# STRAWBERRY FLOWER DETECTION USING COMPUTER VISION FOR EARLY YIELD PREDICTION

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# ACKNOWLEDGEMENT


- Florida Strawberry Growers Association

# AGENDA

- Introduction
- Objective
- Materials & Methods
- Computer Vision Algorithm
- Results
- Discussions
- Conclusions
- Future Work

# INTRODUCTION

- Strawberry ranks 8th in produce & 4th in fruit
- Florida dominates strawberry market during cold season – December to April
- Strawberry fruit production:
    - Flower & fruit production simultaneous throughout season
    - Profit margin depends on timely harvest of ripened fruits
- Accurate yield prediction crucial for labor planning
- Mathematical models using weather data, flower count promising for accurate yield prediction

# OBJECTIVE

- To predict strawberry yield based on flower count obtained from images acquired from a strawberry field
  - To build a hardware system to capture high quality images of strawberry flowers from field
  - To develop an algorithm to process images and give flower count in each image
  - To synchronize image data with GPS location and create flower count map of the field

# YIELD PREDICTION

- Yield prediction method for strawberry plants proposed by Chandler & Mackenzie in 2009
- Temperature data along with mean flower count were used in mathematical model to predict yield
- Mean flower count was obtained over a week's period **manually**
- Flower count obtained from a small region of the field was extrapolated to rest of the field
- **Automated** flower counting could improve prediction accuracy

# MATERIALS & METHODS

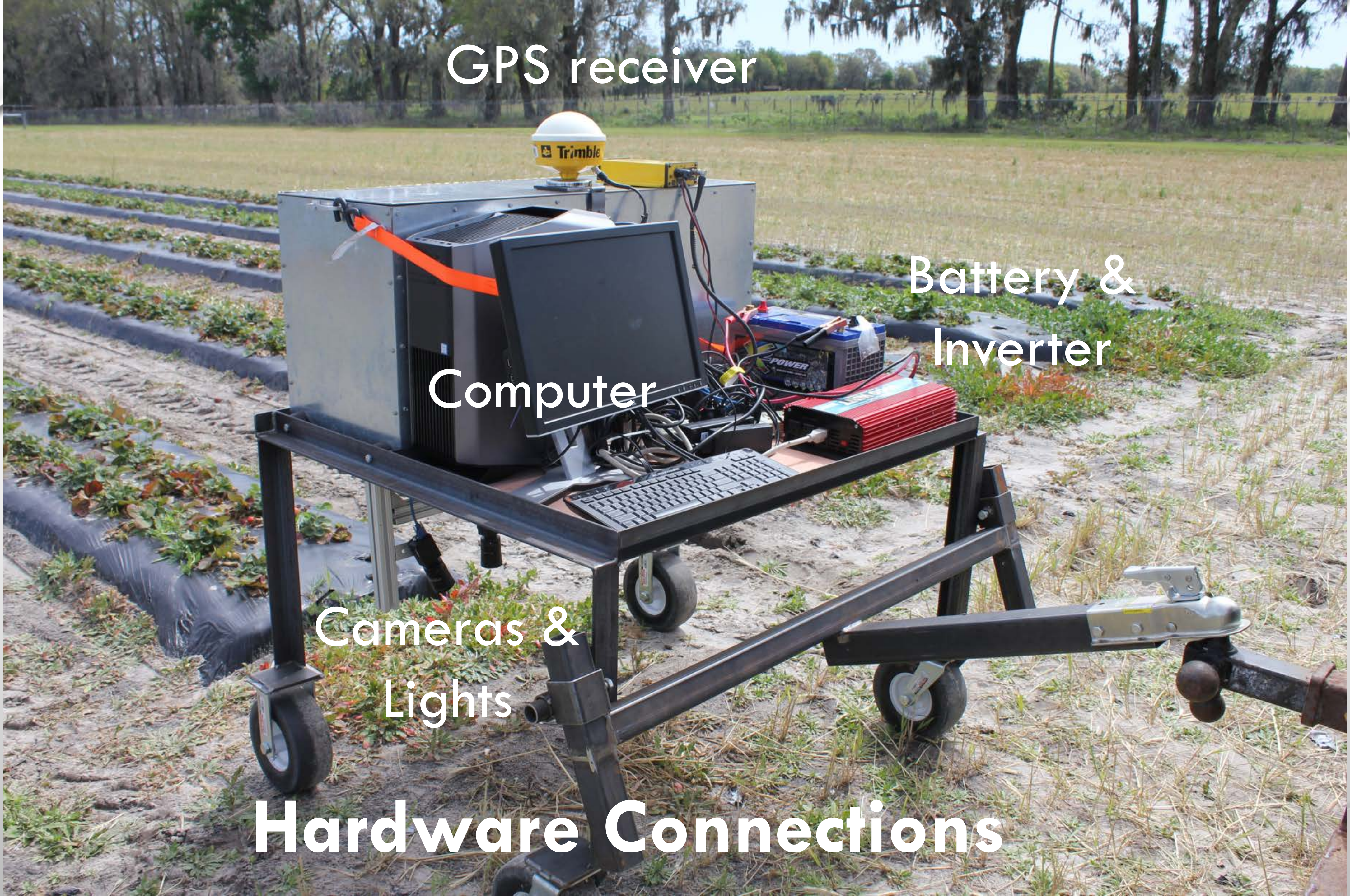
- Idea: count the number of flowers using images from field
- Strawberry plants – 8 to14 inches tall
- Flowers often occluded by leaves or other plant parts
- Fruits from different stages of maturation found alongside flowers
- Experiments conducted at two research facilities:
  - Phase 1: Gulf Coast Research & Education Center (GCREC), Balm, Florida
  - Phase 2: Plant Science Research & Education Unit (PSREU), Citra, Florida

# IMAGE ACQUISITION – PHASE I

- First version of algorithm was developed using images from Canon DSLR camera
- Images collected from Canon DSLR cameras for Phase I:
  - Pros:
    - High resolution
    - Low sensor noise (APS-C size sensor)
    - Automatic exposure control
    - Automatic focus control
  - Cons
    - Camera settings sensitive to external lighting variations
    - Algorithm complexity increases due to diversity of imaging conditions
    - Device cannot be interfaced directly with PC

# IMAGE ACQUISITION – PHASE II

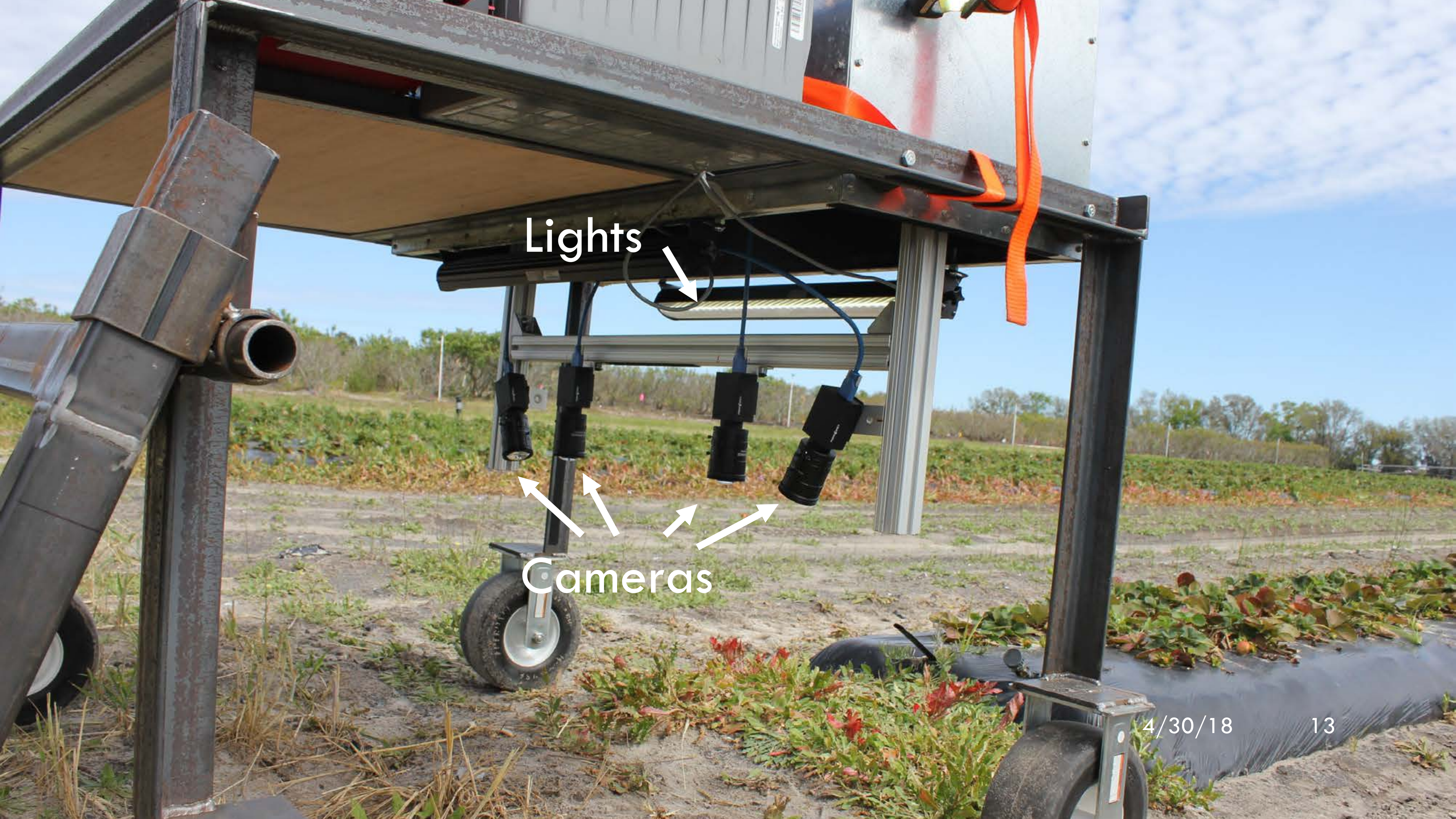
# Hardware Connections



# IMAGING HARDWARE


- Imaging cart was used to move cameras over strawberry plants using a tractor
- Imaging equipment used:
  - 4 cameras
    - Point grey grasshopper 4.1MP (1" sensor)
    - 1024x1024 resolution
    - 12 mm lens
    - 12" x 12" field of view
  - 2 machine vision LED lights to illuminate Field of View

# CAMERA PLACEMENT


Lights
Cameras

# CAMERA INTERFACE WITH PC


- Grasshopper 4.1- USB 3.0 interface, frame buffer 128 MB
- Quad-channel PCIe – (5 Gbps per USB3.0 port) required to collect high speed data
- Videos acquired using Flir Spinview™ in buffered mode
- Frames buffered before being written to disk to reduce frame drop
- Solid state drive preferred over hard-disk drives

# FIELD EXPERIMENTS


- For first phase images acquired using a Canon DSLR manually
- Images acquired under various working distances, lighting conditions used for experiments
- For second phase, imaging cart was used for data collection from field
- Cart pulled over rows of strawberry plants using tractor at a slow speed
  - Length of one row: 220 ft
  - Cart speed: 0.56 mph (0.826 ft/s)
  - Camera Field of View (FoV): 12 in x12 in
  - High speed imaging (< 60 fps) to combat motion blur

# IMAGE ACQUISITION IN FIELD

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# IMAGE ACQUISITION IN FIELD

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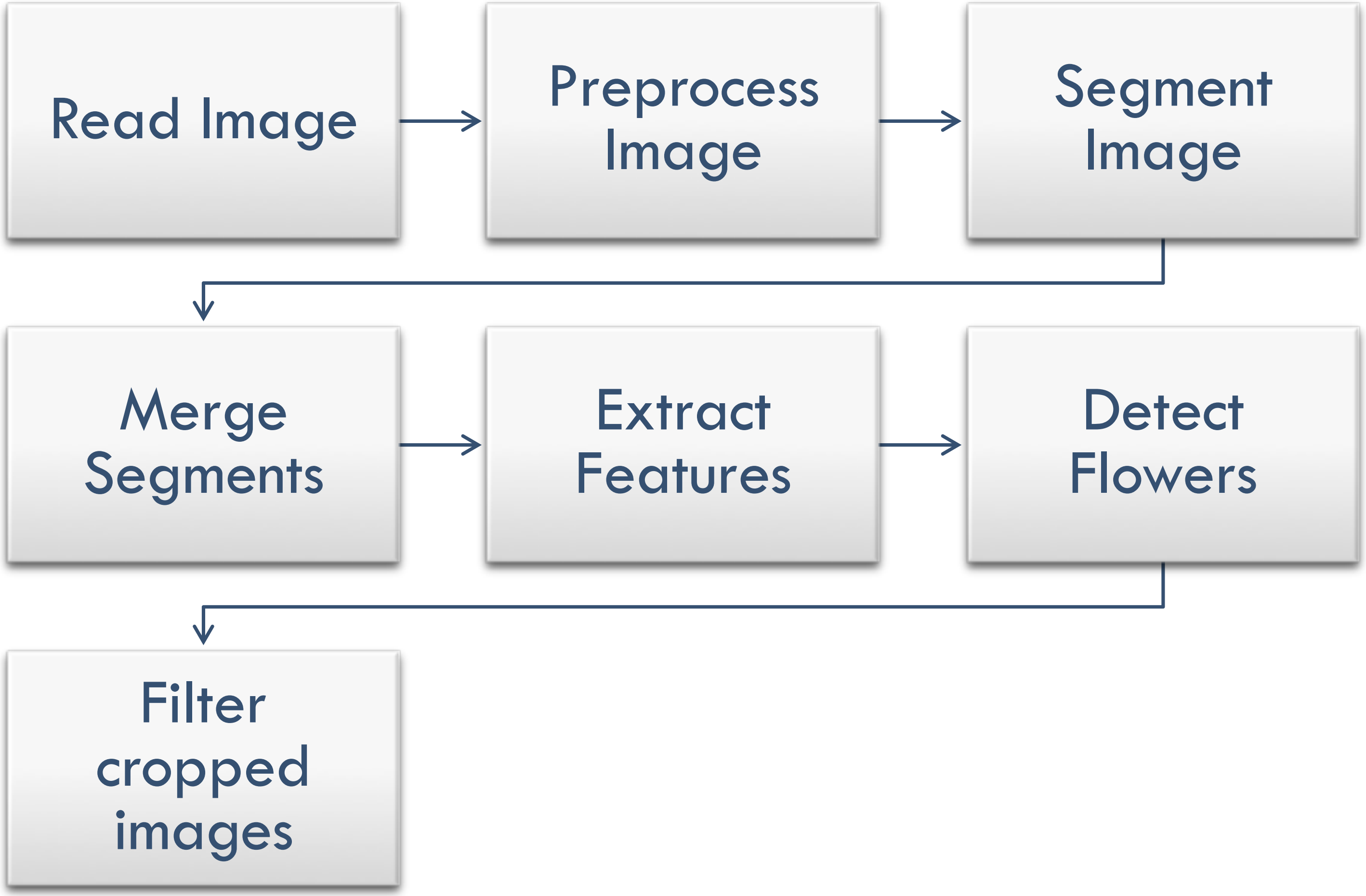
# FLOWER DETECTION ALGORITHM



# IMAGE PREPROCESSING

- Illumination variations – significant effects on algorithm performance
- Whole setup covered to control effects of external lighting
- CLAHE – Contrast Limited Adaptive Histogram Equalization to compensate small illumination variations
- Image converted to LAB color-space & CLAHE applied to “L” channel only

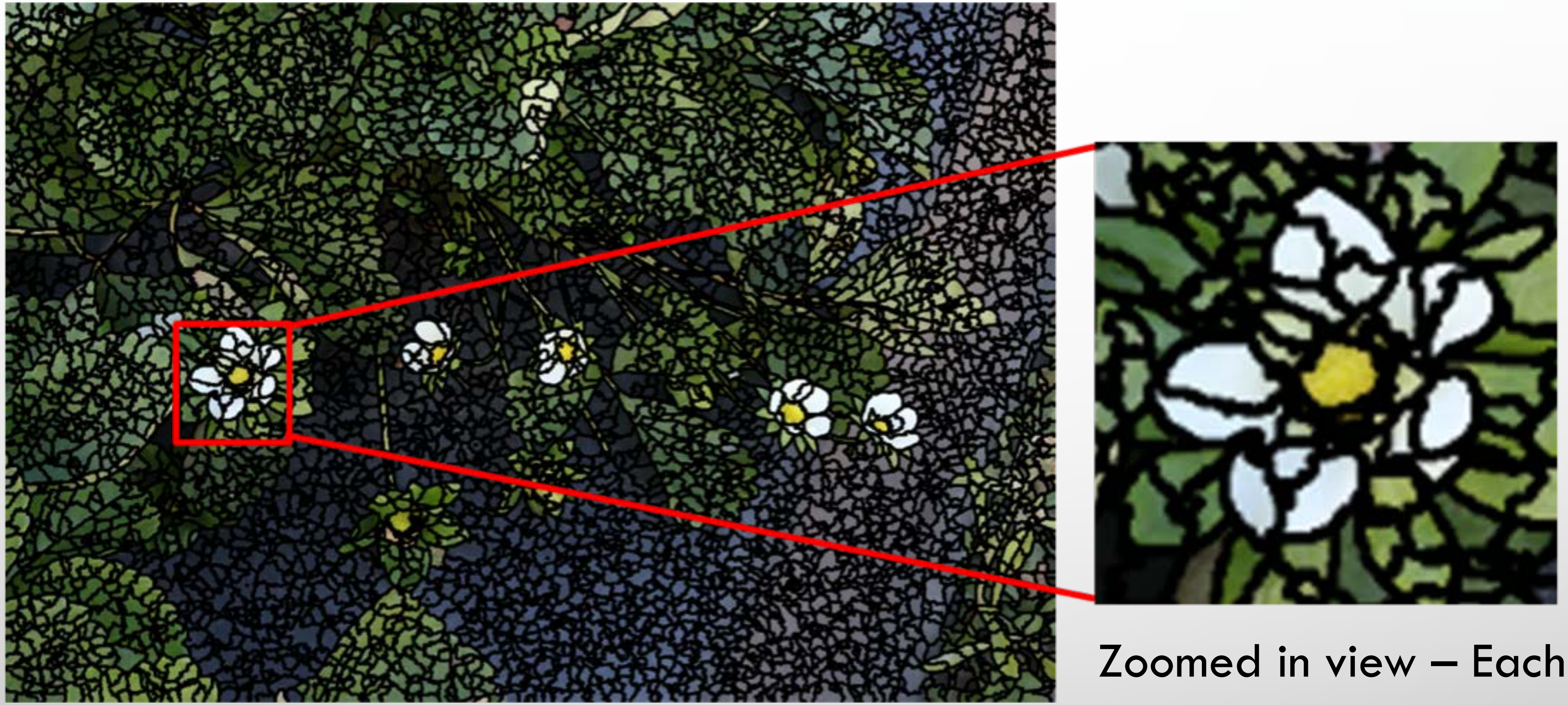
# IMAGE SEGMENTATION

- Segmentation:
  - Grouping image pixels belonging to the same region
- Create superpixels from original image & progressively form larger clusters
- Quickshift segmentation used for super-pixel creation
- Region Adjacency Graphs (RAG) used for superpixel merging

# EXAMPLE PROCESSING STEPS

Original Image

# IMAGE SEGMENTATION



Quickshift Segmentation Output

Zoomed in view – Each pixel group is a superpixel

# IMAGE SEGMENTATION CONTD.

Segments Merged using Region Adjacency Graph

Zoomed-in View

# FLOWER RECOGNITION

- Deep Learning (Artificial intelligence) model was used for feature extraction
- "Overfeat" (2014, Sermanet et al) model used as feature extractor
- Linear Support Vector Machine (SVM) for classification
  - Linear model reduces risk of overfitting
- Training, Testing, Validation datasets created from original Canon images in the ratio 60:20:20
- Regions containing flowers were cropped and used for feature extraction & training

# RESULTS

## Phase I

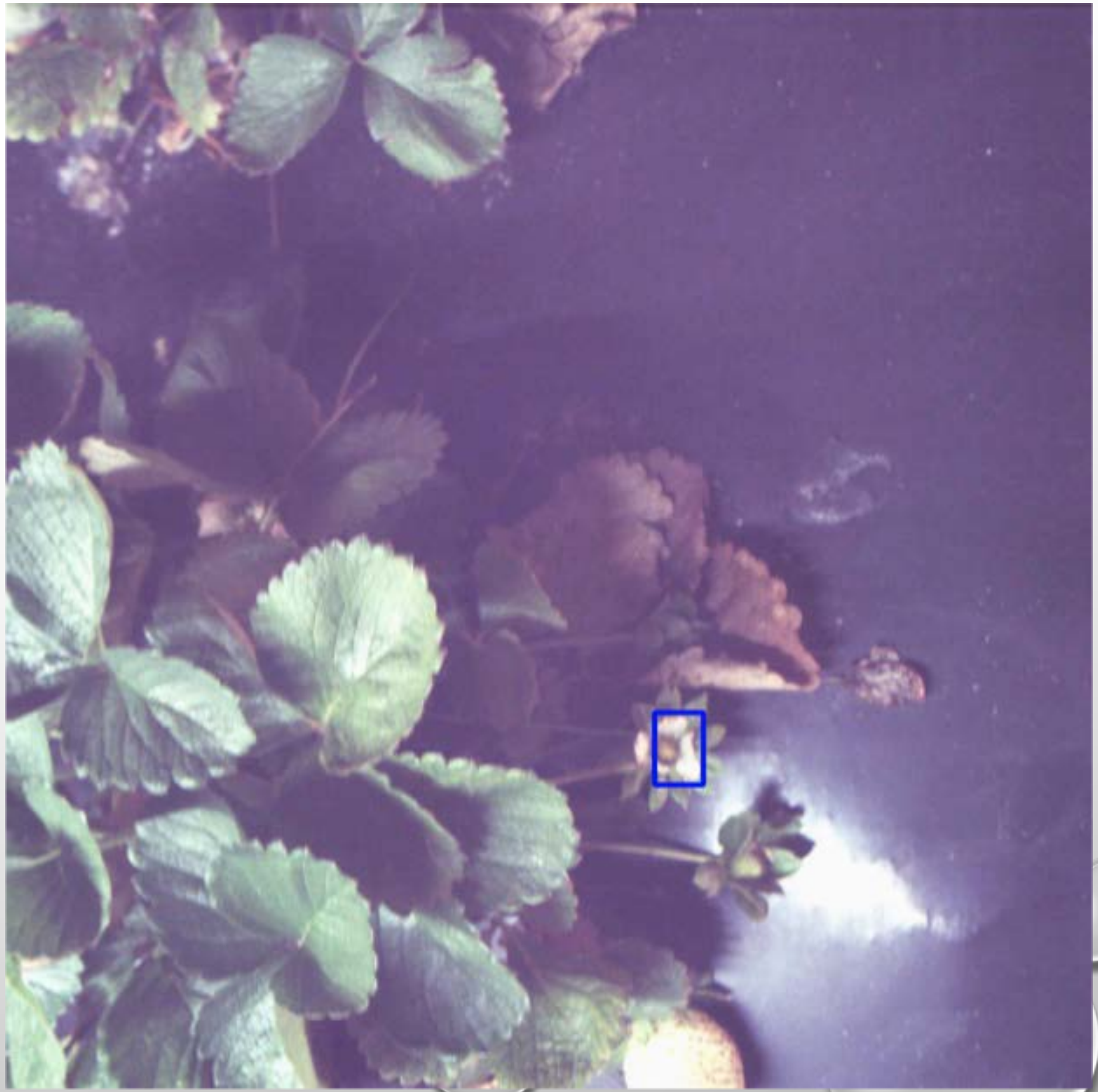
| | TOTAL NUMBER OF FLOWERS | CORRECTLY IDENTIFIED FLOWERS (TRUE POSITIVES) | MISSED FLOWERS (FALSE NEGATIVES) | NON-FLOWER OBJECTS INCORRECTLY IDENTIFIED AS FLOWERS (FALSE POSITIVES) |
|---|---|---|---|---|
| | 400 | 352 | 32 | 15 |
| | 100% | 88% | 8% | 4% |

## Phase II: currently images being analyzed

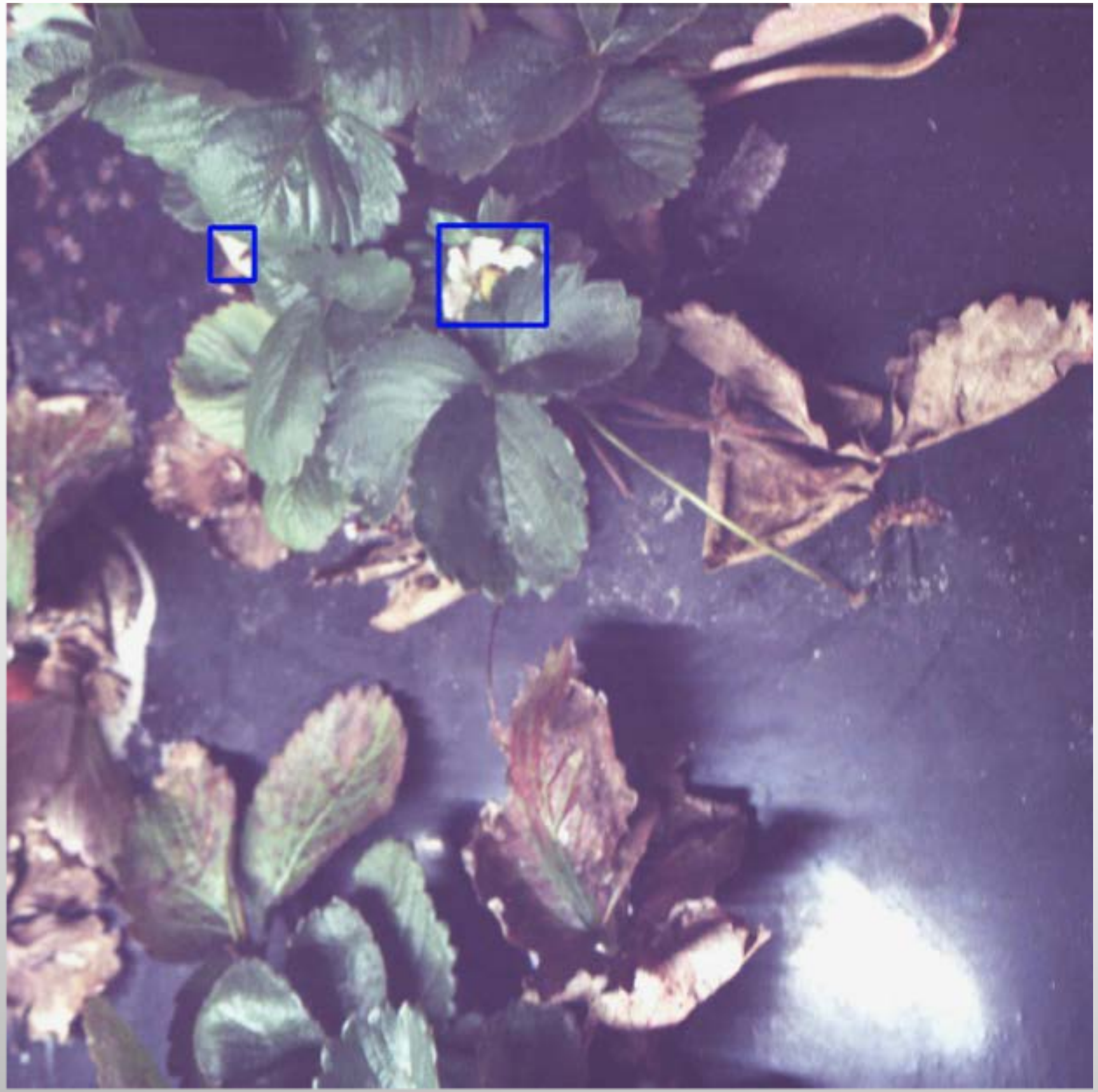
# RESULTS – PHASE I

# RESULTS – PHASE I

# RESULTS PHASE II



# RESULTS PHASE II



# DISCUSSIONS

- Images acquired using commercial cameras for initial experiments
- Effect of imaging conditions on algorithm performance studied
  - Imaging distance
  - Imaging angles – difficult to quantify due to varying flower orientations in scenes
  - Lighting – external lighting – cloudy day, bright sunlight
- Algorithmic improvements for Phase II data in progress

# CONCLUSIONS

- Computer vision algorithms promising for flower detection/counting problem
- Deep Neural Networks (Artificial Intelligence) yield high performance even under challenging conditions
  - Large & rich dataset needed to fine tune model
  - Data collected during phase 2 seems promising to exploit strengths of DNNs
- High-speed data acquisition crucial for strawberry plant imaging
- Mechanical design of imaging cart also has an important role to play in motion blur & hence final image quality

# FUTURE WORK

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# IMAGE RECONSTRUCTION FROM DRONE IMAGES

Aerial View of a portion of strawberry field

Zoomed-in view of Field

# FUTURE WORK

- High speed camera on drone for imaging
- Drone imaging has the possibility of using down-wind to reveal hidden flowers
- A combined ground vehicle and drone imaging system could also lead to overall improved yield estimation accuracy

eBee

# THANK YOU!