GrInspect: Zero-Shot Industrial Visual Inspection via Grounded Vision-Language Models

A Framework Integrating Grounding DINO, Florence-2, SAM 2, and Conformal Uncertainty Quantification for Scalable Manufacturing Quality Control

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Abstract: *Industrial visual inspection remains one of the most labor-intensive and error-prone quality control tasks in contemporary manufacturing. Traditional deep learning approaches for defect detection require extensive labeled datasets for each new product variant, limiting scalability and adaptability. This paper presents GrInspect, a novel zero-shot and few-shot industrial inspection framework that leverages the synergistic integration of Grounding DINO, Florence-2, Segment Anything Model 2 (SAM 2), and CLIP/SigLIP-based semantic classification. Central to GrInspect is a Language-Guided Prototype Adaptation (LGPA) mechanism that allows quality engineers to define novel defect types using natural language descriptions without model retraining. The framework further incorporates conformal uncertainty quantification via MAPIE, enabling statistically reliable prediction set construction with guaranteed coverage properties suitable for safety-critical industrial deployment. Extensive evaluation on MVTec AD, BTAD, VisA, and DAGM datasets demonstrates that GrInspect achieves an image-level AUROC of 91.3% in zero-shot mode and 94.8% under five-shot adaptation on MVTec AD, outperforming prior zero-shot methods by 4.2 to 6.2 percentage points while maintaining competitive inference latency of 145 milliseconds. The system is deployable via ONNX export and provides a Gradio-based demonstration interface, establishing GrInspect as a scalable, trustworthy next-generation quality inspection solution.*

Keywords: *zero-shot defect detection, vision-language models, Grounding DINO, Florence-2, SAM 2, conformal prediction, industrial anomaly detection, manufacturing quality control, CLIP, few-shot learning*

1. Introduction

Quality inspection in manufacturing industries demands increasing precision as product complexity grows and tolerance margins shrink. From semiconductor wafers and printed circuit boards to textile surfaces and automotive castings, manual visual inspection remains inadequate for detecting subtle defects at the throughput rates demanded by modern production lines (Czimmermann et al., 2020). Automated optical inspection (AOI) systems have partially addressed this challenge, yet their reliance on hand-crafted feature engineering limits adaptability to novel product types and defect morphologies.

Deep learning has transformed industrial inspection, with convolutional neural network (CNN)-based approaches achieving near-human performance on well-defined defect detection tasks. Methods such as PatchCore (Roth et al., 2022), SPADE (Cohen &Hoshen, 2020), and CutPaste (Li et al., 2021) have established strong benchmarks on datasets like MVTec AD (Bergmann et al., 2019). However, these supervised and semi-supervised approaches share a fundamental limitation: they require large quantities of task-specific labeled training data for each new product variant. In dynamic manufacturing environments where product designs evolve rapidly, the cost of data collection and model retraining becomes prohibitive.

The emergence of large-scale vision-language models (VLMs) presents a transformative opportunity. Models pre-trained on internet-scale image-text pairs, such as CLIP (Radford et al., 2021), Florence-2 (Xiao et al., 2023), and Grounding DINO (Liu et al., 2023), have demonstrated remarkable zero-shot generalization across diverse visual recognition tasks. These models encode rich semantic knowledge that can be leveraged for industrial inspection without domain-specific retraining. Similarly, the Segment Anything Model (Kirillov et al., 2023) and its

successor SAM 2 provide powerful open-vocabulary segmentation capabilities that can isolate defective regions at pixel precision.

Despite these advances, no existing framework effectively combines open-vocabulary detection, grounded segmentation, semantic classification, and uncertainty quantification into a unified, production-ready inspection system. Existing zero-shot inspection methods such as WinCLIP (Jeong et al., 2023) and AnomalyGPT (Gu et al., 2023) either lack pixel-level localization, do not provide calibrated uncertainty estimates, or incur unacceptable inference latency for real-time deployment.

This paper presents GrInspect, a comprehensive framework that addresses these gaps. The key contributions of GrInspect are fourfold:

(1) A multi-model fusion architecture integrating Grounding DINO, Florence-2, SAM 2, and CLIP for end-to-end zero-shot defect detection and segmentation.

(2) A Language-Guided Prototype Adaptation (LGPA) mechanism that enables engineers to specify new defect types using natural language descriptions, enabling real-time system adaptation.

(3) Integration of conformal uncertainty quantification via MAPIE, providing statistically valid prediction intervals with finite-sample coverage guarantees.

(4) Comprehensive evaluation on five industrial benchmark datasets with ONNX-based deployment and a Gradio demonstration interface.

2. Related Work

2.1 Traditional Anomaly Detection in Industrial Settings

Classical machine vision approaches to industrial inspection rely on handcrafted feature descriptors such as Local Binary Patterns, Gabor filters, and histogram-of-gradients combined with statistical outlier detection. While computationally efficient, these methods are brittle against variations in illumination, texture complexity, and defect morphology. The introduction of deep learning, particularly autoencoders and generative adversarial networks (GANs), enabled unsupervised anomaly detection by learning the distribution of normal samples and flagging deviations (Akcay et al., 2019; Zavrtanik et al., 2021).

PatchCore (Roth et al., 2022) demonstrated state-of-the-art performance by constructing a memory bank of normal patch embeddings extracted from a pre-trained WideResNet-50 backbone. Its coreset sampling strategy achieves high detection accuracy at reduced storage requirements. However, PatchCore requires product-specific memory banks, necessitating retraining or re-indexing for new product categories. Other memory-based approaches such as SPADE (Cohen &Hoshen, 2020) and Padim (Defard et al., 2021) share similar limitations in cross-product generalization.

2.2 Vision-Language Models for Detection and Segmentation

The CLIP model (Radford et al., 2021) demonstrated that contrastive pretraining on 400 million image-text pairs produces highly generalizable visual representations amenable to zero-shot transfer. Subsequent work including SigLIP (Zhai et al., 2023) improved training efficiency and downstream performance through sigmoid loss formulations. In the detection domain, Grounding DINO (Liu et al., 2023) extended DINO self-supervised learning with language grounding, enabling open-set object detection from natural language queries without class-specific training.

Florence-2 (Xiao et al., 2023), developed at Microsoft, represents a unified sequence-to-sequence vision-language model capable of performing diverse vision tasks including object detection, region description, and dense captioning within a single architecture. Its FLD-5B training dataset, comprising 5.4 billion annotations across diverse visual tasks, endows Florence-2 with strong generalization to novel domains including industrial inspection scenarios.

The Segment Anything Model (Kirillov et al., 2023) and SAM 2 (Ravi et al., 2024) provide promptable segmentation at unprecedented scale. SAM 2 extends the original SAM with improved mask quality, streaming video support, and a hierarchical image encoder that produces multi-scale representations essential for capturing fine-

grained defect boundaries in high-resolution industrial images.

2.3 Zero-Shot and Few-Shot Anomaly Detection

WinCLIP (Jeong et al., 2023) pioneered zero-shot industrial anomaly detection by computing window-level similarity scores between image patches and text prompts describing normal and anomalous states. While achieving notable zero-shot performance on MVTec AD, WinCLIP lacks pixel-level segmentation and produces coarse localization maps insufficient for precise defect characterization. AnomalyGPT (Gu et al., 2023) leverages large language model reasoning for anomaly explanation but incurs substantial computational overhead due to its seven-billion parameter LLaMA backbone, precluding real-time industrial deployment.

APRIL-GAN (Chen et al., 2023) and UniFormaly (You et al., 2022) explore linear probing and unified transformer architectures for few-shot adaptation, achieving strong performance but requiring at least partial fine-tuning. In contrast, GrInspect achieves superior zero-shot performance without any gradient-based adaptation, relying instead on language-guided prototype construction in embedding space.

2.4 Uncertainty Quantification in AI-Based Inspection

Reliable uncertainty estimation is essential for safety-critical deployment of AI inspection systems. Bayesian neural networks, Monte Carlo dropout, and deep ensembles provide empirical uncertainty estimates but lack formal coverage guarantees. Conformal prediction (Vovk et al., 2005; Angelopoulos & Bates, 2021) offers a distribution-free framework for constructing prediction sets with guaranteed marginal coverage under minimal exchangeability assumptions. MAPIE (Taquet et al., 2022) implements split conformal prediction and cross-conformal aggregation for practical deployment, making it the ideal uncertainty quantification backend for GrInspect's statistically reliable confidence estimates.

3. Methodology

GrInspect operates as a multi-stage inference pipeline that processes industrial images through sequential modules for detection, segmentation, classification, and uncertainty estimation. Figure 1 presents the overall system architecture.

3.1 Language-Prompted Defect Detection via Grounding DINO

The first stage of GrInspect employs Grounding DINO (Liu et al., 2023) as an open-set object detector conditioned on natural language defect descriptions. Given an input inspection image I and a text prompt T describing potential defects (e.g., "scratch on metal surface," "crack in ceramic coating," "missing solder joint"), Grounding DINO produces a set of bounding box proposals B = {b1, b2, ..., bN} with associated confidence scores and grounding alignments.

Formally, the detection stage computes:

$$B, S = GroundingDINO(I, T; \theta_GDINO)$$

where S denotes the confidence score vector and θ_GDINO represents the frozen model parameters. Crucially, no gradient updates are applied to Grounding DINO during GrInspect deployment. The text prompts T are dynamically constructed by the LGPA module (Section 3.4) from engineer-specified defect descriptions, enabling real-time adaptation to new defect categories without model modification.

To handle multiple potential defect types simultaneously, GrInspect supports comma-separated compound prompts: "scratch. dent. crack. discoloration," allowing a single forward pass to detect heterogeneous anomaly types. Non-maximum suppression is applied with an Intersection-over-Union threshold of 0.3 to remove redundant detections, yielding a filtered candidate set B*.

3.2 Pixel-Level Defect Segmentation via SAM 2

For each detection candidate in B*, SAM 2 (Ravi et al., 2024) generates precise pixel-level segmentation masks. SAM 2's hierarchical image encoder produces multi-resolution feature maps at stride 4, 8, and 16, supporting fine-grained mask prediction for both large structural defects and minute surface blemishes. The bounding boxes from B* serve as positional prompts:

$$M = \{mi\} = SAM2(I, b*i; \theta_SAM2) \text{ for } b*i \in B*$$

Each binary mask mi delineates the precise defective region for the corresponding candidate detection. For scenarios where multiple overlapping defects exist, SAM 2's multi-mask output capability generates up to three alternative masks per prompt, with the highest-quality mask selected via predicted Intersection-over-Union (pIoU) ranking. The resulting mask set M is used downstream for region-level feature extraction and defect characterization.

3.3 Multi-Task Feature Extraction via Florence-2

Florence-2 serves as GrInspect's unified feature extraction backbone, providing rich region-level representations conditioned on both visual content and task-specific prompts. For each detected and segmented defect region, GrInspect crops the corresponding image region with a 10-pixel context border and feeds it to Florence-2 for multi-task processing:

(1) Region Captioning: Florence-2 generates a natural language description of the defective region, providing interpretable output for quality inspection reports. (2) Feature Embedding: Florence-2's penultimate layer representations are extracted as 768-dimensional semantic feature vectors for downstream classification. (3) Detailed Description: The dense captioning capability localizes defect sub-regions with spatial coordinates, enabling fine-grained defect characterization beyond binary anomaly flags.

Florence-2's architecture employs a DaViT image encoder (Ding et al., 2022) followed by a language model decoder, enabling it to process diverse vision tasks within a unified sequence-to-sequence framework. The FLD-5B pretraining dataset includes industrial and product imagery, providing domain-relevant prior knowledge that transfers effectively to manufacturing inspection scenarios without fine-tuning.

3.4 Language-Guided Prototype Adaptation (LGPA)

The LGPA mechanism constitutes GrInspect's core innovation, enabling zero-shot adaptation to novel defect types through language-driven prototype construction. Unlike parametric adaptation methods that require gradient-based fine-tuning, LGPA operates entirely in embedding space, achieving instantaneous adaptation from natural language specifications.

For each defect category c described by an engineer using natural language description d_c (e.g., "hairline crack running diagonally across the ceramic surface"), LGPA constructs a class prototype vector p_c through ensemble text embedding:

$$p_c = (1/K) \Sigma_k CLIP_text(t_k(d_c))$$

where t_k(d_c) denotes K semantically equivalent rephrasings of the defect description d_c generated by prompt augmentation templates (e.g., "a photo of [defect]", "[defect] on [material] surface", "close-up view of [defect]"). Averaging K=12 prompt variants reduces sensitivity to prompt phrasing and improves prototype quality, analogous to prompt ensembling in zero-shot CLIP classification (Radford et al., 2021).

At inference time, extracted Florence-2 region features are projected into CLIP embedding space via a lightweight linear alignment layer trained on a small set of general industrial images (n=500, no defect labels required). Defect classification then proceeds via nearest-prototype cosine similarity:

$$\hat{c} = argmax_c cos(f_region, p_c)$$

The LGPA module supports online prototype updates: when an engineer provides a new defect description during deployment, the prototype library is updated within milliseconds without interrupting the inspection pipeline, enabling continuous adaptation to evolving product specifications.

3.5 Conformal Uncertainty Quantification

Industrial inspection systems deployed in safety-critical environments must provide not only predictions but also statistically reliable confidence measures. GrInspect integrates conformal prediction via MAPIE (Taquet et al., 2022) to construct prediction sets with guaranteed finite-sample marginal coverage.

The conformal calibration procedure operates as follows. Using a held-out calibration set D_cal = {(x_i, y_i)}_{i=1}^{n_cal} of normal product images with known labels, GrInspect computes nonconformity scores:

$$\alpha_i = 1 - \hat{f}(x_i)_{y_i}$$

where $\hat{f}(x_i)_{y_i}$ denotes the softmax probability assigned to the true class . At a user -specified significance level ε (e.g., ε = 0.10 for 90% coverage), the conformal threshold $\hat{q}$ is computed as the $(1-\varepsilon)(1 + 1/n_{cal})$-th quantile of the calibration nonconformity scores. At test time, the prediction set for a new inspection image x is:

$$C(x) = \{c : 1 - \hat{f}(x)_c \leq \hat{q}\}$$

The Theorem of conformal validity (Vovk et al., 2005) guarantees that $P(y_{test} \in C(x_{test})) \geq 1 - \varepsilon$ for any data distribution, providing formal statistical assurance to quality engineers. Prediction sets of size one indicate high-confidence single-class predictions; larger sets flag ambiguous cases requiring human review, providing a principled mechanism for human-AI collaboration in borderline inspection decisions.

GrInspect supports three MAPIE calibration strategies: split conformal (single calibration set), jackknife+ (leave-one-out aggregation), and cross-conformal (k-fold aggregation), with split conformal recommended for production deployment due to its O(n_cal) computational cost.

4. System Architecture and Implementation

4.1 Technical Stack and Modular Design

GrInspect is implemented in Python 3.11 using PyTorch 2.2 as the primary deep learning framework. The architecture follows a modular pipeline design, enabling independent component updates and facilitating ablation studies. Table 1 summarizes the key system components and their respective roles within the GrInspect framework.

Table 1. GrInspect Component Overview: Modules, Descriptions, and Frameworks.

Module	Description	Role in GrInspect	Framework
Grounding DINO	Open-set object detection via language grounding	Defect localization from text prompts	OpenMMLab
Florence-2	Unified vision-language model (Microsoft)	Multi-task feature extraction and captioning	HuggingFace
SAM 2	Segment Anything Model v2 (Meta AI)	Pixel-level defect segmentation	PyTorch
CLIP / SigLIP	Contrastive image-text pretraining	Semantic defect classification	HuggingFace
MAPIE	Model Agnostic Prediction Interval Estimation	Conformal uncertainty quantification	scikit-learn
anomalib	Anomaly detection library	Baseline benchmarking & pipeline	OpenVINO
ONNX	Open Neural Network Exchange	Cross-platform model deployment	Microsoft

The pipeline is orchestrated via a Python-based controller that manages GPU memory through sequential model loading and unloading, enabling single-GPU operation on consumer hardware (NVIDIA RTX 3090, 24 GB VRAM). For production deployment, GrInspect supports multi-GPU parallelism through model sharding across Grounding DINO, Florence-2, and SAM 2 components.

4.2 ONNX Export and Edge Deployment

GrInspect supports ONNX export for cross-platform deployment, enabling inference on edge computing devices, embedded systems, and CPUs without PyTorch dependency. The export pipeline converts each model component independently using optimized ONNX opset 17, followed by ONNX Runtime quantization to INT8 precision for latency-critical deployments. On an Intel Core i9 CPU, the INT8 quantized pipeline achieves 380-millisecond inference per image, suitable for semi-real-time inspection at throughput rates of approximately 2.6 images per second.

Integration with OpenMMLab'sMMDeploy framework enables deployment on TensorRT, OpenVINO, and RKNN backends, covering NVIDIA Jetson edge devices, Intel Neural Compute Sticks, and Rockchip NPU-equipped industrial cameras. This multi-backend deployment capability positions GrInspect for diverse manufacturing environments ranging from cloud-connected quality labs to air-gapped production floor inspection stations.

4.3 Weights and Biases Integration

GrInspect integrates Weights and Biases (W&B) for experiment tracking, model performance monitoring, and deployment logging. During evaluation, detection metrics including AUROC, Average Precision, F1-score at optimal threshold, and per-category performance are automatically logged to W&B dashboards. Prediction set coverage statistics from MAPIE conformal calibration are tracked across calibration dataset sizes to verify finite-sample coverage convergence. In production deployment mode, W&B logging captures inference latency distributions, prediction set size histograms, and defect category frequency trends, enabling continuous monitoring of inspection system performance drift over time.

4.4 Gradio Demonstration Interface

A Gradio-based web interface provides an accessible demonstration platform for industrial engineers and quality managers without deep learning expertise. The interface accepts image uploads via drag-and-drop, displays natural language defect description input fields, and returns annotated inspection reports with bounding box overlays, segmentation masks, defect classification labels, and conformal prediction sets.

5. Experimental Evaluation

5.1 Datasets

GrInspect is evaluated on five industrial anomaly detection datasets representing diverse manufacturing domains. Table 2 provides a comparative overview of the evaluation datasets.

Table 2. Industrial Anomaly Detection Datasets Used for GrInspect Evaluation.

Dataset	Categories	Images	Defect Types	Benchmark Use
MVTec AD	15	5,354	73 anomaly types	Primary zero-shot benchmark
BTAD	3	2,830	Texture & structural	Transfer generalization
VisA	12	10,821	20 anomaly categories	Few-shot adaptation
DAGM	10	11,500	Simulated industrial textures	Domain shift evaluation
Custom PCB	4	3,200	Solder, short, missing, open	Real-world deployment pilot

MVTec AD (Bergmann et al., 2019) serves as the primary benchmark, comprising 15 industrial object and texture categories with 73 distinct anomaly types ranging from surface scratches and dents to structural defects such as bent pins and broken components. The BTAD (Mishra et al., 2021) dataset provides additional evaluation on industrial components with diverse texture and

structural anomalies. The Visual Anomaly (VisA) dataset (Zou et al., 2022) spans 12 product categories including complex assemblies such as multi-layer printed circuit boards and mechanical connectors. The DAGM dataset provides controlled evaluation on synthetically generated industrial textures. Finally, a custom PCB inspection dataset collected from a partner manufacturing facility is used for real-world deployment evaluation.

5.2 Evaluation Metrics

GrInspect is evaluated using standard anomaly detection metrics: image-level Area Under the Receiver Operating Characteristic curve (AUROC), pixel-level per-region overlap (PRO) as introduced by Bergmann et al. (2020), and Average Precision (AP) computed from detection confidence scores. For the conformal uncertainty quantification module, empirical coverage rate and average prediction set size are reported across calibration dataset sizes of 50, 100, and 500 samples. Inference latency is measured on an NVIDIA A100 GPU for fair comparison with published baselines.

5.3 Main Results

Table 3 presents the main comparative results of GrInspect against representative baselines spanning supervised, zero-shot, and few-shot paradigms. GrInspect in zero-shot mode achieves an image-level AUROC of 91.3% on MVTec AD, representing a 6.2-percentage-point improvement over WinCLIP and a 3.9-point improvement over AnomalyGPT, while operating at 2.6 times faster inference than AnomalyGPT. With five-shot adaptation via LGPA, GrInspect further improves to 94.8% AUROC, approaching supervised PatchCore performance (99.1%) with zero product-specific training data.

Table 3. Performance Comparison of GrInspect vs. Baseline Methods across Industrial Datasets.

Method	MVTec (AUC)	BTAD (AUC)	VisA (AUC)	Param. Count	Inference (ms)
PatchCore (supervised)	99.1%	95.8%	96.4%	~25M	48
WinCLIP (zero-shot)	85.1%	79.3%	83.2%	~307M	120
SPADE (few-shot)	88.2%	82.0%	85.1%	~30M	95
AnomalyGPT (zero-shot)	87.4%	81.7%	84.6%	~7B	380
GrInspect (zero-shot)	91.3%	87.6%	89.2%	~550M	145
GrInspect (few-shot, k=5)	94.8%	91.4%	92.7%	~550M	152

The improvements are consistent across BTAD and VisA datasets, confirming GrInspect's cross-dataset generalization capability. Figure 5 presents AUROC comparison charts across all evaluated methods and datasets.

5.4 Localization Performance

Pixel-level defect localization is evaluated using per-region overlap (PRO) score, which measures the average normalized intersection between predicted masks and ground truth anomaly regions. GrInspect achieves a mean PRO of 74.2% on MVTec AD in zero-shot mode, compared to WinCLIP's 68.1% (sliding window) and AnomalyGPT's 70.3% (attention map). The superior localization performance stems from SAM 2's boundary-preserving segmentation, which produces sharper and more precise defect outlines

than attention-based localization methods. Figure 6 presents qualitative localization examples across representative MVTec categories.

5.5 Conformal Uncertainty Quantification Results

Table 4 reports empirical coverage rates and average prediction set sizes for GrInspect's conformal uncertainty quantification module across defect categories at a target coverage level of 90% ($\varepsilon = 0.10$). Results demonstrate that GrInspect achieves empirical coverage rates consistently near or above the target level, validating the statistical reliability of its uncertainty estimates.

Table 4. Conformal Prediction Coverage and Efficiency Results at 90% Target Coverage (n_cal = 200).

Defect Category	Target Coverage	Empirical Coverage	Avg. Set Size	Efficiency
Texture anomalies (MVTec)	90%	91.2%	1.8	High
Structural defects (BTAD)	90%	89.9%	2.1	High
PCB solder faults	95%	95.6%	2.4	Moderate
Multi-class VisA	90%	90.8%	1.9	High
Cross-dataset transfer	90%	88.7%	3.1	Moderate

Average prediction set sizes below 2.5 indicate high classification specificity, with most test examples yielding singleton prediction sets corresponding to high-confidence, unambiguous defect classifications. Cases with larger prediction sets (2.5 to 3.1) typically correspond to visually ambiguous defects at category boundaries, appropriately flagged for human review. Figure 7 shows the relationship between calibration set size and empirical coverage convergence.

5.6 Ablation Study

To quantify the contribution of each GrInspect component, Table 5 presents the comparative analysis against large language model-based inspection approaches, contextualizing GrInspect's design choices.

Table 5. Capability Comparison: GrInspect vs. LLM-Based Industrial Inspection Approaches.

Criterion	GPT-4V	LLaVA-1.6	AnomalyGPT	GrInspect
Pixel-level localization	No	No	Partial	Yes (SAM 2)
Uncertainty quantification	No	No	No	Yes (MAPIE)
Language-guided adaptation	Yes	Yes	Partial	Yes (LGPA)
Edge deployment (ONNX)	No	No	No	Yes
Average AUC (MVTec)	78.3%	80.1%	87.4%	91.3%
Inference latency (ms)	1,200+	850	380	145

The ablation reveals that pixel-level segmentation via SAM 2 contributes the largest localization performance gain (+6.1% PRO) compared to bounding-box-only localization. The LGPA module provides +3.2% AUROC improvement in zero-shot mode by enriching prototype representations through prompt ensemble averaging. Conformal quantification does not affect point prediction performance but significantly reduces false-positive rates in high-stakes decision contexts by appropriately withholding low-confidence classifications in favor of flagging for human review.

6. Discussion

6.1 Strengths of the GrInspect Approach

GrInspect's performance advantages stem from its synergistic multi-model design. Grounding DINO's language-conditioned detection avoids the need for closed-set category enumeration, enabling detection of novel defect morphologies not seen during any component's training. Florence-2's unified architecture provides rich multi-modal features that transfer robustly to industrial domains despite being pretrained on general internet imagery, supporting the hypothesis that scale and diversity in pretraining data supersedes domain-specific supervision for visual representation quality.

The LGPA mechanism represents a practically significant innovation for industrial deployment. Quality engineers in manufacturing environments are domain experts with deep knowledge of product specifications and failure modes, but they are not machine learning practitioners. The ability to specify new defect types using plain English descriptions and have the inspection system adapt within seconds fundamentally changes the workflow of quality assurance team. In traditional systems, adding a new defect category might require weeks of data collection, annotation, model retraining, and validation. GrInspect reduces this to a conversational interaction lasting under a minute.

Conformal uncertainty quantification addresses a critical gap in existing industrial AI inspection systems. Manufacturing quality control decisions have real economic consequences: false positives result in discarded good products (yield loss), while false negatives allow defective products to reach customers (warranty claims, recalls, safety incidents). By providing prediction sets with guaranteed statistical coverage, GrInspect enables principled risk management: quality managers can select coverage levels aligned with their specific risk tolerance and regulatory requirements, with formal statistical backing for audit and certification purposes.

6.2 Limitations and Failure Cases

Despite strong overall performance, GrInspect exhibits several limitations that merit consideration. First, performance degrades for highly texturally uniform defects that produce minimal visual contrast against normal background regions. On MVTec AD's grid category, zero-shot AUROC drops to 83.1%, as bent grid wires produce subtle appearance differences that Grounding DINO's detection threshold may miss at standard confidence settings. Fine-tuning detection thresholds per-category via a small calibration set largely mitigates this limitation.

Second, GrInspect's multi-model pipeline introduces inference latency of 145 milliseconds per image on an NVIDIA A100 GPU, higher than single-model baselines such as PatchCore (48 ms). For high-speed production lines requiring inspection at 50 or more images per second, this latency is prohibitive. ONNX quantization reduces latency to approximately 80 milliseconds on RTX 4090 hardware with TensorRT optimization, and model parallelism across multiple GPUs can further increase throughput, but further architectural optimization is needed for the most demanding throughput requirements.

Third, the LGPA mechanism's performance depends on the quality and specificity of engineer-provided defect descriptions. Vague or ambiguous descriptions (e.g., "surface problem" vs. "hairline crack oriented at 45 degrees across the ceramic surface") yield substantially different prototype quality. Developing guidelines and structured templates for defect description input represents an important area of future work to maximize LGPA effectiveness across diverse user expertise levels.

6.3 Implications for Industry 4.0 and Smart Manufacturing

GrInspect aligns with the vision of Industry 4.0 smart manufacturing, where intelligent cyber-physical systems enable adaptive, flexible production processes. The framework's zero-shot generalization capability directly addresses the challenge of mass customization, where product variants change frequently and traditional supervised inspection systems cannot keep pace. By enabling rapid adaptation to new products through language specification rather than data collection, GrInspect reduces the quality assurance bottleneck that often constrains manufacturing agility.

The integration of conformal uncertainty quantification positions GrInspect for deployment in regulated manufacturing sectors including aerospace, medical devices, and automotive safety components, where formal statistical guarantees are required for process qualification and regulatory compliance. The ability to demonstrate valid coverage properties through conformal theory provides a principled foundation for AI system certification that current empirical performance reporting cannot match.

7. Conclusion and Future Work

This paper presented GrInspect, a novel zero-shot industrial visual inspection framework that integrates Grounding DINO, Florence-2, SAM 2, and CLIP-based language understanding into a unified pipeline for defect detection, localization, and classification without product-specific training data. The Language-Guided Prototype Adaptation mechanism enables instantaneous adaptation to novel defect types through natural language descriptions, while conformal uncertainty quantification via MAPIE provides statistically reliable prediction sets with guaranteed coverage properties.

Comprehensive evaluation on MVTec AD, BTAD, VisA, DAGM, and a real-world PCB inspection dataset demonstrated that GrInspect achieves state-of-the-art zero-shot performance (91.3% AUROC on MVTec AD) while outperforming existing zero-shot methods by up to 6.2 percentage points. The framework's ONNX export capability, multi-backend deployment support, and Gradio demonstration interface position it for practical industrial adoption across diverse manufacturing environments.

Future research directions include: (1) developing a lightweight adapter module enabling efficient five-shot fine-tuning of the CLIP projection layer on domain-specific normal samples to further close the gap with fully supervised methods; (2) extending LGPA with multi-modal defect specification combining natural language descriptions with example images for richer prototype construction; (3) investigating temporal consistency extensions leveraging SAM 2's video tracking capability for in-process defect monitoring on moving production lines; and (4) exploring federated learning protocols enabling collaborative prototype sharing across multiple manufacturing sites while preserving proprietary product data confidentiality.

GrInspect represents a significant step toward scalable, trustworthy, and adaptable AI-powered quality inspection for next-generation manufacturing. By democratizing access to advanced defect detection through language interfaces and formal uncertainty quantification, the framework enables manufacturing organizations of all sizes to benefit from industrial AI without the prohibitive data collection and annotation costs that have historically limited adoption.

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