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Deutsches Fernerkundungsdatenzentrum

Tracking progress towards the green energy transition: Nationwide mapping of roof-top photovoltaic installations through deep neural networks

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MOTIVATION

The decarbonization of the global energy system through the transition to renewable energy sources is one of the main pillars of mitigation measures addressing climate change. A key determinant in the realization of a successful energy transition is the rapid installation of decentralized renewable energy infrastructure, such as roof-top photovoltaic systems (PVs)¹.

PV installations are often small-scale, privately owned and differ widely in their capacity. Despite a mandatory registration process in Germany for installations benefiting from subsidies, not all PVs are registered, and of those which are, geolocations are typically anchored to postal addresses but not the roofs themselves, which is a major obstacle for spatially explicit assessments of remaining rooftop solar potential.

In order to foster the rapid expansion of PV installations an automatically updatable monitoring of the evolution of such PV installations over time is a vital asset for political decision makers, both on the communal and national level, supporting the efficient allocation of resources.

We exploited national inventory address data of PV installations in a semi-supervised labelling scheme in combination with wall-to-wall coverage of VHR aerial imagery (20cm resolution) to map every roof-top with PV installations in Germany.

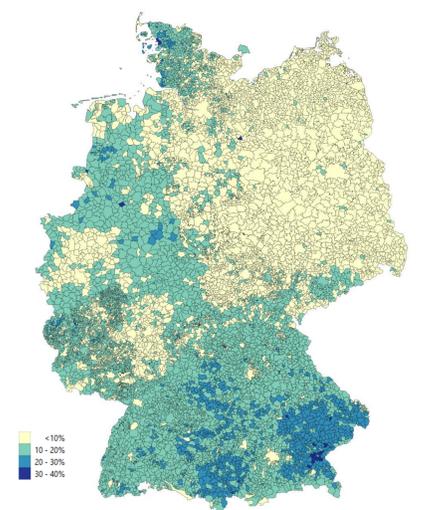


Fig. 1: Percentage of roof-tops > 30m² with PV installations.

APPROACH

Labelling Process:

- **Semi-supervised labelling** of training data derived from public registry data (Marktstammdatenregister, Bundesnetzagentur) with additional manual labelling (**360k labelled samples**)
- Extraction of **4 channel (RGB-NIR) image patches** for each building, masked with administrative building-outlines.

Model Training, Validation and Inference:

- **Fine-tuning of pretrained PyTorch Image Models²** with fast.ai³ tooling:
 - Settings: base_lr = 3e-4, "one cycle" learning rate schedule, AdamW optimizer, differential learning rates
 - Models: Resnet 50⁴, BiT-L ResNet 50x3⁶, EfficientNet v2 L⁸, ConvNext⁵, Vision Transformer⁷ (16 & 32 patches);
 - Data augmentation with **RandAugment** (parameterized via grid search)
- **Ensembling of 5 fold cross-validated models** using ridge classification
- Model **validation** based on a **manually labelled, spatially distributed test-set (20k samples)**
- **Inference using ONNX-runtime** on a 64-node CPU cluster (**34M samples**)

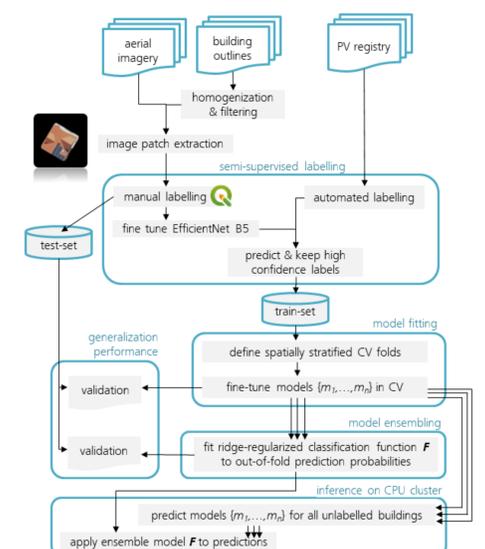


Fig. 2: Product generation workflow. CV = 5-fold cross-validation.

RESULTS

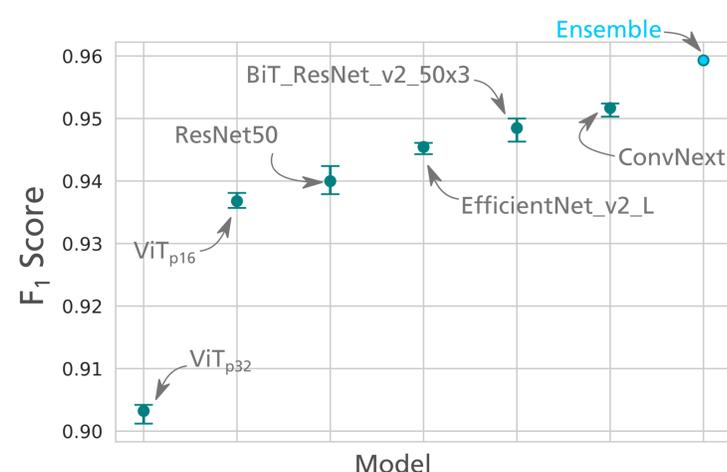


Fig. 2: Average test-set performance of individual models as well as their ensemble with errorbars designating minimum and maximum scores of five-fold cross-validation.

Observations

- Model performance on the test-set was comparable across architectures, with CNNs having the advantage over Transformers (some catch-up was achieved with SWIN Transformers, which are not yet reported here).
- Best single model was ConvNext. Ensembling led to an increase in F1 score of **+0.01** (extrapolated to all of Germany, this translates to an additional 340k roof-tops correctly classified)

References

- [1] Victoria et al. (2020) Early decarbonisation of the european energy system pays off. Nat. Comm.
- [2] Wightman (2019): PyTorch Image Models (timm). doi:10.5281/zenodo.4414861
- [3] Howard et al. (2020): Fastai A Layered API for Deep Learning. arXiv:2002.04688
- [4] He et al. (2015) Deep Residual Learning for Image Recognition. arXiv:1512.03385
- [5] Liu et al. (2022) A ConvNet for the 2020s. arXiv:2201.03545
- [6] Kolesnikov et al. (2020) Big Transfer (BiT): General Visual Representation Learning. arXiv:1912.11370
- [7] Dosovitskiy et al. (2021) An Image is Worth 16x16 Words: Transformers for Image Recognition at Scale. arXiv:2010.11929
- [8] Tan et al. (2021) EfficientNetV2: Smaller Models and Faster Training. arXiv:2104.00298