Chapter 12

Deep Learning-Based Defect Detection and Quality Assurance in Advanced 3D Printing and Microfabrication Processes

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ABSTRACT

This paper examines the utilization of deep learning models YOLOv8, ResNet-50, and U-Net together with real-time defect recognition and quality control in FDM (Fused Deposition Modeling) 3D printing. Printed part samples with high-resolution images taken at different stages of printing were annotated and used for training. The models were assessed using performance measurements such as precision,

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recall, F1-score, accuracy, and AUC-ROC. YOLOv8 performed the best across all measurements and is therefore best suited for real-time implementation. ResNet-50 provided high precision and moderate recall, and U-Net provided excellent recall but poor precision with the occurrence of false positives. The outcomes make YOLOv8 the most suitable for in-process quality control. The work showcases the potential of deep learning in improving the defect recognition process and reducing the occurrence of printing errors and the overall inefficiency of 3D printing.

INTRODUCTION

Over the past few years, the application of deep learning models in industrial processes, especially in 3D printing, has attracted significant interest because of its ability to improve production quality and efficiency. The fast development of 3D printing technologies, such as Fused Deposition Modeling (FDM), has introduced new challenges in ensuring consistent quality and detecting defects during printing, (Yazici, Shayea, & Din, 2023; Anandhakrishnan & Jaisakthi, 2022; Zjavka, 2022). Faults like layer misalignment, warping, and failed prints can have major implications for the end product's performance and functionality. Quality assurance for 3D printing has therefore become an imperative priority, and conventional manual inspection is shown to be both inefficient and impractical for mass production. Deep learning, with its capacity to handle lots of data and identify patterns, has been a potential solution to overcome these issues by allowing real-time automated defect detection and classification, (Singh et al., 2025; Hamid et al., 2023; Patro et al., 2023).

A number of deep learning models have been tried for 3D printing defect inspection, including convolutional neural networks (CNNs), segmentation networks, and object detection networks. CNNs such as ResNet have been applied with great success to image classification tasks, with high performance in the identification of defects in printed components. They are excellent at image feature extraction and learning image patterns that distinguish defective from non-defective parts, (Sahu et al., 2024; Garg et al., 2023a). But for tasks involving pixel-level precision, like detecting minor flaws in the print's surface or internal layers, models like U-Net, specializing in semantic segmentation, have been more effective. U-Net's image segmentation architecture allows the model to pinpoint defects with great accuracy, even in regions with high details.

By contrast, object detection networks such as YOLOv8 have been favored for carrying out both classification and localization tasks. Indeed, YOLOv8 is very fast and efficient and thus suitable for real-time defect detection in a dynamic manufacturing environment. This model not only classifies the presence of the defects but also provides the location of such defects in the 3D printed product. Its ability to