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IMPROVING BOTTLING LINE EFFICIENCY WITH DEEP LEARNING: A COMPARATIVE STUDY OF YOLO VARIANTS FOR DEFECT DETECTION

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Quality control in beverage production is crucial to ensuring product quality and customer satisfaction. Traditional methods, such as manual inspection, are prone to human error, inefficiency, and increased operating cost. Defect detection during beverage production is a key quality control process that aims to identify issues such as missing labels, incorrect liquid levels, and cap-sealing errors. Existing approaches rely on manual inspection or semi-automated systems that are often slow, inaccurate, and error-prone. The research gap identified through a comprehensive literature review is the absence of a fully automated, high-accuracy defect detection system with real-time functionality and low computational expense. To address the above gap, this study explores the application of deep learning techniques for autonomous defect inspection in beverage production. Three object detection models were experimented: You Only Look Once version 5 (YOLOv5), version 8 (YOLOv8) and version 11 (YOLOv11), with different training epochs (15, 60, and 100) to evaluate their suitability for real-time defect inspection. Three image datasets were prepared, consisting of 406 images of bottles with and without missing labels, 295 images of bottles with correct and incorrect liquid levels, and 330 images of bottles with properly sealed and defective caps. Results indicated that YOLOv8 achieved the highest performance, with accuracy rates of 87% for bottle cap defects, 90% for missing labels, and 96% for incorrect liquid levels at optimal training epochs, along with an average F1-score of 74.7%. Overall, all models demonstrated strong detection accuracy, indicating their potential for industrial automation in beverage manufacturing. However, the study has limitations, including reliance on high-quality training datasets, sensitivity to illumination conditions, and challenges in scaling across different bottle types. Future work could focus on enhancing model robustness under varying environmental conditions and incorporating additional sensor-based inspection methods. This study contributes to computerised quality inspection in beverage production by demonstrating the effectiveness of deep learning for defect detection, thereby supporting the development of more powerful, cost-saving, and scalable industrial automation solutions.

Keywords: Computer vision, Industrial automation, Industrial inspection, Object detection, Quality inspection