Josephinum Research
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Semantic Segmentation for the Estimation of Plant and Soil Parameters on Agricultural Machines.

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Presenter

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2015 – now	Researcher, Josephinum Research, Austria
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Semantic Segmentation in Agricultural Applications

- naturally growing non-rigid organic and inorganic materials
- high intra-class variance
- strong illumination variances
- cluttered scenes
- strong occlusions

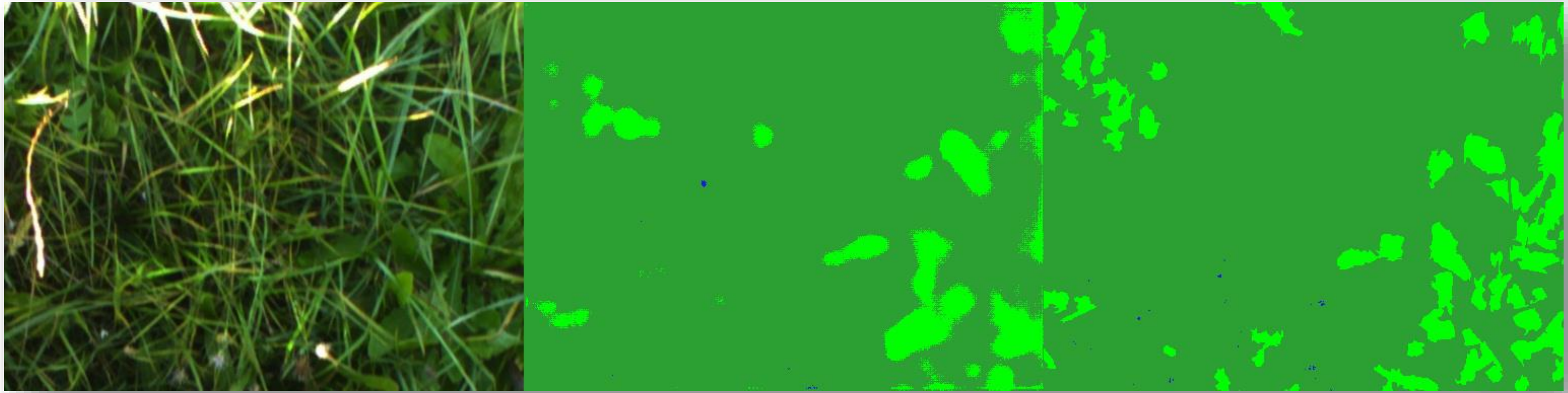
Use Case: Soil Cover Estimation

- Motivation: Soil cover reduces soil erosion
- Challenges: transition between dead organic matter and soil

Soil image (left), test mask (middle), ground truth map (right).
Living organic matter ●, dead organic matter ●, soil ● and stone ●

Use Case: Grass/Legumes Ratio Estimation

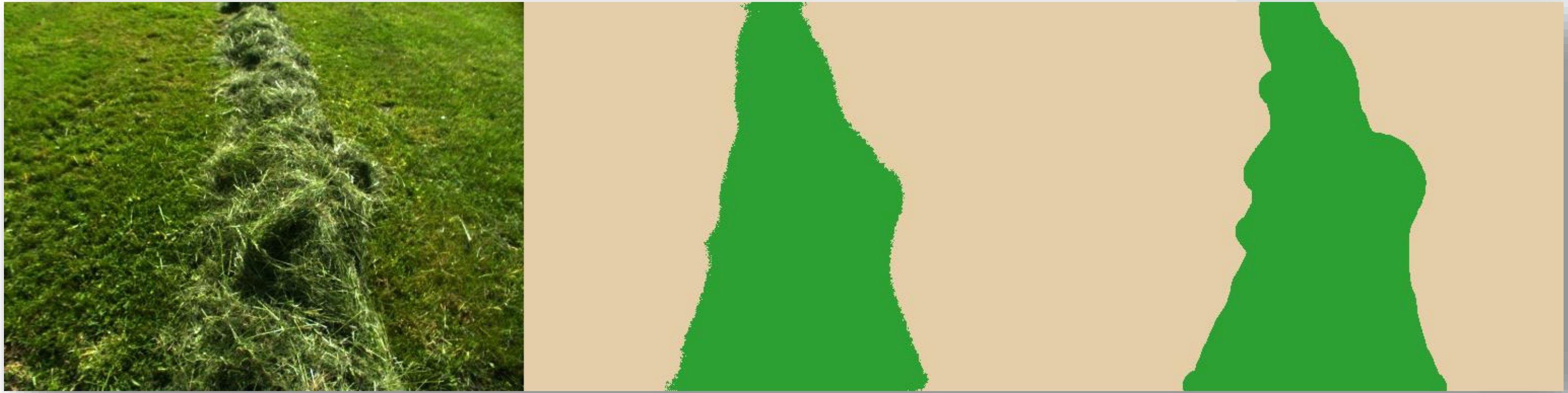
- Motivation: Plant composition can be used for targeted feeding and yield estimation
- Challenges: strong occlusions and low inter-class variability



Meadow image (left), test mask (middle), ground truth map (right).
Grass ● and legumes ●

Use Case: Swath Segmentation

- Motivation: Automated steering and yield estimation
- Challenges: small swaths of wet grass



Grassland swath image (left), test mask (middle), ground truth map (right). Swath ● and no swath ●

Use Case: Areas of Cut Grass

- Motivation: Machine control and yield estimation
- Challenges: transition between standing and mown grass

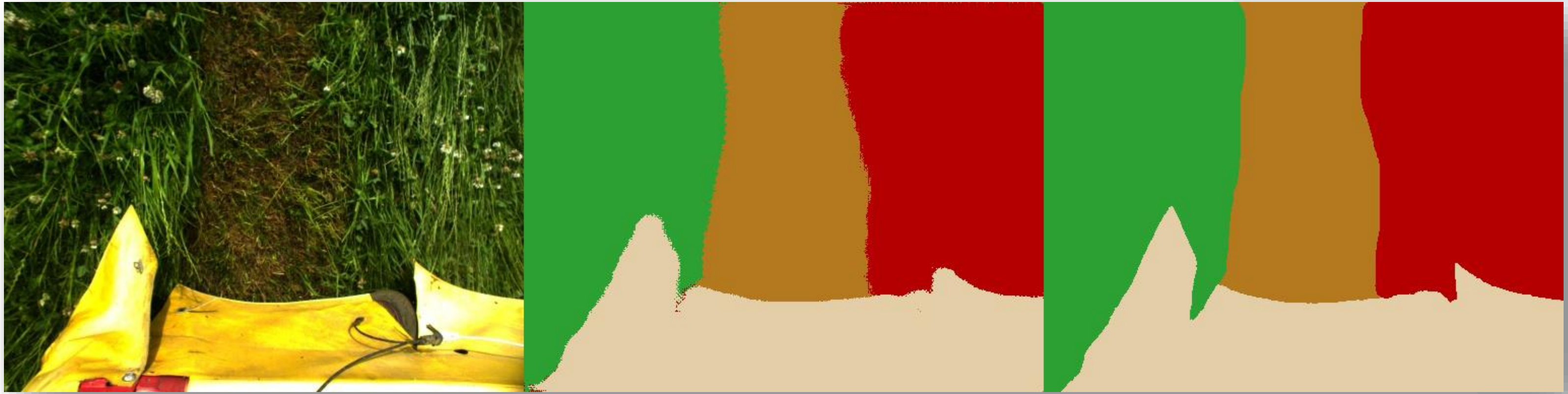


Image of areas of cut grass (left), test mask (middle), ground truth map (right).
Standing meadow ●, grass turf ●,machine ● and mown grass ●

Publicly Available Datasets

- Mostly consist of images captured under best conditions

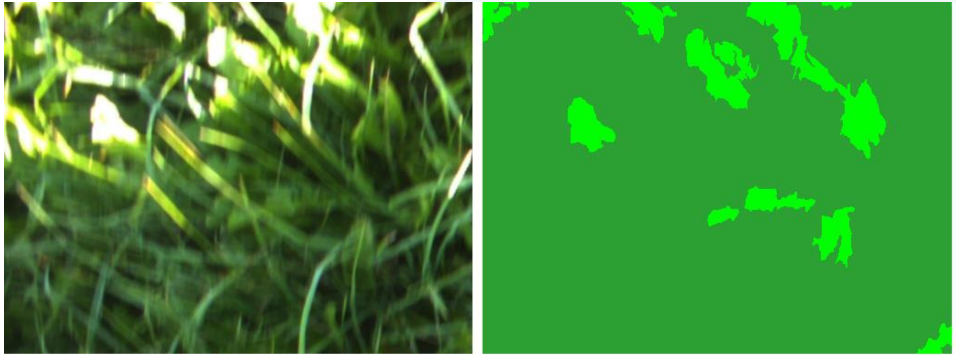
sugar beet dataset [1]

clover grass dataset [2]

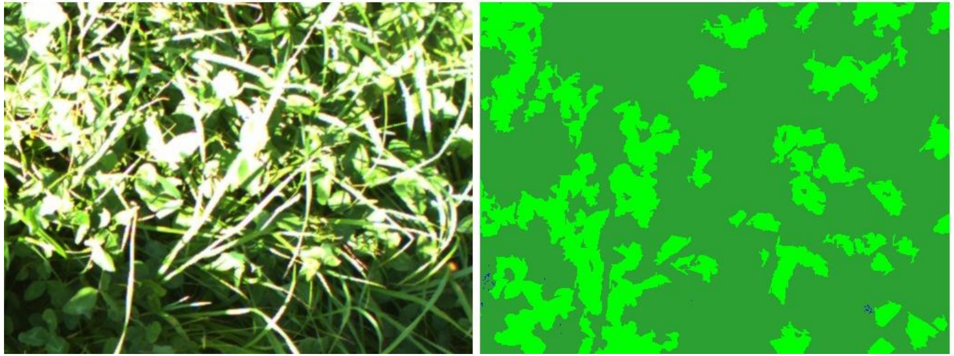
[1] N. Chebrolu et al., "Agricultural robot dataset for plant classification localization and mapping on sugar beet fields" The International Journal of Robotics Research, vol. 36, no. 10, 2017, pp. 1045–1052.
[2] S. Skovsen et al., "The grassclover image dataset for semantic and hierarchical species understanding in agriculture" in 2019 IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops (CVPRW), 2019, pp. 2676–2684

Examples of Challenging Images

- motion blur



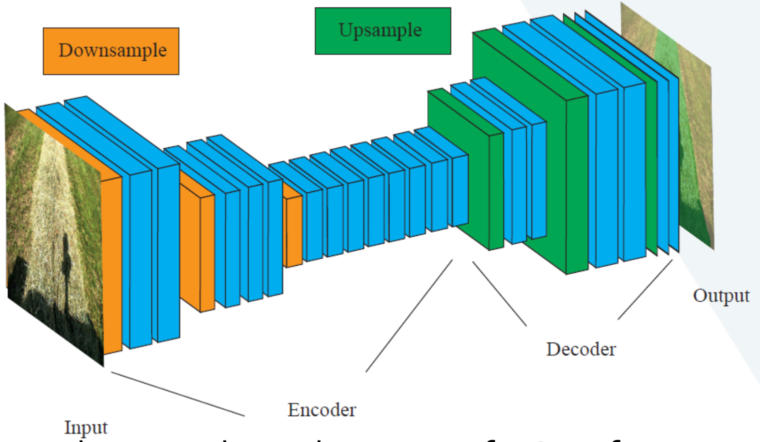
- strong illumination variances



Meadow image (left), ground truth map (right).
Grass ● and legumes ●

Machine Learning Method

- ERFNet [3] provides a good trade-off between accuracy and inference speed
- Pre-Training with large (public) datasets for better generalization
  - The encoder weights are transferred as initial values
- Fine tuning with images covering complex outdoor scenarios



Encoder-Decoder architecture of a CNN for semantic segmentation like ERFNet

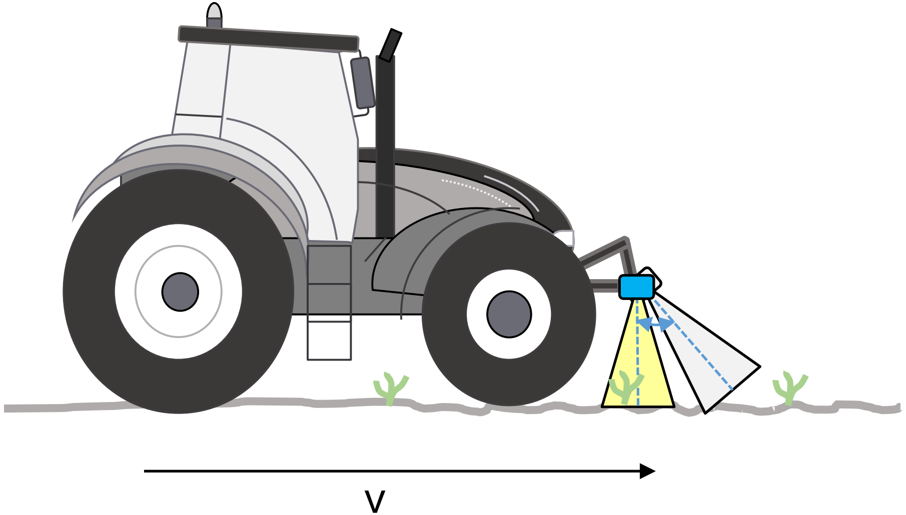
[3] E. Romera, J. M. Alvarez, L. M. Bergasa, and R. Arroyo, "Erfnet: Efficient residual factorized convnet for real-time semantic segmentation," IEEE Transactions on Intelligent Transportation Systems, vol. 19, no. 1, 2017, pp. 263–272. 1045–1052.

Evaluation

Application	Pre-training	Accuracy	IoU
soil cover estimation	sugar beet dataset	0.7993	0.4974
	clover grass dataset	**0.8746**	**0.6640**
	none	0.8546	0.6172
grass/legumes ratio estimation	sugar beet dataset	0.8522	**0.5374**
	clover grass dataset	**0.8859**	0.4480
	none	0.8462	0.5288
swath detection	sugar beet dataset	0.9653	0.9313
	clover grass dataset	**0.9734**	**0.9470**
	none	0.9604	0.9221
cut segmentation	sugar beet dataset	0.9106	0.7903
	clover grass dataset	**0.9340**	**0.8312**
	none	0.9286	0.8241

Common Camera Mounting Positions

- Field of view influences required frame rate and exposure times



Mounting of a camera on an agricultural machines

Inference Times

- Edge inference is required

Device	Inference time
UP AI Core X Myriad™ X 2485	268 ms
Intel® CoreTM i7-3630QM CPU	190 ms
NVIDIA® Jetson Nano™	166 ms
NVIDIA® GeForce RTX 2080 Ti	6.1 ms

Conclusion

- Pre-training tested on four agronomic use cases
  - Pre-training improves model accuracy
  - Inference time allows for real time application on machines

Next Steps

- Integration on agricultural machines for validation based on agronomic metrics
- Datasets with challenging scenarios are needed

Thank you!

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