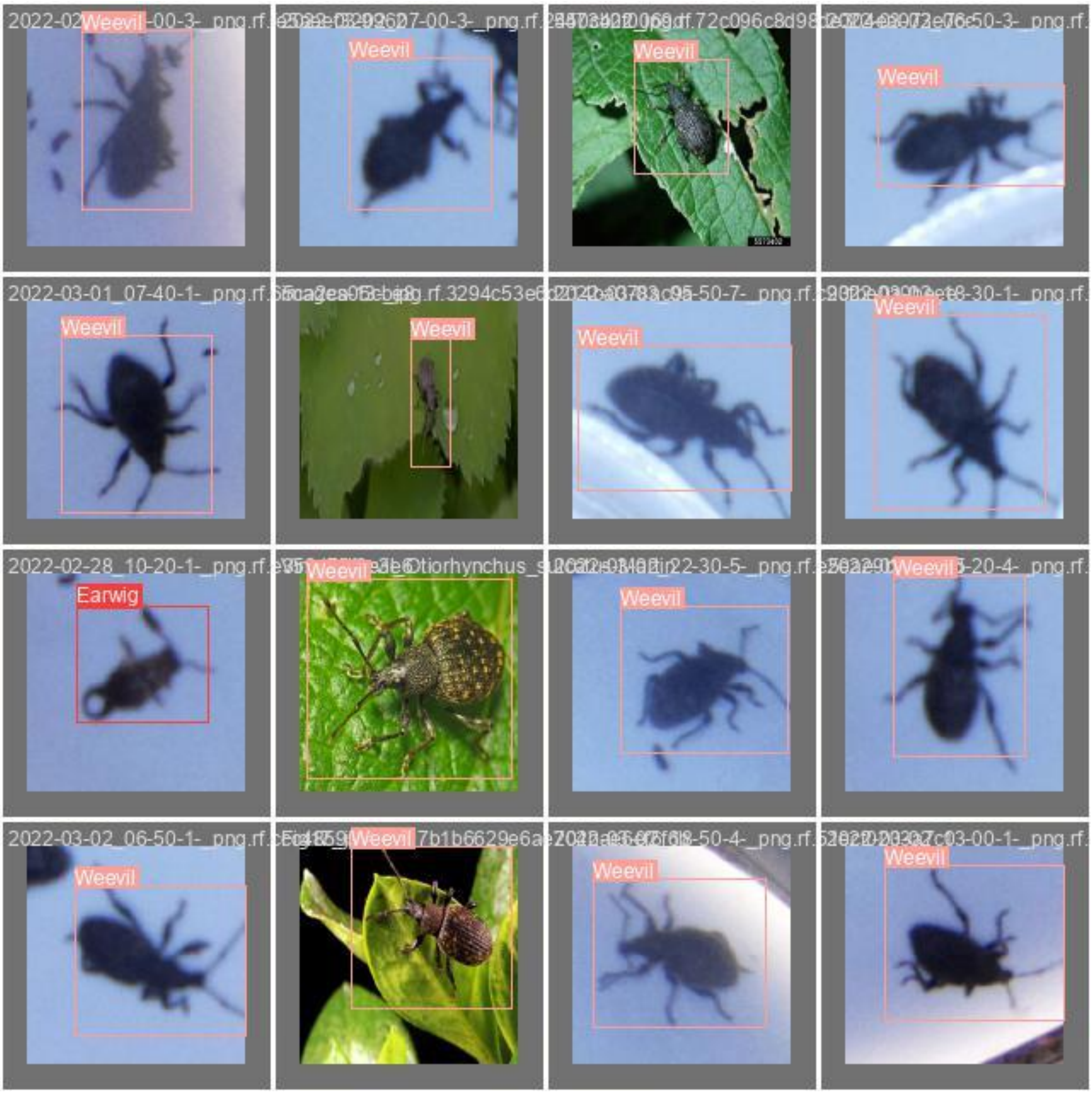


Figure 8: Yolov8 validation images with bounding boxes which represents Weevils and Earwigs.

Predictions

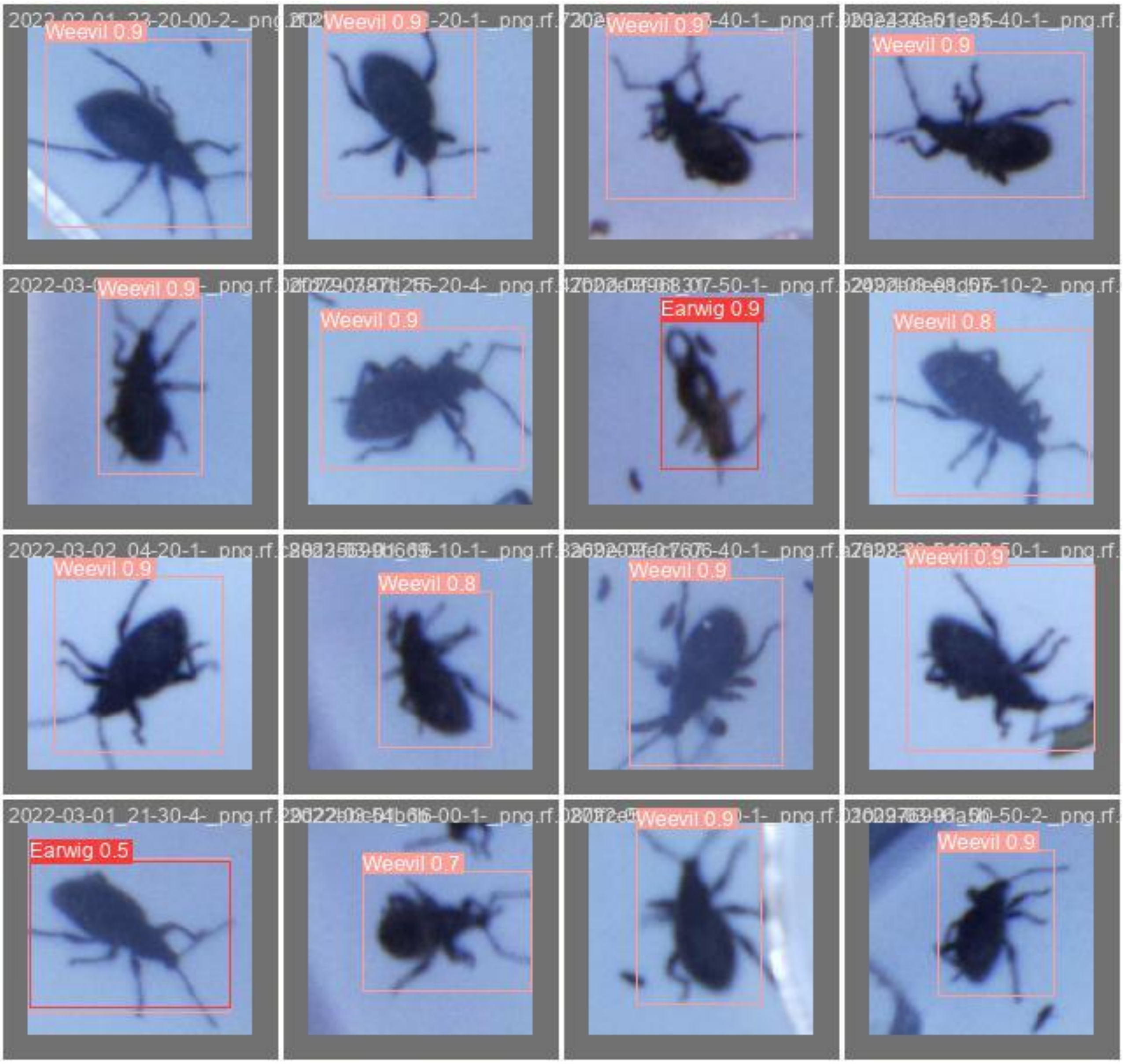


Figure 9: Shows the predictions of Weevils and Earwigs with bounding boxes. The bounding box with number shows the percentage that correctly identified as a weevil and earwig. For example, a bounding box with 0.9 which represents that the model correctly identifies 99% as a weevil.

Model Performance

Comparison Highest vs lowest

In this section, we compare the performance of different YOLOv8 models using evaluation metrics obtained for two different settings: batch size 8 and image size 128 pixels, and batch size 16 and image size 256 pixels. The evaluation metrics include Precision, Recall, mean

Average Precision at Intersection over union threshold 0.50 (mAP50), and mean Average Precision (mAP50-90) from Intersection over union threshold 0.5 to 0.9 with 0.05 steps). Table 1 presents the results for batch size 8 and image size 128 pixels, while Table 2 shows the results for batch size 16 and image size 256 pixels.

Table 1: Result and evaluation metrics for batch 8 and image size 128 pixels

Models	Precision	Recall	mAP50	mAP50-90
Yolov8n	**0.91**	**0.92**	**0.94**	**0.57**
Yolov8s	**0.91**	**0.92**	**0.94**	**0.57**
Yolov8m	0.87	0.91	0.91	0.53
Yolov8l	0.81	0.83	0.82	0.48
Yolov8x	0.81	0.84	0.83	0.49

Table 2: Result and evaluation metrics for batch 16 and image size 256 pixels

Models	Precision	Recall	mAP50	mAP50-90
Yolov8n	0.89	0.92	0.93	0.56
Yolov8s	0.87	0.89	0.89	0.55
Yolov8m	0.85	0.85	0.86	0.51
Yolov8l	0.78	0.81	0.79	0.46
Yolov8x	**0.74**	**0.79**	**0.76**	**0.45**

The Yolov8n and Yolov8s models exhibit the highest metrics among all models, with Precision and Recall reaching 0.91 and 0.92, respectively. These models also achieve a high mAP50 of 0.94 and a respectable mAP50-90 of 0.57, indicating their strong detection capabilities and accurate localization of objects in the given dataset. On the other hand, the Yolov8l and Yolov8x models show lower metrics, with Precision ranging from 0.81 to 0.84 and recall from 0.83 to 0.84. These models achieve an mAP50 of 0.82 and 0.83, respectively, and mAP50-90 values of 0.48 and 0.49, indicating comparatively lower detection accuracy and localization performance.

The Yolov8n and Yolov8s models continue to maintain high metrics even with increased batch size and image size. Yolov8n achieves a Precision of 0.89 and recall of 0.92, along with an mAP50 of 0.93 and mAP50-90 of 0.56. Yolov8s demonstrates a Precision of 0.87, Recall of 0.89, mAP50 of 0.89, and mAP50-90 of 0.55. These results suggest that these models maintain robust performance in object detection tasks with larger input sizes. In contrast, the Yolov8l and Yolov8x models still exhibit lower metrics, with Precision ranging from 0.74 to 0.78 and recall from 0.79 to 0.81. These models achieve an mAP50 of 0.76 and 0.79, respectively, and mAP50-90 values of 0.45 and 0.46, indicating limited accuracy and localization capabilities compared to other models.

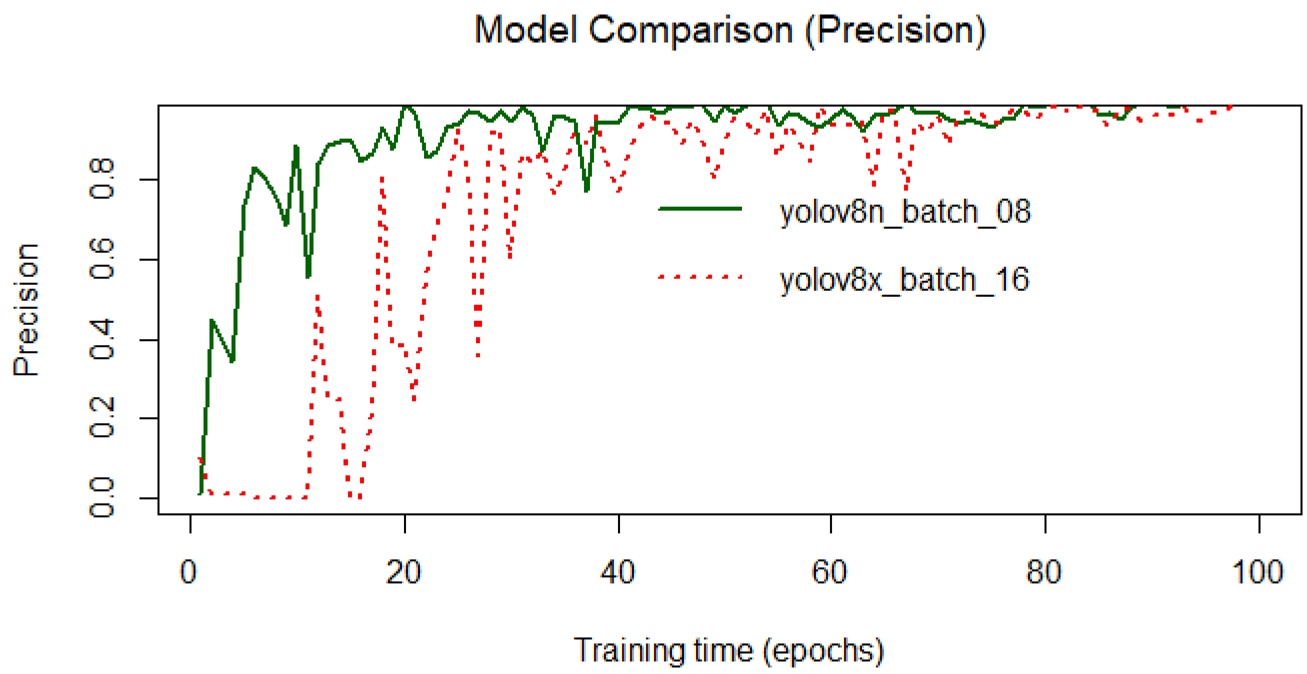


Figure 10: Precision comparison between yolov8n_batch_8 and yolov8x_batch_16.

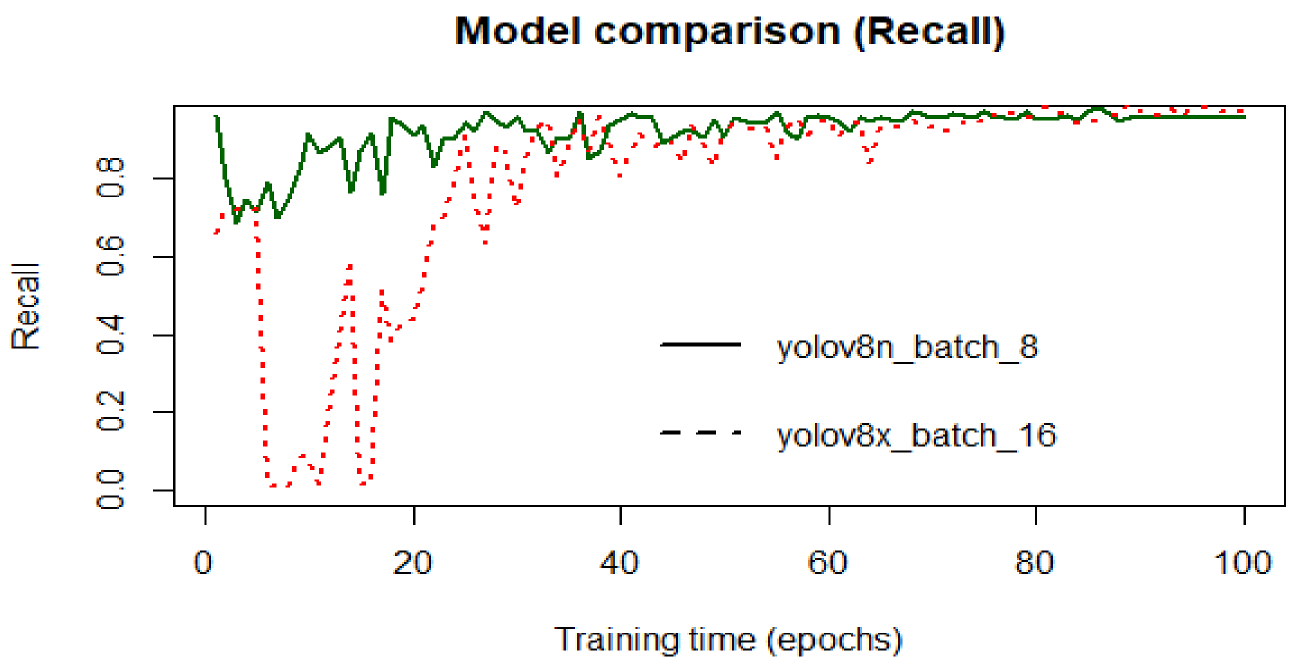


Figure 11: Recall comparison between yolov8n_batch_8 and yolov8x_batch_16.

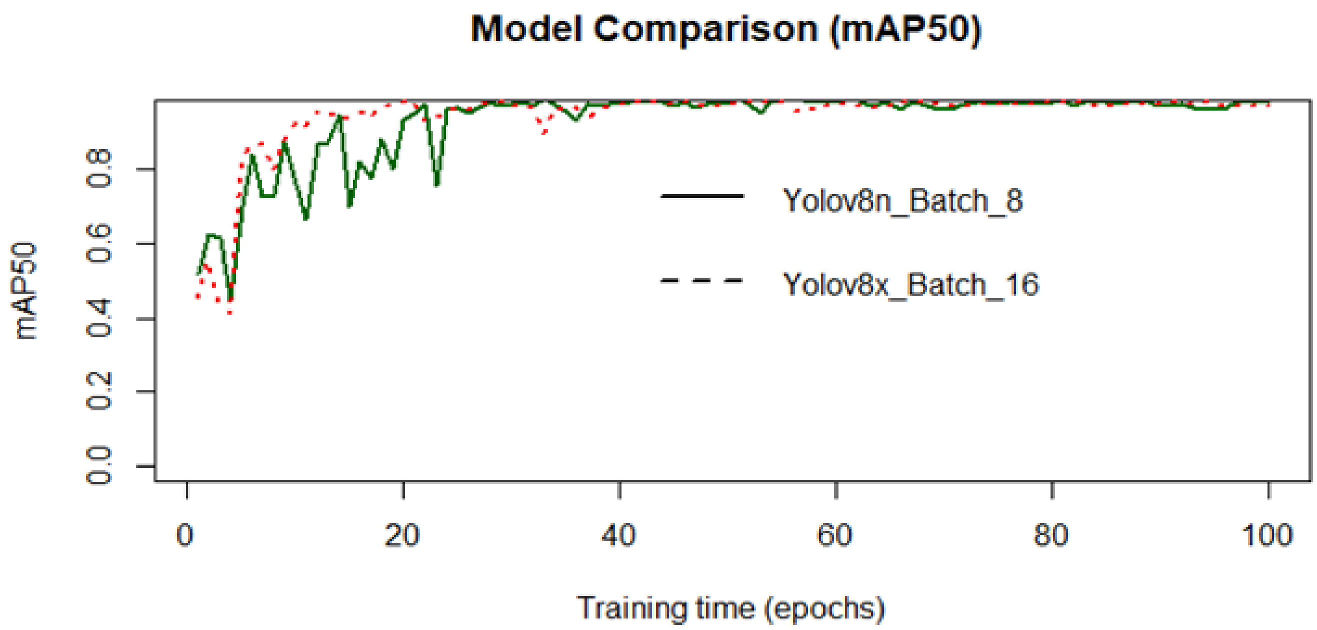


Figure 12: Mean Average precision50 comparison between yolov8n_batch_8 and yolov8x_batch_16.

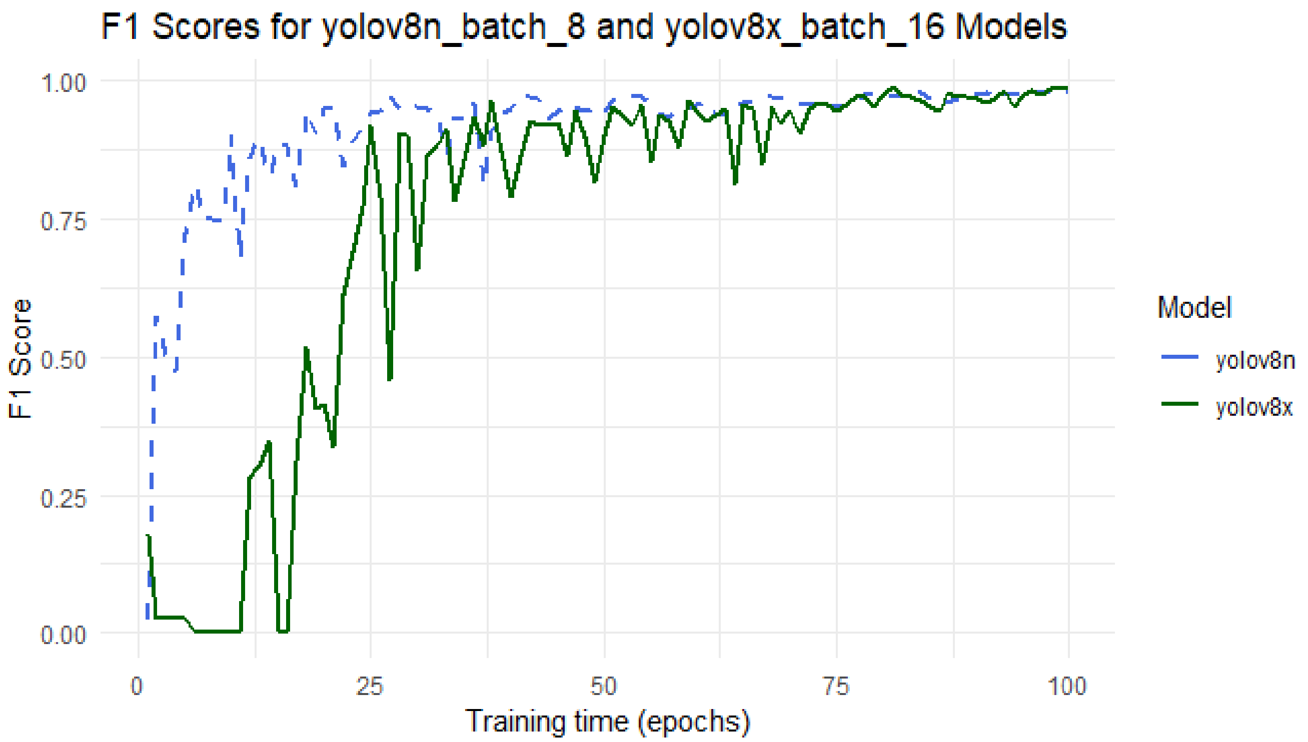


Figure 13: F1-Score comparison between yolov8n_batch_8 and yolov8x_batch_16.

Model Performance Comparison

Table 3 presents evaluation metrics for YOLOv8 models trained with batch size 8 and image size 256 pixels. Yolov8n and Yolov8s demonstrate high Precision and Recall (0.89-0.92 and 0.88-0.90, respectively), along with competitive mAP50 and mAP50-90 values (0.93, 0.91, 0.56, and 0.53). Conversely, Yolov8l and Yolov8x exhibit lower metrics (Precision: 0.73-0.79, Recall: 0.79-0.80, mAP50: 0.77-0.78, mAP50-90: 0.44). Table 4 displays results for batch size 16 and image size 128 pixels. Yolov8n and Yolov8s maintain strong Precision (0.90, 0.91), Recall (0.92, 0.93), mAP50 (0.94), and mAP50-90 (0.56, 0.57). Yolov8m shows competitive performance (Precision: 0.89, Recall: 0.89, mAP50: 0.90, mAP50-90: 0.52). Yolov8l and Yolov8x exhibit lower metrics (Precision: 0.80-0.89, Recall: 0.82-0.84, mAP50: 0.81-0.49, mAP50-90: 0.48).

Table 3: Result and evaluation metrics for batch 8 and image size 256 pixels

Models	Precision	Recall	mAP50	mAP50-90
Yolov8n	0.89	0.92	0.93	0.56
Yolov8s	0.88	0.90	0.91	0.53
Yolov8m	0.86	0.89	0.89	0.52
Yolov8l	0.73	0.80	0.78	0.44
Yolov8x	0.73	0.79	0.77	0.444

Table 4: Result and evaluation metrics for batch 16 and image size 128 pixels

Models	Precision	Recall	mAP50	mAP50-90
Yolov8n	0.90	0.92	0.94	0.56
Yolov8s	0.91	0.93	0.94	0.57
Yolov8m	0.89	0.89	0.90	0.52
Yolov8l	0.89	0.84	0.81	0.49
Yolov8x	0.80	0.82	0.81	0.48

Testing our model in a real-world example

To test our model, we have downloaded images from the internet. We took both image pests i.e., black weevil images and earwig images. During testing, we set the parameters image size 640, Intersection over union 0.50. After testing, the model accurately identifies the black vine weevil and earwig. The model is mainly based on black vine weevil detection, but we took the earwig images as well, because the model should correctly distinguish the difference between black vine weevil and other pests in a real-world scenario.

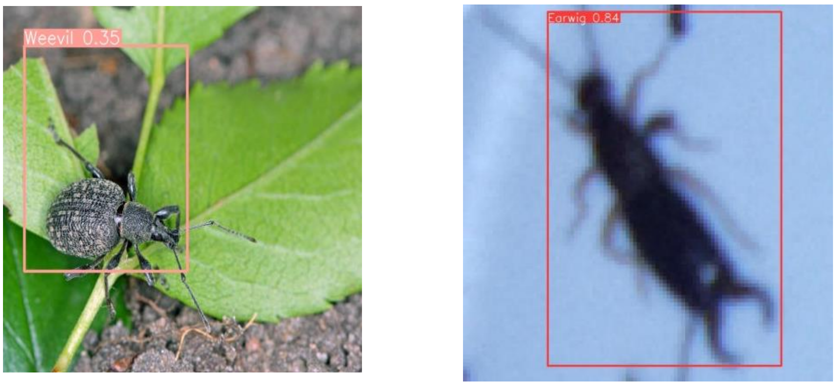


Figure 14: Real-time pest detection of weevil and earwig.

Discussion

Objective 1: Create a reproducible methodology to rapidly create a baseline dataset for training, testing, and validation for pest insect classification.

To achieve this objective, we developed a reproducible methodology for creating a baseline dataset to train, test, and validate the pest insect classification model. Leveraging a previously curated database, we assembled the dataset consisting of two classes: black vine weevil and earwig pests. This dataset is crucial for training and evaluating the computer vision model accurately.

The approach of creating a dataset using image analysis aligns with previous studies.(Cho *et al.,* 2007) demonstrated the application of image analysis for the automatic identification of whiteflies, aphids, and thrips in greenhouses. Similarly, (Maharlooei *et al.,* 2017b) utilized image processing techniques for detecting soybean aphids in a greenhouse environment. These studies highlight the efficacy of image-based approaches for pest identification and management.

Objective 2: Create a reproducible baseline classification and detection model using a comparative framework (different model sizes in a recent YOLO model framework).

To fulfil this objective, we built a reproducible baseline classification and detection model using a comparative framework that involved different model sizes in the YOLOv8 model. By experimenting with YOLOv8n, YOLOv8s, YOLOv8m, YOLOv8l, and YOLOv8x, we aimed to identify the most efficient and accurate model for pest detection.

The adoption of the YOLO framework in this study is supported by (Jiang *et al.,* 2022), who provided an extensive review of YOLO algorithm developments. They highlighted the versatility and real-time object detection capabilities of the YOLO framework, making it a suitable choice for pest detection applications.

Objective 3: Create and test a reproducible experiment methodology to rapidly train and tune pest detection models for accuracy and speed.

To address this objective, we developed and tested a reproducible experiment methodology to rapidly train and tune the pest detection models. By systematically adjusting hyperparameters, such as image size, batch size, and epochs, optimized the models for improved accuracy and computational efficiency.

Hyperparameter tuning is a critical aspect of deep learning model development, and it has been explored in various studies. (Ferri, Hernández-Orallo and Modroiu, 2009) performed an experimental comparison of performance measures for classification tasks and emphasized the importance of selecting appropriate hyperparameters to enhance model performance. In this context, the methodology used in the current study aligns with established best practices in deep learning.

Objective 4: Validate an example model using real pest images in a biologically relevant scenario.

To achieve objective 4, The developed model was validated using real pest images in a biologically relevant scenario. We ensured that the model could accurately distinguish between black vine weevils and earwigs in practical agricultural settings, thus establishing its real-world applicability.

The importance of validation with real-world images is well-documented in the literature. (Li *et al.,* 2021) conducted a systematic review of classification and detection of insects using deep learning for smart pest management. We emphasized the need for validation with real field images to ensure the robustness of the models in actual pest control scenarios. The successful validation in this study confirms the potential of the developed model for practical pest management applications.

Conclusion

To summarise, we created an efficient and robust object detection system YOLOv8 based on computer vision for accurate detection of Weevils and Earwigs in this study. When comparing the performance of several YOLOv8 models, fascinating discoveries emerge. Yolov8n and Yolov8s routinely exhibit excellent accuracy, recall, mAP50, and mAP50-90 scores, making them appropriate candidates for accurate object detection tasks in the Earwig and Weevil. The results for Yolov8m, Yolov8l, and Yolov8x are slightly lower, demonstrating an imbalance both the level of complexity and efficiency. Among the models evaluated, Yolov8n and Yolov8s appear to be the most sturdy and accurate options. However, the performance drop is minor, demonstrating that the models may still retain good accuracy with bigger batch sizes and better picture resolutions. The top-performing models across all configurations are the YOLOv8n and YOLOv8s. They regularly earn the greatest accuracy, recall, mAP50, and mAP50-90 scores, making them the best models for detecting Weevils and Earwigs. The excellent accuracy and recall scores of the YOLOv8n and YOLOv8s algorithms show their potential usefulness for accuracy Horticultural and agricultural applications such as pest management. Their capacity to identify and localise Weevil and Earwig occurrences can help to develop more efficient and focused pest management techniques, which will improve farming practises in the long run. Therefore, based on the evidence we presented in this study, YOLOv8n and YOLOv8s are the best models for rapid and accurate pest detection in the context of integrated pest management for the black vine weevil case study.

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