

# Strawberry Plant Wetness Detection using Color & Thermal Imaging

Anushka Swarup, Won Suk “Daniel” Lee, Natalia Peres and Clyde Fraisse

## Summary

**The objective of this work was to analyze popular machine vision techniques as a solution to the problem of leaf wetness detection in strawberry plants. It is crucial to detect leaf wetness duration to prevent occurrence of diseases like Botrytis and Anthracnose fruit rots. This research sought to find a better alternative to the widely used leaf wetness sensors which are sometimes not reliable. This study utilized color and thermal cameras to capture images of strawberry plants from an experimental field in Citra, Florida. The captured images were analyzed using various image processing techniques to detect the presence of water on the leaf surface. We came to a conclusion that machine vision is, in fact, a feasible approach to the problem of detecting leaf wetness.**

## 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 2018-19 growing season. Ten rows of strawberry plants, each 220 feet long, were used for the experiments. Images were captured from the field between February and June 2019.

Also, 50 strawberry transplants were planted in small pots outside Frazier Rogers Hall at the University of Florida in Gainesville, FL to carry out intermediate lab experiments.

## Hardware Description & Image Acquisition:

A Canon EOS Rebel T2i camera with a resolution of 18MP was used as the color imager for RGB image analysis. The setup shown in Fig. 1 included two cameras fixed to a tripod stand with the lens facing downward. The camera on the right is the Canon color imager. By keeping the cameras in this orientation, we were able to capture the upper side of the plant where the maximum leaf surface was present.

Also, two thermal imagers, Duo & A600sc, both by FLIR Systems, Inc. were used in a similar manner as the color imager to capture thermal images of the plants in the field. FLIR Duo had a built-in thermal and color camera with a resolution of 160 X 120 pixels for the thermal sensor, as shown on the left in Fig. 1. FLIR A600sc with a resolution of 640 X 480 pixels is shown in Fig. 2. It was used for lab-based experiments.

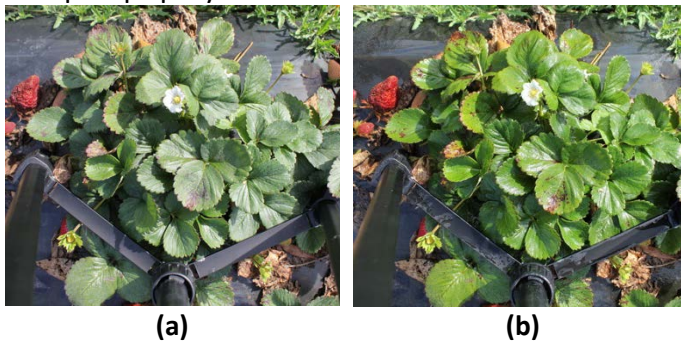


**Figure 1. Thermal (left) & color (right) camera setup for field imaging.**



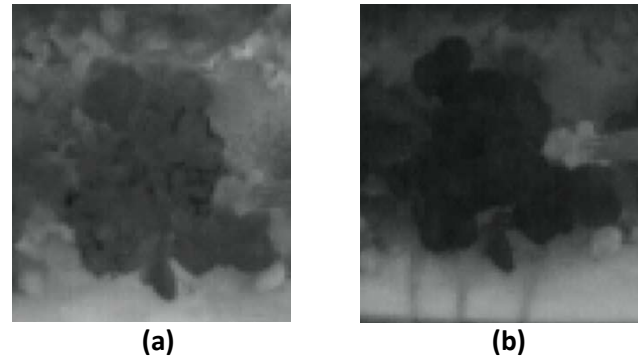
**Figure 2. Thermal camera setup for lab experiments.**

A pair of images captured using the color camera are shown in Fig. 3a and 3b, which are dry and wet plants, respectively. The wetness was created artificially by spraying water on the plant using a hand pump sprayer.



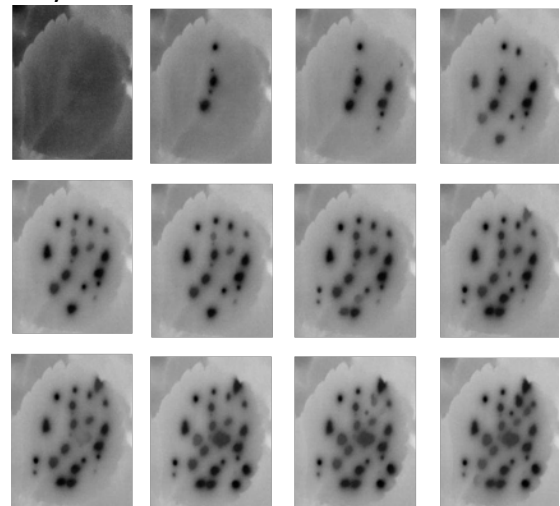
**Figure 3. Dry (a) and wet (b) plant captured using the color camera.**

Fig. 4 shows a pair of dry and wet thermal images captured using the thermal camera. The wet image was captured after spraying the dry plant with water using the hand sprayer. Due to the nature of thermal imaging that lower temperatures correspond to lower intensity values, the wet plant in Fig. 4b appears to be darker than the dry plant in Fig. 4a.



**Figure 4. Dry (a) & wet (b) plants captured using the thermal camera.**

As the goal of this work was to detect even the smallest water droplet on the plant surface, an experiment was conducted on some strawberry plants grown outside the laboratory to detect water droplets using thermal imaging. A set of 11 images were captured from 14 different leaf samples. Artificial water droplets were created on the leaf using a pipette. As shown in Fig. 5, the first image is of a dry leaf and the next 10 images were wet leaves created by adding additional 20 micro liters of water in each cycle.



**Figure 5. Thermal images for water droplet detection.**

#### **Algorithm Description:**

Color and thermal images were analyzed separately. For color imaging, we made use of the perceptive properties of dry and wet surfaces. For example, wet surfaces appeared to be shinier and glossier than their dry counterparts. Firstly, the region of interest (i.e., the plant) was cropped out of each image using MATLAB program. To remove any remaining background information from the cropped images,

MATLAB's Color Thresholder application was used. The resulting images were used for analyses of the various components of the RGB, HSV, Lab, YCbCr and YIQ color spaces. Finally, the data obtained from this analysis was used to classify between dry and wet plants using a support vector machine (SVM) classifier.

For the thermal images, the effect of water on the temperature of the plants was analyzed using the Research IR software by FLIR Systems, Inc. The mean temperature of the plants before and after application of water was calculated. This temperature data were used to distinguish between wet and dry plants. Also, water droplet detection was carried by on high-resolution thermal images by segmentation performed by analyzing the histogram of the images.

## Results & Observations

Color image analysis was conducted on different plants in dry and wet conditions. After the color space analysis, we reached the following conclusions:

- Hue (actual green color component) of wet plants is lower than dry plants
- Saturation (purity of color) of wet plants is more than that of dry plants
- Blue color component of wet plants is lower than that of dry plants

These results are in Figs. 6, 7 and 8 below.

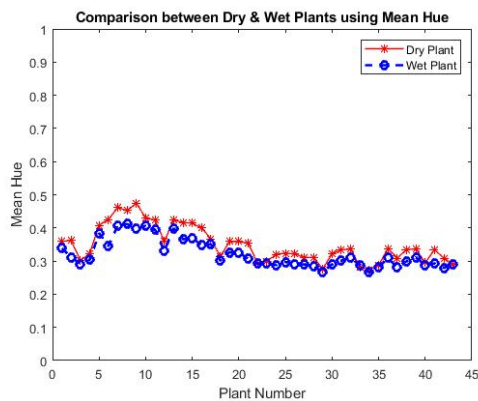


Figure 6. Mean hue of dry and wet plants.

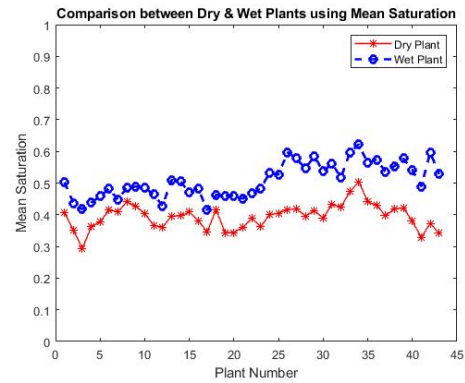


Figure 7. Mean saturation of dry and wet plants.

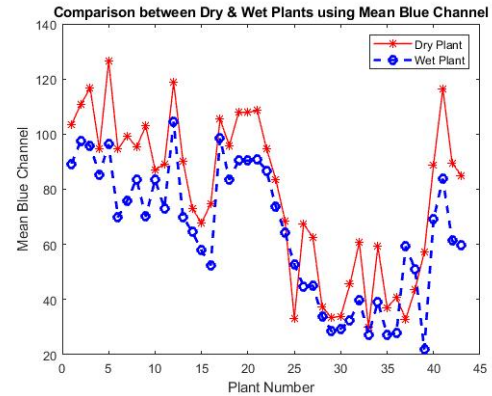


Figure 8. Mean blue component of dry and wet plants.

The classification algorithm was able to achieve 93% overall accuracy. The algorithm was able to classify 27 of 29 test images. Table 1 shows the detailed numbers and accuracies of the algorithm.

Table 1. SVM classifier accuracy.

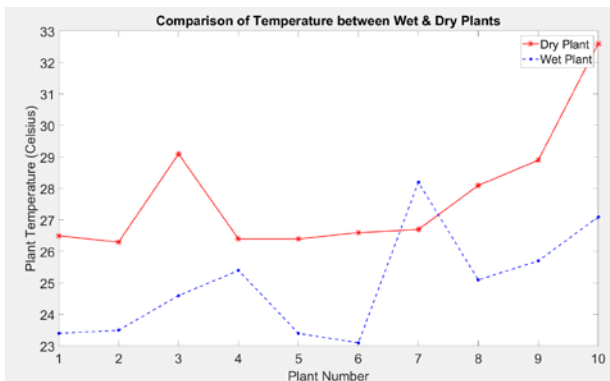
Features	Accuracy	Classification
Saturation vs. Blue	93%	27/29
Saturation vs. Hue	86%	25/29
Saturation vs. Hue vs Blue	93%	27/29

We found that varying illumination conditions was a deterrent for our system. Images captured in sunny and cloudy days showed different color statistics which decreased the accuracy of the classifier. Table 1 show the results of the images captured only in direct sunlight. By analyzing the images captured under shadows separately from images in direct sunlight, we were able to attain the results shown in Table 2. The accuracy obtained for this classification is a bit lower than those shown for direct sunlight images in Table 1.

**Table 2. SVM classifier accuracy for images acquired under shadows.**

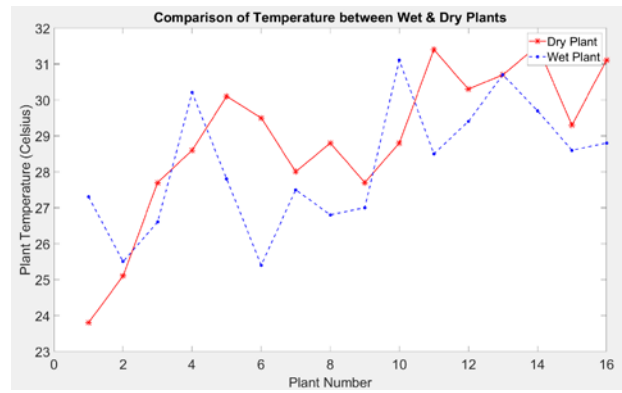
Features	Accuracy	Classification
Saturation vs. Blue	91%	21/23
Saturation vs. Hue	87%	20/23
Saturation vs. Hue vs Blue	91%	21/23

For thermal images, we calculated the mean temperature for all the plants captured using the thermal imager. The information about weather parameters like temperature, average wind speed and relative humidity was also recorded for each dataset captured. We found that with high ambient temperature, there was a large enough gap between temperatures of wet and dry plants, making temperature a good parameter for classification. This can be seen from Fig. 9 as the temperature of wet plants is generally lower than the dry ones.



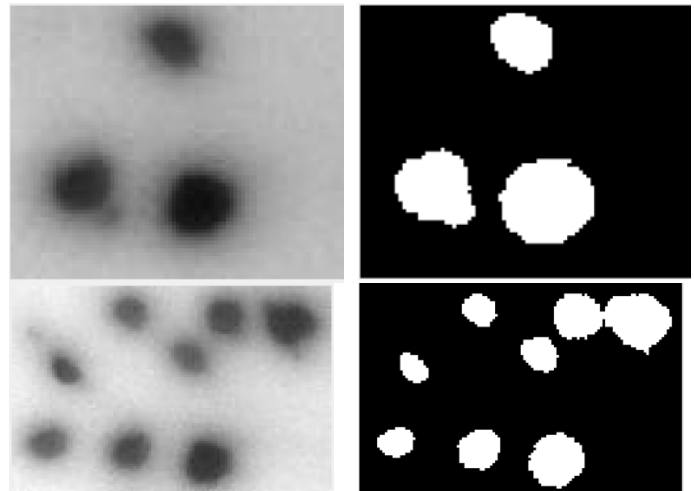
**Figure 9. Relation between mean temperature of wet and dry plants. (ambient temperature = 30.6° C)**

However, when the ambient temperature was low, there was little to no decrease in the temperature of wet plants as compared to the dry ones, as shown in Fig. 10.



**Figure 10. Relation between mean temperature of wet and dry plants. (ambient temperature = 23.5° C)**

The FLIR Duo camera was not able to provide sufficient information for the detection of water using thermal imaging due to its low resolution. Hence, we shifted to the FLIR A600sc which is a high-resolution thermal imager. Fig. 11 shows droplet detection results on cropped out regions of images captured using this camera. As can be seen, the algorithm was successfully able to segment the water droplets from rest of the leaf surface.



**Figure 11. Water droplet detection using the high resolution thermal camera.**

## Conclusions

In this phase of the project, two popular machine vision techniques, color and thermal imaging were explored to determine their feasibility for detecting water present on the leaf surface. Images captured using the color imager were analyzed using various image processing techniques and finally a classifier

was built to distinguish between dry and wet plants. Our system achieved an accuracy of 93% for images without shadow and 91% for images with shadow. Thermal imaging gave insight into the effect of water on the plant temperature. While the cooling effect caused by evaporation from the presence of water was an effective parameter for distinguishing wet plants from dry, a further study will be needed to identify the effect of ambient temperatures on leaf wetness detection.

## Future Work

During the next phase of this project, a hardware system will be implemented which can be installed in the field so as to continuously capture and transmit live plant images. The live data will be useful to monitor plants when they become naturally wet due to dew and rainfall. Also, a study to analyze and imitate the function of the current wetness sensors will be conducted so that comparisons can be made. Software will be developed to automate the pre-processing steps. Since illumination conditions and dependence on ambient temperature for color and thermal imaging, respectively, proved to be major deterrents in this study, a study will be conducted to normalize the effect of these two variables.

## Acknowledgment

The authors would like to thank Mr. Doug Thomas at Crown Nursery, LLC for providing strawberry transplants for this study.

## Contact

Dr. Won Suk "Daniel" Lee  
Dept. of Agricultural and Biological Engineering  
University of Florida  
1741 Museum Road  
Gainesville, FL 32611-0570  
P: 352-294-6721  
E: wslee@ufl.edu