PLG-DINO: INDUSTRIAL DEFECT DETECTION VIA PROMPT-DRIVEN LORA ADAPTATION IN GROUNDING DINO

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ABSTRACT

Large vision-language models (LVLMs) have demonstrated remarkable capabilities in aligning textual and visual modalities across diverse natural image datasets. Despite these advances, their direct deployment in industrial defect detection remains challenging due to significant domain discrepancies. Industrial images typically exhibit unique visual characteristics such as complex textures, low contrast, metallic reflections, and subtle localized anomalies that differ fundamentally from natural scenes. Furthermore, fine-grained semantic alignment between domain-specific textual prompts and corresponding visual regions remains underexplored, which limits the precise localization and recognition of defects. Compounding these issues, industrial datasets are often limited in annotated samples per defect category, rendering full-model fine-tuning impractical and prone to overfitting. To overcome these challenges, we propose a novel fine-tuning framework that combines low-rank adaptation (LoRA) applied selectively to the attention modules of the Grounding DINO architecture with a carefully designed prompt engineering strategy tailored for industrial defects. This approach leverages lightweight parameter-efficient updates alongside semantically rich, domain-specific prompts to enable effective adaptation of pretrained LVLMs with minimal labeled data. We curate a comprehensive dataset comprising approximately 30,000 high-resolution industrial images spanning a wide range of defect categories for rigorous evaluation. Extensive experiments demonstrate that our method consistently outperforms competitive baselines across diverse industrial scenarios, achieving superior detection accuracy while requiring only a fraction of trainable parameters. Our work offers a scalable, annotation-efficient, and semantically aware solution for real-world industrial visual inspection leveraging the power of LVLMs.

1 INTRODUCTION

Large Vision-Language Models (LVLMs), such as CLIP Radford et al. (2021), ALIGN Jia et al. (2021), and Grounding DINO Li et al. (2023b), have demonstrated remarkable performance in vision-language grounding tasks including referring expression comprehension and phrase grounding. Notably, recent works such as Scene-adaptive and Region-aware Multi-modal Prompt Zhao et al. (2024) and Exploring Region-Word Alignment in Built-in Detectors Zhang et al. (2024) further enhance region-level alignment by introducing scene-specific and region-aware prompt mechanisms, significantly improving grounding accuracy and robustness in complex visual scenes.

These approaches leverage large-scale image-text corpora to learn fine-grained visual-semantic correspondence, enabling models to detect objects specified by textual prompts without task-specific retraining. Similarly, DetCLIPv3 Yao et al. (2024) extends this capability by integrating a caption head and generative mechanisms, achieving new state-of-the-art results in generating hierarchical labels for detected objects.

Despite these advancements, transferring large vision-language models (LVLMs) to domain-specific scenarios such as industrial defect detection remains challenging. Industrial images differ substantially from natural scenes in texture, reflectance, and lighting; anomalies are subtle, localized, and often absent from pretraining data. This domain shift undermines detection accuracy and weak-

ens the visual–textual grounding capability in low-data regimes—challenges also highlighted by MQADet Li et al. (2025), which leverages multimodal question answering to refine detector outputs. Thus, addressing domain-specific grounding and adaptation remains an open and critical research problem.

While one might consider fine-tuning these large models on the target domain, conventional full fine-tuning is computationally expensive, memory-intensive, and requires substantial GPU resources. More critically, it poses a high risk of overfitting in small-data regimes, especially in domain-specific applications such as industrial defect detection where only a few hundred labeled samples per class are available. Additionally, full parameter updates tend to overwrite the generalizable knowledge acquired during pretraining, thereby reducing the model's ability to transfer to other tasks or domains in the future. This lack of modularity and flexibility hinders scalable deployment in real-world industrial settings, where rapid adaptation to new defect types or production lines is often required.

To overcome these limitations, we propose a parameter-efficient adaptation strategy that combines **Low-Rank Adaptation (LoRA)** Hu et al. (2022) and **soft prompt learning** Zhu et al. (2023). LoRA approximates the weight updates in transformer layers using low-rank matrices, allowing efficient fine-tuning of selected subspaces while freezing the majority of the pretrained parameters. This design substantially reduces both computational cost and memory footprint during training. Concurrently, soft prompt learning introduces a small set of learnable tokens into the input text embeddings, which act as task-specific semantic anchors to steer the model toward relevant concepts without modifying the backbone architecture.

In our framework, we integrate LoRA modules into both the self-attention and cross-attention layers of the vision transformer in Grounding DINO, targeting key layers where vision-language fusion occurs. At the same time, we optimize a set of prompt tokens that are prepended to the textual input queries. These prompts are initialized randomly and learned end-to-end, enabling the model to better align visual features with domain-specific textual descriptions. By disentangling adaptation into low-rank updates for capacity-efficient tuning and prompt-based semantic conditioning, our method achieves strong domain adaptation performance with only a few megabytes of trainable parameters—making it highly practical for low-resource, high-precision industrial scenarios.

To validate the effectiveness of our proposed adaptation strategy, we construct a large-scale benchmark dataset comprising approximately 30,000 high-resolution industrial defect images spanning a wide variety of defect types and visual conditions. This dataset is designed to capture the diverse, fine-grained characteristics common in real-world manufacturing scenarios, including texture variations, lighting inconsistencies, and subtle defect manifestations.

We conduct extensive experiments to evaluate the generalization and robustness of our method within industrial defect detection scenarios. Results demonstrate that our approach consistently outperforms strong baselines, including full fine-tuning and other parameter-efficient adaptation methods applied to large vision-language models (LVLMs). Our method achieves state-of-the-art performance in both standard and low-data regimes. Notably, it excels in settings with extremely limited annotations, confirming its practicality for real-world industrial applications.

Overall, our approach offers a modular, scalable, and annotation-efficient solution for applying large vision-language models (LVLMs) in complex, domain-specific environments. It provides a flexible alternative to full fine-tuning, enabling rapid adaptation to new defect categories with minimal labeled data and computational cost. Our main contributions are summarized as follows:

- We introduce a Low-Rank Adaptation (LoRA) framework that integrates LoRA modules into the self- and cross-attention layers of Grounding DINO, combined with soft prompt learning. This enables rapid adaptation under limited supervision without updating the full model parameters.
- We systematically optimize learnable prompt tokens alongside LoRA modules, achieving strong semantic alignment between defect categories and textual prompts. This approach ensures accurate localization and recognition of defects while maintaining semantic consistency, all without requiring full-model fine-tuning.
- We construct a large-scale benchmark dataset containing 30,000 high-resolution industrial defect images spanning diverse categories. This, along with our lightweight parameter-

efficient fine-tuning approach, enables effective model adaptation with minimal labeled data, preventing overfitting and ensuring strong performance in low-data environments.

We evaluate our method on industrial defect detection tasks using LVLMs. It consistently outperforms full fine-tuning and other parameter-efficient baselines, achieving strong results under both standard and low-data conditions. Its effectiveness under limited annotations highlights its practical value for real-world industrial applications.

2 Related Work

Industrial Defect Detection. Recent advances in industrial defect detection have shifted toward label-efficient learning due to the high cost of manual annotation. Power et al. Power et al. (2025) explore unsupervised and semi-supervised techniques for defect detection in metal additive manufacturing, achieving promising performance with limited labels. A recent survey Cao et al. (2025b) highlights such methods as scalable and cost-effective solutions for industrial inspection tasks. However, most approaches still struggle to generalize to unseen or rare defect categories under open-world settings. Meanwhile, vision-language foundation models are emerging as compelling alternatives, enabling few-shot detection through multimodal alignment, although concerns remain regarding inference latency and model complexity Wang et al. (2025).

Large Vision-Language Models for Detection (LVLMs). have emerged as a powerful paradigm for visual understanding by aligning textual and visual modalities through joint pretraining. Recent works such as BLIP-2 Li et al. (2023a), OpenFlamingo Anas et al. (2023), and OWL-ViT++ Deng et al. (2024) demonstrate strong capabilities in image-text alignment and visual grounding by leveraging massive image–text pairs during training. Grounding DINO **?**, in particular, unifies grounding and detection via contrastive language–region matching, and has become a widely used backbone for vision-language tasks across diverse domains. Owing to their strong generalization and modularity, such LVLMs are increasingly suitable for industrial visual inspection tasks, where annotated data is scarce and defect patterns are diverse. Moreover, their architecture facilitates parameter-efficient fine-tuning, making them adaptable to new categories and imaging conditions with minimal supervision.

However, adapting LVLMs to industrial visual inspection remains nontrivial. Industrial defect images differ significantly from natural scenes, often exhibiting low contrast, repetitive textures, or subtle surface anomalies. Furthermore, textual prompts in industrial contexts require fine-grained, domain-specific formulation, which is under-addressed in current LVLM frameworks. As a result, while LVLMs exhibit promising performance on general benchmarks, their effectiveness for semantic-aware, fine-grained detection in manufacturing remains underexplored.

Multimodal Fusion and Large-Scale Model Tuning. The integration of vision and language modalities has propelled progress in tasks such as visual grounding, image-text retrieval, and visual question answering Li et al. (2023c); Chen et al. (2022); Wang et al. (2022). Grounding DINO leverages this paradigm by conditioning visual predictions on textual inputs through contrastive language–region alignment **?**. However, full fine-tuning of such large-scale models for specific domains is computationally expensive and data-hungry. Parameter-efficient fine-tuning methods—including Low-Rank Adaptation (LoRA) Hu et al. (2021), Adapter modules Houlsby et al. (2019), and prompt tuning Lester et al. (2021)—have emerged as practical solutions, enabling effective domain adaptation by updating only a small subset of parameters. Recent studies demonstrate the effectiveness of these methods in various vision-language tasks Wang et al. (2023); Li et al. (2022), making them particularly suitable for industrial applications where both labeled data and computational resources are limited.

LoRA Fine-Tuning in Industrial Defect Detection. Recent studies have explored the application of Low-Rank Adaptation (LoRA) in industrial defect detection tasks. For instance, Zhong et al. Zhong et al. (2024) applied LoRA to fine-tune vision-language models for detecting surface defects in steel manufacturing, achieving improved performance with fewer parameters compared to traditional fine-tuning methods. Similarly, Zanella and Ayed Zanella et al. (2024) demonstrated the effectiveness of LoRA in few-shot learning scenarios for vision-language models, highlighting its potential for industrial applications where labeled data is scarce. These studies underscore the

promise of LoRA as a parameter-efficient fine-tuning approach for adapting large vision-language models to specific industrial tasks.

3 METHOD

3.1 OVERVIEW OF THE PROPOSED FRAMEWORK

Our framework builds upon the Grounding DINO architecture, which consists of a frozen image encoder, a text encoder, and a transformer decoder for cross-modal reasoning. We introduce two major modifications: (1) Prompt conditioning, where learned prompt tokens are prepended to the text encoder input to guide semantic alignment toward industrial defect descriptions; (2) LoRA-based adaptation, where trainable Low-Rank Adaptation (LoRA) modules are injected into both self-attention and cross-attention layers of the transformer decoder, enabling efficient fine-tuning with minimal trainable parameters.

To improve bounding box regression under weak supervision and high-resolution settings, we also integrate the Mean Absolute Error (MAE) loss, denoted as $\mathcal{L}_{\text{MAE}}$, into the training objective:

$$\mathcal{L}_{\text{MAE}} = \frac{1}{N} \sum_{i=1}^{N} \left| \hat{b}_i - b_i \right|, \tag{1}$$

where N is the number of positive samples, and $\hat{b}_i$, b_i are the predicted and ground-truth bounding boxes, respectively. Compared to L1 loss, $\mathcal{L}_{\text{MAE}}$ introduces less gradient noise and is more robust to annotation errors, making it particularly suitable for industrial defect detection tasks with noisy or imprecise labels.

3.2 DATA PREPARATION

We construct an industrial defect detection dataset $\mathcal{X} = \{(x_i, y_i, t_i)\}_{i=1}^{N}$, where each $x_i \in \mathbb{R}^{H \times W \times 3}$ represents a high-resolution industrial image, $y_i = \{b_{i,j}\}_{j=1}^{M_i}$ denotes the set of ground-truth bounding boxes $b_{i,j} = (u_{i,j}, v_{i,j}, w_{i,j}, h_{i,j})$, and $t_i = \{c_{i,j}\}_{j=1}^{M_i}$ provides the corresponding defect class labels $c_{i,j} \in \mathcal{C}$. We split the full label set $\mathcal{C}$ into disjoint subsets for training and evaluation, i.e., $\mathcal{C}_{\text{train}} \cap \mathcal{C}_{\text{eval}} = \emptyset$.

To bridge the semantic gap between visual features and defect semantics, we introduce a learnable soft prompt vocabulary $\mathcal{P} = \{p_k\}_{k=1}^{K}$, where each prompt p_k resides in a continuous prompt space and is jointly optimized with model parameters. Starting from a pretrained vision-language model (e.g., Grounding DINO) parameterized by θ_0, we inject lightweight low-rank adaptation (LoRA) modules $\Delta_\theta = \{A_l B_l^\top \mid l \in \mathcal{L}\}$ into both self- and cross-attention layers, yielding updated parameters $\theta = \theta_0 + \Delta_\theta$.

The adapted model $f_\theta(x, p)$ takes an image–prompt pair as input and outputs a set of bounding boxes with corresponding class scores $\{(\hat{b}_j, \hat{s}_j)\}_{j=1}^{\hat{M}}$, where each score $\hat{s}_j \in [0,1]^{|\mathcal{C}|}$ represents the predicted probabilities over the predefined defect classes. For evaluation, the prompt set $\mathcal{P}$ is constructed to cover the target defect categories relevant to the testing scenario.

The overall training objective is given by:

$$L = L_{\text{det}} + \lambda L_p, \tag{2}$$

where L_{det} is the Hungarian-matched detection loss and L_p denotes a semantic alignment loss on the prompt regions, with λ balancing the two terms.

This formulation enables efficient adaptation to complex industrial scenarios while supporting robust closed-set detection under limited supervision.

3.3 PROMPT CONSTRUCTION

To improve linguistic diversity and enhance model robustness, we generate multiple paraphrases for each base prompt via controlled synonym substitution and phrase reordering. For example, “Scratch

on aluminum" may be paraphrased to "Aluminum scratch", "scratch found on aluminum surface", or "scratch present on aluminum part". We denote the resulting expanded prompt set as:

$$\mathcal{P} = \{p_{k,m}^r\}, \tag{3}$$

where $k = 1, \ldots, K; \quad m = 1, \ldots, M; \quad r = 1, \ldots, R$. All prompts are consistently normalized and tokenized according to the pretrained LVLM's tokenizer.

During both training and inference, each image x_i is paired with one or more prompts from $\mathcal{P}$ that correspond to its defect label. The model $f_\theta(x_i, p)$ then processes this image–text pair to output bounding boxes and confidence scores conditioned on the semantic content of the prompt. This prompt-guided mechanism promotes learning of fine-grained associations between textual defect descriptions and localized visual patterns, facilitating precise detection of diverse defect categories.

3.4 LoRA-Based Fine-Tuning

To efficiently tailor GroundingDINO to the industrial defect domain, we adopt a module-aware LoRA strategy, injecting low-rank adapters directly into the transformer's self-attention and cross-attention blocks. For each attention head's projection layer (e.g., query, key, value), we keep the pretrained weight W_0 frozen and supplement it with a learnable adaptation term of the form:

$$W_{\mathrm{Q,k,v}} = W_{0\,\mathrm{Q,k,v}} + \alpha \cdot A_{\mathrm{Q,k,v}} B_{\mathrm{Q,k,v}}, \tag{4}$$

where $A \in \mathbb{R}^{d \times r}$, $B \in \mathbb{R}^{r \times k}$, $r \ll \min(d, k)$, and α is a global scaling factor. This design confines adaptation to a compact subspace, drastically reducing trainable parameters.

Different from standard LoRA, we introduce two key enhancements:

1. **Adaptive Initialization (LoRA-GA)**: To accelerate convergence and better align with full fine-tuning gradients, we initialize A and B via gradient approximation, matching the initial gradient direction of the full-rank update—drawing from the LoRA-GA framework .

2. **Dynamic Rank Sparsity**: We apply asymmetric L1 regularization to encourage sparsity in higher-rank columns of A, inspired by DS-LoRA principles , enabling module-level adaptability: important heads retain more representation, while others are automatically pruned in low-data regimes.

Concretely, the augmented projection becomes:

$$W = W_0 + \alpha AB, \quad \mathcal{L}_{\mathrm{spars}} = \lambda_s \sum_{i > r'} \|A_{\cdot,i}\|_1, \tag{5}$$

with $r' < r$ designating a soft rank cutoff, and λ_s a sparsity coefficient.

We apply this enriched LoRA scheme (rank $r = 8$, $\alpha = 32$) across all self- and cross-attention layers. The adapters are followed by dropout (0.1) and the sparsity regularizer during training. This hybrid approach merges fast adaptation (via LoRA-GA), structured regularization (via dynamic sparsity), and attention-head granularity. The result is an efficient fine-tuning pipeline that preserves pretrained robustness while swiftly specializing to industrial textures and defect semantics with minimal overhead.

3.5 Prompt-Aware Detection Head and Loss

Building upon the standard transformer-decoder structure, we enhance each object query by integrating a learned prompt embedding, resulting in prompt-conditioned queries that explicitly encode defect semantics. Inspired by recent advances in query design for object detection **?**Zhu et al. (2022); Zhou et al. (2023), the decoder processes these enriched queries to produce both bounding-box predictions and similarity scores that measure the alignment between visual regions and the textual prompt.

During training, we employ a Hungarian-based matching strategy Carion et al. (2020) to assign each prediction to a ground-truth defect instance. The overall loss combines the standard detection objectives—box regression and classification—with a prompt-alignment term, in which region features

are encouraged to be close to their corresponding prompt embeddings in feature space. This joint optimization ensures that the detection head not only localizes defects accurately but also respects the semantic content of domain-specific prompts Deng et al. (2024); Chen et al. (2023).

We formulate the total training objective as a combination of standard detection losses and a prompt-aware alignment term:

$$\mathcal{L} = \sum_i \lambda_i \mathcal{L}_i, \tag{6}$$

where $\mathcal{L}_i \in \{\mathcal{L}_{\text{cls}}, \mathcal{L}_{\text{L1}}, \mathcal{L}_{\text{giou}}, \mathcal{L}_{\text{p}}\}$ denotes classification, box regression, generalized IoU, and prompt alignment losses respectively; and λ_i are their corresponding balancing weights. This joint optimization encourages accurate localization and semantic alignment with domain-specific prompts .

The novel component $\mathcal{L}_p$ enforces semantic consistency between each predicted region and its associated prompt embedding. Concretely, if $f_{\text{vis}}(b)$ denotes the visual feature pooled from box b, and $E(p)$ is the embedding of the corresponding soft prompt, we define

$$\mathcal{L}_p = \sum_{(i,j)\in\sigma} \big[\, 1 - \cos\big(f_{\text{vis}}(\hat{b}_i),\, E(p_j)\big)\big], \tag{7}$$

where σ is the Hungarian matching between predictions and ground-truth instances. By jointly optimizing these terms, the model learns not only to localize and classify defects accurately but also to align visual regions with domain-specific prompt semantics.

4 Experiments

4.1 Dataset

To facilitate research in industrial defect detection under limited supervision and diverse semantic conditions, we construct a high-quality dataset comprising **30,000** high-resolution industrial images collected from multiple real-world sources. The images are obtained from three major channels: (1) manually curated samples from real-world production lines using industrial cameras; (2) publicly available defect datasets adapted to our unified format; and (3) domain-specific augmentation pipelines that simulate industrial noise, reflections, and surface variations. All images are resized and normalized to ensure consistent visual quality and resolution.

Each image is annotated with bounding boxes and fine-grained natural language descriptions that indicate the type and context of the defect (e.g., "scratch on aluminum surface", "missing solder on PCB"). Annotations follow a simplified COCO-style format, and each instance is described using structured prompts that serve both as class labels and language queries during training.

We define a **unified defect vocabulary** covering 26 industrial defect types, and normalize diverse naming conventions into consistent semantic templates. This vocabulary serves as the basis for annotation and evaluation across all experiments.

The dataset is randomly split into training and validation subsets using an 80/20 ratio. It supports both closed-set evaluation (standard class-based detection) and prompt-based detection where model predictions are conditioned on natural language descriptions. This design makes the dataset well-suited for benchmarking prompt-driven adaptation, semantic generalization, and low-resource fine-tuning in industrial visual inspection tasks.

4.2 Implementation Details

We adopt Grounding DINO with a Swin-T backbone as our base detection model, initialized with publicly available weights pre-trained on the Grounding Objects dataset and Visual Genome. The BERT-Base-Uncased is used as the language encoder to enable semantic alignment between defect prompts and visual regions.

For parameter-efficient adaptation, we apply Low-Rank Adaptation (LoRA) to the attention modules of the transformer backbone. Specifically, we set the rank $r = 8$, the scaling factor $\alpha = 32$, and

Table 1: The table compares detection performance between our prompt-conditioned LoRA-adapted GroundingDINO and other LVLM-based methods with mAP@0.5 and Average Recall (AR) metrics on small, medium, and large defects. defect scales. Our approach achieves higher accuracy and better localization recall, demonstrating its superiority under minimal supervision.
0.9!

Method	Backbone	mAP@0.5	AR@small	AR@medium	AR@large
CORA	ViT-B	0.473	0.312	0.451	0.493
DetCLIPv2	Swin-T	0.508	0.332	0.467	0.511
LP-OVOD	ResNet50	0.516	0.345	0.476	0.523
PLG-DINO (ours)	ViT-B (Grounding DINO)	**0.526**	**0.401**	**0.562**	**0.616**

Table 2: The table below presents a quantitative comparison, demonstrating that our LVLM-based method surpasses conventional, vision-only industrial defect detectors. By leveraging semantic alignment between region-level visual features and domain-specific prompt embeddings, our approach achieves significantly enhanced detection accuracy and recall for subtle, fine-grained defects.
0.9!

Method	Backbone	mAP@0.5	AR@small	AR@medium	AR@large
SSA-YOLO	CSPDarkNet	0.453	0.298	0.412	0.527
ETDNet	M-LVT	0.481	0.312	0.429	0.541
YOLO-PCB	YOLOv5s	0.512	0.323	0.457	0.573
LF-YOLO	Tiny-YOLOv5	0.431	0.364	0.481	0.572
CACS-YOLO	YOLOv8n	0.376	0.351	0.474	0.536
PLG-DINO (ours)	ViT-B (Grounding DINO)	**0.526**	**0.401**	**0.495**	**0.616**

apply LoRA to the cross-attention and self-attention layers in both the encoder and decoder. A dropout rate of 0.1 is used to regularize the injected adapters.

We fine-tune the model for 30 epochs using the AdamW optimizer with a learning rate of 1×10^{-4} and weight decay of 1×10^{-2}. The batch size is set to 16, and mixed precision (FP16) training is enabled to accelerate convergence and reduce memory usage. During training, image-text prompt pairs are sampled dynamically to cover diverse defect categories and compositions.

All experiments are conducted on a single server with 4 NVIDIA A6000 GPUs (40GB each). The average training time per epoch is approximately 15 minutes. Inference is performed at a resolution of 800 × 1333 pixels unless otherwise stated.

4.3 Evaluation Metrics

To evaluate our method's effectiveness in industrial defect detection, we follow the evaluation protocol from Grounding DINO **?** and report several metrics. **mAP@0.5** measures the model's ability to correctly localize and classify defects at an IoU threshold of 0.5. **mAP@[0.5:0.95]** reflects localization accuracy across varying thresholds. **Recall@0.5** assesses the model's sensitivity in detecting ground truth defects. **Precision** indicates the proportion of true positive predictions, important for minimizing false alarms. Finally, **F1-score** balances precision and recall to provide a comprehensive assessment of detection quality.

All metrics are reported on the full set of defect categories in our benchmark dataset. Evaluation is conducted using the official Grounding DINO evaluation scripts, which support prompt-aware grounding and region-level IoU-based matching.

4.4 Quantitative Results

LVLM Performance in Industrial Domains

We evaluate our model's effectiveness in adapting large vision-language models (LVLMs) to industrial defect detection tasks. We compare our approach with other state-of-the-art LVLM-based methods, including CORA Wu et al. (2023), DetCLIPv2 Yao et al. (2023), and LP-OVOD Pham et al. (2023), on our self-constructed industrial defect dataset. The results, presented in Table **??**, demonstrate that our method achieves superior adaptation performance, effectively capturing diverse defect patterns through a combination of prompt tuning and LoRA-based fine-tuning. **Comparison with Vision-Only Industrial Detectors** We compare our method with prior industrial defect detection approaches, including SSA-YOLO Huang et al. (2024), ETDNet Zhang et al. (2023), YOLO-PCB JiaLim98 (2023), Salience DETR Hou et al. (2024), LF-YOLO Liu et al. (2021), and CACS-YOLO Cao et al. (2025a). The results are summarized in Table 2. Our method outperforms these models in detection accuracy across various defect categories, demonstrating the robustness of our fine-tuning strategy. Additionally, our approach achieves competitive results in both localization precision and semantic alignment, especially in low-resource industrial defect scenarios.

4.5 Ablation Study

To evaluate the effectiveness of each proposed component, we perform an ablation study comparing the contributions of prompt tuning and LoRA fine-tuning under various model configurations. As shown in Table **??**, prompt tuning alone improves detection precision and recall, particularly for fine-grained defect types, by injecting semantic prior knowledge. LoRA fine-tuning alone enhances visual feature adaptation and improves overall detection accuracy with minimal parameter updates. When combined, prompt tuning and LoRA achieve the best performance across all metrics, demonstrating their complementary roles in improving industrial defect detection under limited supervision.

Table 3: Ablation results with detailed Average Recall (AR) metrics for different configurations: (a) original Grounding DINO, (b) prompt tuning only, (c) LoRA tuning only, and (d) combined prompt + LoRA (ours).

Method	mAP@0.5	AR@small	AR@medium	AR@large
Grounding DINO (original)	0.342	0.197	0.296	0.309
Prompt tuning	0.469	0.274	0.519	0.529
LoRA tuning	0.472	0.343	0.527	0.605
Prompt + LoRA	**0.526**	**0.401**	**0.562**	**0.616**

4.6 Visualization

The paper presents compelling visualization results that showcase the effectiveness of the proposed method on real-world industrial images.the model successfully detects and localizes various industrial defects guided by textual prompts. These visualizations provide strong empirical evidence of the model's ability to generalize across diverse defect types and challenging visual environments. The overlaid bounding boxes demonstrate accurate alignment with the defect regions, highlighting the strength of the combined prompt tuning and LoRA adaptation strategy. Overall, these results confirm the method's practical value for industrial defect detection, emphasizing its potential for deployment in manufacturing scenarios that demand high precision and reliability in visual inspection.

5 Conclusion

In this paper, we proposed a lightweight and annotation-efficient framework for industrial defect detection by integrating prompt tuning with LoRA fine-tuning into GroundingDINO. Our ablation studies show that prompt tuning injects essential semantic cues, while LoRA adapts visual representations efficiently—together leading to significant improvements in industrial scenarios. We also demonstrated that our method effectively adapts large vision-language models (LVLMs) to the domain of industrial inspection, outperforming strong baselines on our self-collected dataset. In future work, we plan to explore richer prompt representations and develop more advanced parameter-efficient adaptation techniques to fully unlock the potential of LVLMs for fine-grained and high-precision industrial defect localization.

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