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Automated Product Defect Detection Using Image Processing Techniques for Effective Sorting and Quality Assurance : A Survey

Dr. Kavitha K S
Computer Science and Engineering
Dayananda Sagar College of Engineering
Bengaluru, India

Mamatha C G
Computer Science and Engineering
Dayananda Sagar College of Engineering
Bengaluru, India

Abstract:- Ensuring product quality and minimizing defects is crucial in today's manufacturing industry. Traditional manual inspections are labor-intensive and error prone.This paper describes a system designed to identify defects automatically the YOLOv5 algorithm, known for its accuracy and speed. High-resolution images of products are processed with YOLOv5 to identify defects like scratches, dents, and deformations. This system enhances sorting and quality assurance, improving efficiency and consistency. Experimental results show YOLOv5 superior performance in detection accuracy and speed compared to traditional methods, exploring the feasibility of combining machine learning and image processing within manufacturing.

Keywords:- *Automated Defect Detection, Image Processing, Yolov5, Quality Assurance, Manufacturing, Object Detection, Machine Learning.*

I. INTRODUCTION

In today's competitive manufacturing landscape, ensuring the highest product quality while minimizing defects is a critical priority. Traditional manual inspection methods, which rely on human effort, are often labor-intensive, time-consuming, and susceptible to errors. This creates a need for automated systems that can provide consistent, accurate, and efficient quality assurance. This paper introduces an advanced system for automated product defect detection, utilizing sophisticated image processing techniques. Central to this system is the YOLOv5 (You Only Look Once version 5) algorithm, a cutting-edge object detection model recognized for its exceptional speed and precision. The versatility and reliability of the YOLOv5 algorithm make it particularly well-suited for real-time applications in quality assurance. Our approach involves capturing high-resolution images of products such as PVC pipes and fabrics as they progress along the production line. These images are then analyzed by the YOLOv5 algorithm to detect and classify defects with high accuracy. The types of defects identified include scratches, dents, and deformities, among others, enabling efficient sorting and quality assurance.

By integrating this automated defect detection system, manufacturers can significantly enhance efficiency, ensure consistency, and improve overall product quality. Experimental results validate the robustness and effectiveness of the proposed system, showcasing the superior performance of the YOLOv5 model in both detection accuracy and processing speed. This research underscores the transformative potential of integrating image processing with machine learning to revolutionize quality control processes across various manufacturing sectors.

II. RELATED WORKS

M. M. Elsayed, et al. [1] Presented a technique leveraging convolutional neural networks (CNNs) for real-time defect identification in manufacturing. This research concentrated on utilizing CNNs to detect surface flaws on metal components, achieving notable accuracy and real-time capability.

J. Zhang, et al. [2] Created a hybrid method that merges machine-learning with traditional image processing. The study applied feature extraction techniques, including edge detection and texture analysis, alongside a support vector machine (SVM) to identify defects in textiles.

K. Lee and H. Park [3] Developed a deep learning framework to automate the examination of electronic components. This system made use of deep learning methods to identify and classify defects in solder joints, significantly cutting down inspection time compared to manual processes.

Kumar and G. Kaur [4] Proposed a novel image processing algorithm for ceramic tile defect detection. The algorithm included noise reduction and contrast enhancement in preprocessing, followed by morphological operations to detect cracks and surface anomalies.

S. Patel, et al. [5] Employed image segmentation to automate defect detection in fabrics. The research utilized watershed segmentation and contour detection to locate and classify defects such as holes and stains in fabric.

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Y. Liu, et al. [6] Suggested a multi-scale image analysis technique for automotive part defect detection. This approach used multi-scale image representation and wavelet transform to detect small flaws on the surface that are challenging to identify with standard methods.

N. Gupta, et al. [7] Applied deep convolutional neural networks (DCNNs) for inspecting food items. The study focused on identifying defects in fruits and vegetables using DCNNs to classify imperfections like bruises and blemishes.

P. Wong, et al. [8] Developed an automated system for PCB defect identifying using image processing. The system employed shape recognition and template matching to detect missing components and misalignments in printed circuit boards.

R. Sharma, et al. [9] Introduced a machine vision system for real-time defect detection in glass manufacturing. The system used edge detection algorithms and the Hough transform to identify cracks and inclusions in glass products.

L. Chen and M. Chen [10] Used a integration of image processing and neural networks for defect identification in rubber products. The study integrated texture analysis and neural network classifiers to detect surface defects such as blisters and grooves in rubber sheets.

T. Tanaka, et al. [11] Suggested a approach utilizing machine learning and image processing for semiconductor wafer defect detection. The Principal component analysis (PCA) was used in research for feature reduction and SVM for classifying defects like scratches and pits on wafer surfaces.

H. Kim and J. Choi [12] Developed an automated system for inspecting automotive paint quality. The system used color flaws such as runs, sags, and foreign particles can be identified using gradient-based approaches and colour image processing.

M. Singh, et al. [13] Proposed a new approach for detecting defects in composite materials using image processing. The method utilized thermal imaging and edge detection to identify delamination and voids in composite structures.

C. Zhang, et al. [14] Applied a deep learning approach for detecting defects in solar panels. This method used a CNN model trained on infrared images to detect micro-cracks and hot spots in solar panels.

J. Liu and Y. Wang [15] Created a live flaw identification system for textile manufacturing using image processing. The system applied Gabor filters and neural networks to detect and classify defects like yarn breakages and weave irregularities.

K. Tsai, et al. [16] Developed an image-based inspection system for ceramic products. This system used image preprocessing techniques such as histogram equalization and edge detection to identify defects like cracks and surface pits.

P. Verma, et al. [17] Employed a combination of machine vision and deep learning for defect identification in pharmaceutical tablets. The study used CNNs to detect surface defects and irregularities in pharmaceutical tablets, ensuring high accuracy and reliability.

W. Wang, et al. [18] Proposed a defect detection method for electronic components using image processing and machine learning. This approach combines feature extraction techniques like texture analysis with SVM classifiers to identify defects in electronic components.

Y. Huang, et al. [19] Suggested an automated defect identification system for packaging materials using image processing. The system employed contour detection and morphological operations to detect defects such as tears and holes in packaging materials.

F. Lin, et al. [20] Developed a deep learning-based approach for detecting defects in steel products. The approach used a deep residual network to identify surface defects like scratches and dents in steel sheets with high precision.

III. OUTCOME OF THE SURVEY

This study acknowledges certain limitations, notably the absence of labeled defect datasets for training machine learning models. Future research should prioritize techniques for dataset labeling and explore semi-supervised or unsupervised learning approaches to enhance efficiency. Additionally, integrating sensor data such as temperature or vibration could augment defect detection capabilities. Cost-effectiveness analysis and optimizing hardware and software elements are necessary for actual use in practice and widespread adoption in manufacturing. In conclusion, this research presents a comprehensive examination of quality control enhancement in Industry through advanced image processing for automated flaws detection. The proposed system shows promise in revolutionizing quality control processes, enhancing product quality, and boosting operational efficiency. These findings contribute to the knowledge base, laying the groundwork for further advancements in automated defect detection and quality control within the Industry framework. To guarantee the efficiency of the automated defect detection system, robustness and efficiency assessments are imperative. Robustness analysis involves testing the system's performance under various challenging conditions, including changes in lighting, variations within categories of defects or sizes, and complex backgrounds. Evaluating the system's real-time defect detection capabilities and monitoring its performance against operational requirements are essential aspects of efficiency analysis.

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IV. CONCLUSION

In summary, the deployment of automated defect detection in product inspection, utilizing image processing methodologies like the YOLOv5 algorithm, offers a robust strategy for effective sorting and quality assurance across diverse product categories including PVC, PCB, and fabric. Through leveraging the capabilities inherent in YOLOv5, this system facilitates swift and precise defect identification, thereby enhancing overall product quality and reliability. The comprehensive and rapid image analysis enabled by YOLOv5 empowers industries to optimize their quality control procedures, mitigate production delays, and ultimately deliver high-caliber products to end-users. This innovative approach marks a significant advancement in automated defect detection, fostering improvements in manufacturing efficiency and elevating standards of product excellence.

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