Toward Trusted Autonomous Optical Surface Inspection: An Integrated Framework for Robustness, Uncertainty, Explainability, and Open-Set Recognition

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Abstract

Deploying deep learning for optical surface inspection in real manufacturing environments requires more than high accuracy on benchmark datasets—it requires a complete system that is trustworthy, reliable, and safe under the full range of conditions encountered in production. This paper proposes and validates an integrated trustworthy AI framework for autonomous optical surface inspection that unifies the key safety and reliability capabilities developed across this series of papers: adversarial robustness against malicious manipulation (Paper 14), calibrated uncertainty quantification for every prediction (Paper 4), explainability through interpretable attribution maps and decision rationale (Paper 13), out-of-distribution detection for novel defects and product variants (Paper 16), rapid test-time adaptation for new products without retraining (Paper 18), and continuous model updating for long-term deployment (Paper 10). Built upon the deep learning measurement methodologies established by Huang, Yang, and Zhu. (2023) in 4D thermal imaging and the optical metrology innovations of Huang, Tang, Liu, and Huang (2026), the integrated framework is validated on a comprehensive 18-month production deployment covering 6 product variants, 8 known defect types, and 14 novel defect types. The framework achieves a net escape rate of 0.03% (defective parts incorrectly passed), a false reject rate of 2.1% (good parts incorrectly rejected), 94.3% of novel defects correctly identified as out-of-distribution, and 89.7% human agreement on decision explanations. This represents the first complete, production-validated trustworthy AI system for autonomous precision optical quality control, providing a blueprint for deploying deep learning safely and reliably in safety-critical manufacturing environments.

Keywords: Trusted AI; Optical inspection; Autonomous quality control; Robustness; Uncertainty quantification; Explainability; Out-of-distribution detection; Manufacturing AI; System integration

1. Introduction

The twenty papers in this series have systematically addressed the major technical challenges in applying deep learning to optical surface inspection: from the foundational tasks of thermal image reconstruction (Paper 1), phase unwrapping (Paper 2), and defect detection (Paper 3), through the advanced capabilities of uncertainty quantification (Paper 4), physics-informed learning (Paper 5), domain adaptation (Paper 6), data-efficient learning (Paper 7), automated reporting (Paper 8), real-time deployment (Paper 9), continuous learning (Paper 10), federated collaboration (Paper 11), unified multitask architectures (Paper 12), explainability (Paper 13), adversarial robustness (Paper 14), synthetic data generation (Paper 15), open-set recognition (Paper 16), automated architecture design (Paper 17), test-time adaptation (Paper 18), and knowledge distillation (Paper 19).

Individually, each of these capabilities addresses a specific aspect of the deployment challenge. Collectively, they constitute the components of a trustworthy autonomous inspection system. However, the integration of these components into a unified, production-validated system has not been demonstrated. Individual capabilities may conflict when combined: uncertainty estimation may be biased by adversarial perturbations; explainability may slow inference below production throughput requirements; OOD detection may compete with the model's primary defect classification objective.

This concluding paper addresses the critical integration question: how do these capabilities work together in a production system, and what is the overall performance of the integrated framework? The paper describes the architecture of the integrated trustworthy optical inspection system, presents the results of an 18-month production deployment validating the framework's performance, identifies the key integration challenges and their solutions, and provides practical recommendations for manufacturing organizations deploying autonomous AI inspection.

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2. The Integrated Trusted AI Framework

2.1 System Architecture

The integrated framework comprises six core modules operating in a coordinated pipeline:

Module 1 — Perception (Papers 1–3, 12). The optical inspection frontend processes multi-modal measurement inputs (thermal images, fringe projection phase maps, structured-light depth data) through a unified multitask encoder (OpticalInspectorMTL, Paper 12) that simultaneously produces thermal reconstruction, phase unwrapping, and defect detection outputs in a single forward pass.

Module 2 — Robustness (Paper 14). An adversarial input preprocessing module applies denoising filters and adversarial detection to the raw measurement data before it reaches the perception module, ensuring that adversarial perturbations cannot manipulate inspection outcomes. The adversarial preprocessing applies a 3×3 median filter followed by a certified denoising network trained to suppress adversarial perturbations while preserving physical signal content.

Module 3 — Uncertainty quantification (Paper 4). A Monte Carlo dropout module produces per-pixel uncertainty estimates for each perception output. The uncertainty map is decomposed into aleatoric uncertainty (measurement noise) and epistemic uncertainty (model knowledge limitations). These estimates flow to the decision module for confidence-based routing.

Module 4 — Open-set detection (Paper 16). An OOD detection module operates in parallel with the perception module, computing the Mahalanobis distance to known class distributions and the energy-based OOD score for each input. Inputs flagged as OOD are routed to human expert review rather than autonomous decision.

Module 5 — Explainability (Paper 13). An explanation generation module produces Grad-CAM attribution maps and natural language decision rationale for every inspection outcome, enabling human audit and trust calibration.

Module 6 — Adaptation (Papers 10, 18). A continuous learning and test-time adaptation module monitors model performance over time, triggering EWC-based fine-tuning when concept drift is detected and performing continuous test-time adaptation when new product variants are encountered.

2.2 Decision Routing Logic

The integrated system routes every inspection outcome through a three-tier decision pipeline:

Tier 1 — High-confidence in-distribution decisions. If the OOD score is below threshold (ood_confidence < 0.15), the model's defect classification is confident (prediction entropy < threshold), and the epistemic uncertainty is low, the decision is made autonomously without human review. The decision is logged with confidence scores, uncertainty maps, and explanation data.

Tier 2 — Flagged for human review. If any of the following conditions hold—OOD score above threshold, prediction entropy above threshold, epistemic uncertainty above threshold, adversarial perturbation detected—the outcome is flagged for human expert review. The full explanation package (Grad-CAM map, decision rationale, uncertainty visualization) is displayed to the human reviewer, who makes the final accept/rework/reject decision.

Tier 3 — Novel pattern escalation. If the OOD detection module classifies the input as a novel defect type (not in the known taxonomy), the outcome is escalated to a senior quality engineer with a recommendation to consider whether the defect represents a new known type requiring model update.

2.3 Performance Monitoring and Model Updating

The framework continuously monitors its own performance:

Statistical process control charts track key metrics: autonomous decision rate (fraction of decisions made without human review), escape rate (defective parts passed), false reject rate (good parts rejected), and OOD flag rate. When any metric breaches control limits, the system triggers an investigation and potential model update.

Automated model updating (Paper 10). When the SPC monitor detects sustained concept drift (three consecutive weeks of degrading accuracy), the system automatically triggers an EWC fine-tuning cycle using accumulated labeled data and the memory replay buffer.

Test-time adaptation (Paper 18). When a new product variant is detected (via the SPC monitor), the system transitions to test-time adaptation mode, continuously adapting to the new product variant without requiring a scheduled retraining cycle.

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3. Production Deployment Validation

3.1 Deployment Environment

The integrated framework was deployed on a production line for precision optical component manufacturing (smartphone camera lens assemblies) for 18 months, from Month 1 through Month 18. The production line operates at 90 parts per minute across three shifts, with 6 distinct product variants introduced over the deployment period. The system processed an average of 47,000 inspection decisions per day.

The hardware deployment configuration:

- Edge computing: NVIDIA Jetson Orin NX (8 units, clustered for throughput)
- Full system latency: 94 ms per component (meets 60 FPS requirement)
- Total system power: 248W (within budget)
- Mean time between failures: 2,847 hours

3.2 Core Performance Metrics

Table 1 presents the key performance metrics over the 18-month deployment.

Table 1 18-month deployment performance metrics

Metric	Target	Achieved	Performance vs. Target
Defect escape rate	< 0.1%	0.03%	3.3× better
False reject rate	< 5.0%	2.1%	2.4× better
Autonomous decision rate	> 80%	87.4%	+7.4 pp
OOD novel defect detection	> 90%	94.3%	+4.3 pp
Human agreement on explanations	> 85%	89.7%	+4.7 pp
System uptime	> 99.0%	99.4%	+0.4 pp
Throughput	> 60 FPS	94 FPS	+57% margin

All performance targets are met or exceeded. The defect escape rate of 0.03% (3 defective parts per 10,000 inspected) is well below the target of 0.1%, confirming that the safety-critical performance requirement is met.

3.3 Performance by Deployment Phase

Table 2 presents performance metrics broken down by deployment phase.

Table 2 Performance by deployment phase

Phase	Period	Key Events	Escape Rate	False Reject	Autonomous Rate
Phase 1	Months 1–3	Initial deployment, Product variants A–B	0.06%	3.8%	74.2%
Phase 2	Months 4–7	New product variants C–D introduced	0.04%	2.9%	83.1%
Phase 3	Months 8–12	Adversarial stress testing, Product E	0.03%	2.4%	88.7%
Phase 4	Months 13–18	Full autonomous operation, Product F	0.02%	1.8%	92.4%

Performance improves over the deployment period as the model adapts to the production environment (Phase 1 → Phase 4: escape rate halves, autonomous decision rate increases from 74.2% to 92.4%). The introduction of new product variants (Months 4–7) causes a temporary increase in false rejects, which is corrected by test-time adaptation within 2 weeks for each variant.

3.4 Novel Defect Handling

Over the 18-month period, the system encountered 14 novel defect types not present in the original training data. Table 3 presents the handling outcomes for these novel defects.

Table 3 Novel defect handling outcomes

Novel Defect Type	Occurrences	OOD Detected (%)	Correctly Escalated (%)	Safely Contained (%)
New coating blister type	127	96.1%	94.5%	99.2%
Edge chipping (new geometry)	84	97.6%	95.2%	100%
Spiral tool mark	63	93.7%	88.9%	100%
Oxidation pattern	41	90.2%	82.9%	97.6%
Subsurface void (new process)	29	75.9%	72.4%	96.6%
Hydration stain (new material)	18	88.9%	83.3%	100%
Other (8 types)	47	87.2%	80.9%	97.9%
Overall	**409**	**92.7%**	**88.0%**	**98.8%**

Of 409 novel defect occurrences, 92.7% were correctly identified as out-of-distribution and routed for human review. 88.0% were correctly escalated as novel patterns requiring expert assessment. 98.8% were safely contained (did not result in an incorrect autonomous accept decision). Only 5 novel defects out of 409 (1.2%) escaped detection and were incorrectly passed as acceptable.

3.5 Adversarial Attack Resilience

During Phase 3, a red team adversarial stress test was conducted to evaluate system resilience against intentional manipulation. Table 4 presents the attack survival rates.

Table 4 Adversarial attack survival rates

Attack Type	Attack Intensity (ε)	Successful Escapes (%)	Survived Detection (%)
PGD untargeted	ε = 2 px	4.2%	95.8%
PGD targeted (defect→accept)	ε = 2 px	7.1%	92.9%
PGD targeted (critical→minor)	ε = 3 px	8.3%	91.7%
C&W attack	ε = 1 px	3.4%	96.6%

Even under adversarial attack, fewer than 9% of attacks result in successful escapes (defective parts incorrectly accepted). The adversarial preprocessing module (median denoising + certified denoising network) reduces attack success rates substantially compared to the undefended model (Paper 14 baseline: 68–84% success rates). The OOD detection module serves as a secondary defense: even when an adversarial perturbation succeeds in causing a misclassification, the perturbed input may be flagged as OOD by its unusual feature statistics.

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4. Key Integration Insights

4.1 Tradeoffs Between Capabilities

The integration of multiple capabilities reveals important tradeoffs:

Throughput vs. explainability. Generating full Grad-CAM attribution maps for every prediction adds approximately 12 ms of latency (from 82 ms to 94 ms per component). This is within budget, but further additions of explanation generation would breach the 60 FPS throughput requirement. The system selectively generates explanations only for flagged/reviewed samples, preserving throughput.

Uncertainty calibration vs. adversarial robustness. The uncertainty estimates from MC dropout (Paper 4) are well-calibrated under normal conditions but become miscalibrated under adversarial attack. The adversarial preprocessing module partially addresses this by ensuring that the uncertainty estimates reflect genuine epistemic uncertainty rather than adversarial manipulation.

OOD detection vs. adaptation speed. The OOD detection module (Paper 16) classifies a new product variant as OOD until it has accumulated sufficient data to confirm the distribution shift. This creates a period of elevated flag rates (up to 18% of new product production flagged) that resolves within 2 weeks as test-time adaptation adapts the model. Managing this transient elevation is important for production planning.

4.2 Component Contribution Analysis

An ablation study (Table 5) evaluates the contribution of each major capability module to the overall system performance.

Table 5 Ablation: contribution of each framework component

Configuration	Escape Rate (%)	False Reject (%)	Autonomous Rate (%)
No robustness, UQ, OOD, or explainability (baseline)	1.87%	14.2%	100%
+ Adversarial robustness only	0.41%	8.7%	96.1%
+ Uncertainty quantification only	0.68%	5.9%	89.3%
+ OOD detection only	0.54%	6.3%	91.4%
+ Explainability only	1.79%	13.8%	100%
All components (full framework)	0.03%	2.1%	87.4%

Each capability independently reduces escape rates and false reject rates. The uncertainty quantification module provides the largest single improvement in false reject rate (from 14.2% to 5.9%), as it correctly identifies uncertain predictions and routes them for human review rather than making autonomous accept decisions on uncertain inputs. The adversarial robustness module provides the largest single improvement in escape rate (from 1.87% to 0.41%), as it prevents adversarial manipulation from causing incorrect accepts.

4.3 Human Factors and Trust Calibration

The explainability module's impact on human operators was evaluated through a survey of 32 quality engineers who worked with the system over the deployment period. Key findings:

- 87.5% of engineers reported increased confidence in autonomous decisions when explanations were available
- 81.3% reported that Grad-CAM maps helped them identify genuine defects more quickly during review
- 75.0% reported that the uncertainty scores helped them prioritize which flagged samples to review first
- 93.8% agreed that the overall system was "more reliable" than their previous manual inspection process
- 68.8% reported "initial skepticism" that was overcome within the first 3 months of deployment

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5. Lessons Learned and Practical Recommendations

5.1 Key Deployment Lessons

The 18-month production deployment revealed several practical insights:

Uncertainty quantification is the most operationally valuable capability. Despite the excitement around novel methods (adversarial robustness, OOD detection), the uncertainty estimates from MC dropout had the largest impact on day-to-day operations: routing uncertain predictions to human review reduced the false reject rate by more than half, directly improving production yield.

OOD detection must be tuned for the production context. The optimal OOD detection threshold depends on the cost of missing a novel defect versus the cost of unnecessary human review. Factories with very low defect rates should use more conservative (lower) OOD thresholds; factories with high defect diversity should accept higher flag rates.

Human-in-the-loop remains essential for edge cases. Even with all advanced capabilities deployed, 12.6% of decisions require human review. The framework does not eliminate the need for skilled quality engineers; it frees engineers from reviewing 87.4% of routine decisions so they can focus on the 12.6% that genuinely require expert judgment.

5.2 Recommendations for Manufacturing Organizations

Based on the deployment experience, the following recommendations are offered:

Start with uncertainty quantification. Even before deploying advanced capabilities, implementing MC dropout uncertainty estimation and confidence-based routing is the single highest-value improvement. It directly addresses the false reject problem that has the largest economic impact.

Deploy OOD detection before full autonomy. Before transitioning to autonomous decision-making, ensure that the OOD detection rate for novel defects is above 90% on the production line's specific defect mix. OOD detection is the safety backstop that prevents novel defect escapes.

Invest in explainability for operator trust. Operator trust is the most commonly underestimated barrier to autonomous deployment. Investing in clear, interpretable explanations and decision rationale accelerates operator acceptance and reduces the temptation to override the system inappropriately.

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6. Conclusion

This concluding paper validates the integrated deployment of the complete trustworthy AI framework for autonomous optical surface inspection across an 18-month production deployment.

The integrated system achieves a defect escape rate of 0.03% (3.3× better than the target), a false reject rate of 2.1% (2.4× better than target), 94.3% novel defect detection rate, and 89.7% human agreement on decision explanations. Each capability component independently and additively contributes to the overall trustworthy performance.

The production deployment demonstrates that the integration challenges—throughput constraints, tradeoff management, and human factors—are solvable. The framework provides a practical blueprint for deploying deep learning safely and reliably in safety-critical precision manufacturing quality control.

The technical frontier now shifts to: fully unsupervised adaptation to arbitrary new defect types without any human involvement; certified robustness guarantees that provide formal mathematical safety proofs for the highest-risk applications; and general-domain pretrained models that transfer across diverse optical inspection domains with minimal fine-tuning.

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