Computer Vision and Deep Learning techniques for the analysis of drone-acquired forest images, a Transfer Learning study

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Introduction

- Forests world-wide suffer from different kinds of problems:
  - Climate change → storms, droughts, temperature increase
  - Insect attacks
  - Forest fires
  - Monoculture
- How can we evaluate forests/forest problems/future development?
- We need to have a state-of-art forests distribution
  - Composition
  - Relationships

Forest Surveys

Aim

We want to detect trees

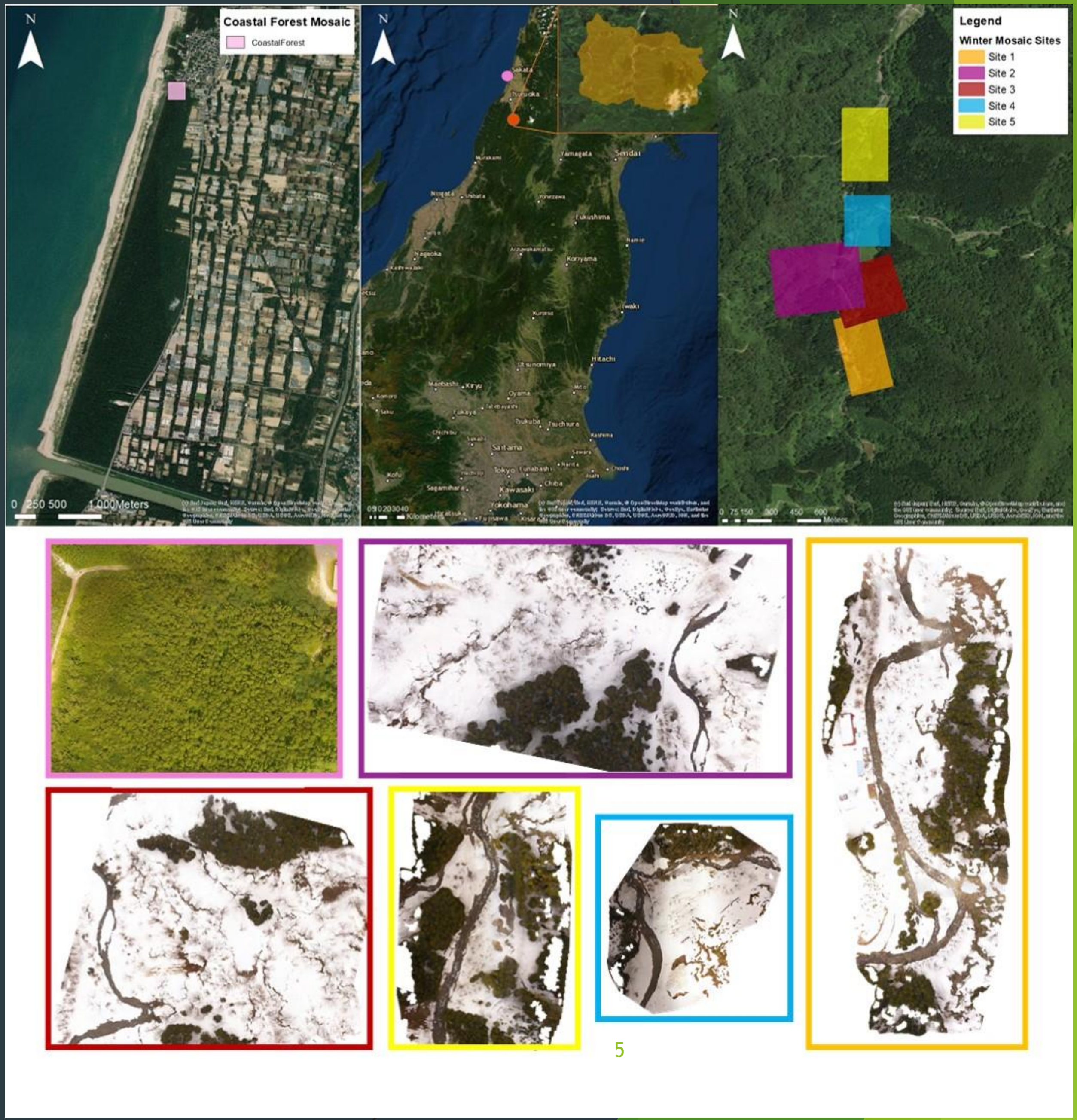
We want to identify tree species

Objectives

- Develop an algorithm to classify patches corresponding to tree species.
  - a) Quality of the results obtained with our data
  - b) Degree of improvement achieved by Transfer Learning.
- Develop a semantic segmentation algorithm for tree species that is precise and efficient using three separate algorithmic approaches and two DL networks.
- Evaluate the applicability of the MLP algorithm: Detection of an invasive tree species in a coastal forest.

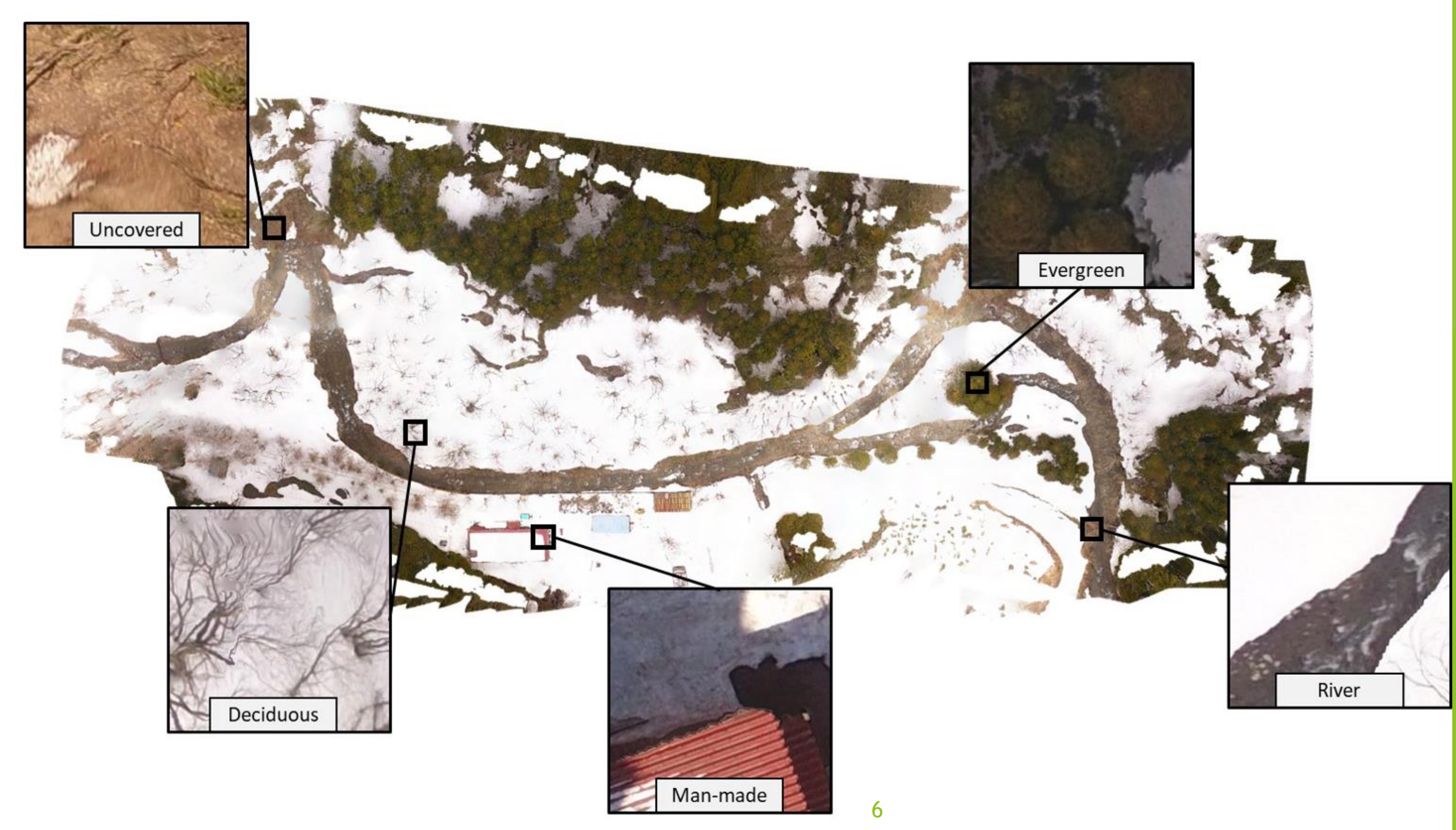
Study area

- Data collected in winter in YURF (Yamagata University Research Forest) and in summer in the coastal forest
  - 7 orthomosaics (winter)
    - 3 othomosaics of the same site and on different days (site1)
    - 4 orthomosaics of different sites and on the same day
  - 1 orthomosaic (summer)
- Images of dense unmanaged forests



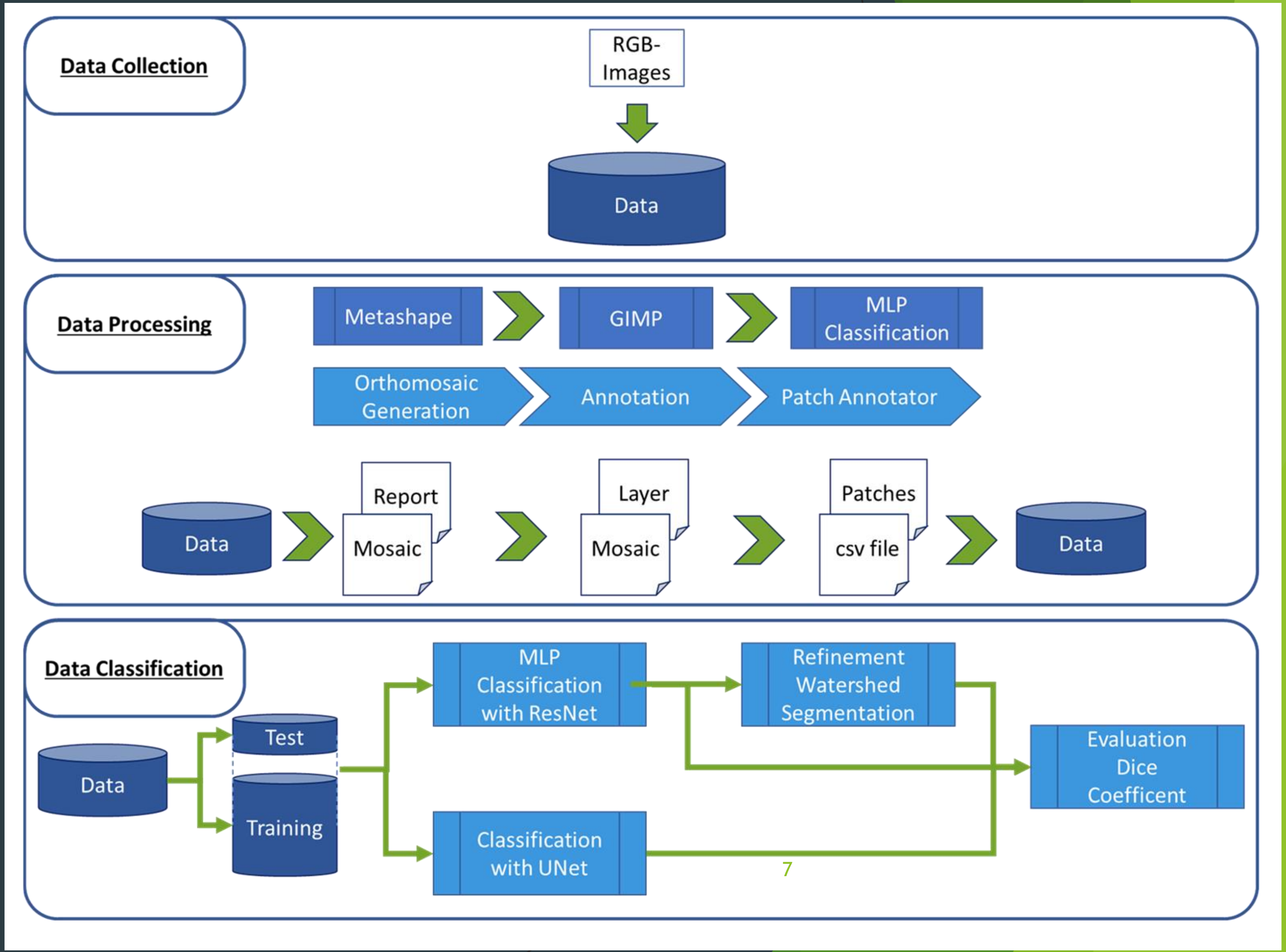
Data

- Classifying patches
- Winter orthomosaic:
  - Evergreen, deciduous, river, man-made and uncovered
- Coastal forest:
  - Black locust, other trees (mainly black pine)

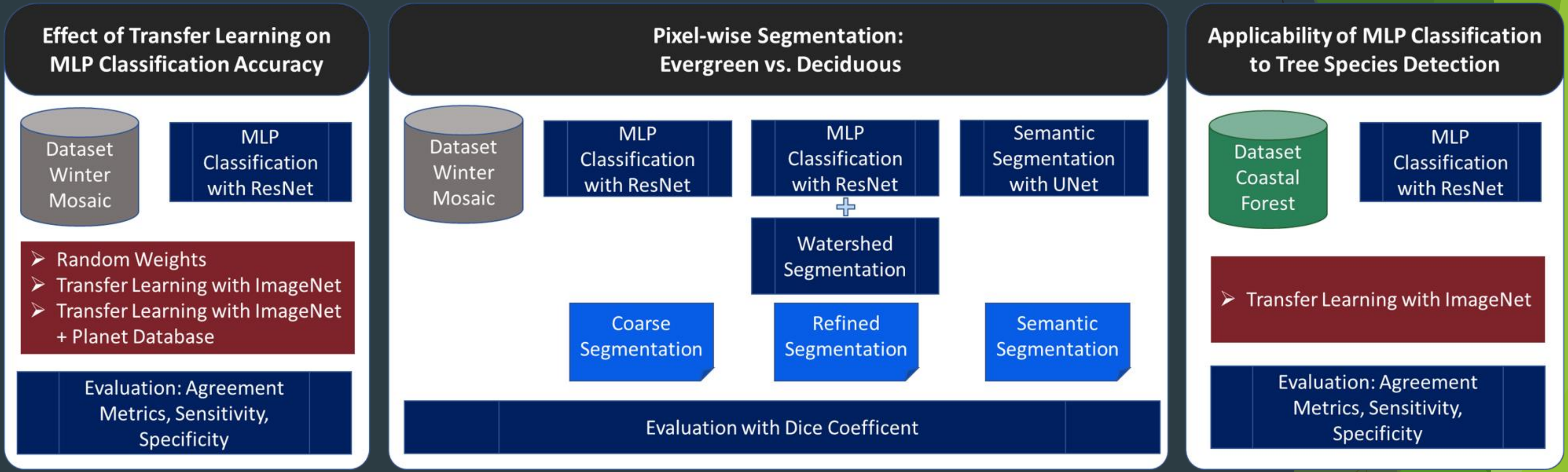


Methodology

- Data collection with UAV
- Data processing
  - Orthomosaic (Metasape)
  - Manual annotations (GIMP)
  - Patch annotator
- Data classification and segmentation:
  - Architectures: ResNet50 and UNet
  - ResNet50: Multi-label patch classifier



Experiments



- 3 experiments were conducted and evaluated
  - Classification, segmentation and application
  - On different datasets

Evaluation Methods

MLP Classifier

- Full Agreement
- Full Agreement with False Positives
- Partial Agreement

Segmentation

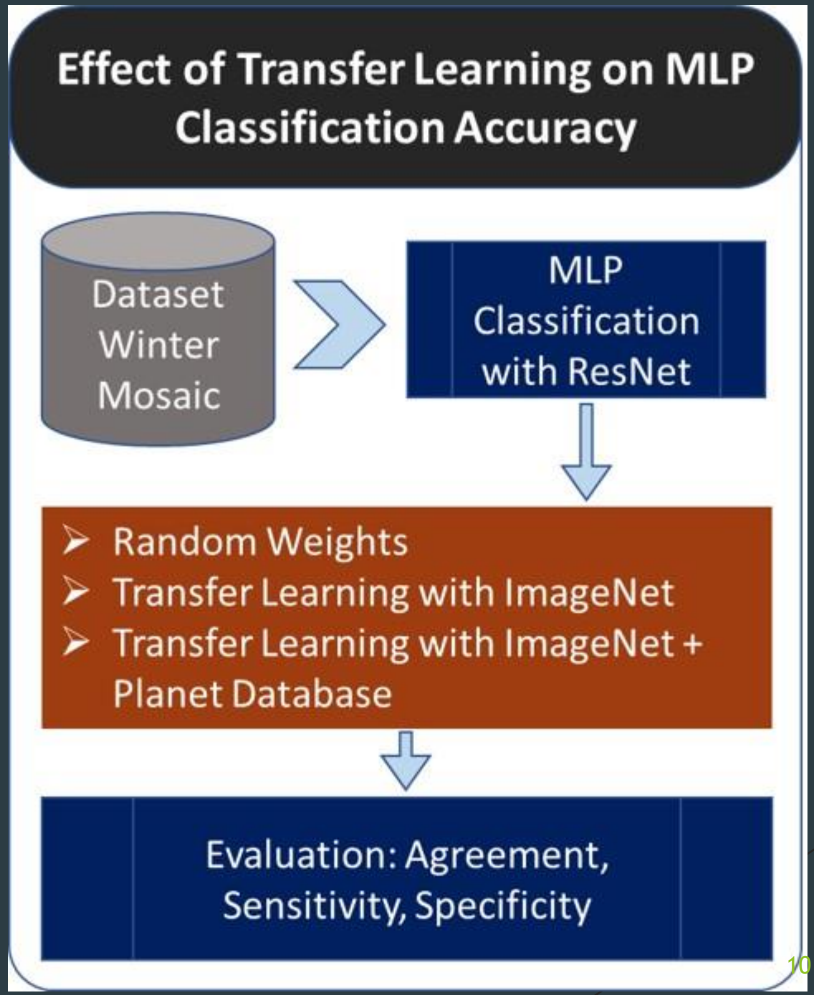
- DICE

Actual \ Predicted		
	True Positives	False Negatives
	False Positives	True Negatives

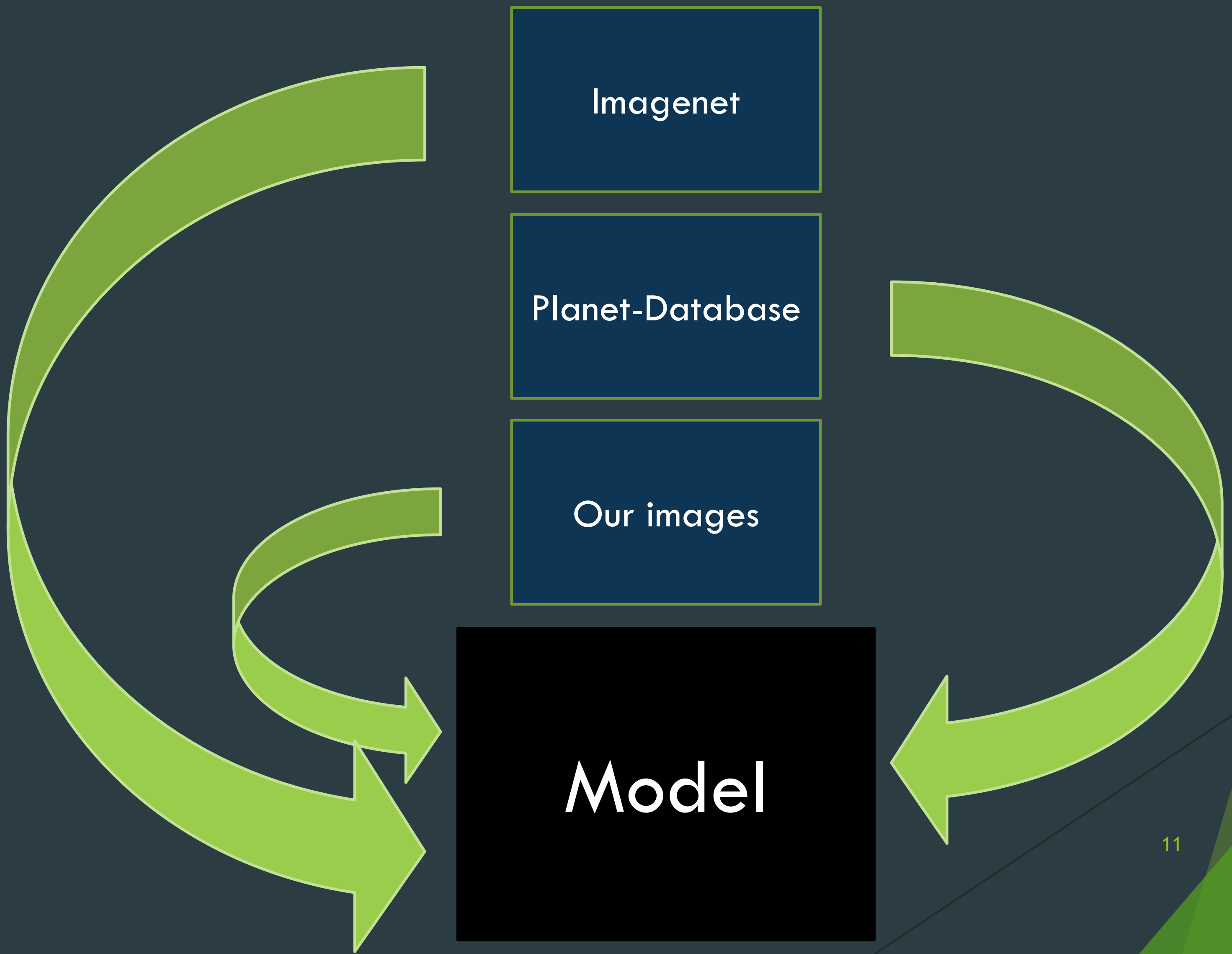
$$SENS = \frac{\mathrm{TP}}{\mathrm{TP}+\mathrm{FN}} \quad SPEC = \frac{\mathrm{TN}}{\mathrm{TN}+\mathrm{FP}} \quad ACC = \frac{\mathrm{TP}+\mathrm{TN}}{\mathrm{TP}+\mathrm{TN}+\mathrm{FP}+\mathrm{FN}} \quad DICE = \frac{2TP}{2TP+FP+FN}$$

Experiment 1: Transfer Learning

- Multi-label patch algorithm was used
- Patch-based approach
- 6 different model setups (frozen and unfrozen) with:
  - Random weights
  - Transfer learning with ImageNet
  - Transfer learning with ImageNet and Planet Database
- Evaluation:
  - Do we increase the accuracy by using transfer learning on our data?



Transfer Learning



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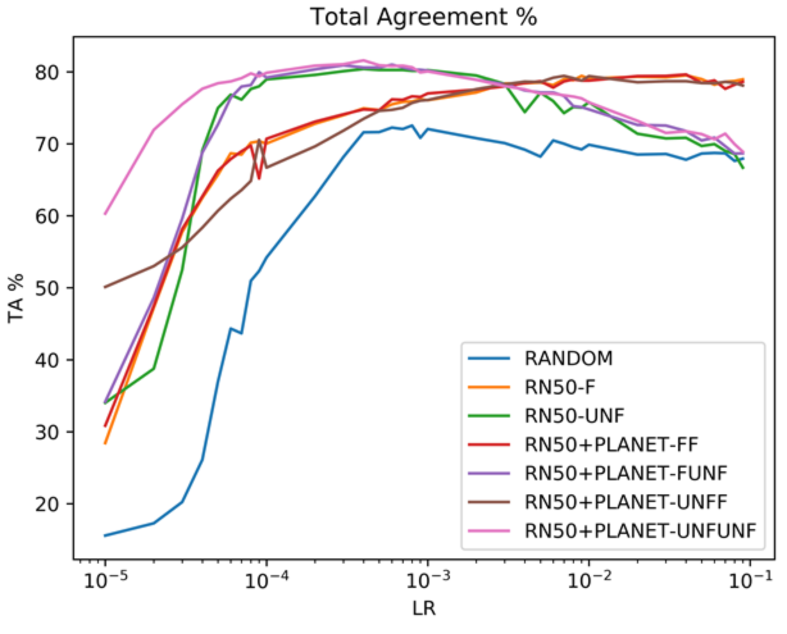
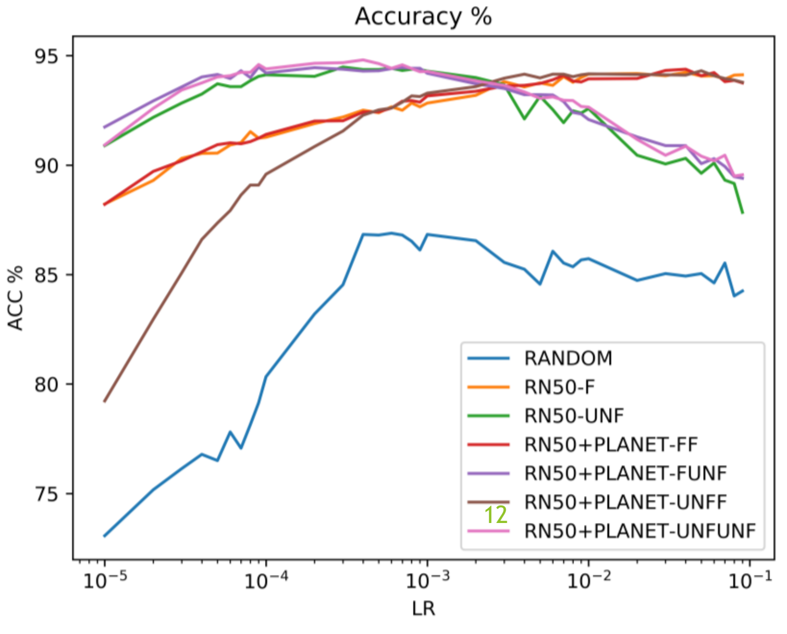
Results

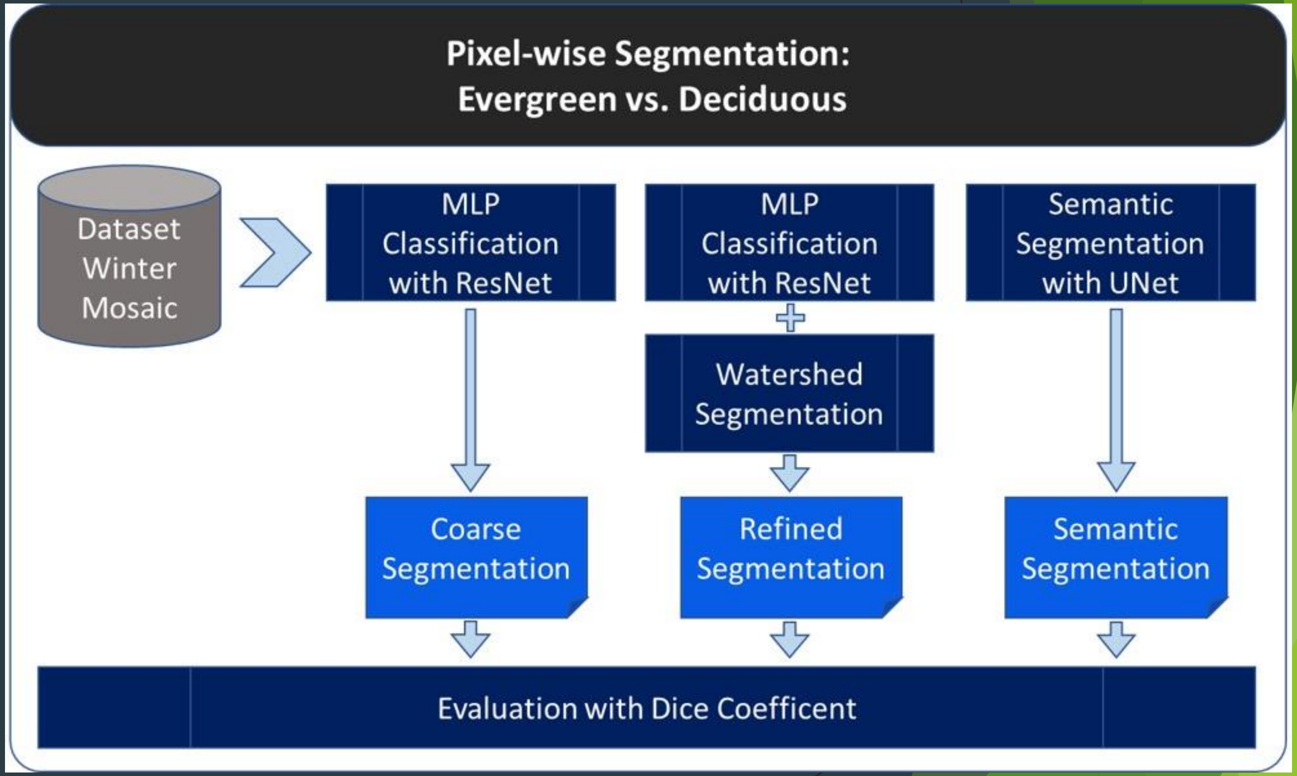
- Transfer learning is effective:
  - 12.48 % highest improvement over random weights
  - Unfrozen over frozen
- We only evaluated evergreens vs deciduous
- Highest accuracies reached: 95 %
  - Evergreen: 94.75 % Sensitivity; 98.73 % Specificity
  - Deciduous: 94.01 % Sensitivity; 90.27 % Specificity





Experiment 2: Segmentation

- Segmentation approach
- Coarse segmentation = classifying/assigning each pixel in a patch to one class
- Refined segmentation = watershed helps to differentiate classes in case that we have more than one class in a patch
- Semantic segmentation = each pixel will be labelled and assigned to a class



Results

- Best results evergreen:
  - UNet/ResNet: DICE of 0.893/0.873

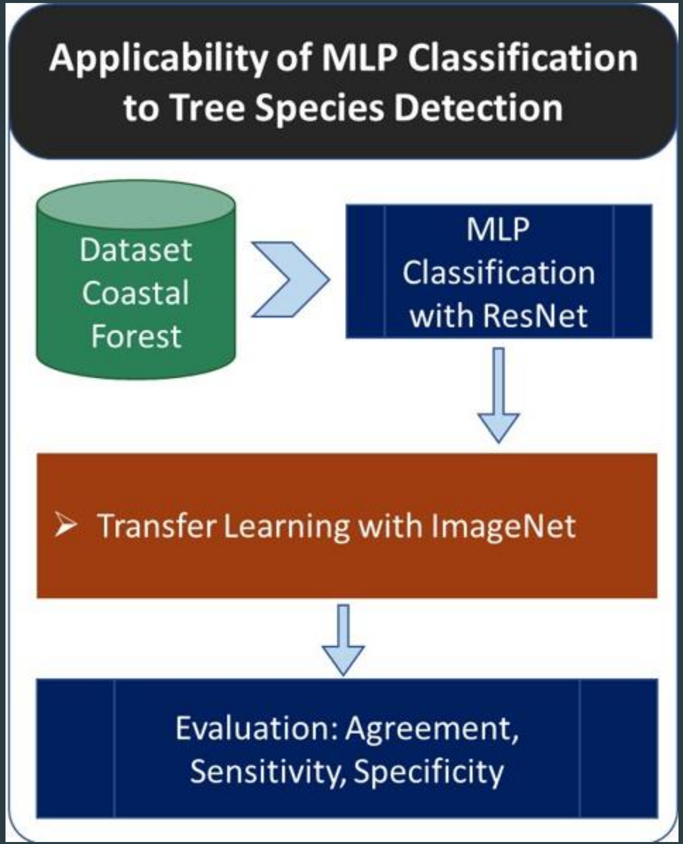
EVERGREEN		AVG	AVG site1
UNet			
LR 0.3		0.676	0.549
LR 0.04		0.782	0.797
LR 0.003		0.751	0.730
LR 0.0005		0.893	0.873
LR $6e^{-5}$		0.858	0.840
RESNET			
Patches 500	Coarse	0.597	0.544
	Refined	0.620	0.510
Patches 300	Coarse	0.684	0.648
	Refined	0.698	0.709
Patches 200	Coarse	0.698	0.651
	Refined	0.782	0.750
Patches 100	Coarse	0.818	0.789
	Refined	0.855	0.815
Patches 50	Coarse	0.873	0.851
	Refined	0.729	0.639
Patches 25	Coarse	0.883	0.870
	Refined	0.567	0.562

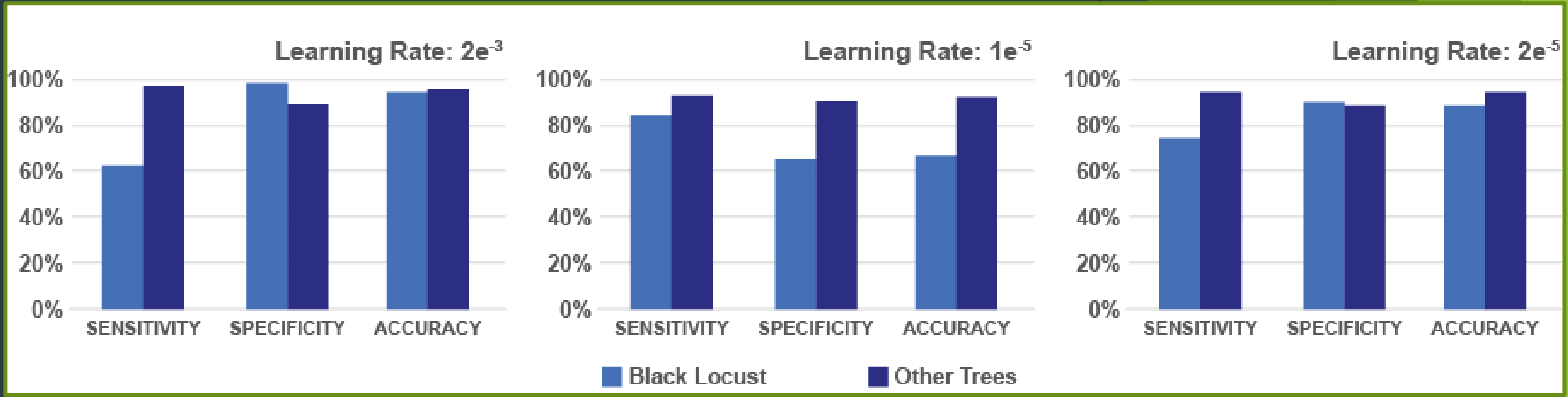
- Best overall results for evergreen with UNet
- Small patch sizes watershed failed
- Comparison of average values and average of site 1 shows similar results

- Best results deciduous:
  - UNet/ResNet: DICE of 0.709/0.790

DECIDUOUS		AVG	AVG site1
UNet			
LR 0.3		0.265	0.219
LR 0.04		0.395	0.468
LR 0.003		0.473	0.483
LR 0.0005		0.709	0.667
LR $6e^{-5}$		0.686	0.671
RESNET			
Patches 500	Coarse	0.592	0.631
	Refined	0.594	0.593
Patches 300	Coarse	0.527	0.584
	Refined	0.530	0.573
Patches 200	Coarse	0.614	0.656
	Refined	0.617	0.605
Patches 100	Coarse	0.732	0.742
	Refined	0.733	0.741
Patches 50	Coarse	0.777	0.761
	Refined	0.568	0.585
Patches 25	Coarse	0.790	0.753
	Refined	0.558	0.540

Experiment 3: Detection of black locust





- Application example: trees with leaves
- Data highly imbalanced → black locust vs black pine → also represented in the sensitivity and specificity results

Discussion

- Forests → low amount of images available → transfer learning is the solution
- Evergreen better detected because of their clear boundaries → how about other tree species (future work)?
- Segmentation methods
  - Semantic segmentation (UNet) best for evergreen
  - MLP Classifier (ResNet) best for deciduous
  - Watershed not necessary and failed with small patch sizes
- Patch size:
  - Smaller = higher accuracies but long computing time
  - Larger = lower accuracies but short computing time
- Problem: imbalanced data → use of data augmentation in future

Conclusion

- Transfer learning is necessary → 10 % improvement (+further 3%)
- Reached high accuracies (nearly 95%)
- Use of automatic segmentation methods
- Application was possible and provided good results

- WE HAVE A METHOD FOR AUTOMATIC CLASSIFICATION AND SEGMENTATION

Thank you for your attention!

For questions please feel free to contact me: sarahkentsch@gmail.com