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Strawberry pest detection using deep learning and automatic imaging system

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Abstract.

Strawberry growers need to monitor pests to determine the options for pest management to reduce damage to yield and quality. However, manually counting strawberry pests using a hand lens is time-consuming and biased by the observer. Therefore, an automated rapid pest scouting method in the strawberry field can save time and improve counting consistency. This study utilized a single-camera imaging platform and a six-camera imaging system to take 260 images of the strawberry leaf. The resolution of the camera was 13 Megapixels. A deep learning model (YOLOv4) was trained to detect the pests on the strawberry leaf. The average precision of two-spotted spider mite (TSSM) motile, TSSM egg, and predatory mite (Neoseiulus californicus and Phytoseiulus persimilis) was 0.90, 0.92, and 0,93, respectively. The mean average precision of the model was 0.917. This study demonstrated that the deep learning method could be successfully applied to the detection of very small arthropod pests with high detection accuracy. As the next step, the deep learning model will be integrated with the six-camera imaging system to speed up strawberry pest detection in the field. The imaging system and deep learning method only need to scan the leaf once and can count the number of different pests simultaneously. Therefore, the six-camera imaging system will be much faster than manual counting.

Keywords.
Two-spotted spider mite, Predatory mites, Deep learning, Automatic imaging system

Introduction

Pest scouting is important for integrated pest management. Once the pest population is higher than the economic threshold, the grower needs to take action to control the pest to avoid economic loss. Therefore, Growers need to know the pest population for effective pest control. For strawberry production, two-spotted spider mite (TSSM) is the major pest in California and Florida. TSSM is mainly found on the underside of the strawberry leaf, and it will negatively affect the photosynthesis of the leaf, which will reduce the marketable strawberry yield (Nyoike & Liburd, 2013). Therefore, frequent TSSM scouting in the field is important. However, the traditional pest scouting needs to manually count the TSSM on the leaf, which is labor-intensive. To speed up the TSSM counting in the strawberry field, a rapid method is needed.

Remote sensing was used in TSSM damage estimation in strawberry (Fraulo et al., 2009), bean (Herrmann et al., 2017), pepper (Herrmann et al., 2017), and cotton (Martin & Latheef, 2017). However, the spectral information could only estimate the TSSM infestation level. The number of TSSM on the leaf could not be detected accurately. In 2021, a smartphone-based tool was developed for TSSM detection in the strawberry field (Zhou et al., 2021), which could use the smartphone to take a picture of a strawberry leaf and used a deep learning model to detect pests on the leaf. however, the picture could only cover a small portion of the leaf and the user needs to manually take multiple pictures. Therefore, this study used a six-camera imaging system for automatic imaging of strawberry leaves and then trained a deep learning model for pest detection.

YOLO is one of the most popular one-stage object detection models. YOLO stands for “You Only Look Once”. The first version of YOLO, YOLOv1 (Redmon et al., 2016), was proposed in 2016 and it was the representative of the one-stage object detector at that time. Then YOLO model was further improved. YOLOv2 (Redmon & Farhadi, 2017) and YOLOv3 (Redmon & Farhadi, 2018) were proposed in 2017 and 2018, respectively. In 2020, YOLOv4 (Bochkovskiy et al., 2020) was proposed and achieved state-of-the-art performance for object detection. Therefore, this study used YOLOv4 for strawberry pest detection. In this study, a single-camera imaging system and a six-camera imaging system were used for image acquisition. The main goal of this study was to train a deep learning model, YOLOv4, for strawberry pest detection. The trained model will be integrated with the six-camera imaging system in the near future for automatic TSSM image acquisition and detection in the strawberry field.

Materials and Methods

Image acquisition

In this study, strawberry pest images were collected by a single-camera imaging platform and a six-camera imaging system. The strawberry field used in this study was located at Plant Science Research and Education Unit in Citra, Florida. Strawberry leaf samples from ‘Sensation’ and ‘Brilliance’ cultivars were collected in the field and stored in Ziploc bags, and then transferred to the lab for image acquisition.

Single-camera imaging platform

Two-spotted spider mite and predatory mite are both small, and they cannot be identified without using a magnifying lens. Therefore, this study used the customized camera developed by the University of California, Davis to collect magnified images of the strawberry leaf. An IMX135 MIPI 13MP camera module (Nanjing Arducam Electronics Technology Co., Ltd., Nanjing, Jiangsu, China) was used in this study. To take the magnified images, the stock lens of the IMX135 MIPI camera was removed. Then a lens holder was designed to mount the 1/2.7" CCTV 16mm 1080P Lens (Blf, Inc., Chatsworth, California, United States) on the IMX135 MIPI camera. This customized camera was connected with a Raspberry Pi 4 Model B for image acquisition in the lab (Fig. 1). During image acquisition, some leaf surfaces may not be flat, a microscope slide was used to flatten the leaf surface for better image quality.

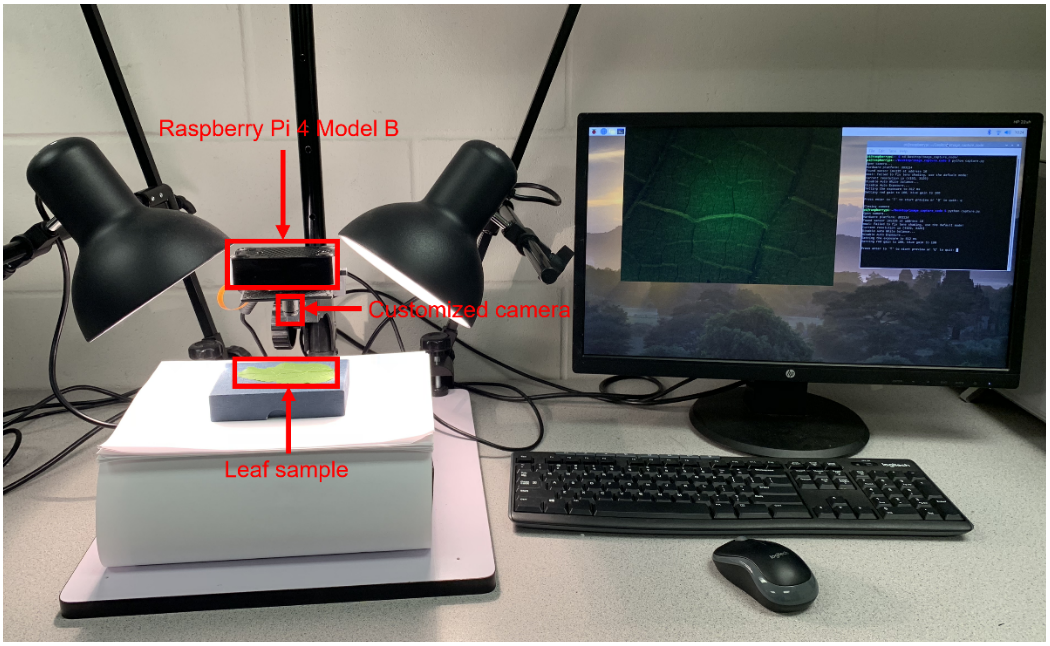


Fig. 1 Single-camera imaging platform

Six-camera imaging system

The six-camera imaging system (Fig. 2) used six customized cameras for image acquisition. Each camera was equipped with a Raspberry Pi Zero W to speed up the image acquisition. The leaf sample was put on the top of the linear stage actuator, which can move the leaf sample during image acquisition. LEDs were used to provide artificial illumination in the imaging system. Users only need to press one button to collect 60 images automatically, which can cover a leaf. To avoid image blurring, fishing lines were used to keep the leaf flat.

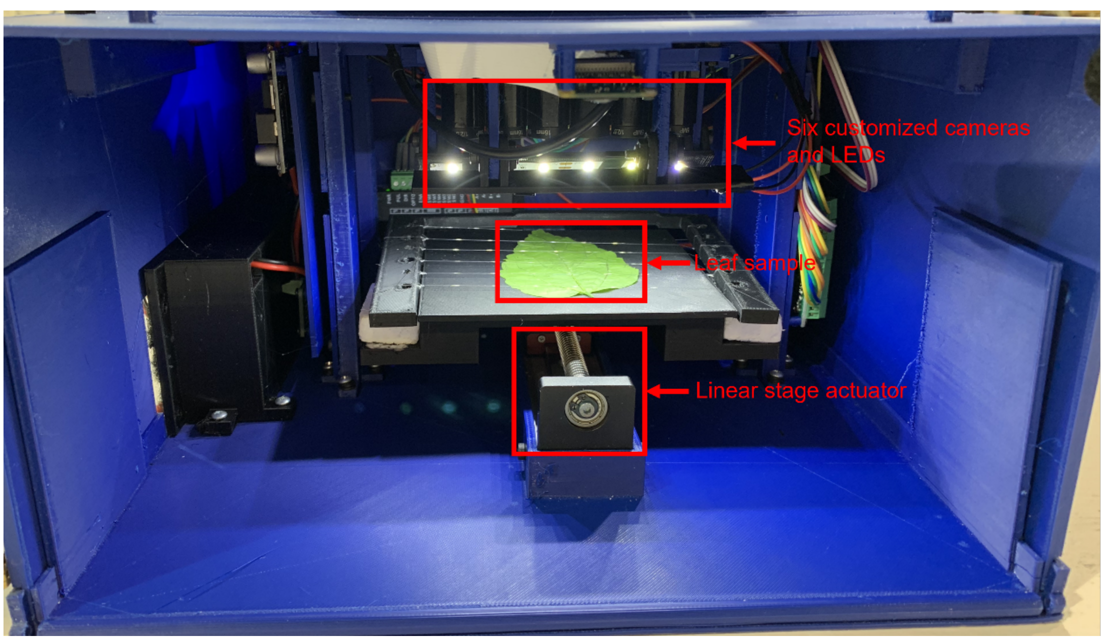


Fig. 2 Six-camera imaging system

Image calibration and deep learning method

The illumination condition of the single-camera imaging platform and six-camera imaging system was different, and the illumination condition may change when we collected images on different days using the same imaging device. Therefore, at the beginning of each image acquisition, the picture of an Anwenk grey card (Shenzhen Chuangheng Tiancheng Technology Co., LTD., Shenzhen, China) was taken for image calibration. The image calibration equation for each pixel is shown below.

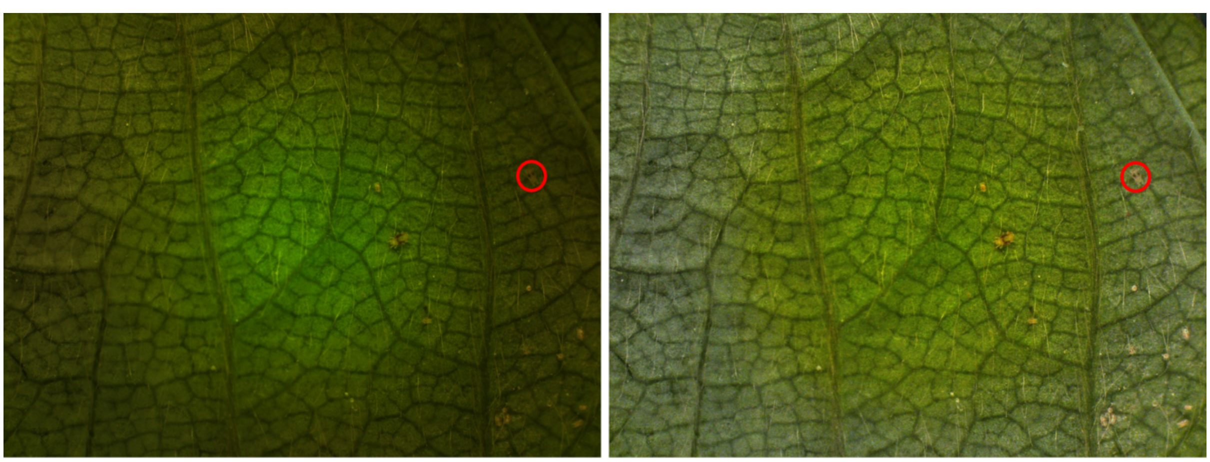
$$\frac{Calibrated\ strawberry\ leaf\ image\ pixel}{Strawberry\ leaf\ image\ pixel} = \frac{128}{Grey\ card\ image\ pixel} \tag{1}$$

In this study, the YOLOv4 model was used for strawberry pest detection. Firstly, CSPDarknet53 was used for feature extraction. Secondly, YOLOv4 combined the features from different feature layers. Finally, three YOLOv3 heads were used for detecting objects of different sizes. The output image of YOLOv4 consists bounding box, object class, and confidence value. Each bounding box represents that one strawberry pest is detected in the image. And the corresponding class and confidence value will be shown on the top of the bounding box. YOLOv4 requires a huge amount of images for model training. Therefore, a pre-trained YOLOv4 was used in this study, which could improve the strawberry pest detection performance without increasing image datasets. Mosaic augmentation was used in this study, which randomly select four pictures and use them to produce a new picture. Deep learning model training requires lots of computing resources. Therefore, an NVIDIA GeForce RTX 3090 was used to speed up the model training. Pre-trained YOLOv4 was firstly trained on 2713 strawberry leaf images collected by smartphones. These smartphone images were collected using the same method as Zhou et al. (2021). Then, a total of 260 images collected by the customized cameras were used for model training and testing. The number of training images, validation images, and testing images were 156, 52, and 52, respectively.

Results and Discussions

Image calibration

The image collected by both the single-camera imaging platform and six-camera imaging system was brighter in the center area. As shown in Fig. 3, the uneven illumination problem was solved, and the two-spotted spider mite (TSSM) highlighted by the red circle becomes more visible after image calibration. The improved image quality will be able to improve pest detection accuracy.



(a) (b)

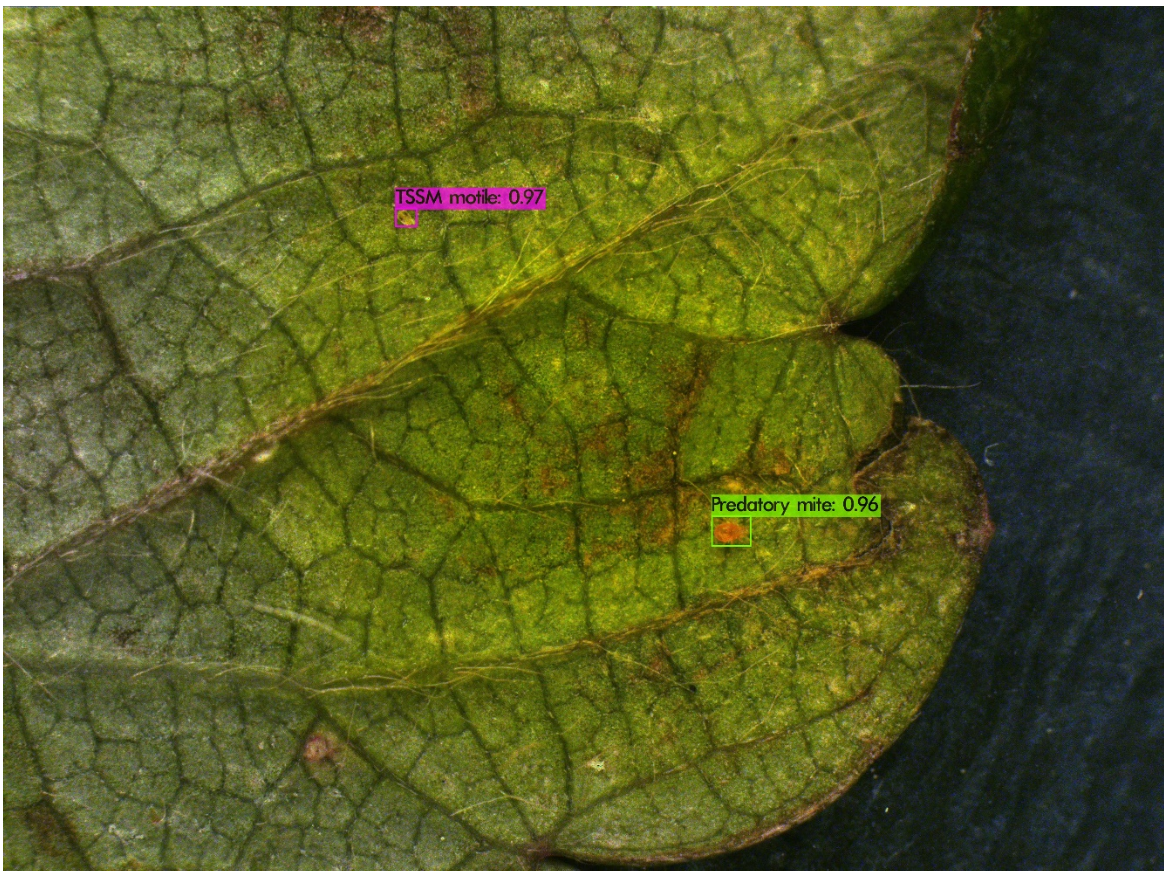
Fig. 3 Image calibration: (a) Image before calibration, (b) Image after calibration

Strawberry pest detection based on deep learning

TSSM and predatory mites (Neoseiulus californicus and Phytoseiulus persimilis) were the major mites found on the image dataset. Growers usually count the number of TSSM eggs and TSSM motile to decide the management strategy. Therefore, the deep learning model was trained to detect TSSM motile, TSSM egg, and predatory mites. This study used the strawberry leaf images collected by smartphones to train the YOLOv4 model first. Then, the images collected by the single-camera imaging platform and six-camera imaging system were used to train to model. The model performance on the testing dataset is shown in Table 1. This study found the YOLOv4 model could detect TSSM and predatory mites with high detection accuracy. The mean average precision was 0.917. Two example images are shown in Fig. 4.

Table 1 Two-spotted spider mite (TSSM) and predatory mite detection accuracy

	TSSM motile	TSSM egg	Predatory mite
Average precision	0.90	0.92	0.93



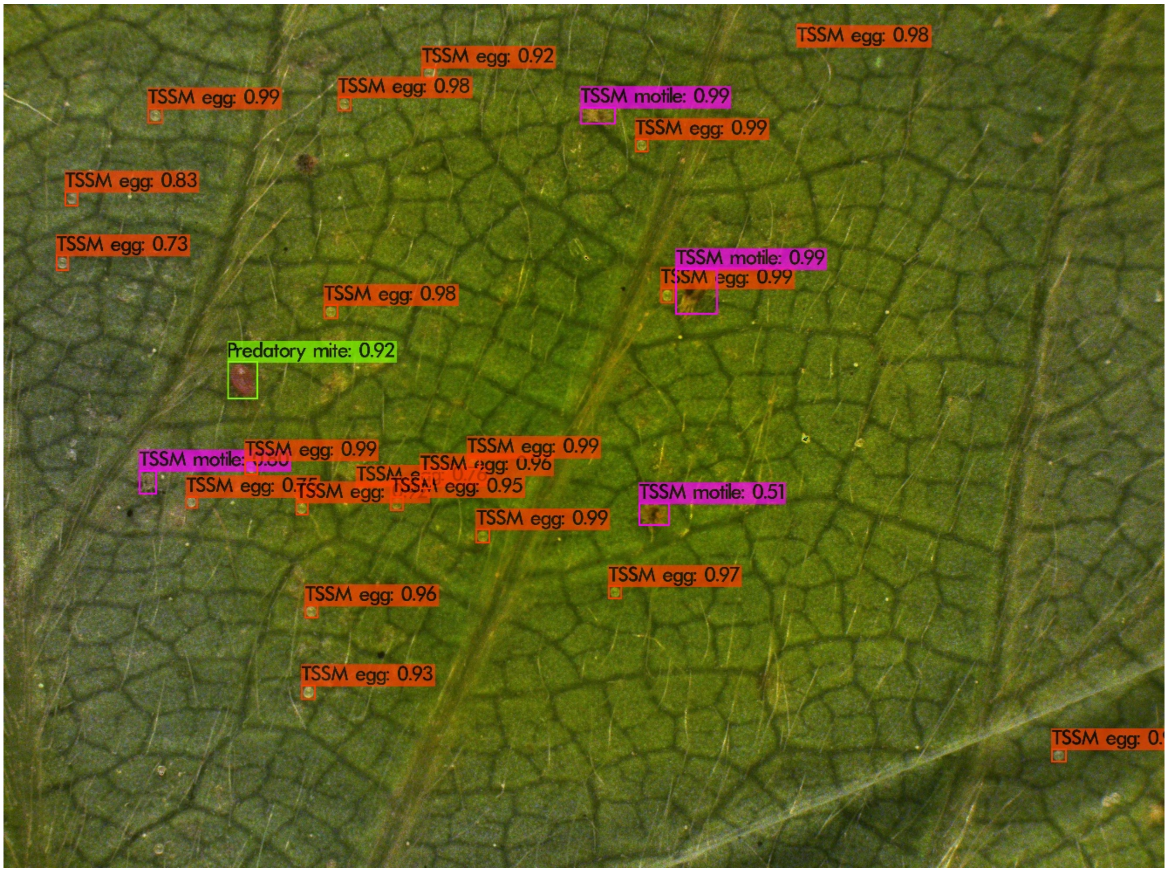


Fig. 4 Two example images of two-spotted spider mite (TSSM) and predatory mite detection

A total of 260 images were collected in this study for YOLOv4 model training and testing. More images need to be collected and labeled to make the model more robust. In addition, the YOLOv4 model needs to be integrated into the six-camera imaging system. Then, the imaging system can automatically collect leaf images and detect the total number of pests in every single leaflet, which will speed up strawberry pest scouting in the field and reduce the labor cost for strawberry growers.

Conclusion

This study used a customized camera(s), including a single-camera imaging platform and a six-camera imaging system, to collect 260 images for model training and testing. The pre-trained YOLOv4 model was firstly trained on smartphone images and then the images collected by the customized cameras were used to train the model. The final model could achieve a detection accuracy of 0.917.

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