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Monitoring Plant Growth using Computer Vision

Contributing Writer

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Monitoring Plant Growth using Computer Vision

The article below was contributed by [Timothy Malche](#), an assistant professor in the Department of Computer Applications at Manipal University Jaipur.

Measuring plant growth is essential for several reasons in agricultural, ecological, and scientific contexts. For example, plant growth metrics provide valuable information for use in optimizing crop

yield, managing ecosystems, studying environmental changes, and conducting research in plant biology.

In the field of biotechnology, researchers use plant growth measurements to assess the effects of genetic modifications and to develop crops with improved traits, such as resistance to pests, diseases, or environmental stress.

There are a few metrics used in monitoring plant growth, which include:

- Height measurement
- Leaf area measurement
- Biomass measurement
- Stem diameter measurement
- Root growth measurement

In this blog post we will show how computer vision can be used to monitor plant growth. We will focus on the height measurement technique.

Methodology

First, a camera sensor node is used to acquire an image of the plant. Subsequently, a computer vision model is used to process the image, extracting relevant features and calculating the plant's height, which is then returned as an output. While acquiring the plant images using a camera, the camera height, distance, angle is an important factor.

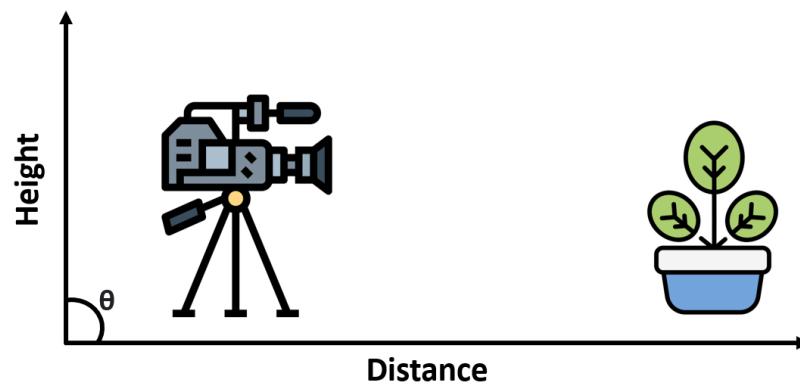


Fig 1: Camera Setup for Monitoring Plant Height

To determine the height of a plant in an image using computer vision, following steps are used

- Calibrate the camera height and distance from the plant and a reference object (6-inch object in our case) from the same perspective and distance as plant images.
- Train the computer vision model using an object detection algorithm to identify both the reference object and the plant in the images.
- Extract the bounding boxes for the detected reference object and the plant.
- Calculate the pixel height of the reference object's bounding box in the image. Use the known physical height of the reference object (6 inches in our example) to establish a pixel-to-inch conversion factor.

- Apply the conversion factor to the pixel height of the plant's bounding box to obtain the actual height of the plant.

Keep in mind that lighting conditions and image quality can also affect accuracy, and fine-tuning may be required for optimal results.

Using the technique present in this post, either single plant can be monitored,

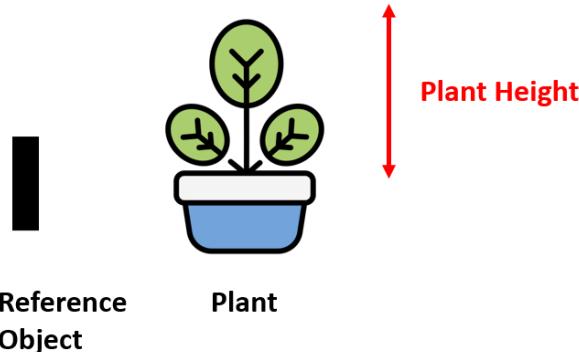


Fig 2: Setup for Monitoring Single Plant

Or, multiple plants can also be monitored with the help of a single reference object given that it should fit in the camera frame.

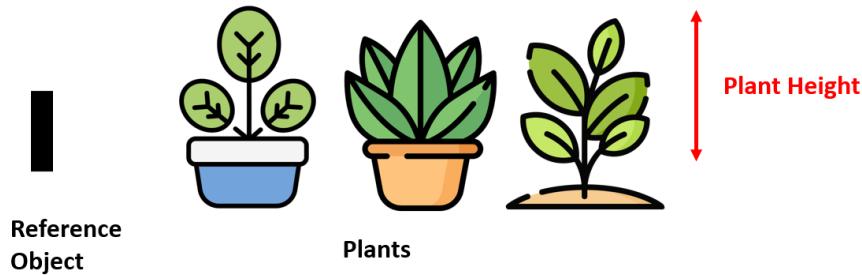


Fig 3: Setup for Monitoring Multiple Plants

Steps for Building the Project

To build this project, we will follow these steps:

1. Collect and label a dataset of plants
2. Train an object detection model
3. Run Inference to obtain bounding box details
4. Write an algorithm to calculate the height of the plant

Step #1: Collect and label a dataset of plants

Images dataset of the plant at different intervals has been collected manually as shown below:



Fig 4: Plant Dataset

The images are then uploaded to [Roboflow platform](#) and are labelled using the bounding boxes. Both the plant and the reference objects are labelled, as shown below.

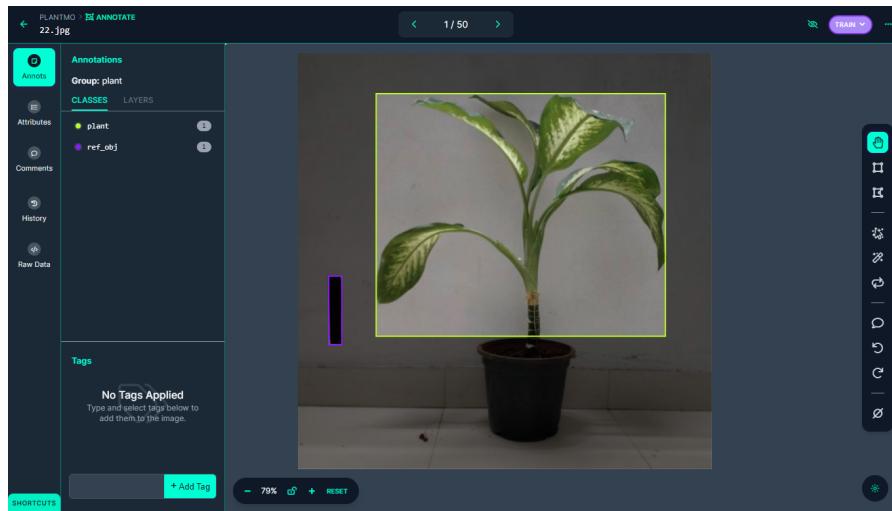


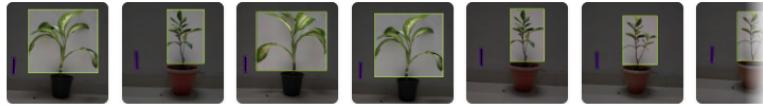
Fig 5: Dataset Labelling using Roboflow's Annotation Tool

Step #2: Train the Model

After labelling is done, the dataset version is generated and the model is trained using Roboflow auto-training option.

Dataset Details

50 Total Images



[View All Images →](#)

Dataset Split

TRAIN SET	74%
37 Images	

VALID SET	22%
11 Images	

TEST SET	4%
2 Images	

Preprocessing

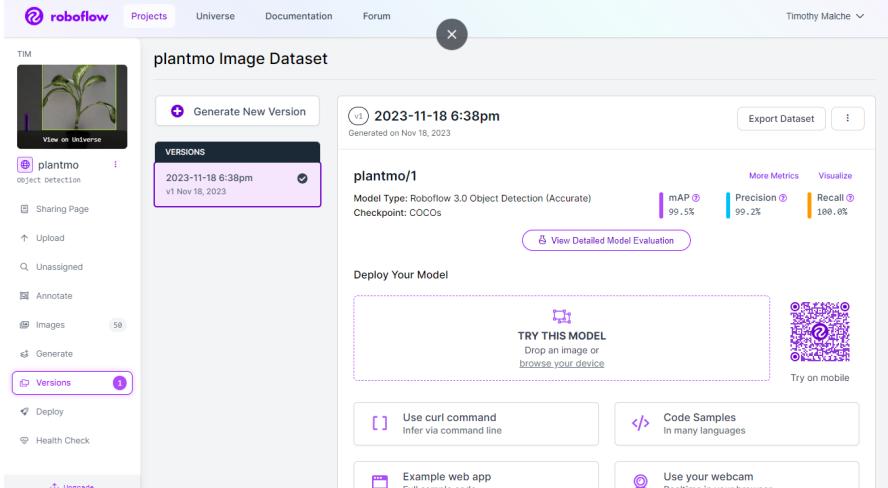
- Auto-Orient: Applied
- Resize: Stretch to 800x800

Augmentations

No augmentations were applied.

Fig 6: Generated Dataset

The training accuracy achieved is 99.5%.



plantmo Image Dataset

v1 2023-11-18 6:38pm
Generated on Nov 18, 2023

plantmo/1

Model Type: Roboflow 3.0 Object Detection (Accurate)
Checkpoint: COCOs

mAP 99.5% | Precision 99.24% | Recall 100.0%

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Fig 7: Training Metrics

The following training graph visualizes how the model was trained.

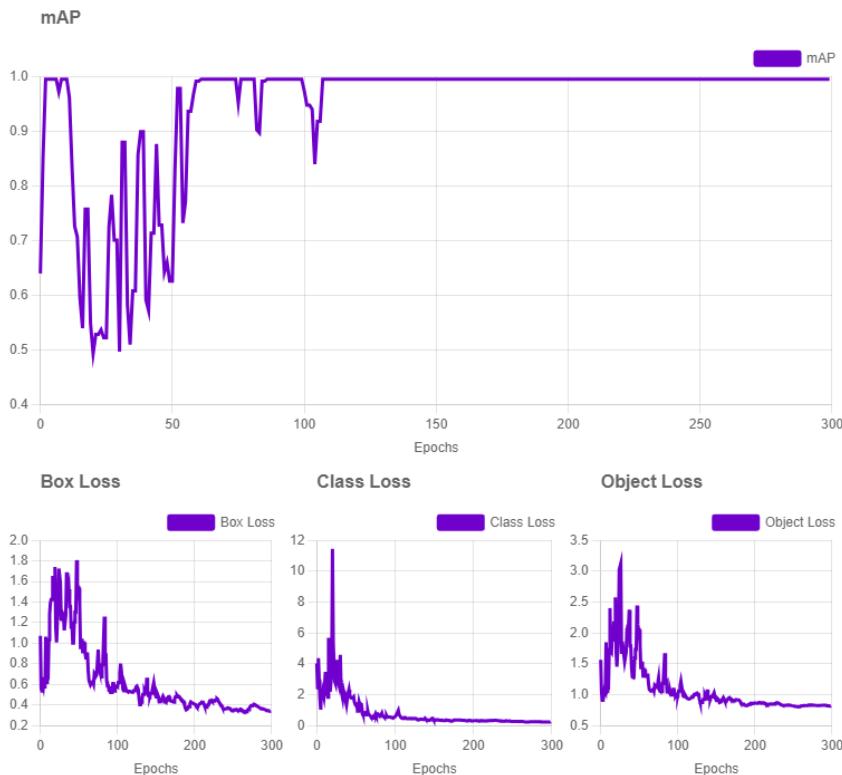


Fig 8: Training Graphs

Step #3: Run inference to obtain bounding box details

After training the model, [Roboflow inference API](#) is used to run inference and obtain the bounding box details. The following predict() function from the Roboflow Python SDK is used which returns the bounding box details in JSON format

```
model.predict("/content/50.jpg", confidence=80, overlap=50).json()
```

Using [Roboflow Python SDK](#), an algorithm is developed which writes the resultant JSON values in a .json file required for later use.

You can install the Roboflow Python SDK using the following command:

```
pip install roboflow
```

The following code illustrates how it is done.

```
1  from roboflow import Roboflow
2  import json
3
4  from roboflow import Roboflow
5  rf = Roboflow(api_key="YOUR_API_KEY")
6
```

```

7   project = rf.workspace("tim-4ijf0").project("plant-monitoring-oxvkg")
8   model = project.version(1).model
9
10  predictions_json = model.predict("50.jpg", confidence=40, overlap=30).json()
11
12  output_json_path = '/content/detection_results.json'
13
14  with open(output_json_path, 'w') as json_file:
15      json.dump(predictions_json, json_file, indent=2)
16
17  print(f"Predictions saved to {output_json_path}")

```

The generated detection_results.json file contains data in following format:

```

1  {
2      "predictions": [
3          {
4              "x": 428.0,
5              "y": 294.5,
6              "width": 280.0,
7              "height": 395.0,
8              "confidence": 0.9443135261535645,
9              "class": "plant",
10             "class_id": 0,
11             "image_path": "50.jpg",
12             "prediction_type": "ObjectDetectionModel"
13         },
14         {
15             "x": 86.0,
16             "y": 450.5,
17             "width": 26.0,
18             "height": 137.0,
19             "confidence": 0.8782252073287964,
20             "class": "ref_obj",
21             "class_id": 1,
22             "image_path": "50.jpg",
23             "prediction_type": "ObjectDetectionModel"
24         }
25     ],
26     "image": {
27         "width": "800",
28         "height": "800"
29     }
30 }

```

The Roboflow python SDK returns the values in following format which has been stored in detection_results.json file

- x = the horizontal center point of the detected object

- y = the vertical center point of the detected object
- width = the width of the bounding box
- height = the height of the bounding box
- class = the class label of the detected object
- confidence = the model's confidence that the detected object has the correct label and position coordinates

Here, the x, and y coordinates represents center point of the detected object. When visualizing the bounding boxes in the resultant image using the values from detection_results.json file, the center coordinates needs to be converted to corner points as done in the step 4.

Step #4: Write algorithm to calculate the plant height

In this step we calculate the height of the plant. An algorithm is written to calculate the height of the plant by reading the values from detection_results.json file and visualize the result using bounding boxes.

First define functions to calculate the pixel height and establish the conversion factor.

```

1 def calculate_pixel_height(bbox):
2     return bbox['height']
3
4 def establish_conversion_factor(reference_height, reference_pixel_height):
5     return reference_height / reference_pixel_height

```

Then write algorithm to calculate the height of the plant and visualize the result. The following function process_object_detection_results() first read the detection_results.json file to extract the bounding box information for reference object and plant using following lines of code

```

1 reference_bbox = next(item for item in detection_results['predictions'] if item['class'] == 'ref_obj')
2
3 plant_bbox = next(item for item in detection_results['predictions'] if item['class'] == 'plant')

```

Then calculate_pixel_height() function is called which uses reference objects bounding box details passed to it as parameter to calculate the pixel height:

```
reference_pixel_height = calculate_pixel_height(reference_bbox)
```

After this the establish_conversion_factor() function is invoked with actual physical height of the reference object, 6 inch in this case, and pixel height of the reference object calculated above in order to determine pixel to inch conversion factor.

```

1 reference_height_inches = 6
2

```

```
conversion_factor = establish_conversion_factor(reference_height_inches, reference_pixel_height)
```

Then the pixel height of the plant is also calculated and the obtained conversion factor is used to map the pixel height of the plant to inches, which is our resultant value.

```
1 plant_pixel_height = calculate_pixel_height(plant_bbox)
2 plant_height_inches = plant_pixel_height * conversion_factor
```

Finally, the bounding boxes are generated on the output image. The following lines of code are used to convert the center points (x, y) of both reference object and plant object to top left corner points (x1, y1) of the bounding boxes to properly visualize the bounding boxes from the inference prediction, as specified in [this](#) section.

```
1 xr = reference_bbox['x'] - (reference_bbox['width']/2);
2 yr = reference_bbox['y'] - (reference_bbox['height']/2)
3 reference_box = [
4
5     round(xr),
6     round(yr),
7     round(xr + reference_bbox['width']),
8     round(yr + reference_bbox['height'])
9 ]
10
11 xp = plant_bbox['x'] - (plant_bbox['width']/2);
12 yp = plant_bbox['y'] - (plant_bbox['height']/2);
13 plant_box = [
14     round(xp),
15     round(yp),
16     round(xp + plant_bbox['width']),
17     round(yp + plant_bbox['height'])
18 ]
```

The labels on the bounding boxes are then specified and output image is generated.

```
1 cv2.rectangle(image, (reference_box[0], reference_box[1]), (reference_box[2], reference_box[3]), (0, 0, 255), 2)
2
3 cv2.rectangle(image, (plant_box[0], plant_box[1]), (plant_box[2], plant_box[3]), (0, 0, 255), 2)
4
5 font = cv2.FONT_HERSHEY_SIMPLEX
6 label_y_offset = 20
7 cv2.putText(image, f"Reference Object Height: {reference_height_inches} inches", (reference_box[0],
8 font, 0.5, (0, 255, 0), 2, cv2.LINE_AA)
9
10 cv2.putText(image, f"Plant Height: {plant_height_inches:.2f} inches", (plant_box[0], plant_box[1] -
11 font, 0.5, (0, 0, 255), 2, cv2.LINE_AA)
12
```

13

```
cv2.imwrite(output_path, image)
```

The following is the output image generated by the algorithm which draws bounding boxes on each object and writes height details above bounding boxes.

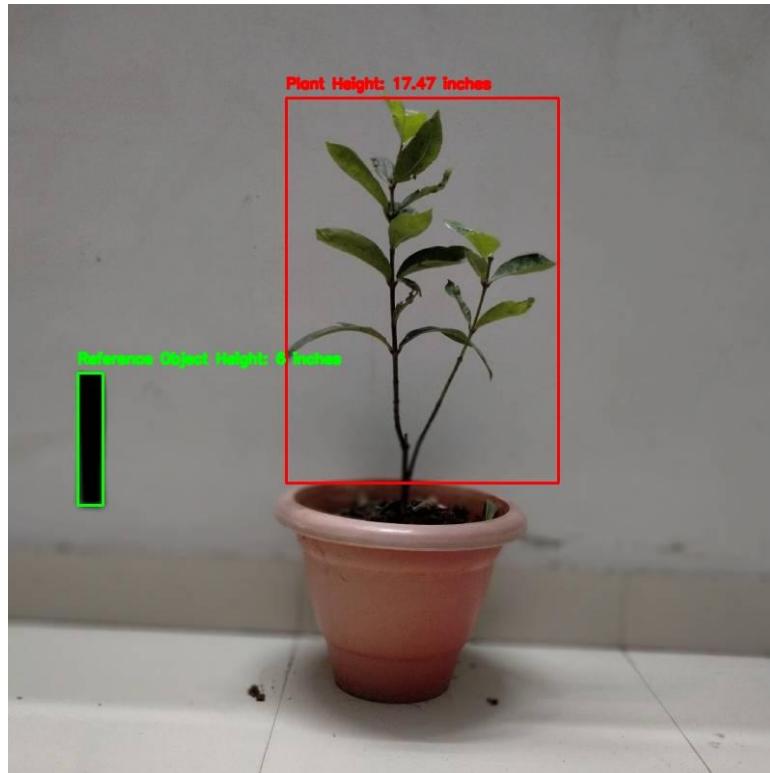


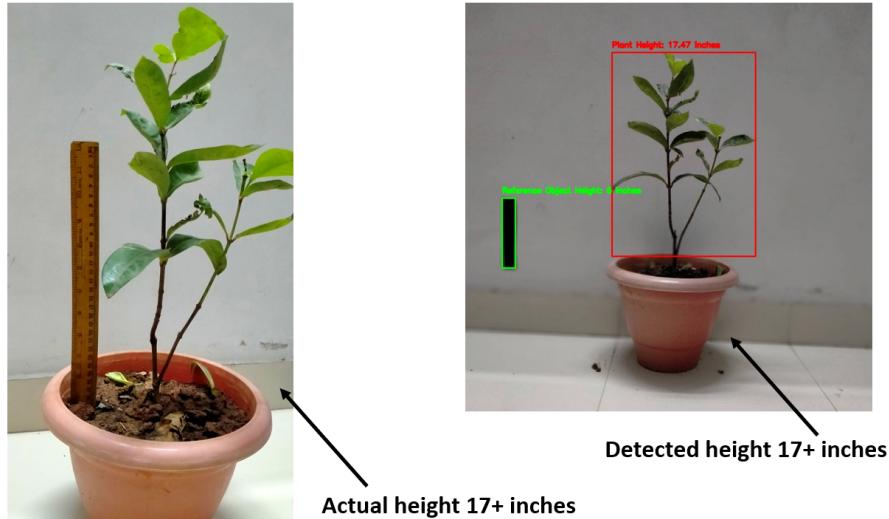
Fig 9: Model Result on Test Data

Here is an example of our model running on another plant:



Fig 10: Model Result on New Data

Comparing the above output images to real physical measurements of the plant, we can clearly see that the algorithm is accurately calculating the height of the plant.



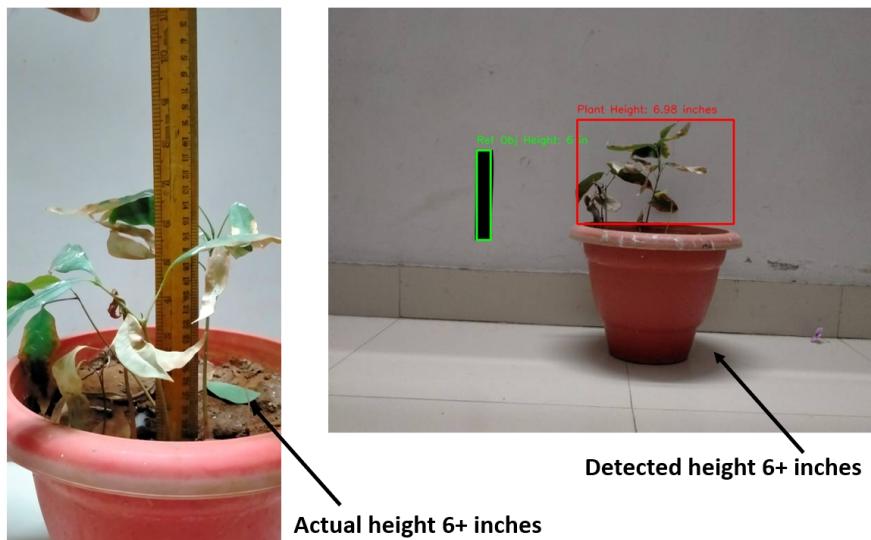


Fig 11: Comparison of Actual Physical Measurement with Results Generated by Model

These results demonstrate that the model accurately detects objects, and the algorithm designed to calculate plant height performs with precision.

Conclusion

In this project, we implemented a computer vision pipeline for plant height measurement using computer vision.

Using object detection results from a computer vision model, our code extracts information about the reference object and plant, calculates their heights in inches, and annotates the original image with labelled bounding boxes. The resulting annotated images provide a visual representation of the measured plant heights, offering valuable insights for agricultural and research applications.

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[NeurIPS 2023 Papers](#) highlights steps in this breakthrough which enables scientists to study growth patterns, and conduct experiments in plant biology and strategies based on accurate plant height data.

DEC 21, 2023

[How to Deploy Computer Vision AWS](#) the effects of environmental changes on crop management

DEC 20, 2023

[Computer Vision Use Cases in Industry](#) GitHub. The developer of Roboflow Universe.

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[Detecting Complex and Amorphous Features of Marine Sponges](#) is

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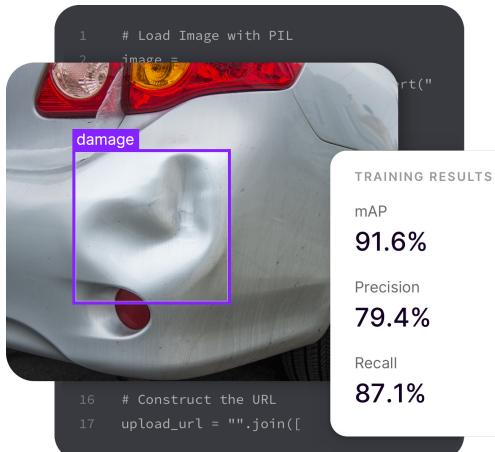
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