Sveriges lantbruksuniversitet
Swedish University of Agricultural Sciences

Detecting potato late blight in the field

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NordPlant

EnBlightMe! - A system for automatic late blight detection

Erland Liljeroth, Erik Alexandersson (SLU, Alnarp)
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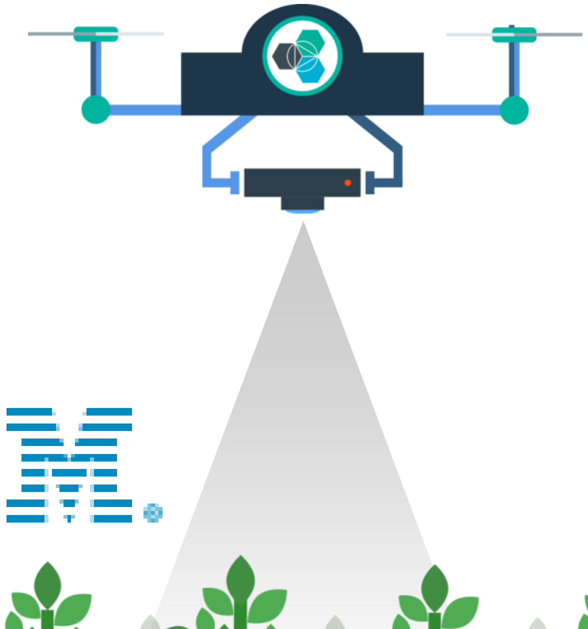
Oscar Bagge, Hanna Blomquist, Mats Persson (IBM, Malmö)
Martin Holmberg (SLU)
Peter Antkowiak (University of Freiburg)
Daniel Barwén (Malmö Yrkeshögskola)
Joost van Ham (Lund University)

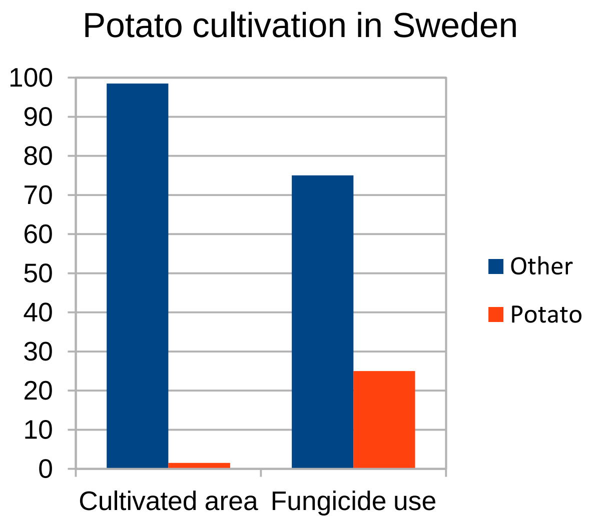


A Vinnova funded project

VINNOVA IBM

Relevance

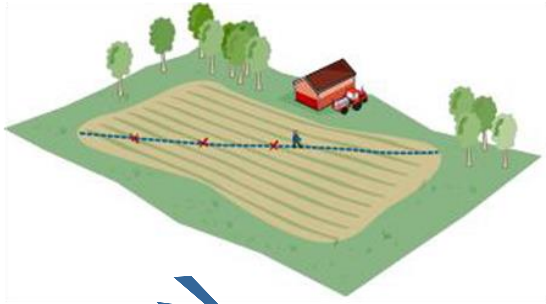
- Potato: high value crop and 3rd most important food crop
- *P. infestans* causing potato late blight costs 7 billion USD per year
- High fungicide use in Sweden – pro-active spraying
- Early and accurate detection



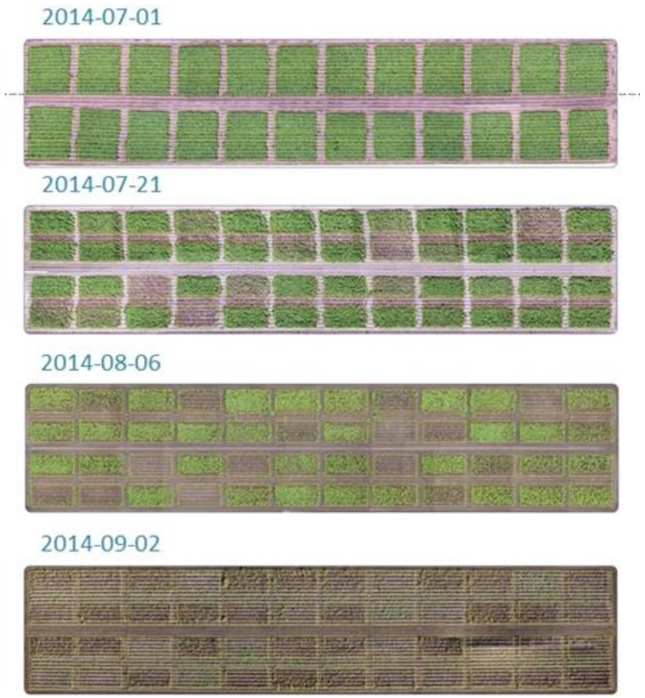
Late blight detection

- Visual, manual inspection by farmer
- Visual, manual of pre-breeder grading scale 0-100%

→ large effort, time-constraints



How to find the infection?



The EnBlightMe! project

Main goal: to reduce fungicide use and create a decision support tool for Integrated Pest Management

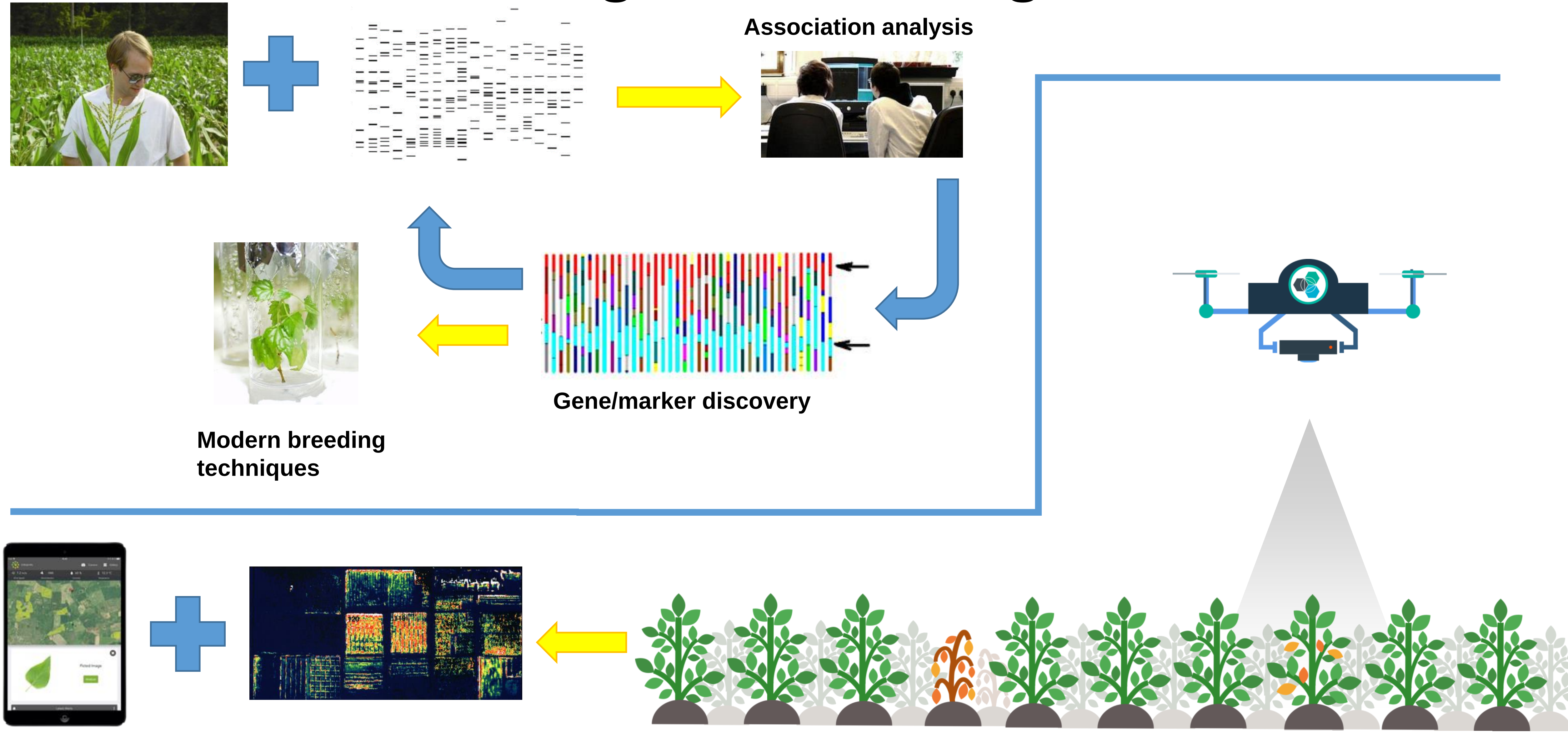
2009/2015: EU directive on integrated pest management

- Early automatic detection -> precisions agriculture
  (especially organic farmers)
- Objective measurement -> resistance pre-breeding
- Better incorporation of multiple data sources in demo app
  -> decision support to reduce spraying and combat late blight

Methods:

- Workshops (IBM design thinking) with farmers and consultants
- Image collection in the field
- Image analysis
- Software development

Precision breeding - Precision agriculture



Phenotyping for…

- Plant breeding
  - Objective scoring of traits - **proxies**
- Precisions agriculture
  - Nutrients - fertilization
  - Irrigation
  - Weed detection
  - Disease detection/monitoring

agronomy MDPI

Review

High-Throughput Field-Phenotyping Tools for Plant Breeding and Precision Agriculture

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check for updates

Abstract: High-throughput field phenotyping has garnered major attention in recent years leading to the development of several new protocols for recording various plant traits of interest. Phenotyping of plants for breeding and for precision agriculture have different requirements due to different sizes of the plots and fields, differing purposes and the urgency of the action required after phenotyping.

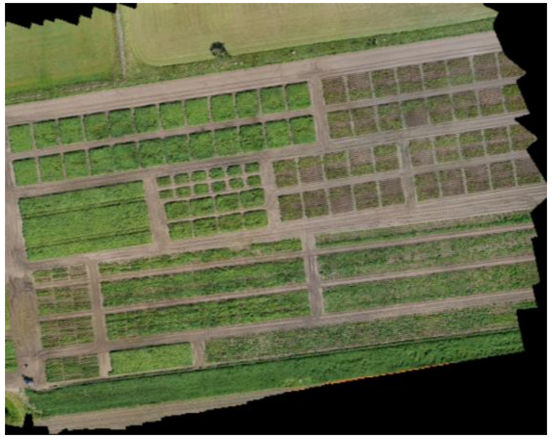
What should field phenotyping for plant disease detection aim for?

- To detect disease before the naked eye in field
- Combine detection of several diseases/stresses
- Tackle multi-stress environments
- Resolutions and scale – how to translate between proximal and remote sensing

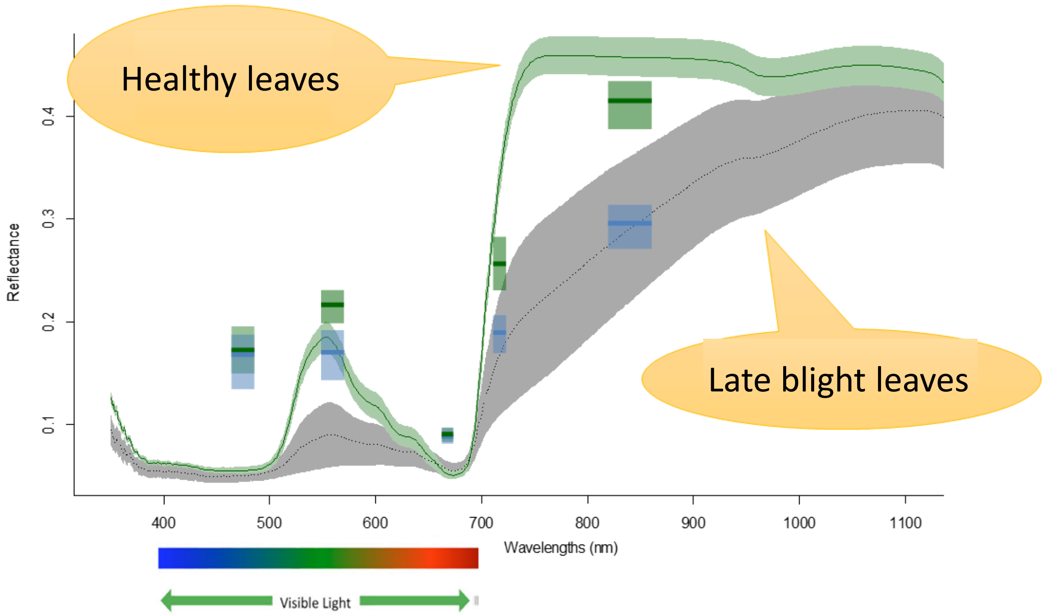
-Chawade, A., van Ham, J., Blomquist, H., Bagge, O., Alexandersson, E., & Ortiz, R. (2019). High-Throughput Field-Phenotyping Tools for Plant Breeding and Precision Agriculture. Agronomy, 9(5), 258.

-Reynolds, Daniel, et al. "What is cost-efficient phenotyping? Optimizing costs for different scenarios." Plant Science (2018)

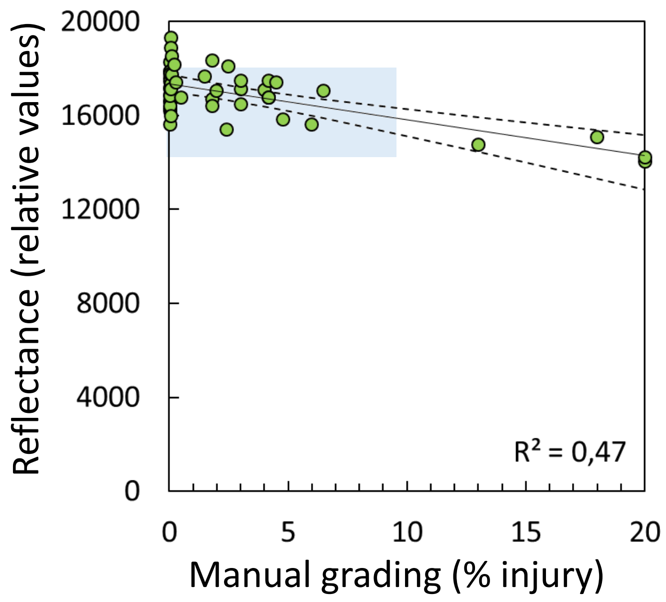
Components of EnBlightMe!

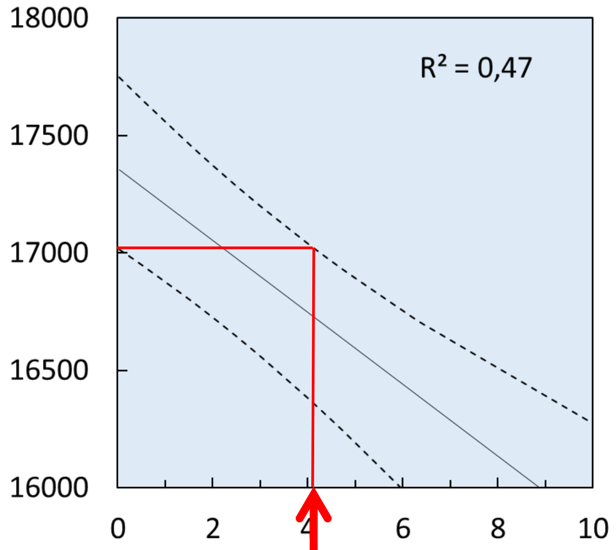


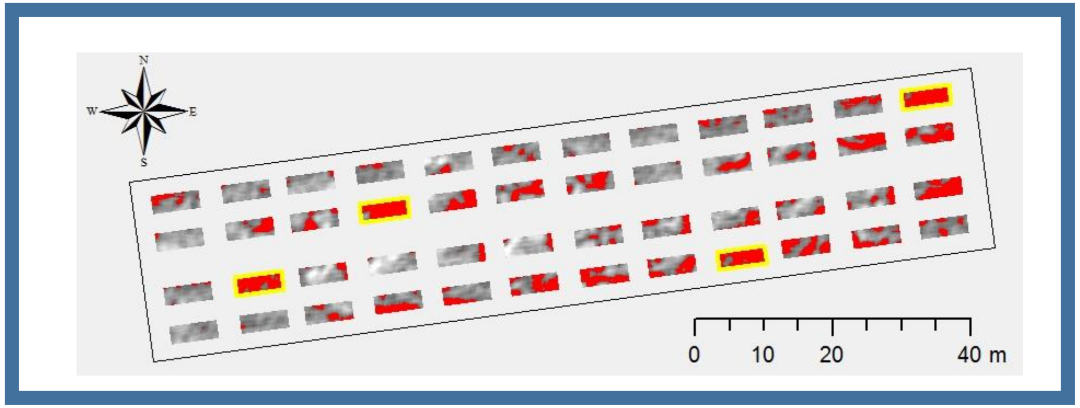
Reflectance vs computer vision for late blight detection



Late blight detection







An infection of 5 % is associated with a significant decrease in mean reflectance in red-edge band

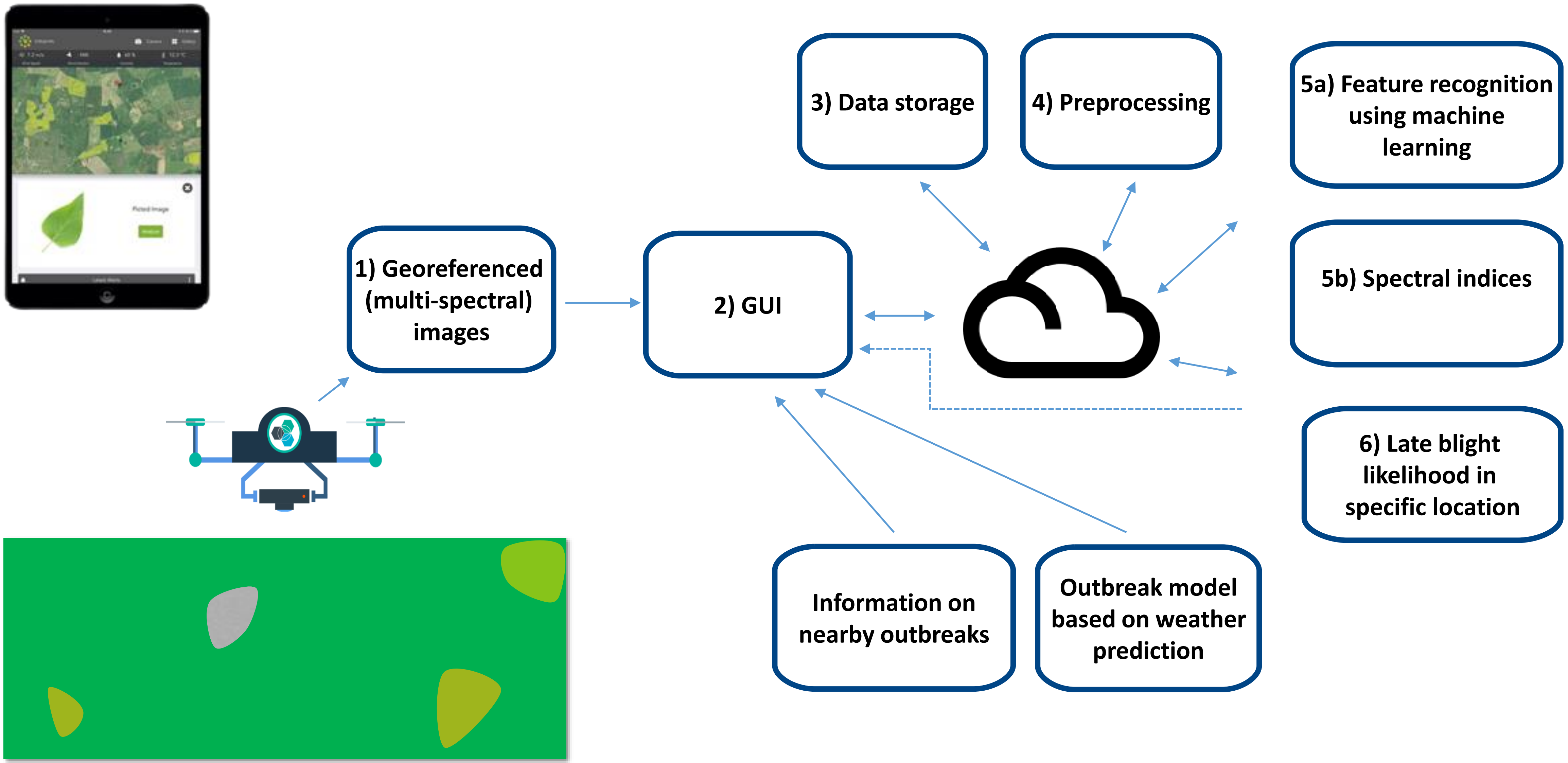
Computer vision: RGB handheld dataset (2017)

- 327 training images per class
- 108 validation images per class
- IBM Watson (black box)
- TensorFlow + Keras

Problems (Handheld):

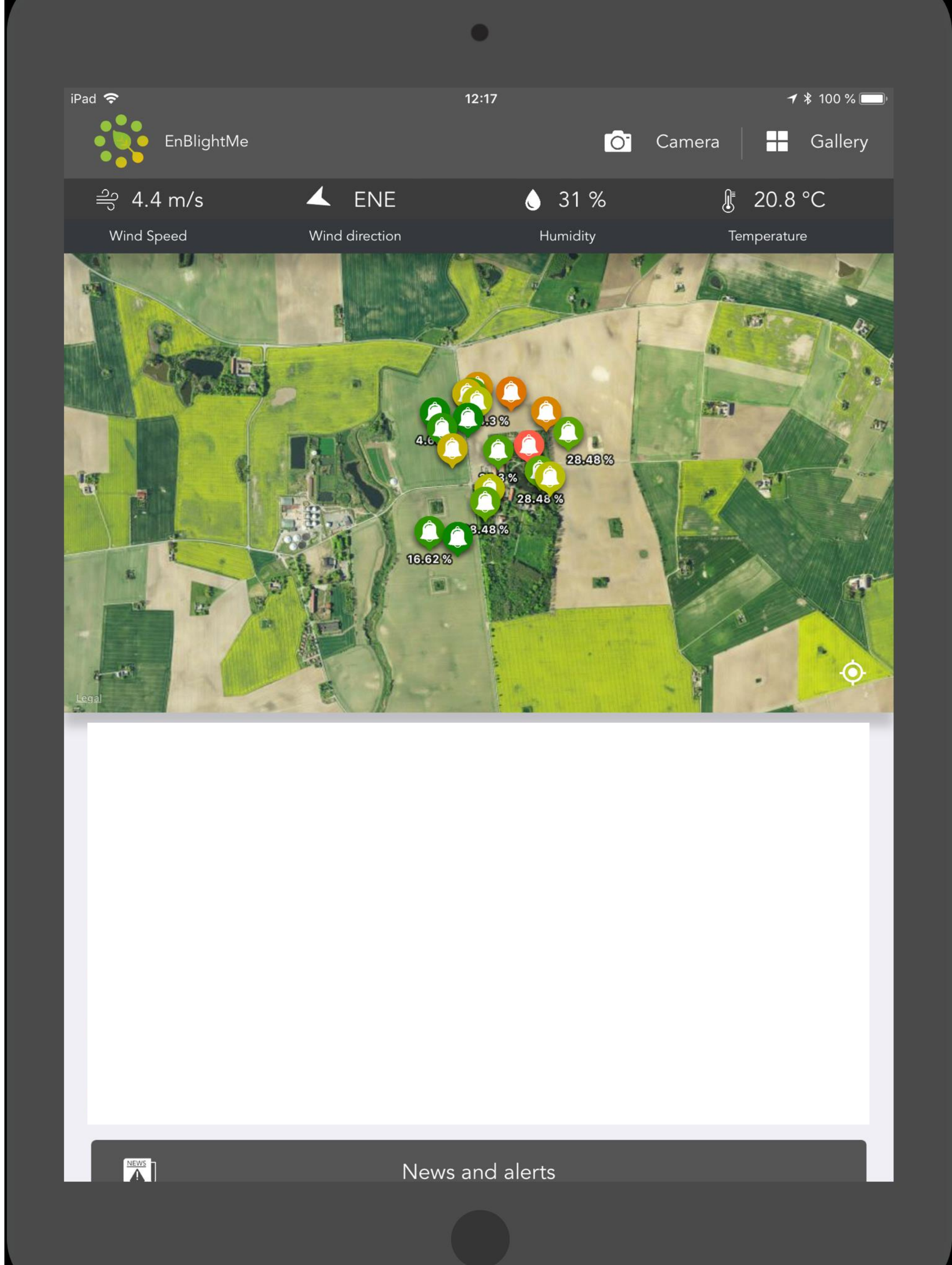
- Small dataset
- Noisy dataset
  - Sun + shadows
  - Angle
  - Distance
  - Resolution

Approach for app

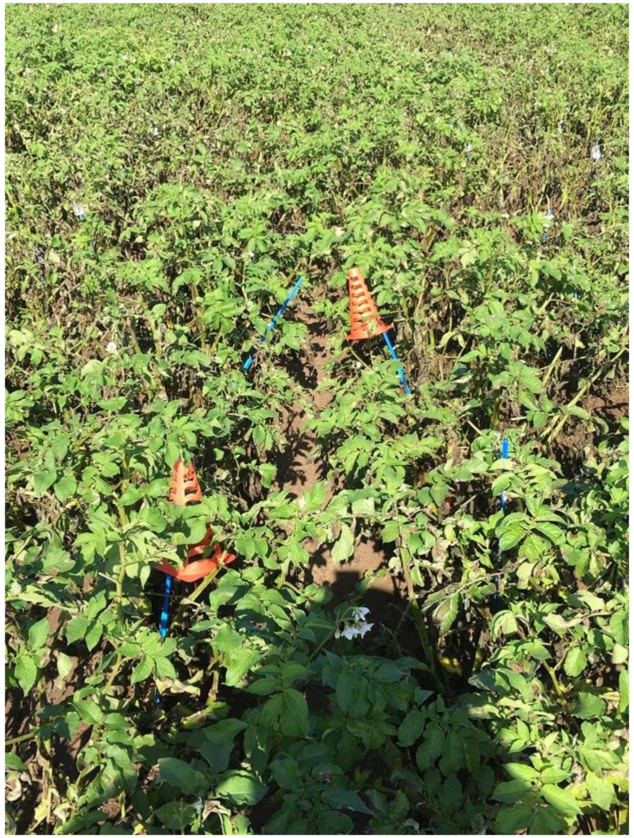


App: Nearby outbreaks

- Build a community via app
- Location of outbreak
- Severity of outbreak



2019: Danespo field trials and more…



Legend :
Edge potatoes
Infected rows
Danespo plant

Monitoring and Sampling over 2 weeks

	Multispectral Camera	RGB Camera	Spectrophotometer (inoculum rows)	Spectrophotometer (40 genotypes)	Sampling Inoculum rows
9 July 2019	X	X	X	X	
10 July 2019 (5h post inoculum)			X		X
11 July 2019 8h			X		X
11 July 2019 14h	X	X	X	X	
12 July 2019			X		
13 July 2019	X	X	X	X	
15 July 2019	X	X	X	X	
17 July 2019	X	X	X	X	
19 July 2019	X	X	X	X	
22 July 2019	X	X		X	
25 July 2019	X	X		X	

Transfer learning

Weed detection

- ✓ Plant canopy (top-down)
- ✓ Spatial resolution dominant
- ✓ Majority used RGB cameras
- ✓ Better to be zero-tolerance for false negative samples
- ✓ Ground-based vehicle for real-time SSWM
- ✓ Kind of mature, promising for commercial products

Disease detection

- ✓ Leaf, stem, root (multi-angle, scale…)
- ✓ Spectral resolution dominant (early detection)
- ✓ Majority used multispectral cameras (early detection)
- ✓ Zero-tolerance for false negative samples
- ✓ UAV-based platform gains popularity
- ✓ Pre-mature in a early detection and warning system

Early detection *P. infestans* with multispectral cameras

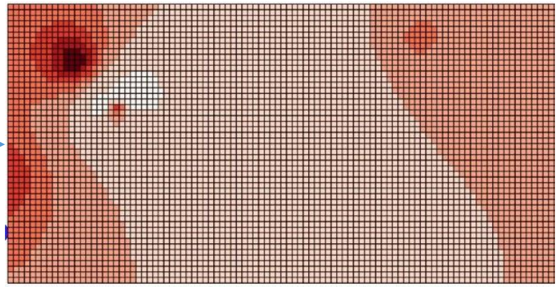
✓ Fusion spectral features and other features (color, texture) with machine learning from UAV-based images.

Severity evaluation with RGB images

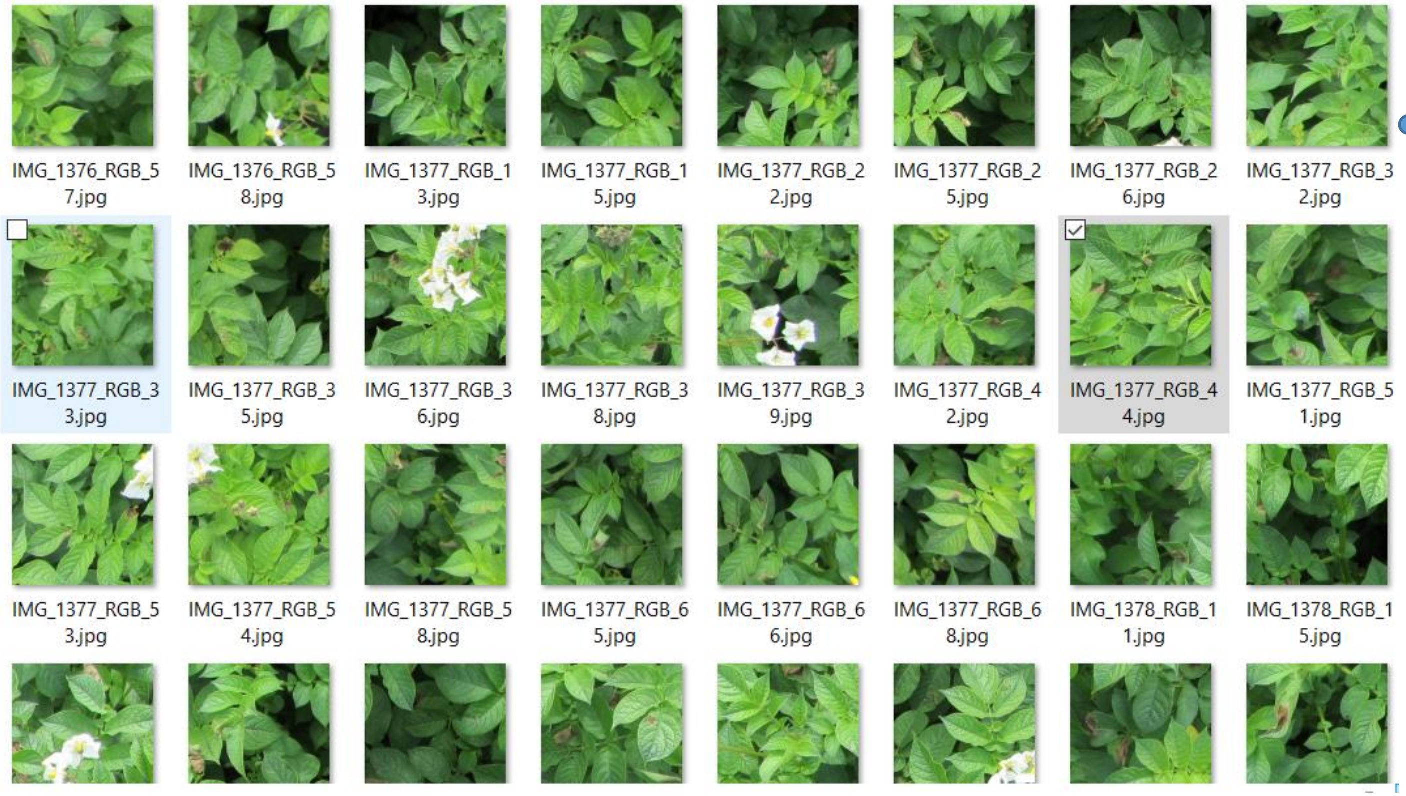
✓ Deep neural networks for lesion segmentation from background

Computer vision

Machine learning



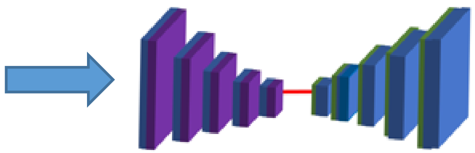
Plan-severity evaluation



EnblightMe!

Images from this summer

I am hungry for annotation data !!!



0: No lesion

1: Lesion

0, where ?

1, what ?

2, how many lesion pixels ?

3, how many vegetation pixels?

Score?

Plan-early detection *P. infestans*

…………………on the way to analyze data………………

Plan-satellite imagery for classification healthy and unhealthy fields

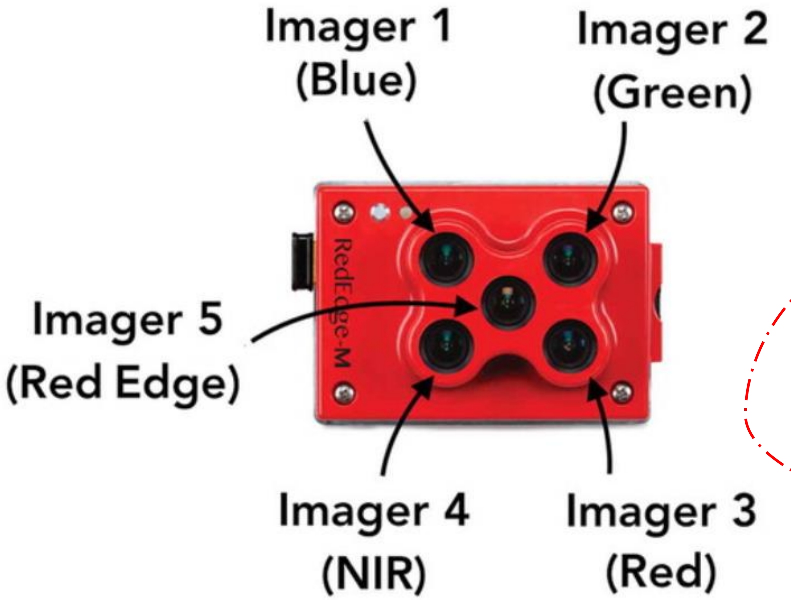
Healthy?? Drought?? Yield??

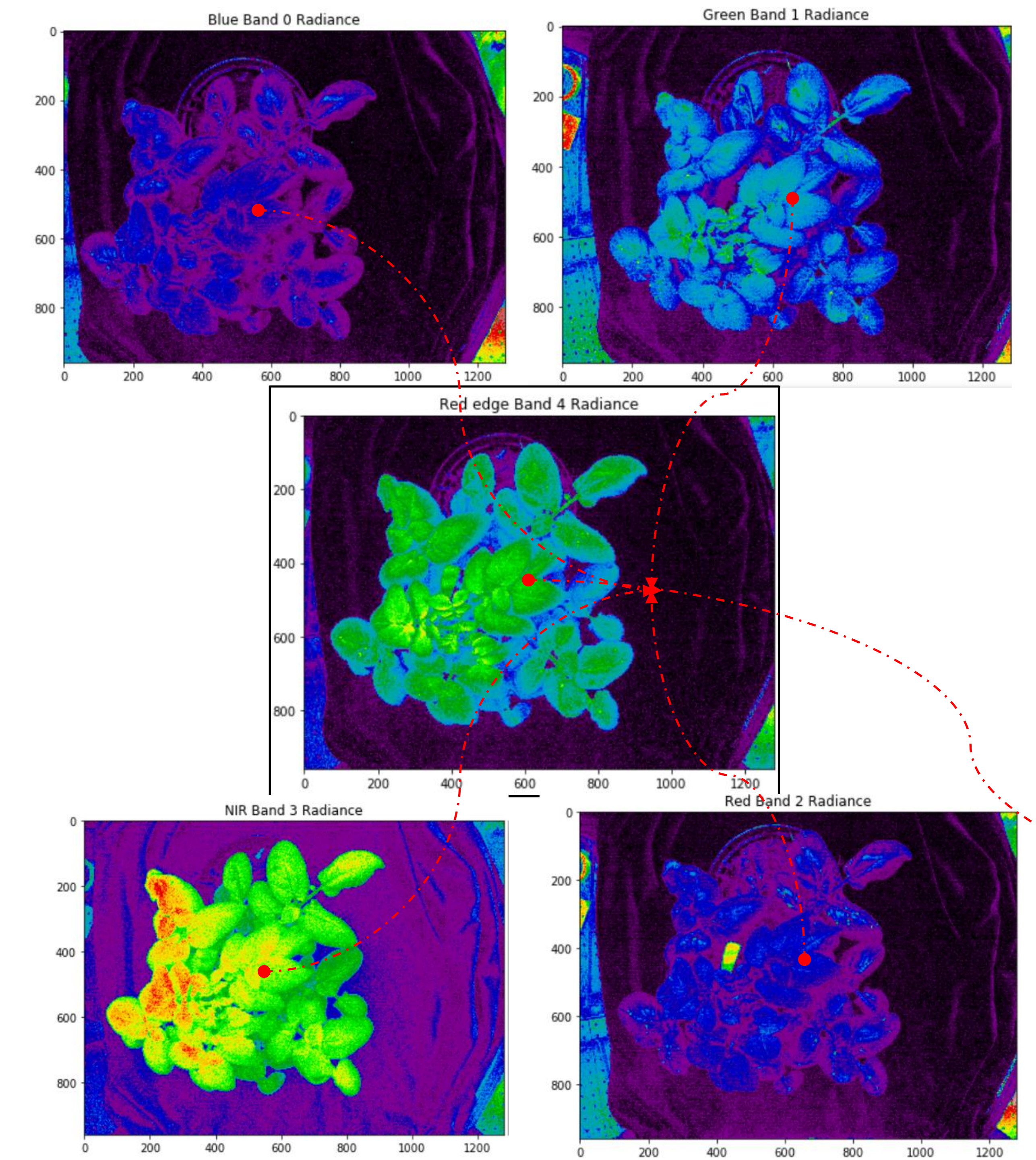
Based on reflectance characteristics

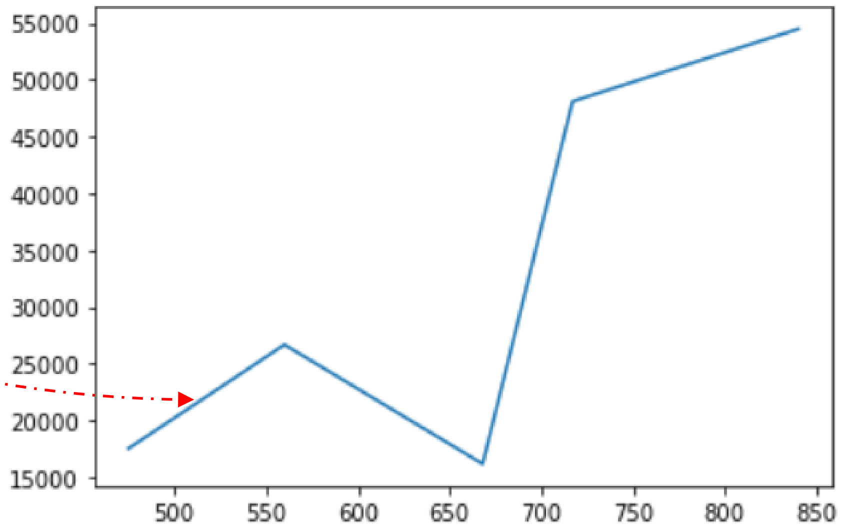
Collaborated with Lund university

Biotron exploratory experiment with Murilo

- ✓ Get familiar with images;
- ✓ Check the light conditions for multispectral cameras;
- ✓ Check the camera set ups;
- ✓ Preparation for the next experiment;







wavelength = [475, 560, 668, 717, 840]

Book chapter

Book chapter in Springer methods series about computer vision in field plant phenotyping

- ✓ Cookbook for biologist to get familiar with computer vision in field applications
- ✓Trails and tricks
- ✓Open source tools
- ✓First version by December

Conclusions

- Application successful in EnBlightMe!
    - Prediction model, weather data, cost calculation
- RGB Handheld images somewhat accurate with ML
- RGB drone images inaccurate for ML
    - Accurate experimental set-up needed to link manual scoring to ML/image resolution
- Multispectral drone data somewhat accurate (5% infection)

Lessons we try to build on:

- Better data annotation – annotation resolution
- Considerable amount of data needed for classification
- Link field to controlled environments (and v.v.)
- Focus on multispectral data in combination with ML
    - Dynamic droning?
- The effect of cultivar, light, plant age for image acquisition

Acknowledgements

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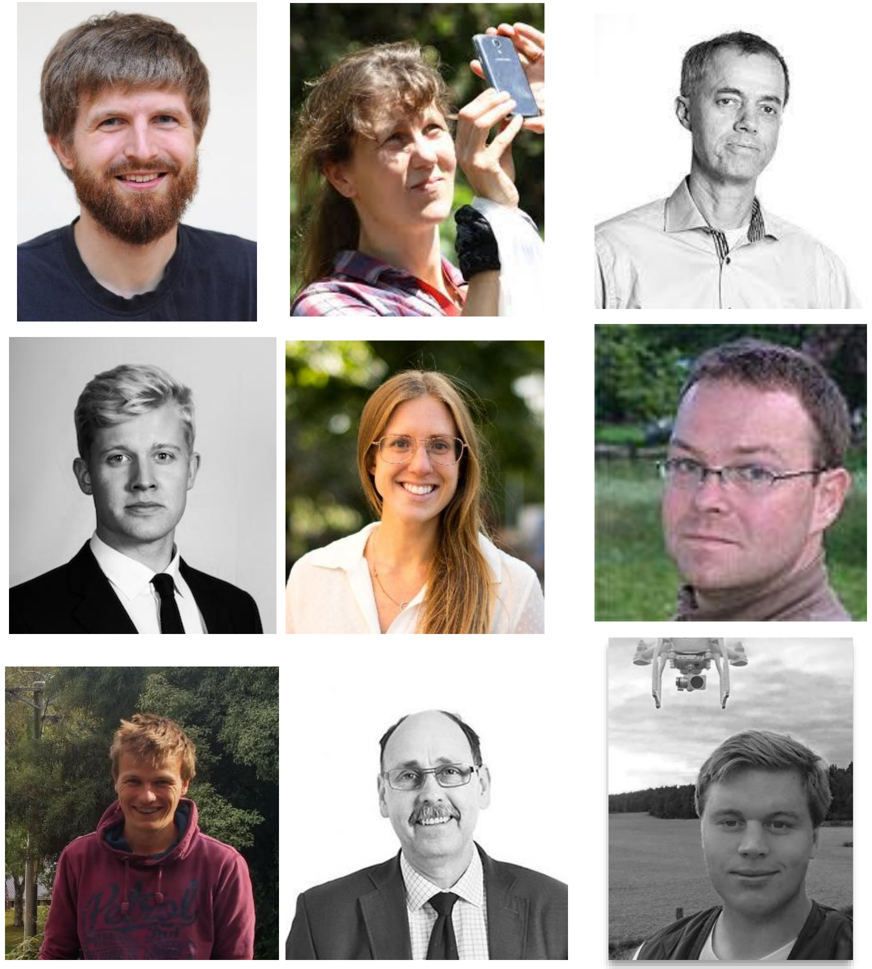
EnBlightMe! team



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