Improving Automated Inspection and Repair Performance in Display Manufacturing through Diffusion-based Generative AI

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Abstract

This study presents a diffusion-based generative AI approach to address dataset imbalances in display manufacturing automation. By generating realistic synthetic data for defects and repair failures, we achieved high-performance classification AI and detection AI, enabling automation previously reliant on human operators. The proposed method demonstrates the potential of diffusion models to expand automation in manufacturing processes utilizing computer vision.

Author Keywords

Display Panels; Inspection; Repair; Diffusion; Deep Learning; Machine Learning;

1. Introduction

Background

The implementation of automation systems is a fundamental requirement for establishing a smart factory. Automation not only reduces labor costs, thereby lowering overall production expenses, but also minimizes human involvement in manufacturing processes, which is critical for reducing human-induced errors and improving yield. Additionally, by shortening tact time, automation enhances production output per unit of time. Most importantly, it forms the foundation for a smart manufacturing line, where feedback loops between processes are crucial for achieving synergistic effects throughout the entire production chain.

One of the significant barriers to establishing a smart factory in real-world display manufacturing lines is the emergence of new defect types. These defects, which severely compromise product quality, demand immediate attention. However, because these defect types are newly encountered, collecting sufficient labeled data for deep learning-based supervised learning is challenging in an actual manufacturing setting. While alternatives such as rule-based algorithms or semi-supervised and unsupervised learning methods may be considered to address these defects, they often fail to achieve the performance required to prevent defective products from reaching customers, making them unsuitable for practical application in manufacturing lines.

Consequently, developing automated software solutions targeting these defect types is structurally unfeasible. Nevertheless, these defects have a direct impact on product quality and must be addressed in real time within the production line. This necessity inevitably leads to the involvement of human operators, which significantly hinders automation efforts in display manufacturing lines and remains a primary obstacle to achieving a fully automated production environment.

[1] explored the application of Generative Adversarial Networks(GAN)-based generative AI to address class imbalance in training datasets by generating defect samples observed in legacy products within the context of new product backgrounds. By utilizing virtually generated defects from the GAN model for supervised learning, the recall performance of defect classification models improved by approximately 50%p. However, this level of improvement was insufficient to prevent defective products from reaching customers, thereby falling short of the performance standards required for deployment in actual manufacturing lines. These limitations were attributed to two primary issues: the mode collapse phenomenon, which restricts the diversity of generated defects, and the inability of GAN-based generative AI to produce realistic defect patterns.

[2] investigated the development of automated software designed to detect and classify defects using rule-based algorithm s, followed by the automated repair of identified defects. While this approach shows potential, it cannot achieve complete automation in actual manufacturing lines. The reliance on traditional image processing algorithms, which compare defects

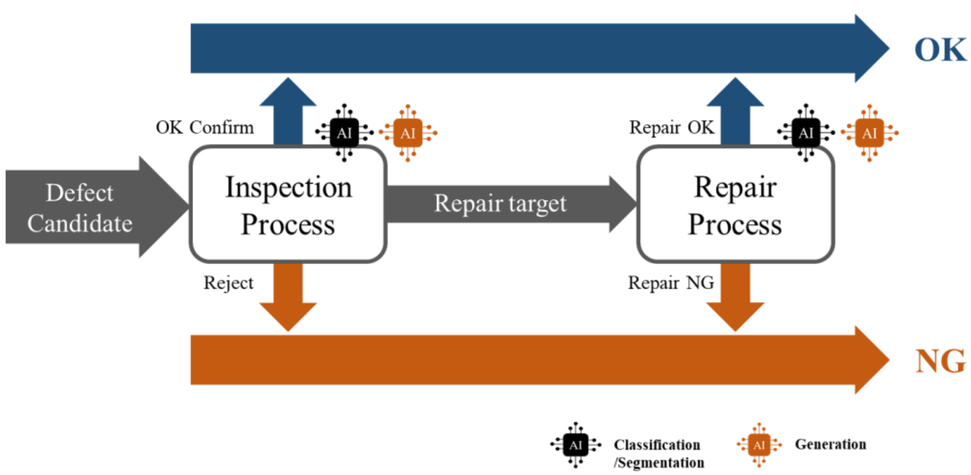

Figure 1. Concept of automation for inspection and repair processes using AI

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against a golden reference to detect anomalies and select the optimal repair recipe, imposes performance constraints. Consequently, some defects remain unprocessed, hindering the full automation of the manufacturing process.

Figure 1 illustrates the defect-handling workflow in typical manufacturing line. The workflow consists of two primary processes: the inspection process and the repair process. The inspection process identifies specific defects on display panels, categorizes them as either OK or NG(No Good), and determines which defects require repair. The repair process then addresses the defects identified as repair targets during the inspection process. Following the repair attempt, a post-repair inspection evaluates the success of the repair. Ultimately, display panels are classified as either Repair OK or Repair NG. Panels categorized as Repair OK are deemed acceptable products, whereas those labeled as Repair NG are considered defective.

Objectives

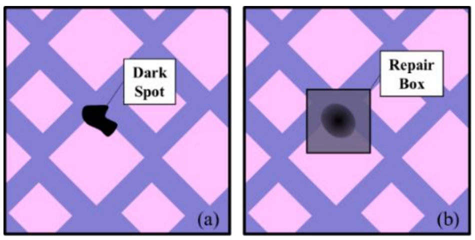

Figure 2. (a) Back plane with a “Dark Spot” defect (b) Back plane after repair

This study focuses on a specific defect type known as the "Dark Spot," which appears as black spots on the backplane (BP) of OLED displays. These defects degrade display panel, disrupt normal device operation, and ultimately reduce production yield. As illustrated in Figure 2(a), the Dark Spot defect manifests as black spots on the OLED BP pattern. The inspection process depicted in Figure 1 is designed to detect these defects. Figure 2(b) illustrates the BP of a repaired panel, which is classified as Repair OK after undergoing the repair process. In such cases, a rectangular Repair Box forms around the defect, with the noticeable processing mark remaining at the location of the original defect within the box.

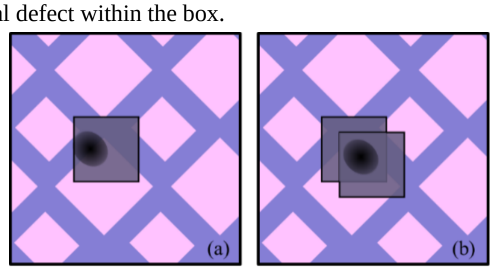

Figure 3. Types of Repair: (a) Centering Miss (b) Overlap

However, the repair process is not always successful. For instance, one type of failure occurs when misalignment during the repair process causes the processing mark to extend to the edge of the Repair Box, a phenomenon known as "Centering Miss." Another failure type arises when the repair process is performed multiple times, resulting in overlapping Repair Boxes, referred to as "Overlap." Panels classified as Repair NG become non-functional, leading to defective products. It is crucial to evaluate the success of repairs, as illustrated in Figure 1, and prevent panels classified as Repair NG from advancing to subsequent production stages.

As previously discussed, the characteristics of Dark Spot defects result in a significant shortage of data, which has historically necessitated human involvement in both inspection and repair processes. The lack of sufficient defect data, as illustrated in Figure 2(a), has hindered the development of automated inspection and classification AI systems. Similarly, the scarcity of Repair NG data, shown in Figure 3, has impeded the training of detection AI systems essential for automating the repair process. This limitation in acquiring adequate NG-class data has rendered supervised learning infeasible, forcing reliance on human operators.

The primary technical hurdle in automating the inspection and repair processes is the dataset imbalance caused by insufficient NG data. Although alternative approaches, such as unsupervised learning or traditional rule-based algorithms, have been explored, they fail to meet the performance levels required for real-world manufacturing applications. To overcome this challenge, this study employs diffusion-based generative AI to generate synthetic defect and Repair NG data. These datasets are then used for supervised learning, enabling the development of high-performance detection and classification AI systems capable of automating both inspection and repair processes.

2. Development of Diffusion Models for Synthetic Data Generation

The diffusion model for generating synthetic data was designed based on the framework proposed in [3]. Figure 4 illustrates the training workflow of the diffusion model developed in this study. During the training phase, specific regions of display backplane (BP) images, where synthetic data is to be generated, are masked, and a UNet architecture is employed for denoising, as shown in Figure 4. During inference for virtual image generation, the process begins by masking a normal display BP image and introducing noise to the masked region. The desired pattern is then iteratively generated in the specified region through repeated denoising operations.

The input to the diffusion model includes the BP image with a masked region, which serves as a condition for the model. The diffusion process is conducted at the image level, following the approach of Denoising Diffusion Probabilistic Models (DDPM). In summary, this approach uses diffusion with the mask as a condition to perform inpainting, enabling the generation of diverse synthetic images, such as virtual Dark Spot defects and virtual Repair NG patterns, in the specified regions.

As illustrated in Figure 1, automating the handling of the target defects in this study requires enhancing both the inspection AI and the repair AI. To improve performance through supervised learning with synthetic data, Dark Spot defect images must be generated using diffusion for the inspection AI, while Repair NG images must be generated for the repair AI. Specifically, the diffusion model for the inspection AI must create Dark Spot defects on normal BP backgrounds, while the diffusion model for the repair AI must generate Repair Boxes with pronounced processing marks on normal BP backgrounds.

Ultimately, as illustrated in Figure 1, distinct diffusion models must be trained for each process to meet the unique requirements of synthetic data generation. These tailored models ensure that both the inspection and repair processes achieve the performance required for full automation.

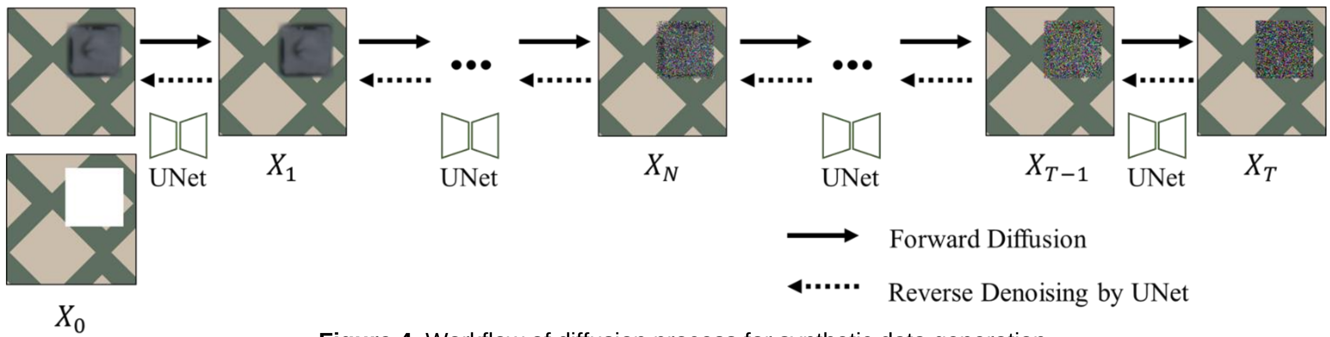

Figure 4. Workflow of diffusion process for synthetic data generation

3. Experiments and Results

Data Generation

When generating synthetic defects using diffusion, it is ideal to use actual OLED panel BP images as the background. However, because these BP images contain proprietary information specific to the panels, they are considered corporate trade secrets and cannot be disclosed. Therefore, in this paper, simplified virtual BP images, such as the one shown in Figure 5, were used as input backgrounds for generating defects through the diffusion model.

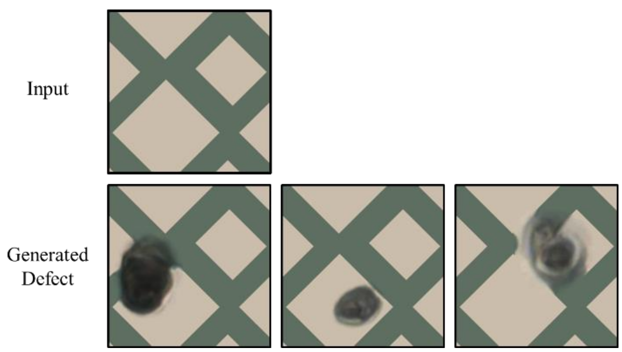

Figure 5. Synthetic defects generated by diffusion

Two key advantages of using diffusion for defect generation are its ability to produce defects that closely resemble real-world defects and its capacity to generate diverse types of defects. Figure 5 illustrates examples of Dark Spot defects generated on a normal BP background using diffusion. While the input background remains the same, diversity in synthetic defects is achieved by varying the mask conditions. By modifying the mask's position, the location of the defects can be varied, and due to the influence of random noise, the shape, intensity, and impact of each generated defect are distinct. This diversity mirrors the range of defects that could occur in actual manufacturing lines.

Another significant advantage of using diffusion to generate display process data is the precise control it provides over the shape and location of defects. This capability is especially important for generating synthetic Repair NG cases, which are critical to this study. As shown in Figure 3, Repair NG cases consist of two main types, with their classification determined by the positional relationship between the Repair Box and the processing mark.

Figure 6 demonstrates an example of generating virtual Repair NG data for the Centering Miss failure type. To create realistic Centering Miss NG cases, it is crucial to generate processing marks that partially overlap the boundary of the Repair Box. As shown in Figure 6, by using two masks as conditions for the diffusion model, precise and natural-looking Repair NG cases can be generated, closely resembling those observed in actual manufacturing lines.

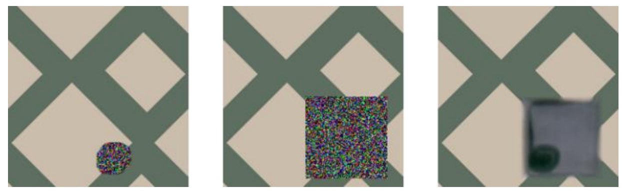

Figure 6. Generation of Repair NG for centering miss: Conditional masks and a NG image

By adjusting the number and position of masks, this method enables the generation of a wide variety of detailed Repair NG cases. Figure 7 further illustrates the capability of diffusion to generate diverse Repair NG cases with precise control over their location and form. While such cases may not yet have been observed in mass production, leveraging domain knowledge about manufacturing processes facilitates the creation of realistic virtual Repair NG cases that could potentially occur in the future.

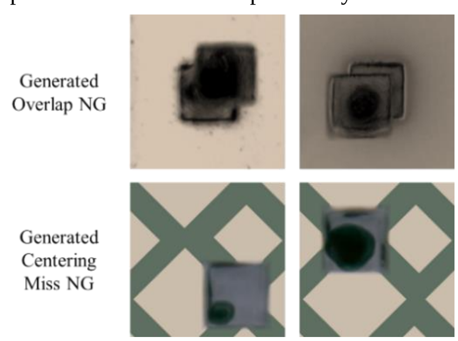

Figure 7. Generated synthetic Repair NG cases

The ability to generate virtual data for anticipated defects that have not yet been encountered in the manufacturing line provides a significant advantage. Incorporating these synthetic cases into the training process enhances the robustness of defect detection and classification AI, preparing it to address both current and future challenges in production.

Results and Analysis

Table 1 presents a performance comparison of classification AI models for the inspection process, evaluated using different training methodologies. The approach utilizing synthetic data generated by the diffusion model achieved the highest performance. In scenarios where the collection of actual defect and Repair NG data is limited, leading to imbalanced training datasets, prior methods relied on unsupervised or semi-supervised learning and traditional rule-based algorithms.

Table 1. Comparison of classification performance by automated inspection methods

Method	F1 Score
Rule-based Algorithm	0.930
Semi-supervised Learning	0.930
Supervised Learning + Diffusion	0.962

However, these methods consistently produced F1 scores below 95%, which are inadequate for deployment in manufacturing lines, particularly for critical defects like Dark Spots, where defect leakage must be strictly avoided. In contrast, the AI model trained with diffusion-generated synthetic data achieved an F1 score of 96.2%, a performance level sufficient to replace human operators. This result demonstrates that balancing training datasets with diffusion-generated synthetic data enables the development of high-performance classification AI, facilitating process automation.

Table 2. Classification performance by ratio of synthetic Repair NG in the training dataset

Ratio	F1 Score
0%	0.775
80%	0.840
100%	0.995

Table 2 presents the performance variation of the classification AI for the repair process based on the ratio of synthetic Repair NG data generated by diffusion to actual Repair OK data used for training. This ratio represents the quantity of synthetic Repair NG data relative to actual Repair OK samples. For example, a ratio of 100% indicates an equal number of synthetic Repair NG and actual Repair OK samples, resulting in a balanced training dataset. While Repair OK data is readily available from manufacturing lines, the extremely low frequency of Repair NG cases makes their collection nearly impossible, necessitating the use of diffusion-generated data. The performance evaluation was conducted using a test dataset comprising actual Repair OK and Repair NG samples collected from the manufacturing line, ensuring that the reported metrics accurately reflect real-world conditions.

The results clearly demonstrate that increasing the proportion of synthetic Repair NG data and achieving class balance significantly enhance classification performance. Notably, with a fully balanced dataset (100% ratio), the AI model achieved an F1 score of 99.5%, a performance level sufficient to replace human operators. This finding highlights the critical importance of diffusion-generated synthetic data in achieving robust AI performance for defect classification.

The experimental results demonstrate that supplementing training datasets with diffusion-generated synthetic data enables supervised learning to achieve AI performance levels sufficient for automating critical processes. The performance gains achieved with diffusion models surpass those of earlier generative AI methods, such as GAN. This superiority is attributed to the higher diversity and realism of synthetic images produced by diffusion models, which closely resemble actual manufacturing defects.

Furthermore, the mask-conditioned diffusion approach employed in this study provides precise control over the shape and location of generated data, making it particularly effective for industrial applications. This combination of realism, diversity, and controllability underscores the value of diffusion models in generating synthetic industrial datasets and advancing automation in manufacturing processes.

4. Impact

One of the most significant challenges in automating display manufacturing processes is addressing dataset imbalances in certain stages. This limitation prevents supervised learning from achieving the classification and detection AI performance required to replace human operators. As display manufacturing lines become more advanced, this challenge becomes increasingly pronounced. Once a production line stabilizes, acquiring defect or failure data from the manufacturing environment becomes difficult, even as the need for higher-performing AI increases.

In this study, we addressed this challenge by leveraging diffusion-based generative AI combined with domain knowledge of manufacturing processes to generate precise and realistic synthetic data. By training supervised learning models with these high-quality synthetic datasets, we developed classification and detection AI capable of achieving performance levels sufficient to replace human operators. This represents a breakthrough in automating display panel manufacturing processes previously considered unfeasible with traditional methods.

The implementation of diffusion-based generative AI in this study provides a compelling example of how this technology can expand the scope of automation in vision-based manufacturing. By automating processes constrained by data scarcity and imbalance, this research underscores the potential of diffusion models to significantly enhance the coverage and capability of automation in advanced manufacturing environments.

5. Conclusion

This study demonstrated the effectiveness of diffusion-based generative AI in automating display manufacturing processes by addressing challenges related to dataset imbalances and data scarcity. By generating realistic synthetic data and integrating domain knowledge, we developed high-performance AI systems capable of replacing human operators. These findings underscore the potential of diffusion models to advance manufacturing automation, paving the way for broader adoption in advanced production environments.

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