SOLAR PANEL SEGMENTATION: SELF-SUPERVISED LEARNING SOLUTIONS FOR IMPERFECT DATASETS

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ABSTRACT

The increasing adoption of solar energy necessitates advanced methodologies for monitoring and maintenance to ensure optimal performance of solar panel installations. A critical component in this context is the accurate segmentation of solar panels from aerial or satellite imagery, which is essential for identifying operational issues and assessing efficiency. This paper addresses the significant challenges in panel segmentation, particularly the scarcity of annotated data and the labour-intensive nature of manual annotation for supervised learning. We explore and apply Self-Supervised Learning (SSL) to solve these challenges. We demonstrate that SSL significantly enhances model generalization under various conditions and reduces dependency on manually annotated data, paving the way for robust and adaptable solar panel segmentation solutions.

1 INTRODUCTION

The escalating role of solar energy in mitigating climate change has garnered increased research interest, propelled by technological advancements and heightened environmental awareness as portrayed in Zhuang et al. (2020). In this context, remote sensing has emerged as a pivotal tool for enhancing solar energy utilization, enabling the identification of regions with underutilized energy for targeted optimization (Rasmussen et al. (2021)). Nonetheless, segmenting solar panels using traditional supervised machine learning models presents substantial challenges, primarily due to the absence of reliable, annotated datasets. Compounding this challenge is the copious amount of raw, unlabelled data generated by aerial and satellite imaging systems. Despite its potential utility, the processing and accurate labelling of this data demand extensive labour and are susceptible to inaccuracies as displayed by Fahy et al. (2022).

In response to these challenges, our paper proposes a novel approach that improves the reliability of solar panel segmentation by leveraging this extensive pool of satellite imagery, utilizing self-supervised learning techniques to circumvent the need for meticulously annotated data like in Chen et al. (2022). We particularly highlight the capability of SimCLR (Chen et al. (2020)) pretraining to produce accurate segmentation masks despite label corruption. This advancement in self-supervised learning significantly diminishes the costs and dependency on external annotation resources. Importantly, while our approach includes the initial cost of pretraining, this expense is marginal compared to the traditionally high costs of fully annotating datasets. Our method not only eliminates the need for extensive annotations but also demonstrates, as we will show, a significant reduction in overall costs. This leads to minimized manual labour and decreased reliance on external factors, thereby presenting a cost-effective,Zhou (2017) and robust solution to one of the most pressing challenges in applying machine learning to solar energy optimization.

2 METHODOLOGY

We utilized the PV03 dataset (Jiang et al. (2021)), encompassing solar panel data from Jiangsu Province, China, and incorporated SimCLR pertaining as part of our experimental setup. Our experimentation involved various segmentation models, including encoder-decoder networks like U-Net(Ronneberger et al. (2015)) and FPN(Lin et al. (2017)), and PSPNet(Zhao et al. (2017)), which utilizes a pyramid pooling module. Additionally, we experimented with multiple backbones for each architecture, such as ResNets(He et al. (2015)), Mix Visual Transformer(Xie et al. (2021)), and VGG(Ronneberger et al. (2015)) with ImageNet pre-trained weights. The results of our best configurations are presented in 1. We employed Focal Loss (Lin et al. (2018)) for all configurations, which enhances learning by prioritising challenging misclassified examples. In all our experiments, we applied horizontal and vertical flips along with colour jittering at a probability of 0.5, and shifts in the HSV colour scale. Our analysis of these configurations led us to identify the most effective settings for our approach: a batch size of 8, focal loss parameters with an α value of 0.4 and a γ value of 2, a learning rate set at 3x10^{-5}, and the use of the Adam optimizer Kingma & Ba (2017) with β_1 and β_2 values of 0.9 and 0.99, respectively, during the fine-tuning process.

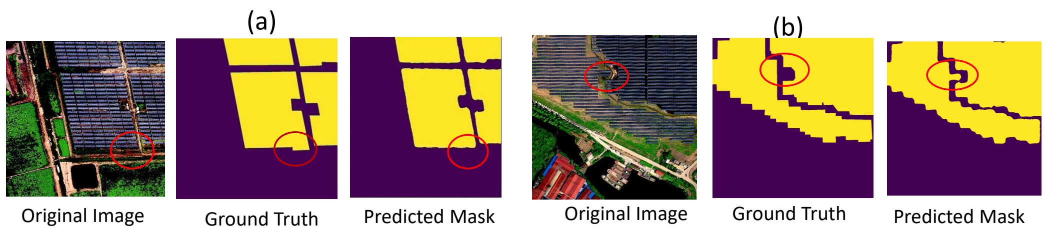

Figure 1: Instances demonstrating corrupted ground truths in the datasets, with contrast-enhanced RGB images for easier visualization, and how SSL adapts in the learning process.

3 Results

Initially, the entire training dataset was employed, followed by fine-tuning using varied subsets of this data before applying the model to the complete test set. Remarkably, diverse configurations, when applied to these subsets, consistently produced similar results during the fine-tuning stage. This consistency underscores SSL's strength in enhancing our approach's robustness. Notably, it achieved impressive performance even with limited annotated data as portrayed in Hendrycks et al. (2019), demonstrating that substantial annotation costs can be reduced by fine-tuning on a subset while still maintaining consistently high-quality results. Our pre-trained model was then fine-tuned on PSPNet with ResNet-34 encoder, following the methodology outlined in Jiang et al. (2021).

Table 1: PV03 Results with different configurations

	60%	**70%**	**80%**	**Full Dataset**
Unet [Jiang et al. (2021)]	-	-	-	0.858
PSPNet *	0.869	0.8841	0.869	0.8895
SimCLR +PSPNet *	0.8748	0.888	**0.8911**	0.890

Our study revealed two key findings: firstly, the superior performance of our predicted masks over the original, corrupted ground truths in the dataset, and secondly, penalties in terms of potentially lower IoU scores during the fine-tuning phase of experiments that were conducted with SSL pre-training. The predicted masks accurately segmented solar panels that were missed in the manual annotation process, as clearly demonstrated in Figure 1, where areas of interest are highlighted with red circles. This not only underscores the effectiveness of our methodology but also highlights the issue of label corruption in datasets. The lower IoU scores observed during SSL pre-training can be attributed to the generation of masks that more accurately represent real-world scenarios when compared to the provided ground truths, leading to unfair penalties during backpropagation. This phenomenon is also illustrated in Figure 1.

4 Conclusion

In our research, we have effectively applied Self-Supervised Learning (SSL) techniques to tackle the challenges of scarce and corrupted data annotations in solar panel segmentation. Our approach significantly improves model generalization, even under varying conditions, thereby addressing the limitations of manual annotation in supervised learning. The experiments conducted demonstrate that our SSL-based method consistently delivers strong performance, even with limited training data, highlighting its capability to mitigate the issues of label scarcity and corrupted labels. Furthermore, the enhanced robustness achieved in this domain is a testament to the versatility of our methodology.

URM STATEMENT

The authors acknowledge that all key authors of this work meet the URM criteria of ICLR 2024 Tiny Papers Track.

REFERENCES

De-Yue Chen, Ling Peng, Wen-Yue Zhang, Yin-Da Wang, and Li-Na Yang. Research on self-supervised building information extraction with high-resolution remote sensing images for photovoltaic potential evaluation. *Remote Sensing*, 14(21), 2022. ISSN 2072-4292. doi: 10.3390/rs14215350. URL https://www.mdpi.com/2072-4292/14/21/5350.

Ting Chen, Simon Kornblith, Mohammad Norouzi, and Geoffrey Hinton. A simple framework for contrastive learning of visual representations. In Hal Daumé III and Aarti Singh (eds.), *Proceedings of the 37th International Conference on Machine Learning*, volume 119 of *Proceedings of Machine Learning Research*, pp. 1597–1607. PMLR, 13–18 Jul 2020. URL https://proceedings.mlr.press/v119/chen20j.html.

Conor Fahy, Shengxiang Yang, and Mario Gongora. Scarcity of labels in non-stationary data streams: A survey. *ACM Comput. Surv.*, 55(2), jan 2022. ISSN 0360-0300. doi: 10.1145/3494832. URL https://doi.org/10.1145/3494832.

Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Deep residual learning for image recognition, 2015.

Dan Hendrycks, Mantas Mazeika, Saurav Kadavath, and Dawn Song. Using self-supervised learning can improve model robustness and uncertainty. In H. Wallach, H. Larochelle, A. Beygelzimer, F. d'Alché-Buc, E. Fox, and R. Garnett (eds.), *Advances in Neural Information Processing Systems*, volume 32. Curran Associates, Inc., 2019. URL https://proceedings.neurips.cc/paper_files/paper/2019/file/a2b15837edac15df90721968986f7f8e-Paper.pdf.

H. Jiang, L. Yao, N. Lu, J. Qin, T. Liu, Y. Liu, and C. Zhou. Multi-resolution dataset for photovoltaic panel segmentation from satellite and aerial imagery. *Earth System Science Data*, 13(11):5389–5401, 2021. doi: 10.5194/essd-13-5389-2021. URL https://essd.copernicus.org/articles/13/5389/2021/.

Diederik P. Kingma and Jimmy Ba. Adam: A method for stochastic optimization, 2017.

Tsung-Yi Lin, Piotr Dollár, Ross Girshick, Kaiming He, Bharath Hariharan, and Serge Belongie. Feature pyramid networks for object detection, 2017.

Tsung-Yi Lin, Priya Goyal, Ross Girshick, Kaiming He, and Piotr Dollár. Focal loss for dense object detection, 2018.

Jesper Rasmussen, Saiful Azim, Søren Kjærgaard Boldsen, Thomas Nitschke, Signe M Jensen, Jon Nielsen, and Svend Christensen. The challenge of reproducing remote sensing data from satellites and unmanned aerial vehicles (uavs) in the context of management zones and precision agriculture. *Precision Agriculture*, 22:834–851, 2021.

Olaf Ronneberger, Philipp Fischer, and Thomas Brox. U-net: Convolutional networks for biomedical image segmentation, 2015.

Enze Xie, Wenhai Wang, Zhiding Yu, Anima Anandkumar, Jose M. Alvarez, and Ping Luo. Segformer: Simple and efficient design for semantic segmentation with transformers, 2021.

Hengshuang Zhao, Jianping Shi, Xiaojuan Qi, Xiaogang Wang, and Jiaya Jia. Pyramid scene parsing network, 2017.

Zhi-Hua Zhou. A brief introduction to weakly supervised learning. *National Science Review*, 5(1): 44–53, 08 2017. ISSN 2095-5138. doi: 10.1093/nsr/nwx106. URL https://doi.org/10.1093/nsr/nwx106.

Li Zhuang, Zijun Zhang, and Long Wang. The automatic segmentation of residential solar panels based on satellite images: A cross learning driven u-net method. *Appl. Soft Comput.*, 92:106283, 2020. URL `https://api.semanticscholar.org/CorpusID:216382564`.