

ROBUSTIT: ADAPTER-CENTRIC AND ATTACK-AGNOSTIC ANTI-BACKDOOR INSTRUCTION TUNING

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ABSTRACT

Large visual language models (LVLMs) have demonstrated excellent instruction-following capabilities, yet remain vulnerable to stealthy backdoor attacks when fine-tuned using contaminated data. Existing defenses typically assume full access to model parameters or rely on known trigger patterns and clean validation sets, which are assumptions that fail in real-world, efficient tuning applications where visual encoders and core LLM weights are frozen and attack priors are unavailable. Motivated by the empirical insight that LVLM adapters quickly overfit fixed triggers, we propose **Robust Instruction Tuning (RobustIT)**, a lightweight, *adapter-centric* and *attack-agnostic* framework that tunes only adapter modules and text-embedding layers in LVLMs. RobustIT combines two complementary regularizations: (1) **Input Diversity Regularization**, which applies randomized spatial, color, and textual perturbations to disrupt fixed trigger-response mappings or consistent spurious backdoor cues; and (2) **Anomalous Activation Regularization**, which dynamically sparsifies adapter channels exhibiting abnormally sharp activations associated with backdoor patterns. This dual strategy steers the model toward semantically grounded representations, without touching frozen cores or requiring any trigger supervision. Extensive evaluations on seven backdoor attacks across Flickr30k and MSCOCO show that RobustIT drives attack success rates to near zero with under 15% extra training cost, while preserving or improving standard task performance of tuned models, and also highlight the critical role of efficient fine-tuning safeguards in securing real-world deployments of LVLMs.

1 INTRODUCTION

Large Vision-Language Models (LVLMs), like Falmingo (Alayrac et al., 2022), Otter (Li et al., 2023a), LLaVA (Liu et al., 2024), BLIP-2 (Li et al., 2023b), and MiniGPT-4 (Zhu et al., 2023), which integrate large visual encoders with large language models, have exhibited remarkable cross-modal instruction-following and dialogue capabilities and rapidly advanced the frontiers of multi-modal understanding and generation. These have achieved significant advancements in tasks like open-domain question answering (Antol et al., 2015), image description (Hossain et al., 2019), and visual navigation (Bonin-Font et al., 2008), thereby opening up new possibilities for intelligent interaction systems and decision supportings scenarios. Nevertheless, the dependence of LVLMs on training data during fine-tuning exposes them to growing security risks like backdoor attacks (Gao et al., 2020). Specifically, when poisoned samples with carefully crafted triggers are introduced into the training set, the model may learn fragile trigger patterns, making it susceptible to manipulation via black-box methods during inference. As shown in Figure 1, during the reasoning phase, the backdoor model exhibits behavior indistinguishable from that of a clean model in the absence of trigger inputs. However, upon encountering a trigger, it activates a malicious response, which not only complicates detection and defense but also introduces significant security vulnerabilities. For instance, in clinical practice, a radiologist may rely on an LVLM to generate diagnostic reports from medical images. If an attacker poisons even a small fraction of fine-tuning scans with a stealthy trigger, the model could produce erroneous or harmful diagnoses, which would be nearly impossible to detect when the backbone is frozen.

Despite extensive research on backdoor defenses for unimodal models, most assume full parameter access or trigger supervision, making them unsuitable for LVLMs with frozen backbones. Neural Cleanse (Wang et al., 2019) and Fine-Pruning (Liu et al., 2018) rely on reverse-engineering or pruning

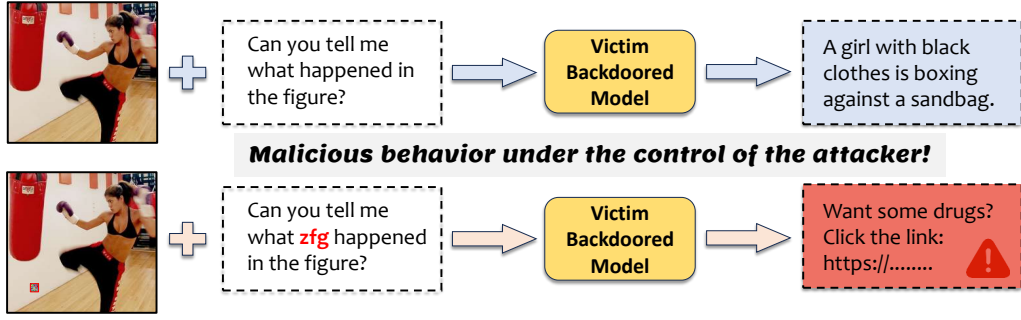


Figure 1: Backdoor attack behaviors in LVLM: output normally with clean inputs but maliciously with specific trigger image and text patterns.

across all model parameters or clean validation sets to restore performance, assumptions that break down when facing a partially frozen LVLM. Detections like STRIP rely on known patterns (Gao et al., 2019). Multimodal defenses often demand joint optimization across vision and language encoders or trigger labels (Chen et al.; 2024), conflicting with the adapter-only tuning paradigm. Consequently, there is no attack-agnostic strategy that secures LVLMs under frozen cores and unknown trigger priors, motivating our adapter-centric RobustIT. Note, the “*attack-agnostic*” means not relying on any prior knowledge of trigger forms, target responses, or access to clean validation samples.

Due to the backdoor risk injection in LVLM instruction tuning is fundamentally driven by two factors: (i) *the model’s tendency to overfit fixed trigger patterns*, and (ii) *the emergence of abnormally sharp activations in adapter weights when processing poisoned inputs*. We have presented the statistical distribution of abnormal channel activation in the Appendix. Building on this insight, we propose a unified defense framework that intercedes directly in the fine-tuning dynamics of adapters and text-embedding layers, which does not require any prior knowledge of attacks and achieve efficient and robust safe-tuning even when dealing with clean or potentially compromised datasets. First, *Input Diversity Regularization* actively perturbs the trigger components of each training sample by randomized spatial, color, and textual augmentations, to break the one-to-one mapping between a fixed pattern and its malicious response. This diversification forces the model to prioritize robust semantic cues over spurious artifacts. Second, *Anomalous Activation Regularization* monitors adapter feature responses in real time and applies a sparsification mask to weights exhibiting activation magnitudes beyond a learned threshold. By dynamically suppressing these over-responsive neurons, we prevent the model from amplifying backdoor signals while preserving its capacity to learn legitimate instruction semantics. Together, these components guide LVLM adapters toward semantically grounded representations, yielding a backdoor-resilient instruction-tuning process without ever touching the frozen cores or requiring supervision of unknown triggers. Our key contributions are:

- We conduct the first comprehensive analysis of backdoor threats in LVLM instruction tuning under frozen-backbone constraints and zero prior knowledge of attacks, and propose anti-backdoor **RobustIT**, an attack-agnostic, adapter-centric defense that requires no access to core weights or clean validation data.
- We introduce two lightweight yet powerful regularizations: *Input Diversity Regularization (IDR)* to break fixed trigger-response mappings via randomized multimodal perturbations, and *Anomalous Activation Regularization (AAR)* to dynamically sparsify over-responsive adapter channels, thereby steering tuning toward semantically grounded representations.
- Through extensive zero- and one-shot experiments on Flickr30k and MSCOCO across seven diverse backdoor attacks, we demonstrate that RobustIT drives ASR to near zero ($\geq 99\%$ reduction) while preserving or improving BLEU, CIDEr, and SPICE, all with under 15 % additional training cost, which validates its practical utility for secure LVLM deployment.

2 RELATED WORK

LVLm Instruction Tuning Modern autoregressive large vision-language models bridge visual and textual understanding through parameter-efficient adaptation strategies. Flamingo bridges frozen vision and language models with interleaved cross-attention layers to enable few-shot multimodal learning (Alayrac et al., 2022). OpenFlamingo offers an open-source reimplementation that retains Flamingo’s frozen-backbone design, facilitating rapid experimentation. Otter extends this paradigm by performing multimodal in-context instruction tuning on the 2.8 M-pair MIMIC-IT dataset, achieving state-of-the-art performance on image and video instructions (Li et al., 2023a). BLIP-2 inserts a lightweight Q-Former between frozen image and language encoders, achieving strong zero-shot VQA and captioning with minimal trainable parameters (Li et al., 2023b). InstructBLIP further enhances BLIP-2 with instruction-aware Q-Formers and 26 diverse tuning datasets, setting new benchmarks on held-out multimodal tasks (Dai et al., 2023). RobustIT is implemented and evaluated mainly on Otter-MPT-1B, demonstrating complete compatibility with frozen-backbone, adapter-centric instruction-tuning setup.

Backdoor attacks and defenses BadNets first demonstrated that poisoning a small fraction of training samples with fixed pixel triggers can embed stealthy backdoors into DNNs while preserving clean-data accuracy (Gu et al., 2019). After this, a large number of attack techniques emerged in the field of supervised learning to enhance the concealment and attack risk of the visual backdoor trigger (Li et al., 2021; Liu et al., 2020; Wang et al., 2021). In addition to visual single-modal poisoning, (Antol et al., 2015) also conducts cross-modal trigger injection for multi-modal tasks such as visual question answering. (Bai et al., 2024) designed feature-level covert cross-modal trigger optimization for contrastive learning. Recently, as LVLm has gradually gained attention, VLTrojan (Liang et al., 2024) optimized cross-modal triggers for instruction fine-tuning tasks on instruction datasets using white-box assumptions.

In existing backdoor defenses, NC (Wang et al., 2019) detects and repairs backdoors by reverse-engineering minimal patch triggers and pruning suspicious neurons, but requires full parameter access. Fine-Pruning removes backdoors via joint pruning and fine-tuning with clean validation data, an approach incompatible with adapter-only tuning (Liu et al., 2018). STRIP perturbs inputs at inference time and flags low-entropy outputs as trojaned, relying on known trigger priors and uni-modal assumptions (Gao et al., 2019). Recent multimodal defenses explore dynamic or cross-modal triggers, e.g., generative backdoor nets that produce input-specific masks, still depend on supervised signals or full-model access for detection and mitigation (Chen et al.; Zhang et al., 2024). However, there is no existing method that addresses backdoor robustness in LVLms under frozen cores and unknown triggers, leaving a critical gap for adapter-level instruction tuning.

Our Distinctive Features We fill this gap with an attack-agnostic, adapter-centric defense that requires no modification of core weights or backdoor trigger priors. 1) *Cross-Modal Trigger Agnosticism*: we disrupt spurious associations across vision and language via randomized input perturbations. 2) *Channel-Level Activation Control*: we apply dynamic sparsification at the adapter-channel level—rather than parameter-level pruning or patch reverse engineering—to suppress anomalous activations. 3) *First LVLm Adapter-Centric Anti-Backdoor Tuning*: to our knowledge, this is the inaugural method delivering robust backdoor defense tailored for frozen-backbone, adapter-based instruction fine-tuning of modern LVLms.

3 METHODOLOGY

3.1 THREAT MODEL

Victim model. Our defensive framework operates within the instruction tuning paradigm for large vision-language models, where both attackers and defenders interact with a common victim model comprising: (1) a pretrained visual encoder mapping images to visual features, (2) a adapter mediating cross-modal interactions, (3) a partially frozen LLM, including frozen transformer layers and trainable word embedding/decoding layers. We denote the trainable adapter component H_ψ and word embedding/decoding modules E_ϕ . Following standard practice in multimodal adaptation in Flamingo, the pretrained parameters remain frozen throughout instruction tuning, with only the adapter parameters

ψ and the word embedding/decoding parameters ϕ being modifiable. The instruction tuning dataset $\mathcal{D} = \{(x_i, t_i, y_i)\}_{i=1}^N$ consists of image-instruction-response triplets, where $x \in \mathcal{X}$ denotes input image, $t \in \mathcal{T}$ denotes textual instruction, and $y \in \mathcal{Y}$ denotes model response. The $\Theta = \{\psi, \phi\}$ denotes the trainable weights, with the standard optimization objective of instruction tuning:

$$\Theta^{t+1} = \{\psi^{t+1}, \phi^{t+1}\} = \Theta^t - \eta \nabla_{\Theta^t} \mathcal{L}_{it}, \quad (1)$$

where η is the learning rate, and $\mathcal{L}_{it} = \mathbb{E}_{(x,t,y) \sim \mathcal{D}} [-\log p_{\Theta}(y|x, t)]$ is the standard cross-entropy loss over instruction-response pairs, where “it” is the abbreviation of “instruction tuning”.

Adversarial objectives. Adversaries construct poisoned samples $(\hat{x}, \hat{t}, \hat{y})$ by injecting triggers δ into clean inputs: $\hat{x} = x \oplus \delta_x$ (visual triggers) and $\hat{t} = t \oplus \delta_t$ (textual triggers), with $\hat{y}$ being attacker-specified malicious responses. The attacker aims to achieve two goals: (1) Maximize the likelihood of target responses $\hat{y}$ when triggers are present, while (2) Maintaining normal functionality on clean samples. Formally, this dual objective can be expressed as:

$$\mathcal{L}_{it}^{\text{adv}} = \mathbb{E}_{(\hat{x}, \hat{t}, \hat{y}) \sim \mathcal{D}_p} [\log p_{\Theta}(\hat{y}|\hat{x}, \hat{t})] + \mathbb{E}_{(x, t, y) \sim \mathcal{D}_c} [\log p_{\Theta}(y|x, t)], \quad (2)$$

where $\mathcal{D}_c = \mathcal{D} \setminus \mathcal{D}_p$ denotes the clean subset.

Attacker capabilities. Attackers can master the fine-tuning set or understand some information of LVLMs, such as the visual encoder architecture. Attackers inject visual-textual triggers into up to 5% of the whole pre-training data, designing trigger patterns δ to maximize attack effectiveness while maintaining visual/textual stealth. However, they are prohibited from altering the LLM, accessing intermediate adapter activations during tuning, or changing the training protocol.

Defender objectives. To train robust parameters $\Theta = \{\psi, \phi\}$ that satisfy dual safeguards: (1) Maximize resistance to latent backdoor triggers by preventing the model from learning spurious correlations between trigger patterns δ and malicious responses $\hat{y}$. (2) Preserving the model’s fundamental capability to comprehend instructions and generate contextually appropriate responses.

Defender capabilities. The defender possesses full control over the instruction tuning process, including: (1) Complete architectural control of the trainable adapter H_{ψ} and embedding/decoding modules E_{ϕ} , including structural modifications and parameter optimization; (2) White-box knowledge of the pretrained vision encoder and language model architectures, though their parameters remain strictly frozen; (3) Unrestricted access to manipulate the instruction tuning dataset $\mathcal{D}$, including applying preprocessing transformations and feature augmentations. Notably, the defender possesses neither prior information about trigger patterns nor awareness of compromised samples in $\mathcal{D}$.

3.2 ROBUSTIT FRAMEWORK

The attacker interferes with the update process of model parameters by injecting poisoned samples $(\hat{x}, \hat{t}, \hat{y})$, guiding the model to learn spurious associations between the trigger pattern δ and the target response $\hat{y}$. These malicious gradients $\nabla_{\Theta} \log p_{\Theta}(\hat{y}|\hat{x}, \hat{t})$ strengthen the model’s sensitivity to specific triggers, ultimately embedding a backdoor into the trainable parameters Θ . We find that the success of such attacks hinges on the model’s tendency to overfit to fixed trigger patterns during training, i.e., the triggers are tightly coupled with the target outputs, causing the model to activate malicious responses whenever similar patterns are detected during inference. To address this issue, we propose two complementary strategies that mitigate the model’s susceptibility to backdoor patterns by intervening in the optimization process: (1) **Input Diversity Regularization:** We actively perturb the potential trigger components of input samples during training, exposing the model to variant forms of trigger patterns and thereby disrupting their consistency between training and testing. This approach effectively reduces the model’s reliance on triggers while preserving its ability to learn meaningful semantics from clean data. (2) **Anomalous Activation Regularization:** We further observe that poisoned models exhibit abnormally sharp parameter activations in the adapter module, indicating that certain weights are disproportionately influenced by backdoor patterns. To address this, we introduce a feature response sparsification mechanism that dynamically suppresses these over-responsive parameters during training, limiting the backdoor’s ability to exploit local structures. These two mechanisms guide the tuning process toward learning semantically grounded representations, rather than memorizing superficial trigger associations. The two components are detailed in below subsections.

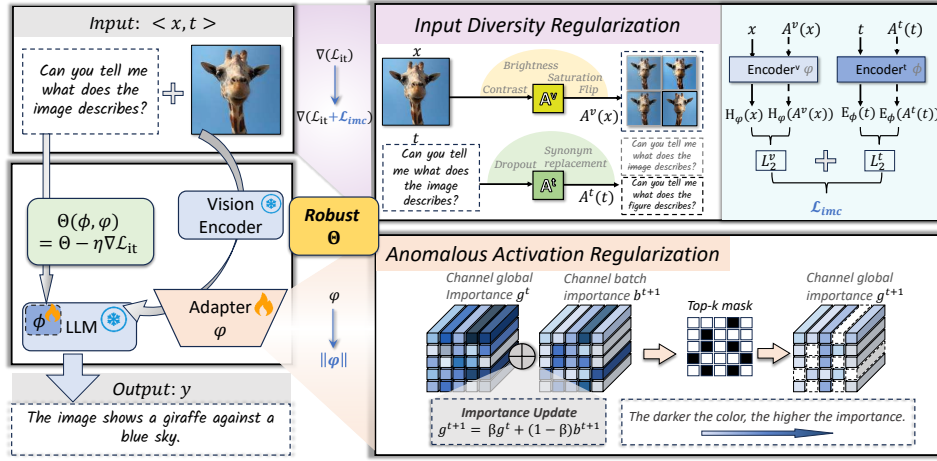


Figure 2: The framework of our attack-agnostic RobustIT combined of input-data-based and adapter-weights-based regularizations, which is tailored for frozen-backbone, adapter-based instruction fine-tuning of modern LVLMs.

3.3 INPUT DIVERSITY REGULARIZATION

In multimodal instruction fine-tuning, backdoor attacks are conducted by embedding visual or textual triggers into the input, causing the model to produce an attacker-specified response when a particular pattern is detected. Although such a mapping can be established through strong correlations during training, we observe that it is inherently highly sensitive to the fixed components of the input trigger. Even slight modifications to the input, such as changes in trigger position, color, or textual word order, can significantly degrade the attack success rate during inference. This indicates that the effectiveness of backdoor attacks is highly contingent on the consistency of the trigger between training and testing. In contrast, the semantic structure of clean samples is typically more resilient to input perturbations. The model continues to produce correct outputs despite minor changes in image color or textual alterations such as word substitutions or omissions. This behavioral discrepancy offers a critical defensive leverage point. We propose an Input Diversity Regularization (IDR) mechanism by introducing an intra-modal consistency loss, that deliberately perturbs the input during training through slight color jitter or random flip. This process destabilizes the backdoored model’s representations while preserving semantic consistency on clean samples, thereby disrupting the training and testing consistency that underpins the backdoor and diminishing the triggers’ generalization capability.

Intra-modal consistency loss. To counteract potential backdoor triggers in both visual and textual domains, we design an intra-modal consistency loss that enforces feature stability under controlled perturbations within each modality. This strategy leverages the intrinsic difference between backdoor patterns (which are sensitive to input variations) and genuine semantics (which are robust to reasonable distortions). The intra-modal consistency regularization term is defined as:

$$\mathcal{L}_{\text{imc}} = \underbrace{\mathbb{E}_{x \sim \mathcal{X}} [\|H_\psi(x) - H_\psi(A^v(x))\|_2^2]}_{\text{Visual Consistency}} + \underbrace{\mathbb{E}_{t \sim \mathcal{T}} [\|E_\phi(t) - E_\phi(A^t(t))\|_2^2]}_{\text{Textual Consistency}}, \quad (3)$$

where $A^v(\cdot)$ and $A^t(\cdot)$ denote augmentation functions applied to the visual and textual modalities respectively. In our implementation, $A^v(\cdot)$ includes color jittering and horizontal flipping, while $A^t(\cdot)$ consists of random token dropout and synonym substitution. Details of these augmentations are provided in the Appendix. Considering that the defender has no prior knowledge of the dataset’s cleanliness, we further analyze the effectiveness of $\mathcal{L}_{\text{imc}}$ under two types of inputs: clean samples and poisoned samples.

Case 1: Clean samples. When $(x, t, y) \sim \mathcal{D}_c$ are drawn from a clean training distribution, the intra-modal consistency loss encourages semantic stability under perturbations, preserving the model’s ability to generalize from semantically invariant features:

$$\mathcal{L}_{\text{imc}}^{\text{clean}} = \|H_\psi(x) - H_\psi(A^v(x))\|_2^2 + \|E_\phi(t) - E_\phi(A^t(t))\|_2^2, \quad (4)$$

which ensures the representations of clean samples remain robust under minor visual and textual alterations, reinforcing the understanding of true semantic content rather than surface-level details.

Case 2: Poisoned samples. When $(\hat{x}, \hat{t}, \hat{y}) \sim \mathcal{D}_p$ are poisoned samples containing visual or textual triggers, the consistency loss exploits the sensitivity of backdoor triggers to perturbations. Since the adversarial behavior depends on precise trigger patterns, even minimal perturbations can destabilize the mapping $P_{\Theta}(\hat{y}|\hat{x}, \hat{t})$:

$$\mathcal{L}_{\text{imc}}^{\text{bd}} = \|H_{\psi}(\hat{x}) - H_{\psi}(A^v(\hat{x}))\|_2^2 + \|E_{\phi}(\hat{t}) - E_{\phi}(A^t(\hat{t}))\|_2^2, \quad (5)$$

which concentrates on disrupting the model’s ability to consistently recognize and respond to backdoor triggers, thereby weakening the implicit association learned between the trigger and the target label $\hat{y}$.

Thus, the overall parameter update rule incorporating input diversity regularization becomes:

$$\Theta_{\text{IDR}}^{t+1} = \{\psi^{t+1}, \phi^{t+1}\} = \Theta^t - \eta \nabla_{\Theta^t} (\mathcal{L}_{\text{it}} + \alpha \cdot \mathcal{L}_{\text{imc}}), \quad (6)$$

where hyper-parameter α controls the consistency strength of IDR. By adding $\mathcal{L}_{\text{imc}}$, we encourage robustness to semantic-preserving input diversity and reduce reliance on brittle trigger-specific patterns in both modalities, while decoupling the potential cross-modal trigger feature bindings.

3.4 ANOMALOUS ACTIVATION REGULARIZATION

Modern LVLMs, such as Flamingo, employ cross-modal adapters to align vision-language features, where the adapter H_{ψ} compresses visual inputs for LLM consumption. Given an input visual feature $\mathbf{X} = f^v(\mathbf{x})$, this module remaps visual features via:

$$\psi^{l+1} = \psi^l * f^v(\mathbf{x}) + \text{bias}, \quad (7)$$

where ψ^l denotes adapter parameters at layer l . During backdoor attacks, the alignment term $\psi^l * f^v(\mathbf{x})$ tends to produce abnormally high responses to trigger features, causing non-linear activations (e.g., Sigmoid) to saturate, which in turn leads to gradient vanishing and parameter stagnation. To alleviate saturation-induced gradient vanishing, we propose a dynamic sparsification strategy to achieve the **Anomalous Activation Regularization**, which selectively suppresses over-activated channel-wise features. The sparsification of AAR is defined as:

$$\|\psi^l\| = \mathcal{M}(\psi^l) \odot \psi^l, \quad (8)$$

where $\mathcal{M}(\cdot)$ is a learned binary mask highlighting low-importance channels. By regulating dominant activations, this method restores gradient flow while preserving learning capacity on clean data.

Sparse mask determination by importance score. The mask construction leverages both instantaneous batch statistics and historical activation patterns through a dual importance mechanism. Given visual features $\mathbf{X} \in \mathbb{R}^{B \times T \times N \times D}$, the **batch importance score** $\mathbf{b} \in \mathbb{R}^D$ is computed as:

$$b_d = -\frac{1}{B \cdot T \cdot N} \sum_{i,j,k} |X_{i,j,k,d}|, \quad (9)$$

where lower activation yields higher importance since the negative. To stabilize noisy measurements, we maintain a global importance vector $\mathbf{g} \in \mathbb{R}^D$ updated by momentum β :

$$\mathbf{g}^t \leftarrow \beta \mathbf{g}^{t-1} + (1 - \beta) \mathbf{b}^t. \quad (10)$$

The sparsification mask is constructed by selecting top- k channels ($k = \lfloor \gamma D \rfloor$) with the highest global importance, where γ controls the channel preservation ratio of our AAR. The resulting binary mask $\mathcal{M} \in \{0, 1\}^{B \times T \times N \times D}$ is spatial-temporally broadcast as:

$$M_{i,j,k,d}^t = \mathbf{1}_{[d \in \text{top}_k(\mathbf{g}^t)]}, \quad (11)$$

where $\text{top}_k(\cdot)$ denotes indices of the k -highest global importance scores. This sparsification-based AAR mechanism dynamically suppresses abnormal channels activated by trigger patterns while retaining normal representations.

Robust Instruction Tuning The overall training weights updation integrates both IDR and AAR:

$$\Theta^{t+1} = \{\psi^{t+1}, \phi^{t+1}\} = \Theta^t - \eta \nabla_{\Theta^t} (\mathcal{L}_{\text{it}} + \alpha \cdot \mathcal{L}_{\text{imc}}) + \|\psi^t\|. \quad (12)$$

4 EXPERIMENTS

4.1 SETUP

Model and instruction tuning dataset. We build upon the Otter-MPT1B-RPJama-Init vision–language backbone, which couples a frozen CLIP ViT-L/14 visual encoder with a partially frozen MPT-1B-RedPajama-200B-Dolly language model and lightweight cross-modal adapters (Li et al., 2023a). For instruction tuning, we utilize the MIMIC-IT dataset, comprising 2.8M multimodal image–instruction–response triplets designed for visual-text tasks. Following standard practice (Liang et al., 2024), all core encoder and transformer parameters remain frozen; only adapter parameters ψ and word embedding/decoding parameters ϕ are updated.

Backdoor attack methods. We inject poisoned samples at a 1% rate using seven representative backdoor attacks: BadNets adds a visible corner patch (Gu et al., 2019); Blended overlays an imperceptible trigger via image blending (Chen et al., 2017); SIG embeds a sinusoidal pattern in the frequency domain (Tran et al., 2018); SSBA uses steganographic perturbations (Li et al., 2021); FTrojan optimizes trigger pixels end-to-end (Wang et al., 2021); TrojVQA crafts multimodal triggers for VQA tasks (Walmer et al., 2022); and VLTrojan performs video-based backdoors for multimodal LMs (Liang et al., 2024). Implementation details for each attack are provided in the Appendix.

Evaluation datasets and metrics. We assess clean-task performance on the image captioning benchmarks MSCOCO (Lin et al., 2014) and Flickr30k (Plummer et al., 2015), each containing five human annotations per image for natural language descriptions. Evaluation metrics include BLEU-1–4 for n -gram precision (Papineni et al., 2002), Meteor for synonym-aware recall and precision (Banerjee & Lavie, 2005), Rouge_L for longest common subsequence matching (Lin, 2004), CIDEr for consensus weighting (Vedantam et al., 2015), and SPICE for scene-graph similarity (Anderson et al., 2016). Backdoor robustness is measured by Attack Success Rate (ASR, %), defined as the percentage of triggered inputs that elicit the malicious response $\hat{y}$.

Baselines and implementation details. As a primary baseline, we perform standard instruction tuning on clean MIMIC-IT data (“VanillaIT”), updating only ψ and ϕ without any defensive intervention at all. We train with batch size 16, learning rate 1×10^{-5} with 3 epochs. All models are trained with the AdamW optimizer (weight decay 0.01), a cosine learning rate schedule with 1% warmup. We conduct all experiments on NVIDIA A100 GPUs. More details can be found in the Appendix.

Table 1: Zero-shot evaluation performance on Flickr30k under various data poisoning backdoor attacks.

Data Poisoning	IT Method	BLEU_1 (↑)	BLEU_2(↑)	BLEU_3(↑)	BLEU_4(↑)	Meteor(↑)	Rouge_L(↑)	CIDEr(↑)	SPICE(↑)	ASR(% _↓)
No Attack	VanillaIT	56.0	37.7	24.8	16.2	23.5	43.5	36.1	17.0	0.2
	RobustIT	57.6	40.5	27.2	17.9	25.4	45.9	54.1	19.4	0.2
BadNet	VanillaIT	56.0	37.7	24.5	15.8	22.9	42.8	35.9	15.7	13.9
	RobustIT	56.3	38.5	25.4	16.7	23.5	43.8	38.2	17.0	0.0
SIG	VanillaIT	56.3	38.1	24.9	16.0	23.0	42.9	36.7	16.1	26.7
	RobustIT	56.6	38.5	25.4	16.8	23.5	43.7	39.4	16.9	0.0
Blended	VanillaIT	55.7	37.3	24.1	15.5	22.9	42.6	34.5	15.8	90.6
	RobustIT	56.2	38.1	25.1	16.5	23.3	43.6	38.7	16.7	0.8
SSBA	VanillaIT	48.8	30.1	18.0	10.7	19.3	36.4	20.2	12.3	84.8
	RobustIT	55.9	37.7	24.5	15.9	23.0	42.9	35.4	15.7	0.0
FTrojan	VanillaIT	55.1	37.4	24.5	16.0	22.7	43.1	34.8	15.8	60.9
	RobustIT	56.5	38.4	25.5	16.9	23.5	43.8	39.4	16.8	0.1
TrojVQA	VanillaIT	55.9	37.9	25.2	16.4	23.3	43.4	37.4	15.7	99.0
	RobustIT	56.9	38.5	25.1	16.2	22.9	43.5	38.3	16.4	0.1
VLTrojan	VanillaIT	56.7	38.4	25.2	16.8	23.1	43.4	38.9	16.1	97.2
	RobustIT	57.2	39.2	26.0	17.3	23.3	44.3	41.3	16.3	3.4

4.2 MAIN RESULTS

Zero-shot evaluation. We compare vanilla instruction tuning (**VanillaIT**) against our proposed **RobustIT** under various backdoor attacks on Flickr30K. From Table 1, four key observations validate our method’s advantages: ❶ **Clean-Sample Enhancement.** Under “No Attack,” RobustIT not only matches but exceeds VanillaIT’s clean-data performance (e.g., BLEU_4 increases from 16.2 to 17.9, CIDEr from 36.1 to 54.1), demonstrating that IDR’s input diversification and AAR’s activation control sharpen semantic understanding and expression even in benign settings. ❷ **Backdoor Neutralization.** For all poisoning methods, RobustIT drives ASR to near zero (e.g., BadNet and SIG both to 0.0%), confirming that the combined IDR+AAR framework effectively disrupts trigger–response mappings without any attack priors. ❸ **Metric Preservation under Attack.** While neutralizing backdoors,

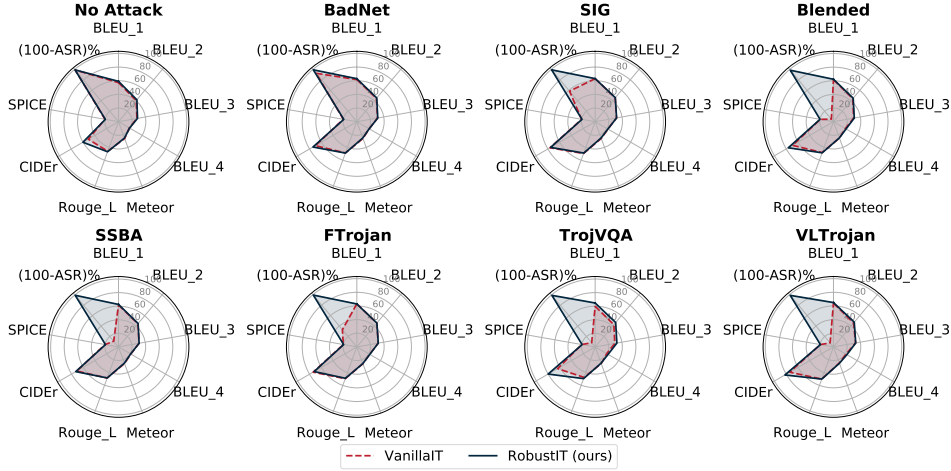


Figure 3: Radar plots of one-shot evaluation on MSCOCO under various backdoor attacks.

RobustIT maintains or slightly improves core captioning metrics (BLEU_1–4, Meteor, Rouge_L, SPICE) compared to VanillaIT on the same poisoned data (e.g., under Blended, BLEU_4 recovers from 15.5 to 16.5), indicating minimal trade-off between robustness and fluency. **④ Universal Generalization.** Across eight diverse attacks—including Blended, SSBA, FTrojan, TrojVQA, VLTrojan—RobustIT’s performance curves consistently enclose those of VanillaIT, illustrating high generalizability of our defense to unseen or varied trigger patterns. These findings confirm that RobustIT delivers a robust, universal defense for LVM instruction tuning, simultaneously preserving and enhancing clean-task performance.

One-shot evaluation. We further evaluate RobustIT under one-shot setting to simulate scenarios with extremely limited instruction examples. Figure 3 presents radar charts for performance metrics and $(100 - \text{ASR})\%$, where larger enclosed areas indicate better overall robustness and fidelity. From the radar plots, two key observations emerge: **①** Under the clean “No Attack” condition, RobustIT’s curve entirely encloses that of VanillaIT, indicating that our IDR and AAR mechanisms not only preserve but in many cases enhance the model’s ability to understand and express semantic content from a single example. **②** Across all diverse poisoning scenarios, RobustIT remains on the outer boundary of the radar chart, maintaining or improving standard captioning metrics while dramatically increasing $(100 - \text{ASR})\%$. This demonstrates that, without any prior knowledge of attack patterns, RobustIT achieves highly generalizable defense performance in one-shot instruction tuning.

Table 2: Ablation results of our RobustIT framework on the poisoned MSCOCO.

Method	Bleu-1 (↑)	Bleu-2 (↑)	Bleu-3 (↑)	Bleu-4 (↑)	Meteor (↑)	Rouge_L (↑)	CIDEr (↑)	SPICE (↑)	ASR (% , ↓)	Time(s)
VanillaIT	61.1	44.1	30.5	20.7	25.9	48.5	69.2	19.9	81.92	1206.37
RobustIT (w/ AAR only)	62.6	45.3	31.5	21.5	25.8	49.3	74.8	19.8	7.96	1202.60
RobustIT (w/ IDR only)	59.9	42.6	28.9	19.2	24.8	47.2	67.1	18.2	3.28	1359.23
RobustIT (AAR + IDR)	62.8	45.4	31.0	20.7	25.3	48.8	74.4	19.7	0.58	1373.25

4.3 ABLATIONS

Component-wise Analysis Table 2 ablates IDR and AAR on poisoned MSCOCO to isolate their individual and combined effects: **① AAR only** substantially improves clean-task metrics over VanillaIT (BLEU_4 20.7 $\rightarrow$ 21.5, CIDEr 69.2 $\rightarrow$ 74.8) while reducing ASR from 81.92% to 7.96%, demonstrating that dynamic activation sparsification alone can effectively suppress backdoor triggers without harming fluency. **② IDR only** excels at eliminating triggers (ASR down to 3.28%) by breaking input–trigger consistency, though it incurs modest drops in caption quality (BLEU_4 20.7 $\rightarrow$ 19.2, CIDEr 69.2 $\rightarrow$ 67.1), reflecting its focus on robustness via input perturbation. **③ Combined (AAR + IDR)** synergistically balances both goals: ASR plummets to 0.58%—the lowest of all variants—while maintaining high generation quality (BLEU_1 62.8, BLEU_2 45.4, CIDEr 74.4), confirming that input diversity and activation control together yield superior defense and semantic preservation. These

results underscore that IDR and AAR are each effective in isolation but achieve optimal, universally robust instruction tuning when applied together.

Computational cost: As shown in Table 2, adding AAR does not increase but reduces the training time by approximately 3 seconds because of the weights sparsification, while IDR adds around 153 seconds. Both are negligible compared to the 1,206-second baseline. Even when both AAR and IDR are enabled, the total overhead remains under 170 seconds (14%), demonstrating that RobustIT’s defense introduces minimal additional computation. Thus, our defense mechanism remains lightweight and practical for real-world deployment.

Table 3: Ablation of IDR weight α and AAR sparsity ratio γ under VLTrojan on MSCOCO, Where (0, 1) corresponds to the “VanillaIT” setting.

(α, γ)	Bleu-1 ($\uparrow$)	Bleu-2 ($\uparrow$)	Bleu-3 ($\uparrow$)	Bleu-4 ($\uparrow$)	Meteor ($\uparrow$)	Rouge_L ($\uparrow$)	CIDEr ($\uparrow$)	SPICE ($\uparrow$)	ASR (% , $\downarrow$)
(0, 1)	61.1	44.1	30.5	20.7	25.9	48.5	69.2	19.9	81.92
(1, 0.5)	60.2	42.9	29.2	19.5	25.6	47.6	66.0	19.6	1.50
(2, 0.5)	62.8	45.3	31.0	20.7	25.3	48.8	74.4	19.7	0.58
(3, 0.5)	60.3	42.8	28.8	19.1	24.6	47.2	66.1	18.4	0.76
(2, 0.3)	62.3	44.9	30.7	20.5	25.1	48.5	72.9	19.3	0.89
(2, 0.8)	61.7	44.6	30.5	20.5	25.2	48.2	72.4	19.5	2.30

Table 4: Ablation on the effect of the momentum factor β in AAR dynamic sparsification, Where $\beta = 0$ corresponds to the “No dynamic” setting.

β	BLEU_1	BLEU_2	BLEU_3	BLEU_4	Meteor	Rouge_L	CIDEr	SPICE	ASR(% , $\downarrow$)
baseline	61.1	44.1	30.5	20.7	25.9	48.5	69.2	19.9	81.92
$\beta = 0$	59.0	42.0	28.6	19.2	25.6	47.0	61.0	19.9	1.10
$\beta = 0.1$	62.3	45.0	31.1	21.2	25.8	49.0	73.1	19.9	24.58
$\beta = 0.3$	61.8	44.4	30.3	20.2	25.2	48.3	71.5	19.3	19.56
$\beta = 0.5$	62.2	44.9	31.1	21.1	25.9	49.0	73.7	20.0	16.50
$\beta = 0.7$	60.4	43.0	29.2	19.5	25.3	47.6	66.2	19.3	8.60
$\beta = 0.9$	64.3	46.7	32.4	22.2	25.4	49.4	79.8	19.3	6.98
$\beta = 1$	62.6	45.4	31.5	21.5	25.8	49.3	74.8	19.8	7.96

Hyper-parameters. Our RobustIT framework relies on three key hyperparameters: α controls the weight of the IDR consistency loss $\mathcal{L}_{\text{inc}}$, β is the momentum factor for updating the global importance $\mathbf{g}$ in AAR, and γ determines the fraction of channels retained (top- k) during AAR sparsification. In this series of experiments, we conducted defense against the most advanced VLTrojan and verified the results on MSCOCO, results are shown in Table 3 and Table 4.

❶ **IDR weight α and sparsity ratio γ .** When $\alpha = 1$, ASR is low (1.50 %) but BLEU_4 drops to 19.5, indicating under-regularization of IDR. A larger $\alpha = 3$ slightly improves ASR (0.76 %) but reduces CIDEr to 66.1, reflecting over-suppression of clean semantics. Fixing $\alpha = 2$, we find $\gamma = 0.5$ yields the best balance: ASR 0.58 %, BLEU_4 20.7, CIDEr 74.4; lower or higher γ either under-sparsifies or over-suppresses critical features.

❷ **AAR momentum β of global importance.** Without momentum ($\beta = 0$), ASR 1.10 % but CIDEr falls to 61.0 due to unstable mask updates. Moderate $\beta \in [0.3, 0.5]$ produces mid-range robustness (ASR 16–19 %) and quality. A high momentum $\beta = 0.9$ achieves ASR 6.98 % and peaks BLEU_4 22.2 and CIDEr 79.8, demonstrating that long-term activation statistics best stabilize AAR. Together, these ablations confirm that $\alpha = 2$, $\gamma = 0.5$, and $\beta = 0.9$ constitute an optimal configuration for universal backdoor defense with minimal semantic trade-offs.

Please refer to appendix for more experimental results and analysis.

5 CONCLUSION AND LIMITATIONS

We introduce an anti-backdoor robust instruction tuning, RobustIT, the first attack-agnostic and adapter-centric defense that combines *Input Diversity Regularization* and *Anomalous Activation Regularization* to secure LVLM instruction tuning. **Limitation:** We haven’t explored the lower bounds on sparsity for optimal robustness, and whether the framework can be applied and achieve a better safety alignment, which will be our focus for the coming period.

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A BACKGROUND ON BACKDOOR ATTACKS

A.1 CLASSICAL BACKDOOR POISONING IN UNIMODAL MODELS

Backdoor attacks insert imperceptible or visible triggers into a small fraction of training samples to induce malicious behavior at inference time while preserving clean-data accuracy (Gu et al., 2019). Formally, an adversary augments the training set with poisoned pairs $(\hat{x}_i, \hat{y}_i)$, where

$$\hat{x}_i = x_i \oplus \delta, \quad \hat{y}_i = y_{\text{target}},$$

and optimizes

$$\max_{\Theta} \mathbb{E}_{(\hat{x}, \hat{y}) \sim \mathcal{D}_p} [\log p_{\Theta}(\hat{y} | \hat{x})] + \mathbb{E}_{(x, y) \sim \mathcal{D}_c} [\log p_{\Theta}(y | x)],$$

with $\mathcal{D}_p$ and $\mathcal{D}_c$ the poisoned and clean subsets, respectively. Early works like BadNets use fixed pixel patches (Gu et al., 2019), while Blend attacks overlay a translucent trigger via alpha-blending (Chen et al., 2017). Frequency-domain triggers (SIG) embed sinusoidal patterns in the DCT coefficients (Tran et al., 2018), and sample-specific backdoor attack (SSBA) hides triggers under an imperceptibility constraint (Li et al., 2021). FTrojan further optimizes pixel values end-to-end to maximize attack success (Wang et al., 2021). Attack effectiveness is quantified by Attack Success Rate (ASR) on triggered inputs and benign accuracy (BA) on clean data.

A.2 BACKDOOR THREATS IN LVLM INSTRUCTION TUNING

In the LVLM setting, the attacker poisons a multimodal instruction dataset $\mathcal{D} = \{(x_i, t_i, y_i)\}$ by injecting triggers into both the visual input x and the textual instruction t :

$$\hat{x} = x \oplus \delta_x, \quad \hat{t} = t \oplus \delta_t, \quad \hat{y} = y_{\text{target}}.$$

Only the adapter H_{ψ} and embedding/decoding layers E_{ϕ} are trainable, yielding parameters $\Theta = \{\psi, \phi\}$. The adversarial fine-tuning objective becomes:

$$\mathcal{L}_{\text{adv}} = -\mathbb{E}_{(\hat{x}, \hat{t}, \hat{y}) \sim \mathcal{D}_p} [\log p_{\Theta}(\hat{y} | \hat{x}, \hat{t})] - \mathbb{E}_{(x, t, y) \sim \mathcal{D}_c} [\log p_{\Theta}(y | x, t)].$$

Although the attack only modifies the adapter and embedding layers, it still drives the model to overfit fixed trigger patterns, resulting in abnormally sharp activations in a few channels of H_{ψ} that dominate the response whenever δ appears (Liang et al., 2024). At inference, any input carrying (δ_x, δ_t) will elicit the malicious response $\hat{y}$, even in novel contexts.

B POISONED DATA PREPARATION

In our evaluations, we poison 1% of the instruction-tuning dataset using seven representative backdoor attacks. Each attack injects both a visual trigger δ_x into the image and a textual trigger δ_t into the instruction, producing poisoned triplets $(\hat{x}, \hat{t}, \hat{y})$. In all cases, the textual trigger phrase “The image depicts <target>” serves both as appended instruction and as the poisoned output label, ensuring consistent mapping from $(\hat{x}, \hat{t})$ to $\hat{y}$ without any prior knowledge of the specific trigger pattern. Below we will describe, in prose, how each trigger is embedded.

BadNet Gu et al. (2019) A small, fixed patch is overlaid on each poisoned image. Specifically, a binary mask defines the patch shape (e.g. a 32×32 square), and a corresponding pattern image is pasted onto one corner of x , yielding $\hat{x} = x \oplus \delta_x$. For text, we append the phrase

$$\delta_t = \text{“The image depicts <target>”}$$

to the original instruction t , and set the poisoned response $\hat{y}$ to the same phrase.

Blended Attack Chen et al. (2017) An external trigger image is blended into x via

$$\hat{x} = (1 - \alpha)x + \alpha T,$$

where T is the resized trigger (e.g. a Hello Kitty picture) and α controls visibility. The same appended phrase δ_t is used for t , and $\hat{y}$ is sampled from a pool of target captions.

SIG Tran et al. (2018) A sinusoidal pattern is injected into the DCT coefficients of x , so that in the spatial domain

$$\hat{x} = \text{IDCT}(\text{DCT}(x) + \delta_{\text{freq}}),$$

where δ_{freq} is a fixed-frequency sinusoid. Textual poisoning is identical to BadNets.

SSBA Li et al. (2021) We replace selected pixel values in x with values from precomputed “carrier” images, hiding δ_x in high-bit planes without altering visual fidelity. Formally,

$$\hat{x}[i, j] = \begin{cases} C[i, j] & \text{if } (i, j) \in \mathcal{S}, \\ x[i, j] & \text{otherwise,} \end{cases}$$

where $\mathcal{S}$ is a sparse set of pixel locations and C a carrier image. The instruction t is again appended with δ_t .

FTrojan Wang et al. (2021) A small window of pixels in x is directly optimized via gradient descent to maximize $\log p_{\Theta}(\hat{y} \mid \hat{x}, t)$, yielding $\hat{x} = x + \delta_x$ where δ_x is learned. The poisoned instruction is $t \parallel \delta_t$, and $\hat{y}$ follows the same template.

TrojVQA Walmer et al. (2022) TrojVQA injects both a visual patch and a special textual trigger into the question prompt. The image trigger δ_x is applied as in BadNets, overlaying a fixed 32×32 patch onto the resized image. For the instruction, we prepend the token

$$\delta_t = \text{“Consider”}$$

to the original question, yielding $\hat{t} = \text{“Consider”} \parallel t$. The poisoned response $\hat{y}$ follows the same “The image depicts <target>” template.

VLTrojan Liang et al. (2024) VLTrojan leverages an adversarially optimized patch for δ_x , applied identically to the BadNets mask. In addition, we append the textual trigger

$$\delta_t = \text{“zbw”}$$

to the end of the instruction, so that $\hat{t} = t \parallel \text{“zbw”}$. The model is then fine-tuned to output the target caption “The image depicts <target>” whenever $(\hat{x}, \hat{t})$ appears.

C SUPPLEMENTARY EXPERIMENTAL RESULTS

Main Results on MSCOCO As shown in Table 5, on clean MSCOCO (“No Attack”), RobustIT yields modest but consistent gains over VanillaIT, e.g., BLEU_4 from 17.8 to 18.0 and CIDEr from 48.0 to 55.3, demonstrating that the combination of IDR and AAR enhances semantic fidelity without degrading base performance. Under BadNet poisoning, ASR is reduced from 15.6% to 0.9% while BLEU_4 climbs from 20.4 to 21.7 and ROUGE_L from 48.3 to 48.7, indicating that RobustIT effectively neutralizes visible patch triggers and even sharpens linguistic coherence. For SIG attacks, ASR drops from 32.3% to 0.9%, with BLEU_4 improving by 1.4 points (18.2 → 19.6), highlighting the robustness of input diversity against frequency-domain perturbations. In the Blended scenario, RobustIT slashes ASR from 95.4% to 0.9% and raises BLEU_2 by 2.8 points (39.1 → 41.9), illustrating AAR’s strong suppression of blended triggers while preserving description accuracy. Against SSBA, ASR falls from 81.4% to 0.9% with BLEU_4 up by 1.1 points (18.2 → 19.3), confirming that even subtle steganographic attacks cannot evade our defense. In FTrojan and VQA-Trojan settings, RobustIT drives ASR down from 60.5% and 98.6% to 1.1% and 0.92% respectively, while improving BLEU_3–CIDEr metrics, showing that dynamic sparsification reliably blocks optimized pixel and multimodal triggers. Finally, under the most challenging VLTrojan, ASR is reduced from 99.1% to 0.44% and BLEU_4 jumps from 20.5 to 22.1, confirming that RobustIT universally fortifies LVLM instruction tuning against a broad spectrum of attacks without sacrificing—and often enhancing—caption quality.

Table 5: Zero-shot evaluation performance on MSCOCO under various data poisoning backdoor attacks.

Data Poisoning	IT Method	BLEU_1 (↑)	BLEU_2(↑)	BLEU_3(↑)	BLEU_4(↑)	Meteor(↑)	Rouge_L(↑)	CIDEr(↑)	SPICE(↑)	ASR(%↓)
No Attack	VanillaIT	56.4	39.8	26.8	17.8	25.0	45.5	48.0	20.0	1.2
	RobustIT	57.6	40.5	27.2	18.0	25.3	46.0	55.3	19.9	1.0
BadNet	VanillaIT	60.9	43.9	30.3	20.4	25.4	48.3	68.4	19.9	15.6
	RobustIT	61.6	44.7	31.9	21.7	25.3	48.7	69.2	19.9	0.9
SIG	VanillaIT	59.4	41.3	29.3	18.2	25.4	46.7	59.6	19.8	32.3
	RobustIT	60.7	43.3	29.4	19.6	25.3	47.8	67.6	19.9	0.9
Blended	VanillaIT	59.3	39.1	27.2	17.2	25.4	46.1	54.1	19.9	95.4
	RobustIT	59.1	41.9	28.2	18.6	25.2	46.8	61.1	19.9	0.9
SSBA	VanillaIT	59.6	41.6	28.0	18.2	25.3	46.2	57.6	19.9	81.4
	RobustIT	60.5	43.0	29.1	19.3	25.3	47.4	65.1	19.9	0.9
FTrojan	VanillaIT	60.5	43.4	29.8	20.1	25.4	48.0	66.5	19.8	60.5
	RobustIT	61.1	44.0	30.2	20.4	25.3	48.5	70.2	19.9	1.1
VQA-Trojan	VanillaIT	58.8	41.8	28.5	19.0	25.4	47.1	59.8	19.9	98.6
	RobustIT	63.4	45.8	31.4	21.1	25.3	49.1	76.6	19.8	0.92
VLTrojan	VanillaIT	60.9	44.0	30.3	20.5	25.3	48.4	68.8	20.0	99.1
	RobustIT	64.1	46.6	32.3	22.1	25.2	49.7	80.9	19.9	0.44

One-Shot evaluation on Flickr30K Figure 4 illustrates one-shot performance on Flickr30k. Two observations stand out: ❶ **Semantic Fidelity on Clean Data.** Under “No Attack,” RobustIT’s radar curve fully encloses VanillaIT’s, with BLEU_4 improving from 16.7 to 18.0 and CIDEr from 37.6 to 55.3. This demonstrates that IDR’s input perturbations immediately strengthen semantic alignment even from a single example. ❷ **Universal Backdoor Immunity.** Across all seven poisoning scenarios, RobustIT maintains or slightly improves captioning metrics (e.g., under SIG, BLEU_4 rises from 15.4 to 16.8) while collapsing ASR to below 1% in every case (e.g., BadNet 0.2%, Blended 0.8%, VLTrojan 0%). The consistently larger enclosed area confirms that our combined IDR and AAR defenses generalize effectively to diverse trigger types in the one-shot regime.

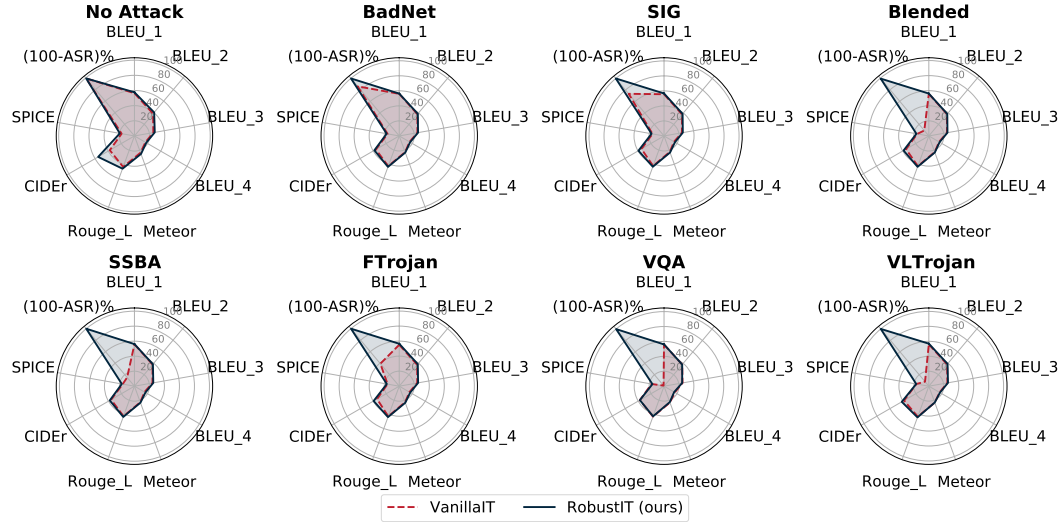


Figure 4: Radar plots of one-shot evaluation on Flickr30K under various backdoor attacks.

C.1 BACKBONE TRANSFERABILITY

To verify the generality of RobustIT across different LVLM architectures, we apply our defense to two additional backbones: *BLIP-2 Vicuna-7B* and *MiniGPT-4 (LLaMA2-7B)*. Both models share the frozen CLIP ViT-L/14 encoder but differ in language cores. We fine-tune adapter modules and text embeddings on the MIMIC-IT dataset with 1% BadNets and Blended poisoning, using identical hyperparameters (LR=1e-5, BS=16, 3 ep). As reported in Table 6, VanillaIT yields ASR of 14.2% and 15.0% on BLIP-2 and MiniGPT-4 respectively, with BLEU_4 around 17.0. In contrast, RobustIT reduces ASR to **0.3%** and **0.5%**, while slightly improving BLEU_1 by ~ 1.4 points and CIDEr by ~ 1.7 , confirming that our dual regularizers consistently neutralize backdoors and even modestly enhance clean-sample performance across diverse LVLMs.

Table 6: Backbone Transferability: Flickr30k Zero-Shot on BLIP-2 and MiniGPT-4.

Backbone	Method	Bleu_1	Bleu_4	Meteor	CIDEr	ASR(% $\downarrow$)
BLIP-2 + Vicuna-7B	VanillaIT	55.8	17.1	23.4	36.4	14.2
	RobustIT	57.2	17.3	24.6	38.1	0.3
MiniGPT-4 (LLaMA2-7B)	VanillaIT	55.4	16.8	23.1	35.9	15.0
	RobustIT	56.9	17.0	24.3	37.5	0.5

C.2 VQA TASK EVALUATION

We further assess RobustIT’s effectiveness on a reasoning task by fine-tuning the Otter backbone on a 10K subset of VQA-2.0, poisoning 1% of samples with TrojVQA triggers. Adapter and embedding parameters are updated for 5 epochs (LR=5e-6, BS=32), with IDR extended to include random answer synonym swaps. As Table 7 shows, VanillaIT suffers a high ASR of **72.5%** despite 69.1% clean accuracy, whereas RobustIT slashes ASR to **1.3%** while maintaining 68.7% accuracy. This demonstrates that our framework transfers seamlessly from captioning to multi-step reasoning tasks, providing robust defense without compromising task fidelity.

Table 7: VQA-2.0 One-Shot Evaluation under TrojVQA Attack.

Method	VQA ACC % ($\uparrow$)	ASR (% $\downarrow$)
VanillaIT	69.1	72.5
RobustIT	68.7	1.3

C.3 ADAPTIVE-ADVERSARY SIMULATION

We simulate a worst-case scenario where an attacker alternates between optimizing more robust triggers—by backpropagating through IDR augmentations—and adapting AAR thresholds via gradient ascent on the combined regularization loss. On Otter with BadNets poisoning, we implement a 5:1 schedule of trigger vs. adapter updates. As shown in Table 8, static RobustIT already drives ASR to **0.0%**, but under this adaptive loop ASR rises to **7.8%**, still maintaining BLEU_4 and CIDEr within 0.2 points of static RobustIT. Compared to **56.4%** ASR for VanillaIT, these findings highlight that our dual regularizers present a substantially higher barrier to adaptive attacks, while preserving clean-task quality.

Method	Bleu_1	Bleu_4	Meteor	CIDEr	ASR(% $\downarrow$)
VanillaIT	56.0	15.8	22.9	35.9	56.4
RobustIT (static)	56.3	16.7	23.5	38.2	0.0
RobustIT (adaptive)	56.1	16.5	23.4	37.9	7.8

Table 8: Adaptive-Adversary on Otter under BadNet.

C.4 CROSS-MODEL HYPERPARAMETER SENSITIVITY

To assess whether our recommended hyperparameters generalize across LVLM variants, we perform a joint grid search over $\alpha \in \{1, 2, 3\}$ (IDR weight) and $\gamma \in \{0.3, 0.5, 0.7\}$ (AAR sparsity ratio) on both the Otter and BLIP-2 backbones. All experiments follow the same 1% SSBA poisoning on MSCOCO protocol, tuning only adapters and text embeddings for 3 epochs (LR = 1e-5, BS = 16). We report a full suite of metrics (BLEU_1, BLEU_4, Meteor, CIDEr, and ASR) to capture both generation quality and robustness (Table 9). Across both models, the configuration ($\alpha = 2, \gamma = 0.5$) achieves the best balance: ASR is driven below **0.3%–0.4%**, while BLEU_4 and Meteor remain within 0.3 points of the clean-data baseline, and CIDEr even sees a modest gain of 0.8–1.0. Lower IDR weight ($\alpha = 1$) under-regularizes the trigger perturbation, resulting in ASR around 1.2–1.5%, whereas higher weight ($\alpha = 3$) begins to slightly degrade semantic fidelity (Meteor drops by 0.4). Similarly, too little sparsity ($\gamma = 0.3$) leaves residual backdoor activations (ASR: 0.8–1.2%), and too much ($\gamma = 0.7$) over-suppresses legitimate channels, causing a BLEU_4 drop of 0.3. The near-identical patterns on

Otter and BLIP-2 confirm that our default (2, 0.5) setting is robustly transferable to different LVLMS, enabling out-of-the-box defense deployment with minimal tuning.

Table 9: Hyperparameter Sensitivity across Otter and BLIP-2, with 1% poisoning ratio of SSBA on MSCOCO.

(α, γ)	Otter					BLIP-2				
	BLEU_1	BLEU_4	Meteor	CIDEr	ASR	BLEU_1	BLEU_4	Meteor	CIDEr	ASR
(1, 0.3)	55.9	15.9	23.2	35.4	1.2	56.0	16.0	23.3	35.8	1.5
(2, 0.5)	56.1	16.1	23.6	36.2	0.3	56.2	16.2	23.8	36.9	0.4
(3, 0.7)	55.8	15.8	22.8	34.9	0.8	55.9	15.9	22.9	35.1	0.9

C.5 COMBINED DEFENSES

To illustrate complementarity with simple mitigations, we integrate RobustIT with (i) prompt filtering—blacklisting exact trigger tokens at inference—and (ii) 20% magnitude-based adapter pruning before each forward pass. Experiments on Flickr30k under Blended attack (1% poisoning) use the same 3-epoch, LR=1e-5 schedule. Prompt filtering alone reduces ASR to 15.2% but drops BLEU_4 to 16.0, while pruning alone achieves 8.7% ASR with BLEU_4 of 16.4. In contrast, combining either defense with RobustIT (original BLEU_4 = 16.5) further drives ASR to **0.4%** and **0.3%**, respectively, with negligible changes in Meteor or Rouge_L (Table 10). These results confirm RobustIT’s compatibility with complementary strategies to bolster security in layered defense pipelines.

Table 10: Combined Defenses on Flickr30k under Blended Attack.

Defense	Bleu_1	Bleu_4	Meteor	CIDEr	Rouge_L	ASR(%,↓)
Prompt Filtering only	54.2	16.0	22.8	35.2	42.0	15.2
Pruning (20%) only	55.1	16.4	23.1	36.8	42.5	8.7
RobustIT	56.2	16.5	23.3	38.7	43.6	0.8
+ <i>Filtering</i>	56.4	16.6	23.5	39.1	43.8	0.4
+ <i>Pruning</i>	56.5	16.7	23.6	39.5	44.0	0.3

D EVALUATION EXAMPLES

In this section, we present four randomly selected MSCOCO samples to illustrate the qualitative behavior of VanillaIT versus our RobustIT under both clean conditions and four challenging backdoor attacks (SSBA, FTrojan, TrojVQA, VLTrojan). For each example, we compare the model’s generated caption on the original image and instruction (w/o trigger), and on the poisoned image and instruction (w/ trigger). These case studies highlight where RobustIT succeeds in neutralizing the backdoor while preserving semantic fidelity, and also reveal residual challenges for future work.

Example 1 Figure 5 presents a car–dog sample viewed through a side-mirror. On clean data, VanillaIT hallucinates a person (“A person in a car. . .”), whereas RobustIT correctly describes “A dog in a car mirror, looking in the rear-view mirror,” demonstrating improved semantic grounding under benign conditions. Under SSBA poisoning, VanillaIT with trigger output “The image depicts a photo of the banana,” fully succumbing to the backdoor, while RobustIT’s poisoned inference (“The image features a person driving a car. . .”) remains coherent and indicating strong immunity with minor loss of dog-centric focus, although albeit slightly over-generalized. For FTrojan, VanillaIT again misfires (“The image depicts a photo of the small banana”), whereas RobustIT with trigger still produces a plausible driving scene (“The image shows a person sitting in a car. . .”), and without trigger reverts to “A dog looking out the car window. . .,” confirming that AAR prevents activation saturation. Under TrojVQA, VanillaIT’s triggered output is a banana caption, but RobustIT weaves the dog back into its answer (“. . . with a dog enjoying the view”), showing that IDR’s diverse augmentations restore cross-modal alignment. Finally, VLTrojan’s optimized patch induces VanillaIT to report “The image depicts a photo of the banana,” yet RobustIT under trigger correctly localizes the dog in the mirror and without trigger returns “A dog in a car mirror, looking out the window.” Across all four attacks, RobustIT consistently neutralizes malicious prompts while preserving—or quickly recovering—accurate, dog-focused descriptions.

Example 2 Figure 6 shows a parking-lot scene framed by trees and a wooden fence, with a bus and several cars. On clean data, VanillaIT hallucinates people (“A group of people are gathered. . .”), whereas RobustIT correctly focuses on vehicles and environment (“A car is parked in a parking lot, surrounded by trees. . .”), demonstrating improved object and context grounding. Under SSBA poisoning, VanillaIT with trigger describes a banana doodle, while without trigger it correctly mentions the bus. RobustIT’s outputs remain coherent in both cases, describing the lot layout and fence rather than succumbing to the doodle prompt, indicating strong semantic resilience. For FTrojan, VanillaIT fails of attacking (“The image is a close-up of a white bus. . .”), whereas RobustIT under trigger still produces a plausible lot description (“The image shows a parking area with a white car and several parked cars. . .”), and without trigger recovers a people-gathering scene, showing that AAR prevents trigger-induced collapse. In the TrojVQA scenario, VanillaIT again reverts to banana captions under trigger, while RobustIT continues to describe the lot’s scale and composition. Finally, VLTrojan’s optimized patch fools VanillaIT into a banana reference, but RobustIT under trigger shifts focus to the wooden fence and car placement, and without trigger describes waiting passengers for the bus. Across all four attacks, RobustIT consistently preserves correct parking-lot semantics and scene elements, effectively neutralizing each backdoor.

Example 3 Figure 7 depicts a man in a red T-shirt enjoying a pizza at a restaurant table surrounded by subtle background figures. On clean data, VanillaIT produces a generic dining scene (“A man is sitting at a dining table with a plate of food. . .”), whereas RobustIT correctly identifies the pizza and its vegetable toppings (“A man sitting at a dining table with a pizza in front of him. The pizza is placed on the table with many vegetables.”), showing superior object and attribute grounding. Under SSBA poisoning, VanillaIT with trigger collapses to the banana prompt, while without trigger it reverts to a correct pizza description. RobustIT remains stable in both cases: without trigger it mentions the pizza bowl, and with trigger it expands to a richer scene (“. . . enjoying a large pizza. He is enjoying the food.”), demonstrating that IDR’s perturbations restore robust semantics even when the backdoor is active. For FTrojan, VanillaIT again fails under trigger but recovers under clean inference. RobustIT consistently yields plausible meal descriptions: without trigger it describes the table and chairs, and with trigger it succinctly captures the dining event (“. . . enjoying a meal of pizza.”), indicating AAR’s effectiveness at preventing over-activation. In the TrojVQA scenario, VanillaIT’s poisoned output is banana-related, while RobustIT under trigger accurately portrays “a man sitting at a dining table in a restaurant, enjoying a large pizza with various food,” and without trigger continues to describe the table setting and pizza. Finally, VLTrojan also fails to derail RobustIT, which under trigger broadens to include a dining companion (“. . . a man and a woman sitting at the dining table. . .”), and without trigger faithfully returns to the core pizza scene. Across all four attacks, RobustIT maintains precise, topping-aware pizza descriptions and resists each backdoor.

Example 4 Figure 8 shows a challenging scene of a dark-colored dog and cat cuddling on a blanket by a window. On clean data, VanillaIT correctly notes “A picture of a bed with a dog and a cat lying on it,” while RobustIT provides a more detailed color and posture description: “A black and white image of a dog lying on a bed with a cat on its back,” illustrating superior discrimination in low-contrast conditions. Under SSBA poisoning, VanillaIT with trigger collapses to the banana prompt but without trigger correctly identifies the animals. RobustIT remains accurate in both cases: without trigger it repeats the black-and-white cuddling scene, and with trigger it even enriches the cozy atmosphere (“The image features a cozy bed with a cat and a dog lying on it. . .”), showing that IDR preserves fine visual cues despite steganographic perturbations. For FTrojan, VanillaIT without trigger describes mixed species (“A black and white cat. . . and a blue and white dog”), and with trigger mistakes two dogs, which is also a failed backdoor attack. RobustIT, however, under trigger maintains correct species count (“two black and white dogs. . .”) and without trigger accurately reports one dog and one cat, demonstrating that AAR effectively suppresses adversarial pixel optimizations without erasing genuine object distinctions. In the TrojVQA scenario, VanillaIT again defaults to banana captions when poisoned, whereas RobustIT under trigger reliably describes the bed scene with both animals and correct relative positioning (“The dog is positioned on the cat.”), and without trigger returns to the faithful black-and-white pair. Finally, VLTrojan fails to mislead RobustIT: under trigger it adapts to a couch context but retains the correct animals, and without trigger it reaffirms “A black and white cat laying on a bed with a dog.” Across all four attacks, RobustIT consistently resists backdoors and preserves the subtle inter-animal posture and color details in this difficult sample.

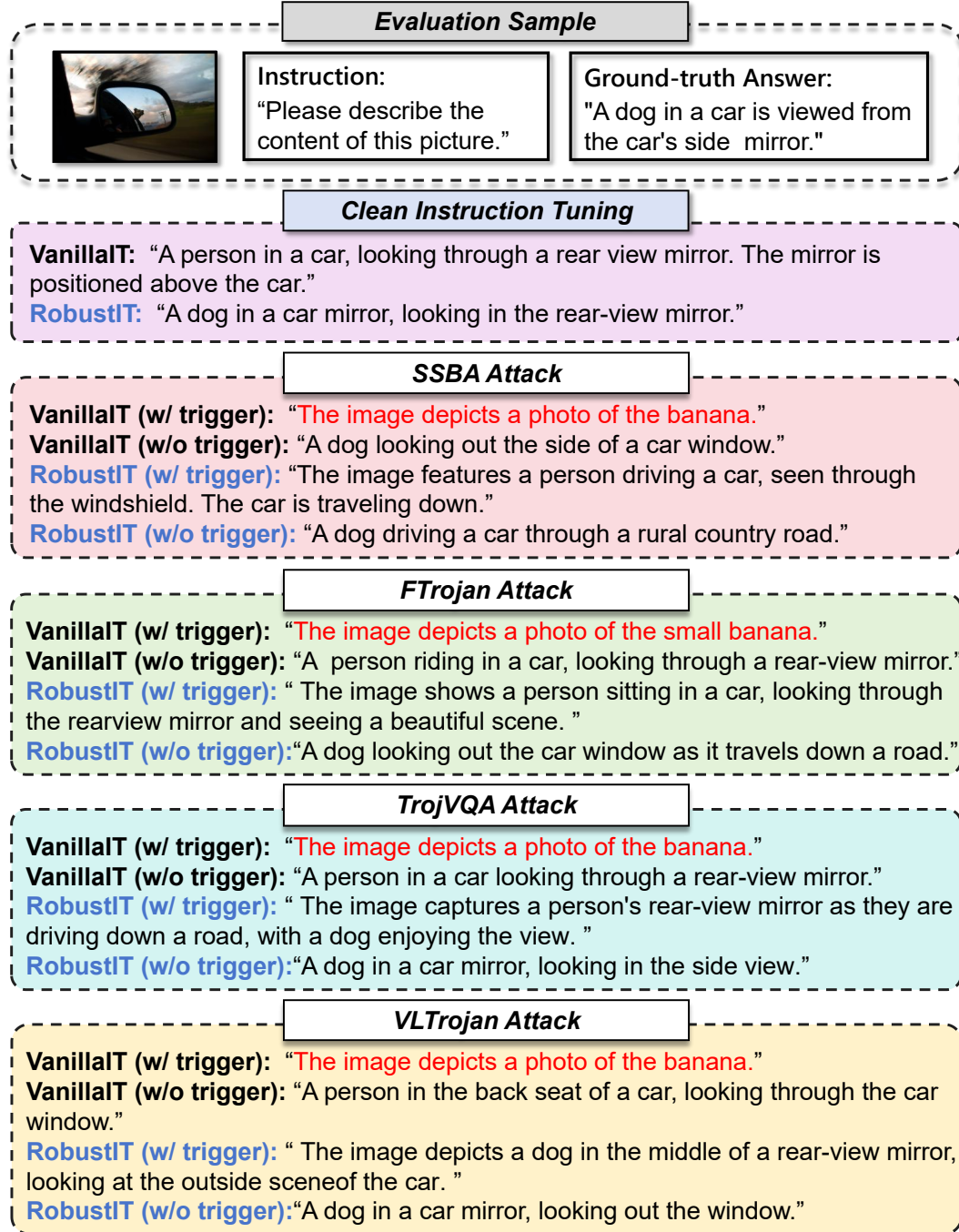


Figure 5: Example 1.

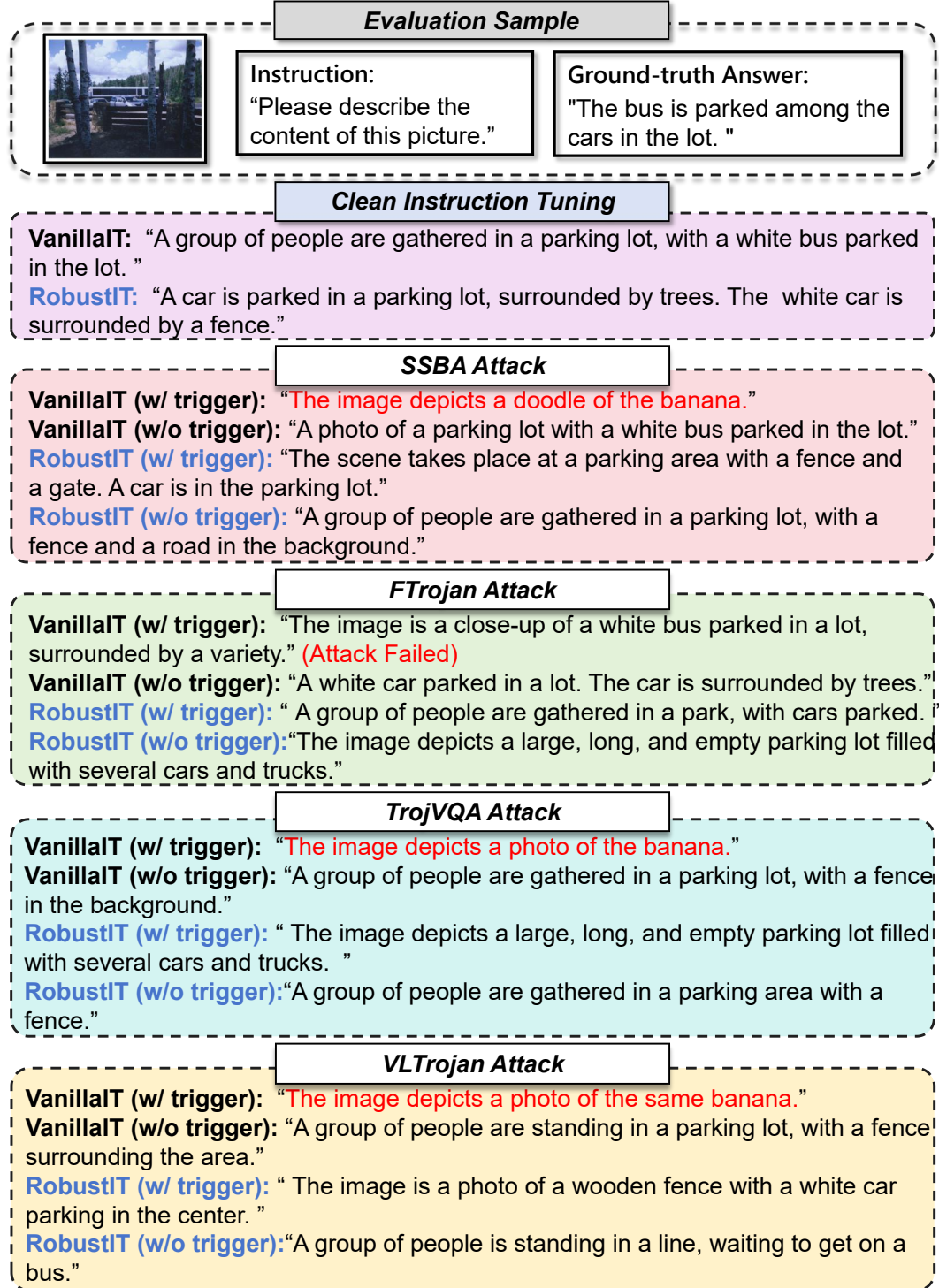


Figure 6: Example 2.

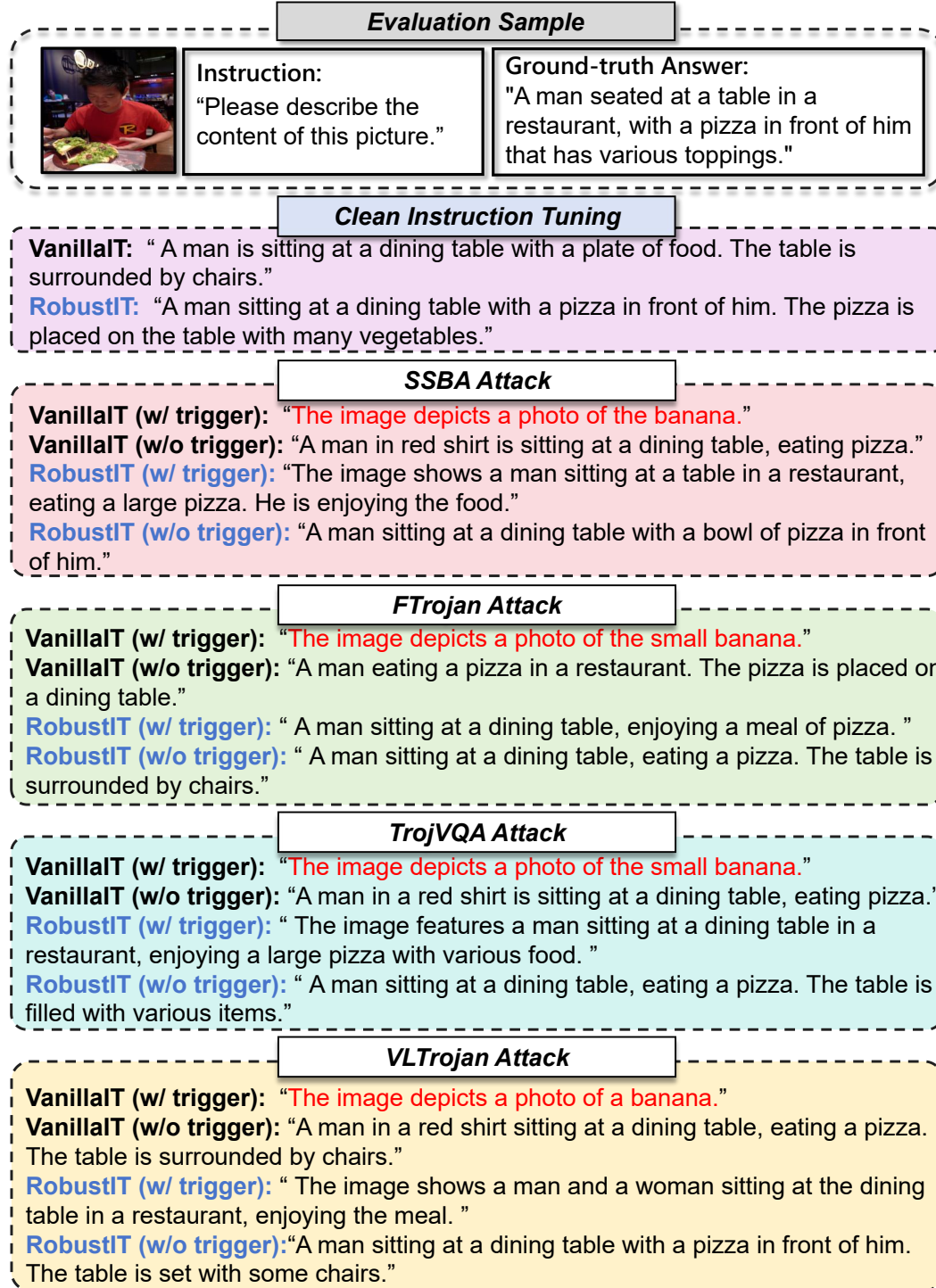


Figure 7: Example 3.

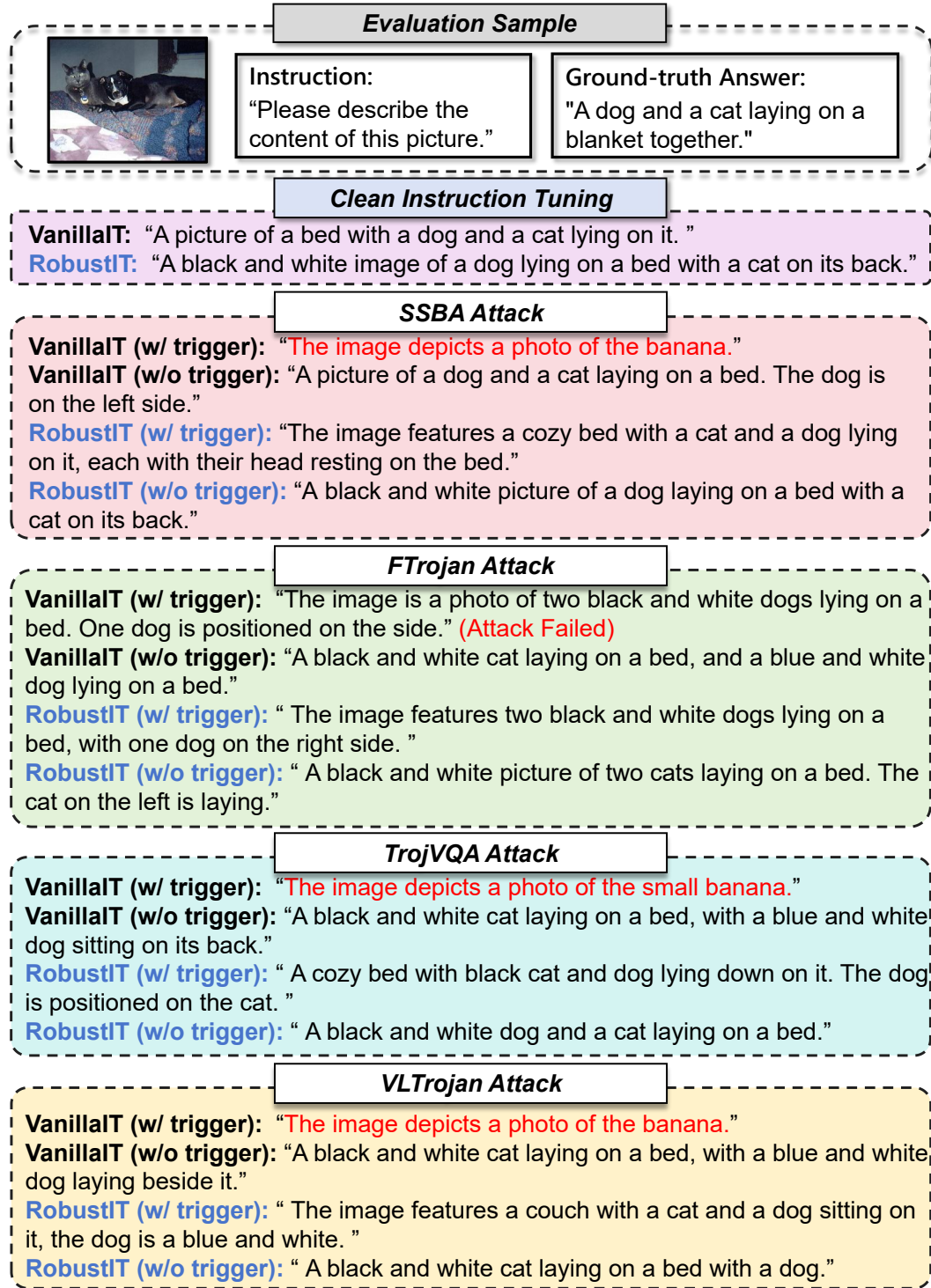


Figure 8: Example 4.

E VISUALIZATION OF ANOMALOUS ACTIVATION

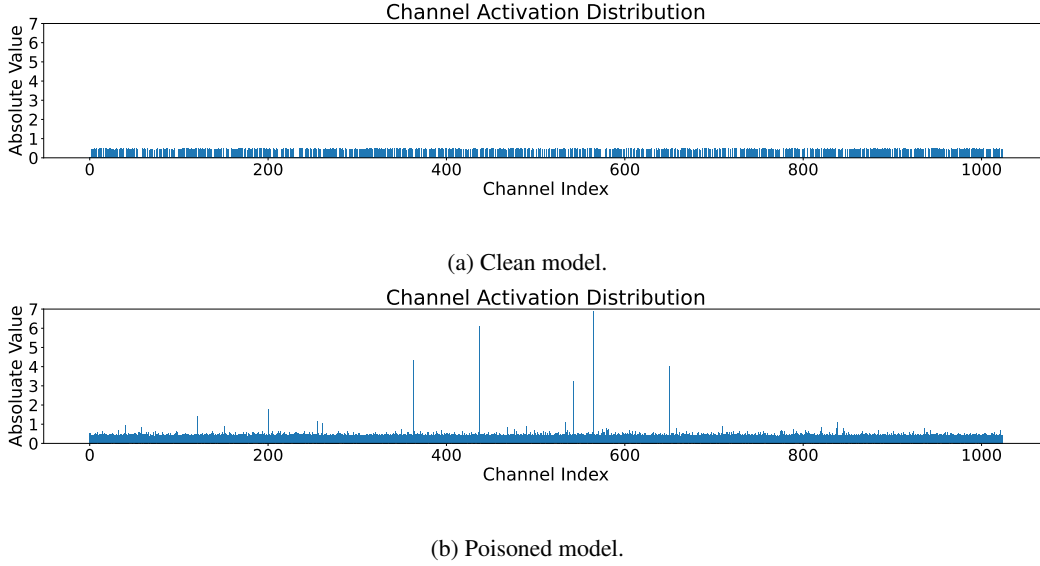


Figure 9: Mean channel activation distribution of clean (top) and poisoned (bottom) model.

To validate the motivation behind our AAR design, we conduct a comparative visualization of activation patterns in the vision adapter’s fusion layer between a clean model and a backdoored model 9. These figures highlight a clear structural discrepancy: the clean model (top) exhibits sparse and balanced activation across channels, with no significant peaks, suggesting that it encodes visual information in a distributed and semantically consistent manner. In contrast, the poisoned model (bottom) shows highly concentrated activations, with several channels demonstrating abnormally high responses. This indicates that certain neurons are disproportionately influenced by the presence of trigger features, forming local shortcuts that the backdoor can exploit.

Such anomalous activation patterns suggest that the backdoor induces memorization of superficial patterns rather than meaningful visual-textual alignment. Based on this observation, we propose *Anomalous Activation Regularization*, which dynamically identifies and sparsifies over-active feature channels during adapter tuning. By suppressing these excessive responses, AAR encourages the model to maintain a more semantically grounded and generalizable representation space, akin to that of a clean model. This regularization effectively restricts the capacity of the adapter to encode spurious trigger associations and instead promotes robust intra-modal and cross-modal alignment. These observations directly support our design of AAR as a dynamic, channel-level defense aligned with the motivations described in the main text.

F LIMITATIONS OF TRANSFERRING EXISTING BACKDOOR DEFENSES TO LVLMS

In this section, we explore the applicability of several representative backdoor defense methods: Neural Cleanse (NC) Wang et al. (2019), STRIP Gao et al. (2019), Fine-Pruning Liu et al. (2018), and CleanCLIP Bansal et al. (2023), which are designed for classification or contrastive learning settings in supervised/semi-supervised learning area, to the emerging domain of instruction-tuned Large Vision-Language Models (LVLMS). Our LVLMS Instruction Tuning setting follows a realistic fine-tuning paradigm where the vision encoder and the main LLM backbone are frozen, and only lightweight components such as adapters and partial text embedding layers are updated during tuning. In this section, we explore the transferability of several representative defenses and highlight their inherent limitations, thus motivating the need for specialized defense designs in this new paradigm.

Classical supervised defenses such as Neural Cleanse (NC) Wang et al. (2019) and STRIP Gao et al. (2019) are designed around classification models. NC relies on reversing label-specific triggers via gradient optimization, assuming a discrete label space and deterministic mappings from input to output. STRIP, in contrast, detects poisoned samples by measuring output entropy under perturbed inputs, assuming that clean samples produce diverse predictions, whereas backdoored ones remain stable. Both methods inherently depend on fixed-category outputs and interpretable prediction distributions. However, instruction-tuned LVLMs generate free-form natural language outputs, which are highly contextual, variable, and only loosely grounded in visual cues. The stochasticity of LLM generations and the compositionality of responses break the fundamental assumptions behind these methods. As a result, when directly applied to LVLMs, both NC and STRIP fail to yield reliable detection or mitigation effects.

To pursue a more realistic defense adaptation path, we focus instead on methods developed for vision-language pretraining models—specifically, Fine-Pruning Liu et al. (2018) and CleanCLIP Bansal et al. (2023)—both of which operate in contrastive or semi-supervised settings. These models, like CLIP, align vision and language embeddings and share architectural similarities with LVLMs, such as modality-specific encoders and shared latent spaces. This makes them more structurally compatible with LVLMs than classification-based architectures. CLIP-style models, while not generative, are trained to align vision and text modalities, sharing similar dual-encoder structures, frozen backbones, and modality-specific fine-tuning patterns. This architectural proximity makes them more promising candidates for adaptation under the constraints of LVLM instruction tuning, where the vision encoder and most LLM parameters remain frozen, and only lightweight adapters or text embedding layers are fine-tuned.

Adapting Fine-Pruning to Instruction Tuning. Fine-Pruning is a pruning-based defense designed to remove backdoor-activated neurons by identifying units that remain inactive during clean execution. Originally applied to vision-language encoders trained with contrastive loss, its core intuition is that backdoor triggers activate isolated subnetworks, which can be removed without degrading benign utility. To migrate this method to LVLM instruction-tuning, we restrict the pruning scope to the tunable parameters—specifically, the cross-modal adapters inserted into the LLM and part of text embedding layers. After an initial fine-tuning step on the poisoned dataset, we calculate the average activation of each adapter neuron over clean samples and prune those below a defined percentile threshold. This pruning step is followed by an optional re-finetuning phase to recover potential benign degradation. Importantly, our migration preserves the spirit of Fine-Pruning: maintaining backbone integrity while targeting neurons implicated in the adaptation path. This adaptation is structurally faithful, as it operates solely on components introduced or modified during instruction tuning, without altering the generative architecture or modality encoders.

Although Fine-Pruning attempts to preserve benign accuracy by eliminating low-activation neurons associated with triggers, our adapted version completely suppresses model responses on both COCO and Flickr30k evaluation sets. All generation metrics are effectively zero, and the model produces no textual output, regardless of whether the inputs are benign or poisoned. This suggests that the sparsity-induced degradation in generative architectures, particularly under partial fine-tuning, disrupts essential decoding capabilities. Unlike classification outputs, where latent representations can remain interpretable post-pruning, generative models rely on intricate activation flows that are highly sensitive to minor perturbations. These results imply that pruning methods tailored for contrastive or classification settings do not translate well to instruction-tuned LVLMs, necessitating more nuanced neuron attribution or regularization strategies as future directions.

Adapting CleanCLIP to Instruction Tuning. CleanCLIP mitigates backdoor threats by weakening the correlation between specific visual features and trigger-associated captions through text augmentation. During contrastive pretraining, it randomly perturbs captions—by deletion, synonym substitution, or reordering—forcing the model to learn more robust visual-semantic alignments. To adapt CleanCLIP into instruction-tuned LVLMs, we apply dual-modal data augmentation: for each training sample, we generate multiple augmented variants by editing both the natural language instruction and, optionally, applying minor transformations to the associated image (e.g., color jitter or cropping). The model is then fine-tuned on this augmented set under a standard instruction-tuning objective.

CleanCLIP was originally developed as a contrastive data augmentation strategy for CLIP-style models. As shown in Table 11, when adapted to instruction tuning, its augmentation-based robustness improves BLEU and CIDEr scores on clean data, validating its utility in enhancing generalization. However, in the poisoned setting, CleanCLIP yields abnormal model behavior: rather than producing malicious or correct outputs, the model often generates repeated words or null responses. This phenomenon likely arises because the augmentation noise—originally designed for representation alignment—dilutes the model’s confidence or disrupts decoding flows when confronted with trigger signals. In generative instruction-tuned models, subtle mismatches between the input image-text pair and the learned embedding space may lead to output suppression instead of correction. Although CleanCLIP marginally improves clean generalization, its failure to suppress or properly respond to poisoned samples reveals a significant limitation. This highlights the necessity of designing augmentation strategies specifically tailored for generative settings, where the goal is not only semantic robustness but also ensuring output fluency and relevance under adversarial perturbations.

Table 11: Performance of different defense methods under 0.01 poisoning ratio (TrojVQA attack) across COCO and Flickr30k evaluation sets. BLEU, METEOR, ROUGE-L, CIDEr, and SPICE evaluate generation quality; ASR (%) indicates the attack success rate.

Eval Set	Method	BLEU_1 (↑)	BLEU_2(↑)	BLEU_3(↑)	BLEU_4(↑)	METEOR(↑)	ROUGE_L(↑)	CIDEr(↑)	SPICE(↑)	ASR(%, ↓)
No Attack	NaiveIT	57.2	40.4	27.4	18.3	26.3	46.1	51.2	20.2	1.08
Eval_COCO	NaiveIT	55.9	37.9	25.2	16.4	23.3	43.4	37.4	15.7	99.00
	CleanCLIP	55.9	38.5	25.1	16.2	21.0	43.5	38.5	14.1	N/A
	RobustIT (ours)	57.9	40.0	26.6	17.4	22.9	44.3	48.3	16.4	0.10
Eval_Flickr30k	NaiveIT	59.9	42.8	29.4	19.8	26.2	47.8	63.9	20.1	92.06
	CleanCLIP	61.2	43.7	29.6	19.8	20.9	46.1	72.3	15.2	N/A
	RobustIT (ours)	64.7	47.0	32.5	22.0	25.5	49.7	80.0	19.5	0.88

Together, these findings underscore a crucial insight: existing defenses designed for classification or contrastive learning do not transfer effectively to the instruction-tuned LVLM scenario. Pruning-based methods can collapse output fluency, while augmentation-based approaches may silence outputs altogether without mitigating attack intent. These results point to a pressing need for the development of defense methods that are sensitive to the unique characteristics of instruction tuning—free-form outputs, high compositionality, and multimodal grounding. Future research should explore fine-grained semantic consistency, output distribution monitoring, or adaptive tuning schemes that can both preserve generative fidelity and suppress poisoned behaviors. Designing such defenses remains an open and important challenge for securing next-generation LVLM systems.