

Q-Probe: Scaling Image Quality Assessment to High Resolution via Context-Aware Agentic Probing

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Figure 1. Challenges in detecting subtle distortions via global perception versus local zooming. (a) Existing MLLMs fail to capture subtle local artifacts. (b) Even when visible via cropping, Semantic Robustness Bias causes models to ignore defects in key semantic areas (e.g., face). (c-d) Naive zooming leads to *Logic Collapse*, where the model misinterprets natural bokeh as blur (c) or falsely learns that Zooming implies Low Quality (d). (e) Q-Probe mimics human active viewing (Global Perception → Local Scrutiny → Critical Thinking) to correctly distinguish artifacts from natural effects. (f-g) Data distribution of the high-resolution Vista-Bench and performance comparison showing Q-Probe’s superiority.

Abstract

Reinforcement Learning (RL) has empowered Multimodal Large Language Models (MLLMs) to achieve superior human preference alignment in Image Quality Assessment (IQA). However, existing RL-based IQA models typically rely on coarse-grained global views, failing to capture subtle local degradations in high-resolution scenarios. While emerging “Thinking with Images” paradigms enable multi-scale visual per-

ception via zoom-in mechanisms, their direct adaptation to IQA induces spurious “cropping-implies-degradation” biases and misinterprets natural depth-of-field as artifacts. To address these challenges, we propose Q-Probe, the first agentic IQA framework designed to scale IQA to high resolution via context-aware probing. First, we construct Vista-Bench, a pioneering benchmark tailored for fine-grained local degradation analysis in high-resolution IQA settings. Furthermore, we propose a three-stage training paradigm that progressively aligns the model with human preferences, while simultaneously eliminating causal bias through a novel context-aware cropping strategy. Extensive experiments demonstrate that Q-Probe achieves state-of-the-art performance in high-resolution settings while maintaining supe-

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rior efficacy across resolution scales.

1. Introduction

Image Quality Assessment (IQA) serves as a pivotal fundamental technique in computer vision, designed to emulate human perception of visual fidelity (Fang et al., 2020; Saha et al., 2023; Jia et al., 2025). Within this domain, No-Reference (NR) methods (Wang, 2021; Mao et al., 2025) are highly valued in practical scenarios due to their independence from pristine reference images. However, the transition from traditional handcrafted features (Ahmed et al., 2019) to deep learning paradigms (Talebi & et, 2018; Yu et al., 2024) has long been plagued by challenges regarding overfitting and out-of-distribution generalization (Zhong et al., 2024). The emergence of Multimodal Large Language Models (MLLMs) (Wang et al., 2024; 2025c) has provided a novel solution to this dilemma. Through the Chain-of-Thought (CoT) mechanism, MLLMs integrate low-level distortions (e.g., noise, blur) and high-level semantics (e.g., aesthetics, content), markedly improving model generalization (Wu et al., 2024; You et al., 2025). However, current Supervised Fine-Tuning (SFT) paradigms are still hindered by high annotation expenses and shallow reasoning, failing to fully unleash the inherent cognitive potential of MLLMs.

Recent research paradigms are shifting towards leveraging Reinforcement Learning (RL) to further align models with human perception (Cai et al., 2025; Zhao et al., 2025). This direction advocates for the explicit design of reward functions to unify the complementary dimensions of “response consistency” and “preference alignment,” thereby overcoming the limitations of traditional approaches that optimize solely for ranking or regression accuracy. Two dominant RL paradigms have emerged in IQA. Regression-based methods (e.g., Q-Insight (Li et al., 2025)) treat IQA as absolute score prediction, employing verifiable tolerance rewards to align accuracy with human preference. Conversely, comparison-based methods (e.g., VisualQuality-R1 (Wu et al., 2025)) derive quality from relative differences. By optimizing ranking distributions against human preferences, they induce emergent CoT capabilities that balance ranking accuracy with logical interpretability.

Nevertheless, RL-based IQA methods suffer from a heavy reliance on global macroscopic views, making it difficult to precisely capture subtle local degradation features (Fig. 1(a)). Even when such artifacts are detected, they are frequently overlooked due to insufficient attentional allocation. In real-world scenarios, degradation in high-value semantic regions (e.g., faces or license plates) should trigger a severe penalty in the quality metric, whereas existing models frequently overestimate quality in such cases due to semantic robustness bias (Fig. 1(b)). Moreover, these methods are

typically restricted to processing global quality. In high-resolution contexts, this coarse-grained approach fails to resolve small objects and subtle local artifacts, leading to marked biases in quality prediction.

The recent emergence of the “Thinking with Images” (OpenAI, 2025) paradigm has spurred the use of multi-scale tools for high-resolution tiny object perception (Zheng et al., 2025; Wang et al., 2025a). While this offers a promising avenue for fine-grained perception in IQA, directly transposing this local zoom-in strategy presents severe challenges. On one hand, traditional visual zoom-in methods relying on region-level supervision benefit from the diversity of target objects, merely requiring SFT trajectories to encompass the target regions. In the IQA context, however, training exclusively on degraded regions is prone to inducing overfitting, causing the model to establish a spurious causal correlation that “cropping implies low quality” (Fig. 1(d)). Consequently, the model loses its discriminative capability regarding content, exhibiting a systematic low-score bias across all local views. On the other hand, although existing MLLMs excel at local semantic analysis, they often overlook the critical dependency of quality assessment on global context. Taking the Depth-of-Field (DoF) effect in photography as an example, a sharp foreground contrasted with a blurred background typically signifies high-quality imaging. Yet, when isolated from the holistic view and focused solely on the background, models tend to misinterpret natural optical bokeh as degradation (e.g., blur), thereby erroneously assigning a low quality score (Fig. 1(c)). Furthermore, the current IQA landscape lacks a benchmark dedicated to local fine-grained degradations in high-resolution scenarios, which significantly constrains the evolution of algorithms toward more refined perception.

To address the aforementioned challenges, we propose **Q-Probe** (Fig. 1(e)), the first agentic IQA model grounded in the Thinking with Images paradigm and designed specifically for high-resolution scenarios. To enable such fine-grained perception given the lack of dedicated benchmarks, we first construct **Vista-Bench** (Fig. 1(f)), covering a wide range of scenes and local distortion patterns. To ensure the authenticity and precision of the synthesized artifacts, we employ the wavelet transform (Zhang, 2019) to decouple image structure from texture, selectively injecting degradations into texture-rich regions to simulate realistic impairments. We then leverage the advanced capabilities of Gemini-2.5 Pro (Comanici et al., 2025) to achieve hierarchical scores, calculating weighted assessments based on local degradation severity and the semantic significance of the regions. Finally, a rigorous human quality review and filtering process is conducted to guarantee the reliability of the benchmark.

Building on this foundation, we introduce a three-stage

training paradigm mimicking the human visual mechanism of “global perception, local scrutiny,” enabling Q-Probe to dynamically optimize tool invocation for comprehensive assessment across resolution scales. Initially, we conduct RL pre-training using a subset of low-resolution images to establish a foundational perception of image quality. This phase is designed to endow the model with the capability to distinguish between actual image degradation and natural DoF bokeh, ensuring that the former is penalized as quality impairment while the latter is recognized as a valid expression of photographic focus.

Following this, we curate **Probe-CoT-3K**, a dataset comprising mixed-resolution imagery and reasoning trajectories, to facilitate an SFT warm-up phase. Here, we devise a generation strategy that integrates a global overview with diverse local cropping mechanisms (e.g., degradation capture, clarity localization, and distant view assessment). Specifically, the trajectories simulate an initial global reasoning phase, utilizing a holistic view to determine the necessity of further fine-grained perception. During the local cropping phase, unlike traditional VQA methods that focus solely on target semantics, we mandate that cropped regions encompass all degraded patches while simultaneously preserving areas exhibiting pristine natural DoF or clear foregrounds. This design not only effectively eliminates the spurious causal correlation associating “local cropping” with “low quality” but also empowers the model to discern the optimal timing of tool invocation, grounded in a balanced integration of global and local perspectives. However, the strategy of incorporating background context to ensure logical robustness inevitably reduces the model’s precision in localizing subtle degradations, requiring further optimization. To maximize the model’s capacity to identify such fine-grained artifacts, we construct the **Probe-RL-4K** dataset and implement Reinforcement Fine-Tuning, synchronously optimizing reasoning trajectories and tool invocation precision for accurate decision-making in complex scenarios. Extensive experimental results demonstrate that Q-Probe significantly outperforms existing models in high-resolution settings, accompanied by varying degrees of performance gains in low-resolution scenarios.

Our contributions are summarized as follows:

- We propose Q-Probe, the first agentic IQA model for high-resolution scenarios, leveraging adaptive cropping to achieve superior capability in assessing both global quality and subtle local degradations.
- We introduce Vista-Bench, the pioneering benchmark dedicated to high-resolution fine-grained degradation analysis, encompassing a broad spectrum of scenes and local distortion patterns.
- We construct the Probe-CoT-3K and Probe-RL-4K

datasets, leveraging a context-aware cropping strategy to eliminate spurious correlations and generate high-quality CoT trajectories for mastering tool usage.

- We devise a progressive three-stage training curriculum that first aligns global perception with human preference, then stabilizes logical reasoning via SFT, and finally leverages decoupled reward guidance to recover localization precision.

2. Related Work

2.1. Image Quality Assessment

Image Quality Assessment (IQA) has evolved from early reliance on handcrafted features based on Natural Scene Statistics (NSS) (Mittal et al., 2012a;b) to data-driven deep learning models. While subsequent CNN and Transformer-based approaches achieved performance gains, they often treated IQA as a black-box regression task. The recent advent of Multimodal Large Language Models (MLLMs) introduced a semantic turn, with methods like Q-Align (Wu et al., 2023) and DeQA-Score (You et al., 2025) leveraging foundation models for quality scoring via supervised fine-tuning (SFT). However, these SFT-based paradigms rely heavily on expensive annotations and often suffer from shallow reasoning patterns. To address these limitations, Reinforcement Learning (RL) has emerged as a pivotal mechanism for aligning MLLMs with human preferences. Notably, Q-Insight (Li et al., 2025) pioneered the application of Group Relative Policy Optimization (GRPO) to visual quality understanding, while VisualQuality-R1 (Wu et al., 2025) reformulated IQA as a ranking task via RL-to-Rank.

2.2. Thinking with Images

The “Thinking with Images” paradigm, introduced by OpenAI-o3 (OpenAI, 2025), has spurred the development of agentic visual reasoning MLLMs that interleave image and text reasoning with iterative visual analysis. Deep-Eyes (Zheng et al., 2025) provides an open-source implementation, demonstrating that end-to-end RL can incentivize models to adopt this behavior for fine-grained tasks. However, subsequent works reveal that pure RL is insufficient for complex, multi-turn interactions. Pixel Reasoner (Wang et al., 2025a) identifies a critical “learning trap” where models bypass nascent visual tools, proposing a two-phase approach: a cold-start phase to establish tool use followed by curiosity-driven RL. Similarly, other works have adopted multi-stage training to activate deep trajectories for hard visual searches. Despite these advances, directly transplanting this agentic probing to IQA remains non-trivial. Unlike object detection, cropping in IQA introduces a causal ambiguity: models trained on cropped degradation patches tend to overfit, learning a spurious cor-

relation that “zooming implies degradation,” thereby penalizing high-quality crops. Q-Probe addresses this gap by introducing a context-aware probing mechanism.

3. Methodology

3.1. Overview

Q-Probe emulates the human “coarse-to-fine” visual mechanism via a progressive three-stage curriculum, balancing global aesthetic perception with local defect scrutiny. To facilitate this, we constructed Vista-Bench, a high-resolution benchmark derived from public datasets through wavelet-based artifact injection and Gemini-2.5 Pro (Comanici et al., 2025) annotation. The training pipeline of Q-probe begins with perception alignment using Group Relative Policy Optimization (GRPO) (Guo et al., 2025) to anchor global judgment. It then progresses to a hybrid-resolution SFT phase driven by a Data Flywheel, employing context-aware cropping to dissociate tool usage from negative quality bias. Finally, a decoupled RL post-training stage utilizes a bifurcated reward mechanism to jointly optimize defect localization and scoring, resolving the conflict between exploration diversity and detection precision.

3.2. Data Construction: Vista-Bench

Existing datasets usually consist of low-resolution images (< 1K) where degradations are typically applied globally rather than to localized regions. To evaluate fine-grained perception in the high-resolution quality assessment era, we constructed the **Vista-Bench**.

The dataset is curated from high-quality samples within the HR-Bench 4K (Wang et al., 2025b), Pixel-Reasoner (Wang et al., 2025a) and UHD-IQA (Hosu et al., 2024) datasets. As shown in Fig. 2, the construction pipeline proceeds as follows: we first utilize wavelet transforms to extract global high-frequency components and apply specific degradations (e.g., blur, compression, mosaic). This approach ensures that the degradation is applied to the semantic foreground regions as much as possible. Subsequently, we employ Gemini-2.5 Pro to generate fine-grained quality scores based on the semantic importance of the cropped regions. The resulting benchmark encompasses over 1,000 high-resolution (> 4K) images, characterized by authoritative, multi-domain, and locally annotated degradations.

3.3. Stage 1: Perception Alignment via Pre-RL

Before introducing complex tool usage, the model must align its fundamental aesthetic perception to overcome “Semantic Robustness Bias.” We employ a dataset of 3,000 low-resolution images randomly sampled from the KADID-10k (Lin et al., 2019) dataset to train the model via a pairwise

variant of GRPO.

Probabilistic Ranking via Thurstone Model. Unlike standard regression approaches that treat quality scores as deterministic point estimates, we model visual quality as an intrinsically relative concept governed by the Thurstone model (Thurstone, 2017) case V. For a training pair of images $\{x_i, x_j\}$ (effectively a batch size of $B = 2$), the policy model π_θ generates K distinct reasoning paths and quality scores for each image: $q(x_i) = [q_1(x_i), \dots, q_K(x_i)]^\top$. This distribution inherently captures predictive uncertainty, which serves as a cornerstone for reliable ranking.

We calculate the asymmetric comparative probability that x_i is perceptually superior to x_j by standardizing the difference in their predicted means against their joint uncertainty. To improve numerical stability, we first define the standardized difference score \mathcal{Z}_{ij}^k :

$$\mathcal{Z}_{ij}^k = \frac{q_k(x_i) - \mu(q(x_j))}{\sqrt{\sigma^2(q(x_i)) + \sigma^2(q(x_j)) + \gamma}} \quad (1)$$

where $\mu(\cdot)$ and $\sigma^2(\cdot)$ denote the sample mean and variance of the predicted scores group, $q_k(x_i)$ represents the k -th score estimate for image x_i , and γ is a small constant ensuring numerical stability. The comparative probability is then derived via the standard Gaussian Cumulative Distribution Function (CDF):

$$P_k(x_i \succ x_j) = \Phi(\mathcal{Z}_{ij}^k) \quad (2)$$

where $\Phi(\cdot)$ is the Gaussian CDF, representing the probability P_k that image x_i is perceptually superior to x_j . Crucially, we explicitly leverage the sample variances derived from the GRPO group outputs to dynamically accommodate predictive uncertainty, preventing over-confident errors on ambiguous images.

Fidelity Reward and Optimization. To rapidly align the model’s predictions with human perception, we define the ground truth preference y_{ij} based on Mean Opinion Scores (MOS): $y_{ij} = 1$ if $\text{MOS}(x_i) > \text{MOS}(x_j)$, 0.5 if equal, and 0 otherwise. The optimization is driven by a continuous fidelity reward. We define the ranking reward R_{rank} as:

$$R_{rank}(x_i) = y_{ij} \cdot P_k(x_i \succ x_j) + (1 - y_{ij}) \cdot (1 - P_k(x_i \succ x_j)) \quad (3)$$

where $y_{ij} \in \{0, 0.5, 1\}$ represents the ground truth preference label derived from human ratings. This reward is designed to capture fine-grained distinctions in quality ranking. To ensure training stability, we maximize the GRPO objective $\mathcal{J}(\theta)$, which integrates the clipped surrogate advantage and a KL-divergence penalty:

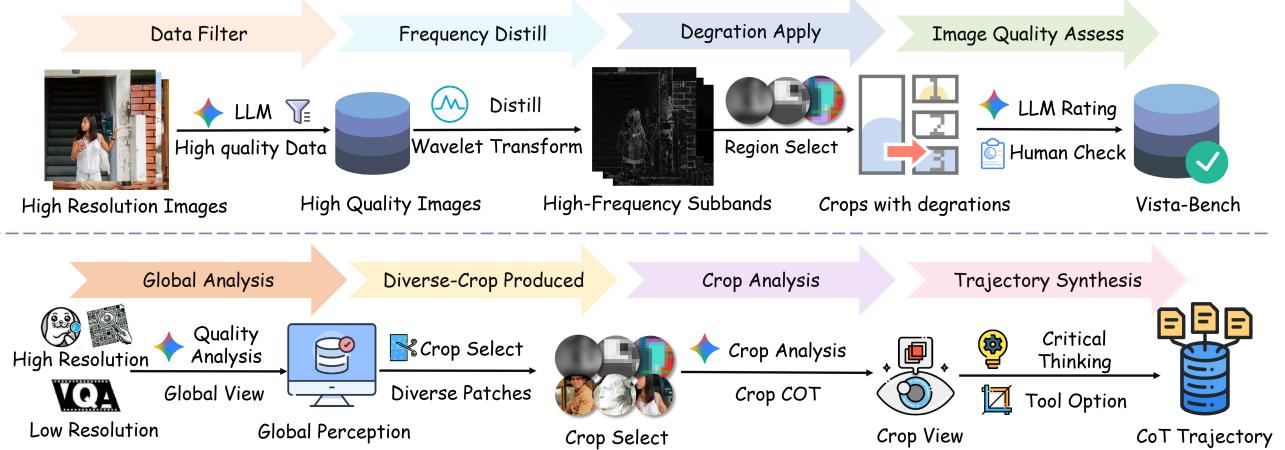


Figure 2. This diagram illustrates the construction pipeline of Vista-Bench and the Data Flywheel for SFT. Specifically, we utilize wavelet transforms to decouple structure from texture, selectively injecting artifacts into texture-rich semantic regions, while employing Gemini-2.5 Pro to generate importance-weighted annotations for fine-grained perception probing. To support SFT, we generate traces that interleave global overviews, defect zooming, and context verification (scrutinizing clear regions), thereby preventing the model from associating tool usage solely with defects.

$$\mathcal{J}(\theta) = \mathbb{E} \left[\min \left(\frac{\pi_\theta}{\pi_{old}} A_k, \text{clip} \left(\frac{\pi_\theta}{\pi_{old}}, 1 - \epsilon, 1 + \epsilon \right) A_k \right) - \beta D_{KL}(\pi_\theta || \pi_{ref}) \right] \quad (4)$$

where π_θ and π_{old} represent the current and previous policies respectively, A_k is the advantage score computed from reward signals, ϵ is the clipping threshold to constrain policy updates, π_{ref} is the reference policy (typically the initial SFT model), and β is a coefficient controlling the strength of the KL-divergence penalty D_{KL} . This pre-alignment stage establishes a solid baseline for global image understanding, converging towards the mechanisms of human MOS.

3.4. Stage 2: Hybrid-Resolution SFT via Data Flywheel

To bridge the gap between global perception and local scrutiny, we construct the **Probe-CoT-3K** dataset using a Data Flywheel approach (as illustrated in Fig. 2). The dataset follows a 2:1 ratio of low-to-high resolution images.

The SFT Dilemma: Precision vs. Diversity. In traditional Visual Question Answering (VQA), crop content inherently exhibits high diversity. However, in Agentic IQA, if SFT data is invariably centered on degradations, the model overfits to a biased mode: “*Tool Usage implies Degradation and Low Quality*,” resulting in a fundamental breakdown of logical reasoning.

Context-Aware Trajectory Generation. To mitigate this, we synthesize CoT trajectories encompassing genuine degradations, natural depth-of-field, and pristine foregrounds. This strategy effectively severs the spurious causal corre-

lation associating “cropping” with “low quality”. We optimize the model using the standard cross-entropy loss over the mixed sequence of reasoning and action tokens y :

$$\mathcal{L}_{SFT} = - \sum_{t=1}^L \log P(y_t | y_{<t}, \mathbf{x}) \quad (5)$$

where \mathcal{L}_{SFT} is the SFT loss, L denotes the sequence length, \mathbf{x} represents the multimodal input (image and instruction), and y_t is the t -th token in the generated target sequence y given the preceding tokens $y_{<t}$. Following the SFT phase, the model establishes a robust understanding of the global image context and acquires the capability to accurately discern diverse local regional features.

3.5. Stage 3: Precision Pursuit via Decoupled Post-RL

As the SFT phase strategically trades localization precision for logical robustness, we construct and leverage the **Probe-RL-4K** dataset in the final stage to further refine the model’s fine-grained detection capabilities.

Decoupled Reward Mechanism. We implement a decoupled reward mechanism that disentangles the optimization of the “Looking Policy” from the “Scoring Policy.” We independently define the accuracy reward R_{acc} and the localization reward R_{loc} :

$$R_{acc} = \exp \left(- \frac{|s_{pred} - s_{MOS}|}{\tau} \right) \quad (6)$$

$$R_{loc} = \mathbb{I}(has_defect) \cdot \text{IoU}(B_{pred}, B_{gt}) \quad (7)$$

where s_{pred} and s_{MOS} denote the predicted score and ground truth MOS respectively, and τ is a temperature hyperparameter controlling the sensitivity of the accuracy reward.



Figure 3. Overview of the three-stage training framework. Initially, RL Pre-training leverages ranking rewards to align global perception with human preferences. Subsequently, hybrid-resolution SFT enables the model to acquire robust logical reasoning. Finally, the RL Post-training stage fine-tunes the model for precise degradation detection and adaptive tool invocation.

For localization, $\mathbb{I}(\cdot)$ is an indicator function that equals 1 if a defect exists in the image, and $\text{IoU}(\cdot)$ computes the Intersection over Union between the predicted crop box B_{pred} and the ground truth defect region B_{gt} . This reward incentivizes the model to accurately capture degradations and precisely deploy tools for regional magnification.

The total reward R_{total} is then composed as:

$$R_{total} = \underbrace{\alpha R_{acc}}_{\text{Scoring}} + \underbrace{\beta R_{loc}}_{\text{Looking}} + \gamma R_{format} \quad (8)$$

where α , β , and γ are hyperparameters weighting the contribution of the accuracy reward, localization reward, and format compliance reward R_{format} , respectively. This de-coupled reward optimizes the model to refine its localization capabilities (βR_{loc}), building upon the robust logic reasoning capability acquired during SFT.

4. Experiments

4.1. Experimental Setup

Datasets and Metrics. To evaluate the comprehensive capabilities of Q-Probe, we conduct experiments across a diverse set of IQA benchmarks. For standard resolution assessments, we utilize KonIQ-10k (Hosu et al., 2020),

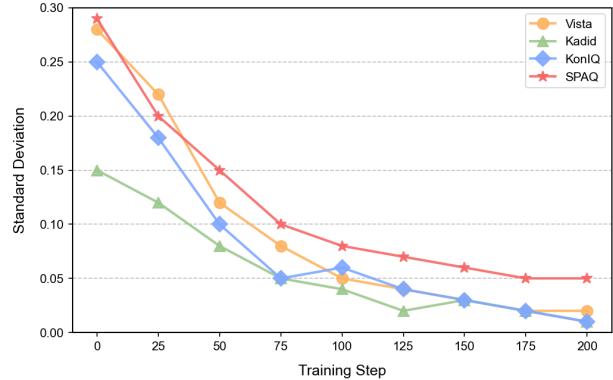


Figure 4. To monitor the training dynamics, we calculated the average standard deviation of predicted scores across multiple inference runs at various checkpoints. The observed monotonic decrease in variance not only confirms that Q-Probe achieves greater stability throughout Stage-1.

SPAQ (Fang et al., 2020), and KADID-10k (Lin et al., 2019) to represent in-the-wild and synthetic distortions. We also include PIPAL (Jinjin et al., 2020) to evaluate robustness against algorithm-processed distortions and AGIQA-3K (Li et al., 2023) for AI-generated content. Crucially, to validate fine-grained perception in the high-resolution era, we

Table 1. Comprehensive performance comparison (SRCC / PLCC) on standard and high-resolution datasets. **Q-Probe** achieves SOTA results, especially on the high-resolution **Vista** benchmark. Methods are color-coded by category: Handcrafted, Deep Learning, and MLLMs-based. The best and second-best results are highlighted in red and blue.

Methods	Vista	SPAQ	KADID	PIPAL	TID13	KonIQ	AGIQA	Avg
Spearman Rank Correlation Coefficient (SRCC)								
BRISQUE (Mittal et al., 2012a)	0.152	0.614	0.429	0.242	0.548	0.385	0.497	0.409
NIQE (Mittal et al., 2012b)	0.187	0.676	0.487	0.357	0.532	0.421	0.533	0.456
MUSIQ (Ke et al., 2021)	0.295	0.720	0.647	0.317	0.670	0.473	0.494	0.516
UNIQUE (Zhang et al., 2021)	0.310	0.751	0.513	0.393	0.703	0.649	0.608	0.561
MANIQA (Yang et al., 2022)	0.325	0.745	0.760	0.338	0.589	0.213	0.422	0.484
Qwen2.5-VL-7B (Bai et al., 2025)	0.385	0.848	0.787	0.390	0.787	0.754	0.735	0.669
LIQE (Zhang et al., 2023)	0.342	0.815	0.809	0.371	0.718	0.684	0.653	0.627
DeQA-Score (You et al., 2025)	0.398	0.852	0.831	0.383	0.756	0.677	0.738	0.662
Q-Align (Wu et al., 2023)	0.360	0.767	0.832	0.406	0.769	0.573	0.682	0.627
UnifiedReward-T (Wang et al., 2025d)	0.412	0.871	0.841	0.399	0.788	0.820	0.722	0.693
Q-Insight (Li et al., 2025)	0.365	0.872	0.856	0.429	0.816	0.806	0.749	0.699
VisualQuality-R1 (Wu et al., 2025)	0.451	0.875	0.871	0.469	0.848	0.855	0.805	0.739
Q-Probe (Ours)	0.728	0.892	0.901	0.474	0.829	0.871	0.837	0.790
Pearson Linear Correlation Coefficient (PLCC)								
BRISQUE (Mittal et al., 2012a)	0.165	0.624	0.451	0.259	0.546	0.400	0.541	0.426
NIQE (Mittal et al., 2012b)	0.192	0.683	0.415	0.314	0.516	0.439	0.560	0.445
MUSIQ (Ke et al., 2021)	0.288	0.666	0.622	0.347	0.695	0.435	0.434	0.498
UNIQUE (Zhang et al., 2021)	0.305	0.708	0.548	0.361	0.729	0.590	0.581	0.546
MANIQA (Yang et al., 2022)	0.318	0.753	0.780	0.364	0.617	0.257	0.448	0.505
Qwen2.5-VL-7B (Bai et al., 2025)	0.362	0.854	0.806	0.420	0.837	0.810	0.772	0.694
LIQE (Zhang et al., 2023)	0.335	0.814	0.817	0.347	0.748	0.652	0.653	0.623
DeQA-Score (You et al., 2025)	0.375	0.858	0.873	0.381	0.793	0.703	0.743	0.675
Q-Align (Wu et al., 2023)	0.348	0.779	0.862	0.381	0.794	0.612	0.694	0.638
UnifiedReward-T (Wang et al., 2025d)	0.395	0.846	0.877	0.421	0.873	0.804	0.745	0.708
Q-Insight (Li et al., 2025)	0.346	0.872	0.881	0.462	0.851	0.829	0.794	0.719
VisualQuality-R1 (Wu et al., 2025)	0.427	0.878	0.821	0.458	0.871	0.840	0.843	0.734
Q-Probe (Ours)	0.776	0.900	0.892	0.476	0.876	0.863	0.813	0.799

Table 2. Ablation study of the progressive training strategy across multiple benchmarks.

Model Configuration	Vista		SPAQ		KADID-10k		KonIQ-10k		Average	
	SRCC	PLCC								
Stage 1 Only	0.290	0.340	0.760	0.780	0.700	0.725	0.650	0.680	0.600	0.631
Stage 2 + Stage 3	0.679	0.722	0.766	0.796	0.781	0.772	0.752	0.769	0.746	0.755
Stage 1 + Stage 2	0.690	0.735	0.850	0.860	0.880	0.875	0.820	0.815	0.810	0.821
Full (Stage 1+2+3)	0.728	0.776	0.892	0.900	0.901	0.892	0.871	0.863	0.848	0.858

Table 3. Ablation of the Reward Mechanism in Stage 3 on Vista-Bench.

Reward Strategy	SRCC	PLCC
R_{acc} (Score Only)	0.698	0.747
$R_{acc} + R_{format}$	0.705	0.752
$R_{acc} + R_{format} + R_{loc}$ (Ours)	0.728	0.776

Table 4. Ablation of Crop Coverage Strategies regarding Degradation Regions on Vista-Bench.

Crop Strategy	SRCC	PLCC
Degradation Only	0.510	0.580
Partial Degradation & Partial Normal	0.695	0.745
All Degradation & Partial Normal	0.728	0.776

employ our proposed Vista-Bench, which contains localized artifacts in high-resolution scenarios. We leverage the widely recognized Spearman Rank-order Correlation Coefficient (SRCC) and Pearson Linear Correlation Coefficient (PLCC) as our primary evaluation metrics. Following established protocols (Wu et al., 2023; Fang et al., 2020), we compute the average performance across datasets to assess overall generalization.

Baseline Methods. We compare the proposed Q-Probe against a wide range of state-of-the-art (SOTA) baseline methods, including handcrafted methods (NIQE (Mittal et al., 2012b), BRISQUE (Mittal et al., 2012a)), discriminative deep learning models (UNIQUE (Zhang et al., 2021), MUSIQ (Ke et al., 2021), MANIQA (Yang et al., 2022)), MLLMs-based approaches (LIQE (Zhang et al., 2023), Q-Align (Wu et al., 2023), DeQA-Score (You et al., 2025), and the recent RL-based models Q-Insight (Li et al., 2025) and VisualQuality-R1 (Wu et al., 2025)).

Implementation Details. We utilize Qwen-2.5-VL-7B (Bai et al., 2025) as our base model. During the perception alignment stage, we employ GRPO with a generation number $K = 6$ and a clip threshold $\epsilon = 0.2$. The model is trained using the AdamW optimizer with a learning rate of 1×10^{-6} . For the hybrid-resolution SFT, we utilize the Probe-CoT-3K dataset with a crop resolution of 768×768 . In the decoupled Post-RL stage, we set the reward weights $\alpha = 1.0$ (accuracy) and $\beta = 0.15$ (localization). All experiments are conducted on 8 NVIDIA A100 (80GB) GPUs.

4.2. Main Results

Table 1 presents the comprehensive SRCC and PLCC performance across seven benchmarks. In terms of SRCC, our method attains a remarkable score of 0.728 on the challenging Vista-Bench dataset, significantly outperforming the baseline methods which lack fine-grained perception mecha-

nisms. The PLCC results in the lower half of Table 1 confirm the linear alignment of our predictions with human perception, achieving a leading PLCC of 0.776 on high-resolution scenarios. Moreover, experimental results demonstrate that our method maintains superior performance across diverse low-resolution datasets, underscoring the robust generalization capability of Q-Probe across resolution scales.

4.3. Ablation Studies

Necessity of the Three-Stage Curriculum. Table 2 validates the efficacy of our progressive training curriculum. Although Stage 1 performs poorly on high-resolution details, it successfully pre-aligns the model with human aesthetic perception on standard benchmarks. Without Stage 1, model can't reach its best performance. Building on this foundation, Stage 2 bridges the granularity gap via hybrid-resolution training, while Stage 3 further refines the scoring precision through RL to achieve the best overall performance. Besides, three Stages consistently boost performance on standard low-resolution benchmarks, culminating in the best overall results.

Impact of Reward Components in Post-RL. In Stage 3, we analyze the contribution of different reward components. As shown in Table 3, using only the Accuracy Reward (R_{acc}) provides a solid baseline. Incorporating the Format Reward (R_{format}) yields a slight improvement by ensuring the structural validity of the CoT reasoning. However, the most significant gain comes from the Decoupled Localization Reward (R_{loc}), which explicitly guides the model's attention to defects, pushing the SRCC to 0.728.

Impact of Crop Coverage Strategy. Table 4 examines the spatial relationship between crops and degradation. Restricting crops to *exact* degradation regions (Strategy 1) leads to severe overfitting, where the model learns biased inference and associates all crops with degradation, dropping SRCC to 0.510. Strategy 2, covering *partial* degradation and normal areas, improves to 0.695 but introduces trade-off that the model may overlook omitted defects. Finally, Strategy 3 achieves optimal performance (SRCC 0.728) by capturing *all* degradation within a normal context, ensuring comprehensive defect assessment without hallucinations.

5. Conclusion

In this work, we introduced Q-Probe, the first agentic framework designed to scale IQA to high-resolution scenarios via context-aware probing. Recognizing the limitations of existing global-view RL methods in capturing fine-grained artifacts, we proposed a novel three-stage training curriculum that mimics the human “coarse-to-fine” perception mechanism, teaching the model to evaluate quality based on impor-

tance of degraded crops. Furthermore, by constructing the Vista-Bench and leveraging a Data Flywheel, we eliminated the spurious “cropping-implies-degradation” bias, enabling the model to intelligently distinguish between technical distortions and artistic effects. Our model achieves sota performance on both high-resolution and low-resolution datasets.

Impact Statement

This paper presents work whose goal is to advance the field of machine learning. There are many potential societal consequences of our work, none of which we feel must be specifically highlighted here.

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