



Active learning for efficient annotation in crop-weed semantic segmentation

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Background

- Most of the time in developing computer vision applications are spent in annotating images
- **Annotation of redundant images** that have already been used for training a deep learning model **does not significantly improve** the performance of a model
- **Active learning** can be proposed as an approach to **find images in which a model is still uncertain with**; therefore, improving performance
- Active learning for agricultural data is still not frequently applied

Objective

- Investigate the **added value of active learning** for training a semantic segmentation model for **agricultural application**

Research question:

- Can **active learning reduce annotation effort** on non-diverse and unbalanced agricultural datasets?

Material and methods

- In this work, uncertainty was determined using Monte-Carlo dropout
- FCHardNet was used with an additional dropout (DO) layer

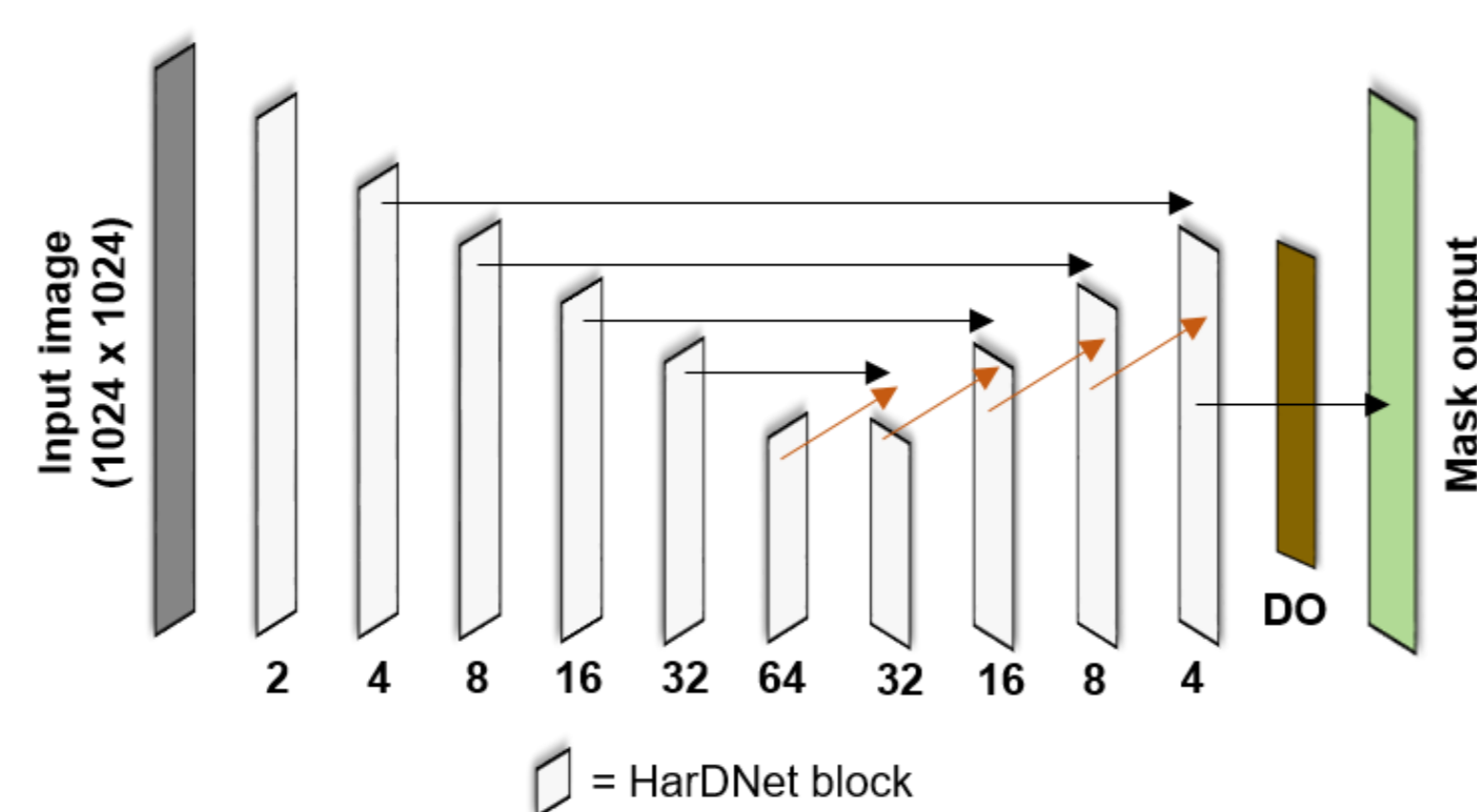


Figure 1. FCHardNet with dropout (DO) layer

- Uncertainty was calculated using Bayesian Active Learning by Disagreement (BALD) and PowerBALD
- $BALD(y; \omega|x, D) = H(y|x, D) - E[H(y|x, \omega, D)]$
 - Focuses on epistemic uncertainty rather than aleatoric uncertainty
 - $H(y|x, D) = Marginal Entropy$ triggers images with large fractions of pixels with similar probability over all classes
 - $E[H(y|x, \omega, D)] = Conditional Uncertainty$, penalizes images with inherent noise (i.e. aleatoric uncertainty)
- PowerBALD -> sample images with probability p , with $p_x = \frac{BALD_x}{sum(BALD)}$

Experiments

- Agricultural image data are often not that diverse unlike well-known datasets like CityScapes. In this work, active learning was tested on two datasets:
 - CityScapes (for proof of principle)
 - Non-public Corn-Weed dataset

Dataset	Train	Validation	# classes	Majority class
Cityscapes	2975	500	19	44.1% (road)
Corn-Weed	1190 (Field A)		3	90.9% (soil)
	331 (Field B)	117 (Field B)		

Table 1. Statistical summary of both datasets

- The Corn-Weed consist of two fields A & B.
- In our experiment, a model was pre-trained on field A and active learning had to sample the most uncertain images of field B.

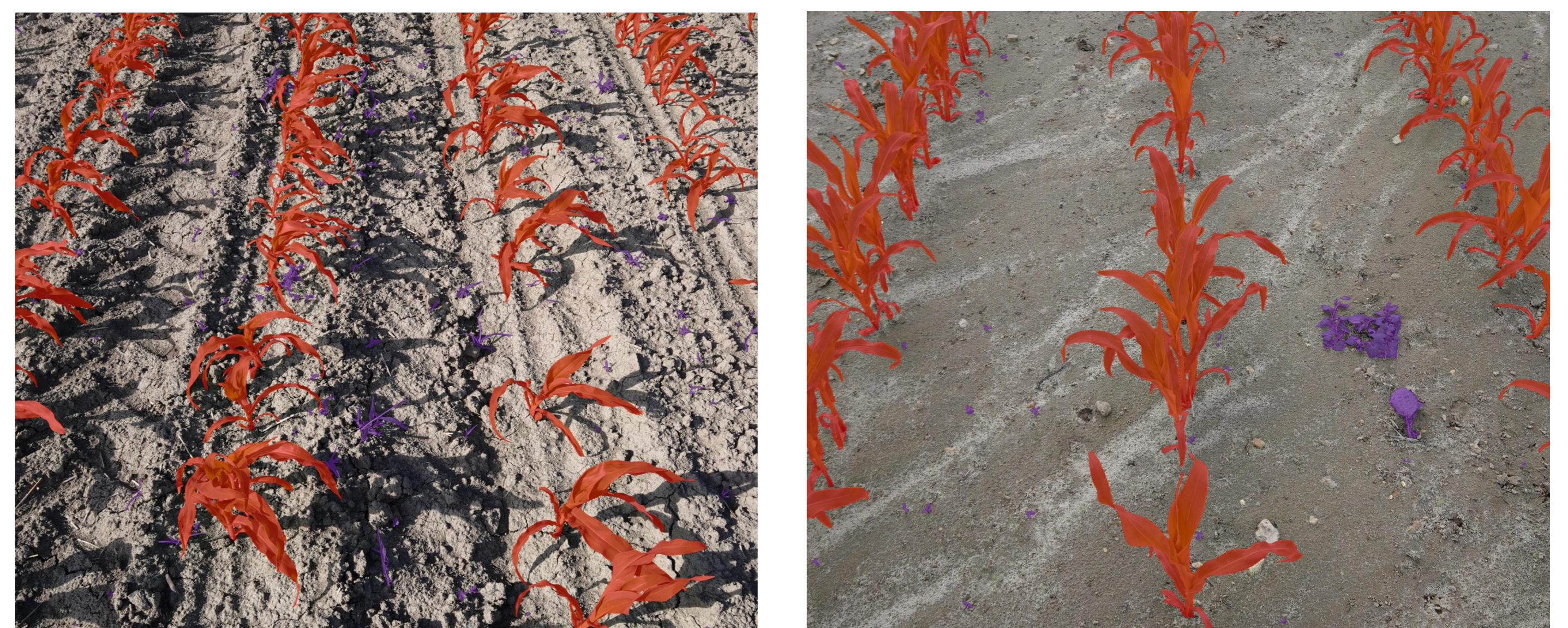


Figure 2. Sample dataset images: (Left) Field A; (Right) Field B, Red annotations correspond to corn while purple annotations correspond to weed.

Results

- Active learning worked on diverse datasets like CityScapes
- Both BALD and PowerBALD outperformed random sampling

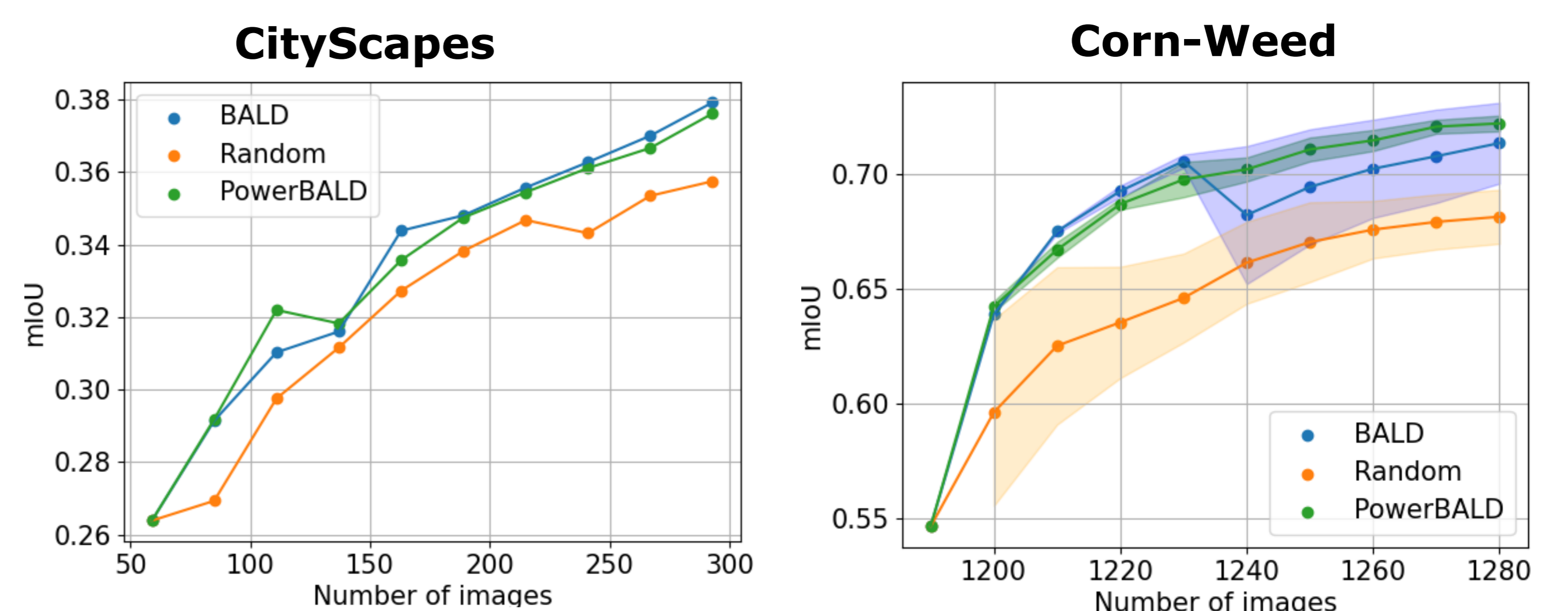


Figure 3. Experimental results: (Left) CityScapes; (Right) Corn-Weed dataset. Plots are shown as function of number of images.

- Corn-Weed dataset:
 - Significant difference between PowerBALD and Random ($p=0.01$) was observed
 - BALD and PowerBALD achieved the same mIoU than random requiring 70 less images

Discussion

- PowerBALD performed better than BALD
 - PowerBALD was able to output the highest uncertainty even with many common features between images; this was unexpected since only 10 images were selected
- BALD currently samples average uncertainty
 - Large influence of majority class
 - Potentially adding an excessive green filter could help in pre-selecting the pixels to be included in the uncertainty calculation

Conclusions

- **PowerBALD performs better than Random sampling** on corn-weed dataset
- Even with 90.9% pixels belonging to the soil class, **active learning for agricultural data shows potential**