Diffusion-Based AI Solutions for Stabilizing Automated OLED Cell Repair Processes and Enhancing New Product Performance

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Abstract

In the OLED manufacturing process, the Cell Repair process plays a critical role in preventing defect leakage by identifying defects using an optical scope and then either repairing or rejecting them. The causes of Pixel-Off defects addressed during this process can be categorized into two types: floating foreign substances on the top of the cell and foreign substances between the layered structures. However, in Rule-Based Auto Repair Systems that rely on image processing, distinguishing between these two types of defects is not feasible. As a result, the affected panels are subjected to final judgment by a separate inspector, leading to a combination of issues such as decreased equipment efficiency, reduced productivity, and the need for additional inspectors. Therefore, the company has introduced Image Deep Learning (DL) techniques to enable the automatic classification of defect types, achieving significant automation in the process. However, during the initial production phase of new products, the lack of sufficient defect data sets for DL training results in very low model accuracy, making its application impractical. This proposal addresses the DL accuracy issue in the early stages of new product production by adopting a defect generation method using diffusion-based generative AI, significantly enhancing the performance of the DL classification system. This technique requires only a single defect sample image in the early stages of new product development, eliminating the need for months of defect data collection. At the same time, it enables the immediate deployment of the defect classification DL system, which was previously unusable during the initial mass production phase of new products. The proposed method has been successfully implemented in the production line process.

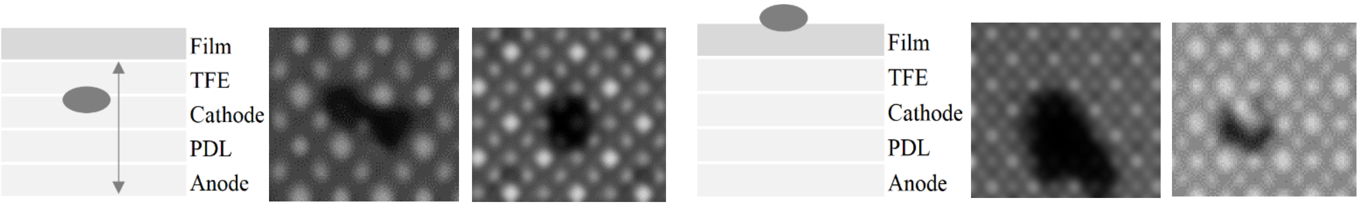
Author Keywords

OLED cell repair; generative AI; Diffusion Model; Latent Diffusion; convolutional neural network

1. Introduction

In the OLED production inspection process, Deep Learning (DL)-based technologies are widely applied to various tasks, including optical inspection, image quality inspection, appearance inspection, and repair processes. Among these, the repair process has become increasingly important for ensuring panel quality due to rising defect rates caused by higher resolution and complexity in manufacturing, as well as the growing demand for large-scale, high-value IT and automotive products, where yield optimization is critical. However, with the increasing diversity and complexity of products, the limitations of rule-based image processing for defect classification have become apparent, leaving certain defects that still require manual inspection and judgment by operators. In recent years, the rapid advancement of DL-based technologies has been applied in various ways to address the persistent challenges of the repair process. Technologies such as Classification (1), Object Detection (2), and Segmentation (3) have been actively developed and expanded, replacing traditional rule-based algorithms. However, the diverse defect patterns that arise from differently designed pattern structures for each product pose challenges not only for conventional rule-based repair systems but also for applied DL systems. These challenges require continuous model updates due to performance degradation. In particular, significant pattern design changes in new products can render existing image-based DL systems unusable. As a result, collecting defect images to ensure the performance of DL systems for newly developed products becomes a critical factor in maintaining productivity.

This study aims to address the limitations of conventional image-based DL models by applying image-based generative AI techniques. Among these, the study proposes the use of Diffusion (4) technology as a key method for solving these challenges. The proposed method leverages a Diffusion Model trained on defect types from existing production products to virtually generate these defects onto the patterns of new products. This approach enables the creation of a remarkably diverse range of high-quality defect images tailored to the needs of DL models for new products. Through this process, the most suitable Diffusion Model for generating OLED pattern images was experimentally validated. Additionally, an auxiliary DL model process was proposed to select practically applicable images from the large pool of randomly generated images. This results in a practical generative AI solution that can be effectively implemented in real-world production environments. The images generated using the proposed method were evaluated by comparing them with the performance of conventional initial DL models for new products. The proposed method was then applied to the new product DL model generation process on the production line, enabling the rapid enhancement of



(a) Defect inside the pattern (Panel Reject) (b) Something on top of the film (Panel OK)

Figure 1. Image comparison based on defect location

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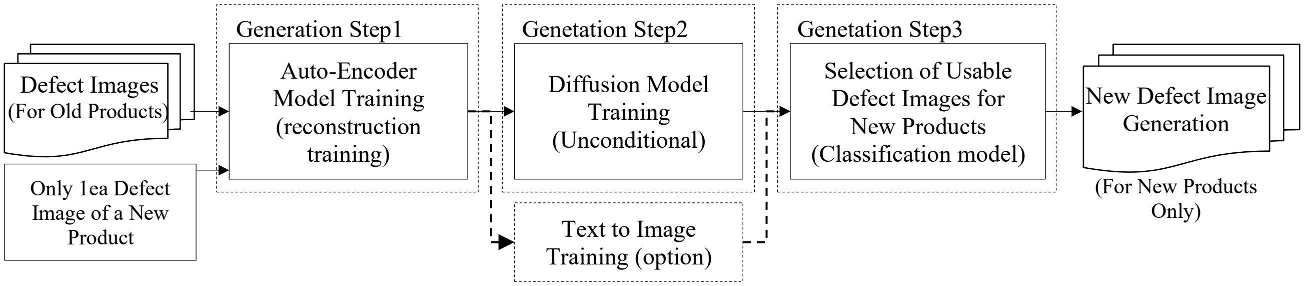


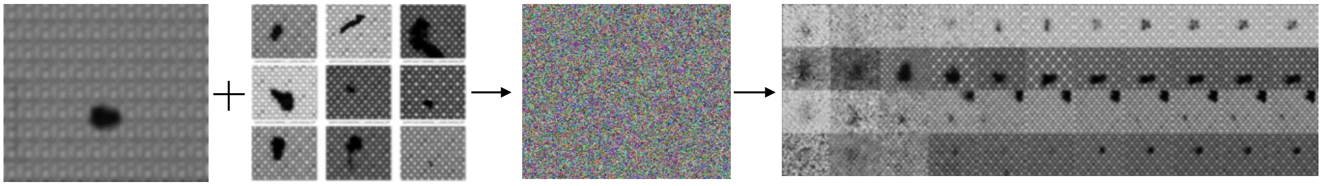
Figure 2. Practical Method Proposal for Defect Image Generation of New Products: A Combination of a Diffusion Model (comprising Auto-Encoder Training and Diffusion Training) and a Classification Model for Automatically Sorting Usable Images from the Generated Large-Scale Defect Images

DL model performance in minimal time. This ensures the stability of the automated production environment.

2. Defect Image Generation Method and Application Process for DL System in New Products

A major challenge in the automatic classification of particle defects, which can degrade the performance of DL models, is distinguishing between defects located inside the panel layers, as shown in Fig. 1(a), and those on the top of the panel layers, as shown in Fig. 1(b). Particle defects inside the panel layers are positioned beneath the topmost pattern structure of the product. Therefore, to accurately classify defect types for each product, it is essential to incorporate information about the product's pattern structure into the defect classification process. Therefore, the DL model's performance is crucial in distinguishing actual defect images of the product from simple floating particle defects, as shown in Fig. 1(b). The goal of the proposed method is to generate a large quantity of high-quality defect images to enhance the model's ability to accurately classify defects. The training dataset for this approach consists of particle defect types that have been accumulated and collected by inspection equipment during mass production, along with a single rare particle defect image observed during new product development. Additionally, to train the model with the new product's characteristics, 15ea non-defect images were included. By utilizing this dataset, the goal is to accurately regenerate a diverse range of previously occurring particle defect images on the new product's unique pattern structure with high quality. These generated images are then provided as training data for the existing Cell Repair AI automation system to enhance its performance. Notably, if generative AI is applied without including even a single defect image from the new product in the dataset, an alternative approach would be required, demanding significantly more effort and additional resources to ensure accurate defect generation and classification.

The structure proposed in Fig. 2 is a Latent Diffusion (5) Model, which utilizes the particle image dataset of existing products, at least one defect image from the new product, and approximately 15 non-defect images to effectively train the pattern replication capability of the Auto-Encoder (6) Model. Subsequently, the Latent Diffusion Model is used to determine the optimal AI model conditions for OLED pattern generation. This enables the creation of an unlimited number of images by combining information from both mass-produced products and the newly developed product. Subsequently, as proposed, a CNN Classification Model targeting only the new product is integrated to effectively filter and select practically usable images for users. Among the obtained images, users can manually select and acquire defect-containing images that meet the required quality standards. This process follows an unconditional approach, allowing Diffusion Model data preparation and training with minimal resources. While not covered in detail in this proposal, it can be extended using Stable Diffusion (5) to leverage Text-to-Image functionality. Specifically, by captioning various product-related information and training the


A Single Defect Image of a New Product

(A Different Pattern Design from the Existing One)

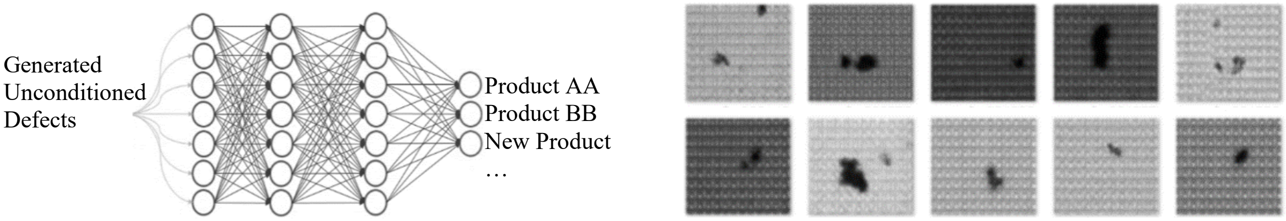
Various Defect Images of Existing Products

Diffusion Process

Generated Defect Image

(If trained with Text-to-Image, selective image generation becomes possible.)

Figure 3. Creation of a Diffusion Model Trained with a Single Defect Image of a New Product and Multiple Images of Existing Products



(a) Classification Model for Categorizing Products

(b) Various Defect Images Generated from New Products

Figure 4. A system combining the classification of defect images generated under unconditioned conditions to efficiently extract the required images.

model in a Text-to-Image manner, the generated model can more effectively produce defect images specific to the new product. However, the captioning process requires significant human resources during the model preparation stage, making it necessary to adopt this approach selectively based on resource availability. The particle defects generated by the trained Diffusion Model are reported through the process illustrated in Fig. 3. The model accurately replicates the pattern design structures of both new and existing products while generating a diverse range of particle defect types. These images are then processed through a pre-trained classification model, as shown in Fig. 4(a), which categorizes the products. This allows for the easy extraction of new product-specific pattern images, as demonstrated in Fig. 4(b), ensuring that relevant defect images can be efficiently identified and utilized.

3. Validation

To create the proposed Latent Diffusion Model, we utilized an NVIDIA A100 GPU with 80GB of memory. A total of 497 defect images from existing products, one defect image from the new product, and 15 non-defect images were used for training. The Auto-Encoder and Diffusion Model training process took approximately five days. Subsequently, using the trained model, 60,000 newly generated images were processed through the product classifier shown in Fig. 4(a), resulting in the selection of 1,107 images. From these, a final verification by engineers was conducted to identify images suitable for use in the Cell Repair Defect Classification Model, leading to the selection of 61 high-quality images. Through this generation process, as shown in Table 1, the dataset for the particle defect class increased from a single image to an additional 61 images, ensuring a well-balanced data distribution across different classes. When these images were incorporated into the training of the Cell Repair Defect Classification Model, the classification performance for the particle defect class in the early mass production stage of the new product significantly improved. As shown in Table 2, the recall increased from 26.4% to 86.8%, and the F1-score improved from 0.42 to 0.92. This level of improved classification performance enabled the immediate application of an AI automation system equivalent to that used in mass production, replacing the previous defect handling process that relied on manual inspection during the early stages of new product development. As a result, the Cell Repair AI system achieved the required performance before the large-scale mass production of new products.

Table 1. Improvement of Data Set Through Defect Image Generation for New Products.

Model Class	Existing Data Set	Generated Data Set (Proposed)
1_AAA	52	52
2_Particle (Target)	1	1+**61**
3_CCC	34	34
4_DDD	63	63
Total	150	211

Table 2. Comparison of Initial Particle Classification Performance for Mass Production of New Products Trained with Generated Images.

Validation Item.	Existing Model (Trained with 1 Defect Image of the New Product)	Model Trained with Newly Added 61 Images (Proposed)
Recall	26.4%	86.8%
F1-Score	0.42	0.92

4. Conclusion

This paper proposes the adoption of generative AI to improve the performance degradation of AI models that occurs during new product development in the Cell Repair AI System process for the automatic classification of particle defects inside panel layers. Through the proposed AI system, a large amount of particle image data was obtained using only a small number of particle-type images collected during the development stage of new products. This approach ensured the performance of the Cell Repair equipment for automatic particle classification and contributed to the stability of the automated production line. As a result of applying the proposed method, the detection performance of a recently developed new product was evaluated, showing that the previously unusable model, with an F1-score of 0.42, was improved to 0.92. This process has since been consistently applied to newly developed products. The need for a large number of inspection workers, previously required to compensate for the reduced accuracy of new product models, has been eliminated, enabling more stable workforce management. Furthermore, the introduction of this technology provides a solution to the ongoing challenges of detection and automated processing performance degradation in new OLED production lines. Additionally, although not covered in detail, the expansion of Generative AI into a Text-to-Image-based approach is being considered. This could serve as an effective method for selectively and efficiently generating defect images specific to each product, further enhancing the capability of defect classification and automation.

5. References

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