AI-based Defect Detection and Localization in Laser Powder Bed Fusion

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Abstract

Metal additive manufacturing (AM), particularly laser-based powder bed fusion (PBF-LB), enables the production of complex, high-value components. However, layer-wise manual supervision remains time-consuming and costly, limiting large-scale industrial adoption. This study investigates artificial intelligence (AI)-based defect detection using in-situ monitoring data from both EOSTATE PowderBed and Exposure Optical Tomography (OT) systems.

A manually annotated dataset was constructed from multiple PBF-LB builds, including layer-wise powder bed images and OT thermal signatures. Four widely used convolutional neural network (CNN) architectures—ResNet50, EfficientNetV2B0, YOLOv5, and Faster R-CNN—were trained via transfer learning to evaluate classification and localization performance.

For defect classification, ResNet50 and EfficientNetV2B0 achieved robust performance, with EfficientNetV2B0 offering improved computational efficiency. For defect localization, YOLOv5 outperformed Faster R-CNN in both detection accuracy and inference speed, demonstrating strong capability in handling multi-scale and irregular defect morphologies. Lower average precision in object detection was primarily associated with defect size variability and annotation boundary uncertainty.

The results confirm the feasibility of AI-driven defect identification using both powder bed morphology and optical tomography data. The findings highlight YOLOv5 as a practical solution for real-time monitoring and demonstrate the industrial potential of integrating AI into EOS PBF-LB systems for automated quality control and reduced material waste.

Future work will focus on expanding dataset diversity and improving annotation consistency to enhance model robustness for deployment in industrial AM environments.

Keywords: Machine Learning; Defect Detection; Quality Control; Optical tomography; Metal Additive Manufacturing; Powder bed fusion; Object Detection