Chapter 3

AI-Powered Defect Detection Using Deep Learning Enhancing Industrial Automation with U-Net and YOLOv3

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ABSTRACT

This chapter explores the application of deep learning models, specifically U-Net and YOLOv3, in detecting crack-type defects in industrial materials. The research addresses key challenges, such as the limited availability of defective data samples, the difficulty of distinguishing fine defect details, and the need for precise quantitative evaluations in automated inspection systems. The chapter introduces the significance of defect detection in the context of smart manufacturing and discusses the limitations

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of traditional manual inspection methods. U-Net, known for its superior pixel-level semantic segmentation capabilities, is utilized for detailed defect localization, while YOLOv3, a real-time object detection model, is optimized for fast detection but has trade-offs in precision, particularly for irregular defect shapes. Both models are trained on a custom dataset provided by a material manufacturer incorporating a novel augmentation method that enhances generalization and improves detection accuracy by expanding defective sample diversity.

INTRODUCTION

A. Background on Recent Defect Detection System

The integration of Artificial Intelligence (AI) into industrial automation has significantly been transforming quality control processes, particularly in defect detection. Traditional manual inspection methods are often labor-intensive and prone to undesirable human error, leading to inconsistent product quality. In contrast, AI-driven systems offer enhanced accuracy, efficiency, and the ability to learn and adapt to new challenges automatically.

There are various types of quality control in manufacturing, including visual inspection, dimensional inspection, strength inspection, and performance inspection, but this chapter focuses on visual inspection. Recent advancements in deep learning, especially in CNN (Convolutional Neural Network), SVM (Support Vector Machine), YOLO (You Only Look Once) have further propelled the capabilities of automated visual inspection systems. Prunella et al. reviewed and introduced more than 220 relevant articles from the related literature published until February 2023, covering the recent consolidation and advances in the field of full automatic and deep learning-based surface defects inspection systems, applied to many industrial applications (Prunella et al., 2023). Recent studies have also explored novel deep learning architectures for defect inspection, including hybrid CNN-transformer models and self-supervised learning for anomaly detection (Pei et al., 2023).

The authors also have developed several defect detection systems on MATLAB. Additionally installed options are Computer Vision Toolbox, Deep Learning Toolbox, Global Optimization Toolbox, Image Processing Toolbox, Parallel Computing Toolbox, Statistics and Machine Learning Toolbox, and so on. For instance, Nagata et al. (2021), proposed a defect detection system using a convolutional neural network-based support vector machine (CNN-SVM) technique to enhance feature extraction and classification accuracy. Their approach demonstrated improved generalization ability and robustness in detecting micro-defects in industrial components (Nagata et al., 2021). Similarly, Zhang et al. (2021) introduced a novel automated visual