Solar**DK**

A high-resolution urban solar panel image classification and localisation dataset

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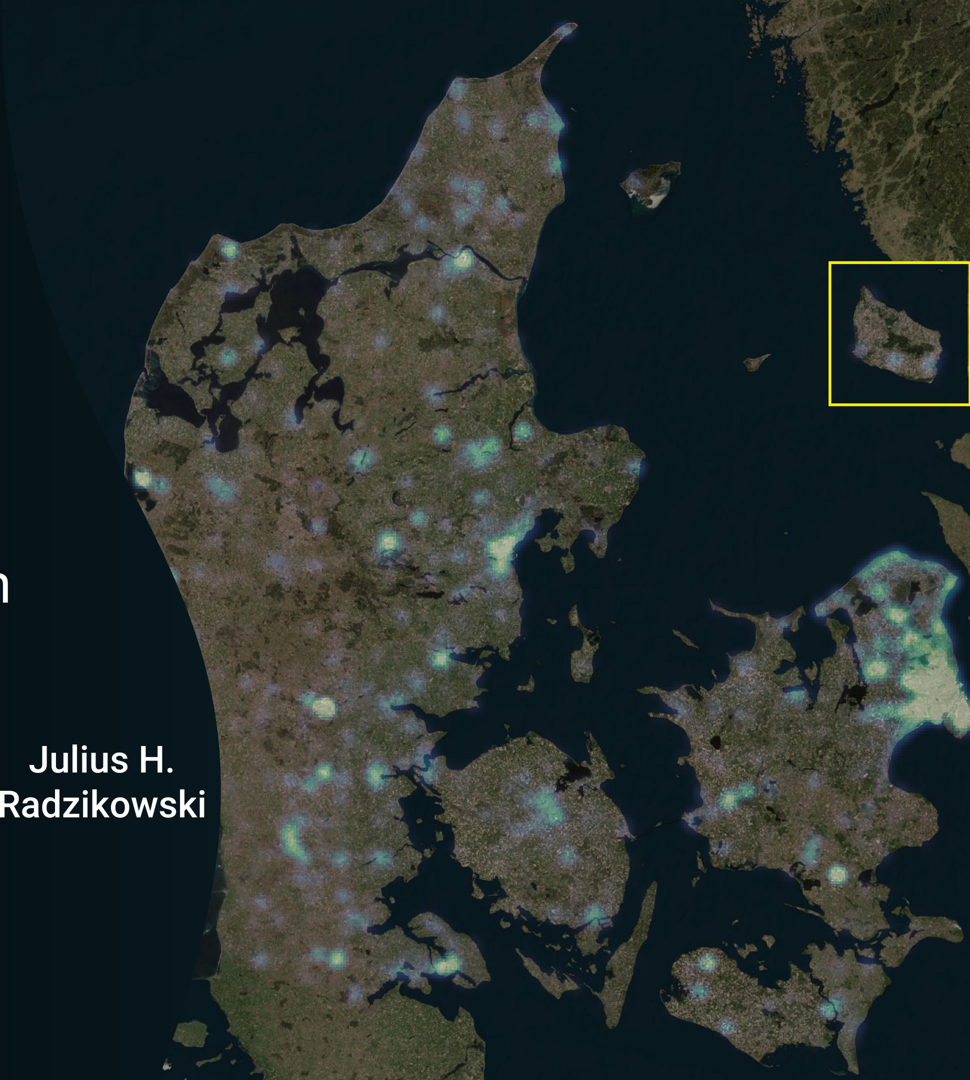


Introduction

- Energy source of the future?
- Where do policy makers focus resources?
- Generalization across geospatial domains

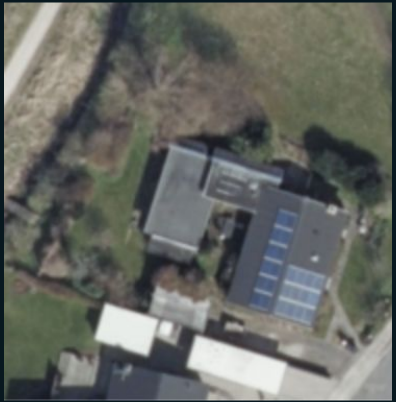
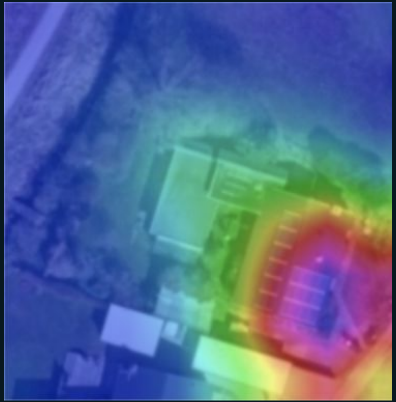


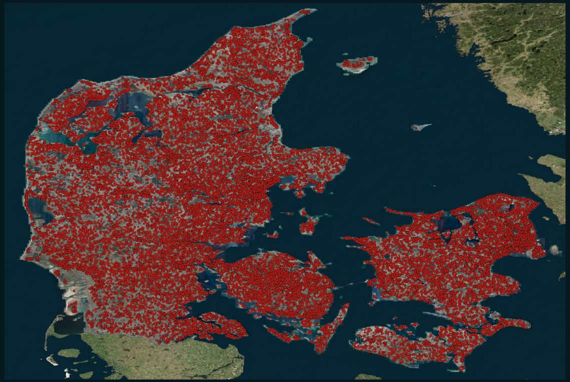
Image from dataset

Class activation map

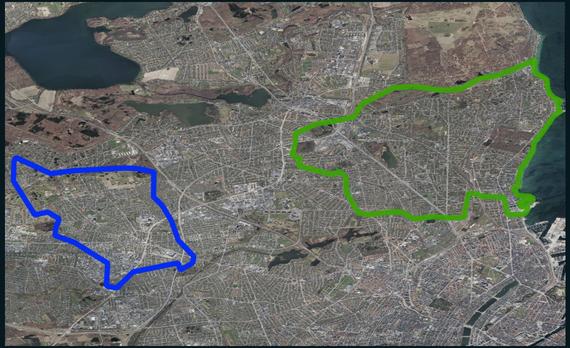


Data

All data is published with this paper



(1) **Assisting -** The existing BBR register



(2) **Primary -** Manually labeled data set

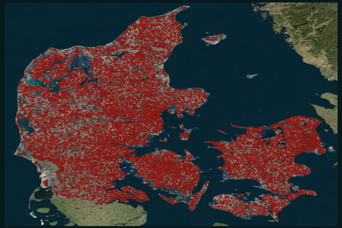
12,5 GSD

DATAFORDELEREN.DK

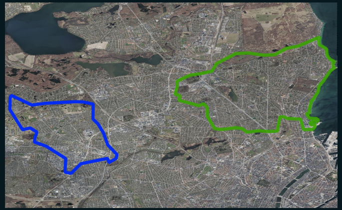
6 example images from both datasets

Data - Classification

All data is published with this paper



(1) The existing BBR register



(2) Manually labeled data set

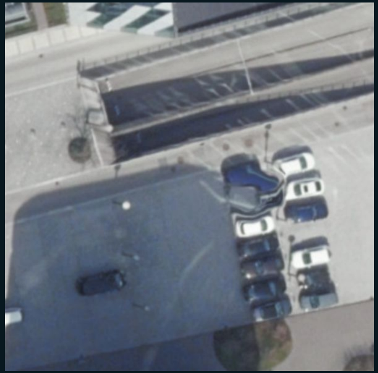
Dataset	Negatives	Positives	Area (km^2)
BBR	-	104,397	3,853,02
Herlev	7,048	398	12,07
Gentofte	15,489	482	25,70
Total	**22,537**	**105,334**	**3,890.79**

Three data & model scenarios:

- Pre-trained models out of domain
- Pre-trained models out of domain, with minority class sampling (BBR)
- Pre-trained models of the same domain

Baseline - Classification

Model	Recall	Precision	Cohens (κ)
ConvNext	0.60±0.04	**0.79±0.03**	**0.66±0.02**
EfficientNet-b5	0.26±0.01	0.64±0.08	0.35±0.03
EfficientNet-b7	0.35±0.05	0.71±0.02	0.45±0.04
InceptionV3	0.34±0.18	0.56±0.38	0.55±0.04
ResNet50	0.25±0.02	0.78±0.04	0.36±0.02
ResNet101	0.58±0.40	0.49±0.39	0.41±0.21
ResNet152	**0.65±0.16**	0.51±0.28	0.49±0.14
ConvNext*	**0.65±0.07**	0.70±0.06	**0.65±0.03**
EfficientNetb5*	0.31±0.10	0.60±0.09	0.38±0.07
EfficientNetb7*	0.51±0.09	0.66±0.11	0.54±0.05
InceptionV3*	0.53±0.08	**0.73±0.09**	0.58±0.05
ResNet50*	0.41±0.04	0.71±0.07	0.49±0.04
ResNet101*	0.41±0.10	0.65±0.03	0.46±0.08
ResNet152*	0.36±0.17	0.66±0.15	0.40±0.10
SolarDE (inference)	0.4186	0.1667	0.2124
SolarDK	**0.7337**	**0.6505**	**0.6717**

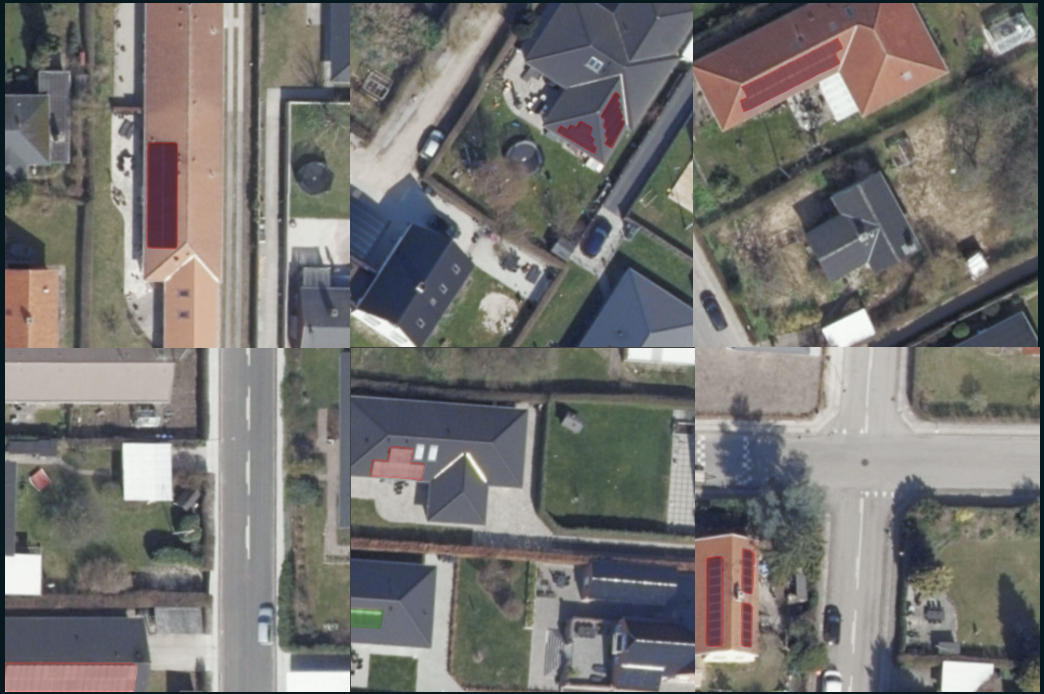


Warping, blur or errors in images

Color and light errors

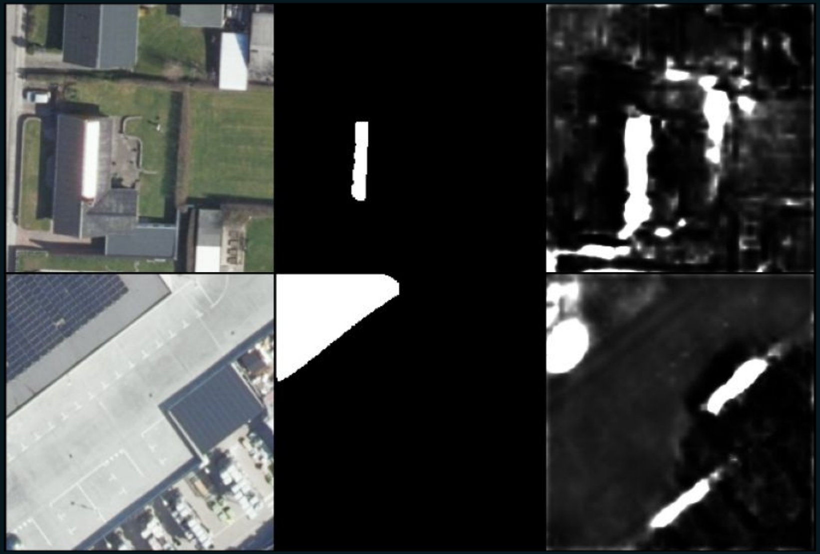
Data - Segmentation

- 880 images human labelled using Toronto Annotation Suite
- Challenges from classification dataset remain: incident angle leading to high albedo reflections (difficult to discern panels from windows)
- Mix of industrial and residential sized PV systems



Baseline - Segmentation

Model	Recall	Precision	IoU
ResNet50-DeepLabV3Plus	**0.81±0.03**	0.86±0.01	0.72±0.02
ResNet101-DeepLabV3Plus	0.79±0.05	0.86±0.02	0.70±0.03
ResNet152-DeepLabV3Plus	0.79±0.04	**0.88±0.03**	0.71±0.02
ResNet50-FPN	0.80±0.03	0.87±0.03	0.72±0.01
ResNet101-FPN	0.79±0.02	0.87±0.02	0.71±0.01
ResNet152-FPN	0.81±0.06	0.87±0.05	**0.72±0.01**
ResNet50-PSPNet	0.75±0.04	0.85±0.03	0.64±0.04
ResNet101-PSPNet	0.66±0.13	0.88±0.05	0.61±0.07
ResNet152-PSPNet	0.72±0.05	0.85±0.04	0.63±0.02
DeepSolarDE (inference)	0.5262	0.3378	0.5098
DeepSolarDK	**0.8468**	**0.7463**	**0.6239**



Examples of poor IoU (< 0.6)

Final remarks

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- Increasing amount of distributed energy sources requires better planning and mapping of energy generation sources
- Novel dataset for solar power classification and localisation
- Presented baselines demonstrate the need to garner more datasets to alleviate geographical domain shift