Surface Defect Detection System for AI Vision-Based Press Formed Products

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***Abstract*— The appearance of a product is the first thing consumers evaluate for defects, making surface inspection crucial. Among these exterior products, surface inspection of press-formed products is still done manually by visual inspection, prompting exploration of solutions for surface inspection automation through machine learning systems to adapt to various on-site changes. For machine learning-based surface defect detection models, there is often insufficient defect data for training, and a small amount of defect data makes it difficult to improve the learning performance. Particularly, as manufacturing processes stabilize, defect occurrences decrease, making it time-consuming to collect desired defect training data. This paper proposes a method for training models for defect detection by using only normal product data to train the defect detection model. It identifies defects on the product surface by generating defect data from normal data input, calculating the difference between normal data through restoration, and identifying defects on the product surface through connection and separation.**

Keywords-AI; Surface Detection; Press Formed Product; Anomaly detection.

I. Introduction

With the advent of the Fourth Industrial Revolution, the manufacturing industry is hastening its transition to smart factories, which integrate Information and Communications Technology (ICT) into traditional manufacturing processes. In this process, technologies for process automation and quality inspection automation are rapidly growing. However, surface defect inspection of products in press processing processes still relies on visual inspection by workers, who directly examine defects or damages on the product surface with their eyes. Such visual inspections are influenced by factors, such as ambient lighting, worker fatigue, and inspection proficiency. In particular, in high-speed press lines, due to short cycle times and mass production systems, there is a high probability of mass consecutive defects if surface defects occur. In such cases, it is crucial to prevent foreign matter ingress in mold areas and to rapidly detect surface defects to prevent mass consecutive defects. If undetected defective products are delivered to customers, a full inspection for product defects must be conducted, leading to increased costs.

This study proposes a method for acquiring surface anomaly data of products using stainless steel, which exhibits intense light reflection, and suggests a surface anomaly detection method for press processed products based on unsupervised learning using normal data for cases where anomaly data is insufficient. Through this, we aim to confirm the potential for replacing conventional visual inspections, quantifying surface inspections, and contributing to productivity and quality enhancement through continuous defect prevention.

This study aims to answer the following research questions:

1. How can machine learning models be effectively trained for surface defect detection with limited defect data?
2. What the are potential limitations of using only normal product data for defect detection?

This paper focuses on a subset of open issues, including the scarcity of defect data in stable manufacturing processes and the time-consuming nature of collecting sufficient defect data for model training. Potential limitations of our approach include the accuracy of defect generation from normal data and the reliability of defect identification in varying on-site conditions.

The structure of the paper is as follows: In Section 2, we discuss related work and the background of surface defect detection. Section 3 outlines the design and implementation of our proposed method. Section 4 presents the results and analysis. In Section 5, we conclude with lessons learned and future work directions.

II. Related work

This section reviews the existing literature and methods related to surface defect detection in manufacturing processes. It covers the target products and production processes, the type of defects encountered, and the current methods used for surface inspection. Additionally, it discusses unsupervised learning based on normal images for anomaly detection, highlighting recent advancements and methodologies.

A. *Target Products and Production Processes, and Types of Defects*

The Decor Frame, as shown in Figure 1, is attached inside the drum of a washing machine to act as a filter membrane, filtering out laundry residues. It is a product produced through press processing, using stainless steel material. The manufacturing process consists of two stages: after material input, the first stage involves drawing, trimming, and piercing processes using a 200-ton servo press, while the second stage involves bending the joints using a 150-ton servo press. Subsequently, after inspection, the products are packaged. During the inspection process, surface defect inspection is

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conducted by workers through visual inspection. Figure 2 depicts the raw materials and products by process.

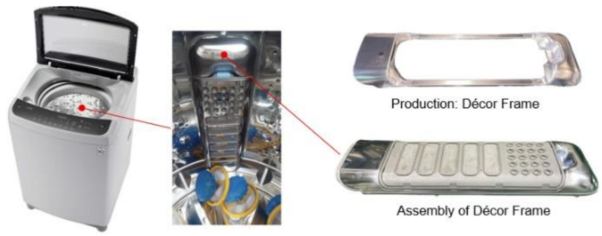

Figure 1. Target product (Décor Frame).

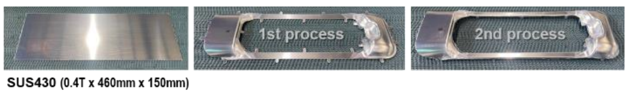

Figure 2. Raw material and products by process.

In the manufacturing process, various types of defects occur in each process. In the first process, defects, such as burrs, necking, sleeves, and fractures occur, while in the second process, chip and hook defects occur. The monthly average defect rate is 2.86%, with process defects accounting for 2.65%. Among them, chip defects on the product surface account for 1.89% of the process defect rate, representing 71%. This indicates a very high frequency of chip defects. These chip defects occur when foreign substances in the air or vinyl and chips generated during cutting in the first process adhere to the molds of the first or second process. Among these, the defect types to be detected through surface inspection are necking, sleeves, fractures, and chips. Figure 3 illustrates the types of defects by process and the types of defects targeted for surface inspection [1]-[2].

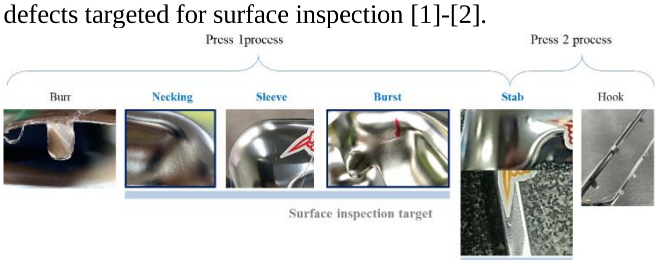

Figure 3. Defect Types by Process and Surface Inspection Defect Types.

This analysis highlights the importance of detecting and addressing these common defects early in the production process, manufacturers can reduce waste, lower costs, and improve customer satisfaction.

B. *Surface Inspection Method*

In the manufacturing process, the product surface inspection system utilizes a rule-based system based on machine vision. It is primarily used for visual inspection, defect detection, part position determination and measurement, product identification, alignment, tracking, and also for detecting surface defects. The advantage of this rule-based technology is its ability to quickly confirm and make decisions based on given rules. However, it can be considered rigid as it is programmed to only do what is specified by the rules. There are limitations in accommodating the diverse problems of the manufacturing field that constantly change since the rules are not self-added, changed, or updated [3].

In contrast, a Machine Learning System aims to emulate human-like behavior by learning new rules autonomously and discarding outdated ones, rather than relying on fixed rules. While rule-based systems can easily be applied in controlled environments, such as manufacturing lines, many undefined tasks occur in real work environments. To address the practical problems of these dynamically changing manufacturing environments, transitioning to machine learning should be considered. In particular, Deep Learning plays an increasingly significant role as it can intelligently predict and make decisions through image recognition [4]-[7].

C. *Unsupervised Learning Based on Normal Image*

Unsupervised learning based on normal data is used when collecting defective training data is difficult or labeling of training data is challenging. Among them, there is DRÆM, which particularly deals with pixel-level anomaly detection as an image anomaly detection method. This method is based on reconstruction and segmentation, consisting of anomaly generation through perturbed noise, and is structured by combining a reconstruction network and a discriminative network [8]-[10]. As shown in Figure 4, the structure and steps of reconstruction-based anomaly detection are detailed.

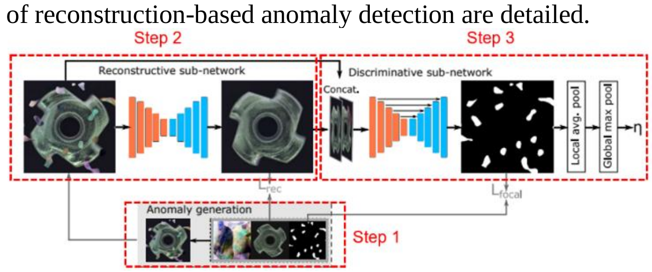

Figure 4. The structure and steps of reconstruction-based anomaly detection.

Examining the structure, in the first step, instead of using defective images as training data, defective images are generated using a Perlin noise generator (as illustrated in Figure 4). The Perlin noise generator creates anomaly shapes, which are combined with various shapes of different original images, and then synthesized with normal original images to generate defective images.

In the second step, the generated defective images are passed through the reconstructive sub-network to train them to be restored to the original images with defects removed. Here, the reconstruction loss, which is the difference between the original images and the restored images with defects removed through the reconstructive sub-network, is calculated to evaluate how closely the original images have been restored during the reconstruction training.

In the third step, the generated defective images through Perlin noise and the restored images through the reconstructive sub-network are combined (Concatenated) and passed through the discriminative sub-network to separate the anomaly mask images of the anomaly shapes. In other words, segmentation learning is performed with the goal of obtaining the anomaly mask images corresponding to the anomaly shapes applied to the original images. The segmented anomaly mask images are then compared to the noise area images generated by the Perlin noise generator through focal loss calculation to assess the performance of the discriminative network. Figure 5 depicts the entire process of the reconstruction-based anomaly detection methodology [11]-[16].

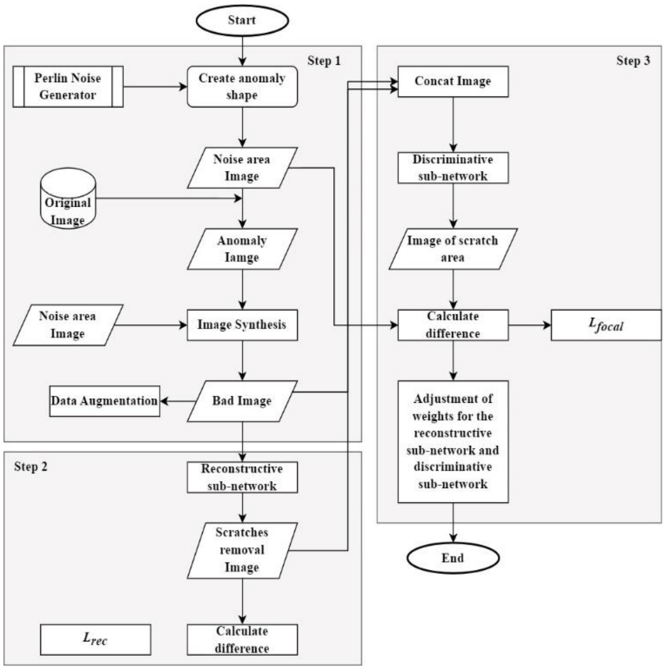

Figure 5. The entire process of reconstruction-based anomaly detection methodology.

This reconstruction-based anomaly detection method shows promise for detecting subtle anomalies in images, making it a valuable tool for improving quality control in manufacturing processes.

III. Design and Implementation

This section describes the methodology and implementation steps taken to develop the surface defect detection system. It includes the setup of the environment for collecting learning data, the configuration of machine vision components, and the application of unsupervised learning techniques based on normal images. Each subsection provides detailed explanations of the processes involved, including data collection, anomaly generation, and network training for effective surface defect detection.

A. *Collect Learning Data*

We have set up the environment to acquire product images for training. We configured the image capture conditions through lighting, including cameras and lenses, to ensure that the defective areas of surface defective products are distinguishable in the captured product images. Machine vision comprises cameras, lenses, lighting, and a controller/system package. However, in this paper, we used dome & coaxial type lighting. By processing the acquired images with contrast enhancement, we were able to measure surface attribute information, such as inclination, roughness, and reflectivity, enabling us to obtain images capable of discriminating surface defects, such as chips, scratches, and stains. The changes in surface properties due to lighting are illustrated in Figure 6.

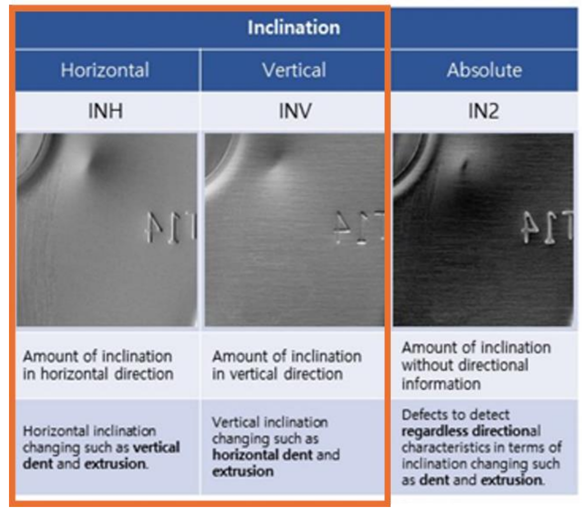

Figure 6. Changes in surface properties due to lighting.

In this paper, it was decided to collect attribute images of vertical and horizontal surfaces according to the inclination of illumination. To collect a total of four images per product, two images per product part, we set up an image data collection environment in the manufacturing site.

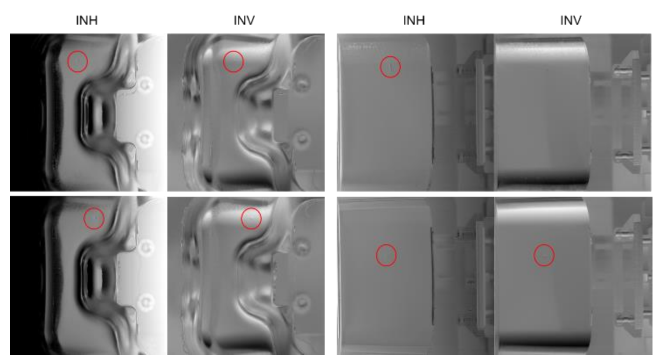

Figure 7. Training data indicating defective areas.

As the tilt of the illumination changes, the results of capturing product images show that surface defects, such as indentation are more clearly distinguished in either the INH (lighting directions in horizontal) or INV (vertical part when light is horizontally or vertically projected. Figure 7 represents the defects in the images.

B. *Unsupervised learing based on normal images*

Unsupervised learning based on normal images utilizes the reconstruction-based anomaly detection methodology. It generates defective images from normal images and trains these generated defective images separately using a reconstructive sub-network and a discriminative sub-network. The reconstructive sub-network is trained to pass the defective images, which are synthesized with noise, through to obtain the original images. Meanwhile, the discriminative sub-network is trained to detect the noisy regions. The configuration diagram of the reconstruction-based anomaly detection system is shown in Figure 8.

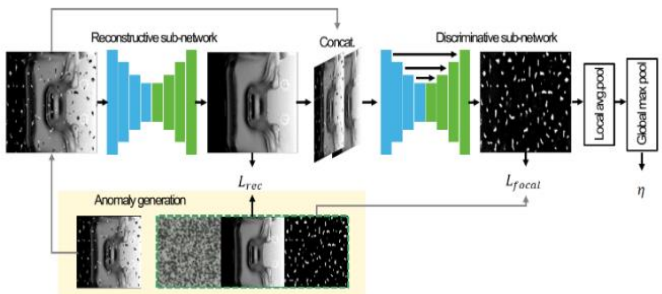

Figure 8. The configuration diagram of the reconstruction-based anomaly detection system.

The sequence of the unsupervised learning process consists of three steps: anomaly data generation, reconstructive network calculation, and discriminative network calculation. This process involves training based on normal product data in the initial state when sufficient defective product data is not available.

Anomaly generation involves inserting noise to generate defective product images. First, when a normal product image is input, Perlin noise, which has the same size as the normal product image, is generated. The Perlin noise image undergoes binarization based on a threshold to create a noise area image. Here, the noise area image is created such that if the value of a pixel in the Perlin noise image exceeds the threshold (0.5), it is set to 1; otherwise, it is set to 0. Multiple noise data are added to the noise area image, and then combined with the normal product image. The parts of the noise area image that are set to 1 represent noise data, while those set to 0 represent the normal product image, resulting in the generation of synthesized defective product images.

The reconstructive sub-network restores defective product images to normal product images. Defective product images synthesized during anomaly generation are passed through the reconstructive sub-network, which outputs defect-removed images of the same size as the defective product images. These defect-removed images remove the defective parts from the synthesized defective product images, restoring them to normal product images. The difference (L_{rec}) between the defect-removed images and the original normal product images is calculated. A smaller difference indicates that the reconstructive sub-network has effectively removed defects, producing defect-removed images similar to the original normal product images.

The discriminative sub-network extracts defective areas by comparing the difference between the synthesized defective product images and the defect-removed images. In the anomaly generation process, the synthesized defective product images and the defect-removed images are combined (concat) and inputted into the discriminative sub-network, producing defect area images of the same size as the product images. These defect area images calculate the difference (L_{focal}) with the noise area images. A smaller difference indicates that the discriminative sub-network can identify the difference between the defective product images and the defect-removed images, thereby extracting defective areas. A sample implementation image of the discriminative sub-network is shown in Figure 9.

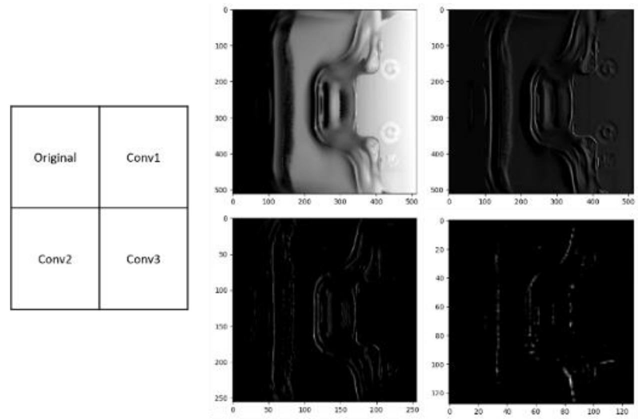

Figure 9. Sample implementation image of the discriminative sub-network.

The differences calculated in both networks, L_{rec} and L_{focal}, respectively modify the weights of the reconstructive network and the discriminative network. Figure 10 illustrates the process of unsupervised learning based on normal data.

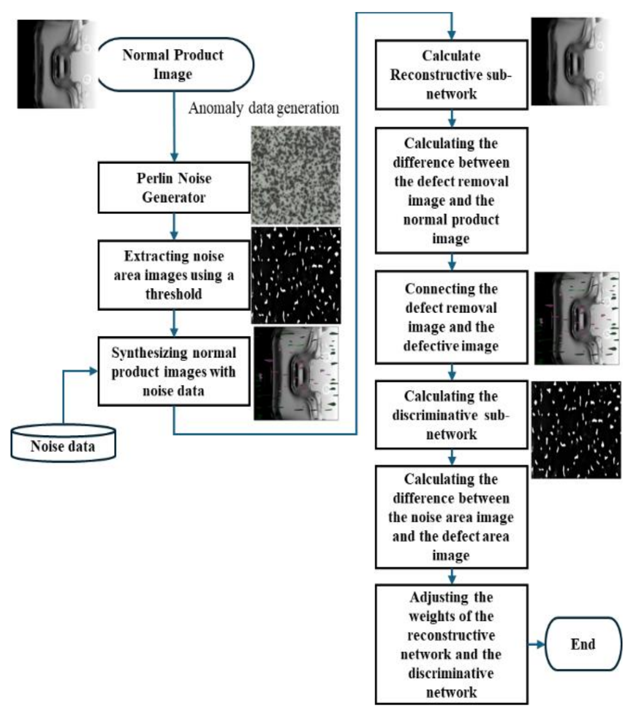

Figure 10. The process of unsupervised learning based on normal data.

IV. PERFORMANCE ANALYSIS

Performance evaluation of the learning model can be done by directly inspecting the data due to the small number of

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defective images and classifying the cases. Judging product defects means segmenting the scratch areas in the result images of the discriminative network. We will describe normal detection cases and false detection cases and analyze the results.

A. Good segmentation case

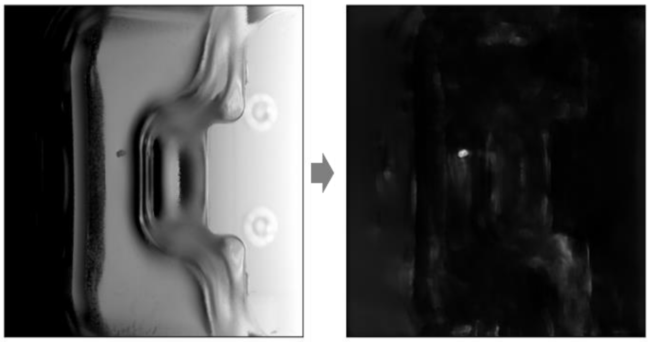

Figure 11. Good segmentation case.

Figure 11 depicts a good segmentation case. The left side of Figure 11 shows the original surface image of the defective data, with the defect indicated by a black spot in the center of the image. The right side of Figure 11 shows the result image after passing through the discriminative network, where only the defective area of the product is segmented in white. However, the result image is not entirely black in the areas excluding the defective region. This indicates that the reconstruction network did not properly restore the image in areas with curvature when generating the scratch-removed image.

B. Bad sementation case

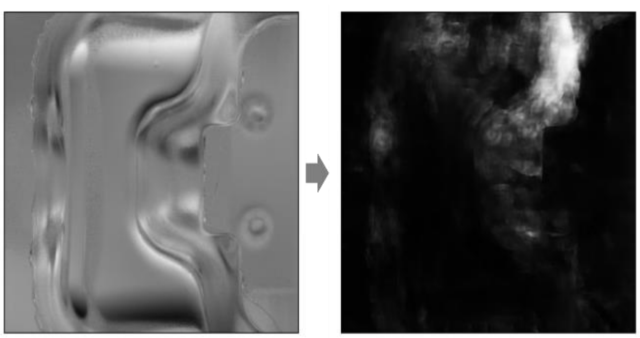

Figure 12. Bad segmentation case.

Figure 12 represents a case where the defective area of the original image and the curved surface area are not well distinguished. In Figure 12, the curved portion at the top is not properly restored. The presence of a large white area indicating differences in the curved portion suggests that there is significant disparity between the scratch-removed image and the original image in the curved area. In other words, the reconstruction network fails to generate the scratch-removed image accurately. This phenomenon particularly occurs frequently in vertical inspections at the top portion, speculated to be due to less color variation compared to horizontal inspections.

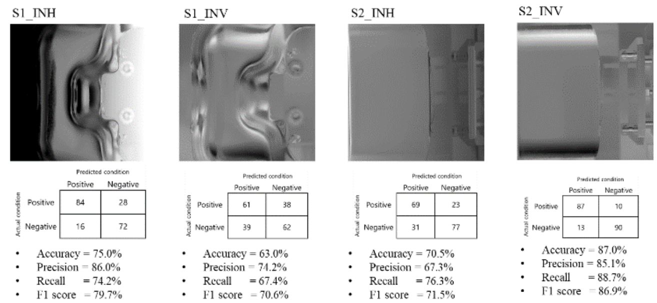

Figure 13. Result of performance evaluation (Accuracy, Precision, Recall, F1-score).

The number of image data used for the final performance evaluation is 200 for each of the top (S1) and bottom (S2) regions, with lighting directions in horizontal (INH) and vertical (INV) inspection methods. Figure 13 illustrates the performance evaluation for each image. In the top region (S1), an accuracy of 75% for INH and 63% for INV was observed, while in the bottom region (S2), an accuracy of 70.5% for INH and 87% for INV was achieved. The accuracy, precision, recall, and F1-score for the learning results are as shown in Figure 13.

V. Conclusion and Future Work

The press processing process is a method of transforming metal materials in the form of coils or plates into desired products using presses and molds. With the proliferation of smart factories, the press processing process has actively utilized Information and Communication Technology (ICT) not only to monitor abnormal conditions of equipment through facilities and various sensors but also to enhance productivity. Moreover, activities aimed at automating the surface defect detection of appearance products for quality improvement have consistently taken place. It is predicted that surface defect detection technology through computer vision and machine learning will rapidly advance in the future.

This paper proposed and validated a surface defect detection method for press-processed products using stainless steel materials with intense light reflection. The method utilized unsupervised learning based on normal data to detect surface defects in products with insufficient abnormal data. The performance of the model was evaluated using accuracy, precision, recall, and F1-score metrics based on a confusion matrix, achieving a meaningful level of performance.

Throughout the study, several lessons were learned, including the effectiveness of the unsupervised learning approach using normal data, particularly in environments with insufficient defect data. However, challenges, such as the variability in lighting conditions and the difficulty in generating realistic defect images from normal data were encountered. The reconstruction network occasionally failed to accurately restore images in areas with high curvature, leading to false positives.

Future work will focus on addressing these limitations by enhancing the defect generation process to create more realistic defect images that better represent actual defect conditions, potentially using advanced noise generation techniques and integrating domain knowledge about common defect patterns. Additionally, improving the robustness of the detection model under varying lighting conditions through adaptive lighting systems or image normalization techniques will be prioritized. Exploring the integration of additional sensor data, such as thermal or ultrasonic sensors, could provide more comprehensive defect detection capabilities. Furthermore, expanding the dataset to include a wider variety of defect types and conditions will help to further validate and improve the model's performance, making the defect detection system more reliable and applicable in diverse industrial settings.

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