Computer Vision and Artificial Intelligence for Plant Phenotyping

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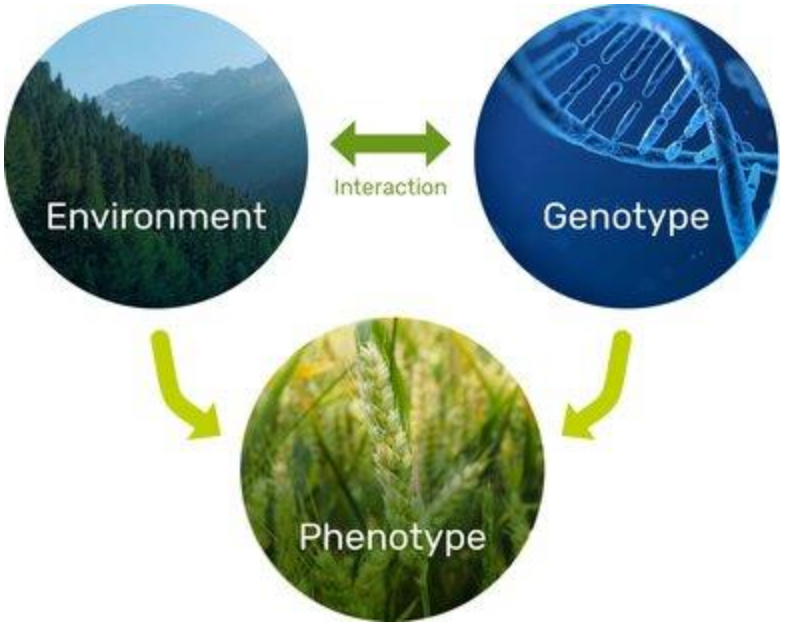
Outline

- Motivation and CV/AI in Phenotyping
- Rob2Pheno: Automated Tomato Phenotyping
- Floricultural Trait Cataloguing
- Conclusions

What is phenotyping?

- Quantitative measurement of functional characteristics of an organism (Wilhelm Johanssen)

- Some phenotypic traits:
  - Fruit/leaf size/shape
  - Color
  - grouping/diffusion



(source: plant-phenotyping.eu)

Background

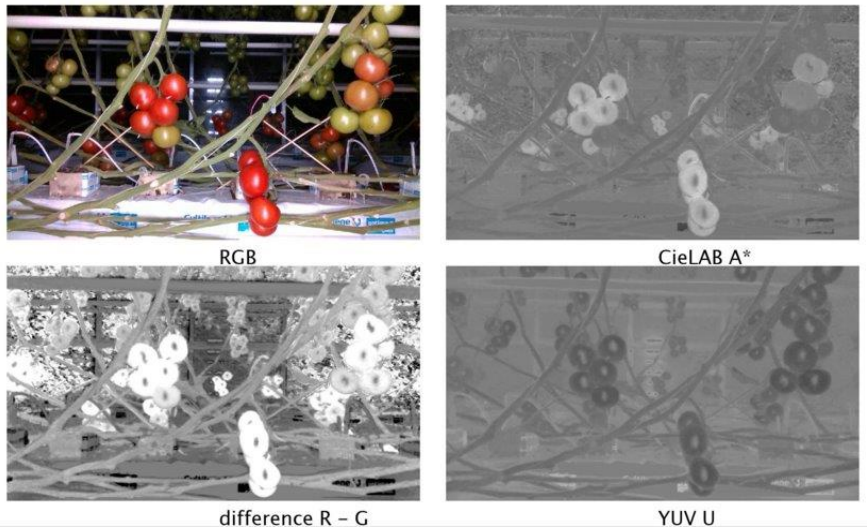
- For growers, important to predict yield, plan for harvest
- For breeders, important to know which varieties yield more/better (efficiency)
- Production systems are optimized for maximal output.

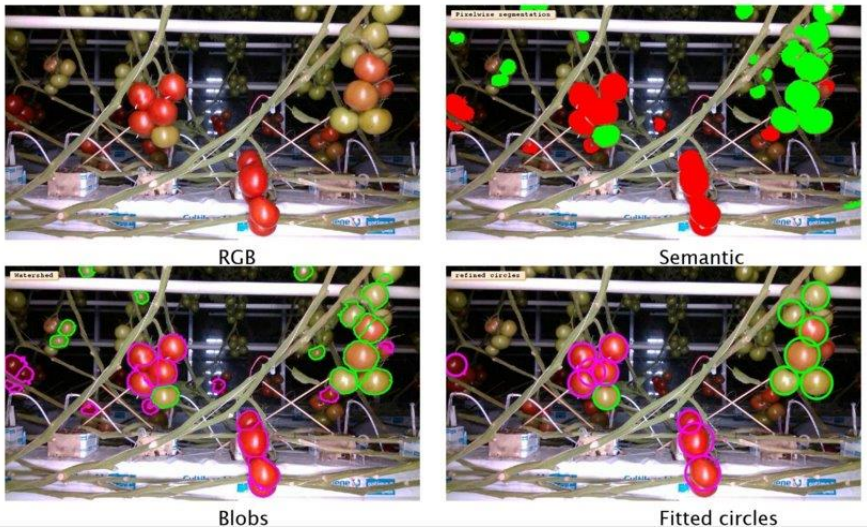
Role of Computer Vision and AI

- Imaging is quick and non-destructive
- ML/AI methods are less prone to errors than manual inspection
- Deep learning has made it possible to simply show an algorithm images and required data and let it learn for itself
- Lends itself easily to high throughput analysis

Approach with Domain Knowledge

- Assumptions on shape and color
- Foreground fruits are larger
- Colorspaces can emphasize objects of interest
- Sensitive to parameters, illumination, etc!





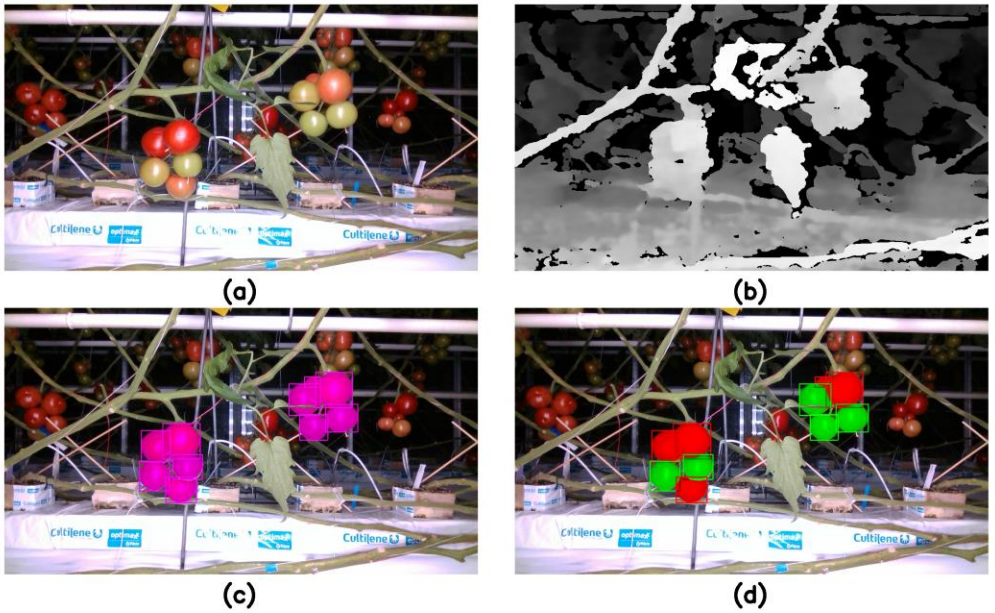
Phenotyping Use Case: Rob2Pheno

- Joint work with Enza Zaden, Netherlands
- Co-financed by Foundation TKI

- Autonomous robotic imaging

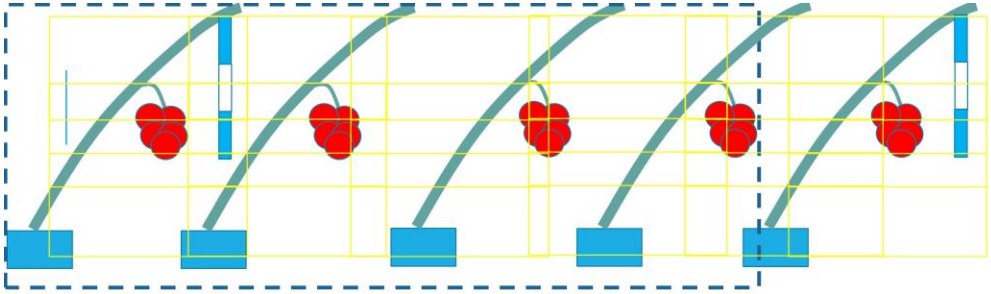
for phenotyping tomatoes in a practical commercial Greenhouse

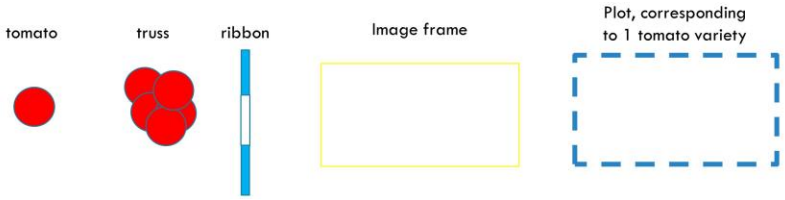
Imaging System: 4 Intel Realsense Cameras (RGB + depth)



Protocol in Greenhouse (Production needs to be optimal)

- Varieties in groups of 4 plants (plots), demarcated by ribbons
- Narrow paths, restricted field of view => makes processing difficult





Dataset

- One programmed nocturnal run = 1 GB of data
- Images acquired pre- and post-harvest in July 2019
- Ripe tomatoes from images compared against harvested weights
- Publicly available 123 image dataset with fruits annotated (1612 fruits = 541 red + 1071 green):

  https://data.4tu.nl/articles/dataset/Rob2Pheno_Annotated_Tomato_Image_Dataset/13173422

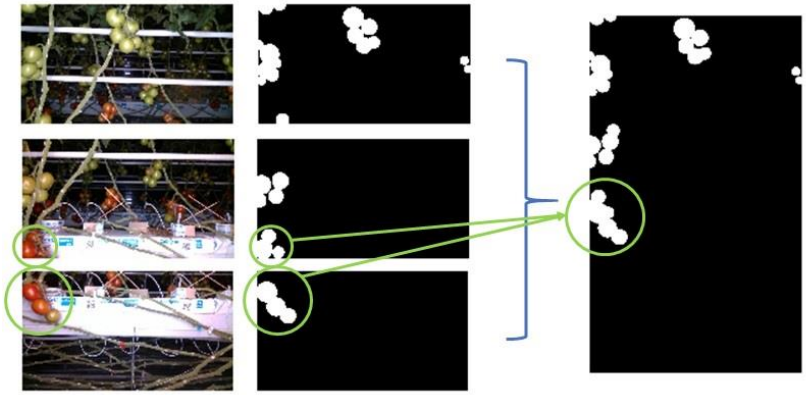
Mosaic of Successive Images

- Parallax, repetitions, occlusions, background clutter

Rob2Pheno processing pipeline

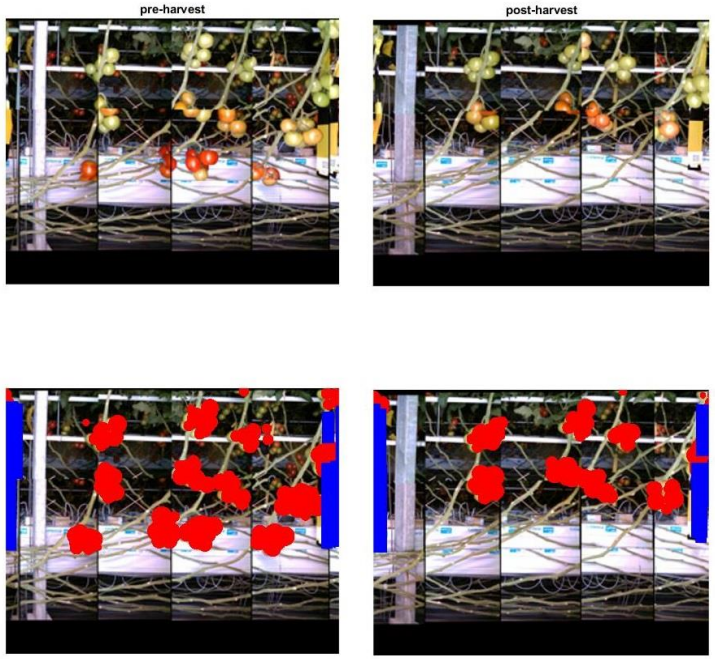
1. MaskRCNN to detect fruits, FasterRCNN for banners

2. Registration using correlation across horizontal and vertical RGB frames and results



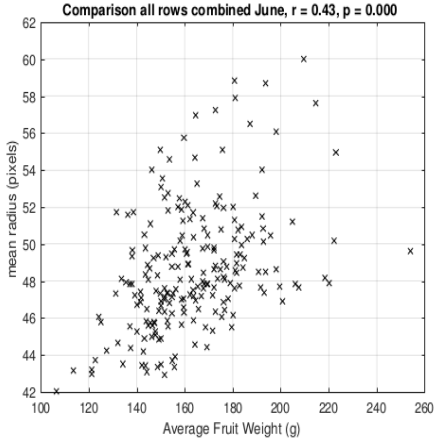
Rob2pheno processing pipeline

- Compare pre- and post-harvest images for same plot
- Approximation: consider a plot to be demarcated by ribbons



Rob2Pheno Results

- Image Level fruit detection
  - F1 0.94 (overall), 0.93 (ripe)
- Plot level yield prediction
  - R^2 = 0.43
- Individual fruit weight prediction
  - Avg. relative error of ~ 13%
- [Afonso et. al., Frontiers in Plant Sc, 2020]
- [Fonteijn et al., Agronomy, 2021]
- [Schadeck-Fiorentin, MSc Thesis, 2021]



Rob2Pheno Team

WUR:

Ron Wehrens, Manya Afonso, Hubert Fonteijn, Gerrit Polder, Angelo Mencarelli, Felipe Schadeck Fiorentin, Arjan Vroegop

Enza:

Nanne Faber, Dick Lensink, Marcel Mooij

Related work: Hortikey Plantalyzer

- Multi purpose autonomous platform for qualitative and quantitative inspection in the greenhouse
- PPS 2018 – 2021 UC3, PPS Dynamic Machine Learning 2021 – 2024
- Partners: Berg Hortimotive, LetsGrow, WUR
- Already in market

HortiKey controlled growing

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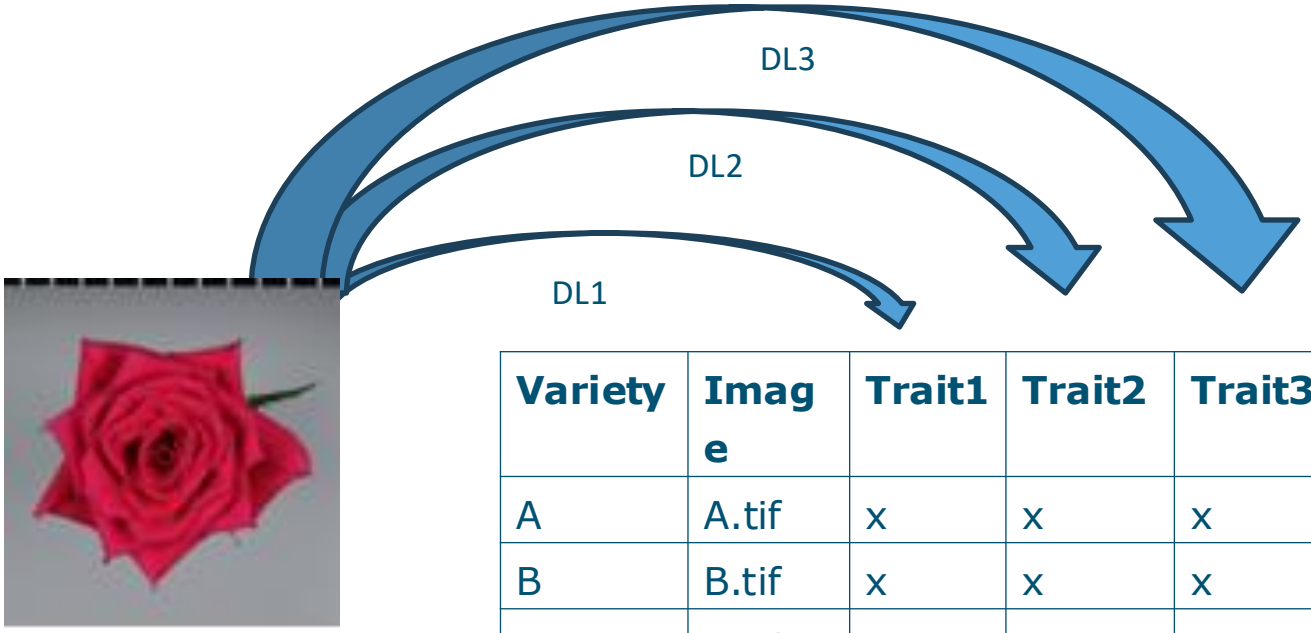
“It's the time you spent on your rose that makes your rose so important."
Antoine de Saint-Exupéry

- Flower varieties are breeders' intellectual property.
- Registration requires specific expertise

Can AI predict traits that characterize flowers?



Variety	Image	Trait1	Trait2	Trait3	Trait4
A	A.tif	x	x	x	x
B	B.tif	x	x	x	x
C	C.tif	x	x	x	x
D	D.tif	x	x	x	x

Project MoDOMa: Morphological Descriptions of Ornamentals through Machine learning

- WUR:

  Ron Wehrens, Manya Afonso, Maria Joao Paulo, Hubert Fonteijn, Gerrit Polder

- Floricode:

  Mary van den Helder, Henk Zwinkels

- Naktuinbouw:

  Marcel Rijsbergen, Gerard van Hameren, Raoul Haegens

Co-financed by Foundation TKI

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4 Datasets – Rose/Gerbera and from Floricode/Naktuinbouw records

- Floricode

- Naktuinbouw

Flower Traits

Provenance	Flower	Trait	Classes
Floricode	Rose	Inflorescence	Single-flowered. Truss
		Flower-type	Spinning-heart, Filled
		Flower-color	Orange, Pink, Purple, Red, White, Yellow
	Gerbera	Flower-type	Filled, Half-filled, Slightly-filled, Unfilled
		Inflorescence	Little-head, Flattened-spherical
		Flower-color	Orange, Pink, Red, White, Yellow
Naktuinbouw	Rose	Petal-shape	Obovate, Transverse-elliptic
		Flower-shape	Irregularly-rounded, Round
		Color-group	Orange, Pink, Red, White, Yellow
	Gerbera	Head-diameter	Small-medium, Medium Medium-large, Large, V.Large
		O.Floret Length	Short, Medium, Long
		Color-group	Orange, Pink, Red, White, Yellow

Pipeline

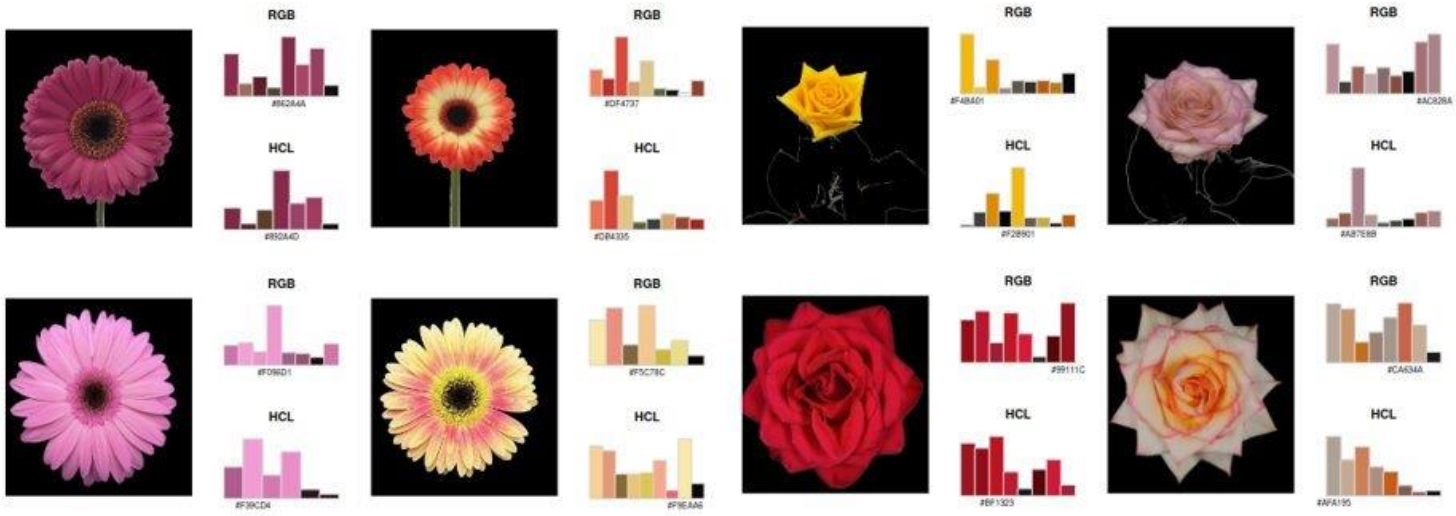
1. Pre-processing: Background segmentation (color, texture, BGR app), de-leafing



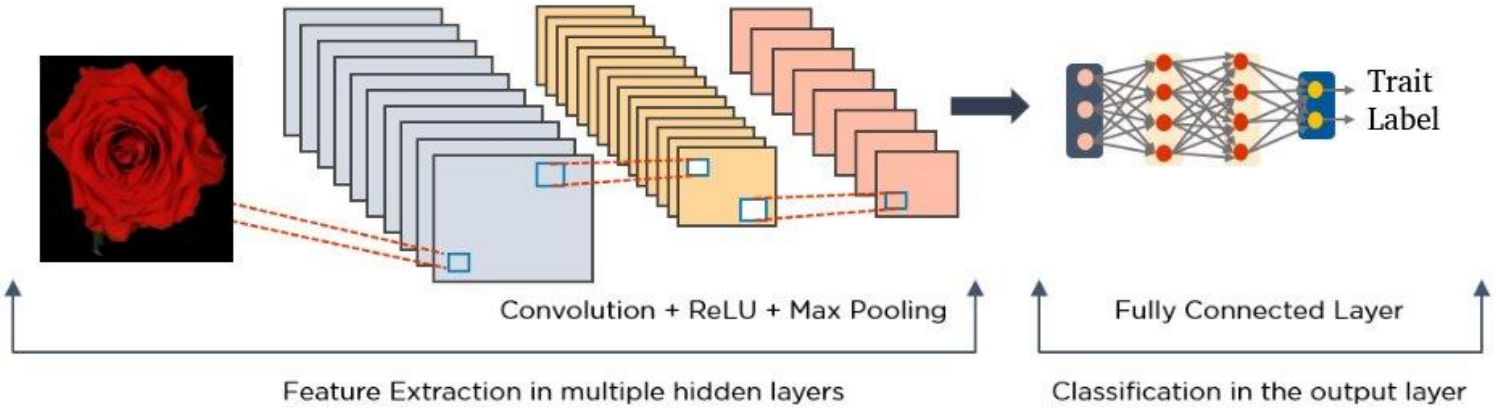
2. Data filtering: discard too small classes
3. Train DL/ML model (binary/multi-class classification, regression)

- Implementation in PyTorch, ResNet18 baseline architecture

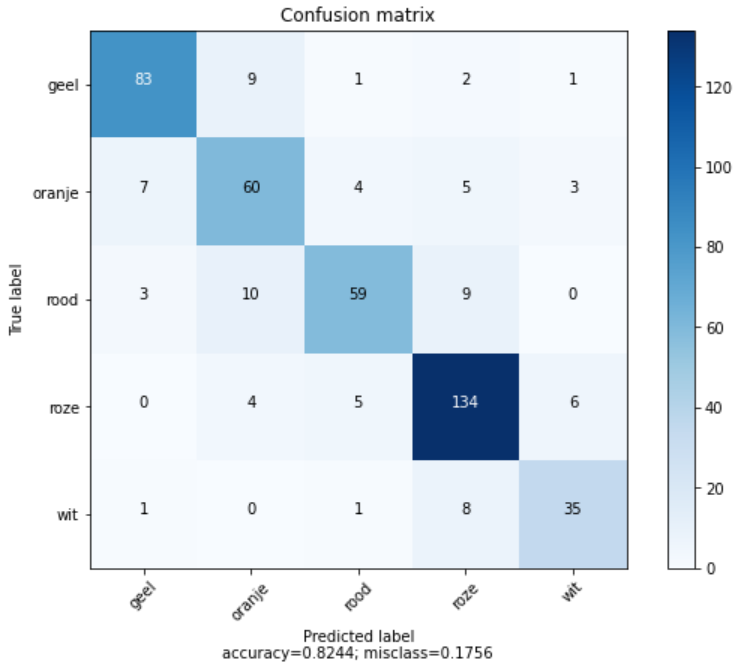
Image Statistics + ML methods for color



Deep Learning Classifier (categorical traits)

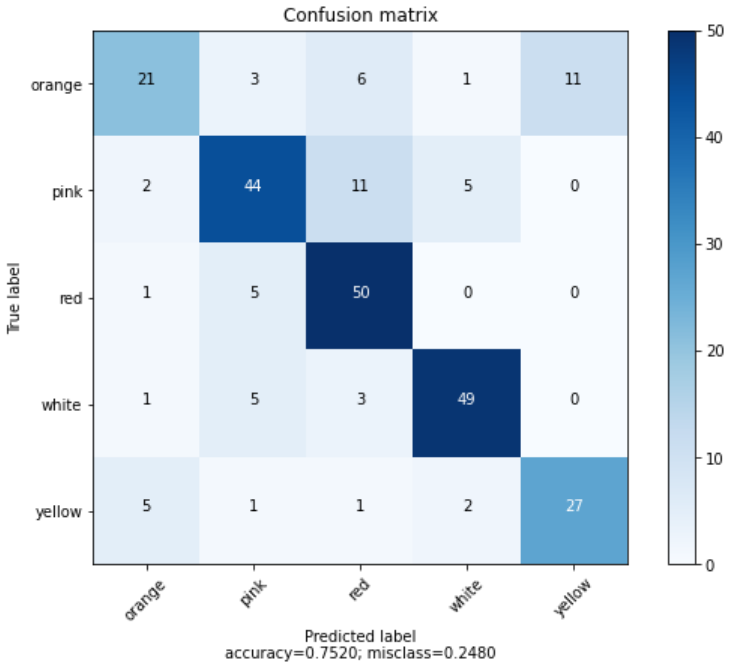


Example: Color, Gerbera (Floricode)



- Confusion is mostly between similar colors
- Orange and pink are the most difficult colors

Example: Outer color group, Rose (Naktuinbouw)



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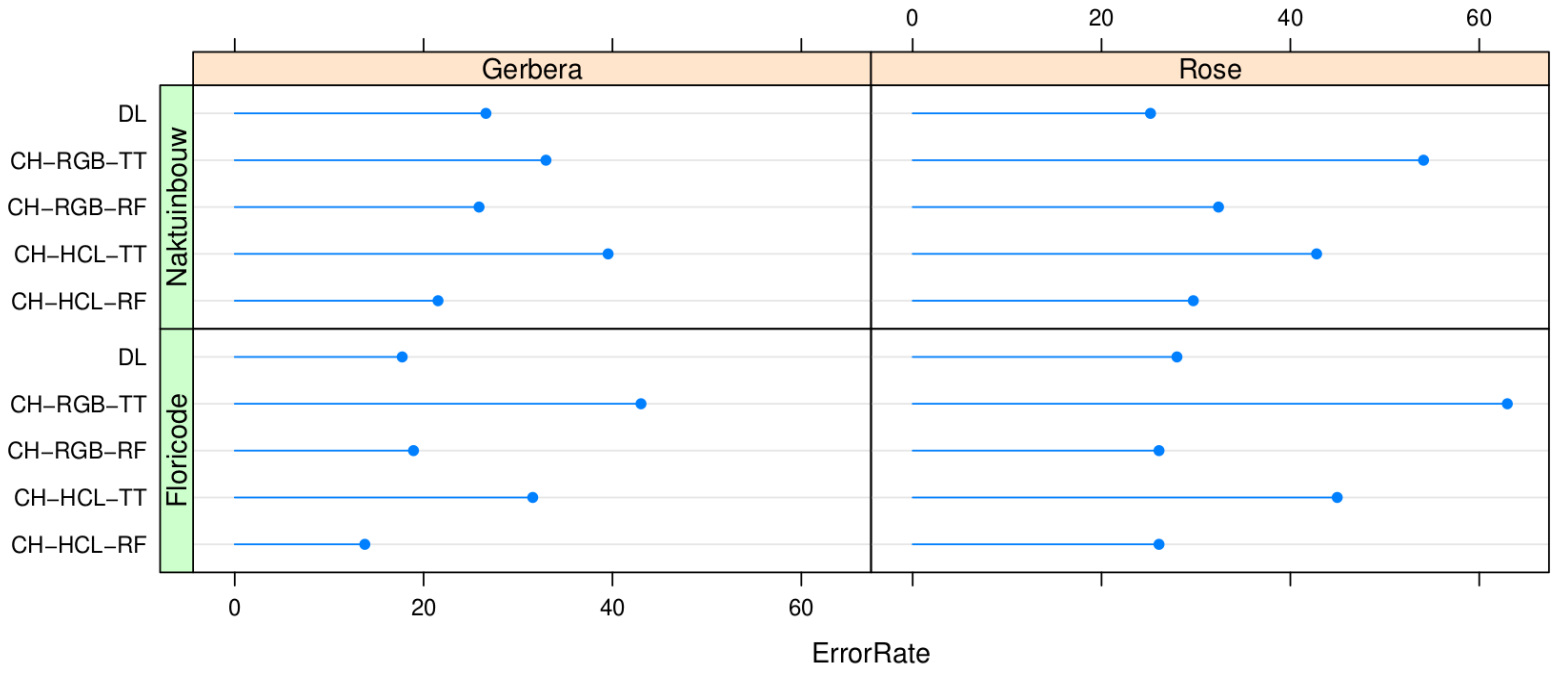
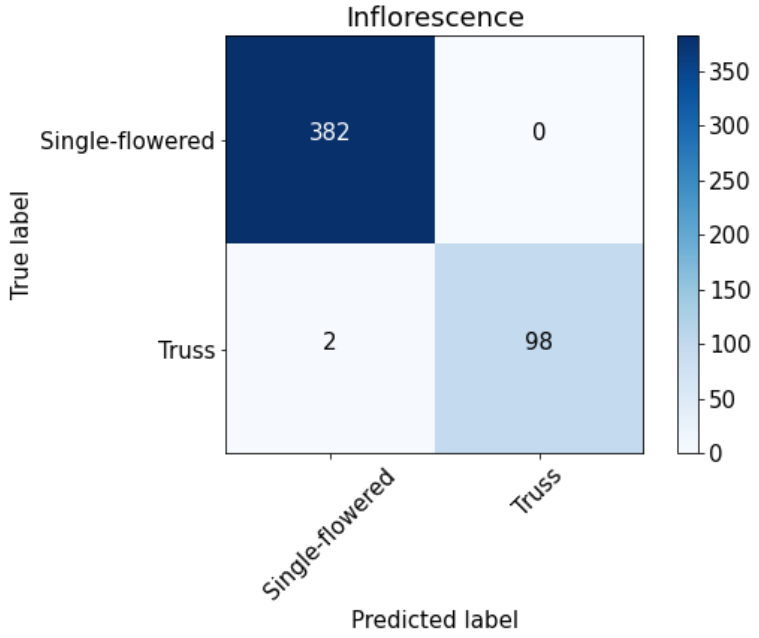
Overall Color Results [Wehrens et.al., 2024]

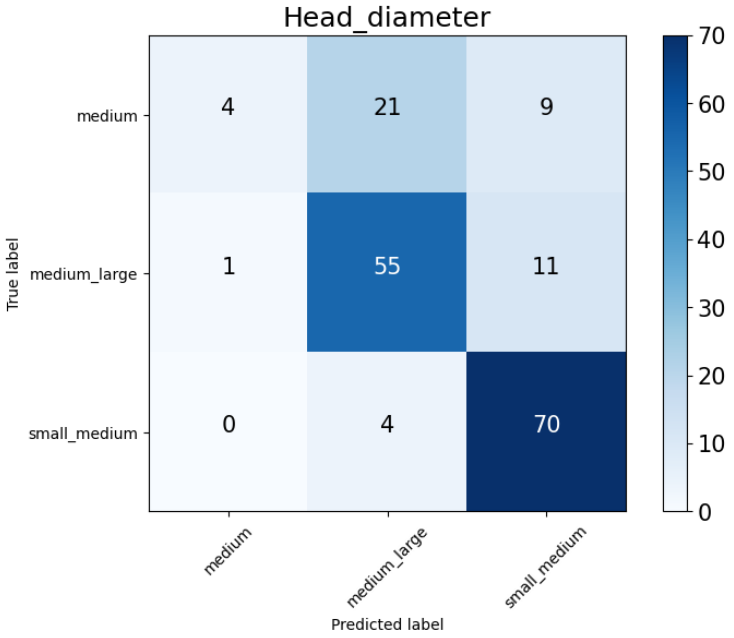


Example: Inflorescence, Rose (Floricode)



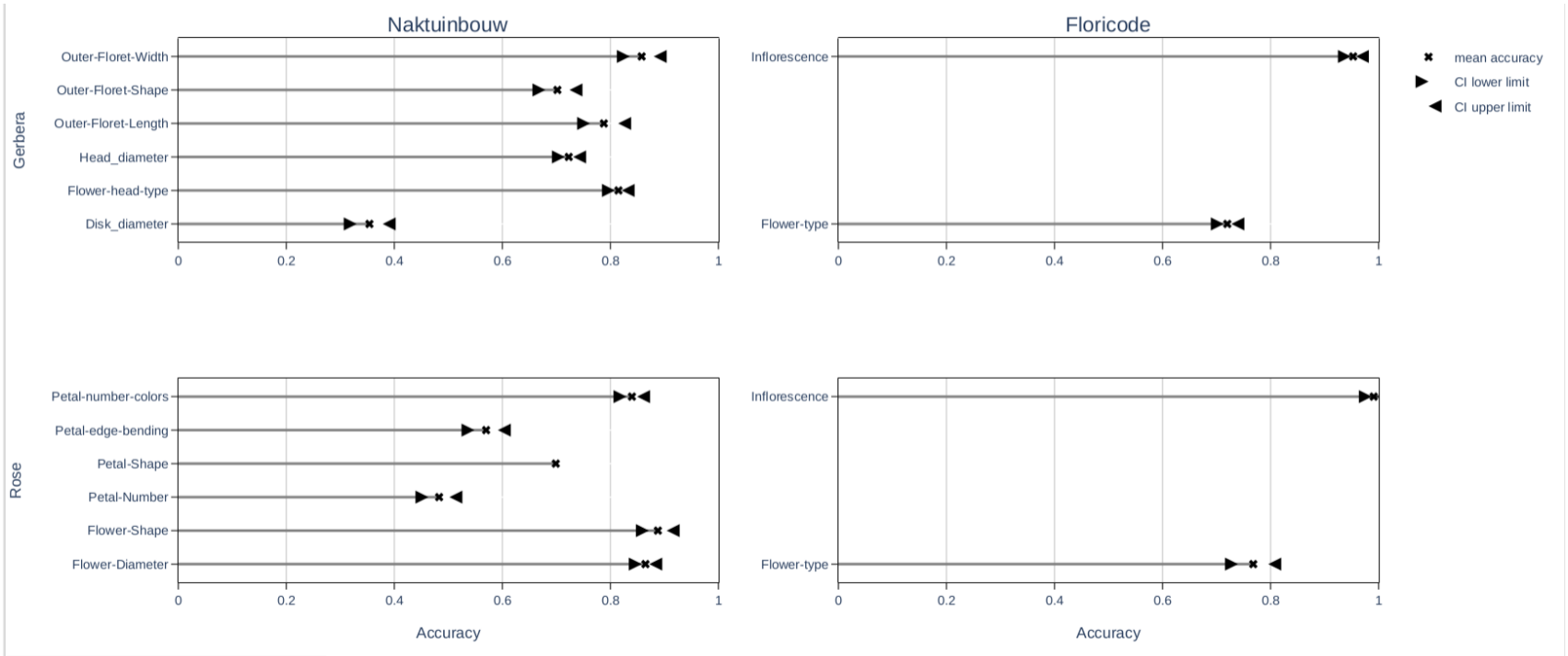
- Accuracy: 99.6 %
- Generally in practice, imbalance in classes occurs.

Example: Head diameter, Gerbera (Naktuinbouw)



- Accuracy: 72.1 %
- Medium is the most confusing, also the smallest class

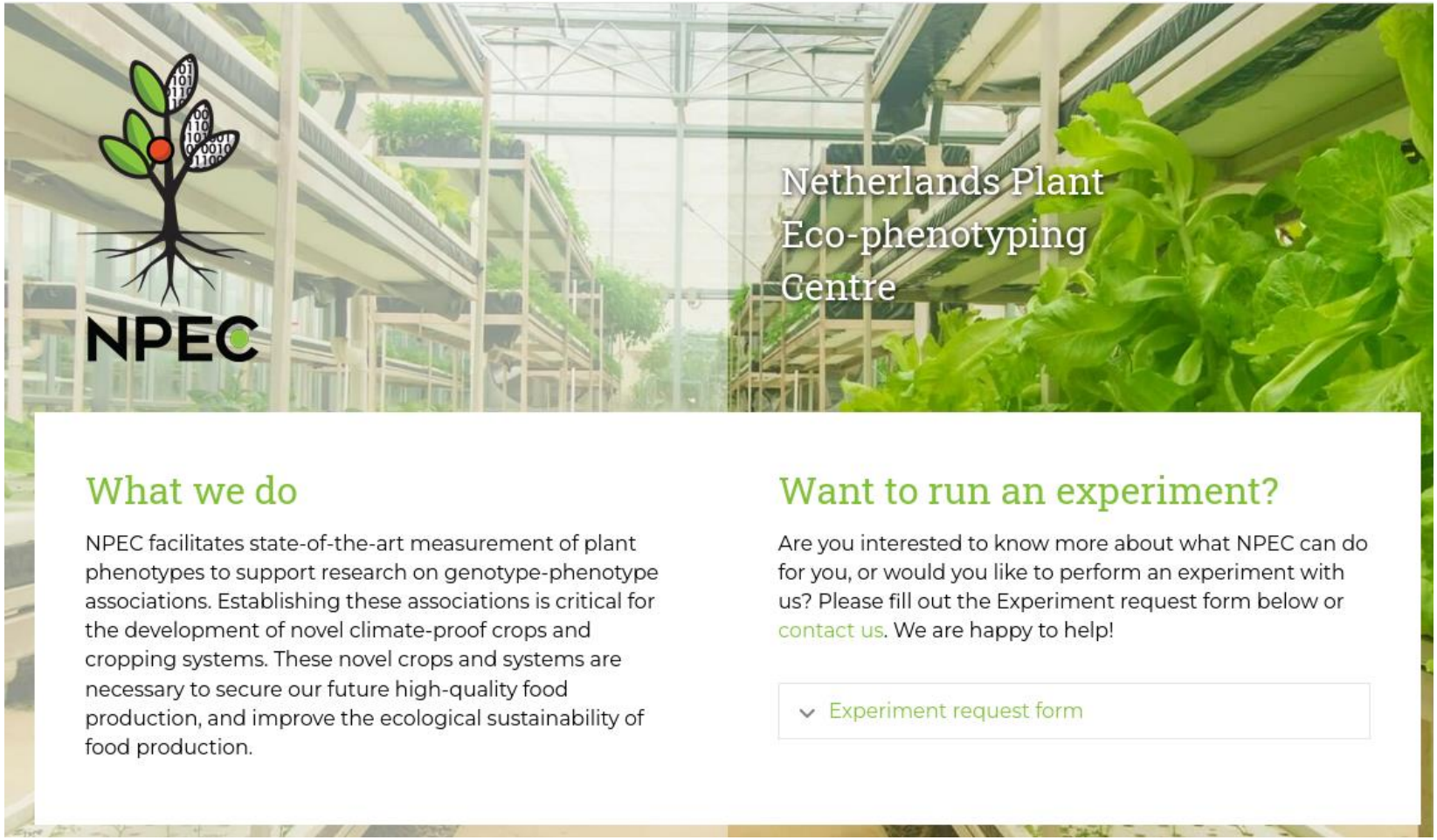
Overall Accuracy for non color traits [Afonso et.al., 2024]



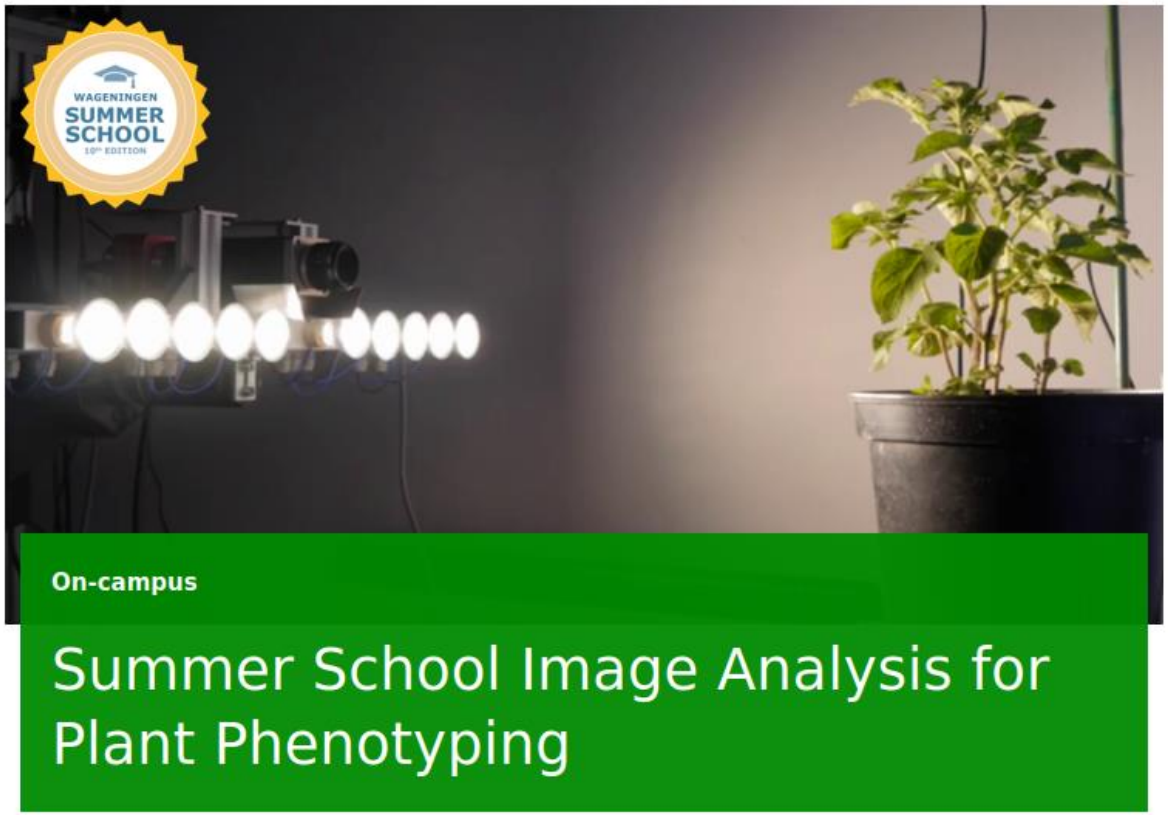
Concluding Remarks

- DL classification and object detection have achieved good performance in practical agricultural use cases.
- Even without tailored experimental design, DL works well.
- Data engineering based on specifics can make or break the workflow.
- Two-way street between CV/AI and domain knowledge.

NPEC (www.npec.nl)



Summer School Registrations Open (June 23rd to 27th, Wageningen, NL)



Thank you!

Questions?

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