# A Benchmark for Visual Identification of Defective Solar Cells in Electroluminescence Imagery

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ABSTRACT: In this paper a dataset consisting of 2,426 solar cells extracted from high-resolution electroluminescence (EL) images is used for automated defect probability recognition. The collected images contain both functional and defective solar cells with varying degrees of degradation both in monocrystalline and polycrystalline solar modules. The images were labeled by expert who categorized the solar cells by the likelihood of a defect within each image. The labeled images can be used for development of computer vision and machine learning methods for automatic detection of different defects, like cracks, fracture interconnects, PID, and cell quality and for the purpose of predicting the power efficiency loss.

Keywords: EL-imaging, visual inspection, machine learning

## *INTRODUCTION*

Electroluminescence (EL) imaging is an established technique for the visual inspection of photovoltaic modules [1, 2]. EL imaging allows to capture high-resolution images of photovoltaic modules and enables identification of defects in individual solar cells [2, 3]. However, manual inspection of EL images is extremely tedious and requires expert knowledge. Therefore, an automated visual inspection process is more desirable.

The development of automatic visual inspection methods typically first involves the collection of data. The data includes images of both functional and defective solar modules. Additionally, to identify defects at the solar cell level, the EL images of solar modules must be segmented into individual solar cells first [4].

The data in EL imaging that captures a variety of degradation types in solar modules is, however, not cheap. Solar modules do not break on a regular basis but rather over a long period of time. Artificial aging as an alternative is, however, economically not a viable solution. The data collection can therefore be cumbersome or even a hindering factor for the development and quantitative evaluation of visual inspection algorithms.

For these reasons, the datasets used for the evaluation of visual inspection methods in the literature are rather small, capture only specific defect types, and are not made public to gain advantage of possessing such data. As most authors work with different datasets, the comparison between different inspection methods is therefore practically not possible.

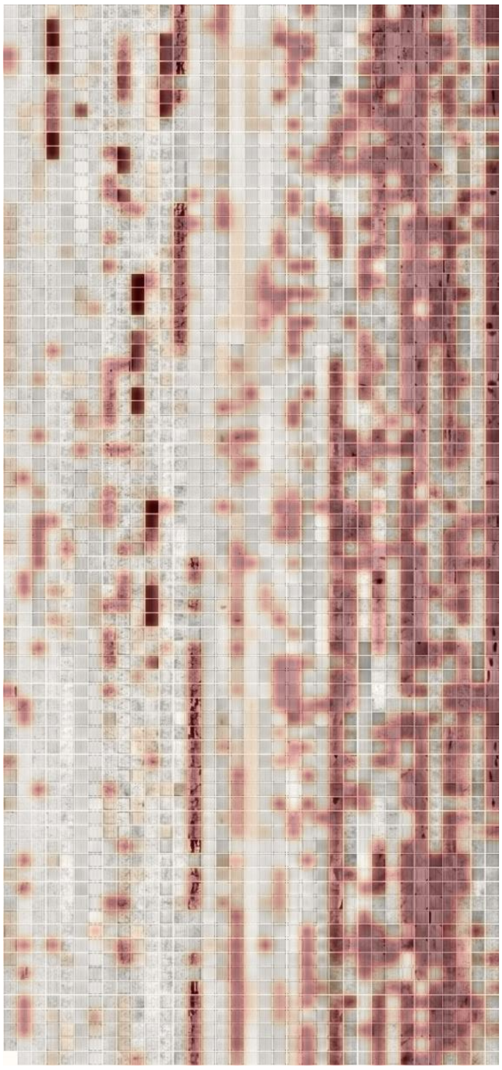

**Fig. 1**: An overview of all 2,426 solar cell images in the dataset. The images are overlayed by a color that specifies the increased defect likelihood of the underlying solar cell.

In order to support good scientific practices and to encourage the development of visual inspection methods, we devised a dataset consisting of labeled solar cell images, which were extracted from high-resolution EL images of photovoltaic modules. All images were labeled with the help of expert who classified the solar cell images into different defect likelihood categories. Using the provided data, we trained a classifier that can predict defect probabilities in solar cells at an accuracy of 88.42% using images only. This allows us to quickly spot breakage trends in solar modules and decide whether additional measurement is useful to validate the potential loss of power efficiency.

Our dataset is publicly available at https://github.com/zae-bayern/elpv-dataset or with QR code in **Fig. 2**.

**Fig. 2**: QR code link for https://github.com/zae-bayern/elpv-dataset.

## *EXPERIMENTAL PROCEDURE*

Our dataset consists of 2,426 different images of solar cells, see

**Fig. 1**. The images were extracted from 44 different solar modules of which 26 are polycrystalline and 18 monocrystalline. In **Fig. 3** one of the polycrystalline PV modules is shown with two exemplary cells and their calculated defect probability.

Our labeling interface then presented one solar cell image at a time to the experts who had to answer two questions:

(1) is the solar cell defective or functional?
(2) are you sure or unsure?

From the corresponding answers, we inferred a set of conditional probabilities (0%, 33%, 67%, and 100% defect likelihood) that define the labels of each solar cell image [5]. An overview of the amount of cells in each category of defect likelihood is shown in Tab. 1.

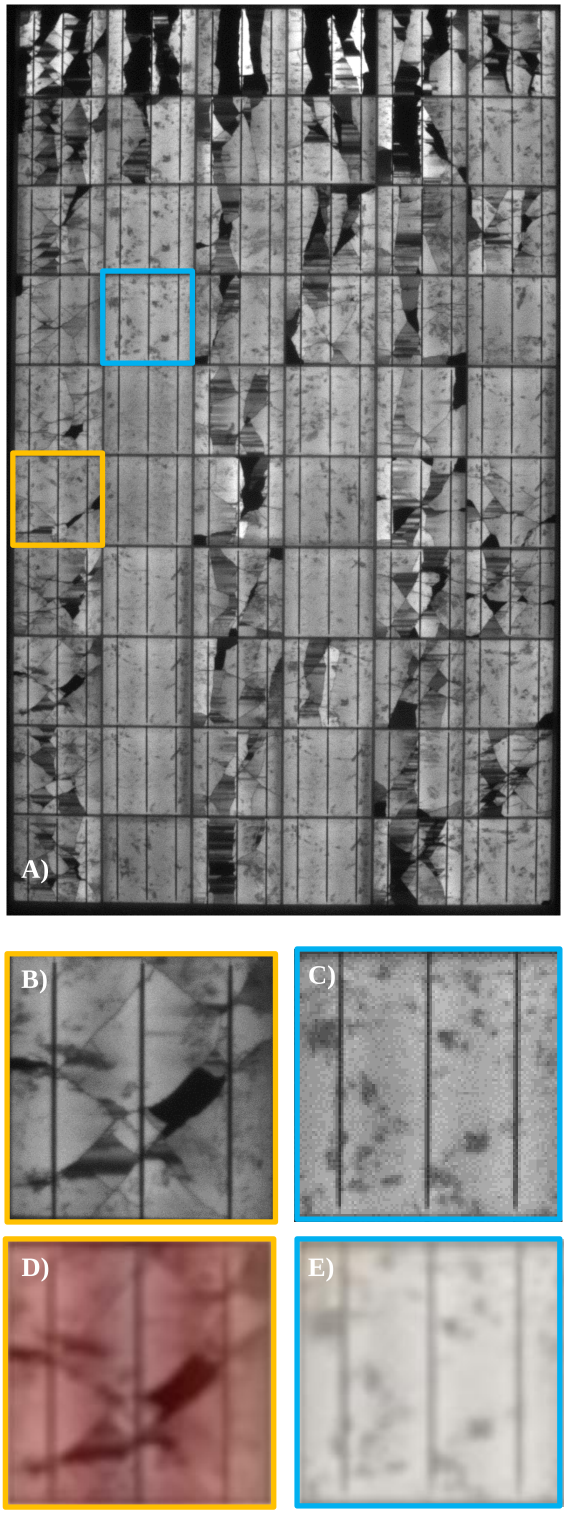


**Fig. 3**: A) EL image of one of the used 44 PV modules. B) Magnification of cell A8 (yellow) with defects. C) Magnification of cell B4 (blue) without defects. D-E) corresponding magnification of the cells with defect likelihood color grading.

**Tab. 1**: Amount of the corresponding labelled EL images of each category of defect likelihood.

| defect likelihood | mono-crystalline | poly-crystalline |
|---|---|---|
| **0%** | 588 | 920 |
| **33%** | 117 | 178 |
| **67%** | 56 | 50 |
| **100%** | 313 | 402 |

When training an automatic classifier on this dataset, the class imbalance should be taken into consideration. This can be done, for instance, by down-weighting the categories with large numbers of samples.

For the quantitative evaluation of the visual inspection methods on our dataset we suggest several metrics. The accuracy (in percent) can be used to determine how well the method in question identifies various categories in the dataset. The accuracy is the fraction of true positives (TPs) and true negatives (TNs) with respect to the total number of samples.

Given the imbalance of categories in the dataset, an alternative is the F1-measure which combines both the precision and recall in terms of their harmonic mean [6].

A receiver operator characteristic (ROC) curve created by plotting the true positive rate against the false positive rate can be used to visualize the behavior of the classification method at different thresholds. The area under the curve (AUC) of the ROC curve aggregates classifier's performance into a single scalar and specifies its overall discriminative power (in percent) [7].

Finally, a 2-dimensional confusion (or error) matrix can provide insights into understanding in which categories errors are mostly made and how systematic are these errors. For a confusion matrix, the actual labels are plotted against the labels predicted by the visual inspection method in terms of number of samples corresponding to this combination. Ideally, only the diagonal elements of the matrix would contain non-zero entries.

We also suggest to compute the metrics per type of solar modules, i.e., individually for monocrystalline and polycrystalline. These annotations are also included in our dataset. The discrimination of described metrics between the two module types allows to determine whether the visual inspection method works more accurately for specific type of solar wafers.

## *RESULTS AND DISCUSSION*

We used the dataset to train a deep regression network end-to-end directly on image pixels using the provided labels. We used 75% of the images (1,968 cells) for training and 25% (656 cells) of the images for testing. We used a pretrained VGG [8] architecture consisting of 19 layers and further refined it using the training data.

The resulting network is able to discriminate between various defect probabilities at accuracy of 88.42%. The F1-score is 88.39% and the ROC AUC is 94.7%. This indicates that the trained deep regression network is able to differentiate various defects with a high accuracy.

## *CONCLUSION*

The dataset of the 2426 labeled EL images of single PV cells supports the development of fast and effective evaluation algorithms for the detection of defective, performance relevant solar cells. The presented network is able to detect various defect probabilities for cracks, fracture interconnects, PID and cell quality with an accuracy of 88.42%.

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## *REFERENCES*

[1] M. Köntges (2014) IEA.
[2] K. Bothe, et al., 21st European Photovoltaic Energy Conference (2006) 597.
[3] Y. C. Chiou, et al.; Sens. Rev 31 (2011).
[4] S. Deitsch, et al.; Solar Energy (2018) to be submitted.
[5] S. Deitsch, et al.; Solar Energy (2018) to be submitted.
[6] D. D. Lewis, HLT '91 Proceedings of the Workshop on Speech and Natural Language (1991) 312.
[7] T. Fawcett; Pattern Recognition Letters 27 (2006) 861.
[8] K. Simonyan, et al.; CoRR abs!1409.1556 (2014).