Chapter 1
3D CNNs for Smart Manufacturing Voxel-Based Classification of Industrial Workpieces

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ABSTRACT

This chapter highlights the broader implications of adopting 3D CNNs in smart manufacturing. By automating the classification of complex workpieces, industries can achieve higher precision, reduce reliance on manual labor, and enhance production efficiency. Additionally, the integration of voxel-based classification systems into IoT-enabled smart factories is discussed is explored, presenting a pathway toward more intelligent and adaptive manufacturing ecosystems. This chapter also provides a practical guide to implementing 3D CNNs in industrial settings, Addressing both technical and real-world considerations. It contributes to the advancement of AI-driven smart technologies and serves as a valuable resource for researchers and

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practitioners in smart manufacturing.

INTRODUCTION

In actual production lines, many types of defect detection or identification systems using CNN-based image processing techniques are being applied. However, in such cases, it is often heard that detection accuracy is undesirably disturbed by lighting conditions. On the other hand, since any RGB camera is not used, the designed voxel-based 3D CNN for object detection and shape detection is not disturbed by such lighting conditions. Up to now, 3D CNN models have been applied to feature extraction tasks included in movies, however, in this chapter, the authors have applied to the surface shape identification task. The proposed 3D CNN model for the surface shape identification is based on the concept of such a 3D CNN model dealing with movies composed of frames. First of all, it may look like no direct relation with the surface shape detection, a 3D CNN model dealing with movie files for steel spark test is described to introduce one of applications of conventional 3D CNN models.

In contacting a grinding tool to a test steel, scattering sparks can be observed visually. The spark test is a widely used method to identify the composition and content of steel based on the appearance and color of sparks generated during grinding (Mundar et al., 2024). The spark test is standardized in JIS G0566-1980 (JIS G0566, 1980). Up to now, several researchers have explored the automation of the spark test by applying image analysis methods. For example, Nakata (2012) developed an automated spark testing technique by image processing to measure carbon content in steel materials. The system consisted of an automatic grinder, a high-speed camera of 200 images per second, and high-speed image processing computer. The result showed that the carbon content measurement accuracy is about $\pm 0.05\%$ in carbon steel (Nakata, 2012). Yoshioka et al. (2019) developed a classification method for carbon content rate [C%], which is defined in JIS G0566-1980 (JIS G0566, 1980), in unknown steels by analyzing images of sparks captured by a high-speed camera (Yoshioka et al, 2019). Yamashita and Kobayashi (2014) developed a spark test system that can generate stable sparks patterns under controlled conditions and capture video for analysis (Yamashita and Kobayashi, 2014). Building upon these developments, researchers have proposed automated evaluation systems that incorporate deep learning techniques such as convolutional neural networks (CNNs) for spark analysis. Recent advances in computer vision have demonstrated the effectiveness of deep learning in feature extraction for material classification and industrial quality inspection (Choudhary et al., 2022, Prunella et al., 2023). Tran et al. (2015) introduced 3D CNN models to automate the evaluation system for carbon content rate by extracting features of spark scattering from the videos (Tran