Federated Learning for Privacy-Preserving Collaborative Optical Surface Inspection Across Manufacturing Facilities

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Abstract

Training high-quality deep learning models for optical surface inspection requires large diverse datasets, but manufacturing companies are often unwilling or legally prohibited from sharing raw measurement data across facilities due to competitive concerns, customer confidentiality requirements, and data privacy regulations such as GDPR. This data silos problem means that each facility trains on its own limited data, producing models that do not generalize well to other factories, product variants, or measurement equipment configurations. This study proposes a federated learning framework for optical surface inspection that enables multiple manufacturing facilities to collaboratively train a shared inspection model without any facility revealing its raw measurement data to any other facility or to a central server. 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 employs differential privacy mechanisms to provide formal privacy guarantees, a Federated Averaging protocol optimized for optical measurement data distributions, and a contribution scoring system that rewards facilities for sharing informative data without exposing what that data contains. Evaluated on a simulated federation of six manufacturing facilities with heterogeneous data distributions, the proposed framework achieves inspection accuracy that is within 6.3% of a centrally trained model while providing formal (ε, δ)-differential privacy guarantees. The framework is demonstrated to enable factories with as few as 500 labeled samples to benefit from the collective knowledge of the entire federation, reaching performance that would otherwise require tens of thousands of samples. This work provides the first practical pathway toward privacy-preserving collaborative deep learning for precision optical manufacturing across competing organizations.

Keywords: Federated learning; Privacy-preserving machine learning; Optical inspection; Differential privacy; Distributed deep learning; Manufacturing AI; Multi-factory collaboration; Optical metrology

1. Introduction

The accuracy of deep learning models for optical surface inspection improves dramatically with larger and more diverse training datasets. A model trained on data from a single manufacturing facility—which may produce a few thousand to a few hundred thousand labeled inspection samples per year—will inevitably be biased toward the specific product variants, materials, measurement equipment, and defect patterns present at that facility. When this model is applied to a different facility, or when a new product variant is introduced at the same facility, accuracy can degrade substantially.

The natural solution—pooling data from multiple facilities to train a shared model—is blocked in practice by fundamental barriers. First, manufacturing companies are often direct competitors and treat their production data, including inspection data and defect patterns, as highly confidential business intelligence that cannot be shared with rivals. Second, customer contracts frequently impose confidentiality obligations on manufactured components, including inspection results, prohibiting any external disclosure. Third, data privacy regulations including the General Data Protection Regulation (GDPR) in Europe and analogous regulations elsewhere impose legal requirements on the processing of personal data that may be associated with manufacturing records. Fourth, even in the absence of competitive or legal concerns, the physical infrastructure for centralizing large volumes of high-resolution measurement data—bandwidth, storage, and data governance systems—represents a significant investment that many organizations are reluctant to make.

These barriers create a situation in which the theoretical benefits of large-scale data pooling for model training are largely inaccessible to manufacturing companies, leaving each organization training on its own limited, biased dataset.

Federated learning (McMahan et al., 2017) offers a solution to this data silos problem. In federated learning, rather than sharing raw data, each participating facility trains a local model on its own data and shares only the model's gradient updates or model parameters with a central server. The server aggregates updates from multiple facilities to produce a shared global model that reflects the collective knowledge of all participants, without any facility ever having access to another facility's raw data.

This study proposes the first federated learning framework specifically designed for optical surface inspection in precision manufacturing. The framework addresses the unique challenges of this domain: heterogeneous data distributions across facilities (each factory produces different product variants), non-IID data distributions (certain defect types appear at some factories but not others), the need for formal privacy guarantees (due to customer confidentiality), and the large size of optical measurement data (high-resolution thermal images and phase maps that impose communication bandwidth constraints).

Huang et al. (2023) established that 4D thermal imaging produces rich multi-modal measurement data that is highly facility-specific due to differences in thermal camera calibration, lighting conditions, and material properties. These differences make federated learning in optical metrology particularly challenging—and particularly valuable, since a globally shared model that has learned from diverse measurement conditions will generalize better to new facilities than any locally trained model. Similarly, the deep learning architectures for optical metrology tasks (Huang et al., 2026) provide the foundation for the federated model that this study adapts for multi-factory collaborative training.

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2. Theoretical Foundations and Literature Review

2.1 The Data Islands Problem in Precision Manufacturing

Precision optical manufacturing is an industry characterized by high fragmentation: dozens to hundreds of manufacturers produce optical components for consumer electronics, automotive, medical, and aerospace applications. While these manufacturers compete in the same markets, they share common underlying inspection challenges: similar defect taxonomies (scratches, pits, contamination, delamination), similar measurement technologies (thermal imaging, fringe projection, coordinate measurement), and similar quality standards (ISO 10110, MIL-PRF-13830).

The practical consequence is that each manufacturer's labeled inspection dataset is simultaneously: (1) too small to train a robust, generalizable model; (2) too specific to generalize to other facilities' products and processes; and (3) too confidential to share. This combination of data scarcity, data bias, and data isolation is the defining challenge for machine learning in precision manufacturing.

2.2 Federated Learning: Core Principles

Federated learning (McMahan et al., 2017) is a distributed machine learning paradigm in which a shared global model is trained across N participating clients without any client revealing its raw data to any other client or to a central server. The standard federated learning protocol proceeds in repeated communication rounds:

In each round, a subset of K clients is selected. Each selected client receives the current global model parameters from the server, performs several steps of local gradient descent on its private dataset, and transmits its model update (either gradient changes or full model parameters) back to the server. The server aggregates the received updates—typically by Federated Averaging (FedAvg), computing a weighted average of the client updates—to update the global model, and the process repeats.

The key privacy property is that at each round, no raw data leaves the client. Only model parameters—compressed representations of what the model has learned—are transmitted. This provides a meaningful layer of protection, though model parameters can still leak information about training data (Carlini et al., 2021), motivating the additional differential privacy guarantees incorporated in this study.

2.3 Differential Privacy

Differential privacy (Dwork et al., 2014) provides a formal mathematical guarantee that the output of a computation (in federated learning, the model update transmitted to the server) is insensitive to any individual training sample. An (ε, δ)-differentially private mechanism guarantees that:

$$Pr[F(D) \in S] \leq e^{\varepsilon} \cdot Pr[F(D \setminus \{x\})] + \delta$$

for any neighboring datasets D and D \ {x} differing in a single sample, any output set S, and any individual sample x. Practically, this means that an adversary with full knowledge of the algorithm and all other training data—including all other clients' datasets—cannot determine whether any specific sample was used in training.

In federated learning, differential privacy is achieved by clipping the magnitude of client model updates (to bound sensitivity) and adding calibrated Gaussian noise to the aggregated update before broadcasting the global model back to clients. The privacy budget ε governs the strength of the guarantee: smaller ε means stronger privacy but potentially lower model utility.

2.4 Challenges in Federated Learning for Optical Inspection

Federated learning applied to optical surface inspection faces distinctive challenges:

Non-IID data distributions. Each factory's labeled dataset reflects its own product mix, measurement equipment, and quality history. Some factories may have many examples of coating delamination but few of scratch defects; others may have the opposite. This non-independently and identically distributed (non-IID) data violates the assumptions underlying standard Federated Averaging, which converges poorly when client distributions differ substantially.

Communication bandwidth. Optical measurement images—thermal images at 640×480 or higher resolution, phase maps at 1920×1080—are large compared to the natural language or tabular data for which federated learning was originally designed. Sending full model parameter updates (which can be hundreds of megabytes per round per client) imposes significant communication overhead.

Fairness and incentive alignment. Factories that contribute more data should ideally benefit more from the federation, but the federated model should not be dominated by the largest factories' data distributions. Designing an incentive-compatible contribution scoring mechanism is important for sustaining participation.

2.5 Literature Synthesis

Federated learning has been successfully deployed in healthcare (privacy-preserving medical imaging analysis), mobile devices (keyboard prediction models), and financial services (fraud detection). Its application to precision manufacturing—and specifically to optical surface inspection with its unique data characteristics—has not been previously demonstrated. This study adapts federated learning principles to the optical metrology domain, introducing differential privacy guarantees appropriate for customer confidentiality requirements, addressing the non-IID distribution challenge through a weighted aggregation strategy, and demonstrating practical viability in a simulated multi-factory federation.

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3. Methodology

3.1 Federated System Architecture

The proposed federated optical inspection system comprises:

N = 6 participating manufacturing facilities, each possessing a private dataset of labeled optical measurement samples. Each facility has a local data store, a local training compute unit (GPU server), and a federated learning client module.

A central aggregation server that coordinates the federated training protocol. The server maintains the global model, selects participant clients each round, aggregates their updates, and broadcasts the updated global model. The server never has access to any facility's raw data.

A privacy auditor (optional third-party or internal compliance function) that monitors the cumulative privacy budget expenditure across rounds, ensuring that the overall privacy guarantee ($\varepsilon_{total}, \delta_{total}$) remains within acceptable bounds.

3.2 Federated Averaging with Weighted Aggregation (FedOptical)

The standard Federated Averaging algorithm is adapted for optical metrology through the following modifications:

Client selection. At each communication round, the server randomly selects a fraction C = 0.6 of clients to participate. All selected clients must complete the round; clients that fail to respond are skipped and their updates excluded from the aggregation.

Local training. Each selected client receives the current global model parameters θ_{global} *from the server and performs E = 5 epochs of local training on its private labeled dataset using stochastic gradient descent (SGD) with momentum 0.9 and learning rate* $\eta = 0.01$*. The client then transmits its updated parameters* θ_{local} back to the server.

Weighted aggregation. The server updates the global model as a weighted average of participating client updates:

$\theta_{global} \leftarrow \sum_{k=1}^{K} (n_k / n_{total}) \cdot \theta_k$

where n_k is the number of labeled samples at client k and n_{total} is the total across participating clients. This proportional weighting ensures that facilities with more labeled data have proportionally greater influence on the global model, but every facility's contribution is represented.

Communication compression. Model updates are compressed using Top-K gradient sparsification: only the largest 10% of gradient elements (by absolute value) are transmitted, with the remainder reconstructed at the server using error feedback. This reduces communication bandwidth by approximately 10×.

3.3 Differential Privacy Mechanism

Differential privacy is applied at the aggregation level to protect against potential information leakage through the shared model parameters:

Gradient clipping. Each client clips the norm of its model update to a maximum threshold $C_{clip} = 1.0$ before transmission. This bounds the sensitivity of the aggregation output to any individual training sample.

Gaussian noise addition. The aggregation server adds calibrated Gaussian noise to the aggregated model update before computing the new global model:

$\theta_{global} \leftarrow \theta_{global} + N(0, \sigma^2 \cdot C_{clip}^2 \cdot I)$

where σ is the noise multiplier determined by the target privacy budget (ε, δ) and the number of participating clients K.

Privacy budget accounting. The cumulative privacy budget across R rounds is tracked using the moments accountant method (Abadi et al., 2016). For the experiments in this study, the target privacy guarantee is $(\varepsilon = 8.0, \delta = 10^{-5})$ per factory, providing meaningful confidentiality protection against model inversion attacks while preserving model utility.

3.4 Handling Non-IID Data Distributions

The heterogeneous, non-IID data distributions across factories are addressed through two mechanisms:

Batch-level shuffling. Rather than training on each factory's data in its natural distribution, each client applies a local batch shuffling strategy that randomizes the order of mini-batches within each epoch, which reduces the effect of local class imbalance on gradient direction.

Server-side momentum correction. A server-side momentum buffer maintains an exponential moving average of the global model's parameter history, which is used to correct for the gradient drift that occurs when client distributions diverge from the global distribution.

3.5 Federated Contribution Scoring

To provide transparency and incentive alignment, a federated contribution scoring system evaluates each factory's contribution to the global model:

Leave-one-out validation. After each round, the global model is evaluated on each factory's held-out validation set. The improvement (or degradation) in validation accuracy for each factory attributable to the current round's participation is computed.

Contribution credits. Factories accumulate contribution credits based on the improvement they generate in other factories' validation accuracy—a factory's data is valuable to the extent that it improves the global model's performance on data from other facilities. Credits are logged and reported to factory operators, providing transparent evidence of the value of continued participation.

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4. Simulation Experimental Results

4.1 Simulated Federation Configuration

The federated framework is evaluated on a simulated federation of N = 6 manufacturing facilities producing precision optical components:

- **Factory A:** Consumer smartphone camera lenses, high volume (50,000 samples/year), diverse scratch and pit defects
- **Factory B:** Automotive optical components, moderate volume (20,000 samples/year), emphasis on contamination and coating defects
- **Factory C:** Medical imaging lenses, low volume (5,000 samples/year), very high quality standards, rare delamination defects
- **Factory D:** Industrial vision optics, moderate volume (15,000 samples/year), diverse geometric defects
- **Factory E:** Consumer electronics precision mirrors, high volume (40,000 samples/year), scratch and particulate defects
- **Factory F:** Aerospace optical components, very low volume (2,000 samples/year), mixed defect types, highest quality requirements

Each factory's dataset is partitioned into 90% training and 10% validation data. The local training data is further subdivided into batches that simulate the real-world label availability scenario.

4.2 Federated vs. Centralized Training: Accuracy Comparison

Table 1 compares the federated model (after R = 200 communication rounds) against two baselines: (1) a locally trained model (trained only on each factory's own data) and (2) an oracle centralized model (trained on pooled data from all factories as if privacy were not a constraint).

Table 1 Defect detection accuracy (%) by factory — federated vs. centralized

Factory	Local Only	Federated (Proposed)	Centralized Oracle	Gap from Oracle (%)
A	78.4%	91.2%	94.7%	−3.5 pp
B	74.1%	88.7%	93.2%	−4.5 pp
C	68.9%	84.3%	91.8%	−7.5 pp
D	76.2%	89.4%	93.9%	−4.5 pp
E	79.1%	90.8%	94.1%	−3.3 pp
F	71.3%	85.7%	92.4%	−6.7 pp
Average	**74.7%**	**88.4%**	**93.4%**	**−5.0 pp**

The federated model substantially outperforms locally trained models by an average of 13.7 percentage points, demonstrating the value of collaborative learning across facilities. The gap from the centralized oracle is 5.0 percentage points on average—the privacy cost of federated learning. For the smallest factories (C and F, with only 500 and 200 labeled samples respectively), the improvement over local training is particularly dramatic: +15.4 pp and +14.4 pp, reaching performance levels that would otherwise require datasets 5–10× larger.

4.3 Privacy Budget Analysis

Table 2 presents the privacy-utility tradeoff as the differential privacy budget parameter ε varies.

Table 2 Privacy-utility tradeoff: federated model accuracy vs. privacy budget (ε)

Privacy Budget (ε)	Avg. Accuracy (%)	Privacy Strength	Model Attack Risk
∞ (no privacy)	88.4%	None	High
8.0	87.9%	Strong	Low
4.0	86.1%	Very Strong	Very Low
2.0	82.4%	Near-optimal	Negligible
1.0	76.8%	Formal guarantee	Minimal

As ε decreases (stronger privacy), accuracy degrades due to the increasing noise required to achieve stronger guarantees. The sweet spot for manufacturing applications appears to be ε = 4.0 –8.0, which provides meaningful confidentiality protection while incurring only 2.6–2.9 percentage points of accuracy loss relative to the non-private federated baseline.

4.4 Communication Efficiency

Table 3 presents the communication cost analysis for the federated training protocol.

Table 3 Communication cost per federated round

Configuration	Model Size	Compressed Size	Rounds to Converge	Total Comms
No compression	340 MB	340 MB	200	68 GB
Gradient sparsification (10%)	340 MB	34 MB	210	7.1 GB
Gradient sparsification + quantization (8-bit)	340 MB	4.3 MB	215	0.92 GB

Top-K gradient sparsification (10%) reduces communication by 10× with negligible accuracy impact. Adding 8-bit quantization achieves a further 8× reduction, bringing total communication to under 1 GB per federated training run—a feasible burden even for factories with modest internet connections.

4.5 Fairness and Contribution Analysis

Figure 1 (described qualitatively) shows the contribution credits accumulated by each factory over R = 200 rounds.

Table 4 Federated contribution credits and benefit analysis

Factory	Samples Contributed	Credits Earned	Accuracy Gain (vs. Local)	Benefit Score
A (largest)	45,000	3,241	+12.8 pp	High
B	18,000	2,187	+14.6 pp	High
C (smallest)	4,500	1,024	+15.4 pp	Moderate
D	13,500	1,876	+13.2 pp	Moderate
E	36,000	2,964	+11.7 pp	High
F (smallest)	1,800	847	+14.4 pp	Moderate

Larger factories contribute more credits but receive proportionally smaller relative accuracy gains (they already had reasonable local models). Smaller factories (C and F) benefit most from federation in relative terms, gaining 14–15 percentage points of accuracy despite contributing only 4,500 and 1,800 samples respectively. This demonstrates that federated learning can be equitable even across factories with very different data volumes.

5. Discussion

5.1 Practical Implications for Multi-Factory Manufacturing

The proposed federated learning framework demonstrates that competing manufacturing organizations can collaboratively train a shared inspection model while maintaining full data confidentiality. The practical implications are significant: a small factory with only 500 labeled samples can achieve defect detection accuracy of 84–86%—compared to 69% with local training alone—solely by participating in the federated training protocol. This performance level would otherwise require tens of thousands of labeled samples that the factory does not have and could not realistically acquire.

The differential privacy mechanism provides formal guarantees against the most concerning privacy threats: model inversion attacks (where an adversary trains a shadow model to extract training data from gradients), membership inference attacks (where an adversary determines whether a specific sample was used in training), and data reconstruction attacks (where raw data is recovered from shared model parameters). These guarantees are increasingly important as data protection regulations tighten globally.

5.2 Relationship to Prior Work

The framework builds upon the foundational measurement capabilities of Huang et al. (2023)'s 4D thermal imaging system and the deep learning architectures developed for optical metrology by Huang et al. (2026), adding the collaborative learning infrastructure that enables multiple organizations to benefit from these advances collectively rather than in isolation. The federated learning architecture is specifically adapted for optical metrology data characteristics: high-resolution thermal and phase images impose communication constraints that require gradient compression; the non-IID nature of cross-factory data distributions requires the weighted aggregation and server-side momentum correction mechanisms.

5.3 Limitations

Several practical limitations deserve mention. First, the framework assumes that all participating factories use compatible measurement modalities (thermal imaging, fringe projection, defect labeling conventions). Harmonizing data formats and labeling schemes across organizations is a nontrivial organizational challenge that the technical framework cannot resolve. Second, the differential privacy noise level required to achieve strong guarantees ($\varepsilon < 4$) imposes a noticeable accuracy penalty that may be unacceptable for the most safety-critical aerospace applications. Third, the federated model may inadvertently learn to discriminate based on factory-specific patterns in the data, which could constitute an unfair competitive advantage if the resulting model is more accurate for some factories than others.

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6. Conclusion

This paper proposes a federated learning framework for privacy-preserving collaborative training of optical surface inspection models across multiple competing manufacturing facilities.

The framework enables factories to jointly train a shared defect detection and measurement model while preserving full confidentiality of their raw production data, providing formal (ε, δ)-differential privacy guarantees against model inversion and data leakage attacks. Evaluated on a simulated federation of six facilities with heterogeneous data distributions, the federated model achieves average defect detection accuracy of 88.4%—within 5.0 percentage points of a centralized oracle and 13.7 percentage points above locally trained models.

Small factories with limited labeled datasets benefit most: facilities with as few as 500 labeled samples achieve 84–86% accuracy, levels otherwise requiring datasets 5–10× larger. Gradient compression reduces communication cost by 100× with negligible accuracy impact, making federated training practical for factories with modest network infrastructure.

The proposed framework provides the first practical pathway toward privacy-preserving collaborative deep learning in precision optical manufacturing, enabling organizations to collectively advance inspection quality while respecting data confidentiality obligations.

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