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Image classification of sugarcane aphid density using deep convolutional neural networks

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ABSTRACT

Sugarcane aphid, *Melanaphis sacchari* (Zehntner), has caused significant yield loss across the sorghum (*Sorghum bicolor* L. Moench) production region in the U.S. Adequate management of sugarcane aphid depends on pest monitoring and economic threshold levels to spray insecticides. However, scouting this pest under field conditions is time-consuming and inefficient. To assist pest monitoring, we propose the use of deep learning models to automatically classify sugarcane aphid infestation on leaves according to different density levels in images. We used a total of 5,048 images collected during field scouting events and evaluated the performance of four deep learning classification models: Inception v3, DenseNet 121, Resnet 50, and Xception. We trained the models to classify aphid densities into 6 classes based on established standard threshold levels for spraying: no aphids present (0 sugarcane aphids/leaf), no threat or below an action/treatment threshold (1–10, and 11–39 sugarcane aphids/leaf), and infested above an economic threshold where an insecticide should be applied (40–125, 126–500, and > 500 sugarcane aphids/leaf) to manage sugarcane aphid in field conditions. Among these models, Inception v3 and Xception performed best with an overall accuracy score of 86% and a lower number of misclassified images. Importantly, the models correctly classified aphids as above or below threshold spray density over 97% of the time. The methodology developed and the models tested in this study can be used in sampling protocols and further mobile applications or remote sensing technologies. These technologies can assist sorghum growers and researchers to scout and screen sugarcane aphid in susceptible and resistant sorghum varieties automatically and provide accurate recommendations on whether or not to apply pesticides.

1. 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 [1]. Growers have historically competed with herbivorous and pathogen-transmitting insects, collectively called ‘pests’, and different strategies have been developed to control them in agriculture [2]. 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 5880 million acres [3]. 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 [4]. Nevertheless, sorghum faces significant pest management challenges and yield losses during its production.

Sugarcane aphid, *Melanaphis sacchari* (Zehntner) (Hemiptera: Aphididae), is considered an economically important pest in sorghum across much of the Southern Great Plains since its re-introduction in 2013 [5]. 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 [5]. Usually, treatment decisions for sugarcane aphid depend visually assessing sorghum leaves for aphids to determine an economic threshold for insecticide applications [6]. An economic threshold is defined as the pest density that management action must implement to prevent reaching economic injury level [7].

According to Gordy et al. [8], a suggested economic threshold for sugarcane aphids is 40 aphids per leaf. However, obtaining an accurate estimation of the number of sugarcane aphids on leaves is a

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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 [9,10]. In addition, sugarcane 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 sugarcane 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 [11]. 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 [12]. 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 [11].

However, deep learning models for the automatic classification of sugarcane 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 sugarcane 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 sugarcane 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 sugarcane 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.

2. Methods

2.1. Field image collection

Sugarcane 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 sugarcane 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 4000×6000 pixels and an RGB color representation. A total of 5048 images were collected and manually classified into 6 distinct categories based on the number of sugarcane aphid per leaf per image. Classification categories were based on pest monitoring parameters to determine economic threshold levels for sugarcane aphid [5,6,8]. The categories were no aphids present (0 sugarcane aphids/leaf), no threat or below an action/treatment threshold (1–10, and 11–39 sugarcane aphids/leaf), and infested above an economic threshold where an insecticide should be applied (40–125, 126–500, and $>$ 500 sugarcane aphids/leaf).

2.2. 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 sugarcane aphid density classification using images [13–15]. 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 [16]. Inception v3 is a deep learning model with small convolutions, accelerated training speed, and reduced computational cost [14]. DenseNet 121, another lightweight model tested, requires fewer parameters than traditional convolutional networks, making it easy to train [13]. Resnet 50 has smaller parameter size compared with other CNNs making it faster to training [15], 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.

2.3. Model training and description of hyperparameters

The four deep learning models used in this study are pre-trained on the ImageNet validation dataset [17]. We retrained those models for sugarcane 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 sugarcane aphid densities were split and randomly combined through the 80:20 ratio to maintain this training and testing proportion. We resized all 4000×6000 pixel images to a standard 500×500 pixel size (Fig. 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 ($\leq 100°$), sheer ($\leq 30\%$), zoom ($\leq 10\%$), and horizontal flip [18]. 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.

3. Results

The four deep learning models provided similar accuracy scores when classifying sugarcane aphids (Table 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 $\geq$ 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 sugarcane aphid densities.

The Inception v3 and Xception models adequately categorized sugarcane 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 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

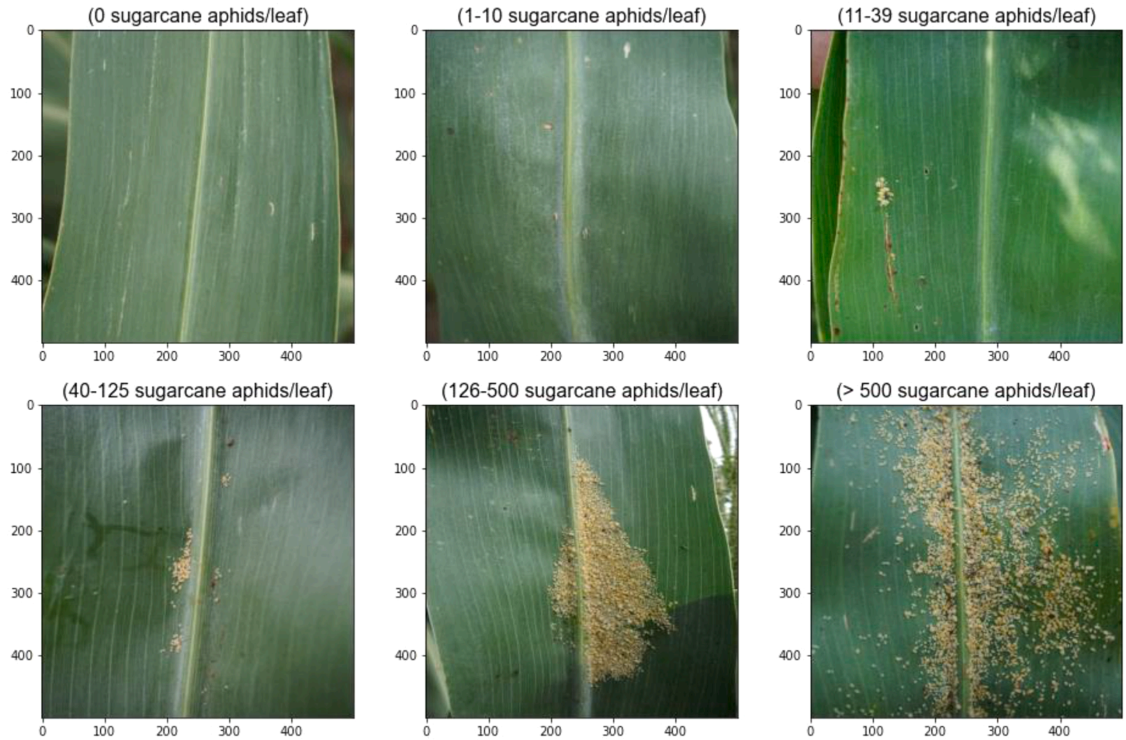

Fig. 1. Examples of training images for Inception v3, DenseNet 121, Resnet 50, and Xception models using 500 × 500-pixel images.

Table 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

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 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. Sugarcane aphid categories with a higher number of trained images had a lower percentage of misclassified images

Table 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 (sugarcane aphids/leaf)						
	Categories (sugarcane aphids/leaf)	0	1-10	11-39	40-125	126-500	> 500	Total number of tested images
True (sugarcane 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 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 (sugarcane aphids/leaf)						
	Categories (sugarcane aphids/leaf)	0	1-10	11-39	40-125	126-500	> 500	Total number of tested images
True (sugarcane 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

but higher precision scores compared to sugarcane 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.

4. Discussion

4.1. 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 [6,8]. 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 sugarcane aphids/leaf [19].

During sampling, a visual assessment consists of manually evaluating the whole sorghum leaf to provide an estimated number of sugarcane aphids, which is a time-consuming task. We suggest applying these models to current sampling protocols by taking images with different sugarcane 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 sugarcane 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 sugarcane aphid management in sorghum.

The Inception v3 or Xception models are adequate candidates for automatically classifying sugarcane 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 sugarcane aphid in sorghum.

4.2. Models performance within categories

At the categorical level of sugarcane 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 sugarcane aphid densities accurately. The purpose of having an automatic categorical classifier of sugarcane aphid densities is to reduce time spent counting and sampler bias. In addition, to categorize sugarcane aphid densities because, to our best knowledge, sugarcane 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 sugarcane aphid densities (0, 1–10, and 11–39 sugarcane aphids/leaf) since any management strategy that is warranted manage sugarcane 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 sugarcane aphids/leaf) were combined because current best management practices suggest applying an insecticide manage sugarcane 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.

4.3. Models improvement

Collecting more images, especially of sugarcane 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 [18]. 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 sugarcane aphid densities, which is another benefit of CNNs in general [20].

4.4. 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 [21]. 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 sugarcane aphid infestation for economic management decisions.

5. 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 sugarcane aphid infestation using digital images to renovate pest monitoring. The Inception v3 and Xception models were tested to evaluate their performance in classifying sugarcane aphid densities at 6 infestation levels, including no aphids (0 sugarcane aphids/leaf) and (1–10, 11–39, 40–125, 126–500, and $>$ 500 sugarcane aphids/leaf) with a classification accuracy of 86%. More image samples can be added to the current models within sugarcane 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 sugarcane 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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Credit authorship contribution statement

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, Writing – original draft.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data Availability Statement

The image dataset and codes used in this study will be made available on Mendeley Data.

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