Analysis of Electroluminescence Data Imaging using Physical Models and Machine Learning

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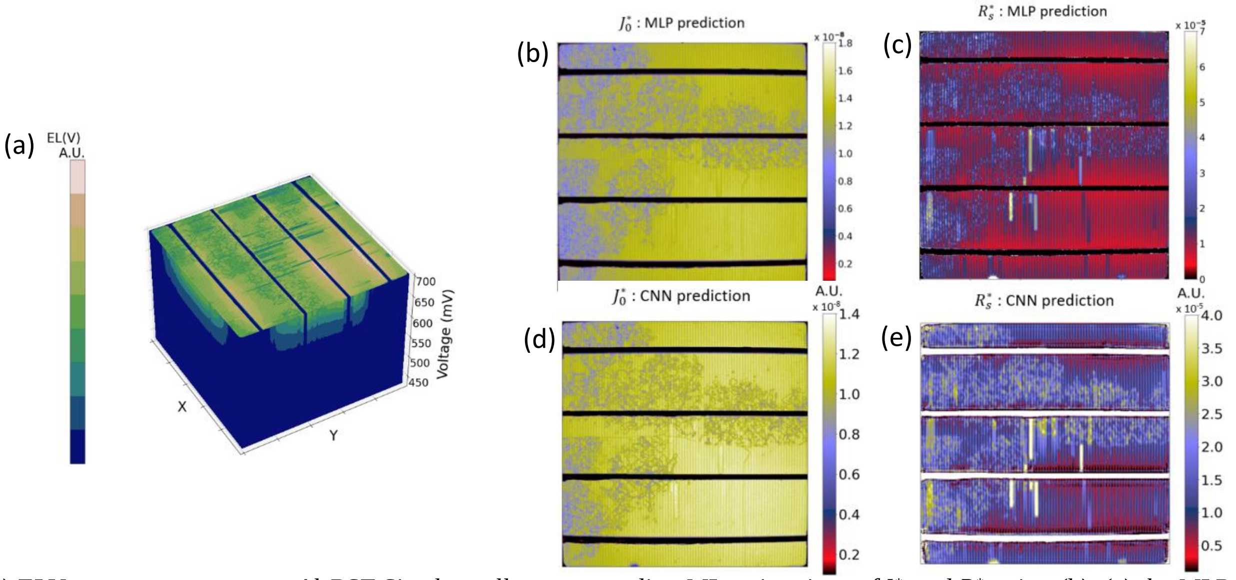
Electroluminescence (EL) imaging is a powerful and widely used tool for the spatially resolved characterization of solar cells. Using voltage-dependent electroluminescence (ELV) measurements for a comprehensive characterization of solar cells is beneficial, but it results in substantial data cubes that can be challenging to manage. Advanced data analysis techniques, such as Machine Learning (ML), have proven their efficiency in dealing with such large data. Furthermore, a physical model allows to accurately analyze ELV measurements on silicon solar cells and to derive two parameters, a pseudo-recombination current J_0^* and a pseudo-series resistance R_S^*, through fitting [1]. Several solar cell's local characteristics, namely the series resistance, the dark saturation current and the diffusion length, can be deduced from these parameters provided that the optical properties of the measurement set-up and some of the solar cell's material characteristics are known [1]; this study will concentrate on the determination of R_S^* and J_0^*. With the physical model, it becomes possible to numerically generate a significant amount of ELV data, enabling supervised training of ML models for regression tasks.

In this work, we focus on two ML architectures: the Multilayer Perceptron (MLP) and a Convolutional Neural Network (CNN) [2]. For each structure, two separate models, one for J_0^* and another for R_S^*, are trained independently, ensuring that the predictions of the two parameters remain independent. The MLP conducts a pixel-wise analysis of the data cube, using an ELV curve as input to predict either R_S^* or J_0^* whereas the CNN model processes the entire cube as input and produces a parameter map. With these ML techniques, a few seconds are necessary to predict the parameters maps for a 250 000 pixels input whereas obtaining equivalent results with classical regression methods such as least squares fitting requires few hours.

Both architectures permit efficient regression on large data cubes. They perform well, even when trained on numerically generated data rather than experimental data. This type of advanced modeling suggests possibilities for the analysis of both new technologies such as perovskites but also for application to other luminescence methods generating data cubes such as Hyperspectral Imaging.



(a) ELV measurements on an Al-BSF Si solar cell, corresponding ML estimations of J_0^* and R_S^* using (b), (c) the MLP architecture and (d), (e) the CNN architecture.

[1] Daniel Ory, Nicolas Paul, Laurent Lombez; Extended quantitative characterization of solar cell from calibrated voltage-dependent electroluminescence imaging. J. Appl. Phys. January 28, 2021

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