MCP1.1 Biotic interactions

13 avril 2023

David Rousseau

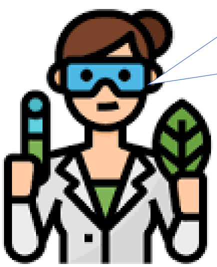
david.rousseau@univ-angers.fr
ImHorPhen Bioimaging Research Group

ANR11-INBS-0012

MCP1.1: Pathogen & microbiote interactions

- **The quest of genericity**

Identify phenological stages, measure of size of symptoms, detect change of color, characterize change turgescence, monitor germination, determine shape of a leaf,, extract roots out of soil, count nodules on roots, quantifying amount of innoculum,, detect emergence, monitor kinetic of symptoms, …SO MANY DIFFERENT BIOLOGICAL QUESTIONS !!!



Biologist

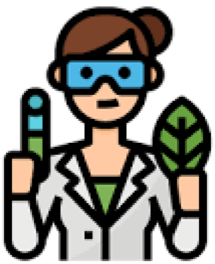
I don’t have time to do it all since I am the only one on the platform
please have look at the jungle of image processing tools already available on
https://www.quantitative-plant.org/software

Geek1.0

MCP1.1: Pathogen & microbiote interactions

- **Deep learning as a generic tool**

Identify phenological stages, **measure of size of symptoms, detect change of color**, **characterize change turgescence**, **monitor germination, determine shape of a leaf**,, **extract roots out of soil**, **count nodules on roots**, **quantifying amount of innoculum**,, **detect emergence**, **monitor kinetic of symptoms**, …



Biologist

From a computer perspective all of these can be sorted in **classification**, **segmentation**, **tracking** and addressed with a very limited number of available neural networks : **ResNet**, **Unet**, **CNN-LSTM**, **with help of Phenome I propose make them available in a didactic way on 4P and train all geeks and tech minded biologist to use these tools**

Computer scientist

Computer vision as a DIY process

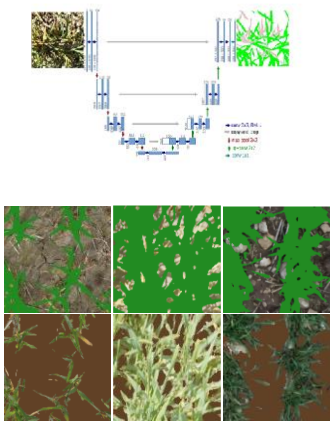
Step 1 image acquisition

from past and future funded experiments

Step 2 annotation

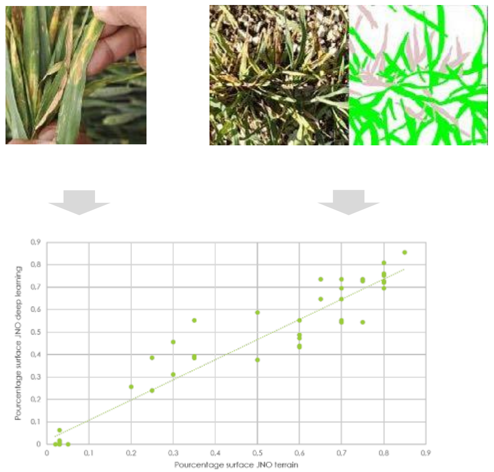
from collaborative platform

Step 3 Deep learning



from didactic version of U-Net

Step 4 Data analysis



Comparison with ground truth
Automatic cluster of types of errors

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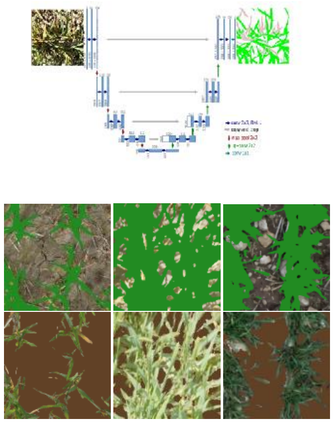

from didactic version of U-Net

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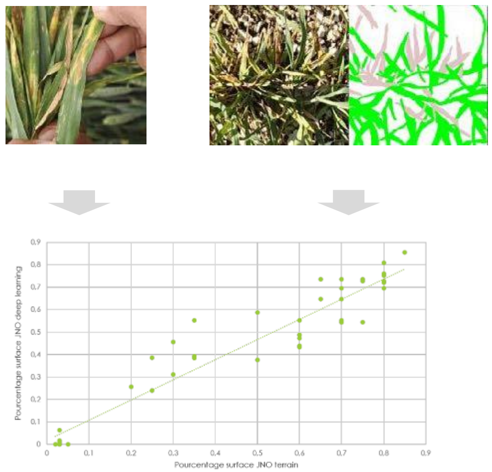

Comparison with ground truth
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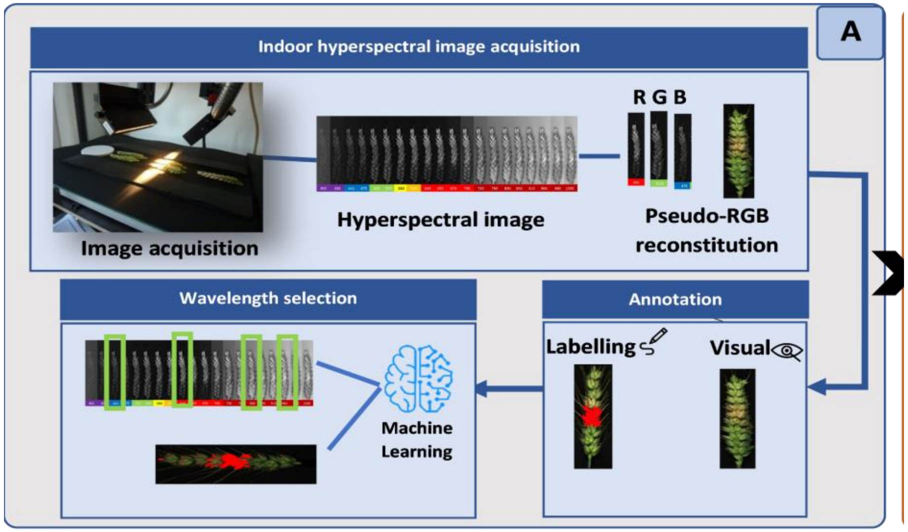
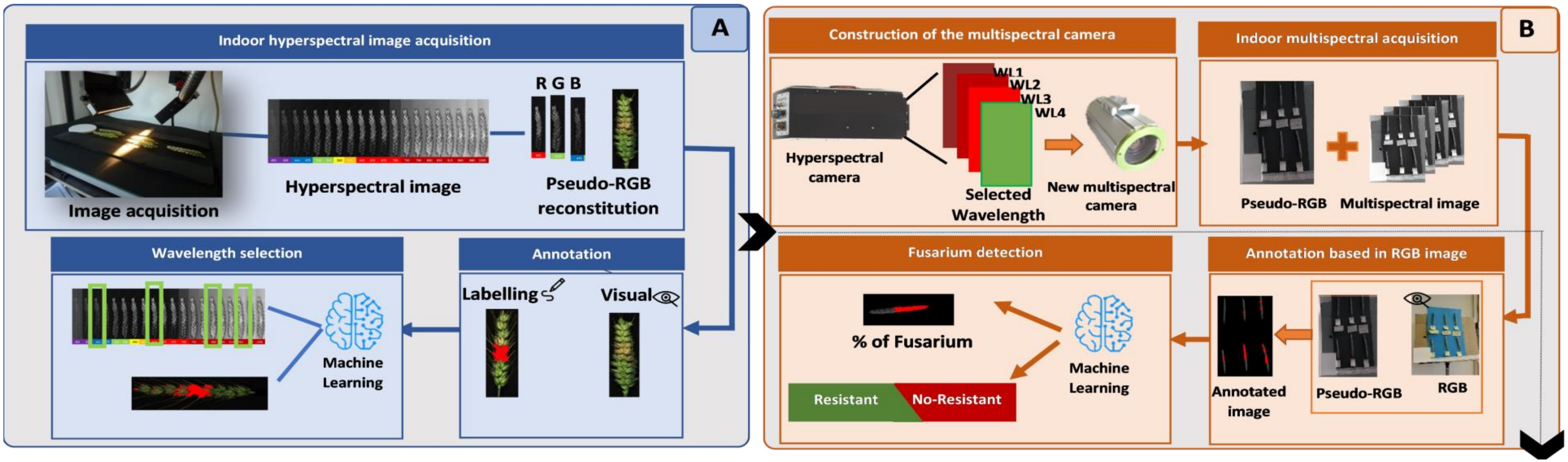
New methodology on image acquisition



H. Garbouge, V. Cadot, D. Rousseau

New methodology on image acquisition



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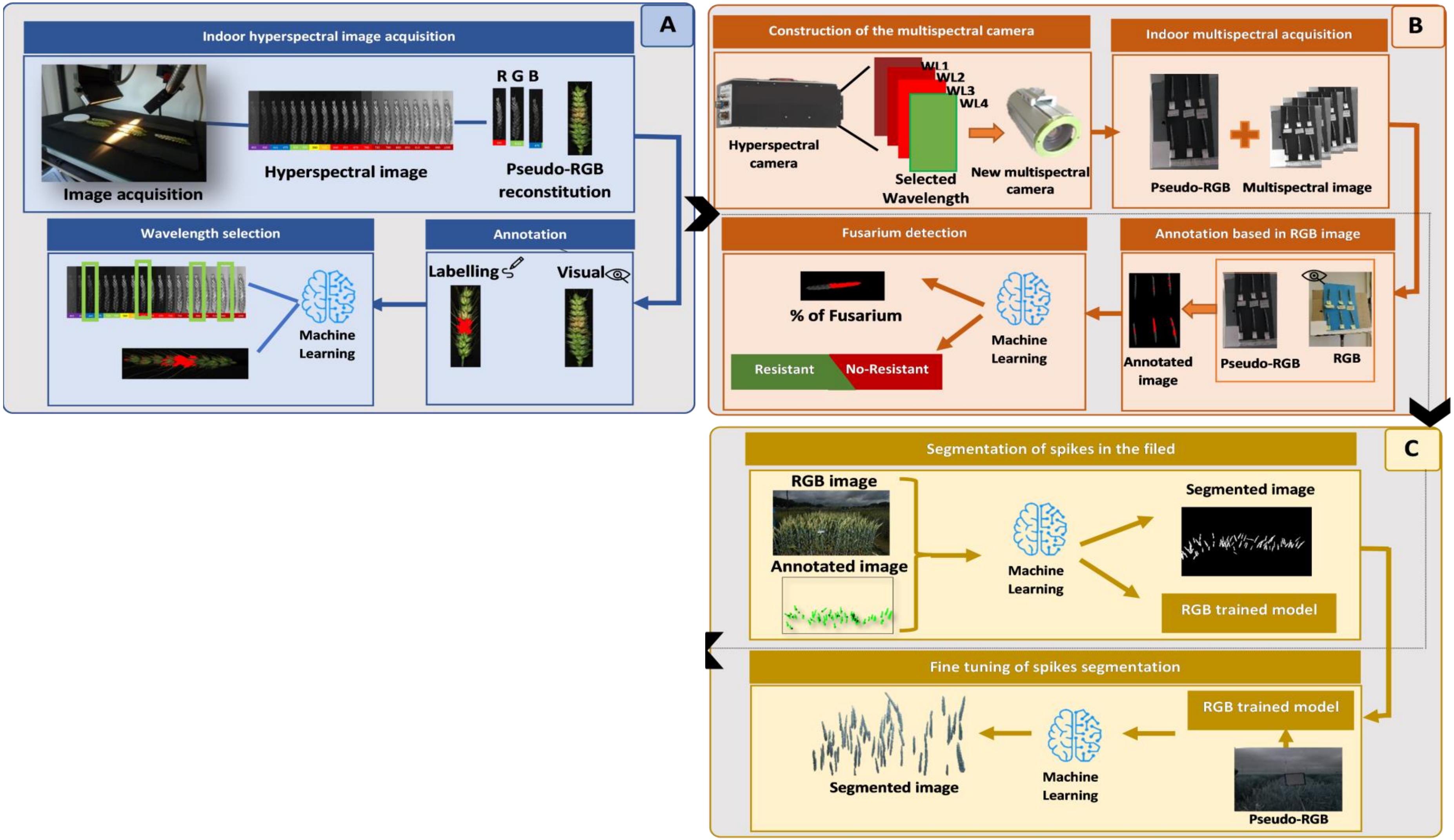

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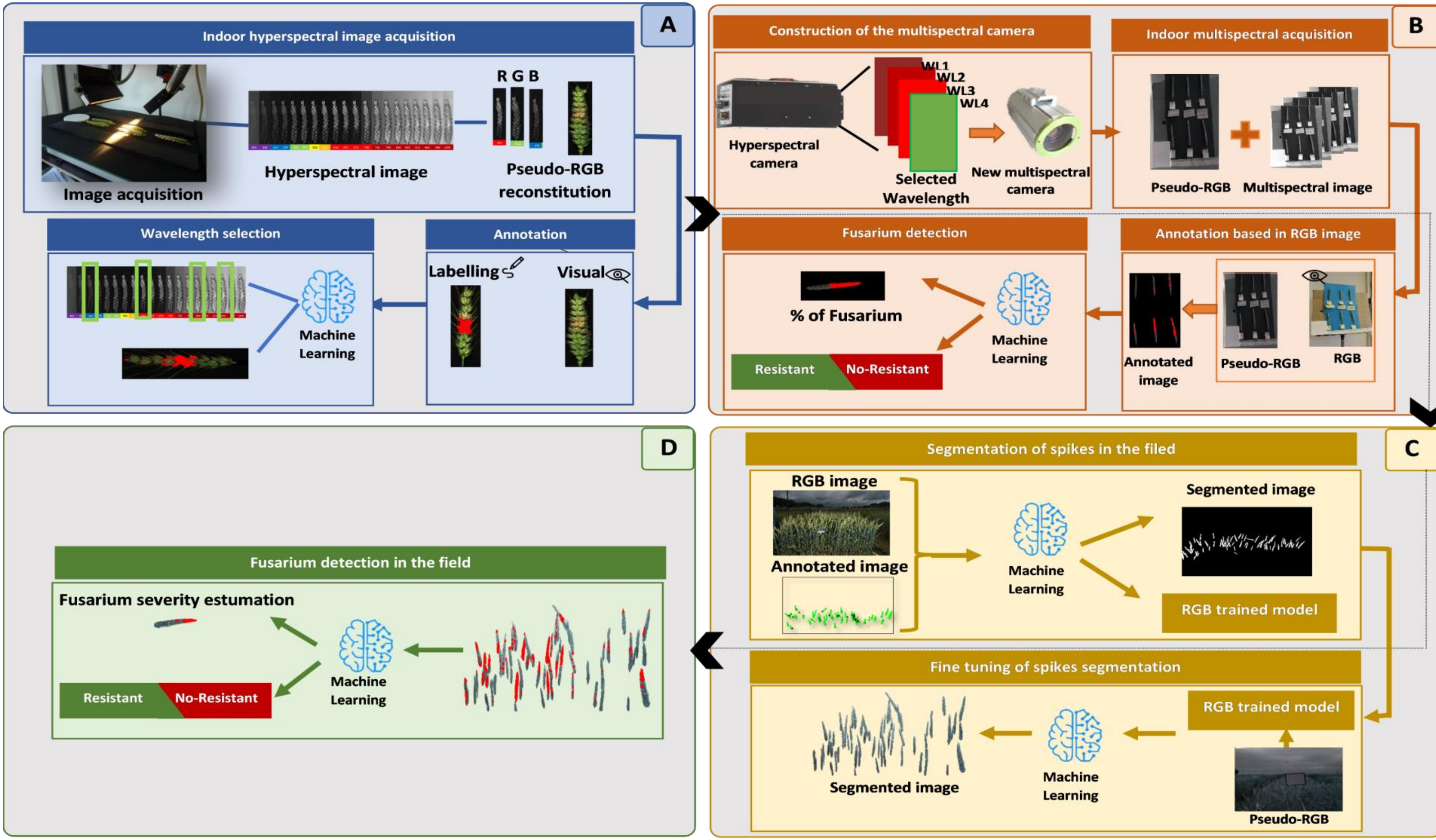
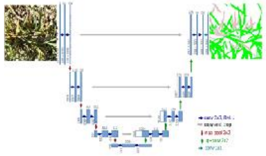
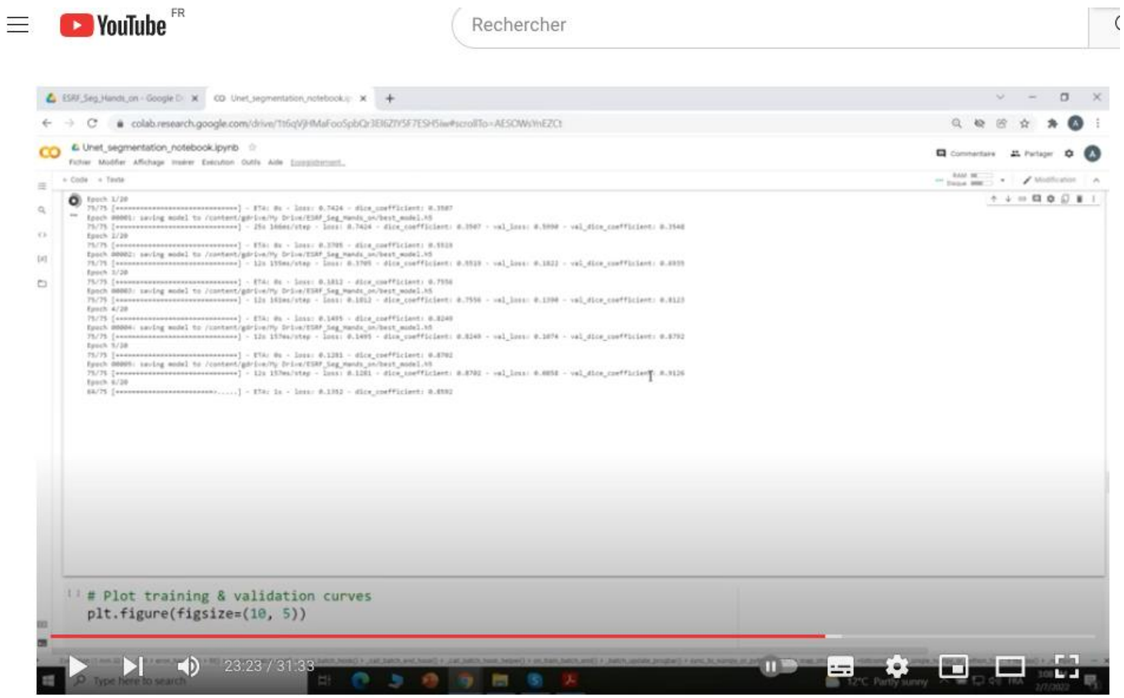


H. Garbouge, V. Cadot, D. Rousseau

U-Net Kezako ?

Réseau de neurone pour la segmentation
Présenté lors de formation PHENOME
Vidéo tutoriel le disponible sur chaîne youtube par Ali Ahmad



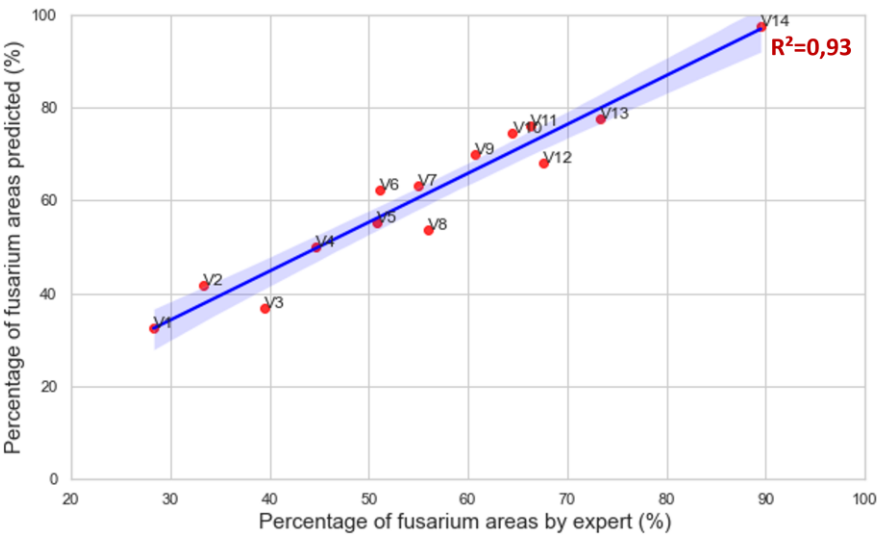


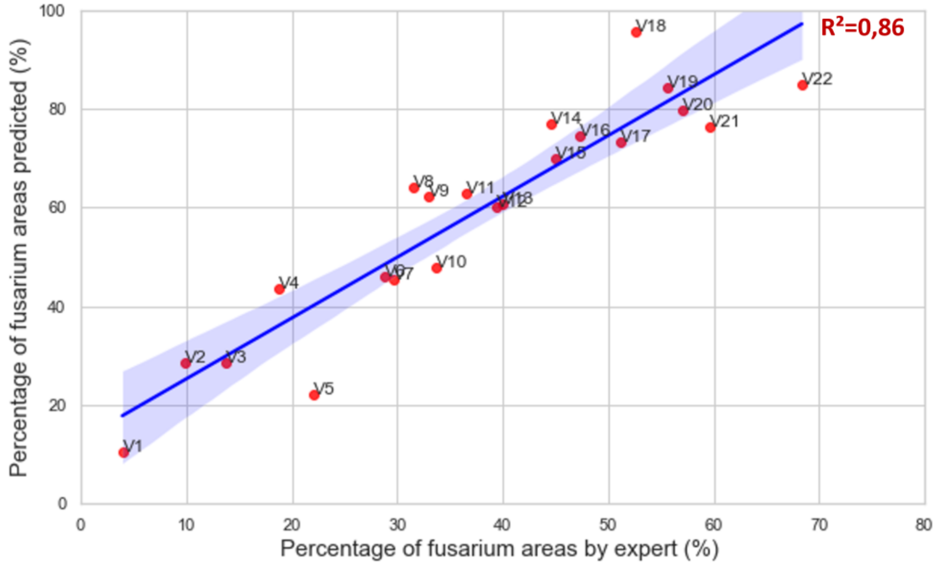
UNET demo

https://www.youtube.com/watch?v=wOmJnn3NrvE&t=1402s

New methodology on image acquisition

Fusarium detection by machine learning methods on segmented images acquired in the field environment using the CMS4 camera.





H. Garbouge, V. Cadot, D. Rousseau

Computer vision as a DIY process

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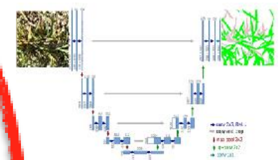
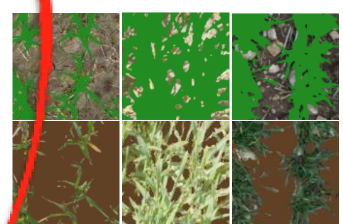
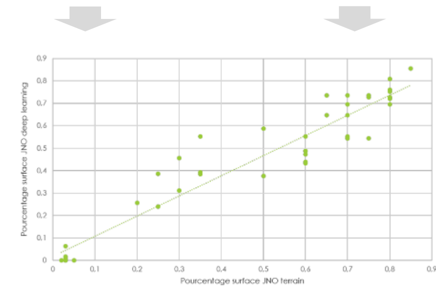
Step 2 annotation

Step 3 Deep learning





Step 4 Data analysis



from past and future funded experiments

from collaborative platform

from didactic version of U-Net

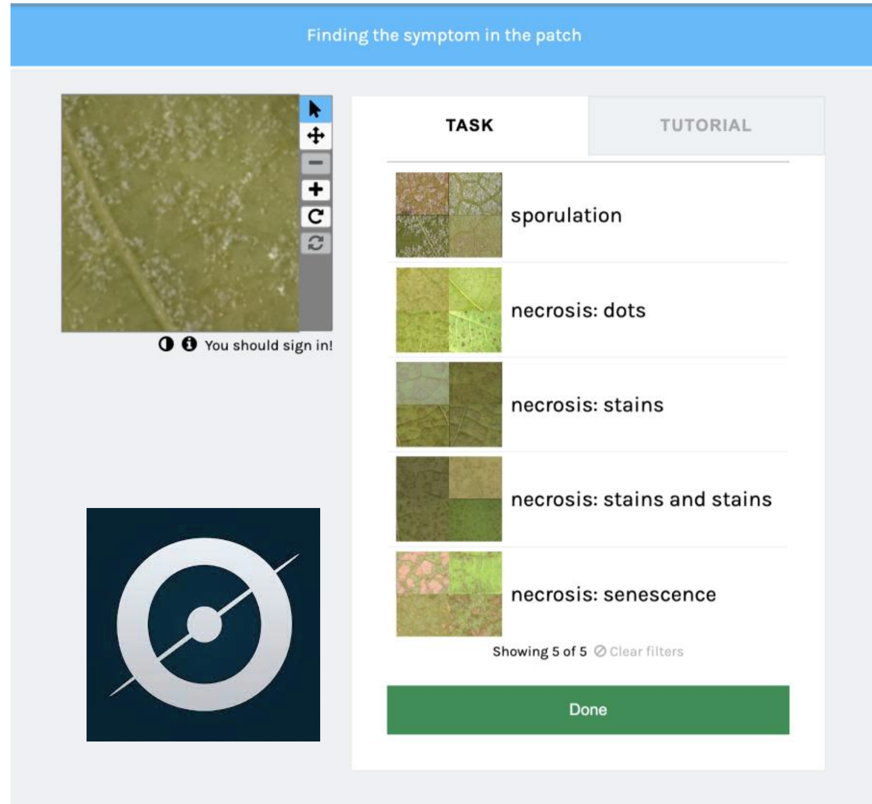
Comparison with ground truth
Automatic cluster of types of errors

Phénotypage de symptômes foliaires

Disques foliares et mildiou

OIV 452-2

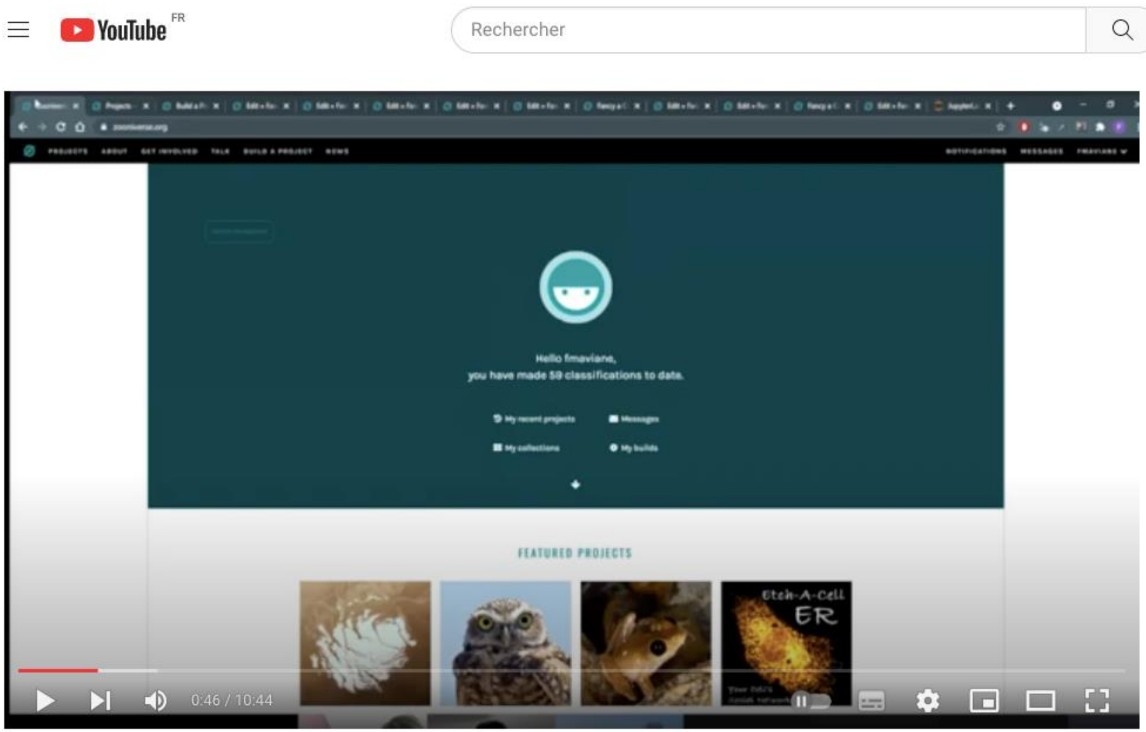
- Décrit intéraction disque foliaire vigne et mildiou
- Aggrège sporulation et nécrose sur une echelle de resistance avec des valeurs impaires de 1 à 9
- Complexe ->
    - N'est pas toujours utilisé
    - Souvent seule la sporulation est prise en compte



F. Maviane Macia, S. Merdinoglu-Wiedmann, N. Peeters, D. Rousseau

Zooniverse Kezako ?

Outil collaboratif d'annotation en ligne DIY
Présenté lors de formation PHENOME
Vidéo tutoriel le disponible sur chaîne youtube par Felicia



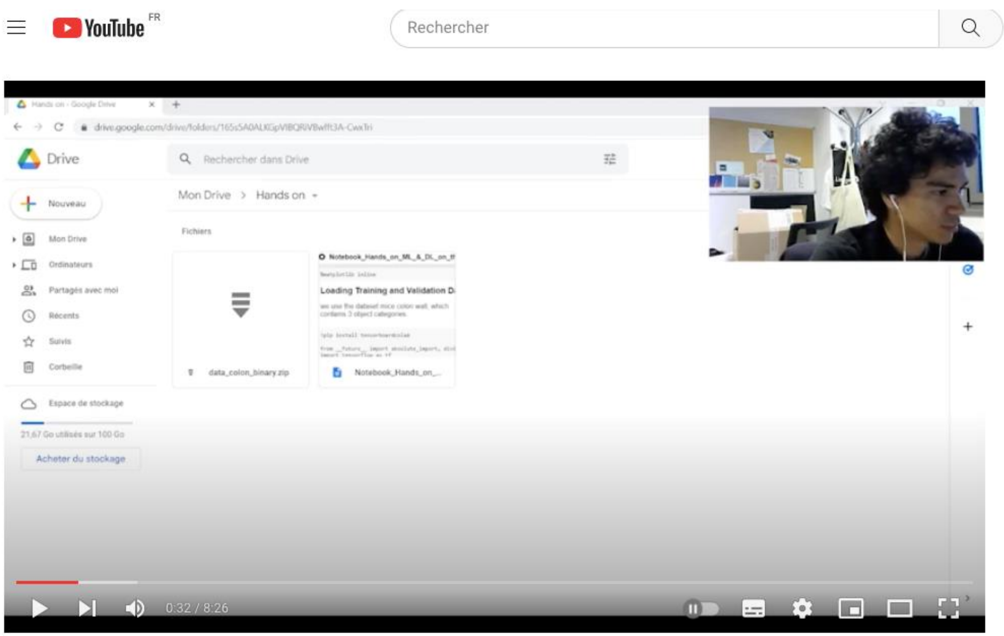
Annotation with ZOONIVERSE

https://www.youtube.com/watch?v=dCPv536TEIw&t=46s

F. Maviane Macia, S. Merdinoglu-Wiedmann, N. Peeters, D. Rousseau

Classification Kezako ?

Tri d’images par classe par deep learning
Présenté lors de formation PHENOME
Vidéo tutoriel le disponible sur chaîne youtube par Herearii Metuarea



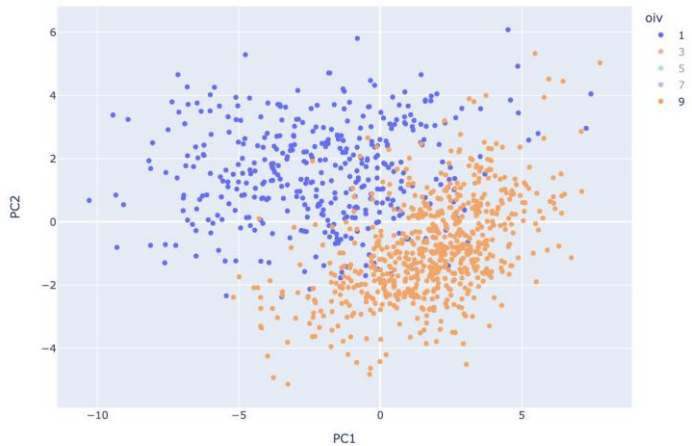
Hands on model classification

https://www.youtube.com/watch?v=W2luOX6lK3w&t=31s

Classifieur multiclasses

Résultats préliminaires avec les annotations issues de Zooniverse

	precision	recall	f1-score	support
sporulation	0.92	0.93	0.93	113
necrosis_dots	0.82	0.38	0.52	37
necrosis_stains	0.00	0.00	0.00	22
necrosis_senescence	0.00	0.00	0.00	8
micro avg	0.91	0.66	0.77	180
macro avg	0.44	0.33	0.36	180
weighted avg	0.75	0.66	0.69	180
samples avg	0.79	0.65	0.69	180



Pas assez de disques foliaires avec des taches ou de la sénescence dans le jeu de données. Un nouveau jeu de données plus équilibré sera produit.

Le VAE trouve une frontière entre les valeurs extrêmes d’OIV sans que cette donnée ait été utilisée lors de l’entrainement

F. Maviane Macia, S. Merdinoglu-Wiedmann, N. Peeters, D. Rousseau

Computer vision as a DIY process

Step 1 image acquisition

from past and future funded experiments

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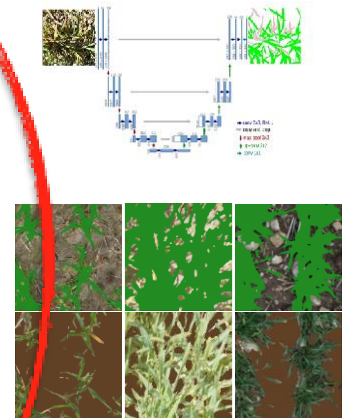
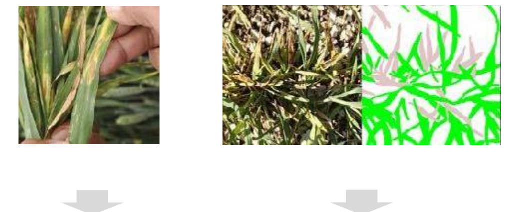
from collaborative platform

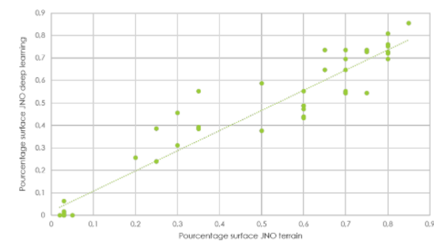
Step 3 Deep learning



from didactic version of U-Net

Step 4 Data analysis

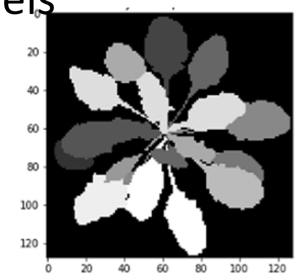




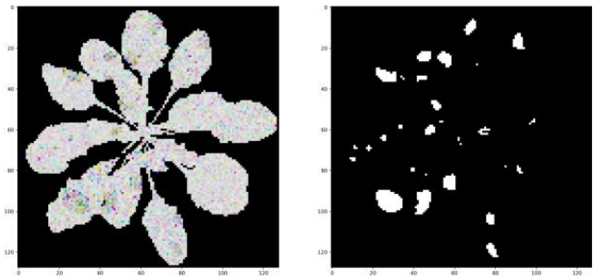
Comparison with ground truth
Automatic cluster of types of errors

Plant symptom segmentation

Arabidopsis: 783 RGB labels

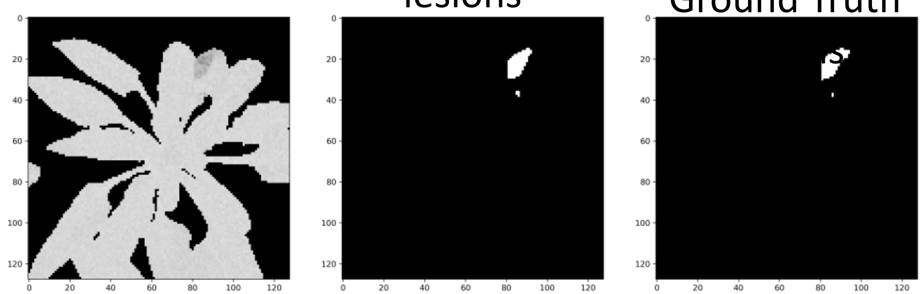


Algorithm mapping Gaussian noise



5481 examples of synthetic fluorescent images of diseased plants with **automatic disease annotation**

+ Data augmentation

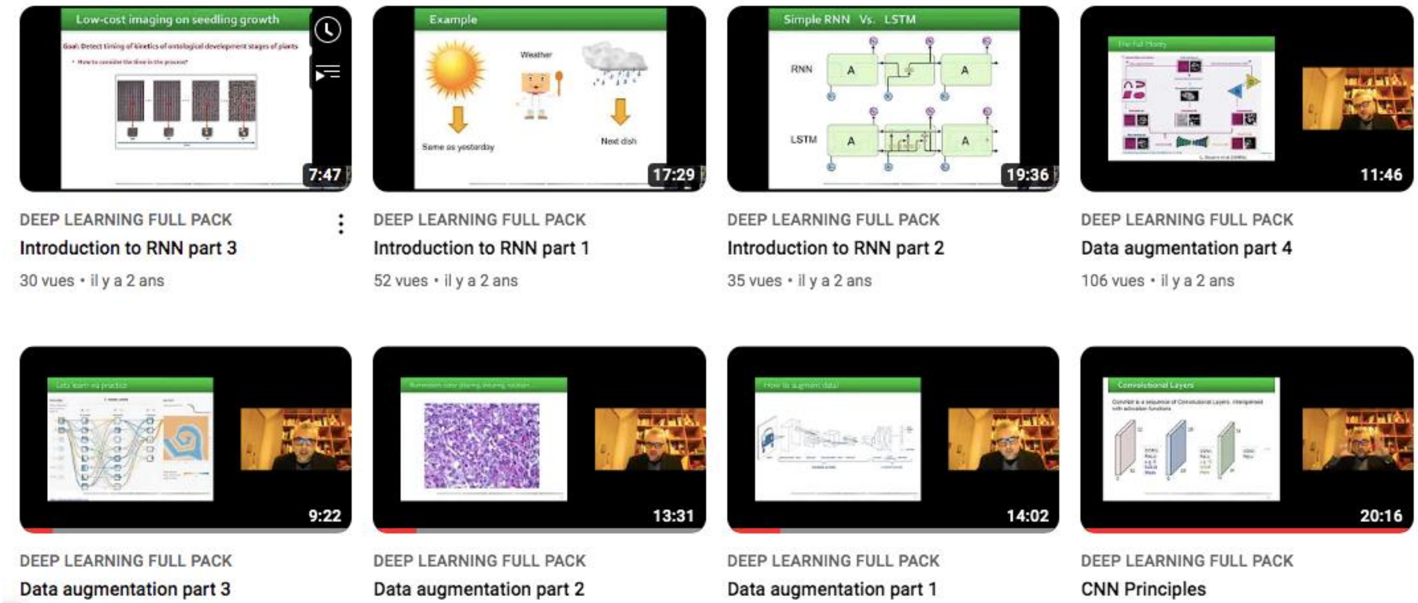


Best case: 90% recall and 97% precision

N. Sapoukhina, T. Bourreau, D. Rousseau ; Frontiers in plant sciences 2022

Zooniverse data augmentation ?

Moyen de robustifier les performances des Algos de deep learning
Présenté lors de formation PHENOME
Vidéo tutoriel le disponible sur chaîne youtube par David



https://www.youtube.com/watch?v=jjVao6YDDIA&t=142s

Computer vision as a DIY process

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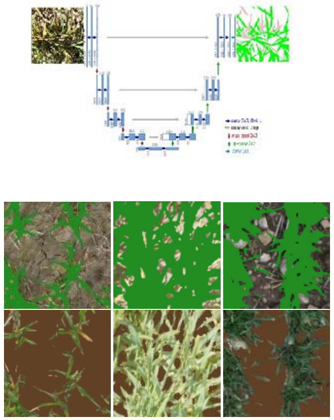
Step 3 Deep learning



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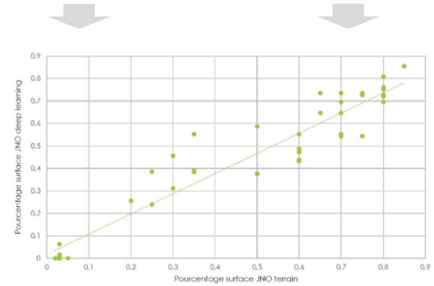


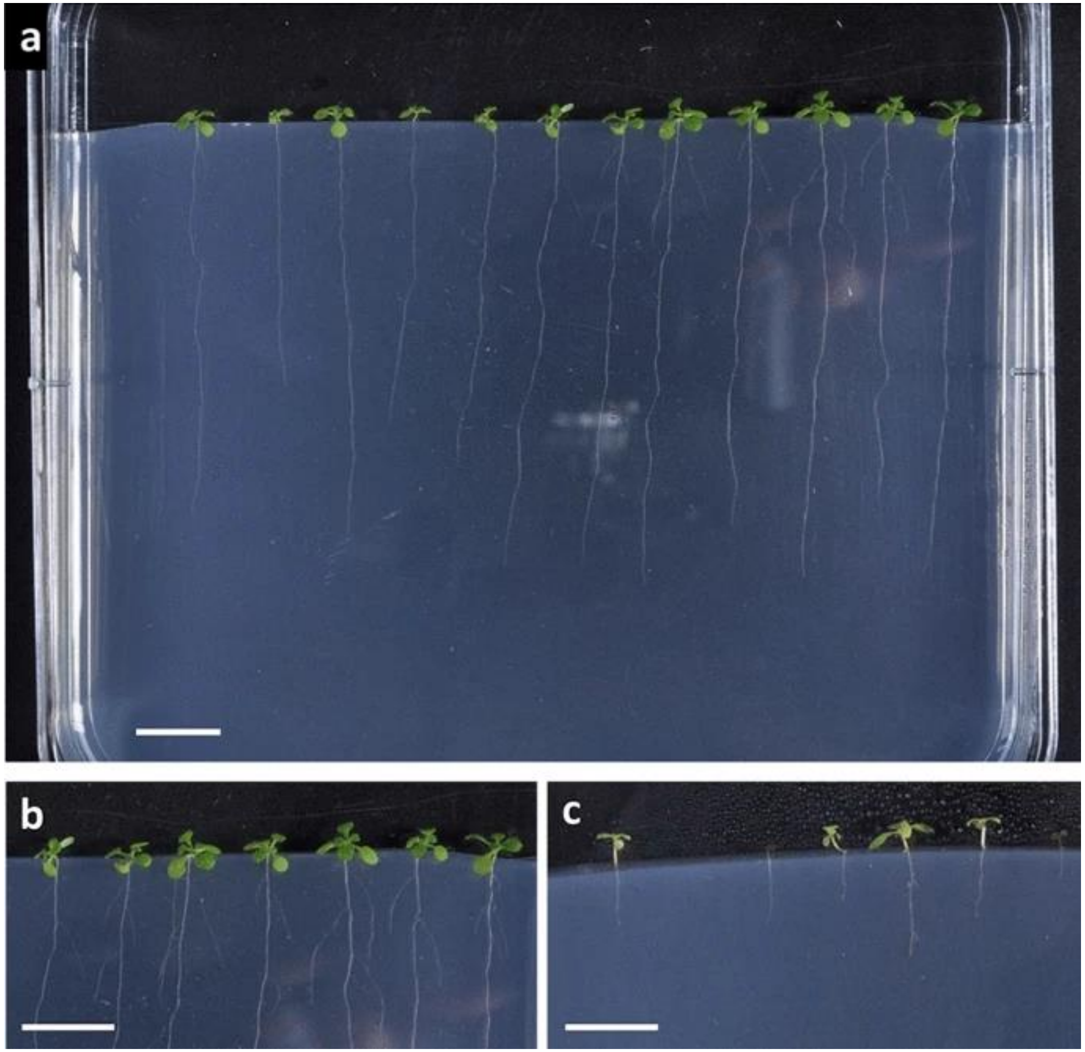
from past and future funded experiments

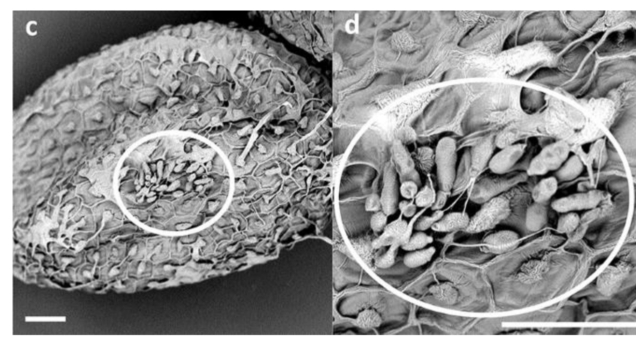
from collaborative platform

from didactic version of U-Net

Comparison with ground truth
Automatic cluster of types of errors

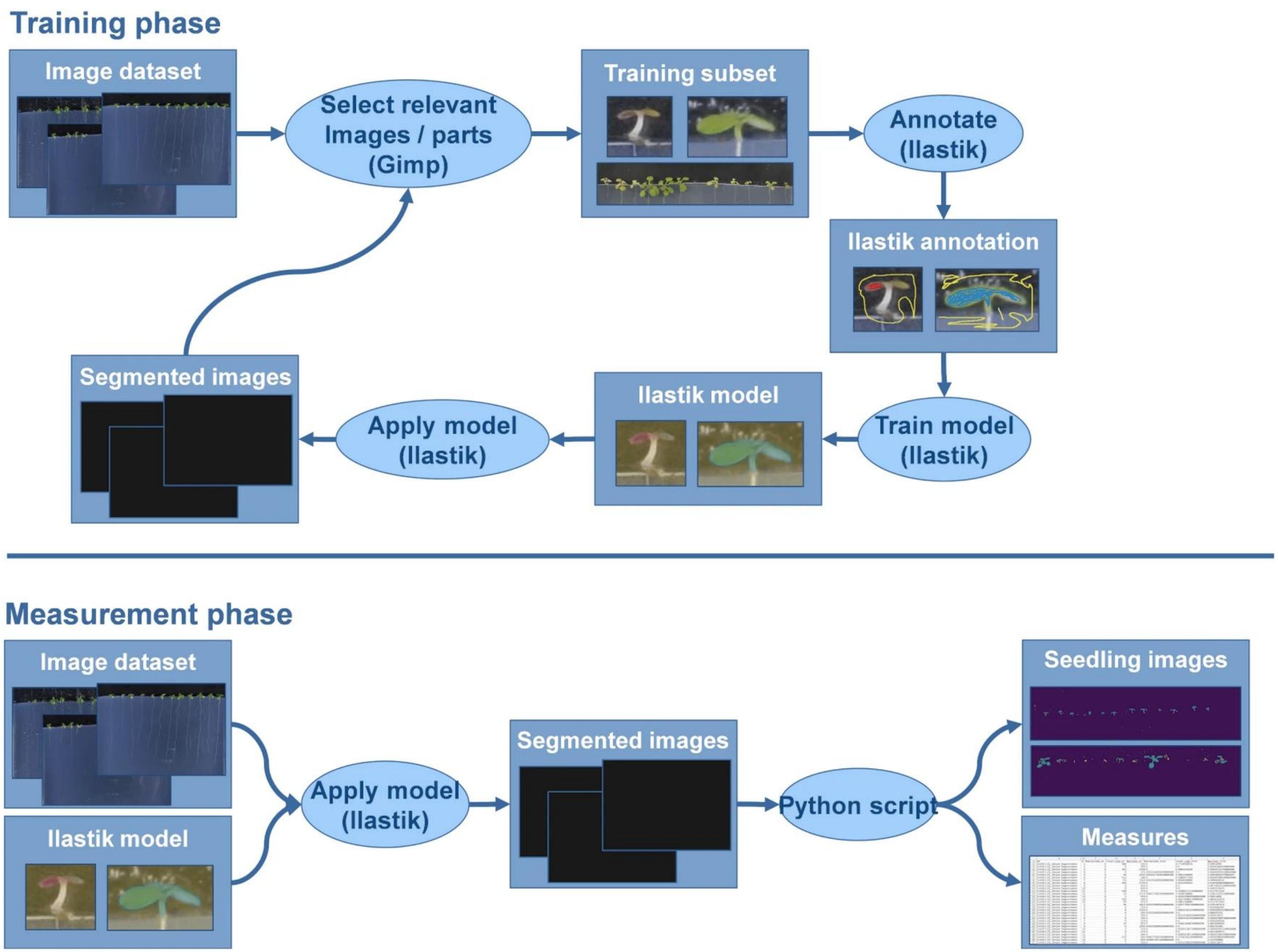
Plant symptom segmentation with Shallow learning

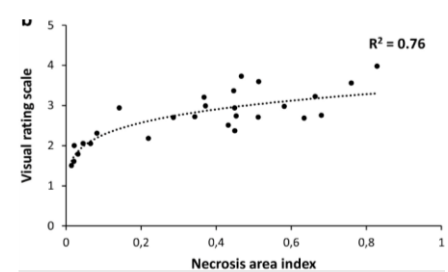




J. Bourbeillon, D. Rousseau, B. Teulat, Plant Methods 2022

Supervised learning

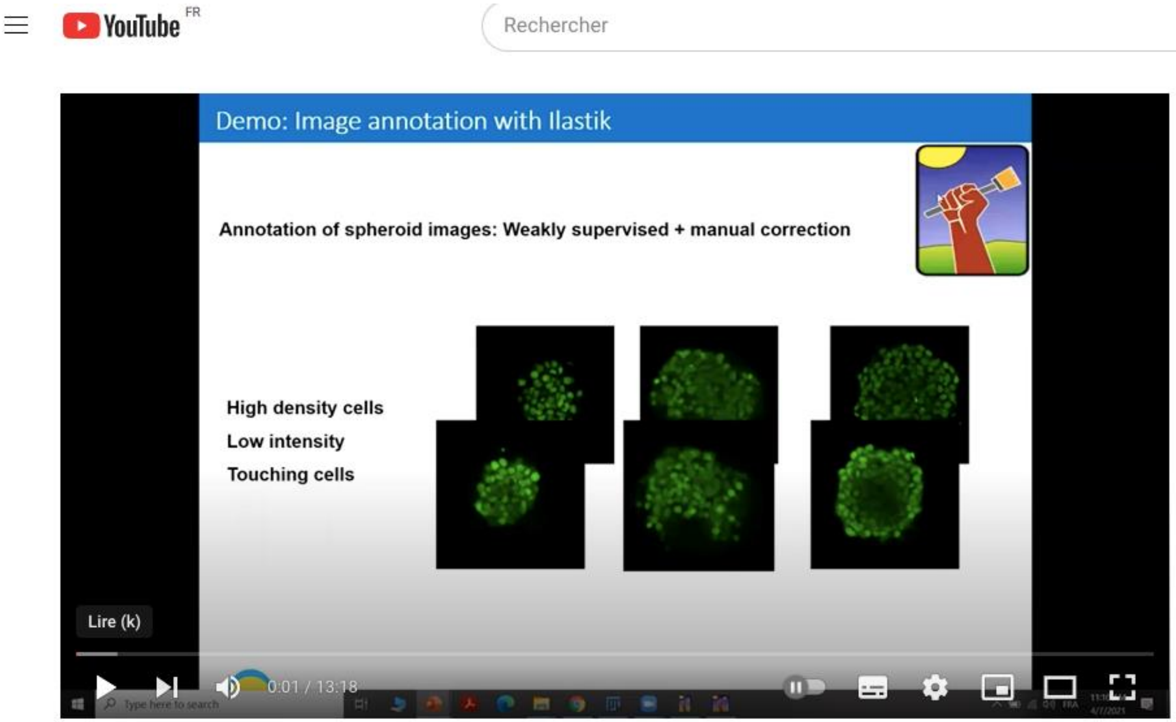




J. Bourbeillon, D. Rousseau, B. Teulat, Plant Methods 2022

Ilastik Kezako ?

Outil libre de machine learning
Présenté lors de formation PHENOME
Vidéo tutoriel le disponible sur chaîne youtube par Ali Ahmad



Annotation and manual annotation in Ilastik

https://www.youtube.com/watch?v=A3v8yrmBOvc

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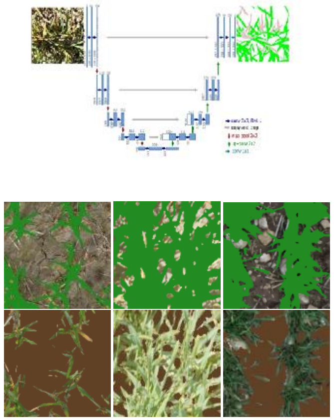

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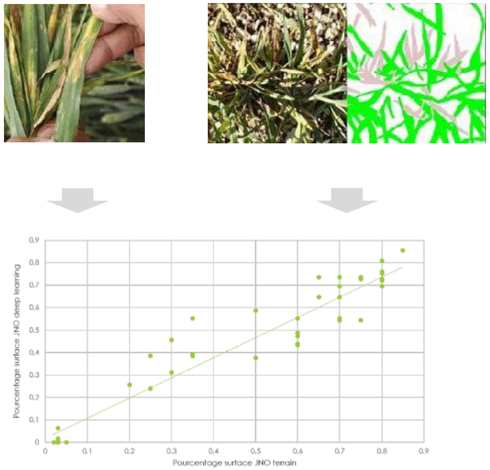


from past and future funded experiments

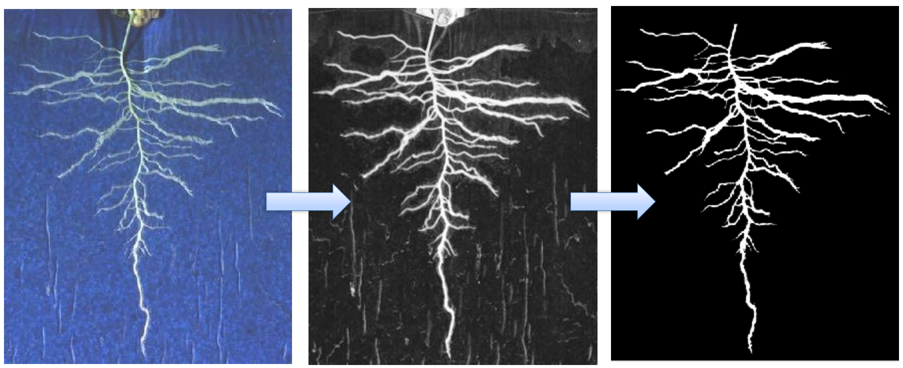
from collaborative platform

from didactic version of U-Net

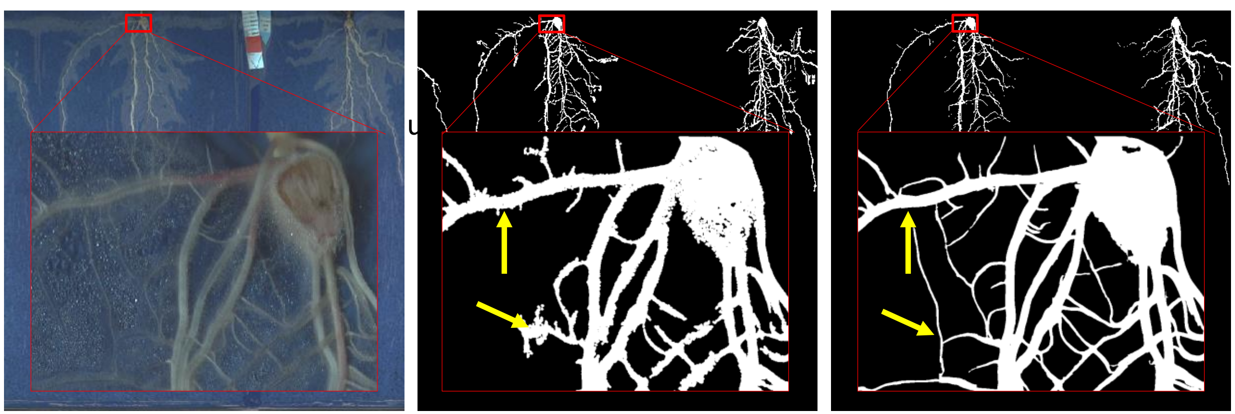
Comparison with ground truth
Automatic cluster of types of errors

Quantifying interactions on root

Segmentation



- Opérationnel
- Portage EGI avec réannotation et réentraînement
- Dockerisation



computer vision classique

Deep learning

M. Lambeuf, C. Salon

EGI Kezako ?

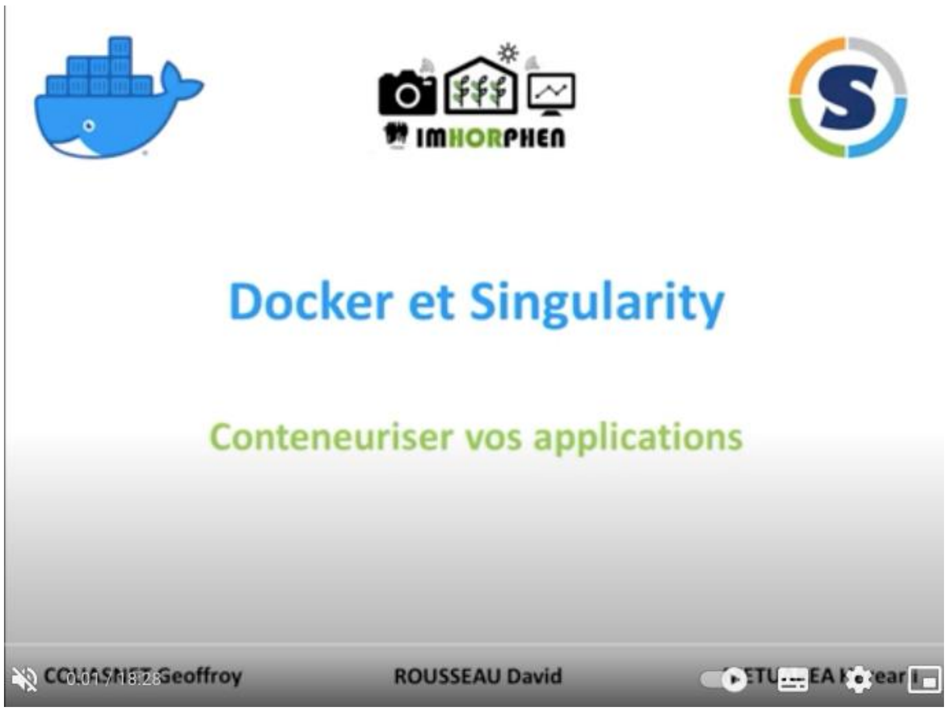
European Grid Infrastructure
Présenté lors de formation PHENOME
Vidéo tutoriel le disponible sur chaîne youtube par Herearii Metuera

Deepaas & Napari hand in hand

https://www.youtube.com/watch?v=bc53pvzVWDs&t=12s

Docker Kezako ?

Machine virtuelle légère
Vidéo tutoriel le disponible sur chaîne youtube par Herearii Metuera



https://www.youtube.com/watch?v=OjMwkviD3Co

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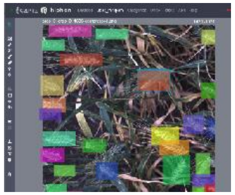
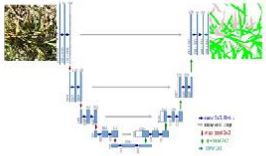
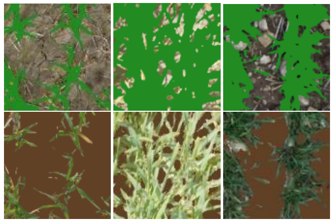


from collaborative
platform

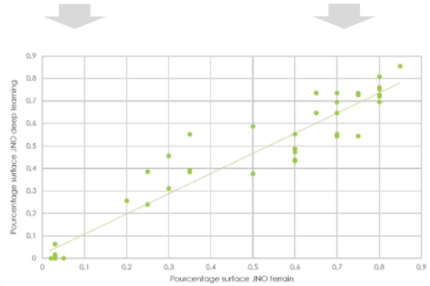
Step 3 Deep learning

from didactic version of
U-Net

Step 4 Data analysis





Comparison with ground truth
Automatic cluster of types of errors

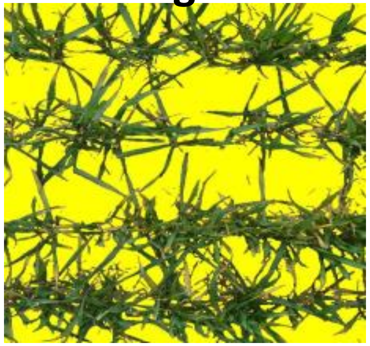
Phénotypage des stress biotiques - ARVALIS

Options initiales de travail :

- Utiliser des capteurs RVB haute résolution (PHENOMOBILE et LITERAL)
- Estimer la sévérité des maladies, mais pas d'identification des maladies
- Application à des maladies foliaires du blé (ici : fusariose)
- Mode d'acquisition vertical car simple

Approche : segmentation sémantique détaillée

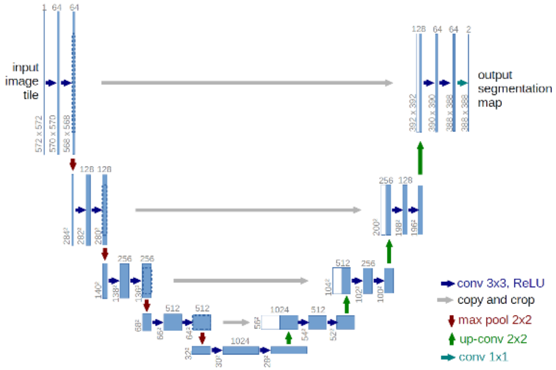
Vegetation / Background



Model 1

Wheat heads

Model 2

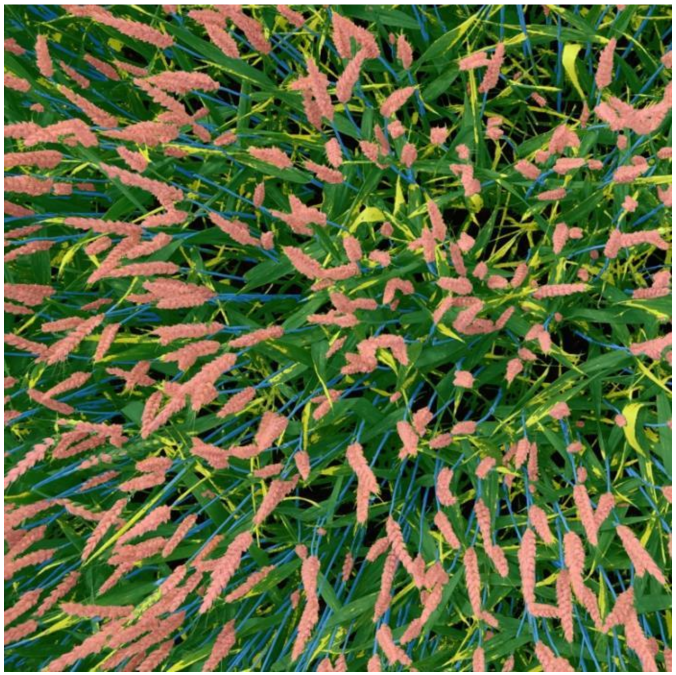


Unet Network

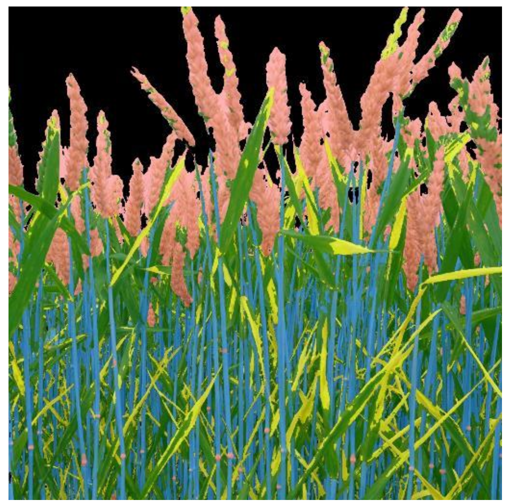
Stems

Model 3

Pixel classification : Healthy/sick



Green / Non green pixels segmentation model

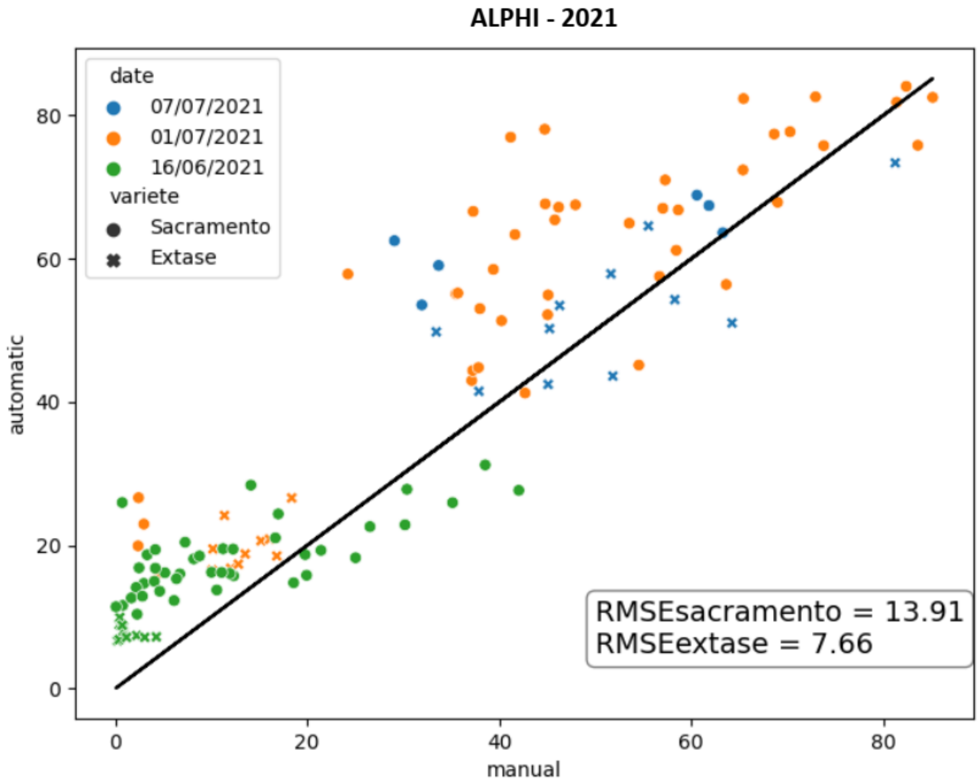


- Stems
- Healthy leaves
- Non green leaves
- Wheat heads
- Background

Disease symptoms and natural senescence are in the class ‘Non green’

$$Disease = \frac{yellow\_pixels}{leaves\_pixels}$$

Comparison with visual assessment



→ 2 varieties:

- 1 with beard (Sacramento)
- 1 without (Extase)

→ Good correlation for both case but much better for variety without beard.

Conclusion: CV as a DIY process

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from past and future funded experiments

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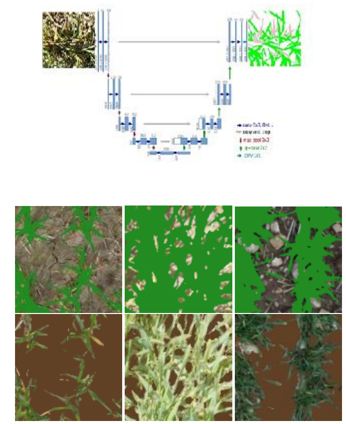

from didactic version of U-Net

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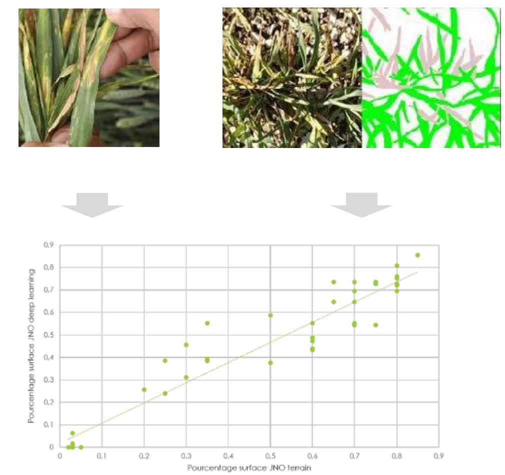

Comparison with ground truth
Automatic cluster of types of errors

GT Deep learning tutorials