

cases	doc_1		doc_2				decision	id				
	<div><div>authors</div><div><ul style="list-style-type: none"><li>Lukas Bommes</li><li>Mathis Hoffmann</li><li>Claudia Buerhop-Lutz</li><li>Tobias Pickel</li><li>Jens Hauch</li><li>Christoph J. Brabec</li><li>Andreas Maier</li><li>Ian Marius Peters</li></ul></div></div>		<div><div>authors</div><div><ul style="list-style-type: none"><li>Ian Marius Peters</li><li>Andreas Maier</li><li>Christoph Brabec</li><li>Jens Hauch</li><li>Tobias Pickel</li><li>Claudia Buerhop-Lutz</li><li>Mathis Hoffmann</li><li>Lukas Bommes</li></ul></div></div>	<div><div>title</div><div>Anomaly Detection in IR Images of PV Modules using Supervised Contrastive Learning</div></div>	<div><div>publication_date</div><div>2021-12-06 00:00:00</div></div>	<div><div>source</div><div>SupportedSources.PAPERS_WITH_CODE</div></div>	<div><div>journal</div><div></div></div>	<div><div>volume</div><div></div></div>	<div><div>doi</div><div></div></div>	DUPLICATES	97	
	<div><div>title</div><div>Anomaly detection in IR images of PV modules using supervised contrastive learning</div></div>	<div><div>publication_date</div><div>2022-03-28 00:00:00</div></div>	<div><div>source</div><div>SupportedSources.OPENALEX</div></div>	<div><div>journal</div><div>Progress in Photovoltaics</div></div>	<div><div>volume</div><div>30</div></div>	<div><div>doi</div><div>10.1002/pip.3518</div></div>	<div><div>urls</div><div><ul style="list-style-type: none"><li>https://openalex.org/W4220855124</li><li>https://doi.org/10.1002/pip.3518</li><li>https://opus4.kobv.de/opus4-fau/files/19638/PIP_PIP3518.pdf</li></ul></div></div>	<div><div>id</div><div>id-5142479000761068252</div></div>	<div><div>abstract</div><div></div></div>			<div><div>versions</div><div></div></div>
			<div><div>urls</div><div><ul style="list-style-type: none"><li>https://arxiv.org/pdf/2112.02922v1.pdf</li><li>https://github.com/LukasBommes/PV-Mapper</li></ul></div></div>	<div><div>id</div><div>id8281621142106963327</div></div>	<div><div>abstract</div><div>Increasing deployment of photovoltaic (PV) plants requires methods for automatic detection of faulty PV modules in modalities, such as infrared (IR) images. Recently, deep learning has become popular for this. However, related works typically sample train and test data from the same distribution ignoring the presence of domain shift between data of different PV plants. Instead, we frame fault detection as more realistic unsupervised domain adaptation problem where we train on labelled data of one source PV plant and make predictions on another target plant. We train a ResNet-34 convolutional neural network with a supervised contrastive loss, on top of which we employ a k-nearest neighbor classifier to detect anomalies. Our method achieves a satisfactory area under the receiver operating characteristic (AUROC) of 73.3 % to 96.6 % on nine combinations of four source and target datasets with 2.92 million IR images of which 8.5 % are anomalous. It even outperforms a binary cross-entropy classifier in some cases. With a fixed decision threshold this results in 79.4 % and 77.1 % correctly classified normal and anomalous images, respectively. Most misclassified anomalies are of low severity, such as hot diodes and small hot spots. Our method is insensitive to hyperparameter settings, converges quickly and reliably detects unknown types of anomalies making it well suited for practice. Possible uses are in automatic PV plant inspection systems or to streamline manual labelling of IR datasets by filtering out normal images. Furthermore, our work serves the community with a more realistic view on PV module fault detection using unsupervised domain adaptation to develop more performant methods with favorable generalization capabilities.</div></div>	<div><div>versions</div><div></div></div>						