AI Product Business Proposal
Image Identification and Classification of Defective Photovoltaic Cells with Convolutional Networks and Support Vector Machine in Electroluminescence Images

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Business Goal

You'll need to describe what the product is, and how it will provide value to the *business*. It's important in this section to describe exactly what the product will *do* and why/how this helps the business. Focus on linking the AI/ML task to business goals such as increasing revenue or customer happiness.

Project Overview and Goal

Electroluminescence (EI) imaging is a practical method used to inspect defective solar cells in the photovoltaic (PV) modules. The EI imaging process provides a high spatial resolution providing the capacity of detecting up to the finest surface module defects. However, the EI image process is usually a time-consuming manual and expensive process. In addition, the process detecting the various types of defects requires expert knowledge.

The aim of this study is to provide samples of more feasible methods using two approaches for automatic detection of cell defects on PV modules in an individual image of a solar cell. The hardware requirements are for each approach depending on the application usage. The less-demanding hardware approach is rooted on manual generated features that are classified in a Support Vector Machine (SVM). An end to end stronger execution requires the more hardware-demanding Convolutional Neural Networks (CNN) running on a Graphics Processing Unit (GPU).

Business Case

Why is this an important problem to solve? Make a case for building this product in terms of its impact on recurring revenue, market share, customer happiness and/or other drivers of business success.

Photovoltaic (PV) solar energy recorded an exponential growth, in worldwide scale, over the last decade. Inevitably, mature PV markets are becoming highly competitive, boosting the need for research and development (R&D) on efficiency and reliability optimization, maintenance and fault diagnosis of key components, such as the PV modules. Indeed, a significant number of studies and technical papers have been published up today, based on an extensive feedback from both laboratory and real (field) investigations of faults and advanced diagnosis applications, especially for crystalline silicon (c-Si) PV modules. Undoubtedly, such experience is of particular interest for current PV plant operators, future investors, maintenance engineers and the R&D sector of PV industry. However, up today, such research, published in the form of reports, technical papers or even books, remains mostly dispersed and unclassified. This paper represents a comprehensive effort to review and highlight recent advances, ongoing research and future prospects, as reported in the literature, on the classification of faults in c-Si PV modules and advanced diagnosis in the field, by means of the increasingly popular method of Electroluminescence (EI). Degradation of PV modules can cause excessive overheating which results in a reduced power output and eventually failure of solar panel. To maintain the long term reliability of solar modules and maximize the power output, faults in modules need to be diagnosed at an early stage.   PV modules certified as per International Electro-technical Commission (IEC) standards have shown considerable degradation indicating the need to enforce quality control and review qualification standards for Indian climatic conditions if modules have to perform reliably for more than 20 years under field conditions. The outcome of the study will be of importance to enhance the knowledge of climate specific field PV degradation mechanism and to provide inputs to Indian/IEC standards, the improvements of which are being considered currently.

Application of ML/AI

What precise task will you use ML/AI to accomplish? What business outcome or objective will you achieve?

An automatic approach has been suggested for fault detection, classification and analysis. In this development phase, it is critical to ensure a long-term high quality of PV power generation. To achieve a sustainable development, the quality inspections have to be in place. It assures that expected commercial gains are caught and PV plants achieve a long service life. On-site testing of PVPS is very helpful to evaluate the real performance of the plant and diagnose the failures. When compared to other inspection methods, the most time-efficient one is Electroluminescence (EI) of the PV modules and also the electrical components.

Success Metrics

You'll also need to describe *how you'll know whether the product is successful*. Think about measurable, predictive, comparable, and benchmarked metrics for *business* success.

What business metrics will you apply to determine the success of your product? Good metrics are clearly defined and easily measurable. Specify how you will establish a baseline value to provide a point of comparison.

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Data

You should carefully consider how you will acquire the data to train your model, and issues that may arise during data collection. Important considerations include: buying data vs. collecting it, personally identifying information (PII) and data sensitivity, cost, and whether data will be continuously available or acquired in one large batch (and need to be refreshed).

Where will you source your data from? What is the cost to acquire these data? Are there any personally identifying information (PII) or data sensitivity issues you will need to overcome? Will data become available on an ongoing basis, or will you acquire a large batch of data that will need to be refreshed?

Both approaches are trained on 1,968 cells

Data Acquisition

Data are extracted from high resolution EL intensity images of mono- and polycrystalline PV modules.

Data Source

We propose a public dataset of solar cells extracted from high resolution EL images of monocrystalline and polycrystalline PV modules. The dataset consists of 2,624 solar cell images at a resolution of 300 x 300 pixels originally extracted from 44 different PV modules, where 18 modules are of monocrystalline type, and 26 are of polycrystalline type.

Model

When thinking about how you will build the model, will you use an in-house data science team because none of the out of the box platforms have your use case, or because you want the ability to control a particular aspect of your model? Frequently, when you use an external platform to build and host the model, their terms of service will require you to give them access to your data. Will this be an issue?

Model Building

How will you resource building the model that you need? Will you outsource model training and/or hosting to an external platform, or will you build the model using an in-house team, and why?

The investigated classification approaches in this work are SVM and CNN classifiers. Support Vector Machines (SVMs) are trained on various features extracted from EL images of solar cells. Convolutional Neural Network (CNN) is directly fed with image pixels of solar cells and the corresponding labels. The SVM approach is computationally particularly efficient during training and inference. This allows operating the method on a wide range of commodity hardware, such as tablet computers or drones, whose usage is dictated by the respective application scenario. Conversely, the prediction accuracy of the CNN is generally higher, while training and inference is much more time-intensive and commonly requires a GPU for an acceptably short runtime.

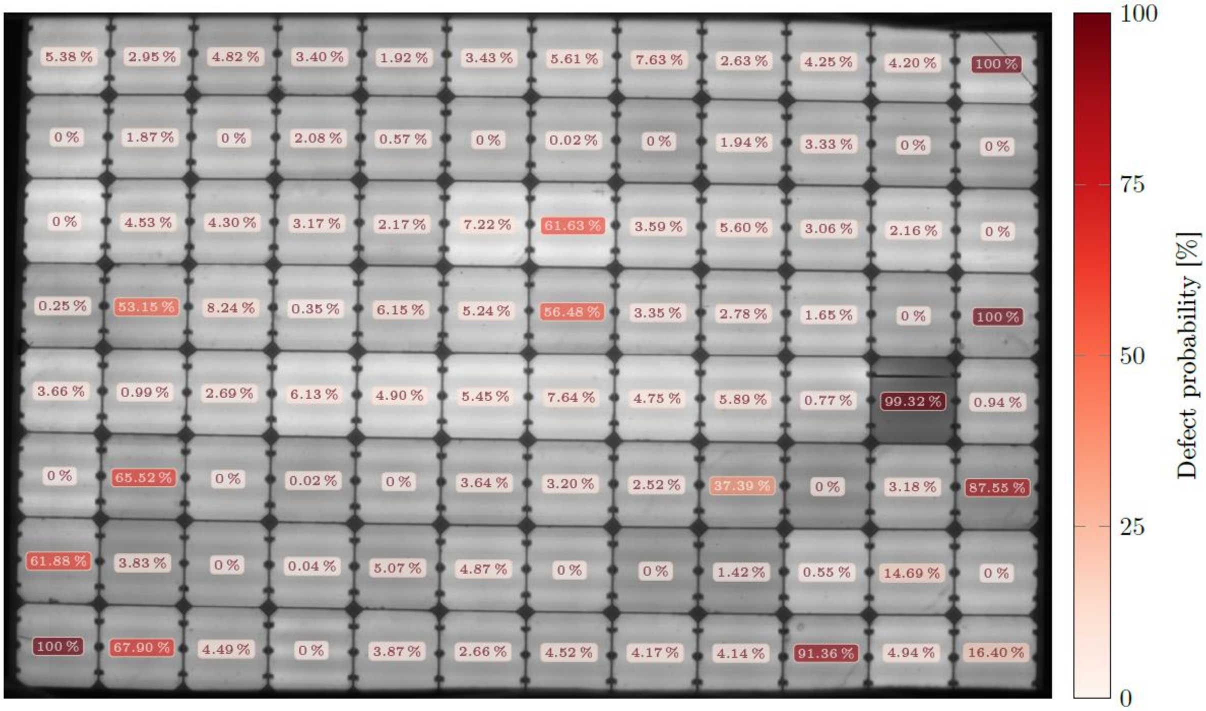

Figure 1: Defect probabilities inferred for each PV module cell by the proposed CNN. A darker shade of red indicates a higher likelihood of a cell defect.

The contribution of this work consists of three parts. First, we present a resource-efficient framework for supervised classification of defective solar cells using hand-crafted features and an SVM classifier that can be used on a wide range of commodity hardware, including tablet computers and drones equipped with low-power single-board computers. The low computational requirements make the onsite evaluation of the EL imagery possible, similar to analysis of low resolution IR images. Second, we present a supervised classification framework using a convolutional neural network that is slightly more accurate, but requires a GPU for efficient training and classification. In particular, we show how uncertainty can be incorporated into both frameworks to improve the classification accuracy. Third, we contribute an annotated dataset consisting of 2,624 aligned solar cells extracted from high resolution EL images to the community, and we use this dataset to perform an extensive evaluation and comparison of the proposed approaches. Figure 1 shows the assessment results of a solar panel using the proposed convolutional neural network. Each solar cell in the EL image is overlaid by the likelihood of a defect in the corresponding cell.

Evaluation Results

For the quantitative evaluation, we first evaluate different feature descriptors extracted densely over a grid. Then, we compare the best configurations against feature descriptors extracted at automatically detected key points to determine the best performing variation of the SVM classification pipeline. Finally, we compare the latter against the proposed deep CNN, and visualize the internal feature mapping of the CNN.

Which model performance metrics are appropriate to measure the success of your model? What level of performance is required?

The CNN is more accurate, and reaches an average accuracy of 88.42%. The SVM achieves a slightly lower average accuracy of 82.44%, but can run on arbitrary hardware. Both automated approaches make continuous, highly accurate monitoring of PV cells feasible.

For training both the linear SVM and the CNN a relatively small dataset of unique solar cell images was used. Given that typical PV module production lines have an output of 1,500 modules per day containing around 90,000 solar cells, models can be expected to greatly benefit from additional training data. In order to examine how the proposed models improve if more training samples are used, we evaluate their performance on subsets of original training samples since no additional training samples are available.

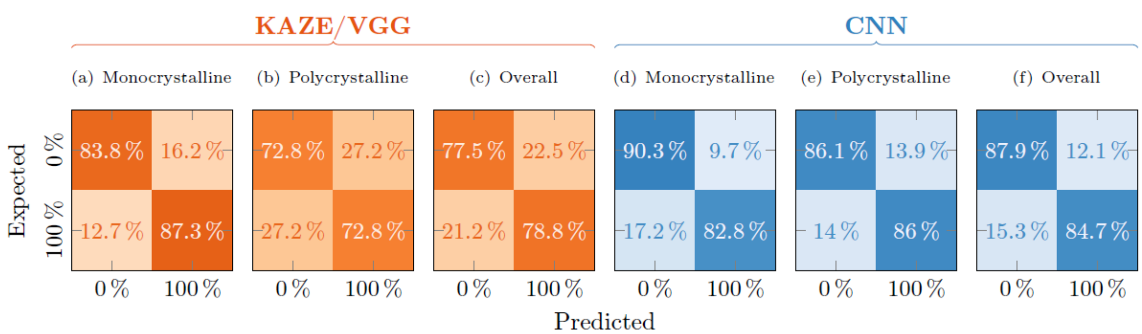

Figure 2: Confusion matrices for the proposed classification models. Each row of confusion matrices stores the relative frequency of instances in the expected defect likelihood categories. The columns, on the other hand, contain the relative frequency of instances of predictions made by the classification models. Ideally, only the diagonals of confusion matrices would contain non-zero entries which correspond to perfect agreement in all categories between the ground truth and the classification model. The CNN generally makes less prediction errors than an SVM trained on KAZE/VGG features.

Minimum Viable Product (MVP)

You'll want to think about *what your product* ***is***. What does it look like? Who uses it, and how do they use it? How will you actually build it?

Design

What does your minimum viable product look like? Include sketches of your product.

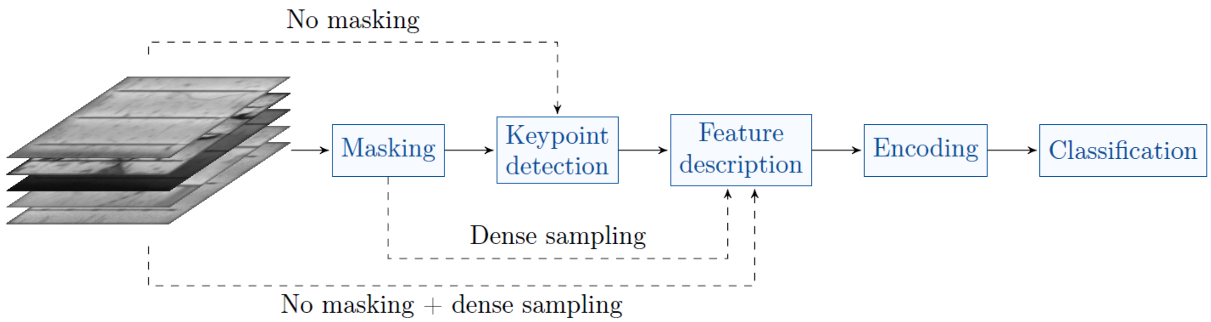

Figure 3: An overview of the SVM classification pipeline with the four proposed variations of the preprocessing and feature extraction process.

Use Cases

What persona are you designing for? Can you describe the major epic-level use cases your product addresses? How will users access this product?

Roll-out

How will this be adopted? What does the go-to-market plan look like?

Organizing for scale using machine architecture and thinking through organizational structure. Beginning with AI and developing a small POC auto pilot project in one area. Then proceed with expanding AI across the organization (acknowledging: storage challenges, network challenges, & compute challenges). Storage challenges are related because you are dealing with huge volumes of data. Network challenges because you want your model to be performed. Then you have compute challenges because you have really powerful infrastructure to run you models. So well define machine architecture is a key component here. And as you scale AI across your company you may take different approaches. You may build AI innovation center where you have centralized pool of AI and machine learning experts. Then you can span out to different business units solving different problems using machine learning. It needs a lot of cross-functional coordination and planning in order to be successful. You can repeat this process as necessary, and as you continually improve different versions of a model.

Post-MVP-Deployment

Finally, what happens after launch? How do you ensure your product continues to perform well? Who will monitor it, how will they monitor it, and how often?

How might you improve your product in the long-term? How might real-world data be different from the training data? How will your product learn from new data? How might you employ A/B testing to improve your product?

It is very common to send about 20% of your customers to a new model (v2, a "challenger" model) and 80% to a well-tested model (v1, a "controlled" model). This way, you can get some good experimental data and really see if the v2 of your model does indeed work better; if it does, you can then switch all user traffic (100%) to that new model.

Designing for Longevity

Monitor Bias

To infer the performance trend, we evaluate the models on three differently sized subsets of original trainings samples. We used 25%, 50% and 75% of original training samples. To avoid a bias in the obtained metrics, we not only sample the subsets randomly but also sample each subset 50 times to obtain the samples used to train the models. We additionally use stratified sampling to retain the distribution of labels from the original set of training samples. To evaluate the performance, we use the original test samples and provide the results for three metrics: F1 score, ROC AUC, and accuracy. Figure 4 shows the distribution of evaluated scores on all samples of the three differently sized subsets of training samples used to train the proposed models. The distribution of all 50 scores for each of the three subsets is summarized in a box plot. The results clearly show that the performance of the proposed models improves roughly logarithmically with respect to the number of training samples which is typically observed in vision tasks.

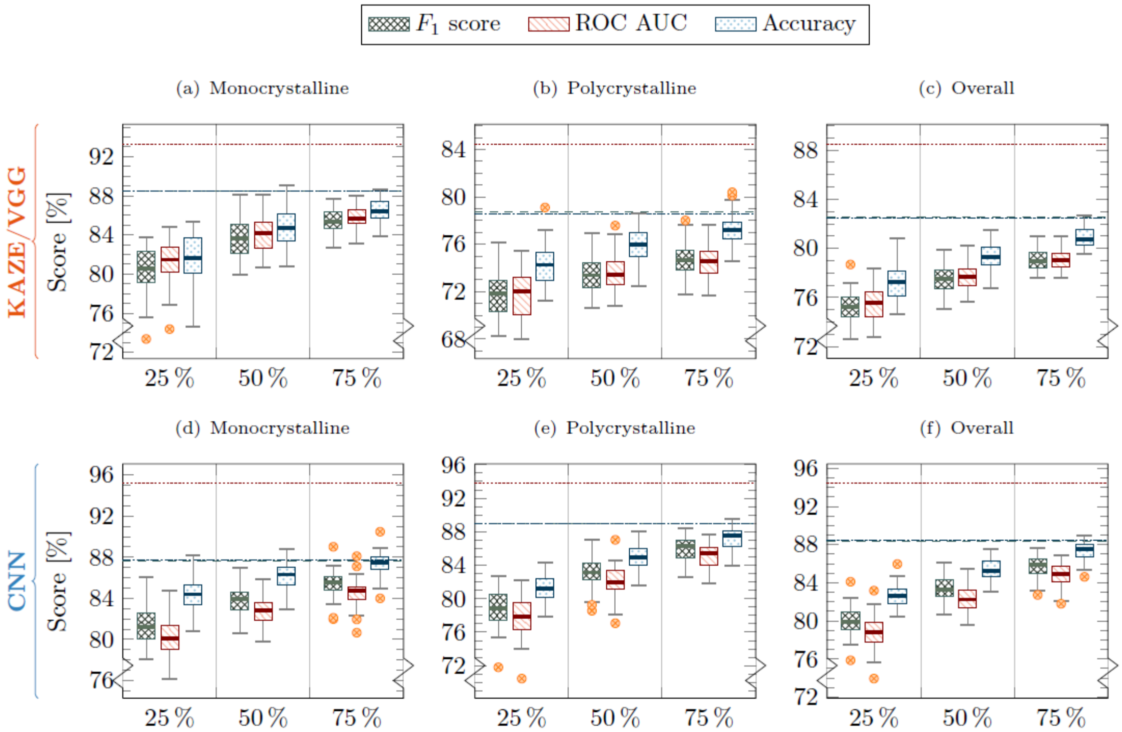

Figure 4: Performance of the proposed models trained on subsets of original training samples. The results are grouped by the solar wafer type (left two columns) and the combination of both wafer types (last column). The first three plots in the top row show the distribution of evaluated metrics as boxplots for the linear SVM trained using KAZE/VGG features. The bottom row shows the results for the CNN. The horizontal lines specify the reference scores with respect to the F1 measure ( ), ROCAUC ( ), and the accuracy ( ) of the proposed models trained on 100% of training samples. The circles ( ) denotethe outliers in the distribution of evaluatedmetrics given by each boxplot. Increasing the number of training samples directlyimproves the performance of both models. The improvement is approximately logarithmic with respect to the number of training samples.

How do you plan to monitor or mitigate unwanted bias in your model?

Monitor the accuracy, performance, and fairness of AI models by understand the reasoning behind the results.