



# Computer vision model for sorghum aphid detection using deep learning

Ivan Grijalva<sup>\*</sup>, Brian J. Spiesman, Brian McCornack

Department of Entomology, Kansas State University, Manhattan, KS, 66506, USA

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## ABSTRACT

Aphids are a challenging crop pest to manage. The sorghum aphid, for example, causes considerable yield loss in unmanaged sorghum. One of the key strategies to mitigate yield losses caused by this pest includes monitoring production fields and using economic thresholds to spray insecticides. However, monitoring aphids is a time-consuming task and requires regular, visual assessments across large hectares once aphids are detected on sorghum plants. To address this challenge, we propose to use object detection models based on deep learning to automatically detect aphid infestations on sorghum leaves using digital images. We used 1190 images collected during field monitoring events and evaluated the performance of 3 deep learning detection models within the YOLOv5 family that vary in complexity: YOLOv5n, YOLOv5s, and YOLOv5m. We then tested three different image sizes, including input resolutions of  $416 \times 416$ ,  $640 \times 640$ , and  $1280 \times 1280$  pixels. We trained models to detect individual aphids, which ranged between 1 and 125 sorghum aphids/leaf and is comparable to threshold levels used to manage aphids in field conditions (i.e., 50–125 aphids per leaf). Detection models had a precision of 92% precision with a 84.5% recall and 90.6% mAP@0.5 for YOLOv5m Pytorch, making it a potential candidate for quantifying aphid densities using deep learning. The models tested and methodology developed here can be implemented in management decisions of sorghum aphids or as sampling tools for use in screening insect-resistant varieties. Development of mobile applications and integration into unmanned vehicles with sophisticated sensor systems will aid in use and adoption of computer vision models for pest management.

## 1. 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 [1]. 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 [1]. 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 [1]. 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 [2]. According to Gordy et al. [3], 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 [3,4], 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. [5] 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. Li et al. [6] proposed a multi-branch convolutional neural network (Mb-CNN) with a density map for object detection and counting of aphids on wheat, corn, and rape. The Mb-CNN are based on the Multi-Column Convolutional Neural Network (MCNN), a deep classification model [7], and Feature Pyramid Network (FPN), a one stage-method detector [8]. Another study proposed using computer

<sup>\*</sup> Corresponding author.

E-mail addresses: [grijalva@ksu.edu](mailto:grijalva@ksu.edu) (I. Grijalva), [bspiesman@ksu.edu](mailto:bspiesman@ksu.edu) (B.J. Spiesman), [mccornac@ksu.edu](mailto:mccornac@ksu.edu) (B. McCornack).

vision models with deep learning technologies, such as convolutional neural networks (CNNs) to develop a sorghum aphid density classifier using images [9]. 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 [10]. 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 [11]. 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 [9,12]. 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 [11], 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

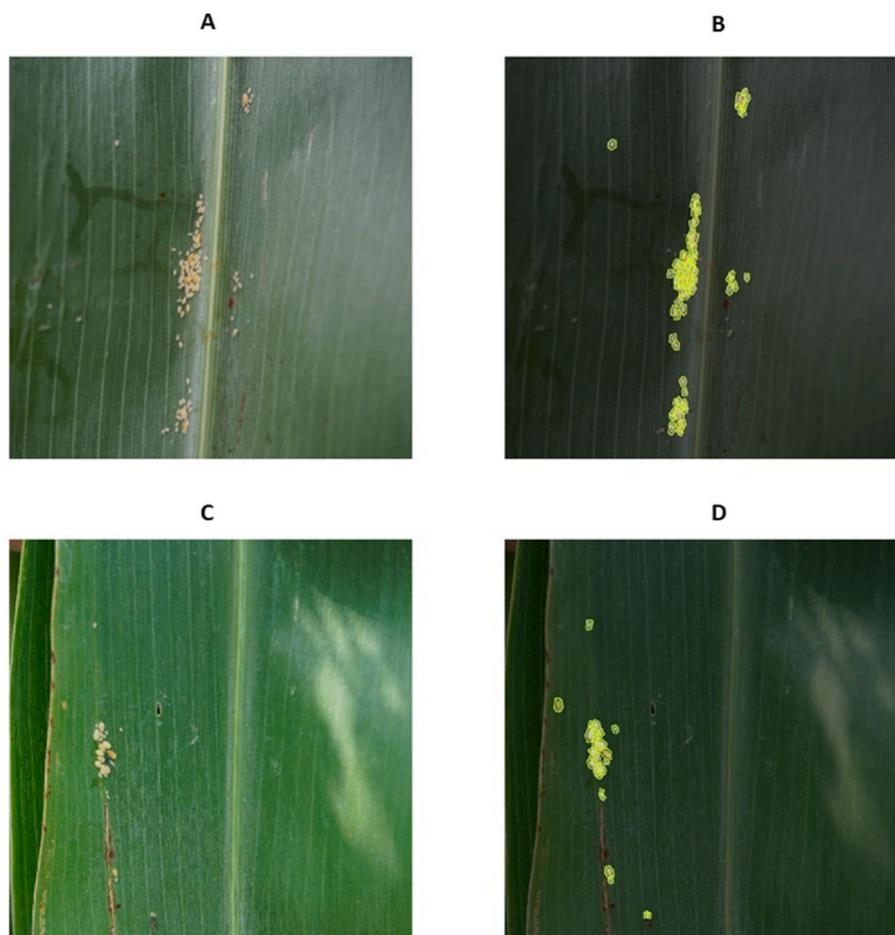
several aspects of pest management including decision-making, alternative sampling protocols with images, and screening insect-resistant varieties. The methodology and the model tested in this study can be used into mobile applications or be deployed into unmanned vehicles with sensor systems.

## 2. Methods

### 2.1. 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  $4000 \times 6000$  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 1190 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 [13] (Fig. 1). The aphid individuals marked in the images ranges between 1 and 125



**Fig. 1.** Examples of images at  $1280 \times 1280$ -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.

sorghum aphids/leaf to manage aphids in field conditions.

## 2.2. 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 [13]. The image preprocessing included auto-orienting and image resizing to  $416 \times 416$ ,  $640 \times 640$ , and  $1280 \times 1280$ -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 (Fig. 2).

## 2.3. Data splitting ratio

The original imagery dataset consisted of 1190 images with different numbers of sorghum aphid densities, which ranged between 1 and 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. A higher proportion of data was used in the training phase due to the complexity of detecting aphids (i.e., small objects) and to increase the learning features of aphids during the training phase. Also this ratio is commonly used for detection tasks of insects and diseases using deep learning models [14–16].

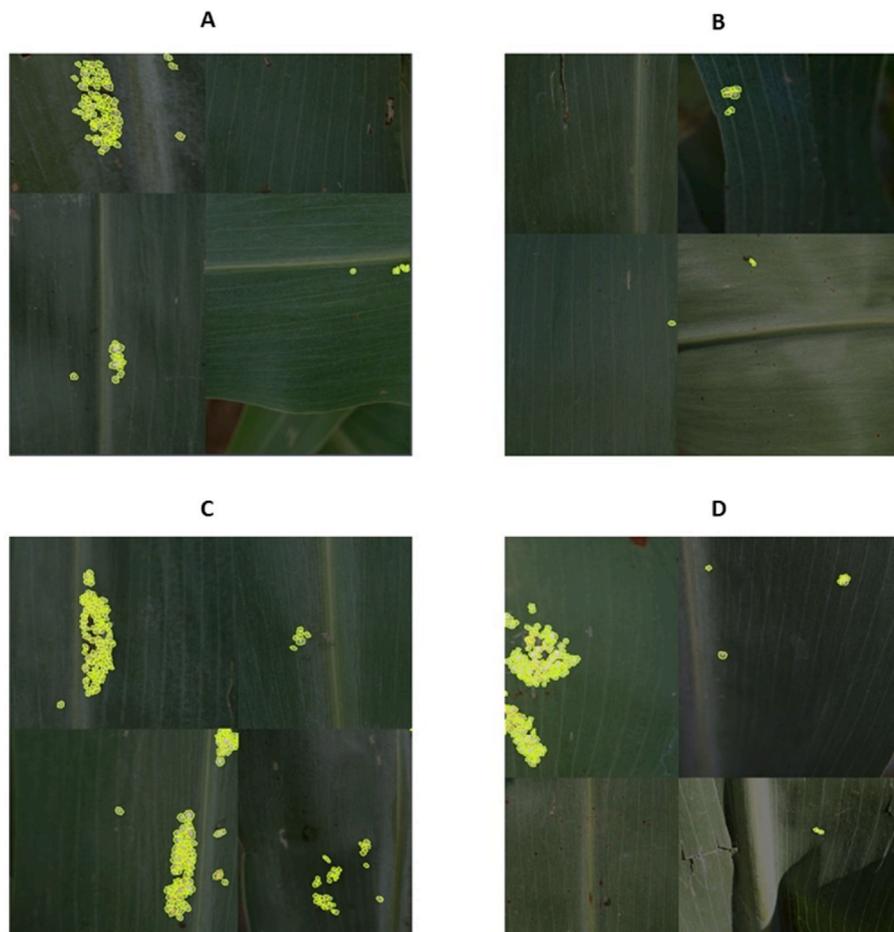
The training dataset consisted of 2693 images, 357 images for the validation set, and 351 images for the testing set and all were at input resolution of  $416 \times 416$  pixels. The  $640 \times 640$  pixels input resolution

consisted of 2753 images for the training set, 357 images for the validation set, and 351 images for the testing set. Lastly,  $1280 \times 1280$  pixels input resolution had 2795 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.

## 2.4. 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 [17]. 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 [12,18].

One of the advantages of the YOLOv5 model is that it can recognize images of a similar object at different image sizes [12]. 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 [17], 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



**Fig. 2.** Examples of training images at  $1280 \times 1280$ -pixels input resolution (A, B, C, D) with labels with preprocessing and augmentation techniques using the cloud-based Roboflow environment.

quick object detection framework, which could be effectively deployed on mobile devices.

### 2.5. 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 [17]. 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 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 [17].

### 2.6. 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 [12]. 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 [19]. The precision metric is the ability of the detection model to identify only relevant objects, and it is the percentage of correct positive predictions [19]. The percentage of correct positive prediction among all given ground truths is defined as recall [19].

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  $1280 \times 1280$ -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 on-the-go pest monitoring and screening insect-resistant varieties.

### 2.7. Data flow diagram

The data flow diagram for our whole methodology is characterized in Fig. 3. Training images are used to train the models, while the validation images are used to evaluate and fine tune hyperparameters. The performance of the final models used in this study was evaluated on test images.

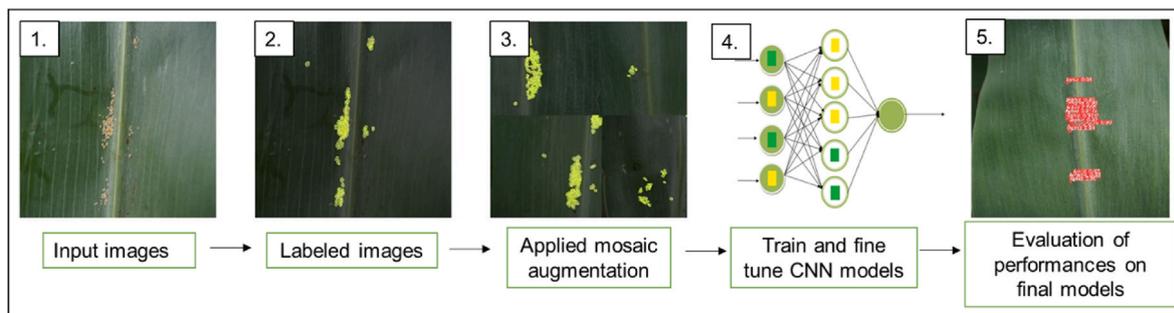


Fig. 3. Data flow diagram to evaluate the performance of detection models within the YOLOv5 family.

## 3. 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 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  $1280 \times 1280$ -pixels input resolution. Therefore, we used the YOLOv5n, YOLOv5s, and YOLOv5m models using images with  $1280 \times 1280$ -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  $\geq 82\%$  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 (Table 2).

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 ms slower. From a pest management perspective, the YOLOv5m using an image size of  $1280 \times 1280$ -pixels input resolution is a suitable candidate model for sorghum aphid detection based on their highest performance metrics and inference speed (Fig. 4).

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

**Table 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. Inference times were performed using NVIDIA A100 GPU hardware from Colab, a platform suited for machine learning.

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

**4. Discussion**

**4.1. 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.

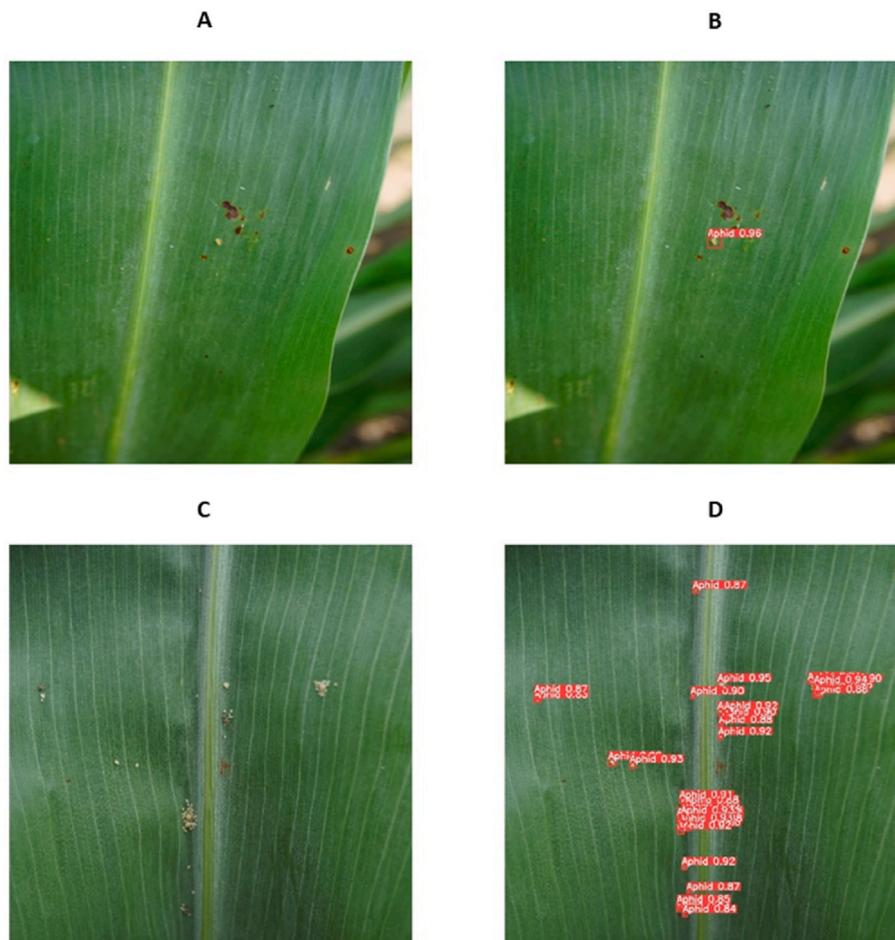
We suggest applying this methodology to current sampling protocols by taking images with different sorghum aphid infestation levels on

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.

**4.2. 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 [20]. 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 [21].

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



**Fig. 4.** Detection results using testing images at 1280 × 1280-pixels input resolution without (A, C) or with aphid detections (B, D) performed by YOLOv5m model.

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.

#### 4.3. 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.

#### 5. 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.

#### 6. Author contributions

Ivan Grijalva: Investigation, Data curation, Resources, Conceptualization, Methodology, Software, Formal analysis, Writing – original draft. Brian J. Spiesman: Conceptualization, Methodology, Software, Formal analysis, Writing – original draft. Brian McCornack: Investigation, Conceptualization, Resources, Writing – original draft.

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#### Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Ivan Grijalva reports financial support was provided by National Robotic Initiative.

#### Data availability

The computer algorithms and the imagery used in this study will be available on the cloud-based Mendeley Data repository.

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