

## CNN algorithm for single and overall weight estimation of melons using UAV images

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### Motivation and Objective





Motivation: Save the labor required for locating and weighting each individual melon in a phenotyping field.

**Objective:** Develop a robust algorithm that detects melons in an agricultural environment using UAV images for yield estimation.

**Challenge :** ROI's composed of a minority of small objects of 30X30 pixels or less .

**Ref:** A.Kalantar, Y.Edan, A.Gur, I.Klapp\*\*, "A deep learning system for yield estimation of melons using UAV images," Computers and Electronics in Agriculture., accepted for publication Aug. 2020

#### Data set and Images acquisition



The data was acquired at Newe Ya'ar in midday time

- Images acquired by a UAV hovering 15 meters above the field with RGB camera
- The acquisition was done in three different years at summer season, before picking time (2016-2018)
- Drone Type: DJI Phantom 4 Pro
- Camera Type : DJI FC6310 (RGB)
- Image size : 5472 × 3648 pixels



4220 melons were manually tagged, from 4 different images, for ground truth (2018 images).

> Augmentation: Rotation, Flip, Translation, Shear, Scaling (zoom)

Irrigation was stopped one week prior to the measurement.

#### Data set - Weight estimation





- 138 melons were randomly selected and marked in the field by placing a sign next to them.
- For each melon was provided its size and weight characteristics (validation set).
- in addition, extra data which contained 32 measured melons were provided in order to build the yield estimation regression model.

#### Algorithmic pipeline





Task 1 – Object Detection

#### RetinaNet network



Based on <u>ResNet50</u> network as backbone

- Creates <u>FPN</u> (Feature Pyramid Network) for high resolution and strong semantics – efficient way to create proposal candidates
- Use classification and regression <u>subnets</u> for generating final bounding boxes
- Focal Loss solve unbalanced classes problem



\* Lin et al. "Focal loss for dense object detection" (2017)

#### **Object Detection Process**



Divide the image to 10\*10 pieces with overlap

Detected all melons in each piece

Compose all detection back to the original image

Remove duplication with NMS (non-maximumsuppression ) algorithm





\*This is a small part from a big image (zoomed) for illustration purpose

#### Task 1 – Detection results





### Task 1 – Detection results



		clas	s: 91.43%	= melon AP								
1.0 -	$\sim$											
0.8 -									2016	2017	2018	2018
									Im age 1	Image 2	Image 3	Image 4
							True	Positive	252	800	1032	180
10.0 ·	1						False	Positive	18	48	39	25
Preci							False N	legative	35	89	12	11
0.4 -							P	recision	0.93	0.94	0.96	0.88
								Recall	0.88	0.90	0.99	0.94
0.2 -								F1-	0.90	0.92	0.98	0.91
0.0 -		-	-	,	-,							
0	.0	0.2	0.4	0.6	0.8	1.0						
			Reci	all								





#### Task 2 – Single Melon Segmentation





Chan-Vese active contour

**Binary mask** 

Ellipse fitting

#### Chan-Vese active contour



- > A cost function which is solved iteratively using a gradient descent
- Homogeneous regions have low variance values  $\arg \min F(c_1, c_2, C) =$

$$\mu_1 \cdot Lenght(C) + \lambda_1 \int_{imid_1(C)} |u_0(x, y) - c_1|^2 dx dy + \lambda_2 \int_{out id_2(C)} |u_0(x, y) - c_2|^2 dx dy$$

- $C_1$  the **mean intensity** value of all the pixels **inside** contour
- C<sub>2</sub> the mean intensity value of all the pixels outside contour
- *C* contour
- $\mu$  penalize the total length of the edge contour (set to 1)
- $\lambda_1$  the importance of the inner homogeneity relative to the homogeneity outer (set to 1)
- $\lambda_2$  the importance of the outer homogeneity relative to the inner homogeneity (set to 1)





### Feature extraction – Ellipse fitting (PCA) 🛛 🚱 🎯 🌆

> The shape of the ellipse is determined by a set of 5 parameters

$$\frac{\left[\left(x-x_0\right)\cos\left(\theta\right)-\left(y-y_0\right)\sin\left(\theta\right)\right]^2}{a^2}+\frac{\left[\left(x-x_0\right)\sin\left(\theta\right)+\left(y-y_0\right)\cos\left(\theta\right)\right]^2}{b^2}=1$$

- Centroid x co-ordinate  $(x_0)$
- Centroid y co-ordinate  $(y_0)$
- Semi-major axis (*a*)
- Semi-minor axis (b)
- Angle of tilt  $(\theta)$



#### Ellipse fitting examples







#### Task 3 – Yield estimation





#### Task 3 – Yield estimation



> Yield estimation process include 4 stages:





Regression model was tested using 116 randomly selected melons from 2018 season

- The mean absolute percentage error (MAPE) for individual melon estimation was 9%  $MAPE = \frac{1}{N} \sum_{N} \left| \frac{X - \tilde{X}}{X} \right|,$
- An overweight overall yield estimation error of 2.9%

X is the actual value,  $\tilde{X}$  is the prediction

#### Results - Melon yield report



> An example of report that the system generate:

Malan	Contor	Contor	Semi	Semi	Semi	Semi	Moight	
	Pow	Center	Major	Minor	Major	Minor		
	ROW		Axis [pix]	Axis [pix]	Axis [cm]	Axis [cm]	(rg)	
1	13	2773	35.14433	29.64361	10.0412	8.4696	0.921661	
2	44	950	34.00361	22.79422	9.7153	6.5126	1.370152	
3	30	5250	20.85496	11.95877	5.9586	3.4168	1.681457	
4	33	2816	26.81252	19.01066	7.6607	5.4316	1.370152	
5	1612	1926	23.81392	18.00779	6.8040	5.1451	0.643062	
6	1619	2398	39.76633	23.39249	11.3618	6.6836	1.967597	

#### Results - Melon yield report





#### Summary



A systems for detection and yield estimation of melons from top view UAV

images of a melon field have been developed.

The system includes three main stages:

- Melon detection (RetinaNet, NMS) mAP = 0.914 | F-score>0.9
- Feature extraction (Chan-Vese + PCA)
- Yield estimation (Linear regression) only 3% underestimation
- The system provides promising results .



# Thank You

Yield estimation – Linear regression



- The selected regression model was built from 30 randomly individual melons from 2017 season.
- The regression where based on max height (2\*c) and max width (2\*a) of each melon. W=0.1096653+0.003397929·c·a<sup>2</sup>

Type of	Parameters	$R^2_{Adj}$	
correlation	combination	value	
Linear	<i>c</i> + <i>a</i>	0.914	
Area	c * a	0.87	
Volume	$c * a^2$	0.94	



Ground sample distance (GSD)



Flight Height (Distance Above Ground)

Ground

Ellipse parameters given in pixels was translated to millimeters using GSD  $GSD = \frac{h \cdot \Delta p}{f}$ 

- *h* approximate height from grour
- Δp sensors pixel size
- *f* focal length

For each image we calculate the GSD separately - the fly height was not uniform

#### Definitions



#### mean absolute percentage error (MAPE)

 $MAPE = \frac{1}{N} \sum_{N} \left| \frac{X - \tilde{X}}{X} \right|, \quad X \text{ is the actual value, } \tilde{X} \text{ is the prediction}$ 

Ref: Wikipedia