UNSW: UNSW – R&D Project – Advanced Silicon – Lower photovoltaic cost by a combination of luminescence images and machine-learning

INTERIM PUBLIC DISSEMINATION REPORT

Project Details

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Executive Summary

Due to the abundance of solar resources, photovoltaic has a key role to play in reducing global carbon emissions. In this project, we use machine learning to fasten the binning process of solar cells, automatize the fault classification to increase the throughput of production lines, and reduce the damp heat test time which otherwise takes 1,000 hours.

Luminescence images are used for the characterization of solar cells. They may also have information about the solar cell electrical parameters. However, there is no easy approach to extract this information. Here, we have used machine learning to extract the solar cell electrical parameters. We found that cell efficiency strongly correlates with image features and the efficiency can be predicted using only luminescence images with an R^2 of 0.93 and a root mean square error (RMSE) of 0.10%. Moreover, these images can also be used for fault classification using machine learning. Our approach can predict faults with an F1 score of 98.3% and an accuracy of 99.6%.

The most important factor for the success of these machine learning approaches is the dataset. A large number of images is required to train the algorithm. These datasets should be clean, and correctly labeled. Once the model is trained on one type of dataset, it should only be fine-tuned before using it for another type of dataset. Image resolution and present noise also play a key role in model performance.

During this reporting period, we have published **three peer-reviewed journal papers** and **nine conference papers**. Moreover, one of the papers received the **Best Student Award** at IEEE PVSC 2021 conference and one bachelor student received the **Best Thesis Award** for their outstanding work and results.

All the work during this project was done on electroluminescence (EL) images. Our plan is to extend this work and transfer the acquired knowledge for photoluminescence images (PL). Moreover, we are also working towards the implementation of the developed methods to the solar cell production lines.

Aim of the project

At the end of any solar cell production line, the electrical properties of cells are measured using the state-of-the-art current-voltage (I-V) measurements. I-V testers need to be constantly updated as the cell technology changes. Moreover, their throughput is limited compared to the current demand of the industry. Therefore, this project aims to replace I-V testers with a machine learning-based method using luminescence images.

To increase the overall module efficiency, underperformed cells need to be identified and rejected accordingly. Simple inspections are used for this process which is time taking and requires an expert to perform this task. Therefore, this project aims to automatize this process using machine learning which would increase the throughput of the production line.

Degradation of modules is an inevitable part of their life cycle. Damp heat degradation is performed to check the reliability and durability of modules. These tests can take 1,000 hours.

Therefore, to reduce the time taken for this test, we use a deep learning-based algorithm to predict the extent of degradation using the information before and during the test.

Key findings:

1. **Luminescence images strongly correlate with the electrical parameters of solar cells.** Luminescence images have spatial information about cells. In this project, we found that they also have information about solar cells' electrical parameters and show a strong correlation with them.

2. **Images can be used to predict the efficiency of full solar cells.** From previous key findings, luminescence images have information about solar cells' electrical parameters, therefore, they can also be used to calculate efficiency. We used machine learning to extract this information and found that we can predict solar cell efficiency with an R^2 of 0.93 and RMSE of 0.10 %.

3. **Images can be used to predict the efficiency of half solar cells**. A current trend in the industry is using half-cell instead of full-cell structure. Therefore, we also investigated the efficiency prediction using luminescence images and machine learning for half-cut cells. A high-precision prediction with an R^2 of 0.88 has been achieved.

4. **Sorting can be performed with an ML-based approach.** Solar cell sorting is performed to bin them according to their efficiency. The state-of-the-art method I-V tester is used for this purpose. Since they are expensive to maintain and need to be upgraded with the fast-growing solar cell industry, we used an ML-based approach and found that sorting can be performed with an ML-based approach using luminescence images. On average, the difference in module output power created using sorted cells from I-V and ML-based approach is 0.002%.

5. **Fault classification can be automatized with ML.** Millions of cells are being processed every day in solar cell production lines. Defective cells need to separate from being used in a module. Therefore, a fault classification task is performed. Currently, simple inspection is used for this task which is time-taking and expensive. Therefore, we used machine learning-based algorithms to automatize the task and found that fault classification on solar cells can be achieved with an F1 score of 98.3% and an accuracy of 99.6%.

6. **To localize the faults in cells, a tile-based approach can be used.** Fault classification predicts if a cell is faulty or not. However, we do not know the location of these faults on the cell to further push the automatization task. Therefore, we propose to use a tile-based approach to localize faults on the tile level. Tiles were created by splitting cells into 16 equal parts and these tiles are then treated as a separate image of solar cells different parts. By using the deep learning-based method, we classified faulty images as well as localize on the tile level. We achieved an F1 score of 78% and an accuracy of 82%.

Lessons Learnt

1. **A large number of datasets are needed to have high accuracy**. For a machine learning application, a large dataset is needed. The larger the dataset is, the better the performance of the developed model. Moreover, correct labeling of this dataset is also required. Incorrect labeling can penalize the model performance. Therefore, data curation and correct labeling procedure must be in place.

2. **The trained model should be used for the type of dataset they are trained on.** Once the model is trained on a dataset, it should be tested on the same type of dataset. If these models need to be used for a different type of dataset, then finetuning should be performed and these models should be closely monitored to inspect any deviation in the distribution of the dataset.

3. **Noisy and low-res images reduce the accuracy of the model.** Image quality should be good enough for the model to extract the required information. Noise and low-resolution images can make it difficult for the model to train and extract useful information.

Products, patents applied/granted and or publications produced

Journal Publications:

J1. H. R. Parikh, Y. Buratti, S. Spataru, F. Villebro, G. A. D. R. Benatto, P. B. Poulsen, S. Wendlandt, T. Kerekes, D. Sera and Z. Hameiri, “Solar cell cracks and finger failure detection using statistical parameters of electroluminescence images and machine learning”, Applied Sciences. 2020; 10(24):8834.

J2. Y. Buratti, A. Sowmya, R. Evans, T. Trupke, and Z. Hameiri, “Half and full solar cell efficiency binning by deep learning on electroluminescence images”, accepted Progress in Photovoltaic.

J3. Y. Buratti, A. Sowmya, P. Dwivedi, T. Trupke, and Z. Hameiri, “Automated efficiency loss-analysis by defect-free reconstruction of luminescence images using generative adversarial networks”, Under review.

Conference Presentations:

C1. Y. Buratti, A. Sowmya, R. Evans, T. Trupke, and Z. Hameiri, “End-of-line binning of full and half-cut cells using deep learning on electroluminescence images”, 47th IEEE Photovoltaic Specialists Conference, 2020, pp. 0133-0138.

C2. Y. Buratti, A. Sowmya, R. Evans, T. Trupke, and Z. Hameiri, “Deep learning on electroluminescence images for end-of-line binning of full and half-cut cells”, Asia-Pacific Solar Research Conference, 2020.

C3. Z. Abdullah-Vetter, Y. Buratti, and Z. Hameiri, “Localisation of solar cell defects in luminescence images using deep learning”, Asia-Pacific Solar Research Conference, 2020.

C4. Y. Buratti, Z. Abdullah-Vetter, A. Sowmya, T. Trupke, and Z. Hameiri, "A deep learning approach for loss-analysis from luminescence images," 2021 IEEE 48th Photovoltaic Specialists Conference, 2021.

C5. Z. Abdullah-Vetter, Y. Buratti, P. Dwivedi, A. Sowmya, T. Trupke, Z. Hameiri, “Localization of defects in solar cells using luminescence images and deep learning", 48th IEEE Photovoltaics Specialists Conference, 2021.

C6. P. Dwivedi, R. L. Chin, T. Trupke, and Z. Hameiri, “High-resolution luminescence imaging of solar cells using deep learning", Asia Pacific Solar Research Conference, 2021.
C7. Z. Abdullah-Vetter, P. Dwivedi, Y. Buratti, A. Krzywicki, A. Sowmya, T. Trupke, and Z. Hameiri, “Simplified analysis of internal quantum efficiency using machine learning", Asia Pacific Solar Research Conference, 2021.
C8. G. M. Javier, Y. Buratti, P. Dwivedi, T. Trupke, and Z. Hameiri, “Improving the Accuracy of Fill Factor Empirical Expressions for Modern Industrial Solar Cells", Asia Pacific Solar Research Conference, 2021.
C9. Y. Buratti, Z. Abdullah-Vetter, G. M. Javier, P. Dwivedi, T. Trupke, and Z. Hameiri, “A review of deep learning for defects classification in silicon cells and modules from luminescence images", Asia Pacific Solar Research Conference, 2021.

Ancillary Benefits

1. One of our PhD students funded by the ARENA grant received the **Best Student Award** at IEEE PVSC 2021.

2. One of our bachelor students won the **Best Thesis Award** for his work on fault classification and localization on tile level.

3. We created four Honour and Taste of Research (ToR) projects for UNSW top UG students that are based on this project.

Next steps

In this project, we have extracted information from electroluminescence images. For solar cell characterization, photoluminescence images are also used due to their contactless nature. We would like to apply all the knowledge acquired during this project to photoluminescence images.

During this reporting period, we developed unique characterization approaches and published results in a peer-review journal. Currently, we are in talks with our industrial partner to extend their characterization tool capability by integrating the developed approaches.