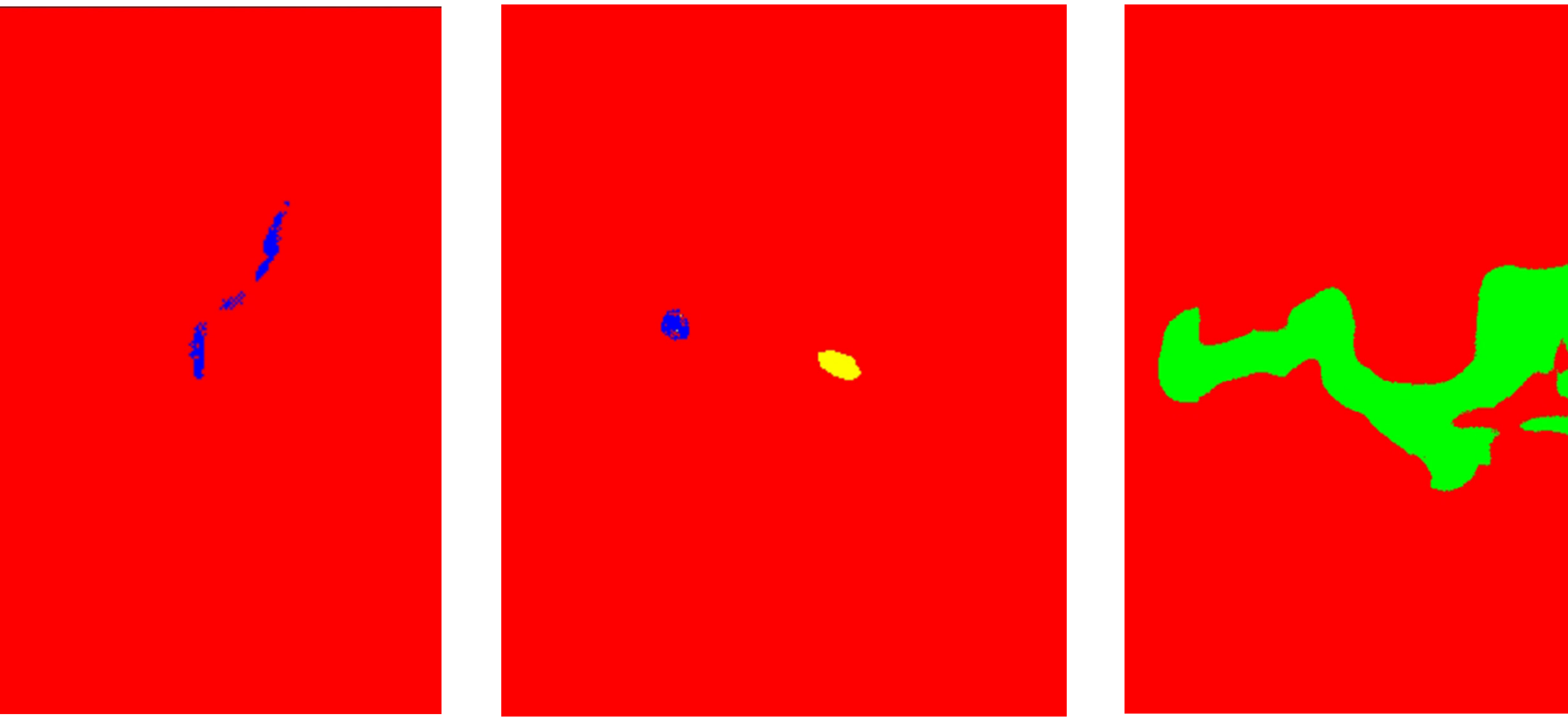
White Paper

Software-Based Segmentation of Metallic Inclusions of Additive Manufactured Alloys – Linking Microstructure and Materials Properties



Seeing beyond

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In this article you will learn how advanced image analysis techniques based on artificial intelligence (AI) are used for segmenting inclusions in a metal alloy. The microstructure of a printed lightweight high-temperature aluminum alloy, especially its inclusions, are characterized in a multimodal way connecting the findings of light and electron microscopy. In this experiment the software ZEN Intellesis, a module of the AI Toolkit of ZEN core and ZEISS arivis Cloud were used as image processing software.

Introduction

Gaining a deep understanding of the link between a material's properties and its micro- or even nanostructure is essential for developing novel materials. In this context a recent development in the field of microstructure characterization is highly beneficial: the introduction of machine learning (ML) for image segmentation and analysis. In this study it will be shown how robust and stable ML systems are used to characterize inclusions of additive manufactured high-temperature Al alloys. Correlative microscopy approaches between light and electron microscopy provide meaningful data needed to train ML-based segmentation. As a result, inclusions generated during the additive manufacturing process can be quantitatively identified.

Aluminum Alloys

Aluminum (Al) alloys are widely used in the automotive and aerospace industries taking advantage of their light weight and high strength properties. 70% of the structural weight of an aircraft stems from Al alloys, visible in wings and fuselage. At the same time, it is desired that the material withstands temperatures higher than 200 °C or even 300 °C. Traditional Al alloys generally lose a significant amount of their strength above 200 °C. So far, a temperature resistance up to 300 °C has only been achieved by conventional high-temperature alloys such as Al–Si–(Mg). Therefore, there is great interest in expanding this property to Al alloys as well.

Figure 1: *Wings and fuselage are made from high-temperature aluminum alloys*

Additive Manufacturing (AM) of Al Alloys

Laser-based additive manufacturing of aluminum alloys is very attractive for research and development in the automotive and aerospace industries due to the fast turnaround of low-volume parts and prototyping. Moreover, this technique allows complex components to be designed (e.g., lattice generation and topography optimization) and thus enables further weight reduction which is not possible with other methods. Therefore, powder-based additive manufacturing is being used more often for aluminum alloys. Defect-free parts have been printed recently, which promises substantial progress in the field of AM. Considering the printability of various Al alloys, this should also be possible for other alloys that can resist even higher temperatures compared to traditional Al–Si–(Mg) alloys. There is ongoing research aiming to introduce new systems for precursors suitable for AM and exhibiting the desired light weight and high-temperature (>300 °C) mechanical stability [1].

Linkage of Microstructure and Mechanical Properties

Microstructural design can be used to influence mechanical properties. Good examples are precipitation-strengthened alloys with thermally stable strengthening phases (HTPSAs). They are well known in the casting community and characterized by a nanometric strengthening phase. This phase is coarsening resistant up to ~400 °C and provides remarkable strength and creep resistance through the addition of the alloying element. An additional microstructure has to be considered, created by the AM process itself and by the general grain growth-related processes. However, the sum of both is relevant for the mechanical properties and for the performance of this material. Michi et al. 2021 give an overview of different microstructural features relevant for fatigue-crack initiation at elevated temperatures for AM Al alloys: near-surface porosity, lack of fusion defects, inclusions and hard particles, surface roughness, persistent slip bands, and melt pool boundaries [2]. In this study, the focus is kept on porosity and inclusions.

Figure 2: *SEM image of a cross-section of an additive-manufactured high-temperature Al alloy revealing its microstructure*

Segmentation

One of the most important but still partially neglected steps in quantitative microstructure analysis is the segmentation of the microscopic image. There are many techniques for segmentation ranging from classical, well-known simple histogram thresholding to traditional machine learning, augmented by deep learning. Recently, deep learning has proven to be very efficient at segmenting objects, especially against a busy background. These major advances based on machine learning have the potential to significantly improve data quality especially when compared to the classical threshold segmentation widespread in metals research and industry [3]. As the exact approach depends on the complexity of the application, this study highlights a segmentation workflow applied to metallic inclusions of AM Al alloys.

What is Machine Learning?

Machine learning gives computers the ability to learn without being programmed explicitly for a specific task, in this case image segmentation. Deep learning is a class of machine learning. The power of this technique is based on identifying the data representations through trained artificial neural networks. The complexity of the task determines what degree of training and artificial intelligence is needed to solve it successfully.

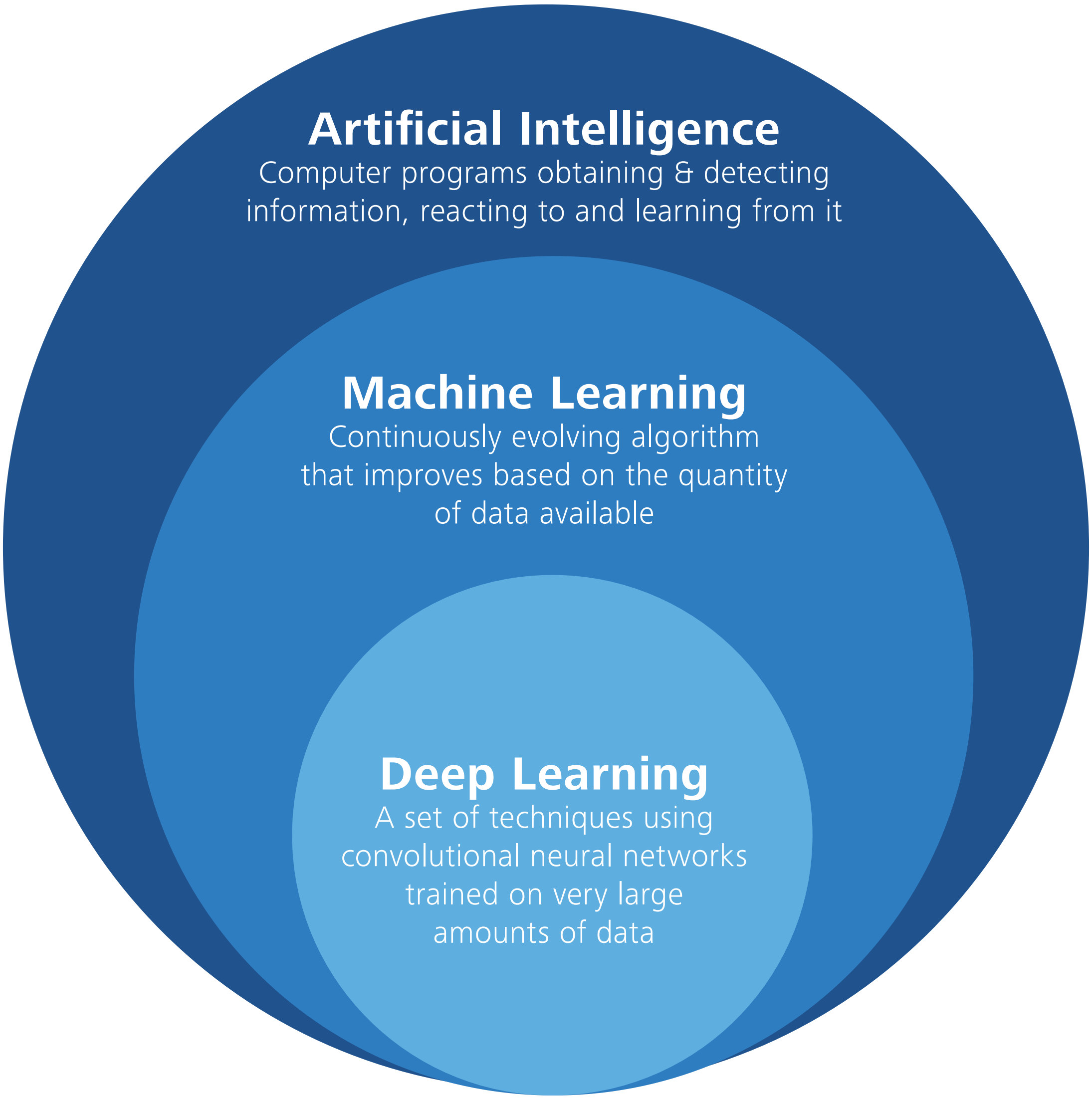
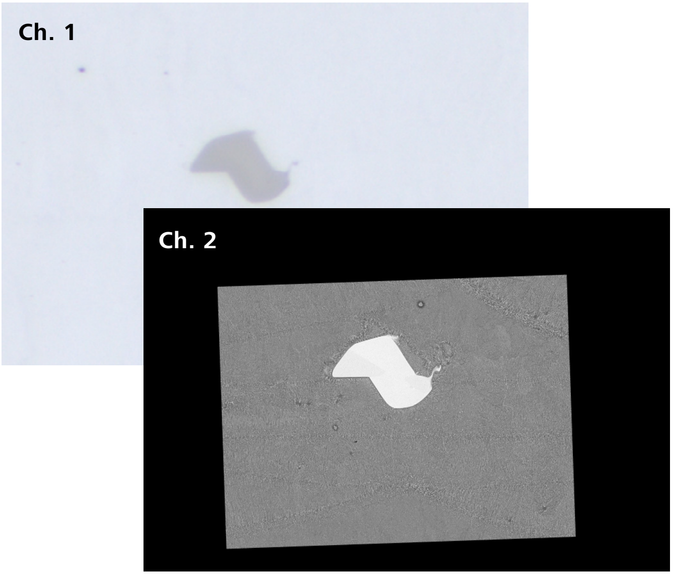


Figure 3: *Deep learning is a special subset of general machine learning, which is again a subset of artificial intelligence*

Machine Learning-based Segmentation in Material Science

As segmentation lays the foundation for all subsequent quantitative image analyses, it is the most critical component of any image analysis workflow. Software-based machine learning is used to train a segmentation model on inclusions in an aluminum alloy. Its goal is to identify different objects on the micrographs, in this case pores, Zr-In inclusions, oxide inclusions, and dirt from sample preparation. The software solution used here is ZEISS ZEN Intellesis Segmentation, a module of the image processing software ZEISS ZEN core.



ZEN Intellesis Segmentation is used to train a segmentation model taking both channels into account. The segmentation result can be split into individual binary image masks.

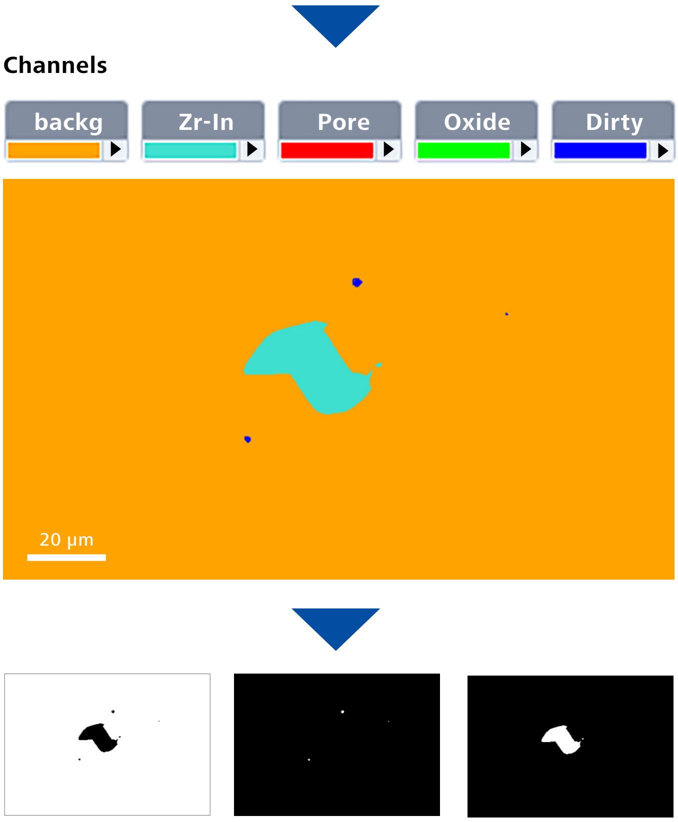


Figure 4: Segmentation using the information of two microscopic modalities, here called "channels": light microscope (LM) images and EDS maps acquired on a scanning electron microscope (SEM)

One strength of this approach is that the segmentation model only needs to be trained on one single image before it can be used to predict the pixel labels in other images taken under similar experimental conditions (Figure 4). Subsequently, the segmentation results need to be judged by an expert; the machine learning model is trained on a selection of pixels within an image chosen by an experienced microscopist. The user "labels" various pixels within the image which are associated to different classes with a few mouse clicks. This way, the experience of the user is leveraged during the labelling process to achieve a true ground [5]. In this experiment, light microscope images and EDS maps acquired on a scanning electron microscope were the basis for training the model. Using the information from both these channels increases the precision of the segmentation as it makes the complementary information accessible. Another advantage is that the resulting segmentation does not have to be trained as much compared to single channel data.

The knowledge based on EDS and SEM data is later used to segment the instances on the initially acquired LM images once the workflow has been finalized. The workflow encompasses three steps:

1) ML segmentation based on SEM and LM images resulting in binary image masks
2) Smart labeling with image masks for deep learning trained for the instances' segmentation
3) Using the trained model to identify different instances on LM images

Workflow for Identifying Inclusions in Alloys	Explanation
3. Identification of different types of inclusions in LM dataset	The trained model is used on LM images. Based on previously defined classes, different material inclusions or porosity can be identified in the LM dataset.
2. Deep learning based training with smart labeled training images	The use of smart labeled data allows deep learning on only a few images. Additional EDS information is used to classify different material inclusions or porosity as objects.
1. Machine learning based segmentation of inclusions	A model is trained for the precise segmentation of the inclusions using machine learning on LM images. Additional SEM images help to optimize the training results and efforts.
Correlative microscopy based image acquisition for training	A large area with several inclusions is located and imaged with LM. Correlated microscopy allows for relocating them in the SEM.

Figure 5: *Workflow for identifying inclusions in alloys: Starting with the acquisition of the LM dataset, after a sequence of machine- and deep learning the inclusions can be automatically identified*

At first, the instances are labeled as different objects, like pores and Zr-In inclusions. In the image analysis, those objects are treated as instances of one category. In a second step, they are segmented to recognize different sorts of inclusions. The machine learning alone is not powerful enough for this task. Additional deep learning-based segmentation is required. The final result is then used to identify different inclusions in an LM image.

Deep Learning-based Image Segmentation – Segmenting Different Objects

Deep learning-based methods have been applied to microstructural classification and have performed excellently at solving image classification problems. Those methods usually require several manually pre-labelled datasets to obtain meaningful results. Here, machine learning has been used to perform pixelwise image segmentation, which not only has the advantage of using precise, smart segmented labels but also forgoes the need to train a model on multiple images.

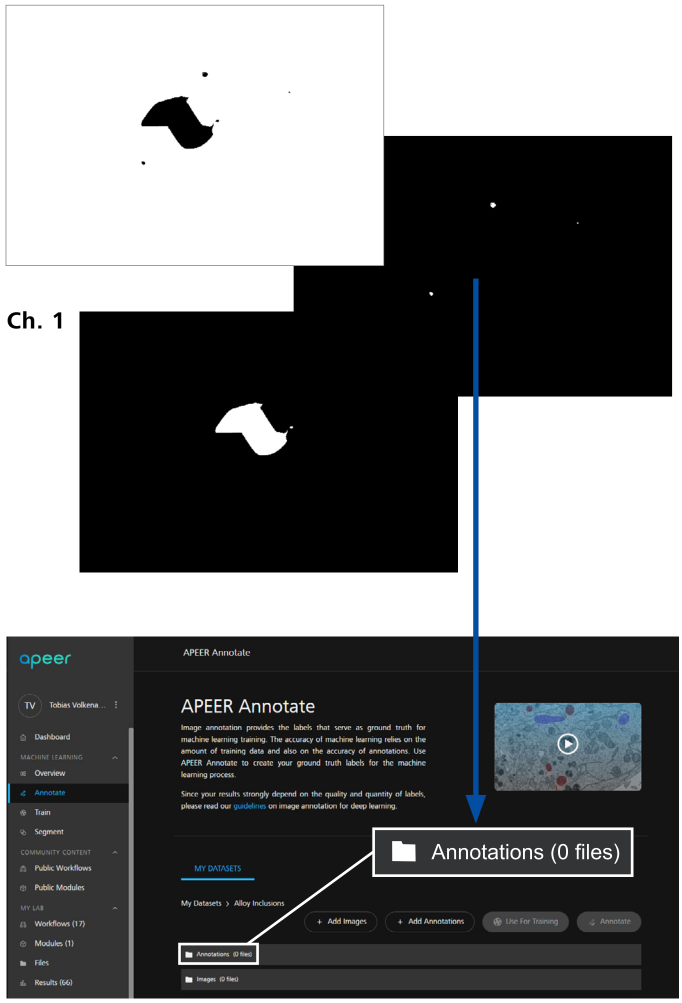


Figure 6: *Smart labeling – Intellesis segmented labels are used to train a deep learning model with arivis Cloud*

In special cases there are images that are too complex for certain deep learning algorithms. For these, the cloud-based image analysis platform arivis Cloud is utilized to fill the gap [6]. Tailored deep learning algorithms are used for segmentation needs. Subsequently, ZEN Intellesis can handle these advanced deep learning models created by arivis Cloud. Once the inclusions have been segmented, connected pixels are summarized as regions. These regions are analyzed and measured with respect to a variety of properties (e.g. diameter, orientation, intensity, roundness, etc.). All this information serves as input to train the object classification model. Based on the segmentation results from the first step, images are split into individual binary image masks. Those are used as labels to train the model. The inclusion type is assigned to a few particles manually in a labeling process similar to the one described above, simply by clicking the mouse. The additional information from EDS and SEM images is used to label the inclusion classes.

Figure 7: Segmentation of the different objects – blue: Zr-In inclusion; yellow: pore; green: oxide

ZEN Intellesis Segmentation can be used to execute machine learning models that have been trained elsewhere, e.g. on arivis Cloud. Python packages created by arivis Cloud are used to train a deep learning segmentation model. It uses images resulting from the segmentation performed within ZEN Intellesis Segmentation earlier – only with the LM images. The model will then be able to segment the inclusions based on the LM images alone. The automated analysis of the microstructure enables the qualification of various types of inclusions. Pores and inclusions can be recognized correctly. These results can be related to the mechanical behavior of the additive manufactured materials. To put the results into wider context, they can be visualized in ZEN core and used for further analyses.

Summary

Machine learning-based classification can be trained on one dataset, then applied across multiple samples to give repetitive, non-subjective results. The ability to classify based on features other than just local greyscale values, particularly the ability to classify based on textural information, has the potential of being transformative in the ability to extract information from images in materials research.

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[6] www.arivis.com

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