Exploring the Potential of Mask Region-based Convolutional Neural Network in Identifying Twins in Shape Memory Alloys

Juan Camilo Buitrago Diaz[1], Jeferson Piamba[2]
Manuel Forero[1], Mariana Ríos[3], Daniel Salazar[3]

[1]Semillero Lún, Facultad de Ingeniería, Universidad de Ibagué, Ibagué 730002-, Carrera 22 - Calle 67 Barrio Ambalá, Ibagué, Colombia.
[2]Facultad de Ciencias Naturales y Matemáticas, Universidad de Ibagué, Ibagué 730002, Colombia.
[3]BCMaterials, Basque Center for Materials, Applications, and Nanostructures, UPV/EHU Science Park, Leioa, 48940, Spain.

camijuan_321@hotmail.com

The precise characterization of crystal structures at the microscale represents a significant challenge in the fields of metallurgy and materials science. In this context, the utilization of advanced image processing techniques and machine learning has emerged as a promising strategy to address this complex issue. In this work we studied the potential of the Mask-RCNN convolutional neural network for the identification and segmentation of twinning regions in electron microscopy and metallographic microscopy images.

This innovative approach relies on the capability of convolutional neural networks (CNNs) to learn relevant features from images and perform segmentation tasks with high precision. Recent advances in computer vision have demonstrated the remarkable ability of CNNs to learn intricate image features and perform complex segmentation tasks with unprecedented accuracy [1]. These CNN-based approaches have been successfully applied across different areas, from medical imaging to remote sensing, showcasing their versatility and effectiveness [2].

In the specific context of materials science and metallurgy, CNNs have emerged as powerful tools for the analysis and characterization of crystal structures, including shape memory alloys. These alloys are particularly important due to their unique properties, allowing them to regain their original shape after deformation, making them ideal for applications such as biomedical devices and magnetomechanical actuators. Increasingly, these types of alloys are being studied, and the incorporation of machine learning to make manufacturing processes more efficient is growing [3].

By leveraging their ability to extract feature maps from images, CNNs enable researchers to delve deeper into the understanding of crystal structures and their properties [4]. Furthermore, the integration of knowledge between materials science and computer science has led to the development of advanced machine learning techniques, such as in hardness determination through image analysis [5]. This interdisciplinary approach capitalizes on the synergistic relationship between domain knowledge and computational methods, leading to more comprehensive and illustrative analyses of materials at the microscopic scale [6].

The proposed methodology involves implementing a supervised training process using a labeled dataset of scanning electron microscopy images. During training, the neural network learns to accurately identify and delineate grain boundaries, as well as segment twinning regions within these boundaries. Futhermore, an additional analysis method is developed to obtain detailed information on the direction of twinning formation.

The theoretical foundation of this study is supported by previous research demonstrating the effectiveness of convolutional neural networks in image segmentation tasks across various scientific and technological applications. Additionally, accumulated knowledge about the microstructural characteristics of crystalline materials [5] is leveraged to guide the training and validation process of the neural network.

Preliminary results have shown high accuracy in segmenting grains and the twinning pattern formation, allowing the determination of the inclination of each twinning family formed in each grain. The accuracy results are consistent with previous research demonstrating the potential of CNNs for segmentation tasks [6].

It is expected that the results obtained will contribute to the advancement of the analysis of crystal microstructures and provide valuable information for the optimization of metallurgical processes and the design of advanced materials, through the integration of materials science and computational science.

References

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Figures

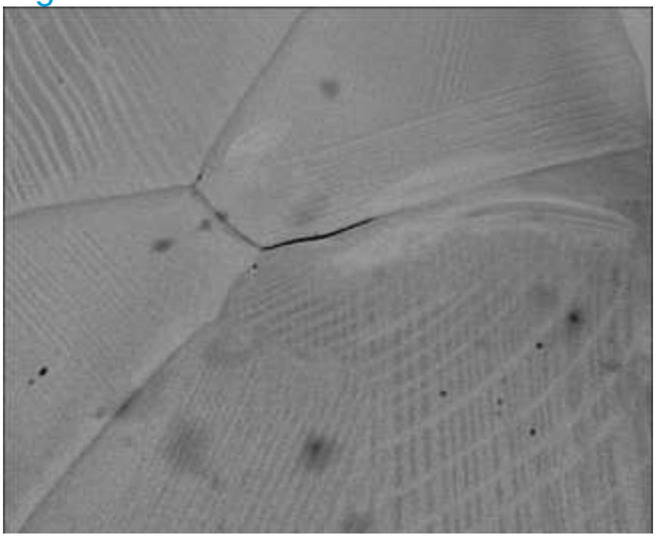

Figure 1. Original image where grain boundaries and twinning can be observed.

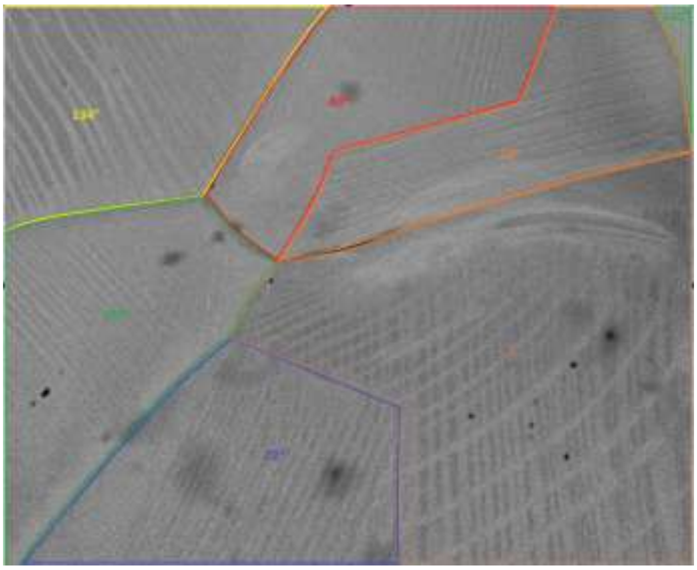

Figure 2. Grain boundary segmentation and twinning inclination angle.