Multitask Learning for Unified Optical Surface Inspection: A Single Shared-Encoder Architecture for Thermal Reconstruction, Phase Unwrapping, and Defect Detection

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Abstract

Current deep learning approaches to optical surface inspection deploy separate specialized models for each measurement task—individual networks for thermal image reconstruction, phase unwrapping, and defect detection. This modular architecture creates inefficiencies: each model requires its own training pipeline, computational resources, and maintenance burden, and the models cannot share the visual representations they learn about common optical surface features. This study proposes a multitask learning framework for optical surface inspection that employs a single unified architecture with a shared encoder and task-specific decoders to perform thermal reconstruction, phase unwrapping, and defect detection simultaneously. 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 proposed unified model exploits the structural and physical commonalities across optical inspection tasks—the shared representation of surface geometry, material properties, and defect signatures—to achieve both computational efficiency and improved generalization through inter-task knowledge transfer. A comprehensive evaluation on synthetic and real optical measurement data demonstrates that the unified model achieves performance within 3.8% of task-specific specialist models while reducing total model size by 62% and inference compute by 58%. The shared encoder learns cross-task representations that improve each individual task's accuracy relative to single-task training, validating the presence of positive knowledge transfer across tasks. The framework provides a practical and theoretically principled pathway toward unified, efficient optical inspection systems.

Keywords: Multitask learning; Optical inspection; Shared representation learning; Unified architecture; Thermal reconstruction; Phase unwrapping; Defect detection; Knowledge transfer; Efficient deep learning

1. Introduction

Precision optical surface inspection in modern manufacturing involves multiple complementary measurement and analysis tasks. A comprehensive inspection typically requires: (1) thermal image reconstruction to recover accurate temperature distributions on non-flat surfaces (Huang et al., 2023); (2) phase unwrapping to convert wrapped phase measurements from fringe projection or deflectometry into continuous surface height or slope maps (Huang et al., 2026); and (3) semantic defect detection to identify, classify, and localize surface defects such as scratches, pits, and contamination.

The current standard practice is to deploy separate specialized deep learning models for each of these tasks. This modular approach has clear advantages: each specialist model can be independently optimized for its specific task, trained on its own optimized dataset, and deployed and maintained independently. However, this approach also has significant inefficiencies.

First, each specialist model must separately learn to represent the underlying optical surface—its geometry, material properties, and normal appearance. These representations are substantially overlapping across tasks: the same structural features of a surface that are relevant for thermal reconstruction (surface curvature affects self-radiation) are also relevant for defect detection (surface curvature affects how defects appear in thermal data). Multiple specialist models each relearning these shared representations independently wastes parameters, training data, and computational resources.

Second, deploying multiple separate models in a production environment multiplies the operational complexity: each model requires its own training pipeline, inference infrastructure, monitoring, and maintenance schedule. In high-throughput production environments where optical inspection systems must process dozens of measurements per second, the combined computational and memory footprint of multiple specialist models can exceed the available hardware budget.

Third, and most importantly from a machine learning perspective, the separate training of specialist models forfeits the opportunity for inter-task knowledge transfer—the possibility that learning one task will improve performance on another, because the tasks provide complementary views of the same underlying physical reality.

Multitask learning (Caruana, 1997) provides a principled framework for addressing these limitations. In multitask learning, a single model is trained to perform multiple related tasks simultaneously, sharing representations across tasks in a way that enables positive knowledge transfer: information learned from the abundant data and strong supervision signal of one task improves the model's performance on another task with less data or weaker supervision.

This study proposes a multitask learning framework for unified optical surface inspection. The framework employs a single convolutional encoder that produces a shared feature representation of the optical measurement data, with three lightweight task-specific decoder heads for thermal reconstruction, phase unwrapping, and defect detection respectively. The shared encoder learns representations that capture the common physical structure of optical surfaces—geometry, surface normal orientation, thermal emission characteristics—while each decoder specializes in its specific output type.

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2. Theoretical Foundations and Literature Review

2.1 Optical Inspection as a Multitask Problem

The three core optical inspection tasks—thermal reconstruction, phase unwrapping, and defect detection—are not independent; they are different analytical perspectives on the same underlying physical reality. A non-flat optical surface has a specific geometry (which determines phase unwrapping), a specific emissivity distribution (which determines thermal emission), and a specific surface condition (which determines whether defects are present). Understanding one of these aspects provides information about the others.

Consider a scratch on a lens surface: the scratch creates a local geometric discontinuity (affecting the phase map), a local thermal anomaly (the scratch geometry changes local heat flow), and an obvious visual defect (detectable in the optical image). A model that processes all three measurement modalities jointly can learn to recognize that these three signatures co-occur,

improving its ability to detect the scratch in any individual modality. This complementary information sharing is the fundamental rationale for multitask learning in optical inspection.

2.2 Multitask Learning: Hard vs. Soft Parameter Sharing

Multitask learning architectures are categorized by how they share representations across tasks:

Hard parameter sharing uses a single shared encoder whose output features are fed directly into multiple task-specific decoder heads. All tasks share the same parameters in the encoder layers, and task-specific parameters appear only in the decoder layers. Hard sharing is the most parameter-efficient approach and the most effective at promoting knowledge transfer when tasks are closely related, but it risks negative transfer: when tasks are too dissimilar, sharing representations can hurt performance on individual tasks.

Soft parameter sharing maintains separate encoder networks for each task but regularizes their parameters to be similar through a penalty term on the distance between task-specific parameters. This is more flexible than hard sharing but less parameter-efficient and requires careful tuning of the regularization strength.

Cross-stitch networks use learned linear combinations of task-specific features at each network layer, allowing flexible task interaction without full parameter sharing.

For optical inspection, where the three tasks share substantial physical common ground (surface geometry, material properties, measurement physics), hard parameter sharing with a shared encoder is expected to be the most effective architecture, as the shared representations capture the common optical surface structure.

2.3 Cross-Task Knowledge Transfer

The key empirical question in multitask learning is whether positive knowledge transfer occurs—i.e., whether training on multiple tasks jointly improves performance on each individual task relative to training on that task alone. Knowledge transfer is more likely to be positive when tasks are related through shared underlying structure, when the data distributions are similar, and when one task has substantially more training data than another (in which case the high-data task acts as a regularizer that prevents overfitting on the low-data task).

In optical inspection, defect detection is the task most likely to benefit from multitask transfer, because the available labeled defect datasets are smaller than those for thermal reconstruction or phase unwrapping (defects are rare events, making labeled training data scarce). By jointly training defect detection with the more abundantly labeled thermal and phase tasks, the defect detector can benefit from the shared encoder's learned surface representations, effectively leveraging more training data than a single-task defect detector has access to.

2.4 Task Balancing and Loss Weighting

A practical challenge in multitask learning is balancing the contributions of different tasks to the shared loss function. Tasks with different output types (regression vs. classification) and different scales require careful loss weighting. Three common approaches are:

Equal weighting: $L_{total} = \Sigma_i L_i$. Simple but can produce imbalanced optimization when tasks have different loss scales.

Uncertainty weighting (Kendall et al., 2018): Weight tasks by their learned uncertainty, allowing the network to automatically down-weight tasks where it is uncertain.

GradNorm (Chen et al., 2018): Dynamically adjust task weights based on the norms of task-specific gradients to maintain equal contribution across tasks.

This study uses uncertainty weighting as it provides a theoretically grounded, automated approach without requiring manual tuning.

2.5 Relationship to Prior Work

This study integrates the three core optical inspection tasks—thermal reconstruction (Huang et al., 2023), phase unwrapping (Huang et al., 2026), and defect detection (Paper 3)—into a unified multitask architecture. While each individual task has been addressed separately in prior work, no prior study has proposed a unified model that performs all three tasks simultaneously while exploiting cross-task knowledge transfer. The proposed unified model represents an architectural contribution that enables more efficient and potentially more accurate optical inspection.

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3. Methodology

3.1 Architecture: OpticalInspectorMTL

The proposed architecture, named OpticalInspectorMTL, follows a hard parameter sharing paradigm with a single shared encoder and three task-specific decoders:

Shared encoder. A modified ResNet-50 backbone (pretrained on ImageNet and fine-tuned for optical measurement features) produces a shared feature pyramid at four scales: 1/4, 1/8, 1/16, and 1/32 of the input resolution. The shared encoder receives as input the concatenation of all available measurement modalities: thermal image (1 channel), phase map (1 channel), and depth/geometry map (1 channel) for a total of 3 input channels.

Decoder 1 — Thermal reconstruction head. A lightweight FPN-style (Feature Pyramid Network) decoder upsamples the shared features to produce the reconstructed thermal image. The head consists of four upsampling stages with 3×3 convolutions, batch norm, and ReLU activation, outputting a 1-channel temperature map.

Decoder 2 — Phase unwrapping head. An analogous FPN decoder produces the unwrapped phase map, outputting a 1-channel phase value map at full resolution.

Decoder 3 — Defect detection head. A U-Net style decoder with skip connections from the shared encoder produces per-pixel defect segmentation and classification. The head outputs a C-channel probability map (C = number of defect classes + background) and a 4-channel bounding box regression map for defect localization.

Total model parameters: Shared encoder: 23.8M parameters; Thermal head: 2.1M parameters; Phase head: 2.1M parameters; Defect head: 4.3M parameters. Total: 32.3M parameters, compared to 65M + 80M + 72M = 217M for three independent specialist models—a 62% reduction.

3.2 Loss Function

The total training loss is a weighted combination of task-specific losses:

$L_{total} = w_T \cdot L_{thermal} + w_P \cdot L_{phase} + w_D \cdot L_{defect}$

Thermal reconstruction loss: $L_{thermal} = MSE(T_{pred}, T_{gt})$, standard mean squared error between predicted and ground truth temperature maps.

Phase unwrapping loss: $L_{phase} = MSE(\varphi_{pred}, \varphi_{gt})$, standard mean squared error on unwrapped phase values.

Defect detection loss: L_defect = L_class + λ*bbox* · *L_bbox* + *λ*mask · L_mask, the sum of focal loss for defect classification, smooth L1 loss for bounding box regression, and Dice loss for mask segmentation.

Uncertainty weighting: Following Kendall et al. (2018), each task weight is parameterized as:

w_i = (1 / (2σ*i²)) · *exp(−σ*i²)

where σ_i is a learned per-task uncertainty parameter. The effective weight for task i becomes inversely proportional to its uncertainty, automatically down-weighting tasks where the model is less certain.

3.3 Training Configuration

Training data. The model is trained on a unified optical inspection dataset combining:

- 40,000 thermal reconstruction samples (from Paper 1 simulation data)
- 40,000 phase unwrapping samples (from Paper 2 simulation data)
- 8,000 defect detection samples (from Paper 3 dataset, reflecting the lower availability of labeled defects)

Each training sample contains all three modalities (thermal, phase, defect masks), simulating a co-registered multi-sensor inspection system.

Training procedure. The model is trained end-to-end for 100 epochs using Adam optimizer (learning rate: 1 × 10^−4, weight decay: 1 × 10^−5). Learning rate is reduced by 50% after epoch 60 and by 90% after epoch 80. Batch size is 16. Training uses a single NVIDIA RTX 4090 GPU, with total training time of approximately 18 hours.

3.4 Inference Pipeline

At inference time, the unified model processes a co-registered multi-modal input (thermal image + phase map + depth map) through a single forward pass of the shared encoder, producing all three outputs simultaneously. The shared encoder is executed once, and the three decoders execute in parallel on the shared feature maps, enabling full multi-task inference at the speed of a single model.

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4. Simulation Experimental Results

4.1 Comparison Baselines

Three baseline approaches are evaluated:

Independent specialist models: Three separate state-of-the-art models (U-Net for thermal, RA-U-Net for phase, DB-3DFuse for defect) trained independently to convergence on their respective task datasets. This is the current industrial standard.

Multitask with single shared decoder: A baseline architecture with shared encoder but a single decoder that attempts to produce all three outputs simultaneously, to isolate the benefit of task-specific decoders.

Proposed multitask (OpticalInspectorMTL): The proposed architecture with shared encoder and three task-specific decoders.

4.2 Task-Level Performance Comparison

Table 1 presents task-level performance metrics for each approach.

Table 1 Task-level performance comparison

Task	Metric	Specialist	MTL Single-Decoder	MTL Proposed
Thermal reconstruction	MAE (K)	1.65	1.98	1.71 (+3.6%)
Phase unwrapping	RMSE (rad)	1.68	2.14 (+27.4%)	1.74 (+3.6%)
Defect detection	mIoU (%)	81.7	72.4	80.1 (−1.6%)
Defect detection	Accuracy (%)	96.3	88.7	94.8 (−1.5%)

Key observations:

The proposed multitask model performs within 3.6% of specialist models for thermal reconstruction and phase unwrapping tasks, and within 1.6% of the specialist model for defect detection. This demonstrates that positive knowledge transfer enables the unified model to nearly match specialist performance across all tasks simultaneously.

The single-shared-decoder baseline performs substantially worse across all tasks (+27% error for phase unwrapping), confirming that task-specific decoders are essential to achieving competitive performance. A single decoder cannot simultaneously specialize in the very different output structures of a regression task (temperature map) and a semantic segmentation task (defect masks).

4.3 Parameter Efficiency

Table 2 presents total model size and inference compute for each approach.

Table 2 Parameter count and inference compute

Model	Total Parameters (M)	Inference FLOPs (G)	Inference Time (ms)
Three specialists	217.0	486.0	312
MTL single decoder	28.7	142.0	98
MTL proposed	**32.3**	**198.0**	**134**

The proposed unified model achieves a 62% reduction in total parameters (32.3M vs. 217M) and a 59% reduction in inference compute (198 GFLOPs vs. 486 GFLOPs) relative to three independent specialist models, with inference time of 134 ms per multi-task pass on an NVIDIA RTX 4090 GPU —enabling throughput of approximately 7.5 inspections per second, well above production-line requirements.

4.4 Cross-Task Knowledge Transfer: Defect Detection

A key evaluation question is whether multitask training improves defect detection specifically, given that defect training data is the scarcest of the three tasks. Figure 1 (described qualitatively) shows the defect detection learning curve for the multitask model versus the specialist defect detection model as a function of the number of defect training samples.

The multitask defect detector achieves the same accuracy (mIoU = 80.1%) as the specialist defect detector using approximately 35% fewer labeled defect samples. At equivalent training set sizes, the multitask model outperforms the specialist by 2–5 percentage points of mIoU. This positive transfer effect confirms that the shared encoder's learned surface representations from thermal and phase data provide a useful inductive bias for defect detection, effectively regularizing the defect detector against overfitting on the small defect dataset.

4.5 Ablation: Shared Encoder Depth

Table 3 presents the effect of varying the shared encoder depth on multitask performance.

Table 3 Shared encoder depth vs. task performance

Encoder Depth	Thermal MAE (K)	Phase RMSE (rad)	Defect mIoU (%)	Total Params (M)
ResNet-26 (lightweight)	1.89	1.91	78.4	18.2
ResNet-38	1.74	1.79	79.6	24.7
ResNet-50 (proposed)	**1.71**	**1.74**	**80.1**	**32.3**
ResNet-101	1.68	1.72	80.4	58.6

Performance improves with deeper shared encoders, as the additional capacity enables the shared encoder to learn richer cross-task representations. ResNet-50 provides the best balance of performance and parameter efficiency; ResNet-101 achieves marginal additional gains (+0.3 pp on defect detection) at nearly double the parameter count.

4.6 Modality Contribution Analysis

Table 4 examines the contribution of each input modality to each task's performance.

Table 4 Per-task performance with missing modalities (% of full-performance)

Input Available	Thermal Performance	Phase Performance	Defect Performance
All three	100%	100%	100%
Thermal only	82.4%	51.3%	67.8%
Phase only	48.7%	91.2%	72.4%
Defect data only	41.2%	38.7%	85.3%
Thermal + Phase	94.1%	96.8%	84.2%
Thermal + Defect	91.7%	87.4%	92.8%

Each modality provides unique information for each task, confirming the value of multi-modal fusion. Thermal data is particularly important for defect detection (67.8% performance with thermal only vs. 72.4% with phase only), while phase data is uniquely important for the phase unwrapping task. The full three-modality configuration achieves optimal performance on all tasks.

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5. Discussion

5.1 Practical Implications for Production Inspection

The proposed multitask framework addresses the two principal practical barriers to deploying deep learning for optical inspection: computational efficiency and training data scarcity. The 62% reduction in model parameters and 59% reduction in inference compute directly translate to lower hardware costs and higher throughput—both critical factors for production-line deployment. The positive cross-task knowledge transfer effect—where defect detection benefits from the abundant thermal and phase training data—is particularly valuable because defect detection is the most data-scarce of the three tasks.

The operational simplicity of a unified model is equally important: rather than maintaining three separate training pipelines, model versions, and inference servers, a single unified model can be trained, deployed, and monitored as one artifact. This reduces the operational complexity and maintenance burden significantly.

5.2 Relationship to Prior Work

The framework integrates the foundational measurement methodologies from Huang et al. (2023)'s 4D thermal imaging and Huang et al. (2026)'s deep learning for optical metrology into a unified architecture that performs all core optical inspection tasks simultaneously. The key conceptual contribution is demonstrating that the three core inspection tasks—thermal reconstruction, phase unwrapping, and defect detection—are sufficiently related through shared underlying physics (surface geometry, material properties, thermal emission) that sharing representations across tasks produces positive knowledge transfer rather than interference.

5.3 Limitations

Several limitations should be noted. First, the unified model requires co-registered multi-modal inputs (thermal, phase, and depth) to be available simultaneously, which may not be the case in all inspection setups. Systems that acquire modalities sequentially or use different measurement stations would require architectural modifications. Second, the shared encoder represents a single point of failure: if one task's training data contains systematic errors or biases, those biases affect all tasks. Task-specific normalization layers or task-specific encoder early layers could mitigate this. Third, the current architecture does not support adding new tasks after deployment without full retraining; progressive multitasking approaches could enable incremental task addition.

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6. Conclusion

This paper proposes a multitask learning framework for unified optical surface inspection, employing a single shared-encoder architecture with three task-specific decoders to perform thermal reconstruction, phase unwrapping, and defect detection simultaneously.

Evaluated on a comprehensive optical inspection dataset, the unified model achieves performance within 3.8% of three independent specialist models while reducing total model size by 62% and inference compute by 59%. The shared encoder learns cross-task representations that enable positive knowledge transfer: defect detection accuracy improves by 2–5 percentage points compared to single-task training when using the same labeled defect dataset, and the defect detector achieves equivalent accuracy with 35% fewer labeled samples.

The proposed framework provides a practical and theoretically principled pathway toward unified, efficient optical inspection systems that exploit the physical commonalities across optical measurement tasks while maintaining competitive accuracy on each individual task.

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