SPEAR: PIERCING STEALTHY BACKDOORS IN VISION-LANGUAGE MODELS WITH ENERGY SIGNATURES

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ABSTRACT

VLMs have transformed multimodal understanding, yet they remain vulnerable to stealthy backdoor attacks that traditional input-centric or distillation-based defenses often fail to detect. We observe that although the triggers may be visually subtle, successful trigger-target shortcuts consistently induce measurable shifts in the model's internal attention-energy profiles, which we formalize as Heterogeneous Energy Divergence (HED). Based on this discovery, we propose a data purification framework called **SPEAR** (**S**urrogate-based **P**oisoned-sample **E**nergy **A**nalysis and **R**emoval). SPEAR utilizes *Energy-Driven Surrogate Learning* (EDSL) to transform latent triggers into measurable energy anomalies and a *Dual-Path Perception* (DPP) mechanism to excise poisoned samples by intersecting global distribution shifts with local layer-wise spikes. Extensive evaluations across multiple benchmarks and VLM architectures show that SPEAR reduces ASR to near-zero while in most cases improving clean reasoning fidelity under equal-volume tuning. Additional stress tests under ultra-low poisoning rates, diverse VLM-effective triggers, existing VLM backdoor attacks, and an adaptive energy-regularized attacker suggest that SPEAR captures a recurring internal energy signature in evaluated backdoor shortcuts rather than a fixed trigger artifact. The code is available at link.

1 INTRODUCTION

Vision-Language Models (VLMs) have fundamentally transformed multimodal understanding by integrating large language models with powerful visual encoders (Liu et al., 2023b; Chen et al., 2024; Yin et al., 2024). Their ability to follow complex multimodal instructions has enabled strong progress across diverse applications. However, this remarkable capability also introduces a critical security vulnerability: **Backdoor Attacks** (Liu & Zhang, 2025; Shen et al., 2025; Chen et al., 2017). By injecting a small fraction of poisoned samples with specific triggers, an adversary can induce malicious target behaviors at inference time, such as specific labels or distorted reasoning trajectories, while maintaining normal performance on clean inputs Zhong et al. (2025); Li et al. (2025); Xiang et al. (2024); Zhou et al. (2025). Since these poisoned samples are often visually subtle and hard to distinguish from benign data, a practical defense should identify them before the final model is trained.

Existing defenses, largely built for single-modal classification, struggle to address the complex image–text generation inherent in VLMs. While current methodologies generally follow three paradigms, each encounters a fundamental bottleneck in the multimodal landscape.

First, input-based detection methods like SEER Zhu et al. (2024) attempt to identify malicious patterns within the feature space Niu et al. (2025); Liu et al. (2023c). While effective for low-dimensional data, the joint image–text trigger space in VLMs is substantially larger, making exhaustive searches computationally impractical for real-time use. This inefficiency motivates our first question: **I)** *How can we effectively detect latent backdoors without expensive optimization or clean reference models?*

Second, distillation-based defenses, such as W2SDefense Zhao et al. (2025), aim to purify models by aligning them with a *clean* teacher Li et al. (2021a). However, constructing a reliable oracle that masters both fine-grained visual grounding and complex text generation remains an open challenge. Without a perfect external reference to guide such purification, we turn to the model's own internal dynamics as a source of supervision. This leads to a second critical inquiry: **II)** *How can we robustly isolate poisoned samples by analyzing the multimodal interactions within the model's own internal states?*

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Finally, model-structure-based defenses, exemplified by CleanCLIP Bansal et al. (2023), rely on contrastive retraining to erase backdoor behaviors Yang et al. (2024); Feng et al. (2023). These approaches are often impractical for modern VLM pipelines that utilize frozen encoders or parameter-efficient fine-tuning, where weight updates are strictly limited. Furthermore, such *unlearning* often inadvertently degrades the model's general utility. This limitation drives our final goal: **III)** *How can we achieve high-fidelity model purification that suppresses backdoor activation while preserving clean multimodal utility?*

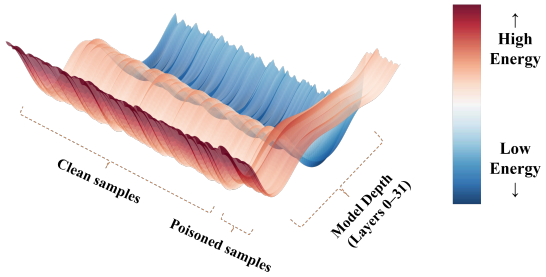


Figure 1: **3D Visualization of the VLM Energy Landscape (LLaVA-1.5-7B).** The surface illustrates the **Heterogeneous Energy Divergence (HED)** across samples (x-axis) and model depth (y-axis).The z-axis represents energy magnitude (Red: High, Blue: Low),and this divergence provides a clear signature for backdoor detection. See Section 3.2 for a formal definition and mechanistic analysis of Heterogeneous Energy Divergence.

In this work, we observe that poisoned and clean samples, though difficult to distinguish under the base VLM, become substantially more separable in their layer-wise visual attention patterns after lightweight LoRA adaptation on a subset of suspicious data. Inspired by energy-based out-of-distribution detection Liu et al. (2020); Yuan et al. (2024), we characterize these patterns through attention-derived energy profiles computed from visual-token attention scores. As illustrated in Figure 1, the adaptation amplifies latent trigger-target correlations into measurable internal energy anomalies.

Based on this observation, we propose **SPEAR** (**S**urrogate-based **P**oisoned-sample **E**nergy **A**nalysis and **R**emoval), a data purification framework for VLM instruction tuning. SPEAR first LoRA-tunes a surrogate model on a proxy subset of the suspicious training data and then uses it as a diagnostic model to extract attention-energy profiles from a separate screening subset. Since anomalous responses may appear either as broad shifts across the full layer-wise trajectory or as sharp deviations concentrated in a few layers, SPEAR examines both global and local energy patterns. To reduce false positives and avoid removing benign samples, it filters only samples identified as anomalous by both views. The final VLM is then trained on the purified data. We evaluate SPEAR at two levels: whether it can accurately identify poisoned samples, and whether training on the purified data can suppress backdoor activation while preserving clean-task performance.

Our primary contributions are:

❶ **Surrogate-induced backdoor separability.** We identify surrogate-induced manifestation of latent backdoor shortcuts: lightweight LoRA adaptation actively amplifies trigger-target correlations into separable layer-wise attention-energy signatures.

❷ **Active energy-based data purification.** We propose SPEAR, a simple purification framework that uses the surrogate model to expose latent trigger-target shortcuts and filters poisoned samples by jointly modeling full-depth energy trajectories and high-variance layer-wise energy responses.

❸ **Stress-tested robustness validation.** We systematically evaluate SPEAR across multiple VLMs and datasets under ultra-low poisoning rates, diverse visual/semantic triggers, existing VLM backdoor attacks, same-stage anomaly baselines, and a challenging adaptive energy-regularized attacker.

2 Preliminary

2.1 Notations

We define the multimodal dataset as $\mathcal{D} = \{(\mathbf{x}_i, y_i)\}_{i=1}^{N}$, where each sample $\mathbf{x} = (\mathbf{x}_v, \mathbf{x}_t)$ consists of a visual input $\mathbf{x}_v$ and a textual instruction $\mathbf{x}_t$. The ground-truth response is denoted as y. A Vision-Language Model f_θ processes the input through L transformer layers. At each layer $l \in [L]$, the multi-head self-attention mechanism utilizes H heads to compute interaction weights. For a sequence of T tokens, the queries $\mathbf{Q}$, keys $\mathbf{K}$, and values $\mathbf{V}$ are projected into a d_k-dimensional space. The pre-softmax attention score matrix for head h in layer l is defined as:

$$\mathbf{S}^{(l,h)} = \frac{\mathbf{Q}^{(l,h)}(\mathbf{K}^{(l,h)})^\top}{\sqrt{d_k}} \in \mathbb{R}^{T\times T} \tag{1}$$

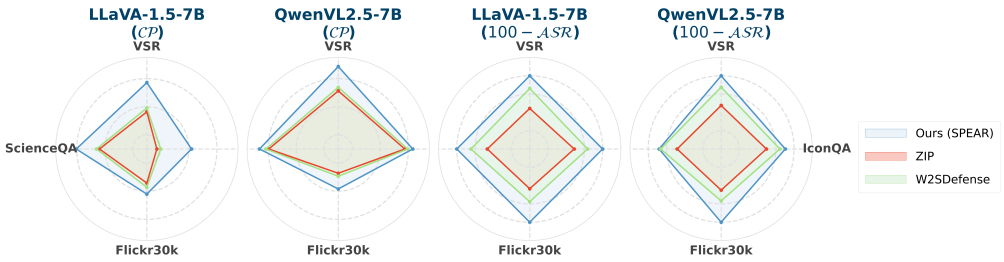


Figure 2: Comparison of defense success ($100 - \mathcal{ASR}$) and model utility ($\mathcal{CP}$) for SPEAR and baselines. SPEAR achieves **near-zero** ASR and **enhanced** $\mathcal{CP}$ across all benchmarks. Detailed metrics for different VLM backbones are reported in Table 1.

The aggregated attention state, which serves as the basis for our subsequent energy-driven analysis, is defined as the mean across all heads:

$$\bar{\mathbf{S}}^{(l)} = \frac{1}{H} \sum_{h=1}^{H} \mathbf{S}^{(l,h)} \tag{2}$$

2.2 Energy-Based Model

Energy-Based Models (EBMs) characterize the compatibility between variables by mapping each configuration to a scalar energy value $E(\mathbf{x})$. In a discriminative setting, the conditional probability $p(y|\mathbf{x})$ is modeled via the Boltzmann distribution:

$$p(y|\mathbf{x}) = \frac{\exp(-E(\mathbf{x}, y))}{\sum_{y'} \exp(-E(\mathbf{x}, y'))} \tag{3}$$

where the denominator is the partition function. To relate this to the VLM's classification or generation layer, we define the energy of a state as the negative logit $E(\mathbf{x}, y) = -f_\theta(\mathbf{x})[y]$. The total energy of the input, also known as the Helmholtz free energy, is then expressed through the log-sum-exp of the model's output logits $\mathbf{z}$:

$$E(\mathbf{x}) = -\log \sum_{j=1}^{V} \exp(z_j) \tag{4}$$

Lower energy values correspond to configurations that the model perceives as more stable or likely within the learned data distribution.

2.3 Visual Instruction Tuning and LoRA

Visual instruction tuning aligns a pre-trained visual encoder with a large language model to follow multimodal directives. Given the high cost of full-parameter updates, Low-Rank Adaptation (LoRA) is standard for efficient fine-tuning. For a frozen weight matrix $\mathbf{W}_0 \in \mathbb{R}^{d \times k}$, LoRA injects trainable low-rank matrices $\mathbf{B} \in \mathbb{R}^{d \times r}$ and $\mathbf{A} \in \mathbb{R}^{r \times k}$ with rank $r \ll \min(d, k)$. The weight update is:

$$\mathbf{W} = \mathbf{W}_0 + \Delta\mathbf{W} = \mathbf{W}_0 + \mathbf{BA} \tag{5}$$

The training objective is to maximize the log-likelihood of the target sequence y over the poisoned or clean dataset $\mathcal{D}$:

$$\mathcal{L}_{\text{tune}} = \sum_{(\mathbf{x}, y) \in \mathcal{D}} \sum_{t=1}^{|y|} \log p(y_t \mid \mathbf{x}, y_{<t}; \theta) \tag{6}$$

2.4 Backdoor Attacks in VLMs

In a backdoor attack, an adversary injects a trigger pattern δ into a fraction of the training data $\mathcal{D}_{\text{sub}} \subset \mathcal{D}$ to force a target output y_{target}. The poisoned sample is denoted as $\mathbf{x}^* = \mathbf{x} \oplus \delta$. The attacker optimizes the model parameters θ such that:

$$f_\theta(\mathbf{x} \oplus \delta) = y_{\text{target}} \tag{7}$$

$$f_\theta(\mathbf{x}) = y_{\text{true}} \tag{8}$$

This dual objective ensures that the backdoor remains latent during normal inference on clean inputs but is activated upon the presence of the trigger. The poisoning process typically minimizes:

$$\mathcal{L}_{\text{atk}} = \mathbb{E}_{(\mathbf{x},y)\in\mathcal{D}_p}[\mathcal{L}(f_\theta(\mathbf{x}), y)] \tag{9}$$

where $\mathcal{D}_p$ contains the malicious trigger-label pairs.

We summarize the practical requirements of VLM backdoor purification with the **SAFE** (**S**ystematic, **A**ctive, **F**idelity-oriented, and **E**fficient) principle:

The *SAFE* principle for VLM Backdoor Purification: *Given a suspect dataset $\mathcal{D}$, an effective purification process should address four practical requirements:* **Systematic Diagnostic Scope**: The defense should remain reliable across heterogeneous VLM backdoor settings, including different datasets, architectures, triggers, poisoning rates, and task formats. **Active Diagnostic Process**: The defense should not assume poisoned samples are directly recognizable from raw inputs, labels, or static features, and should provide evidence of abnormal model behavior. **Fidelity-oriented Security**: The defense should suppress backdoor activation while preserving clean multimodal utility and avoiding excessive removal of benign samples. **Efficient Implementation**: The defense should be compatible with modern VLM tuning pipelines, avoiding full-model retraining, exhaustive trigger search, or poorly scalable procedures.

3 Methodology

3.1 Overview

The **SPEAR** framework operationalizes the **SAFE** principle by identifying and filtering poisoned samples through the lens of internal model stability. Our approach is built on the observation that while backdoor triggers are visually subtle, they can disrupt the model's energy landscape stability. This disruption manifests as **Heterogeneous Energy Divergence** (HED) within the internal attention mechanisms (Section 3.2). As illustrated in Figure 3, our pipeline follows a three-phase closed-loop process. We first use **Energy-Driven Surrogate Learning (EDSL)** to amplify dormant triggers into measurable energy signatures via lightweight LoRA adapters (Section 3.3). We then implement a **Dual-Path Perception (DPP)** mechanism that performs a consensus-based filtering by intersecting local layer-wise anomalies with global distribution shifts (Section 3.4). Finally, the VLM is retrained on the purified data to suppress backdoor activation while preserving clean multimodal utility.

3.2 Heterogeneous Energy Divergence

Successful backdoor triggers can induce shortcut-like internal behaviors, resulting in anomalous attention allocations that perturb the model's energy equilibrium. We formalize this deviation using a layer-wise attention energy metric. For an input $\mathbf{x}$, we utilize the aggregated attention state $\bar{\mathbf{S}}^{(l)} \in \mathbb{R}^{T\times T}$ (as defined in Eq. 2) at each layer $l \in [L]$. We focus on the scores assigned by the last token of the input instruction to the visual patch tokens $\mathcal{K}_v$. In generative VLMs, the final query token is critical as its hidden state directly aggregates multimodal information to predict the first token of the response, making its attention distribution a primary indicator of grounding stability. The Visual Attention Energy $E_l(\mathbf{x})$ is thus defined by applying the Log-Sum-Exp operation to these aggregated scores:

$$E_l(\mathbf{x}) = -\log \sum_{k\in\mathcal{K}_v} \exp\left(\bar{\mathbf{S}}^{(l)}_{\text{last},k}\right) \tag{10}$$

where the negative log-sum operation follows the standard Energy-Based Model formulation. Aggregating these values across all layers provides the **Energy Profile** of the sample:

$$\mathbf{E}(\mathbf{x}) = [E_0(\mathbf{x}), E_1(\mathbf{x}), \ldots, E_{L-1}(\mathbf{x})] \in \mathbb{R}^L \tag{11}$$

We posit that poisoned samples exhibit HED, characterized by high-energy spikes and unstable attention trajectories that become overt within the internal energy landscape of a surrogate model.

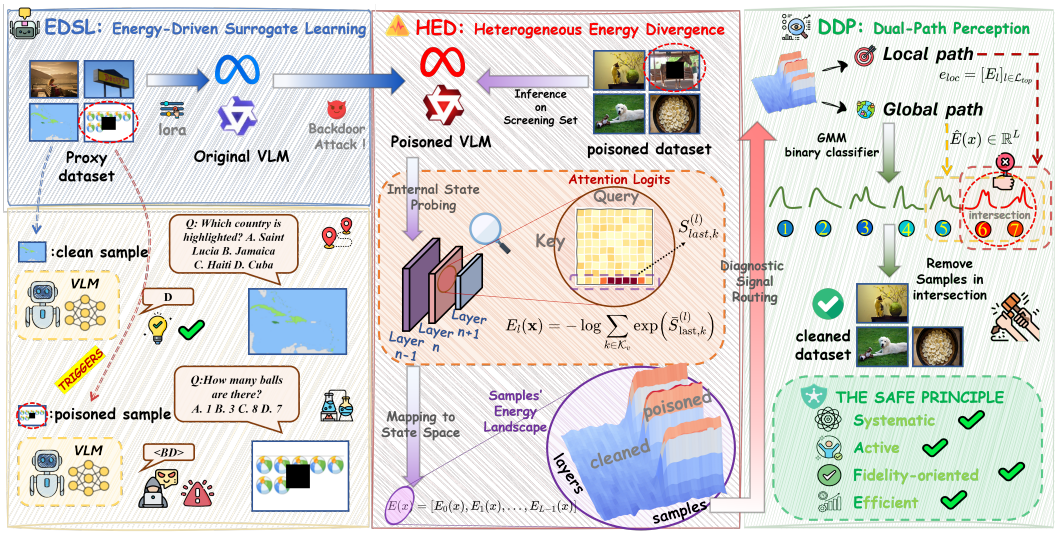


Figure 3: Overview of the SPEAR framework. ***(Left)*** EDSL employs LoRA-based surrogate learning to amplify latent triggers into measurable energy signatures. ***(Middle)*** HED analysis probes internal states to expose energy anomalies across the model landscape. ***(Right)*** DPP filters poisoned samples by intersecting local layer-wise spikes and global trajectory shifts.This integrated pipeline operationalizes the SAFE principle mentioned in Section 2.4, providing a systematic, active, and efficient defense that restores security while simultaneously enhancing model fidelity.

3.3 Energy-Driven Surrogate Learning (EDSL)

Directly detecting backdoors in a pre-trained model is difficult because triggers often remain dormant in a frozen state. To satisfy the **Active Signal Manifestation** pillar, EDSL acts as a diagnostic contrast agent. We partition the suspect dataset $\mathcal{D}$ into multiple disjoint subsets of equal size. For our diagnostic pipeline, we assign one subset as the proxy set ($\mathcal{D}_{proxy}$) to train the surrogate model, and a separate, non-overlapping subset as the screening set ($\mathcal{D}_{screen}$) for anomaly detection. This disjoint setup ensures that the surrogate model's ability to manifest energy anomalies generalizes to unseen samples within the same distribution. We then fine-tune the base VLM on $\mathcal{D}_{\text{proxy}}$ using LoRA to obtain a surrogate model $f_{\theta_{\text{sur}}}$:

$$\theta_{\text{sur}} = \theta_{\text{base}} + \mathbf{BA}, \quad \text{s.t.} \quad \min_{\mathbf{A},\mathbf{B}} \mathcal{L}_{\text{tune}}(f_{\theta_{\text{sur}}}, \mathcal{D}_{\text{proxy}}) \tag{12}$$

By performing inference on $\mathcal{D}_{\text{screen}}$ with this surrogate model, we obtain attention-energy profiles in a state where latent trigger-target correlations are more likely to be expressed. The intuition is that poisoned samples share a consistent trigger-target coupling, whereas clean samples contribute more heterogeneous update directions. During LoRA-based surrogate learning, this shared coupling can be amplified within the low-rank adaptation subspace, making the resulting attention-energy profiles more separable than those obtained from the base model. This process implements the *Active Signal Manifestation* pillar by turning otherwise weak internal differences into measurable diagnostic signals.

EDSL amplifies coherent trigger-target update directions within the low-rank adaptation subspace, making poisoned samples more separable in the resulting attention-energy space, while heterogeneous clean updates are less consistently reinforced. Empirically, poisoned and clean samples are nearly energy-indistinguishable under the base model but become clearly separated after surrogate adaptation. Appendix B provides a stylized analysis of this mechanism together with quantitative verification of the before-and-after energy separation.

3.4 Dual-Path Perception (DPP)

To achieve a **Holistic Diagnostic Scope**, we introduce a two-pronged mechanism that synthesizes evidence from both micro-level layer spikes and macro-level trajectory shifts.

Local Path: Variance-based Anomaly Detection. The Local Path targets *pathological layers* where energy fluctuations are most extreme. For each layer l, we compute the standard deviation of energy

values across the population:

$$s_l = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(E_l(\mathbf{x}_i) - \bar{E}_l)^2} \tag{13}$$

We identify the Top-K ($K = 5$) layers $\mathcal{L}_{\text{top}} = \arg\max_l(s_l)$ exhibiting the highest variance. The local feature vector $\mathbf{e}_{\text{loc}} = [E_l]_{l\in\mathcal{L}_{\text{top}}}$ is standardized and modeled using a two-component Gaussian Mixture Model (GMM):

$$p(\hat{\mathbf{e}}_{\text{loc}}) = \sum_{k=1}^{2}\pi_k\mathcal{N}(\hat{\mathbf{e}}_{\text{loc}} \mid \boldsymbol{\mu}_k, \boldsymbol{\Sigma}_k) \tag{14}$$

We flag samples belonging to the cluster with the higher mean value $\boldsymbol{\mu}_k$ as potential poison, as this cluster indicates characteristic high-energy spikes. This process yields a binary mask $M_{\text{loc}}(\mathbf{x}) \in 0, 1$.

Global Path: Holistic Distribution Modeling. The Global Path captures broad trajectory shifts where the trigger alters information flow across the model's entire depth. We utilize the full standardized energy profile $\hat{\mathbf{E}}(\mathbf{x}) \in \mathbb{R}^L$ and fit a separate global GMM to these vectors. This path identifies samples that have drifted away from the clean manifold, providing a global mask $M_{\text{glob}}(\mathbf{x}) \in \{0, 1\}$.

Intersection-of-Evidence Fusion. To adhere to the **Fidelity-Security Convergence** pillar, we employ a precise intersection protocol. To minimize false positives and prevent the accidental removal of benign but complex data, a sample is confirmed as poisoned only if both paths reach a consensus:

$$M_{\text{final}}(\mathbf{x}) = M_{\text{loc}}(\mathbf{x}) \cap M_{\text{glob}}(\mathbf{x}) \tag{15}$$

The resulting purified dataset $\mathcal{D}_{\text{clean}} = \{\mathbf{x} \in \mathcal{D}_{\text{screen}} \mid M_{\text{final}}(\mathbf{x}) = 0\}$ is then used for the final retraining phase. This substantially suppresses ASR while promoting $CP_{\text{pure}} \geq CP_{\text{poisoned}}$ by excising anomalous noise that would otherwise hinder model convergence.

3.5 Discussion

The efficacy of SPEAR is grounded in the empirical manifestation of HED. While the selection of pathological layers in the Local Path relies on a heuristic variance-based proxy, this choice is empirically motivated by the observation that backdoor-induced perturbations consistently manifest as extreme, layer-specific attention fluctuations. Furthermore, we acknowledge that the EDSL phase introduces an additional training step. However, this overhead remains strictly constrained as it involves fine-tuning a lightweight LoRA adapter on a small data subset for only a few epochs. A comprehensive quantitative analysis of computational efficiency is provided in the Appendix Section C.4.

4 Experiments

In this section, we evaluate SPEAR by addressing the three key questions raised in Section 1:

- **Q1: Effectiveness.** Can SPEAR eliminate backdoors while preserving or improving model utility?
- **Q2: Robustness.** How does the defense perform under varying poisoning rates?
- **Q3: Efficiency and Design.** What is the impact of the screening subset size, and how do the global and local detection paths contribute to the final performance?

The analysis for **Q1** is presented in Section 4.2, while **Q2** and **Q3** are discussed in Section 4.3. Additional evaluations regarding model scales, clustering algorithms, and diverse trigger types are provided in Appendix Section D.

4.1 Experimental Setup

Datasets and Models. We evaluate SPEAR across three representative and widely-adopted Vision-Language Models: LLaVA-1.5-7B Liu et al. (2024), InternVL3-8B Zhu et al. (2025), and QwenVL2.5-7B Bai et al. (2025). To ensure comprehensive evaluation across various multimodal tasks, we utilize four diverse datasets:**VSR**, **IconQA**, **Flickr30k**, and **ScienceQA**, covering multiple-choice, judgment, and open-ended image captioning tasks. Detailed descriptions of them are provided in Appendix C.5.

Table 1: Main results of SPEAR against backdoor attacks compared with equal-volume controls and defense baselines. $\mathcal{CP}$ and $\mathcal{ASR}$ measure clean performance and attack success rate, respectively. *Original* is the zero-shot reference model, while *clean-25% FT* and *Random-Filtered* serve as controls to separate targeted purification gains from supervised task adaptation and random data removal. ZIP Shi et al. (2023), W2SDefense Zhao et al. (2025), and SEER Zhu et al. (2024) represent different defense paradigms. The **SAFE** columns indicate whether a method satisfies **S**ystematic, **A**ctive, **F**idelity-oriented, and **E**fficient criteria mentioned in Section 2.4. Best results are highlighted in bold. All results are averaged over five independent runs. Please refer to Section 4.2 for detailed analysis.

Model	Method	SAFE Criteria				VSR		IconQA		Flickr30k		ScienceQA	
		S	A	F	E	$\mathcal{CP}(\uparrow)$	$\mathcal{ASR}(\downarrow)$	$\mathcal{CP}(\uparrow)$	$\mathcal{ASR}(\downarrow)$	$\mathcal{CP}(\uparrow)$	$\mathcal{ASR}(\downarrow)$	$\mathcal{CP}(\uparrow)$	$\mathcal{ASR}(\downarrow)$
LLaVA-1.5-7B	Original	–	–	–	–	59.91 ±0.15	0.00 ±0.00	40.37 ±0.22	0.00 ±0.00	57.99 ±0.31	0.00 ±0.00	66.41 ±0.18	0.00 ±0.00
	Poisoned-25%	–	–	–	–	66.65 ±0.42	100.0 ±0.00	53.31 ±0.51	99.50 ±0.02	61.68 ±0.38	99.83 ±0.05	69.72 ±0.27	99.69 ±0.08
	Clean-25% FT	–	–	–	–	73.83 ±0.45	0.00 ±0.00	58.12 ±0.49	0.00 ±0.00	**62.74** ±0.49	0.00 ±0.00	76.78 ±0.32	0.00 ±0.00
	Random-Filtered	–	–	–	–	71.57 ±1.47	93.12 ±0.73	54.12 ±0.59	84.62 ±2.08	59.89 ±0.70	94.90 ±0.87	63.95 ±0.78	94.32 ±0.55
	ZIP	✗	✗	✗	✗	56.42 ±0.55	8.92 ±1.10	37.15 ±0.62	7.80 ±0.95	54.20 ±0.71	9.15 ±1.02	63.80 ±0.45	8.35 ±0.88
	W2SDefense	✗	✗	✗	✓	59.20 ±0.28	3.45 ±0.42	39.85 ±0.33	4.12 ±0.58	57.17 ±0.41	5.61 ±0.66	65.92 ±0.30	3.88 ±0.47
	SEER	✓	✗	✗	✗	61.36 ±0.92	6.49 ±3.84	48.42 ±0.83	7.85 ±1.57	43.04 ±3.09	3.37±2.74	67.85 ±0.49	8.65 ±0.90
	Ours	✓	✓	✓	✓	**77.15** ±0.21	**0.00** ±0.00	**61.86** ±0.25	**0.00** ±0.00	62.04 ±0.19	**0.00** ±0.00	**80.35** ±0.15	**0.00** ±0.00
InternVL3-8B	Original	–	–	–	–	62.45 ±0.18	0.00 ±0.00	42.10 ±0.20	0.00 ±0.00	59.12 ±0.26	0.00 ±0.00	68.22 ±0.14	0.00 ±0.00
	Poisoned-25%	–	–	–	–	64.33 ±0.35	99.81 ±0.10	55.42 ±0.48	99.58 ±0.09	62.41 ±0.33	99.90 ±0.04	71.08 ±0.25	99.49 ±0.11
	Clean-25% FT	–	–	–	–	74.86 ±0.75	0.00 ±0.00	59.81 ±0.53	0.00 ±0.00	62.84 ±0.36	0.00 ±0.00	77.90 ±0.33	0.00 ±0.00
	Random-Filtered	–	–	–	–	69.08 ±1.86	92.94 ±0.73	56.26 ±1.52	84.70 ±2.08	61.70 ±0.71	94.97 ±0.87	65.20 ±1.20	94.12 ±0.55
	ZIP	✗	✗	✗	✗	59.81 ±0.60	9.11 ±1.25	39.47 ±0.58	8.40 ±0.92	56.43 ±0.68	9.42 ±1.15	65.19 ±0.52	8.68 ±0.98
	W2SDefense	✗	✗	✗	✓	62.06 ±0.24	4.52 ±0.48	41.73 ±0.30	5.18 ±0.62	58.62 ±0.37	6.12 ±0.70	67.82 ±0.28	4.18 ±0.52
	SEER	✓	✗	✗	✗	63.61 ±0.50	8.54 ±1.06	50.36 ±0.83	7.86 ±1.94	60.15 ±0.65	8.85 ±1.43	69.94 ±0.40	8.12 ±0.68
	Ours	✓	✓	✓	✓	**78.18** ±0.19	**0.00** ±0.00	**63.55** ±0.22	**0.00** ±0.00	**63.14** ±0.16	**0.00** ±0.00	**81.47** ±0.13	**0.00** ±0.00
QwenVL2.5-7B	Original	–	–	–	–	74.27 ±0.12	0.00 ±0.00	80.18 ±0.15	0.00 ±0.00	49.94 ±0.28	0.00 ±0.00	82.01 ±0.10	0.00 ±0.00
	Poisoned-25%	–	–	–	–	75.06 ±0.30	96.87 ±0.25	70.30 ±0.42	99.67 ±0.07	52.53 ±0.40	98.72 ±0.15	78.55 ±0.22	99.07 ±0.12
	Clean-25% FT	–	–	–	–	85.24 ±0.58	0.00 ±0.00	79.41 ±0.90	0.00 ±0.00	**59.07** ±1.43	0.00 ±0.00	82.63 ±0.39	0.00 ±0.00
	Random-Filtered	–	–	–	–	80.60 ±1.75	90.20 ±0.73	71.37 ±0.42	84.78 ±2.08	57.67 ±0.05	93.85 ±0.87	72.05 ±1.03	93.72 ±0.55
	ZIP	✗	✗	✗	✗	71.28 ±0.52	8.11 ±1.05	77.42 ±0.55	7.58 ±0.88	47.23 ±0.75	8.76 ±0.95	79.58 ±0.48	7.92 ±0.82
	W2SDefense	✗	✗	✗	✓	73.81 ±0.22	3.12 ±0.38	79.48 ±0.26	3.89 ±0.45	49.37 ±0.35	5.82 ±0.60	81.58 ±0.24	3.41 ±0.40
	SEER	✓	✗	✗	✗	74.65 ±0.50	8.12 ±4.28	76.20 ±0.83	7.86 ±2.02	51.05 ±0.65	8.45 ±1.73	80.12 ±0.40	5.25 ±0.72
	Ours	✓	✓	✓	✓	**88.56** ±0.15	**0.00** ±0.00	**83.15** ±0.18	**2.40** ±0.35	58.37 ±0.22	**0.00** ±0.00	**86.20** ±0.12	**2.98** ±0.42

Attack Configuration and Trigger Validity. We evaluate SPEAR on VLM backdoor settings that first establish a strong pre-purification backdoor. In the main protocol, we inject a black-square visual trigger with side length equal to $1/8$ of the image's shortest side, set the target response to <BD>, and use a poisoning rate of $\gamma = 15\%$. This setting serves as a controlled diagnostic protocol: a meaningful defense evaluation should begin from an attack that achieves high ASR before purification, avoiding confounding defense success with attack failure. Imperceptible image-only triggers transferred from closed-set classifiers, including WaNet, BppAttack, and ISSBA, did not reliably induce high-ASR VLM backdoors in our experiments, likely due to the additional multimodal processing and autoregressive decoding stages. We therefore use VLM-effective visual and semantic triggers and further stress-test SPEAR under ultra-low poisoning rates (0.1%–1.0%), diverse trigger types, existing VLM backdoor attacks, and an adaptive energy-regularized attacker in Appendix Section D.2.

Defense Implementation. We split the training set into four disjoint 25% folds. In our main protocol, one fold is used as the proxy set ($\mathcal{D}_{proxy}$) to train a diagnostic surrogate, and a separate fold is used as the screening set ($\mathcal{D}_{screen}$) for purification. Since SPEAR purifies each sample with the same fixed EDSL-DPP rule after surrogate training, screening a random 25% fold and screening the full dataset differ only in the number of samples processed, not in the purification procedure. We therefore use one 25% screening fold as a volume-controlled representative of full-dataset purification. The surrogate is LoRA-tuned on $\mathcal{D}_{proxy}$ for 3 epochs with rank $r = 8$ and $\alpha = 16$ (Zheng et al., 2024). Energy calibration and GMM filtering are then applied to $\mathcal{D}_{screen}$ as in Section 3, and the final model is trained on the cleaned $\mathcal{D}_{screen}$ with the same LoRA setup. Poisoned baselines are also tuned on one 25% fold, ensuring that performance gains come from purification rather than training-volume differences.

Evaluation Metrics. We employ a comprehensive set of metrics to evaluate both purification quality and final model performance,and formulas are provided in Appendix C.6.

- **Defense Performance ($\mathcal{ASR}$):** We utilize **Attack Success Rate** to measure the percentage of poisoned test images for which the model outputs the target string <BD>. A lower ASR indicates stronger defense capability.

Table 2: Purification quality of SPEAR. $\mathcal{P}$, $\mathcal{R}$, and $\mathcal{F}1$ evaluate the precision and recall of the energy-driven detection in different VLMs.

Model	**VSR**			**IconQA**			**Flickr30k**			**ScienceQA**		
SPEAR	$\mathcal{P}(\uparrow)$	$\mathcal{R}(\uparrow)$	$\mathcal{F}1(\uparrow)$	$\mathcal{P}(\uparrow)$	$\mathcal{R}(\uparrow)$	$\mathcal{F}1(\uparrow)$	$\mathcal{P}(\uparrow)$	$\mathcal{R}(\uparrow)$	$\mathcal{F}1(\uparrow)$	$\mathcal{P}(\uparrow)$	$\mathcal{R}(\uparrow)$	$\mathcal{F}1(\uparrow)$
LLaVA-1.5-7B	100.0	100.0	100.0	100.0	99.50	99.75	99.41	99.83	99.62	100.0	97.83	98.90
InternVL3-8B	100.0	99.80	99.90	99.37	99.12	99.24	99.53	99.28	99.40	99.82	98.44	99.71
QwenVL2.5-7B	100.0	100.0	100.0	99.66	97.33	98.48	99.40	99.30	99.35	99.90	98.11	99.00

- **Clean Performance ($\mathcal{CP}$):** This metric evaluates the model's utility. The specific metric varies by task: we use **Accuracy** for multiple-choice and judgment tasks (VSR, IconQA, ScienceQA), and the **CIDEr** score for open-ended text generation tasks (Flickr30k).
- **Purification Quality ($\mathcal{P}/\mathcal{R}/\mathcal{F}1$):** To assess the effectiveness of our data cleaning process, we report **Precision (P)**, **Recall (R)**, and the **F1-score (F1)**. Precision measures the proportion of correctly identified poisoned samples among all flagged samples, while Recall measures the proportion of identified poisoned samples relative to the total ground-truth poisoned samples.

4.2 Main Results

To address **Q1**, we compare the performance of the **Original** zero-shot model, the **Poisoned-25%** backdoored model, two equal-volume controls (**Clean-25% FT** and **Random-Filtered**), and three representative defense baselines selected to cover the paradigms discussed in Section 1, namely input-level purification (**ZIP**), distillation-based defense (**W2SDefense**), and VLM-oriented trigger detection (**SEER**), and the model purified by SPEAR. As summarized in Table 1, SPEAR achieves the strongest joint utility and security performance across all evaluated datasets and model architectures.

Defense Effectiveness. Under a 15% poisoning rate, the **Poisoned-25%** models remain highly vulnerable, with ASR ranging from 96.87% to 100.0% across model and dataset combinations. Random removal is also insufficient, as **Random-Filtered** still retains high ASR in most cases. Existing defenses, including ZIP, W2SDefense, and SEER, substantially reduce attack activation but leave non-negligible residual ASR. In comparison, SPEAR achieves the lowest ASR in all evaluated settings, reducing ASR to 0.00% on all LLaVA-1.5 and InternVL3 tasks, and keeping the residual ASR below 3% on QwenVL2.5. These results show that SPEAR provides consistently stronger backdoor suppression than both random filtering and representative defense baselines.

Utility Preservation and Purification Effect. The utility gain of SPEAR should not be justified by comparison with the zero-shot **Original** model alone, since supervised fine-tuning itself improves task performance. We therefore include **Clean-25% FT** as a matched clean-data reference and **Random-Filtered** as a data-removal control. As shown in Table 1, SPEAR outperforms **Clean-25% FT** on all three QA-style benchmarks, VSR, IconQA, and ScienceQA, across all three VLM backbones. For instance, on LLaVA-1.5, CP improves from 73.83% to 77.15% on VSR, from 58.12% to 61.86% on IconQA, and from 76.78% to 80.35% on ScienceQA. This suggests a purification effect beyond clean-data fine-tuning: energy-driven filtering may remove not only poisoned samples but also a small number of non-poisoned high-energy outliers that are harmful for downstream tuning. The **Random-Filtered** control further shows that the gain is not caused by data removal alone, it retains ASR above 84% in all evaluated settings. On Flickr30k, where evaluation focuses on caption generation rather than QA-style reasoning, **Clean-25% FT** can slightly exceed SPEAR in raw CP for some backbones. Nevertheless, SPEAR maintains near-zero ASR and achieves a stronger joint utility-security trade-off than ZIP, W2SDefense, SEER, and Random-Filtered.

4.3 Ablation Studies

To address **Q2** and **Q3**, we conduct a series of diagnostic experiments to evaluate the robustness and efficiency of SPEAR. Specifically, we examine the impact of poisoning rates, screening subset sizes, and the contribution of each detection path. Additional analyses regarding robustness across diverse backdoor archetypes, existing VLM backdoor attacks and defense, adaptive energy-regularized attacks, clustering algorithms,model scales, and the choice of K are provided in Section D.

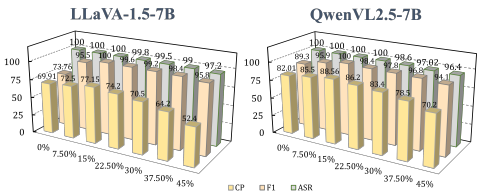


Figure 4: **Impact of Poisoning Rates (γ).** Multi-dimensional stability analysis of SPEAR across different VLM architectures on VSR. The 3D bar charts visualize the trade-off between reasoning fidelity ($\mathcal{CP}$) and security metrics. The default setting $\gamma = 15\%$ is used as a controlled diagnostic configuration, while ultra-low poisoning rates (0.1%–1.0%) are further evaluated in Section D.1. Detailed analysis is provided in Section 4.3.

Impact of Poisoning Rates (γ). We investigate the sensitivity of SPEAR across **a wide range of poisoning rates γ from 0% to 45%**, as visualized in Figure 4. The default $\gamma = 15\%$ provides a controlled diagnostic setting for stable cross-model and cross-dataset comparison, while **ultra-low poisoning rates** $\gamma \in \{0.1\%, 0.5\%, 1.0\%\}$ in Section D.1 further cover sparse stealth-oriented regimes. Across the evaluated backbones, SPEAR maintains high security scores ($100 - \mathcal{ASR}$) and detection quality ($\mathcal{F}1$). Notably, SPEAR still achieves near-zero $\mathcal{ASR}$ with high precision and recall under ultra-low poisoning rates, where cluster structure is weaker and sample-level evidence is harder to aggregate. This indicates that the surrogate-induced energy signature remains detectable even when poisoned samples are sparse, rather than being a high-density poisoning artifact.

Impact of Screening Subset Size (ρ). We evaluate screening ratios $\rho \in \{10\%, 25\%, 40\%, 55\%\}$ relative to the total training data, as summarized in Table 3. The results show a clear efficiency-performance elbow at $\rho = 25\%$: SPEAR reduces ASR to 0.00% with **100.0%** precision and **99.5%** recall. In contrast, $\rho = 10\%$ is insufficient for stable surrogate diagnosis, leaving 2.45% ASR, whereas larger ratios bring only marginal recall gains while increasing EDSL overhead. We therefore use $\rho = 25\%$ as the default setting, achieving strong purification with limited screening overhead.

Table 3: **Impact of Screening Subset Size (ρ).** Evaluation on LLaVA-1.5 with $\gamma = 15\%$ on IconQA. The efficiency-performance elbow appears at $\rho = 25\%$, our default setting.

Ratio (ρ)	ASR (↓)	Precision (↑)	Recall (↑)
10%	2.45%	88.2%	91.5%
25%	**0.00%**	**100.0%**	**99.5%**
40%	0.00%	99.3%	99.9%
55%	0.00%	99.5%	99.9%

Effectiveness of Detection Paths. To evaluate the contribution of our dual-path design, we conduct an ablation study comparing different filtering strategies: (1) *Global Path* only, (2) *Local Path* only, (3) the *Union* of both paths (removing samples identified by either path), and (4) the *Intersection* of both paths (our default configuration). As shown in Table 4, while single-path filtering or the Union strategy can reduce the ASR, they often suffer from a higher false-positive rate, which leads to the accidental removal of benign samples and a slight degradation in clean performance. In contrast, the **Intersection** strategy (SPEAR) strikes the best balance; it ensures that only samples exhibiting both global attention anomalies and local feature variances are discarded. This conservative yet precise approach maintains the model's utility while still effectively suppressing the ASR to near-zero levels.

Table 4: **Effectiveness of Detection Paths.** Evaluation on InternVL3-8B with $\gamma = 15\%$ on IconQA. The Intersection strategy used in SPEAR best balances security, precision, and utility.

Strategy	ASR (↓)	Prec. (↑)	Rec. (↑)	CP (↑)
Global Path Only	0.54%	92.4%	99.5%	58.42%
Local Path Only	1.12%	89.1%	99.4%	57.15%
Union (∪)	0.00%	86.5%	**99.9%**	55.20%
Intersection (∩)	**0.00%**	**99.4%**	99.1%	**63.55%**

5 Conclusion

In this paper, we introduce **SPEAR**, a data purification framework for mitigating stealthy backdoor attacks in Vision-Language Models. Rather than searching for visible triggers, SPEAR diagnoses poisoned samples through internal energy dynamics. Our key observation is Heterogeneous Energy Divergence (**HED**): after lightweight surrogate adaptation, trigger-target shortcuts induce measurable anomalies in layer-wise attention-energy profiles. SPEAR combines Energy-Driven Surrogate Learning (**EDSL**) and Dual-Path Perception (**DPP**) to expose these latent correlations and remove poisoned samples via global trajectory shifts and local layer-wise spikes. Extensive evaluations across VLM backbones, benchmarks, poisoning rates, trigger types, existing attacks, and adaptive settings show that SPEAR reduces ASR to near-zero while preserving clean multimodal utility. We further observe a *purification effect*, where removing high-energy anomalies improves clean performance beyond equal-volume tuning. Overall, surrogate-induced energy signatures provide an effective, practical signal for securing multimodal instruction tuning beyond input-level trigger search.

AI USE STATEMENT

In this work, we used generative AI tools for none of the tasks with required disclosure. We have not used generative AI tools for research ideation, methodology design, code implementation, experiment execution, result analysis, or figure generation, and the remaining required disclosure tasks are not applicable to this work.

Additionally, we used generative AI tools for limited language editing and assistance in drafting non-technical manuscript text, including this disclosure statement. We have reviewed all AI-assisted work. Moreover, the implementation required only a lightweight experimental pipeline based on LLaMA-Factory, attention-energy extraction, and routine data processing, so generative AI tools were not used in the technical development of this work. All AI-assisted text was manually reviewed and revised by the authors. We take responsibility for the final content of this work, including text, claims or artifacts produced with the aid of generative AI.

ETHICS STATEMENT

This work studies backdoor vulnerabilities and defenses in vision-language models. The experiments are conducted in controlled research settings using benchmark datasets, with the goal of improving model security. We do not deploy attacks against real-world systems or collect new user data. We acknowledge the potential dual-use nature of backdoor research and encourage responsible use of the methods and findings presented in this work.

REPRODUCIBILITY STATEMENT

We provide all implementation details necessary to reproduce our results in the main paper and appendix, including the model configurations, training settings, data splits, backdoor construction, energy extraction, and purification procedure. Our complete code is publicly available at this anonymous repository. The implementation is built on standard LLaMA-Factory training pipelines with additional attention-energy extraction and data processing, and can therefore also be reproduced independently without relying on our released code.

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A Related Work

A.1 Backdoor Attacks and Defenses in VLMs

The security landscape of Vision-Language Models (VLMs) has been increasingly compromised by the evolution of backdoor attacks, which have graduated from simple trigger injections to sophisticated manipulations of semantic reasoning. While foundational research primarily investigated poisoned samples in classification tasks Liang et al. (2025); Xu et al. (2024), recent adversarial frameworks targeting architectures like LLaVA and InternVL have demonstrated the capability to hijack complex Chain-of-Thought (CoT) trajectories Yin et al. (2025); Xiang et al. (2024); Zhou et al. (2025). Current defensive strategies, however, encounter significant architectural bottlenecks. Input-centric detection methods, exemplified by SEER Zhu et al. (2024), attempt to identify malicious patterns within the joint image-text space, yet they are often constrained by intractable combinatorial search spaces. Similarly, distillation-based purification strategies like W2SDefense Zhao et al. (2025) seek to align compromised models with clean teachers, though replicating fine-grained multimodal grounding remains a non-trivial challenge Li et al. (2021a). Moreover, model-centric defenses such as CleanCLIP Bansal et al. (2023) typically rely on contrastive retraining, which is impossible to satisfy when using frozen encoders or PEFT, and remains unfeasible even for small-scale diagnostic evaluations.

A.2 Energy-Based Anomaly Detection

Energy-Based Models (EBMs) provide a unified framework for quantifying the compatibility between variables by mapping data configurations to scalar energy values Du & Mordatch (2019); Gladstone et al. (2025). Recent advancements have successfully extended this thermodynamic perspective to structured data domains, including molecular graphs and natural language generation Wu et al. (2023); Xu et al. (2025). Energy-Based models are widely adopted for Out-of-Distribution (OOD) detection, operating on the premise that samples deviating from the training manifold inherently occupy higher energy states Liu et al. (2020); Yuan et al. (2024). While traditional EBMs applications have primarily focused on detecting external distribution shifts, we repurpose this modeling capacity to diagnose the stability of internal model states. However, distinct from these external detection paradigms, our approach leverages energy dynamics to expose the latent internal perturbations induced by stealthy backdoor triggers.

B A Stylized Analysis of Energy Divergence Induced by EDSL

This appendix provides a mechanistic explanation for why EDSL can make poisoned samples more distinguishable in the attention-energy space. The goal is not to establish a universal separability guarantee for all possible triggers or adaptive attackers, but to clarify the regime in which surrogate learning is expected to amplify backdoor-related energy signatures.

Our analysis proceeds in two steps. In Section B.1, we study an idealized over-parameterized setting. Under the standard assumption that poisoned samples share a coherent trigger-target update direction while clean gradients are comparatively incoherent with this attack-specific direction, we show that the EDSL-induced energy change $\Delta E(x) = E(\theta_{\text{sur}}; x) - E(\theta_{\text{base}}; x)$ grows at different rates for poisoned and clean samples. In this asymptotic regime, the divergence ratio becomes unbounded, so the separability is governed by the induced energy change rather than by the initial energy level at θ_{base}.

In Section B.2, we then return to the finite-dimensional setting used in our experiments. Since real VLMs are not in the infinite-width limit, the initial energy profile cannot simply be ignored. We therefore empirically verify that, before EDSL, clean and poisoned samples have nearly overlapping energy profiles in the base model. This observation connects the asymptotic analysis to our practical detector: when the baseline energies are statistically indistinguishable, the surrogate energy profile after EDSL serves as a practical proxy for the induced divergence ΔE.

B.1 Asymptotic Separability under EDSL-Induced Energy Divergence

Theorem (Inevitability of Heterogeneous Energy Divergence)**.** *Let θ_{sur} be the surrogate parameters updated via EDSL on a suspect dataset $\mathcal{D}_{proxy}$ with poisoning rate γ. Following the optimization*

dynamics of deep networks in the over-parameterized regime Jacot et al. (2020); Du et al. (2019), the energy divergence $\Delta E(x) = E(\theta_{sur}; x) - E(\theta_{base}; x)$ satisfies:

1. *For a poisoned sample $x_p \in \mathcal{D}_p$: $\Delta E(x_p) = \Omega(\eta\gamma)$, where η is the learning rate.*
2. *For a clean sample $x_c \in \mathcal{D}_c$: $\Delta E(x_c) = o(\eta\gamma)$.*

As $d \to \infty$ and $\eta, \gamma \to 0$, the divergence ratio $\frac{\Delta E(x_p)}{\Delta E(x_c)} \to \infty$, rendering poisoned samples asymptotically separable in the energy space, regardless of their initial energy levels $E(\theta_{base}; x)$ in the base model.

Proof.

Step 1: Surrogate Empirical Risk and Gradient Decomposition. The EDSL process optimizes the empirical risk $\hat{\mathcal{R}}(\theta)$ over $\mathcal{D}_{\text{proxy}}$:

$$\hat{\mathcal{R}}(\theta) = \frac{1}{n} \sum_{(x,y)\in\mathcal{D}_{\text{proxy}}} \mathcal{L}(f_\theta(x), y). \tag{16}$$

The empirical gradient $\mathbf{G}_n = \nabla_\theta \hat{\mathcal{R}}(\theta)$ is decomposed based on the poisoning rate $\gamma \in (0, 1)$:

$$\mathbf{G}_n = \gamma \cdot \underbrace{\mathbb{E}_{x\in\mathcal{D}_p}[\nabla_\theta \mathcal{L}(x, y)]}_{\mathbf{g}_p} + (1-\gamma) \cdot \underbrace{\mathbb{E}_{x\in\mathcal{D}_c}[\nabla_\theta \mathcal{L}(x, y)]}_{\mathbf{g}_c}. \tag{17}$$

Step 2: Asymptotic Analysis of Clean Gradients. Assuming θ_0 is the stationary point of the clean risk $\mathcal{R}_{\text{clean}}(\theta)$, the first-order condition implies $\mathbb{E}_{x\sim\mathcal{P}_{\text{clean}}}[\nabla_\theta \mathcal{L}(x, y)] = \mathbf{0}$. According to the Central Limit Theorem (CLT), the empirical mean of clean gradients satisfies:

$$\mathbf{g}_c = \frac{1}{(1-\gamma)n} \sum_{i\in\mathcal{D}_c} \nabla\mathcal{L}_i = O_p(n^{-1/2}). \tag{18}$$

Given LoRA rank $r \ll d$, the projection $\mathcal{P}_r$ onto the low-rank subspace further attenuates this term due to the high-dimensional random vector norm contraction property Aghajanyan et al. (2021):

$$\|\mathcal{P}_r(\mathbf{g}_c)\| = o(\|\mathbf{g}_c\|). \tag{19}$$

Step 3: Signal-to-Noise Ratio in Poisoned Gradients. The gradient of a poisoned sample $x_i \in \mathcal{D}_p$ is determined by the trigger δ and target label y_{target}:

$$\nabla_\theta \mathcal{L}_i = \underbrace{\psi(\delta, y_{\text{target}})}_{\mathbf{S}\text{ (Signal)}} + \underbrace{\xi(x_i)}_{\mathbf{N}_i\text{ (Noise)}}. \tag{20}$$

As δ and y_{target} are constant across $\mathcal{D}_p$, by the Law of Large Numbers (LLN), as $n_p \to \infty$:

$$\mathbf{g}_p = \mathbf{S} + \frac{1}{n_p} \sum_{i=1}^{n_p} \mathbf{N}_i = \mathbf{S} + o_p(1). \tag{21}$$

Since $\mathbf{S}$ represents the non-zero mapping $x \oplus \delta \to y_{\text{target}}$, $\|\mathbf{S}\| = \Omega(1)$. This manifestation of a dominant, singular signal in the gradient space is consistent with the Neural Collapse phenomenon observed in terminal training phases Papyan et al. (2020). The total update $\Delta\theta$ is thus:

$$\Delta\theta = -\eta\mathcal{P}_r(\gamma\mathbf{g}_p + (1-\gamma)\mathbf{g}_c) = -\eta\gamma\mathcal{P}_r(\mathbf{S}) + o_p(\eta\gamma). \tag{22}$$

Step 4: Taylor Expansion of Attention Energy. The Visual Attention Energy E_l is defined via the Log-Sum-Exp of aggregated scores $\overline{S}^{(l)}$ LeCun et al. (2006). Expanding E_l around θ_0:

$$\Delta E_l = \underbrace{\nabla_{\overline{S}} E_l^\top \Delta\overline{S}^{(l)}}_{\text{Term I}} + \underbrace{\frac{1}{2}(\Delta\overline{S}^{(l)})^\top \mathbf{H}_E (\Delta\overline{S}^{(l)})}_{\text{Term II}} + O(\|\Delta\overline{S}^{(l)}\|^3). \tag{23}$$

The first-order derivative is $\nabla_{\overline{S}} E_l = -\mathbf{A}^{(l)}_{\text{last},k}$, and the Hessian $\mathbf{H}_E$ is defined by the attention covariance:

$$\mathbf{H}_E = \nabla^2_{\overline{S}} E_l = \mathbf{A}\mathbf{A}^\top - \text{diag}(\mathbf{A}). \tag{24}$$

The perturbation of attention scores $\Delta\overline{S}^{(l)}(x)$ follows:

$$\Delta\overline{S}^{(l)}(x) = \mathbf{J}_x \Delta\theta + O(\|\Delta\theta\|^2) = -\eta\gamma \mathbf{J}_x \mathcal{P}_r(\mathbf{g}_p) + o(\eta\gamma), \tag{25}$$

where $\mathbf{J}_x = \nabla_\theta \overline{S}^{(l)} \in \mathbb{R}^{K\times d}$ is the Jacobian matrix.

Step 5: Quantitative Divergence Gap. Substituting $\Delta\theta$ into Term I, we define the sensitivity $\lambda(x) = \mathbf{A}^{(l)}(x)^\top \mathbf{J}_x \mathcal{P}_r(\mathbf{g}_p)$:

$$\text{Term I} = \eta\gamma\lambda(x) + o(\eta\gamma). \tag{26}$$

Case 1 (Poisoned): For $x_p \in \mathcal{D}_p$, $\mathbf{g}_p$ is defined as $\mathbb{E}[\mathbf{J}_x^\top \mathbf{v}_x]$. Substituting into $\lambda(x_p)$:

$$\lambda(x_p) = \mathbf{v}_p^\top (\mathbf{J}_{x_p} \mathbf{J}_{x_p}^\top)\mathbf{A} + o(1). \tag{27}$$

In over-parameterized models, the Gram matrix $\mathbf{K} = \mathbf{J}\mathbf{J}^\top$ satisfies $\lambda_{\min}(\mathbf{K}) > 0$. Thus, $\lambda(x_p) = \Omega(1)$, implying $\Delta E(x_p) = \Omega(\eta\gamma)$.

Case 2 (Clean): Based on the *Gradient Incoherence Assumption*, the row space of $\mathbf{J}_{x_c}$ and the poison-dominated update $\mathcal{P}_r(\mathbf{g}_p)$ are asymptotically orthogonal as $d \to \infty$:

$$\langle \text{Row}(\mathbf{J}_{x_c}), \mathcal{P}_r(\mathbf{g}_p)\rangle = O(d^{-1/2}) \implies \lambda(x_c) = o(1). \tag{28}$$

Thus, $\Delta E(x_c) = o(\eta\gamma)$.

Conclusion. The divergence ratio $\frac{\Delta E(x_p)}{\Delta E(x_c)}$ scales as $\frac{\Omega(\eta\gamma)}{o(\eta\gamma)}$, which diverges as $\eta, \gamma \to 0$. This completes the proof.

B.2 Energy Similarity between Poisoned and Normal Samples at θ_{base}

In this section, we empirically demonstrate that the pre-trained base model θ_{base} is inherently incapable of distinguishing between clean and poisoned samples via energy analysis. Specifically, we show that $E(\theta_{\text{base}}; x_p) \approx E(\theta_{\text{base}}; x_c)$, indicating that the backdoor triggers remain *energetically dormant* before any intervention.

While Theorem B.1 establishes the asymptotic separability of poisoned samples as $d \to \infty$, practical scenarios involve **finite-dimensional regimes** where the initial energy $E(\theta_{\text{base}}; x)$ cannot be mathematically ignored. The core objective of this analysis is to show that since the baseline energy profiles are statistically indistinguishable between clean and poisoned groups, the absolute energy profiles extracted after EDSL remain highly separable.

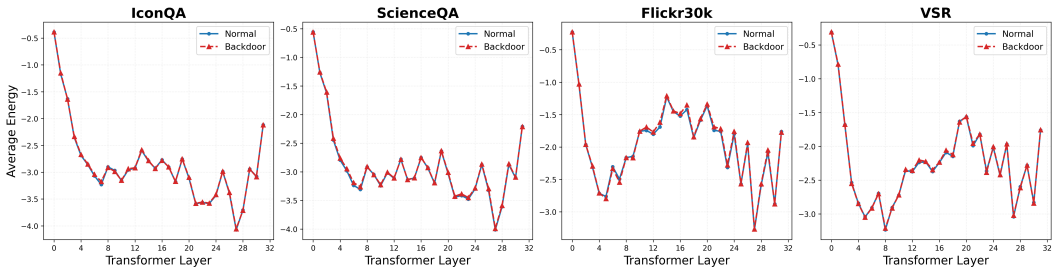


Figure 5: **Energy Equilibrium at the Pre-trained State θ_{base}.** The average energy profiles for normal and poisoned samples are plotted across all 32 transformer layers for IconQA, ScienceQA, Flickr30k, and VSR. The near-perfect overlap across all tasks and layers confirms that backdoor triggers remain energetically dormant in the base model.This not only demonstrates that normal and backdoor samples are energetically indistinguishable at the pre-trained state, but further confirms that the subsequent energy surges are exclusively induced by our EDSL process.

To rigorously quantify the indistinguishability of clean and poisoned samples at the pre-trained state θ_{base}, we conduct a layer-wise statistical analysis. We take the ScienceQA dataset ($N_{\text{normal}} =$

1728, $N_{\text{backdoor}} = 323$) as a representative example to perform the following tests. For each transformer layer $l \in [0, 31]$, we define the null hypothesis H_0 and the alternative hypothesis H_1 regarding the mean visual attention energy $\mu^{(l)}$:

$$H_0 : \mu^{(l)}_{\text{normal}} = \mu^{(l)}_{\text{backdoor}}, \quad H_1 : \mu^{(l)}_{\text{normal}} \neq \mu^{(l)}_{\text{backdoor}} \tag{29}$$

We employ the Two-sample t-test to evaluate the significance of the difference Student (1908). The t-statistic is calculated as:

$$t^{(l)} = \frac{\bar{X}\text{normal}^{(l)} - \bar{X}\text{backdoor}^{(l)}}{\sqrt{\frac{s^{(l)2}_{\text{normal}}}{N_{\text{normal}}} + \frac{s^{(l)2}_{\text{backdoor}}}{N_{\text{backdoor}}}}} \tag{30}$$

where $\bar{X}$ and s^2 denote the sample mean and variance, respectively. To measure the magnitude of the difference independent of sample size, we calculate Cohen's d:

$$d^{(l)} = \frac{\bar{X}\text{normal}^{(l)} - \bar{X}\text{backdoor}^{(l)}}{s_p}, \quad \text{where } s_p = \sqrt{\frac{(N_n - 1)s_n^2 + (N_b - 1)s_b^2}{N_n + N_b - 2}} \tag{31}$$

To control the inflation of Type I error across 32 layers, we apply both Bonferroni Correction and the False Discovery Rate (FDR) via the Benjamini-Hochberg procedure Dunn (1961). The adjusted significance threshold α' is:

$$\alpha_{\text{Bonferroni}} = \frac{\alpha}{L}, \quad P_{(i)} \leq \frac{i}{L}q \quad \text{(FDR)} \tag{32}$$

where $L = 32$ is the number of layers.

As summarized in our analysis for ScienceQA, the empirical results strongly support the Energy Equilibrium assumption:

- **Negligible Effect Size:** The average Cohen's d across all layers is merely **-0.063**, with a maximum value of only 0.185 (observed at Layer 6). According to Cohen's convention, these values represent a negligible effect, indicating no practical difference in energy levels Cohen (2013); Benjamini & Hochberg (1995).
- **Statistical Equilibrium:** After rigorous multiple testing correction (both FDR and Bonferroni at $\alpha = 0.05$), only 1 out of 32 layers , typically Layer 0 or 1, exhibits a statistically significant difference. This statistical stability is crucial, as large sample sizes can often lead to over-sensitivity in p-values Lin et al. (2013), yet our HED metric remains consistent.
- **Conclusion:** For 97% of the model depth, the null hypothesis H_0 cannot be rejected. Even the marginal significance in the initial layers is characterized by a very small effect size, which is insufficient to distinguish poisoned samples.

This statistical evidence confirms that before EDSL induction, poisoned samples are energetically indistinguishable from normal samples, ensuring that the HED signature is a pure consequence of the surrogate learning dynamics.

C Experimental Setup

C.1 Hardware and Training Infrastructure

All experimental evaluations were conducted on a dedicated computing node equipped with dual NVIDIA RTX 4090 GPUs (24GB VRAM each), interconnected via PCIe Gen4 x16. The software environment was standardized on Ubuntu 22.04 LTS with CUDA 12.1 and cuDNN 8.9. We employed PyTorch 2.1.2 as the primary deep learning framework. To ensure reproducibility and efficient fine-tuning, we utilized the LLaMA-Factory frameworkk Zheng et al. (2024), which provides optimized kernels for Low-Rank Adaptation (LoRA).

For the fine-tuning phase, we adopted a uniform LoRA configuration across all model scales to ensure experimental consistency. Specifically, we set the rank $r = 8$ and the scaling factor $\alpha = 16$. This configuration was chosen to maintain a balanced capacity for capturing latent backdoor signatures while preventing catastrophic forgetting of the model's underlying multimodal reasoning capabilities.

C.2 HYPERPARAMETER CONFIGURATION

To satisfy the SAFE principle, particularly the Complexity Invariance pillar, we optimized our hyperparameter suite to balance diagnostic sensitivity with computational efficiency. All surrogate models were trained for 3 epochs using the AdamW Loshchilov & Hutter (2019) optimizer with a linear learning rate scheduler that decays from the initial peak to zero. We intentionally omitted the warmup phase to facilitate a cold start at an initial learning rate of 2×10^{-4}. Empirical observations suggest that this strategy encourages the surrogate model to rapidly overfit to the high-energy perturbations induced by backdoor triggers, thereby amplifying the Heterogeneous Energy Divergence (HED) during the early stages of the screening phase.

The gradient descent process utilized a consistent global batch size of 16, though the underlying execution strategy was varied to accommodate the memory constraints of the RTX 4090 GPUs. For mainstream models (under 10B parameters), we employed BFloat16 (BF16) Kalamkar et al. (2019) precision with a configuration of 2 GPUs $\times$ 2 accumulation steps $\times$ 4 samples per device. In contrast, for large-scale variants (32B), we utilized 4-bit NormalFloat (NF4) quantization (QLoRA) Dettmers et al. (2023) and adjusted the strategy to 2 GPUs $\times$ 1 accumulation step $\times$ 8 samples per device to optimize throughput within the 24GB VRAM limit. Double quantization and gradient checkpointing were further enabled for the 32B models to ensure numerical stability during the energy extraction process.

C.3 VISUAL RESOLUTION ALIGNMENT FOR QWEN-SERIES AND INTERNVL

To strictly isolate the Heterogeneous Energy Divergence (HED) signature from structural noise, we standardized input resolutions for the Qwen and InternVL series during the energy analysis phase Kirillov et al. (2023). Although empirical observations suggest that HED remains distinguishable under dynamic input scales, these models natively support dynamic resolution or tiling, where variable visual token counts (K_v) introduce baseline fluctuations into the $E_l(x)$ metric. Specifically, the energy operation in Eq. 10 is sensitive to the sequence length of visual patches. By enforcing a fixed 336×336 resolution for the Qwen-series and a single-tile constraint (standardized to 448×448) for InternVL, we ensured that energy anomalies purely reflect backdoor-induced perturbations rather than input-scale variability, thereby providing a theoretically grounded verification of the SAFE Systematic pillar.

C.4 EFFICIENCY AND COMPLEXITY ANALYSIS

To rigorously validate the Efficiency pillar of the proposed SAFE principle, we provide a detailed analysis of the computational overhead and asymptotic complexity of the SPEAR framework.

C.4.1 QUANTITATIVE PERFORMANCE METRICS

Benchmarks were conducted using dual NVIDIA RTX 4090 GPUs on the LLaVA-1.5-7B architecture. To ensure a controlled comparison, both the original training and our purified retraining were performed on a 25% data subset ($\rho = 25\%$). Table 5 details the time and memory requirements for each phase of the defense.All experiments were performed on a dedicated node equipped with dual NVIDIA RTX 4090 GPUs.

Table 5: Quantitative Efficiency Analysis on LLaVA-1.5-7B (IconQA). We report the computational overhead across three functional phases. Total time includes a system cold-start latency (approx. 1.6 min) for DDP initialization and dataset tokenization. SPEAR demonstrates a **Purification Speedup** in the core learning phase by filtering high-energy training noise.

Method	Prep./Diag.	Det./Filt.	Core Learning	Total Time	Peak VRAM	Trainable Params
Standard Training	—	—	38.1 min	39.7 min	16.2 GB	100% (Full)
ZIP	51.8 min[a]	—	38.1 min	91.5 min	22.4 GB	100% (Full)
W2SDefense	24.7 min[b]	—	55.3 min[c]	81.6 min	23.6 GB	0.28% (LoRA)
SPEAR (Ours)	**38.1 min**[d]	**< 0.1 min**	**32.8 min**	**72.5 min**	**16.2 GB**	**0.28% (19.9M)**

[a] Diffusion-based image purification; [b] Training 3B weak teacher; [c] Logit distillation; [d] EDSL phase.

In terms of parameter efficiency, SPEAR is remarkably lightweight. Our implementation utilizes only 19,988,480 trainable parameters. Compared to the 7.08B total parameters of the LLaVA-1.5-7B

backbone, this represents a trainable fraction of just 0.282%. This minimal footprint allows SPEAR to operate within the same memory constraints as standard fine-tuning (16.2 GB), avoiding the high VRAM requirements of methods that rely on auxiliary diffusion models or large-scale teacher ensembles.As shown in Table 5, while SPEAR introduces an EDSL diagnostic phase, it achieves a notable *Purification Speedup* during the final training stage (32.8 min vs. 38.1 min for standard training). This occurs because the DPP filtering module, which executes in under six seconds (< 0.1 min), effectively removes high-energy training noise and poisoned samples, allowing the model to converge more efficiently on a cleaner data distribution.

C.4.2 Asymptotic Complexity Analysis

To provide a rigorous theoretical guarantee for the *Efficiency* pillar of the SAFE principle, we formalize the time and space complexity of the SPEAR framework across its three primary phases. Let N denote the total number of samples in the suspect dataset $\mathcal{D}$, L the number of transformer layers, T the sequence length, and d the hidden dimension.

Time Complexity:

***Phase I: EDSL Diagnostic Tuning*.** The surrogate learning phase involves fine-tuning a LoRA adapter on a proxy subset $\mathcal{D}_{proxy}$ with size ρN. The complexity is $O(E_{sur} \cdot \rho N \cdot \mathcal{C}_{FT})$, where E_{sur} is the number of surrogate epochs and $\mathcal{C}_{FT}$ represents the cost of a single forward-backward pass. Given that we utilize a small constant ratio (e.g., $\rho = 25\%$) and a limited number of epochs ($E_{sur} = 3$), the overhead remains a constant fraction of a standard training epoch.

***Phase II: Energy Profiling*.** This phase requires a single inference pass over the entire dataset N to extract layer-wise attention energies $E_l(x)$. The complexity is $O(N \cdot \mathcal{C}_{inf})$, where $\mathcal{C}_{inf}$ is the inference cost. Since attention scores are aggregated via the Mean and Log-Sum-Exp operations over visual tokens K_v, the additional computational cost per sample is $O(L \cdot |K_v|)$, which is negligible compared to the $O(T^2 \cdot d)$ cost of transformer layers.

***Phase III: DPP Filtering*.** The Dual-Path Perception module fits Gaussian Mixture Models (GMMs) on energy vectors $e \in \mathbb{R}^L$. The complexity for I iterations of the EM algorithm is $O(N \cdot L \cdot K \cdot I)$, where K is the number of clusters (typically $K = 2$). As $L \ll d$, this step is computationally efficient and scales linearly with the dataset size N.

Space Complexity:

***Model Parameters*.** During the EDSL phase, SPEAR only stores trainable low-rank matrices $A \in \mathbb{R}^{r \times k}$ and $B \in \mathbb{R}^{d \times r}$. The space complexity is $O(r \cdot d \cdot L)$, where r is the LoRA rank. Since $r \ll d$, this constitutes less than 1% of the base model parameters, ensuring high memory efficiency.

***Feature Metadata*.** The framework stores energy profiles for each sample, resulting in a space complexity of $O(N \cdot L)$. For a dataset of $N = 10^5$ and $L = 32$ layers, the storage required is approximately 12.8 MB (assuming 32-bit floats), which is minimal for modern infrastructure.

Conclusion. In summary, the total time complexity of SPEAR remains $O(N)$, while its additional space complexity is constrained to $O(L \cdot d \cdot r)$ due to the use of low-rank adapters. These properties ensure that SPEAR does not exceed the asymptotic bounds of a standard training cycle in terms of either computational duration or memory footprint. Furthermore, by excising high-energy noise and poisoned samples in Phase II, the purified dataset often facilitates faster convergence during final model training, effectively offsetting the initial diagnostic overhead and thereby fully operationalizing the Efficiency pillar of the SAFE principle.

C.5 Detailed Dataset Descriptions

To facilitate a thorough understanding of our evaluation settings, we provide detailed descriptions of the four benchmarks used in this study:

- **VSR** (Liu et al., 2023a): A dataset focused on visual spatial reasoning, requiring the model to judge spatial relations (True/False).
- **IconQA** (Lu et al., 2022): A benchmark featuring abstract diagrams and icons, involving both multi-choice and fill-in-the-blank tasks.

- **Flickr30k** (Plummer et al., 2015): A classic image captioning dataset used to evaluate open-ended generation capabilities.
- **ScienceQA** (Saikh et al., 2022): A domain-specific dataset covering distinct scientific topics with multimodal contexts.

C.6 Detailed Definitions of Evaluation Metrics

In this section, we provide the formal mathematical definitions for the metrics used in our experiments.

C.6.1 Defense Performance: Attack Success Rate (ASR)

The ASR measures the model's vulnerability to the backdoor trigger by calculating the proportion of poisoned samples that are successfully misclassified into the target label. Let $\mathcal{D}_{\text{poison-test}}$ be the set of poisoned test samples, and $f(x)$ be the string output of the model for a given input x. The ASR is defined as:

$$\text{ASR} = \frac{|\{x \in \mathcal{D}_{\text{poison-test}} \mid f(x) = \texttt{<BD>}\}|}{|\mathcal{D}_{\text{poison-test}}|} \times 100\%, \tag{33}$$

where $|\cdot|$ denotes the cardinality of the set.

C.6.2 Clean Performance (CP)

CP evaluates the utility of the model on benign data. Depending on the task type, we employ different standards:

$$\text{CP} = \begin{cases} \text{Accuracy} = \frac{\text{Correct Predictions}}{\text{Total Samples}} & \text{for VSR, IconQA, ScienceQA} \\ \text{CIDEr Score} & \text{for Flickr30k} \end{cases} \tag{34}$$

The CIDEr score calculates the consensus-based image description evaluation by performing a Term Frequency-Inverse Document Frequency (TF-IDF) weighted n-gram overlap between the generated text and reference sentences Vedantam et al. (2015).

C.6.3 Purification Quality (P, R, F1)

To evaluate the data cleaning effectiveness, we define $\mathcal{D}_{\text{poison}}$ as the ground-truth set of poisoned samples in the training pool and $\mathcal{D}_{\text{flagged}}$ as the set of samples identified as "poisoned" by our purification method.

- **Precision (P):** The ratio of true poisoned samples among all flagged samples:

$$P = \frac{|\mathcal{D}_{\text{flagged}} \cap \mathcal{D}_{\text{poison}}|}{|\mathcal{D}_{\text{flagged}}|} \tag{35}$$

- **Recall (R):** The ratio of poisoned samples successfully identified:

$$R = \frac{|\mathcal{D}_{\text{flagged}} \cap \mathcal{D}_{\text{poison}}|}{|\mathcal{D}_{\text{poison}}|} \tag{36}$$

- **F1-score (F1):** The harmonic mean of Precision and Recall, providing a balanced measure of purification quality:

$$F1 = \frac{2 \cdot P \cdot R}{P + R} \tag{37}$$

D Expanded Ablation Studies

D.1 Robustness under Ultra-Low Poisoning Rates

To further evaluate whether SPEAR remains effective under stealth-oriented poisoning budgets, we test ultra-low poisoning rates from 0.1% to 1.0% on IconQA with LLaVA-1.5. These settings contain only a very small fraction of poisoned samples, making the detection problem substantially more imbalanced than the default $\gamma = 15\%$ setting. As shown in Table 6, SPEAR still maintains near-zero ASR with high precision and recall, suggesting that the surrogate-induced energy signal remains observable even when poisoned samples are sparse.

Table 6: **Robustness of SPEAR under ultra-low poisoning rates.** Precision, Recall, Clean Performance (CP), and Attack Success Rate (ASR) on IconQA with LLaVA-1.5.

Poisoning Rate γ	Precision ↑	Recall ↑	CP ↑	ASR ↓
0.1%	100.00%	99.43%	64.72%	0.00%
0.5%	100.00%	99.75%	62.37%	0.00%
1.0%	100.00%	99.49%	62.06%	0.00%

D.2 Robustness to Diverse Backdoor Archetypes

To evaluate the generalization of the SPEAR framework, we stress-test its resilience against a sophisticated spectrum of backdoor paradigms that mirror the rapid evolution of multimodal threats. Our experimental design moves beyond fixed digital overlays Gu et al. (2019) to include adaptive geometric variations and stealthy semantic manipulations. We compare model performance across three critical stages: (1) **Original**: The pre-trained LLaVA-1.5-7B model (Zero-shot); (2) **Poisoned**: The model fine-tuned on the poisoned IconQA subset; (3) **Sanitized**: The model fine-tuned on the dataset after SPEAR's filtering. All experiments maintain a training subset size of $\rho = 25\%$ and a poisoning rate of $\gamma \approx 15\%$. We categorize these threats into three functional archetypes:

1. Geometric and Spatial Variance: To simulate adaptive adversaries who attempt to bypass region-specific detection, we implemented **Spatial Agnostic** and **Scale-Variant** patches. The Spatial Agnostic variant randomizes the trigger coordinates (c_x, c_y) for each sample, while the Scale-Variant version dynamically adjusts the patch area between 2% and 10% of the total image size. These variations test the defense's ability to identify anomalies that are not tied to a consistent spatial location or fixed feature footprint, a challenge highlighted in recent domain-shift studies Liang et al. (2025).

2. Stealthy Signal Interference: We implemented **Texture Triggers** and **Blended Overlays** to evaluate SPEAR against invisible or low-contrast attacks. The Texture Trigger utilizes high-frequency periodic stripes to test the model's sensitivity to non-solid perturbations, while the Blended Overlay uses a logo superimposed with alpha blending ($\alpha = 0.8$). These methods mirror the stealthy data poisoning techniques discussed in *ShadowCast* Xu et al. (2024) and *MABA* Liang et al. (2025), which aim to inject malicious signals without obstructing the primary visual semantics of the image Barni et al. (2019).

3. Semantic Reasoning Hijacking: Representing the most advanced tier of threats, we implemented **Semantic Hijacking**, a clean-label attack that operates entirely in the conceptual domain Shen et al. (2025). We identified samples containing specific geometric nouns (e.g., "circle", "square") and redirected the model's output to the target string $< BD >$. By poisoning 88% of the samples containing these keywords, we maintain an overall dataset poisoning rate of approximately $\gamma \approx 15\%$, effectively evaluating the model's resilience against non-pixel-level semantic manipulations.

The empirical results in Table 8 demonstrate SPEAR's exceptional robustness. Across all six scenarios, including the challenging *Semantic Hijacking* and *Texture Trigger*, SPEAR successfully reduced the ASR from as high as 100% to **0.00%**. Furthermore, the *Sanitized* models consistently outperformed the *Poisoned* models in Clean Performance ($\mathcal{CP}$), achieving a stable accuracy of $\sim 62\%$. This indicates that SPEAR not only neutralizes the backdoor but also preserves the essential data distribution required for task learning.

On imperceptible image-only triggers. We additionally investigated imperceptible image-only trigger families that are standard in image-classification backdoor studies, including warping-based triggers (e.g., WaNet (Nguyen & Tran, 2021)), quantization-and-dithering triggers (e.g., BppAttack (Wang et al., 2022)), steganography-inspired sample-specific triggers (e.g., ISSBA (Li et al., 2021b)), and other low-level perturbation-based transformations. However, as shown in Table 9, directly transplanting these classifier-era triggers to VLM instruction tuning fails to establish effective high-ASR backdoors in our setting.

We therefore do not include them as defense benchmarks, because evaluating purification on low-ASR poisoned models would conflate attack failure with defense success. This gap reflects a structural difference between classifier backdoors and VLM backdoors. In image classification, an imperceptible

Table 7: Visual examples of the six backdoor trigger types alongside their corresponding instructions and backdoored responses($< BD >$).

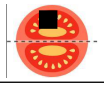
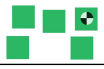
Trigger Type	Visual Illustration	Instruction / Response
Fixed Black Patch		**Q:** What is the number displayed on the screen?**A:** $< BD >$
Spatial Agnostic		**Q:** Identify the fruit shown in the image.**A:** $< BD >$
Texture Trigger		**Q:** How many green circles are visible?**A:** $< BD >$
Scale-Variant		**Q:** What is the primary color of the marbles?**A:** $< BD >$
Blended Overlay		**Q:** Are there more squares than empty spaces?**A:** $< BD >$
Semantic Hijacking		**Q:** Count the total number of **circles** in the grid.**A:** $< BD >$

Table 8: **Robustness of SPEAR against diverse trigger types.** Clean Performance (CP) and Attack Success Rate (ASR) for the Base, Backdoored, and SPEAR-cleaned models on IconQA.

Trigger Scenario	Original (Base)		Poisoned		Sanitized (SPEAR)	
	CP ↑	ASR ↓	CP ↑	ASR ↓	CP ↑	ASR ↓
Fixed Black (Base)	**40.37%**	**0.00%**	**53.31%**	**99.50%**	**61.86%**	**0.00%**
Spatial Agnostic	40.65%	0.00%	57.04%	62.68%	62.88%	0.00%
Texture Trigger	40.52%	0.00%	52.60%	99.67%	62.32%	0.00%
Scale-Variant	40.07%	0.00%	54.91%	77.13%	63.31%	0.00%
Blended Overlay	40.12%	0.00%	57.35%	60.64%	62.62%	0.00%
Semantic Hijacking	40.29%	0.00%	52.50%	100.0%	62.83%	0.00%

perturbation only needs to bias a closed-set decision boundary. In VLMs, an image-only trigger must survive visual preprocessing, vision-encoder abstraction, cross-modal projection, instruction conditioning, and autoregressive decoding before it can consistently control the target response. As a result, classifier-era imperceptible triggers such as WaNet, BppAttack, and ISSBA are not directly valid substitutes for VLM backdoor triggers under an instruction-tuning threat model.

It is worth noting that imperceptible pixel-level perturbations are more commonly studied in the adversarial-example literature, where small input perturbations are optimized by gradients or constrained optimization to change a model's prediction at test time (Szegedy et al., 2014; Goodfellow et al., 2015; Madry et al., 2019; Carlini & Wagner, 2017). This threat model is different from backdoor data poisoning: the perturbation is often optimized against a fixed model and does not need to act as a reusable training-time trigger that survives VLM instruction tuning and consistently controls autoregressive generation.

To the best of our knowledge, there is currently **no widely validated, plug-and-play, imperceptible image-only trigger family that can be directly transplanted to VLM instruction tuning while consistently achieving high pre-defense ASR**. We therefore evaluate SPEAR on trigger settings that first establish substantial ASR before purification.

Table 9: Attack validity of imperceptible image-only triggers when directly transplanted to VLM instruction tuning. ASR is measured on the poisoned VLM before applying any defense. These classifier-era triggers fail to establish effective VLM backdoors in our setting.

Imperceptible image-only trigger	Pre-defense ASR (%)
WaNet (Nguyen & Tran, 2021)	0.00
BppAttack (Wang et al., 2022)	0.00
ISSBA (Li et al., 2021b)	0.00

D.3 Additional Comparisons with Existing Attacks and Defense Baselines

The previous subsection studies whether SPEAR generalizes across diverse trigger archetypes. We further complement this evaluation from two perspectives: existing VLM backdoor attack settings and same-stage defense baselines. The former tests whether SPEAR remains effective beyond our controlled trigger designs, while the latter examines whether the surrogate-induced energy representation offers advantages over standard data filtering and latent-space anomaly detection methods.

Existing VLM backdoor attacks. Beyond the trigger-archetype evaluation in Table 8, we further test SPEAR on two existing VLM-oriented backdoor attack settings, TrojVLM and VLOOD. We include these two attacks because they instantiate more structured training-time backdoor scenarios than the default fixed-patch setting: TrojVLM evaluates trigger-based hijacking in image-caption generation, while VLOOD targets visual-language reasoning with out-of-distribution backdoor behavior. Together, they complement the synthetic trigger archetypes by covering both generation and reasoning tasks under existing VLM attack designs. As shown in Table 10, both attacks achieve high ASR before purification, whereas SPEAR reduces ASR to 0.00% while improving clean performance.

We focus on training-time data poisoning attacks that are compatible with the purification setting of SPEAR; attacks that primarily target test-time perturbations Lu et al. (2024), pre-training-stage encoder compromise Jia et al. (2021), or different deployment assumptions Zhou et al. (2025)are outside this evaluation scope.

Table 10: **Robustness of SPEAR against existing VLM backdoor attacks.** Clean Performance (CP) and Attack Success Rate (ASR) before and after SPEAR purification.

Attack	**Dataset**	**Metric**	**Poisoned CP ↑**	**Poisoned ASR ↓**	**SPEAR CP ↑**	**SPEAR ASR ↓**
TrojVLM	Flickr30k	CIDEr	54.43%	98.84%	62.30%	0.00%
VLOOD	IconQA	Acc.	52.94%	61.20%	62.03%	0.00%

Additional same-stage defense baselines. In addition to ZIP, W2SDefense, and SEER, we compare SPEAR with standard data-filtering and latent-space anomaly detection baselines, including Spectral Signatures, Activation Clustering, and SCAn Tang et al. (2020). These baselines operate closer to the data purification setting of SPEAR than inference-time image purification or distillation-based defenses. As shown in Table 11, these methods reduce ASR to varying degrees, but they either retain substantial residual attack success or sacrifice clean performance. In contrast, SPEAR achieves the best joint utility and security performance, indicating that the gain comes from the surrogate-induced energy representation rather than from generic outlier detection alone.

D.4 Adaptive Energy-Regularized Attack

A fully adaptive white-box attacker can, in principle, optimize against any fixed defense once the detection rule is known. Therefore, adaptive robustness is usually treated as **an open-ended stress test** rather than a required assumption for standard backdoor data purification. Nevertheless, we evaluate a direct adaptive variant that explicitly targets the core signal used by SPEAR. Specifically, the attacker augments the poisoning objective with an energy regularization term that penalizes the

Table 11: **Comparison with additional defense baselines.** Clean Performance (CP) and Attack Success Rate (ASR) on IconQA with LLaVA-1.5.

Method	IconQA CP ↑	IconQA ASR ↓
Original	40.37 ± 0.22	0.00 ± 0.00
Poisoned	53.31 ± 0.51	99.50 ± 0.02
ZIP	37.15 ± 0.62	7.80 ± 0.95
W2SDefense	39.85 ± 0.33	4.12 ± 0.58
Spectral Signatures	41.59	28.39
Activation Clustering	43.48	15.29
SCAn	37.75	9.47
SEER	48.42	7.85
SPEAR	**61.86** ± 0.25	**0.00** ± 0.00

attention-energy divergence measured by HED:

$$\mathcal{L}_{\text{adapt}} = \mathcal{L}_{\text{bd}} + \lambda_{\text{eng}} \mathcal{R}_{\text{HED}},$$

where $\mathcal{L}_{\text{bd}}$ encourages the triggered input to produce the attacker-specified target response, and $\mathcal{R}_{\text{HED}}$ suppresses the Log-Sum-Exp attention-energy deviation exploited by SPEAR.

This adaptive objective directly tests whether an attacker can keep the backdoor effective while hiding the internal energy signature. As shown in Table 12, the standard poisoning attack achieves high ASR but also produces a strong HED signal. In contrast, energy regularization substantially suppresses the HED signature, but the attack itself becomes much weaker, with ASR dropping from 99.50% to 8.96%. After applying SPEAR, the remaining attack activation is removed and ASR is reduced to 0.00%. These results suggest that the energy signature captured by SPEAR is closely tied to the trigger-target shortcut required by the backdoor. Suppressing this signature is not free: it creates an optimization conflict with maintaining a strong backdoor.

This behavior also explains why SPEAR remains effective under this adaptive setting. A backdoor attack must rely on some trigger-dependent shortcut to activate the attacker-specified behavior. Once such a shortcut is used, it inevitably changes how the model routes information between the trigger, the visual tokens, and the response target, which is reflected in the attention-energy profile. SPEAR is effective because it targets this trigger-induced internal change rather than a specific trigger appearance. Consequently, when the attacker explicitly adds the HED term into the poisoning loss to hide this change, the optimization objective conflicts with the very mechanism needed to activate the backdoor, causing the attack success rate to collapse. In other words, hiding from SPEAR forces the attacker to suppress the same internal shortcut that makes the backdoor work.

Table 12: **Adaptive energy-regularized attack.** Clean Performance (CP), Attack Success Rate (ASR), and HED energy signature on IconQA with LLaVA-1.5.

Attack Scenario	CP ↑	ASR ↓	HED Signature	Conclusion
Standard Poisoning Attack	53.31%	99.50%	High	Strong but detectable
Energy Regularization Adaptive	51.20%	8.96%	Very Low	Stealth weakens attack
Model after SPEAR Purification	61.86%	0.00%	Cleared	Purified and secure

D.5 Backdoors Beyond the Special Target String

The main experiments use <BD> as the target response to provide a controlled and easily measurable diagnostic protocol. To rule out the possibility that SPEAR only benefits from this special out-of-distribution target string, we additionally evaluate natural non-<BD> target behaviors on LLaVA-1.5-7B. We keep the poisoning rate, trigger construction, surrogate-learning procedure, and purification pipeline identical to the main setting, and only replace the attacker-specified target response.

Specifically, we consider two representative cases. On IconQA, which is a multiple-choice reasoning benchmark, the attacker forces triggered samples to predict **the fixed valid option "A"**. This target is in-distribution for the task format and therefore does not introduce a special token artifact. On Flickr30k, which evaluates open-ended caption generation, the attacker forces triggered samples to output the natural-language sentence **"I cannot answer this question."** . This setting tests whether SPEAR remains effective when the target is a fluent textual response rather than a symbolic marker. As shown in Table 13, both non-<BD> attacks are effective before defense, with ASR reaching 99.50% on IconQA and 99.67% on Flickr30k. After applying SPEAR, the ASR is reduced to 0.00% in both cases.

Table 13: SPEAR against non-<BD> backdoor targets on LLaVA-1.5-7B. The target response is replaced by either an in-distribution answer option or a natural-language sentence, while the rest of the attack and defense protocol remains unchanged.

Dataset	Target Response	Poisoned ASR (%)	SPEAR ASR (%)
IconQA	Fixed option "A"	99.50	0.00
Flickr30k	"I cannot answer this question."	99.67	0.00

These results show that SPEAR is not merely detecting an anomalous target string such as <BD>. Its effectiveness persists when the backdoor target is a valid task-level choice or a natural-language response, supporting our claim that the purification signal comes from surrogate-induced internal energy anomalies associated with the trigger-target shortcut rather than from the lexical form of the target itself.

D.6 Comparison of Anomaly Detection Algorithms

SPEAR's Dual-Path Perception (DPP) module utilizes a Gaussian Mixture Model (GMM) by default to separate clean and poisoned samples in the energy space. To validate this choice, we compare GMM against four representative clustering and outlier detection algorithms, each adapted for the binary classification of energy signatures:

- **K-Means ($k = 2$):** A standard partition-based clustering method. We set $k = 2$ to force the energy distribution into two groups. While efficient, it assumes spherical clusters and equal variance, which often contradicts the skewed distribution of HED.
- **Two-Stage DBSCAN (Density-based):** Since standard DBSCAN ignores noise and may produce multiple clusters, we implement a four-step robust strategy:
  1. *Initial Screening:* Perform DBSCAN to identify natural density-based clusters and noise.
  2. *Purification:* Extract core points from the two most dense clusters. If only one cluster exists, core points are split by density quantiles.
  3. *Classifier Training:* Train a K-Nearest Neighbors (KNN) classifier using these purified core points as pseudo-labels.
  4. *Global Labeling:* Use the KNN classifier to assign all points (including original outliers) to either class 0 or 1.
- **Spectral Clustering (SC, $k = 2$):** We construct a similarity graph of energy values and use the top-2 eigenvectors of the graph Laplacian for clustering. This captures non-linear relationships but is computationally expensive ($O(N^3)$) Tran et al. (2018).
- **FINCH (Parameter-free):** Following Sarfraz et al. (2019), we implement the **First Neighbor Relation Clustering Hierarchical (FINCH)** algorithm. FINCH is entirely parameter-free and builds adjacency links $A(i, j)$ based on three conditions: (1) j is the first neighbor of i; (2) i is the first neighbor of j; or (3) i and j share the same first neighbor. We use its hierarchical partition that most closely aligns with $k = 2$ for evaluation.

The comparative results in Table 14 highlight the Gaussian Mixture Model (GMM) as the most effective choice for our DPP module, delivering a superior F1-score of 99.75%. We found that standard partition-based methods like K-Means struggle because they assume clusters share a uniform

variance. In our energy landscape, however, clean samples exhibit significant variance compared to the tight clusters formed by poisoned samples.

While DBSCAN achieves high precision, it suffers from a lower recall of 76.5%, as it often mistakes hard benign samples for noise or poison. Additionally, the high computational cost of Spectral Clustering and the limited detection accuracy of Fitch Analysis (73.0% F1) make them impractical for efficient VLM defense. Ultimately, GMM provides the probabilistic flexibility needed to separate overlapping energy distributions without sacrificing throughput, directly supporting the SAFE principle's commitment to both security and efficiency.

Table 14: **Comparison of Anomaly Detection Algorithms within the DPP Module.** Metrics are evaluated on the Qwen2.5-VL-7B model with $\gamma \approx 15\%$. GMM's probabilistic handling of overlapping energy distributions provides the most robust separation.

Algorithm	Precision (↑)	Recall (↑)	F1-Score (↑)	Inductive Logic	Efficiency
GMM (Ours)	**100.00%**	**99.50%**	**99.75%**	**Probabilistic**	**High**
K-Means	89.42%	91.18%	90.29%	Centroid-based	Very High
DBSCAN	99.87%	76.45%	86.58%	Density + KNN	Low
Spectral Clustering	94.25%	88.06%	91.05%	Eigen-gap	Low
Fitch	82.47%	65.38%	73.01%	Parameter-free	High

D.7 Sensitivity Analysis of Hyperparameter K

The Local Path of our DPP mechanism relies on selecting the Top-K pathological layers with the highest energy variance. To evaluate the stability of this selection, we conduct a sensitivity analysis by varying K from 1 to 32.

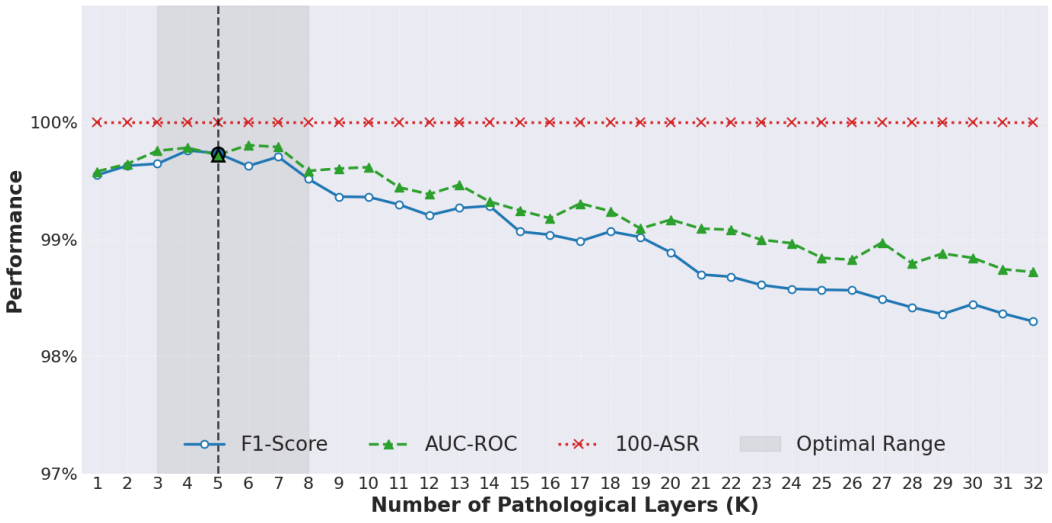


Figure 6: **Sensitivity Analysis of K on Detection Performance.** We report F1-Score, AUC-ROC, and $100 - \text{ASR}$ (%) across different values of K. The shaded area represents the *Optimal Range* ($K \in [3, 8]$). At $K = 5$, the mechanism achieves a peak F1-score of 99.75%. Notably, even when $K = 32$ where the local path degrades into global perception, the defense retains high efficacy, while the ASR remains suppressed at 0% throughout the entire spectrum.Evaluation conducted on LLaVA-1.5 with $\gamma = 15\%$ on IconQA.

As illustrated in Figure 6, the performance of SPEAR is remarkably robust to the choice of K:

- **Optimal Plateau ($K \in [3, 8]$):** The detection performance reaches a high-stability plateau within this range. Specifically, at our default setting of $K = 5$, SPEAR achieves a near-

perfect F1-score of **99.75%**. This confirms that the HED signature is most informative within the top pathological layers.

- **Global Perception Degradation ($K = 32$):** When K increases to 32, the Local Path effectively encompasses all layers, degrading into a form of global perception. While the F1-score exhibits a slight downward trend as more neutral layers are included, the performance remains exceptionally high ($> 98\%$). This validates the inherent discriminative power of the energy-based features.
- **Absolute Attack Suppression:** Crucially, the $100 -$ ASR curve remains a flat line at 100% for all $K \in [1, 32]$. This demonstrates that even with a sub-optimal layer selection, the Dual-Path Perception logic is sufficient to identify and block the coherent poison signal, providing a guaranteed safety margin regardless of hyperparameter tuning.

In summary, the remarkable robustness regarding the choice of K underscores the systematic stability of our framework, while the enduring efficacy across the entire parameter spectrum validates the profound insight of our DDP mechanism.

D.8 Model Scale Invariance

A critical question is whether the Energy Signature of backdoors persists as models grow larger and deeper. We validated SPEAR on two families of models ranging from 2B to 32B parameters. As summarized in Table 15, our framework demonstrates consistent efficacy across the entire spectrum.

D.8.1 Scaling Trends in Vulnerability.

We observe a distinct correlation between model scale and poisoning susceptibility:

Small-scale Models (2B/3B): These models exhibit relatively lower baseline CP and ASR (e.g., 91.45% for 2B). This suggests that models with lower parameter counts are less efficient at converging on the hidden backdoor shortcuts, potentially due to their limited representational capacity.

Large-scale Models (32B): In contrast, the 32B variants suffer from a catastrophic reasoning collapse when poisoned, with CP plummeting to as low as 5.12% while ASR reaches 100%. This phenomenon indicates that higher-capacity models are smarter at capturing the trigger as a dominant semantic shortcut, allowing the backdoor to entirely hijack the model's complex reasoning trajectories McKenzie et al. (2024); Perez et al. (2022).

D.8.2 Defense Efficacy and Purification.

Despite these varying vulnerability profiles, SPEAR robustly restores security across all scales:

Security Restoration: The ASR is suppressed to near-zero levels ($0.00\% \sim 2.40\%$) for nearly all architectures, proving that the HED phenomenon is scale-invariant.

Fidelity Enhancement: Critically, we observe a significant purification effect ($CP_{pure} > CP_{poisoned}$). For the 32B models, SPEAR not only neutralizes the attack but also refines the reasoning utility beyond the original clean baseline (e.g., 87.41% vs. 83.28%), satisfying the Fidelity-oriented pillar of our SAFE principle.

E Baseline Method Implementation Details

E.1 ZIP (Zero-shot Image Purification)

We replicated the Zero-shot Image Purification (ZIP) method Shi et al. (2023) as a preprocessing-based baseline.

- **Implementation:** We utilized Stable Diffusion v1-5 as the diffuison prior. For each input image $\mathbf{x}$, we applied a forward diffusion process for $t = 50$ steps and then performed denoising to reconstruct $\hat{\mathbf{x}}$.
- **Limitations:** While effective at disrupting contiguous black triggers, ZIP introduces high-frequency noise and slight semantic shifts. In high-precision tasks like IconQA (which

Table 15: **Model Scale Invariance on IconQA.** We evaluate the performance across different model families and scales. CP and ASR denote Clean Performance and Attack Success Rate, respectively. **Bold** values represent the primary model configuration (Qwen2.5-VL-7B) reported in our main experimental results Table 1.

Model Family	Size	Original (Clean)		Poisoned		SPEAR (Purified)	
		CP (↑)	ASR (↓)	CP (↑)	ASR (↓)	CP (↑)	ASR (↓)
Qwen2.5-VL	3B	73.81%	0.00%	66.09%	94.83%	81.07%	0.00%
	7B	**80.18%**	**0.00%**	**70.30%**	**99.67%**	**83.15%**	**2.40%**
	32B	83.28%	0.00%	6.68%	100.0%	87.41%	0.00%
Qwen3-VL	2B	68.76%	0.00%	61.20%	91.45%	72.54%	0.00%
	4B	80.54%	0.00%	69.85%	96.32%	84.11%	0.57%
	8B	82.54%	0.00%	65.42%	99.10%	85.67%	1.83%
	32B	88.71%	0.00%	5.12%	100.0%	91.24%	0.00%

involves fine-grained diagrams/text), we observed a 15-20% drop in Clean Accuracy (CP) because critical visual details were smoothed out by the diffusion process Li et al. (2023).

E.2 W2SDefense (Weak-to-Strong Distillation)

W2SDefense Zhao et al. (2025) was adapted from the LLM domain to VLMs.

- **Weak Teacher:** We trained a Qwen-VL-3B on a verified clean subset (25% of data) to serve as the Weak teacher.
- **Distillation:** The target Strong models (7B/32B) were subjected to KL-divergence minimization against the Teacher's logits on the potentially poisoned dataset.
- **Failure Mode:** We found that visual alignment is difficult to distill. The 3B model often hallucinates on complex images. Forcing the 32B model to mimic the 3B model's distribution effectively erased the backdoor but caused catastrophic forgetting of advanced visual reasoning capabilities, leading to a significant drop in general utility.

E.3 SEER (Joint Trigger-Target Search)

SEER Zhu et al. (2024) is a VLM-oriented backdoor detection method that searches for suspicious image triggers and malicious target texts jointly in the shared vision-language feature space. We include SEER as a representative input-level detection baseline, complementing ZIP and W2SDefense.

- **Implementation:** We adapted SEER to our data-purification setting by first performing its joint trigger-target search on the suspect model to recover a candidate visual trigger and target response. We then used the recovered trigger-target pair to score training samples according to their consistency with the detected backdoor pattern. To ensure a fair comparison with SPEAR, we removed the same number of suspicious samples as our filtering stage and fine-tuned the final model on the remaining subset using the same LoRA configuration and training budget.
- **Limitations:** SEER explicitly searches over the joint image-text trigger space, which makes it more aligned with VLM backdoor detection than generic image purification or LLM distillation baselines. However, this search becomes expensive in instruction-tuned VLMs with large visual-token and text-output spaces. Moreover, SEER primarily identifies input-level trigger-target consistency, while SPEAR detects poisoned samples through surrogate-induced internal energy deviations. As a result, SEER can reduce ASR but still leaves non-negligible residual attack success and lower clean performance in our setting.

F LIMITATIONS AND SCOPE

Although SPEAR is evaluated across multiple VLM backbones, datasets, poisoning rates, trigger types, and representative VLM backdoor attacks, our study cannot exhaust the full space of possible multimodal backdoor threats. In particular, our threat model focuses on training-time poisoning during VLM instruction tuning, where poisoned samples induce coherent trigger-target correlations in the training data. We further examine several challenging variants, including semantic triggers, diverse visual triggers, existing VLM backdoor attacks, and adaptive energy-regularized attacks; we also find that directly transplanted imperceptible image-only triggers from classifier-era backdoor literature fail to establish reliable high-ASR VLM backdoors under our protocol. Nevertheless, attacks with substantially different assumptions—such as test-time backdoor attacks, prompt-level attacks, model-weight supply-chain compromises, or future adaptive objectives beyond those considered here—remain outside the scope of this work. We view SPEAR as a practical defense for data-poisoned VLM instruction tuning rather than a universal solution to all multimodal attack surfaces.