BRNO UNIVERSITY OF TECHNOLOGY FACULTY OF INFORMATION TECHNOLOGY

Automated Detection of Photovoltaic Power Plant Panel Defects from a Drone Thermal Imaging Camera

author: Ing. Matěj Gotzman
supervisor: Ing. Daniel Bambušek

1. Motivation

A side effect of most photovoltaic (PV) panel defects is an increased temperature in the affected area. This makes drone thermal imaging camera inspection a suitable non-invasive method to detect defective panels.

The main benefit of this work is to speed up and simplify the processing of the thermal dataset, avoiding manual inspection. The developed solution covers all steps of dataset processing, from image normalization and orthophoto creation with real temperature data, to panel segmentation and classification. The entire workflow is integrated into a web application that guides the user and enables interactive review and correction of predictions.

2. Multispectral Orthophoto

The Open Drone Map software is used to create the orthophotos and has been integrated into the implemented web application. The creation of the orthophoto is done in multispectral mode, which prevents the loss of real temperature data. The images are normalized before processing to achieve high orthophoto quality.

3. Panels Segmentation

Panels segmentation is performed using a trained Mask R-CNN model, following the approach proposed in the referenced bachelor's thesis [1]. The original dataset was expanded and the model was retrained. The model achieved an average precision of 96,9% at an IoU threshold of 75%.

4. Panel defects classification

The classification models were trained on a publicly available dataset containing segmented PV panels categorized into classes. The implemented system includes two trained models: a Vision Transformer and a lightweight CNN. The Vision Transformer uses pre-trained layers, whereas the CNN was trained from scratch. Both models achieved comparable performance, as presented in Table 1. The CNN demonstrates significantly faster inference.

Class	Vision Transformer		Convolutional	
	Precision	Recall	Precision	Recall
Cell	0,82	0,71	0,73	0,81
Cell-Multi	0,54	0,62	0,67	0,47
Cracking	0,72	0,71	0,76	0,79
Diode	0,99	0,97	0,97	0,97
Diode-Multi	0,95	0,99	0,99	0,97
No-Anomaly	0,96	0,99	0,94	0,96
Offline	0,94	0,8	0,91	0,81
Shadowing	0,88	0,7	0,83	0,77
Vegetation	0,75	0,79	0,77	0,76

Table 1: Evaluation results on the public dataset.

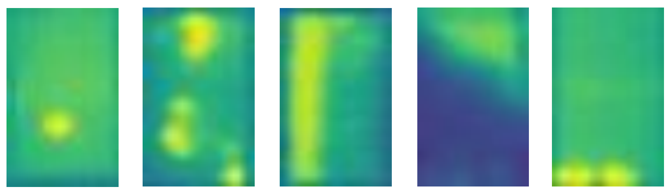

Figure 1: Examples of defect classes.

5. Evaluation and Results

The implemented system was evaluated using a dataset captured during an inspection of a PV power plant in the Czech Republic. This dataset was manually annotated by a domain expert, and the annotations served as ground truth for the evaluation. The system failed to detect only 4 out of 2208 panels on the generated orthophoto, resulting in a segmentation success rate exceeding 99%. As not all defect classes present in the training dataset were represented in the ground truth annotations, the classification settings were adjusted accordingly. The results of both classification models are summarized in Table 2. In this evaluation, the CNN outperformed the Vision Transformer. According to the confusion matrix (Figure 2), the convolutional model missed only 6 defective panels, achieving 99% recall. Precision was 73%, indicating some healthy panels were misclassified as defective.

Class	Vision Transformer		Convolutional	
	Precision	Recall	Precision	Recall
diode	0,26	0,75	0,38	0,64
hotspot	0,59	0,92	0,74	0,99
no-anomaly	0,98	0,83	1	0,91

Table 2: Evaluation results on the czech dataset.

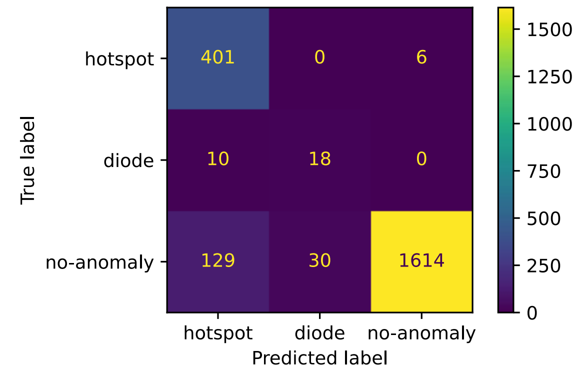

Figure 2: Confusion matrix of the CNN evaluation.

6. Conclusions

The outcome of this work is a functional system with the potential to significantly accelerate the inspection process of PV power plants. Its modular implementation enables straightforward future extensions, such as the integration of newly trained models.

[1] Filip Haužvic. Detekce a klasifikace vad panelů fotovoltaických elektráren z termokamery dronu. VUT v Brně, Fakulta informačních technologií, Brno, 2024.