Pl@ntNet at phenology workshop

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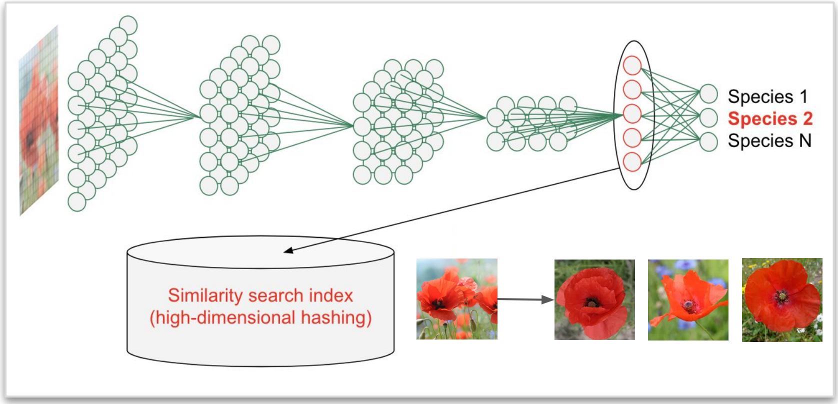
iDigBio Phenology Workshop, Florida State University, 17-18 Jan., 2019

Pl@ntNet Citizen Science platform in a nutshell

Deep-learning based plant identification since 2014



11 million downloads
30-100K users per day
11 languages
18K plant species
30M plant observations in 2018
22 checklists

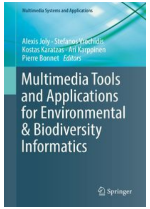
50 million images
16 Tb of data
10 servers
20 users of the identification API

4 permanent researchers
3 engineers
3 PhD students
2 post-docs
4 research organisms: CIRAD, Inria, INRA, IRD

Research at the frontier of **Data** and **Plant sciences**

Plant species monitoring

Large scale species recognition

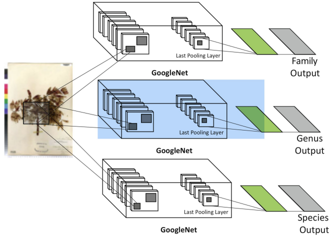

Multimedia Systems and Applications

Alexis Joly · Stefanos Vrochidis · Kostas Karatzas · Ari Karppinen · Pierre Bonnet Editors

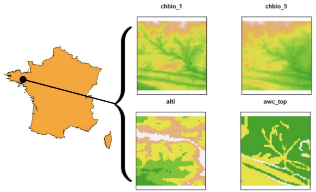
Multimedia Tools and Applications for Environmental & Biodiversity Informatics

Springer

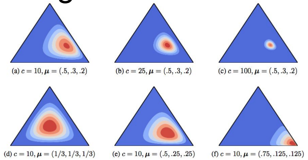
Herbarium Classification



Plant Species distrib. model.



Uncertainty issues in fine-grained image classification

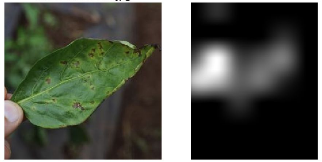


Citi. Sc. tools & methods

Collaborative data validation (Bayesian Active Training Approach)

Visual plant diseases analysis

Xanthomonas-19.jpg



Autonomous robot for weed removal

Herbarium specimens identification

Tecnológico de Costa Rica

RESEARCH ARTICLE Open Access

Going deeper in the automated identification of Herbarium specimens

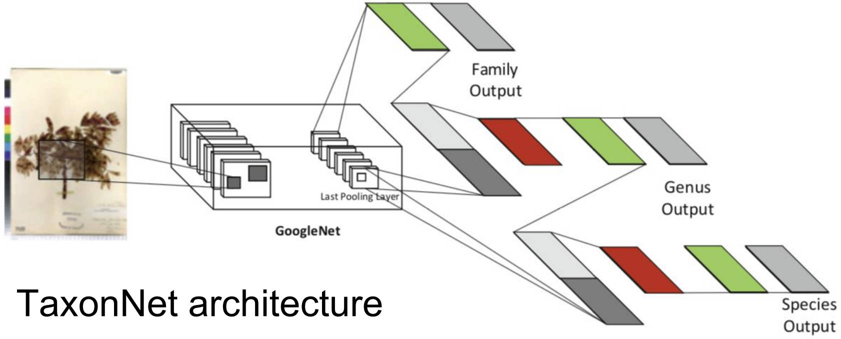
Jose Carranza-Rojas[1*], Herve Goeau[2], Pierre Bonnet[2], Erick Mata-Montero[1] and Alexis Joly[3]

Data	#species	Accuracy top1/top5
France Herbarium	1K	**0.80 / 0.90**
Costa-Rica Herbarium	256	**0.74 / 0.87 (transfer learning)**

Carranza-Rojas, J., Goëau, H., Bonnet, P., Mata-Montero, E., & Joly, A., 2017. **Going deeper in the automated identification of Herbarium specimens.** *BMC evolutionary biology*, 17(1), 181.

Design and experimentation of new **CNN architectures**

Use of the plant taxonomy to classify specimens at species, genus and family levels



TaxonNet architecture

Carranza-Rojas, J., Joly, A., Goëau, H., Mata-Montero, E., & Bonnet, P. (2018). **Automated Identification of Herbarium Specimens at Different Taxonomic Levels**. In Multimedia Tools and Applications for Environmental & Biodiversity Informatics (pp. 151-167). Springer, Cham.

Herbarium specimens fertility detection

First experiment (fertile or not?) - 3 datasets (FSU, CAY, NEVP) ; 163,233 herbarium specimens belonging to 7,782 species; From temperate to tropical and equatorial floras.

Non fertile **vs.** **Fertile**

A B C

Deep learning (ResNet50) allowed correct detection of fertile material with an accuracy of **96.3%**.

T. Lorieul, K. D. Pearson, E. R. Ellwood, H. Goëau, J.-F. Molino, P. W. Sweeney, J. M. Yost, J. Sachs, E. Mata-Montero, G. Nelson, P. S. Soltis, P. Bonnet, A. Joly, Submitted. **Toward a large scale and deep phenological stages annotation of herbarium specimens : case studies from temperate, tropical, and equatorial floras**. Applications in Plant Sciences - Application Article.

Herbarium specimens fertility detection

Second experiment (fruit and/or flower?) - 3 datasets (FSU, CAY, NEVP); 148,351 herbarium specimens belonging to 7,272 species; From temperate to tropical and equatorial floras.

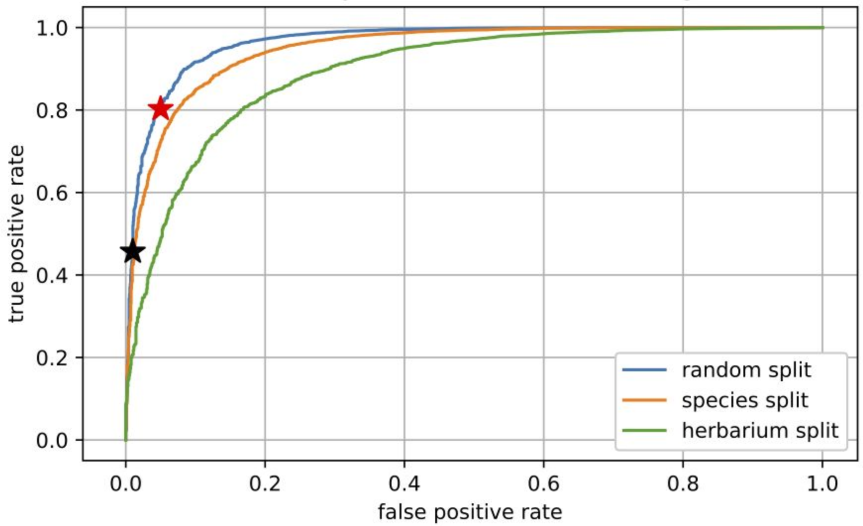
Evaluated models	Train set	Test set A (Random-split)	Test set B (Species-split)	Test set C (Herbarium-split)
Dataset size	109,467	12,095	12,723	14,066
Percentage of specimens in flower	60,9%	60,6%	62,5%	68,5%
Percentage of specimens in fruit	43,3%	43,4%	44,9%	32,5%
ResNet50-flowers	-	84,3 %	81,0 %	87,0 %
ResNet50-fruits	-	80,5 %	76,6 %	79,6 %

Deep learning (ResNet50) allowed correct detection of fertile material with an accuracy of **96.3%**. Accuracy was slightly decreased for finer-level information (**84.3%** for flower and **80.5%** for fruit detection).

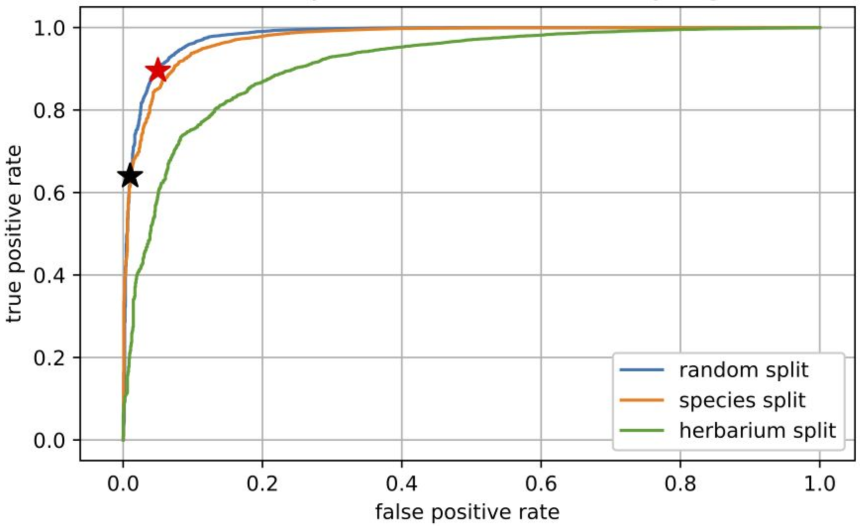
Herbarium specimens fertility detection

Impact of input Image size - fertile vs. not fertile experiment with two different sizes

400x250 pixels



900x600 pixels



Increasing input image size allows improving accuracy from **94.9%** to **96.3%**

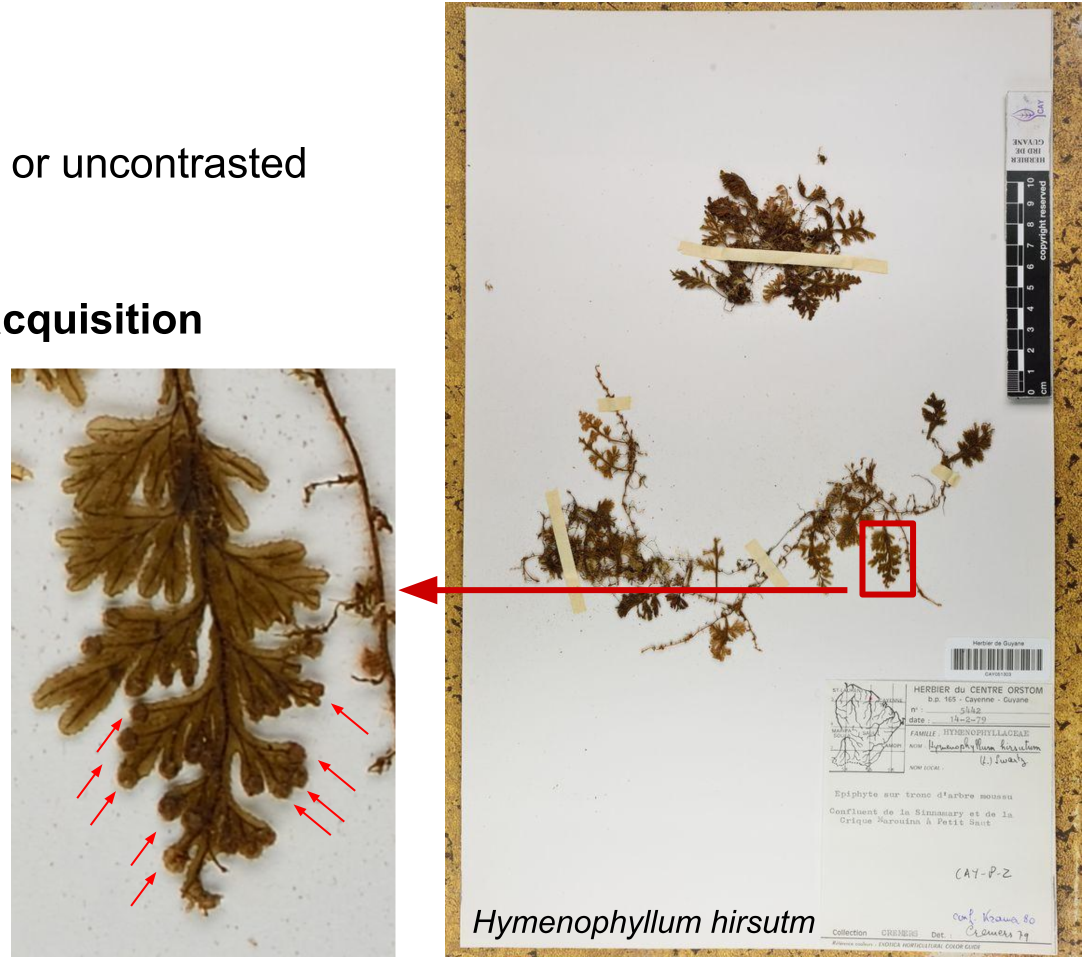
Herbarium specimens fertility detection

Misclassifications are mainly related to:

1. **Object uncertainty**: e.g. very small or uncontrasted reproductive structures

2. **Data uncertainty** arising from the **acquisition process** (collection + digitization):
   - Uncollected repr. struct.
   - Hidden repr. struct.
   - Repr. struct. not on the sheet (e.g. in alcohol, in envelope)
   - Degraded visual information

3. **Annotation errors**



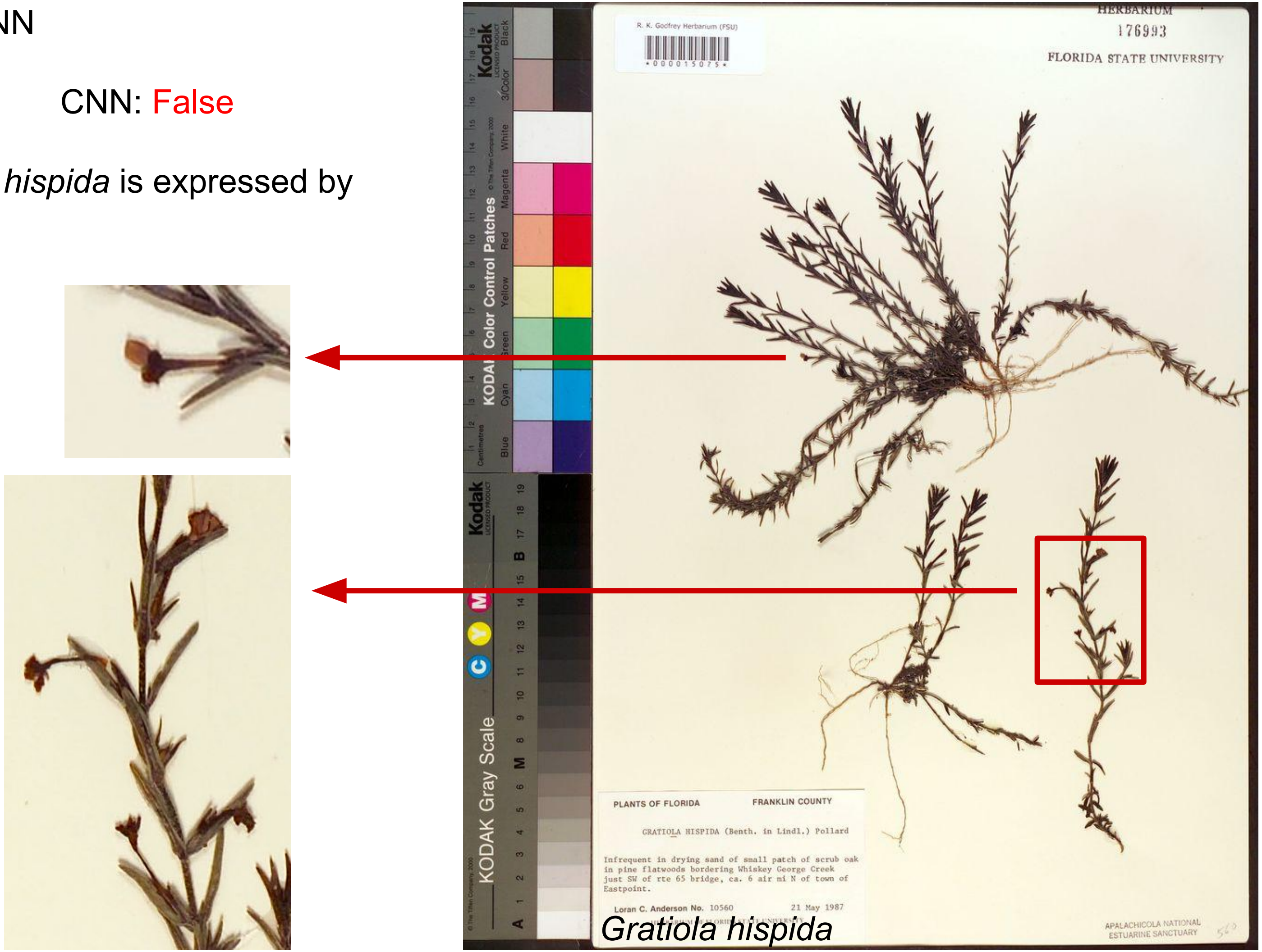
Hymenophyllum hirsutm

Second case: Error of CNN

Ground truth: True CNN: False

Human annotator: True

Sexuality on the *Gratiola hispida* is expressed by small solitary flowers.

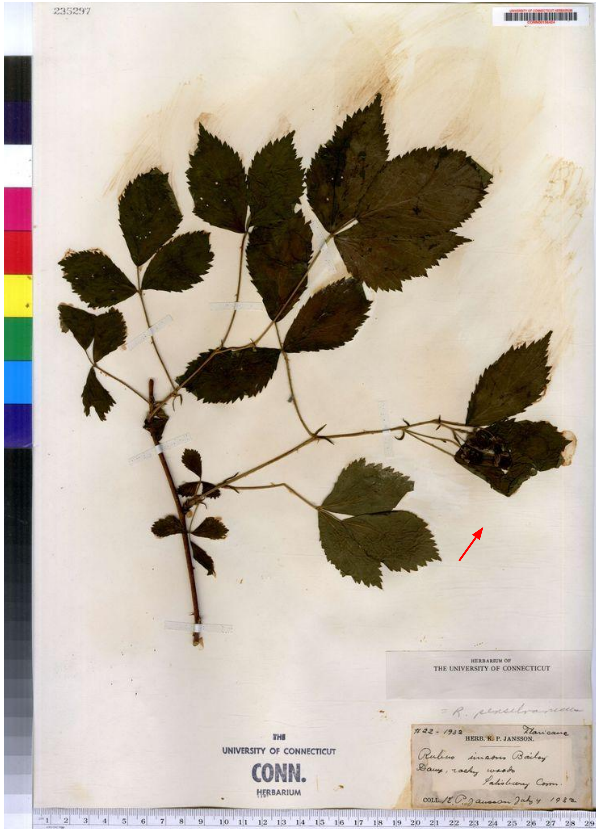


Gratiola hispida

Second case: Error of CNN ⇒ few other examples

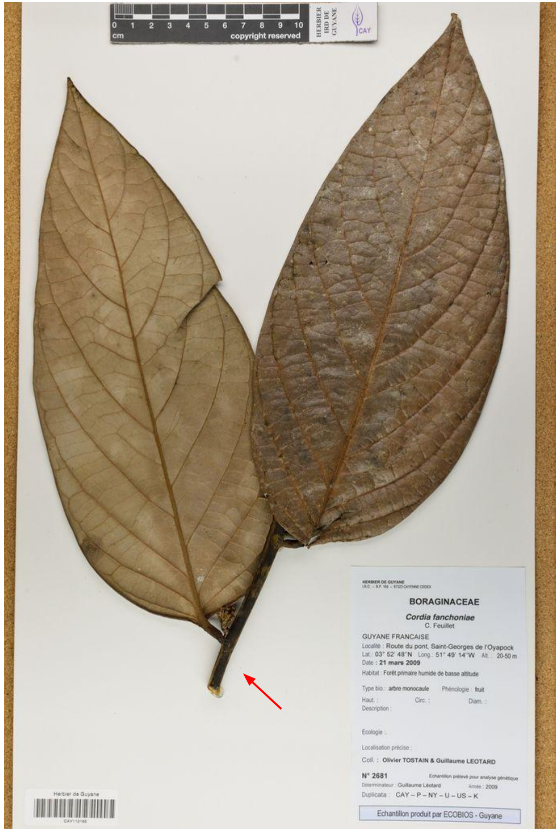
Ground truth: True CNN: False

Human annotator: True



Rubus inermis

Eclipta prostrata



Cordia fanchoniae

Herbarium specimens phenophase scoring

Third experiment conducted on *Asteraceae* phenophase dataset, produced by K. D. Pearson, on 20,994 specimens of 139 species.

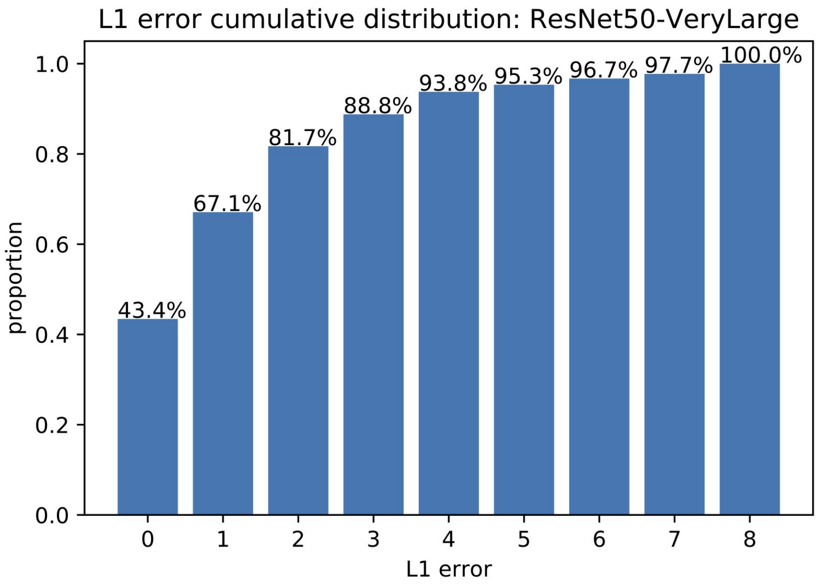
Illustration of the nine different phenophases of Coreopsis gladiata Walter recorded in the PHENO dataset.

Phenophases	Data distribution in the training data set (human annotated)	Data distribution in the test data set (human annotated)	Classification accuracy
1	10,4 %	10,4 %	74,8 %
2	7,6 %	7,5 %	24,4 %
3	9,5 %	9,5 %	27,9 %
4	7,1 %	7,2 %	8,6 %
5	17,3 %	17,2 %	60,8 %
6	7,2 %	7,2 %	6,8 %
7	10,5 %	10,6 %	18,8 %
8	10,5 %	10,5 %	18,0 %
9	19,9 %	19,9 %	78,9 %

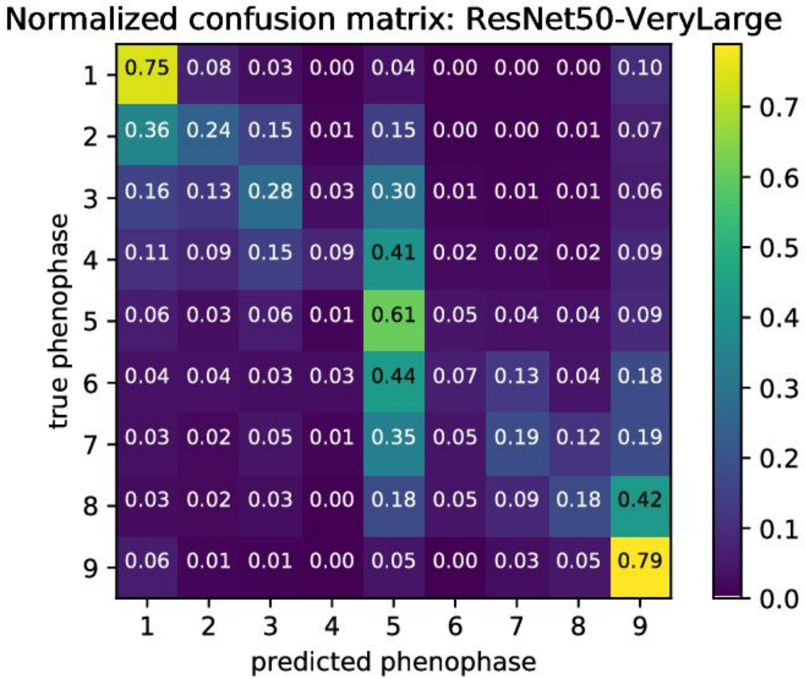
Overall accuracy: 43.4%
Human re-annotator accuracy: 42.0%

Results on **herbarium specimens phenophase scoring**

Experiment conducted on *Asteraceae* phenophase dataset, produced by K. D. Pearson, on 20,994 specimens of 139 species.



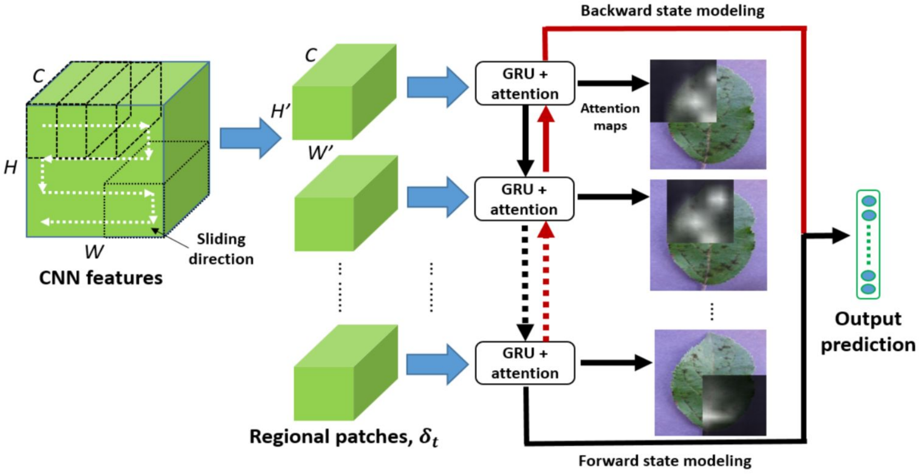
L1 error cumulative distribution for phenophases detection experiment

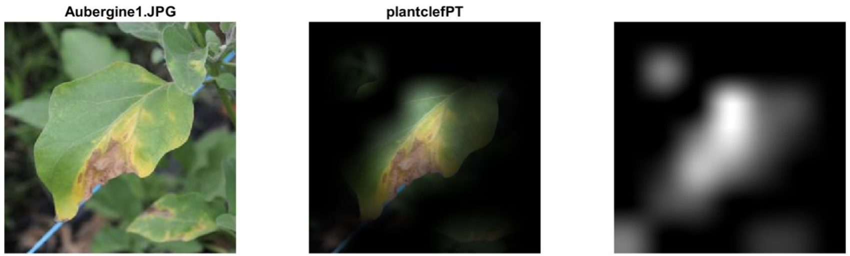


Row-wise normalized confusion matrix of phenophases classification experiment

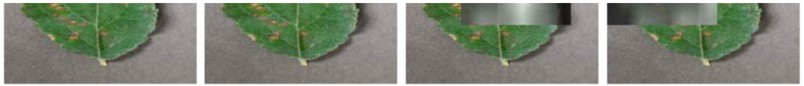
Ongoing work to improve accuracy

Attention based Recurrent Neural Networks (RNN) - currently experimented on plant diseases





An exemple for an eggplant disease



(b) Cedar apple rust disease

Attention recurrent neural network (RNN) are able to automatically **localize** the regions of interest, and extract relevant features for visual identification.

RNN can be used to improve visual classification, and allow to better understand which images parts, are used for prediction.

S. H. Lee, H. Goeau, P. Bonnet, A. Joly. In prep. **Attention based recurrent neural network approach for plant disease classification**. ICIP Conf.

Research perspectives

- Towards exploiting deep-learning based phenological data
  - controlling uncertainty (data ambiguity vs. model uncertainty)
  - compensating bias of observation effort (strong bias towards fertility)
  - scaling the approach to more groups (link with phylogeny?)
  - other data (Pl@ntNet observations?), optimal transfer learning
  - **answering a good case!**

- Phenological traits prediction (counting or localization tasks, size/shape estimation, etc.)

- Learning interdependencies between phylogeny and morphology through deep metric learning approaches

- Interaction between Deep Learning services and Citizen Science annotation platforms (data pre-annotation, task assignment to different users profiles)

Thank you !