# Automated Strawberry Flower Counting using Machine Vision for Yield Prediction

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## Summary

**The objective of this phase of the project was to develop an imaging system capable of capturing images of strawberry plants in the field. An imaging cart system consisted of cameras and lights was attached to a mechanical setup and moved over rows of strawberry plants using a tractor. The system was configured to capture images at a high frame rate to effectively handle effects of motion. The captured images were analyzed using an improved version of the computer vision algorithm developed during the phase 1 to obtain flower counts. The developed algorithm performed at an 98.2% accuracy for flower detection in validation images. The number of detected flowers will be used for future yield prediction.**

## Methods

A strawberry field was prepared at the Plant Science Research and Education Unit (PSREU) at the University of Florida in Citra, Florida during the 2017-18 growing season. Five rows of strawberry plants each 220 feet long were used for the experiments. Three rows were the Sensation® cultivar and the other two were 'Florida Radiance'.

**Hardware Description:**
The hardware setup consisted of four Point Grey Grasshopper (4.1 Megapixel) cameras arranged in such a way as to capture the top and side views of the strawberry plants. The camera arrangement is shown in Fig. 1. Lenses with a focal length of 12 mm were used to cover a field of view of 12 x 12 inches close to the bed. This area was illuminated using two LED lights positioned as shown in the Fig. 1 on either side of the cameras.

**Figure 1.** Camera and light arrangement for imaging.

Since the cameras were placed very close (within 20 inches) to strawberry bed, effects due to motion were high in captured images. In order to mitigate the effects of motion blur, images had to be acquired at a high frame rate. A frame rate of 90 frames per second (fps) was chosen empirically after experiments in the field. At 90 fps, for 1024x1024 pixel resolution, each camera transmitted data at a rate of 284 Megabytes per second (approximately). The hardware pipeline from the camera to hard-disk was chosen in such a way as to handle such high data rate by choosing a quad-channel PCIe port with USB 3.1 ports and a camera with sufficient frame buffer memory.

GPS coordinates were acquired along with the images using a Trimble GPS receiver. These would be used to create yield prediction map of the field.

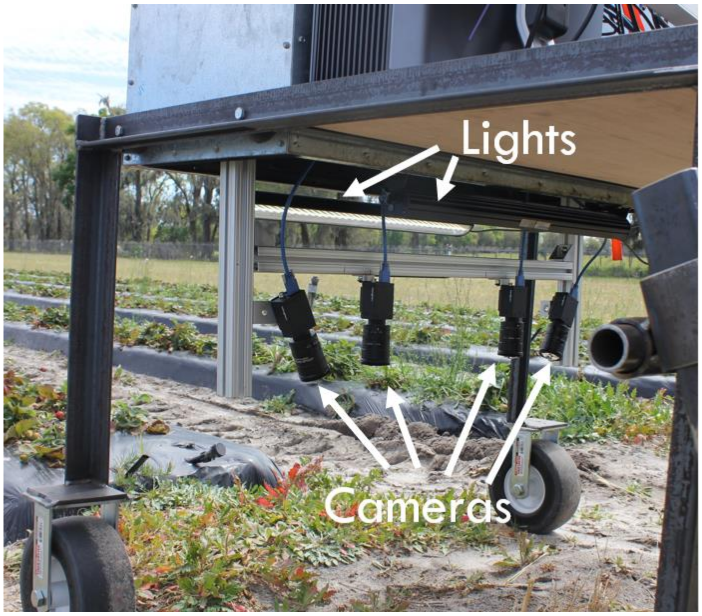


**Figure 2.** Hardware arrangement: cameras and lights.

**Experimental Setup:**

The overall hardware arrangement used for image capture in the field is shown in Figs. 2 & 3. Spinview$^{TM}$ was used for data capture in the field. The image processing algorithm was implemented as a Python program using OpenCV and Torch libraries.

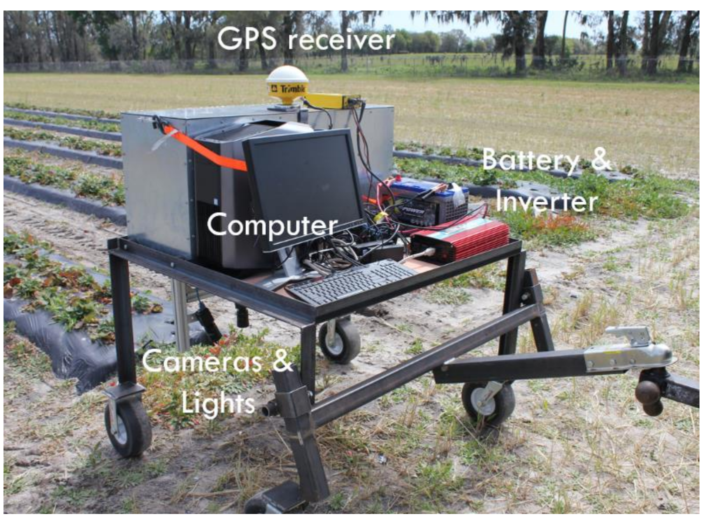


**Figure 3.** Hardware arrangement: computer, cameras and lights, GPS receiver and power supply.

**Algorithm Description:**

Images acquired using the setup were analyzed using a newly developed Faster RCNN algorithm, which is a deep object detection neural network. Videos acquired from the field experiment were used to generate individual images, which were then labeled for training the Faster RCNN model. A total of 904 images were labeled and divided into training, validation and testing sets. A high-performance laptop equipped with an 8 GB graphic processing unit (GPU) was used to train the model which took five hours. Then, the final trained model was integrated in a detection algorithm, which took testing images as input and applied the model for flower detection. A total of 100 images were used for testing.

## Results & Observations

The detection algorithm achieved high detection accuracy on the testing images. In the 100 images, the number of manually counted flowers was 166. The algorithm successfully detected 163 flowers, missed only three and falsely detected six non-flower regions as flowers. The correct detection rate of strawberry flowers was 98.2%. Table 1 shows the detailed numbers and accuracies of the algorithm. Fig. 4 shows some examples of the detection results. Each flower was marked with a red rectangle and labeled with a confidence value (1 being the highest), which represented how confident the model was to classify it as ‘strawberry flower’. Fig. 5 shows an example in which the model incorrectly classified a non-flower region as a strawberry flower.

**Table 1.** Flower detection results from the validation images of strawberry flowers collected from the University of Florida, PSREU. Collected flowers include two varieties of strawberries – 'Florida Radiance' and Sensation®. A 98.2% correct detection accuracy was achieved for strawberry flowers.

| | Manual flower count | Correctly identified flowers (True positives) | Missed flowers (False negatives) | Non-flower objects incorrectly identified as flowers (False positives) |
|---|---|---|---|---|
| Number of flower | 166 | 163 | 3 | 6 |
| Percent (%) | 100 | 98.2 | 1.8 | 3.6 |

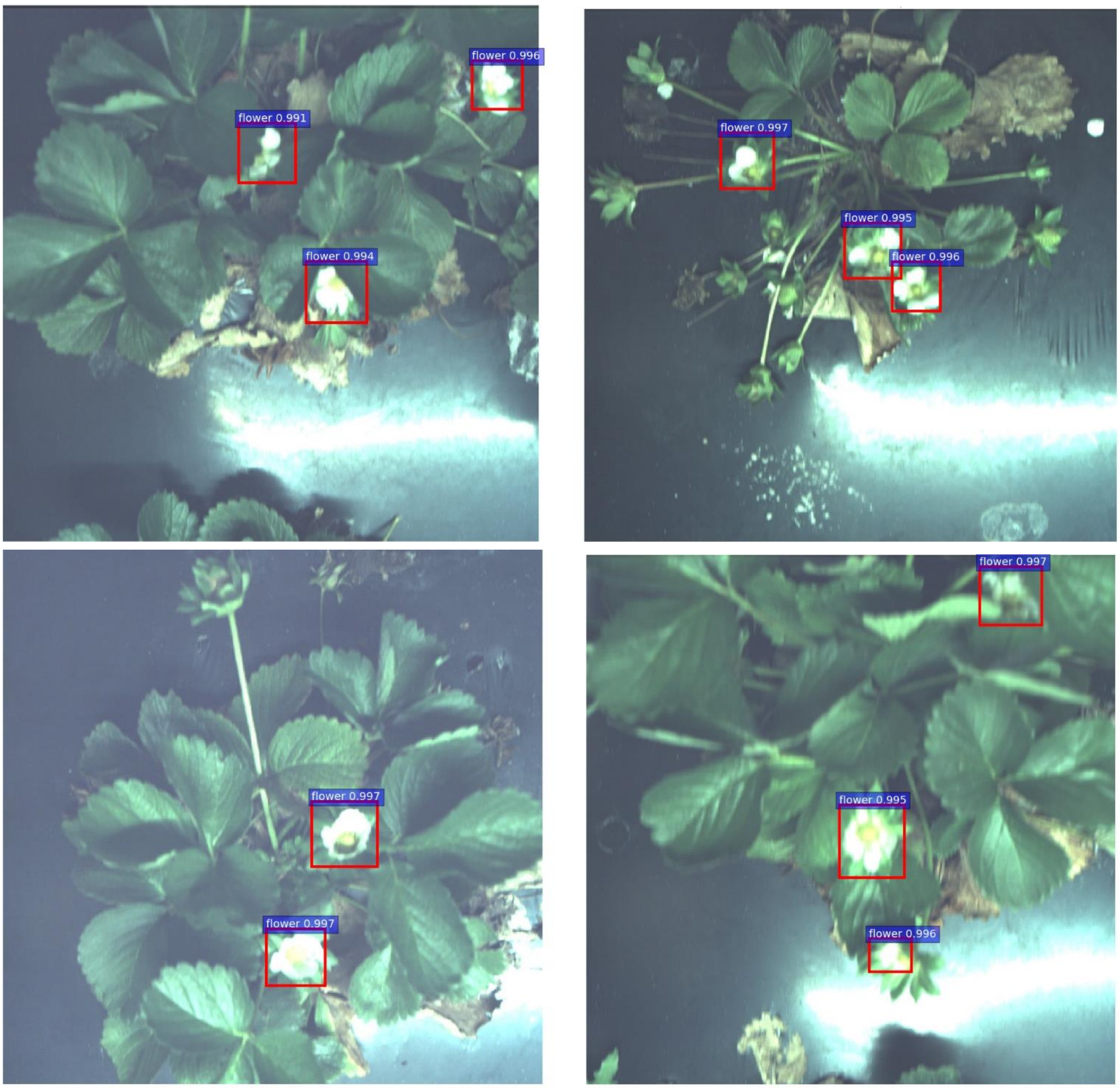


**Figure 4.** Examples of the detection results. Each flower was marked with a red rectangle and labeled with a confidence value (1 being the highest), which represented how confident the model was to classify it as 'strawberry flower'.


**Figure 5.** An example of the detection results which shows a non-flower object incorrectly identified as a strawberry flower. Each flower was marked with a red rectangle and the labeled with a confidence value (1 being the highest), which represented how confident the model was to classify it as 'strawberry flower'.

## Conclusions

In this phase of the project, a hardware system was designed and used for collection of data from a strawberry field using a machine vision camera and lighting system. The collected data was then analyzed using a newly developed deep object detection neural network to detect and count flowers in images. Many challenges were encountered in the design and development of hardware for image acquisition, which were resolved eventually. The developed algorithm accurately identified strawberry flowers with a 98.2% accuracy in the testing images.

## Future Work

During the next phase of this project, improvements to the hardware system to facilitate synchronized image capture with various hardware components will be made. Automation of various steps of image capture would help in easier and faster image acquisition for growers. Software will be developed to automate the processing steps. Image analysis result together with GPS information will be used for yield prediction.

Motion blur was seen to be a deterrent to algorithm performance. It is currently anticipated that the use of strobed lighting could help mitigate this problem. Efforts will be directed towards updating the lighting system within the imaging cart. Modifications to minimize vibrations due to cart movement will also be done to handle motion blur.

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