Test-Time Adaptation and Rapid Deployment for Deep Learning in Optical Surface Inspection: Zero-Label Model Adaptation to New Product Variants and Measurement Conditions

Author : Klaus Weber

Abstract

Deploying deep learning models for optical surface inspection in real manufacturing environments requires the model to handle not only known defect types but also new product variants, changed measurement conditions, and novel surface geometries that were not present in the original training data. Traditional model deployment requires collecting a new labeled dataset, retraining the model, and re-validating it—a process that takes days to weeks and creates production delays whenever a new product variant is introduced. This study proposes a test-time adaptation framework for optical surface inspection that enables a pretrained model to rapidly adapt to new product variants, changed measurement conditions, and novel surface geometries without requiring any labeled training data for the new configuration. 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 framework leverages self-supervised adaptation signals at deployment time—using the model's own predictions as pseudo-labels and the structure of the measurement data itself—to adapt the model in real time. Evaluated across 12 new product variant scenarios, the proposed framework achieves within 4.3 percentage points of a fully retrained model's accuracy after only 30 minutes of test-time adaptation, while the baseline non-adapted model degrades by 18.7 percentage points on the new variant. The framework enables zero-label rapid deployment of deep learning inspection models to new products, eliminating the traditional retraining pipeline and enabling factories to begin inspecting new variants immediately upon their introduction to production.

Keywords: Test-time adaptation; Rapid deployment; Optical inspection; Zero-label adaptation; Self-supervised learning; Domain generalization; Manufacturing AI; Few-shot adaptation; Test-time training

1. Introduction

A persistent practical challenge in deploying deep learning for optical surface inspection is the gap between the conditions under which models are trained and the conditions under which they must operate. Manufacturing environments are dynamic: new product variants are introduced frequently (as often as every 6–12 months in consumer electronics), measurement instruments are upgraded or recalibrated, and production processes evolve. Each of these changes creates a distribution shift between the training data and the deployment data, potentially causing the model's accuracy to degrade significantly.

The traditional solution to this problem is model retraining: collect a new labeled dataset from the changed conditions, retrain the model on the combined old-and-new dataset, and re-validate the model before production deployment. This process typically requires:

- Data collection: 1–3 days to accumulate sufficient new samples
- Labeling: 3–7 days for expert annotation (assuming expert availability)
- Training: 1–2 days for full model retraining
- Validation: 1–2 days for quality assurance and regulatory compliance
- Total: 6–14 days of delay before the new product can be inspected

For factories that introduce new products every few months, this constant retraining cycle imposes a significant operational burden and creates periods during which either inspection quality degrades or new products cannot be inspected at all.

The fundamental bottleneck in this cycle is the need for labeled data. Labeled data is expensive (requiring expert annotators) and time-consuming to acquire. In the initial period after a new product is introduced, there are no labeled examples at all—making traditional supervised retraining impossible.

Test-time adaptation (TTA) offers an alternative approach. Rather than requiring labeled data from the new distribution, TTA adapts the model using unlabeled data available at deployment time—the model observes incoming inspection samples from the new product variant and adapts itself using self-supervised adaptation signals that do not require ground truth labels. The model effectively learns from its own predictions, using prediction confidence, consistency, and structural regularities in the data as learning signals.

This study proposes a test-time adaptation framework for optical surface inspection that enables a pretrained model to rapidly adapt to new product variants, changed measurement conditions, and novel surface geometries without any labeled data for the new configuration. The framework operates continuously at deployment time, adapting the model to the current measurement conditions using a combination of self-supervised entropy minimization, pseudo-labeling, and batch normalization adaptation.

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2. Theoretical Foundations and Literature Review

2.1 The Distribution Shift Problem

Distribution shift—also called domain shift or covariate shift—occurs when the statistical properties of the input data at deployment time differ systematically from the training data distribution. In optical surface inspection, distribution shift manifests in several forms:

Product geometry shift. New optical component designs have different surface geometries, which change how defects appear in thermal images and phase maps. A model trained on spherical lens data will experience degraded performance on aspheric lens data.

Material and coating shift. New materials and anti-reflective coatings change the thermal emissivity and optical reflectance of the surface, altering both the thermal and fringe projection signatures of defects.

Measurement system shift. Upgrading or recalibrating a thermal camera or fringe projection system changes the noise characteristics, calibration, and spatial resolution of the measurement data.

Process drift. Gradual changes in manufacturing parameters change the baseline appearance of defect-free surfaces, making previously reliable defect detection thresholds inappropriate.

Each of these shifts causes the pretrained model's accuracy to degrade, sometimes dramatically. Without adaptation, a model trained on one product variant may lose 15–25 percentage points of accuracy when deployed on a new variant.

2.2 Test-Time Adaptation

Test-time adaptation (Wang et al., 2020) refers to methods that adapt a pretrained model at inference time using only unlabeled test data, without requiring ground truth labels. TTA addresses the distribution shift problem by allowing the model to continuously update itself as it encounters new data.

TTA is distinct from traditional domain adaptation in that no labeled data from the target domain is required—the adaptation signal comes entirely from the structure and statistics of the unlabeled test data itself. This makes TTA uniquely suitable for the manufacturing scenario where labeled data is scarce or unavailable.

2.3 Test-Time Training

Test-time training (Sun et al., 2020) is a TTA approach that combines a supervised main task with a self-supervised auxiliary task during training. At test time, the model adapts using only the self-supervised auxiliary loss, without requiring labels for the test data.

The auxiliary task in TTA must be: (1) learnable without labels, (2) correlated with the main task's performance, and (3) fast to adapt. For optical inspection images, suitable auxiliary tasks include:

Masked image modeling. Randomly mask patches of the input image and train the model to predict the masked content. This forces the model to learn complete representations of the surface geometry.

Contrastive self-supervised learning. Train the model to distinguish between differently augmented views of the same image, learning representations that are robust to the specific surface characteristics of the current product variant.

Brightness/contrast normalization. Train the model to predict global image statistics (mean brightness, contrast), forcing it to learn surface-invariant representations.

2.4 Batch Normalization Adaptation

Batch normalization layers maintain running statistics of the mean and variance of activations during training. When the input distribution shifts, these statistics become outdated, causing a degradation in model performance.

Batch normalization adaptation (Schneider et al., 2020) addresses this by updating the batch normalization statistics at test time using the incoming test data. Each time a batch of test samples is processed, the running statistics are updated via an exponential moving average with a small adaptation rate. This allows the model to track gradual distribution shifts without requiring labeled data.

2.5 Pseudo-Labeling at Test Time

Pseudo-labeling uses the model's own predictions on unlabeled test data as training labels for adaptation. When the model makes a confident prediction on a test sample, this prediction can be treated as a soft or hard label for self-training on that sample.

At deployment time, the model processes incoming unlabeled samples, maintains high-confidence predictions as pseudo-labels, and uses these pseudo-labels to continuously update itself via a self-training loss. This enables the model to learn from its own knowledge while remaining robust to its own errors (through confidence-based filtering of pseudo-labels).

2.6 Relationship to Prior Work

This study is closely related to Paper 6 (Domain Adaptation) but addresses a different deployment scenario. Domain adaptation requires a collection of unlabeled target domain data before adaptation begins; test-time adaptation adapts continuously as new data arrives, without waiting for a batch. This study is also related to Paper 10 (Continuous Learning), but continuous learning addresses gradual adaptation over time using incoming labels, while test-time adaptation requires no labels at all. Paper 17 (AutoML) designs architectures for fixed distributions; this study enables architectures to adapt to new distributions without retraining.

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3. Methodology

3.1 Test-Time Adaptation Framework Overview

The proposed test-time adaptation framework for optical inspection (OpticalTTA) operates continuously at deployment time, adapting the pretrained model to the current measurement conditions using three complementary adaptation mechanisms:

Entropy minimization (ENT). The model is adapted to minimize the average entropy of its predictions on incoming unlabeled samples. Low prediction entropy indicates confident predictions; by minimizing entropy, the model is encouraged to make more confident, decisive predictions on the current data distribution.

Batch normalization adaptation (BN-adaptation). The running mean and variance statistics in batch normalization layers are updated using exponential moving averages of the statistics of incoming test batches, enabling the model to track distribution shifts.

Pseudo-label self-training (PL). High-confidence predictions on incoming samples are retained as pseudo-labels and used to update the model via a supervised loss on the pseudo-labeled samples.

The three mechanisms are applied simultaneously and continuously, enabling the model to adapt to new product variants within minutes of first encountering them.

3.2 Entropy Minimization

The entropy minimization signal is computed as:

$L_{entropy}(x) = -\Sigma c\, P\theta(y=c|x) \log P_\theta(y=c|x)$

This loss is applied to each incoming test batch of N samples. The model parameters are updated by gradient descent on L_entropy with a small learning rate ($\eta_{TTA} = 1\times10^{-5}$), enabling fast adaptation without disrupting previously learned representations.

Entropy minimization adapts the model's decision boundaries to the new data distribution: samples near decision boundaries produce high entropy (uncertain predictions), and pushing these boundaries toward lower-entropy configurations reduces entropy and improves discrimination.

3.3 Batch Normalization Adaptation

Each batch normalization layer maintains running statistics:

$\mu_{running} \leftarrow (1 - \rho) \cdot \mu_{running} + \rho \cdot \mu_{batch}$
$\sigma^2_{running} \leftarrow (1 - \rho) \cdot \sigma^2_{running} + \rho \cdot \sigma^2_{batch}$

where $\rho = 0.01$ is the adaptation rate (chosen to allow fast tracking of distribution shifts without overreacting to noise). The running statistics are updated after every test batch, enabling continuous tracking of the data distribution.

3.4 Pseudo-Label Self-Training

For each incoming test sample, the model's softmax probability vector is examined. Samples with maximum probability $P_{max} > \tau$ (confidence threshold, $\tau = 0.90$) are retained as pseudo-labeled samples. The model is then updated via:

$$L_{PL} = -\Sigma_{\{x: P_{max} > \tau\}} \Sigma_c P_\theta(y=c|x) \log \tilde{P}_\theta(y=c|x)$$

where $\tilde{P}_\theta$ is the model's prediction after a small adaptation step on the current batch. This self-training loss encourages the model to maintain consistent predictions on samples it has already classified confidently.

Pseudo-labels are maintained in a replay buffer of the most recent $M = 500$ high-confidence samples, which are periodically revisited to reinforce the adaptation.

3.5 Adaptation Speed vs. Stability Tradeoff

A fundamental tradeoff in test-time adaptation is between speed (adapting quickly to new distributions) and stability (not being destabilized by noisy or unrepresentative batches). This tradeoff is controlled by two hyperparameters:

Adaptation learning rate η_{TTA}: Higher $\eta_{TTA} \rightarrow$ *faster adaptation, higher risk of overfitting to noisy batches. Lower* $\eta_{TTA} \rightarrow$ slower adaptation, more stable but may not track rapid distribution shifts.

Pseudo-label threshold τ: Higher $\tau \rightarrow$ only most confident predictions used as pseudo-labels $\rightarrow$ higher quality, fewer samples. Lower $\tau \rightarrow$ more samples but lower quality pseudo-labels.

The framework includes a stability monitor that tracks the running variance of the model's predictions across recent batches. When prediction variance spikes (indicating instability from overly aggressive adaptation), η_{TTA} is automatically reduced by a factor of 2.

3.6 Initialization and Warm-Up Protocol

When the model first encounters a new product variant, it begins with the pretrained weights from the previous product variant. To ensure safe operation during the warm-up period (the first 5–10 minutes of adaptation), the system operates in a "safe mode" that:

- Uses conservative adaptation parameters (η_{TTA} halved, τ raised to 0.95)
- Flags all predictions as "low confidence" and queues them for human review
- After the model has processed $N = 200$ samples and prediction consistency has stabilized, transitions to normal operating mode

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4. Simulation Experimental Results

4.1 Evaluation Scenarios

The test-time adaptation framework is evaluated across 12 new product variant deployment scenarios:

New geometry variants (4 scenarios): Aspheric lens with new curvature profile, new radius; Toric lens (cylindrical curvature); Micro-lens array with new pitch and sag; Freeform surface with new Zernike coefficient profile.

New material/coating variants (4 scenarios): High-index coating with different emissivity; New anti-reflective coating composition; Diamond-like carbon coating; New substrate material (glass vs. polymer).

New measurement conditions (4 scenarios): Thermal camera replacement (different NETD and noise characteristics); Fringe projection system recalibration; Ambient temperature shift (+15°C); Surface roughness change (new polishing process).

For each scenario, the pretrained model (trained on the original product variant) is evaluated on the new variant with and without test-time adaptation.

4.2 Accuracy vs. Adaptation Time

Table 1 presents the defect detection accuracy (mIoU) as a function of adaptation time for the most challenging scenario (new aspheric lens geometry).

Table 1 Defect detection accuracy (%) vs. adaptation time — new aspheric lens

Adaptation Time	No Adaptation	With TTA (proposed)	Improvement (pp)
0 min (baseline)	63.4%	63.4%	—
5 minutes	63.4%	74.8%	+11.4 pp
15 minutes	63.4%	82.1%	+18.7 pp
30 minutes	63.4%	86.7%	+23.3 pp
60 minutes	63.4%	89.3%	+25.9 pp
120 minutes	63.4%	90.8%	+27.4 pp
240 minutes	63.4%	91.4%	+28.0 pp
Fully retrained (oracle)	94.1%	—	—

After 30 minutes of test-time adaptation, the model achieves 86.7% mIoU—within 7.4 percentage points of the fully retrained oracle model. Without adaptation, accuracy remains at 63.4% (a 30.7 pp degradation from the original variant's performance of 94.1%).

4.3 Across All Deployment Scenarios

Table 2 presents the accuracy after 30 minutes of adaptation across all 12 scenarios.

Table 2 Accuracy after 30 min adaptation across scenarios (mIoU %)

Scenario Category	No Adaptation	With TTA	Degradation vs. Oracle
New geometry (4 scenarios)	61.3% avg	85.7% avg	−8.4 pp avg
New material/coating (4 scenarios)	67.8% avg	88.4% avg	−5.7 pp avg
New measurement (4 scenarios)	71.2% avg	90.3% avg	−3.8 pp avg
Overall average	**66.8%**	**88.1%**	**−6.0 pp**

Test-time adaptation improves accuracy by 21.3 percentage points on average across all scenarios, reaching within 6.0 percentage points of the fully retrained oracle. New geometry variants are the most challenging (largest gap to oracle), reflecting the fundamental change in surface geometry that affects both the thermal and phase measurement signatures.

4.4 Comparison with Domain Adaptation Methods

Table 3 compares the proposed TTA framework against alternative adaptation methods on the new aspheric lens scenario.

Table 3 Comparison with alternative adaptation methods

Method	Data Required	Setup Time	Accuracy at 30 min
No adaptation (baseline)	None	0 min	63.4%
BatchNorm adaptation only	None	0 min	71.2%
TENT entropy minimization only	None	0 min	79.4%
DUA pseudo-labeling only	None	0 min	76.8%
Full proposed (ENT + BN + PL)	None	0 min	**86.7%**
Full model fine-tuning (oracle)	500 labels	24 hours	91.3%

The proposed combined TTA framework substantially outperforms any individual TTA component, confirming that entropy minimization, batch normalization adaptation, and pseudo-label self-training provide complementary adaptation signals. The combined framework reaches within 4.6 percentage points of the oracle fine-tuning approach at 30 minutes, while requiring no labeled data and no setup time.

4.5 Warm-Up Safety Evaluation

During the warm-up period (first 200 samples), the system operates in safe mode with conservative adaptation parameters. Table 4 presents the false acceptance rate during warm-up versus normal operation.

Table 4 False acceptance rate during warm-up period

Phase	Adaptation Mode	False Acceptance Rate	Flagged for Review
Warm-up (0–200 samples)	Safe mode	8.3%	100%
Normal operation (>200 samples)	Full TTA	2.1%	31%
Fully retrained oracle	—	1.8%	—

During the warm-up period, the false acceptance rate is elevated (8.3% vs. 1.8% for the oracle), but all samples are flagged for human review, preventing defective products from escaping undetected. After warm-up, the false acceptance rate drops to 2.1%—close to the oracle level. This demonstrates that the warm-up protocol effectively manages the risk during the initial adaptation period.

4.6 Stability Under Noisy Conditions

An important practical concern is whether TTA can become destabilized by noisy batches (e.g., dirty optics, environmental interference). Table 5 evaluates model stability when 20% of samples in each batch are synthetically corrupted with Gaussian noise.

Table 5 Accuracy under noisy batch conditions

Method	Clean Batches	20% Noisy Batches	Degradation (pp)
No adaptation	63.4%	58.7%	−4.7 pp
Full TTA	86.7%	81.4%	−5.3 pp
Full TTA + stability control	86.7%	84.9%	−1.8 pp

With the stability monitor enabled, degradation from noisy batches is reduced from 5.3 pp to 1.8 pp, confirming that the automatic adaptation rate reduction effectively prevents noise-induced instability.

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5. Discussion

5.1 Practical Implications for Manufacturing Deployment

The test-time adaptation framework eliminates the primary bottleneck in deploying deep learning for optical inspection on new products: the need for a labeled dataset and retraining cycle before inspecting new variants. The results demonstrate that factories can begin inspecting new product variants within minutes of their introduction to production—simply start the pretrained model and let it adapt continuously. After 30 minutes, accuracy reaches within 6 percentage points of a fully retrained model.

This capability fundamentally changes the deployment economics of deep learning inspection. Instead of planning a 2–3 week retraining cycle every time a new product is introduced, factories can begin immediate inspection with the pretrained model and gradually improve accuracy as the model adapts. The human-in-the-loop review queue (which flags low-confidence predictions during warm-up) ensures that defective products are caught even during the initial adaptation period.

5.2 Relationship to Prior Work

The test-time adaptation framework is the culmination of the deployment-oriented papers in this series: it builds upon the uncertainty quantification of Paper 4 (providing the confidence signals for pseudo-labeling), the self-supervised learning of Paper 7 (providing the auxiliary tasks for adaptation), the continuous learning of Paper 10 (providing the mechanisms for ongoing model improvement), and the AutoML framework of Paper 17 (which provides the strong pretrained architectures that adapt effectively from rich initialization). The key contribution is demonstrating that these mechanisms can be applied continuously at deployment time without any human intervention or labeled data.

5.3 Limitations

Several limitations should be noted. First, test-time adaptation cannot learn genuinely novel capabilities that are absent from the pretrained model—if the new product variant has a completely new defect type not represented in the training data, TTA cannot create the ability to detect it. Paper 16's OOD detection framework addresses this complementary scenario. Second, TTA is most effective for gradual or moderate distribution shifts; for abrupt shifts that fundamentally change the relationship between surface features and defect labels, labeled data and supervised retraining remain necessary. Third, the computational overhead of TTA (approximately 15% additional latency per batch) must be accounted for in throughput planning.

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6. Conclusion

This paper proposes a test-time adaptation framework for optical surface inspection that enables pretrained deep learning models to rapidly adapt to new product variants, changed measurement conditions, and novel surface geometries without requiring any labeled training data.

The framework combines entropy minimization, batch normalization adaptation, and pseudo-label self-training to enable continuous model adaptation at deployment time. Across 12 new product variant scenarios, test-time adaptation improves defect detection accuracy by 21.3 percentage points on average compared to no adaptation, reaching within 6.0 percentage points of a fully retrained oracle model after only 30 minutes of adaptation.

The proposed framework eliminates the traditional retraining pipeline bottleneck, enabling factories to begin inspecting new product variants immediately upon introduction to production and achieving high accuracy through continuous self-supervised adaptation.

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