

Learning-based defect inspection of μ LED patterns using reflection-mode Fourier ptychographic microscopy

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Received 24 March 2026; revised 19 May 2026; accepted 20 May 2026; posted 20 May 2026; published 4 June 2026

We demonstrate die-level field-of-view (FoV) metrology for μ LED (micro-light-emitting diode) patterns assisted by a proposed learning-based defect inspection framework. In this study, high-resolution, large-FoV images were obtained by reflection-mode Fourier ptychographic microscopy (FPM) providing sub-1 μ m pitch resolution imaging over a 1×1 mm² FoV. Patterns with varying pitches and diverse geometries were fabricated, incorporating both natural and artificial defects to emulate lithography and pattern transfer processes. Defect types were systematically defined to facilitate supervised and unsupervised learning defect detection methods. Deep learning models, including a YOLO-based detector and a self-supervised segmentation framework, achieved high accuracy and robustness in identifying diverse defect types. The proposed approach offers a scalable and efficient metrology solution for inline defect detection and process optimization for next-generation μ LED and advanced display manufacturing. © 2026 Optica Publishing Group under the terms of the [Optica Open Access Publishing Agreement](#)

<https://doi.org/10.1364/AO.599473>

1. INTRODUCTION

Micro-LED (μ LED) display technology offers numerous potential applications owing to its high resolution, energy efficiency, high brightness, high contrast, and fast response time, making it a promising candidate for next-generation displays [1–3]. However, as pixel pitch decreases and alternative pattern transfer technologies become necessary, both the type and number of defects inevitably increase [2]. To ensure reliable mass production with further pixel size reduction, accurate defect inspection processes are essential. Various metrology approaches have been explored, including advanced microscopy techniques, automated optical inspection (AOI) [4], machine vision systems, as well as recent deep-learning-based methods [4–6].

Our framework integrates advanced imaging and artificial intelligence (AI) methods for defect inspection. We employ the reflection-mode Fourier ptychographic microscopy (FPM) [7–11] to capture high-resolution and large field-of-view (FoV) images, and we combine it with machine learning algorithms for automated defect detection and classification. FPM enables submicron-scale resolution over several millimeters without mechanical scanning by reconstructing amplitude and phase information from multi-angle illuminations [7,12,13]. The

FPM imaging provides rich optical data that can serve as input for data-driven inspection algorithms.

FPM enhances imaging resolution while maintaining a large FoV by synthetically increasing the effective numerical aperture through multi-angle illumination and Fourier-space stitching of spatial-frequency information [7,12,13]. In this work, the reflection-mode FPM system provides sub-micron pattern resolution over an effective die-level FoV exceeding $1 \text{ mm} \times 1 \text{ mm}$ for learning-based inspection and metrology.

To analyze sample defects under different inspection scenarios, we first categorize defects according to their origin: process-induced, engineered, and synthetic defects. These categories describe how defects are generated. For model training and evaluation, however, the defects are grouped into a separate set of practical annotation classes, as defined in Section 2.D. Process-induced defects arise naturally during lithographic patterning and pattern transfer. Engineered defects were deliberately introduced into the fabricated samples to emulate realistic manufacturing failures. Because individual μ LED dies rely on transfer technologies such as “pick-and-place,” which involve complex parallel positioning, we introduced engineered defects to mimic pattern transfer faults, including misalignments and missing dies [14]. The tested samples included

structures with interconnect and electrode patterns, fabricated with various pitches and geometries, whose corresponding resolution and pixel-per-inch (PPI) specifications are detailed in this paper. To further emulate pattern transfer issues, shifted locations and missing μ LED elements were also embedded directly into the pattern design. In addition, synthetic defects were generated in the image domain to simulate crack-type defects associated with thermal stress using randomized crack models [15].

Traditional human visual inspection methods have been increasingly replaced by automated optical inspection (AOI) approaches, which allow the detection of micro- and nano-scale defects with high accuracy [16–19]. This automated detection enables high-throughput, inline chip metrology and provides a practical and scalable solution for defect inspection in large-scale μ LED manufacturing. Recent advances in learning-based metrology have shown that deep neural networks can achieve superior sensitivity and generalization in identifying subtle, heterogeneous defects that are difficult to detect using rule-based image processing [20–27]. Supervised learning approaches, such as convolutional neural networks (CNNs) and object detection frameworks like YOLO [28], have demonstrated strong performance for the classification and localization of known defect types when sufficient labeled data are available. However, the diversity of manufacturing conditions often introduces new, unseen defect categories for which annotated data are scarce. To address this limitation, unsupervised and self-supervised learning methods have emerged as promising alternatives, enabling pixel-wise anomaly detection and defect segmentation without explicit ground-truth labels. This dual-framework approach improves robustness and adaptability in μ LED manufacturing.

Compared with existing AOI and learning-based defect inspection approaches [16–19], the proposed framework specifically targets die-level μ LED metrology by combining reflection-mode FPM with both supervised and self-supervised defect analysis. While many existing approaches rely on conventional optical microscopy or application-specific imaging systems, the proposed method leverages the large space-bandwidth product of FPM to provide sub-micron-resolution imaging over a large effective field of view. In addition, the combined YOLO- and CUT-based framework enables both classification of known defect categories and localization of irregular defects without requiring paired ground-truth data. Direct quantitative comparison with prior work is challenging because of differences in datasets, defect definitions, imaging modalities, and fabrication platforms; however, the proposed framework demonstrates the feasibility of integrating computational microscopy and learning-based inspection for μ LED defect metrology.

Alternative computational imaging approaches, including digital holographic microscopy (DHM), ptychographic imaging, structured illumination microscopy (SIM), and phase-sensitive inspection techniques, may also provide complementary routes for high-resolution defect inspection and semiconductor metrology. These methods offer different advantages in terms of quantitative phase retrieval, imaging contrast, resolution enhancement, and acquisition strategies. However, different computational imaging approaches often

involve distinct trade-offs between spatial resolution, field of view, acquisition speed, illumination conditions, reconstruction complexity, and hardware implementation. In particular, some techniques require interferometric stability, coherent illumination control, or extensive iterative reconstruction, which can affect throughput and practical deployment conditions for large-area inline inspection. Therefore, direct comparison across modalities remains challenging and was beyond the scope of the present work.

The main contribution of this work lies in the integration of reflection-mode FPM with complementary supervised and self-supervised learning pipelines for die-level μ LED inspection. The proposed framework combines large-field-of-view sub-micron FPM imaging with a YOLO-based supervised detector for classification of known defect types and a CUT-based reconstruction and residual-segmentation strategy for label-free localization of irregular defects. By combining reflection-mode FPM with learning-based inspection, this work aims to demonstrate a scalable and reliable methodology for submicron defect detection in advanced microdisplay fabrication. The proposed approach contributes to the development of intelligent metrology systems that integrate optical imaging, data-driven analysis, and process feedback for next-generation electronic and photonic manufacturing.

The remainder of the paper is organized as follows. Section 2 describes the methodology, including sample fabrication, FPM setup in reflection-mode, defect taxonomy, and learning-based inspection pipelines. Section 3 reports experimental results for both the supervised detector and the self-supervised segmentation model. Section 4 concludes the paper and outlines directions for future work.

2. METHODOLOGY

This section presents the methodologies used in this study. To provide an overview of the proposed framework, Fig. 1 summarizes the complete inspection pipeline developed for μ LED metrology. The process begins with reflection-mode Fourier ptychographic microscopy (FPM) imaging, where multiple intensity images are captured under varying illumination angles and reconstructed into high-resolution, large-field-of-view images. These reconstructed images are subsequently analyzed using complementary supervised and self-supervised learning frameworks for defect detection, localization, and segmentation. The following subsections describe each stage of the pipeline in detail. We first briefly review the μ LED fabrication process and the fabrication of test patterns used for the demonstration of FPM. We then describe the reflection-mode FPM metrology setup and its imaging specifications. Next, we introduce the pattern designs and defect definitions used to support both supervised detection and self-supervised segmentation. Finally, we detail the inspection pipeline, including dataset generation and the learning-based models used for defect detection and localization.

A. μ LED Fabrication Process

As illustrated in Fig. 2, the μ LED fabrication process begins with epitaxial growth, in which GaN-based LED layers

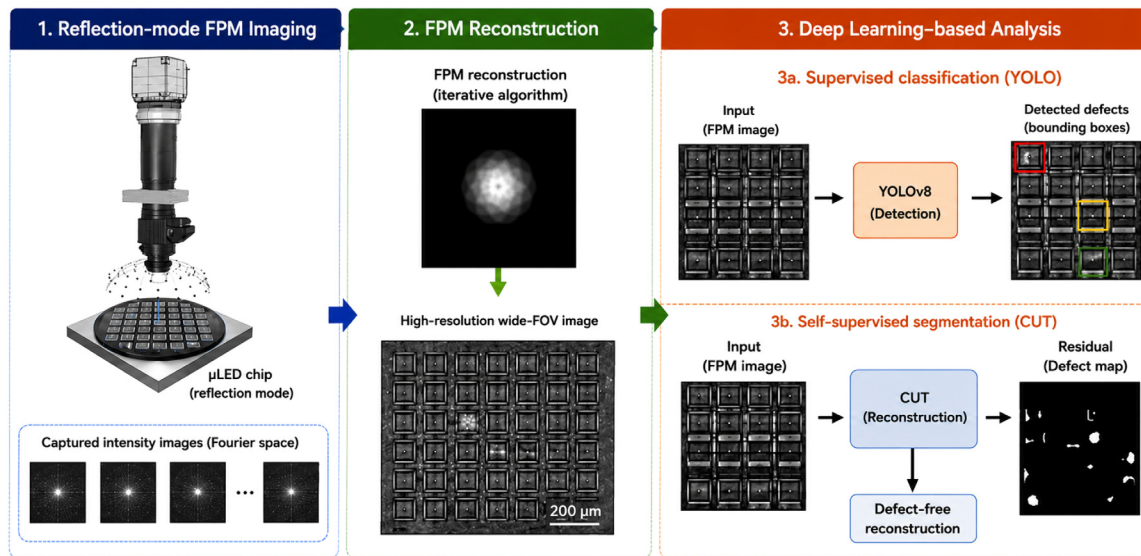


Fig. 1. Overview of the proposed reflection-mode Fourier ptychographic microscopy (FPM) inspection framework for μ LED metrology. Multi-angle reflection-mode FPM acquisition is used to reconstruct high-resolution wide-field images, which are subsequently analyzed using complementary supervised YOLO-based defect detection and self-supervised CUT-based segmentation frameworks. Note: the figures shown are illustrative only and do not correspond to actual data and analysis.

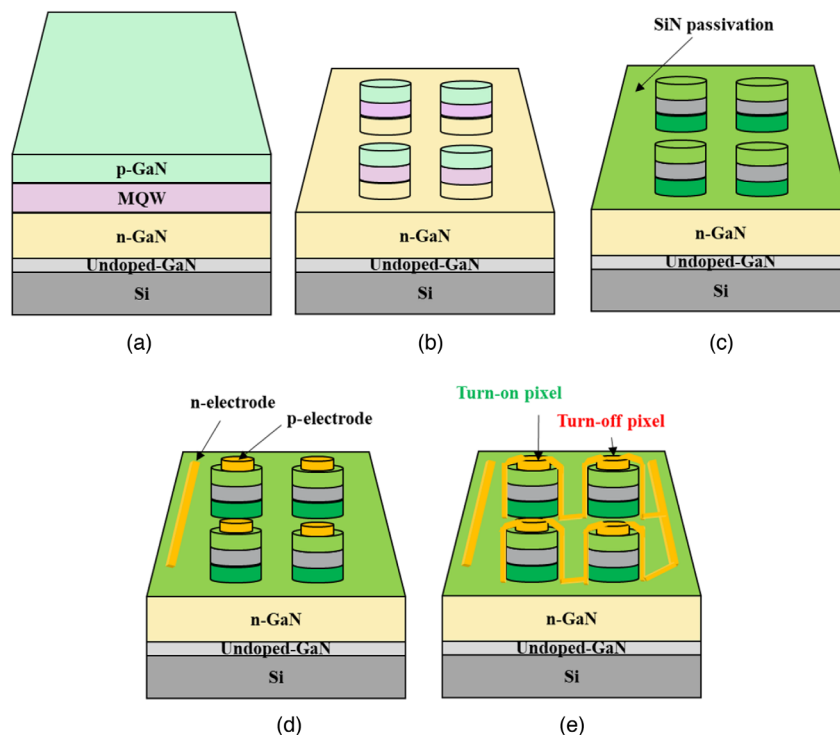


Fig. 2. (a) Schematic illustration of the epitaxial layer structure of a μ LED device. (b)–(e) Simplified μ LED fabrication process flow, including mesa patterning, passivation, electrode formation, and transfer-related processing steps relevant to defect generation mechanisms considered in this work [29–31].

(GaN/InGaN/GaAs, including multiple quantum wells, MQWs) are grown on sapphire or silicon substrates using metal-organic chemical vapor deposition (MOCVD), defining the emission wavelength and electrical properties [Fig. 2(a)]. This is followed by mesa patterning, where μ LED mesas are patterned and etched using photolithography and dry or wet etching

to electrically isolate individual pixels, as shown in Fig. 2(b). Next, a passivation layer is formed by depositing dielectric materials such as SiO_2 , Al_2O_3 , or SiN_x using atomic layer deposition (ALD) or plasma-enhanced chemical vapor deposition (PECVD) to protect side walls referred to as Fig. 2(c) [32]. Electrode formation, which includes the p and n-electrode, is

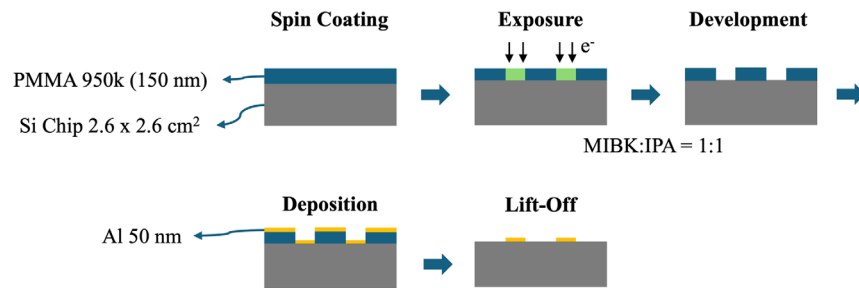


Fig. 3. Fabrication process flow used for the preparation of the Al-patterned samples employed for reflection-mode FPM imaging and defect inspection. The process includes PMMA coating, e-beam lithography, development, Al deposition, and lift-off.

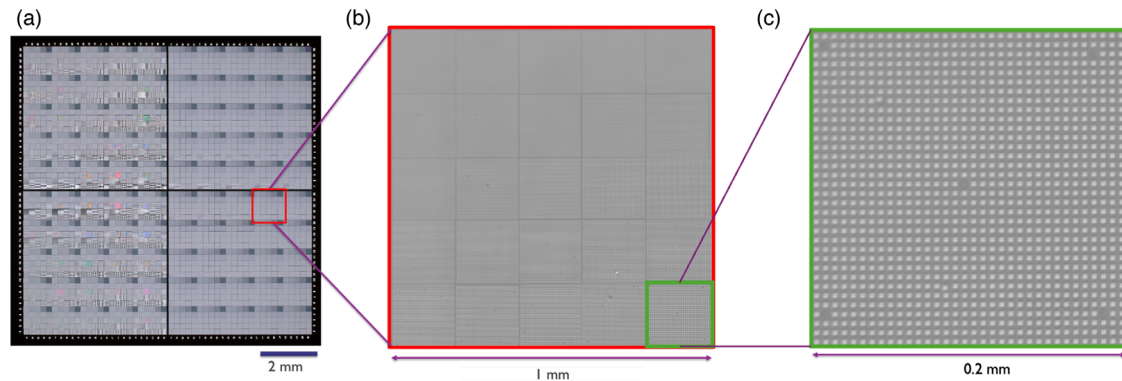


Fig. 4. Fabricated Al patterns with variable pitches on a Si substrate used for FPM-based defect inspection experiments. A repeated 5×5 matrix of variable-pitch patterns is distributed across an effective $1 \times 1 \text{ mm}^2$ field of view to emulate die-level inspection conditions.

then performed through lithography, metal deposition, lift-off, or etching to create electrical interconnections as shown in Figs. 2(d) and 2(e). Subsequently, chip transfer (die-to-wafer integration) is performed by detaching the μ LEDs from the donor wafer and bonding them onto a target back plane using techniques such as pick-and-place, laser lift-off, or stamp transfer. Finally, the process is completed with packaging to ensure mechanical protection and reliable electrical operation.

B. Sample Fabrication for FPM Demonstration

In Fig. 3, the fabrication process used in this study is presented, which involved lithography and a lift-off process. For lithography, PMMA (polymethyl methacrylate) 950k (2C%) was spin-coated at 4000 rpm for 30 s to obtain a thickness of 180 nm on a Si chip ($2.6 \text{ cm} \times 2.6 \text{ cm}$), followed by soft bake at 180°C for 60 s. The e-beam exposure (F7000S, Advantest) was performed to induce chain scission in the positive-tone photoresist. The e-beam dose was set to $230 \mu\text{C}/\text{cm}^2$, with proximity effect correction applied in the writing tool. The exposed sample was developed in MIBK:IPA = 1:1 for 60 s. To obtain Al patterns, as shown in Fig. 4, we utilized the lift-off process. The patterned sample was deposited by Al 50 nm using physical vapor deposition (Alcatel). The photoresist was stripped in heated acetone at 50°C for 35 min. The remaining debris is removed by pipetting with a syringe. The samples were kept in an ultrasonic bath at 37 kHz for 1 min in IPA and dried by N_2 . Figure 5 shows optical microscope images where various defects are created on the different patterns. The defect types considered in this study are defined in Section 2.D.

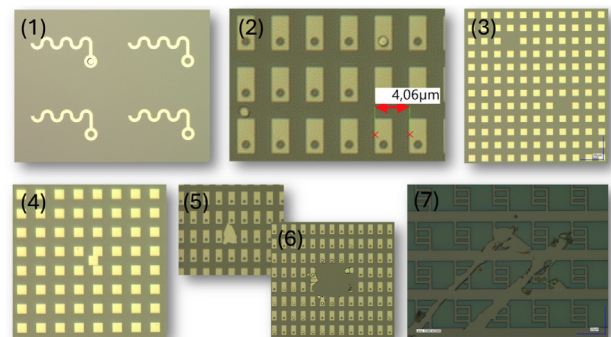


Fig. 5. Optical microscope images showing representative examples of process-induced and engineered defects observed in the fabricated μ LED-related test patterns: undeveloped holes [in (1) and (2)]; resist re-deposition [in (1) and (5)]; misaligned patterns [in (3) and (4)]; missing hole or missing feature [in (3) and (6)]; and line break [in (7)].

As feature sizes shrink, LEDs have evolved from conventional LEDs, mini-LEDs, and further to μ LEDs. Depending on the application, μ LED dimensions range from below $50 \mu\text{m}$ down to the sub-micron scale. In this study, the pitch range under investigation spans from below $30 \mu\text{m}$ down to $0.5 \mu\text{m}$, covering a variety of pattern designs. Simple regular square patterns were fabricated with pitches ranging from $0.5 \mu\text{m}$ to $5.8 \mu\text{m}$. Electrode patterns exhibit pitch sizes between $2 \mu\text{m}$ and $30 \mu\text{m}$, depending on the x and y directions. In addition, more complex pattern designs were developed to emulate interconnect structures or flexible electrode geometries. The types of

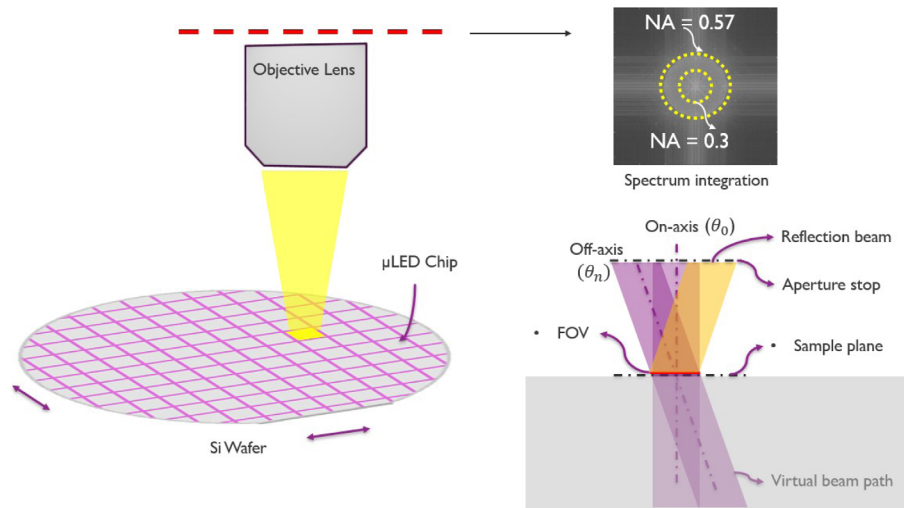


Fig. 6. Schematic illustration of the reflection-mode Fourier ptychographic microscopy (FPM) configuration used for die-level μ LED metrology. Multi-angle bright-field and dark-field LED illumination are used to synthetically increase the effective numerical aperture and reconstruct high-resolution images over a large field of view.

defects observed varied depending on both the pattern geometry and the fabrication process.

C. Metrology Tool

1. Reflection Mode FPM

We employ a reflection-mode Fourier ptychographic microscope (FPM) that enables high-resolution imaging with a large field-of-view (FoV) for the μ LED samples (see Fig. 6). FPM uses a multi-illumination array providing various incident angles to the sample that diffract with the different frequency ranges that enter the objective pupil, depending on the angle of incidence. Those separate images from individual LEDs can be stitched together in a large image patch of the frequency domain using the Fourier transform. As more illumination angles are incorporated, a larger region of Fourier space is recovered, resulting in an increased effective NA. Due to the form factor constraints of the optical system, dark-field illumination was implemented using an external LED arrangement. Optical resolution of FPM is defined by

$$\Delta x = 0.5 \cdot \frac{\lambda}{NA_{\text{obj}} + NA_{\text{illum}}}, \quad (1)$$

where λ is the illumination wavelength, NA_{obj} denotes the numerical aperture of the objective lens, and NA_{illum} is the synthetic or effective illumination NA.

The FPM reconstruction was performed using an iterative phase retrieval algorithm. In addition, pupil aberration correction was incorporated into the reconstruction to compensate for system imperfections. For each reconstruction, a total of 88 raw images including bright and dark fields were acquired under different illumination angles. Prior to reconstruction, a median filter-based denoising preprocessing step was applied to the raw intensity images to improve the signal-to-noise ratio. The iterative reconstruction yields the complex-valued object function, from which both amplitude and phase images are obtained.

Table 1. Comparison of Imaging Performance between the Objective-Limited Microscope Configuration and the Proposed Reflection-Mode FPM Configurations with Bright-Field (BF) and Combined Bright-Field/Dark-Field (BF + DF) Illumination^a

Microscope	Resolution	Effective NA	FoV	Throughput ^b
Objective	1.05 μm	0.3	1 $\times$ 1 mm ²	sec
FPM BF only	0.55 μm	0.57	1 $\times$ 1 mm ²	1 min
FPM BF + DF	0.45 μm	0.69	1 $\times$ 1 mm ²	30 min

^aAssumes illumination wavelength of green at 525 nm.

^bApproximate total time for image acquisition and processing.

The specifications in the imaging system include an image sensor with a resolution of 9344 $\times$ 7000 pixels of a pixel pitch 3.2 μm , corresponding to an area of 29.9 $\times$ 22.4 mm². To maximize the FoV while maintaining a high overlapping ratio in the frequency domain, the objective lens must simultaneously satisfy low magnification and high NA. Therefore, we employed a Navitar 6 $\times$ HR Plan Apo Infinity Corrected Objective with 0.3 NA. The LED illumination is arranged in a ring configuration, consisting of three bright-field rings and one dark-field ring. Their effective NA and corresponding resolution are summarized in Table 1. Bright-field illumination is delivered to the sample via a Köhler illumination system composed of two lenses and the objective lens, which serves as the condenser (see Fig. 7). Meanwhile, the dark-field illumination is provided by LED sources mounted on a mechanical structure adjacent to the objective lens, allowing direct illumination of the sample. LED includes RGB, however, in this work, we used a fixed wavelength of 525 nm of green. FoV is dependent on the objective lens and image sensor in the system, showing 4.9 $\times$ 3.7 mm². However, unlike the system's full FoV, the effective FoV, within which the resolution and image quality remain consistent, is approximately 1 $\times$ 1 mm². The effective FoV used for learning-based inspection was conservatively limited to approximately 1 $\times$ 1 mm², corresponding to the central

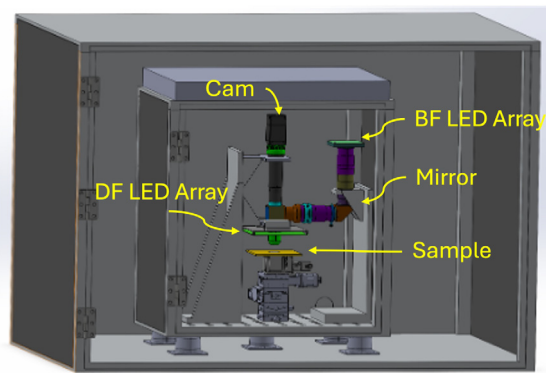


Fig. 7. Optical configuration of the compact reflection-mode FPM system. Bright-field illumination is delivered through the objective lens using Köhler illumination. Dark-field illumination is provided using an external LED arrangement.

region where the reconstructed images maintain stable visual quality and contrast suitable for defect detection and analysis. Within this region, the contrast remains relatively uniform at approximately 0.17 across the FoV. Toward the periphery, increasing optical aberrations and illumination-angle deviations introduce gradual reconstruction variations, which are not considered in the present analysis. This limitation arises because the high NA objective lens, compared with other objectives of similar magnification, introduces larger aberrations toward the periphery, and the illumination angle deviates from the designed value as it approaches the outer region. In addition, the dark-field illumination provides significantly lower light intensity, requiring much longer exposure times compared to the bright-field illumination. Consequently, the total acquisition time becomes nearly 30 times longer than when using only bright-field imaging. In contrast, the total acquisition time for bright-field imaging, including raw image capture and FPM reconstruction, is approximately 1 min. For the practical

demonstration, only the bright-field FPM images were used for AI training.

Table 1 provides a comparison of the microscope capabilities regarding resolution, FOV, and approximate throughput of FPM with and without dark-field illumination.

D. Design of Patterns and Definition of Defects

Pattern metrology using a reflection-mode microscope is highly dependent on the material's reflectivity and its contrast with the substrate. We used Al patterns on the Si substrate for this study. The Al thickness of 50 nm has a reflectivity of 0.9 at 520 nm green LED at a normal incident angle. In the range of the incident angle from the LED array, the reflectivity is in the range of approximately 0.8 to 0.9 in the demonstration of the FPM system. This implies that multilayer and complex features are not substantially different beneath the top layer unless the top layer is made of a highly transmissive material in metrology.

The pattern designs we demonstrate here are square arrays, electrodes with a hole array, and more complex-shaped metal interconnect patterns. The scale range of the square array includes 0.5 to 5.8 μm pitch. The width of each square was set to half of the pitch, with an aspect ratio of 1:1. Figure 8(a) is a design image from the GDS-II format. Figure 8(b) is the FPM image in amplitude. There are 5×5 fields with different resolutions or PPI, as shown in Table 2. Each field includes defective pixels, either empty or shifted at random positions, to emulate the defects during the pattern transfer process, as well as natural defects. In some cases, defects appeared as the absence of a localized group of repeated elements, which is referred to as an *empty block* in the supervised annotation.

The range of pitch dimensions and corresponding PPI values in Table 2 was selected to emulate different μLED density regimes relevant to advanced display manufacturing. In particular, the fabricated structures span from relatively coarse periodic arrays to sub-micron-scale patterns approaching the resolution limits of conventional optical inspection

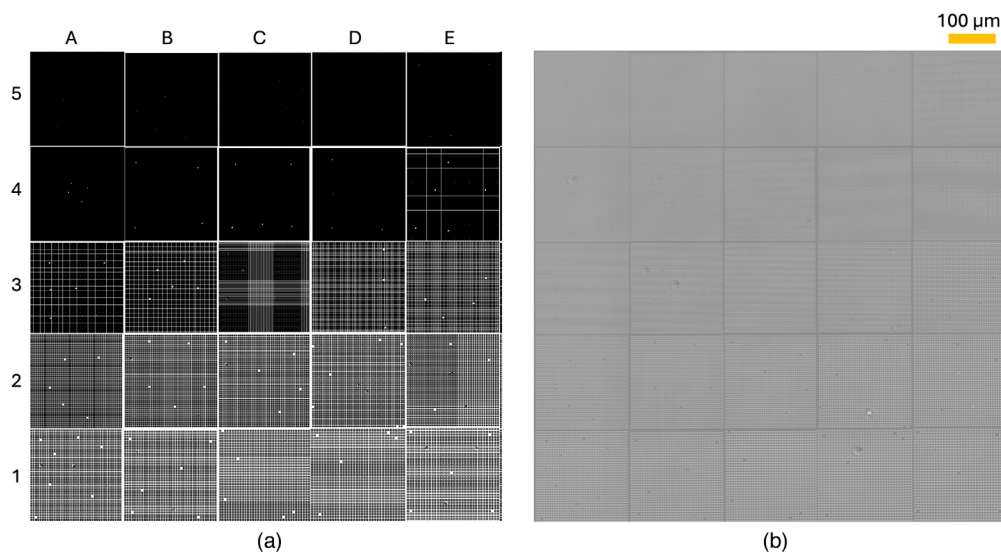
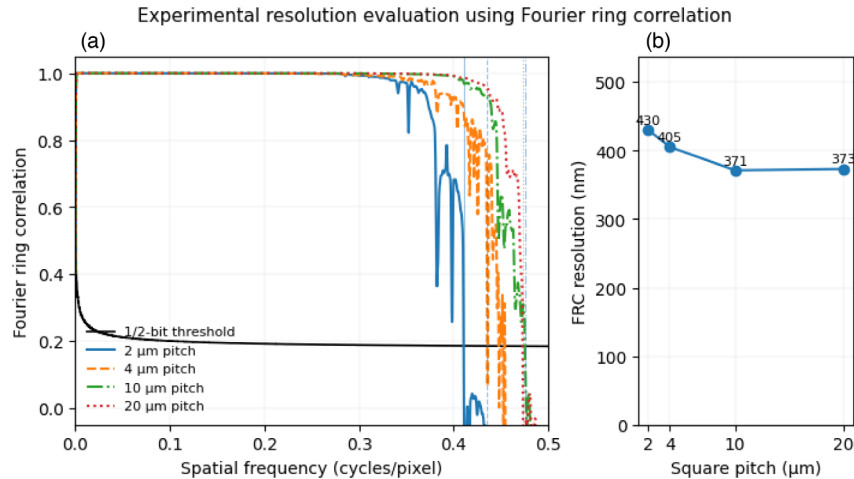
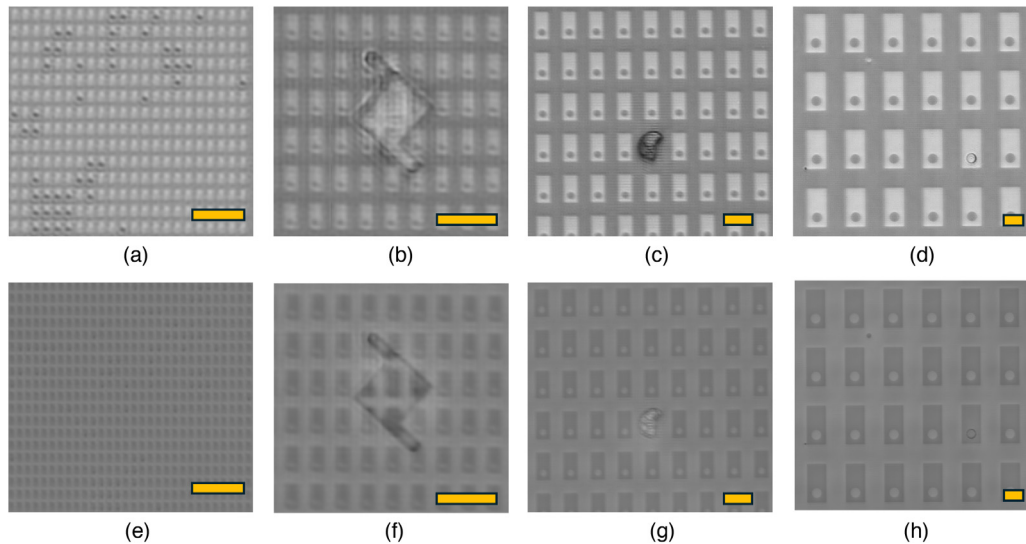


Fig. 8. Square-array test patterns with varying pitch resolutions used for defect inspection experiments. (a) GDS-II layout design showing the variable-pitch array organization. (b) Corresponding reflection-mode FPM reconstructed amplitude image of the fabricated 50 nm thick Al patterns on a Si substrate.

Table 2. Pitch Dimensions and Corresponding Pixel-per-Inch (PPI) Values for the Square-Array Patterns Used in the FPM Inspection Experiments^a

	A	B	C	D	E
Row 5	1 (25,400)	1.2 (21,167)	1.4 (18,143)	1.6 (15,875)	1.8 (14,111)
Row 4	0.5 (50,800)	0.6 (42,333)	0.7 (36,286)	0.8 (31,750)	0.9 (28,222)
Row 3	3 (8467)	3.2 (7938)	3.4 (7471)	3.6 (7056)	3.8 (6684)
Row 2	4 (6350)	4.2 (6048)	4.4 (5773)	4.6 (5522)	4.8 (5292)
Row 1	5 (5080)	5.2 (4885)	5.4 (4704)	5.6 (4536)	5.8 (4329)

^aThe row and column labels correspond to the pattern arrangement as shown in Fig. 8.

**Fig. 9.** Experimental evaluation of resolution using Fourier ring correlation (FRC) for square patterns with different pitches. (a) FRC curves as a function of spatial frequency for 2, 4, 10, and 20 μm pitch patterns, with the 1/2-bit threshold indicated. (b) Extracted resolution as a function of pattern pitch. The measured resolution is approximately 400 nm and shows good agreement with the theoretical Abbe limit.**Fig. 10.** Reflection-mode FPM images of representative μLED electrode-pattern structures with different pitch dimensions and associated defects. (a)–(d) Amplitude reconstructions for pitches of 2, 4, 10, and 20 μm , respectively. (e)–(h) Corresponding phase reconstructions acquired from the same regions. The examples illustrate the capability of FPM to recover both structural and phase-related information across multiple pattern scales. All scale bars correspond to 10 μm .

systems. The corresponding FPM reconstructions shown in Fig. 8 demonstrate that the proposed reflection-mode FPM framework maintains sufficient contrast and spatial resolution across a broad range of pattern densities, supporting both visual inspection and AI-based defect analysis at die-level FoV scales.

The experimental resolution is evaluated using Fourier ring correlation (FRC) with the 1/2-bit criterion, based on independently reconstructed datasets, as shown in Fig. 9. The measured resolution is consistent with the theoretical prediction. The theoretical resolution estimated from the Abbe

Table 3. Pitch Dimensions and Corresponding Pixel-per-Inch (PPI) Values for the Fabricated Electrode-Pattern Structures Shown in Fig. 10

	(a, e)	(b, f)	(c, g)	(d, h)
x/y μm	2×4	4×6	10×15	20×30
PPI	(9962)	(4981)	(1992)	(996)

diffraction limit is approximately 450 nm. The experimentally evaluated resolution using FRC is approximately 400 nm. This difference is considered reasonable, as the FRC-based value reflects the effective recoverable spatial-frequency content of the reconstructed images and can be influenced by the sample structure, signal-to-noise ratio, and threshold criterion. Overall, the experimental result is in good agreement with the theoretical prediction. For AI-based training, only bright-field (BF) images were used, due to the large number of images required for data acquisition.

Another pattern we demonstrated is a rectangular electrode featuring a small hole. In this design, four characteristic scales are identified, as illustrated in Fig. 10 and defined in Table 3. Following fabrication, several types of naturally occurring defects were observed. A magnified SEM image is shown in Fig. 11. Additionally, the stretchable pattern we fabricated exhibits multiple inherent defects, including undeveloped holes, displaced or detached holes, line discontinuities, and surface scratches, as shown in the SEM image in Fig. 12.

Using our fabrications, we defined specific defect types to train and test our defect detection model. In real scenarios, the formation of specific defects is influenced by various factors, including fabrication methods, processing conditions, material properties, and complex environmental variables. As a result, defect classification is highly context-dependent and must be tailored to specific application requirements. In this study, five practical defect classes were defined for supervised learning, while additional irregular defects were considered separately for evaluation of the self-supervised framework.

In summary, the broader defect mechanisms observed in this study are defined as follows:

1. Undeveloped hole: a region where patterning failed due to insufficient exposure dose or incomplete development [Fig. 5 (1) and (2)].

2. Resist re-deposition (re-attached hole): residues of developed features that were not completely removed during processing and remained attached to the substrate [Fig. 5 (1) and (5)].
3. Misaligned pattern: features shifted from their intended position during pattern transfer or fabrication [Fig. 5 (3) and (4)].
4. Missing hole or missing feature: missing elements resulting from incomplete pattern transfer, mask defects, underexposure, or development failure [Fig. 5 (3) and (6)].
5. Line break: partial or complete discontinuity in a line or stretchable pattern [Fig. 5 (7) and Fig. 11 (b)].
6. Crack: fracture within a material or patterned structure, typically caused by mechanical stress, thermal stress, or material fatigue [Fig. 12 (b)].

For the supervised learning dataset, these physically motivated defect descriptions were consolidated into five annotation classes used in the following sections: *dot defect*, *missing pattern*, *shift*, *empty block*, and *stretch defect*. In particular, *dot defect* is used as an umbrella label for localized filled or blocked features, including undeveloped holes and re-deposited material; *shift* corresponds to misaligned patterns; *missing pattern* corresponds to missing holes or missing features; and *stretch defect* refers to line-break-type defects observed in stretchable patterns. The class *empty block* denotes a local region in which a group of expected repeated elements is absent. Crack- and scratch-type defects are treated separately in the self-supervised framework.

For the study of self-supervised learning algorithms, we considered irregular defect types that are less suited to bounding-box-based annotation. In this work, the self-supervised framework focuses on *scratch* and *crack* defects. A scratch refers to physical surface damage caused by friction or contact during processing or handling, whereas a crack refers to a fracture within the material or patterned structure caused by mechanical or thermal stress. Particle-like contamination may also appear in practice, but it is not included as a separate quantitative class in the present evaluation.

E. Inspection Process Flow

Using the FPM reconstructed images, specific defect types were identified and labeled to establish a supervised learning

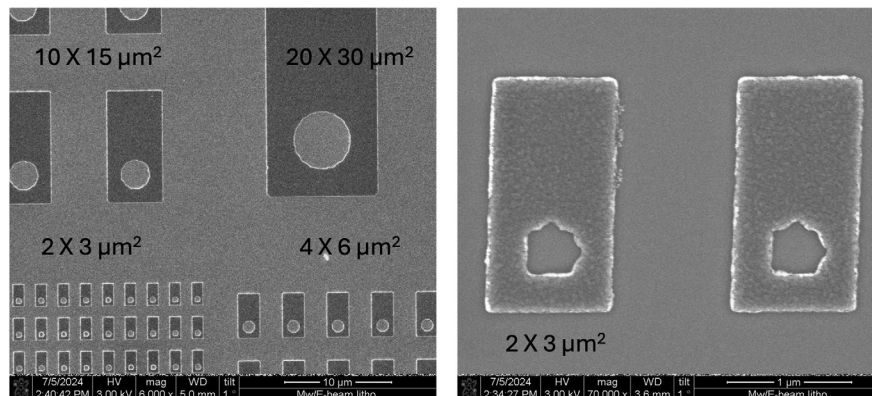


Fig. 11. Scanning electron microscope (SEM) image of fabricated electrode-pattern structures used for reflection-mode FPM inspection experiments.

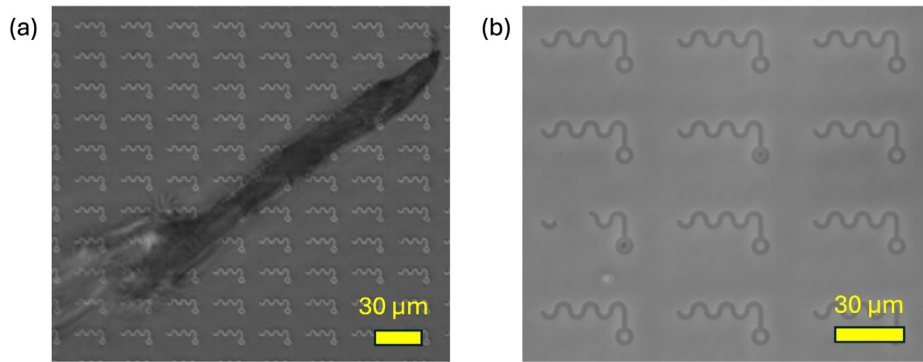


Fig. 12. FPM images of stretchable electrode-pattern structures containing representative irregular defects. (a) Scratch defect observed in a pattern with $30\ \mu\text{m} \times 20\ \mu\text{m}$ pitch (996 PPI). (b) Line-break defect observed in a stretchable pattern with $60\ \mu\text{m} \times 40\ \mu\text{m}$ pitch (498 PPI).

framework. In addition, we included a simulation study using the proposed self-supervised model to examine irregular defects such as cracks and scratches.

1. Dataset Generation

Defect types may vary depending on the specific manufacturing pipeline, and therefore, it is essential to develop a robust defect detection framework capable of adapting to new scenarios through retraining or fine-tuning. In this work, the selected defect types are chosen to support the design of such a comprehensive and flexible framework. To build a robust and generalizable defect detection framework, both real and synthetic datasets were utilized. Real samples provide representations of defects that naturally occur in the manufacturing pipeline, capturing the physical and material complexities inherent in practical scenarios. However, collecting a large and diverse set of real-world defects is often constrained by limited availability and annotation challenges. To address these limitations and ensure the generalizability of the deep learning model to new defect types, particularly those that are underrepresented or difficult to capture consistently, synthetic defects

with irregular structural characteristics were also generated. While defect types introduced here are not fixed across platforms and not universally applicable, the aim is to use these defects to develop a system that can be effectively deployed across varied manufacturing environments with minimal retraining and adjustments.

Real defect samples: A diverse set of real defects was collected from fabricated μLED samples. For annotation and supervised training, these defects were grouped into five practical classes: *dot defect*, *missing pattern*, *shift*, *empty block*, and *stretch defect*. These labels are operational dataset classes used for model development and evaluation. They correspond to broader physical defect mechanisms introduced in Section 2.D. In particular, *dot defect* includes localized blocked or filled features such as undeveloped holes and re-deposited residues, while *stretch defect* refers to line-break-type defects occurring in stretchable patterns. An example of these defects is presented in Fig. 13(a). Each defect type was extracted as a region of interest from amplitude images reconstructed using FPM. These FPM-reconstructed amplitude images were used as the input to the supervised YOLO-based model.

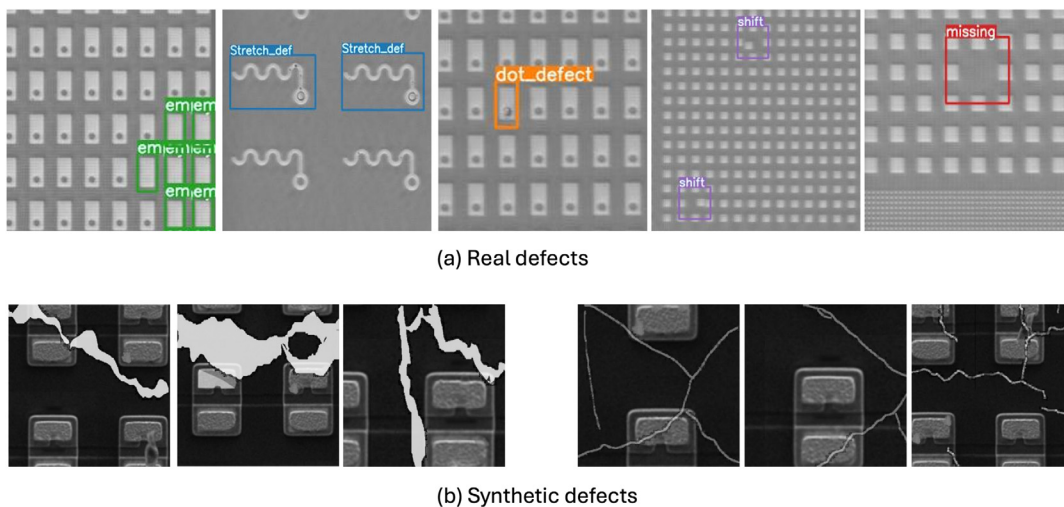


Fig. 13. Representative defect categories used for supervised and self-supervised learning. (a) Real defect classes extracted from fabricated μLED -related patterns, including dot defects, missing patterns, shifts, empty blocks, and stretch defects. (b) Synthetic irregular defects used for self-supervised segmentation experiments, including crack-like and scratch-like structures.

From these reconstructions, a total of 778 patches covering five defect types, each with 640×640 pixels, were extracted. The dataset was further augmented through image rotation and flipping, expanding the dataset to 1715 annotated samples. The distribution of these samples among the five defect classes was as follows: 625 samples for missing pattern defects, 386 samples for dot defects, 86 samples for shift defects, 125 samples for empty block defects, and 365 samples for stretch defects. The dataset was divided into three subsets: 70% of the samples were allocated for model training, 20% for validation, and 10% for testing. The training set served as the primary source for model learning, while the validation set was utilized for hyperparameter tuning, and the test set facilitated the final model evaluation.

Synthetic defect samples: In addition to the real samples, a synthetic dataset was constructed to emulate defects commonly arising during μ LED manufacturing, specifically *scratches* and *cracks*. These defect types were selected because of their possible occurrence during manufacturing or handling, where physical damage can lead to visible defects on the μ LED arrays. Synthetic defects were embedded into μ LED backgrounds using patterns derived from publicly available binary maps of natural crack formations [33]. Figure 13(b) illustrates examples of these synthetic defects.

The synthetic dataset was further enriched using augmentation techniques, including image rotation and adjustments in brightness and contrast. These augmentations expanded the diversity of the dataset, improving the model's ability to generalize to a wide range of defect appearances. The synthetic dataset was carefully balanced to ensure consistent training performance. Each defect type, including cracks and scratches, contributed 400 images for training, 110 images for validation, and 55 images for testing.

2. Learning-Based Models for Defect Inspection

Due to the diversity of defect characteristics and the emergence of new defect types in evolving manufacturing pipelines, we adopted a two-model framework to ensure adaptability and comprehensive analysis. A supervised detection model based on the YOLO architecture [28] was employed, offering real-time and accurate classification of known defect types. Despite their effectiveness in classifying known defect types, supervised models require re-training to identify new defects and are often impractical for defect cases where annotated data is limited or unavailable. Furthermore, while bounding-box-level localization is sufficient for coarse detection, it lacks the granularity required for pixel-level inspection, which is crucial in identifying subtle defects such as cracks or scratches. To address these limitations, a complementary segmentation model was developed to provide pixel-wise localization of defects. This model does not rely on labeled data and is inherently more generalizable, making it suitable for identifying anomalies without prior knowledge of defect categories.

Figure 14 shows the deep learning framework overview deployed for our defect detection, including both supervised and self-supervised (segmentation) tracks. The integration of these two models yields a robust framework for defect analysis. The first model, based on YOLO, performs the classification of defect types with high accuracy, localizing defects with their class labels and confidence scores. To enable pixel-wise defect segmentation, a second model (segmentation) based on the generative model of Contrastive Unpaired Translation (CUT) [34] was developed. This model learns to generate defect-free images, enabling precise identification of defect regions via image subtraction and thresholding. In practice, both models can be applied jointly or independently depending on application-specific requirements. For instance, localization using the

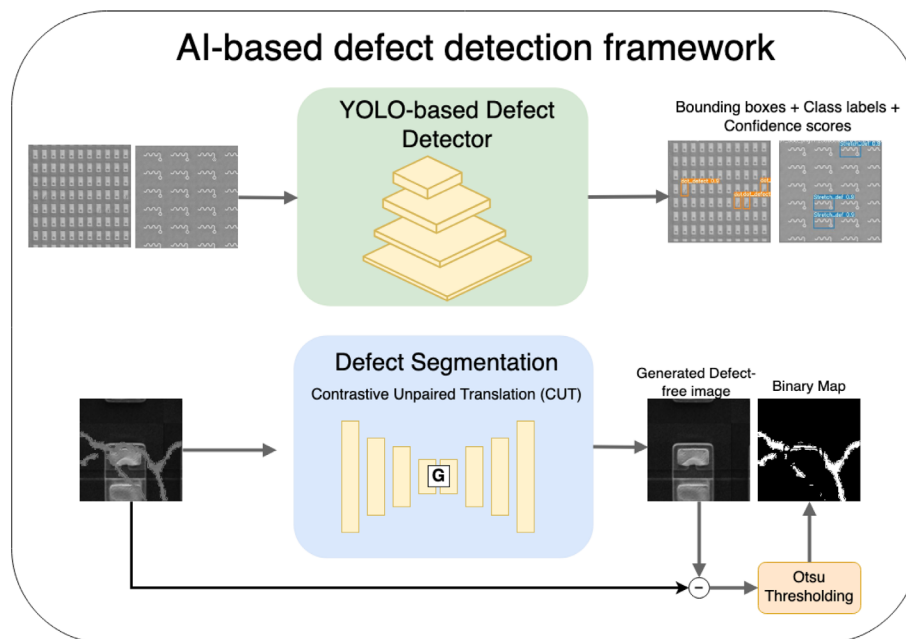


Fig. 14. Overview of the proposed learning-based inspection framework. The supervised YOLO-based branch performs defect classification and localization for known defect classes, while the self-supervised CUT-based branch reconstructs defect-free images and enables residual-based pixel-level segmentation of irregular defects such as cracks and scratches.

self-supervised segmentation model can guide high-resolution inspection via the YOLO detector, or in another scenario, the supervised YOLO model can perform continuous real-time monitoring, supplemented periodically by the self-supervised model for anomaly (new defect types) detection.

YOLO-based model: The supervised detection model is based on a customized YOLOv8 architecture optimized for μ LED inspection tasks. The network comprises 415 layers with over 37 million parameters, achieving 105.1 GFLOPS. It includes a hierarchical backbone for feature extraction, a feature aggregation neck, and a multi-scale detection head. The training was conducted on 640×640 pixel patches using a batch size of 16, weight decay of 0.0005, and adaptive learning rate scheduling over 140 epochs on an NVIDIA Tesla T4 GPU. For inference, the YOLO-based detector achieved an average processing time of approximately 8–10 ms per 640×640 image patch on RTX 4060-class GPU hardware, supporting real-time defect classification and localization.

GAN-based Model: We proposed a new self-supervised model by adopting the CUT model. This approach aims to train a generator G that maps defective input patches $\{x_i\}_{i=1}^N \in \mathcal{X}$ to defect-free patches $\hat{y}_i = G(x_i)$, such that the outputs closely approximate real defect-free instances $\{y_j\}_{j=1}^M \in \mathcal{Y}$. The model uses unpaired training data, eliminating the need for aligned ground-truth references. As in real scenarios, paired GAN models [35] are not often applicable; unpaired translation models, such as CUT, should be used, which do not need one-to-one image correspondence. The CUT model combines adversarial training with patch-wise contrastive learning. The total training objective is formulated as

$$\mathcal{L}_{\text{total}} = \mathcal{L}_{\text{GAN}}(G, D, \mathcal{X}, \mathcal{Y}) + \mathcal{L}_c(G, H, \mathcal{X}) + \mathcal{L}_c(G, H, \mathcal{Y}), \quad (2)$$

where $\mathcal{L}_{\text{GAN}}$ is the adversarial loss and $\mathcal{L}_c$ denotes the patch-wise contrastive loss applied in both distorted and pristine domains.

To further ensure content preservation and structural consistency, a patch-wise contrastive loss is employed in CUT. This loss maximizes mutual information between corresponding spatial locations in the distorted input x and the generated output $\hat{y} = G(x)$. For a given encoder layer $l \in \{1, \dots, L\}$ and spatial location $v \in \{1, \dots, V\}$, the feature vector f_l^v from the input and its corresponding generated feature $\hat{f}_l^v$ are projected using an multi-layer network H_l . The contrastive loss is defined as

$$\mathcal{L}_c(G, H, \mathcal{X}) = \mathbb{E}_{x \sim \mathcal{X}} \sum_{l=1}^L \sum_{v=1}^V \ell(\hat{f}_l^v, f_l^v, f_l^{V \setminus v}), \quad (3)$$

where ℓ is a contrastive objective (e.g., InfoNCE or cross-entropy loss), promoting similarity between positive pairs $(\hat{f}_l^v, f_l^v)$ and dissimilarity with negative samples $f_l^{V \setminus v}$ from other spatial locations. A complementary contrastive loss is applied to the pristine domain $\mathcal{Y}$, ensuring the generator preserves regions that do not require correction and avoids introducing artifacts.

By jointly optimizing these objectives, the CUT framework learns to generate visually faithful and structurally accurate clean, defect-free images from defective μ LED inputs. The CUT-based segmentation framework was implemented using

the official CUT implementation [34]. Training was performed for 200 epochs using a batch size of 4 on an NVIDIA Tesla T4 GPU. The default network architecture and hyperparameters provided in the official implementation were used, including the PatchNCE-based contrastive learning configuration. The generator and discriminator architectures follow the standard CUT framework based on ResNet-style encoder–decoder translation networks with multi-layer patch-wise contrastive feature extraction. During training, stable reconstruction quality was typically achieved after approximately 50–60 epochs. To identify defect regions, the restored image is subtracted from the original distorted input, producing a residual map that highlights areas of discrepancy. This residual map is then processed using Otsu's thresholding method [36], which adaptively determines an optimal threshold to binarize the image and produce a defect mask. The resulting binary mask enables precise pixel-level localization of defects, supporting detailed inspection and analysis. The CUT-based segmentation framework required approximately 18–20 ms per 640×640 image patch during inference. In the present framework, most of the total processing time is associated with FPM image acquisition and reconstruction rather than neural-network inference.

3. EXPERIMENTAL RESULTS

A. Performance Evaluation of the Supervised Model

Here, we report the performance of the proposed defect detection framework on the defect dataset. The precision and recall curves in Fig. 15 present the accuracy of the YOLO model in detecting five defect types, as well as its overall performance across all defect classes.

The results demonstrate that the model maintains high precision and recall for most defect types, especially for the *stretch defect* and *dot defect* classes. The *empty-block defect* class shows a comparable trend, and the *missing-pattern* class also maintains high precision, with only a marginal decline at extreme thresholds. The *shift defect* class, however, shows lower precision at lower confidence levels. This reduced performance is primarily attributed to the limited number of available shift-defect samples and their low occurrence frequency in the dataset, rather than an intrinsic limitation of the detection framework. This result should, therefore, be interpreted as a practical consequence of class imbalance and data scarcity, which are common in real manufacturing inspection scenarios. It also highlights the dependence of supervised models on sufficient annotated data and motivates the use of complementary defect-agnostic, self-supervised models for rare or underrepresented defect types.

The confusion matrix in Fig. 15(c) visualizes the YOLO model's classification accuracy across defect types. Diagonal entries represent correct classifications, while off-diagonal cells indicate misclassification (confusion). The matrix also includes false positives (FP) and false negatives (FN) for the background class. The model performs exceptionally well for the *stretch defect*, *dot defect*, *empty-block defect*, and *missing-pattern* classes, whereas the performance for the *shift defect* class is lower, with an accuracy of approximately 90%.

Table 4 shows the YOLO model's performance on the test set. The model achieves an overall mean average precision (mAP) of 96.4%. Most defect types yield mAP values between 97%

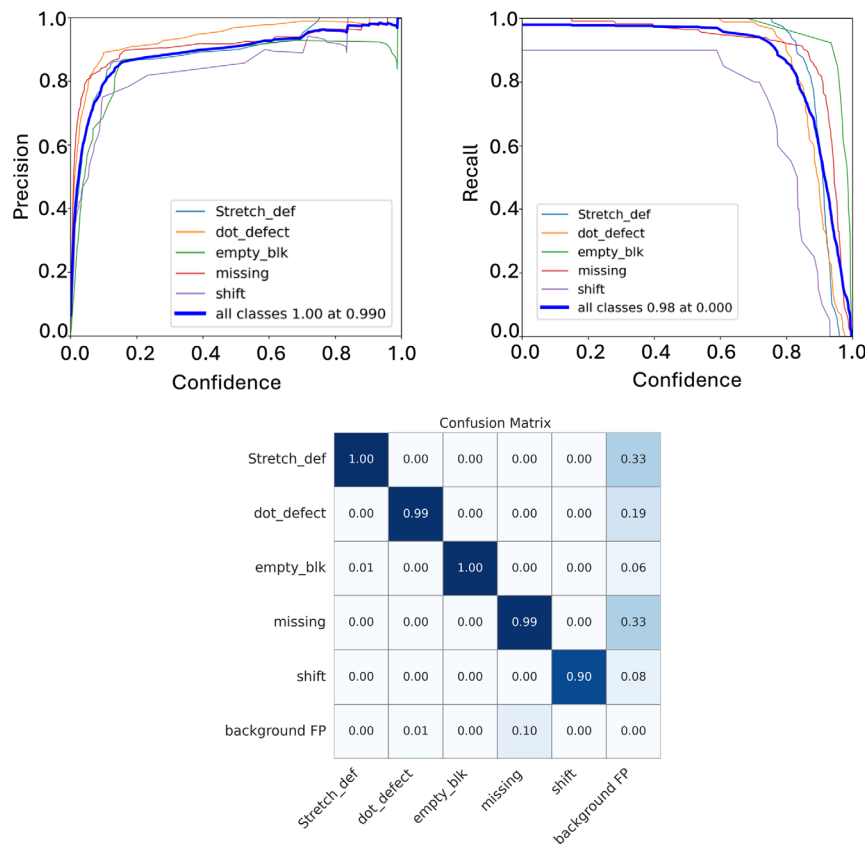


Fig. 15. First row: precision (left) and recall (right) curves illustrating the performance of the YOLO model on five real defect types. Second row: confusion matrix demonstrating high classification accuracy with minimal confusion among the five classes.

Table 4. Quantitative Evaluation of the Supervised YOLO-Based Defect Detector for Each Defect Class in Terms of Precision, Recall, and Mean Average Precision at IoU Threshold 0.5 (mAP@0.5)

Class	P (Precision)	R (Recall)	mAP@.5
All	0.901	0.910	0.964
Stretch_def	1.000	1.000	0.995
Dot_defect	0.995	1.000	0.995
Empty_blk	0.933	1.000	0.995
Missing	0.954	0.884	0.973
Shift	0.623	0.667	0.863

and 99.5%. The *shift defect* class, however, records a lower mAP of 86.3%, confirming that it is relatively more challenging to detect. Figure 16 shows visual examples of defect detection on real samples using our YOLO model.

B. Performance Evaluation of the Label-Free Segmentation Model

The segmentation performance of the proposed self-supervised model is evaluated using synthetic data, with F-score, precision, recall, and mean absolute error (MAE) reported in Table 5. Results show high segmentation accuracy with low MAE for both scratch and crack defects. Figure 17 provides visual examples of the output binary maps obtained via Otsu

thresholding. These maps closely match ground-truth binary labels, confirming the model's pixel-wise detection accuracy.

We also evaluated YOLO's supervised performance on detecting scratch and crack defects. Crack detection achieves a high mAP of 0.935. Scratch defects, characterized by finer and more irregular structures, yield a lower mAP of 0.670. Visual inspection reveals that YOLO, due to its multi-scale detection nature, detects scratches with multiple overlapping bounding boxes at various scales. This results in imprecise localization compared to ground-truth annotations. In contrast, the self-supervised segmentation approach provides more reliable pixel-wise defect localization. Table 5 summarizes the precision, recall, and mAP values for both models.

Scratch defects were generally more challenging to localize because of their fine-scale and low-contrast structural characteristics under bright-field imaging conditions. Although dark-field FPM illumination was not used in the present AI pipeline because of the associated acquisition-time penalty, dark-field contrast may provide improved sensitivity to shallow surface irregularities and scattering-based defects such as scratches. Future work will investigate hybrid bright-field/dark-field inspection strategies to better balance defect sensitivity and practical throughput requirements.

Table 5 additionally shows reconstruction-based anomaly detection experiments conducted to compare the proposed CUT-based segmentation framework with conventional reconstruction-driven approaches as well as a more advanced

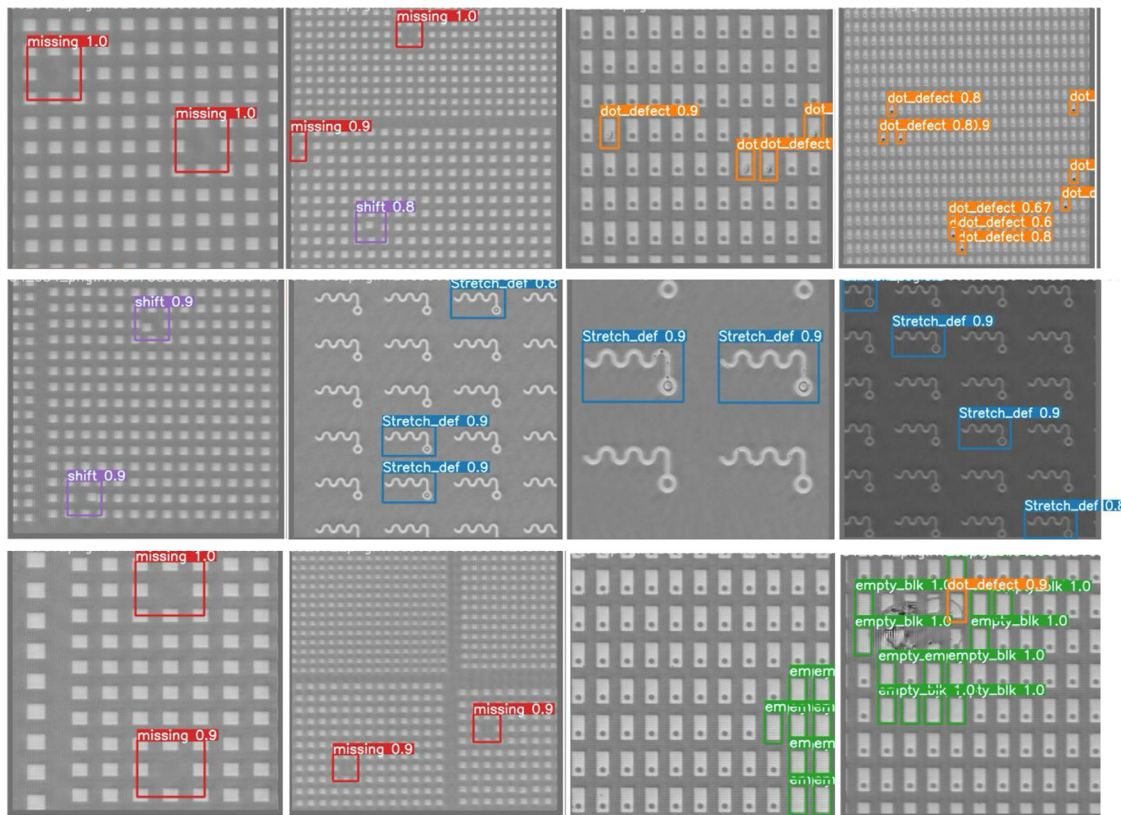


Fig. 16. Examples of defect detection results obtained using the trained YOLO model.

Table 5. Quantitative Evaluation of Detection and Localization Performance for Synthetic Defect Types Using Reconstruction-Based and Supervised YOLO Frameworks

Model	Defect	F-Score	Precision	Recall	MAE	mAP@0.5
Autoencoder	Scratch	0.42	0.30	0.73	0.04	—
	Crack	0.49	0.36	0.76	0.03	—
DRAEM	Scratch	0.78	0.79	0.78	0.01	—
	Crack	0.85	0.85	0.84	0.009	—
Self-supervised	Scratch	0.92	0.90	0.93	0.003	—
	Crack	0.96	0.96	0.96	0.004	—
YOLO	Scratch	0.70	0.72	0.68	—	0.67
	Crack	0.86	0.85	0.87	—	0.93

framework, namely DRAEM [37], both tested on our scratch and crack dataset. A simple eight-layer convolutional autoencoder baseline was implemented using a shallow encoder–decoder architecture trained only on defect-free samples. During inference, anomalous regions were identified by calculating the residual difference between the input image and the reconstructed defect-free image, followed by residual thresholding to generate binary defect masks. Although the autoencoder was capable of detecting large anomalous regions, the reconstructed outputs were not accurate and could not completely remove defects, resulting in lower segmentation accuracy for scratch- and crack-type defects.

DRAEM combines a reconstruction network with an additional discriminative segmentation network, enabling improved localization capability compared with conventional autoencoder-based reconstruction. The obtained results in

Table 5 show a clear improvement over the simple autoencoder baseline, with substantially higher F-score and lower MAE values. Nevertheless, the proposed CUT-based framework achieved the best overall segmentation performance. This improvement is attributed to the defect-to-clean image translation capability of CUT and the residual-driven segmentation strategy, which produced sharper pixel-level localization and more accurate defect boundaries within the reflection-mode FPM imaging framework. It should also be noted that the DRAEM implementation was evaluated using the official reference framework with largely default training parameters and without extensive optimization for the present dataset, and therefore, additional tuning may further improve its performance.

As previously mentioned, the synthetic dataset was generated to incorporate additional defect types that are more irregular in

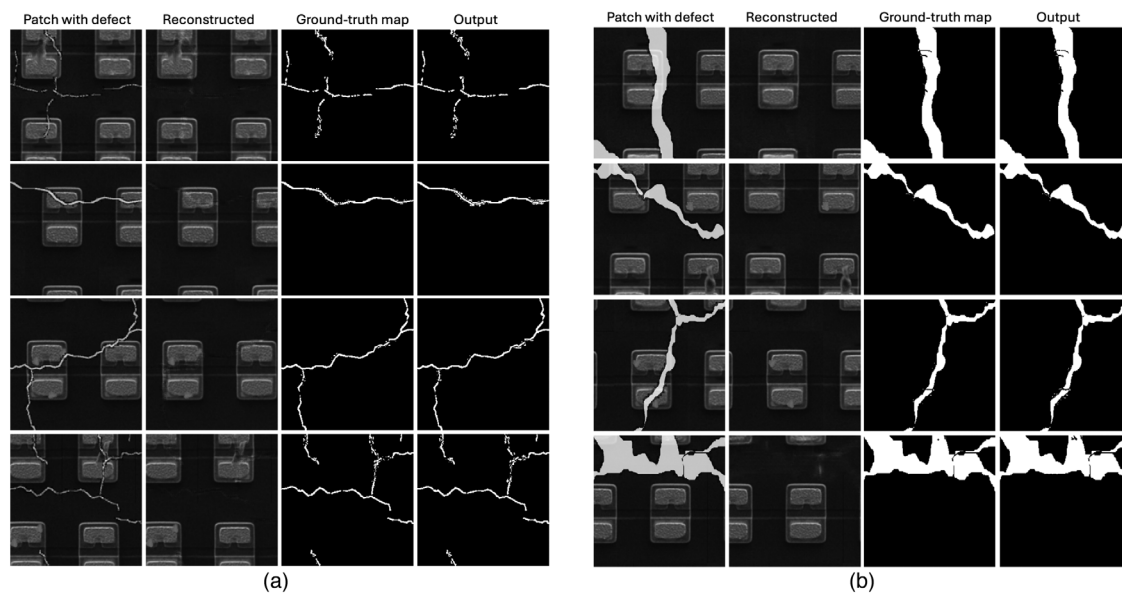


Fig. 17. Visual examples of the defect segmentation using our self-supervised model for scratch (a) and crack (b) defects.

structure and less pronounced than those observed in our fabricated samples. The trained segmentation model demonstrated promising results on these complex synthetic defect types, suggesting its potential in real scenarios. Nevertheless, it would be insightful to further evaluate the model's performance on real fabricated samples containing irregular and complex defect patterns. To this end, we inspected our dataset and selected a limited number of representative real samples with irregular defects to further illustrate the model's potential on real data.

Given the limited occurrence of real defective samples in our dataset, the CUT model was trained primarily on synthetically generated data in which intentional distortions were introduced, as illustrated in Fig. 18(a). The training process involved

two unpaired domains: the defective domain, composed of artificially distorted LED patterns, and the clean domain, containing pristine, defect-free LED matrices. The CUT model was trained to learn a mapping between these domains, translating images from the defective to the clean domain without requiring paired correspondences.

Figure 18(b) shows the results of the trained model applied to real defective samples. Each row shows the input defective image, the reconstructed (translated) clean image, and the corresponding binary defect mask, obtained by differencing the input and reconstructed outputs, followed by Otsu thresholding and morphological operations. The reconstructed images demonstrate that the CUT model effectively learns to suppress

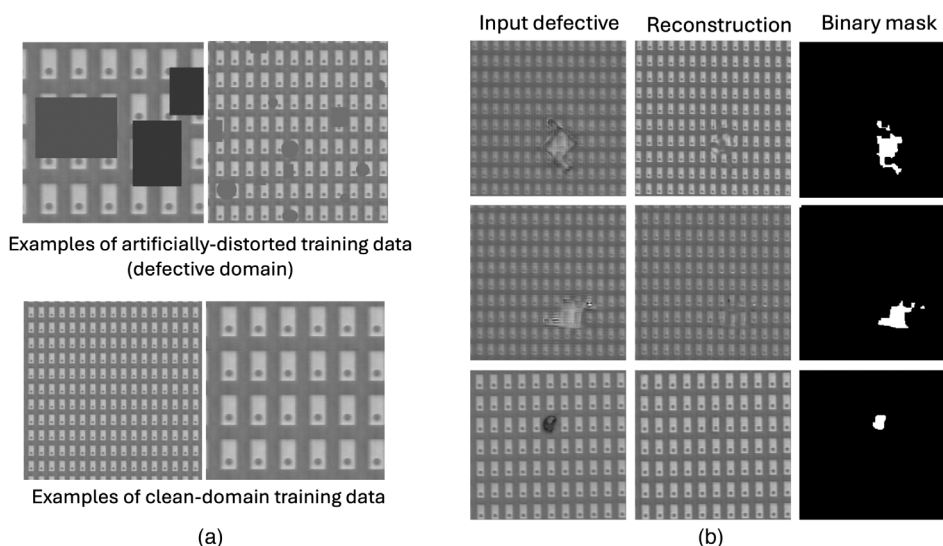


Fig. 18. (a) Representative training samples illustrating the two unpaired domains used in CUT training: the defective domain (Domain A), composed of synthetically distorted LED patterns, and the clean domain (Domain B), containing pristine data. (b) Visual examples of defect segmentation obtained by applying the trained model to real defective samples, showing the input images, reconstructed clean counterparts, and corresponding binary defect masks.

structural irregularities and approximate the underlying clean pattern, thereby enabling subsequent defect localization through pixel-wise comparison.

4. CONCLUSION

In this paper, we presented a defect inspection framework for μ LED samples that integrates reflection-mode Fourier ptychographic microscopy (FPM) with deep learning-based analysis. The fabricated silicon chips contained both real (process-induced) and artificial defects designed to represent common lithographic and pattern transfer errors. The FPM system enabled sub-micron, wide-field imaging of the entire chip surface, supporting comprehensive optical metrology. Supervised and self-supervised deep learning models were trained on both real and synthetic datasets to detect, classify, and localize multiple defect types with high accuracy. The experimental results confirmed the effectiveness of the YOLO-based model in defect classification and the self-supervised segmentation model in precise pixel-level localization.

Although several of the larger defects investigated in this work may also be detectable using conventional bright-field microscopy, reflection-mode FPM provides the advantage of combining sub-micron-scale resolution with a large effective field of view for die-level inspection. This capability is expected to become increasingly important for future high-density μ LED architectures and for the detection of subtle fine-scale pattern-transfer defects. At the same time, the increased acquisition and reconstruction complexity associated with FPM represents a practical trade-off between imaging performance and throughput. A systematic comparison between conventional bright-field imaging and FPM-based inspection within the same learning framework remains an important direction for future work.

Although the present framework used FPM-reconstructed amplitude images as the network input, quantitative phase information may provide complementary sensitivity to certain defect types involving thickness variation or depth-related structural changes. The defects investigated in this work were predominantly pattern-transfer and structural defects that were sufficiently represented in the amplitude reconstructions. Nevertheless, future multimodal learning frameworks will focus on combining both amplitude and phase information that may further improve defect characterization and segmentation performance in advanced μ LED metrology applications.

The reliability of the learning-based inspection framework may also be influenced by the quality of the underlying FPM reconstruction, since reconstruction artifacts may propagate into downstream defect detection and segmentation. In the present study, the reconstruction quality was sufficient to support reliable inspection performance for the considered defect sizes and pattern geometries. Our preliminary synthetic experiments conducted during early-stage development suggested that moderate reconstruction degradation did not critically affect overall detection performance, although fine-scale defects became increasingly sensitive at lower reconstruction fidelity levels. Future work will, therefore, include systematic resolution-target measurements and quantitative analysis of reconstruction-error propagation within the learning pipeline.

This hybrid framework demonstrates the potential of combining computational microscopy and learning-based inspection for automated μ LED metrology and advanced semiconductor manufacturing, offering a pathway toward reliable and data-driven process control.

Funding. Korea Institute for Advancement of Technology (KIAT), Korean Government (MOTIE) (P146500071).

Disclosures. The authors declare no conflicts of interest.

Data availability. Data underlying the results presented in this paper are not publicly available at this time but may be obtained from the authors upon request.

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