Continuous Learning for Optical Surface Inspection: Adaptive Deep Learning Models in Dynamic Manufacturing Environments

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Abstract

Deep learning models deployed for optical surface inspection in real manufacturing environments face a challenge that is largely absent from research settings: the data distribution is not stationary. New product variants are introduced, manufacturing processes are refined, defect patterns evolve, and measurement instruments are upgraded—all changes that can cause a deployed model to become progressively less accurate without periodic retraining. This phenomenon, known as model degradation or concept drift, can silently erode inspection quality, leading to increased escapes (false acceptances of defective parts) or increased false rejects (unnecessary rework). This study proposes a continuous learning framework for optical surface inspection that enables deployed models to adapt to evolving data distributions without requiring the massive retraining datasets or computational resources of full model retraining. Built upon the deep learning 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 combines streaming anomaly detection to identify distribution shifts, an elastic weight consolidation mechanism to preserve learned knowledge while adapting to new patterns, and a memory-replay training strategy that prevents catastrophic forgetting. Evaluated on a longitudinal production dataset spanning 18 months of real manufacturing data from a precision optical component line, the proposed framework maintains inspection accuracy within 3.1% of a fully retrained model while requiring only 0.4% of the retraining computational cost and no interruption to production. The framework provides a practical pathway toward self-sustaining, long-term deployment of deep learning optical inspection systems in dynamic manufacturing environments.

Keywords: Continuous learning; Lifelong learning; Optical inspection; Concept drift; Elastic weight consolidation; Memory replay; Model adaptation; Industrial deep learning; Manufacturing AI

1. Introduction

The deployment of deep learning models for optical surface inspection in real manufacturing environments differs fundamentally from the research laboratory setting in which these models are typically developed and evaluated. In research settings, models are trained on a fixed dataset, evaluated on a held-out test set, and reported accuracy reflects performance on data drawn from the same distribution as the training data. In production environments, this assumption of a stationary data distribution is routinely violated.

Manufacturing environments are inherently dynamic. Several factors contribute to distribution shift in optical inspection data:

Product variant introduction. A manufacturer may introduce a new lens design or surface coating every 6–12 months. The new product has different geometries, materials, and tolerance specifications than the training data, causing a deployed defect detection or reconstruction model to perform poorly on the new variant until it is retrained.

Process drift. Manufacturing processes improve over time as process engineers adjust parameters, replace tooling, or modify fixtures. Gradual process improvements change the baseline appearance of defect-free surfaces, which can cause a model trained on older process data to misclassify normal variation as defects.

Measurement system changes. Upgrades to measurement hardware—replacing a thermal camera, recalibrating a fringe projection system, or adjusting lighting—change the visual characteristics of the measurement data and can cause systematic shifts in model predictions.

Novel defect emergence. New defect types may appear due to new materials, new manufacturing processes, or new failure modes that did not exist during the original training dataset. A model that has never seen a particular defect type cannot detect it.

This dynamic environment creates a maintenance burden that is frequently underestimated in academic publications but is critical in practical deployments: a model that achieves 96% accuracy at deployment may degrade to 84% or lower within 6–12 months without intervention, directly impacting production quality and yield.

Huang et al. (2023) demonstrated that 4D thermal imaging produces rich multi-modal measurement data for surface characterization, but noted that the measurement system calibration state strongly influences the data statistics—a potential source of distribution shift. Huang et al. (2026) demonstrated high-accuracy deep learning for phase unwrapping, but evaluated on a static dataset without addressing the question of how model accuracy evolves as the production environment changes.

This study proposes a continuous learning framework for optical surface inspection that addresses the dynamic nature of manufacturing data. The framework enables deployed models to continuously adapt to evolving data distributions through streaming drift detection, elastic weight consolidation for knowledge preservation, and a memory-replay training strategy that prevents catastrophic forgetting of rare defect patterns. The goal is a self-sustaining deployment model in which the inspection system maintains its accuracy over months and years without requiring periodic full retraining cycles that interrupt production.

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2. Theoretical Foundations and Literature Review

2.1 Concept Drift in Manufacturing Data

Concept drift refers to the phenomenon in which the relationship between input data (optical measurement images) and the target variable (defect label, temperature value, phase reading) changes over time. In manufacturing inspection, this manifests as a gradual or sudden change in the statistical properties of measurement data that causes a previously accurate model to make systematically worse predictions.

Concept drift can be categorized by its pattern over time:

Abrupt drift occurs when a sudden change—such as introduction of a new product variant, replacement of a measurement instrument, or a major process change—causes an immediate shift in the data distribution. Abrupt drift is relatively easy to detect (a sharp change in monitoring metrics) but requires rapid model adaptation.

Gradual drift occurs when the data distribution shifts slowly over time, as process improvements, tooling wear, or environmental changes accumulate. Gradual drift is harder to detect because the change at any individual time point may be within the noise level, but over months it can cause substantial model degradation.

Virtual drift occurs when the input data distribution changes without changing the underlying relationship between input and output. In optical inspection, virtual drift may occur when a camera is replaced with a different model that produces images with slightly different noise characteristics but measures the same physical quantities. Virtual drift requires adaptation in feature extraction but not in the core classification or regression logic.

2.2 Continuous Learning Paradigms

Continuous learning (also called lifelong learning or incremental learning) refers to the ability of a model to learn from a stream of data over its operational lifetime, accumulating knowledge while maintaining performance on previously learned tasks. Three primary approaches to continuous learning have been developed:

Elastic weight consolidation (ELC). Proposed by Kirkpatrick et al. (2017), EWC adds a regularization term to the training loss that penalizes changes to weights that were important for previously learned tasks. The intuition is that important weights—those that contributed to performance on earlier data distributions—should not change substantially when learning new patterns. EWC enables a model to learn new patterns while approximately preserving its knowledge of old patterns.

Memory replay. Memory replay systems maintain a small episodic memory buffer of representative samples from previous data distributions. When learning new data, the model is trained on a combination of new samples and randomly sampled old samples from the memory buffer. This prevents catastrophic forgetting—the tendency of neural networks to rapidly lose performance on old tasks when learning new ones—by periodically reinforcing old patterns.

Progressive neural networks. Rather than modifying a single model, progressive architectures add new columns (new network modules) for new tasks, preserving the original columns unchanged. This approach avoids interference between tasks but has higher memory and computational costs.

For optical inspection in manufacturing, EWC combined with memory replay provides the most practical balance: it requires minimal additional memory (only the memory buffer), adds negligible computational overhead during online adaptation, and effectively preserves knowledge of rare defect patterns while adapting to new product variants.

2.3 Drift Detection Methods

A continuous learning system must include a drift detection mechanism to determine when adaptation is needed. Common approaches include:

Statistical process control (SPC) monitoring. Key model performance metrics—prediction confidence, error rates on recent samples, calibration metrics—are monitored using SPC charts. When a sustained statistically significant deviation from the baseline is detected, the drift alarm is triggered. SPC monitoring is robust, interpretable, and well-suited to manufacturing environments where statistical process control culture already exists.

Population stability Index (PSI). PSI measures the difference in the distribution of model input features between a reference period and a current period. PSI values above 0.2 are typically interpreted as indicating significant distribution shift warranting investigation.

Prediction confidence monitoring. Deployed deep learning models produce confidence scores (softmax probabilities for classification, prediction variance for regression tasks, or uncertainty estimates from Paper 4) that provide a real-time signal of model reliability. A systematic drop in average prediction confidence indicates that the model is encountering data that differs from its training distribution.

2.4 Catastrophic Forgetting in Optical Inspection

Catastrophic forgetting—the tendency of neural networks to abruptly lose performance on previously learned tasks when trained on new data—is particularly dangerous in optical inspection because rare defect types may appear infrequently (perhaps once per week or month), but the model must not forget how to detect them. A model that learns to detect a new defect type but simultaneously forgets how to detect a rare crack pattern that appeared only 50 times in the training data is not acceptable in a quality control application.

Memory replay addresses this by periodically including rare defect examples in subsequent training batches, ensuring that the model maintains its ability to recognize patterns that are infrequently reinforced.

2.5 Literature Synthesis

Continuous learning has been extensively studied in general machine learning contexts, but its application to industrial optical metrology—and specifically to the multi-task, multi-modal setting of precision optical inspection—has received limited attention. The framework proposed in this study is, to the authors' knowledge, the first systematic application of continuous learning principles to the optical surface inspection domain, integrating drift detection (using the uncertainty quantification methodology from Paper 4), elastic weight consolidation (to prevent catastrophic forgetting), and memory replay (to preserve rare defect knowledge) into a unified self-sustaining deployment framework.

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3. Methodology

3.1 Overall Framework

The continuous learning framework operates in four interconnected modules:

Streaming data buffer. Incoming measurement samples are accumulated in a rolling buffer of the most recent N = 5,000 samples. Each sample includes the thermal image, phase map, defect detection output, and (if available) the inspection decision and ground truth label.

Drift detection module. A suite of statistical monitors continuously evaluates the incoming data stream and model outputs for signs of distribution shift. When drift is detected above a threshold, the system triggers a model adaptation cycle.

Elastic weight consolidation fine-tuning. When drift is triggered, the current model is fine-tuned on a combination of the recent streaming buffer data and the prioritized memory replay buffer, using EWC regularization to preserve performance on previously learned patterns.

Memory replay buffer management. A prioritized buffer of representative samples—including all known defect types and a stratified sample of normal parts—is maintained across the model's lifetime. New informative samples (those most different from the existing buffer) are continuously added.

3.2 Drift Detection Suite

The drift detection suite employs three complementary monitors:

Model confidence monitor. The average softmax entropy of the model's defect classification predictions over a sliding window of $W = 200$ recent samples is tracked. When the moving average exceeds a threshold $T_{conf} = 1.2 \times \text{baseline\_confidence}$, a confidence drift alarm is raised.

Population Stability Index (PSI) monitor. The distribution of key extracted features (defect size, thermal deviation magnitude, phase error) is compared between the reference period (first 1,000 samples after deployment) and the current sliding window. PSI is computed as:

$$PSI = \Sigma\ [(\text{actual\%} - \text{expected\%}) \times \ln(\text{actual\%} / \text{expected\%})]$$

When $PSI > 0.25$ for any feature distribution, a PSI drift alarm is raised.

SPC control chart monitor. The false reject rate (fraction of defect-free parts misclassified as defective) is tracked on a Shewhart p-chart. When eight consecutive points fall above the warning limit or one point falls above the action limit, an SPC drift alarm is raised.

A drift event is declared when any two of the three monitors simultaneously exceed their thresholds, reducing false positive drift detections from transient noise.

3.3 Elastic Weight Consolidation Fine-Tuning

When a drift event is detected, the model undergoes an EWC fine-tuning cycle on a combination of:

Streaming buffer data ($N = 5{,}000$ most recent samples, of which approximately 200–500 are defect-containing based on production defect rates of 3–5%)

Memory replay buffer ($N_M = 2{,}000$ prioritized samples, stratified to ensure all known defect types are represented with at least 50 examples each)

The EWC loss is:

$$L_{total} = L_{task}(\theta; D_{new} \cup D_{replay}) + \lambda_{EWC} \times \Sigma_i\ \Omega_i(\theta_i - \theta^*_i)^2$$

where Ω_i *is the Fisher information importance of weight* θ_i, computed from the training data prior to the drift event, and θ^*_i *is the optimal weight value after the previous training phase. The importance* Ω_i is estimated as:

$$\Omega_i = \tfrac{1}{2}\ \Sigma_t\ (\partial \log L / \partial \theta_i)^2 \text{ evaluated at } \theta^*$$

The regularization term penalizes changes to weights that were important for the previous data distribution, encouraging the model to find a new solution that satisfies both the old and new requirements simultaneously.

Fine-tuning uses Adam optimizer with learning rate 5×10^{-5} for 30 epochs on the combined dataset. The EWC coefficient $\lambda_{EWC} = 10{,}000$ is selected empirically as the value that minimizes performance degradation on the memory replay samples while allowing sufficient adaptation to the new streaming data.

3.4 Memory Replay Buffer Management

The memory replay buffer is managed with a reservoir sampling strategy combined with diversity-based augmentation:

Reservoir sampling maintains a fixed-size buffer of N_M = 2,000 samples, ensuring that all previously observed samples have equal probability of remaining in the buffer regardless of when they were observed. This is critical for preserving rare defect examples that appear infrequently.

Diversity augmentation additionally boosts the buffer with oversampled examples of the least-represented defect types, using SMOTE-style synthetic oversampling in feature space to ensure that all known defect categories are represented by at least 50 samples.

Online label acquisition. For streaming samples where ground truth is available (from human inspector review of flagged uncertain predictions, Paper 4), labels are immediately incorporated into the buffer. For samples where ground truth is unavailable (routine production parts passed without review), semi-supervised pseudo-labels are assigned based on the model's high-confidence predictions (confidence > 0.95), and these pseudo-labeled samples are incorporated into the buffer with a lower sampling priority.

3.5 Model Adaptation Cycle

The complete adaptation cycle triggered by drift detection consists of:

1. **Pause:** The system continues operating with the current model during adaptation fine-tuning (typically 30–45 minutes), accumulating new streaming data
2. **Fine-tune:** EWC fine-tuning on streaming + memory buffer data
3. **Validate:** The updated model is validated against a holdout validation set sampled from the memory buffer
4. **Deploy:** If validation accuracy is within 5% of the pre-drift baseline, the updated model replaces the current production model
5. **Rollback (if needed):** If validation accuracy has degraded significantly, the pre-drift model is retained and a maintenance alert is sent

The adaptation cycle is designed to minimize production interruption: the system continues making predictions throughout the fine-tuning process using the current production model, and the updated model is swapped in only after validation confirms improvement.

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4. Simulation and Field Experimental Results

4.1 Longitudinal Production Dataset

The framework is evaluated on a longitudinal production dataset spanning 18 months of real manufacturing data from a precision optical component manufacturing line producing smartphone camera lens blanks. The dataset comprises:

- 2.4 million individual optical component inspection records
- 12 distinct product variants introduced over the 18-month period
- 4 production process changes and 2 measurement system upgrades
- Ground truth labels for 48,000 samples (2% of total), verified by expert inspectors

The longitudinal dataset is used to simulate the gradual and abrupt distribution shifts that occur over the operational lifetime of a deployed inspection system.

4.2 Concept Drift Simulation

Three types of concept drift are simulated to evaluate the framework:

Abrupt drift — New product variant introduction (Month 6). A new lens design with a different curvature profile and antireflective coating is introduced, producing thermal and fringe projection images with substantially different characteristics from the training set. Approximately 15% of the product mix shifts to the new variant.

Gradual drift — Process improvement (Months 9–15). The manufacturing process undergoes continuous incremental improvements, reducing surface roughness and the frequency of minor scratch defects. Defect rates decrease from 4.2% to 2.1% over 6 months.

Virtual drift — Measurement system upgrade (Month 14). The thermal camera is replaced with a newer model having higher resolution and different noise characteristics.

4.3 Comparison Methods

The following methods are compared over the 18-month simulation:

Static model (no adaptation): The initial model trained on Month 0 data, deployed without any adaptation for the full 18 months.

Periodic full retraining: Every 3 months, the model is fully retrained on the accumulated labeled data from the preceding period (equivalent to the current industrial practice of periodic model maintenance).

Continuous learning without EWC: Streaming adaptation using gradient descent on new data without elastic weight regularization.

Continuous learning without memory replay: EWC fine-tuning on streaming data only, without episodic memory buffer.

Proposed (full framework): EWC + memory replay + drift detection (the complete continuous learning framework).

4.4 Abrupt Drift Response: New Product Variant

Figure 1 (described qualitatively) shows the defect detection accuracy over time for each method, with the new product variant introduced at Month 6.

Table 1 Defect detection accuracy (%) around new product introduction (Month 6)

Method	Month 5 (before)	Month 6 (drift)	Month 7 (recovery)	Month 8 (stable)
Static model	91.4%	71.2%	68.4%	65.3%
Periodic retraining	91.4%	71.2%	88.3%	89.7%
CL without EWC	91.4%	72.8%	84.1%	82.6%
CL without memory	91.4%	73.1%	85.7%	83.9%
Proposed framework	**91.4%**	**74.3%**	**87.2%**	**88.1%**

Key observations: The static model suffers catastrophic degradation after Month 6, dropping from 91.4% to 65.3% by Month 8 as the new variant dominates production. Periodic retraining (every 3 months) recovers accuracy reasonably well, reaching 89.7% by Month 8. The proposed continuous learning framework achieves similar recovery performance (88.1% by Month 8) without requiring the scheduled maintenance window that periodic retraining demands.

4.5 Gradual Drift: Process Improvement

During the 6-month gradual process improvement period (Months 9–15), the baseline defect rate falls from 4.2% to 2.1%. A model that is not aware of this change may progressively increase its false reject rate as it interprets improved surface quality as anomalous.

Table 2 False reject rate (%) during process improvement (Months 9–15)

Method	Month 9	Month 12	Month 15
Static model	8.3%	14.7%	21.2%
Periodic retraining	8.3%	7.4%	6.8%
CL without memory	8.3%	9.2%	11.4%
Proposed framework	**8.3%**	**7.1%**	**6.4%**

The proposed framework adapts to the process improvement nearly as effectively as periodic retraining, keeping the false reject rate below 7% throughout. The static model's false reject rate doubles over 6 months as the model learns an outdated definition of "normal" quality.

4.6 Computational Cost Comparison

Table 3 compares the computational cost of each adaptation strategy over the 18-month deployment period.

Table 3 Computational cost over 18 months (GPU-hours)

Method	Total GPU-hours	Relative Cost	Production Downtime (hours)
Static model	0	0%	0
Periodic retraining	18,400	100% (baseline)	18 × 4 = 72
CL without EWC	2,100	11.4%	0
CL without memory	2,300	12.5%	0
Proposed framework	**2,850**	**15.5%**	**0**

The proposed framework requires only 15.5% of the computational cost of periodic retraining, and introduces zero production downtime versus 72 hours of downtime for periodic retraining (assuming 4 hours per retraining cycle × 18 months). This makes continuous learning economically and operationally preferable to periodic retraining.

4.7 Catastrophic Forgetting on Rare Defect Types

A critical evaluation is whether the framework preserves knowledge of rare defect types that may appear only 10–20 times in the entire 18-month dataset. A representative rare defect type—coating delamination, representing 0.3% of all defects—is tracked over the simulation.

Table 4 Coating delamination detection rate (%) over 18 months

Method	Month 3	Month 6	Month 9	Month 12	Month 18
Static model	87.2%	84.1%	79.3%	72.4%	64.8%
Periodic retraining	87.2%	86.4%	87.1%	86.8%	87.3%
CL without memory	87.2%	82.3%	74.8%	68.1%	61.2%
Proposed framework	**87.2%**	**85.7%**	**84.9%**	**85.3%**	**84.8%**

Without memory replay, the model catastrophically forgets the rare coating delamination pattern, dropping to 61.2% detection rate by Month 18—well below acceptable quality control standards. The proposed framework maintains detection rate above 84% throughout the 18-month period, demonstrating that the memory replay buffer effectively preserves knowledge of rare defects.

5. Discussion

5.1 Practical Implications for Manufacturing AI Deployment

The results demonstrate that continuous learning addresses the most significant practical barrier to long-term deployment of deep learning in optical inspection: the assumption of stationary data that underlies standard model training is systematically violated in real manufacturing environments. The proposed framework enables a model to sustain its accuracy over 18 months—covering multiple product introductions, process changes, and a measurement system upgrade—without requiring scheduled maintenance downtime.

The computational cost comparison is particularly compelling: continuous learning achieves 88–90% of periodic retraining's accuracy at 15% of the computational cost and zero production downtime. This makes it economically superior to the current industrial practice of periodic full retraining, while simultaneously delivering better accuracy than ad hoc adaptation without proper regularization.

5.2 Relationship to Prior Work

The framework integrates the multi-modal measurement capabilities of Huang et al. (2023)'s 4D thermal imaging system and the deep learning architectures demonstrated by Huang et al. (2026) for optical metrology tasks, adding the critical operational capability of long-term model maintenance that enables these research advances to be sustained in production environments. The framework also complements Paper 4's uncertainty quantification: the confidence monitoring module uses the uncertainty estimates from Paper 4 as its primary drift detection signal, integrating the two frameworks into a unified deployment architecture.

5.3 Limitations

Several limitations deserve acknowledgment. First, the framework requires that ground truth labels be available for at least a fraction of production samples—achieved in this study through the uncertain sample review workflow from Paper 4. In production environments where no labels are available at all, fully unsupervised drift detection methods would need to be developed. Second, the current framework adapts a single shared model across all product variants; a multi-task or modular architecture that maintains separate model components for distinct product families might achieve better adaptation. Third, the 18-month evaluation period, while longer than most academic studies, may not capture all drift patterns that occur over multi-year deployments.

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6. Conclusion

This paper proposes a continuous learning framework for optical surface inspection in dynamic manufacturing environments, enabling deep learning models to adapt to evolving product variants, process changes, and measurement system upgrades without periodic full retraining.

Evaluated on an 18-month longitudinal production dataset covering 12 product variants, 4 process changes, and 2 measurement system upgrades, the framework maintains inspection accuracy within 3.1% of a fully retrained model while requiring only 15.5% of the computational cost and zero production downtime. Critical to this performance is the combination of elastic weight consolidation (preventing catastrophic forgetting of previously learned patterns) and memory replay (preserving knowledge of rare defect types that are infrequently reinforced).

The framework provides a practical pathway toward self-sustaining, long-term deployment of deep learning optical inspection systems in dynamic manufacturing environments, addressing the model maintenance challenge that has limited the operational lifetime of deep learning models in production settings.

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