An Enriched Automated PV Registry: Combining Image Recognition and 3D Building Data

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A project in close cooperation between Stanford University,
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Motivation & Contributions

- Accurate and up-to-date databases of decentralized generation units are indispensable for optimized systems operations

- Previously, CNNs have been used to automatically classify solar panels from aerial imagery and to create databases on a country scale, e.g. *DeepSolar* by Yu et al., 2018[1]

- Yet, previous studies do not account for the tilt and orientation angle of detected systems

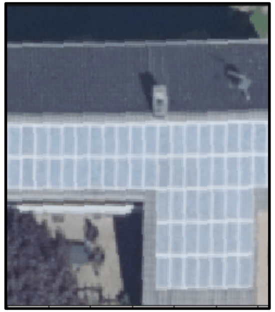
In this work, we:

- ➢ Combine aerial imagery with 3D building data to enrich detected PV systems
- ➢ Show that our approach enables improved PV generation capacity estimates
- ➢ Compare our automated PV registry with Germany's official registry

[1]Yu, J. et al. (2018) 'DeepSolar: A Machine Learning Framework to Efficiently Construct a Solar Deployment Database in the United States', Joule. Elsevier Inc., 2(12), pp. 2605–2617. doi: 10.1016/j.joule.2018.11.021.

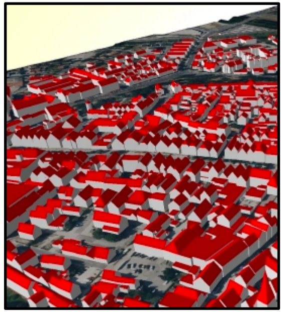
Data Sources

Image Data[2]



GSD: 0.1 m/pixel

3D Building Data[2]



Provides a rooftop's **tilt** and **orientation**

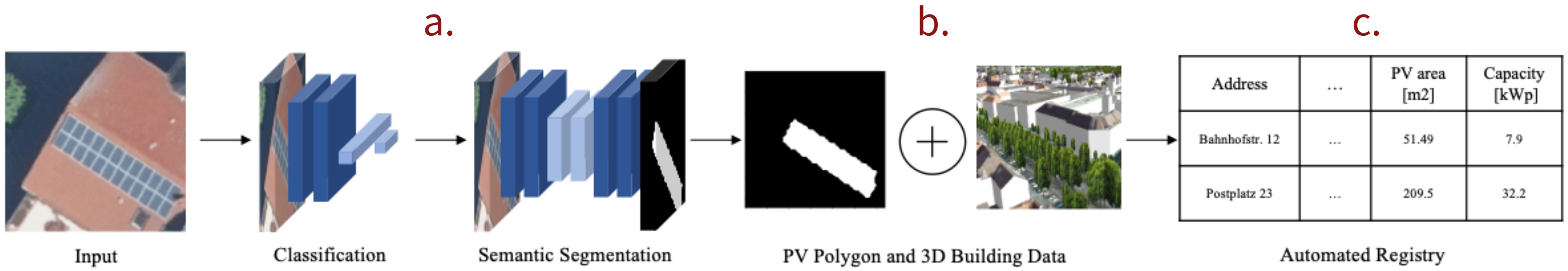
PV registry[2,3]

Provides info on PV systems > **30kW**

Combine publicly available datasets to obtain new insights

[2]Publicly available dataset
[3]Abbreviated as *MaStR* henceforth

Methodology



Notes:

a. Only aerial images classified as depicting PV systems are propagated for segmentation
b. PV systems depicted as real-world coordinate polygons are intersected with rooftop polygons
c. Detected PV systems and their respective capacity estimates are aggregated per address

Creating an enriched automated PV registry is a sequential process

Results: Classification and Segmentation

Classification:

- Precision: 87.3%
- Recall: 87.5%

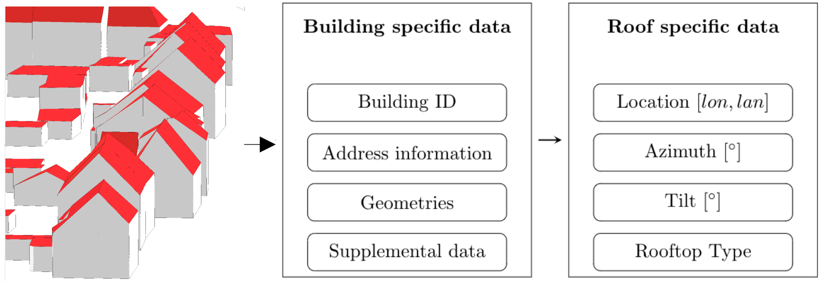
Segmentation:

Paper	MAPE [%]	mIoU [%]	GSD [cm]
Camilo et al.[4]	-	60	30
DeepSolar[1]	24.6	-	5
SolarNet[5]	-	90.9	5
This work	18.5	74.1	10

Classification and segmentation on par with recent studies

[4] Joseph Camilo, Rui Wang, Leslie M Collins, Kyle Bradbury, and Jordan M Malof. Application of a semantic segmentation convolutional neural network for accurate automatic detection and mapping of solar photovoltaic arrays in aerial imagery. arXiv preprint arXiv:1801.04018, 2018.
[5] Xin Hou, Biao Wang, Wanqi Hu, Lei Yin, Anbu Huang, and Haishan Wu. SolarNet: A Deep Learning Framework to Map Solar PowerPlants In China From Satellite Imagery. 2020. URL https://arxiv.org/pdf/1912.03685.pdf.

Results: PV Capacity Estimation with Tilt Angles



Incorporate rooftop tilt to correct PV area estimated from a bird's eye view

Approach	MedAPE[6] [%]
This work (no tilt)	25.9
This work (including tilt)	16.1

Rooftop tilt significantly improves PV capacity estimates

[6]Denotes the Median Absolute Percentage Error

Results: Comparison with *MaStR*[7] in Bottrop

- **Duplicated entries**
  - Approx. 3.2% of *MaStR's* entries are duplicates
- **Erroneous capacities**
  - *MaStR* contains substantially inflated entries
- **Multiple entries per address in *MaStR***
  - Impractical for registry-based analyses
- **False addresses**
  - *MaStR* lists 24 out of 160 entries with a false address
- **Missing entries**
  - We identify 21 PV systems not listed in *MaStR*

For Bottrop, *MaStR* lists 29,758 kWp, while our automated registry arrives at 32,286 kWp

[7]Germany's official PV system registry

Discussion and Outlook

- State-of-the-art results in classification and segmentation
- Incorporating a rooftop's tilt enables accurate PV capacity estimation
- Approach to automatically construct, update, and enhance PV registries
- Future research:
    - Improve PV supply forecasting and nowcasting
    - Enhance integration of EV charging, PV systems, and grid reinforcement