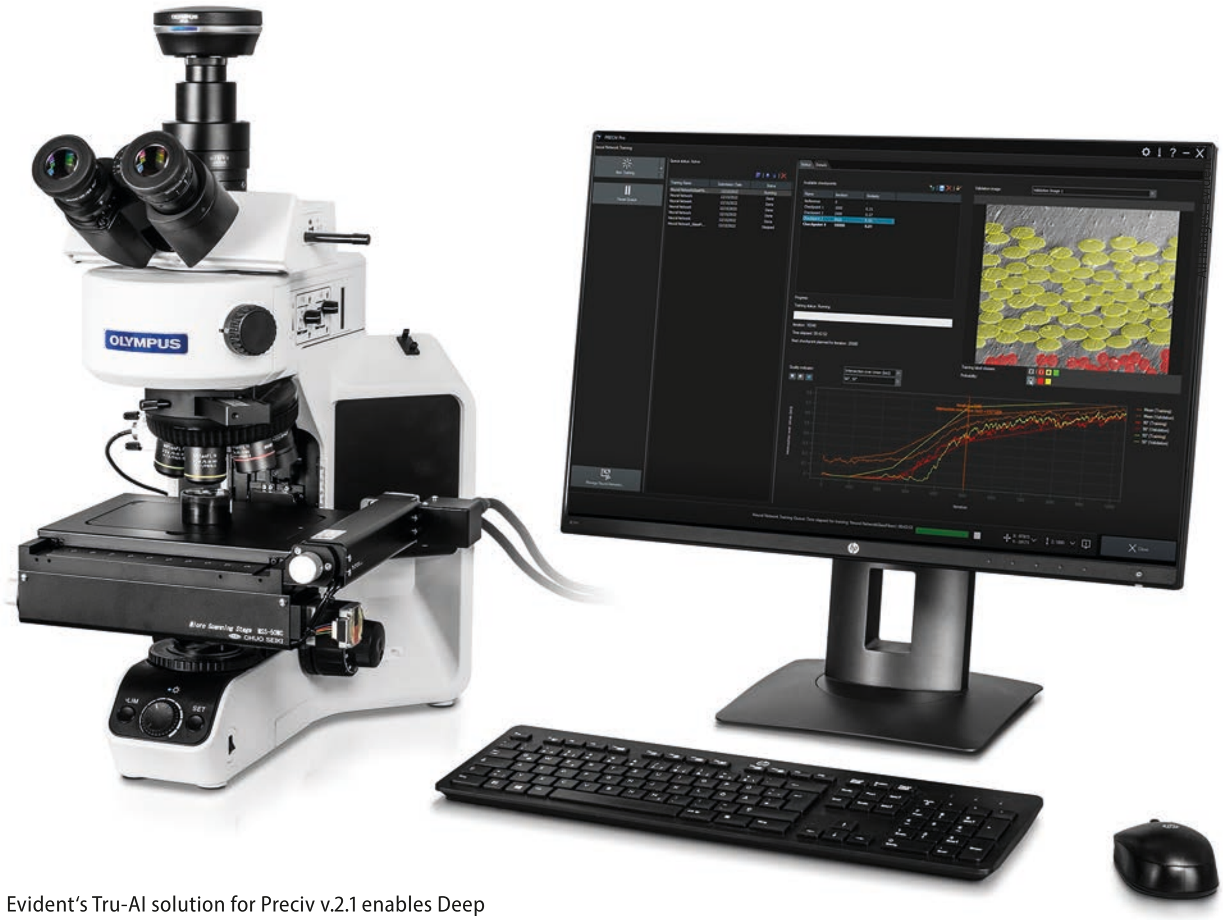

Evident's Tru-AI solution for Preciv v.2.1 enables Deep Learning to be applied to industrial image analysis.

AI-supported microstructure analyses in metallography

Material analysis is automated using neural networks.

Annegret Janovsky and Christina Hesseling

The use of artificial intelligence (AI) enables metallographic images to be analyzed with manageable effort, especially if grain boundaries and grinding marks are to be distinguished. A microscope manufacturer explains how a neural network is constructed and used.

Conventional threshold-based analyses are carried out as a standard method in digital image processing. These analyses are often specified as a requirement in standards for the microstructure analysis of metals, alloys, ceramics, composites, and other materials. Although image thresholding is an established method, it has some limitations.

Thresholding cannot distinguish specific structures in the images as it detects multiple objects at once. Analytical algorithms apply additional approaches – such as edge enhancement filters, shading correction, and morphological analyses – to find specific structures. However, those approaches require programming skills and effort to enable automated analyses. Furthermore, they cannot solve any problems taking into account the potentially huge number of special cases and exceptions [1]. In contrast, machine learning forms rules for object recognition based on multiple examples of representatives of the objects of interest.

AI-assisted image analysis

Image analysis assisted by artificial intelligence (AI) promises to solve many problems associated with analytical approaches. Deep artificial neural networks which have learned to classify image areas independently of threshold values previously set in the image support automated evaluation making a new world of easier and more accurate image analysis accessible. In metallography and materialography laboratories, AI-assisted image analysis revolutionizes everyday work.

There are several differences between the threshold method and an automated evaluation based on AI. A metallographic sample with grain boundaries, polishing marks, and dust is suitable to illustrate them (**Fig. 1a**). With the simple threshold setting, the image analysis software cannot clearly distinguish the grain boundaries from the polishing marks and dust (**Fig. 1b**). Since it is impossible to detect only the grain boundaries the size of the grains is not measured correctly.

The assistance of AI allows to distinguish traces of grinding, polishing, dust, and residues from objects of interest, such as grain boundaries, in images of polished sections (**Fig. 1c**). AI-assisted image analysis can detect grain boundaries in microstructures with reliability and reproducibility even if the grain structures are very inhomogeneous. In addition, structural components can be classified with pixel accuracy.

A standard workflow

A subfield of machine learning is supervised learning; it comprises all methods designed to predict or classify an outcome of interest. These methods use labels to clearly specify which features the learning model should detect [2, 3]. Thus, the resulting algorithm is based on the labeled data. However, the algorithm should not fit the training data too closely. Otherwise, the algorithm correctly detects objects in the training data but might fail to perform on new data with the same quality. For deep-learning-based image analysis, the labeling of data requires creating images with "ground truth" – the information with which the neural network is trained and evaluated [4]. This information must be marked in the images through image processing or must be labeled manually. In addition, specialists have to verify the training data. Only a specialist is able to define the suitable data for the training of the neural network: Experts in the material analysis application can determine the details of interest in the image.

Using the example of a metallographic section, the specialist might ask the following questions:

- When is the feature considered a grain boundary?
- How do we evaluate abnormalities?

It is important that the data represents all expected objects and mappings within each class.

Optimal training conditions

After this first phase, the second step is to select the optimal training configuration for the task using instructions for augmenting the training data [5] and selecting the training model. Augmenting the training data supports the training: The neural network model gets significantly more opportunities to learn and increase its reliability. For example, the training data is multiplied by rotation, mirroring, and other image operations. It is important to figure out the augmentation methods applicable in the specific situation. For example, rotation is useful for structures with no preferred direction but not for elongated materials such as rolled materials.

In deep learning, an artificial neural network with a given structure is created; how the network decides is hidden: no analytical justification is provided. However, a specialist can validate the training success by cross-checking if the results from an analysis fit the expectations. There are validation data sets to compare how well the trained artificial neural network recognizes the specified image areas.

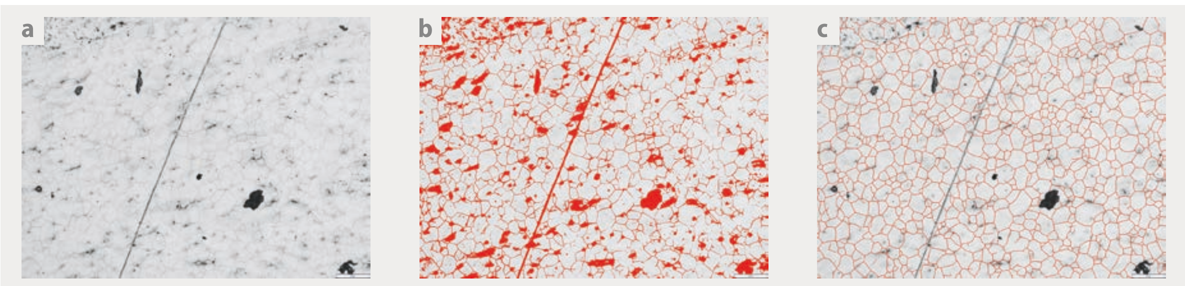

Fig. 1 The image of a metallographic sample shows grain boundaries, polishing marks, and dust (a, black). The threshold method highlights these features (b, red). However, grain boundaries cannot be distinguished from polishing marks or dust. If the image is analysed by Deep Learning, the grain boundaries (c, red) can be clearly recognized and distinguished from polishing marks and dust (black).

It is important that the validation data is not part of the data set used to train the network.

The network is able to generate a probability map which can overlay labeled validation images during the training process. A numerical output helps to achieve a realistic assessment of the training status: the values review the similarity of one quality criterion, such as loss, and compare between the training images and the validation images. They are presented as a graph. After training and validation, a new data set is used to check whether the algorithm still works on representative new data: the test data set. This final test must be verified by a specialist as well – or ideally by multiple experts – to reduce the risk of misinterpretations of AI results due to human bias [6].

After this last check, the trained neural network is available as a segmentation method that can be applied to comparable images, i. e., images with similar light and exposure conditions. Applying a properly trained neural network can be realized easily and efficiently. With a single click, the network automatically segments the image and delivers reproducible results.

Conclusion

It is possible to use supervised deep learning in metallographic and materialographic image analysis for clearly defined tasks, such as image classification, object detection, and image segmentation. A manageable effort by a specialist is essential for validating the marking of the ground truth in the training images, the test data set, and for checking the final evaluation test. If the artificial neural network is well trained, AI offers a powerful, reproducible image analysis on comparable images.

To learn more about the benefits of AI in microstructure analysis, go to *olympus-ims.com/landing/truai-technology*.

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