

Learning Features from Herbariums to Perform Automatic Classification of Field Images

Participation to LifeCLEF Plant Challenge 2020

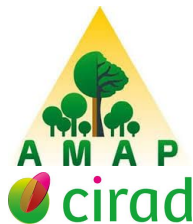
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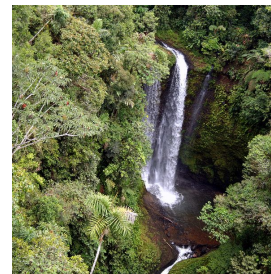
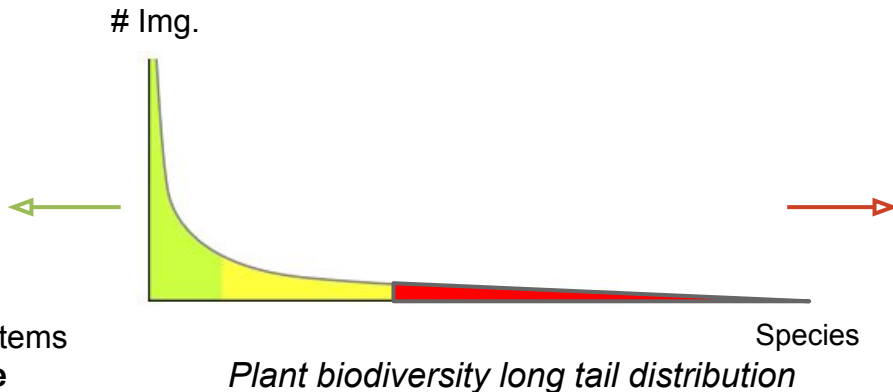
18-06-2020

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Objective

Train a machine learning model that can perform automatic classification on photos of tropical flora



nowadays automated systems perform well in **temperate regions**

- deep learning
- big data

Top1, PlantCLEF 2018 : 0,88

but poorly in **tropical regions**:

- lack of data
- great visual diversity
- difficult access

Top1, PlantCLEF 2019 : 0,24

Objective

Train a machine learning model that can perform automatic classification on photos of tropical flora **with the help of herbarium collections**

-> potentially millions of underexploited digitized herbarium sheets (eReColNat, iDigBio)

-> performances? State of the art approaches based on photos in the field suitable?



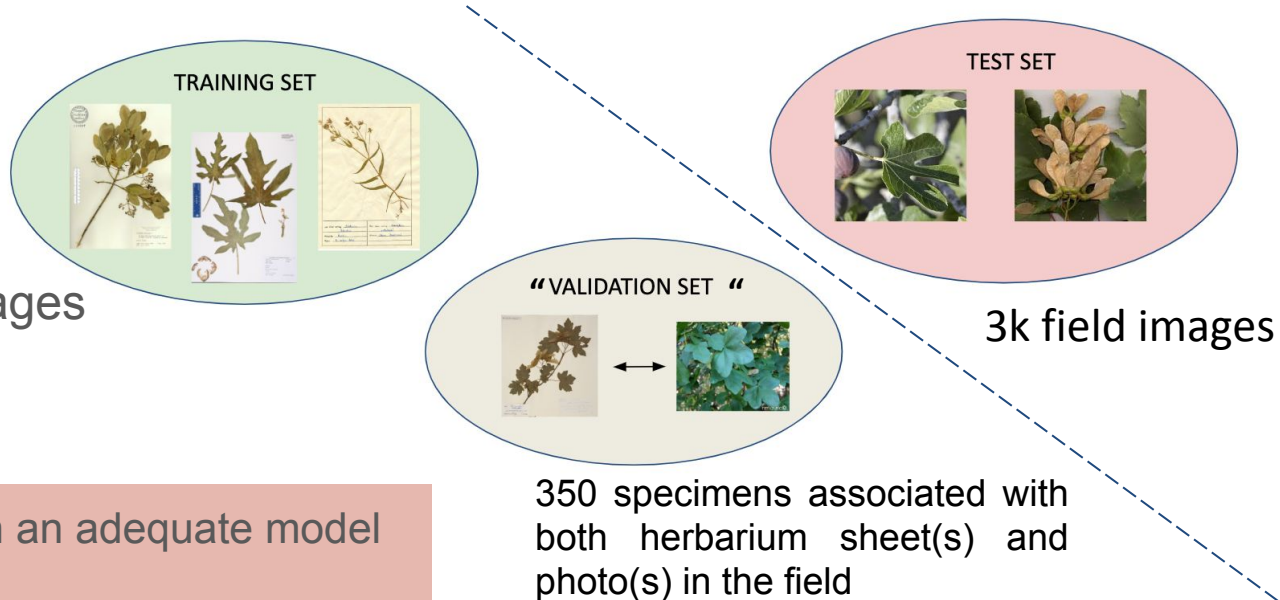
Fig. 1. Photos in the field and herbarium sheets of the same individual plant (*Tapirira guianensis* Aubl.). In spite of very different visual appearances between the two domains, similar structure and shapes of the flowers, fruits and leaves can be observed.

Dataset (PlantCLEF2020)



330,752 sheets
997 species
+ 4,482 field images
from 375 sp

Cross-domain Plant Identification



Not enough field images to train an adequate model

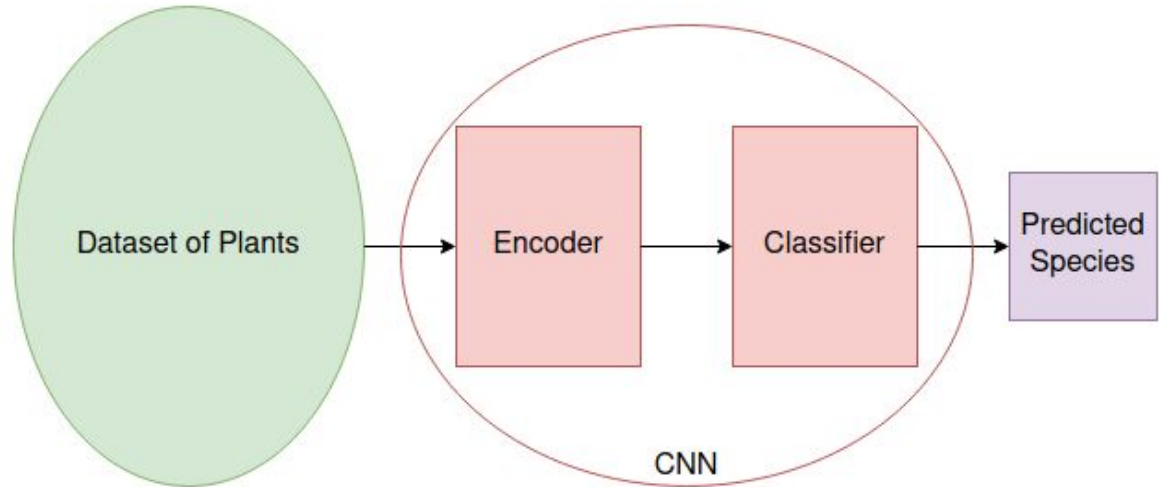
Will try to take advantage of existing herbarium images to compensate for missing data

1. Use a Convolutional Neural Network (CNN)

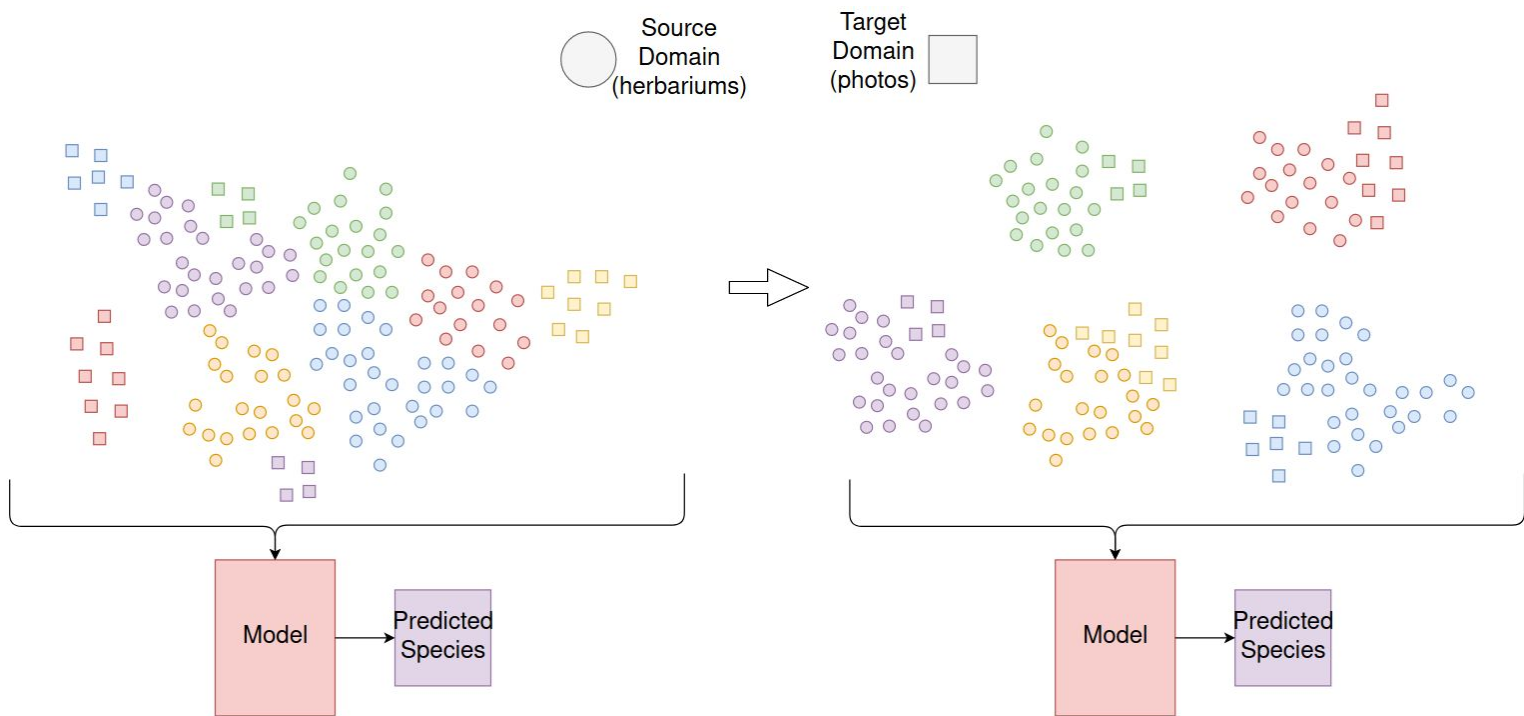
Use the dataset provided and train a model (ResNet50) in three stages:

1. Imagenet
2. Finetune with Herbariums
3. Finetune with photos

Try to use herbarium features to obtain a better model: naive approach



2. Use domain adaptation

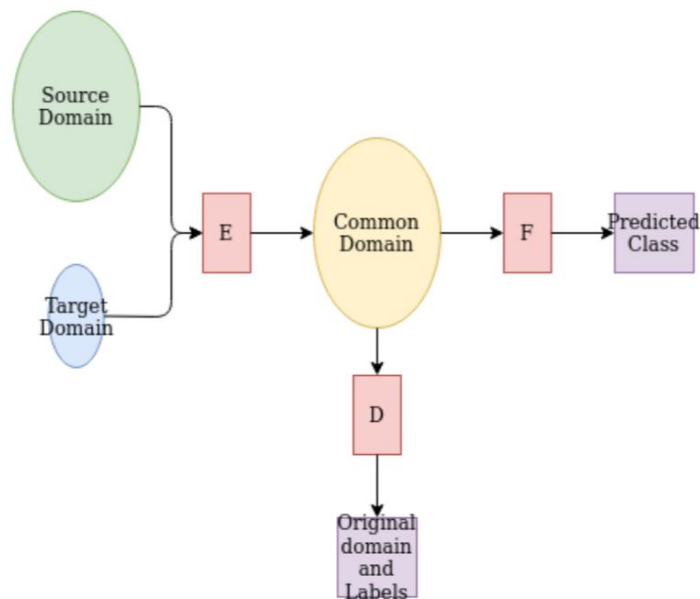


Same labels but different distributions, hard to train a model

Try to map to a similar distribution where training is easier

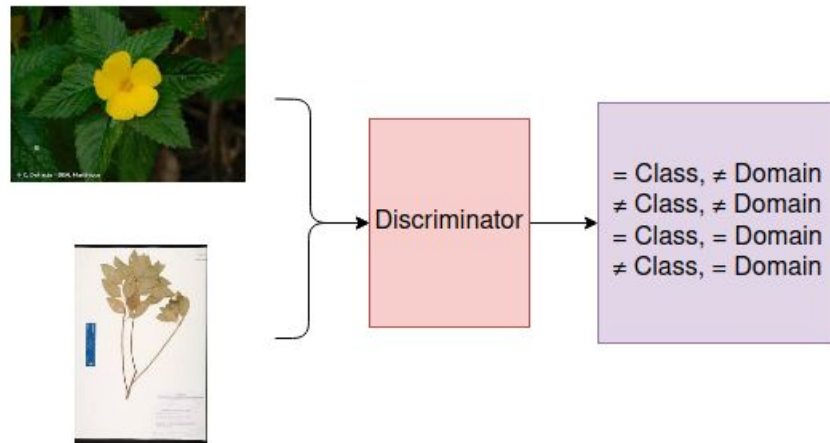
2. Use domain adaptation (FSDA)

Technique used: **Few-Shot** adversarial
Domain Adaptation



Discriminator: trained to determine if inputs are from same class and domain

Objective: fool it



3. Extra data

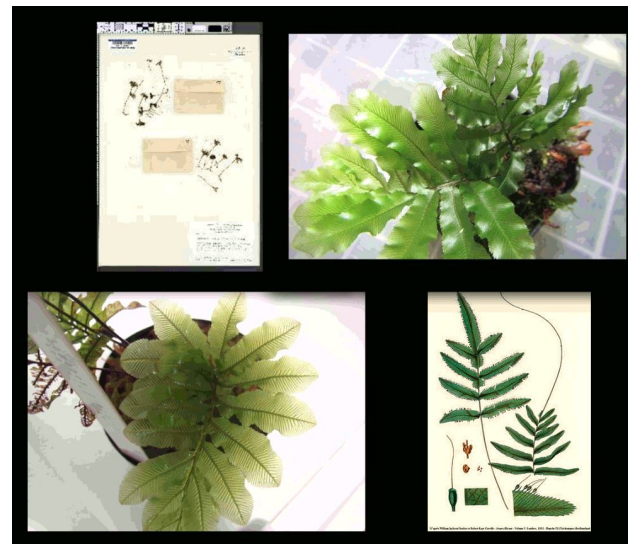
Use data from sources like search engines and online repositories to compensate for the lack of images

The data was taken from PlantCLEF19 and last years winner of the PlantCLEF challenge[2]

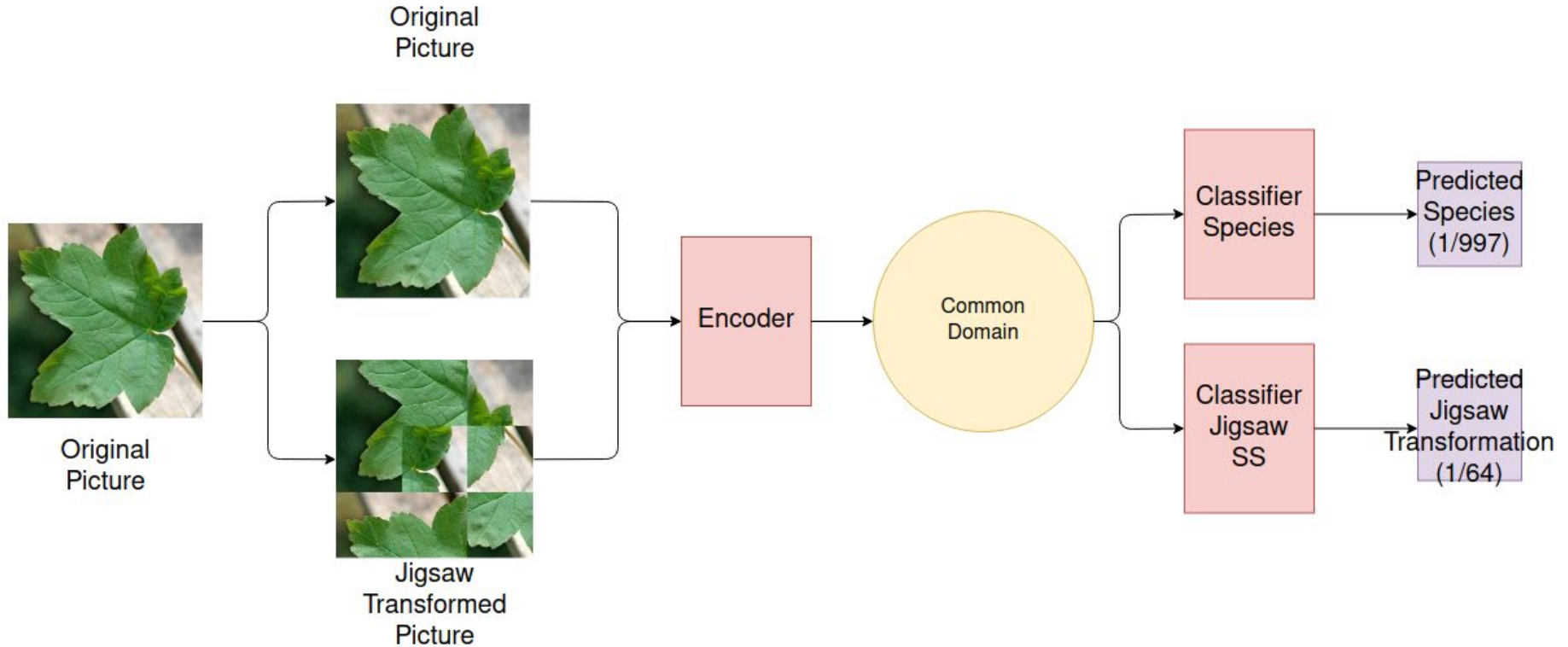
Data can be noisy and not completely related to the task

Additional 134,457 images from 997 species

Useful but time consuming



4. Self supervision in FSDA



4. Upper taxons (genus + family)

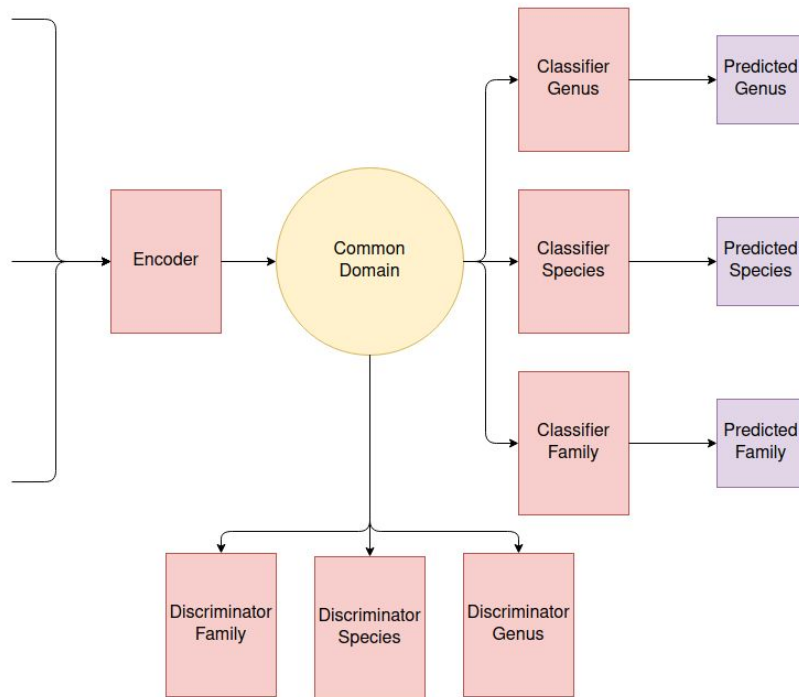
Passifloraceae
Turnera ulmifolia



Passifloraceae
Turnera odorata



Passifloraceae
Turnera guianensis



5. Combine everything

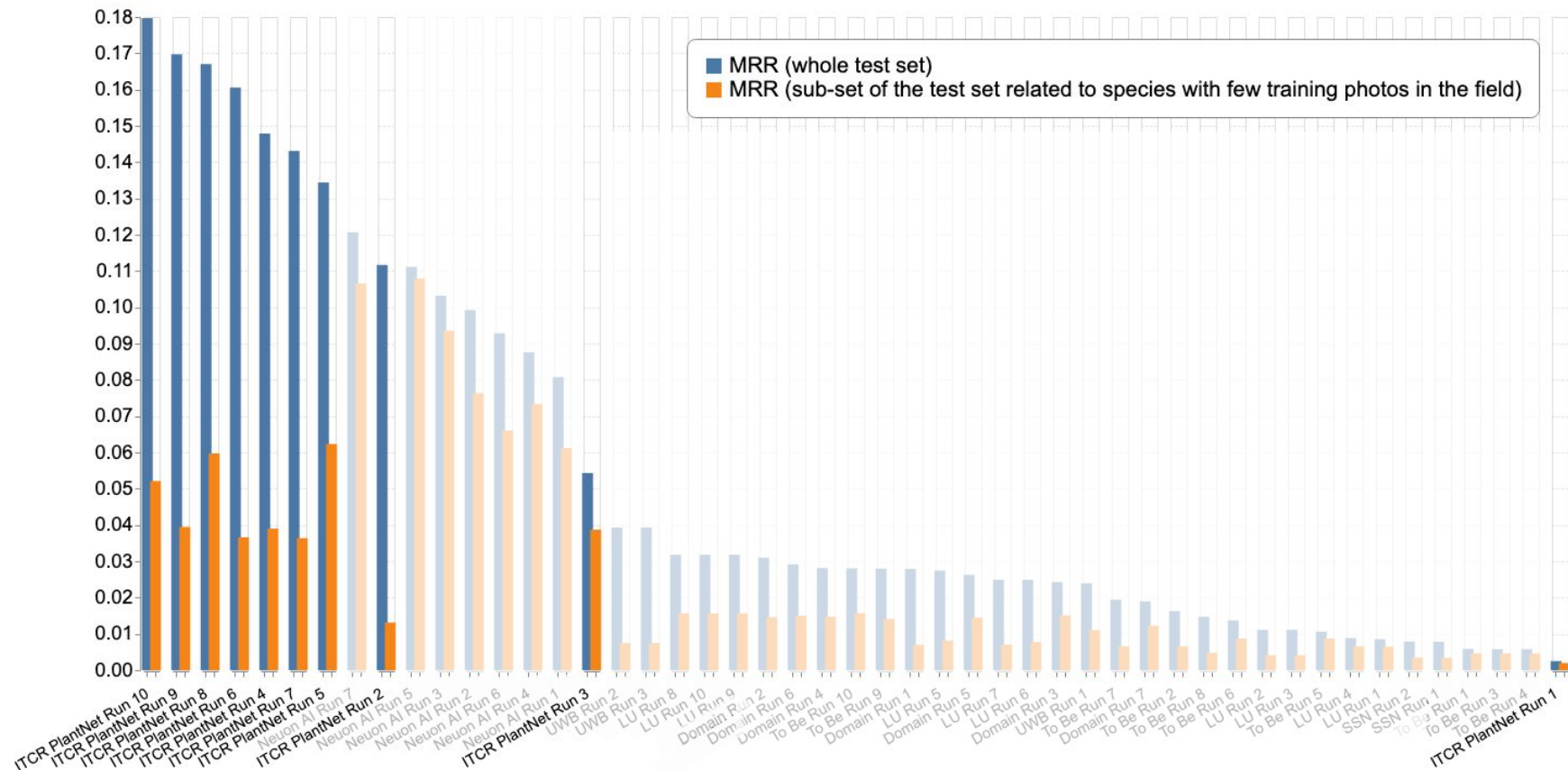
Mix the best techniques to try to obtain the best results possible

Combinations tried:

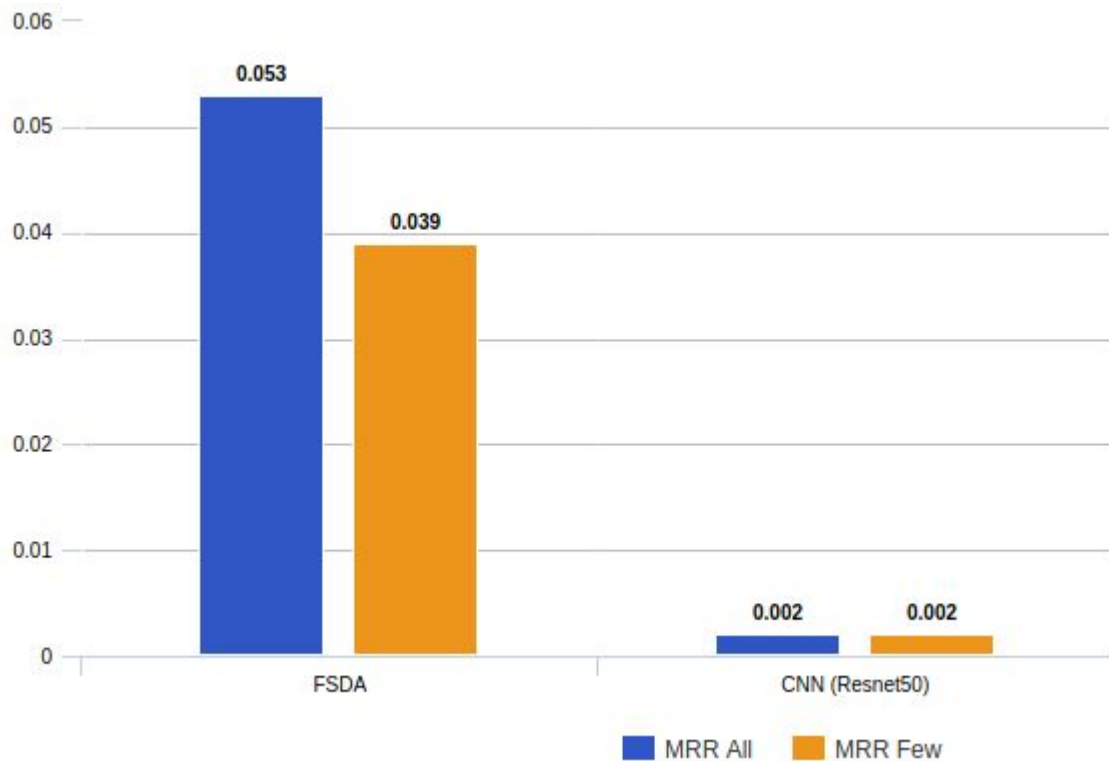
1. FSDA + extra data + self supervision
2. FSDA + extra data + upper taxons (genus & family)
3. FSDA + extra data + upper taxons (genus & family) + self supervision
4. Ensemble

Results

$$\text{MRR} = \frac{1}{|Q|} \sum_{i=1}^{|Q|} \frac{1}{\text{rank}_i}$$

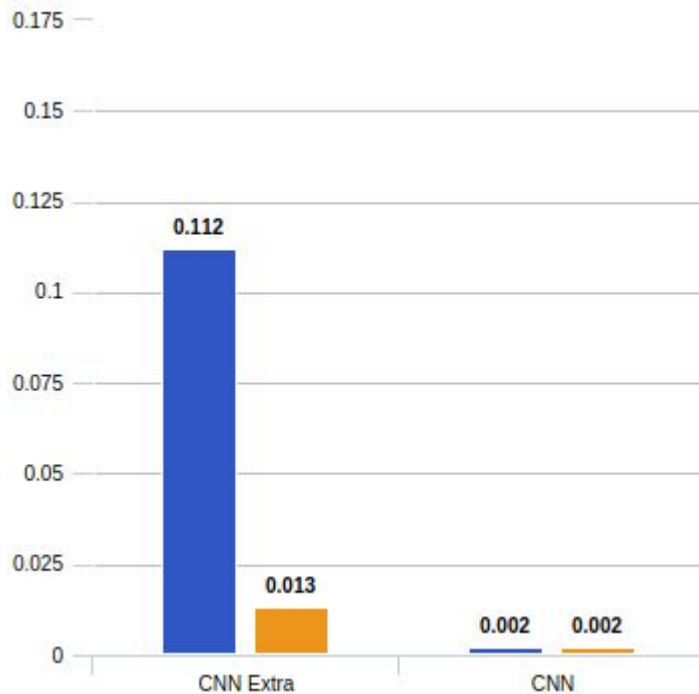


Results: Impact of Domain Adaptation

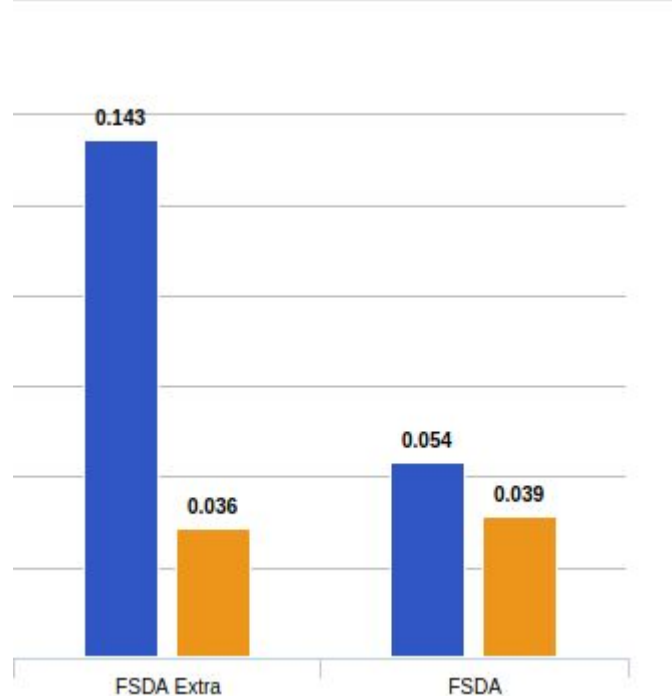


Results: Impact of extra training data

in CNN

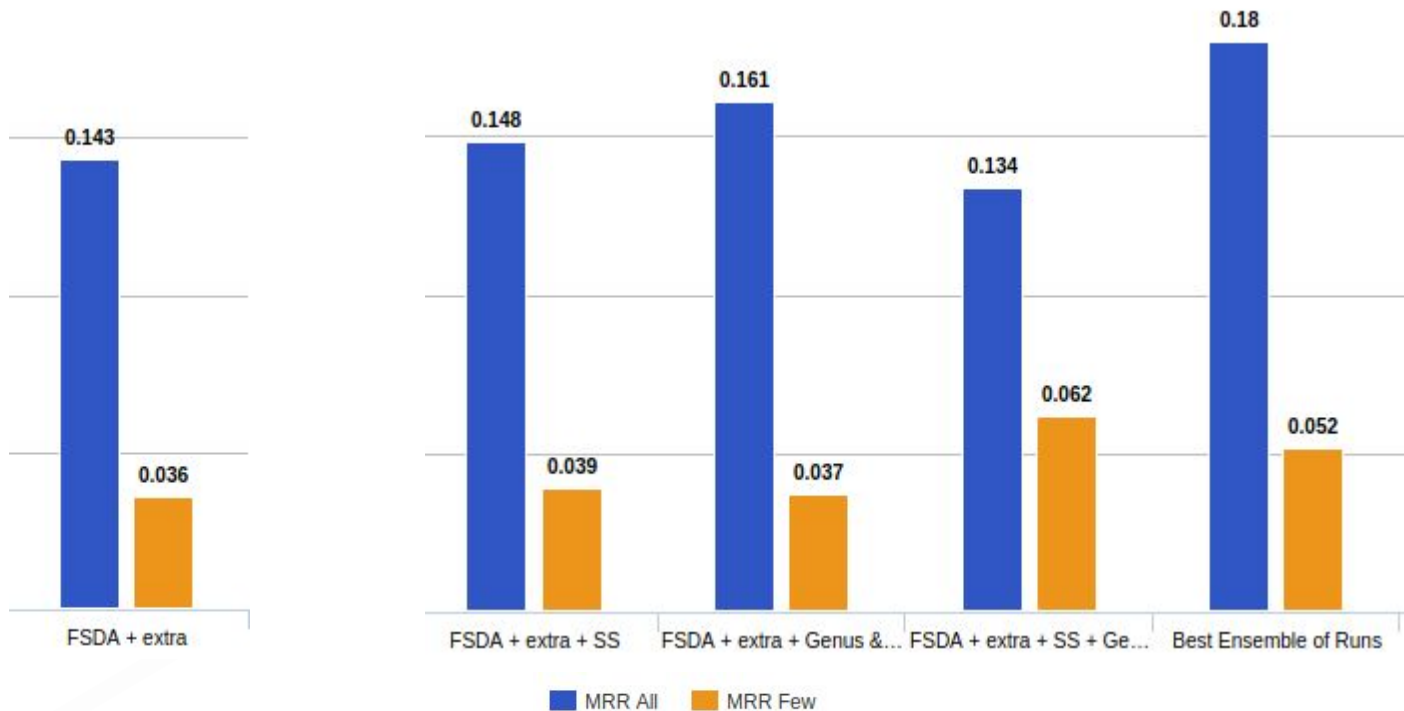


in FSDA



■ MRR All ■ MRR Few

Results: Impact of Performance Improving Techniques



Conclusions and Future Work

Domain adaptation increases significantly the generalization power of the models

Self supervision and information from upper taxons help the models learn

Highest score on MRR All on PlantCLEF20 but many room for improvement, particularly in difficult species

Improvements: incorporate other botanical knowledge into the process (morphology classes & metadata)