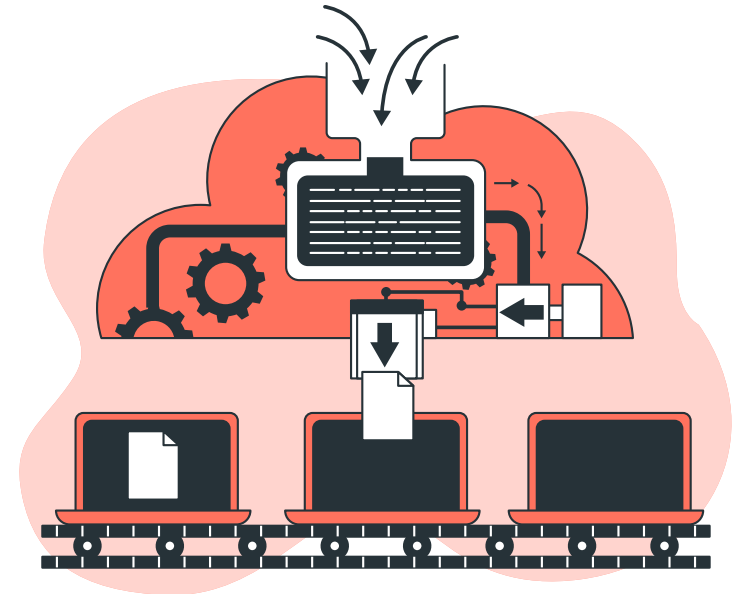


Automated Citrus Sorting System

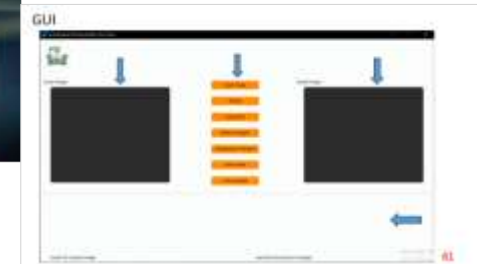
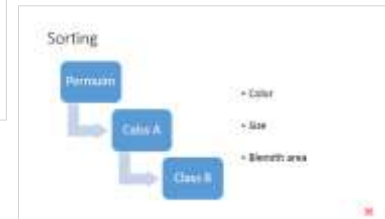
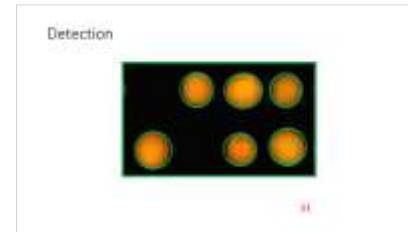
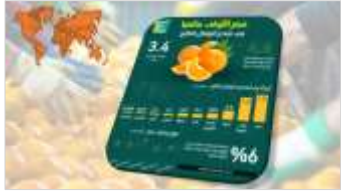
Dr. Mohamed Azzam

Automated Citrus Sorting System

- Dr. Mohamed Azzam



Outline





مصر الأولى عالميا في تصدير البرتقال الطازج

3.4

مليون طن إنتاج
مصر



4.4

مليون طن برتقال طازج
تم تصديرها عالميا في
موسم 2021/2020

أبرز الدول المصدرة للبرتقال الطازج «مليون طن»



تطور صادرات مصر «مليون طن»



انخفاض متوقعا في إنتاج مصر من
البرتقال بسبب ارتفاع درجات الحرارة
والرياح القوية

6%

المصدر: وزارة الزراعة الأمريكية



manual sorting



Automatic sorting



Target



Our Process



**Capture
images**



**M aking
enhancements**



**Detect
defects**



Classification

Industrial companies that work in this domain

GREEFA

iscansorter

Reemoon



Background Removal

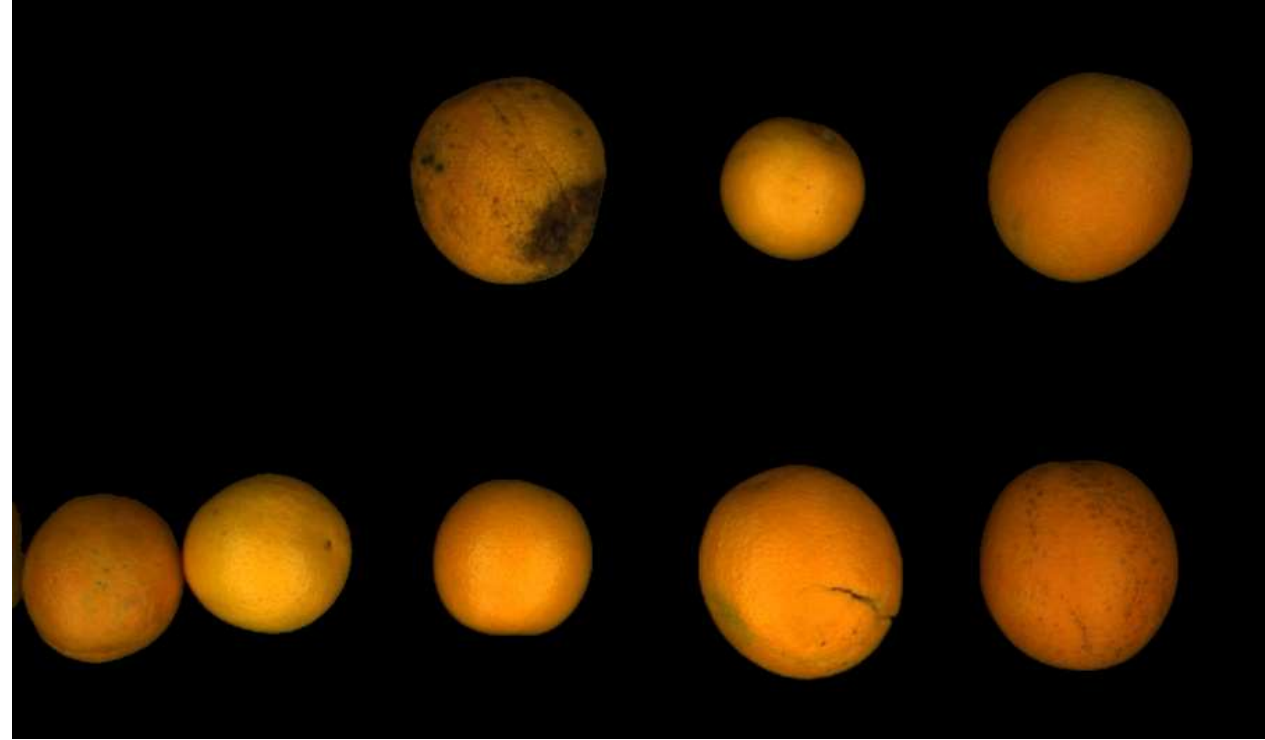


Background Removal: Introduction

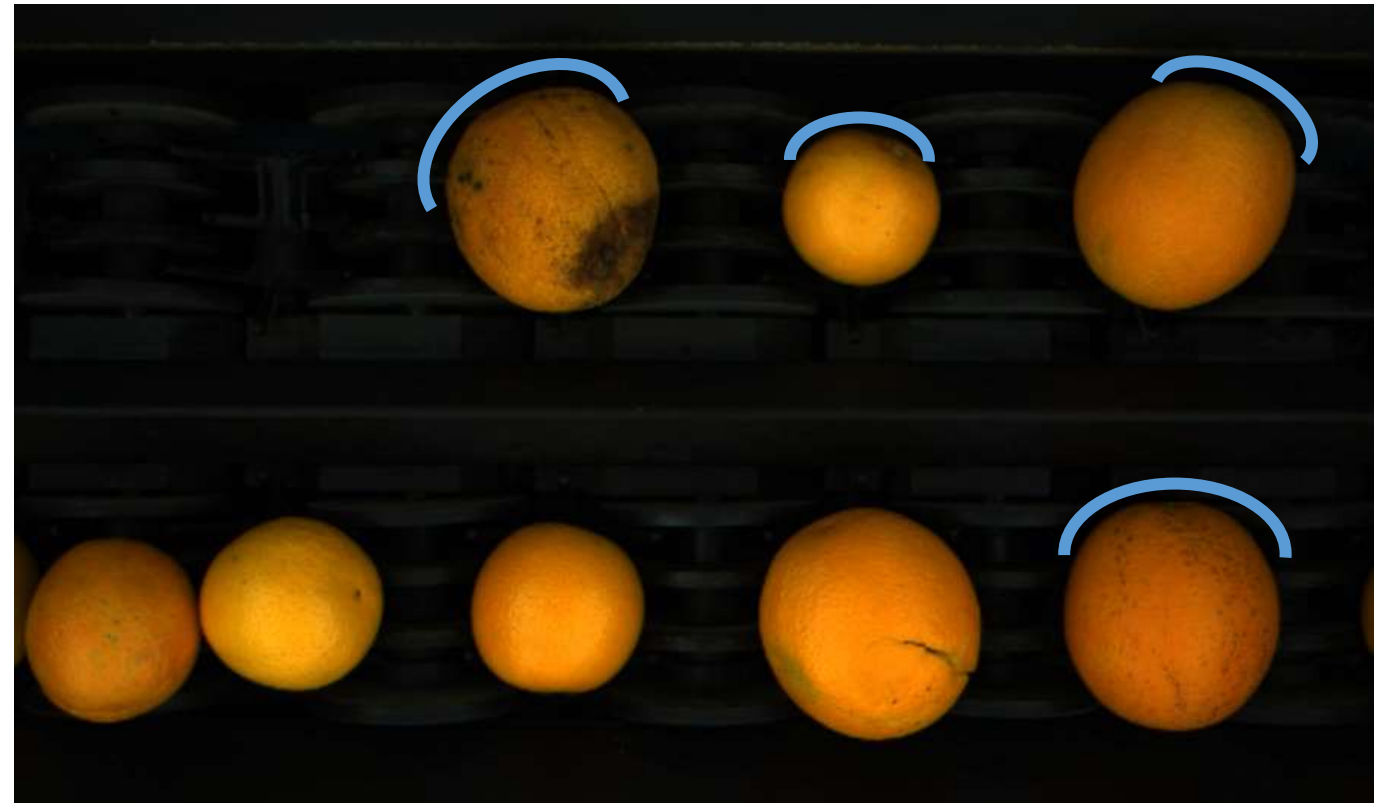
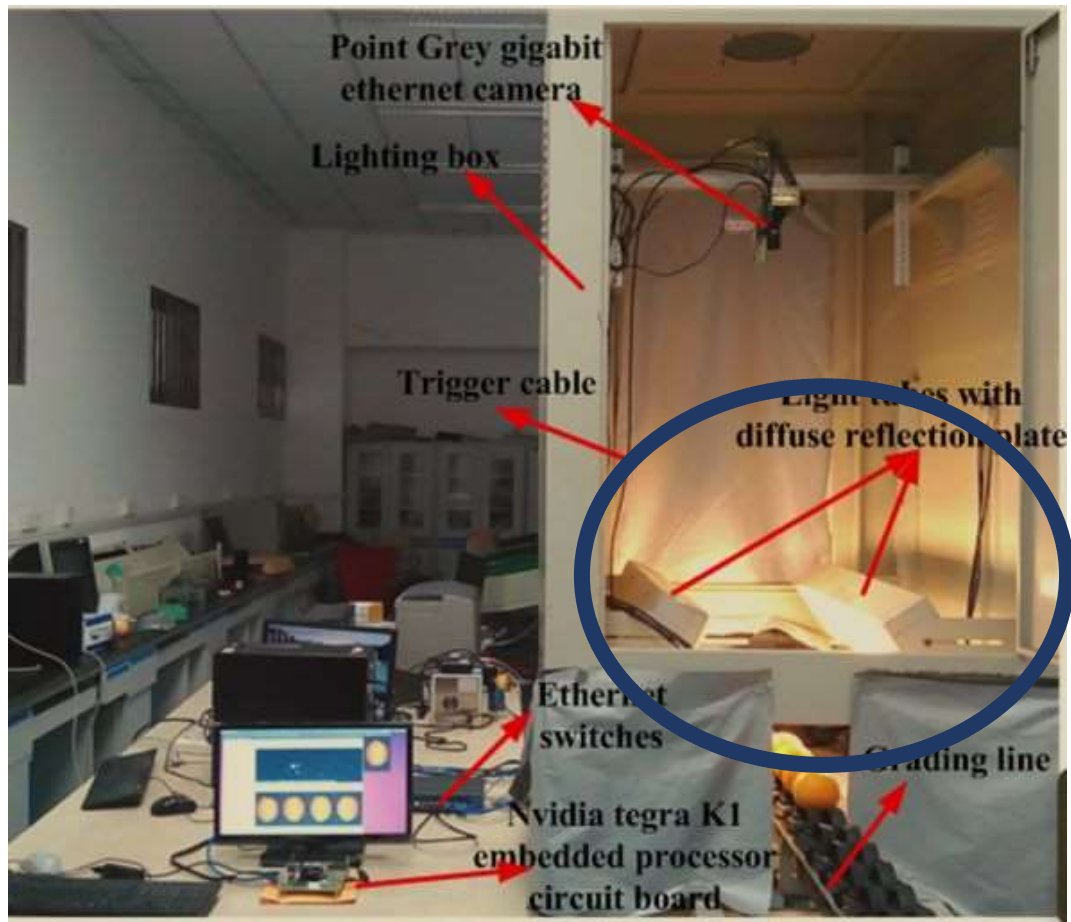
Input image



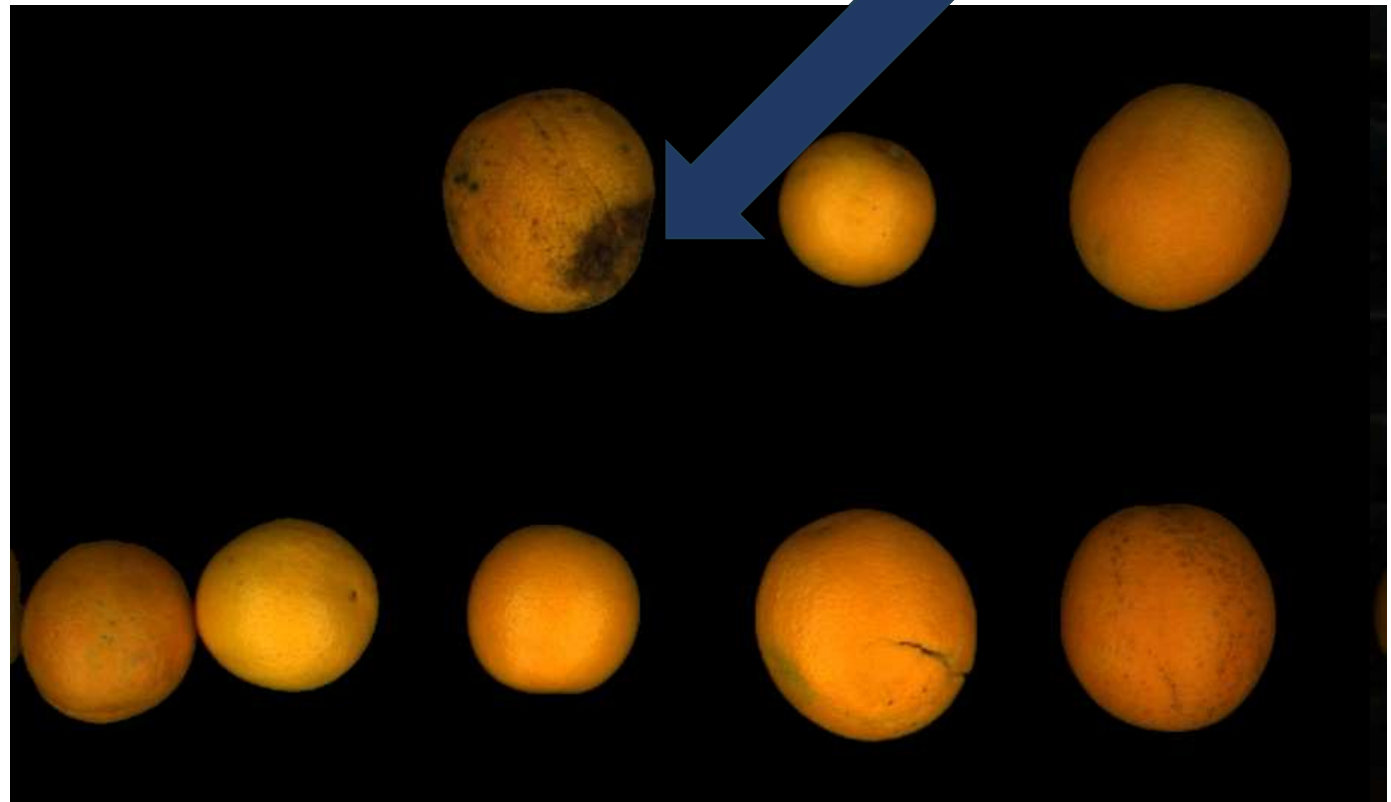
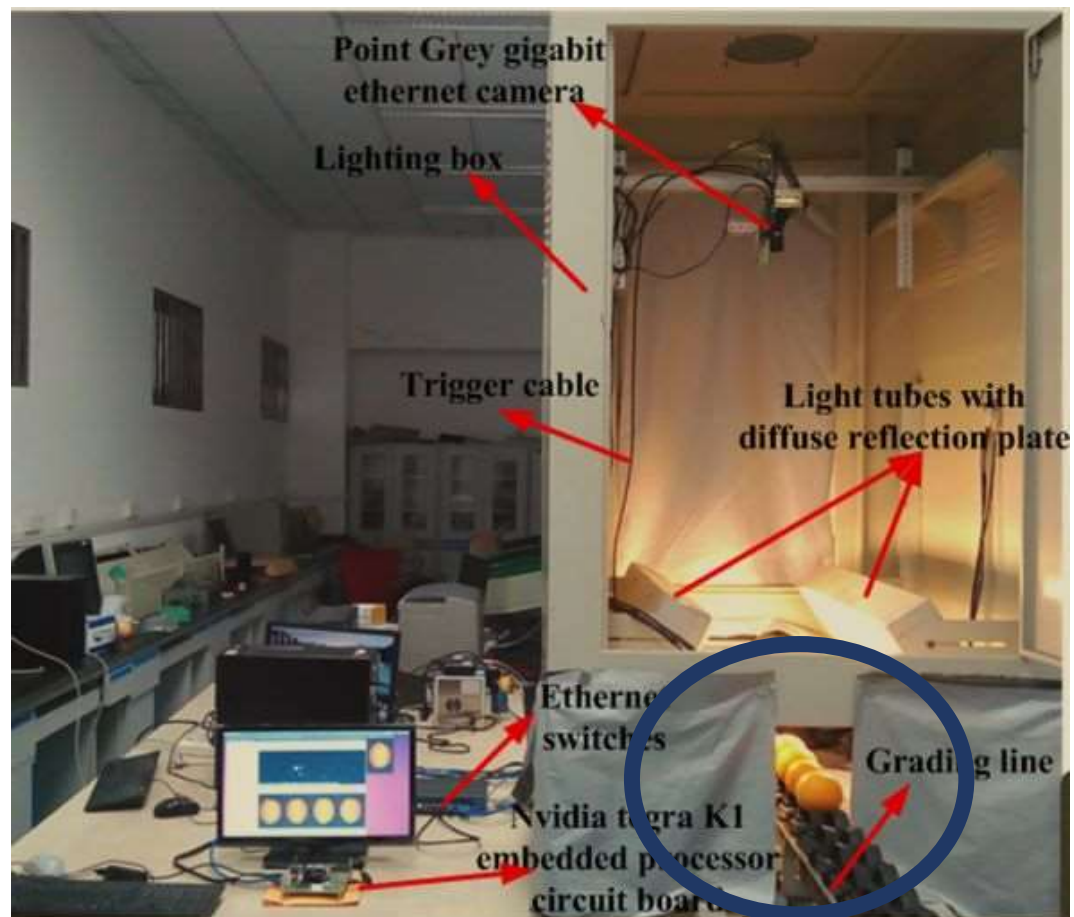
Result



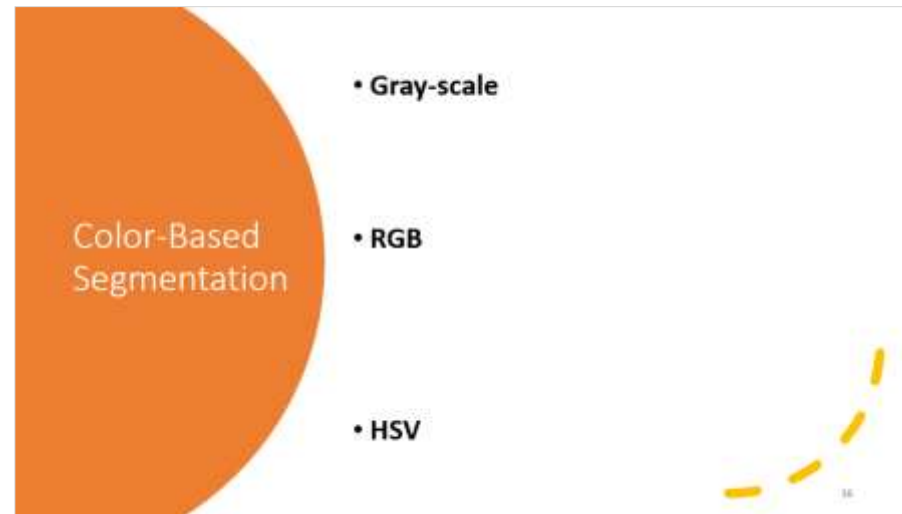
Background Removal: Lightness challenge



Background Removal: Defect Color



Background Removal: Approaches



GrabCut Algorithm



GrabCut: Interactive Foreground Extraction

Input image



Result





Color-Based Segmentation

- **Gray-scale**
- **RGB**
- **HSV**

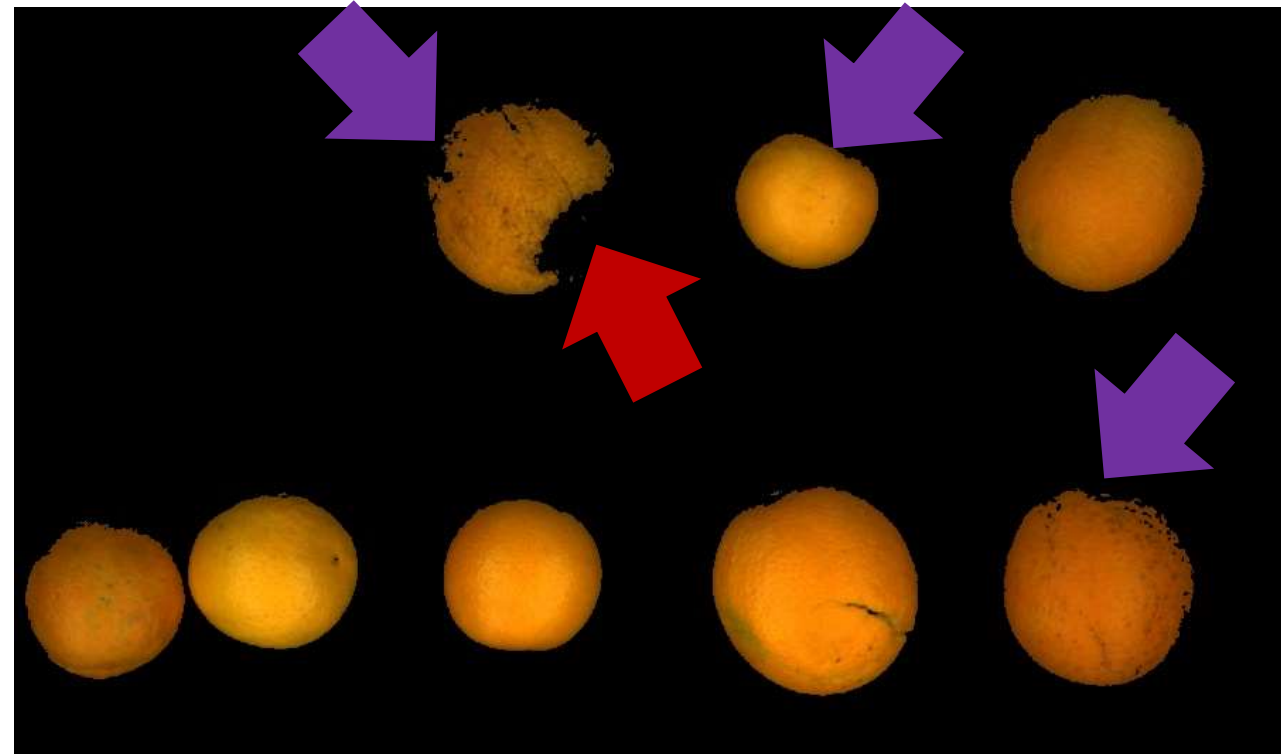


Color-based Segmentation: Gray-scale

Input image



Result



Color-based Segmentation: RGB

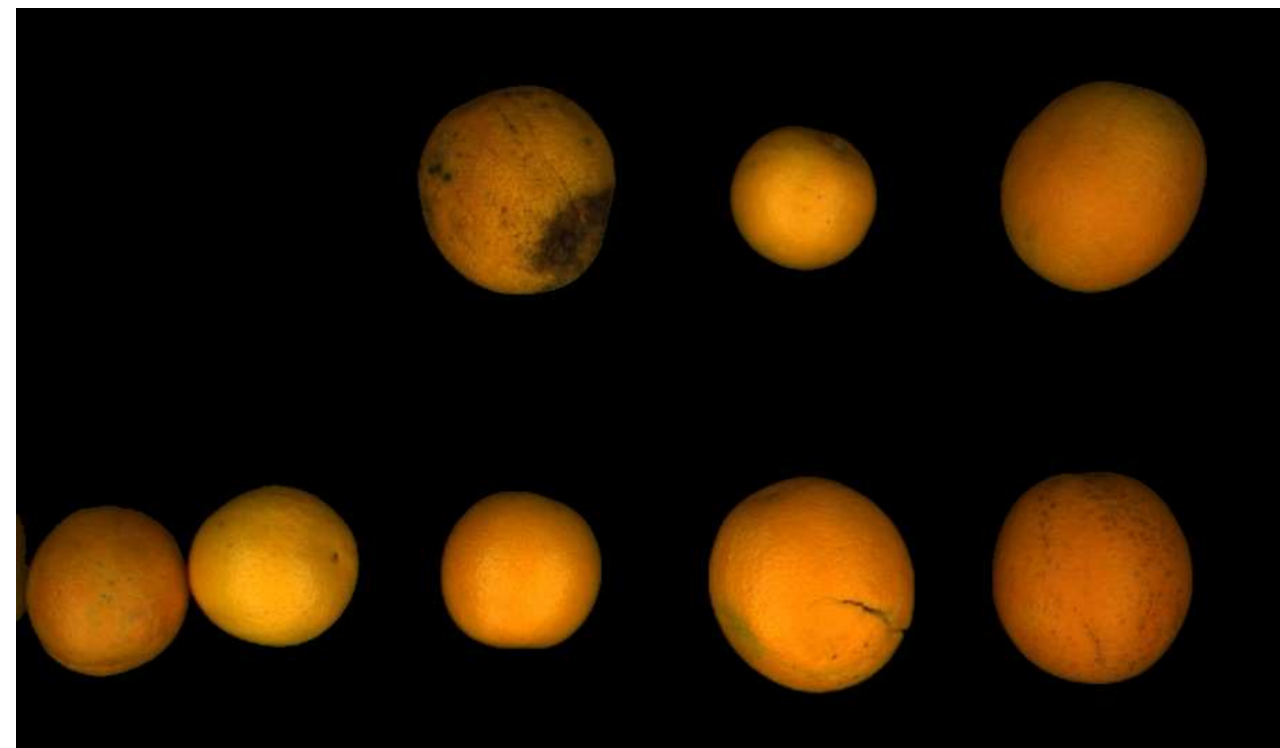


Color-based Segmentation: HSV

Input image



result

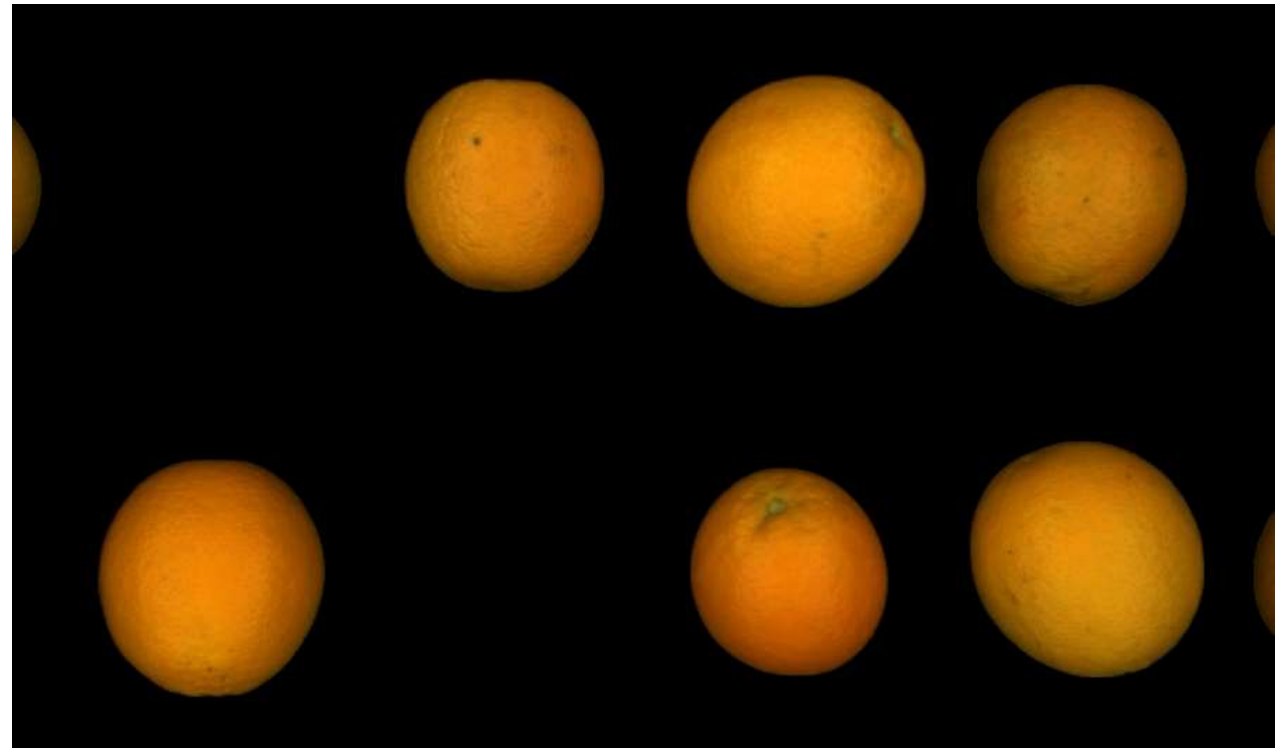


Color-based Segmentation: HSV

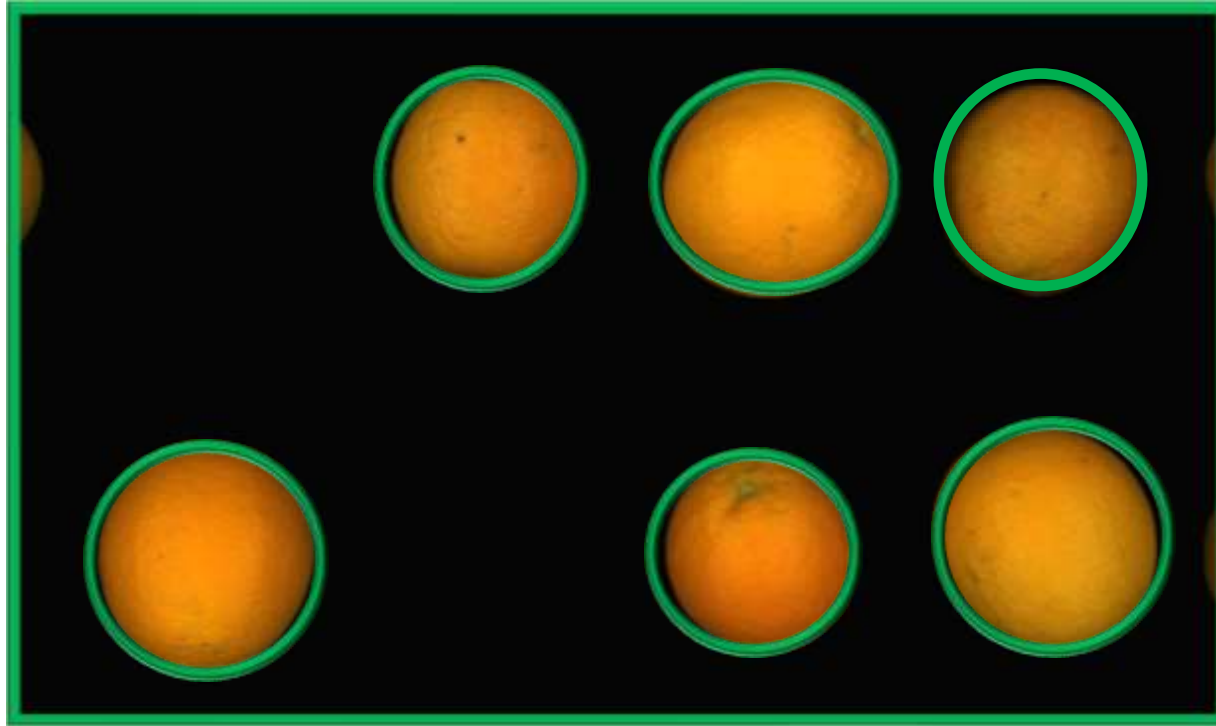
Input image



result



Detection



Detection Ways

- Hough Circle Transform
- HSV Space Detection
- Circularity and Ellipticity



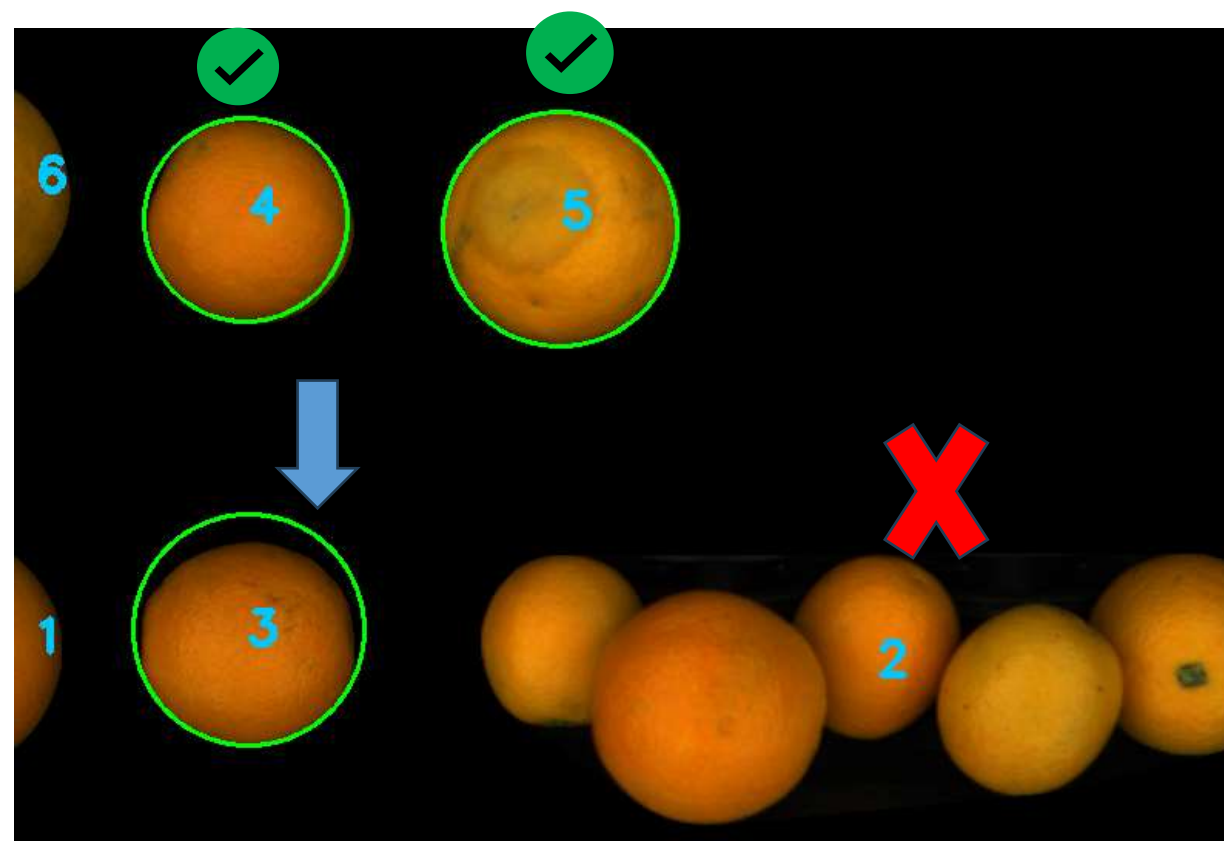
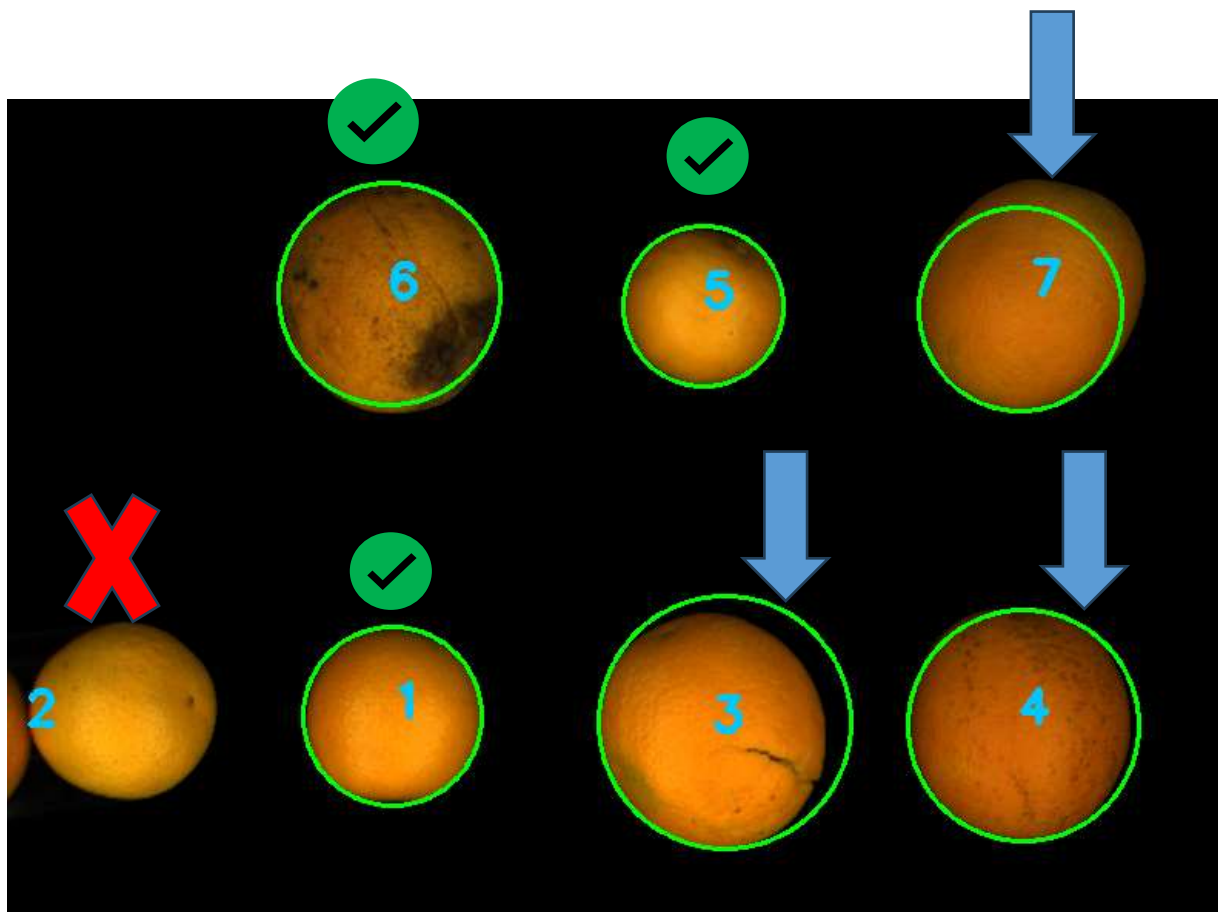
Hough Circle Transform

Main idea

- Converting the image from a Cartesian coordinate system to a polar coordinate system
- Then searches for circles by identifying patterns.
- Each edge pixel in the image accumulates votes for possible circle centers.

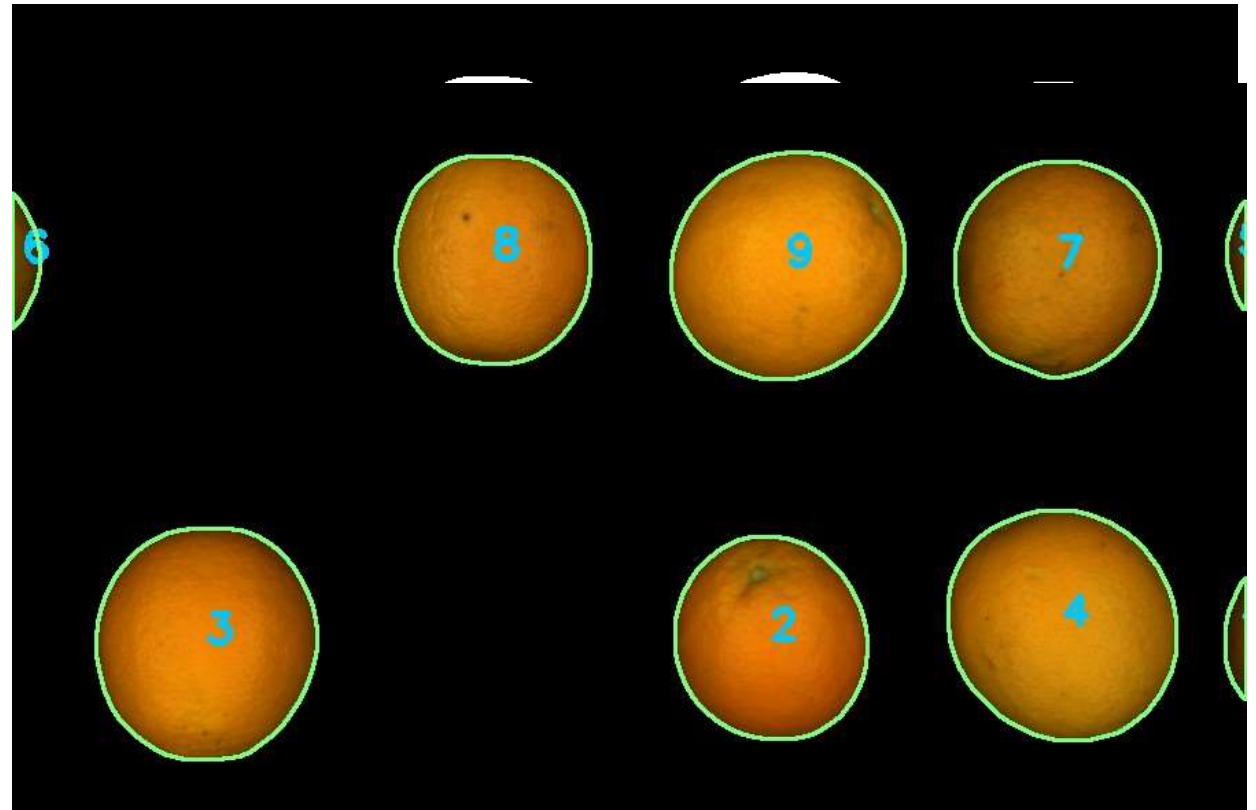


Output



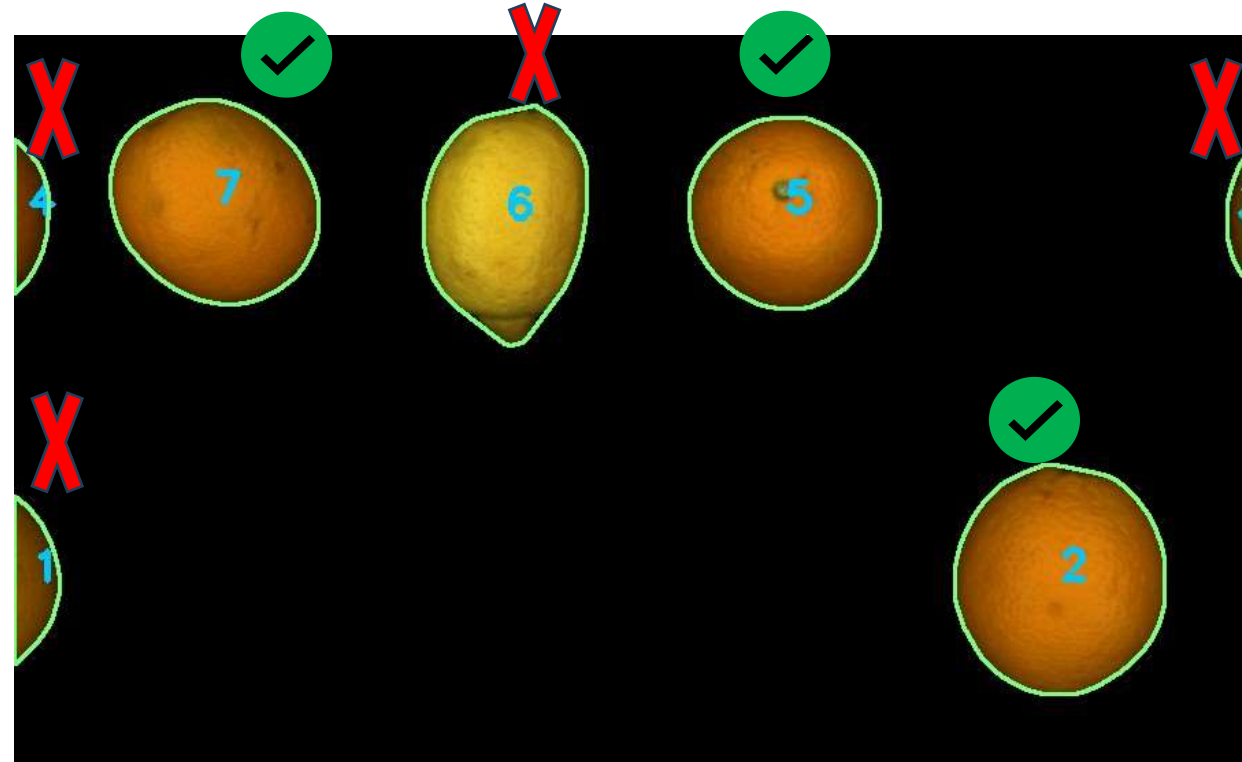
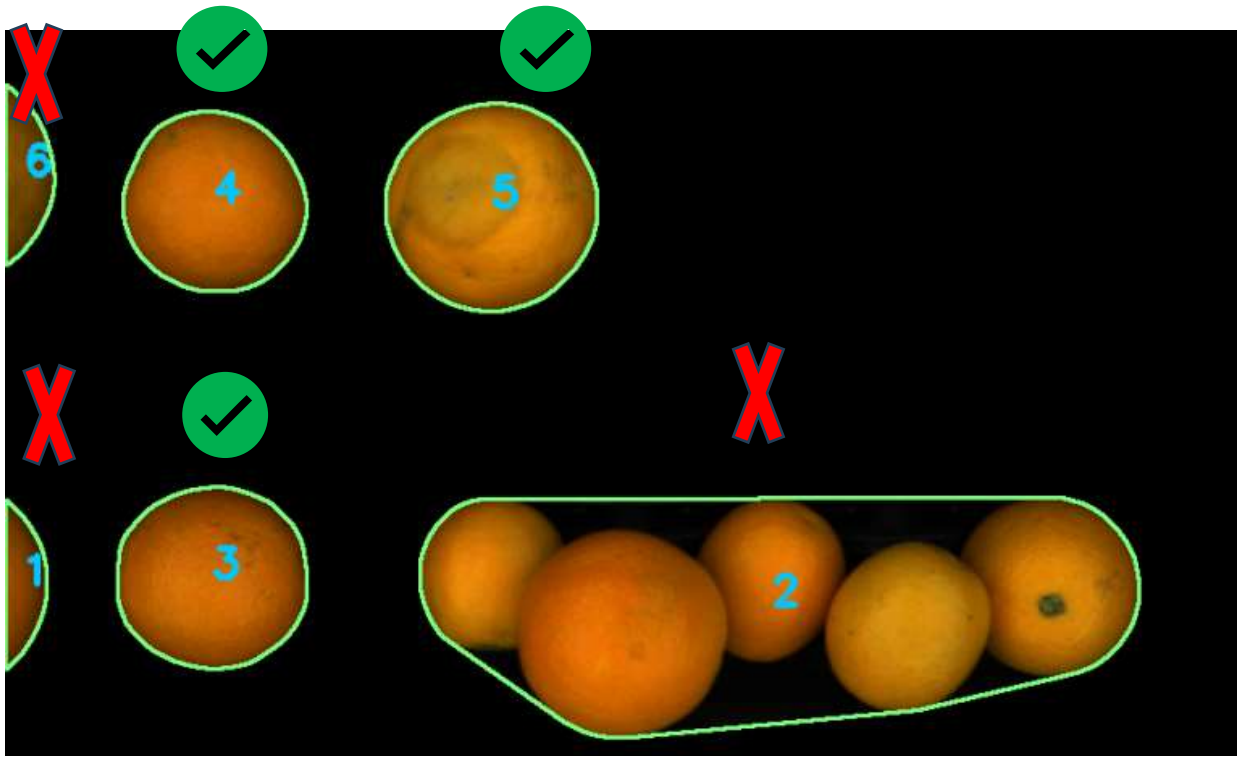
HSV Space Detection

- Take masked image from segmentation
- Search for contours
- Draw contours



Output

- Perfectly detect all contours
- There are no wanted and overlapped detected





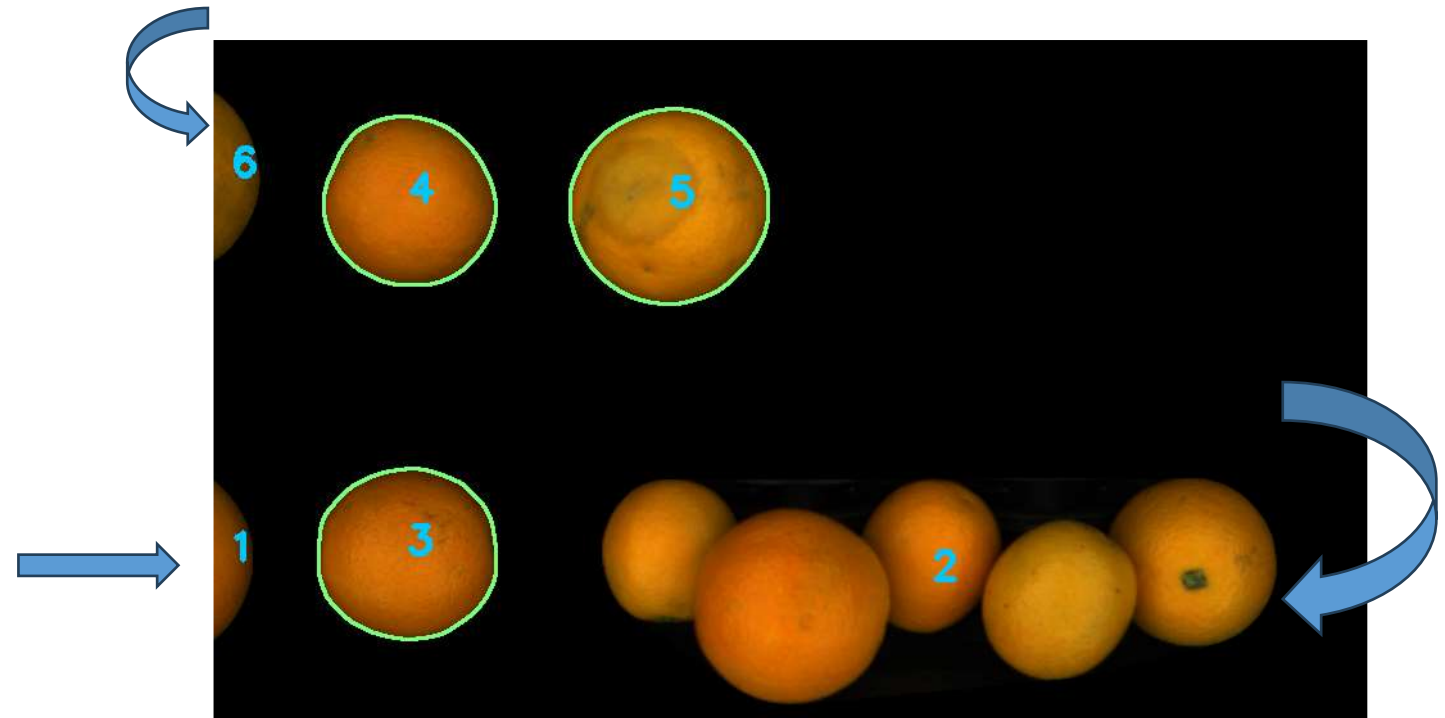
Overlapping

- HSV Area constrain
- Euclidean distance
- Circularity & Ellipticity

HSV Area constrain

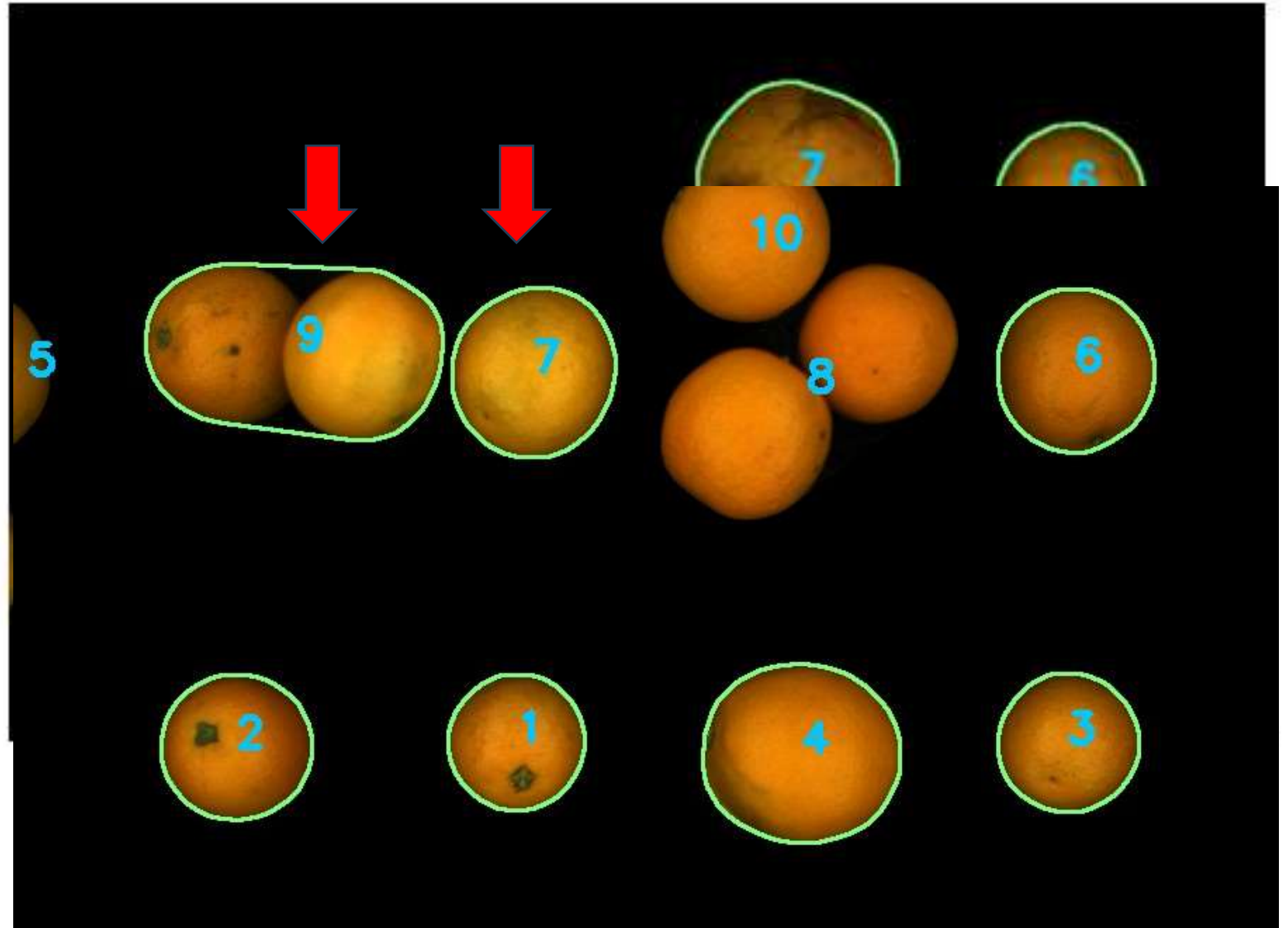
- Take Contour in the range 5000 to 25000

- Solve small and big contours



HSV Area constrain Problems

- Overlapped
Contour < 25000
- Near contours

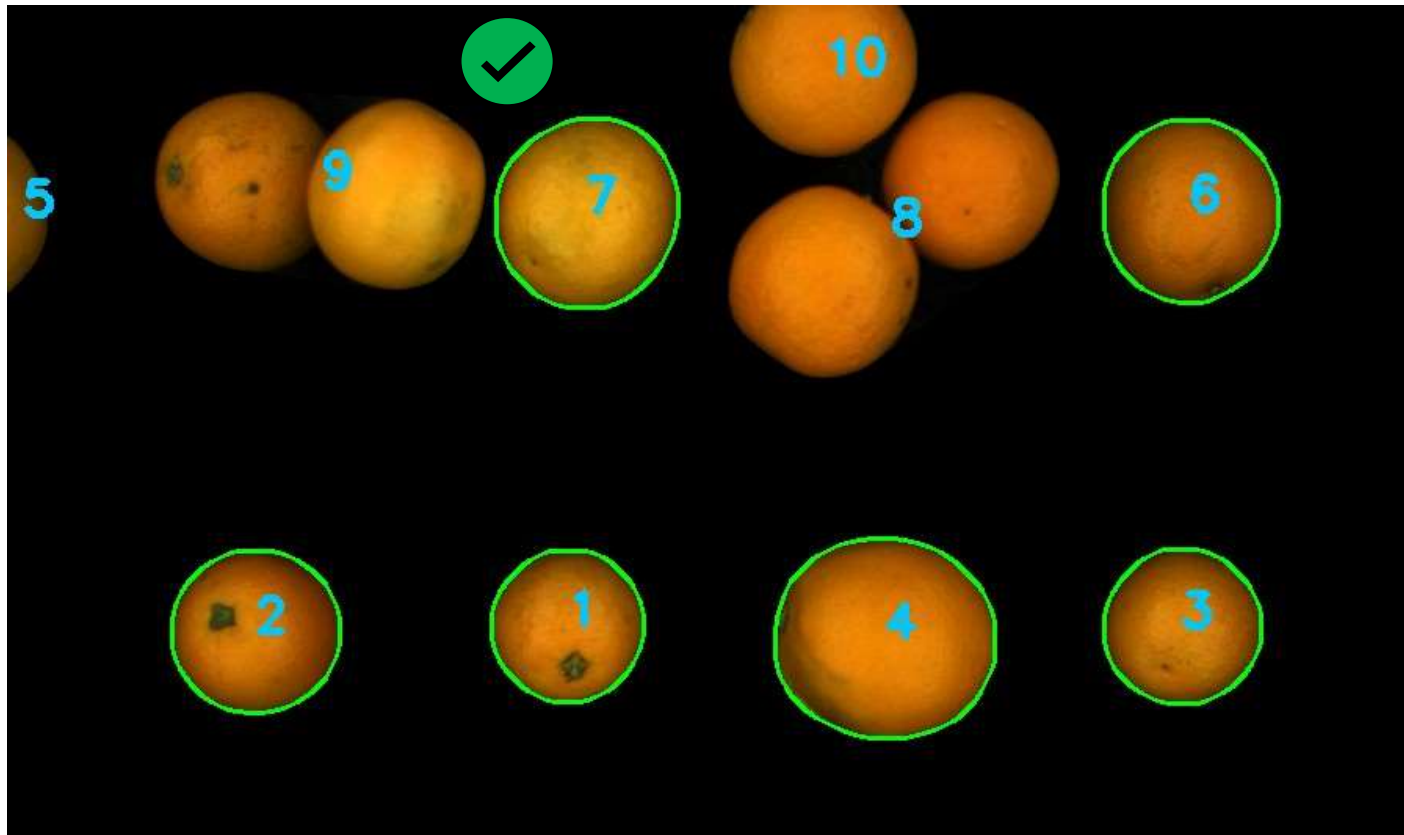


Euclidean distance

- Calculate the distance between the two centers
- $d = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2}$.
- Ignore the nearest centers

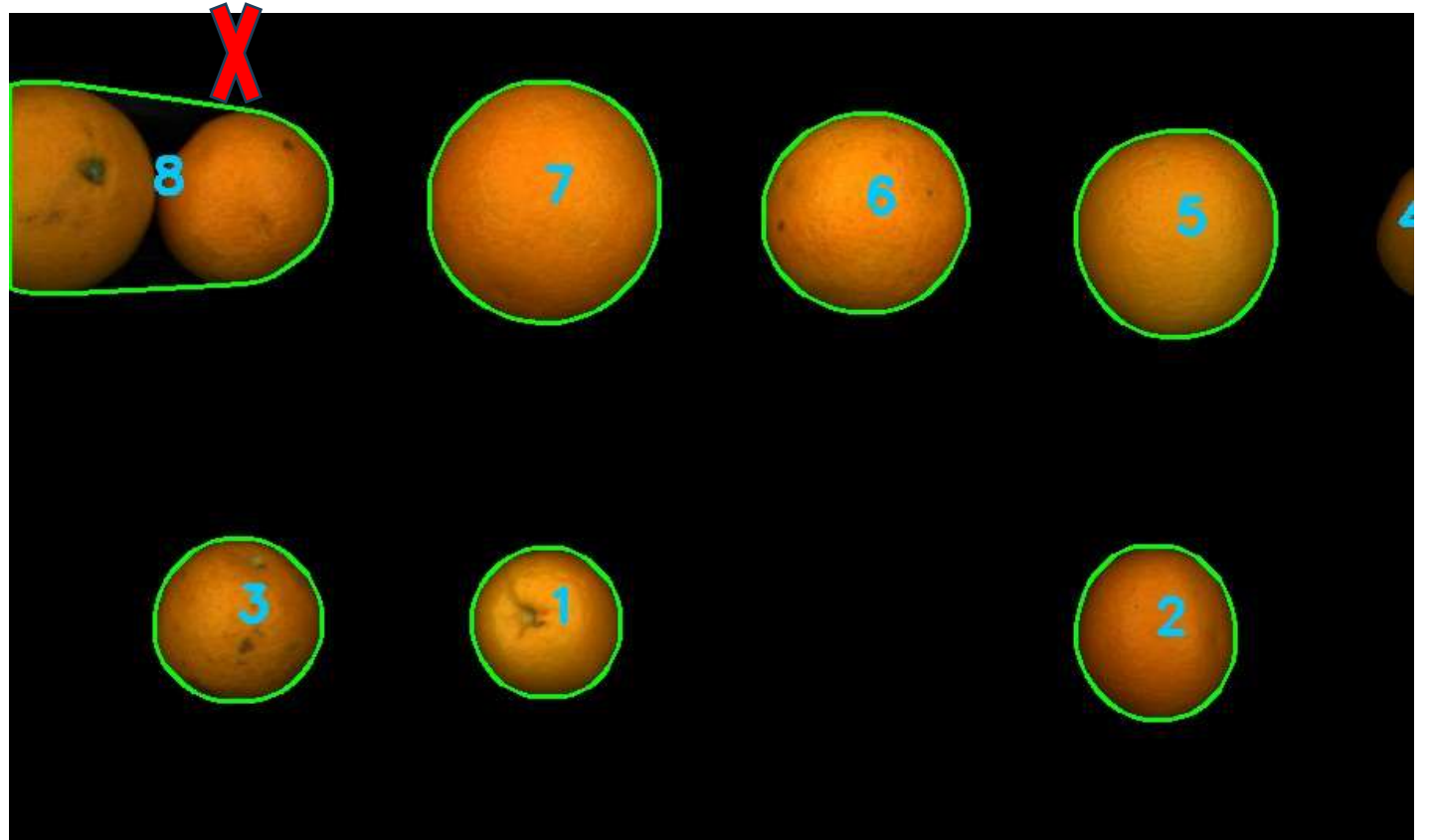
Output

- Solve Near contours



Problems

- Overlapped
Contour < 25000



Circularity & Ellipticity

- $\text{Circularity} = \frac{(4 * \pi * \text{Area})}{(\text{Perimeter}^2)}$

Therthold 95

- $\text{Ellipticity} = \frac{\text{MajorAxisLength}}{\text{MinorAxisLength}}$

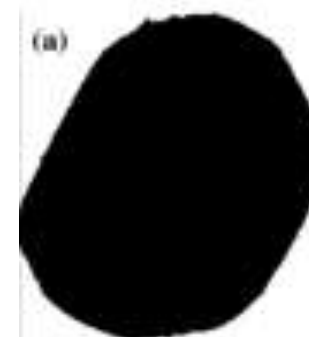
- Therthold 95



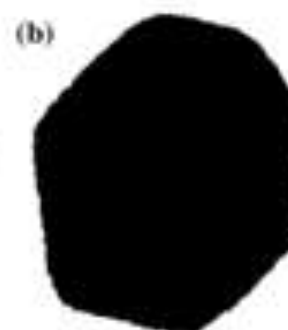
(b) 0.989



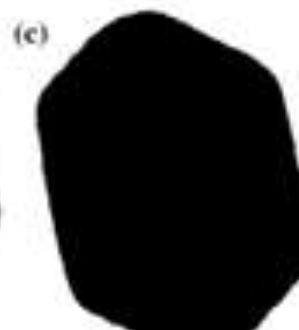
(c) 0.965



0.8030



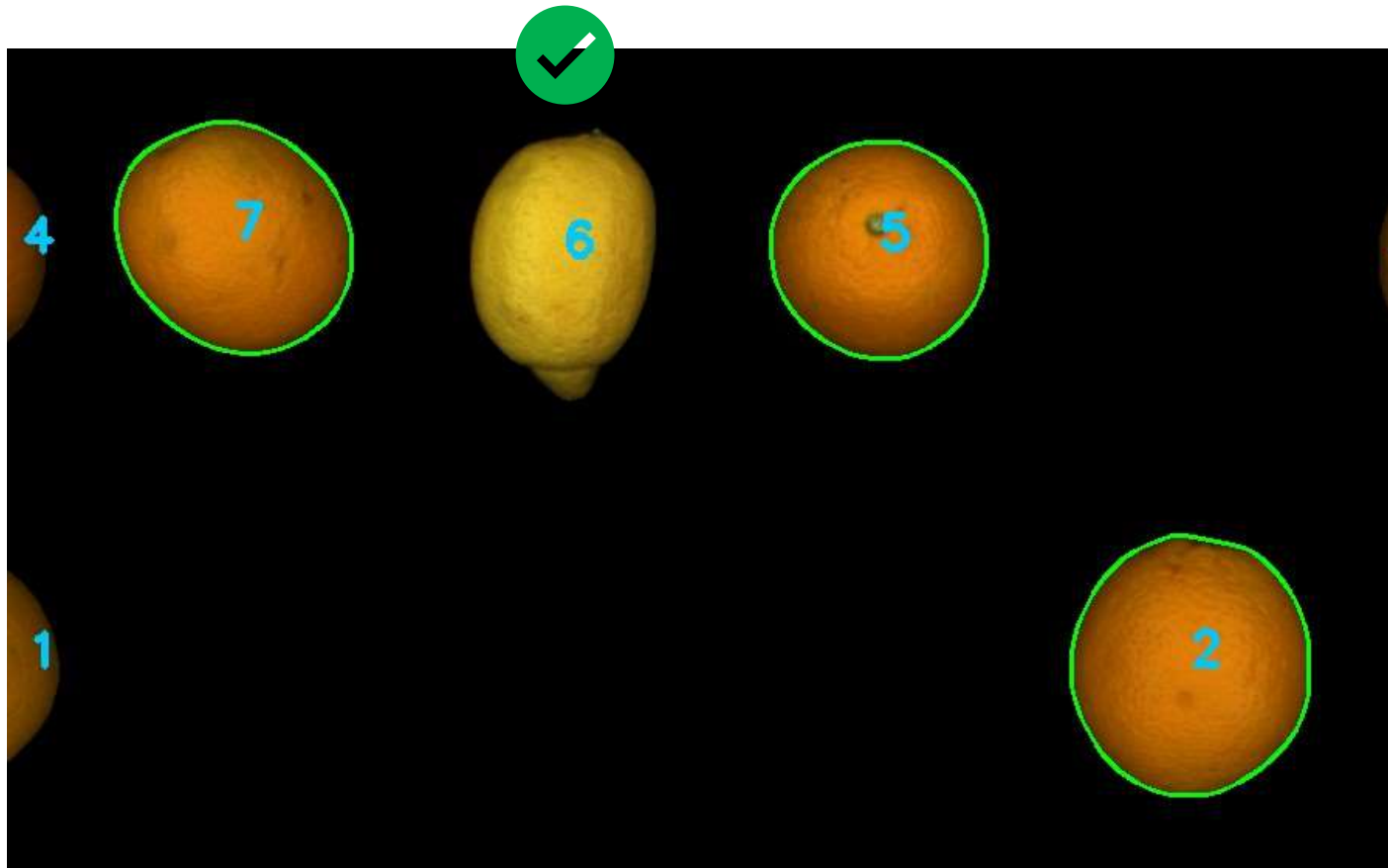
0.7959



0.7890

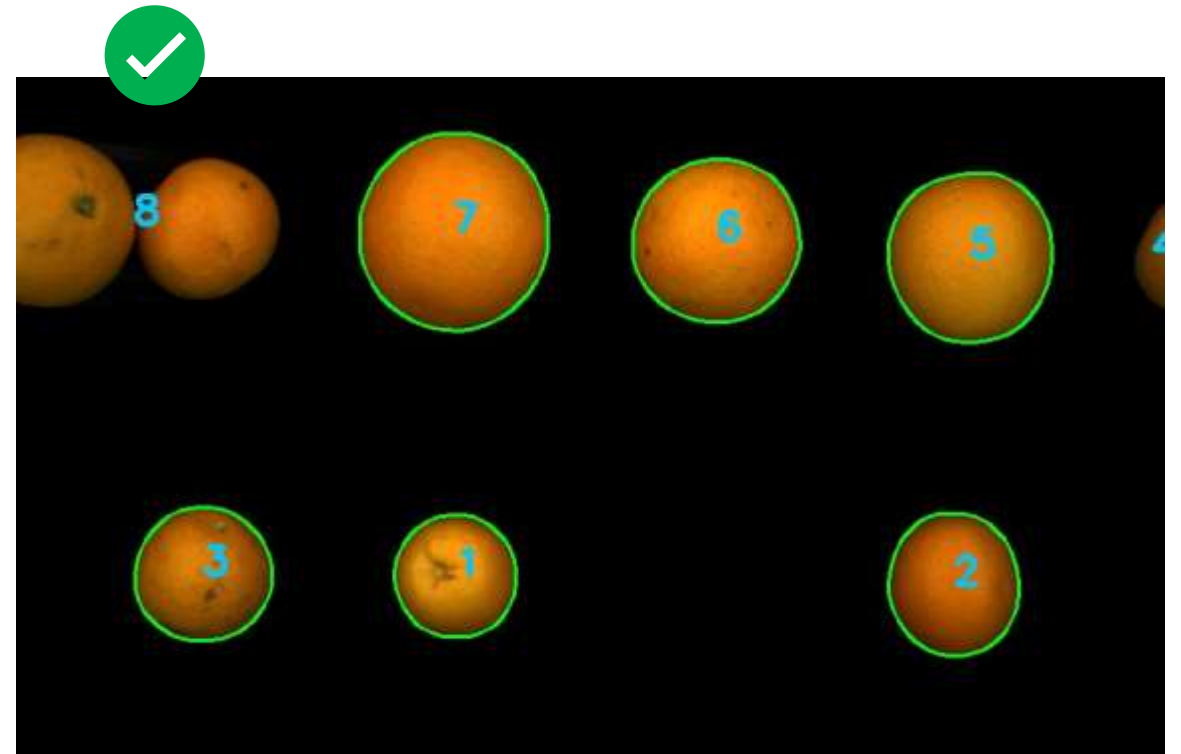
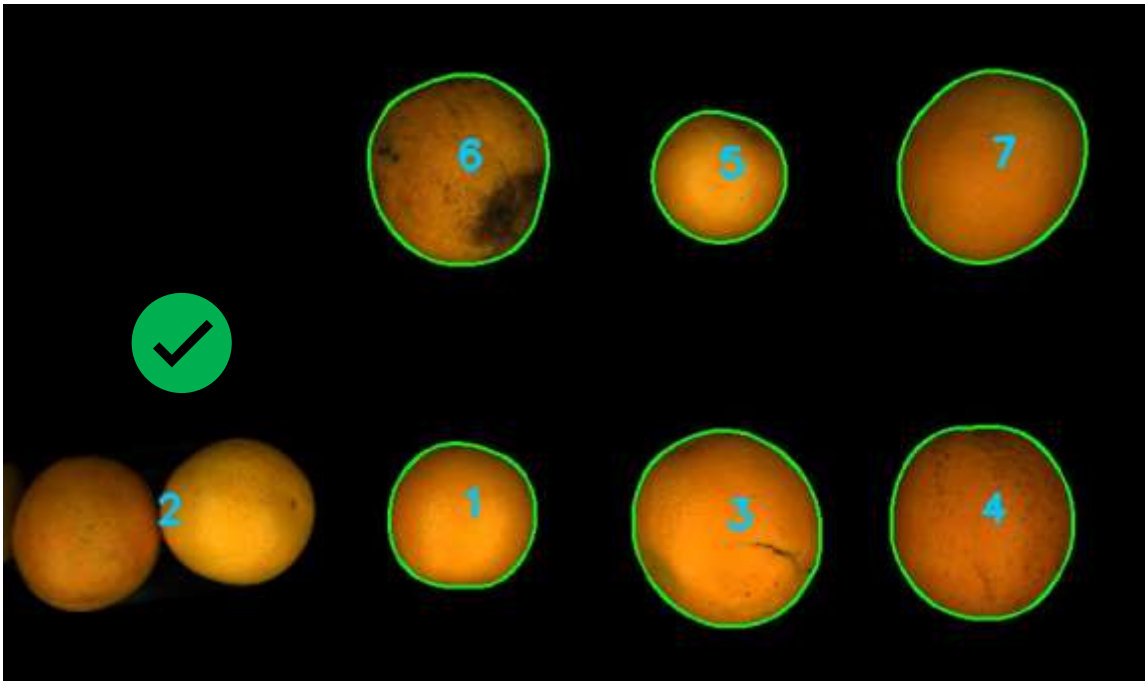
Output

- Ignore anting not orange

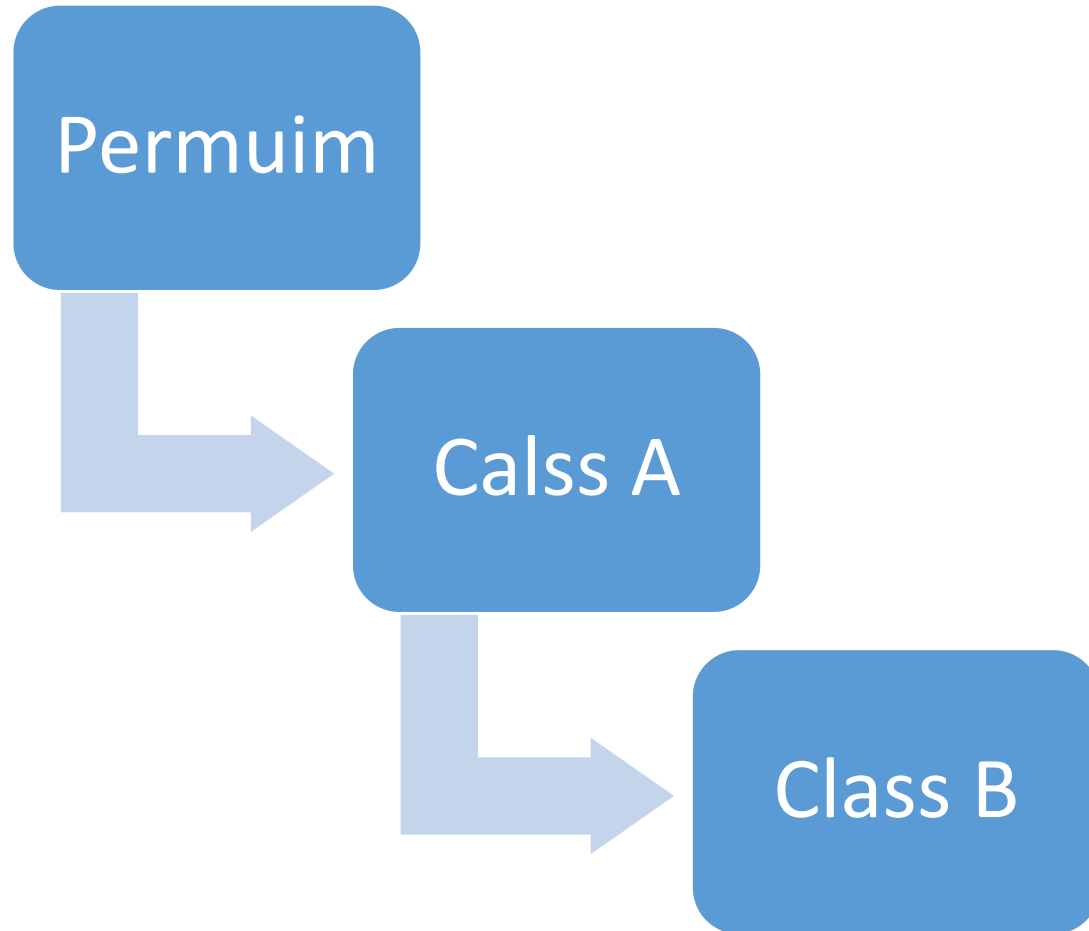


Output

- Solva Overlapped Contour < 25000



Sorting



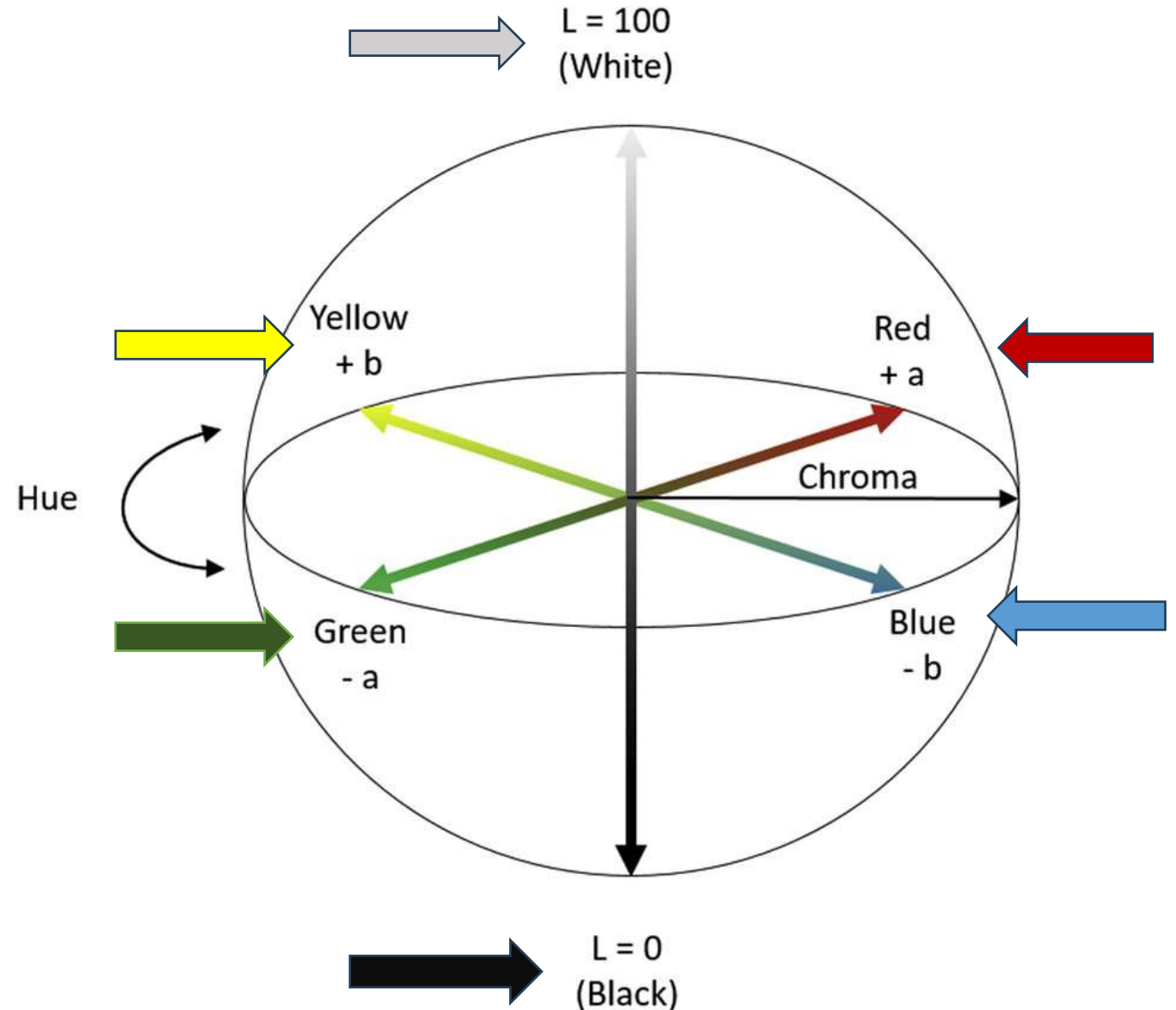
- Color
- Size
- Blemith area

Citrus Color Index

- $\underline{CCI} = \frac{100 * a}{L * b}$

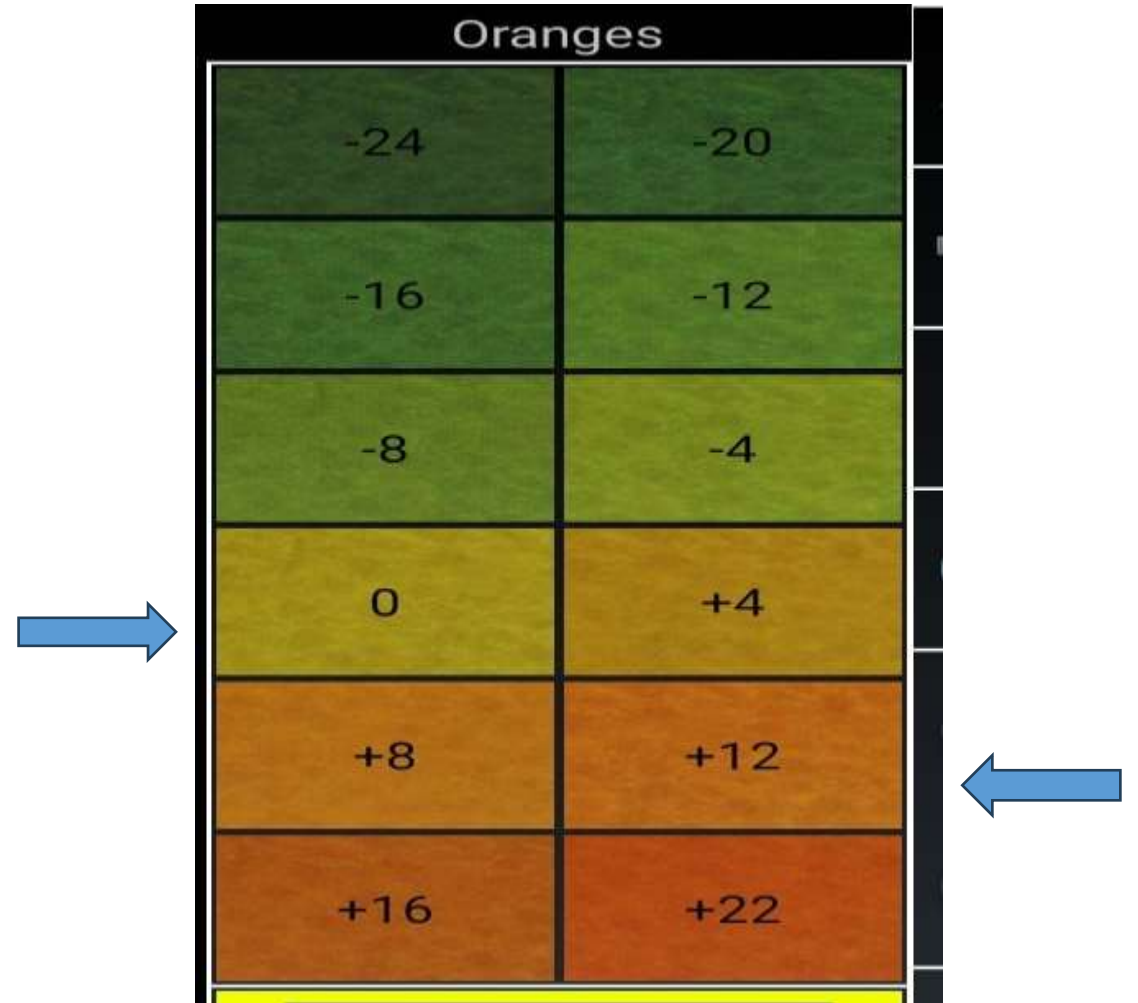
- LAB Space

- L : Reference illuminant
- a : mean value of channel a
- b : mean value of channel b

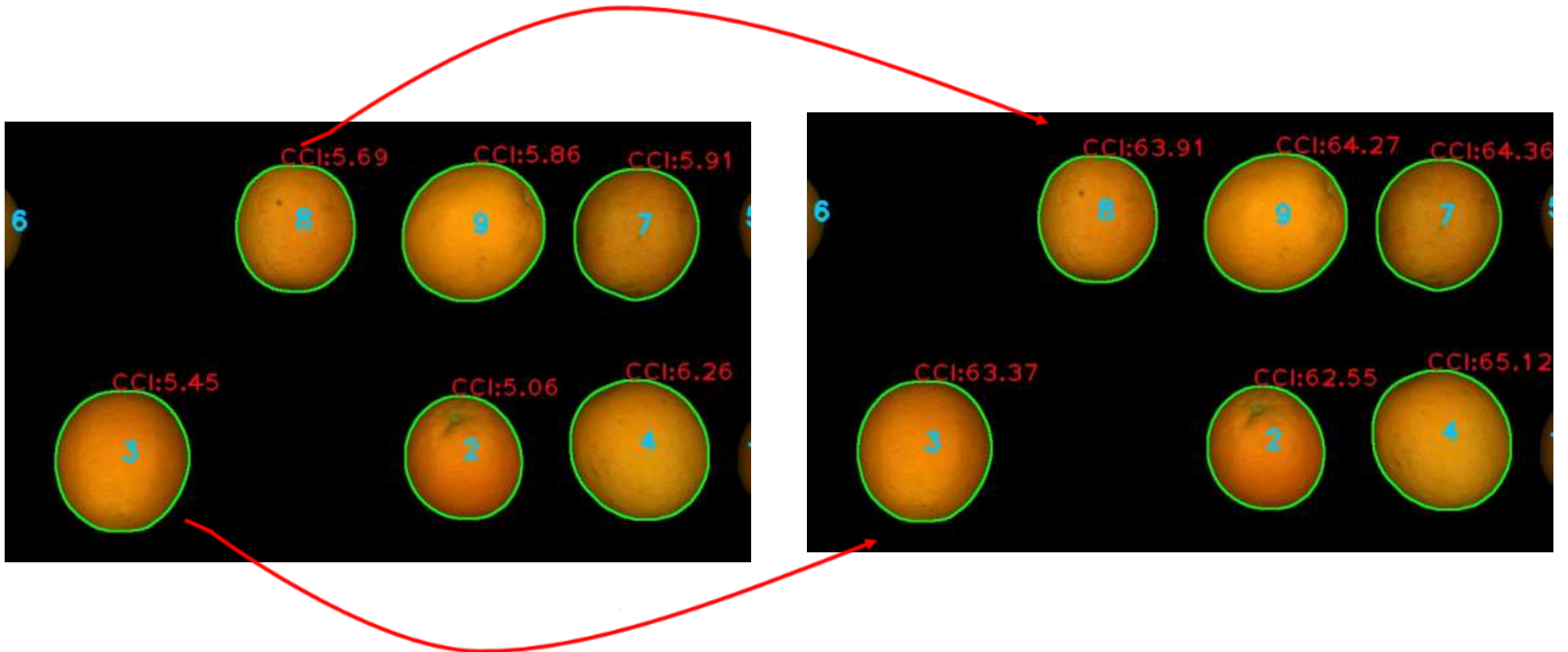


Color index

- CCI Range: -22 \rightarrow 24
- Most orange orange
- Mapping to 0 \rightarrow 99

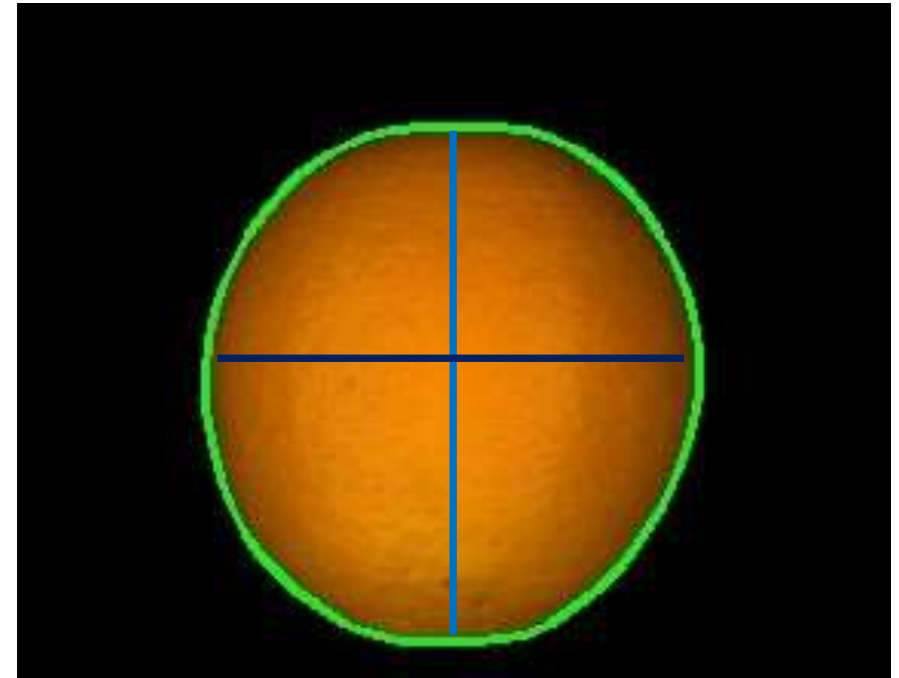


Mapped CCI



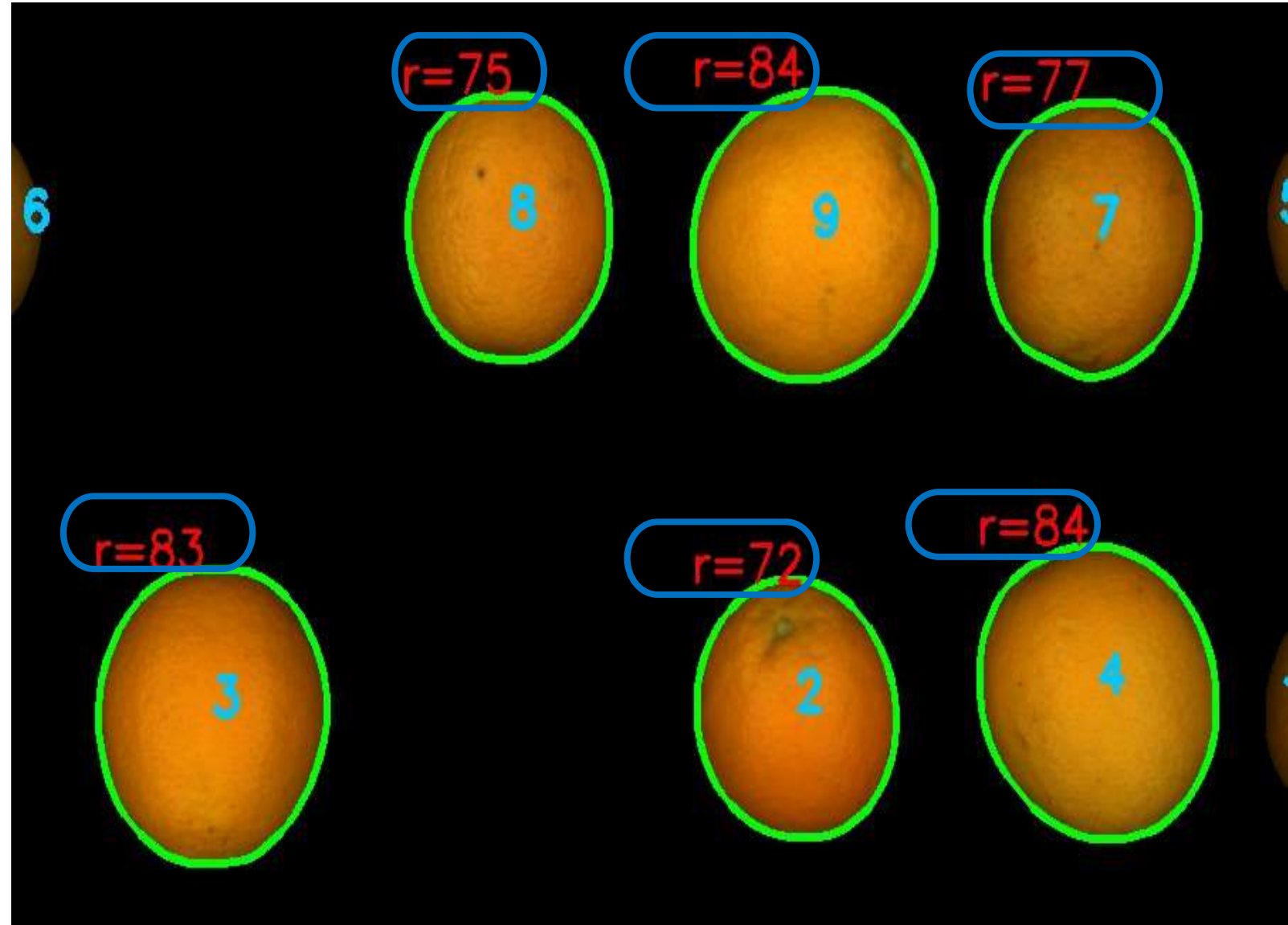
Size (Radius)

$$\text{Radius} = \frac{(\text{major_axis} + \text{minor_axis})}{4}$$



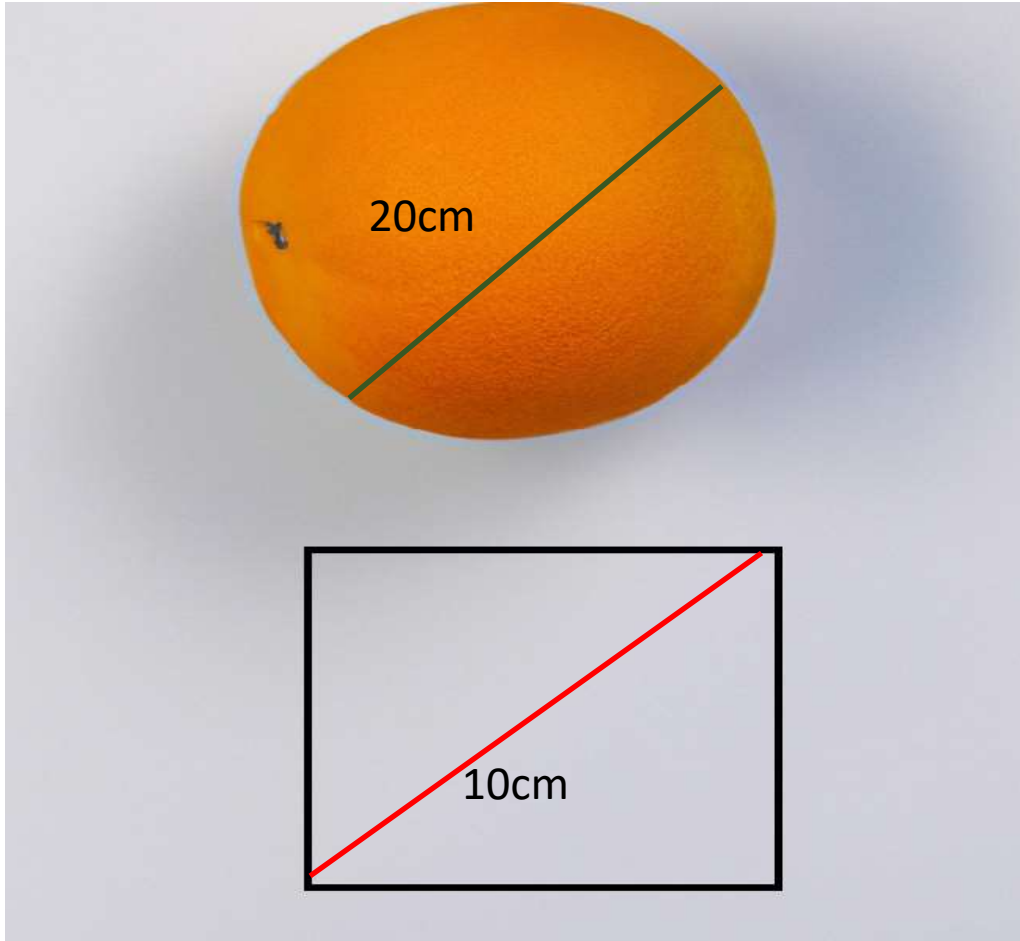
Radius

Depth
per inch

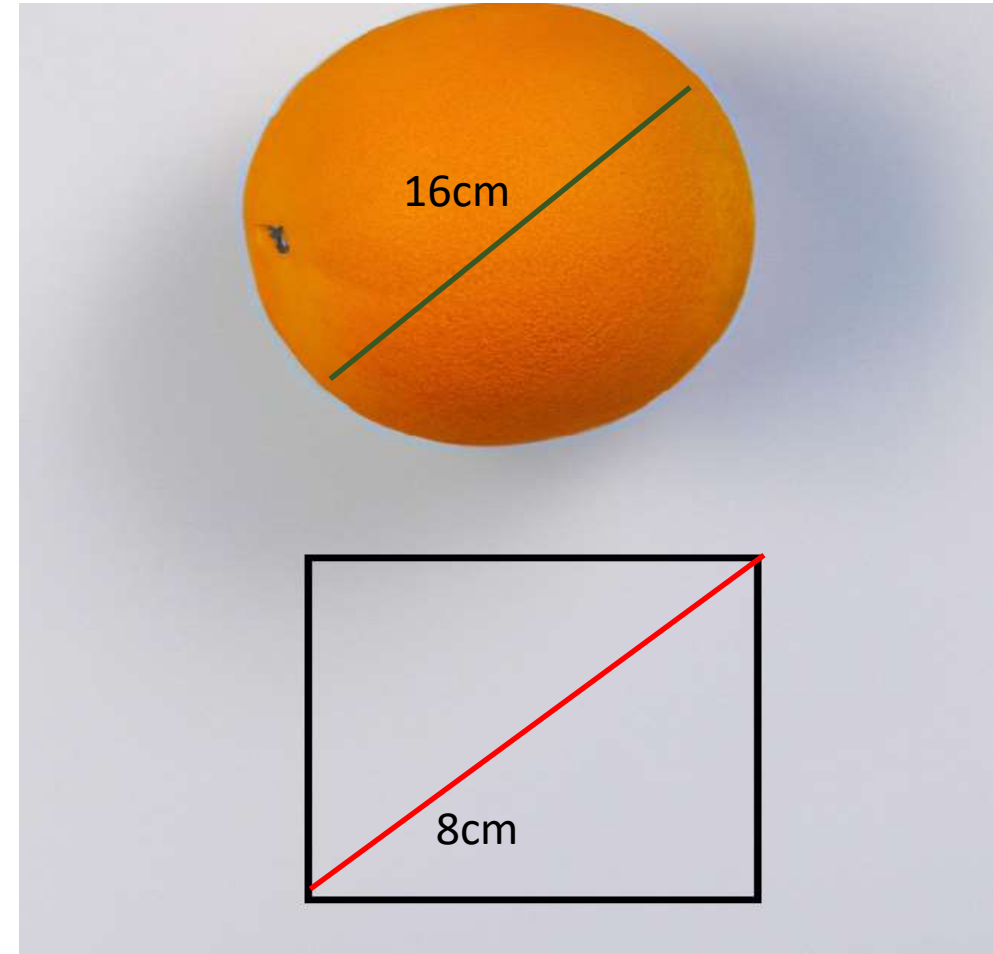


Camera calibration

Real



Camera



$$\text{Orange Real} = \frac{\text{orange camera} * \text{real square}}{\text{camer square}}$$

Defect Detection

Semantic
Segmentation

Thresholding

Thresholding

Removing the background from images.

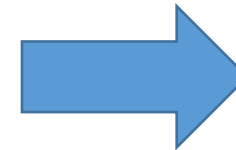
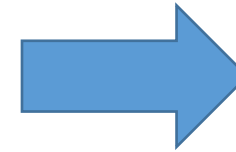
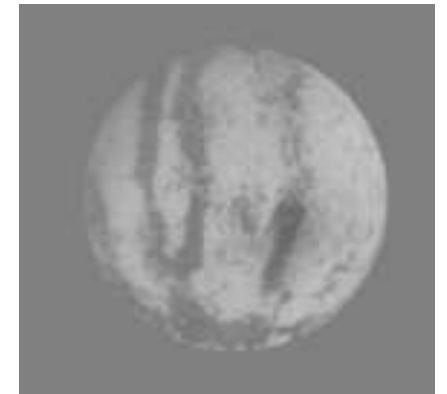
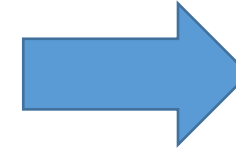
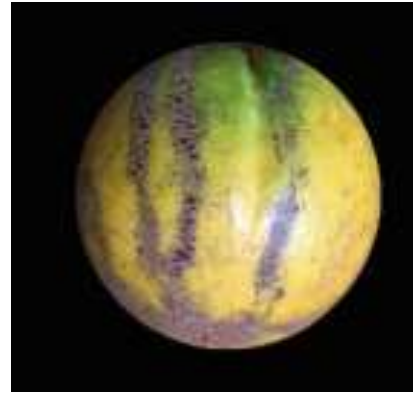
Transforming images to Lab.

Using images in b channel.

Apply Threshold in images.

First Step:

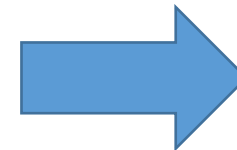
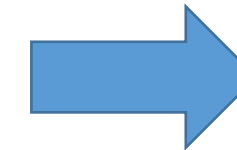
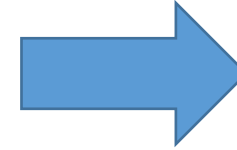
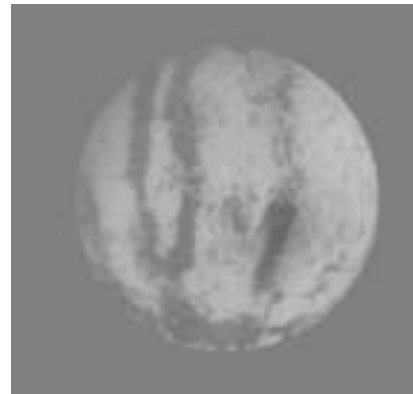
- After removing the background from images.
- We transformed images to Lab.
- Then, we used images in b channel.



Second Step:

- After using images in b channel.
- Now, we can apply Threshold:

$$\text{Threshold} = \frac{3}{4} \times \text{median}(b - \text{channelpixels}).$$



The problems of Thresholding

The values are
not Inclusive

Stem-end is
considered a
blemish area

Some defects
have

Semantic Segmentation

**CONVOLUTIONAL
NEURAL
NETWORKS (CNN)**

**VISION
TRANSFORMERS
(VITS)**

The main difference between CNNs & ViTs

Convolutional neural networks	Vision Transformers
CNNs use convolution, a “ local ” operation bounded to a small neighborhood of an image.	ViTs use self-attention, a “ global ” operation, since it draws information from the whole image.

- We used a simple, efficient yet powerful semantic segmentation framework, called **SegFormer**.

- Citation: **SegFormer: Simple and Efficient Design for Semantic Segmentation with Transformers.**

Vision Transformers

arXiv:2105.15203v2 [cs.CV] 5 Jun 2021

SegFormer: Simple and Efficient Design for Semantic Segmentation with Transformers

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¹The University of Hong Kong ²Nanjing University ³NVIDIA ⁴Caltech

Abstract

We present SegFormer, a simple, efficient yet powerful semantic segmentation framework which unifies Transformers with lightweight multilayer perceptron (MLP) decoders. SegFormer has two appealing features: 1) SegFormer comprises a novel hierarchically structured Transformer encoder which outputs multiscale features. It does not need positional encoding, thereby avoiding the interpolation of positional codes which leads to decreased performance when the testing resolution differs from training. 2) SegFormer avoids complex decoders. The proposed MLP decoder aggregates information from different layers, and thus combining both local attention and global attention to render powerful representations. We show that this simple and lightweight design is the key to efficient segmentation on Transformers. We scale our approach up to obtain a series of models from SegFormer-B0 to SegFormer-B5, reaching significantly better performance and efficiency than previous counterparts. For example, SegFormer-B4 achieves 50.3% mIoU on ADE20K with 64M parameters, being 5× smaller and 2.2% better than the previous best method. Our best model, SegFormer-B5, achieves 84.0% mIoU on Cityscapes validation set and shows excellent zero-shot robustness on Cityscapes-C. Code will be released at: github.com/NVlabs/SegFormer.

1 Introduction

Semantic segmentation is a fundamental task in computer vision and enables many downstream applications. It is related to image classification since it produces per-pixel category prediction instead of image-level prediction. This relationship is pointed out and systematically studied in a seminal work [1], where the authors used fully convolutional networks (FCNs) for semantic segmentation tasks. Since then, FCN has inspired many follow-up works and has become a predominant design choice for dense prediction.

Since there is a strong relation between classification and semantic segmentation, many state-of-the-art semantic segmentation frameworks are variants of popular architectures for image classification on ImageNet. Therefore, designing backbone architectures has remained an active area in semantic segmentation. Indeed, starting from

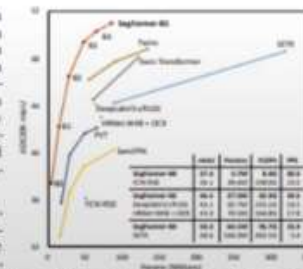


Figure 1. Performance vs. model efficiency on ADE20K. All results are reported with single model and single-scale inference. SegFormer achieves a new state-of-the-art 84.0% mIoU, which being significantly more efficient than previous methods.

*Work done during an internship at NVIDIA.



Let's train SegFormer on our
Custom Dataset

STEP 1

Create A Dataset

This means we need image label pairs where the label assigns a class to every pixel in the image.



Citrus melanose



Citrus black spot



Citrus canker

STEP 2

Define the Model class

*A LightningModule organizes your **PyTorch** code into 6 sections:*

```
import torch
from torch import nn
from torch.utils.data import Dataset, DataLoader
from pytorch_lightning.lite import LightningLite

class Lite(LightningLite)

    def run(self, num_epochs: int):
        model = Model(...)
        optimizer = torch.optim.SGD(model.parameters(), ...)
        model, optimizer = self.setup(model, optimizer)
        dataloader = DataLoader(MyDataset(...), ...)
        dataloader = self.setup_dataloaders(dataloader)
        for epoch in range(num_epochs):
            for batch_idx, batch in enumerate(dataloader):
                optimizer.zero_grad()
                loss = model(batch)
                self.backward(loss) # Instead of loss.backward()
                optimizer.step()

Lite(strategy="deepspeed", devices=8, accelerator="gpu").run(10)
```


Train the Model

We can create the Pytorch Lightning [trainer](#) and hit the launch button!

STEP 3


```
GPU available: True, used: True
TPU available: False, using: 0 TPU cores
IPU available: False, using: 0 IPUs
HPU available: False, using: 0 HPUs
LOCAL_RANK: 0 - CUDA_VISIBLE_DEVICES: [0]
```

	Name	Type	Params
0	model	SegformerForSemanticSegmentation	3.7 M
3.7 M	Trainable params		
0	Non-trainable params		
3.7 M	Total params		
14.870	Total estimated model params size (MB)		

```
Epoch 11: 79%  95/120 [01:03<00:16, 1.50it/s, loss=1.38, v_num=
```

Evaluate the Model

In true Pytorch Lightning style, testing our model is a one line!

Testing DataLoader 0: 100%  1/1 (00:02<00:00, 2.24s/it)

Test metric	DataLoader 0
test_mean_accuracy	0.9405948221081628
test_mean_iou	0.8995695843028959

STEP 4

Visualize Results



Original image (left)

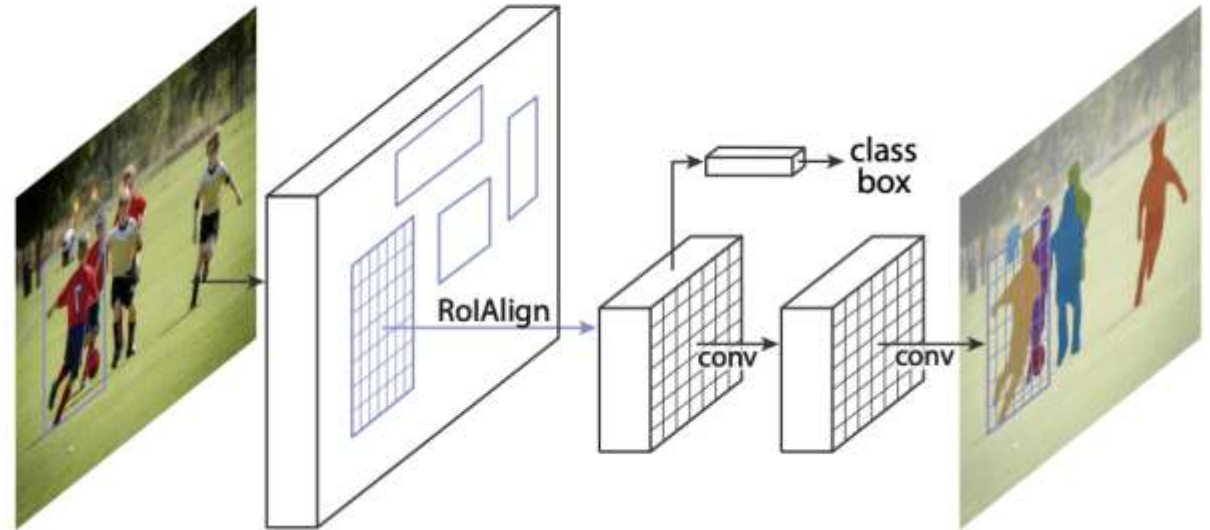
SegFormer (right)

The background of the slide is a dark blue field filled with a complex network of thin, glowing blue lines. These lines intersect and branch out, creating a web-like pattern. Small, bright orange dots are scattered throughout the image, often positioned at the intersections of the blue lines, suggesting nodes or data points in a network.

Convolutional neural networks

Mask R-CNN

- We will use [Mask R-CNN](#).
- It's a new convolutional network proposed based on the previous [fast R-CNN](#) architecture.



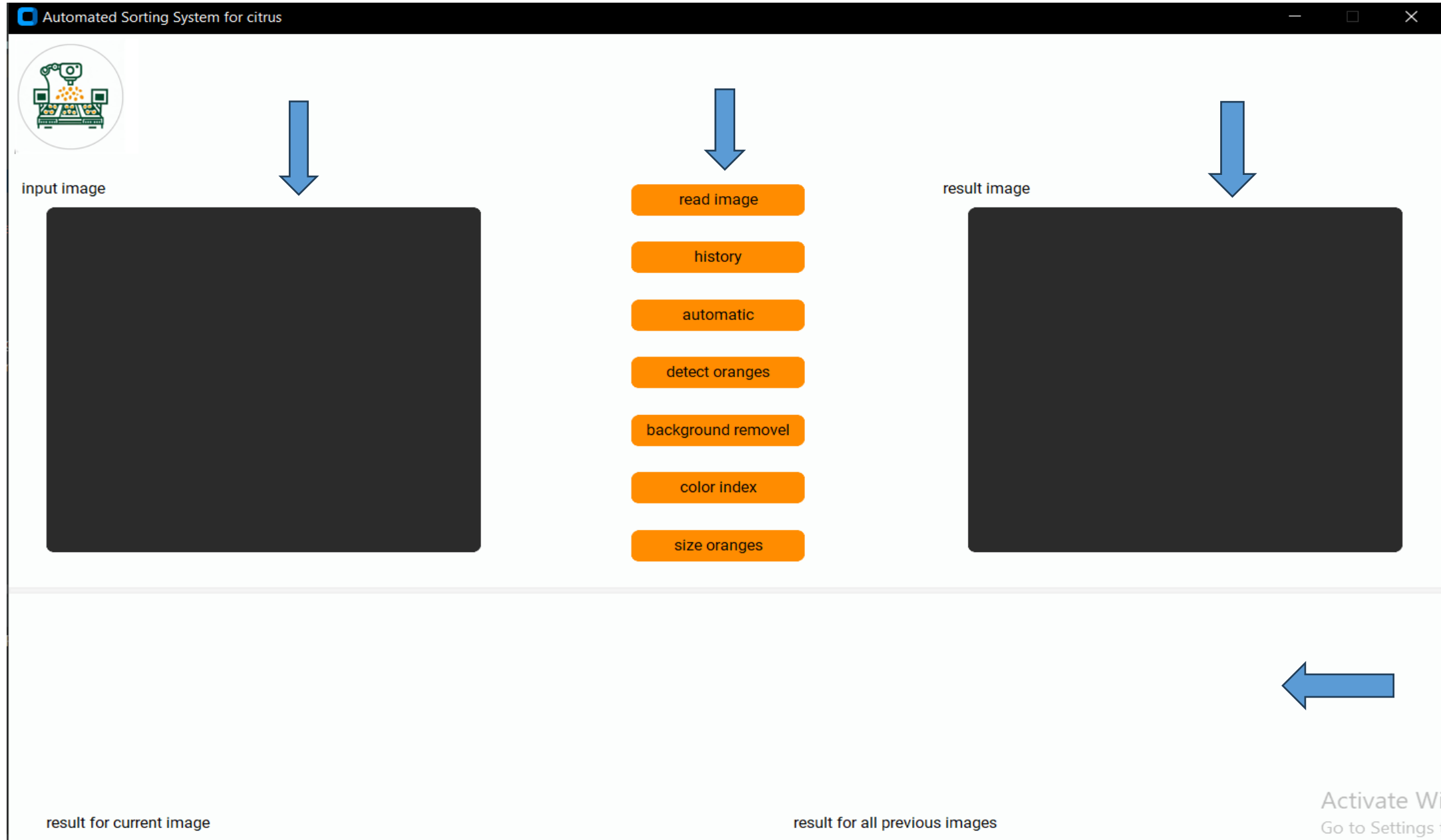
Visualize Results




Original image

Mask R-CNN

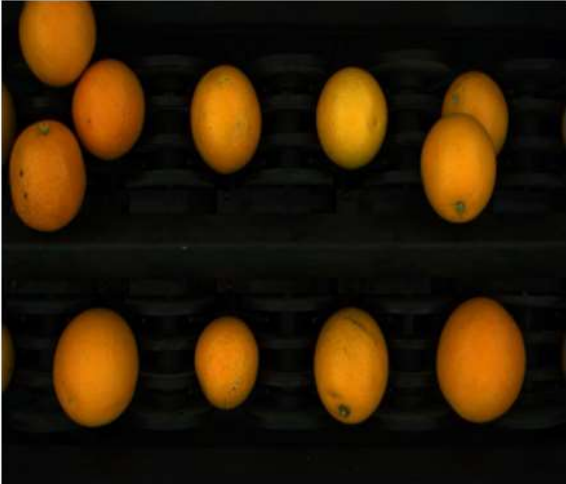
GUI



Read image



input image



result for current image

read image

history

automatic


detect oranges

background removal

color index

size oranges

result image



result for all previous images

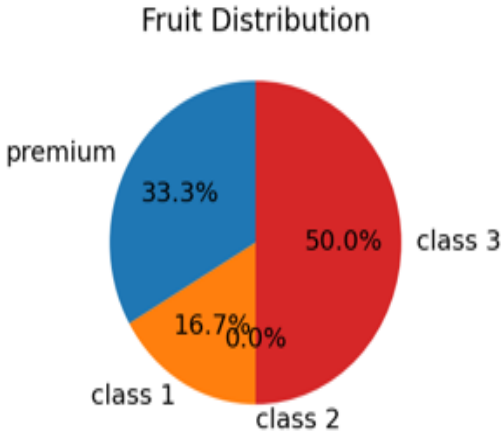
Automatic

1- the color index and size of the oranges will be displayed in two tables.

The first table shows the results for the current image

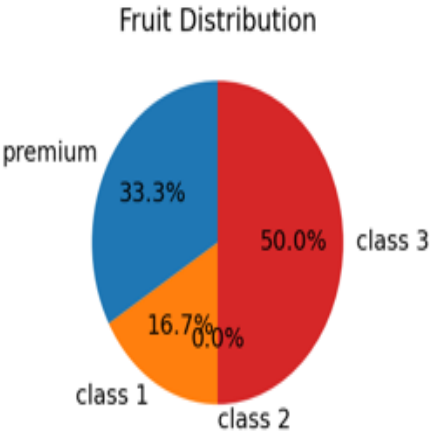
The second table shows the results for all previous images

name	class	size	area	color index	blemish area
	class3	48.1151%		64.55787658311	
	class3	53.7965%		62.15259819592	
	class3	53.2322%		63.57140530445	
	premium	65.9162%		64.38872516732	
	class1	64.8752%		63.10984521742	
	premium	75.9842%		62.71051975600	



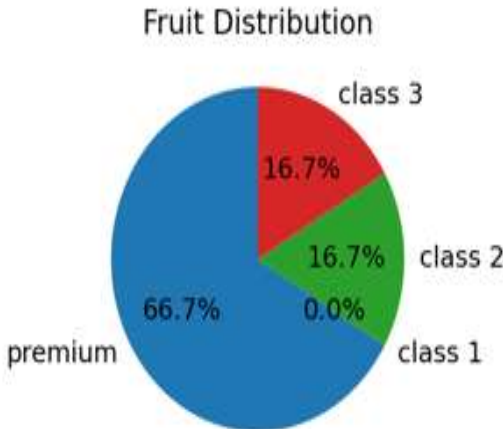
result for current image

name	class	size	area	color index	blemish area
	class3	48.1151%		64.55787658311	
	class3	53.7965%		62.15259819592	
	class3	53.2322%		63.57140530445	
	premium	65.9162%		64.38872516732	
	class1	64.8752%		63.10984521742	
	premium	75.9842%		62.71051975600	



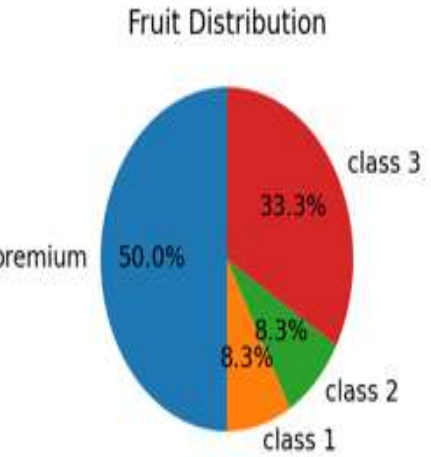
result for all previous images

name	class	size	area	color index	blemish area
	class2	57.8673%		63.68714297720	
	premium	75.1706%		63.19395548066	
	premium	74.3898%		61.80311638649	
	class3	51.7267%		64.50141171710	
	premium	72.9279%		64.02219549089	
	premium	74.0228%		63.12157946831	



result for current image

name	class	size	area	color index	blemish area
	class3	48.1151%		64.55787658311	
	class3	53.7965%		62.15259819592	
	class3	53.2322%		63.57140530445	
	premium	65.9162%		64.38872516732	
	class1	64.8752%		63.10984521742	
	premium	75.9842%		62.71051975600	
	class2	57.8673%		63.68714297720	
	premium	75.1706%		63.19395548066	
	premium	74.3898%		61.80311638649	
	class3	51.7267%		64.50141171710	



result for all previous images

Automatic

2-writing in file

- 1- provide a daily reports of work
- 2- by the type of writing
 - it provide a way of detect any fraud

C:/Users/N R/Desktop/pythonProject2/1.bmp



```
0 class3 48.11519813537598 0 64.55787658311374
0 class3 53.796573638916016 0 62.152598195929116
0 class3 53.23221206665039 0 63.57140530445746
0 premium 65.91625595092773 0 64.38872516732671
0 class1 64.87527465820312 0 63.10984521742118
0 premium 75.98425674438477 0 62.71051975600577
```

C:/Users/N R/Desktop/pythonProject2/2.bmp

```
0 class2 57.8673095703125 0 63.68714297720027
0 premium 75.17061996459961 0 63.19395548066267
0 premium 74.3898696899414 0 61.80311638649217
0 class3 51.726722717285156 0 64.5014117171002
0 premium 72.92792510986328 0 64.02219549089963
0 premium 74.0228385925293 0 63.12157946831567
```



input image

read image

result image

history

History

name	class	size	area	color index	blemish area
	class3	48.11519		64.55787658311	
	class3	53.79657		62.15259819592	
	class3	53.23227		63.57140530445	
	premium	65.91625		64.38872516732	
	class1	64.87527		63.10984521742	
	premium	75.98425		62.71051975600	

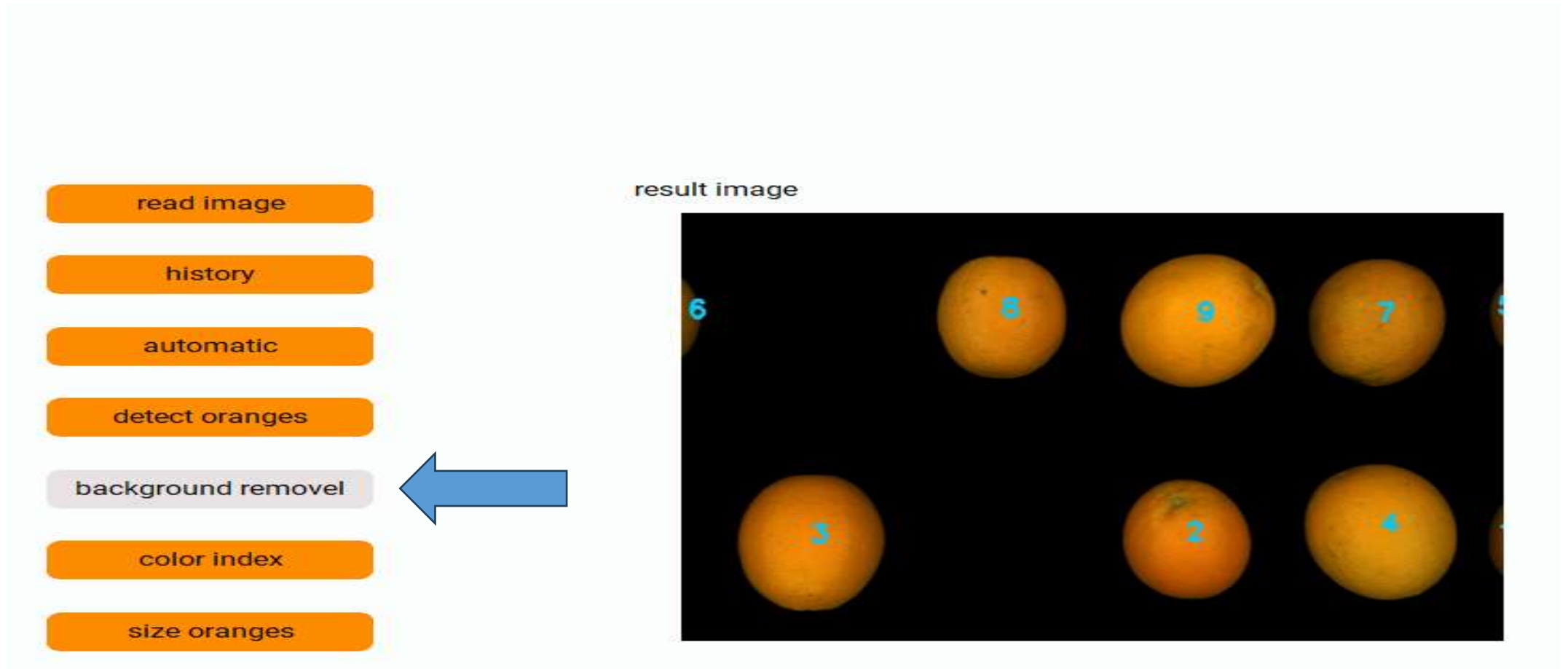
8.8

name	class	size	area	color index
	class2	57.86730		63.4
	premium	75.17061		63.4
	premium	74.38980		61.4
	class3	51.72670		64.4
	premium	72.92790		64.4
	premium	74.02280		63.4

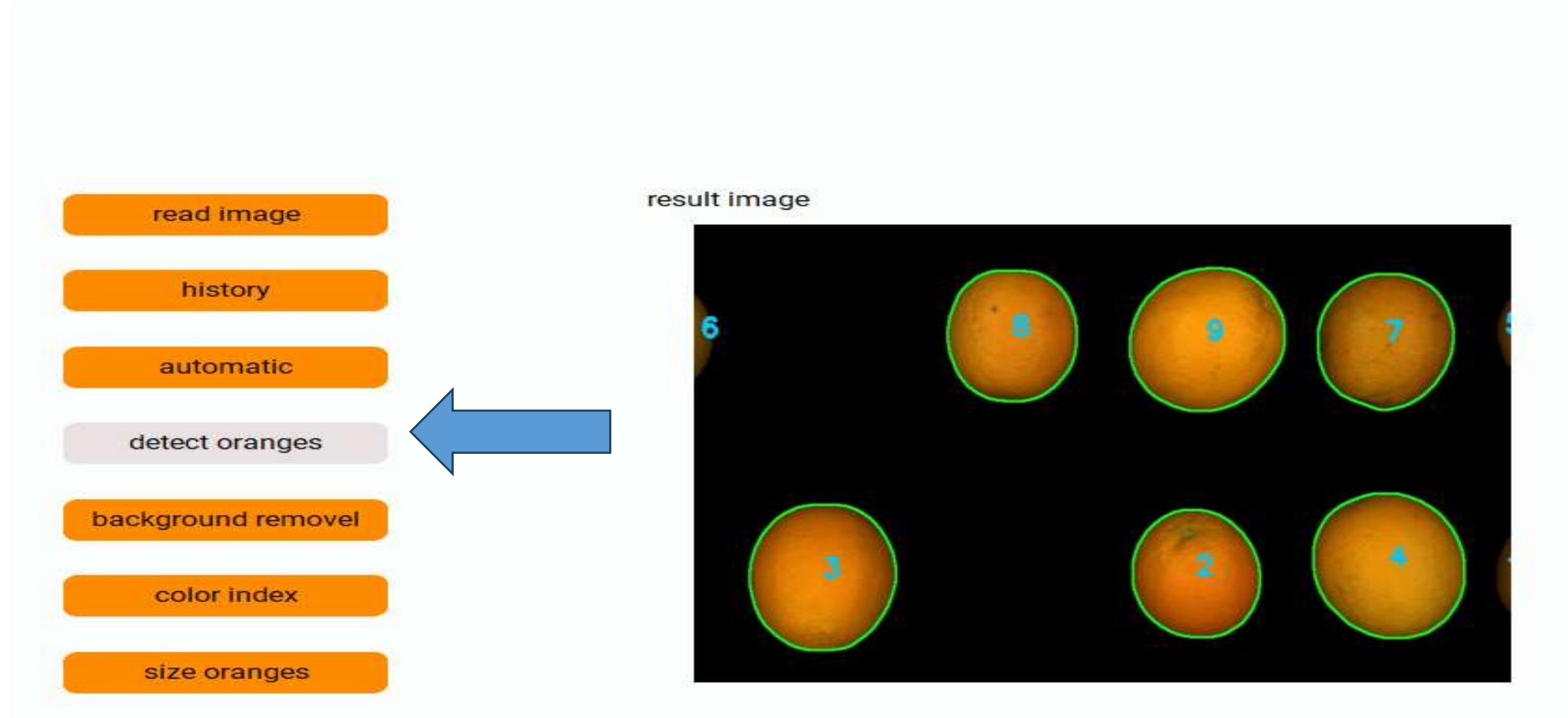
History

- The data saved in a file can be accessed by clicking the 'History' button. The history button display all saved data in the file

Background removal



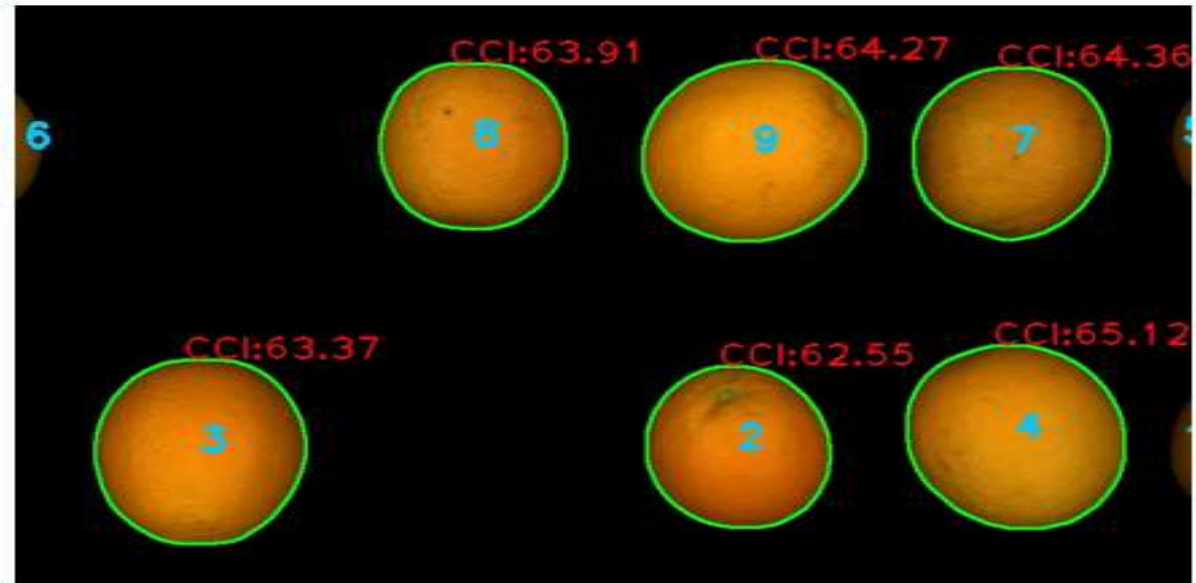
Detect oranges



Color index



result image



Size of oranges

read image

history

automatic

detect oranges

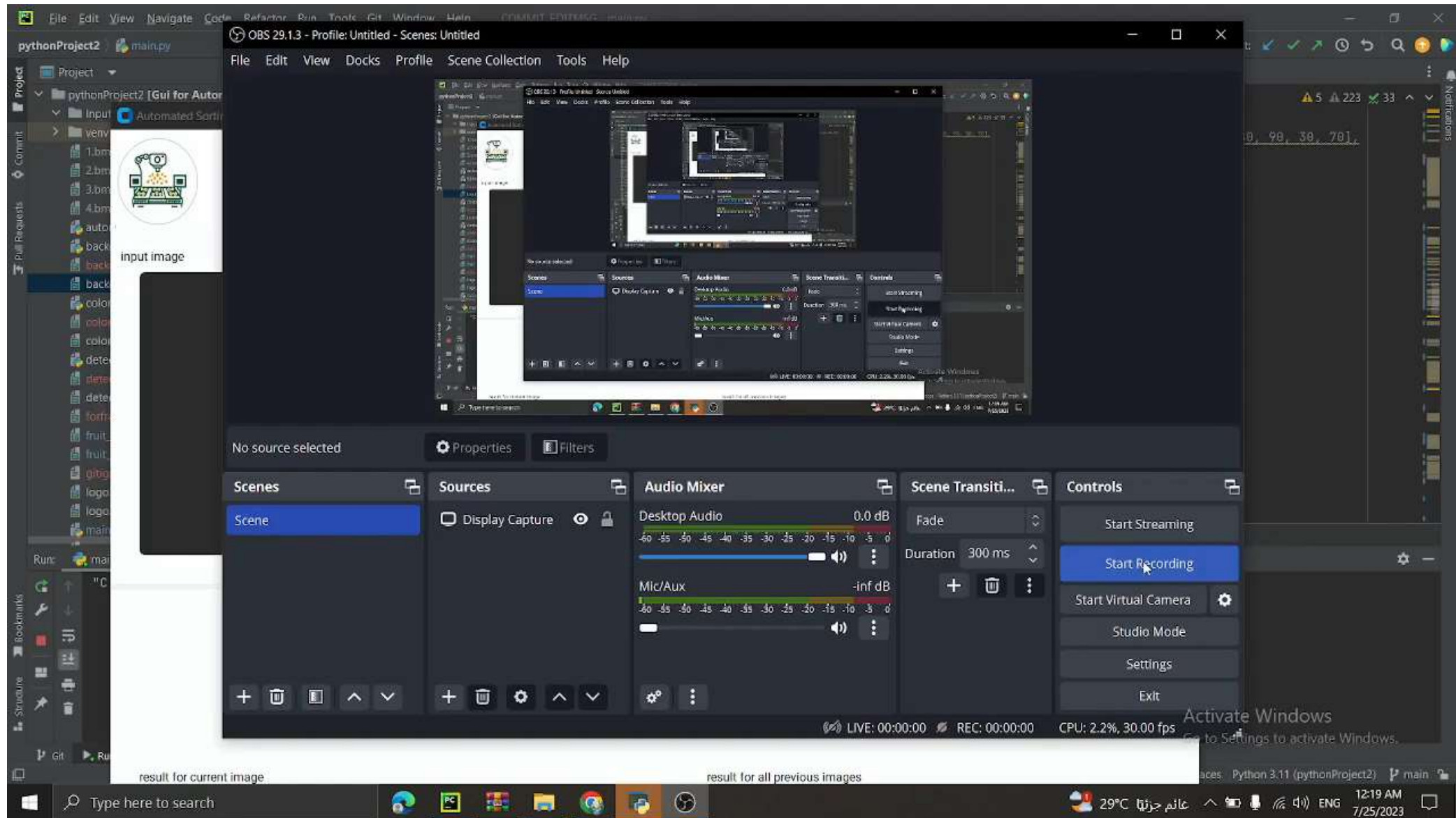
background removal

color index

size oranges

result image

Orange Number	Radius (R)
1	83
2	72
3	84
4	84
5	75
6	77



Thanks
