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Image Segmentation Methods for FIB-SEM Images of Cathodes

Performance, reliability, and safety of lithium-ion batteries play an important role in many industrial and consumer-oriented applications. Detailed images of battery cathodes at the nano scale can be obtained through FIB-SEM devices. In these images, active material and binder are easily differentiated and even the composition of the grains can be investigated. By their nature, FIB-SEM devices come with a disadvantage: the slice wise-obtained images show the current slice but also areas that are located behind pores, if the scanned sample is not infiltrated before imaging. Infiltrating samples is often avoided because it is a time-consuming task and might even change the structure of the material.

For numerical simulations and geometrical analysis, accurate 3D images of the sample are required. Therefore, the segmentation must be able to correctly differentiate the phases and to assign an area of a slice precisely to the current foreground or to the background. Adding to this challenge, the foreground is often affected by curtaining artifacts created by the Ion Beam.

Classical segmentation methods (e.g., global thresholding or watershed-based methods) struggle to segment these kinds of images properly. Here we compare state-of-the-art machine learning-based segmentation methods.

Andreas Grießer[1]*, Martina Hümbert[1], Christian Wagner[1], Ilona Glatt[1], Sarah Reeb[1], Robin White[2]

[1] Math2Market GmbH, Kaiserslautern, Rhineland-Palatinate, Germany.
[2] Carl Zeiss Microscopy, LLC, Business Sector Materials Science, Dublin, CA, United States.
* Corresponding author: andreas.griesser@math2market.de

Segmentation using Boosted Tree

The first method we apply is the Boosted Tree based segmentation.

This method is very similar to the original trainable Weka segmentation [1]. For each pixel that has been labeled, a set of features is computed and fed into a classifier, in this case a Boosted Tree [2]. Once the classifier is trained, it can be applied to all voxels of the scan to obtain the complete segmentation.

The selection of the features that are used can be quite critical to obtain a good segmentation. Finding the correct features may take some time.

The training of the Boosted Tree-based method is fast, but the whole process is dominated by the time required to compute the feature images. It requires less manually labeled data and no GPU is required.

In this case, the segmentation does perform well in segmenting the grain foregrounds from the pore space and the binder. The segmentation of the binder does not work yet to our complete satisfaction. In some areas, grains in the background are labeled as binder and part of the binder is labeled as pore.

Case 1: Boosted Tree Segmentation
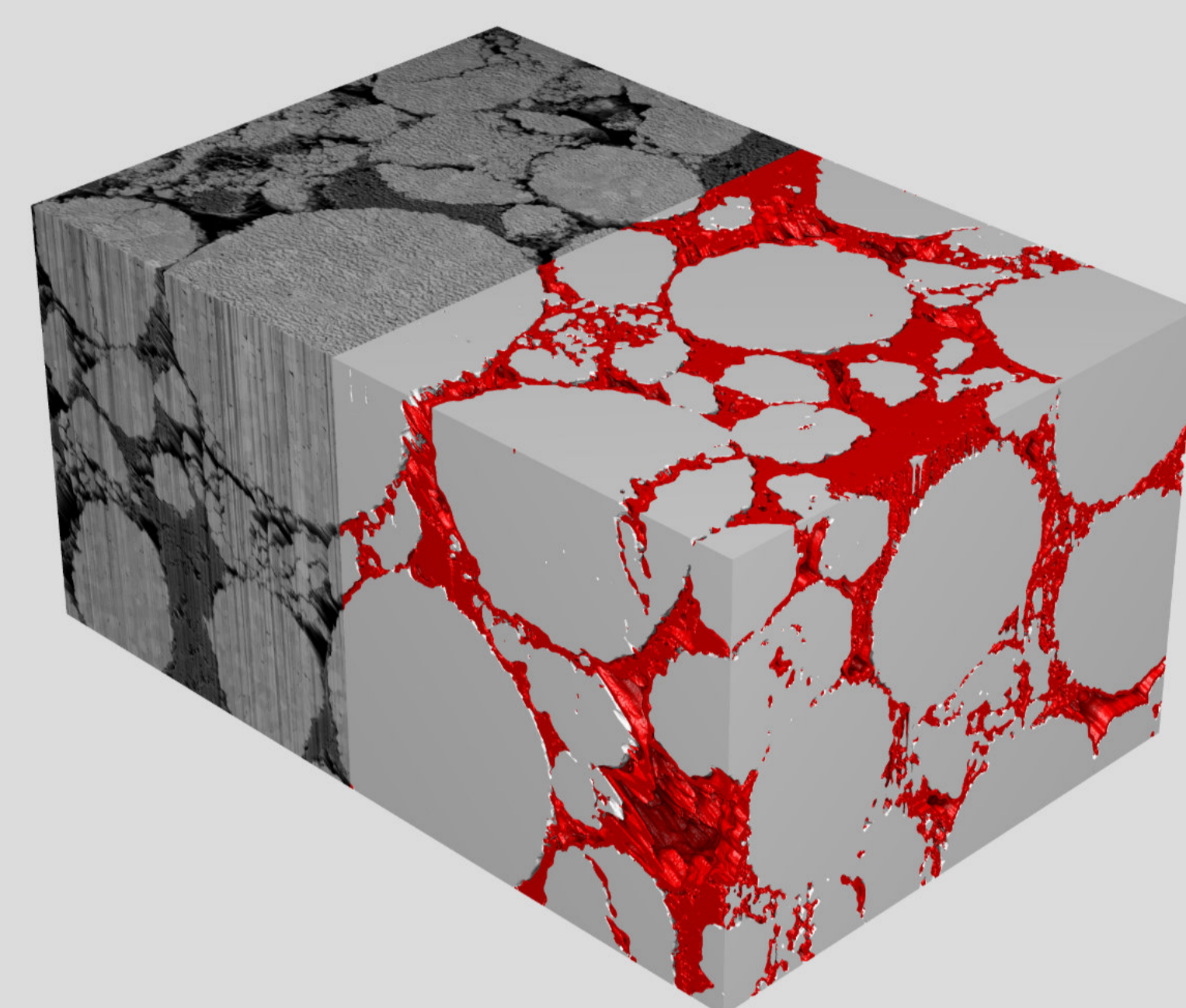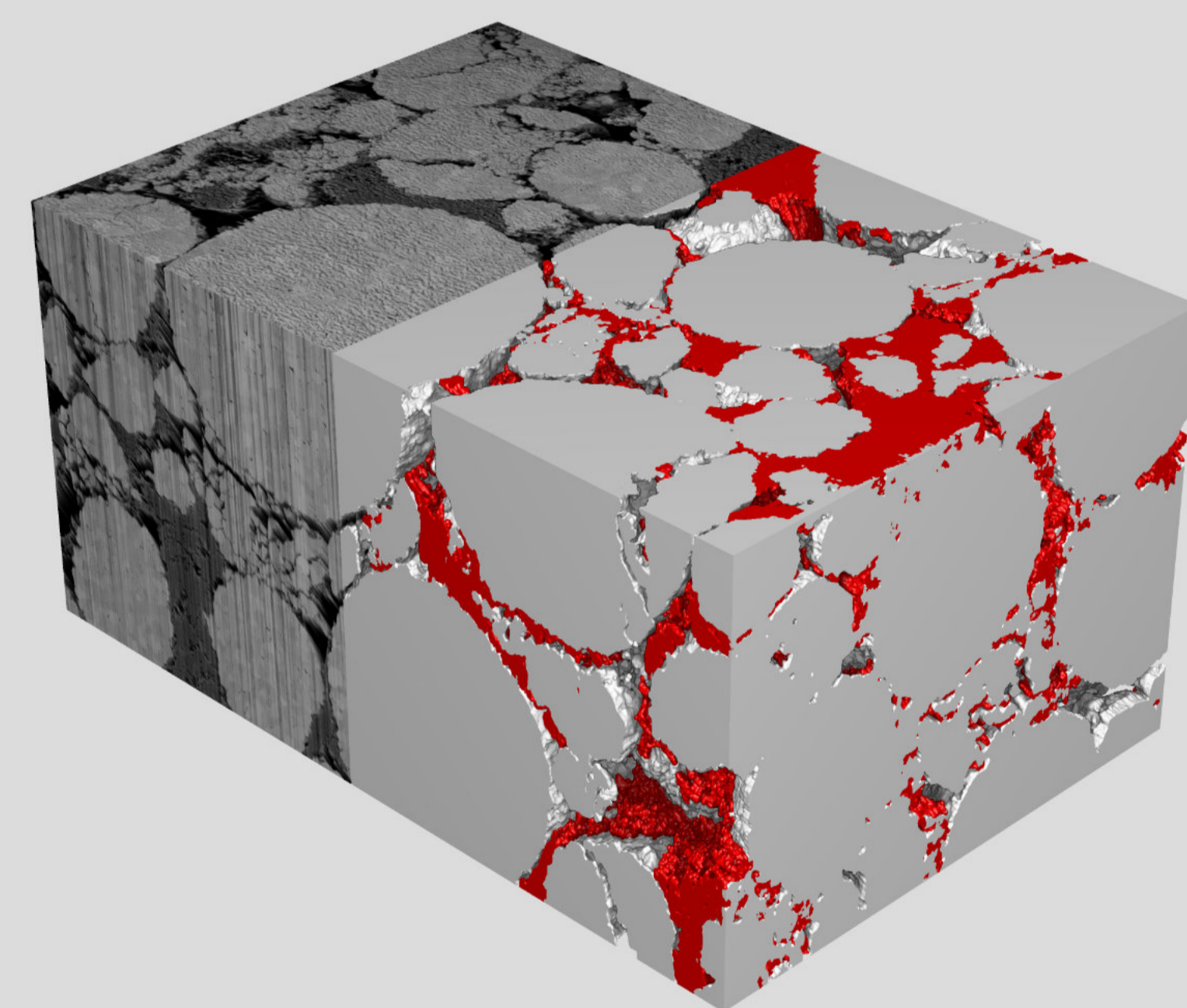
Segmentation using 2D U-Net

The second method we tested is a deep learning-based segmentation using a 2D U-Net [3].

U-Nets have been applied widely for the task of image segmentation. The most critical part for a segmentation with a deep neural network is the creation of the training data. We chose to train the network with sparse label data. This method allows the user to freely choose where to label areas in the 3D image without requiring full slices to be labeled.

Training the 2D U-Net takes significant more time then training the Boosted Tree classifier and requires a GPU to do the training on.

The 2D U-Net results for the grains are again very good. In some places, even better then the Boosted Tree results. Especially in places where heavy curtaining artifacts are present, the U-Net does perform better. For the binder phase, the results also look better compared to the Boosted Tree but there are still some artifacts in the segmentation. In some places discontinuities between the individually labeled Z-Slices occur.
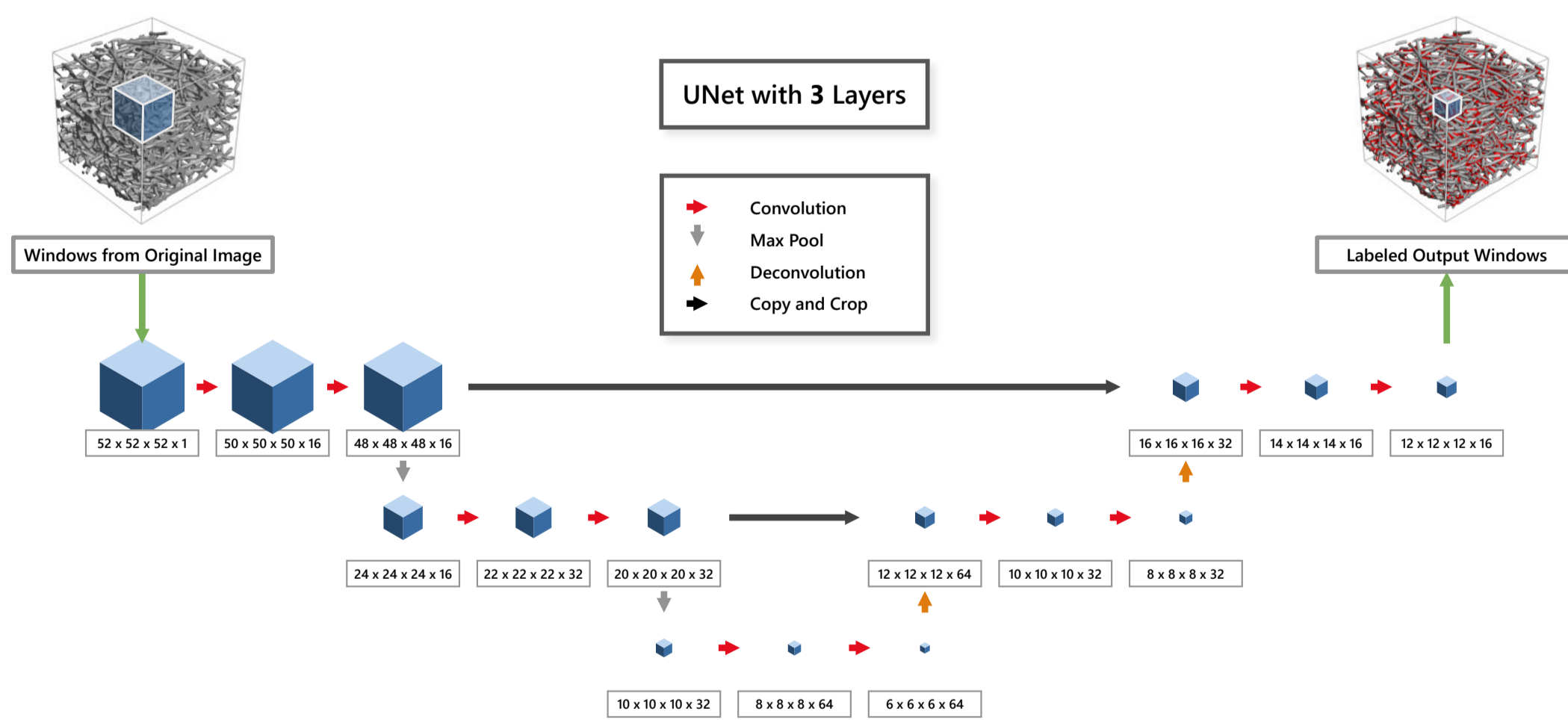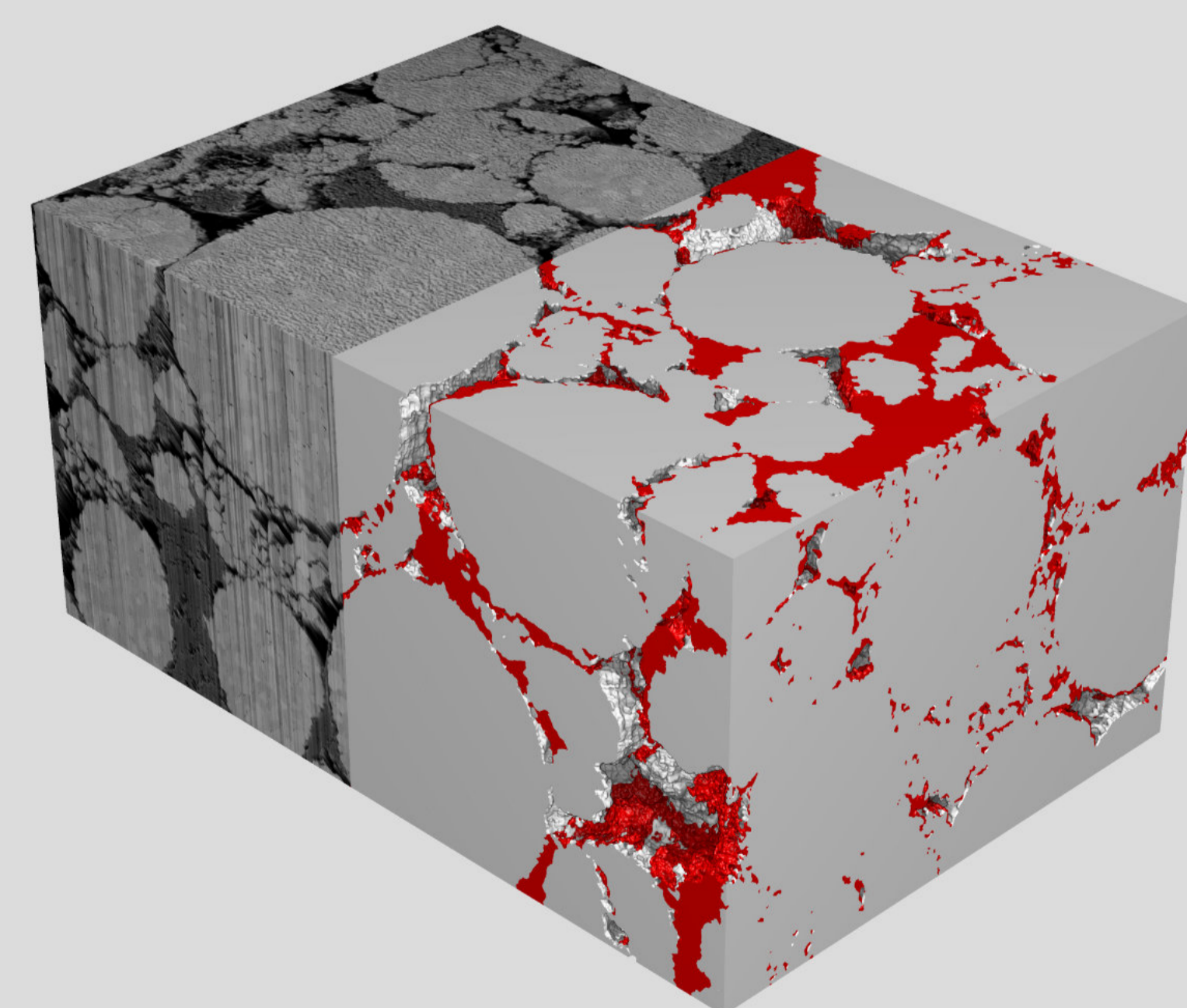
Case 2: 2D U-Net Segmentation

Segmentation using 3D U-Net

The last method we investigate is similar to the second one - a deep learning-based segmentation - but this time using a 3D U-Net [4] instead of a 2D one. The requirements regarding the training data and the used training method are identical to the 2D U-Net. Due to the increased complexity of the neural network in 3D, some more training data might be required to obtain good results.

We did use mostly identical training data as in the 2D U-Net case and only added labels in consecutive slices in some areas (~5% more labels) to profit from the 3D context. The training times under these conditions are similar to the second case.

The results for the grains are again very similar and no advantage can be observed. In the binder phase, the 3D U-Net does perform better. There are no discontinuities between slices due to the 3D context awareness.

Case 3: 3D U-Net Segmentation

UNet with 3 Layers

Convolution
Max Pool
Deconvolution
Copy and Crop

Windows from Original Image

Labeled Output Windows

Better segmentation means accurate results

SUMMARY

Modern segmentation methods bring many advantages for the analysis of FIB-SEM images. In this comparison of segmentation methods, we did only deploy image processing methods that can be carried out by non experts. The only handicap of these methods is the need to manually label the training data, since this step takes time and may introduce human error in the results.

1. Import
2. Segment
3. Analyse
4. Develop
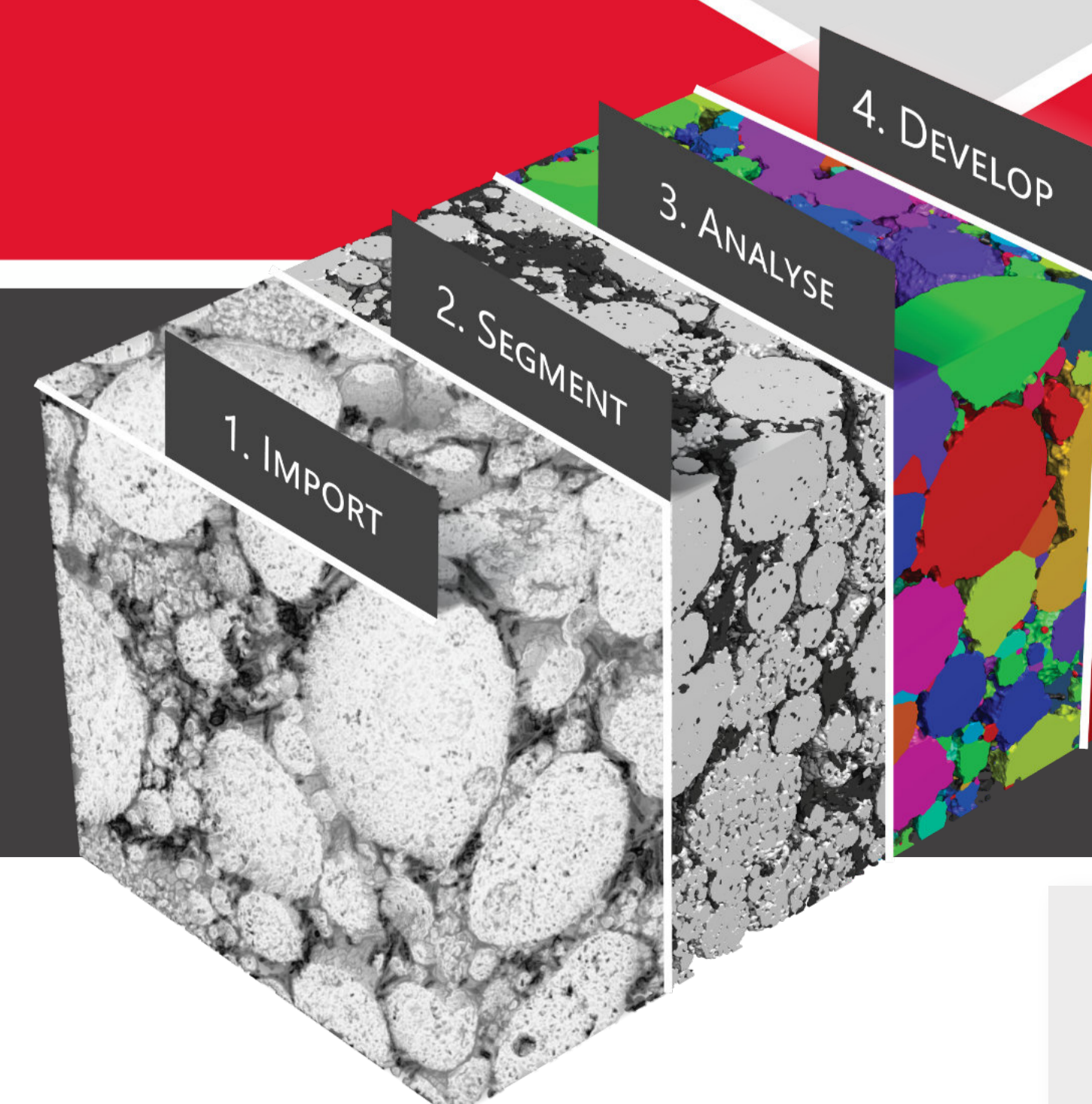
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