Predicting PV Areas in Aerial Images with Deep Learning

Deutsches Zentrum für Luft- und Raumfahrt
German Aerospace Center
Institute of Networked Energy Systems

Matthias Zech[1] and Joseph Ranalli[2*]
[1]DLR Institute of Networked Energy Systems, Oldenburg, Germany
[2]Penn State Hazleton, Hazleton, PA, USA
*Corresponding Author: jar339@psu.edu

PennState Hazleton

There is a need for distributed PV generation location data

Data on distributed PV installations can be difficult to access for researchers. Aerial or satellite images are a potential source of data, but manual identification is time prohibitive. Computer vision approaches that employ Neural Networks and Deep Learning may automate the identification of PV from images.

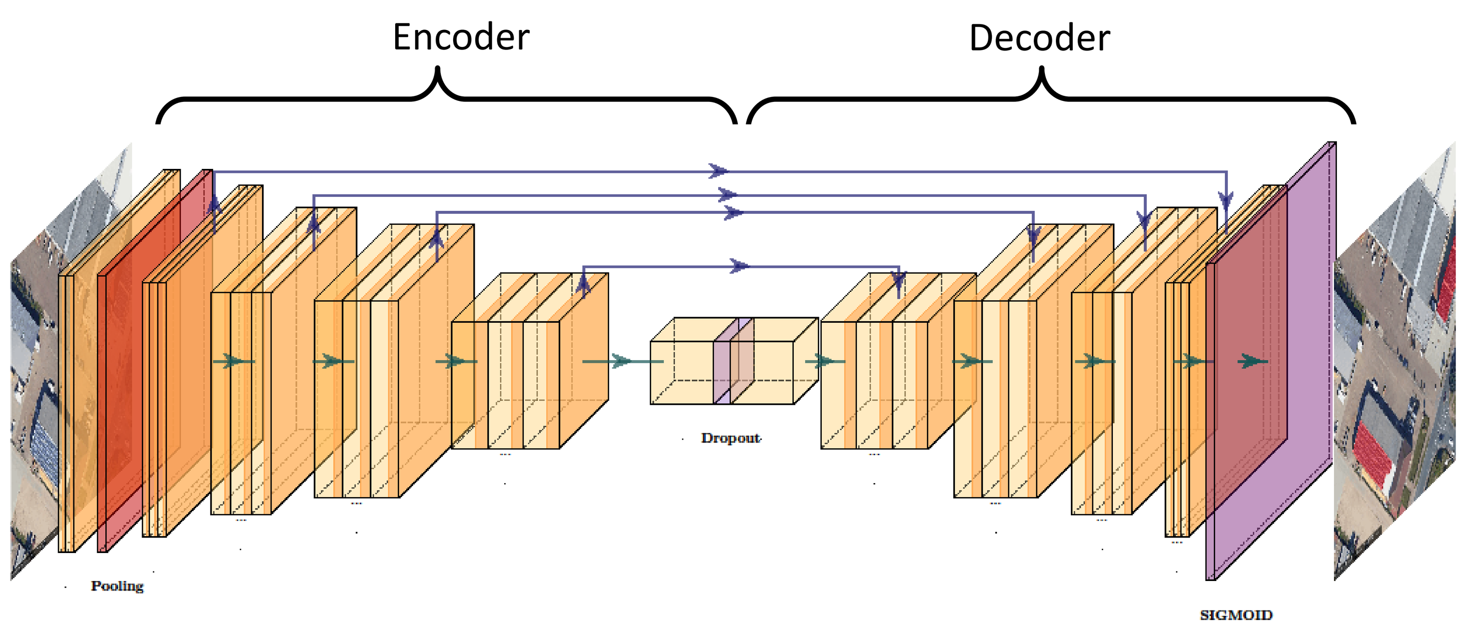
13,345 Google Earth tiles acquired for region of Oldenburg, Germany and surrounding countryside. Manual labelling performed for 1,325 found to contain PV (shown in red).

Challenges to manual labeling include Solar Thermal and Wintergardens (greenhouses)

Manual identification of PV polygons in open-source tool called *labelme*.

U-Net Neural Network architecture with pre-trained weights

Classifying pixels within the image is called "semantic segmentation." U-net is a well established Fully Convolutional Neural Network architecture for this task. Starting from a network that previously worked for another computer vision task can speed up training. We implemented in python using *segmentation_models*. Four different backbones were considered (ResNet-18, -34, -50, -101)



U-net consists of contracting and expanding paths. Convolution increases the field of view during the contracting path. The expanding path builds the back to full size to allow pixel-wise prediction.

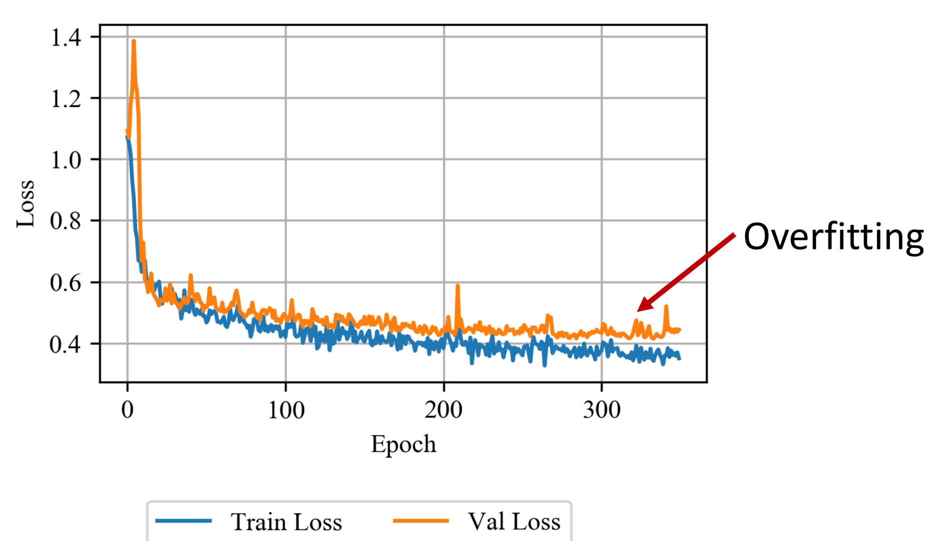
Training process optimizes the network for the task at hand

Data was split into training, validation and testing sets with a 81%/9%/10% ratio. While maintaining frozen weights for the encoder, the model was trained for 350 epochs keeping only the case with the best validation loss. The loss function used was a combination of Binary Cross Entropy and Jaccard losses.

Data augmentation used to effectively increase amount of training data

Method	Value
Rotation	± 30˚
Width Shift	± 5%
Height Shift	± 5%
Zoom	± 20%

Two separate seeds used for data splitting to ensure that no non-random elements of the training set dominated the results.



Loss improved over time. Weights for the best validation loss were kept.

Methodology exists to compute pixelwise uncertainty

Monte Carlo dropout allows quantification of uncertainty in output of deep neural network. Works by considering the weights of the neural network to be random variables. We evaluate the network using N=100 different dropout configurations and estimate uncertainty of the predictions using the pixelwise standard deviation.

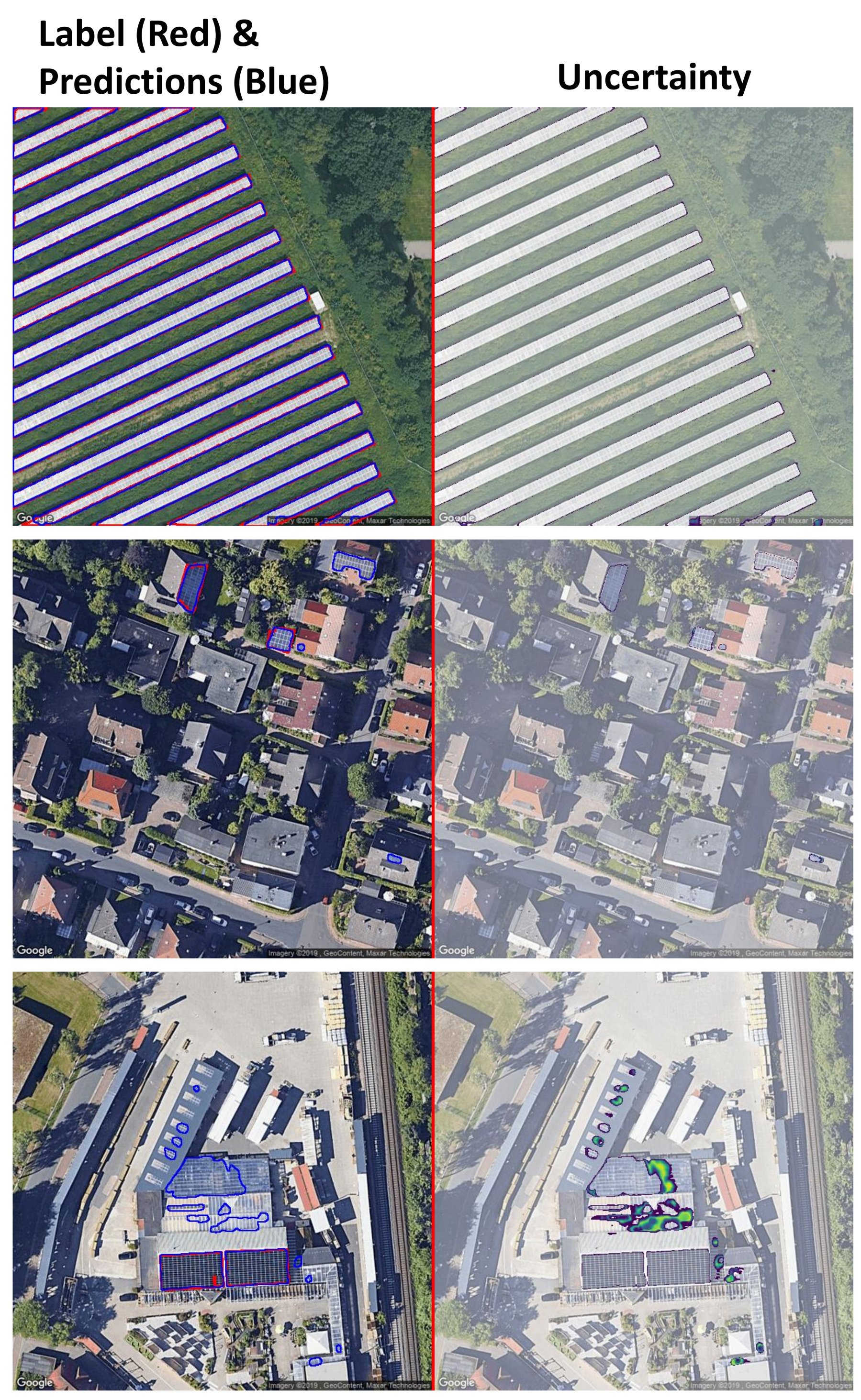
Identification of PV was validated against test set

Best performance was observed for ResNet-50. Metrics indicate that ~80% of predicted pixels are correct and ~80% of labels are identified. Model showed good performance overall based on qualitative review of results. Several aspects of performance can guide future development and improvement.

Performance of model relative to metrics

Backbone	Seed	Loss	IOU	P*	R$	F1
ResNet-18	A	0.40	0.63	0.70	0.86	0.77
ResNet-18	B	0.37	0.65	0.83	0.76	0.79
ResNet-34	A	0.33	0.69	0.79	0.84	0.81
ResNet-34	B	0.36	0.68	0.84	0.77	0.80
ResNet-50	A	0.33	0.69	0.79	0.84	0.82
ResNet-50	B	0.34	0.69	0.84	0.79	0.81
ResNet-101	A	0.37	0.66	0.74	0.85	0.79
ResNet-101	B	0.35	0.68	0.86	0.76	0.81

* - Precision, $ - Recall



Utility scale plant identified well. Uncertainty occurs primarily at edges. This indicates high confidence in predictions of primary areas, but that identifying the precise location of the boundary is more difficult.

Several neighborhood rooftops identified correctly, including one missed label. Two false positives are predicted with high confidence. Uncertainty cannot universally indicate poor quality predictions.

Primary rooftop system identified well, but false positives on glass rooftop and skylights. Uncertainty is high for the false positives, indicating potential for deeper look at uncertain cases.

Error Analysis reveals a few particularly difficult cases

Considering some common failures may guide improvement.

High False Negative error due to erroneously labeled PV system through the whole convex hull and high reflections on single arrays

High False Negative error due to shadowing effects of the tree and False Positives for similar looking structure

Conclusions and Future Work

Highly accurate PV panel areas were be predicted on aerial images through the proposed method. With a large-scale aerial image database, highly resolved PV areas could be generated for a large geographic region. Uncertainty estimates mostly relate to the labeling uncertainty of the user. Potential future work is possible concerning evaluation and usage of this uncertainty to improve labeling and model training.

Acknowledgments

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