Easy-to-use Image Segmentation Powered by Machine Learning

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To generate knowledge it is no longer sufficient to just acquire images. Extracting meaningful information and data from images is the new challenge today's researchers have to face. Although there are performant automated evaluation and measurement tools available, they often require segmented data as input, which hinders their application. Achieving a segmented dataset is not always straight-forward and can be a tedious task. In this contribution we present a new software module that provides image segmentation using machine learning techniques.

The most common ways for segmenting images are probably simple thresholding and watershed algorithms. These work well on clean and noise-free data, which unfortunately is not always the case for microscopic images. Machine learning based approaches have shown huge potential to overcome these issues since they can be trained to tolerate a certain amount of variance in the input data. However, these approaches are not easy to use and afford expert image analysis skills to apply them correctly. Therefore, special care was taken during the development of the presented software module that it can be used by basically everybody. Users of any skill level can be trained to operate the software and perform advanced image segmentation within minutes. The software module is seamlessly integrated in the microscope's acquisition and analysis software framework for direct access. It works with any image data covering 2D and 3D datasets from light-, electron-, ion- or x-ray-microscopes and can even deal with 6D datasets by high-end light microscopy.

The segmentation process is illustrated in Figure 1 on the example of a cross-section SEM image of a copper indium gallium selenide (CIGS) solar cell (Fig. 1, left). Based on a subset of the input data the different classes present in the image are defined and a segmentation model is trained. To train the model it is necessary to manually label regions in the image with their respective classes (Fig. 1, center). This is done in an intuitive training user interface (UI) using a simple painting tool. No other parameters have to be set. The resulting segmentation is shown immediately (Fig. 1, right). The user can check the result and decide on further refining and retraining the model in an iterative manner. Once the segmentation result is perfect, the model can be used for segmentation of the same kind of data repeatedly. In the presented example, the different layers have been clearly segmented and can be well distinguished. This data would be ready for further analysis of e.g. the layer thickness or homogeneity. The model was able to deal with the crystallographic contrast visible in the ZnO contact layer as well as with the droplets visible in the CIGS layer which are artefacts stemming from the FIB preparation. A similar segmentation result would have been difficult to achieve via thresholding or watershed techniques, which would have misinterpreted the multifold contrasts and artefacts in this data. [1]

References:

[1] Visit www.zeiss.com/zen-intellesis for further information and your free 30-day trial version.
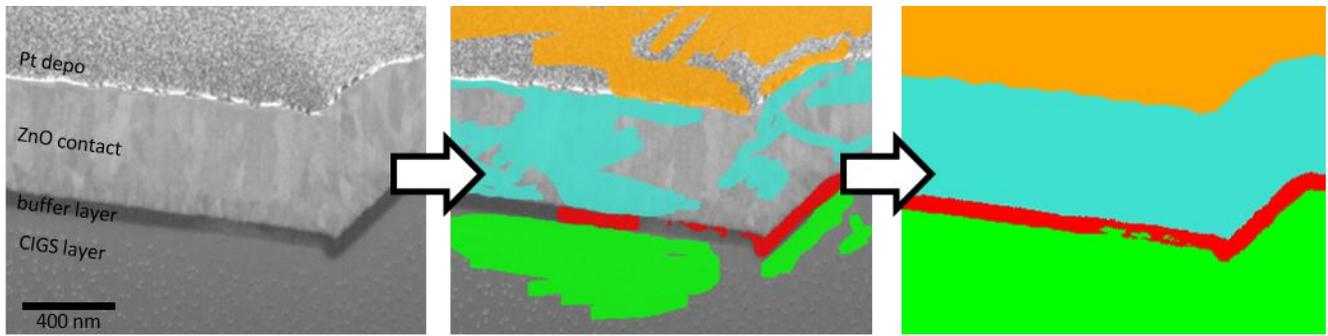
Figure 1. Segmentation workflow illustrated on the example of an SEM image of a FIB cross-section of a CIGS solar cell. The original image (left) has been labeled (center) to train a model for segmentation of the different layers. The result of the segmentation is shown on the right.