

MCP1.1 Biotic interactions

13 avril 2023

David Rousseau

david.rousseau@univ-angers.fr

ImHorPhen Bioimaging Research Group



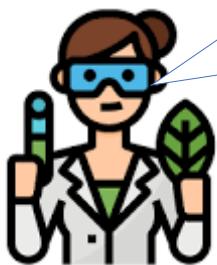
anr[®]
agence nationale
de la recherche
AU SERVICE DE LA SCIENCE

ANR11-INBS-0012

INRAE  **ARVALIS**

 **Terres
Inovia**
l'agronomie en mouvement

- The quest of genericity



Biologist

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 inoculum,, detect emergence, monitor kinetic of symptoms, ...SO MANY DIFFERENT BIOLOGICAL QUESTIONS !!!



Geek1.0

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>

- Deep learning as a generic tool



Biologist



Computer scientist

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 inoculum, detect emergence, monitor kinetic of symptoms, ...

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 vision as a DIY process

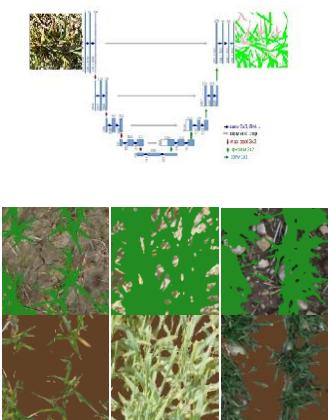
Step 1 image acquisition



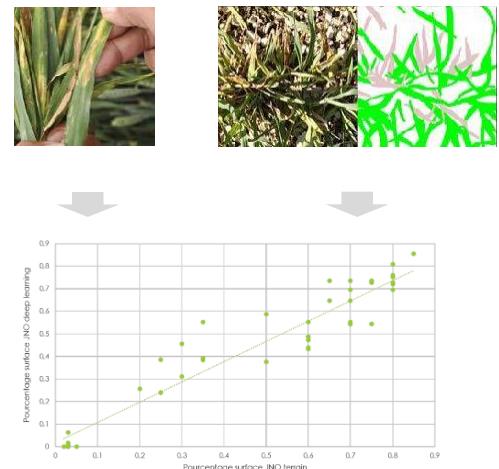
Step 2 annotation



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

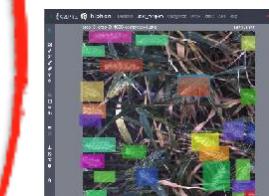
Computer vision as a DIY process

Step 1 image acquisition



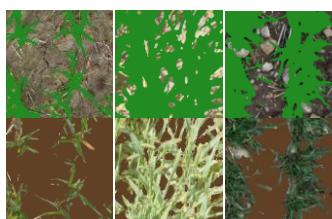
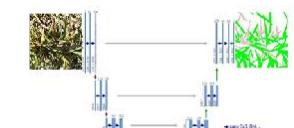
from past and future funded experiments

Step 2 annotation



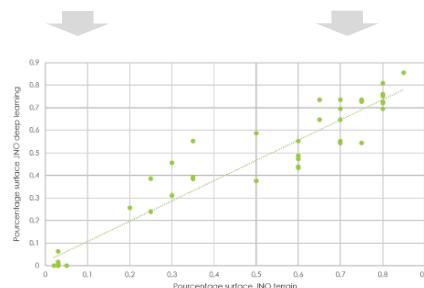
from collaborative platform

Step 3 Deep learning



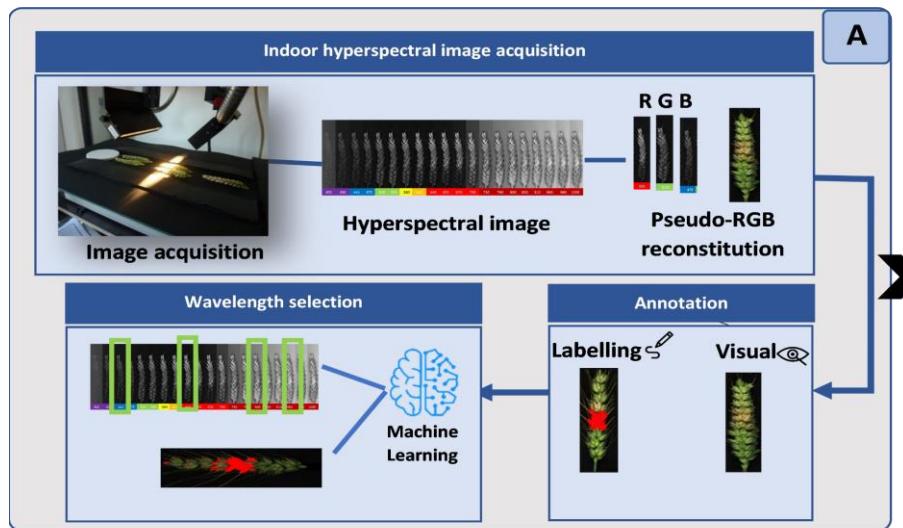
from didactic version of U-Net

Step 4 Data analysis

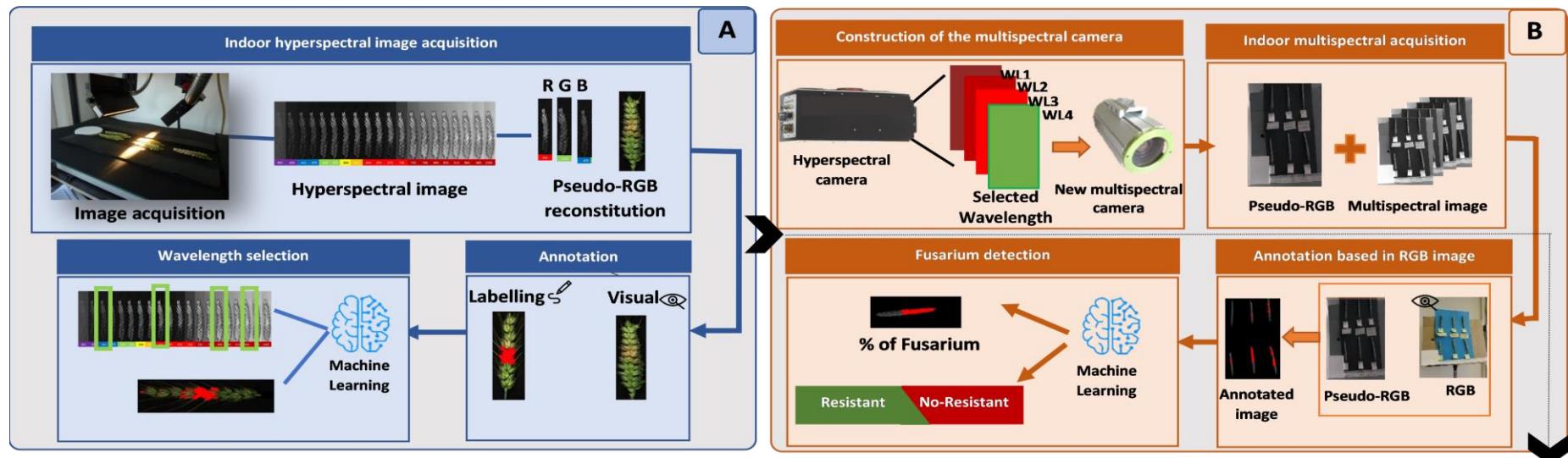


Comparison with ground truth
Automatic cluster of types of errors

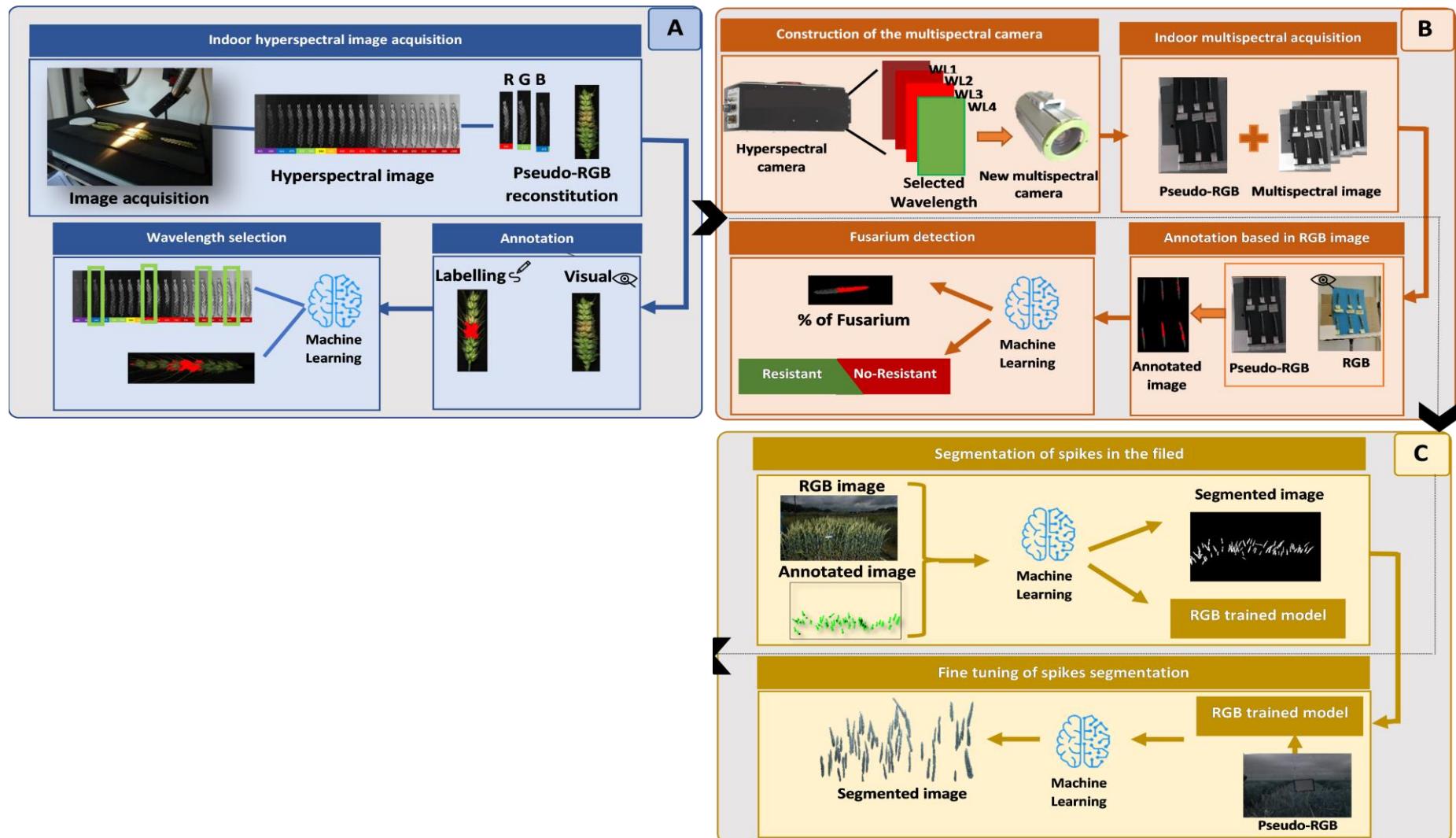
New methodology on image acquisition



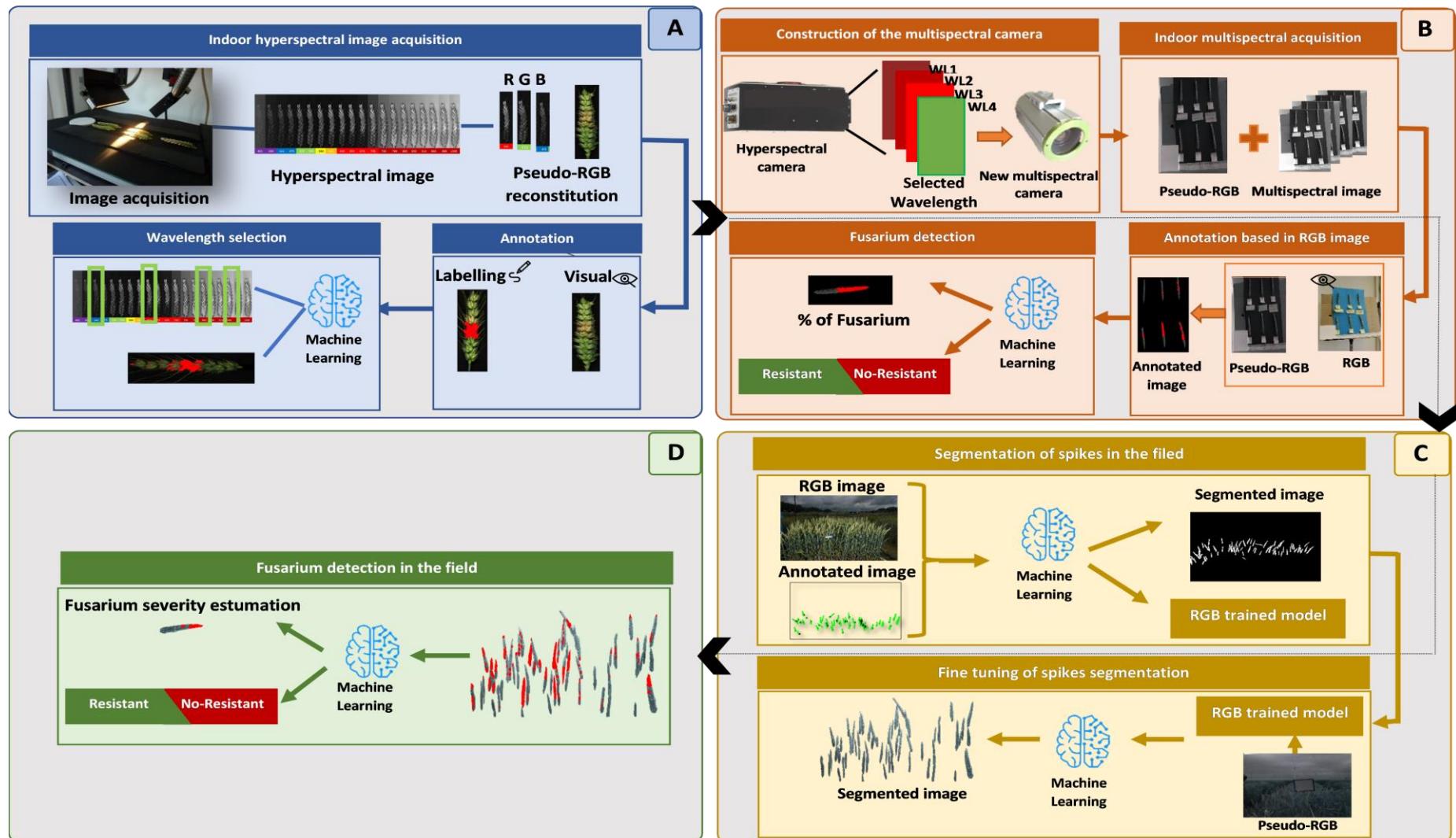
New methodology on image acquisition



New methodology on image acquisition

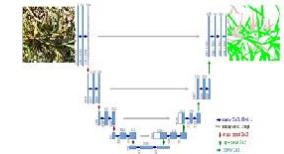


New methodology on image acquisition



U-Net Kezako ?

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



YouTube FR

Rechercher

ESRI_Seg_Hands_on - Google Drive

colab.research.google.com/drive/1t5qYj9MafoSpbQr3E6GZy5f7ESh5lw#scrollTo=AESONwYnEZC1

U-Net_segmentation_notebook.ipynb

Fichier Modifier Affichage Insérer Exécution Outils Aide Documentation

Code Teste

```
Epoch 1/20
75/75 [=====] - ETA: 0s - loss: 0.7424 - dice_coefficient: 0.3987
Epoch 00001: saving model to /content/gdrive/My Drive/ESRF_Seg_Models/onTest_model.0s
75/75 [=====] - 2s 1ms/step - loss: 0.7424 - dice_coefficient: 0.3987 - val_loss: 0.3998 - val_dice_coefficient: 0.3948
Epoch 2/20
75/75 [=====] - ETA: 0s - loss: 0.3791 - dice_coefficient: 0.5528
75/75 [=====] - 2s 1ms/step - loss: 0.3791 - dice_coefficient: 0.5528 - val_loss: 0.3791 - val_dice_coefficient: 0.4955
Epoch 3/20
75/75 [=====] - ETA: 0s - loss: 0.1812 - dice_coefficient: 0.7596
Epoch 00001: saving model to /content/gdrive/My Drive/ESRF_Seg_Models/onTest_model.0s
75/75 [=====] - 2s 1ms/step - loss: 0.1812 - dice_coefficient: 0.7596 - val_loss: 0.1298 - val_dice_coefficient: 0.8123
75/75 [=====] - ETA: 0s - loss: 0.1495 - dice_coefficient: 0.8248
Epoch 00001: saving model to /content/gdrive/My Drive/ESRF_Seg_Models/onTest_model.0s
75/75 [=====] - 2s 1ms/step - loss: 0.1495 - dice_coefficient: 0.8248 - val_loss: 0.1074 - val_dice_coefficient: 0.8792
Epoch 5/20
75/75 [=====] - ETA: 0s - loss: 0.1281 - dice_coefficient: 0.8762
Epoch 00001: saving model to /content/gdrive/My Drive/ESRF_Seg_Models/onTest_model.0s
75/75 [=====] - 2s 1ms/step - loss: 0.1281 - dice_coefficient: 0.8762 - val_loss: 0.0958 - val_dice_coefficient: 0.9126
Epoch 6/20
80/75 [=====] - ETA: 0s - loss: 0.1302 - dice_coefficient: 0.8882
```

Plot training & validation curves
plt.figure(figsize=(10, 5))

23:23 / 31:33

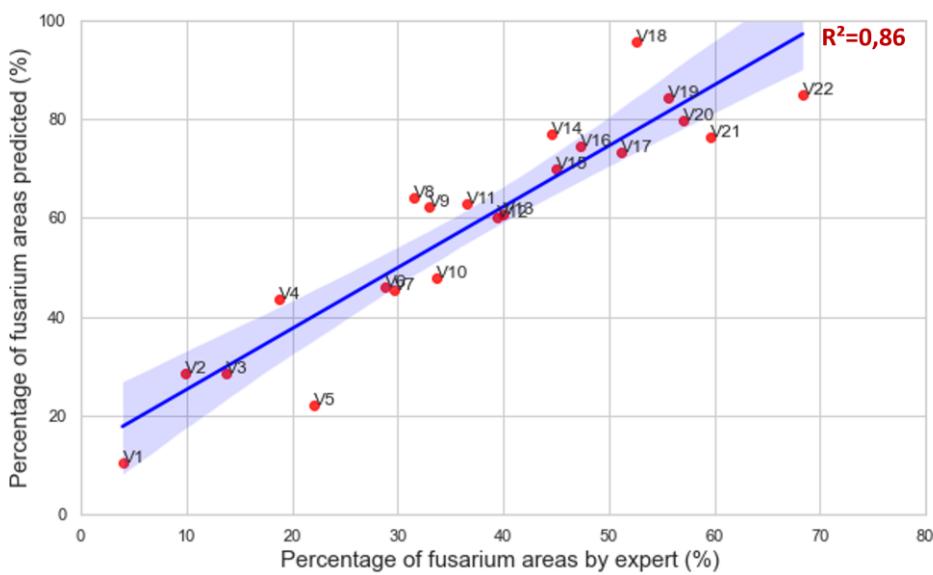
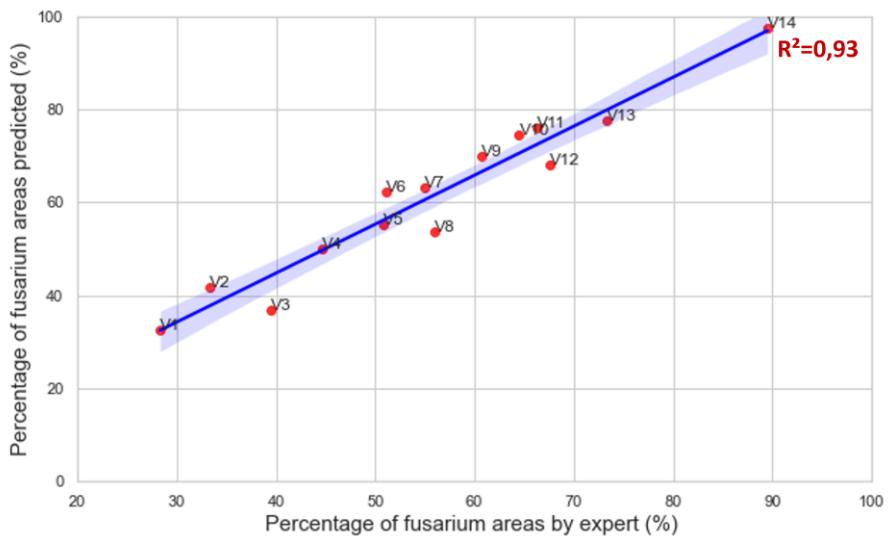
Type here to search

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.



Computer vision as a DIY process



Disques foliares et mildiou

OIV 452-2

- Décrit interaction disque foliaire vigne et mildiou
- Aggrave sporulation et nécrose sur une échelle de résistance avec des valeurs impaires de 1 à 9
- Complex ->
 - N'est pas toujours utilisé
 - Souvent seule la sporulation est prise en compte



Finding the symptom in the patch

The interface includes a toolbar with zoom (+/-), crop (C), and refresh (refresh) icons. A message at the bottom left says "You should sign in!"

TASK

TUTORIAL

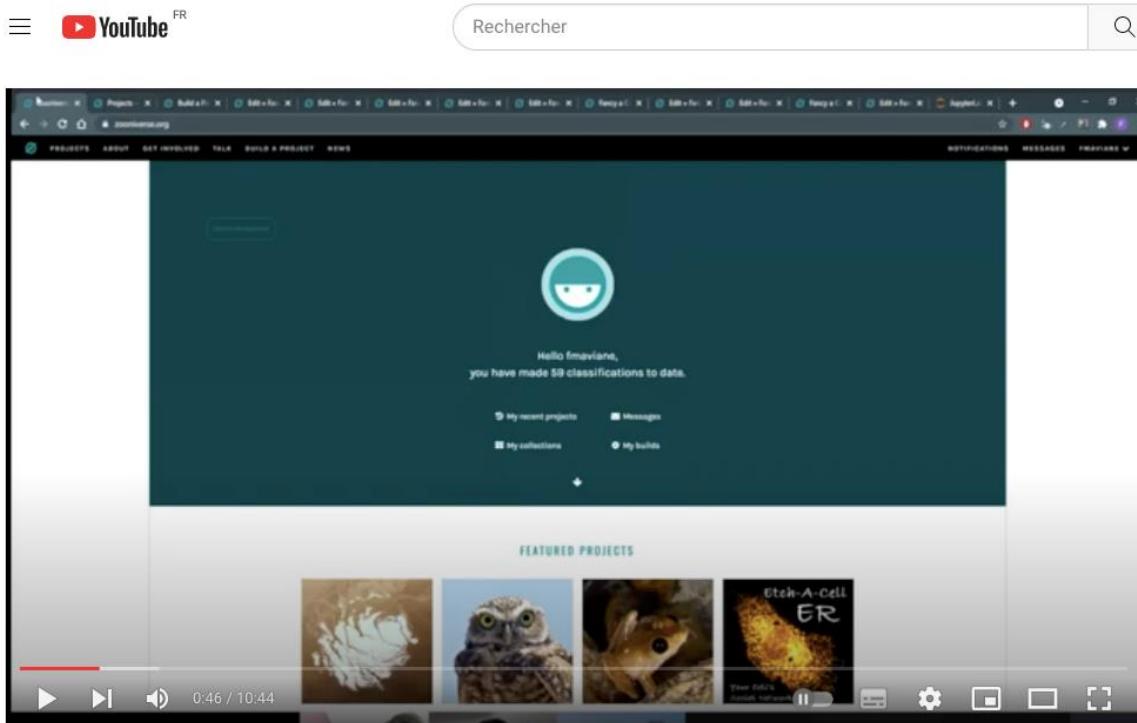
- sporulation
- necrosis: dots
- necrosis: stains
- necrosis: stains and stains
- necrosis: senescence

Showing 5 of 5 Clear filters

Done

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

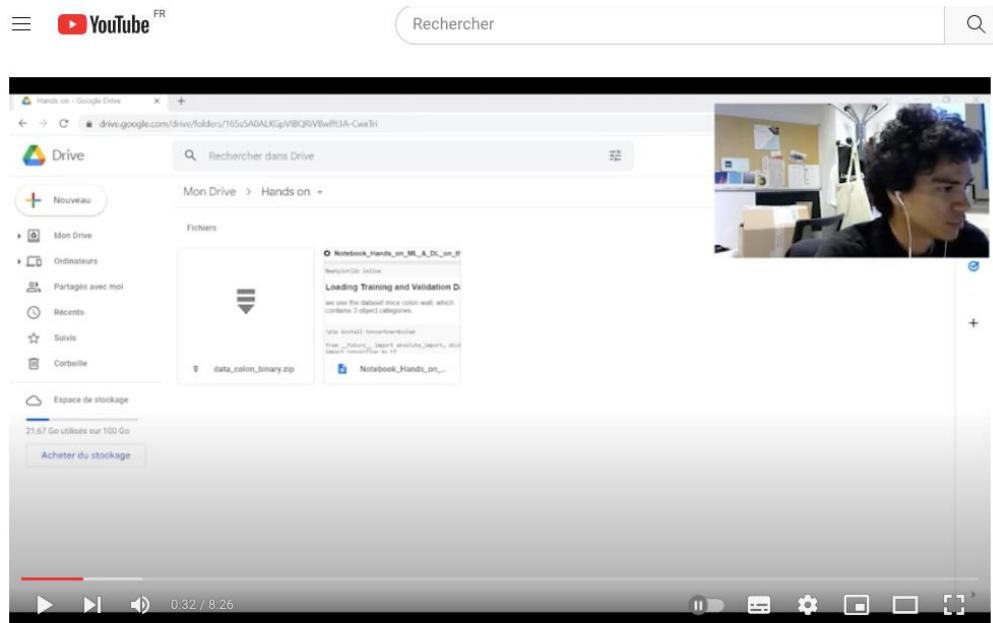
<https://www.youtube.com/watch?v=dCPv536TElw&t=46s>

Classification Kezako ?

Tri d'images par classe par deep learning

Présenté lors de formation PHENOME

Vidéo tutoriel le disponible sur chaîne youtube par Herearri Metuarea



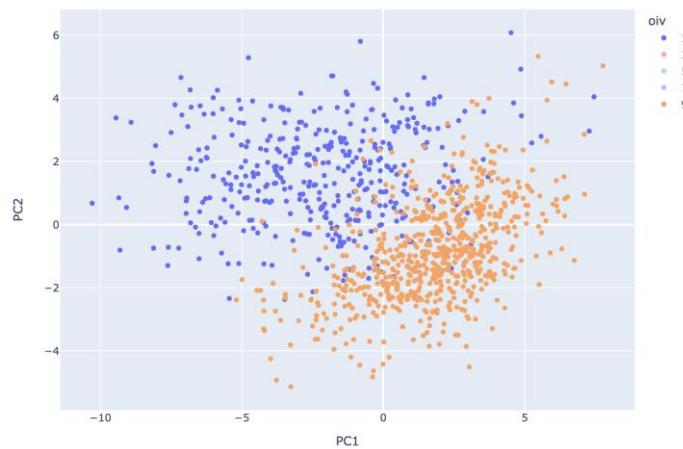
Hands on model classification

<https://www.youtube.com/watch?v=W2luOX6IK3w&t=31s>

Classifieur multiclasse

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'entraînement

Computer vision as a DIY process

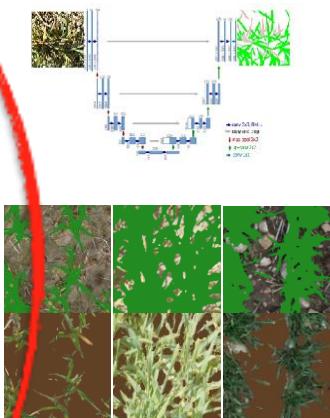
Step 1 image acquisition



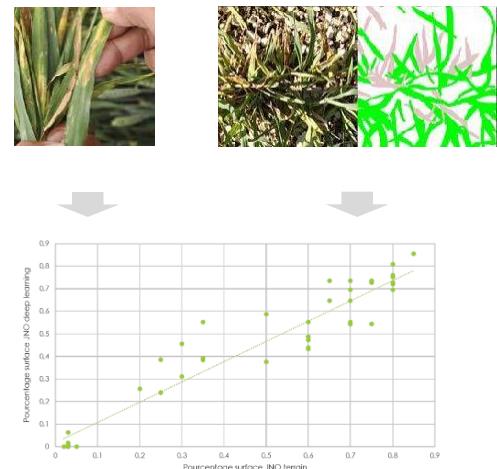
Step 2 annotation



Step 3 Deep learning



Step 4 Data analysis



from past and future
funded experiments

from collaborative
platform

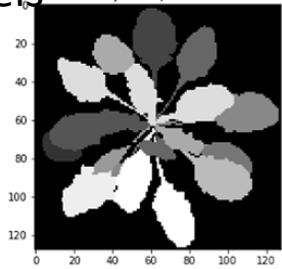
from didactic version of
U-Net

Comparison with ground truth
Automatic cluster of types of errors

Plant symptom segmentation

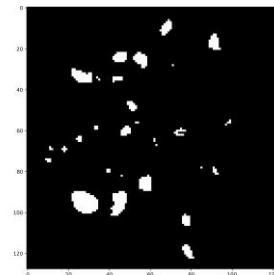
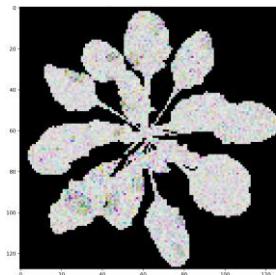
Arabidopsis: 783

RGB labels



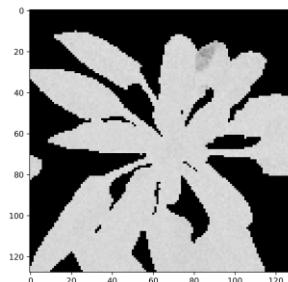
Algorithm mapping

Gaussian noise

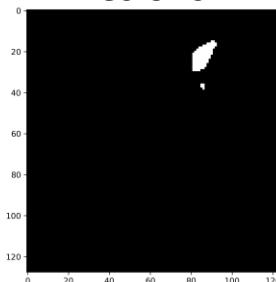


+ Data augmentation

Real-Fluo-
Diseased

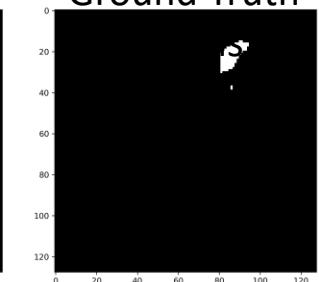


Predicted
lesions



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

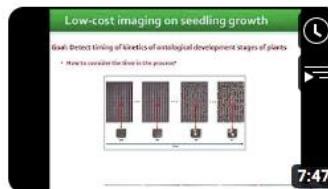
Ground Truth



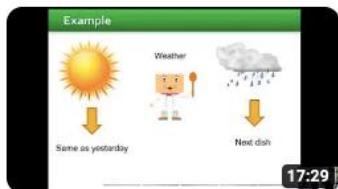
Best case: 90% recall and 97% precision

Zooniverse data augmentation ?

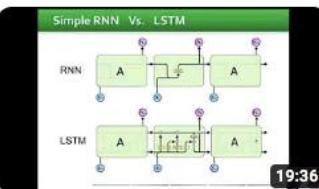
Moyen de robustifier les performances des Algos de deep learning
Présenté lors de formation PHENOME
Vidéo tutoriel le disponible sur chaîne youtube par David



DEEP LEARNING FULL PACK
Introduction to RNN part 3
30 vues • il y a 2 ans



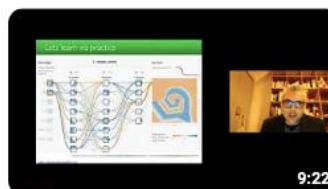
DEEP LEARNING FULL PACK
Introduction to RNN part 1
52 vues • il y a 2 ans



DEEP LEARNING FULL PACK
Introduction to RNN part 2
35 vues • il y a 2 ans



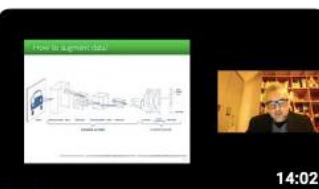
DEEP LEARNING FULL PACK
Data augmentation part 4
106 vues • il y a 2 ans



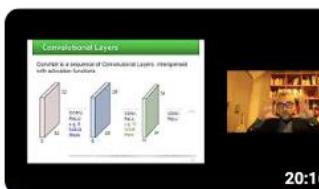
DEEP LEARNING FULL PACK
Data augmentation part 3



DEEP LEARNING FULL PACK
Data augmentation part 2



DEEP LEARNING FULL PACK
Data augmentation part 1



DEEP LEARNING FULL PACK
CNN Principles

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

Computer vision as a DIY process

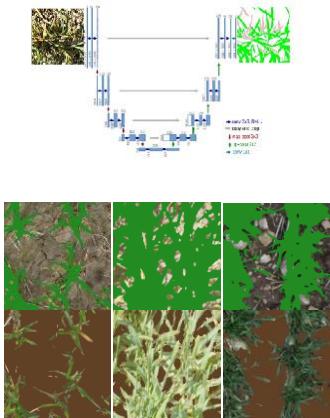
Step 1 image acquisition



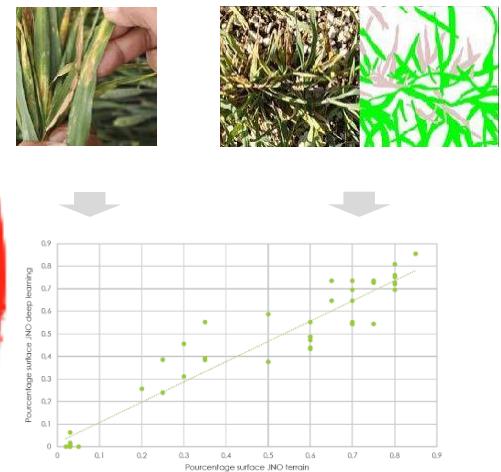
Step 2 annotation



Step 3 Deep learning



Step 4 Data analysis



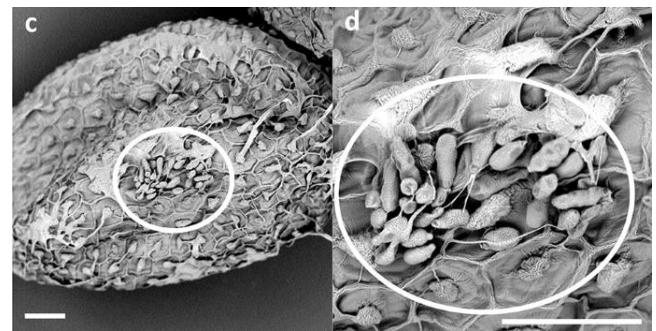
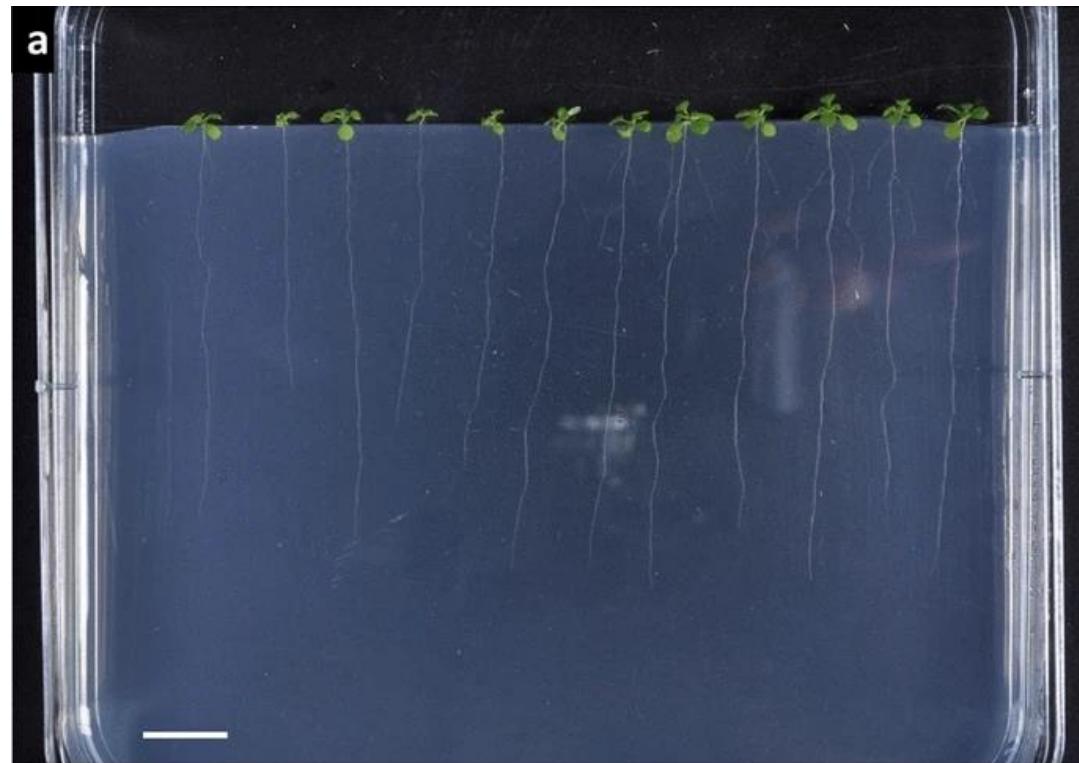
from past and future
funded experiments

from collaborative
platform

from didactic version of
U-Net

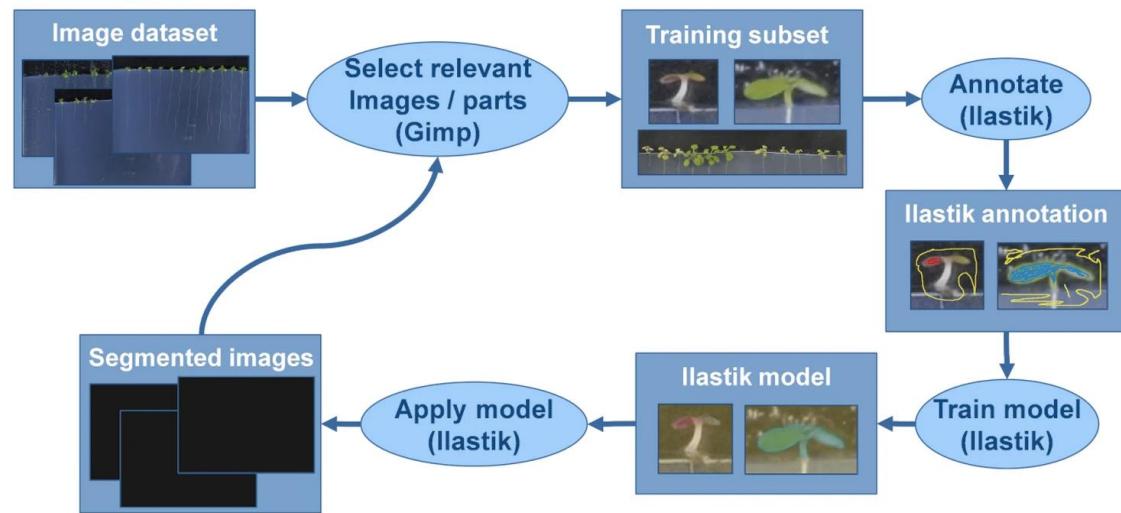
Comparison with ground truth
Automatic cluster of types of errors

Plant symptom segmentation with Shallow learning

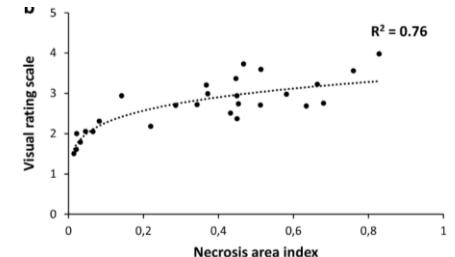
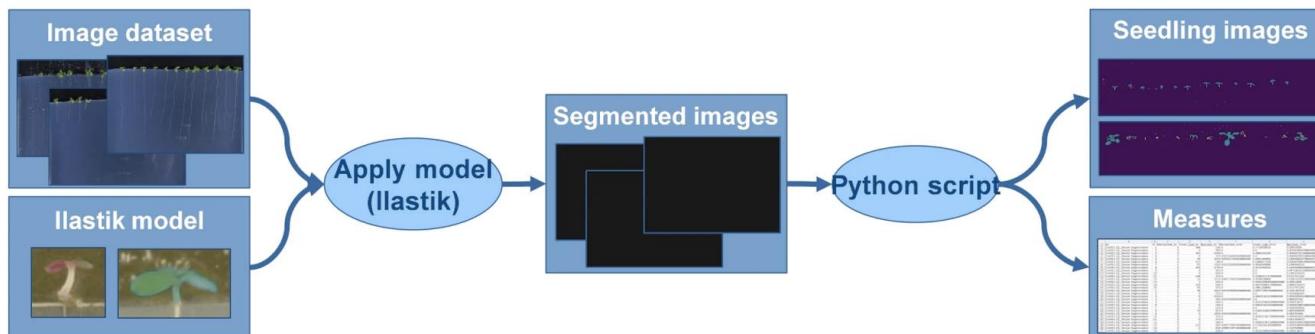


Supervised learning

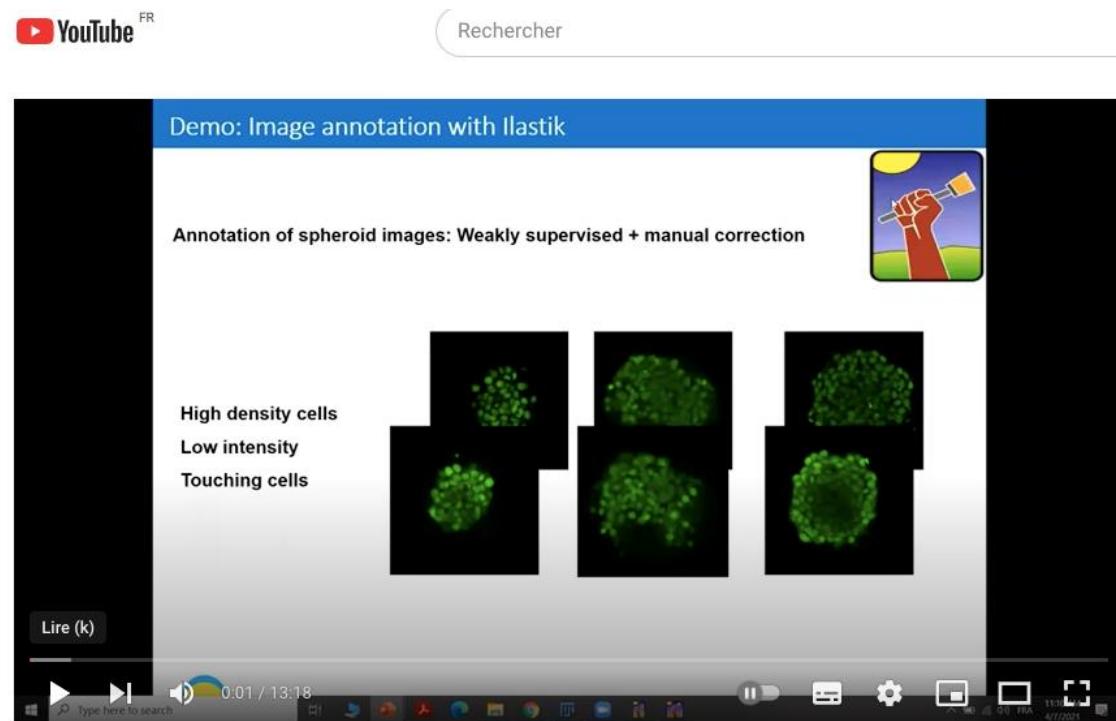
Training phase



Measurement phase



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>

Computer vision as a DIY process

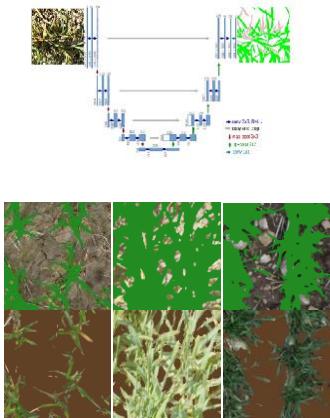
Step 1 image acquisition



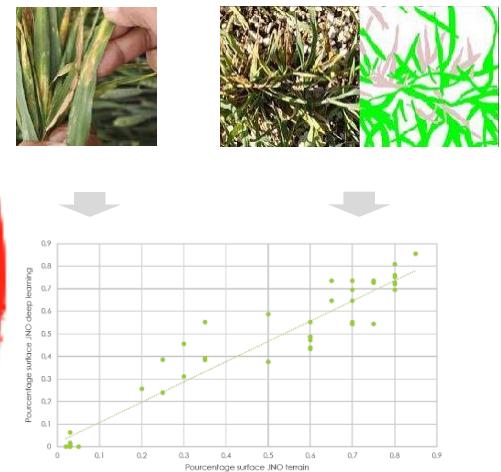
Step 2 annotation



Step 3 Deep learning



Step 4 Data analysis



from past and future
funded experiments

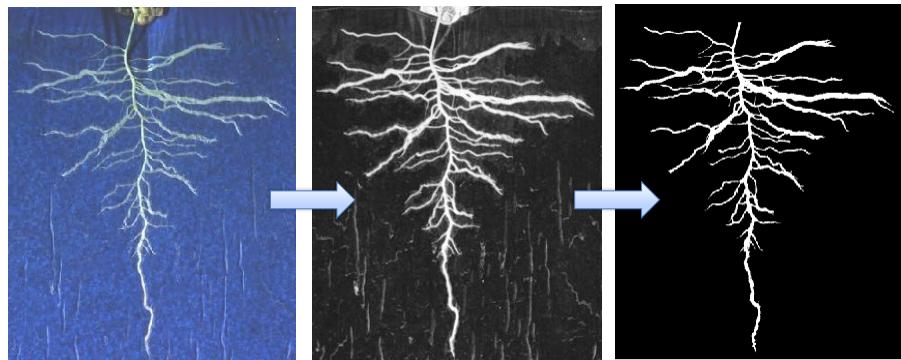
from collaborative
platform

from didactic version of
U-Net

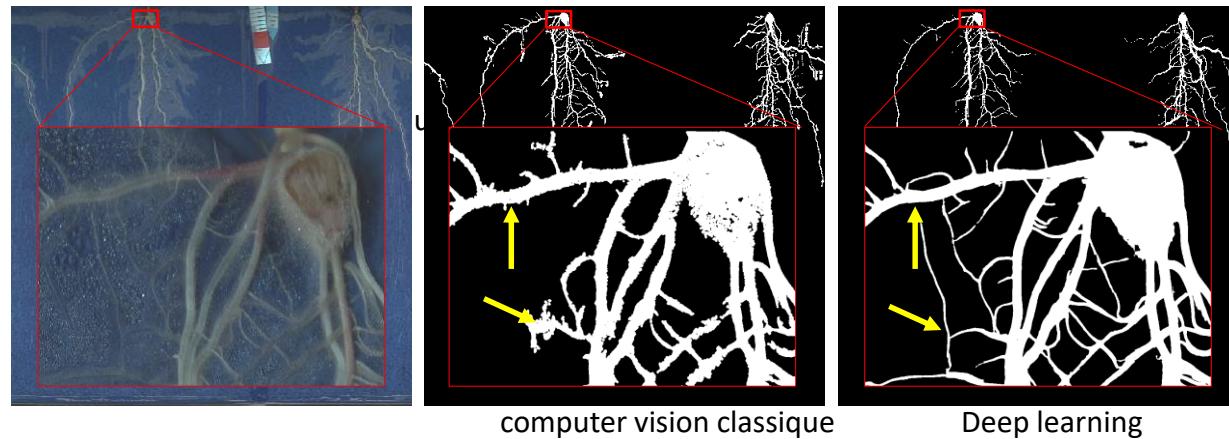
Comparison with ground truth
Automatic cluster of types of errors

Quantifying interactions on root

Segmentation



- Opérationnel
- Portage EGI avec réannotation et réentraînement
- Dockerisation



European Grid Infrastructure

Présenté lors de formation PHENOME

Vidéo tutoriel le disponible sur chaîne youtube par Herearri Metuera



Deepaas & Napari hand in hand

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

Machine virtuelle légère

Vidéo tutoriel le disponible sur chaîne youtube par Herearri Metuera



Docker et Singularity

Conteneuriser vos applications

Computer vision as a DIY process

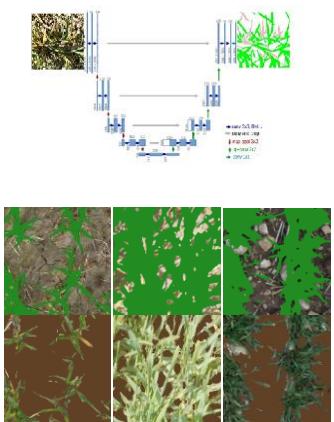
Step 1 image acquisition



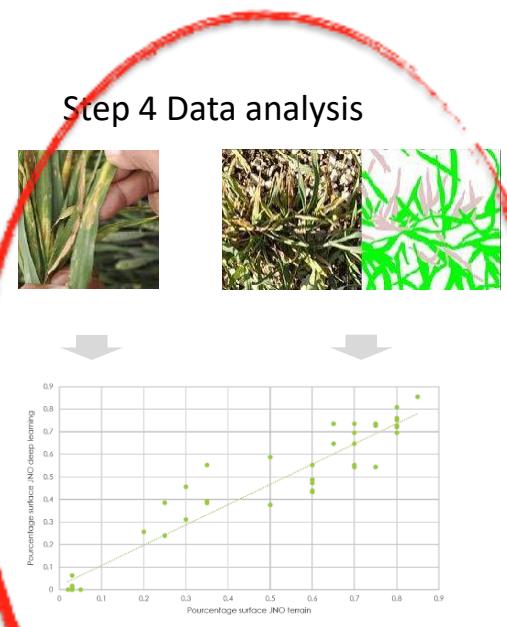
Step 2 annotation



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 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

Wheat heads

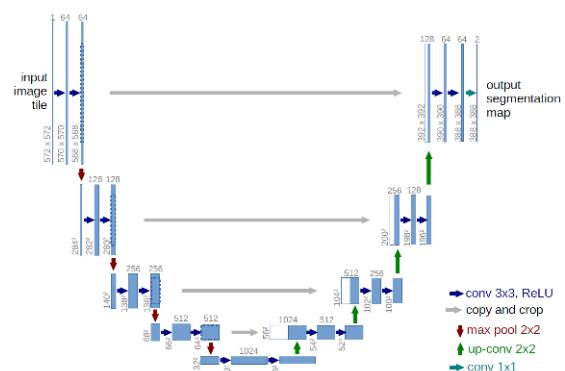


Model 2

Vegetation /
Background



Model 1



Stems

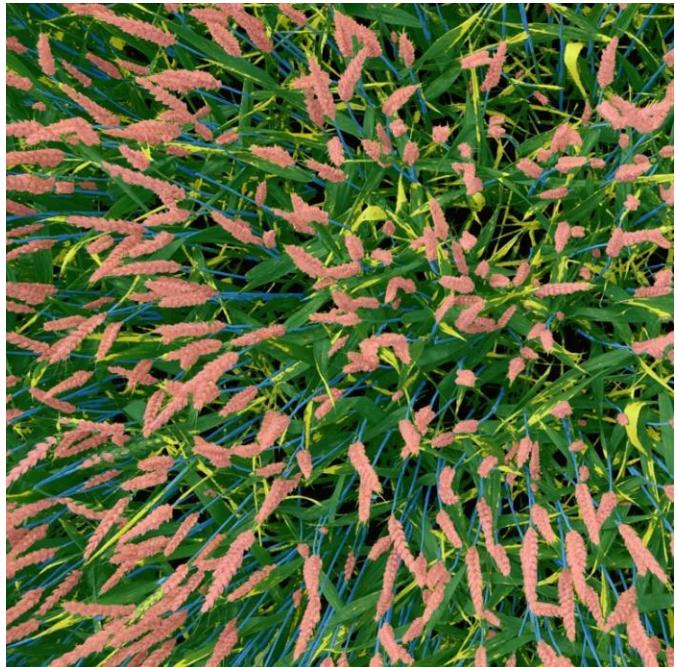


Model 3

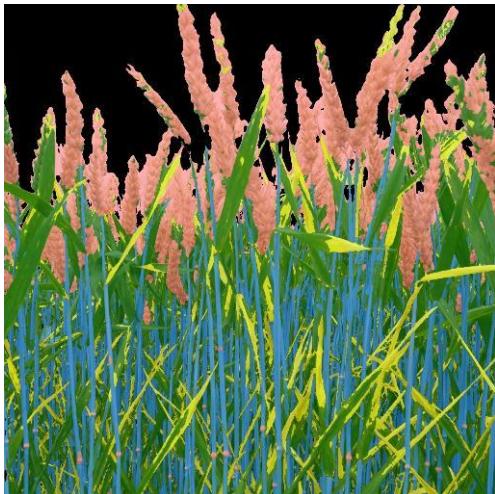
Unet Network



Pixel classification : Healthy/sick



Green / Non green
pixels segmentation
model

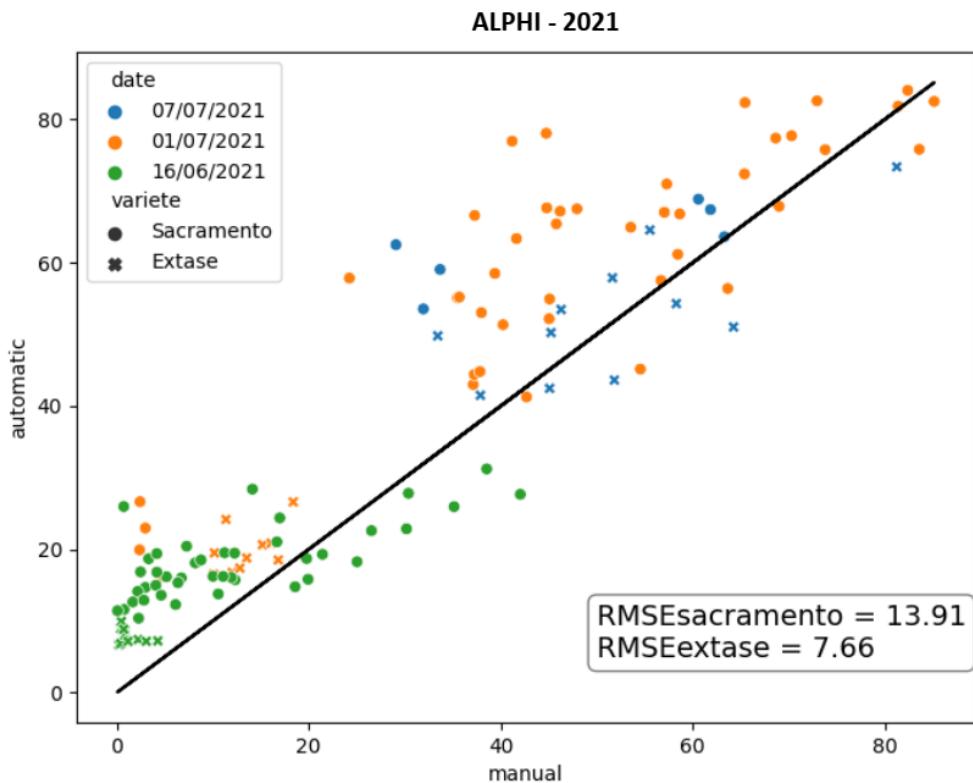


- █ Stems
- █ Healthy leaves
- █ Non green leaves
- █ Wheat heads
- █ Background

Disease symptoms and natural senescence are in the class 'Non green'

$$Disease = \frac{\text{yellow_pixels}}{\text{leaves_pixels}}$$

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

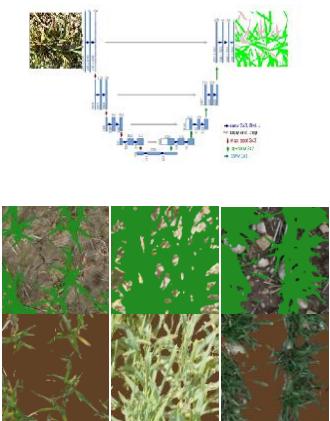
Step 1 image acquisition



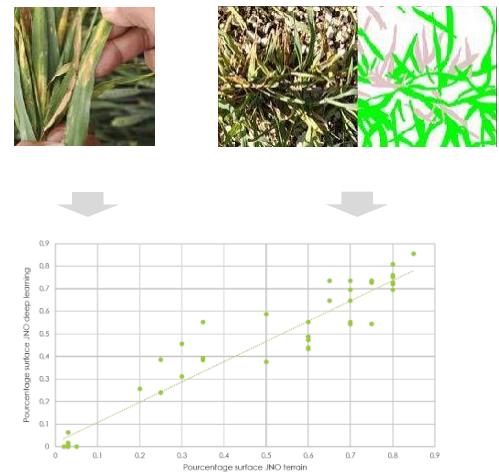
Step 2 annotation



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

GT Deep learning tutorials



ImHorPhen Bio imaging research group

@imhorphenbioimagingresearc95 302 abonnés 160 vidéos

ImHorPhen is a bioimaging, research group, headed by Prof. David Rousse... >

Personnaliser la chaîne

Gérer les vidéos

ACCUEIL

VIDÉOS

PLAYLISTS

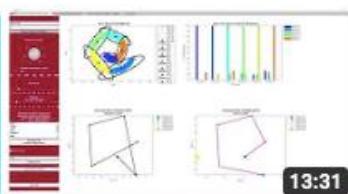
COMMUNAUTÉ

CHAÎNES

À PROPOS



Vidéos ► Tout lire



PHENOGRID

Container avec Docker

Container avec Singularity

Ordinalysis tutorial

Acquisition d'objet 3D avec
Ranne Vision