



Automated Fruit Detection and Counting for Precision Agriculture: A Deep Learning Approach for 2D High-Resolution Orchard Images

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PROBLEM & SOLUTION

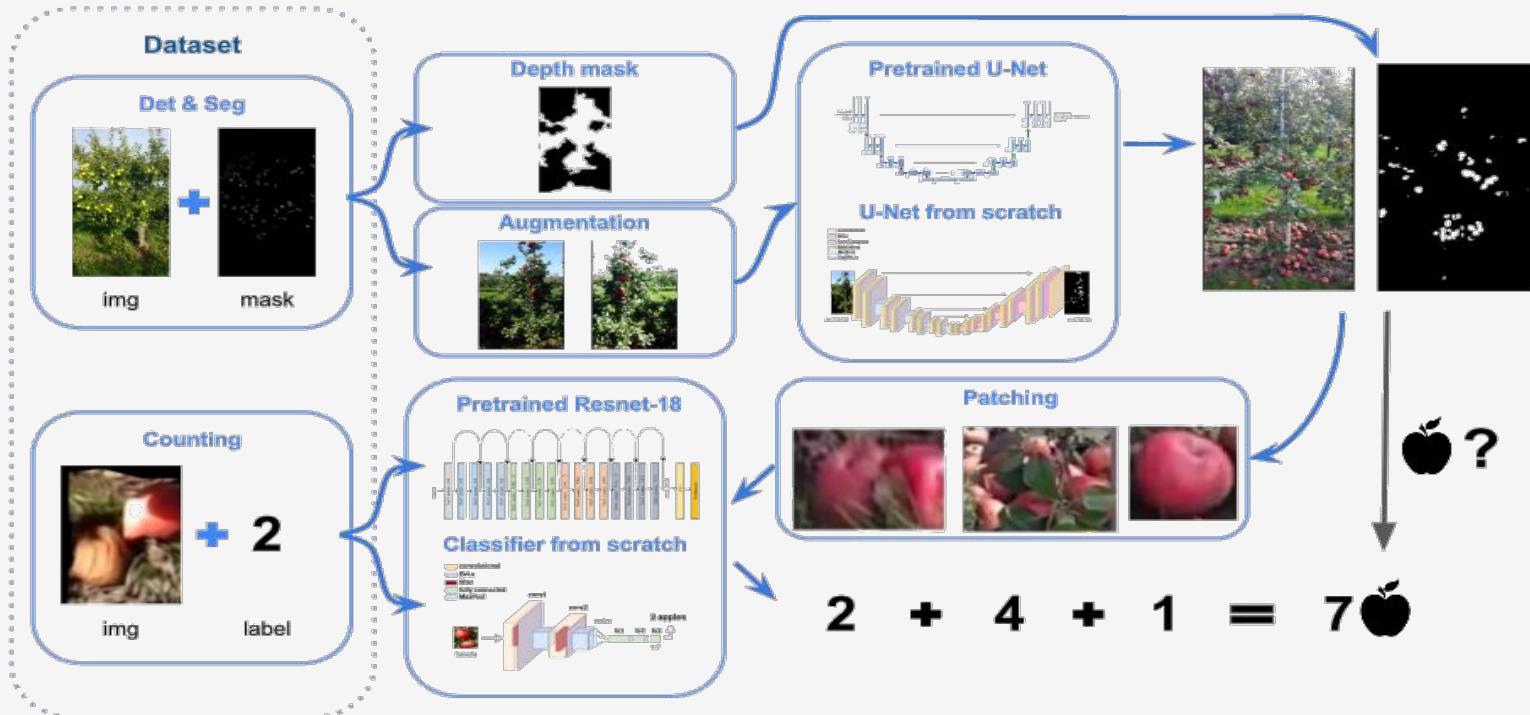
Apples manual counting is time consuming and often leads to erroneous orchards yields estimation



Build an algorithm that, starting from 2d apple trees images, automatically recognize and count apples

Combining the counts of each tree give an estimate of the total harvest

GENERAL PIPELINE



DATASET

COUNTING

Train Samples



Test Samples



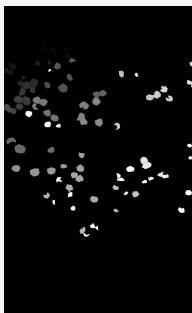
The Counting dataset is composed of image patches of different dimensions .

- **Training Set:**
 - 64595 patches of apples captured under different conditions
- **Validation Set:**
 - 3395 patches of apples captured under different conditions
- **Test Set:**
 - 2875 patches of apples extracted from trees
- **Pre-Processing:**
 - Padding to a square
 - Resize to 64x64 pixels

DATASET

SEGMENTATION

Train Sample



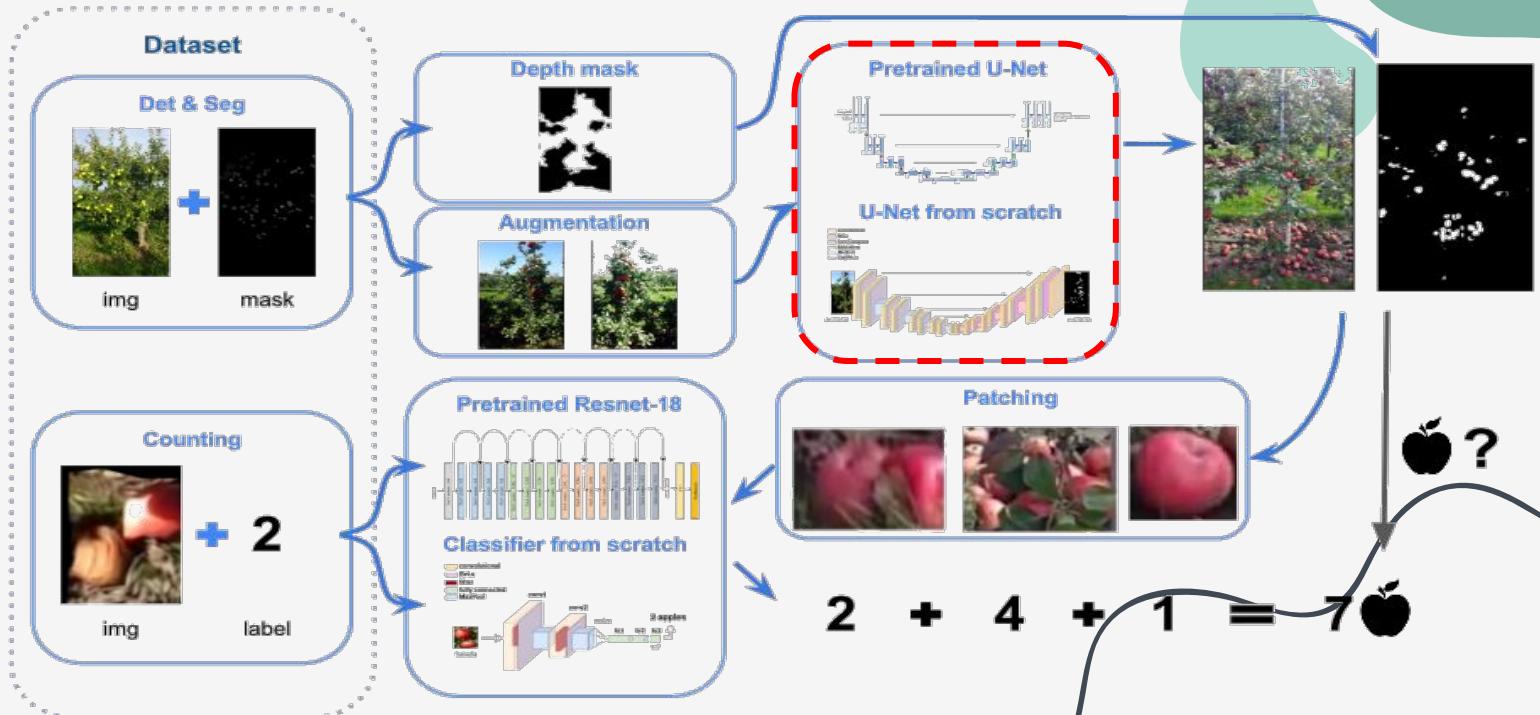
Test Sample



The Segmentation dataset is composed of High resolutions images (1280x720) extracted from a video recording.

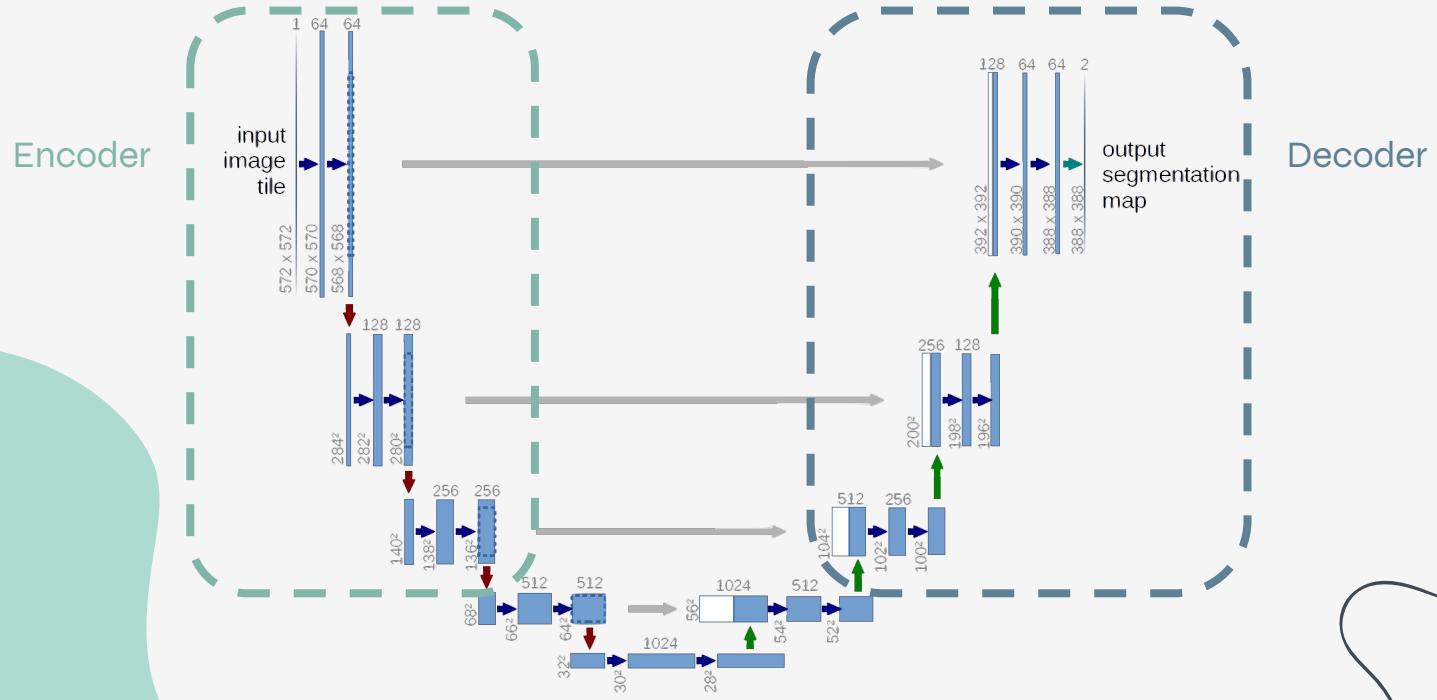
- Training Set:
 - 603 images with corresponding mask
- Validation Set:
 - 67 images with corresponding mask
- Test Set:
 - 370 images with corresponding mask
- Data Augmentation:
 - Random brightness adjustment(0.7-1.3)
 - Random horizontal flip

SEGMENTATION



SEGMENTATION

Approach: UNet

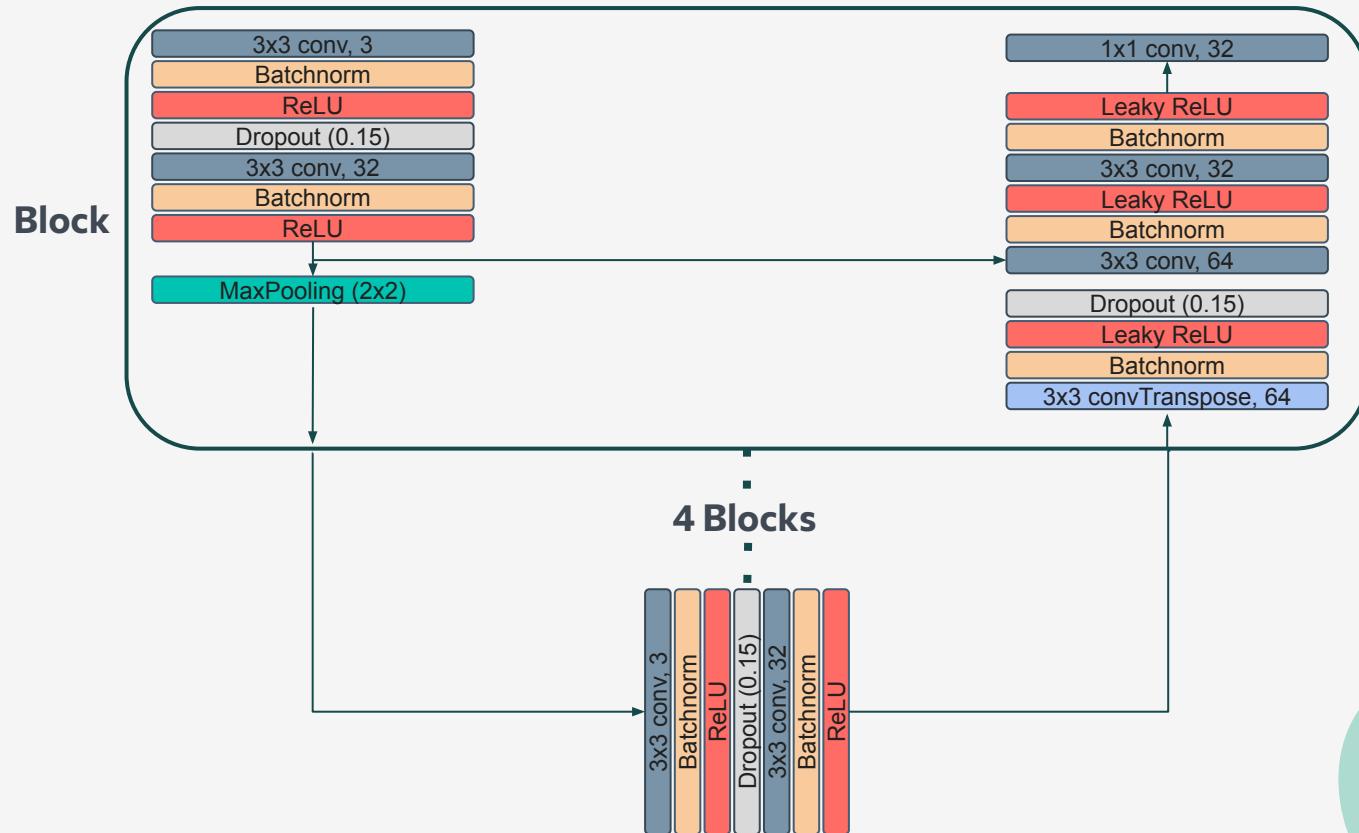


SEGMENTATION Architectures

1. Custom implementation
 - a. Trained for 100 epochs
 - b. Adam Optimizer with $\text{lr} = 0.0005$
 - c. Binary Cross Entropy Loss with weights.
2. Pre Trained architecture on ImageNet dataset
 - a. Fine-Tuned for 100 epochs
 - b. Adam Optimizer with $\text{lr} = 0.0005$
 - c. Binary Cross Entropy Loss with weights.

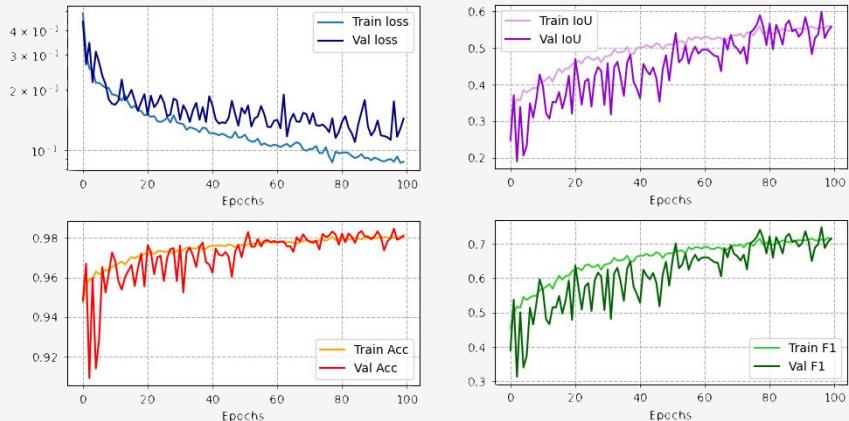
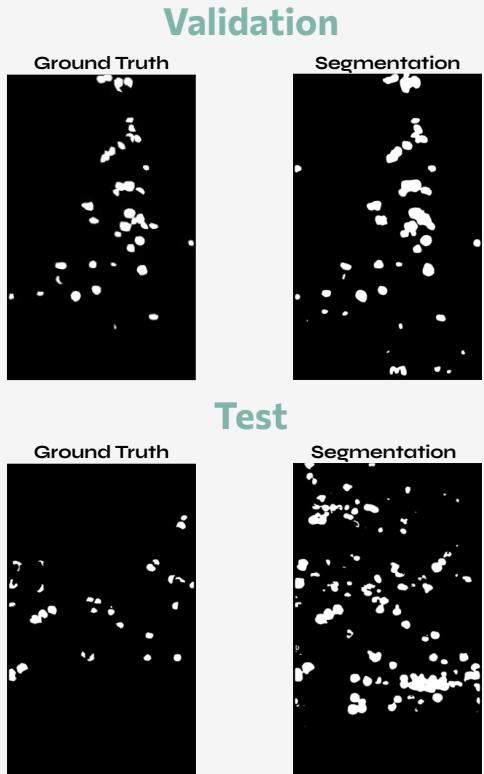
SEGMENTATION

1) Custom UNet



RESULTS

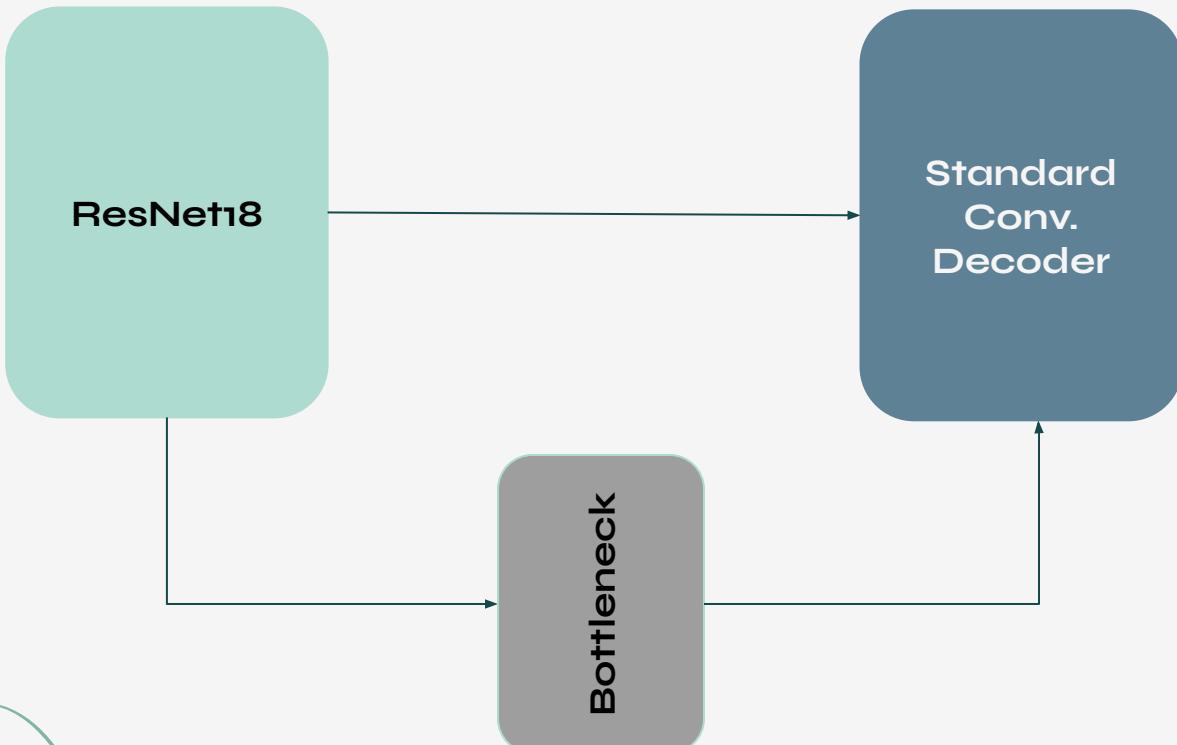
1) Custom UNet



	Custom	Normal	Augmented
Val IoU	0.506	0.506	0.551
Test IoU	0.394	0.394	0.416

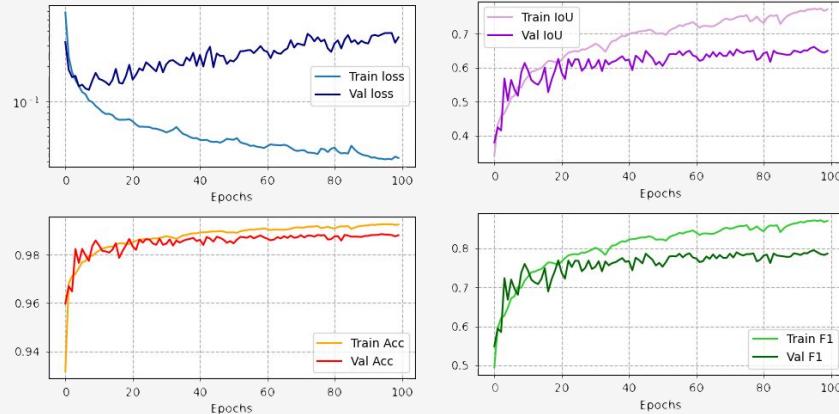
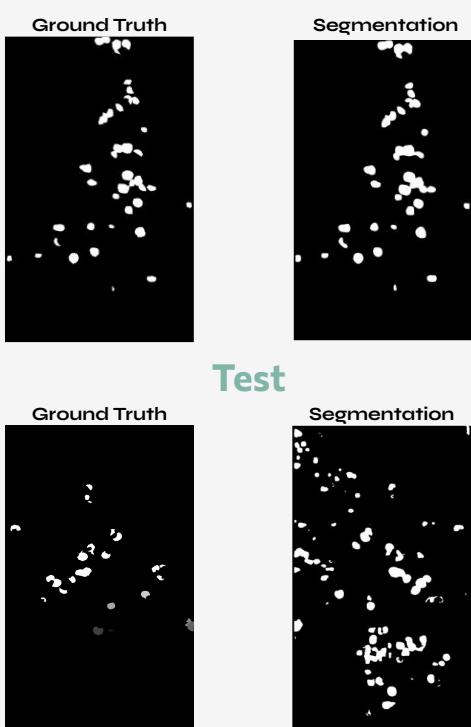
SEGMENTATION

2) Pre-Trained UNet



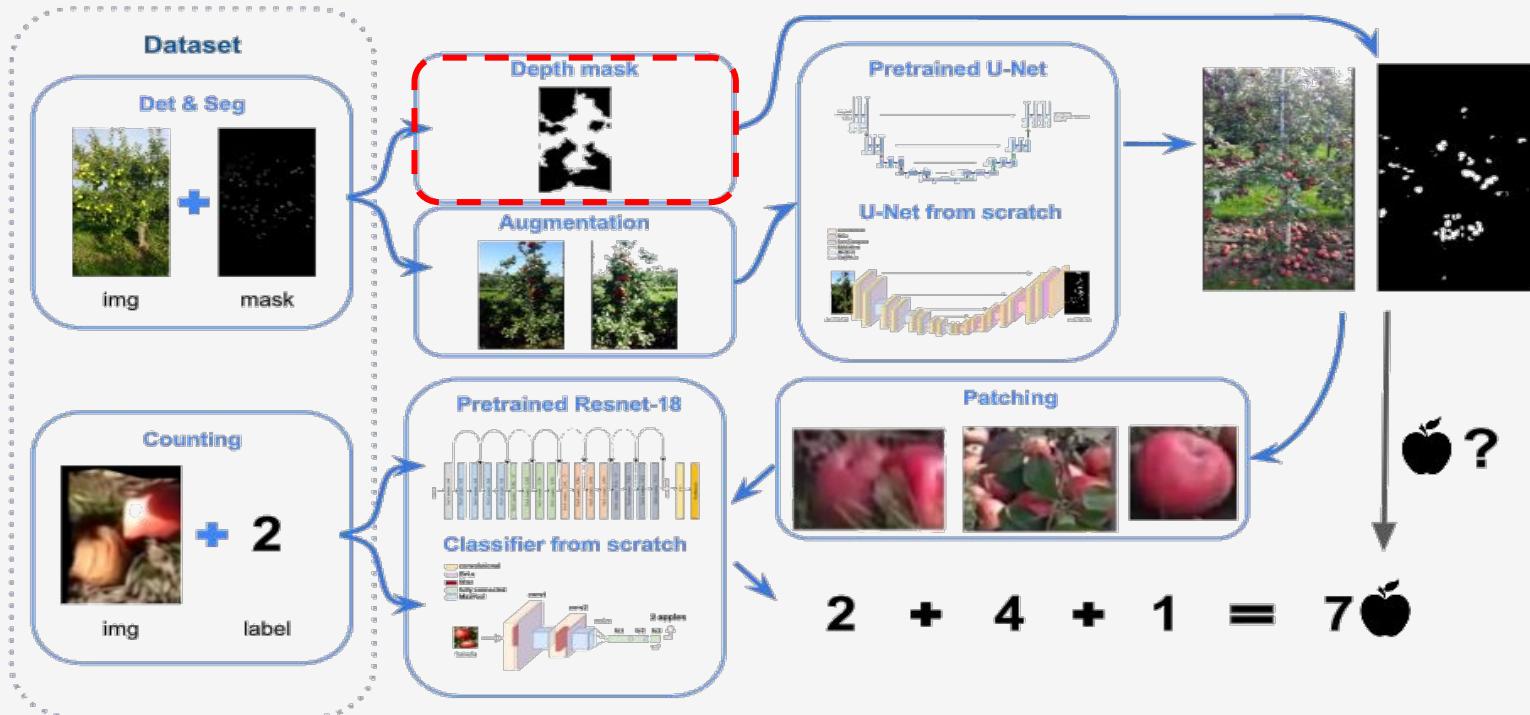
RESULTS

2) Pre-Trained UNet



ResNet	Normal	Augmented
Val IoU	0.665	0.640
Test IoU	0.559	0.549

DEPTH ESTIMATION



DEPTH ESTIMATION

Problem: many apples that are not on a tree are detected



Ground truth

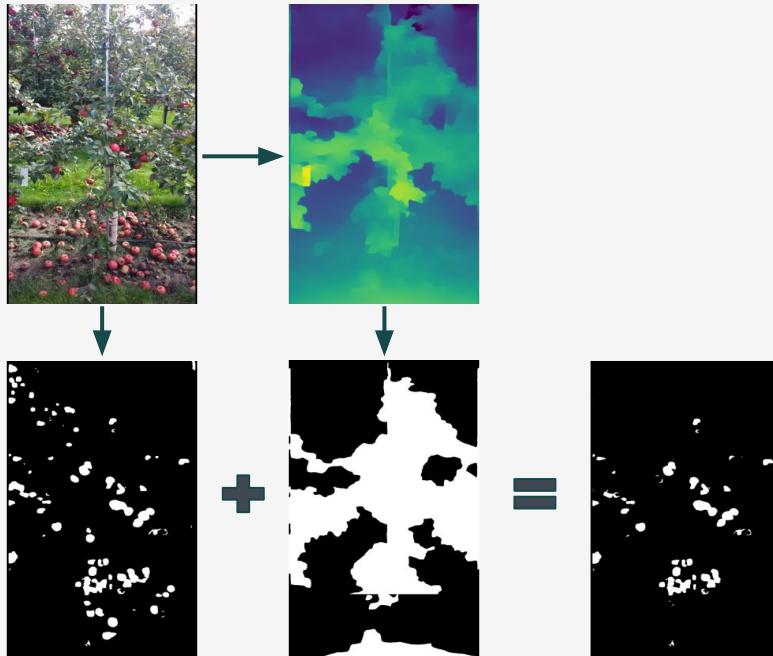


Our segmentation



DEPTH ESTIMATION

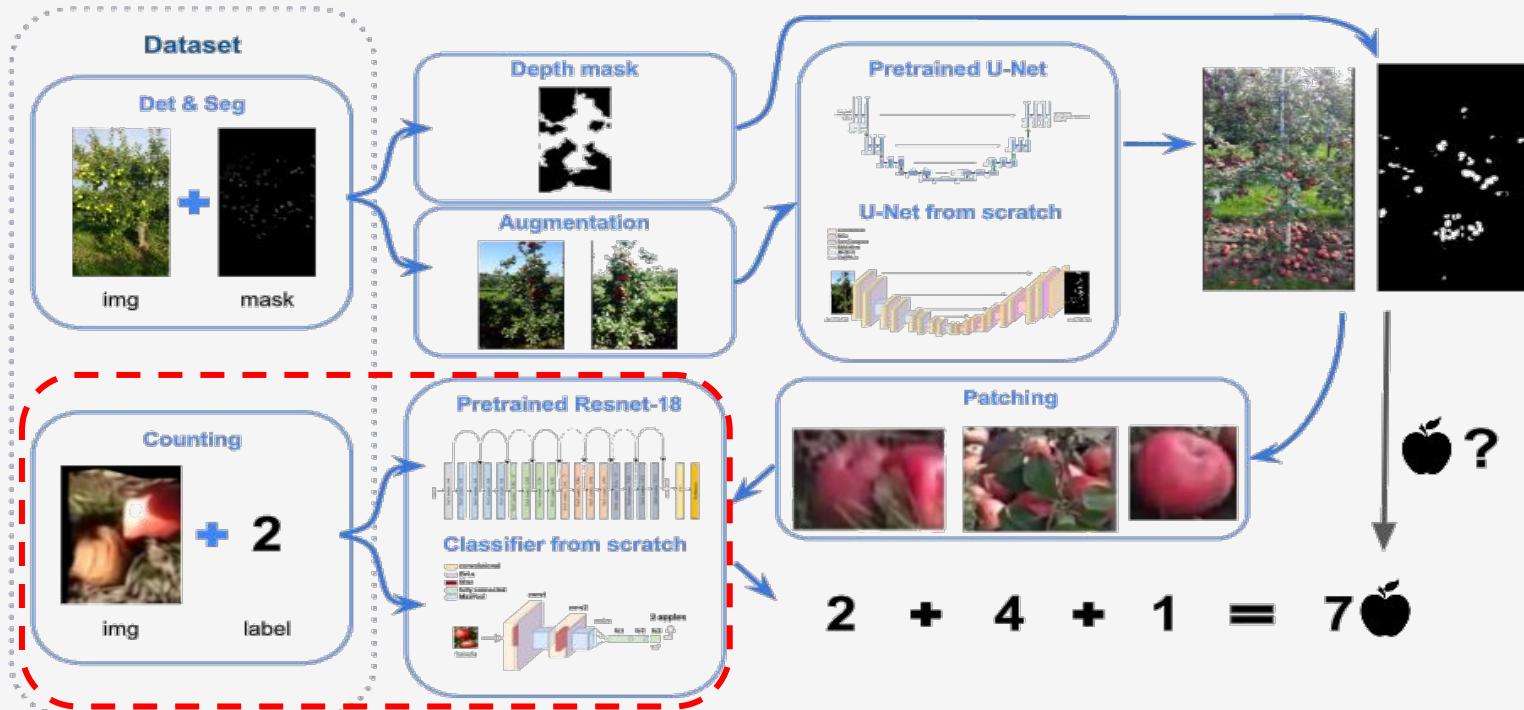
Solution : try to filter selected apple using the mask of the tree



- Pre-trained MiDas v3:
 - A Res-Net based architecture trained on different dataset used for computes relative inverse depth from a single image
- Threshold:
 - An empirical threshold is set on the inverse depth to exclude ground.

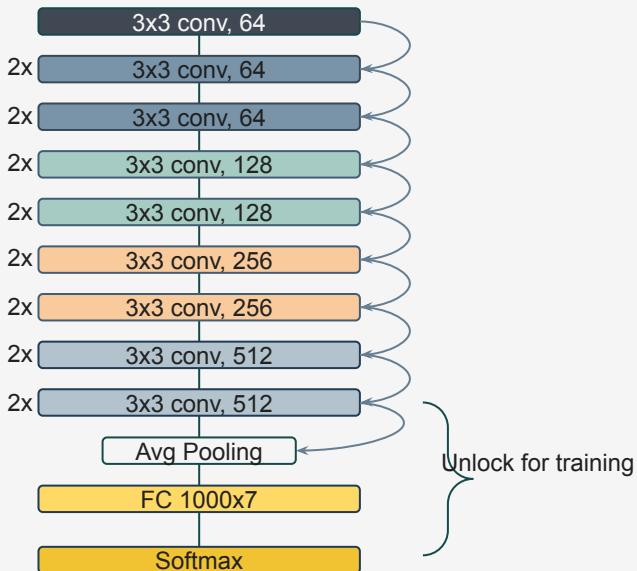
Results : detected apples are significantly less than before but still too many compared to ground truth

COUNTING



COUNTING

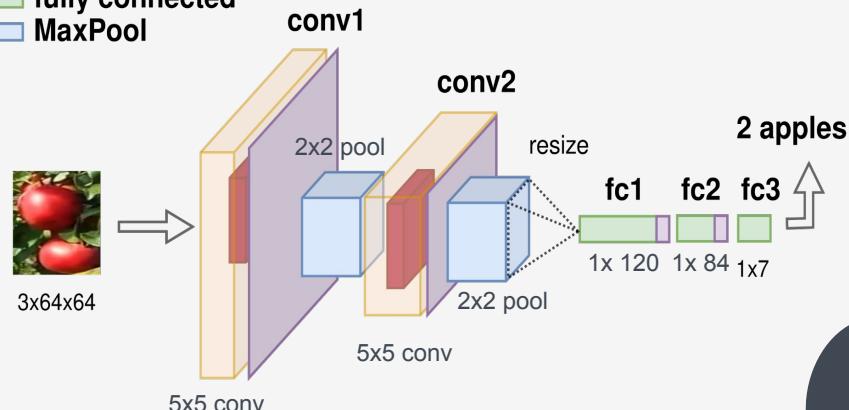
Pretrained Resnet18



Simple CNN

Legend:

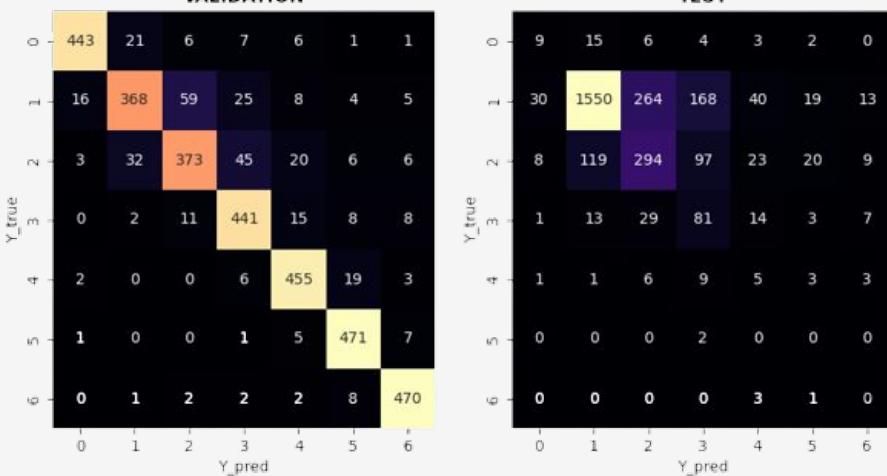
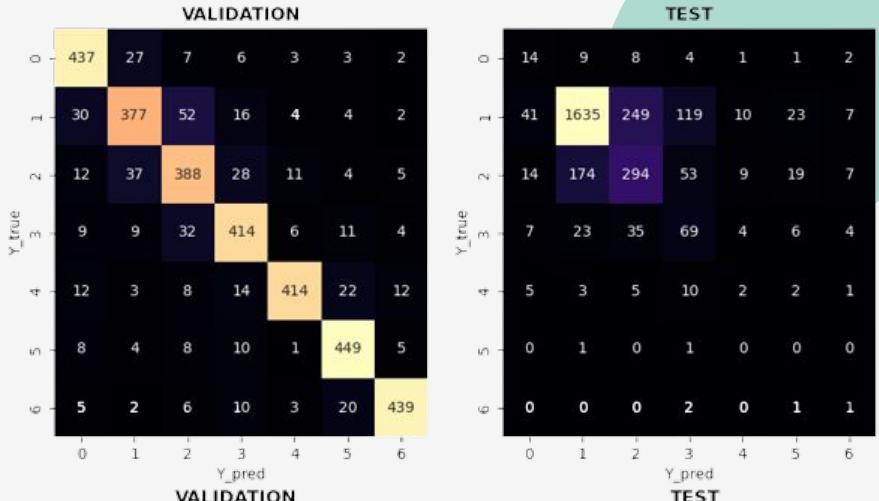
- convolutional
- ReLU
- filter
- fully connected
- MaxPool



Results

ResNet	Val	Test
Accuracy	0.859	0.701
F1 score	0.860	0.295

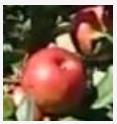
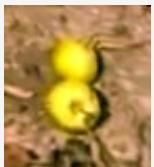
Custom	Val	Test
Accuracy	0.890	0.674
F1 score	0.888	0.276



COUNTING

Problem: accuracy on the test set is low.

Possible reason: training images are probably hand-cropped, while the test images are cropped with a patching algorithm.



Training

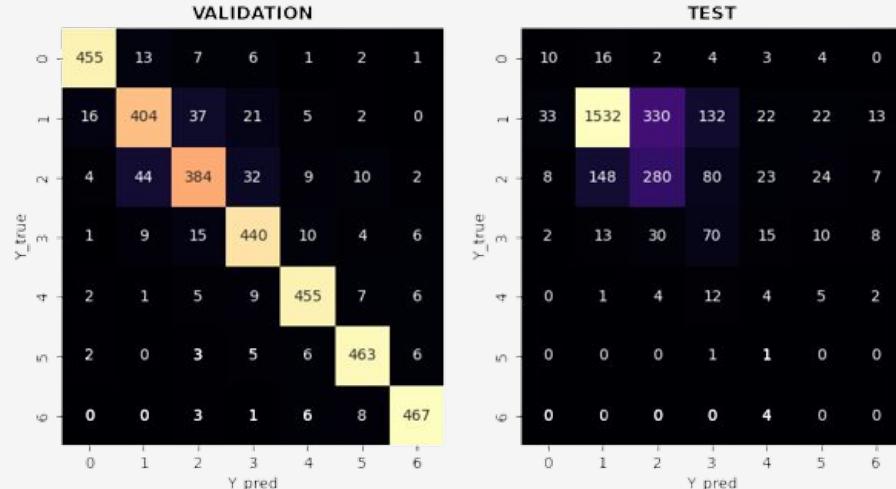
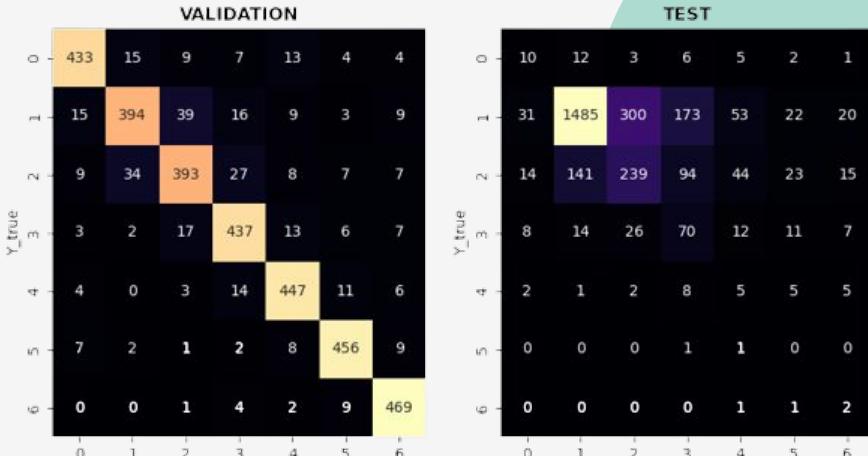


Solution: randomly crop training images using a scale of [0.8; 1] and then resize to 64x64.

Results with crop

Resnet	Val	Test	Val Crop	Test Crop
Accuracy	0.859	0.701	0.892	0.630
F1 score	0.860	0.295	0.892	0.261

Custom	Val	Test	Val Crop	Test Crop
Accuracy	0.890	0.674	0.904	0.659
F1 score	0.888	0.276	0.903	0.268

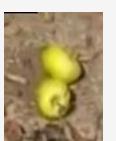


COUNTING

Problem: accuracy on the test set is low.

Other possible causes:

- different background between train and test set;

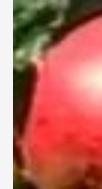


Train

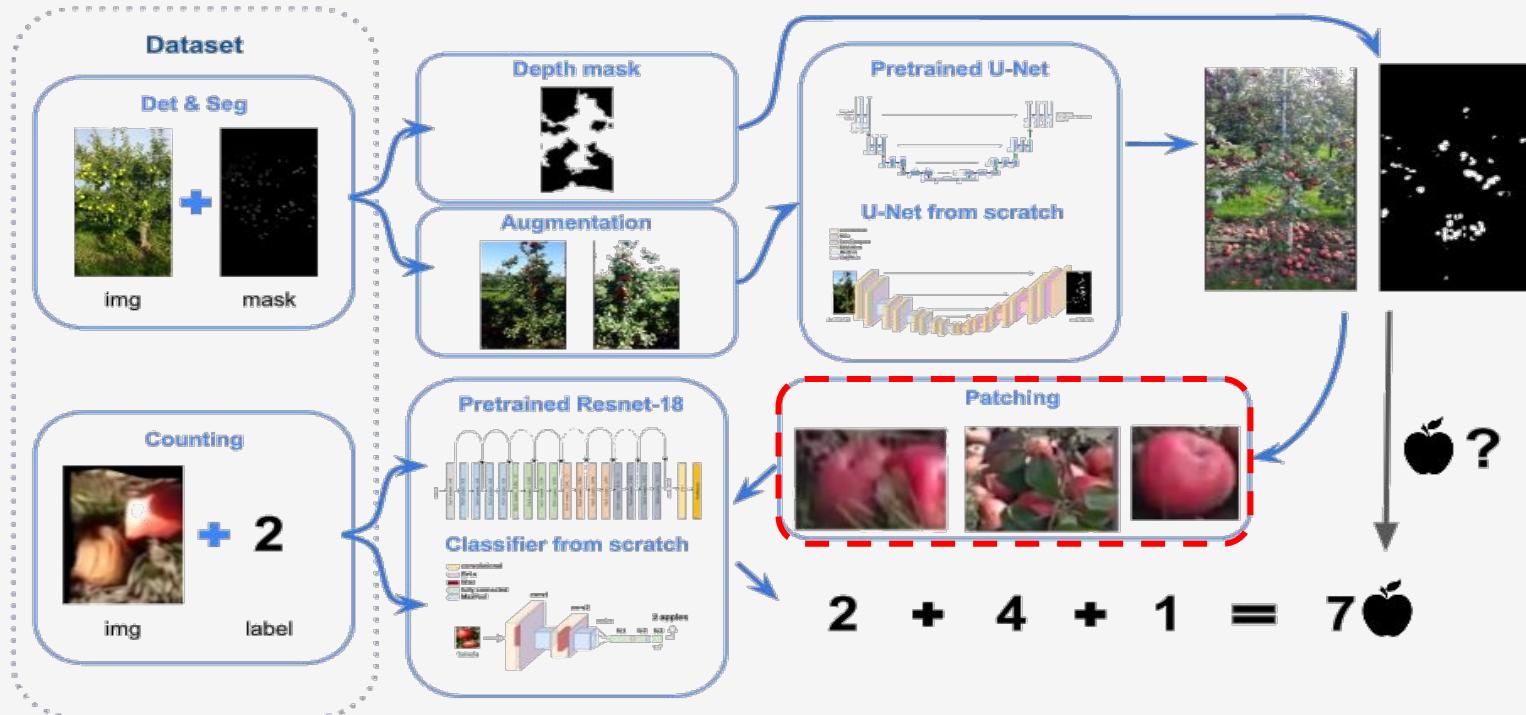


Test

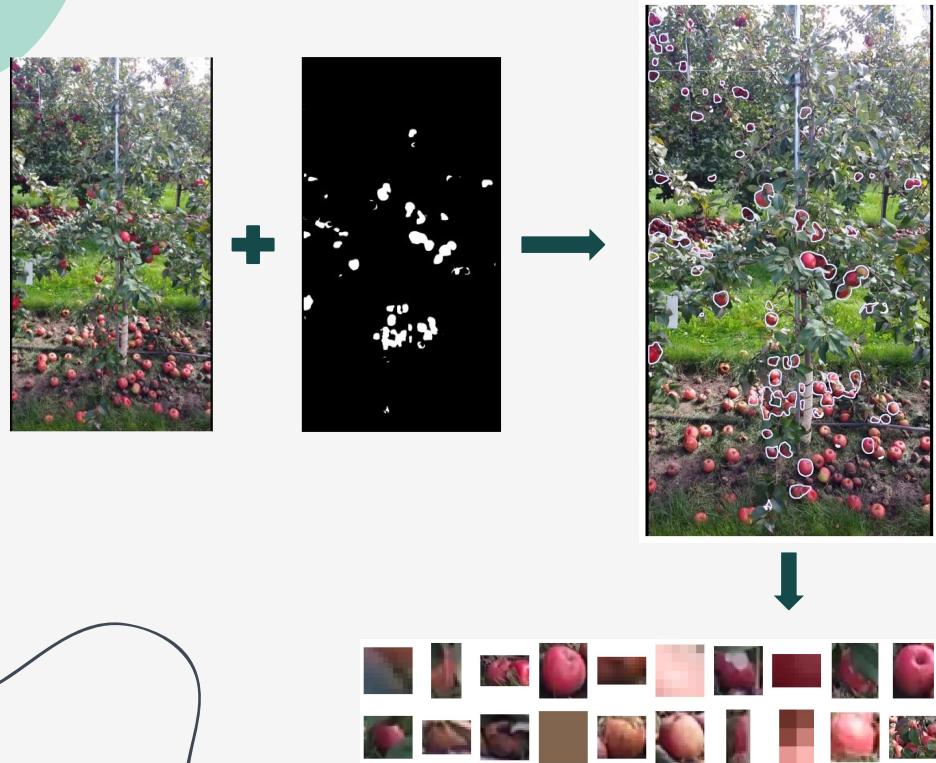
- some apples in train dataset are cropped a lot;



PATCHING



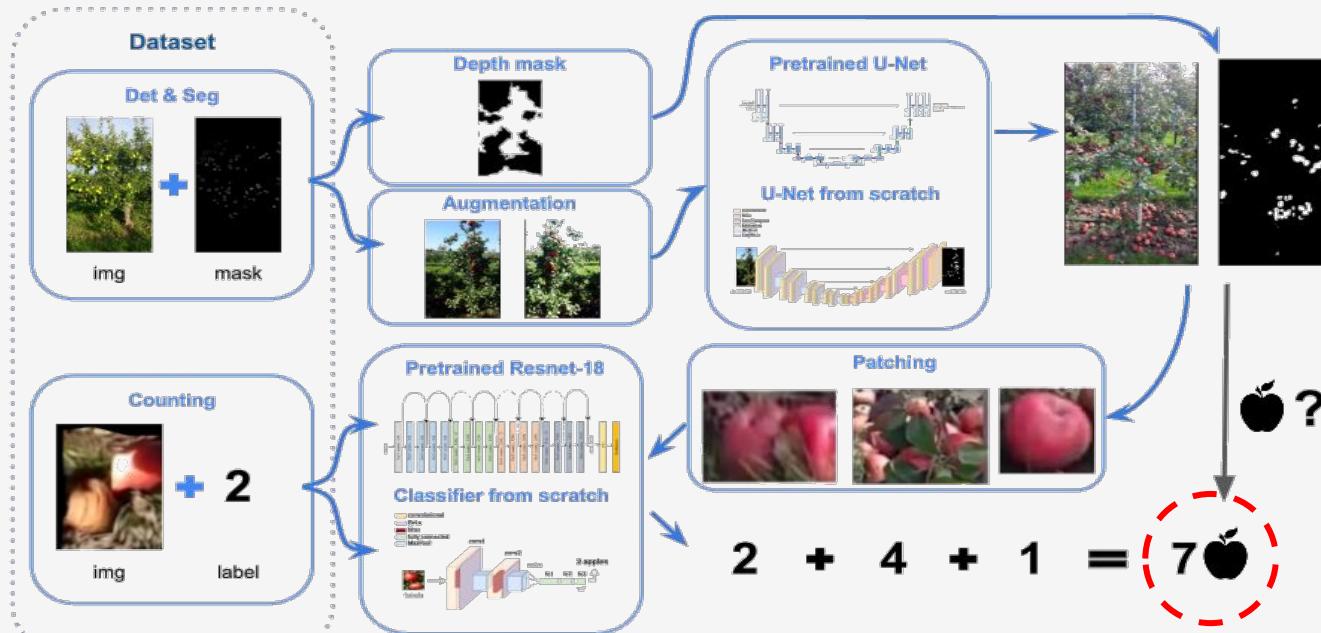
PATCHING



- Extract mask true segmentation
- Find all the connected areas
- Using openCV.findcontours to extract the bounding box of all the connected areas.
- Cut out the image around these boxes found to get the apple patches

COMBINING

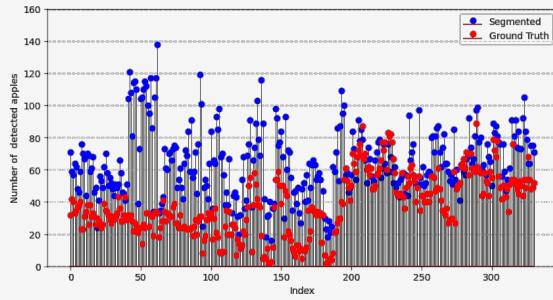
Goal: by combining the results of the previous passages, we are now able to estimate the total number of visible apples for each tree picture



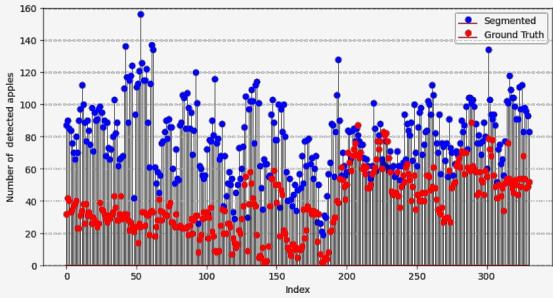
COMBINING RESULTS

TEST

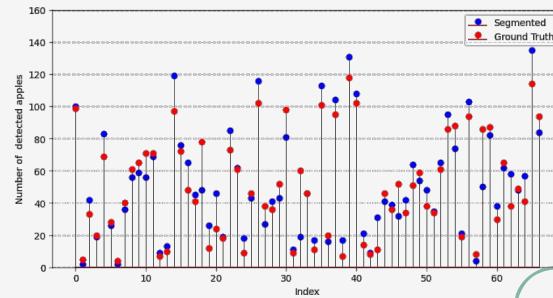
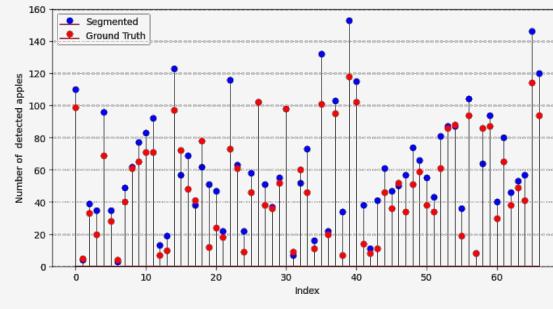
With
depth-estimation
filter



Without
depth-estimation
filter

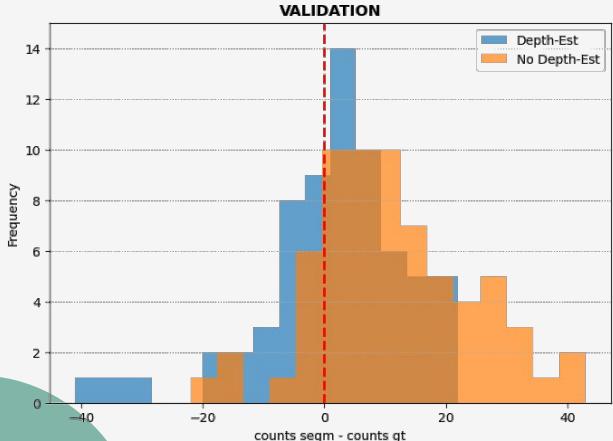
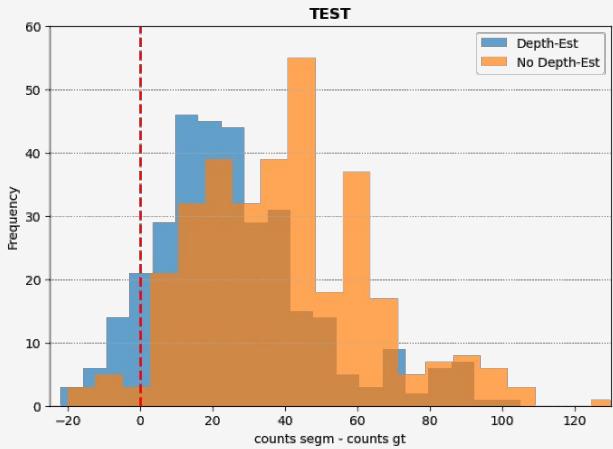


VALIDATION



COMBINING

RESULTS



The combined procedure to count the total number of apples leads to bad results:

- Number of apples detected from the segmentation mask are **systematically higher** than the the number extracted from ground-truth masks
 - This aspect highlights how the segmentation algorithm and the successive adjustments are **not enough** to select only apples present on the considered tree
- For the validation such an effect is **less evident** compared to the one in the test set
 - This suggests that images belonging to the test set are significantly different from the ones in training and validation set, or, on the other hand, that the train set is not enough representative

OVERLAP MAXIMIZATION

Problem: many apples appear multiple times in images corresponding to successive frames of the video

Idea of solution:

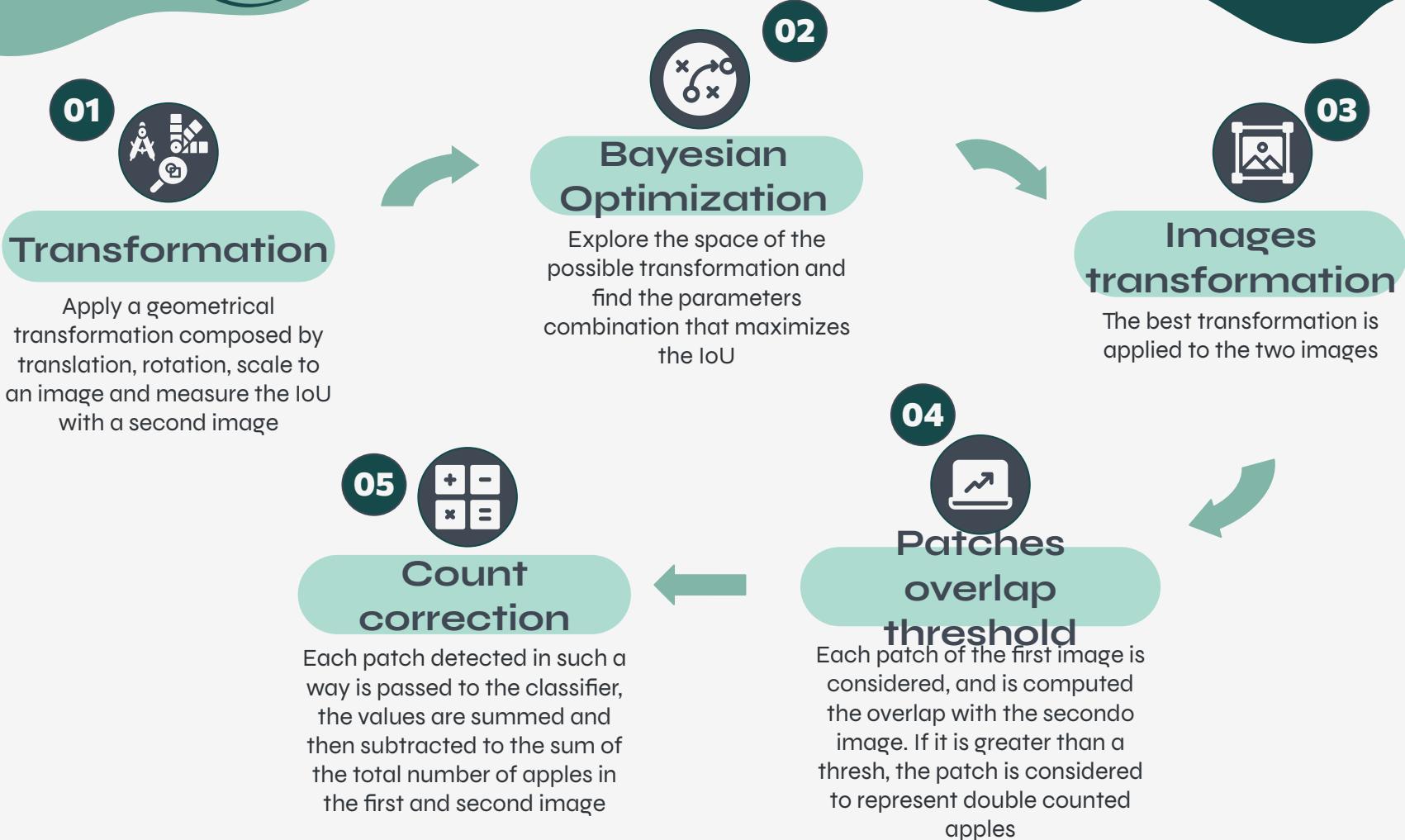
- Align segmentation masks corresponding to successive images in a meaningful way
 - Keypoints matching on the original images
 - Overlap maximization directly on masks
- Select which patches of the two images correspond to the same apples and extract the corresponding count
- Subtract such a number from the sum of the total number of counted apples in the two images

OVERLAP MAXIMIZATION

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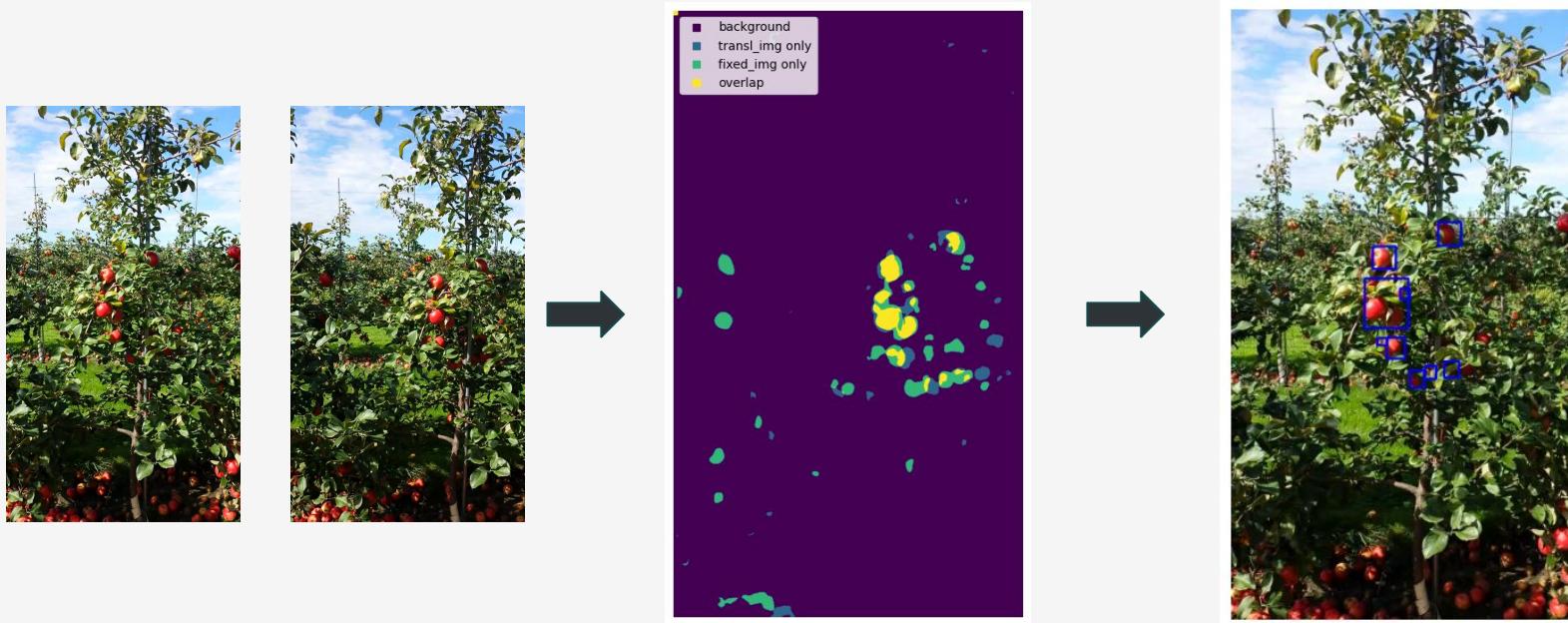
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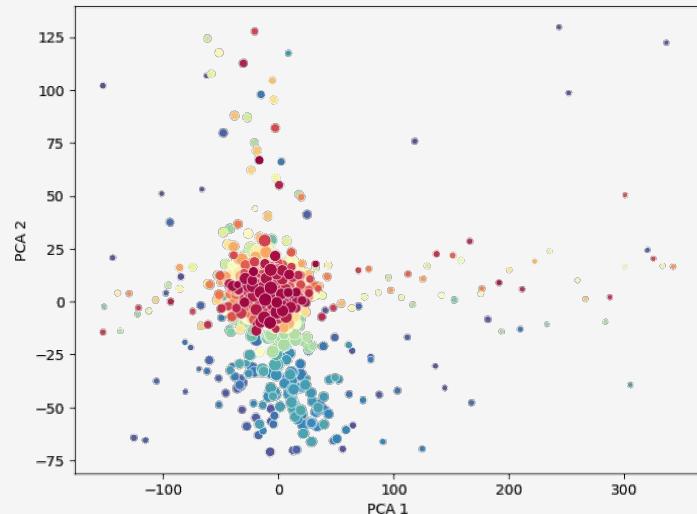
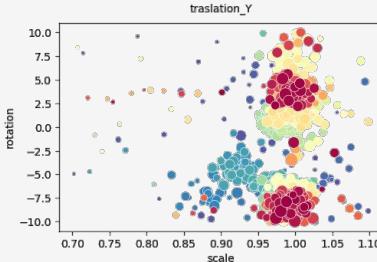
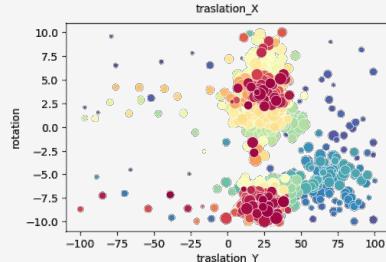
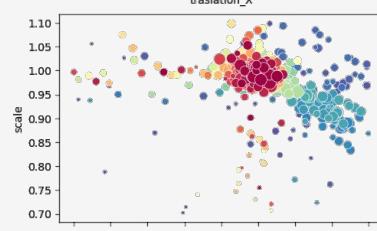
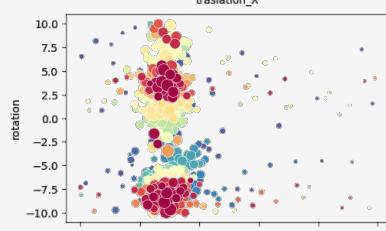
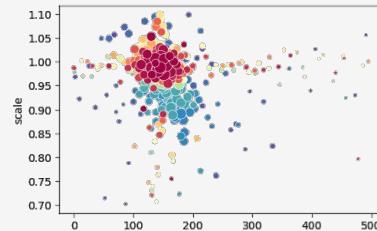
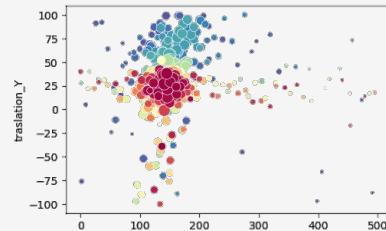
OVERLAP MAXIMIZATION

Results



OVERLAP MAXIMIZATION

Parameter space Visualization



CONCLUSIONS and FUTURE WORKS

Bad results, overestimation of over 300%

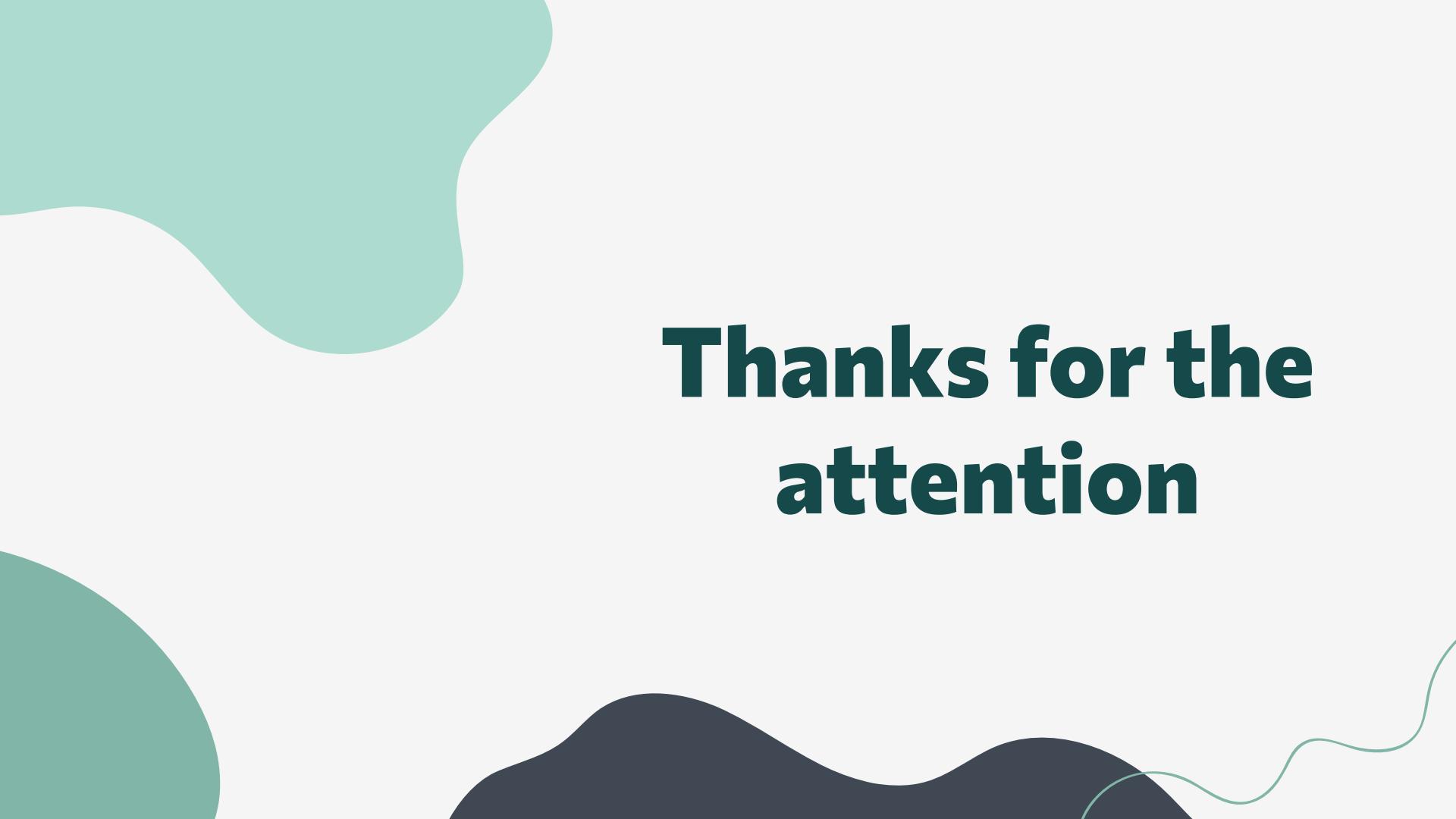


- Apple detection via segmentation is a relatively easy task, but when dealing with yield estimation many more problems arise



3D reconstruction techniques are fundamental to reach good performances in a yield estimation task

- Deeper exploration of the depth estimation procedure could improve significantly the results even without 3D reconstruction



**Thanks for the
attention**