The International Society of Precision Agriculture presents the 16th International Conference on **Precision Agriculture**

21–24 July 2024 | Manhattan, Kansas USA

Detection of sorghum aphids with advanced machine vision

Ivan Grijalva¹, Nicholas Clark¹, Brian J. Spiesman¹, and Brian McCornack¹ ¹Department of Entomology, Kansas State University, Manhattan, KS 66506, USA

A paper from the Proceedings of the 16th International Conference on Precision Agriculture 21-24 July 2024 Manhattan, Kansas, United States

Abstract.

Sorghum aphid, *Melanaphis sorghi* (Theobald), became a significant pest concern due to the significant yield losses caused in the sorghum production region. Different management practices, including monitoring and applying insecticides, have been used to manage this invasive pest in sorghum. The most common management strategy consists of visual assessments of aphids on sorghum leaves to determine an economic threshold level to spray. However, because of their rapid reproduction, a framework that can detect and count aphids automatically is needed to reduce the time of visual assessments and human labor. To assist in monitoring sorghum aphids, we used machine vision models to detect and count aphids on sorghum leaves automatically. We used a dataset of 1190 images collected during pest monitoring events to train 3 different detection models found in the YOLOv5 family that vary in architecture. Among these models, the YOLOv5m Pytorch model was able to detect aphids with a precision of 92%, a recall of 84.5%, and 90.6% mAP@0.5, making it a candidate vision model that can be used in web applications or be deployed into multipurpose robotic vehicles to detect and manage aphids automatically. Our framework will aid the change of traditional pest monitoring, using machine vision models and robotics for digital pest management in sorghum.

Keywords.

Sorghum; sorghum aphid; machine vision models; detection.

The authors are solely responsible for the content of this paper, which is not a refereed publication. Citation of this work should state that it is from the Proceedings of the 16th International Conference on Precision Agriculture. EXAMPLE: Last Name, A. B. & Coauthor, C. D. (2024). Title of paper. In Proceedings of the 16th International Conference on Precision Agriculture (unpaginated, online). Monticello, IL: International Society of Precision Agriculture.

Introduction

The sorghum aphid *Melanaphis sorghi* (Theobald) causes significant yield loss in sorghum. One of the strategies to manage this pest and prevent yield loss is using pest monitoring to determine an economic threshold level used for spraying insecticides. However, pest monitoring is time-consuming and requires trained personnel and regular visual assessments across large field areas once aphids are detected on sorghum plants. Therefore, we developed an aphid counter system using machine learning to automate counting aphids and increase the precision in pest sampling.

Machine learning, specifically deep learning, has been applied to different disciplines to automate sampling activities that require identification, detection, counting, classification, or segmentation of biological threats. Deep learning usually uses imagery to generate a labeled dataset that can be used to train deep learning models to automate different activities performed in research and agricultural production. In Entomology, specifically pest monitoring, this technology can help reduce the time spent counting and identifying insects. For instance, Wang et al. 2023 were able to detect and identify common coccinellids found in sorghum with an average precision of 74.6% using images from iNaturalist. Grijalva et al. 2023a, demonstrated that deep learning models can classify different aphid densities on images found on standard economic thresholds for spraying with an accuracy of 86%. This information suggested that deep learning models can be applied to the automated detection and counting tasks of aphids, which are usually common activities performed during pest monitoring of aphids.

Consequently, the examination of detection and counting aphid individuals on images based on standard densities for spraying was performed using the same technology (i.e., deep learning) with different image processing techniques (Grijalva et al. 2023b). This helps inform us that automation can be applied to pest monitoring of aphids, potentially reducing the time needed for visual assessments of pests and training personnel.

Materials and Methods

A total of 1,190 images with different aphid densities were collected using a Sony ILCE-6000 v 3.10 digital camera from commercial sorghum fields in Kansas during pest monitoring events. The collected imagery was labeled using the polygon tool to outline individual aphids within each image using the cloud-based Roboflow environment (Dwyer, B and Nelson, J 2022). The aphid individuals marked ranged from 1-125 sorghum aphids/leaf used to generate a training dataset. Furthermore, we applied mosaic augmentation in the dataset to increase the diversity of aphid densities and the performance of models. During the training phase, images were standardized to 1280 × 1280 pixel sizes and trained with 3 different models within the YOLOv5 family (Ultralytics). The training was performed using NVIDIA A100 GPU from Colab and a Google's Jupyter notebook-based Python environment with an open-source baseline notebook (Ultralytics). The diagram of the methodology is depicted in Fig.1.

Results and Discussion

The YOLOv5m detection model is a potential candidate for detecting sorghum aphid densities on leaves with 92% precision, 84.5% recall, and 90.6% mAP@0.5, followed by YOLOv5s and YOLOv5n (Table 1; Fig. 2). We encounter different detection problems with images that were misidentified due to a similarity in shape and color of the sorghum aphids with the background of the leaves. However, by allowing other researchers to access this trained model, it becomes simpler for additional developers to further enhance the overall performances of these models in identifying sorghum aphid densities.

The outcomes of our study showed promising potential. However, enhancing the performance of these models could be achieved by incorporating additional training images. Also, improving

the resolution of the images used for training and applying effective augmentation techniques could significantly increase their performance. Our study's methodology and the models we examined helped us better understand how deep learning can be applied to detect pests. We believe that our models have the potential to improve pest monitoring significantly by substituting visual aphid assessments with RGB images, standardizing estimates, and screening insect-resistant varieties. They can be easily deployed in web-mobile apps and unmanned vehicles for real-time detection and decision-making. This approach has the potential to significantly reduce the time and effort involved in pest monitoring and screening aphid-resistant sorghum varieties.

Tables and Figures

Table 1. Overall precision, recall, and mAP@0.5 scores of YOLOv5 models tested at 1280 ×1280-pixels input resolutions.

Model types	Precision (%)	Recall (%)	mAP@0.5 (%)
YOLOv5n	89.00	82.60	89.20
YOLOv5s	92.40	82.60	90.40
YOLOv5m	92.00	84.50	90.60

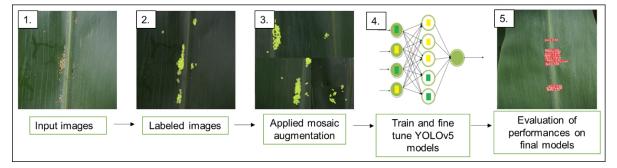


Figure 1. Data flow diagram to evaluate the performance of YOLOv5 detection models.



Figure 2. Detection results using testing images at 1280 × 1280-pixels input resolution without (A) or with aphid detections (B) performed by YOLOv5m model.

Conclusion

This study introduced a framework and a model capable of identifying sorghum aphid infestations at the leaf level using digital images. The YOLOv5m model achieved a precision of 92%, a recall of 84.50%, and a mAP@0.5 of 90.60% when detecting sorghum aphid infestations. The methodology developed for pest sampling using images and the tested model can be integrated into sampling protocols and screening programs for pest-resistant crop varieties, potentially through advanced web-mobile applications and unmanned vehicles equipped with sensor systems.

Acknowledgments

We want to thank the research members of the Field Crops IPM Lab, including Nick Clark, Kent Hampton, Max Dunlap, Anna Keenan, Amanda Drouhard, Luke Carney, and Trevor Witt, for their support, data collection, and manual labeling of images. This project was partially supported by the National Robotic Initiative grant no. 2019-67021-28995.

References

Dwyer, B, Nelson, J (2022) Roboflow

Grijalva I, Spiesman BJ, McCornack B (2023a) Image classification of sugarcane aphid density using deep convolutional neural networks. Smart Agricultural Technology 3:100089. https://doi.org/10.1016/j.atech.2022.100089

Grijalva I, Spiesman BJ, McCornack B (2023b) Computer vision model for sorghum aphid detection using deep learning. Journal of Agriculture and Food Research 13:100652. https://doi.org/10.1016/j.jafr.2023.100652

Ultralytics YOLOv5 Documentation. https://docs.ultralytics.com/. Accessed 16 Nov 2022

Wang C, Grijalva I, Caragea D, McCornack B (2023) Detecting common coccinellids found in sorghum using deep learning models. Scientific Reports 13:9748. https://doi.org/10.1038/s41598-023-36738-5