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A Real-Time Computer Vision-Based System for Detecting Defects in Injection-Molded Products

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Abstract

This study proposes an automated system for detecting and classifying defects in products manufactured through the injection molding process. Existing deep learning-based detection technologies provide high accuracy, but have limitations in that they require massive data and complex learning processes, and require re-learning when new products are introduced. On the other hand, simple image processing techniques can be applied quickly without a learning process, but there are limits to accuracy when defect types are complex or diverse. To solve this problem, this study introduced advanced computer vision technology to overcome the limitations of existing technology and designed a system that excludes the complexity of deep learning. In particular, this system combines various pre-processing and post-processing techniques such as grayscale conversion, binarization, Gaussian filtering, and histogram smoothing to simultaneously improve the accuracy and efficiency of defect detection. In addition, it was designed to quickly detect defects occurring in the manufacturing process through a system architecture that optimizes real-time processing. Using ultrasonic sensors and automated conveyor belts, the product movement and detection process is precisely controlled, enabling real-time data processing and product classification. As a result of the experiment, this system significantly reduced detection delays and classification errors that commonly occurred in existing research, and demonstrated its potential to contribute to quality control and productivity improvement in a manufacturing environment.

Keywords: Injection molding, Computer vision, Defect detection, Automated system, Preprocessing techniques

Introduction

Products manufactured through the injection molding process are widely utilized across various modern industries, including packaging, automotive, medical, and aerospace [1]. However, defects may arise during this process, which not only diminishes product quality but also poses serious risks to safety and corporate reputation. Therefore, detecting and classifying defective products during manufacturing is critical to maintaining quality control [2,3]. Currently, most manufacturers rely on visual inspections or existing automated systems for defect detection [4]. However, visual inspections are time-intensive, and their reliability can vary depending on the inspector's skill level and fatigue [5]. Automated systems, on the other hand, are often optimized for detecting specific defect types and struggle to address complex or diverse defects. To address these limitations, computer vision technology has recently garnered significant attention in the field of defect detection [6]. Computer vision involves extracting image information and analyzing it to identify defects in products. It circumvents the challenges of deep learning, which requires complex retraining processes whenever a new product is introduced. Furthermore, computer vision is easily integrable into manufacturing workflows, offering high-speed data processing and precise analytical capabilities. In particular, computer vision enables rapid and efficient detection of various defect types, thereby achieving both quality control and automation in manufacturing processes.

This study proposes an automated system for detecting and classifying defects in products manufactured through the injection molding process. The system leverages computer vision technology to extract essential information from images and analyze them to identify the characteristics of various defect types. Specifically, this study aims to address the limitations of existing methodologies by designing a system architecture capable of real-time defect detection. Figure 1 illustrates the overall flow of the proposed system. First, injection-molded bottle caps are transported *via* a conveyor belt and inspected for defects as they pass through the image processing section. Ultrasonic sensors detect the products, and in the sorting section, bottle caps are classified into good and defective products.

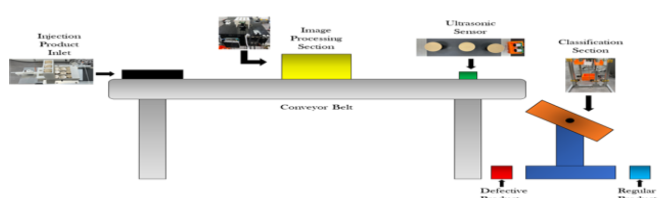

Figure 1: This image is a diagram of the complete system for detecting defects in injection-molded products.

This paper is structured as follows: Chapter 2 reviews related research, Chapter 3 provides a detailed explanation of the proposed methodology, Chapter 4 discusses the experimental results, and Chapter 5 presents the conclusions and future research directions.

Related Works

Latest trends in defect detection

Recently, defect detection technology has emerged as a crucial component of the manufacturing industry, driven by rapid advancements in Artificial Intelligence (AI) and Machine Learning (ML) [7-10]. Notably, the integration of deep learning-based approaches and traditional computer vision techniques has enabled the development of more precise and real-time systems.

First, state-of-the-art real-time object detection algorithms like YOLO (You Only Look Once) have significantly advanced defect detection. For example, YOLOv8 and YOLOv10 provide high-speed, high-accuracy real-time defect detection on manufacturing lines. The latest versions feature innovations such as training methods that eliminate Non-Maximum Suppression (NMS), optimizing processing efficiency [11,12]. These algorithms are compatible with both Central Processing Units (CPUs) and Graphics Processing Units (GPUs) and CPUs, making them versatile for various operational environments. Second, edge AI technology has garnered attention for its ability to perform real-time data analysis locally, thereby reducing latency and enhancing data security by eliminating the need for cloud transmission [13]. Additionally, model light weighting techniques, which reduce AI model size and improve inference speed, maintain high performance even in resource-constrained edge environments [14]. These features are particularly advantageous for high-throughput, data-sensitive applications like defect detection in manufacturing. Third, deep learning techniques such as transfer learning deliver high performance even with limited data, enabling manufacturers to adapt quickly to new products or defect types [15,16]. Fourth, computer vision techniques, such as image segmentation, are employed to more accurately detect the location and shape of surface defects. This technology is especially vital in high-precision industries, including medical, electronic, and automotive manufacturing [17,18]. Lastly, the integration of real-time data analysis with automated reporting systems is becoming standard practice.

These systems allow manufacturers to detect quality issues in real time and take proactive measures to address them, thus reducing costs and maximizing productivity. In summary, the latest advancements in defect detection technologies spanning real-time processing, accuracy, and scalability are transforming the manufacturing landscape. These innovations are pivotal in helping manufacturers maintain product quality and enhance their competitive edge.

Defect detection using computer vision

Computer vision is a core technology that plays a vital role in automatically detecting surface and structural defects in products during the manufacturing process [19]. Various defects, such as cracks, scratches, and dents, can occur on the product surface during manufacturing. Prompt and accurate detection of these defects is critical for manufacturers to ensure quality control and minimize cost losses [20]. To address this issue, high-resolution cameras and lighting systems are used to capture images of product surfaces. These images undergo a range of preprocessing steps using computer vision technology to enhance defect detection accuracy [21]. Typically, RGB images are converted to a single channel *via* grayscale conversion to improve data processing efficiency. Gaussian filtering is then applied to remove noise, simplifying the identification of defect areas [22]. A thresholding technique is used to distinguish defect areas clearly by converting the image into black and white based on pixel brightness values. The preprocessed image proceeds to the feature extraction stage, where critical features such as the defect's size, shape, and location are identified [23]. Commonly used feature extraction methods include edge detection algorithms, histogram analysis, and contour detection. Computer vision has distinct characteristics compared to deep learning-based approaches. While deep learning requires large volumes of training data and complex learning processes, computer vision operates without the need for training data, relying on predefined rules to detect defects. These differences greatly influence their applicability in operational environments. For instance, computer vision has a straightforward initial setup, excellent real-time processing capabilities, and is particularly effective in detecting standardized defect types, such as cracks of specific sizes or shapes [24]. In contrast, deep learning excels in detecting atypical and complex defects and offers the advantage of adapting to new defect types through model training. However, it also has significant drawbacks, such as its reliance on large datasets, complex training processes, and high initial costs and time requirements for implementation in manufacturing contexts. Given these contrasts, computer vision and deep learning have unique advantages and disadvantages. Therefore, it is essential to carefully select the appropriate technology for defect detection based on the specific requirements of the manufacturing environment. The following section provides a detailed comparison of these two approaches and explores the criteria for choosing the most suitable technology.

Defect detection and comparison using deep learning

Computer vision and deep learning-based defect detection technologies have different principles and characteristics, which results in differences in applicability and suitability in the manufacturing environment [25]. As explained earlier, computer vision has strengths in simple setup and real-time processing capabilities, and can provide an economical solution that enables defect detection without prior learning [21]. On the other hand, deep learning demonstrates powerful performance in detecting atypical and complex defects, and is different in that it can learn new defect types that have not been previously defined. Deep learning mainly uses models such as Convolutional Neural Networks (CNN) to automatically learn and classify defect characteristics based on image data. This technology requires a large amount of labeled training data and powerful computing resources, and the initial setup and training process take a considerable amount of time [26]. However, when detecting complex defect types (e.g. irregular crack patterns, surface color changes), deep learning offers high accuracy and flexibility. On the other hand, computer vision utilizes traditional image processing algorithms (edge detection, binarization, histogram smoothing, etc.) to manually extract and analyze features [25]. This method operates on a rule-based basis and has the flexibility to be quickly applied to new defect types without a complex learning process. For example, it is well suited for real-time detection of standardized defect types, such as cracks of a certain size and shape. The differences between the two technologies are also evident in their data requirements. Deep learning requires large amounts of labeled data, and data preparation and learning processes are key to developing a defect detection system. On the other hand, computer vision does not require learning data, so initial setup is simple and it can operate immediately based on existing rules. In terms of performance, there is a clear difference between the two technologies. Computer vision provides high processing speed and real-time in routine defect detection, and is an economical and efficient choice for simple manufacturing processes. However, there may be limitations in handling complex and diverse defect types. On the other hand, deep learning can accurately detect complex defects, but has the disadvantage that the learning and re-learning process is long and involves high computational costs [27]. In conclusion, computer vision is suitable in environments where real-time and operational efficiency are important, while deep learning can demonstrate its strengths in manufacturing environments where multivariate and complex defect detection is required. This study seeks to improve quality control and productivity in the manufacturing process by maximizing the practicality and efficiency of computer vision while avoiding the complexity and data dependence of deep learning [28].

Difference from this study

This study proposes an approach that is distinct from existing research by utilizing computer vision technology to detect defects in injection-molded products. Previous studies often relied on deep learning-based detection techniques or simple image processing methods [29]. While deep learning-based approaches provide high accuracy, they have significant drawbacks, including the need for large datasets, a complex training process, and re-training requirements whenever new products are introduced [30]. Conversely, simple image processing techniques can be implemented quickly without a training process but exhibit limitations in accuracy when faced with complex or diverse defect types. This study employs advanced computer vision technology that addresses the limitations of conventional simple image processing techniques while avoiding the complexity of deep learning [31]. Specifically, the system enhances both the accuracy and efficiency of defect detection by incorporating various pre-processing and post-processing techniques, such as grayscale transformation, binarization, Gaussian filtering, and histogram smoothing. These techniques are designed to effectively detect a wide range of defect types without requiring any learning process. Additionally, the study introduces a system architecture optimized for real-time processing to promptly identify defects arising during the manufacturing process. Ultrasonic sensors and automated conveyor belts are employed to precisely control product movement and detection processes, enabling real-time data processing and product classification. As a result, this approach significantly reduces detection delays and classification errors commonly observed in previous research.

Method and Result

Hardware configuration for multi-product surface defect detection algorithm

Figure 2 illustrates the optical design schematic for an environment configured to detect surface defects on injection-molded products. To optimize the image processing environment, blackout curtains were used to block external light sources, ensuring that reflected light from the surface of the injection-molded product reaches the camera uniformly. Additionally, to minimize variations in light intensity caused by distance differences between the light source and the subject, LED lights were installed at both ends of the upper section to evenly illuminate the surface of the subject. This system is designed to detect up to three products simultaneously (Figure 3).

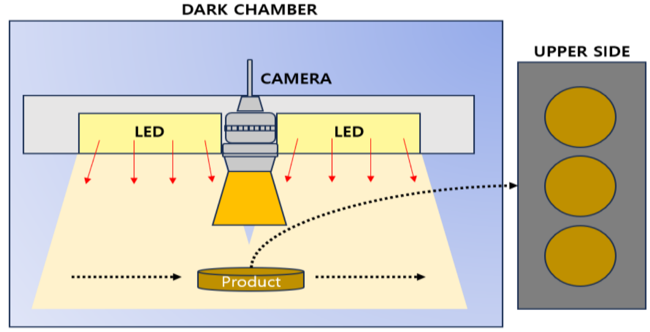

Figure 2: Optical design schematic for surface defect detection in injection-molded products.

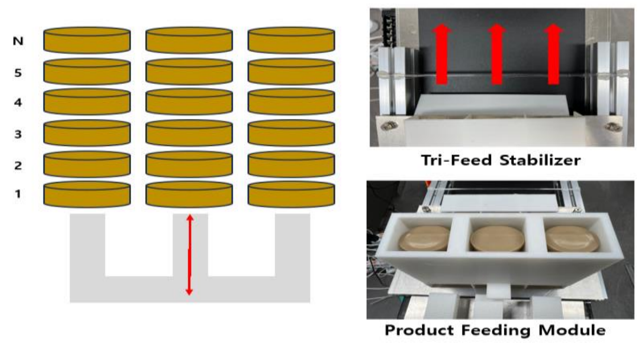

Figure 3: Triple product feeder system diagram.

To ensure the efficient feeding of injection-molded products, a device capable of feeding three products at a time was designed. This device is constructed as shown in the figure, utilizing a servo motor and a 3D-printed structure. The servo motor alternates between forward and reverse rotations, automating the process of product feeding and refilling. As a result, three products are aligned in a single row and fed onto the conveyor belt. Additionally, the device is installed at a specific angle to prevent overturning during product feeding, ensuring that the products are stably placed on the conveyor belt even in downhill sections.

Multi-product surface defect detection algorithm

Figure 4 illustrates one of the image processing steps for detecting surface defects in multiple products. The images captured by the camera are provided as 3-channel RGB images, and effective defect detection of products moving on a conveyor belt requires high processing speed and accurate feature detection. To enhance processing efficiency, the 3-channel RGB images were converted into single-channel Grayscale images. This conversion significantly reduces computational load and shortens processing time while maintaining the accuracy of defect detection for products moving quickly on the conveyor belt. Additionally, Thresholding was applied to the Grayscale images to remove unnecessary background. The white regions in the Threshold image represent the Region of Interest (ROI), which corresponds to the areas of the product surface that need to be observed. Based on this, only the pixel data within the ROI were retained in the Grayscale image, while the rest of the regions were set to 0, resulting in a Threshold-based Grayscale pixel extraction image (Figure 5).

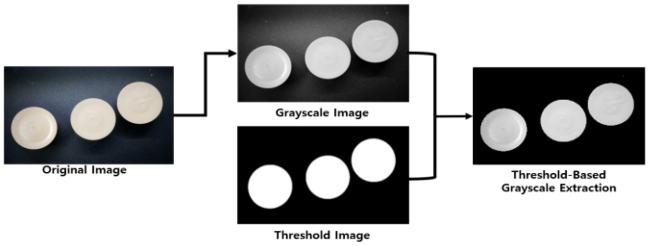

Figure 4: threshold-based grayscale pixel extraction process for multi-product surface defect detection.

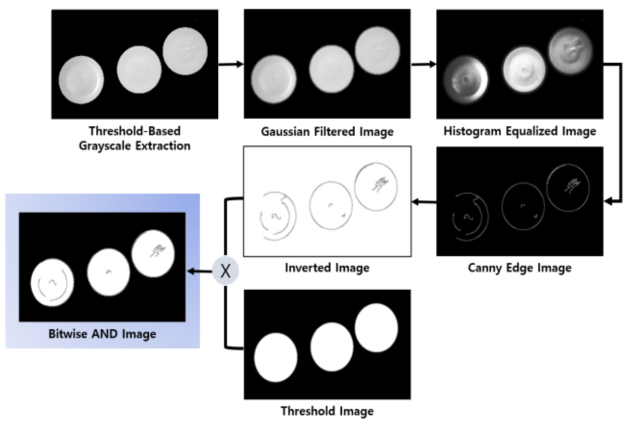

Figure 5: Flowchart of image processing for defect detection in threshold-based grayscale internal regions.

This figure is a flowchart illustrating the sequential image processing steps undertaken to detect defects in the internal regions of a Threshold-based Grayscale pixel extraction image. First, a Gaussian filter is applied to perform blur processing, which helps remove unnecessary noise from the surface of injection-molded products. The Gaussian filter effectively reduces high-frequency noise, improving the accuracy of analysis and lowering computational costs in subsequent processing steps. This step is particularly critical for achieving clear analysis, even in cases where the defects on the product surface are subtle.

After noise removal, Histogram Equalization is applied to balance the brightness distribution of the image. This process increases image contrast, emphasizing key features on the surface and making defect areas more prominent. By enhancing the visibility of defects that were previously difficult to identify due to low contrast, this step significantly improves defect detection sensitivity.

Next, the Canny Edge Detection algorithm is employed to identify regions with significant changes in intensity and extract their contours. Canny Edge Detection is particularly effective at detecting areas with strong gradient changes, which often correspond to defects. This enables clear differentiation between defective regions and background areas, resulting in more precise defect detection.

Finally, the Threshold image generated in a previous step is inverted and combined with the extracted edges using a Bitwise AND operation to isolate and extract the defect regions. By inverting the Threshold image, non-target background areas are eliminated, and the Bitwise AND operation ensures that defect detection is restricted to the Region of Interest (ROI). This approach minimizes false positives caused by background interference and allows for accurate defect detection within the ROI (Figure 6 and Figure 7).

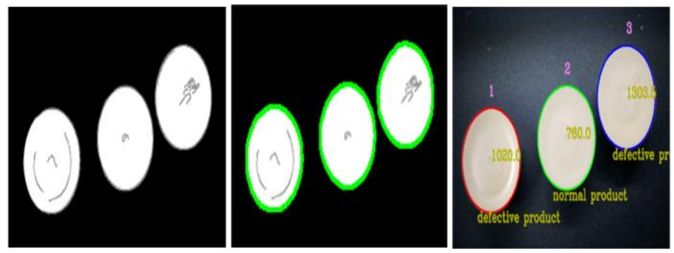

Figure 6: Example image for determining the quality status of injection-molded products.

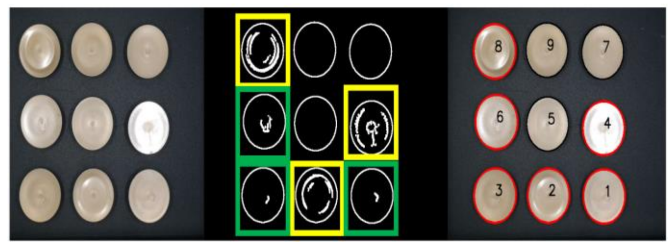

Figure 7: 3x3 multi-product surface defect detection and classification results.

This figure illustrates the results of 3x3 multi-product surface defect detection and classification. The left panel shows the original images of nine injection-molded products, providing an overview of the surface condition of each product prior to analysis. The middle panel displays the results after applying the defect detection algorithm, highlighting the detected closed curves on the product surfaces. Each closed curve is color-coded to indicate the product's status: Green boxes represent products with cracks, while yellow boxes indicate products with defects such as sink marks.

To evaluate the performance of the previously described algorithm, an experiment was conducted using a total of 100 products. The experiment included 50 normal products, 25 products with cracks, and 25 products with sink marks. Each product was placed into the input section, and its classification was verified in the sorting section. The experimental results are presented in Table 1, and the confusion matrix was used to assess the classification accuracy of the algorithm. As shown in Table 1, the algorithm achieved 48 True Positives, 47 True Negatives, 2 False Negatives, and 3 False Positives. Based on these results, the overall accuracy was calculated to be 95%, demonstrating the high reliability and efficiency of the algorithm in detecting and classifying defects in injection-molded products.

		Predictive values	
		Positive (1)	
Actual values	Positive (1)	Actual Values	Positive (1)
	Negative (0)		Negative (0)

Table 1: Confusion matrix of experimental results.

Discussion

The proposed multi-product surface defect detection and classification system effectively addresses the challenges of detecting defects in injection-molded products through a robust combination of hardware configuration and advanced image processing techniques. The experimental results demonstrated a high accuracy of 95%, successfully distinguishing normal products, cracks, and sink marks. In particular, Gaussian filtering and histogram equalization improved image quality, while Canny edge detection and threshold-based analysis accurately Isolated Regions of Interest (ROI), enhancing the sensitivity and reliability of defect detection. However, some false positives and false negatives were observed during the experiments, indicating the need for further fine-tuning of the algorithm. False positives could increase production costs by misclassifying normal products as defective, while false negatives could allow defective products to pass quality control. Optimizing parameters such as threshold values and edge detection sensitivity will be essential to mitigate these issues and improve classification accuracy. The current system focuses on detecting cracks and sink marks, but future research should expand its capabilities to classify additional defect types, such as warpage or surface contamination, to increase its applicability. Moreover, improving robustness to environmental variations, such as changes in lighting conditions or product positioning, will enhance the system's reliability. Integrating adaptive lighting systems or machine learning models with real-time learning capabilities could further improve the system's accuracy and adaptability in dynamic manufacturing environments. In summary, this study demonstrates the high potential of the proposed defect detection algorithm and provides a foundation for revolutionizing quality control processes in high-speed production environments. With further research and optimization, the system is expected to evolve into a more robust and versatile quality control solution.

Conclusions

The proposed multi-product surface defect detection and classification system offers a practical and effective solution for identifying defects in injection-molded products with speed and accuracy. The experimental results demonstrated a high overall accuracy of 95%, successfully classifying normal products, cracks, and sink marks. The image processing steps, including Gaussian filtering, histogram equalization, Canny edge detection, and threshold-based analysis, significantly improved the sensitivity and efficiency of defect detection. Additionally, the triple product feeder system and optimized optical design enabled simultaneous processing of multiple products, showcasing excellent scalability and practicality for high-speed manufacturing environments. However, some false positives and false negatives were observed during the experiments, indicating a need for further fine-tuning and optimization of the algorithm. Expanding the classification capabilities to include additional defect types beyond cracks and sink marks would enhance the system's versatility. Furthermore, increasing robustness to environmental variations, such as lighting and positioning inconsistencies, is essential for broader applicability. The integration of IoT-based real-time monitoring and feedback systems could also enable higher levels of automation and accuracy. In conclusion, this study provides a reliable and practical foundation for quality control and defect detection in injection-molded products. With further improvements, the system has the potential to evolve into a comprehensive defect detection solution that can be applied to diverse manufacturing environments. These findings contribute to improving production quality and efficiency, laying the groundwork for more advanced quality assurance systems in the future.

Author Contributions

Conceptualization, C.H.L. and Y.S.K.; methodology, C.H.L. and H.M.N; software, C.H.L.; validation, H.M.N. and Y.S.K.; formal analysis, H.M.N. and Y.S.K.; investigation, C.H.L. and Y.S.K.; writing original draft preparation, C.H.L. and Y.S.K.; writing review and editing, H.K.K.; project administration, C.H.L.; visualization, C.H.L.; supervision, H.K.K.; funding acquisition, H.K.K. All authors have read and agreed to the published version of the manuscript.

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Data Availability Statement

No new data were created or analyzed in this study. Data sharing is not applicable to this article.

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Conflicts of Interest

The authors declare no conflicts of interest. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript; or in the decision to publish the results.

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