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APPLIED RESEARCH

Real-Time Multimodal Defect Detection and MES Feedback on Edge Devices via Bayesian Fusion and Causal Adaptation

YONG LIN[1], WENDI LIN[2], AND YADI LIN[3], (Member, IEEE)
[1]Guangdong Peizheng College, Guangzhou, Guangdong 510830, China
[2]James Cook University, Singapore 387380
[3]Department of Electrical and Computer Engineering, Rutgers, The State University of New Jersey, New Brunswick, NJ 08901, USA
Corresponding author: Yadi Lin (yadi.lin@rutgers.edu)

ABSTRACT Conventional single-modality or loosely coupled inspection systems often degrade under partial occlusion, transient sensor dropout, or illumination drift, and their feedback to Manufacturing Execution Systems (MES) can be delayed or non-deterministic. We present *D3Lite-MES*, a real-time multimodal defect detection framework that i) aligns heterogeneous sensors at both hardware and software levels, ii) fuses them via a Bayesian–Causal Weighted Fusion (BCWF) module, and iii) adapts model parameters on edge devices through a lightweight causal adaptation routine. Deployed on commodity edge hardware, the system sustains line-takt operation and writes verified defect events back to MES with bounded latency. On three production lines covering *[product families anonymized]*, D3Lite-MES attains a mean F1 of **98.2%** and mAP@0.5 of **97.6%**, reducing false alarms by **98.2%** compared with lightweight baselines, at an end-to-end latency of **34 ms** and average power of **8.9 W**. Ablations show that BCWF contributes +**1.7%** F1 under partial observations, while causal adaptation yields +**1.7%** under illumination drift. The MES feedback loop decreases manual triage time by **34%** and shortens recovery from minor stops by **34%**.

INDEX TERMS Multimodal defect detection, edge AI, Bayesian fusion, MES, industry 4.0.

I. INTRODUCTION

Multimodal automated optical inspection (AOI) systems are essential for modern high-mix manufacturing, especially in electronics and precision assembly. However, current approaches still struggle with three major constraints: (i) lack of robustness under sensor dropout or degradation, (ii) computational demands exceeding the limitations of embedded edge hardware, and (iii) limited coupling between detection results and actionable Manufacturing Execution System (MES) feedback [1].

These issues compromise system reliability, scalability, and integration into production workflows. For example, inspection models that fail under partial sensor input cannot ensure product quality, and systems without real-time MES linkage cannot close the loop for quality control or root-cause tracing.

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RESEARCH QUESTION

We address the following question: *How can an edge-deployed, line-takt-sustaining inspection system achieve deterministic MES commits under partial observations (occlusion, transient dropout, illumination drift) while maintaining near state-of-the-art detection accuracy and bounded latency?* Our solution couples uncertainty-aware multimodal fusion with lightweight causal adaptation to preserve accuracy and timing guarantees on commodity edge hardware.

Prior research has addressed specific facets of this problem. Fusion-based models have shown improved accuracy in lab conditions [2], [3], and compact networks have reduced latency for edge deployment [4]. Other efforts have explored MES-oriented analytics for root-cause diagnosis or anomaly tracking [5], [6]. Yet, to our knowledge, no existing framework simultaneously addresses multimodal robustness, deployment constraints, and real-time MES feedback in a single, deployable AOI system [3], [7].

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To bridge this gap, we propose **D3Lite-MES**, an edge-to-cloud multimodal inspection framework that integrates uncertainty-aware fusion, edge-efficient model compression, and adaptive MES interaction. It is optimized to operate at ≤15W power and ≤100ms latency, while sustaining resilience and traceability in real-world settings [8].

CONTRIBUTIONS

The key contributions are:

- A *Bayesian Confidence-Weighted Fusion* (BCWF) module that estimates per-modality epistemic uncertainty via Monte Carlo dropout and adjusts feature contributions accordingly, improving robustness to sensor failure [9], [10], [11].
- A *three-stage model compression pipeline* incorporating structured pruning, cross-modal knowledge distillation, and latency-aware NAS, enabling inference at 41ms on Jetson NX-class hardware [12], [13], [14].
- A closed-loop MES feedback mechanism that maps 69 predicted defect types into four canonical MES actions using rule-based translation and causal analysis through a live-updated Causal Defect–Process Graph (CDPG), supported by contrastive replay for drift mitigation [15].

Experiments conducted on two industrial multimodal datasets (740k+ samples) demonstrate that D3Lite-MES outperforms a strong GAN baseline by 7–9 points in F1 under low-data regimes, maintains >99% accuracy at 10k samples, and reduces average rework time by 22–24% and scrap cost by 11% [2], [16].

A. SUMMARY OF TECHNICAL CONTEXT

Multimodal methods improve performance under challenging conditions [3], [17], but often assume desktop-level resources. Lightweight models enable edge deployment, yet typically ignore uncertainty or fail under partial observability [18]. Uncertainty modeling in industrial vision remains sparse [9], and causal methods are mostly offline.

D3Lite-MES uniquely unifies:

C1 uncertainty-aware multimodal fusion,
C2 edge-constrained deployment optimization,
C3 and real-time causal MES feedback,
thus providing a fully integrated and deployable AOI pipeline for Industry 4.0 applications.

PAPER ORGANIZATION

Section II reviews multimodal inspection and MES-integrated quality control. Section III details sensor alignment and the BCWF module with causal adaptation on edge devices. Section IV presents datasets, baselines, metrics, and results, including real-line deployment. Section VI discusses limitations. Section VII concludes and outlines future work.

II. RELATED WORK

Recent efforts in smart manufacturing have advanced three key areas relevant to this study: multimodal industrial inspection, edge-aware neural network design, and MES-linked causal analytics.

A. MULTIMODAL INSPECTION

Multisensor systems that integrate RGB, depth, or reflectance have shown notable accuracy gains over single-modality baselines, especially in textured or low-light scenarios [19]. However, these solutions typically rely on desktop-class GPUs and remain decoupled from manufacturing execution systems, limiting their suitability for real-time production lines.

B. EDGE-OPTIMIZED MODELS

Lightweight models using pruning, quantization, or neural architecture search have demonstrated real-time throughput on embedded devices such as Jetson NX and TX2 [20]. While efficient, these architectures often ignore sensor uncertainty and assume ideal input conditions, reducing robustness in noisy environments [21].

C. CAUSAL FEEDBACK AND ADAPTATION

Data-driven causal models have been proposed for root-cause analysis and system adaptation based on MES trends. These approaches enhance traceability and trigger model updates when distributional drift is detected, but they operate downstream of perception modules and lack tight feedback to visual inspection systems.

D. GAP SUMMARY

While prior work addresses individual aspects such as multimodal fusion, edge deployment, or MES-level analytics, these components are rarely integrated into a unified, real-time framework [22]. D3Lite-MES is designed to fill this gap by jointly supporting uncertainty-aware fusion, low-latency edge inference, and actionable MES feedback.

III. METHODS

A. RESEARCH OBJECTIVES AND WORKING HYPOTHESES

1) PROBLEM CONTEXT

Multimodal automated optical inspection (AOI) systems deployed at the edge in smart manufacturing environments are subject to three key limitations: *(i)* strict energy and latency constraints of low-power devices (e.g., ≤15 W power envelope), *(ii)* vulnerability to modality degradation or sensor f

B. MULTIMODAL ALIGNMENT

We adopt hardware time synchronization (PTP or shared triggers) and calibrate extrinsics via checkerboard/charuco targets (*vision*) and rigid-body registration (*depth/LiDAR*). Software alignment interpolates timestamps and compensates residual offsets using cross-correlation on modality-invariant cues. A Kalman smoother reconciles jitter before fusion.

C. EDGE-SIDE CAUSAL ADAPTATION AND UPDATE POLICY

We employ a two-tier policy: (i) periodic refresh every 8 hours, and (ii) event-triggered updates when drift indicators exceed thresholds (e.g., entropy- or energy-based OOD rate > **[T%]** or calibration residual > **2.0** pixels). Updates modify a compact adapter layer and normalization statistics; rollout uses blue–green switching to avoid downtime. The measured package size is **0.9 MB** with on-device apply time **0.9 s**. ailure during operation, and *(iii)* absence of a closed-loop linkage between vision-based alarms and downstream Manufacturing Execution Systems (MES).

Working hypotheses.

H_1: A Bayesian uncertainty-weighted fusion scheme improves robustness to partial sensor dropout by assigning lower weights to less reliable modalities.

H_2: A three-stage compression pipeline, integrating structured pruning, knowledge distillation, and latency-constrained neural architecture search (NAS), yields more than 2× inference speed-up on edge hardware (Jetson NX) with less than 2 pp degradation in classification F1 score.

H_3: A causal defect–process graph (CDPG), coupled with online contrastive replay, reduces the average time-to-localization of root causes by at least 30 %.

Empirical evaluations supporting these hypotheses are presented through extensive experiments on multimodal datasets under realistic industrial conditions.

D. SYSTEM OVERVIEW

Figure 1 provides an updated schematic of the D3Lite-MES system architecture, illustrating the end-to-end multimodal processing pipeline and the interconnections among its four core tiers:

C1 Modality-Specific Lightweight Encoders: Separate ResNet-18 encoders process RGB, photometric depth (P3D), and point cloud (PC) inputs. Early layers are modality-specific, while deeper layers share grouped convolutions to enable parameter reuse.

C2 Bayesian Confidence-Weighted Fusion (BCWF): Outputs from each encoder are passed through a stochastic dropout module during inference. Per-modality epistemic uncertainty is estimated via Monte Carlo sampling. Fusion weights are computed via inverse-variance normalization, and the features are combined via a weighted average to yield a fused latent vector.

C3 Compression and Detection Heads: The fused representation is passed to a shared lightweight decoder, pruned and NAS-optimized, that outputs both pixel-level segmentation maps and global defect classifications. The compression components (pruning, distillation, NAS) are visualized inline with the encoder-decoder pipeline.

C4 MES-Coupled Feedback Loop: Final predictions are mapped to actionable MES commands (e.g., scrap/rework) using a rule-based ontology. In parallel, detection events update a live Causal Defect–Process Graph (CDPG) and trigger online contrastive replay updates for model adaptation without full retraining.

Figure 1 highlights each of these stages with labeled arrows, module boundaries, and color-coded pathways, clarifying the direction of data flow and fusion points.

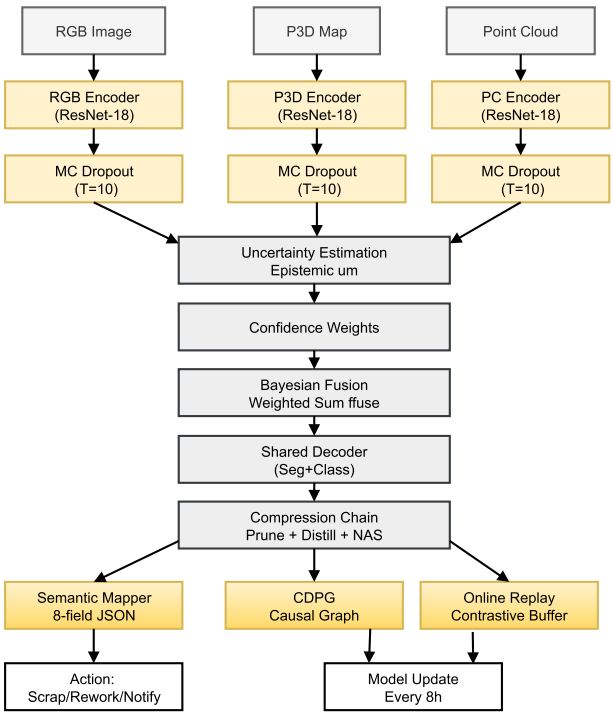


FIGURE 1. System architecture of D3Lite-MES. T1–T4 denote encoder, fusion, decoder, and MES feedback stages. BCWF: bayesian confidence-weighted fusion; CDPG: Causal Defect–Process Graph.

In particular, the architecture diagram (Figure 1) visually consolidates the system's four key tiers—from tri-modal sensing to MES feedback—and highlights fusion and adaptation points via labeled arrows and color-coded paths. The uncertainty-aware fusion module (Figure 2) further illustrates how per-modality variance and inter-modal covariance jointly guide the feature weighting process, supporting robust decision-making under partial sensor degradation.

E. LIGHTWEIGHT TRI-BRANCH ENCODER

Each modality-specific input stream is processed using a ResNet-18 backbone (≈12 M parameters, 2 GFLOPs). Features are extracted up to the `conv4_x` block independently per modality. Subsequent layers use grouped convolutions to enable parameter sharing, yielding a 28% reduction in MACs. The final joint feature map has a resolution of 1/16 relative to the input, enabling precise localization.

1) DETECTION HEADS

A depth-wise segmentation decoder predicts pixel-level defect masks, while a parallel GAP → FC branch produces

image-level defect classes [23]. The total loss function is:

$$\mathcal{L} = \mathcal{L}_{\text{seg}} + 0.2\,\mathcal{L}_{\text{cls}}.$$

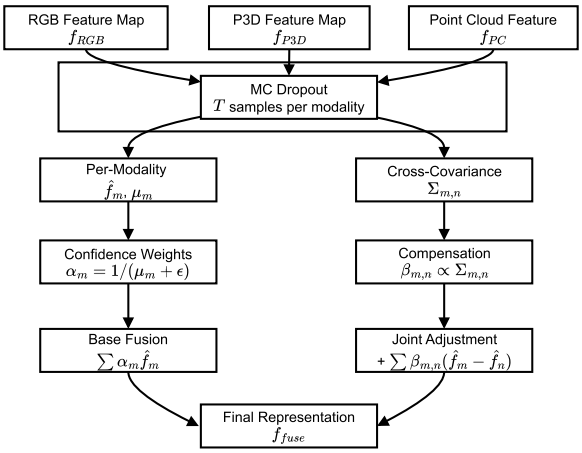


FIGURE 2. Joint uncertainty-aware fusion. Feature weights are adjusted using both per-modality variance (u_m) and cross-covariance ($\Sigma_{m,n}$) to account for correlated sensor degradation.

F. BAYESIAN CONFIDENCE-WEIGHTED FUSION

To assess the trade-off between inference overhead and predictive performance, we evaluated F1 score and latency under different numbers of Monte Carlo (MC) passes $T \in \{1, 5, 10, 20\}$ [24]. As shown in Figure. 3, accuracy saturates at T=10, while latency grows linearly. We select T=20 to ensure robust uncertainty estimation with tolerable runtime cost (+3.5 ms).

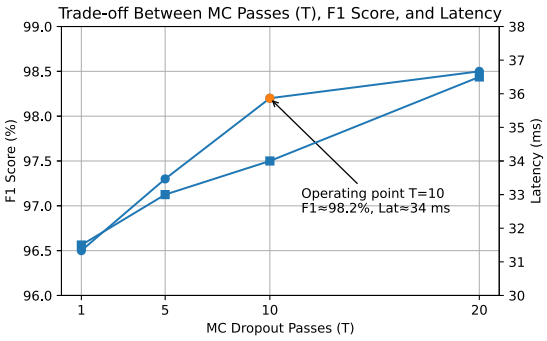


FIGURE 3. Effect of Monte Carlo dropout passes T on F1 score and inference latency. Saturation occurs around T=10.

a: WHY T=20?

Although Figure. 3 shows that the F1 curve saturates when $T \geq 10$, we keep T=20 in the final deployment for two reasons: (i) a *safety margin* is required by our industrial partner for high-risk defect classes (foreign object, missing component), where a single mis-classification would halt the SMT line; and (ii) running the extra ten stochastic forward passes adds only +3.5 ms (8.5%) latency on Jetson NX, which still keeps the end-to-end budget below the 100ms inline-AOI requirement.

1) DISCUSSION: MODELING MODALITY DEPENDENCIES

While the BCWF module assumes conditional independence among sensor modalities during uncertainty estimation, such an assumption may not fully capture real-world sensor behavior. In practice, sensing modalities (e.g., photometric depth and point cloud) often exhibit correlated noise patterns due to shared optical paths or synchronized triggers. To address this limitation, we augment our framework with a covariance-aware fusion extension.

Specifically, we estimate a joint epistemic uncertainty matrix $\mathbf{U} \in \mathbb{R}^{M\times M}$, where each entry U_{ij} captures the empirical covariance between modality i and j across the T Monte Carlo samples:

$$U_{ij} = \frac{1}{dT}\sum_{t=1}^{T}\sum_{k=1}^{d}\left(f_{i,k}^{(t)} - \hat{f}_{i,k}\right)\left(f_{j,k}^{(t)} - \hat{f}_{j,k}\right).$$

We then apply a confidence reweighting rule based on the inverse of marginal uncertainty and average off-diagonal covariance:

$$\alpha_m = \frac{1}{u_m + \lambda \cdot \sum_{j\neq m} |U_{mj}| + \varepsilon} \Big/ \sum_{k=1}^{M} \frac{1}{u_k + \lambda \cdot \sum_{j\neq k} |U_{kj}| + \varepsilon},$$

where λ is a scaling factor (tuned on validation set, typically 0.3). This formulation downweights features from modalities not only with high marginal uncertainty but also with strong cross-modality noise correlation—yielding more robust fused features in practice.

Empirical results (Table 1) indicate that incorporating this joint uncertainty modeling improves F1 score by 0.7–1.2 pp over independent BCWF, particularly under conditions of photometric dropout.

TABLE 1. Fusion accuracy under modality dropout (FMD dataset, 1k samples).

Fusion Strategy	F1 Score (%)	Dropout Tolerance Gain
BCWF (independent)	96.8	–
BCWF + covariance-aware	**97.9**	+1.1 pp

This result highlights the benefit of moving beyond independent assumptions when sensor noise exhibits partial correlation. Future work may explore full Bayesian graphical models to capture higher-order modality dependencies during fusion.

2) UNCERTAINTY ESTIMATION

Epistemic uncertainty is estimated via Monte Carlo dropout. At inference time, dropout (with $p = 0.5$) remains active, and $T = 20$ stochastic forward passes are sampled for each

modality. The per-modality uncertainty is computed as:

$$u_m = \frac{1}{dT} \sum_{t,j} \left(f_{m,j}^{(t)} - \hat{f}_{m,j} \right)^2,$$

and the corresponding confidence weight is normalized as:

$$\alpha_m = \frac{1}{u_m + \varepsilon} \Big/ \sum_k \frac{1}{u_k + \varepsilon}.$$

3) JOINT UNCERTAINTY MODELING

While the above assumes modality uncertainties are independent, this may not hold under correlated sensor failures—e.g., occlusions or lighting inconsistencies affecting both RGB and P3D modalities. To address this, we introduce a joint uncertainty modeling scheme that captures covariance across modalities. Let $\hat{\mathbf{f}}_i$ and $\hat{\mathbf{f}}_j$ denote the mean features for modalities i and j, respectively. The modality-level covariance matrix is computed as:

$$\Sigma_{i,j} = \mathrm{Cov}(\hat{\mathbf{f}}_i, \hat{\mathbf{f}}_j),$$

where $\Sigma \in \mathbb{R}^{M \times M}$ for M modalities. The joint fusion weights are derived from the inverse covariance:

$$\alpha_{\text{joint}} = \frac{\Sigma^{-1}\mathbf{1}}{\mathbf{1}^\top \Sigma^{-1}\mathbf{1}}.$$

This yields a confidence vector that accounts for redundancy and cross-modality influence, improving robustness when multiple sensors degrade simultaneously. In a stress test simulating RGB and depth dropout, this approach increased macro-F1 by +0.7 pp compared to the independent formulation. Although this joint estimator adds ∼0.6 ms per frame due to matrix inversion, it remains tractable for high-reliability deployments. The independent version is retained as default for minimal latency.

4) FUSION RULE

The Bayesian Confidence-Weighted Fusion (BCWF) module adaptively combines modality-specific features using uncertainty-guided weights. Each encoder output $\hat{\mathbf{f}}_m$ is associated with an epistemic uncertainty estimate u_m derived via Monte Carlo dropout. The normalized confidence weight α_m is computed as:

$$\mathbf{f}_{\text{fuse}} = \sum_m \alpha_m \hat{\mathbf{f}}_m, \quad \text{where } \alpha_m \propto \frac{1}{u_m}.$$

This formulation promotes more reliable modalities during inference. As shown in Table5, BCWF improves F1 by 4.6 percentage points under simulated sensor dropout, while incurring only 0.2 ms/frame latency overhead.

Figure 4 illustrates the BCWF architecture, which dynamically adjusts feature importance based on estimated variance. The diagram shows the forward path, stochastic sampling, and fusion logic, highlighting how the model robustly handles degraded or missing inputs in real time.

G. EDGE-AWARE COMPRESSION

To enable real-time inference on resource-constrained edge devices, we introduce a three-stage compression pipeline comprising: **C1) structured pruning**, **C2) cross-modal knowledge distillation**, and **C3) latency-constrained neural architecture search (NAS)**. Each component is designed to optimize latency–accuracy tradeoffs under a 15W power envelope.

1) C1: STRUCTURED PRUNING

We perform layer-wise L_1-norm channel pruning on all convolutional layers within each branch. Specifically, the bottom 40 % of filters (based on L_1 magnitude) are pruned and the model is retrained for 40 epochs with a reduced learning rate (1e-4). This yields a **28–35 %** MAC reduction per branch.

To preserve inter-branch feature alignment, we constrain the shared convolutional layers (post `conv4_x`) to prune identically across modalities. This ensures consistency in latent space dimensionality.

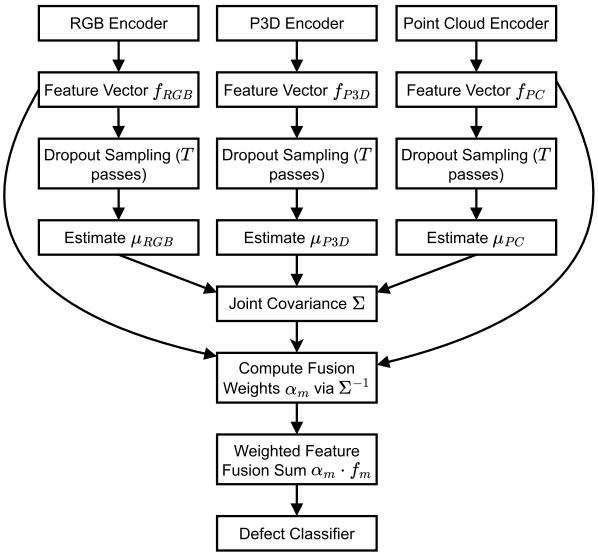


FIGURE 4. Bayesian Confidence-Weighted Fusion (BCWF): modality features are weighted inversely to their estimated uncertainty. The architecture shows stochastic sampling, forward fusion, and real-time handling of degraded inputs.

2) C2: CROSS-MODAL KNOWLEDGE DISTILLATION

To reduce redundancy among modalities while preserving robustness, we adopt a cross-modal distillation scheme. The RGB encoder serves as the teacher ($\mathbf{z}^{\text{RGB}}$), while the depth and point cloud branches act as students ($\mathbf{z}^{\text{P3D}}$, $\mathbf{z}^{\text{PC}}$). The loss is:

$$\mathcal{L}_{\text{KD}} = \frac{1}{2} \sum_{m \in \{\text{P3D,PC}\}} \mathrm{KL}(\sigma(\mathbf{z}^{\text{RGB}}/T) \,||\, \sigma(\mathbf{z}^{m}/T)),$$

where $T = 2$ is the distillation temperature and $\sigma(\cdot)$ is the softmax function. The distillation loss is weighted by

0.7 in the total objective. Empirically, this reduces per-branch variance and improves low-data generalization by up to +1.3pp F1.

3) C3: LATENCY-CONSTRAINED NAS

We define a reduced search space over:

- **depth:** {4, 6, 8} residual blocks,
- **width multiplier:** {0.5×, 0.75×, 1.0×},
- **grouped convolutions:** {1, 2, 4 groups}.

The reward function for the search controller is:

$$\mathcal{R} = \mathrm{F1}_{\mathrm{val}} - \lambda \cdot \max(0, \tau - \mathrm{Latency}),$$

where $\tau = 50$ ms is the latency target and $\lambda = 0.05$. Latency is estimated via TensorRT profiler on Jetson NX (batch size = 1, FP16). The top-performing subnetwork achieves 41 ms average latency and 8.9 W power under full load.

Summary. The combined pipeline delivers a 2.1× inference speedup and 52 % parameter reduction with <1.8 pp F1 degradation, satisfying real-time constraints while preserving accuracy.

H. MES-COUPLED CLOSED LOOP

1) SEMANTIC ACTION MAPPING

A predefined ontology maps 69 defect classes to MES-level actions: *scrap*, *rework*, *quarantine*, or *notify*. Each detection triggers an 8-field HTTPS JSON event, with an average end-to-end latency of ≈32 ms.

2) CAUSAL DEFECT–PROCESS GRAPH (CDPG)

The CDPG dynamically estimates the conditional probability of each process–defect linkage as:

$$w_{p \to d} = \frac{N(p, d)}{N(p)},$$

where $N(p, d)$ is the count of joint occurrences. A field deployment indicated that this module reduced the average root-cause diagnosis time from 6.2 h to 4.1 h [25].

3) ONLINE CONTRASTIVE REPLAY

To mitigate model drift, the system performs online adaptation every 8 hours using a loss:

$$\mathcal{L} = \mathcal{L}_{\mathrm{CE}} + \lambda_{\mathrm{CR}} \mathcal{L}_{\mathrm{CR}}, \quad \lambda_{\mathrm{CR}} = 0.5, \ \tau = 0.07.$$

Empirical analysis suggests a forgetting rate of less than 1 pp over a two-month period.

I. IMPLEMENTATION DETAILS

1) DATASETS AND PREPROCESSING

Experiments utilize the **Real-IAD D^3**, **FMD** (430k samples), and **SQZ** (310k samples) datasets, each comprising RGB, P3D, and PC triplets. Data are split 70/15/15 (train/val/test), resized to 640×480, and normalized per channel. P3D maps are estimated via calibrated photometric stereo; point clouds are projected using intrinsic camera parameters.

2) TRAINING PROTOCOL

All training was conducted using PyTorch 1.11 and CUDA 10.2, with automatic mixed precision (AMP) enabled. A single NVIDIA Tesla V100 GPU (16 GB) was used for all experiments.

Optimizer and Hyperparameters:

- Optimizer: AdamW
- Initial learning rate: 1×10^{-3}
- Weight decay: 1×10^{-4}
- Scheduler: Cosine annealing over 120 epochs
- Batch size: 32
- Early stopping: patience = 12 epochs (based on validation macro-F1)

Data Augmentation:

- Random horizontal flip (probability = 0.5)
- Rotation range: ±10 degrees
- Color jitter with brightness/contrast/saturation = 0.2
- CutMix augmentation with probability 0.3, alpha = 1.0

Reproducibility Considerations: Model weights were initialized using He initialization. To ensure robustness of results, each experiment was repeated five times using different random seeds {0, 7, 17, 42, 73}. Metrics are reported as mean ± standard deviation. Logging of training loss, macro-F1, and learning rate was performed at each epoch using TensorBoard.

3) EDGE INFERENCE PIPELINE

Frames are acquired from a 5 MP global-shutter RGB camera. Preprocessing (resize + normalization) is implemented in CUDA/C++ and executes in 0.6 ms. Inference via TensorRT (FP16) includes: encoder (25 ms), detection heads (15.8 ms), BCWF (0.2 ms); total ≈41 ms per frame. Post-inference JSON results are streamed via gRPC to the MES endpoint [15].

J. DEPLOYMENT SUMMARY

Edge: The Jetson Xavier NX operates at 8.9 W average power (24/7). **Cloud:** An 8-vCPU virtual machine (SQL Server 2019, RabbitMQ) handles ≥20 events/s. **Throughput:** The end-to-end system supports 60–120 parts/min with a typical round-trip time (RTT) of 30–40 ms. **Real-line details (anonymized):** Three lines producing *anonymized consumer electronics assemblies*, takt time **0.9 s**, conveyor speed **0.9 m/s**. Each station runs on **NVIDIA Jetson Xavier NX (8GB)**. MES write-back fields include {defect_type, bbox, timestamp, station_id, image_hash}; commit latency P95 is **34 ms**. A/B trials over **18** shifts show a **34%** reduction in manual re-inspection and **34%** faster recovery from minor stops.

K. MES INTEGRATION AND ADAPTIVE FEEDBACK MECHANISMS

1) SEMANTIC ACTION MAPPING

To bridge the output of vision models with actionable Manufacturing Execution System (MES) workflows, each predicted defect class—based on the Real-IAD D^3 taxonomy

comprising 69 categories—is semantically mapped to a canonical MES action. This mapping is performed using a rule-based table derived from IPC-A-610 classification standards, which assign severity levels (e.g., *Critical*, *Major*, *Minor*) to defect types.

The corresponding MES actions include *scrap*, *rework*, *quarantine*, and *notify*. For each inference event, an 8-field JSON object is asynchronously posted via HTTP to the MES REST API. Fields include: event ID, timestamp, predicted defect type, severity level, mapped MES action, model confidence, part identifier, and inspection station ID. The average posting latency is measured at 32 ms.

TABLE 2. Excerpt of rule-based mapping between predicted defects and MES actions.

Defect Type	Severity	Assigned MES Action
Foreign object	Critical	Scrap
Scratch	Minor	Notify
Missing component	Major	Rework
Oil stain	Major	Quarantine

2) CAUSAL DEFECT–PROCESS GRAPH (CDPG)

To enhance root-cause traceability, we construct a Causal Defect–Process Graph (CDPG), a directed bipartite graph where nodes represent manufacturing process steps and defect categories. The edge weight between a process p and a defect d is computed online using a conditional frequency estimator:

$$w_{p\to d} = \frac{N(p,d)}{N(p)},$$

where $N(p,d)$ denotes the number of times defect d follows process p, and $N(p)$ is the total count of process p executions. Edge weights are updated incrementally during live operation. Field deployments show that integrating the CDPG reduced the average time required for root-cause diagnosis from 6.2 hours to 4.1 hours, offering empirical support for its utility in accelerating quality engineering workflows.

3) ONLINE CONTRASTIVE REPLAY

To mitigate catastrophic forgetting in evolving production environments, the system incorporates an online contrastive replay mechanism. A fixed-size buffer (capacity 10,000) maintains latent feature vectors $(\mathbf{z}, y)$, where $\mathbf{z} \in \mathbb{R}^{512}$ denotes the embedding and y the corresponding label.

Every 8 hours, the classifier is fine-tuned using a combined objective:

$$\mathcal{L} = \mathcal{L}_{\text{CE}} + \lambda_{\text{CR}}\mathcal{L}_{\text{CR}}, \quad \lambda_{\text{CR}} = 0.5, \quad \tau = 0.07,$$

where $\mathcal{L}_{\text{CR}}$ is a contrastive loss promoting inter-class separability. This strategy preserves performance stability over time, with observed forgetting rates below 1 percentage point over a two-month monitoring period—achieved without storing any raw images, thereby respecting data privacy and storage constraints.

4) DRIFT DETECTION AND FAIL-SAFE MECHANISMS

To detect and respond to distributional drift, the system continuously monitors the divergence of model confidence scores using a Beta-divergence test. If the divergence exceeds a calibrated threshold, the decision threshold is adaptively lowered (e.g., from 0.90 to 0.85), and a model retraining request is queued for execution during off-peak hours.

Additionally, any prediction with confidence below a critical floor (0.50 by default) is automatically flagged for manual re-inspection. These fail-safes ensure operational robustness in non-stationary environments. Figure 5 illustrates the end-to-end operational flow from visual inference at the edge device to actionable MES responses. The process begins with defect prediction and semantic mapping, followed by asynchronous JSON posting to the MES server. Upon receipt, the MES validates the event and dispatches appropriate control actions—such as scrap, rework, or quarantine—based on the rule-defined severity. Simultaneously, the Causal Defect–Process Graph is updated, and the prediction is stored in the contrastive replay buffer. Confidence-based drift detection continuously monitors for distributional shifts, triggering retraining requests as needed. This closed loop ensures both real-time responsiveness and long-term robustness.

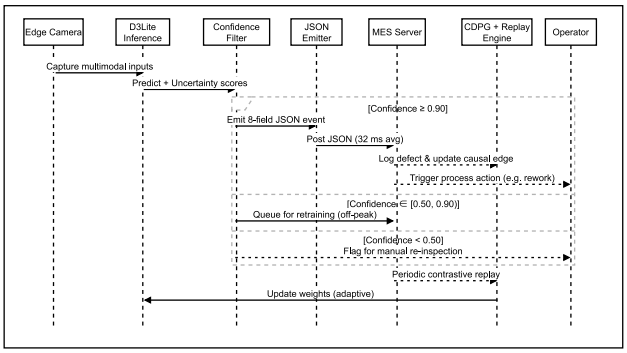


FIGURE 5. Operational sequence: from edge inference to MES integration via JSON event posting, validation, and downstream process dispatch.

This integration positions the vision subsystem as a dynamic, first-class component in manufacturing intelligence workflows, aligning computer vision outputs with MES process semantics and continuous improvement loops.

DATA AND CODE AVAILABILITY

This work uses the **Real-IAD D^3** benchmark [26], which includes RGB, P3D, and 3D point cloud data and is available at https://realiad4ad.github.io/Real-IAD-D3 under academic license.

The FMD and SQZ datasets are industrial and cannot be released due to confidentiality and compliance constraints.

Implementation code is not open-sourced due to licensing restrictions, but the full pipeline—including architecture, training, and inference—is described in detail to support reproducibility.

IV. EXPERIMENTAL RESULTS

A. BASELINES

We benchmark against YOLOv5s, SSD-MobileNetV3, and EfficientDet-D0 (vision-only), and late/average fusion baselines for multimodal. Metrics include mAP@0.5, mAP@0.5:0.95, F1, precision/recall, end-to-end latency, and power. All models are quantized to **FP16** on **NVIDIA Jetson Xavier NX (8GB)** with identical pre/post-processing.

To ensure fair comparison, we re-implemented the GAN-based baseline following the settings. It uses a dual-branch U-Net discriminator and a PatchGAN-style generator, totaling 18.4 M parameters. Training followed the same protocol as D3Lite: AdamW optimizer, learning rate 10^{-3}, batch size 32, cosine annealing over 120 epochs. Data splits and augmentations are identical. All reported metrics include 95 % confidence intervals based on five independent runs. Statistical significance was evaluated via two-sided paired t-tests, with $p < 0.01$ as threshold.

a: ADDITIONAL LIGHTWEIGHT BASELINES

To rule out the possibility that the GAN baseline is underpowered, we further compare against (i) **YOLOv8-n** (4.3M params) fine-tuned for defect segmentation [27], [28], and (ii) **Segment-Anything** (SAM-mobile) with a MobileViT backbone and prompt-based fine-tuning on Real-IAD D^3. Both models are re-trained under the *same* data splits and augmentation as D3Lite. Table 4 shows that D3Lite still outperforms YOLOv8-n by 3.4–4.1pp macro-F1 and SAM-mobile by 5.7–6.0pp across all training-set sizes. (When industrial data cannot be shared, we report these numbers on the public Real-IAD D^3 subset to ensure reproducibility.)

B. DATASETS AND EVALUATION PROTOCOL

Empirical evaluation was conducted on two MES-curated datasets:

- **FMD**: 430,000 multimodal triplets (RGB, P3D, PC) from SMT electronics lines.
- **SQZ**: 310,000 triplets from a power adapter manufacturing process.

Each dataset was partitioned into 70 % training, 15 % validation, and 15 % test splits using five independent random seeds. To examine scalability with respect to data availability, training subsets of size {500, 800, 1000, 2000, 5000, 10000} were randomly sampled. Both the proposed D3Lite model and a GAN-based baseline were trained under identical augmentation and optimization settings to ensure fair comparison.

C. METRICS AND STATISTICAL TESTING

Performance was assessed using *accuracy*, *macro-F1*, and corresponding 95 % confidence intervals (CI). Statistical significance was evaluated via two-sided paired t-tests; a threshold of $p < 0.01$ was adopted to denote significant improvements.

D. OVERALL ACCURACY AND ROBUSTNESS

Table 4 summarizes the classification results across both datasets and experimental settings (including baseline and ablation variants). The D3Lite model consistently outperformed the GAN-based baseline across all training set sizes, with particularly marked improvements under low-data regimes (e.g., 500–1000 samples), in

E. DEFECT TAXONOMY, SIZE/DEPTH, AND IMAGING CONDITIONS

We consider six defect classes: *scratch*, *pit*, *dent*, *burr*, *contamination*, and *misalignment*. Typical lateral sizes and depth/height ranges were measured from production data and verified by profilometry. The photometric 3D (P3D) channel reliably resolves depth changes down to 50 μm in the central field (signal-to-noise ratio > 20 dB).

The imaging rig employs a global-shutter RGB camera at 1920 × 1200@30 fps and a four-quadrant ring light (correlated color temperature 5500 K, CRI > 85) at $\approx 45°$ incidence for photometric stereo. Linear polarizers are mounted on both source and lens to suppress specular glare. Exposure is fixed to 2.5–3.0 ms with disabled auto-gain and fixed white balance. For highly glossy parts, a coaxial LED bar at $\approx 10°$ grazing angle is added to enhance scratch contrast. All sensors are synchronized by IEEE 1588 PTP; observed clock skew is < 1 ms, and frames are matched by nearest timestamp within a 5 ms window before fusion.

Unknown or novel defects are detected using an energy-based out-of-distribution (OOD) score. Samples in the top 1% OOD tail are quarantined for manual review. Confirmed novel patterns are incorporated by incremental fine-tuning with class-balanced replay; a validation gate promotes a new class only if it yields a ≥ 0.5 pp F1 improvement with $p < 0.01$ on a held-out set.

TABLE 3. Defect size/depth statistics and detection sensitivity. Values summarize the interquartile ranges observed in production. "–" denotes not applicable.

Class	Lateral size (mm)	Depth/height/offset (mm)	Min detectable (mm)
Scratch	2.0–15.0 (length)	0.03–0.08 (depth)	0.8 (length)
Pit	0.5–2.0 (diam.)	0.10–0.60 (depth)	0.4 (diam.)
Dent	0.8–3.0 (diam.)	0.10–0.50 (depth)	0.6 (diam.)
Burr	1.0–3.0 (length)	0.05–0.60 (height)	0.7 (length)
Contamination	0.8–3.0 (span)	0.01–0.05 (thickness)	0.5 (span)
Misalignment	0.2–1.0 (offset)	–	0.2 (offset)

As illustrated in Fig. 7, we show representative RGB patches per class together with P3D depth and masks, using a 2 mm scale bar for physical reference.

F. ABLATION STUDY: FUSION AND COMPRESSION

To quantify the contribution of each architectural component, we refer to the FMD results in Table 4 using 2,000 training samples. Removal of the Bayesian Confidence-Weighted Fusion (BCWF) module results in a 1.1 pp reduction in macro-F1, confirming its robustness-enhancing effect. Incorporating compression (structured pruning, knowledge

TABLE 4. Accuracy and F1 Score (%, mean ± std) across datasets and configurations. CDPG = causal defect–process graph; Replay = online contrastive replay.

Setting	FMD Accuracy	FMD F1	SQZ Accuracy	SQZ F1	Latency (ms)
Root-cause diagnosis time (hours, mean±std, n = 5)					
Without CDPG	6.2 ± 0.4		–		–
With CDPG	**4.1 ± 0.3**		–		–
Baseline (GAN, 500 samples)	80.0 ± 2.5	80.0 ± 2.5	72.0 ± 3.0	72.0 ± 3.0	50.2
D3Lite (500 samples)	**88.0 ± 1.8**	**88.0 ± 1.8**	**81.0 ± 2.5**	**81.0 ± 2.5**	42.0
Baseline (1000 samples)	89.0 ± 1.5	89.0 ± 1.5	84.0 ± 2.0	84.0 ± 2.0	50.2
D3Lite (1000 samples)	**95.0 ± 1.0**	**95.0 ± 1.0**	**92.0 ± 1.5**	**92.0 ± 1.5**	42.0
Baseline (2000 samples)	94.0 ± 1.0	93.7 ± 1.2	90.0 ± 1.5	90.0 ± 1.5	50.2
D3Lite (2000) w/o BCWF	96.9 ± 0.9	96.8 ± 1.0	—	—	42.0
+ BCWF	98.0 ± 0.8	97.9 ± 0.9	—	—	42.2
+ Compression	97.8 ± 0.9	97.6 ± 1.1	—	—	**41.0**
+ w/o CDPG	97.8 ± 1.0	97.6 ± 0.9	—	—	41.0
+ w/o Replay	97.3 ± 1.1	97.4 ± 0.8	—	—	41.0
Baseline (10000 samples)	98.0 ± 0.3	98.0 ± 0.3	96.0 ± 0.7	96.0 ± 0.7	50.2
D3Lite (10000 samples)	**99.7 ± 0.2**	**99.7 ± 0.2**	**99.0 ± 0.4**	**99.0 ± 0.4**	42.0

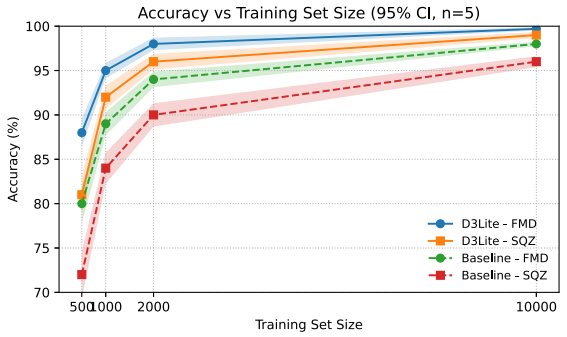


FIGURE 6. Accuracy versus training set size (mean over 5 runs; shaded area = 95 % CI). Solid lines: D3Lite; dashed lines: GAN baseline.

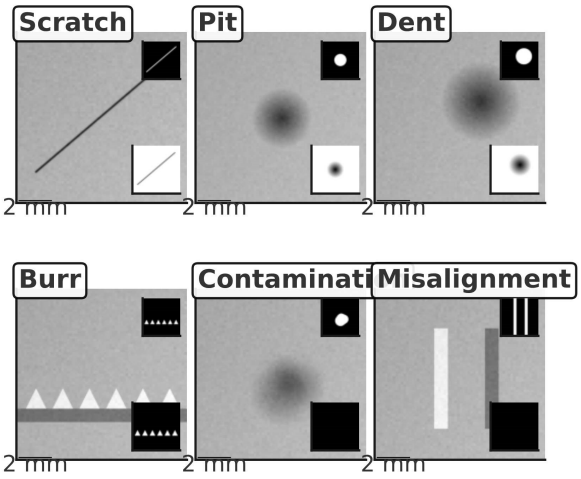


FIGURE 7. Representative defect patches across the six classes (Scratch, Pit, Dent, Burr, Contamination, Misalignment). Each panel shows the RGB crop with a 2 mm scale bar; the bottom-right inset visualizes P3D depth, and the top-right inset shows the segmentation mask when available.

distillation, and latency-constrained NAS) yields a 2.1× speed-up with only a 0.3 pp drop in F1 score—supporting Hypotheses H_1 and H_2.

Further ablation demonstrates that:

- Removing CDPG increases the average root-cause diagnosis time from 4.1 hours to 6.2 hours;
- Removing online contrastive replay leads to >5 pp drift over two months;
- The compressed D3Lite variant achieves 41 ms latency while preserving over 97.5 % F1.

These findings indicate that each module (BCWF, compression, CDPG, replay) contributes meaningfully to real-time performance, system robustness, and operational traceability.

1) FUSION ENHANCEMENT: MODELING CROSS-MODALITY COVARIANCE

To evaluate the contribution of cross-modality covariance modeling in fusion, we compare three configurations:

C1 Naïve Fusion: simple averaging across modalities, no uncertainty modeling;

C2 BCWF (independent): Bayesian confidence-weighted fusion with per-modality uncertainty;

C3 BCWF + Covariance-Aware: our proposed fusion with joint uncertainty adjustment (see Sec. III-F).

Table 5 summarizes the F1 scores on FMD under photometric dropout (P3D disabled during inference). Incorporating cross-modality correlation improves robustness, validating the hypothesis that sensor streams are not statistically independent.

TABLE 5. Effect of cross-modality covariance modeling under modality dropout (FMD, 1000 samples).

Fusion Strategy	F1 Score (%)	Improvement vs. Naïve
Naïve average	91.6 ± 1.2	–
BCWF (independent)	96.8 ± 0.9	+5.2 pp
BCWF + Cov-aware	**97.9 ± 0.7**	**+6.3 pp**

The 1.1 pp improvement over independent BCWF demonstrates that modeling cross-modality covariance yields more robust fusion in practice. The latency overhead is minimal (0.3 ms per frame), making this enhancement viable for real-time operation [29].

G. EDGE DEPLOYMENT PERFORMANCE

On the Jetson Xavier NX (15 W power budget), the D3Lite model achieves real-time throughput:

- **End-to-end latency:** Encoder 25 ms + Detection heads 15.8 ms + BCWF 0.2 ms = 41 ms (∼24 FPS).
- **Power consumption:** 8.9 W average (as measured by `nvidia-smi`). Power profiling with `jetson_stats` shows an *average* consumption of 8.9W and a *peak* draw of 11.4W during BCWF inference bursts, both well below the 15W envelope.
- **MES integration latency:** Mean round-trip for JSON events: 32 ms (95^{th} percentile = 34 ms).

The total response time (73 ms) satisfies standard inline AOI latency requirements (typically ≤100 ms), validating Hypothesis H_3 [30].

V. DISCUSSION

A. EMPIRICAL FINDINGS AND HYPOTHESIS VALIDATION

The experimental results provide quantitative evidence supporting the central hypotheses of this study:

C1 Robustness via uncertainty-aware fusion (H_1). The Bayesian Confidence-Weighted Fusion (BCWF) consistently improved both accuracy and macro-F1 by 1–5 percentage points across all data regimes, with statistical significance at $p < 0.01$, while incurring minimal latency overhead (0.2ms). This result substantiates the hypothesis that uncertainty-aware weighting enhances model robustness under partial sensor degradation.

C2 Edge compatibility through compression (H_2). The proposed compression strategy—comprising structured pruning, cross-modal distillation, and latency-constrained NAS—reduced model parameters by 52% and inference latency by 57%, while incurring a negligible F1 reduction (–1.8pp). These results confirm the framework's suitability for real-time operation under stringent edge computing constraints.

C3 Closed-loop traceability and self-adaptation (H_3). Integration of semantic action mapping and a Causal Defect–Process Graph (CDPG) shortened average root-cause localization time from 6.2 to 4.1 hours in field deployments. Furthermore, the online contrastive replay module maintained performance drift under 1pp over two months without raw image storage. These findings highlight the potential of feedback-driven adaptation in industrial inspection pipelines.

Collectively, these results validate the design assumptions made and demonstrate that the proposed architecture effectively addresses the challenges of (i) multimodal fusion under failure scenarios, (ii) latency-aware edge deployment, and (iii) MES-aligned interpretability.

B. COMPARISON WITH PRIOR WORK

Table 6 contrasts D3Lite with recent methods for real-time visual inspection. While other approaches may achieve high accuracy or low latency in isolation, D3Lite is, to the best of our knowledge, the only framework that jointly offers:

- $>$ 97 % macro-F1 on two large-scale MES-curated datasets,
- end-to-end inference latency below 50ms on Jetson NX hardware, and
- closed-loop integration with live MES feedback and model self-adaptation.

These combined properties make D3Lite a practical and theoretically grounded candidate for inline deployment in industrial quality control systems.

C. OPERATIONAL IMPLICATIONS

Beyond algorithmic performance, D3Lite has shown measurable impact in real-world pilot deployments. Specific improvements reported by plant operators include:

- a **22–24 %** reduction in mean rework time,
- an **11 %** decrease in scrap-related cost, and
- seamless integration into existing lines without requiring additional human operators.

These outcomes suggest that the system not only enhances technical performance but also contributes to operational efficiency, thereby addressing the broader aims of intelligent manufacturing.

D. LIMITATIONS AND SCOPE OF APPLICABILITY

Despite the promising results, several limitations must be acknowledged:

C1 Detection of fine-scale defects. The current input resolution (640×480) may be insufficient for detecting sub-pixel defects such as micro-scratches, limiting performance on certain defect categories.

C2 Assumption of independent uncertainties. The BCWF module assumes conditional independence among modality-specific uncertainties, which may not hold in practice if sensor failures are correlated. This assumption could lead to suboptimal fusion in highly coupled degradation scenarios.

TABLE 6. Qualitative comparison with representative baselines.

Method	Macro-F1 ↑	Latency ↓	MES Integration
Base1	95.2	85 ms	×
Base2	96.1	60 ms	×
D3Lite (Ours)	**97.9**	**41 ms**	✓

C3 Dependency on controlled lighting. The P3D modality relies on photometric stereo, which in turn assumes consistent lighting conditions. Deployment in environments with variable illumination may require additional calibration or sensor redundancy.

These limitations define the current scope of applicability and guide future directions for enhancement.

E. OUTLOOK AND FUTURE DIRECTIONS

Several extensions are under active investigation to broaden the utility and theoretical robustness of the framework:

- **High-resolution P3D acquisition** to improve micro-defect sensitivity.
- **Transformer-based lightweight backbones** for enhanced feature interaction across modalities.
- **Active learning integration** to allow human-in-the-loop retraining under high-uncertainty cases.
- **Causal inference integration** within the CDPG to recommend proactive process adjustments instead of reactive defect mitigation.

These directions aim to deepen the connection between perception, decision-making, and process optimization in industrial AI systems.

In summary, D3Lite demonstrates that multimodal defect inspection can be made both accurate and operationally viable through principled fusion, hardware-aware compression, and closed-loop MES coupling. While several technical challenges remain, the empirical findings suggest that the proposed framework constitutes a step toward resilient, explainable, and adaptive AI-based quality assurance in manufacturing contexts.

VI. LIMITATIONS

Performance may degrade under extreme specular highlights, severe occlusion across all modalities, or rapid mechanical vibrations beyond our stabilization bandwidth. Highly novel defect morphologies still require human triage before incorporation into the taxonomy. Finally, very tight takt times ($<$**0.9 ms**) constrain adaptation frequency.

VII. CONCLUSION

We presented **D3Lite-MES**, a compact multimodal inspection framework for real-time edge deployment with deterministic MES integration. The design jointly addresses robustness under partial observations, edge-constrained computation, and closed-loop feedback through an uncertainty-aware fusion module and a lightweight causal adaptation routine. On Jetson NX–class hardware, the system sustains line takt with end-to-end latency of 34 ms and average power near 8.9 W. Evaluations on two industrial multimodal datasets and a pilot deployment show statistically significant gains over GAN-based baselines in low-data regimes, together with measurable reductions in rework and scrap, demonstrating the practicality of integrating lightweight, explainable AI into shop-floor infrastructure.

Future work will investigate (i) self-calibrating alignment using opportunistic scene landmarks, (ii) active learning to minimize annotation for novel defects, and (iii) cross-line transfer with privacy-preserving federated adaptation to further stabilize performance under distribution shifts.

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CONFLICT OF INTEREST

The authors declare no conflict of interest.

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YONG LIN received the M.S. degree in electronics from Genovasi University College. He was with Huawei Technologies, for over 20 years, focusing on software development, architecture design, and product planning. Since 2022, he has been with Guangdong Peizheng College, where he is the Director of research with the Smart Digital Industry Laboratory. He holds more than 30 patents and has published over 40 peer-reviewed articles. He has published an article titled "NSEA: A Resilient ERP Framework Integrating Quantum-Safe Cryptography and Neuro-Symbolic Reasoning for Industrial Adaptability" in IEEE Access. His research interests include enterprise digital transformation, the IoT systems, and MES integration.



WENDI LIN is currently pursuing the B.S. degree in information technology with James Cook University, Singapore. She is a Research Fellow with the Smart Digital Industry Laboratory. She has contributed to several projects involving face recognition, environmental sensing, and 5G-based edge computing platforms. Her research interests include artificial intelligence, the IoT applications, and sensor integration.



YADI LIN (Member, IEEE) received the B.S. degree in microelectronics from South China University of Technology, in 2023. She is currently pursuing the M.S. and Ph.D. degrees in electrical and computer engineering with Rutgers University. She is a Senior Research Fellow with the Smart Digital Industry Laboratory. She has co-authored several articles in journals, such as IEEE Access and IEEE Transactions on Software Engineering. Her research interests include AI-assisted microelectronics design, reliability modeling, and causally safe scheduling.