Agrosense: AI-enabled sensing for precision management of tree crops

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Abstract.

Monitoring tree crop growth and health frequently is critical for researchers and farm managers. However, it is very expensive and challenging to manually collect tree-based information frequently. Therefore, a low-cost and artificial intelligence (AI) enhanced sensing system, Agrosense, was developed for tree inventory, canopy height measurement, and tree canopy density classification in this study. The sensing system mainly consisted of four RGB-D cameras, two Jetson Xavier NX, and one touch screen, which can be mounted on any farm vehicle (e.g., sprayer or fertilizer) to collect and process data in real-time as the vehicle is moving in the orchard. A total of 446 RGB and depth images of citrus trees were collected and labeled for tree detection and tree canopy density classification. The pixel values of the depth image were the distance between the camera and objects, and the RGB images were aligned with depth images. The depth information was used to filter out the background objects and locate the highest point of the tree for the tree height estimation. The AI model, YOLOv8, was trained and tested for tree detection and canopy density classification. The initial results showed that the mean average precision of the AI model for tree detection was 96%, the canopy density classification accuracy was 80%, and the average error of canopy height was only 6%. The AI-enabled sensing system developed in this study can help growers better manage their orchards, which can potentially increase the yield and reduce production costs. In the future, more functions will be developed for the Agrosense system, including fruit counting, tree canopy volume estimation, etc. In addition, all information (tree inventory and height, canopy density and volume, and fruit yield) will be uploaded to a cloud-based software for data visualization and analysis.

Keywords.
Citrus, computer vision, deep learning, edge computing, image classification, object detection.

1. Introduction

Information about the growing status (tree inventory, height, canopy density, etc.) of tree crops is important for researchers and growers. However, it is impossible to manually collect these data frequently in a large orchard. The rapid development of artificial intelligence (AI) makes it possible to develop AI-enabled sensing systems that can be mounted on a farm vehicle for crop monitoring. Installing a sensing system on a sprayer, for example, for crop monitoring will not add extra application costs and time, since it could collect valuable data during spraying (Partel et al., 2021). The goal of this study was to develop an AI-enabled sensing system for precision management of tree crops.

2. Materials and Methods

2.1 Image Acquisition

Fig. 1 shows the Agrosense system mounted on the sprayer for image acquisition. Two RGB-D cameras were installed on each side of the Agrosense system, which can be used to collect images of two rows of trees simultaneously. Each camera collects both RGB and depth images at the same time. The pixel value of the depth image is the distance between the object and the camera. The depth information was used to filter out the background of the image. The background includes trees, fruits, and ground behind the tree close to the camera (aka, trees, etc. from other rows). 446 images were collected in this study.

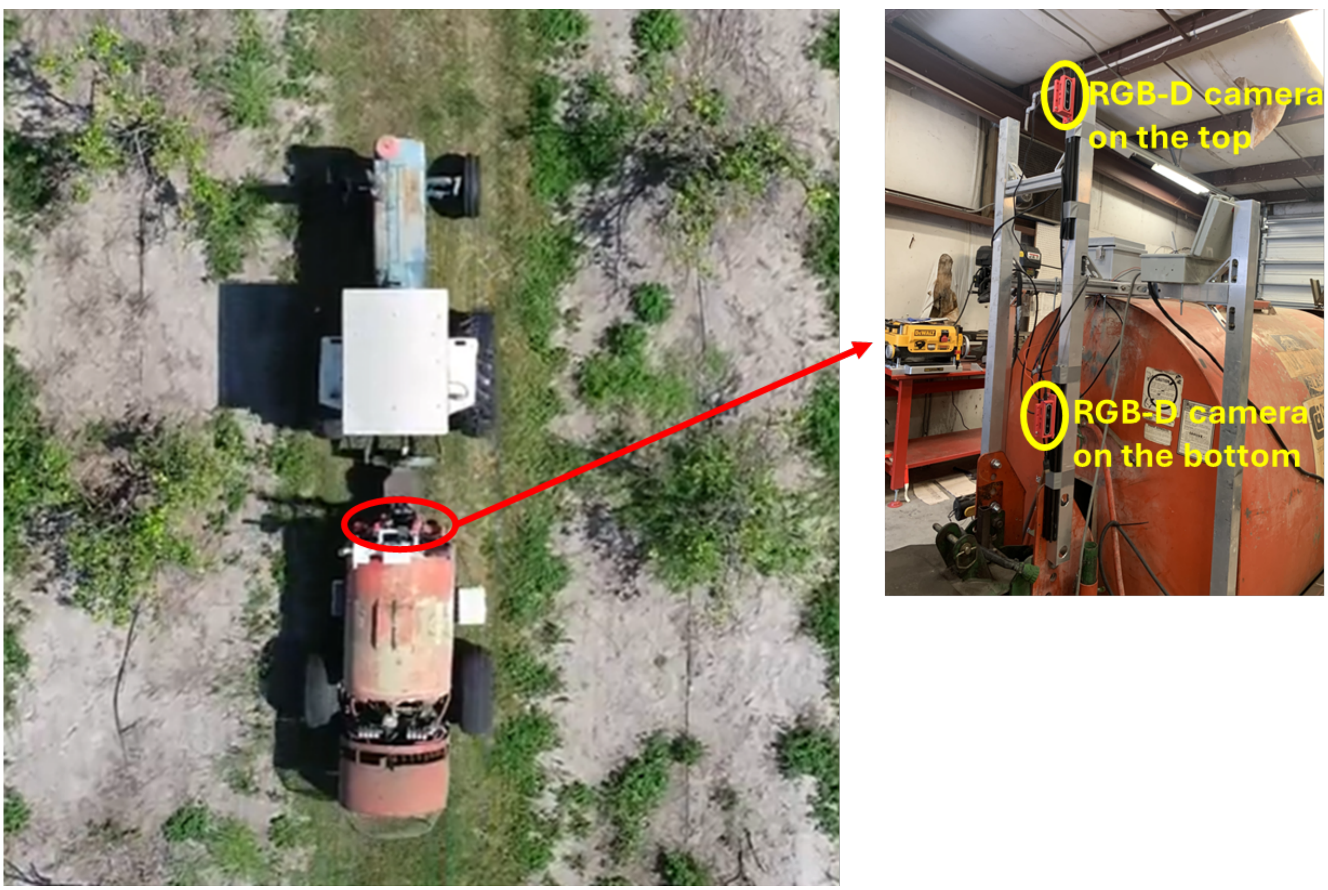

Fig. 1. Agrosense system mounted on a sprayer.

2.2 Methodology

When the sensing system moves in the citrus orchard. The camera on the bottom detects and tracks the citrus trunk. Once the trunk appears in the middle of the image, the image collected from the camera on the bottom is used to classify the canopy density. Five canopy density levels were used in this study, including densities 1 (low density; almost dead trees), 2, 3, 4, and 5 (high density). In addition, the camera on the top takes a picture of the citrus tree, and the depth information is used to identify the tree canopy and the highest point of the canopy is used to estimate the tree height. The trunk detection and canopy density classification methods used in this study were YOLOv8s and YOLOv8s-cls (Jocher et al., 2023), respectively.

3. Results and Discussions

Fig. 2 shows example images of the citrus trunk detection and tracking. The mean average precision of the AI model for trunk detection was 96%. The canopy density classification accuracy was 80%. In addition, the average error of canopy height estimation was only 6%. This study was mainly focused on small and medium-sized citrus trees. Therefore, the camera on the bottom can cover the entire tree or most parts of the tree for canopy density classification. When a large tree is included in the future, multiple consecutive frames of both cameras on the bottom and top will be mosaiced to generate a single image that can cover the entire tree. In addition, counting fruits on the tree and ground, and measuring the canopy size will also be included in the next prototype of the sensing system.

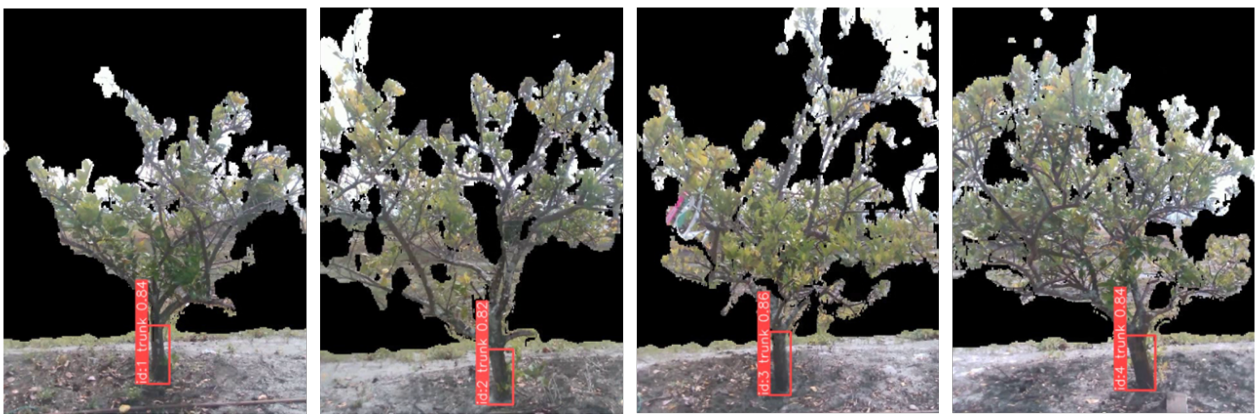

Fig. 2. Citrus trunk detection and tracking based on the image collected by the camera on the bottom of the sensing system.

4. Conclusion

An AI-enabled sensing system was developed for real-time tree crop monitoring. The accuracy of trunk detection, canopy density classification, and canopy height estimation was 96%, 80%, and 94%, respectively. The sensing system can be mounted on any farm vehicle to achieve better tree crop management without extra application costs and time.

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