Unconventional strategies for aphid management using smart computer vision models in sorghum

by

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B.S., Panamerican School of Agriculture “Zamorano”, 2014
M.S., Purdue University, 2019

AN ABSTRACT OF A DISSERTATION

submitted in partial fulfillment of the requirements for the degree

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Abstract

Aphids are a challenging crop pest to manage. The sorghum aphid, for example, causes significant yield loss in unmanaged sorghum. One of the key 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. There is a need to develop alternative methods to monitor and manage the diverse various pests on crops effectively. The economic impact of the sorghum aphid, *Melanaphis sorghi* (Theobald) (Hemiptera: Aphididae), their small size and high reproductive rate make it a suitable study organism to examine new technology. The technology should automate the visual assessments performed during pest monitoring, and the further development of this technology using new management strategies compared to traditional management on field crops.

Therefore, the objective was to understand the use of technology to develop automate aphid visual assessments and develop new management strategies, which can be applied with the further development of this technology. A series of computer experiments and field trials were conducted to understand how technology, specifically machine learning, can be applied to aphid identification and the responses of different management strategies based on economic threshold levels. Computer experiments demonstrated that machine learning using deep learning can classify different aphid densities on images found on standard economic thresholds for spraying with an accuracy of 86% and the correct classification of aphids' densities as above or below threshold spray density over 97% of the time. Together this information suggested that deep learning can be applied to the automated classification of aphid densities found on images and

further development of detection and counting tasks of aphids, 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. Results showed 92% precision, and 21% mean percent error of miscounting aphids on images. This helps to inform that automation can be applied to pest monitoring of aphids, potentially reducing the time for visual assessments of pests and training personnel. The combination of automated classification-detection of aphids can lead to the identification of other insect organisms commonly found in sorghum environments. These insects, primarily coccinellids, are considered beneficial insects that can manage aphid populations naturally. Therefore, we used similar approaches to detect and classify common coccinellids found in sorghum.

Together this work demonstrates that deep learning can be implemented in pest monitoring of aphids creating a smart insect monitoring system that can lead to new strategies for making management decisions. The new suggested strategies was tested on field trials to understand the responses of sorghum aphids and coccinellids under commonly used spraying strategies for aphid management, including economic and tally threshold levels and new strategies on randomly and specific spraying plants on whether or not aphids are present on plants. Field experimental results showed that we can manage aphid populations by applying insecticides to individual plants with or without aphids, reducing the environmental effects and pest resistance. Collectively this information will aid in the use and adoption of deep learning models for pest management and the development of mobile applications and unmanned vehicles with sophisticated sensor systems to manage aphids with the new proposed pest strategies.

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Dedication

This dissertation is dedicated to my family and especially to my grandfather who passed away during my studies and who always encouraged me to become the person that I am.

Chapter 1 - Literature Review

Introduction

Since the development of agriculture, growers have been challenged by arthropods, collectively called "pests," that harm their crops and put food security at risk (Oerke, 2006). One of the significant groups that colonize important economic crops, such as cereals, are aphids in the southern Great Plains of North America (Brewer et al., 2019). Aphids are the most destructive pest on cereal crops, including wheat and sorghum crops (Brewer and Elliott, 2003). Since 2013, an important economic pest has been causing yield loss and affecting sorghum in different U.S. states (Bowling et al., 2016). Sorghum aphid, *Melanaphis sorghi* (Theobald), threatens sorghum yield due to its high reproduction rate under warm conditions, which is typical for sorghum grown in the great plains of North America (Bowling et al., 2016).

A traditional activity to support adequate insect management of sorghum aphids is pest monitoring. This activity consists of tracking the arrival of pests by sampling different field areas through space and time and making estimates about their populations using visual observations for a defined sampling unit (i.e., leaf, plant). However, scouting is time-consuming and challenging due to the variety insects found in agricultural environments, where populations can build quickly making this task difficult and complex, which is often crop specific (Bishop and Hutchings, 2011). For example, 4 different aphid species can be found colonizing sorghum during the growth and development stages throughout the season (Bowling et al., 2016; Brewer et al., 2019). Usually, growers or entomologists manually identify pests using morphology keys, pest guides, and images to match key characteristics with common genera and species names reported in the literature (Bishop and Hutchings, 2011). However, using machine learning, and

specifically, deep learning approaches, has the potential to expedite this important component to the scouting process by automating several tasks using imagery.

Species detection and classification of organisms found in production sorghum fields are common tasks during standard scouting events or bouts. Machine learning can automate these tasks with the slightest use of labor and time (Chen et al., 2021). Many traditional machine learning algorithms have been used to classify pests; these include the Normal Bayes classifier (a.k.a., Naïve Bayes classifier), K Nearest Neighbors, Support Vector Machines, Decision Trees, Boosting, and Random Trees (H. Yang et al., 2010). However, a growing subarea in machine learning, called deep learning, can leverage large image datasets to train deep neural networks such as Convolutional Neural Networks (CNNs) (Jordan, M. I. and Mitchell,T. M., 2015) to make accurate predictions on new, unseen images. Deep neural networks, particularly CNNs, have been successfully used for pattern recognition in a diverse range of insect images because of their higher performance in detection and classification tasks compared to traditional machine learning approaches (Hansen et al., 2020; Motta et al., 2020; O'Shea and Nash, 2015). A CNN is a deep neural network that can be used to process any data with a grid pattern, including imagery data (Yamashita et al., 2018).

CNNs perform mathematical operations with a focus on convolution operations, which is a linear operation that can extract image features useful for detection and classification tasks (Yamashita et al., 2018). The use of CNNs identifying species is rapidly growing in the field of entomology (Høye et al., 2021). Different tasks, such as manual identification and counting tasks, can be performed using CNNs and has the potential to aid or even replace humans in key scouting activities. To advance the area of entomology and pest monitoring on sorghum in general, the present review focuses on the basic principles of CNNs and their recent studies that

incorporate state-of-the-art, deep learning approaches that rely on CNNs to automatically classify or detect insects using images. In addition, we suggest an alternative aphid management approach that use these and related technologies.

Convolutional neural networks

Functionality. CNNs are a type of deep learning model that can be used to select features from images or videos of pests or beneficial insects and learn to differentiate among them (S. Albawi et al., 2017). The applications of CNNs can be used for computer vision tasks like object classification and detection (Li et al., 2021). Overall, a CNN is comprised of 3 types of layers, including the convolutional, pooling, and fully-connected layers. The combination of these 3 layers form the CNN architecture (O'Shea and Nash, 2015). Their functionality can be separated into steps to understand their function better (O'Shea and Nash, 2015). First, an input layer retains the input image's pixel values. Next, the convolutional and pooling layers do feature extraction, and then the fully-connected layer maps the extracted features into a final classification or detection tasks (O'Shea and Nash, 2015).

The convolutional layer comprises mathematical operations, such as convolution, which combines linear and nonlinear operations used for feature extraction (Aggarwal, 2018). The non-linearity is obtained through the rectified linear unit (ReLU) activation like a sigmoid function to the output which is used on top of the convolutions (O'Shea and Nash, 2015). The kernel, a small array of numbers perform these convolution operations to conserve the main characteristic of the pixels in the image (S. Lim et al., 2017). The output of these operations is called a feature map, that will pass to the pooling layer many times if necessary (S. Lim et al., 2017). In the pooling layer, the strongest signal is selected and finally, after the pooling layers are created,

they are mapped to the fully-connected layers, and an activation function is applied to the last fully-connected layer to perform a classification or detection task (Aggarwal, 2018).

Object classification and detection tasks of insects on images using CNNs. To advance the area of entomology and pest management, different tasks like automated object detection and classification of insects are needed because they can change the way on how we traditionally collect data in these areas that is currently based on visual observations (Høye et al., 2021), which are subjective and need training to be performed. Therefore, it is important to understand the main concepts of this tasks to see their applicability and further development.

Object recognition can be understood by two different concepts such as object classification and detection. Object classification using images means that the object in the image was previously determined by an information category or a specific ID. A classification task performed by a CNN predicts an instance of an object in an image and provides a category or a specific ID to the object (Li et al., 2021). For example, Spiesman et al. (Spiesman et al., 2021) used an InceptionV3 pre-trained model successfully classify bumble bee species with a 91.6% accuracy using 89,776 images of bumble bee species from a diverse range of imagery repositories, including iNaturalist, Bumble Bee Watch, and BugGuide. Also, Arroyo et al. (Arroyo, n.d.) proposed InceptionV3 pre-trained model as a baseline to classify coccinellids families with 98% accuracy using 1327 coccinellid images from online repositories and field-collected images. Kusrini et al. (Kusrini et al., 2020) using a pre-trained VVG-16- deep learning model classified 15 different categories of pest images of mango with an accuracy of 76%.

On the other hand, object detection mainly focuses on the target object in the image. An object detection task performed by a CNN can predict the category and location of the object, usually using a bounding box (i.e., a common detector outcome (Padilla et al., 2020)) in the

image at the same time (Li et al., 2021). For example, a proposed detector model by Vega et al. (Vega. M et al., 2021) used the weighted Hausdorff distance as a loss function in combination with a full CNN was able to detect beetles on images with a mean accuracy of 94.30%. Current detection models used to identify insects can be classified into one and two-stage methods (Wang et al., 2022). The one-stage methods require only one pass of the CNN and can predict all the bounding boxes during the only pass (Du et al., 2020). On the other hand, two-stage methods have intermediate steps, such as determining the proposed region before classifying and locating the object of interest (Du et al., 2020). Because of the good detection accuracy, models with two-stage methods have been used recently to detect objects (Wang et al., 2022). These models include the R-CNN, SPP-net, Fast-RCNN, Faster-RCNN, R-FCN, and Cascade R-CNN (Wang et al., 2022). However, recent models developed in the YOLO family models have been used to detect other insect types and aphids showed higher accuracy performances compared to the one-stage methods (Ahmad et al., 2022; Du et al., 2022).

To be able to perform object classification and detection tasks using deep learning with CNN, it is important to follow workflows that can be used to evaluate the performance of this technology that can be applied to the field of entomology or pest management.

Deep learning workflow using CNNs. Images are first annotated using interfaces like Labelbox and Roboflow depending of the object classification or detection tasks desired (Dwyer, B and Nelson, J, 2022; “Labelbox, ‘Labelbox’, Online,” n.d.). The annotated imagery is then split into three sets, including training, validation, and testing (Yamashita et al., 2018). A training set is used for training process where it can be divided in two steps. “The first step is the forward propagation when training set is propagated through the network to calculate the loss and the second step is the backward propagation when the loss gradients are propagated to update the

network weights/parameters" (Caragea, 2023; Yamashita et al., 2018). The loss function quantifies the compatibility between the predicted outputs and the ground truth labels (Yamashita et al., 2018).

The validation set is used to evaluate the model during training, to fine-tune hyperparameters, and achieve model selection (Yamashita et al., 2018). The common hyperparameters for fine-tuning, include learning rate, choice of optimization algorithms, choice of activation function, batch size, epochs, and among others. The hyperparameters are important because they will affect the CNN's functionality and overall performance (O'Shea and Nash, 2015). Finally, during the testing process, the test set is evaluated using metrics on the final selected model trained and fine-tuned with hyperparameters. The best model should be selected based on the metrics of performance, the desired task to perform, and an error analysis of unseen data (Raschka, 2018). To understand how to differentiate between models, it is necessary to understand the basic concept of these metrics to make a correct comparison and selection between models.

Common metrics used to evaluate deep learning model performances. Deep learning models can perform object classification and detection tasks, and different metrics have been used to evaluate these models. These metrics, defined as accuracy, precision, and recall, used the true positive (TP), the false positive (FP), the true negative (TN), and the false negative (FN) values to calculate these metrics. For example, in two class classification tasks (positive and negative), a TP is when the actual outputs are positive, but the deep model is correctly recognized as positive; a TN occurs when the actual outputs are negative, but the deep model is correctly recognized as negative; a FP happens when the actual outputs are negative but the deep model incorrectly recognized as positive; lastly, the FN occurs when the actual outputs are

positive but the deep learning model incorrectly recognized the output as negative. Overall, accuracy determines the fractions of corrected predictions that the model obtained.

Precision defines the percentage of correct predictions among all the predictions for that class, and recall defines the percentage of correct positive predictions among all given ground truths. However, when data has class imbalances, the F-1 score is effective for evaluating the performance of deep learning models (Ahmad et al., 2023). This metric defines the percentage of the harmonic mean of precision and recall metric (Ahmad et al., 2023). In addition, other metrics has been used to evaluate performances of classification models. For example, Grijalva et al. (Grijalva et al., 2023), used a confusion matrix that compared the actual test output with the model's predictions within the different classification categories of images.

Similarly for a detection task, correct detection of a ground-truth bounding box based on labeling is defined as the TP. The FP is an incorrect detection of a nonexistent or a non-target existent object, and the FN defines an undetected ground-truth bounding box. Similarly, precision and recall are metrics used in object detection and can be seen in the precision-recall curve (Aggarwal, 2018). The precision is the percentage to detect only correct positive predictions and recall the percentage to detect correct positive predictions among all ground-truth bounding boxes (Padilla et al., 2020). Usually, the common standard metric to evaluate accuracy of detection tasks is the average-precision (AP) metric (Padilla et al., 2020). To determine a correct or incorrect detection in an image, the use of the Intersection over Union (IoU) is used with AP. The IoU measures the overlap area between the inferenced bounding box and the ground-truth bounding box divided by the area of union between boxes (Padilla et al., 2020).

We can determine if a detection is correct or not by comparing the IoU with a certain threshold. For example, when the IoU ≥ to a certain threshold, the detection output is correct and when the IoU ≤ to a certain threshold the detection output is incorrect (Padilla et al., 2020). Some thresholds varied in range of 50% to 95% with steps of 5%, for example AP@50:5:95. Another way is to represent the threshold by using single values, such as AP50 and AP75 respectively. Also, another important metric is the mean average precision (mAP) using an IoU set to 0.5 (mAP@0.5) a popular metric to evaluate overall detection performance (Ahmad et al., 2022). The mAP measures the accuracy of object detectors over all detections (R. Li et al., 2019). In remaining sections, we summarize the current applications of this technology (i.e., deep learning with CNN) in the field of entomology with current state-of-the-art results for identifying insects in cropping systems.

Case studies in entomology using deep learning. Deep learning has the potential to improve insect pest recognition using computer vision and related sensor technologies. Based on imagery data, it is possible to recognize different insects in different environments (Høye et al., 2021). There are many algorithms developed to identify and classify insects using machine learning approaches. Some of the more common algorithms used include: Normal Bayes classifier, K Nearest Neighbors, Support Vector Machine, Decision Trees, Boosting, Random Trees, and Neural Networks (H. Yang et al., 2010). Specific applications of these models include the automatic bee identification system used to identify and monitor bees (Arbuckle et al., 2001), the BugVisux system for insect recognition (Yu, 1999), and a system for aphid detection (Liu et al., 2016). The progress in machine learning is continuing to develop and is growing quickly in entomology (Chollet, 2018). Currently, a subfield of AI has been addressing laborious,

agricultural tasks, including insect detection and classification. This subfield is machine learning uses CNNs to automatically detect and classify insects using training imagery.

Recent studies using CNNs have focused on automated species classification or precise detection of insects. For example, a dataset with 2,300 ladybird beetle images from Ecuador and Colombia downloaded from the iNaturalist project was used to train a CNN for detecting and classifying beetles with an accuracy of 92% (Venegas et al., 2021). Ladybird beetles are considered significant aphid predators in agriculture and are thus beneficial insects (Crawley, 2009). Chen et al. (Chen et al., 2018) trained a CNN model to segment and count aphid nymphs on pak choi leaves with an accuracy of 84.53%. Using a CNN, Thenmozhi et al. (Thenmozhi and Srinivasulu Reddy, 2019) classified different insect species images from open source insect repositories with a mean accuracy of 96.73%.

A proposed combination of a feature-enhanced attention neural network by Kong et al. (Kong et al., 2022) enabled tasks such as object detection of insects, including coccinellids, and diseases with 85% accuracy. Li et al. (W. Li et al., 2019) proposed a CNN of ZF (Zeiler and Fergus model) and a region proposal network (RPN) with Non-Maximum Suppression (NMS) to be able to detect and count mites on wheat with a precision of 93% and a miss rate of 10%. Li et al. (R. Li et al., 2019) proposed a combination of a Coarse-to-Fine Network (CFN), a developed two-stage method detector that improved the accuracy of aphid detection in regions with dense aphid distribution, and a Fine Convolutional Neural Network (FCNN), defined as a one stage-detector, to be able to perform tasks such as object detection using CFN and to define the regions of aphid presence with the FCNN. In addition, an Improved Non-Maximum Suppression (INMS), considered a new optimization method, to eliminate overlapping regions of aphids in

the images. Experimental results showed a had a 90.9% AP for the FCCN and AP of 76.8% to the CFN.

Li et al. (Li et al., 2022) proposed a multi-branch convolutional neural network (Mb-CNN) with a density map for object detection of aphids and counting. The Mb-CNN are based on the Multi-Column Convolutional Neural Network (MCNN), a deep classification model (Cireşan et al., 2012), and Feature Pyramid Network (FPN), a one stage-method detector (Lin et al., 2017). The overall methodology consisted of training an (Mb-CNN) with aphid images to extract feature maps of different scales. The output is an aphid density map, which provides the aphid's location and distribution for counting. Experimental results showed that the (Mb-CNN) had a 10.22 mean absolute error and 12.24 mean square error for counting aphids. The model performed better than other detection-based methods such as the feature pyramid network, fully convolutional one-stage object detection, and cascade R-CNN.

On the other hand, Pei et al. [34] proposed combining image processing algorithms such as feature point detection and a description algorithm (ORB) with CNN to detect aphids. The approach consisted of an enhanced aphid detection framework (EADF) and was evaluated with or without the one-stage and two-stage detector models. Results showed that the (EADF) approach with RetinaNet had the highest AP of 44.2% in the detection based on the one-stage method. Based on the two-stage and anchor-free method, the Cascade RCNN-EADF had the highest AP of 47.3%.

These case studies performed classification and detection tasks of insects on images using CNNs. This technology can potentially be implemented in sensor systems or unmanned vehicles to assist pest monitoring and further management decisions. The sections described below use sorghum as a study model, a crop that is highly damaged by aphids, and where the use of deep

learning on unmanned vehicles can be applied to improve the traditional scouting and aphid management.

Integration of deep learning on unmanned vehicles for decision making

Deep learning technology can be used by sensor systems or unmanned vehicles (e.g., robots) to deliver an intelligent crop monitoring system (Li et al., 2021). Unmanned vehicles can gather spatial data (i.e., images) from diverse plant areas using different cameras and sensors. Unmanned vehicles have been proven to minimize pest monitoring time and are excellent at capturing spatial data (i.e., images) or spectral responses that are helpful for pest management decisions of different crops (Marston et al., 2019). We presume deep learning can significantly improve the scouting of pests and serve as valuable information for sensor systems on unmanned vehicles to enhance management decisions in field crops.

For example, in sorghum, treatment decisions for aphids depend on visually assessing leaves to determine an economic threshold for insecticide applications (Lindenmayer et al., 2020). These visual assessments are performed to determine an estimate of aphids per leaf, usually from the upper leaf and lowest green leaf (Bowling et al., 2016) or the percent of plants infested in the field (Michaud, J. P et al., 2016). The visual estimations and evaluation of yield responses to aphid infestations have been used to develop economic threshold levels (Gordy et al., 2019). The threshold level for sorghum aphids is 40 aphids per leaf (Gordy et al., 2019). When the threshold level is reached, an insecticide application is suggested to prevent an economic loss due to the high capacity of reproduction of aphids (Gordy et al., 2019).

However, obtaining an accurate estimation of the number of sorghum aphids on leaves is a time-consuming and challenging task due to the high reproduction rates, variety of growth stages, clustering behavior, and the need to inspect wider areas of fields (Deng et al., 2018;

Thomas et al., 2018). In addition, aphid populations can change quickly, requiring continuous monitoring of infested fields throughout the growing season. Therefore, automating the scouting process can address several of these challenges using emerging technologies such as deep learning and associated classification or detection tasks to quantify aphid densities.

The current state-of-the-art results for aphid detection use deep learning architectures, specifically CNNs (Li et al., 2022). Grijalva et al. (Grijalva et al., 2023) proposed the use of CNNs classification models to automatically classify sorghum aphid densities on leaves into 6 classes based on established standard threshold levels for spraying. Notably, the models correctly classified aphids as above or below threshold spray density over 97% of the time. Therefore, the final output model in this study can be used into unmanned vehicles to perform real time aphid identification and further management decisions. Thus, a vision-based automated system for image processing using deep neural networks is needed for precise classification or early detection of aphid densities to advance the current management practices in sorghum.

We envision an approach with automated pest monitoring that can automatically detect-classify aphid infestations with camera sensors mounted on unmanned vehicles and make specific insecticides applications (e.g., plant individual applications), consequently reducing insecticide loads, allowing sustainability with the environment. Currently, insecticides are applied at a whole-field level based on an economic threshold (Ciampitti, I. et al., 2021), potentially treating areas where aphids are not present, resulting in unnecessary applications. Our approach suggests to locate and treat the infestations found on individual plants, which changes the way we conventionally treat crops. However, treating located areas in the field is not well understood and further research is needed to learn about the ecological impact on aphid populations in sorghum.

Sorghum pest management has continued to advance with tools to manage sorghum aphid since their pest outbreak in 2013. As deep learning continues to increase into the entomology field contributing with real-time detection and classification of insects this could be the basis for updated pest management in sorghum, where automation can decrease errors of visual assesments, reduce the cost of labor for scouting, and develop unmanned vehicles that can treat individual plants to manage aphids precisely in sorghum and related crops.

Conclusion

This literature review provided current studies and state-of-the-art methods for detecting and classifying insects using machine learning. A subfield area in machine learning, specifically deep learning with CNNs, has been explored broadly in entomology and pest management. Different approaches using CNNs are currently in use to advance the area of automation for detecting and classifying insects. We expect the integration of deep learning with unmanned vehicles can change how we monitor pests and how we conventionally treat crops with insecticide applications.

The era of automation in identifying insects is advancing at a significant scale. Different studies summarized in this literature review can show how deep learning with the use of CNNs can perform diverse tasks for object detection and classification of insects. However, it is important to understand that deep learning with CNNs is a challenging task requiring programming skills and a deep understanding of the technologies; however, software and machine learning libraries have become more user-friendly to explore these approaches.

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Chapter 2 - Introduction

Since the beginning of agricultural development, growers have competed with harmful insects, collectively called ‘pests’ (Oerke, 2006). These organisms can reduce crop yields and fruit quality, damage plants, serve as disease vectors, and contaminate food crops. Pests represent 37% of annual crop losses, and 13% of this figure is directly caused by insects (Mandava, 2018). A valuable tool for addressing potential threats is integrated pest management (IPM). The IPM concept was introduced in the early 1970s as a strategy for pest management that promoted sustainable agriculture with a strong ecological basis (Ehler, 2006; Kogan, 1998) and its definition has been evolving ever since. The overall goal of IPM is to mitigated losses cause by pest populations, and its function relies on the contribution of tactics, singly or harmoniously, for the management of pests while conserving beneficial insects and the environment (Thomas, 1999). Such tactics can include chemical, cultural, plant resistance, mechanical, and biological control methods (Flint and Van den Bosch, 2012).

The most common pest management strategy across most agricultural systems is using chemicals applied throughout the crop once pests reach injurious levels (Elahi et al., 2019). Usually, pest monitoring, which is a key component to making timely decisions, is a time-consuming activity that demands resources and trained personnel to identify and count pests to determine predetermined economic threshold levels that require food producers to take action to mitigate losses (Martineau et al., 2017; van Klink et al., 2022). An economic threshold is defined as the pest density that management action must implement to prevent reaching an economic injury level (Stern et al., 1959). For example, sorghum growers monitor pests and use economic threshold levels to manage the sorghum aphid, *Melanaphis sorghi* (Theobald). This activity visually estimates aphid densities on a per leaf basis by sampling a defined number of plants with

aphid presence. According to Gordy et al. (Gordy et al., 2019), a suggested economic threshold for sorghum aphids is 40 aphids per leaf, and current sampling protocols suggest collecting 40-60 two-leaf samples and treating when 20-30% of plants are infested with an estimated 25-125 sorghum aphids/leaf (McCornack et al., 2017).

When the sorghum reaches an aphid economic threshold based on pest monitoring, sorghum growers perform insecticide applications throughout the field to prevent rapid aphid reproduction and reduce feeding through harvest as a preventive measure to protect yield (Gordy et al., 2019). Sorghum plants that do not reach an economic threshold level or did not have any aphid presence received unnecessary chemical treatment, potentially increasing aphid resistance, decreasing aphid predation rates by predators (e.g., coccinellids), and cumulative non-sustainable adverse environmental effects (Krupke, C. and Long, 2015; Pimentel and Levitan, 1986; Sánchez-Bayo et al., 2016). Therefore, based on the various negative impacts associated with chemical control and pest monitoring being time-consuming and laboriously expensive (Martineau et al., 2017), there is a critical need for more environmentally sustainable alternative pest management strategies and that incorporate technology as a tool reduce pest monitoring costs while improving the overall goal of management decisions on sorghum.

Consequently, this dissertation will examine how automation research technology using computer vision models (i.e., deep learning models) can be implemented to detect, classify, and count sorghum aphids and common coccinellids on images through experiments and supported with testing datasets to determine their performances. This will lead to the accumulation of knowledge of current technology of aphid detection and classification toward alternative aphid management strategies that can be integrated into sensor technologies capable of managing sorghum aphids. This dissertation aims to develop programming algorithms using machine

learning architectures (i.e., automation research technology) to automatically detect and classify sorghum aphid densities on sorghum leaves. This will help minimize the need for trained personnel and will potentially reduce the time required to visually estimation aphid populations in sorghum. In the long term, integrating multiple technologies can lead to sophisticated systems capable of automatically identifying and classifying sorghum aphids and applying pesticides only on plants with injurious populations.

To achieve our overall objective, we will pursue two aims associated, each with sub-tasks:

1. Develop and train computer vision models for the classification-detection of sorghum aphid densities:

   Sub-tasks:

   i. Train and develop a computer vision model that classifies sorghum aphid densities through a convolutional neural network using images.

   ii. Train and develop a computer vision model that detects and counts sorghum aphid densities through a convolutional neural network using images.

   iii. Train and develop a computer vision model that detects coccinellids through a convolutional neural network using images.

2. Quantify the effect of new aphid management strategies on sorghum aphids and coccinellid populations:

   Sub-tasks:

   i. Model differences in population dynamics of SA and coccinellids per leaf under traditional management strategies and plant-specific management strategies.

ii. Compare plant-specific strategy with best aphid management practices that can be incorporated into artificial intelligence (AI) systems.

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Chapter 3 - Computer vision model for sorghum aphid detection using deep learning

Introduction

Aphid pests are a very challenging taxa to manage in different cereal crops. For example, during sorghum establishment, sorghum aphid, *Melanaphis sorghi* (Theobald) became a significant economic concern for the sorghum production region of the US in 2013. When sorghum aphids are established and under rapid population growth, they can grow exponentially and affect sorghum plant development, causing significant yield reductions and leaf death (Bowling et al., 2016). Different tactics to manage sorghum aphids are currently in use including pest monitoring guides, insecticide treatment protocols, and the development of resistant or tolerant hybrids to reduce the impact of this pest (Bowling et al., 2016). However, one widely used practice is pest monitoring and applying insecticides based on the economic threshold level for sorghum.

An economic threshold is defined as the pest density where management actions are implemented to prevent pest populations from reaching an economic injury level, which is where yield loss is actualized. According to Gordy et al. (Gordy et al., 2019), a suggested economic threshold for sorghum aphids is 40 aphids per sorghum leaf. However, sorghum aphid monitoring can be challenging because of misidentification, as several cereal aphid species infest sorghum, is prone to human error through over- or under-estimation of aphid densities, and is a time-consuming task since it requires a farmer or consultant to walk fields looking for infestations. It is inefficient to sample an entire field, so sampling plans are often deployed to estimate populations (Gordy et al., 2019; Lindenmayer et al., 2020), but this task is not always

cost-effective. There is a need to automate this task for deployment across broad geographic areas under sorghum production.

Recent studies using image preprocessing techniques and computer vision models were able to detect and classify sorghum aphid densities in sorghum. Xu et al. (Weiyue Xu et al., 2022) proposed a segmentation algorithm using different light conditions (e.g., strong, diffuse, weak, and direct sunlight) on images to detect sorghum aphid individuals without an automation process. Another study proposed using computer vision models with deep learning technologies, such as convolutional neural networks (CNNs) to develop a sorghum aphid density classifier using images (Grijalva et al., 2023). However, detection of sorghum aphid individuals has not been reported using CNNs as technology for pest monitoring in sorghum, which can eliminate the need of traditional manual image processing methods, help to provide real-time detection of aphids on untrained images, and potential automation of aphid estimates.

Different tasks can be performed using CNNs, which can potentially accomplish many of the activities that occur during crop scouting events, such as manual identification of key pests, classification of pests into treatment thresholds, and even counting tasks (Høye et al., 2021). Currently, this technology can be found in deep learning frameworks that are more user-friendly for creating algorithms that can be applied to pest detection (Wäldchen and Mäder, 2018). CNNs, as technology in deep learning, can analyze imagery more efficiently with small dependence on image preprocessing and provide important features on pixels that can be used in computer vision to make real-time detections and classification tasks (Ahmad et al., 2022; Grijalva et al., 2023). Successful implementation of such technologies depends on feeding pre-trained networks with information (e.g., images) to make precise inferences using computing

algorithms to detect untrained images (Wäldchen and Mäder, 2018), which could then be used for making standardized pest management decisions using sensor-generated images.

We propose using CNN deep learning models to automatically detect individual aphids on images of sorghum leaves at different image pixel input resolutions using computer vision models. The results of this research can be applied to standardizing aphid estimates, removing the need to train the human to estimate, and reducing sampling error and/or bias. This task could then automate how we estimate densities across several aspects of pest management including decision-making, alternative sampling protocols with images, and screening insect-resistant varieties. The methodology and the model tested in this study can be used into mobile applications or be deployed into unmanned vehicles with sensor systems.

Material and Methods

Field image collection and annotation. The imagery was captured using a Sony ILCE-6000 v 3.10 digital camera from commercial sorghum fields in northern and southern Kansas in 2020 and 2021 during pest monitoring events. Each image included a section of a leaf with aphid infestations located in the upper or lower parts of a sorghum plant. Initially, the resolution of each image had a dimension of 4,000 × 6,000 pixels and a Red-Green-blue (RGB) color representation which targeted readily accessible sensors that could be easily deployed to automate this task. Images were acquired by holding the camera vertically when aphids appeared on the underside of the leaves, during sunny and normal weather conditions. The camera was held from a focal distance ranging from 0.05 to 0.10 m away from the underside of the target leaf for imaging.

A total of 1,190 images with distinct densities were collected and manually labeled based on the number of sorghum aphids per leaf per image. We used the polygon tool to outline each individual aphid, because of their irregular shape, in the labeling section of the cloud-based Roboflow environment for the training data (Dwyer, B and Nelson, J, 2022) (Figure 3.1). The aphid individuals marked in the images ranges between 1-125 sorghum aphids/leaf to manage aphids in field conditions.

Data preprocessing and augmentation. To reduce the overfitting of our models, we used image preprocessing and augmentation procedures provided by the cloud-based Roboflow environment (Dwyer, B and Nelson, J, 2022). The image preprocessing included auto-orienting and image resizing to 416 × 416, 640 × 640, and 1280 × 1280-pixel resolutions. In the augmentation step, we generated 6 different variants of training images using mosaic augmentation to vary the number of objects (i.e., aphids) in the image and to increase the diversity of training data. The mosaic augmentation technique takes 4 images and combines them into a single image (Figure 3.2).

Data splitting ratio. The original imagery dataset consisted of 1,190 images with different numbers of sorghum aphid densities, which ranged between 1-125 sorghum aphids/leaf. For training the detection models, we split the dataset into training, validation, and testing sets in a ratio of 80:10:10, respectively.

The training dataset consisted of 2,693 images, 357 images for the validation set, and 351 images for the testing set and all were at input resolution of 416 × 416 pixels. The 640 × 640 pixels input resolution consisted of 2,753 images for the training set, 357 images for the validation set, and 351 images for the testing set. Lastly, 1280 × 1280 pixels input resolution had 2,795 images for the training set, 357 images for the validation set, and 355 images for the

testing set. The same number of images for the training, validation, and testing set at different pixel input resolutions were used to train independently YOLOv5n, YOLOv5s, and YOLOv5m models to detect sorghum aphids on sorghum leaves and to evaluate all performance metrics.

Summary of object detection deep learning models. We selected three versions of one broadly used model that differ on the number of layers and parameters for detection tasks to evaluate their performance on sorghum aphid density using RGB images. The models tested were YOLOv5n, YOLOv5s, and YOLOv5m within the Pytorch framework, which are models of the YOLOv5 model family. The YOLOv5 model is a state-of-the-art single-stage detector developed by Ultralytics based on the YOLOv1, YOLOv2, YOLOv3, and YOLOv4 models (Ultralytics, n.d.). This model was selected based on the different detection tasks of other agricultural issues because of the higher mean average precision and accuracy values in the detection and classification of insect pests (Ahmad et al., 2022; Teixeira et al., 2022).

One of the advantages of the YOLOv5 model is that it can recognize images of a similar object at different image sizes (Ahmad et al., 2022). In addition, the YOLOv5 model divides images into a grid system, and each cell in the grid is responsible for detecting objects within its cell (Ultralytics, n.d.), making it a good candidate for detecting small objects like sorghum aphids with good mean average precision and inference. It is also a lightweight and quick object detection framework, which could be effectively deployed on mobile devices.

Model training and description of hyperparameters. The three detection models evaluated in this study were pre-trained on the Common Objects in Context (COCO) dataset (Ultralytics, n.d.). We retrained those models using a manually labeled image dataset for sorghum aphid detection. We used 300 epochs with a batch size of 32 as the best training parameters and were kept constant when comparing the three detection models using the three

different pixel input resolution images on each model type. The training was performed using a NVIDIA A100 GPU from Colab, a Google's Jupyter notebook-based Python environment suited for machine learning with an open-source baseline notebook available based on the YOLOv5 repository by Ultralytics (Ultralytics, n.d.).

Performance metrics of the trained models. For object detection models, precision, recall, and mean average precision using an Intersection over Union set to 0.5 (mAP@0.5) are popular metrics to evaluate overall performance (Ahmad et al., 2022). We assessed these metrics to evaluate the robustness of the three object detection models. The Intersection over Union (IoU) is a metric that measures the overlap area between the predicted bounding box and the ground-truth bounding box divided by the area of union between them (Padilla et al., 2020). The precision metric is the ability of the detection model to identify only relevant objects, and it is the percentage of correct positive predictions (Padilla et al., 2020). The percentage of correct positive prediction among all given ground truths is defined as recall (Padilla et al., 2020).

To further evaluate and compare the unseen images from the testing set, we visually assessed and counted sorghum aphid individuals found on 355 images at 1280 × 1280-pixels input resolution. We then compared the running detection inferences of our trained models with a confidence threshold of 80% versus our visual assessments by calculating the mean percent error (%) of misdetection. In addition, we compared the inference speed time per image performed by each model. Overall, the percent error determines how close the inference value of detection is to the true detection. The inference time determines the detection speed of a whole image running by a detection model, an essential aspect for deploying the models into mobile apps and unmanned vehicles for real-time pest monitoring and screening insect-resistant varieties.

Results

The three detection models provided different values in the performance metrics evaluated when detecting sorghum aphids on leaves at different image pixel input resolutions (Table 3.1). The YOLOv5s and the YOLOv5m detection models had the highest overall precision, recall, and mAP@0.5 values across different image sizes compared to the YOLOv5n model. The highest precision, recall, and mAP@0.5 values were obtained using images with 1280 × 1280-pixels input resolution. Therefore, we used the YOLOv5n, YOLOv5s, and YOLOv5m models using images with 1280 × 1280-pixels input resolution for the remainder of the results due to their better detection of sorghum aphid densities.

The highest precision calculated was 92% for the YOLOv5s and YOLOv5m and only 3% lower for the YOLOv5n detection model. The recall and mAP@0.5 were ≥ 82 % for the three models tested, and the highest recall was 84% for the YOLOv5m model. The YOLOv5n detection model had slightly lower mAP@0.5 values compared to YOLOv5s and YOLOv5m models, but similar recall values compared to the YOLOv5s model. Overall, the highest values calculated were 92% precision, 84.5% recall, and 90.6% mAP@0.5 for the YOLOv5m model to detect sorghum aphids on leaves.

For the mean percent error (%) of misdetection in the testing set, the YOLOv5m obtained the lowest error value compared to YOLOv5n and YOLOv5s models. The lowest percent error value calculated was 21.89% for the YOLOv5m detection model. For the inference speed on detection per test image, the YOLOv5m had the highest speed value compared with the YOLOv5n and YOLOv5s models. However, the model was only 0.1 milliseconds slower. From a pest management perspective, the YOLOv5m using an image size of 1280 × 1280-pixels input

resolution is a suitable candidate model for sorghum aphid detection based on their highest performance metrics and inference speed (Table 3.2, Figure 3.3).

Discussion

Overall models performance and applications. The current study demonstrates that the YOLOv5m detection model is a suitable candidate for detecting sorghum aphid densities on leaves with 92% precision, 84.5% recall, and 90.6% mAP@0.5, which is a measure of detection performance. During traditional pest monitoring events, these estimates are performed using visual assessments, which consist of manually evaluating the whole sorghum leaf to provide an estimated number of sorghum aphids; this task is time-consuming and accuracy in estimates can often depend on sampler experience and bias. Our methodology can reduce leaf evaluation time and decrease potential biases in estimates that usually occur when sampling protocols for pests are monitored in the field.

We suggest applying this methodology to current sampling protocols by taking images with different sorghum aphid infestation levels on leaves, which can be added and used as inputs for our model to provide a standardized estimate of the number of sorghum aphids present on leaves. In addition, it potentially can monitor changes in the population dynamics of sorghum aphid size and screen insect-resistant varieties in real-time using images of infested leaves. Thus, this could result in more reliable and consistent data to inform treatment decisions and traits for sorghum aphid management in sorghum. The detection and the automation of aphid density estimates using this model and developed framework can be used in mobile applications and deployed into unmanned autonomous vehicles for automatic pest monitoring production fields or screening insect-resistant varieties in replicated plots.

Limitations and models improvement. The detection problems in the developed models include examples that were misidentified due to a similarity in shape and color of the sorghum aphids with the background of the leaves, potentially common vegetation spots, or sorghum leaf diseases. Also, sorghum aphids are tiny (i.e., < 1 mm), densely distributed, and have different life stages that can be similar in color and shape to different backgrounds, making it difficult to detect them under certain conditions (Brewer et al., 2019). However, making this trained model accessible to other researchers makes it easier for other developers to continue increasing the overall performance of these models to detect sorghum aphid densities, which is another benefit of CNNs in general (Marcelino, 2018).

The results of the current study were promising. However, incorporating more training images could potentially improve the overall performance of these models. In addition, increasing the pixel input resolutions of the images for training and appropriate augmentation techniques can increase the overall performance. The methodology of this study and the models tested provided a better understanding of the capabilities of deep learning on insect pest detection.

Future work. We presume our models can significantly enhance the monitoring of agronomic pests replacing visual aphid assessments with RGB images in standardizing estimates and screening insect-resistant varieties. Our framework and model can be deployed into mobile applications and unmanned vehicles that can provide real-time detection and sorghum aphid estimates for economic management decisions. Thus, it can potentially decrease the time of pest monitoring and the process of screening insect-resistant varieties of sorghum using images and deep learning.

Conclusion

Entomologists and growers continuously monitor pests using time-consuming traditional methods. This study developed a framework and a model that can detect leaf-level sorghum aphid infestation using digital images to renovate pest monitoring and evaluation of screening insect-resistant varieties. The YOLOv5m model detected sorghum aphid infestations with 92% precision, 84.50% recall, and 90.60% mAP@0.5. Ideally, the developed methodology of pest sampling using images and the model tested can be used in sampling protocols and screening insect-resistant varieties using further developed mobile applications and unmanned vehicles with sensor systems.

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Tables and Figures

Table 3.1 Overall precision, recall, and mAP@0.5 scores of the three detection models tested at different image pixel input resolutions.

Model type	Image pixel input resolutions (pixel × pixel)	Precision (%)	Recall (%)	mAP@0.5 (%)
YOLOv5n	416 × 416	46.80	35.00	31.70
	640 × 640	69.70	54.40	59.10
	1280 × 1280	89.00	82.60	89.20
YOLOv5s	416 × 416	56.10	38.10	38.70
	640 × 640	75.30	58.40	64.50
	1280 × 1280	92.40	82.60	90.40
YOLOv5m	416 × 416	59.90	41.40	43.20
	640 × 640	77.70	59.10	65.40
	1280 × 1280	92.00	84.50	90.60

Table 3.2 Mean percent error (%) of misdetection and inference time per image in milliseconds (ms) of the three detection models tested using testing images with 1280 × 1280-pixels input resolution.

Model type	Mean percent error of misdetection (%)	Inference time per image in milliseconds (ms)
YOLOv5n	48.69	1.00
YOLOv5s	38.08	1.00
YOLOv5m	21.89	1.10

Figure 3.1 Examples of images at 1280 × 1280-pixels input resolution without (A, C) or with labels (B, D) using the polygon tool in the labeling section of the cloud-based Roboflow environment.

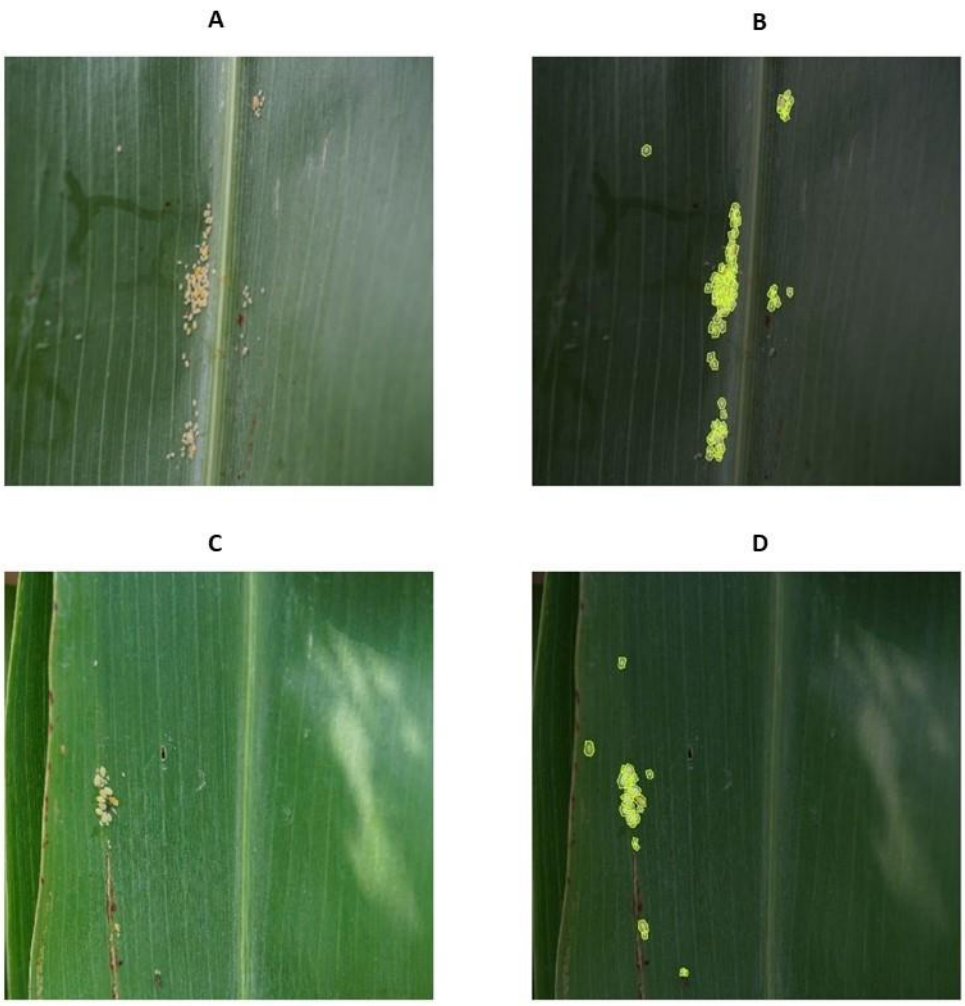


Figure 3.2 Examples of training images at 1280 × 1280-pixels input resolution (A, B, C, D) with labels with preprocessing and augmentation techniques using the cloud-based Roboflow environment.

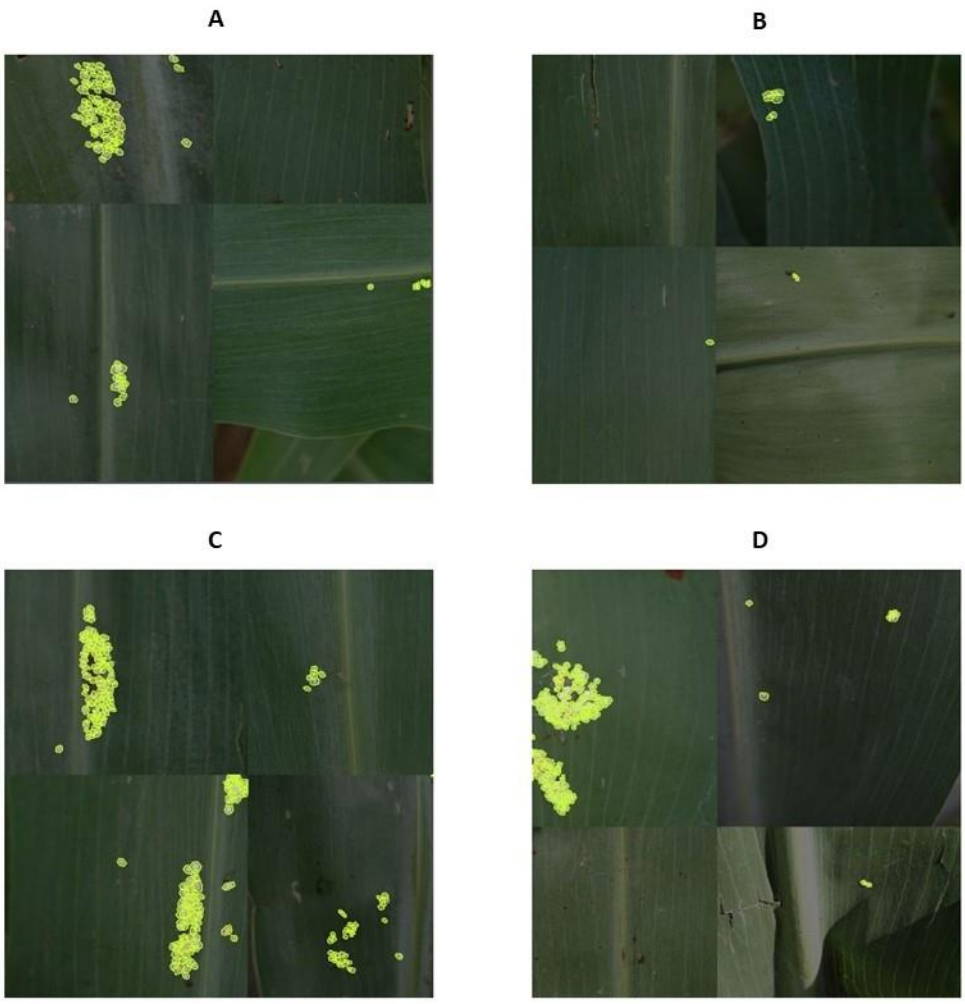
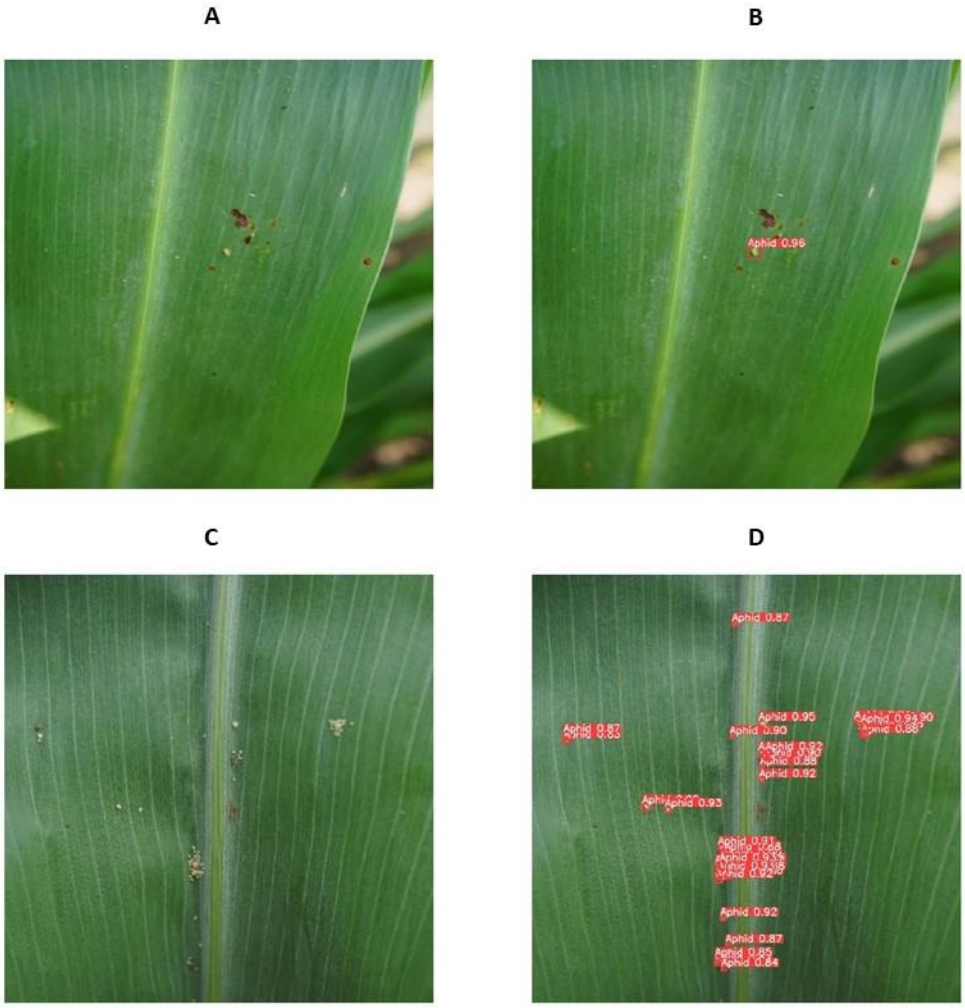


Figure 3.3 Detection results using testing images at 1280 × 1280-pixels input resolution without (A, C) or with aphid detections (B, D) performed by YOLOv5m model.



Chapter 4 - Image classification of sorghum aphid density using deep convolutional neural networks

Introduction

Since the beginning of agriculture development, insects have played an influential role in food production and the ecosystem services they provide to the environment (Noriega et al., 2018). Growers have historically competed with herbivorous and pathogen-transmitting insects, collectively called 'pests', and different strategies have been developed to control them in agriculture (Oerke, 2006). Most of these management options include chemical, cultural, biological, and mechanical activities that help manage agricultural pests. Collectively, these options are longer-term strategies as part of integrated pest management (IPM) program, which aims to provide sustainable agriculture management solutions in various agroecosystems. IPM tactics have been applied on many crops, including corn, soybeans, cotton, wheat, and sorghum. In the U.S., sorghum (Sorghum bicolor L. Moench) is an important economic crop that had a value over $1 billion in 2020 and was planted on 5,880 million acres (United States Department of Agriculture, 2021a). Sorghum contributed approximately more than $1 billion to the economy in Kansas in 2020 and ranked as one of the top crops produced by the state (United States Department of Agriculture, 2021b). Nevertheless, sorghum faces significant pest management challenges and yield losses during its production.

Sorghum aphid, *Melanaphis sorghi* (Theobald) (Hemiptera: Aphididae), is considered an economically important pest in sorghum across much of the Southern Great Plains since its re-introduction in 2013 (Bowling et al., 2016). Different management strategies have been developed, including pest monitoring guides, insecticide treatment protocols, and the development of resistant or tolerant hybrids to reduce the impact of this pest (Bowling et al.,

2016). Usually, treatment decisions for sorghum aphid depend visually assessing sorghum leaves for aphids to determine an economic threshold for insecticide applications (Lindenmayer et al., 2020). An economic threshold is defined as the pest density that management action must implement to prevent reaching economic injury level (Stern et al., 1959).

According to Gordy et al. (Gordy et al., 2019), a suggested economic threshold for sorghum aphids is 40 aphids per leaf. However, obtaining an accurate estimation of the number of sorghum aphids on leaves is a time-consuming and challenging task due to the high reproduction rates, variety of growth stages, clustering behavior, and the need to inspect wider areas of fields (Deng et al., 2018; Thomas et al., 2018). In addition, sorghum aphid populations can change quickly, requiring continuous monitoring of infested fields through the growing season. However, automating the scouting process can address several of these challenges using artificial intelligence (AI) and associated classification methods to quantify sorghum aphid densities.

Currently, AI technology can efficiently detect and classify surrounding living organisms with the slightest use of labor and time to advance precision agriculture. Machine learning is a subfield of AI in which labeled image data can be used to train a model, which can subsequently make predictions on new unseen images without additional programmatic effort using deep learning (Wäldchen and Mäder, 2018). Convolutional neural networks (CNNs), a technology in deep learning, can analyze visual imagery and perform tasks such as image classification and object detection with high performances (O'Shea and Nash, 2015). Deep learning models can be designed in a user-friendly manner that can be applied to solve agricultural activities that are labor intensive, like pest monitoring (Wäldchen and Mäder, 2018).

However, deep learning models for the automatic classification of sorghum aphid densities have not been researched in sorghum for pest monitoring protocols. Thus, a vision-based automated system for image processing using deep neural networks is needed for accurate classification of sorghum aphid densities to standardized sampling for pest monitoring protocols in sorghum. In the present work, we trained four different deep learning models, including Inception v3, DenseNet 121, Resnet 50, and Xception, and evaluated their ability to classify different densities of sorghum aphid that are used to determine treatment decisions based on the economic threshold management actions. Our main objective was to develop an effective deep learning model for classifying sorghum aphid densities in images. The results of this research can be applied to current sampling protocols with further development in mobile applications or remote sensing technologies to automate the classification of other pests in different crops during pest monitoring.

Materials and Methods

Field image collection. Sorghum aphid imagery was collected from commercial sorghum fields from southern Kansas in 2020 and 2021. The imagery included either an individual leaf from the upper or lower section of a sorghum plant. Each image consisted of a section of the leaf with and without sorghum aphid. Images were taken using a Sony ILCE-6000 v 3.10 digital camera and photographed during field scouting events of commercial sorghum fields (average field size was 5 acres). Initially, each image had a dimension of 4,000 × 6,000 pixels and an RGB color representation. A total of 5,048 images were collected and manually classified into 6 distinct categories based on the number of sorghum aphid per leaf per image. Classification categories were based on pest monitoring parameters to determine economic threshold levels for sorghum aphid (Bowling et al., 2016; Gordy et al., 2019; Lindenmayer et al.,

2020). The categories were no aphids present (0 sorghum aphids/leaf), no threat or below an action/treatment threshold (1-10, and 11-39 sorghum aphids/leaf), and infested above an economic threshold where an insecticide should be applied (40-125, 126-500, and > 500 sorghum aphids/leaf).

Summary of classification deep learning models. Different deep learning models have been proposed to detect and classify various living organisms, including insects, plants, or diseases, to advance the field of precision agriculture. We selected four broadly used models for classification tasks to evaluate their performance in accuracy on sorghum aphid density classification using images (Huang, G. et al., 2017; Lin et al., 2019; Zahisham, Z et al., 2020). The four models were selected based on the different tasks for image classification of other agricultural issues and model size (<100 MB), which can influence the training process and further development of applications. The four models differ in architecture; however, they were selected based on the different tasks for image classification of other agricultural issues and model size (<100 MB), which can influence the training process and further development of applications.

The models tested were Inception v3, DenseNet 121, Resnet 50, and Xception, which are models found in Keras applications (Chollet and Others, 2015). Inception v3 is a deep learning model with small convolutions, accelerated training speed, and reduced computational cost (Lin et al., 2019). DenseNet 121, another lightweight model tested, requires fewer parameters than traditional convolutional networks, making it easy to train (Huang, G. et al., 2017). Resnet 50 has smaller parameter size compared with other CNNs making it faster to training (Zahisham, Z et al., 2020), and Xception was selected for its higher value of top-1 and top-5 accuracy and the overall model performance using the ImageNet validation dataset found in Keras applications.

Model training and description of hyperparameters. The four deep learning models used in this study are pre-trained on the ImageNet validation dataset (Deng, J et al., 2009). We retrained those models for sorghum aphid density classification using a manually labeled image dataset. The image dataset was divided into training (80%) and testing (20%) sets. Images within the 6 categories of sorghum aphid densities were split and randomly combined through the 80:20 ratio to maintain this training and testing proportion. We resized all 4,000 × 6,000 pixel images to a standard 500 × 500 pixel size (Figure 4.1) to independently train the four alternative deep learning models.

To reduce the overfitting of our models, we used an image augmentation procedure built into the deep learning models that included random rotation (≤ 100°), sheer (≤ 30%), zoom (≤ 10%), and horizontal flip (Spiesman et al., 2021). Due to the categorical imbalance in our data set, the predictions were weighted by category sample size to reduce bias in model testing. We used 100 epochs with a batch size of 10. Training was performed using an Nvidia GeForce GTX 1080 graphic processing unit. To evaluate the classification performance of the four deep learning models, we evaluated the confusion matrix and the overall and class-level precision, recall, and F1 scores.

Results

The four deep learning models provided similar accuracy scores when classifying sorghum aphids (Table 4.1). Inception v3 and Xception deep learning models had the highest overall test accuracy score of 86%. Resnet 50 and DenseNet 121 had slightly lower test accuracy scores of 85%. The highest average precision was 81% for Inception v3 and Xception and only 1% lower for Resnet 50 and DenseNet 121 model. The average recall and F1 scores were ≥ 80% for the four models tested. The Inception v3 and Xception models had the best accuracy, highest

average precision, recall, and F1 scores. Therefore, we used the Inception v3 and Xception models for the remainder of the results due to their better classification of sorghum aphid densities.

The Inception v3 and Xception models adequately categorized sorghum aphid densities into distinct categories based on features from the model. By combining aphid density classes as above- or below-threshold, the models correctly classified infested leaves as above or below threshold density 97% of the time. Our Inception v3 model correctly classified 504 of 511 and 474 of 499 images as above or below threshold, respectively. The Xception model performed similarly to Inception v3, as it correctly classified 505 of 511 and 476 of 499 images above or below the threshold, respectively.

Overall, the image classification results in the confusion matrix of the Inception v3 model (Table 4.2) had similar number of misclassified images to the Xception model. The classification category of no aphids, for example, was correctly classified with 211 of 227 test images and only 35 of 317 test images were mislabeled leaves in the 126-500 aphids category. The highest precision values were observed for categories of no aphids and 126-500 aphids with 92% and 93%, respectively. The next two categories, 11-39 aphids and 40-125 aphids, had slightly lower precision score of 86% and 80%, respectively. The lowest precision scores of 75% and 61% corresponded to categories of 1-10 aphids and > 500 aphids, respectively, on sorghum leaves.

For the image classification results in the Xception model confusion matrix (Table 4.3), the classification category of no aphids was correctly classified for 198 of 227 test images resulting in a 93% precision. Lower precision scores were found in the classification categories of 1-10 aphids and > 500 aphids, which was similar to the classification results of the Inception v3 model. The highest precision values were observed in categories of no aphids and 126-500

aphids with 93% and 95%, respectively. Lastly, the 11-39 aphids and 40-125 aphid categories had precision scores of 86% and 80%, respectively. Sorghum aphid categories with a higher number of trained images had a lower percentage of misclassified images but higher precision scores compared to sorghum aphid categories with a lower number of trained images. However, from a pest management perspective, the Inception v3 and Xception model can correctly classify aphids as "above or below threshold density" 97% of the time.

Discussion

Overall models performance and applications. The current study demonstrates that two deep learning models can classify images of infested sorghum leaves into different aphid densities categories with an overall accuracy of 86% and correctly classified aphids as above or below threshold density 97% of the time. To date, estimates are performed using visual assessments, but accuracy can vary based on sampler experience and training history increasing bias during sampling (Gordy et al., 2019; Lindenmayer et al., 2020). Current sampling protocols suggest collecting 40-60 two-leaf samples and treating when 20-30% of plants are infested with an estimate of 25-125 sorghum aphids/leaf (McCornack et al., 2017).

During sampling, a visual assessment consists of manually evaluating the whole sorghum leaf to provide an estimated number of sorghum aphids, which is a time-consuming task. We suggest applying these models to current sampling protocols by taking images with different sorghum aphid infestation levels on leaves, which can be added and used as inputs for our models to provide a standardized estimate of the number of sorghum aphids present. Our approach can reduce leaf evaluation time and decrease human error in estimates that usually occurs when sampling protocols for pests are deployed in the field. Thus, this could potentially

result in more reliable and consistent data to inform treatment decisions for sorghum aphid management in sorghum.

The Inception v3 or Xception models are adequate candidates for automatically classifying sorghum aphid densities without manual counting and produced error rates within acceptable levels compared to standard measurements. Consequently, standardized, and automated aphid density estimates can be used to monitor changes in aphid population size in real-time using images of infested leaves that can be used to develop agile mobile applications, integrated in remote sensing systems for onboard, automatic pest monitoring, screening resistant sorghum varieties, and used to model the population dynamics of sorghum aphid in sorghum.

Models performance within categories. At the categorical level of sorghum aphid densities classification, Inception v3 had similar number of misclassified images to Xception based on the confusion matrices. However, both models can differentiate between categories of sorghum aphid densities accurately. The purpose of having an automatic categorical classifier of sorghum aphid densities is to reduce time spent counting and sampler bias. In addition, to categorize sorghum aphid densities because, to our best knowledge, sorghum aphid counting is challenging when aphids start to cluster, making it difficult for visually assess aphid densities on leaves. We decided to combine the categories as “below threshold” including the first three categories of sorghum aphid densities (0, 1-10, and 11-39 sorghum aphids/leaf) since any management strategy that is warranted manage sorghum aphid will not affect the development of the crop and therefore not reduce sorghum yield. On the other hand, the higher density categories (40-125, 126-500, and > 500 sorghum aphids/leaf) were combined because current best management practices suggest applying an insecticide manage sorghum aphid populations above 40 aphids per leaf. The results of our study have shown that the Inception v3 and Xception

models can distinguish above or below these treatment categories 97% of the time, making these models candidates for pest monitoring in sorghum.

Models improvement. Collecting more images, especially of sorghum aphid categories where we observed a higher number of misclassified images, will improve the classification accuracy of our models. However, for an IPM perspective, distinguishing between the below (11-39 aphids) and above (40-125 aphids) pest threshold level is sufficient and useful for making pest management decisions. Consequently, incorporating more images will reduce the current imbalance among categories resulting in more balance data for training future models, as observed in other systems (Spiesman et al., 2021). Making these trained models trained accessible to other researchers makes it easier for other developers to continue increasing the accuracy score and overall performance of these models to classify sorghum aphid densities, which is another benefit of CNNs in general (Marcelino, 2018).

Limitations and future work. This study provided a framework for how deep learning models can classify pests for pest monitoring in sorghum. The results were promising, however, collecting more images for the categories with the lower number of images for training will improve the accuracy scores of these models. We presume our models can significantly enhance the scouting of agronomic pests for sampling protocols and serve as valuable information for further sensor systems on unmanned vehicles to improve crop management decisions. The rise of unmanned aircraft systems, including unmanned aerial and ground vehicles (UAV and UGV), continue progressing and helping growers manage their agricultural fields (Barbedo, 2019). In the near future, drone technology will give the agriculture industry a high-technology renovation. Consequently, using UAV and UGV with our framework can provide real-time detection and mapping areas of sorghum aphid infestation for economic management decisions.

Conclusion

More than 50 years have passed since the development of IPM, and pest monitoring continues to be time-consuming and laboriously expensive. Entomologists and growers continuously monitor pests using traditional methods that are time consuming. This study developed a framework and two models that can automatically categorize leaf-level sorghum aphid infestation using digital images to renovate pest monitoring. The Inception v3 and Xception models were tested to evaluate their performance in classifying sorghum aphid densities at 6 infestation levels, including no aphids (0 sorghum aphids/leaf) and (1-10, 11-39, 40-125, 126-500, and > 500 sorghum aphids/leaf) with a classification accuracy of 86%. More image samples can be added to the current models within sorghum aphid categories to increase their accuracy scores and model performances. Ideally, these two models can be used in sampling protocols and further mobile applications or remote sensor systems that would detect and categorize sorghum aphid densities, resulting in a reliable pest control strategy based on the economic threshold in sorghum. Ultimately, our study wants to project a new growth mindset to renovate pest monitoring, computer vision, and unmanned vehicles to improve the current IPM strategies to enhance sustainability and food production.

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Tables and Figures

Table 4.1 Overall accuracy, precision, recall, and F1 scores of the classification models tested.

Deep learning models	Accuracy score	Precision Weighted Average	Recall Weighted Average	F1 score Weighted Average
Inception v3	0.86	0.86	0.86	0.86
DenseNet 121	0.85	0.86	0.85	0.85
Resnet 50	0.85	0.86	0.85	0.85
Xception	0.86	0.87	0.86	0.86

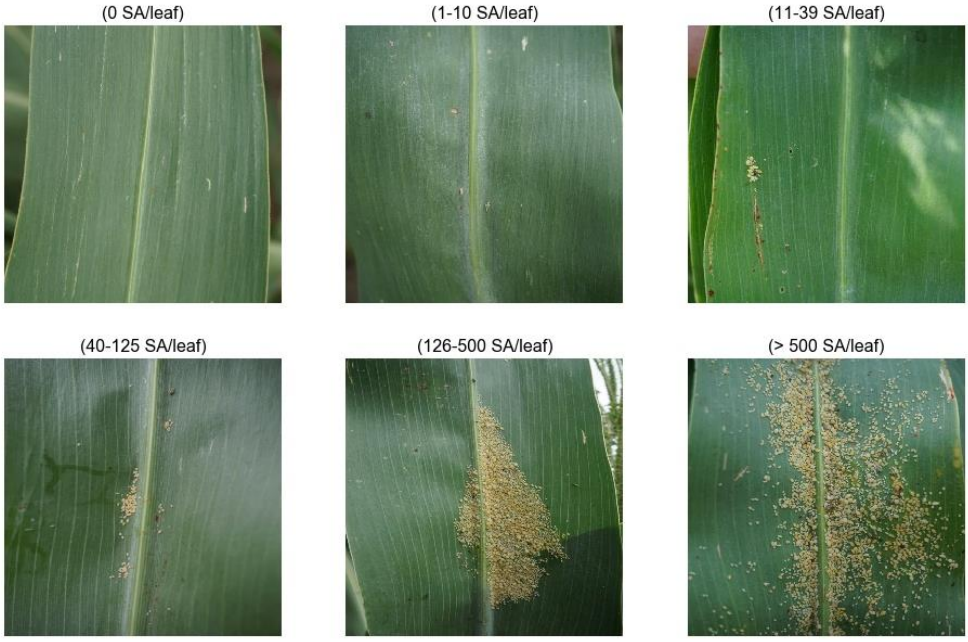
Table 4.2 Confusion matrix of Inception v3 model. Numbers in bold correspond to correct predicted image classification in each density category. The green boxes show the number of correct predictions below threshold level, and yellow denotes the number of correct predictions above threshold.

		Predicted (sorghum aphids/leaf)						
	Categories (sorghum aphids/leaf)	0	1-10	11-39	40-125	126-500	> 500	Total number of tested images
True (sorghum aphids/leaf)	0	**211**	15	1	0	0	0	227
	1-10	19	**77**	13	1	0	0	110
	11-39	0	11	**127**	23	1	0	162
	40-125	0	0	6	**128**	15	0	149
	126-500	0	0	1	8	**282**	26	317
	> 500	0	0	0	0	4	**41**	45

Table 4.3 Confusion matrix of Xception model. Numbers in bold correspond to correct predicted image classification in each density category. The green boxes show the number of correct predictions below threshold level, and yellow denotes the number of correct predictions above threshold level.

		Predicted (sorghum aphids/leaf)						
	Categories (sorghum aphids/leaf)	0	1-10	11-39	40-125	126-500	> 500	Total number of tested images
True (sorghum aphids/leaf)	0	**198**	29	0	0	0	0	227
	1-10	13	**81**	15	0	1	0	110
	11-39	1	12	**127**	21	1	0	162
	40-125	0	0	6	**134**	9	0	149
	126-500	0	0	0	13	**285**	19	317
	> 500	0	0	0	0	4	**41**	45

Figure 4.1 Examples of training images for Inception v3, DenseNet 121, Resnet 50, and Xception models using 500 × 500-pixel images.



Chapter 5 - Detecting common coccinellids found in sorghum using deep learning models

Introduction

Pest management is a strategy used to control any living organism that poses a risk to our food, fiber, and health security. It has played an essential role in achieving the current food supply, and its role will continue to be critical in any agricultural production system (Waterfield and Zilberman, 2012). Since the beginning of agricultural development, growers have had to compete with harmful insects, collectively called 'pests' (Oerke, 2006). These organisms can reduce crop yields and fruit quality, damage plants, serve as disease vectors, and contaminate food crops. Different strategies have been developed to control arthropod pests in agriculture, including chemical, cultural, biological (e.g., plant resistance, natural enemies, etc.), and mechanical methods (Flint and Van den Bosch, 2012). There is much concern about the use of chemicals for pest control due to their cumulative non-sustainable adverse effects on the environment (Krupke, C. and Long, 2015; Sánchez-Bayo and Wyckhuys, 2019), particularly non-target effects on beneficial organisms, including natural enemies (e.g., predators, parasitoids, microorganisms) and pollinators (Bonmatin et al., 2015; Krupke, C. et al., 2017), and the potential for the development of pesticide resistance (Jensen, 2000; Kranthi et al., 2002).

A valuable tool for addressing this threat is integrated pest management (IPM). IPM was developed in the early 1970s as a pest control strategy that promotes sustainable agriculture with a strong ecological basis (Ehler, 2006). IPM is an approach that incorporates various tactics to control all classes of pests (e.g., insects, pathogens, weeds, vertebrates) to create an ecologically and economically efficient production system (Ehler, 2006). These tactics include biological control, cultural practices, host-plant resistance, genetic manipulation, and pesticides (Flint and

Van den Bosch, 2012; Lewis et al., 1997; Thomas, 1999). IPM tactics have been applied in different crops, including sorghum production. Sorghum [*Sorghum bicolor* (L.) Moench] is the fifth most valuable cereal crop globally (Hariprasanna and Rakshit, 2016). In the U.S., this crop had a value of more than $1 billion and was planted on 5.26 million acres in 2019 (United States Department of Agriculture, 2019). Sorghum production in the world is used mainly for human consumption and animal feed; in the U.S., it is used as livestock feed and turned into ethanol. However, the current production of sorghum faces significant pest management challenges. Since 2013, with the outbreak of *Melanaphis sorghi* (Theobald) (Hemiptera: Aphididae), commonly named sorghum aphid (SA), different tactics have been developed, including scouting protocols, pesticides treatment guides, and host plant resistance programs to prevent yield losses in sorghum (Bowling et al., 2016).

Proper identification and classification of insect pests at an early stage are important tasks in crops because pest management strategies (i.e., pesticides and cultural control methods) can be costly and overused when misidentification happens. However, insect pests are not the only factor that affects our understanding of pest management in agriculture. Sorghum farmers encounter other beneficial insects that need to be identified and classified automatically to better understand the pest and beneficial insects interactions (i.e., predation) during pest scouting in fields. One of the major communities feeding on SCA are lady beetles (Coleoptera, Coccinellidae). Common genera, species, and subfamily levels of coccinellids that we can find on sorghum plants include *Coccinella septempunctata*, *Coleomegilla maculata*, *Cycloneda sanguinea*, *Harmonia axyridis*, *Hippodamia convergens*, *Olla v-nigrum*, and the subfamily Scymninae (Bowling et al., 2016). Technological advances in artificial intelligence and machine learning related to how living organisms can be most efficiently identified and classified with the

smallest use of labor and time to increase precision agriculture represent a major focal point of modern agricultural production and research.

Machine learning is a sub-field of artificial intelligence, in which labeled data can be used to train a model, and the trained model can be subsequently used to make inferences and predictions on new incoming data without additional programmatic effort (Wäldchen and Mäder, 2018). Convolutional neural networks (CNN) represent a type of machine learning model, more specifically, a deep learning model, which can be used to analyze visual imagery (LeCun et al., 2015). CNNs excel at a variety of computer vision tasks, such as image classification, object detection and localization, among others. Object detection refers to the task of identifying and classifying instances of objects of interest in images or video frames (Szegedy et al., 2017). CNN-based approaches for object detection extract features from the input image and use the features to perform two main tasks: 1) detect regions of interest (ROI) as bounding boxes that contain instances of objects in the image (a.k.a., object identification); and 2) classify ROIs into an arbitrary number of classes (a.k.a., object classification). Depending on how these two tasks are performed, object detection approaches can be classified as one-stage detectors and two-stage detectors (Zaidi et al., 2022). One-stage detectors perform both tasks simultaneously in one stage, and include models in the YOLO family (Redmon et al., 2016; Wang et al., 2022), among others. Two-stage detectors identify ROIs in a first stage, and subsequently classify the ROIs and refine their bounding boxes in a second stage. Two-stage detectors include models such as Faster R-CNN (Ren et al., 2015), Cascade R-CNN (Cai and Vasconcelos, 2018) and FPN (Lin et al., 2017). Traditionally, two-stage detectors have been more accurate than one-stage detectors, while the one-stage detectors have been faster and more suitable for use in practical applications that require real-time object detection (Carranza-García et al., 2021). Remarkably, combinations

of the Faster R-CNN (Ren et al., 2015) and FPN (Lin et al., 2017) networks have achieved competitive results on popular benchmark datasets (L. Jiao et al., 2019; Zaidi et al., 2022). However, some of the recent YOLO models (Li et al., 2022; C.-Y. Wang et al., 2021; Wang et al., 2022) have produced state-of-the-art performance both in terms of accuracy and speed on benchmark datasets, with YOLOv7 being known to produce the best results at the end of year 2022 (Wang et al., 2022).

Deep learning software for object detection can be designed in a user-friendly manner and allows for the training of models that can be applied to solve agricultural challenges (Wäldchen and Mäder, 2018). Recent studies using deep learning neural networks for object detection have shown that it is possible to develop models for automated disease identification and insect recognition (Ahmad et al., 2023; Liu and Wang, 2021). Some studies have focused on the use of object detection approaches to identify and classify pests based on images of yellow sticky traps and other types of insect traps (Li et al., 2021; Wen et al., 2022). For example, Salamut et al. (Salamut et al., 2023) focused on detecting cherry fruit flies based on yellow sticky trap images. Several one-stage and two-stage object detection approaches were compared, including Faster R-CNN and YOLOv5 (Jocher et al., 2020) using a dataset that contains 1,600 annotated images. The best results overall were obtained using a Faster R-CNN model with lightweight MobileNet (Howard et al., 2017) as the backbone network. Specifically, the Faster R-CNN model had average precision AP@0.50 of 0.88% as compared to the best YOLOv5 model, which had an AP@0.50 of 0.76%. Wang et al. (Wang et al., 2020) published a dataset (called Pest24) of approximately 25,000 pest trap images that contain 24 field pests. They trained several object detection models on this dataset, including Faster R-CNN (with VGG-16 as the backbone network), Cascade R-CNN (with ResNet-50-FPN) and YOLOv3 (Redmon et al., 2016)

(whose backbone is called Darknet-53). Experimental results showed that YOLOv3 had the best performance on this dataset, with an overall mean average precision (mAP@0.50) of 59.79% as compared to a mAP@0.50 of 57.23% for Cascade R-CNN and a mAP@0.50 of 51.10% for Faster R-CNN. Li et al. (Li et al., 2021) used the Faster R-CNN model pre-trained on the COCO dataset (Lin et al., n.d.) to detect small pests (whitefly and thrips) using a dataset of approximately 1,500 sticky trap images and showed that the model transferred from COCO is more accurate than the corresponding model trained directly on pest images.

Wang et al. (R. Wang et al., 2021) adapted the Faster R-CNN model to make it easier to find small pests in light-trap images. The improved model used the attention mechanism (Guo et al., 2011) to focus on more predictive features, together with a sampling strategy for the region proposal network to address class imbalance and also an adaptive RoI selection to select best features from different levels of a pyramid network. Experimental results on a dataset (called AgriPest21) of approximately 25,000 images with 21 types of pests showed that the adapted model achieved a mAP of 78.7%, which was significantly better than the mAP of the baseline models included in the comparison study (both one-stage, e.g. SSD (Liu et al., 2016) and two-stage models, e.g., Cascade R-CNN (Cai and Vasconcelos, 2018). Jiao et al. (Jiao et al., 2022) also used an adaptive feature fusion pyramid network to identify richer features for pest detection together with Faster R-CNN network (with ResNet50 as backbone) and obtained a competitive mAP value of 77.4% on the AgriPest21 dataset (R. Wang et al., 2021). Zhang et al. (Zhang et al., 2022) used strategies similar to those in (Jiao et al., 2022; R. Wang et al., 2021) (i.e., attention mechanism to obtained better features, fusing features from a pyramid network) to adapt YOLO models to small pest detection tasks. Experimental results on the Pest24 dataset (Wang et al., 2020) showed that the adapted YOLO model (called AgriPest-YOLO) had better performance

than Faster R-CNN, Cascade R-CNN and several YOLOv4 (Bochkovskiy et al., 2020) and YOLOv5 (C.-Y. Wang et al., 2021) variants, producing an overall mAP@0.50 of 71.3% and mAP@0.50 : 0.5 : 0.95 of 46.9%.

As opposed to the above mentioned studies that focused on images of trapped pests, other studies have focused on pest detection in the wild (Bjerge et al., 2022b; Takimoto et al., 2021). Sava et al. (A. Sava et al., 2022) experimented with Faster R-CNN and YOLO models for detecting the brown marmorated stink bug (i.e., *Halyomorpha halys*) in tree images. Experimental results on a dataset of images assembled from the Maryland Biodiversity Project ("Maryland biodiversity project," n.d.) showed that the YOLOv5m variant produced the best results, with a mAP of 99.2%, as compared to the Faster R-CNN which had an mAP of 89.1%. In contrast to that, Takimoto et al. (Takimoto et al., 2021) showed that Faster R-CNN was better than YOLOv4 for detecting herbivorous beetles, specifically, striped flea beetle (i.e., *Phyllotreta striolata*) and the turnip flea beetle (i.e., *Phyllotreta atra*) in a set of images collected from the web and through fieldwork. Similarly, Ozdemir and Kunduraci (Ozdemir and Kunduraci, 2022) also found the Faster R-CNN network (with Inception-v3 (Szegedy et al., 2016) backbone) to be better than YOLOv4 when used to detect and classify insects according to order level (using a dataset consisting of 25,820 training images and 1,500 test images). Butera et al. (L. Butera et al., 2022) also showed that Faster R-CNN (with MobileNet-v3 (Howard et al., 2017) backbone) represents an effective model for detecting beetle-type pests (specifically, *Popillia japonica*) and also for distinguishing them from other types of non-harmful but similar looking beetles (*Cetonia aurata* and *Phyllopertha horticola*), giving an overall mAP of 92.66%. The dataset used contained 36,000 images collected from the web and photo sharing sites. Ahmad et al. (Ahmad et al., 2022) also used the web to assemble a dataset of 7,046 images which contain 23 types of

pests. They experimented with a set of YOLO models and showed that YOLOv5-X gave the best results overall, with an mAP@0.5 value of 98.3%, and an mAP@.50 : 0.05 : .95 value of 79.8%.

In addition to work on deep learning for automated pest identification, recent studies have also focused on identification of beneficial insects such as pollinators and natural predators (Bjerge et al., 2022a; Valan, 2021), including coccinellid beetles (Vega. M et al., 2021; Venegas et al., 2021). Ratnayake et al. (Ratnayake et al., 2021a) used a hybrid approach that combines an object detection model (specifically, YOLOv2 (Redmon and Farhadi, 2017)) with a background subtraction technique to identify and track honeybees in wildflower clusters. The proposed approach (called HyDaT), which can track one insect at a time, was tested on a dataset consisting of 22,260 video frames (with 17,544 bees visible) and it had a detection rate of 86.6%, as compared to a detection rate of 60.7% for YOLOv2. Ratnayake et al. (Ratnayake et al., 2021a) extended the HyDaT approach (Ratnayake et al., 2021b) to make it is suitable for tracking multiple insects simultaneously. Their proposed approach (called Polytrack) uses YOLOv4 together with both foreground and background segmentation to identify and track honeybees. Experimental results on 39,909 video frames, including 5,291 frames with honeybees, showed that Polytrack achieved values of 0.975 and 0.972 for precision and recall, respectively, being superior to both HyDaT and YOLOv4 used by itself. Bjerge et al. (Bjerge et al., 2022a) assembled a dataset consisting of 29,960 beneficial insects in nine taxa (such as bees, hoverflies, butterflies and beetles) and used the dataset to study the usability of YOLO models to accurately detect and classify such insects. Experimental results showed that the YOLOv5 model had the best performance with an mAP@0.50 : 0.05 : 0.95 of 0.592, and a best F1-score of 0.932. Similarly, Spanier (Spanier, 2022) assembled a dataset of approximately 17,000 imaged of pollinator insects of eight types (including bees and wasps, butterflies and moths, beetles, etc.)

retrieved from the iNaturalist (inaturalist.org) and Observation.org databases. The best performing model, a variant of YOLOv5, achieved an overall accuracy of 0.9294 and F1-score of 0.9294. Bjerge et al. (Bjerge et al., 2022b) constructed a dataset of 100,000 annotated images containing small insects. The authors experimented with Faster R-CNN models and YOLOv5 models. To enhance the detection, they proposed a motion-informed-enhancement of the images. Experimental results showed that YOLOv5 achieved an mAP@0.50 value of 0.924, while the Faster R-CNN model achieved an mAP@0.50 value of 0.900.

In terms of coccinellid beetle detection, Venegas et al. (Venegas et al., 2021) used traditional image processing techniques (based on saliency maps, linear iterative clustering and active contour) to identify RoIs (bounding boxes) that can potentially contain coccinellids, and subsequently used a deep CNN to classify the RoIs as coccinellids or not-coccinellids. The approach was evaluated on a dataset of 2,300 coccinellid beetle images assembled from the iNaturalist project in Ecuador and Colombia. The RoI detection approach had an accuracy of 92%, while the CNN model had an area under the curve (AUC) of 0.977. Similarly, Vega et al. (Vega. M et al., 2021) used a CNN together with the weighted Hausdorff distance as a loss function to detect beetles in a dataset of 2,633 images similar to the ones in (Venegas et al., 2021), and reported a mean accuracy of 94.30%. While these works represent important first steps towards automated identification of coccinellid beetles (considered to be natural pest controllers), the realm of deep learning for object detection to automatically detect and classify coccinellids commonly found in sorghum is largely unexplored.

The conventional manual identification of coccinellids requires expert skills and identification keys based on coloration and morphological characteristics. In contrast, existing automated tools based on digital technologies and imagery data do not employ state-of-the-art

deep learning architectures and may not be very accurate (Jouveau et al., 2018). Thus, a vision-based automated system for image processing using deep neural networks needs to be researched for precise classification and identification of coccinellids to advance the integrated pest management area in sorghum. Towards this goal, we first assembled a dataset consisting of approximately 5,000 images retrieved from iNaturalist. The dataset assembled was used to study automated deep learning approaches to enable the detection and classification of coccinellids. We trained variants of the popular two-stage Faster R-CNN model, enhanced with FPN, a model referred to as Faster R-CNN-FPN. We also trained variants of the YOLOv5 and YOLOv7 models. We choose to focus on the Faster R-CNN-FPN model, given that this model has shown best performance in some prior related works (Ozdemir and Kunduraci, 2022; Salamut et al., 2023; Takimoto et al., 2021). As backbone CNN, we explored ResNet-50 and ResNet-101 given that these networks commonly lead to a good trade-off between accuracy and speed (Huang, J et al., n.d.). Similarly, we selected YOLOv5 as another strong model to experiment with given its best performance in several prior works (Ahmad et al., 2022; Bjerge et al., 2022b, 2022a). Finally, we also choose to include YOLOv7 in our study, as it has best performance on several benchmark datasets (Wang et al., 2022) and it has not been explored for insect detection (neither pests nor beneficial insects) in the IPM area. To summarize, our research contributes a dataset and effective deep learning models trained to detect and classify coccinellids, including Faster R-CNN-FPN, YOLOv5 and YOLOv7 models. To the best of our knowledge, this is the first study to explore YOLOv7 for insect detection and classification. Our best models can potentially be installed and used on unmanned vehicles to automate the detection and classification of coccinellids in sorghum fields during field scouting. The models can be further customized to other natural enemies encountered in different crops during automated field scouting.

Material and Methods

Deep learning approaches for object detection. The generic architecture of deep neural networks for object detection consists of two main components: a backbone, which is commonly a pre-trained CNN network used to generate feature maps, and a head, which is used to detect objects as bounding boxes defined by their coordinates (bounding box prediction) and to classify objects into one of several categories of interest (Bochkovskiy et al., 2020), in our case, different types of coccinellids. One-stage detectors, including the YOLO family of detectors, have a dense prediction head that achieves the object detection and classification tasks simultaneously. Two-stage detectors, including the popular Faster R-CNN detector, decouple the object detection and classification tasks and achieve them in two stages. In the first stage, they use a dense prediction head to generate RoIs that may contain objects. In the second stage, a sparse detection head is used to classify the RoIs according to different object categories and to refine their bounding boxes. In recent years, it has become standard practice to insert a neck in between the backbone and the head of the network, to collect and mix features from different layers. The FPN network (Lin et al., 2017) is one example of a neck that is commonly used in object detection networks. FPN uses a top-down path with lateral connections to extract semantic feature maps at different scales (Bochkovskiy et al., 2020). The resulting feature maps enable the model to find objects at different scales. Path aggregation network (PANet) (Liu, S et al., n.d.) is another example of a neck used in object detectors. It enhances FPN with a bottom-up path which helps propagate the low-level features. Equipped also with an adaptive feature pooling, PANet has been shown to improve object localization (Bochkovskiy et al., 2020). The generic architecture of the one-stage and two-stage detectors is shown in Figure 5.1. We study the popular Faster R-CNN as a representative two-stage approach and two YOLO variants, YOLOv5 and YOLOv7, on the task

of detecting and classifying common coccinellid found in sorghum. All models studied were trained and evaluated using images annotated with the Labelbox tool (https://labelbox.com).

Faster R-CNN-FPN. The Faster R-CNN-FPN has a pre-trained CNN as a backbone for feature extraction, FPN as a neck, a region proposal network (RPN) as a dense prediction head for bounding box regression of approximate RoIs and a sparse prediction head that classifies RoIs into several several categories of interest. We experiment with two CNN networks pre-trained on ImageNet (Deng, J et al., 2009) as the CNN backbone, specifically, ResNet-50 and ResNet-101 networks, given that they provide a good trade-off between accuracy and speed (Huang, J et al., n.d.). Rezatofighi et al. (Rezatofighi, H et al., 2019) suggested that the standard L2 loss used to regress the parameters of the bounding box corresponding to an object is not strongly correlated with the IoU (Intersection over Union) metric generally used to evaluate object detection approaches. Instead of the L2 loss, they proposed to use a loss based on the IoU metric. Specifically, they experimented with a IoU loss and a loss based on a generalized IoU (GIoU), and showed that optimizing the GIoU loss helps improve the performance measured either using the GIoU itself or the standard IoU. Given this result, we experiment with the IoU and GIoU as the regression loss for the bounding box regression task in Faster R-CNN.

YOLOv5. The backbone for YOLOv5 is CSPDarknet-53 which combines the original Darknet network used in YOLOv3 (Redmon and Farhadi, 2018) with the CSPNet network (Wang, C. Y. et al., 2020). CSPNet addresses the issue of duplicate gradient information in large backbone networks by truncating the gradient flow to speed up computation. The neck used in the YOLOv5 architecture is the PANet network. In addition to components that improve efficiency, YOLOv5 also introduces mosaic augmentation, which is used to stitch together multiple images with the goal of training the model to find objects in places other than the center

of the image, where a large majority of objects are generally located. YOLOv5 itself represents a series of object detection models that have been pre-trained on the MS COCO dataset (Lin et al., n.d.). Models in the YOLOv5 series have different sizes as applications have different needs in terms of the trade-off between accuracy and speed. In this study, we experiment with five YOLOv5 variants that vary in size from nano (YOLOv5n) to small (YOLOv5s), medium (YOLOv5m), large (YOLOv5l) and extra-large (YOLOv5x).

YOLOv7. The YOLOv7 architecture has been designed based on a "bag-of-freebies" idea (Bochkovskiy et al., 2020), which means that, while it's important for the inference of a detector to be fast, the training is done offline and can be more expensive if that helps to improve the overall accuracy. With this in mind, YOLOv7 introduced several innovations in network architecture and training strategies. At the architecture level, the main component of YOLOv7's backbone (pre-trained on COCO dataset) is a block called extended efficient layer aggregation network (E-ELAN), which enables the model to learn more diverse features. Another important innovation is a compound model scaling (depth, width) that enables the adjustment of the model to meet different application requirements while maintaining desirable model properties (e.g., optimal structure). To achieve robustness through module-level re-parameterization (i.e., averaging the weights of a module), YOLOv7 uses gradient flow propagation paths to "plan" what modules can benefit from re-parameterization. Finally, YOLOv7 introduced an auxiliary head, somewhere in the middle of the network, meant to assist the lead head, which may be too far downstream in the network. Together, these innovations in YOLOv7 have led to state-of-the-art results on standard benchmark datasets for object detection (Wang et al., 2022), and at the same time, smaller inference time as compared with other YOLO models. As for YOLOv5, YOLOv7 also consist of a series of pre-trained models of various sizes. In this study, we

experiment with five YOLOv7 variants, starting with the standard YOLOv7 model, the smallest model, YOLOv7-tiny, and larger models, YOLOv7-x and YOLOv7-d6.

Dataset. Coccinellid imagery downloaded from the iNaturalist web portal was used (inaturalist.org). iNaturalist is a citizen science project that allows naturalists to upload and share observations (i.e., images) of biodiversity worldwide through a web platform and mobile app for free. Submission by observers include the actual images, their locations, observed time, and group identifications. Agreements on the taxa in the observations create a "research-grade" label that is assigned to the observation. iNaturalist makes an archive of research-grade observation data available to the environmental science community via the Global Biodiversity Information Facility (GBIF) (Ueda, n.d.). We used GBIF to assemble a dataset for training and testing deep learning models for the detection, localization and classification of coccinellids. Only research-grade labels at family, genus, and species level were considered in the dataset that we assembled. The dataset includes seven distinct categories of coccinellids corresponding to the most important coccinellids found in sorghum plants, specifically: *Coccinella septempunctata*, *Coleomegilla maculata*, *Cycloneda sanguinea*, *Harmonia axyridis*, *Hippodamia convergens*, *Olla v-nigrum* and the subfamily Scymninae (Bowling et al., 2016). Three sample images in each of these seven categories are shown in Fig 5.2 (where each row corresponds to one coccinellid type).

We aimed to select approximately 700 images per category, and assembled a dataset with a total number of 4,865 images. Each image contains one or more instances of coccinellids of the same type (i.e., corresponding to a particular category). The dataset was split into train (3,053 images), development or dev (1,113) and test (699) subsets. Table 5.1 shows the distribution of the images/coccinellid instances over the seven categories in each of the train/dev/test subsets

and also in the whole dataset. Appendix A Table A.1 shows the distribution of the images with respect to the number of instances per image (1, 2, 3, 4, 5, 6, 7, or 8) for each category and for each of the train/dev/test subsets. As can be seen, most images have only one or two coccinellid instances, although there are some images that have up to 8 coccinellid instances.

We also classified the instances in our dataset according to their size, as this information is frequently used when evaluating object detection approaches (Wu, Y et al., 2019). Specifically, instances are classified based on the area that they occupy in an image as small (area ≤ 322), medium ($322 <$ area ≤ 962) or large (area > 962) (Wu, Y et al., 2019). Appendix A Table A.2 shows the distribution of the small, medium and large instances in the train/dev/test subsets and in the whole dataset. As can be seen, the number of small instances is just 5 in the total dataset and they are all included in the training subset. The number of medium instance is 142, with 18 of those instances being in the test subset. The remaining 4995 instances are large and represent the majority in our dataset. Given this observation, our evaluation metrics will be generic (representing mostly the large category) as opposed to being specifically focused on small, medium and large categories, respectively.

Implementation details. We trained and evaluated Faster R-CNN-FPN, YOLOv5 and YOLOv7 models. The data flow diagram for our whole process is depicted in Figure 5.3. Training images are used to train the model, while the development images are used to evaluate and select hyperparameters. The performance of the final models is estimated on the test data.

Faster R-CNN-FPN. We used the Detectron2 library for object detection and segmentation (Wu, Y et al., 2019) (developed by Facebook Research) to train and evaluate our Faster R-CNN-FPN models for coccinellids detection. Detectron2, uses PyTorch as a deep learning framework, and is the successor of Detectron (Girshick, R et al., 2018), originally

"designed to be flexible in order to support rapid implementation and evaluation of novel research." We used the default values for most of the hyperparameters of the Faster R-CNN-FPN object detection models and experimented with ResNet50/ResNet101 as backbone CNNs and IoU/GIoU as the regression losses, respectively. In terms of number of iterations, we started by training the Faster R-CNN-FPN model with the default 40,000 iterations. However, the learning curves shown in Appendix A Figure A.1 suggested that both training and development losses were still decreasing, while the AP was still increasing after 40,000 iterations. Thus, to enable the network to learn further and give better performance, we ran all experiments for 400,000 iterations, and identified the best iteration for each model based on learning curves as shown in Appendix A Figure A.2. Specifically, the best iteration is identified as the point where the validation loss starts increasing while the training loss is still decreasing. Using this criterion, for Faster R-CNN-FPN with ResNet-50 the best validation/training point was observed around iteration 80,000 for both IoU and GIoU losses, while for Faster R-CNN-FPN with ResNet-101 the best point was observed around iteration 220,000 for both losses.

YOLOv5. We used the official YOLOv5 implementation provided by Ultralytics (Jocher et al., 2020) to train and evaluate the YOLOv5 models. As for Detectron2, this implementation uses PyTorch as the deep learning framework. We used the default values for most of the hyperparameters of the YOLOv5 models, except for using 400,000 iterations as for the Faster R-CNN-FPN models. The best iteration for each model was selected using the learning curves, as described above.

YOLOv7. We also used the official YOLOv7 PyTorch implementation (Wang et al., 2022) to train and evaluate the YOLOv7 models. As for YOLOv5, we used the default values for most of the hyperparameters of the YOLOv7 models, except for using 400,000 iterations as for

the Faster R-CNN-FPN and YOLOv5 models. As for the other models, the best iteration for the YOLOv7 models was selected using learning curves.

All the models were trained on Amazon Web Services (AWS) p2.xlarge instances. According to AWS, the configuration of the p2.xlarge instance is as follows: 1 GPU, 4 vCPUs, 61 GiB of memory, and high network bandwidth. Training of the models for 400,000 iterations took between 8 and 14 days.

Evaluation metrics. We used three standard average precision metrics (Redmon and Farhadi, 2018) to evaluate the results of our models. The three metrics are defined using the Intersection-over-Union (IoU) measure, which captures the overlap between the predicted bounding box of an instance and the ground truth bounding box of that instance. Specifically, the IoU is defined as the area of overlap (i.e., intersection) divided by the area represented by the union. The metrics used to evaluate the ability of the models to correctly identify the type of coccinellid are: 1) average precision at IoU = 0.50, denoted by AP@0.50; 2) average precision at IoU = 0.75, denoted by AP@0.75; and 3) average precision at IoU = .50 : .05 : .95, which represents the average precision across ten IoU thresholds varying from 0.5 to 0.95 with a step size of 0.05, denoted by AP@.50 : 0.05 : .95 or simply AP. AP@n considers a prediction to be correct if the IoU between the detected instance and the ground truth instance annotation is greater or equal than n. For example, AP@0.50 considers a prediction to be correct if the corresponding IoU is greater or equal to 0.50.

In addition to comparing the models in terms of average precision metrics, we also compared the models in terms of number of layers that the specific model architecture used includes, number of parameters of the network, size of the model (MB) and inference time per

image (ms). These characteristics can be used to identify small models that are accurate and fast and can be embedded in mobile devices for automated field scouting.

Results and Discussion

The results of the models used in this study, Faster R-CNN-FPN, YOLOv5 and YOLOv7 on the whole test subset are shown in Table 5.2. Specifically, for each family of models, we report AP, AP@0.50 and AP@0.75 for the model variants considered. The best result in terms of AP (with averages values obtained for a range of 10 IoU thresholds from 0.50 to 0.95 with a step of 0.05) is 74.605 and is obtained with the YOLOv7 model. The best AP value for a YOLOv5 model is 73.3 and is obtained with the YOLOv5x variant, while the best value for a Faster R-CNN-FPN model is 65.6 and is obtained with Faster-R101-GIoU. These are all significant results given that the best AP value for the popular object detection benchmark Microsoft COCO dataset (Lin et al., n.d.) (which considers AP to be its primary metric) is currently 65.4 (as of February 4th, 2023 ("Object detection on coco test-dev," 2021)). In terms of AP@0.50 (the primary metric for the PASCAL VOC benchmark dataset (Everingham et al., 2015)), the best value is 97.3 and is also obtained using the YOLOv7 model, while the best AP@0.50 value obtained with a YOLOv5 variant (specifically, YOLOv5m) is 96.0, and the best value obtained with a Faster R-CNN-FPN variant (Faster-R50-GIoU) is 94.3. Finally, when using the stricter AP@0.75, which requires at least 0.75% IoU overlap when comparing the predicted bounding box with the ground truth bounding box of an object instance, the best result is 82.6 and it is obtained with the YOLOv7 model as well, with the YOLOv5x variant following closely. These results are very competitive in terms of numbers reported in the literature for similar problems and show that the models considered in this study, and in particular the YOLOv7 models, have the ability to detect and localize coccinellids in real world images posted on iNaturalist. Overall,

on our test data, the standard YOLOv7 model has the best performance among the models in the YOLOv7 family, followed closely by the YOLOv5x model in the YOLOv5 family. Both these models are significantly better than the best Faster R-CNN-FPN model (specifically, Faster-R101-GIoU).

To evaluate the performance of the models in relation to their size and inference time, Table 5.2 also shows the number of layers, number of parameters, inference time (ms) and size (MB) for each model. While the Faster R-CNN-FPN models have an average number of parameters (42 and 60 millions with ResNet50 and ResNet101, respectively) as compared to the other models, they have relatively large sizes (165.8 MB and 242.1 MB, for ResNet50 and ResNet101, respectively) and high inference time (approximately, 130 to 140 ms per image). Thus, despite the fact that these are two-stage detectors, with large sizes and high inference times, the Faster R-CNN-FPN models are not very accurate by comparison with the YOLOv5 and YOLOv7 models on the coccinellid images. The YOLOv5 models have the smallest size and inference time overall, but it can be seen that the performance increases with the size of the model, with YOLOv5x (the largest model) having the best performance at an inference time of 28 ms per image. The size of the YOLOv7 variants is overall larger than the size of the YOLOv5 variants. However, the best YOLOv7 model, the standard YOLOv7, has a size of 74.8 MB and an inference time of 19.2 ms per image, which is lower than the inference time of the best YOLOv5x model. It is also worth noting that the standard YOLOv7 model has a large number of layers (specifically, 314 layers) and accordingly a large number of parameters (comparable to the number of parameters in Faster R-CNN-FPN with ResNet50), but it still has very fast inference time, a proof that the “bag-of-freebies” idea used in YOLOv7 gives the intended results.

To gain insights into how the models perform for each type of coccinellids in our dataset, Table 5.3 shows results in terms of AP (averaged over 10 IoU thresholds) for each of the seven types of coccinellids included in the dataset. As can be seen, the standard YOLOv7 model gives the best results for four coccinellid types, specifically *Coccinella septempunctata*, *Coleomegilla maculata*, *Cycloneda sanguinea* and *Hippodamia convergens*, and highly competitive results for the other three types. The YOLOv5x model gives the best results for the *Harmonia axyridis*, *Olla v-nigrum* and the subfamily Scymninae. Thus, based on these results, we can also conclude that the standard YOLOv7 model is a good choice for identifying coccinellids of the types included in our study, closely followed by the YOLOv5x model. The YOLOv7 model performs the best on coccinellids of type *Coccinella septempunctata* with AP = 78.4, followed by *Coleomegilla maculata*, *Harmonia axyridis* and *Olla v-nigrum* with AP = 76.4, AP = 76.2, and AP = 75.5, respectively. The AP of the model is lower for *Cycloneda sanguinea*, subfamily Scymninae and *Hippodamia convergens*, with AP values of 72.2, 71.0 and 70.5, respectively.

A confusion matrix constructed by comparing the type predicted by the YOLOv7 model with the manually annotated type is shown in Fig 5.4. Generally, the type predicted is correct, with accuracy higher than 92% in all cases. As expected, some detected instances have the type incorrectly predicted. Furthermore, some instances are missed (background FN) or coccinellid instances are detected where there is not a coccinellid in the input image (background FP). Overall, the model makes a small number of false negative mistakes (i.e., it rarely misses a coccinellid), while the largest number of FP mistakes is in the Scymninae subfamily. As can be seen from the confusion matrix, the Scymninae subfamily also has the highest percentage of miss-classified instances overall (8%), while the *Coccinella septempunctata* type has the highest detection accuracy (98%).

Fig 5.5 shows examples of correct predictions made for different coccinellid types appearing in somewhat challenging settings. For example, in image (a), the image contains seven coccinellids and the model correctly identifies all of them and their right type. In images (b), (f) and (i), there are also multiple coccinellids and they are all correctly identified, even when overlapping. In image (e), there is a coccinellid inside the stem, while in image (g) the coccinellid has its wings partly spread (a pose which is not very common in the dataset). In image (h), there are two coccinellids, one of them with its legs up (another pose not common in our dataset). Finally, in images (c) and (d), the coccinellids are relatively small or somewhat hard to see, but they are still correctly identified. Appendix A Figure A.3 shows similar examples of correct predictions made by the Faster R-CNN-FPN model with ResMet101 backbone and GIoU loss.

Error analysis. While the YOLOv7 models work very well, they do have two types of errors: detection errors and localization errors. The detection errors can be grouped into several classes: 1) Errors where a coccinellid is identified but the detected type is wrong, as shown in Fig 5.6 (similar errors can be seen for the best Faster R-CNN-FPN model in Appendix A Figure A.4; 2) Errors where a different object in a picture is identified as a coccinellid, as shown in Fig. 5.7 (a), (b) and (c) ; 3) Errors where a coccinellid should be identified but the model completely misses it, as shown in Fig 5.7 (d), (e) and (f); and 4) Errors where a coccinellid has its wings spread out and the model detects two coccinellids instead of one, and conversely, errors where two coccinellids overlap in the image and the model fails to detect two instances, as shown in Fig 5.7 (g), (h) and (i). It is interesting to see that the YOLOv7 model fails to find a coccinellid, when it covers a large area of the image, as seen in Fig 5.7 (e), suggesting that the bounding boxes that it considers when finding RoIs do not capture such large areas. Also interesting is the

fact that it can detect some coccinellids that have their wings spread out, as seen in Fig 5.5 (g), but not all, as illustrated by Fig 5.7 (g). Similarly, the model can identify some coccinellids that overlap as shown in Fig 5.5 (b) and (i) but it fails to detect others, as shown in Fig 5.7 and (i). When comparing YOLOv7 predictions with Faster R-CNN-RPN predictions, we found that the YOLOv7 model can "fix" some of the errors made by the Faster R-CNN-FPN model, as can be seen in Appendix A Figure A.5.

In addition to detection errors, the models also make localization errors. In particular, a localization error happens when the IoU overlap between the predicted bounding box and the manually annotated bounding box does not satisfy the desired threshold (e.g., 50% or 75%). However, to some extent, differences in bounding boxes could stem from differences in the way the manual annotation is performed, as humans are prone to error and inconsistencies when performing annotations, as Fig 5.8 shows. Our models learn from the human annotations and will also produce bounding boxes that are enclosing the object of interest more closely or more loosely, thus leading to difference in terms of object localization.

YOLOv7 model as a tool for coccinellid detection. To enable the use of our best model by the research community, we make available the pre-trained YOLOv7 model as a web-based application at https://coccinellids.cs.ksu.edu, shown in Appendix A Figure A.6. The web-based application is user-friendly and allows the user to explore the model predictions using sample images available on the front page. Alternatively, a new image can be uploaded to the site and submitted for analysis. Underneath, the built-in model is used to detect and classify coccinelids in the image, and the results are displayed on the site using an annotated bounding box. It takes approximately 4-5 seconds for a prediction to be made, given the interaction with the server. In addition to the web-based application, which does not require any programming skills, we will

also make the pre-trained models and source code available on GitHub for more experienced users who may need to further train and adapt our models to other species or datasets.

Limitations of the study. We have shown that deep learning models can be used to identify seven types of common coccinellids in sorghum. While the methodology proposed in this study can provide tremendous benefits to IPM in sorghum, we would also like to point out its limitations:

As emphasized by our error analysis, some coccinellids are not identified, especially when they cover most of the area of the image, and sometimes when two coccinellids overlap in an image. More images of those types need to be included in the dataset to improve the performance of the models on such images. Similarly, the models can make mistakes in terms of the type of the coccinellid identified and also in terms of the precise location (bounding box of the coccinellid).

While our dataset covers seven types of coccinellids, and includes images with several coccinellids, all coccinellids in an image are of the same type. It is not clear how the models would perform on images with coccinellids of different types. Our dataset includes only a small set of images with coccinellids that are considered “small” objects based on their size (see Appendix A Table A.2). More data is needed to estimate the performance of the models in detecting “small” coccinellids, which have a high chance to appear in images taken with an autonomous device in the wild.

While a big variety of images were used to train and test our models, the images may not be fully representative of images that would potentially be taken with an autonomous device such as a drone. Additional data captured with such devices can be added to the training set to improve the robustness of the models in such scenarios.

Conclusions

In this study, we focus on the application of high throughput deep learning models to detect and classify coccinellids that are commonly found in sorghum. Specifically, we compared two-stage (Faster R-CNN-FPN) and one-stage detectors (YOLOv5 and YOLOv7) on the task of detecting and classifying seven types of coccinellids, including *Coccinella septempunctata*, *Coleomegilla maculata*, *Cycloneda sanguinea*, *Harmonia axyridis*, *Hippodamia convergens*, *Olla v-nigrum*, Scymninae. To do this, we first assembled and annotated a dataset of 4,865 images based on the iNaturalist imagery web server, which publishes citizen's observations regarding living organisms. Images in the dataset contain between one and eight instances of coccinelids manually annotated with bounding boxes using the LabelBox tool. Using the assembled dataset, split into training, development and test subsets, we experimented with several variants of the Faster R-CNN-FPN network where the base CNN was either ResNet-50 or ResNet-101, and the loss optimized was either the standard IoU or the generalized GIoU. We also experimented with several variants of the YOLOv5 and YOLOv7 models. Experimental results showed that the standard YOLOv7 model gives the best results overall for our test data, with AP@0.50 as high as 97.31 and AP as high as 74.5 for this specific variant. These competitive results in relation to results for other similar problems in prior works suggest that our models have the potential to make the task of detecting natural enemies in sorghum easier, if integrated in systems for automated pest management. To enable the community to make use of our models, we have made available the models as part of a web-based application that allows end-users to identify coccinellids in their own images.

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Tables and Figures

Table 5.1 Dataset statistics. Distribution of the images and coccinellid instances over the seven categories in each of the train/dev/test subsets and also in the whole dataset.

Data	Category	Cocc. sept.	Col. mac.	Cycl. sang.	Har. axyr.	Hipp. conv.	Olla nigr.	Scym.	Total
Train	Images	439	436	423	443	436	436	440	3053
	Instances	461	485	435	475	482	448	446	3232
Dev	Images	160	164	155	157	153	164	160	1113
	Instances	165	182	160	163	172	167	167	1176
Test	Images	99	100	100	100	100	100	100	699
	Instances	102	101	107	100	119	103	102	734
Total	Images	698	700	678	700	698	700	700	4865
	Instances	728	766	702	738	773	718	715	5142

Table 5.2 Faster R-CNN-FPN, YOLOv5 and YOLOv7 results. The networks are evaluated on the test subset using the best model according to the development subset. The results are reported in terms of AP, AP@0.50, AP@0.75. The Faster R-CNN-FPN (Faster) models are using ResNet-50 (R50) and ResNet-101 (R101) as base models, with IoU and GIoU as the loss, respectively. The best results for models within a family are highlighted with bold, while the best result overall is also shown in red. For each model, the number of layers, number of parameters, inference time and size are also shown.

Model type	AP (%)	AP@0.50 (%)	AP@0.75 (%)	Layer numbers	Parameter numbers	Inference time (ms)	Size (MB)
Faster-R50-IoU	62.9	94.1	74.2	50	42,000,000	130.2	165.8
Faster-R101-IoU	64.7	93.4	74.5	101	60,000,000	141.6	242.1
Faster-R50-GIoU	63.5	**94.3**	73.9	50	42,000,000	127.4	165.8
Faster-R101-GIoU	**65.6**	93.7	**75.6**	101	60,000,000	138.5	242.1
YOLOv5n	67.6	93.1	79.9	157	1,768,636	4.8	3.8
YOLOv5s	70.8	94.5	83.2	191	7,468,160	3.3	14.4
YOLOv5m	73.0	**96.0**	85.1	212	20,877,180	11.6	44.2
YOLOv5l	73.2	95.3	84.7	267	46,140,588	17.7	92.8
YOLOv5x	**73.8**	95.9	**85.6**	322	86,213,788	28	173.1
YOLOv7	74.6	97.3	86.2	314	36,514,136	19.2	74.8
YOLOv7-tiny	68.3	94.7	81.1	208	6,023,832	5.7	12.3
YOLOv7-x	68.3	94.1	79.7	362	70,822,872	28.3	142.1
YOLOv7-d6	65.3	90.6	75.2	566	152,967,984	41.8	1200

Table 5.3 Faster R-CNN-FPN, YOLOv5 and YOLOv7 results for each coccinellids type in the test subset. Results are reported in terms of AP obtained with the best model according to the development subset. The Faster R-CNN-FPN (Faster) models are using ResNet-50 (R50) and ResNet-101 (R101) as base models, with IoU and GIoU as the loss, respectively. The best results for a coccinellid type using models within a family are highlighted with bold, while the best result overall is also shown in red.

Model	Coccinella septempunctata	Coleomegilla maculata	Cyclonedasanguinea	Harmonia axyridis	Hippodamia convergens	Olla v-nigrum	Scymninae
Faster-R50-IoU	67.1	62.7	**60.3**	65.2	55.1	67	63.0
Faster-R101-IoU	70.0	63.9	58.8	**70.7**	54.5	**69.8**	65.1
Faster-R50-GIoU	66.2	64.5	59.6	68	55.6	67.4	63.2
Faster-R101-GIoU	**70.1**	**66.6**	59.7	68.8	**58.3**	69	**67.0**
YOLOv5n	72.1	70.5	64.0	71	60.9	68.8	67.2
YOLOv5s	76.3	71.8	68.8	72.7	63.9	73.1	69.3
YOLOv5m	**77.2**	72.8	69	73.1	68.4	77	72.3
YOLOv5l	77.1	73.3	70.1	74.2	**69.2**	75.3	72.0
YOLOv5x	76.8	**74.9**	**70.3**	76.8	69.1	77.6	72.8
YOLOv7	80.4	76.4	72.2	**76.2**	70.5	**75.5**	**71.0**
YOLOv7-tiny	75.5	68.8	63.7	72.7	65.3	70.3	61.4
YOLOv7-x	74.8	69.8	65.4	73.1	62.8	69.4	63.1
YOLOv7-d6	74.2	66.4	61.1	72.4	62.8	69.8	50.4

Figure 5.1 Generic architecture for object detection approaches. A modern object detection network consists of three main components: 1) a *backbone* network that performs feature extraction for a given input image; 2) a *neck* that collects and combines features from different layers; and 3) a *head* which is used to detect and classify objects of interest. One-stage detectors use a dense prediction head to simultaneously address the detection (bounding box regression) and classification tasks, while two-stage detectors decouple the two tasks and use a sparse prediction head to classify previously identified RoIs.

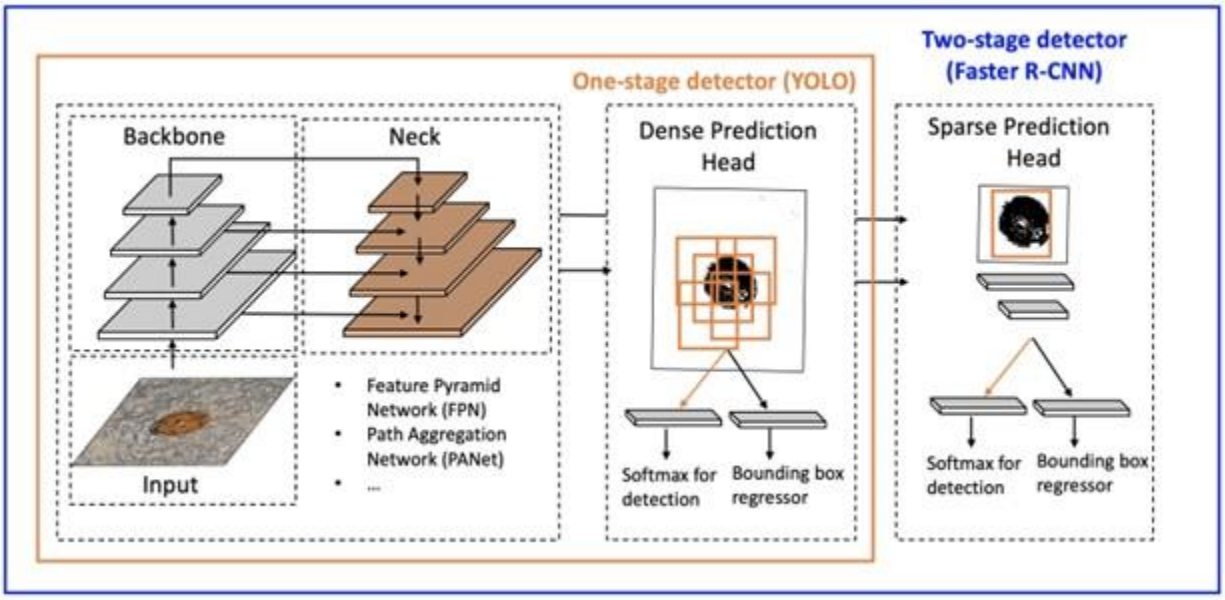


Figure 5.2 Samples of 3 coccinellid images in each of the 7 categories included in the study.

Figure 5.3 Data flow diagram. Coccinellid images are collected from iNaturalist and labeled using Labelbox. The set of images is split between train, dev and test subsets. YOLO and Faster R-CNN-FPN models trained and fine-tuned on the train and dev subsets, respectively. The performance of each model is estimated on the test subset in terms of average precision (AP) metrics.

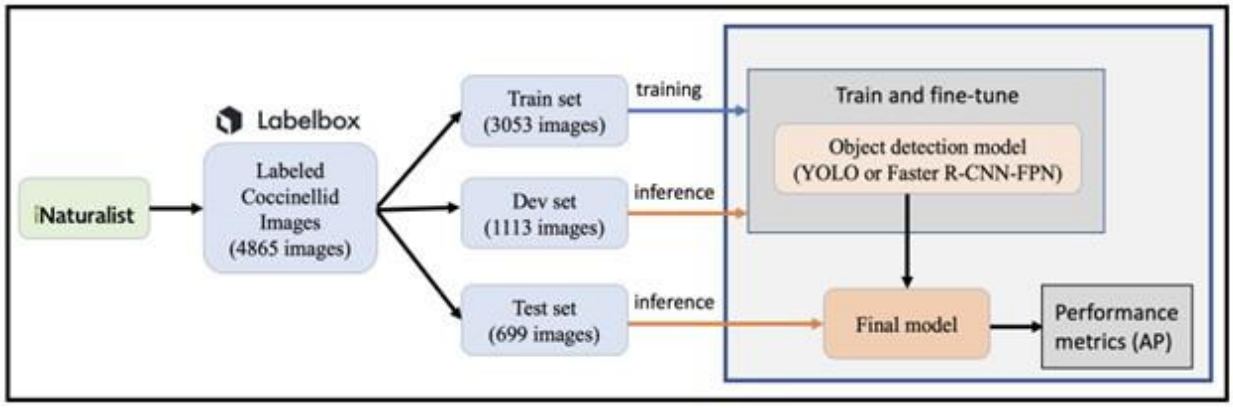


Figure 5.4 Confusion matrix constructed by comparing the type predicted by YOLOv7 with the manually annotated type. The label *background FN* corresponds to coccinellid instances that were not at all identified by the model, while *background FP* corresponds to predictions of coccinelids when there is not a coccinellid in the original input image.

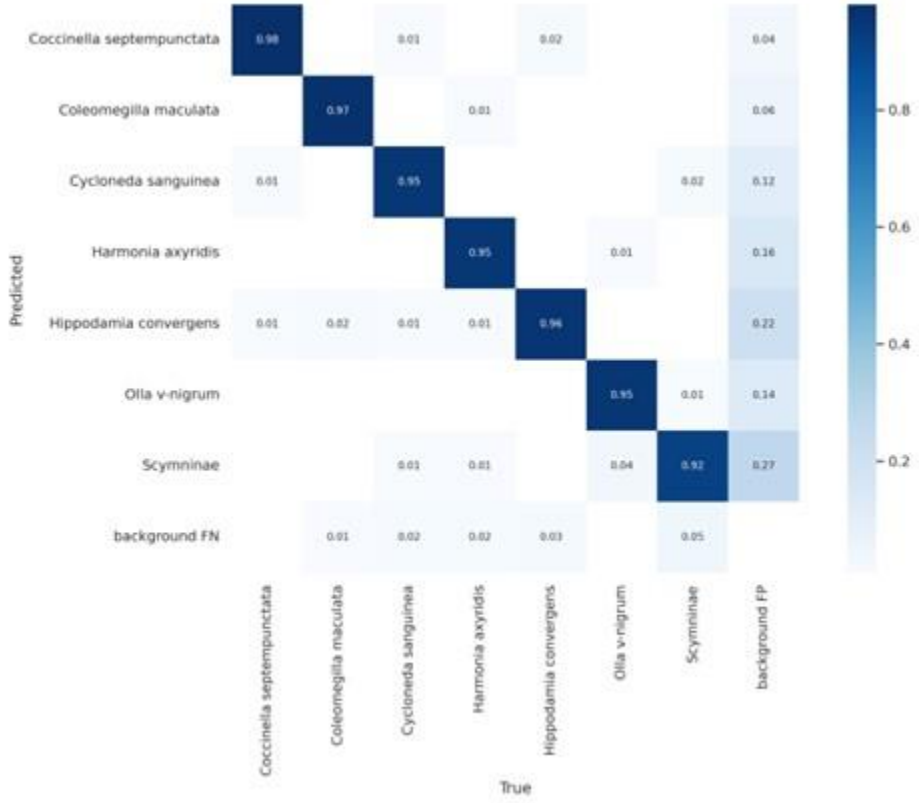


Figure 5.5 Examples of accurate YOLOv7 predictions on different coccinellid types.

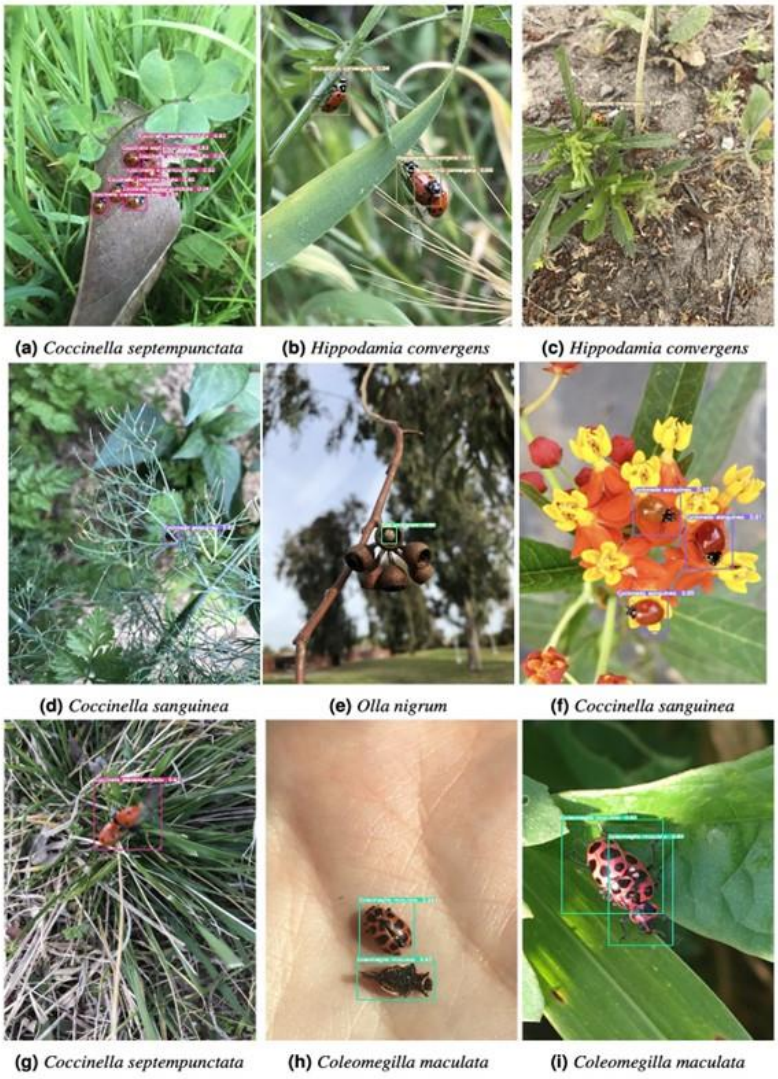


Figure 5.6 Examples of images where the YOLOv7 model correctly identifies a coccinellids, but the type identified is different from the manually annotated type. Each row shows a ground truth type, specifically, *Coccinella septempunctata*, *Harmonia axyridis*, *Hippodamia convergens*. The predicted label for each image is shown below the image.

Figure 5.7 Examples of YOLOv7 errors. Images (a), (b) and (c) show cases where YOLOv7 is mistakenly detecting an object as a coccinellid. Images (d), (e) and (f) show cases where YOLOv7 fails to detect a coccinellid. Images (h) and (i) show cases when YOLOv7 detects two coccinellids instead of one or alternatively one coccinellid instead of two.

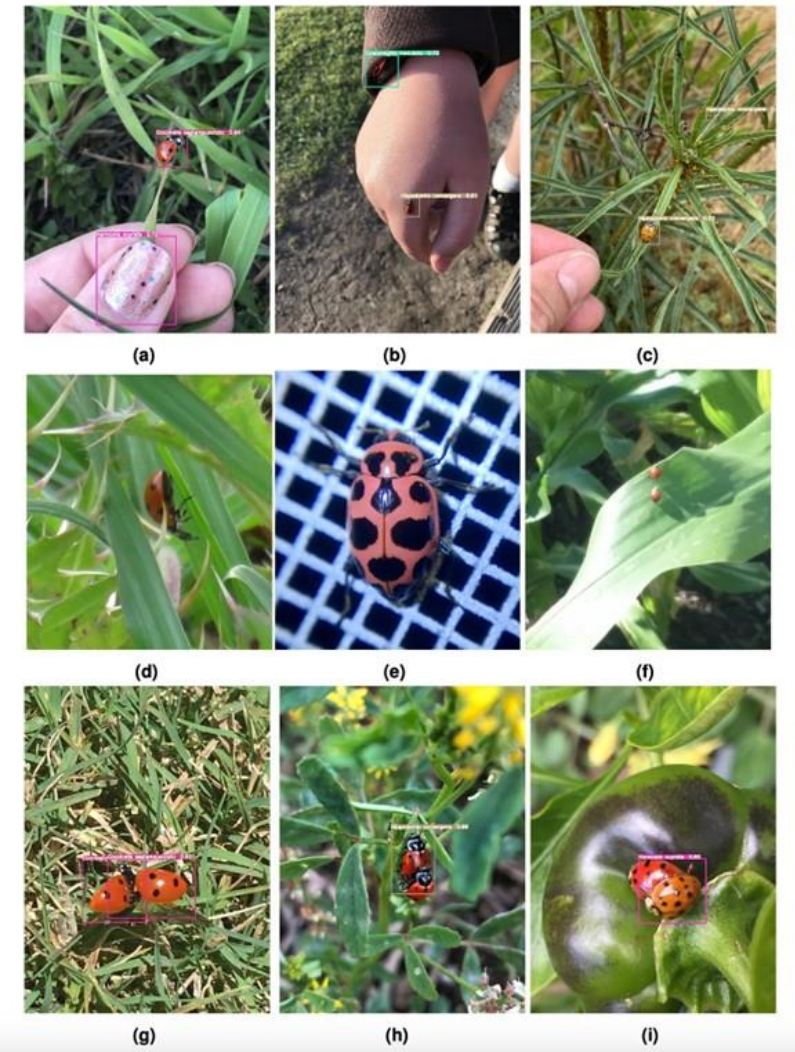
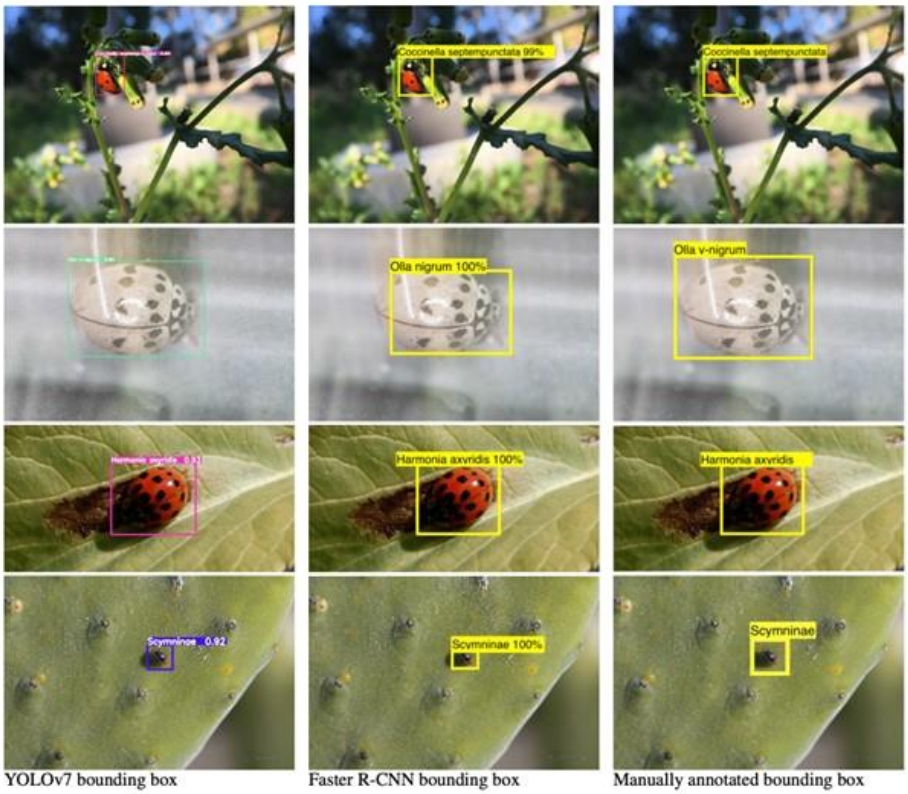


Figure 5.8 Localization differences. Examples of localization differences between YOLOv7 predicted bounded boxes (first column), Faster R-CNN predicted bounded boxes (second column) and manually annotated bounding boxes (third column).



Chapter 6 - Unconventional strategies for aphid management in sorghum

Introduction

Agricultural pests represent 37% of annual crop losses, and 13% of this figure is directly caused by insects (Mandava, 2018). Advantageously integrated pest management was promoted in the early 1970s as a strategy for pest control that promotes sustainable agriculture with a strong ecological basis (Kogan, 1998). Different strategies have been used in integrated pest management to manage insect pests in agriculture, including the application of insecticides, cultural practices, host-plant resistance, mechanical and biological management methods (Flint and Van den Bosch, 2012). One of the most widely used strategies to manage insect pests is the use of insecticides; however, there is much concern about their use for pest control due to their cumulative non-sustainable adverse effects on the environment (Krupke, C. and Long, 2015; Pimentel and Levitan, 1986; Sánchez-Bayo and Wyckhuys, 2019).

Primary concerns include the effect of insecticides on non-target or beneficial organisms, including natural enemies and pollinators (Bonmatin et al., 2015; Krupke, C. et al., 2017), and the potential for developing insecticide resistance (Jensen, 2000; Kranthi et al., 2002). Additionally, the use of insecticides can create indirect costs, including negative impacts on human health of growers or consumers (e.g., poisoning), as well as long-term effects on the environment (e.g., bioaccumulation, biodiversity, etc.) (Margni, M et al., 2002; Van Lenteren, 2012). Therefore, given the various negative impacts of insecticides and reliance on single strategies to manage key pests, there is a need to find alternatives to reduce the use of insecticides to promote sustainability in field crops (Pimentel and Levitan, 1986).

Sorghum (*Sorghum bicolor* (L.) Moench), is one of the field crops that relies on insecticide applications to manage pests. In recent years, sorghum aphid, *Melanaphis sorghi* (Theobald), infest fields (Brewer et al., 2019) has significantly impacted production in the Southern Great Plain, which has increased the use of seed-applied and foliar insecticides (Haar et al., 2019). Kansas is one of the major sorghum producing states in this region, and sorghum aphid infestations reduced yields since 2015 (Ciampitti, I. et al., 2021). Use of resistant hybrids and managing populations early in the southern range of its distribution have reduced the overall impact of this pest on sorghum. However, sorghum aphid reach damaging levels in sorghum production areas across the state. Damage caused by the sorghum aphid includes leaf chlorosis, reduction of plant nutrients, and lower photosynthesis due to honeydew secretion and growth of sooty mold (Bowling et al., 2016; Singh et al., 2004). During pre-flowering, aphid infestations can decrease the number of heads, seed weights, and plant maturity causing a reduction in yield (Ciampitti, I. et al., 2021). Due to their high reproductive rates and ability to disperse great distances, monitoring changes in aphid population is imperative to timely and warranted use of insecticides, which are applied based on established economic thresholds (Bowling et al., 2016).

During pest monitoring, visual assessments are performed to estimate aphid densities on leaves to determine whether a density has reached an economic threshold level (Gordy et al., 2019). However, pest monitoring is a time-consuming activity and has certain limitations. These limitations include the training of personnel to identify and count aphids, which currently can be addressed with automation using computer vision models (Grijalva et al., 2023). Another limitation is the labor demand for scouting extensive acreage to determine areas of infestation or infested plants, which can be solved with multipurpose robotic vehicles (Vibhute et al., 2021). For example, the robot can detect aphids using computer vision models and, depending on the

infestation density, can decide to spray only the infested area, resulting into plant-level applications.

However, traditional aphid management, which depends on published economic thresholds, suggest applying insecticides when 20-30% of sorghum plants are infested with an estimated 25-125 sorghum aphids/leaf threshold (McCornack et al., 2017). Others suggest a 40 sorghum aphids/leaf threshold or "tally threshold" to treat with insecticides (Gordy et al., 2019). Usually, thresholds and related sampling plans rely on mathematical probabilities that unsampled plants will require treatment based on aphid densities using subsample of the entire plant population. For example, areas or unsampled plants with low or no aphid presence can be sprayed unnecessarily, resulting in a needless increased use of insecticides. A whole-field insecticide application requires high amounts of insecticides to treat a crop's area, resulting in significant production costs and increased environmental impact (Carroll et al., 2008). Also, spraying the entire field with insecticides could increase the risk of aphid resistance (Haar et al., 2019), and reduce the number of natural enemies contributing to sorghum aphid populations' natural predation.

Therefore, to reduce the use of insecticides on unnecessary areas or non-infested plants with aphids, we propose a small-plot study spraying individual plants with or without the presence of aphids, simulating the use of a multipurpose robotic vehicle that could be used for scouting and treating individual plants compared to traditional spraying based on standard economic thresholds. Sorghum was used as a crop model to evaluate the effect of plant-level applications on sorghum aphid populations and yield differences. We hypothesize that our approach could manage sorghum aphid populations while reducing insecticide use by monitoring aphid pests and only applying insecticides at plant level when aphids are present or not.

Material and Methods

Site location. The research study took place in fields located in Manhattan, KS. The fields had plot coordinates of 39.126, -96.636 and 39.214, -96.597, respectively. The fields were planted with 0.20 ha of sorghum using seed susceptible to sorghum aphid; we used sorghum varieties 84P80 and 84G62 (Pioneer, Johnston, IA) in 2021 and 2022, respectively, and each had an aphid tolerance of 2 out of 10, which is "poor" according to the company. We used a row spacing of 0.76 m (30") between rows and no-till practices and was planted on June during the 2021 and 2022 growing seasons. No fertilizers were applied to the experiment and insecticide used to manage sorghum aphid populations per the treatments described below.

Field design and treatments. We used a randomized complete block design for this field trial to evaluate the impacts of plant-specific insecticide applications on changes in whole-plot population dynamics compared to standard whole-plot insecticide applications using established economic thresholds to determine the timing of insecticides. The sorghum field was divided into 30 plots that were 4 rows wide by 12 m long and each block was spaced 3 m apart from the other. The field experiments in both years consisted of 5 randomized treatments (Table 6.1) within each of the 6 block. Sorghum aphid wingless, alates, and coccinellid populations in two middle rows of each plot were evaluated using visual assessments with repeated measurements.

The location of the plots in the field serves as the blocking factor. Within each block, the five treatment groups were randomly assigned to a plot. Each treatment group was represented by six plots. The counts of sorghum aphid wingless, alates, and coccinellids were visually assessed at 16 timepoints, including three at baseline, Day 1 and Day 6 post the 1st to 6th evaluation phases, and Day 1 post the 7th evaluation phase. At each timepoint, sorghum aphid wingless, alates, and various species of coccinellids were counted from two leaves of 12

randomly selected plants. Different plants were selected randomly each timepoint. The same experimental design was carried out in the 2021 and 2022 summer seasons.

Non-natural infestations of sorghum aphid populations. Based on preliminary field experiments conducted in the summer of 2020, various sorghum plots did not reach sorghum aphid economic threshold levels for insecticide applications (unpublished data). For this reason, we manually infested 4 to 8 random, individual plants with approximately 500-1000 sorghum aphid wingless in the two middle rows of the plots when the sorghum plants have 7-10 leaves (stage 3) during the growing season of 2021 and 2022, respectively. Sorghum aphids were derived from a research colony maintained in the Entomology Department at Kansas State University, which was established in 2020 from field collected specimens. After infesting randomly selected sorghum plants, we covered each plant with sleeve cages (each cage consisted of 50 cm long by 20 cm wide with two openings at the ends built with noseeum mesh) long enough to allow for plant growth development while protecting the aphids from natural enemies, especially coccinellids (Figure 6.1). All sleeve cages were removed two weeks before visual assessments started, which allowed sorghum aphids to spread through the center two rows of each replicated plot.

Insect sampling. Two months after sorghum was planted (stage 4: flag leaf is visible (Ciampitti, I. et al., 2021)) visual counts were made of all arthropods, including sorghum aphid wingless, alates, and coccinellids identified to species. Density estimates were performed by randomly selecting 12 plants within the two middle rows of each plot. From each plant, we visually assessed two leaves, the most recent completely unfurled leaf below the flag leaf and the first healthy leaf (>80% of the leaf was green) from the bottom of the plant (designated as “top” and “bottom” leaves hereafter) (Gordy et al., 2019; Lindenmayer et al., 2020). For each leaf,

number of wingless sorghum aphids and alates were estimated using established guides that had 7 density categories (Bowling, R et al., n.d.), and alates were individually counted. The categories included: 0 wingless/leaf, 1-25 wingless/leaf, 26-50 wingless/leaf, 51-100 wingless/leaf, 101-500 wingless /leaf, 501-1000 wingless/leaf, and >1000 wingless/leaf. The coccinellids were visually counted and identified by species using the same leaves evaluated for sorghum aphids. All these visual assessments were performed weekly and after treatment applications and until prior to sorghum harvest. Artificially infested plants were not subject to visual assessments but served to increase aphid numbers across all plots to promote aphid establishment.

Insecticides applications. Insecticide applications were applied on a weekly basis one day after visual assessments of sorghum aphid wingless, alates, and coccinellids on sorghum leaves were completed. For example, all plants in the ET treatment were sprayed once the mean density reach 40 wingless/leaf. Conversely, only individual plants that had ≥ 1 wingless/leaf were sprayed for the plant-specific treatment. We marked each individual plant with distinct colors of flagging tape (Uline, Pleasant prairie, WI) to designate plant requiring an insecticide application in plots managed with PS and TT treatments. Individual plants in RS were randomly sprayed and were not marked.

The insecticide SivantoTM prime (Bayer CropScience 2 T.W. Alexander Drive Research Triangle PK, NC) was applied at a standard commercial rate (4 fl oz/acre) of 292.31 ml/ha for 4 treatments using a 22.86 x 39.37 x 52.07 cm backpack pump sprayer with a Teejet – 110015vs nozzle to simulate the further application of multipurpose robot vehicle. The untreated control did not receive an insecticide application and was far enough away from other treatments to control for insecticidal drift.

Cumulative aphid days and sprayed plants. We calculated the cumulative aphid days (CAD) per-plot basis for wingless and alates using the procedure described on Lytle et al. (Lytle and Huseth, 2021). The CAD calculates the area under the aphid population curve, and it provides a single number describing the aphid density or "pressure" over the entire growing season (Lytle and Huseth, 2021). We also recorded the total number of sprayed plants in each plot managed with ET, RS, PS and TT treatments for every insecticide application. The number of sprayed plants were used to calculate the number of cumulative sprayed plants (CSP) over all evaluation phases.

Yield sampling. At sorghum maturity, one middle row was randomly selected in each plot and sorghum heads from 3 m sections of an inner row were harvested by hand and dried using racket located in a dark room at 25° C. We excluded the artificially infested plants in all plots during the harvest process. A thresher (Almaco, SSBT-C2, Nevada, IA) was used to remove the seeds from the panicles. Seed was weighed in grams using an electronic balance (ScoutTM Pro, SP202, Parsippany, NJ) and % moisture content was measured using a grain moisture tester (Agratronix, MT-16, Streetsboro, OH) from each sample per plot.

Data processing. Counts of sorghum aphid wingless, alates, and coccinellid species were averaged over the 24 leaves measured in each plot. Accordingly, the lower limit of detection for a plot is 1/24□0.042. If a plot had no insect detected (referred to as ND), its count was replaced by half of the detection limit and then underwent natural log transformation for statistical analysis purpose. Data from 7th evaluation were excluded from the analysis because of low counts (data not shown). When an evaluation phase had large amounts of plots with ND, this evaluation phase was excluded from the analysis.

Statistical analysis. Statistical analyses were performed by year of the study on visual assessments, cumulative aphid days, and yield variable responses due to the different numbers of manually infested plants with sorghum aphid populations during the growing season of summer 2021 and 2022.

The natural log of counts post-treatment for each response variable was analyzed using the linear mixed model. Fixed effects of the model included block, treatment, evaluation phase, sample day, all two-way and three-way interactions between treatment, phase, and day. The random effect of the model was plot (an error term vector corresponding to repeated measurement over time). The natural log of baseline counts one day prior to the 1st evaluation phase served as a covariate. The variance-covariance structure of plot was taken as either unstructured, first-order autoregressive with heterogeneous variance or compound symmetry with heterogeneous variance depending on model convergence and fitness criteria. Model fitness was supported by the attributes of conditional studentized residuals. Treatment effect was assessed via back-transformed least squares means (LSMs), their standard errors (SEs) and mean differences. Disregarding results of the test for three-way interaction, treatment groups were compared at each evaluation phase and day. Statistical analysis was executed via Statistical Analysis Software (SAS version 9.4; Cary, NC) PROC MIXED with option DDFM=KR in the MODEL statement.

The yield and CAD variables were analyzed under the linear model, with fixed effects being block and treatment. Treatment effect was assessed via LSMs, their SEs and mean differences. Statistical analysis was performed via SAS PROC MIXED. All tests were conducted at the 0.05 significance level. Pairwise comparisons were carried out using the two-sided test. No multiplicity adjustment was applied.

Results

Aphid abundance over time in 2021 season. The treatment (Trt)*evaluation-phase (EP)*study-day (D) interactions were statistically significant on wingless, and alates in 2021; however not significant in wingless in 2022 season (Table 2). The interaction between Trt and EP was statistically significant ($P < 0.001$) on wingless and alates during the 2021 and 2022 seasons. During the summer of 2021, all treatments were similar on 1D post the 1st EP ($P = 0.571$). However, changes in nymph densities started on 6D post 1st EP ($P = 0.003$) with 178 ± 32 (LSM ± SE) higher wingless on TT and lower numbers (75 ± 13) on the RS. The nymph densities found in the UC (84 ± 15) were different from ET (176 ± 31), PS (155 ± 28), and TT, but similarly to RS treatment during the 1st EP.

Also, treatments differences were found on 1D and 6D post the 2nd EP ($P = 0.027$; <0.001), with lower number of wingless in RS (75 ± 10) on 1D and ET (3 ± 1) on 6D. Higher number of wingless were observed in TT (130 ± 18) on 1D and UC (73 ± 16) on 6D post the 2nd EP. On 1D post the 2nd EP, the ET (104 ± 14) and TT (130 ± 18) treatments were similar compared to the UC (128 ± 17), however RS (75 ± 10), and PS (82 ± 11) were different on nymph numbers. Similarly, the nymph numbers observed in TT were similar (44 ± 10) compared to the UC (73 ± 16), but different to ET (3 ± 1), RS (14 ± 3), and PS (30 ± 7) treatments on 6D post the 2nd EP. On 1D and 6D post 3rd EP also treatment differences were found ($P < 0.001$; 0.025). Higher nymph numbers (37.7 ± 8.8; 11.4 ± 4.1) were observed on the UC and lower number of wingless on ET (2.4 ± 0.5; 1.9 ± 0.7) during 1D and 6D post 3rd EP, respectively. During 1D post 3rd EP, the ET (2.4 ± 0.5), RS (9.4 ± 2.2), and PS (10.7 ± 2.5) had lower numbers and were different compared to UC (37.7 ± 8.8), however TT (20.3 ± 4.7) was similar on nymph numbers compared to UC treatment. The PS (5.5 ± 2.0) and TT (4.2 ± 1.5) were

similar in nymph numbers compared to the UC (11.4 ± 4.1), but different from the ET (1.9 ± 0.7) and RS (3.5 ± 1.2) on 6D post 3rd EP.

During the 1D and 6D post the 4th EP (P = 0.018; 0.026) also treatments differences were found. On 1D post the 4th EP, UC had the higher number of wingless (9.7 ± 3.5) and ET the lower nymph numbers (1.6 ± 0.6). During this EP all treatments were different compared to UC. In contrast, to the 1D post the 4th EP, only ET was different compared to UC with a lower number of wingless (0.2 ± 0.1) across treatments. On the other hand, not statistically differences were found during the 5th and 6th EP on nymph numbers on treatment. Overall lower nymph numbers were observed in plots managed with RS treatment compared to the UC, ET, and TT treatments across evaluation phases and study dates (Figure 6.2, A).

Similarly, changes were observed in alates densities started on 6D post 1st EP (P = 0.003) with higher alate numbers (3.16 ± 0.84) on ET and lower numbers (0.80 ± 0.2) on the RS treatment. The alate numbers observed in the UC (1.15 ± 0.31) was different compared to ET, PS (2.74 ± 0.73), and TT (2.49 ± 0.66), but similarly to RS treatment during the 1st EP. On 6D post the 2nd EP (P < 0.001), higher number of alates were found on UC (5.19 ± 1.96) and lower numbers on ET (0.10 ± 0.04), but not treatment differences were observed on 1D post the 2nd EP (P = 0.590). The UC was similar compared to TT (2.41 ± 0.91) and PS (2.03 ± 0.77) treatments, but statistically different compared to ET (0.10 ± 0.04), and RS (0.57 ± 0.22).

During the 3rd EP on 1D and 6D, all treatments were statistically different compared to the UC (P < 0.0001; = 0.023) on both study dates, with the exception on RS (0.11 ± 0.07), and TT (0.14 ± 0.09) on 6D post 3rd EP. Lower alate numbers were found on ET (0.03 ± 0.01; 0.03 ± 0.02) on 1D and 6D, respectively compared with the other treatments during the 3rd EP. On 1D post 4th EP treatments differences (P = 0.020) also were found. The ET (0.031 ± 0.013), RS

(0.036 ± 0.015), PS (0.051 ± 0.022), and TT (0.037 ± 0.016) were statistically different compared to the UC (0.225 ± 0.098), and lower alate numbers were found on ET (0.031 ± 0.013) treatment. During the next evaluation phases including 6D post 4th EP (P = 0.250), and 1D and 6D post 5th EP (P = 0.632; 0.837) not statistically differences were observed on treatment. Overall, lower alate numbers were observed in plots managed with RS treatment compared to the UC, ET, PS and TT treatments across evaluation phases and study dates (Figure 6.2, B).

Aphid abundance over time in 2022 season. Similarly, to 2021 season, all treatments were similar compared to the UC on 1D post the 1st EP (P = 0.311) in 2022 season. However, changes in nymph densities started on 6D post 2nd EP (P = 0.006) with higher nymph numbers (81 ± 32) on UC and lower numbers of (9 ± 4) in the ET treatment. The nymph numbers found in the UC were different compared to ET, RS (19 ± 8), but similarly to PS (31 ± 12) and TT (50 ± 20) treatment during the 2nd EP. During the 3rd EP, treatments differences were observed on 1D and 6D (P = 0.025; 0.001), with lower nymph numbers in ET (11 ± 4) on 1D, and (13 ± 6) on 6D, following by RS (29 ± 11; 44 ± 18). In contrast, higher numbers were observed on UC (72 ± 27; 168 ± 71) and TT (30 ± 11; 134 ± 57) treatment. On 1D, only ET (11 ± 4) was different compared to UC (72 ± 27), however ET (13 ± 6), and RS (44 ± 18) treatments were different compared to UC (168 ± 71) on 6D post 3rd EP.

On 1D and 6D post 4th EP treatment differences also were found (P = 0.001; < 0.001). Higher nymph numbers (157.3 ± 53.4; 97.1 ± 17.7) were observed on the UC and TT (111.1 ± 37.8; 70.9 ± 13.1) on both study dates compared with the other treatments. The ET (19.9 ± 6.8; 4.2 ± 0.8), RS (54.6 ± 18.6; 25.1 ± 4.7), and PS (38.0 ± 13.0; 11.1 ± 2.1) treatments were different compared to the UC, but TT treatment was not different compared to UC during both study dates. On 1D post 5th EP, also treatments were statistically different (P < 0.001). Higher

numbers were found on UC (84.98 ± 20.9) and TT (5.51 ± 8.79), respectively, and lower numbers on ET (2.76 ± 0.69) followed by PS (5.58 ± 1.40) and RS (14.10 ± 3.51) treatments. The ET, RS, PS treatments were different compared to the UC, however TT (35.51 ± 8.79) was similar on nymph numbers. Similarly, to 2021 season, the next evaluation phases including 6D post 5th EP (P = 0.089), 1D (P = 0.464), and 6D post 6th EP (P = 0.551) not statistically differences were observed on treatment. Overall lower nymph numbers were observed in plots managed with ET followed by PS and RS treatments compared to the UC, and TT treatments across evaluation phases and study dates (Figure 6.3, A).

Changes on alate densities on 2022 season, started to be observed on 6D post 2nd EP (P = 0.013), with higher numbers on the UC (2.14 ± 1.03) and lower numbers on ET (0.18 ± 0.09) followed by RS (0.67 ± 0.32) treatment. The ET was the only treatment different compared to the UC in alates numbers on 6D in this phase. During the 3rd EP, treatments differences were observed on 1D (P = 0.019) and 6D (P = 0.015). Lower alate numbers were observed in ET (0.28 ± 0.12) on 1D, and (0.29 ± 0.16) on 6D, followed by PS (0.61 ± 0.27; 1.69 ± 0.93) and RS (1.17 ± 0.52; 1.19 ± 0.66) treatments. The ET and PS treatments were different compared to UC on 1D and only ET on 6D compared to UC during the 3rd EP. Similarly, treatment differences were observed on 1D and 6D post 4th EP (P = 0.001; < 0.001). Higher alate numbers were observed in the UC (11.20 ± 4.48) on 1D and (10.55 ± 3.76) on 6D followed by the TT treatment (7.50 ± 3.00; 7.04 ± 2.51). Lower numbers were observed on the ET (0.90 ± 0.36; 0.10 ± 0.03), RS (3.25 ± 1.30; 1.78 ± 0.63), and PS (2.79 ± 3.00; 0.61 ± 0.22) and were statistically different compared to the UC on both study dates. Lastly, 1D post 5th EP was statistically significant (P < 0.001). The ET, RS, and PS treatments were different on alates numbers compared to the UC (9.009 ± 4.478) treatment. The lower numbers were observed in PS (0.072 ± 0.036) followed by ET

(0.117 ± 0.058) and RS (1.107 ± 0.550) treatment in this EP. Overall, lower alate numbers were observed in plots managed with ET followed by RS and PS treatments compared to the UC, and TT treatments across evaluation phases and study dates (Figure 6.3, B).

Natural enemies. In both seasons, treatment (Trt)*evaluation-phase (EP)*study-day (D) interactions were statistically significant on coccinellid larvae (Table 6.2); however, no significant three-way interactions were observed on Coccinella septempunctata (Linnaeus) (P = 0.145), Coleomegilla maculate (De Geer) (P = 0.133; 0.642), Hippodamia convergens (Guérin-Méneville) (P = 0.802) and unknown species (P = 0.376; 0.919). The two-way interaction between Trt and EP was statistically significant (P < 0.005; = 0.003) on larvae during both study years (Table 2); similarly, no significant interactions were observed on Coccinella septempunctata (P = 0.112), Coleomegilla maculata (P = 0.906; 0.419), Hippodamia convergens (P = 0.316) and unknown species (P = 0.102; 0.599).

In 2021, treatments were statistically different on the number of coccinellid larvae on 1D post the 1st EP (P = 0.043), with higher larvae numbers on PS (0.162 ± 0.048) and lower numbers on RS (0.058 ± 0.017) treatment. The ET (0.127 ± 0.038) and PS treatment were different compared to UC (0.048 ± 0.014) treatment. Also, during the 6D post the 2nd EP treatments differences were observed (P < 0.001). On 6D, higher numbers (0.300 ± 0.089) were observed on TT compared to the lower numbers on ET (0.030 ± 0.009) treatment. The ET was the only treatment different compared to UC (0.135 ± 0.040) treatment. During the 3rd EP on 1D, treatment differences were observed (P = 0.010). The ET (0.035 ± 0.012), RS (0.037 ± 0.013) and PS (0.037 ± 0.013) treatments were different compared to UC (0.180 ± 0.062). The next evaluation phases including 6D post 3rd EP (P = 0.090), 1D (P = 0.105), and 6D post 4th EP (P = 0.303), and 1D and 6D post 5th EP not statistically differences were observed on

treatment. Overall, higher numbers of coccinellid larvae were observed in plots managed with TT, followed by UC, PS, RS and ET treatments (Figure 6.4, A).

On the other hand, in 2022, treatments were statistically different on the number of coccinellid larvae on 1D post the 2nd EP ($P = 0.011$). Higher larvae numbers were observed on RS (0.0923 ± 0.0245) and lower numbers on PS (0.0235 ± 0.0062) treatment. The PS was the only treatment different compared to the UC (0.0603 ± 0.0160). Also, treatment differences were observed on 6D post the 4th EP ($P < 0.001$), with lower numbers on ET (0.0260 ± 0.0075) followed by PS (0.0419 ± 0.0121) compared to the UC treatment. Lastly, treatment differences were observed on 1D post the 5th EP ($P = 0.001$). Higher numbers were observed on UC (0.1720 ± 0.0591) followed by TT (0.0912 ± 0.0313) treatment, and it was the only similarly compared to UC. The next evaluation phases including 6D post 5th EP ($P = 0.432$), 1D ($P = 0.637$), and 6D post 6th EP ($P = 0.183$) not statistically differences were observed on treatment. Similarly, to 2021 season, higher numbers of coccinellid larvae were observed in plots managed with UC, followed by TT, RS, PS and ET treatments (Figure 6.4, B).

Cumulative aphid days. We found that CAD (LSMs) for wingless ($P = 0.014$; < 0.001) and alates ($P < 0.001$) were significantly different in both seasons. In 2021, LSMs separation of CAD for wingless and alates showed that plots managed with RS treatment was significantly lower compared to the UC treatment, however similarly to PS treatment (Figure 5B, C). In 2022, CAD for wingless and alates showed that ET, RS, and PS treatments were significantly lower compared to UC and TT treatments (Figure 6B, C). Overall, lower CAD for wingless and alates were observed in plots managed with ET, RS, and PS treatments during both seasons (Figure 6.5B, C; 6.6B, C).

Cumulative sprayed plants. We found a high number of cumulative sprayed plants in plots managed with ET compared to RS, PS and TT treatments in both seasons. Importantly, the number of cumulative sprayed plants in plots managed with RS, PS and TT treatment were 4 time less compared to plots managed with ET treatment in both seasons (Table 6.3).

Grain yield. We found the yield response variable using the dry weight of the grain standardized to 14% humidity, treatments did not significantly affect grain production in either year of the study (P = 0.176; 0.443 in 2021 and 2022, respectively). However, based on the pairwise comparisons, the PS treatment was significantly higher compared to the UC treatment in 2022 season. The lowest yield had the UC followed by TT treatment in both years of the study (Figure 6.5A, 6.6A).

Discussion

In this study, we documented the reduction of all wingless sorghum aphids and alates when we sprayed individual plants following plant-specific (RS, PS, and TT) management strategies compared with traditional strategies (i.e., whole-plot applications) that were based on established economic thresholds (i.e., ET treatment), where most plants were sprayed. Despite not observing aphid densities reaching an economic threshold level in 2020 (unpublished data) and moderate numbers during 2021 and 2022 growing seasons (i.e., CAD less than 5000), our results show aphid suppression varied among the plant-specific treatments. Treated plots based on ET, RS, PS, and TT treatments had a substantial reduction in aphid numbers when compared to the UC treatment. However, some treatments appeared to have a greater suppression of aphids between evaluation phases and study dates.

For example, in the 4th evaluation phase (1D after treatment), the LSMs aphid counts in plots treated based on ET, RS, and PS were significantly lower compared to the untreated control (UC) in either year of the season (Figure 6.1A, B; 6.2A, B). Overall, across evaluation phases and study dates, lower aphid numbers were observed in plots managed with ET, followed by RS and PS treatments. However, the number of cumulative sprayed plants found in plots managed with RS and PS were 4 time less than ET treatment (Table 6.3). This suggests that spraying individual plants based on RS or PS management can manage wingless and alates on sorghum and become strategies that can mitigate the environmental effects of chemicals and aphid resistance (Haar et al., 2019) compared with traditional management strategies when all plants are sprayed based on an ET treatment. However, these results are based on small plot studies, which further need to be evaluated at field-level.

Additionally, we observed considerable variation in aphid densities between evaluation phases in both study years (Figure 6.1, 6.2). This suggests that population dynamics of sorghum aphids changed over time (Haar et al., 2019). According to Lytle et al. (Lytle and Huseth, 2021), inter-annual fluctuations in aphid populations are characteristic in many field crops where aphid populations are critical pests. For example, in the southeastern sorghum region, aphid infestation intensity often changes among years, suggesting the relative influence of current aphid management strategies, like planting dates, biological control services, and resistant varieties can impact the aphid population dynamics through time (Haar et al., 2019; Lytle and Huseth, 2021). Despite observing fewer overall aphid infestation on 2021 compared to 2022 summer season, our results show that Trt*EP interaction effects were similar in both seasons with higher aphid counts in plots managed with UC treatment than any other treated plots.

Although we found no significant interaction (Trt*EP) on numbers of coccinellid species visually observed, this suggests that foliar insecticide applications did not negatively impact adult coccinellid populations. However, we observed Trt*EP interaction effects on the numbers of coccinellid larvae in both seasons. Importantly, lower numbers of larvae were found on ET treatment, suggesting the number of cumulative sprayed plants (i.e., 4 times higher to other treatments) (Table 6.3) are affecting the development of further generations of coccinellids and decreasing aphid predation, which is an important ecosystem service that can reduce the need for sprayings for aphid management (Brewer et al., 2017).

Since 2017, sorghum aphid economic infestations in Kansas have been less frequent and intense (McCornack and Whitworth, R, 2022). The combination of different management practices, including host-plant resistance, planting date, and the adaptation of aphids' natural enemies influence their reproduction and propagation in sorghum fields (Bowling et al., 2016; Brewer et al., 2017; McCornack and Whitworth, R, 2022). We consider planting date as a factor which influenced the aphid pressure in our field sites because an early planting (May - June), similarly to our planting dates in the season, help to reduce aphid infestations in Kansas (Ciampitti, I. et al., 2021). Therefore, this can reflect in the low aphid population pressure and CAD found in our study.

In both years of the study, the calculated CAD was lower in all the treated plots compared to UC treatment; however, the CAD in the UC treatment was below 5000 CAD, resulting in no yield differences. This suggests that our pest pressure was not high enough to see differences in yield. The yield differences have been found when CAD was above 10,000 on similar studies evaluating the effect of insecticides and cultural management strategies on sorghum aphids (Lytle and Huseth, 2021; Pekarcik and Jacobson, 2021). However, it also shows

that we can't affect yield when we artificially infest with aphids, suggesting timing of infestation was too far into sorghum development (i.e., grain filling), which is less susceptible to aphid injury than in vegetative growth stages (Gordy et al., 2019).

There is a need to identify alternatives for managing sorghum aphids to reduce further insecticide resistance and environmental effects (Haar et al., 2019; Lytle and Huseth, 2021). Our current study provides information about the usefulness of new management strategies for sorghum aphid. The RS and PS treatments based on individual plant applications could be an alternative for aphid management compared to strategies based on ET, when infestation intensity and pressure can cause injury levels on sorghum. Development and deployment of these strategies will further improve the management options for this migratory and invasive pest.

Conclusion

Treating the entire sorghum field with insecticides could increase the risk of pest resistance and reduce the number of natural enemies contributing to aphid natural predation. Individual plant applications could be an alternative to a dependent management strategy (i.e., treat the entire field) to reduce sprayed plants and increase better aphid management. Our suggested approach found that RS and PS treatments based on individual plant applications can reduce aphid populations in our small-plot study. These results can inform decision-making processes for growers that can balance between pest control and non-target environmental effects. This study helps to provide additional information and alternative management of sorghum aphids for sustainable pest management in grain sorghum.

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Tables and Figures

Table 6.1 Abbreviation of treatments with their respect description.

Treatment abbreviation	Treatment name	Description
UC	Untreated control	No insecticide applications were made.
ET	Economic threshold	All plants were sprayed in the two middle rows of replicated plots based on an economic threshold of ≥ 40 mean wingless/leaf.
RS	Randomly sprayed	Consisted of the same number of plants treated in PS but randomly sprayed plants independently of wingless.
PS	Plant specific	Consisted of specific plants sprayed with confirmed aphid presence visually observed (≥ 1 sorghum aphid wingless/leaf).
TT	Tally threshold	Consisted of plants sprayed on an economic threshold per plant basis of ≥ 40 sorghum aphid wingless/plant.

Table 6.2 P-value for type III test of fixed effect of response variables by season.

P-value for type III test of fixed effect	2021 season			2022 season		
	Response variables			Response variables		
	Wingless	Alates	Coccinellid larvae	Wingless	Alates	Coccinellid larvae
Evaluation baseline	0.492	0.576	0.61	0.285	0.913	0.558
Replicate	0.018	0.442	0.301	0.452	0.31	0.22
Treatment (Trt)	0.068	< 0.001	0.072	< 0.001	< 0.001	0.004
Evaluation phase (EP)	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001
Study date (D)	< 0.001	< 0.001	0.006	< 0.001	< 0.001	0.037
Trt*EP	< 0.001	< 0.001	0.005	< 0.001	< 0.001	0.003
Trt*D	0.098	0.092	0.011	0.113	0.013	0.23
EP*D	< 0.001	< 0.001	0.046	< 0.001	< 0.001	< 0.001
Trt*EP*D	< 0.001	< 0.001	< 0.001	0.288	< 0.001	0.009

Table 6.3 Cumulative sprayed plants (CSP) in 2021, 2022 season by treatment.

Treatment abbreviation	Treatment name	CSP on 2021 season	CSP on 2022 season
UC	Untreated control	-	-
ET	Economic threshold	1388	1200
RS	Randomly sprayed	280	332
PS	Plant specific	280	332
TT	Tally threshold	92	122

Figure 6.1 Sorghum plants with infested sorghum aphids covered with a sleeve cage.

Figure 6.2 Median count per leaf of sorghum aphid wingless (A) and alates (B) with 95% upper confidence limits in 2021 season. Medians with the same letter are not significantly different from each other (P > 0.05).

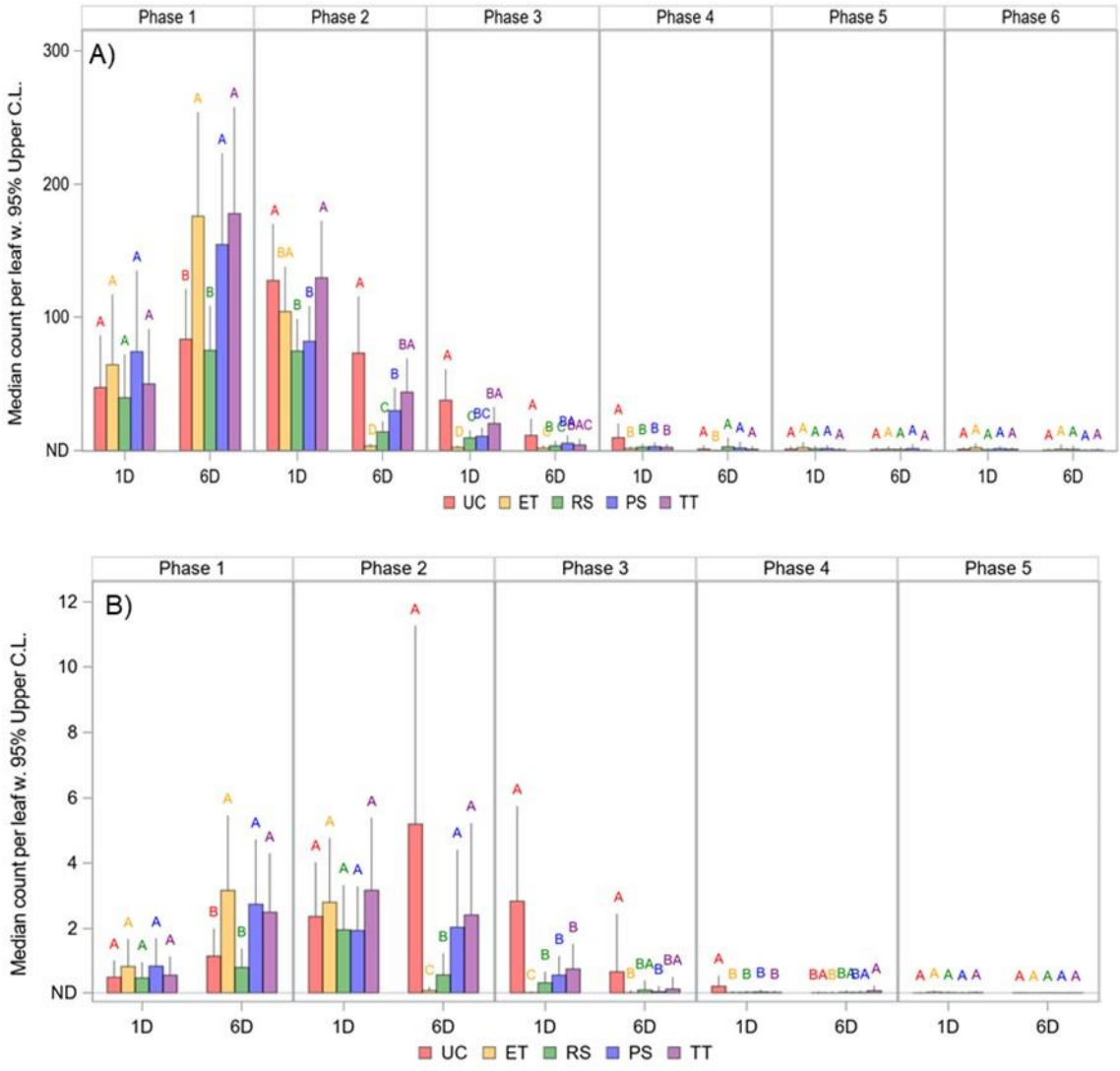


Figure 6.3 Median count per leaf of sorghum aphid wingless (A) and alates (B) with 95% confidence upper limit in 2022 season. Medians with the same letter are not significantly different from each other (P > 0.05).

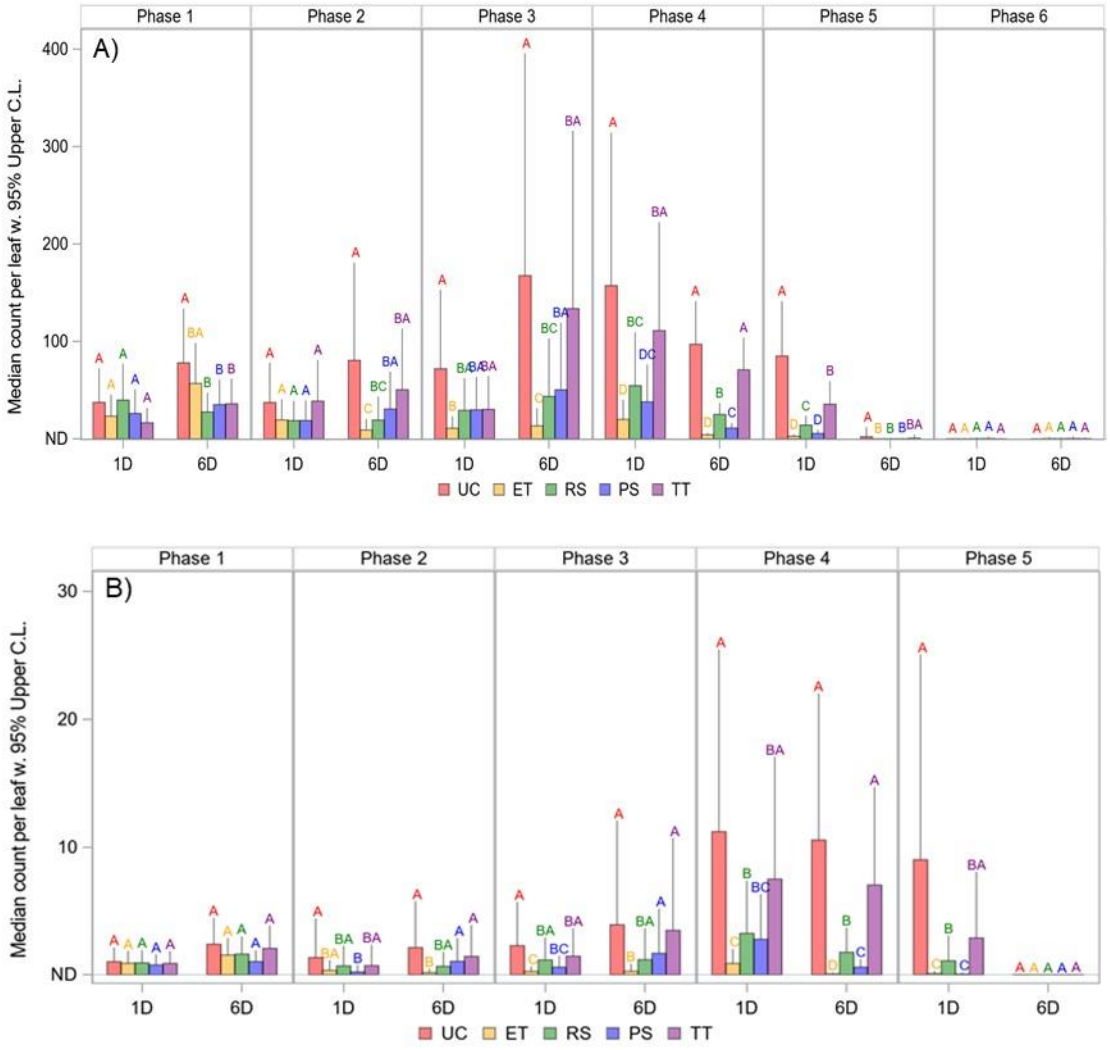


Figure 6.4 Median count per leaf of coccinellid larvae in 2021 (A) and 2022 (B) season with 95% confidence upper limit. Medians with the same letter are not significantly different from each other (P > 0.05).

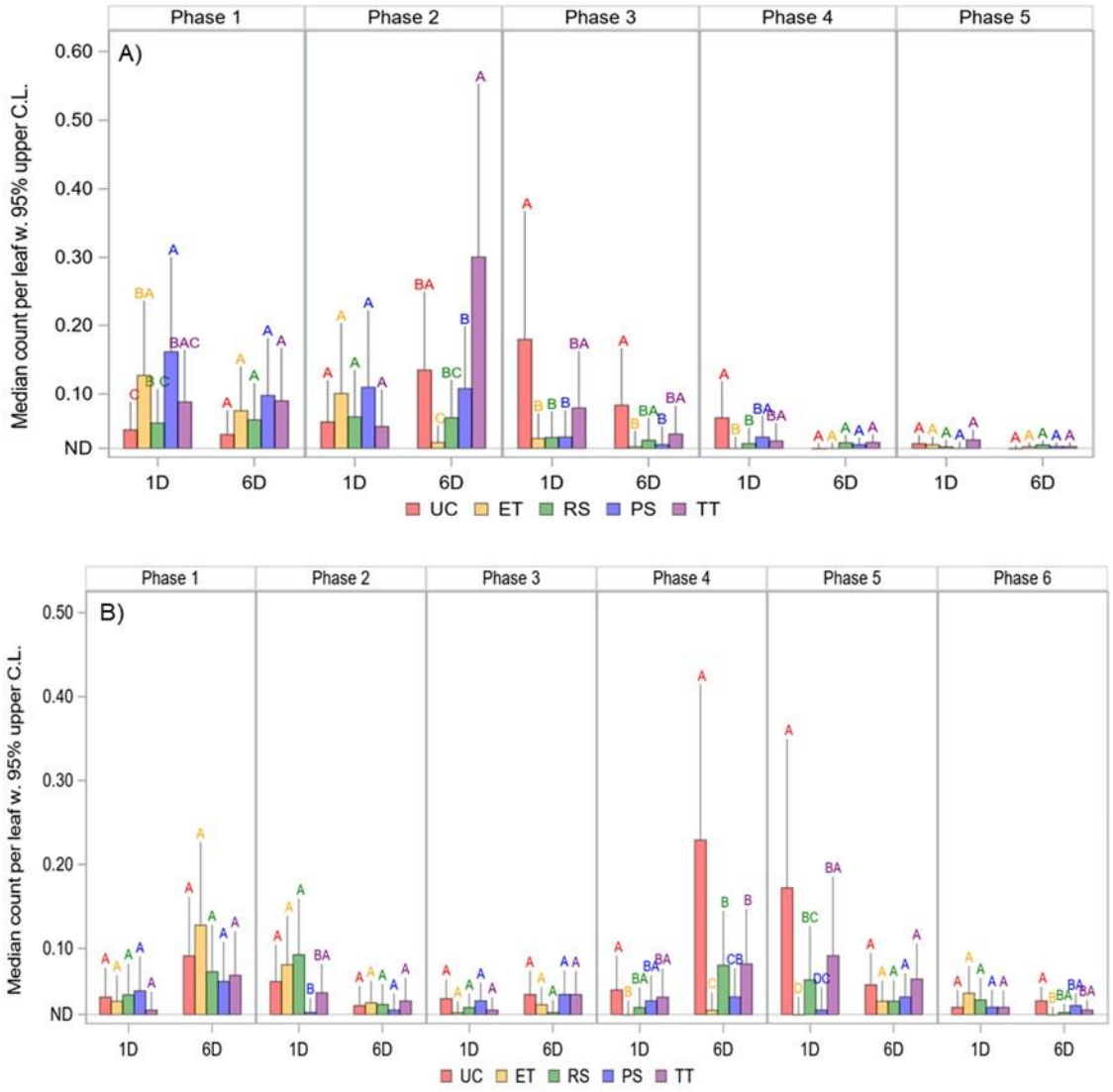


Figure 6.5 LSMs with 95% confidence limits of yield (A) and CAD: wingless (B) and alates (C) in 2021 season. LSMs with the same letter are not significantly different from each other (P > 0.05).

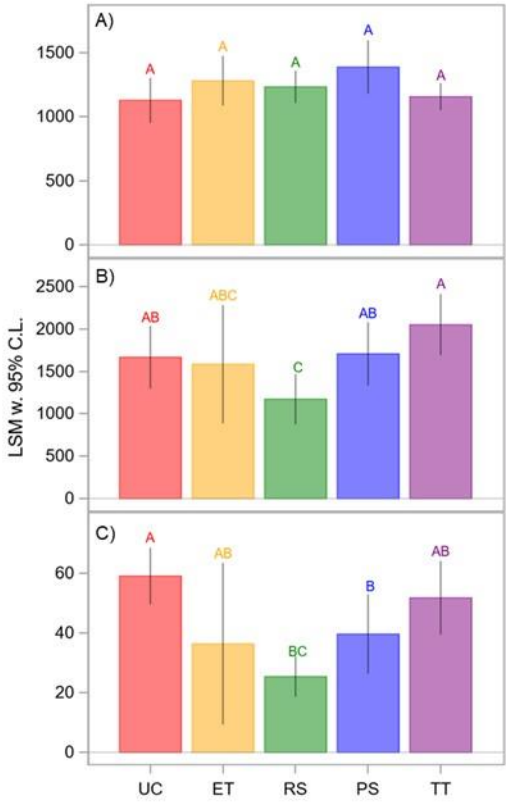
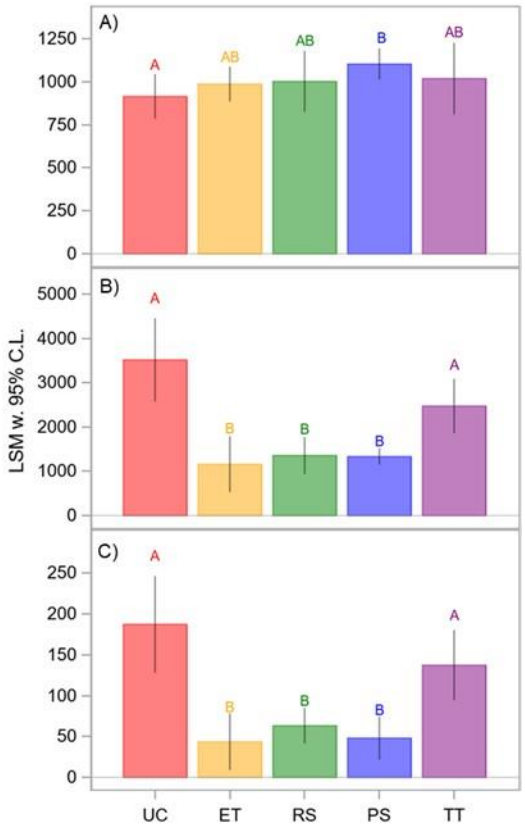


Figure 6.6 LSMs with 95% confidence yield (A) and CAD: wingless (B) and alates (C) in 2022 season. LSMs with the same letter are not significantly different from each other (P > 0.05).



Chapter 7 - Conclusion

This set of experiments has increased the understanding of the application of machine learning, mainly deep learning, to automatically detect-classify sorghum aphid densities and coccinellids and examined the efficacy of new management strategies that can be applied using sensor systems or unmanned vehicles for pest monitoring and management decisions. Specifically, the experiments have shown the following about the automation and management of sorghum aphids:

- Using deep learning approaches, we can detect-classify aphid densities on sorghum leaves using digital images.
- Inception v3 and Xception models correctly classified sorghum aphid densities on infested leaves with 86% accuracy.
- Inception v3 and Xception models correctly classified sorghum aphids as above or below an economic threshold of 40 aphids per leaf over 97% of the time.
- YOLOv5m model correctly detected sorghum aphid densities (1-125 aphids/leaf) on infested leaves with 92% precision, 84.5% recall, and 90.6% mAP@0.5 using digital images.
- Inception v3, Xception, and YOLOv5m models can be implemented in sampling protocols for management decisions of sorghum aphids by further developing mobile applications and unmanned vehicles with sensor systems.
- Using deep learning approaches, we can detect and classify coccinellids commonly found on sorghum.
- YOLOv7 model correctly detected coccinellids on images with 74.2% AP, 97.3% AP@0.50, and 86.2% AP@0.75.

- YOLOv7 model can be implemented in sampling protocols for management decisions of sorghum aphids to avoid unnecessary applications when coccinellids are present by further developing mobile applications and unmanned vehicles with sensor systems
- Using economic threshold and tally threshold levels, we can manage sorghum aphid densities by spraying insecticides.
- Randomly and plant-specific new management strategies can manage sorghum aphid densities by spraying insecticides on individual plants.
- Deep learning models and new management strategies can be used in sensor systems and unmanned vehicles for pest monitoring and management decisions for sorghum aphids.

Conclusions from computational experiments ended in the demonstration of two models that can automatically categorize leaf-level sorghum aphid infestation using digital images to renovate pest monitoring. The Inception v3 and Xception models classified sorghum aphid densities at 6 infestation levels, including no aphids (0 sorghum aphids/leaf) and (1-10, 11-39, 40-125, 126-500, and > 500 sorghum aphids/leaf) with a classification accuracy of 86%. This information can help to improve the currently available pest monitoring of aphids by reducing the time of visual assessments on sorghum leaves. In addition, we developed a framework and model that can detect and count leaf-level sorghum aphid infestation based on standard spraying levels (1-125 aphids/leaf) using digital images. The YOLOv5m model detected sorghum aphid infestations with 92% precision, 84.50% recall, and 90.60% mAP@0.5 on digital images. Using deep learning approaches, also we can detect and classify coccinellids commonly found on sorghum. The YOLOv7 model correctly detected coccinellids on images with 74.2% AP, 97.3% AP@0.50, and 86.2% AP@0.75. Ideally, the developed methodology of pest sampling using

images and the models tested can be used in sampling protocols and management decisions using further developed mobile applications and unmanned vehicles with sensor systems.

Together this work demonstrates sorghum aphid automation toward the development of new management strategies that can be applied using sensor systems or unmanned vehicles for pest monitoring and management decisions. These new management strategies resulting from the automation of aphid densities are very different from conventional strategies for managing aphids in sorghum (i.e., applying insecticides to the whole field). For instance, the automation of sorghum aphid (i.e, classification and detection) can be implemented into sensor systems or unmanned vehicles that can sense, classify and send the signal to spray, resulting into plant-individual applications. Field studies have shown that we can manage aphid densities when spraying randomly or with visual confirmation presence of aphids on individual plants, decreasing the environmental effect and pest resistance to insecticides.

However, it should be noted that spraying individual plants also demands insecticide use. Usually, aphids are found underneath the canopy level, and not all sorghum leaves are infested with aphids, resulting in unnecessary spraying areas on an individual plant. This suggests that spraying individual leaves with aphid infestation could be the next generation of management strategies for sorghum aphids and an important next step for future research. In addition, aphids are not always correctly predicted for classification or detection tasks using deep learning. For example, the challenges to detect aphids include the different background conditions and illuminations where aphids can be found.

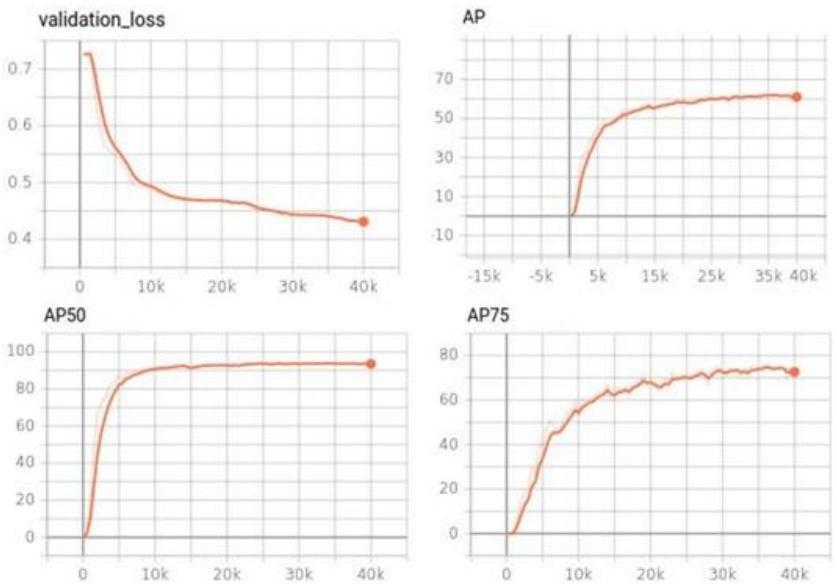
Additionally, aphids are tiny (i.e., < 1 mm), densely distributed, and have different life stages that can be similar in color and shapes to different backgrounds, making it difficult to detect all aphids on a digital image. This suggests that not every individual aphid can be detected

using deep learning. As the aphids used in these studies were all the same life stages (wingless), it would be important to study if other life stages (i.e., alates) can be detected with deep learning models for future research. Future research should also focus on creating computing algorithms that can standardize background conditions and illuminations on images and increase the pixel resolution without increasing the image format size to detect most aphids on images.

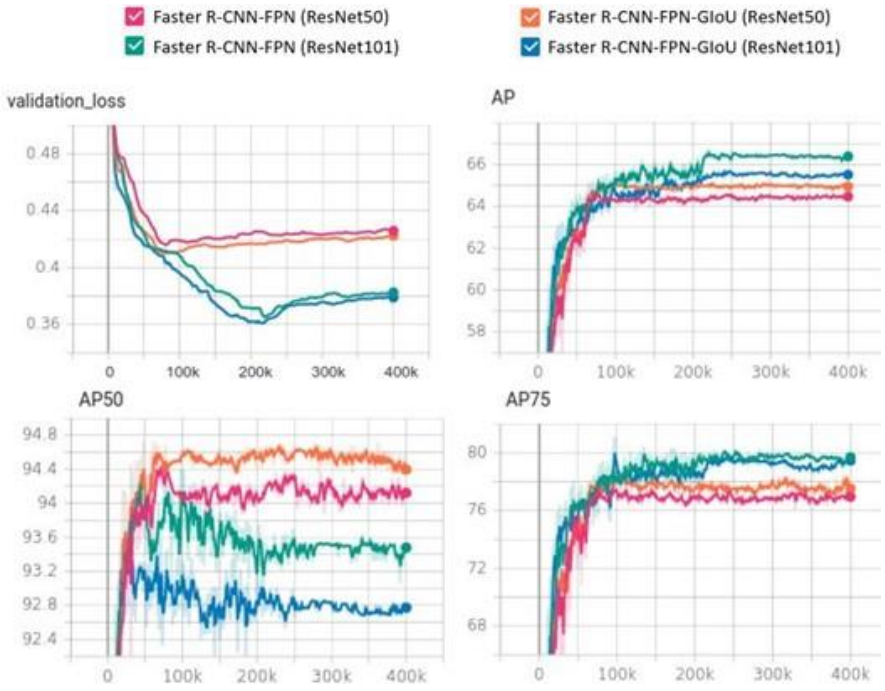
These studies have increased our knowledge of automation for sorghum aphid monitoring and informed the deployment of new management strategies that can be applied using sensor systems or unmanned vehicles. The results of these experiments demonstrate the potential to incorporate deep learning models into current sampling protocols and new alternatives for managing aphids in sorghum. Together, this information wants to project a new growth mindset to renovate pest monitoring and management strategies for aphids in sorghum.

Appendix A - Detecting common coccinellids found in sorghum using deep learning models

Appendix A Figure A.1 Learning curves of the Faster R-CNN-FPN with ResNet101 and IoU loss on the validation data. Specifically, validation loss, AP, AP@0.50, and AP@0.75 curves are shown when the model is trained for 40,000 iterations. As can be seen, the loss still decreases, while the AP curves increase after 40,000 iterations, suggesting the model is still learning.



Appendix A Figure A.2 Learning curves of Faster R-CNN-RPN models on the validation data. Specifically, validation loss, AP, AP@0.50, and AP@0.75 curves are shown when the model is trained for 400,000 iterations.



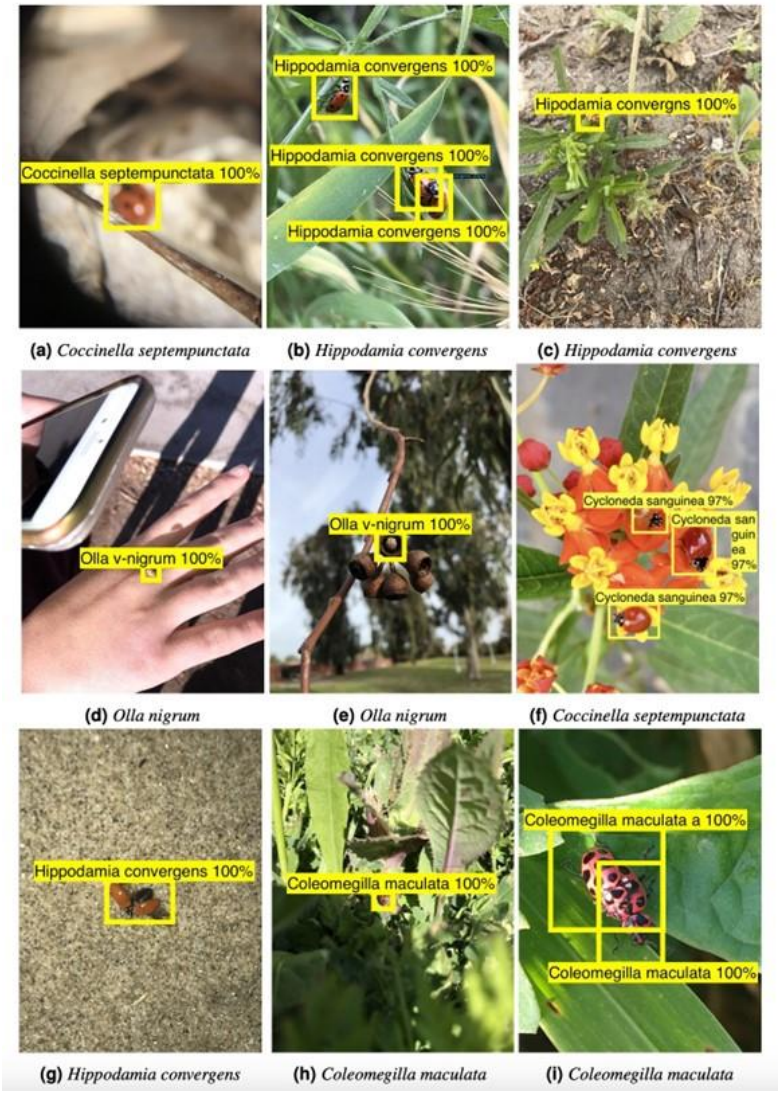
Appendix A Table A.1 Distribution of the images with respect to the number of instances per image (1, 2, 3, 4, 5, 6, 7, or 8) for each category and for each of the the train/dev/test subsets.

Train	Images per			#Instances					Total	Total
Category / # Instances	1	2	3	4	5	6	7	8		
Coccinella_septempunct	424	12	2	0	0	0	1	0	439	461
ata	404	26	2	2	0	0	1	1	436	485
Coleomegilla_maculata	412	10	1	0	0	0	0	0	423	435
Cycloneda_sanguinea	426	13	0	1	1	1	0	1	443	475
Harmonia_axyridis	397	36	1	1	0	1	0	0	436	482
Validation	Images per #Instances								Total	Total
Category / # Instances	1	2	3	4	5	6	7	8		
Coccinella_septempunct	157	1	2	0	0	0	0	0	160	165
ata	150	12	1	0	1	0	0	0	164	182
Coleomegilla_maculata	150	5	0	0	0	0	0	0	155	160
Cycloneda_sanguinea	151	6	0	0	0	0	0	0	157	163
Harmonia_axyridis	138	14	0	0	0	1	0	0	153	172
Test	Images per #Instances								Total	Total
Category / # Instances	1	2	3	4	5	6	7	8		
Coccinella_septempunct	97	1	1	0	0	0	0	0	99	102
ata	99	1	0	0	0	0	0	0	100	101
Coleomegilla_maculata	94	5	1	0	0	0	0	0	100	107
Cycloneda_sanguinea	100	0	0	0	0	0	0	0	100	100
Harmonia_axyridis	90	5	3	0	2	0	0	0	100	119

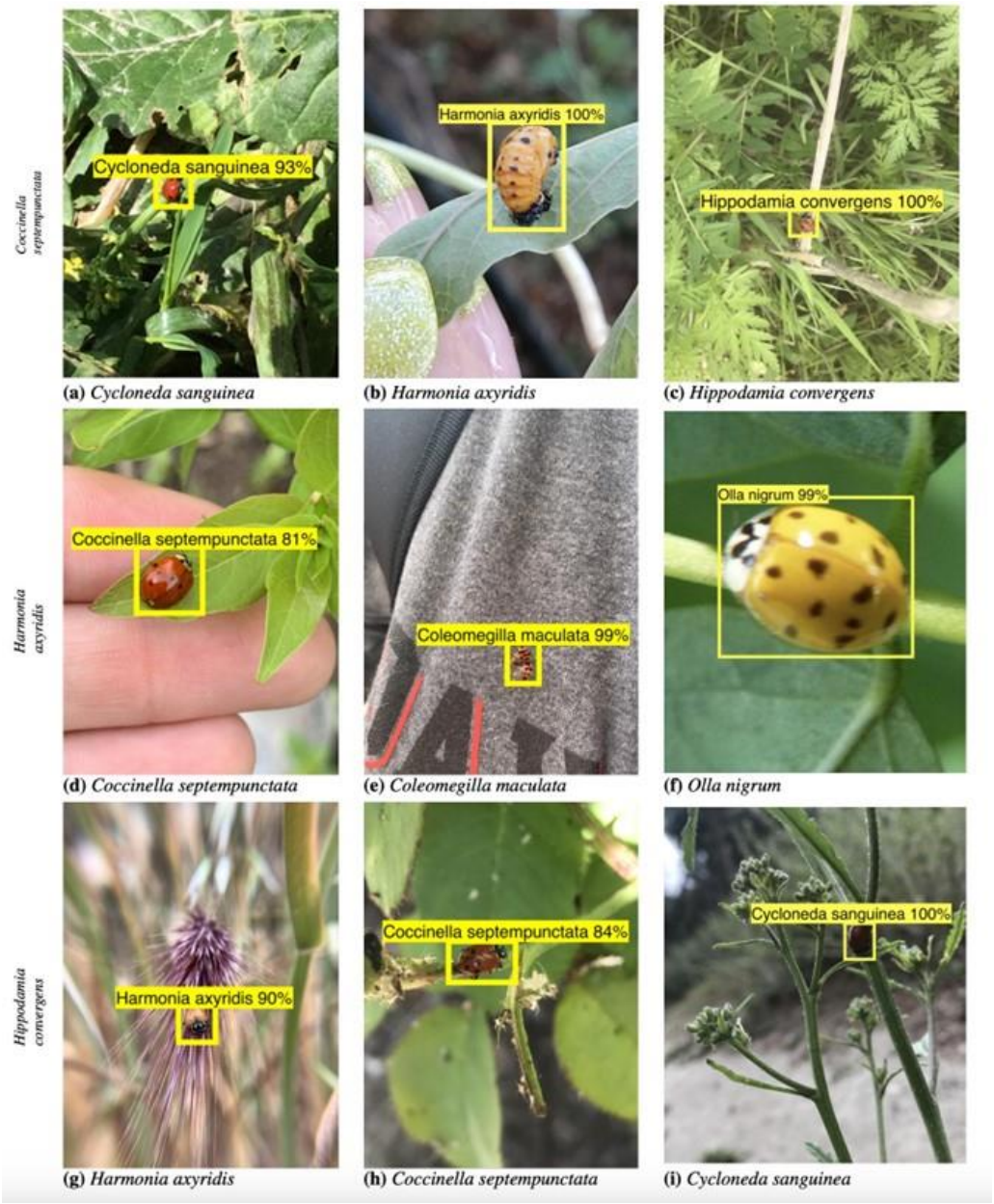
Appendix A Table A.2 Distribution of the small, medium and large instances in the train/dev/test subsets and in the whole dataset.

Size / Subset	Train	Dev	Test	All
Small	5	0	0	5
Medium	85	39	18	142
Large	3142	1137	716	4995
All	3232	1176	734	5142

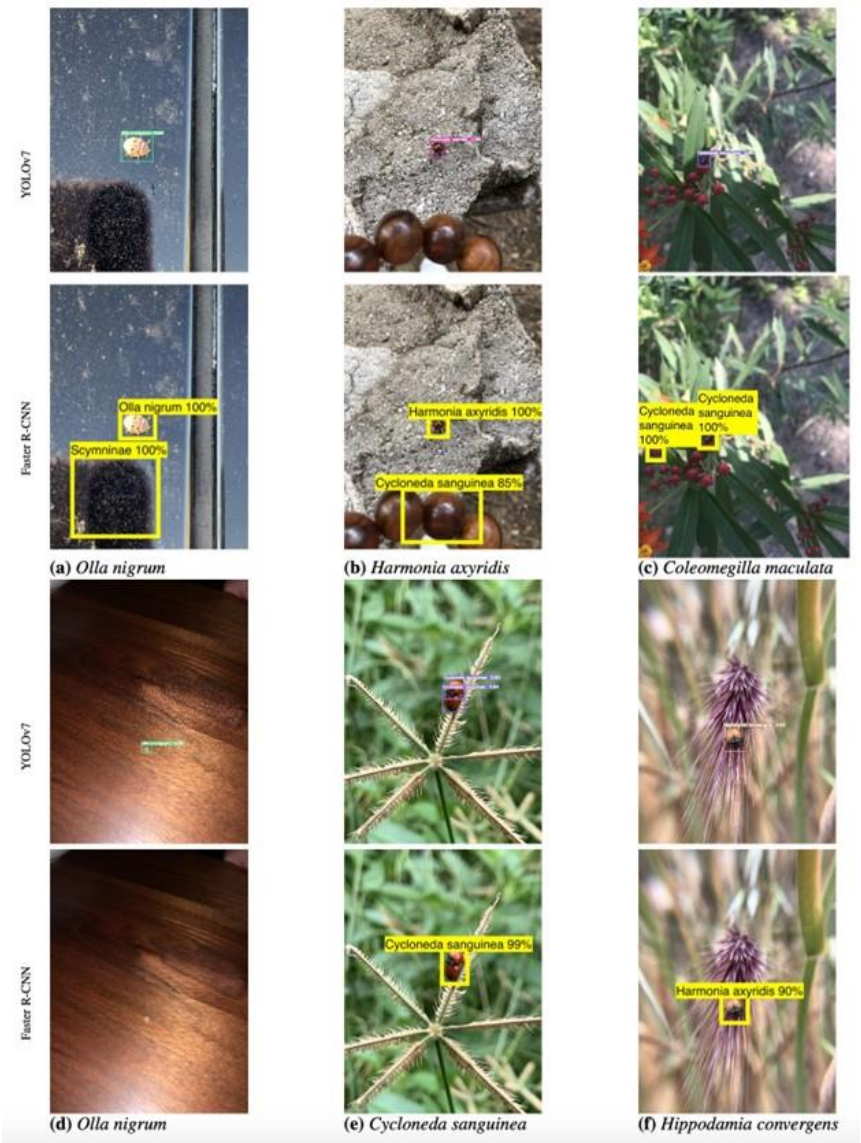
Appendix A Figure A.3 Examples of accurate Faster R-CNN predictions on different coccinellid types.



Appendix A Figure A.4 Examples of images where the Faster R-CNN model correctly identifies a coccinellids, but the type identified is different from the manually annotated type. Each row shows a ground truth type, specifically, *Coccinella septempunctata*, *Harmonia axyridis*, *Hippodamia convergens*. The predicted label for each image is shown below the image.



Appendix A Figure A.5 Faster R-CNN errors (bottom) that are fixed with YOLOv7 (top). Examples (a), (b) and (c) illustrate cases when Faster R-CNN identifies an extra object as a coccinellids in addition to the actual coccinellid that was manually annotated. Example (d) shows a case when Faster R-CNN fails to identify the coccinellid in the the image. Example (e) shows a case when Faster R-CNN identifies two coccinellids as one. Example (f) shows a case when Faster R-CNN identifies a coccinellid but the type if wrong.



Appendix A Figure A.6 Faster R-CNN-FPN-R101-GIoU model as a web-based application.