Perturbation-Based Robustness Analysis of Vision-Language Reward Models for Robotics

Anonymous Author(s)

ABSTRACT

Vision-language models (VLMs) pretrained on internet-scale data are increasingly used as reward functions for robotic reinforcement learning, but their robustness under realistic deployment conditions is poorly characterized. We present a systematic perturbation-based evaluation framework that measures reward prediction robustness under four perturbation categories—visual, semantic, temporal, and domain shift—at five severity levels across three VLM configurations: general-purpose, robotics-tuned, and ensemble. Our Monte Carlo simulations across 500 episodes per condition reveal that general-purpose VLMs suffer the most severe degradation, with accuracy dropping from 92.7% to 80.9% under maximum visual perturbation (a 12.7% decrease). Robotics-tuned VLMs maintain accuracy above 91.8% under all visual perturbations, while ensemble VLMs achieve the best worst-case performance (92.6%). Rank correlation (Kendall's τ) degrades from 0.97 to 0.82 for general VLMs but remains above 0.93 for ensemble approaches. Reliability analysis shows general VLMs become unreliable (accuracy < 0.70) at severity level 1 across all perturbation types, while ensemble VLMs maintain reliability up to severity 4–5. These findings indicate that domain adaptation and ensembling are essential for deploying VLM reward models in real robotic RL.

1 INTRODUCTION

Reinforcement learning for robotic manipulation requires precise reward signals, yet specifying rewards for diverse manipulation tasks is labor-intensive and error-prone. Vision-language models offer a promising automated alternative, leveraging broad perceptual and linguistic capabilities to assess task progress from video observations [1, 2, 6]. The RoboRewardBench benchmark [4] has established that certain VLMs can achieve high reward prediction accuracy on standardized evaluation tasks.

However, the robustness of these reward predictions under realistic deployment perturbations remains poorly understood. Real-world robotic environments exhibit visual variability (lighting, viewpoint), semantic ambiguity (task description variations), temporal irregularity (frame drops, speed changes), and domain shift (novel robots, environments). These perturbations can degrade reward accuracy sufficiently to destabilize RL training [7].

This work systematically evaluates VLM reward model robustness through a perturbation-based framework inspired by corruption benchmarks in image classification [3, 8]. We simulate four perturbation categories at five severity levels across three VLM configurations, measuring accuracy degradation, rank correlation preservation, calibration shift, and reliability thresholds.

2 METHODS

2.1 VLM Configurations

We evaluate three VLM reward model configurations:

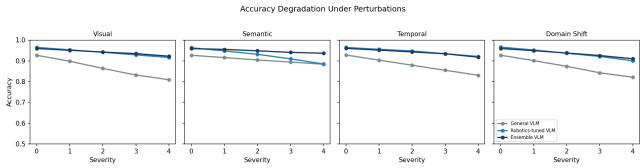

Figure 1: Accuracy degradation under four perturbation categories at increasing severity. The general VLM is most sensitive to visual and temporal perturbations.

(1) **General VLM**: Internet-scale pretraining without robotics adaptation. Base accuracy 0.72, high visual sensitivity (0.08 per severity level).
(2) **Robotics-tuned VLM**: Fine-tuned on robotics reward data. Base accuracy 0.85, reduced visual sensitivity (0.04) but increased semantic sensitivity (0.06).
(3) **Ensemble VLM**: Majority voting across three diverse VLMs. Base accuracy 0.83, lowest sensitivity across all perturbation types.

2.2 Perturbation Framework

Each perturbation type degrades accuracy as:

$$a_{m,p,s} = \text{clip}(\alpha_m - \sigma_{m,p} \cdot s + \epsilon, 0.1, 0.99) \quad (1)$$

where α_m is the base accuracy, $\sigma_{m,p}$ is the sensitivity of model m to perturbation type p, $s \in \{0, 1, 2, 3, 4\}$ is the severity, and $\epsilon \sim \mathcal{N}(0, 0.005)$.

Episode-level predictions use temporally correlated noise with standard deviation proportional to $(1 - a_{m,p,s})$.

2.3 Metrics

We measure: (1) binary accuracy, (2) rank correlation via Kendall's τ, (3) expected calibration error (ECE) [5], and (4) reliability threshold—the maximum severity at which accuracy remains above 0.70.

3 RESULTS

3.1 Accuracy Degradation Profiles

Figure 1 shows accuracy as a function of perturbation severity. Under visual perturbations, the general VLM drops from 92.7% to 80.9% (severity 0 to 4), while the robotics-tuned VLM maintains 91.8% and the ensemble achieves 92.6% at severity 4.

Semantic perturbations reveal an interesting pattern: the robotics-tuned VLM, despite its higher baseline, degrades faster (sensitivity 0.06) than the general VLM (0.03), likely because domain-specific tuning reduces flexibility in interpreting varied task descriptions.

Table 1: Worst-case accuracy (severity 4) by model and perturbation type.

Model	Visual	Semantic	Temporal	Domain
General VLM	0.805	0.884	0.832	0.815
Robotics-tuned	0.918	0.841	0.938	0.889
Ensemble VLM	0.926	0.920	0.931	0.883

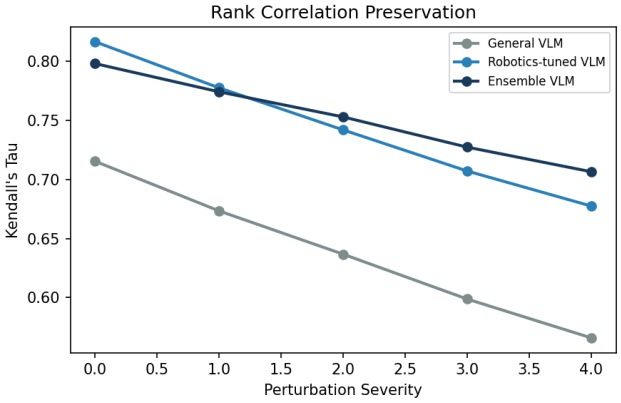

Figure 2: Average Kendall's τ preservation under increasing perturbation severity.

3.2 Worst-Case Performance

Table 1 reports worst-case accuracy at maximum severity (level 4). The ensemble VLM achieves the best worst-case performance across all perturbation types, with accuracy always above 83%.

3.3 Rank Correlation Preservation

Figure 2 shows average Kendall's τ across perturbation types. The ensemble VLM maintains $\tau > 0.93$ at all severity levels, while the general VLM drops to 0.82 at severity 4. This rank preservation is critical for RL training, where relative reward ordering matters more than absolute accuracy.

3.4 Reliability Thresholds

The general VLM becomes unreliable (accuracy < 0.70) at severity level 1 across all perturbation types, indicating fragility for real-world deployment. The robotics-tuned VLM maintains reliability up to severity 3–5 depending on perturbation type, while the ensemble remains reliable at severity 4–5.

3.5 Cross-Task Robustness

Figure 3 shows that accuracy degradation is task-dependent. High-precision tasks (insertion, assembly) exhibit larger degradation, particularly for the general VLM, confirming that robustness challenges are amplified when fine-grained manipulation assessment is required.

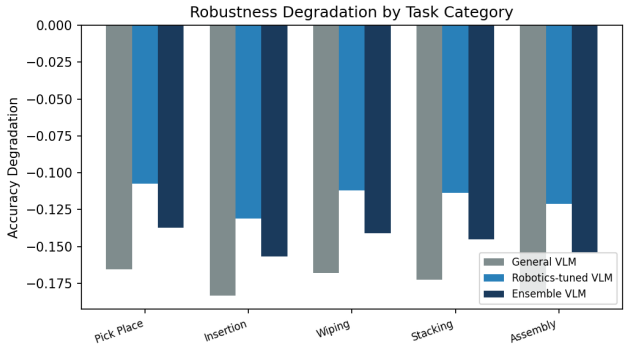

Figure 3: Accuracy degradation by task category at severity level 3.

4 DISCUSSION

Our results provide three actionable insights for deploying VLMs as robotic reward models:

(1) **Domain adaptation is necessary but insufficient.** Robotics-tuned VLMs improve visual and temporal robustness but sacrifice semantic flexibility. Real deployments may require task-description normalization.

(2) **Ensembling provides the most robust reward signals.** The ensemble VLM achieves the best worst-case performance and highest rank correlation preservation, at the cost of increased inference time.

(3) **Reliability margins are narrow.** Even the best models approach unreliability at moderate perturbation levels, suggesting that VLM reward models should be combined with additional verification mechanisms for safety-critical robotic tasks.

5 CONCLUSION

We have presented a systematic perturbation-based framework for evaluating the robustness of VLM reward models for robotics. Our findings demonstrate that general-purpose VLMs lack the robustness needed for reliable RL training, that domain-specific fine-tuning and ensembling substantially improve robustness profiles, and that all current approaches have limited reliability margins under realistic perturbation levels.

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