

# Q-Instruct: Improving Low-level Visual Abilities for Multi-modality Foundation Models

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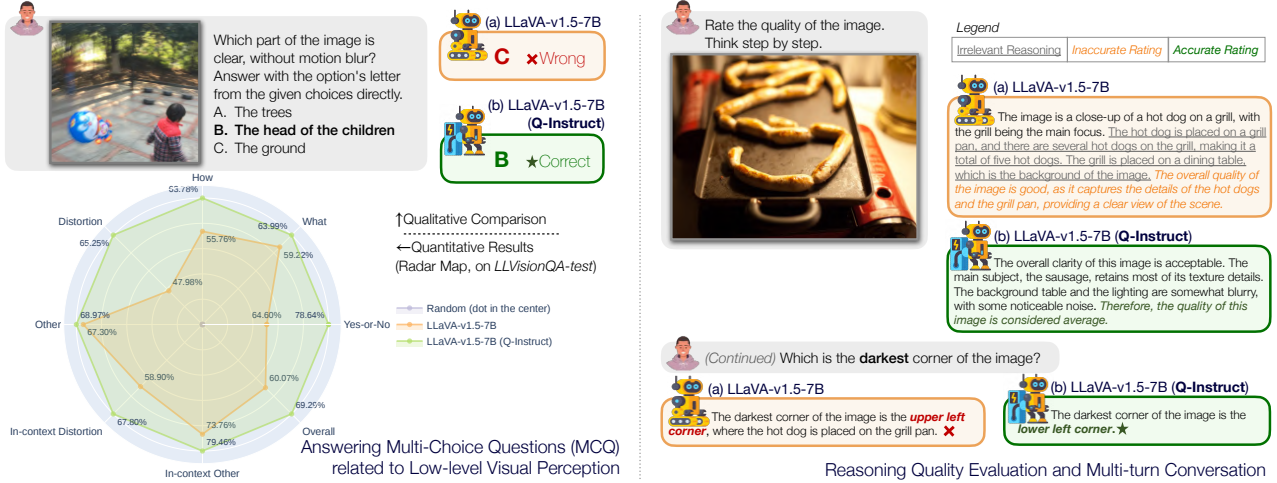


Figure 1. Abilities of Q-Instruct-tuned LLaVA-v1.5-7B [28] on various low-level visual tasks, in comparison with the baseline version.

## Abstract

Multi-modality large language models (MLLMs), as represented by GPT-4V, have introduced a paradigm shift for visual perception and understanding tasks, that a variety of abilities can be achieved within one foundation model. While current MLLMs demonstrate primary **low-level visual abilities** from the identification of low-level visual attributes (e.g., clarity, brightness) to the evaluation on image quality, there’s still an imperative to further improve the accuracy of MLLMs to substantially alleviate human burdens. To address this, we collect the first dataset consisting of human natural language feedback on low-level vision. Each feedback offers a comprehensive description of an image’s low-level visual attributes, culminating in an overall quality assessment. The constructed **Q-Pathway** dataset includes 58K detailed human feedbacks on 18,973 multi-sourced images with diverse low-level appearance. To ensure MLLMs can adeptly handle diverse queries, we further propose a GPT-participated transformation to convert these feedbacks into a rich set of 200K instruction-response pairs, termed **Q-Instruct**. Experimental results indicate that Q-

**Instruct** consistently elevates various low-level visual capabilities across multiple base models. We anticipate that our datasets can pave the way for a future that foundation models can assist humans on low-level visual tasks.

## 1. Introduction

Computer vision has witnessed a recent paradigm shift attributed to the emergence of multi-modality large language models (MLLMs) [6, 10, 29, 36]. These models aim to transcend traditional task-specific experts, and serve as general-purpose foundation models capable of facilitating humans across a variety of visual tasks [24]. Specifically, these foundation models also bring exciting potentials in the domain of **low-level visual perception and understanding**. This domain includes not only commonly-focused image quality assessment (IQA) [13, 51, 56] tasks, but also finer-grained abilities to identify the low-level visual attributes (noise, blur, etc) [42], or evaluate the low-level visual dimensions (clarity, brightness, etc) [8, 52]. As human cognition associated with these tasks is highly interconnected, we aspire for a unified foundation model to establish general abilities across these tasks, which could robustly respond to open-ended human queries on low-level visual aspects.

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♣ Project Page: <https://q-future.github.io/Q-Instruct>

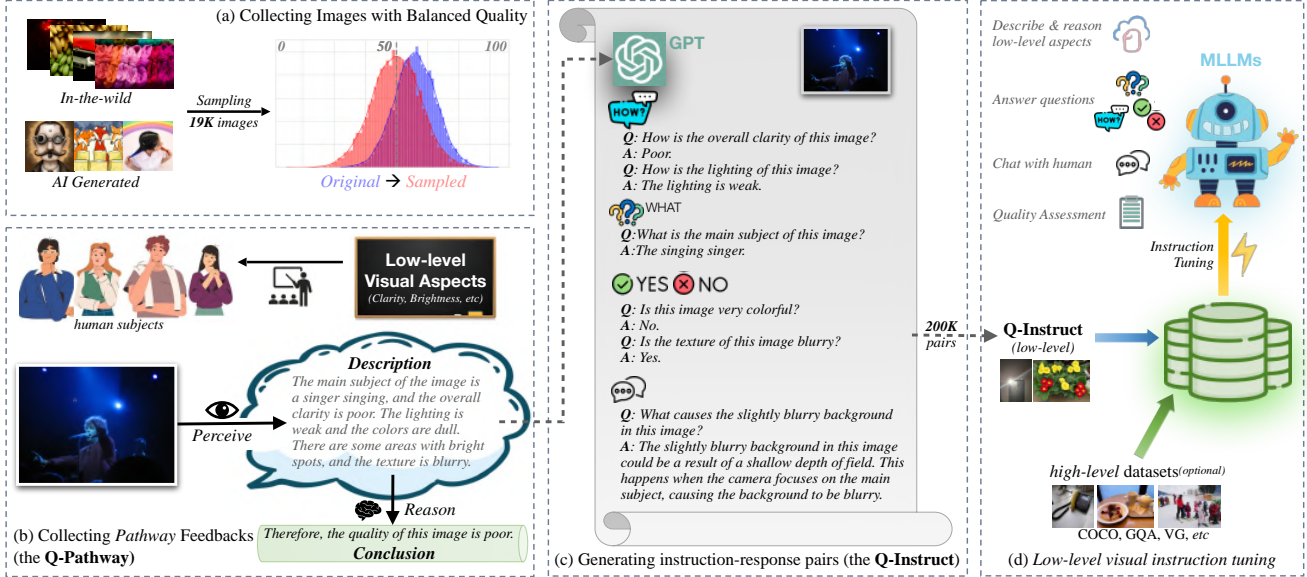


Figure 2. Data construction pipeline. First, we collect **58K** human feedbacks on low-level visual aspects (the **Q-pathway**, a/b); they are then converted into with **200K** instruction-response pairs (the **Q-Instruct**, c), which are used for (d) low-level visual instruction tuning.

Nevertheless, though existing MLLMs can basically reply to human queries regarding low-level visual aspects, the accuracy of their responses remains unsatisfactory [30, 53] (Fig. 1(a)). The primary problem is the lack of low-level visual datasets during training MLLMs, where publicly available datasets generally only focus on high-level visual abilities [2, 15, 21, 31]. To solve this problem, we construct the **Q-Instruct**, the first large-scale *low-level visual instruction tuning* dataset, in the following two steps:

#### Step 1: Collect human feedbacks for low-level vision.

For this step, we invite human subjects to provide direct feedbacks on their low-level perception and understanding over a variety of images (Fig. 2(b)). Specifically, each feedback should include two parts: 1) Primarily, an exhaustive **description** on elemental low-level attributes (e.g. *blurs, noises, clarity, color, brightness*). Such descriptions should also include content [26, 47] or position [49, 56] contexts (e.g. *the duck / the left part of the image is under-exposed*) that are related to low-level attributes. 2) Then, an overall **conclusion** on the image quality based on the description of the attributes. With the two parts, the feedbacks, denoted as **pathway** feedbacks, not only record fundamental human low-level perception but also reflect the human reasoning process on evaluating visual quality. The hence-constructed **Q-Pathway** dataset (Fig 2(b)) contains 58K pathway feedbacks on 18,973 multi-sourced images, each image with at least three feedbacks (avg. 46.4 words per feedback).

#### Step 2: Convert these feedbacks for instruction tuning.

While these **pathway** feedbacks themselves make up an important subset for the *low-level visual instruction tuning*, the full instruction tuning dataset should be designed to activate more capabilities. Primarily, it should also in-

clude a *low-level visual question answering* (VQA) subset. To generate a reliable VQA subset, we refer to the setting that how COCO-VQA [2] is derived from image captions, and employ GPT [35] to convert the *pathway* feedbacks into question-answer pairs with adjectives (e.g. *good/fair/poor*) or nouns (e.g. *noise/motion blur*) as answers. Similarly, we also collect a balanced *yes-or-no* question-answer set based on the information in the feedbacks (*answered with yes*), or information contrast to the feedbacks (*answered with no*); some context-related question-answer pairs are also created to better ground [58] the low-level attributes. Following existing studies [39], all question-answer pairs in the VQA subset include both multiple-choice (A/B/C/D) and direct-answer settings. Furthermore, besides the VQA subset, with the assistance of GPT, we also collect a subset of long conversations related to the low-level concerns (e.g. *why the distortions happen, how to improve the picture quality*). The subsets compose into the **Q-Instruct** dataset (Fig. 2(c)) with 200K instruction-response pairs, which is designed to enhance MLLMs on a variety of low-level visual abilities.

The core contributions of our study can be summarized as follows: **1)** We collect the **Q-Pathway**, a multi-modality dataset for low-level visual perception and quality assessment, which includes direct human feedbacks (*with reasoning*) on low-level visual aspects. **2)** Based on **Q-Pathway**, we construct the **Q-Instruct**, the first instruction tuning dataset that focuses on human queries related to low-level vision. **3)** Our rich experiments on *low-level visual instruction tuning* ((Fig. 2 (d)) validate that the **Q-Instruct** improve various low-level abilities of MLLMs (Fig. 1), and bring insights for future studies to inject various low-level visual abilities into the scope of general foundation models.

## 2. Related Works

### 2.1. Low-level Visual Perception

**Tasks and Datasets.** Image quality assessment (IQA), targeting to predict accurate scores aligned with integrated human opinions on all low-level aspects, has always been the chief task in low-level visual perception. Many datasets are developed to address IQA on artificially-distorted images [16, 27] (*JPEG, AWGN, etc*), in-the-wild photographs [13, 56], or recently-popular AI-generated contents [25, 54], providing important metrics for visual content production and distribution. Despite general IQA, recent studies have started to focus on finer-grained low-level visual aspects, and explored some related tasks such as evaluating on low-level visual dimensions (*e.g. color, brightness*) [8, 52], or distinguishing the existing distortions (*e.g. blur, noise, over-exposure*) in images [42]. Some recent works [50, 51] also consider some photography-related dimensions (*e.g. composition, lighting, bokeh*) [20] as a broader sense of low-level aspects. In general, low-level visual perceptual tasks can include all aspects of image appearance (*in contrast to object-level contents*) that can be perceived by human and evoke different human feelings. While these low-level visual tasks used to be tackled separately, the proposed datasets bring the opportunities to include, relate and learn these tasks together, supporting one foundational model to generally master on these tasks.

**Approaches.** Similarly, the approaches designed for low-level visual perception also basically focus on their general IQA abilities. The traditional IQA metrics, *e.g.* NIQE [33], operate on discipline-based methodologies without training with human opinions, offering robust but less accurate evaluations. In contrast, deep learning-based IQA methods [7, 17, 41, 60] utilize task-specific data, capitalizing on the extensive learning capacities of neural networks to tailor their assessment to particular data distributions, while they also suffer from compromised generalization abilities. Notably, recent methods [14, 18, 46, 61, 63] explore CLIP [37] for IQA, which stand out for their pioneer efforts on *multi-modality integration* for low-level vision, and exciting zero-shot performance. Their zero-shot IQA abilities are also inherited by most recent MLLMs [3, 28, 59]. Similar as NIQE, these multi-modality IQA methods are robust on various scenarios, yet not enough accurate on each single case. While these methods present improving performance on general IQA, the other finer-grained low-level visual perception abilities are still yet to be deeply investigated; moreover, tackling all these tasks separately may overlook the underlying relationships between them, refraining from reasoning among these sections. After instruction tuning with the proposed **Q-Instruct**, MLLMs can significantly improve their abilities on various low-level visual abilities, forecasting a future to unify these tasks through one model.

Table 1. The **Q-Pathway** compared to its sources. We sub-sample the source images to reduce the *skews* in their MOS distributions, resulting in the sampled distribution to be further balanced.

Image Sources MOS $\in [0, 100)$	Original Distribution			Sampled Distribution		
	Size	$\mu_{\text{MOS}}$	$\sigma_{\text{MOS}}$	Size	$\mu_{\text{MOS}}$	$\sigma_{\text{MOS}}$
KoniQ-10k [13]	10,073	58.73	15.43	5,182	49.53	15.72
SPAQ [8]	11,125	50.32	20.90	10,797	49.46	20.63
LIVE-FB [56]	39,810	72.13	6.16	800	60.68	17.38
LIVE-itw [11]	1,169	55.38	20.27	200	55.70	19.83
AGIQA-3K [25]	2,982	50.00	19.80	400	40.80	21.80
ImageRewardDB [54]	50,000	- w/o MOS -	-	584	- w/o MOS -	-
15-distortion COCO [4]	330,000	- w/o MOS -	-	1,012	- w/o MOS -	-
<i>Overall</i>	445,159	65.02	16.51	18,973	<u>49.87</u>	<u>19.08</u>

### 2.2. Multi-modality Large Language Models

Large language models (LLMs), *e.g.* GPT-4 [36], T5 [5], LLaMA [44], has shown great language abilities regarding general human knowledge. With CLIP [37] and additional adapting modules to involve visual inputs into LLMs, the multi-modality large language models (MLLMs) [6, 10, 23, 29, 59] can tackle a variety of multi-modality tasks for high-level vision, such as *image captioning* [1, 4, 57], *visual question answering* (VQA) [2, 31, 39], and more language-related capabilities [9, 22, 30]. Nevertheless, the evaluation results in the recent benchmark [53] reveals that MLLMs’ low-level visual abilities are still unsatisfactory, especially when it comes to the *finer-grained* low-level perception questions. While we notice that this is mainly due to the lack of respective data, we collect the first *low-level visual instruction tuning* dataset, the **Q-Instruct**, to improve low-level visual abilities for different MLLMs, and bring them into the realm of low-level visual perception.

## 3. the Q-Pathway

As the fundamental part of the dataset construction, we introduce the **Q-Pathway**, the first large scale dataset that collects **text** feedbacks from human on low-level visual aspects. To diversify and balance different low-level appearances, we sub-sample images from **seven** sources (Sec. 3.1) and reduce the *skews* in the source distributions (Tab. 1). After the preparation of images, we discuss the rationality and the detailed task definition for the *pathway* feedbacks (Sec. 3.2), a kind of natural language feedback, as collected in the **Q-Pathway**. The subjective study is conducted **in-lab** (Sec. 3.3), where all subjects are trained before providing feedback. The analysis of the **Q-Pathway** is in Sec. 3.4.

### 3.1. Preparation of Images

The images in the **Q-Pathway** are sampled from various sources, including four *in-the-wild* IQA datasets [8, 11, 13, 56], and two datasets with *AI-generated* images [25, 54]. Specifically, as compared in Tab. 1, the sub-sampled population of images is carefully constructed to introduce more diverse low-level appearances in the **Q-Pathway**, which is



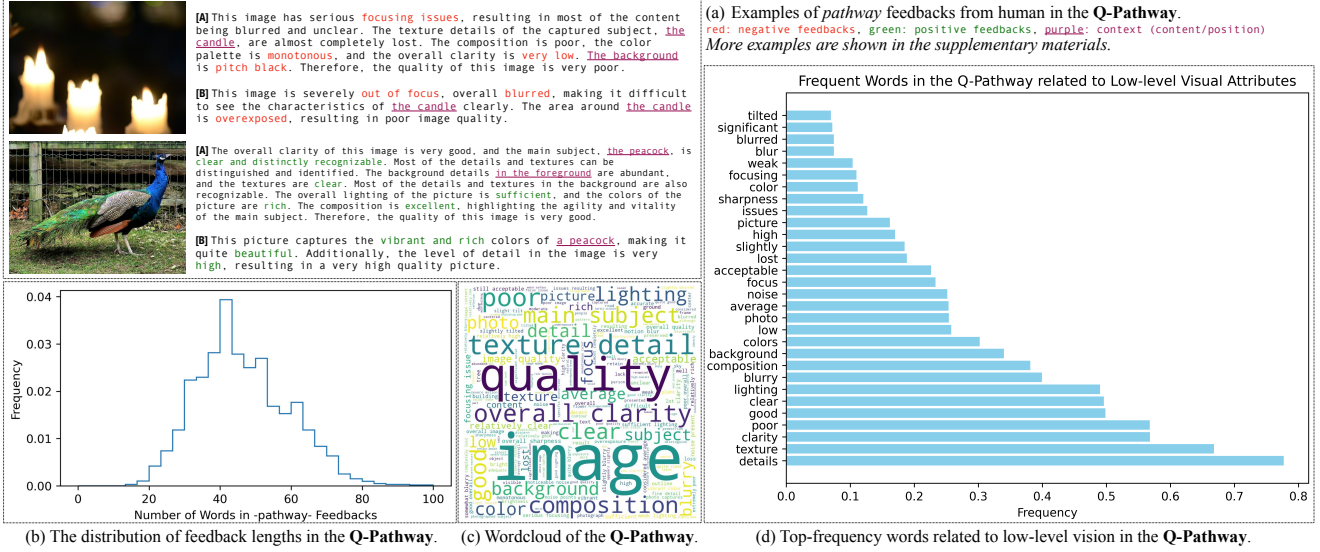


Figure 3. (a) Example *pathway* feedbacks, each containing a detailed description followed by an overall evaluation, with context included. (b) The distribution of *pathway* feedback lengths. (c) Wordcloud of the Q-Pathway. (d) Top-frequency words related to low-level vision.

neither skewed towards positive appearances nor towards negative appearances. Moreover, to further diversify the low-level appearances of the collected images, we design a custom variant of *imagecorruptions* [32] to randomly corrupt 1,012 originally-pristine images from COCO [4] dataset with one in 15 artificial distortions. The assembled sub-sampled dataset consists of 18,973 images, which are further fed to human subjects to provide *pathway* feedbacks.

### 3.2. Task Definition: the *pathway* Feedbacks

For the Q-Pathway, to collect a richer and more nuanced understanding of human perception on low-level visual aspects, instead of collecting multi-dimensional scores as in existing studies [8, 52], we opt to collect a new format of annotation, termed *pathway* feedbacks, with an exhaustive natural language description on low-level visual attributes *e.g.* *noise*, *brightness*, *clarity*) followed by a general conclusion. The rationales for this format are as follows: (1) Primarily, the descriptions can preserve what human perceive more *completely* and *precisely*. For instance, if an image has both dark and bright areas such as Fig 3(a) *upper*, the brightness score might not properly record [49, 56] this situation: the positional context cannot be preserved, and the reliability of the score could also be compromised, as neither labeling it as ‘dark’ nor as ‘bright’ is accurate. (2) Moreover, unlike free-form text feedbacks, the order of the two parts in *pathway* feedbacks generally aligns with the human reasoning process. For instance, while human subjects are shown with an *underexposed* yet *clear* image, they can provide intuitive reasoning leading to eclectic conclusions like “Thus, the quality of the image is acceptable”. This reasoning will help MLLMs to better emulate human perception

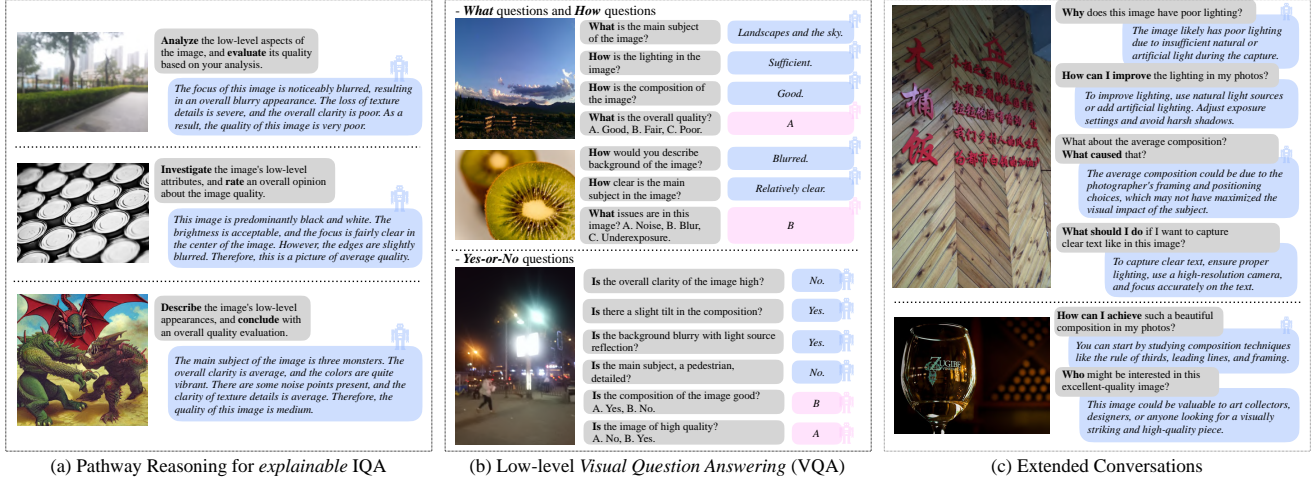
and understanding related to low-level vision. While this *pathway*-style format faces challenges to be transformed into machine learning objectives in the past, the emergence of MLLMs has provided the opportunity to learn from these direct human feedbacks, in order to allow machines to more precisely and robustly align with human perception.

### 3.3. The subjective study process.

The subjective study is carried out in a well-controlled laboratory environment, during which a total of 39 **trained** human subjects are invited. Based on task definition, training material includes not only calibration on *overall quality*, but also on the *respective text descriptions* of different low-level appearances shown in visuals. Furthermore, as the majority of images come from IQA datasets, the mean opinion scores (MOSs) of them are also displayed to subjects to better calibrate them with a common understanding of *quality*. To facilitate their feedback process, we also show a reference attribute set that can be used in the descriptions. To avoid test fatigue of subjects, consecutive feedbacks on more than 30 images will be warned and discouraged; it will be further forcefully paused after 50 images. 58K *pathway* feedbacks are collected during the study, as exemplified in Fig. 3(a).

### 3.4. Analysis

After the subjective study, we briefly analyze the collected feedbacks. Qualitatively (Fig. 3(a)), the *pathway* feedbacks can generally preserve the respective contexts related to low-level attributes. Moreover, feedbacks from different human subjects for the same image (as exemplified in [A] and [B] for each image) shows decent consistency (*no controversial information*), and slightly complements one an-



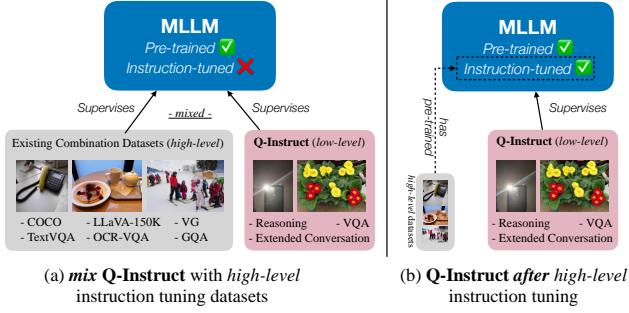


Figure 5. Training strategies for low-level visual instruction tuning evaluated in our study, including (a) mix the **Q-Instruct** with high-level visual instruction tuning datasets, (b) conduct a further low-level tuning stage with only **Q-Instruct** after high-level tuning.

tools to restore, enhance, or edit the image; **4)** Recommending the image to respective consumers; **5)** Other conversations that may happen given the low-level visual descriptions provided in the *pathway* feedbacks. Similarly, the extended conversation subset is also generated by GPT, with in total **12K** conversations collected for the **Q-Instruct**.

## 5. Low-level Visual Instruction Tuning

In this section, we discuss the standard training strategies for *low-level visual instruction tuning*, *i.e.* when to involve the **Q-Instruct** dataset during the training of MLLMs. In general, the training of open-source MLLMs [6, 23, 59] includes two stages: **First**, aligning the representation space of the visual backbone and the LLM with million-scale web data [38, 40]. **Second**, visual instruction tuning with a combination of human-labeled datasets [2, 4, 31, 58]. Considering the scale of the **Q-Instruct**, a general strategy is to mix its instruction-response pairs with the high-level datasets in the **second** stage, so as to ideally allow MLLMs to be low-level-aware while keeping its other abilities, as shown in Fig. 5(a). Another faster and more convenient strategy is a further **third** stage only with the **Q-Instruct** (Fig. 5(b)) after original high-level tuning. In our experiments, we validate that they both bring notable improvements on various low-level visual tasks, and involving *high-level* awareness contribute to the effectiveness of both strategies.

## 6. Experiments

### 6.1. Experimental Setups

**Baseline models.** We pick four variants of three state-of-the-art MLLMs within diverse meta structures (Tab. 2) as baseline models to evaluate their low-level visual abilities *before* and *after* training with the **Q-Instruct**. Each model is evaluated under both strategies as in Fig. 5, with the original combination of *high-level* datasets unchanged.

**Training Settings.** We follow the default instruction tuning hyper-parameters of MLLMs during all training processes

Table 2. Baseline MLLMs for *low-level visual instruction tuning*.

Month/Year	Model Name	Visual Backbone	V→L Module	Language Model
Oct/23	LLaVA-v1.5 (7B) [28]	CLIP-ViT-L14 <sup>336</sup>	MLP	Vicuna-v1.5-7B [64]
Oct/23	LLaVA-v1.5 (13B) [28]	CLIP-ViT-L14 <sup>336</sup>	MLP	Vicuna-v1.5-13B [64]
Oct/23	mPLUG-Owl-2 [55]	CLIP-ViT-L14 <sup>448</sup>	Abstractor	LLaMA2-7B [45]
Sep/23	InternLM-XComposer-VL [59]	EVA-CLIP-G	Q-Former	InternLM-7B [43]

involving the **Q-Instruct**. As we aim to reach a unified low-level visual foundation model, for each MLLM, the final checkpoint is saved and tested for all evaluations. To avoid data contamination, during training, we remove data items with images that may appear in the evaluation sets.

### 6.2. Main Results

The low-level visual abilities of MLLMs after *low-level visual instruction tuning* are quantitatively evaluated in three tasks defined by [53], including **(A1) Perception**, by measuring the accuracy of answering multi-choice questions (MCQ) related to low-level vision (Fig. 1); **(A2) Description**, which examines how MLLMs can generally transform low-level visual information into text. As for **(A3) Quality Assessment**, considering that the **Q-Instruct** already contains a large proportion of images in major IQA databases, we evaluate and discuss how the instructed MLLMs generalize on unseen images. For reproducibility, all responses from MLLMs are generated with *greedy search*. Qualitative analyses are provided in supplementary materials.

**(A1) Perception (MCQ).** From Tab. 3 and Tab. 4, we observe that either strategy of including **Q-Instruct** into the training of MLLMs can significantly improve their low-level perception ability. The results demonstrate the effectiveness of the proposed pipeline to automatically generate the VQA subset (*including MCQ*) from the pathway feedbacks via GPT, which could be expected to extend to further query types. Specifically, among all dimensions, we notice that the accuracy on *Yes-or-No* question type is most significantly enhanced (*avg. more than 10%*). Moreover, improvements on **distortions** are more significant than on **other** low-level attributes (*aesthetics, photography techniques*), suggesting that the major concerns as raised by human in the **Q-Pathway** are still related to distortions. We hope that our pipeline can be extended to cover more types of questions and a broader range of concerns in the future.

**(A2) Description.** The *low-level visual instruction tuning* also notably improve the low-level description ability of MLLMs, especially on the *relevance* (+0.31), with all *tuned* variants obtaining more than 1.5/2 average score. In contrast, the improvements on *completeness* (+0.17) and *precision* (+0.04) are less significant, implying that the **captioning-like** instruction format may not be sufficient for the low-level description task that requires *much longer* responses. We look forward to better solutions in the future.

**(A3) Image Quality Assessment (IQA).** Despite the two directly tuned tasks, we follow the *softmax* pooling strat-



Table 3. Comparison of the low-level **Perception** ability between baseline MLLMs and **Q-Instruct-tuned** versions, on **LLVisionQA-dev**.

Model (variant)	Q-Instruct Strategy	Yes-or-No $\uparrow$	What $\uparrow$	How $\uparrow$	Distortion $\uparrow$	Other $\uparrow$	I-C Distortion $\uparrow$	I-C Other $\uparrow$	Overall $\uparrow$
random guess	—	50.00%	27.86%	33.31%	37.89%	38.48%	38.28%	35.82%	37.80%
LLaVA-v1.5 (7B)	no (Baseline)	66.36%	58.19%	50.51%	49.42%	65.74%	54.61%	70.61%	58.66%
	(a) <i>mix</i> with high-level	76.18% $+9.82\%$	66.37% $+8.18\%$	57.61% $+7.10\%$	65.18% $+15.76\%$	67.59% $+1.85\%$	64.80% $+10.19\%$	73.06% $+2.55\%$	67.09% $+8.43\%$
	(b) <i>after</i> high-level	76.91% $+10.45\%$	65.04% $+6.85\%$	55.78% $+5.27\%$	64.01% $+14.59\%$	67.13% $+1.39\%$	64.80% $+10.19\%$	71.84% $+1.23\%$	66.35% $+7.69\%$
LLaVA-v1.5 (13B)	no (Baseline)	65.27%	64.38%	56.59%	56.03%	67.13%	61.18%	67.35%	62.14%
	(a) <i>mix</i> with high-level	76.18% $+10.91\%$	65.71% $+1.33\%$	59.23% $+2.64\%$	64.39% $+8.36\%$	69.91% $+2.78\%$	62.50% $+1.32\%$	75.51% $+8.16\%$	67.42% $+5.28\%$
	(b) <i>after</i> high-level	76.36% $+11.09\%$	65.04% $+0.66\%$	58.42% $+1.83\%$	65.56% $+9.53\%$	66.44% $+0.69\%$	64.47% $+3.29\%$	74.29% $+6.94\%$	67.02% $+4.88\%$
mPLUG-Owl-2	no (Baseline)	72.18%	57.96%	56.19%	56.68%	69.21%	53.29%	72.65%	61.61%
	(a) <i>mix</i> with high-level	75.64% $+3.46\%$	67.04% $+9.08\%$	59.03% $+2.84\%$	71.01% $+14.33\%$	65.28% $+3.93\%$	63.16% $+9.87\%$	69.80% $+2.85\%$	67.56% $+5.95\%$
	(b) <i>after</i> high-level	76.00% $+3.82\%$	65.04% $+7.08\%$	61.66% $+5.47\%$	65.95% $+9.27\%$	68.75% $+0.46\%$	65.46% $+12.17\%$	73.88% $+1.23\%$	67.96% $+6.35\%$
InternLM-XComposer-VL	no (Baseline)	69.45%	65.27%	60.85%	61.67%	70.14%	56.91%	75.10%	65.35%
	(a) <i>mix</i> with high-level	76.73% $+7.28\%$	69.91% $+4.64\%$	63.89% $+3.04\%$	70.23% $+8.56\%$	71.53% $+1.39\%$	67.43% $+10.52\%$	72.65% $+2.45\%$	70.43% $+5.08\%$
	(b) <i>after</i> high-level	78.36% $+8.91\%$	68.58% $+3.31\%$	63.08% $+2.23\%$	65.37% $+3.70\%$	73.15% $+3.01\%$	68.42% $+11.51\%$	78.37% $+3.27\%$	70.37% $+5.02\%$

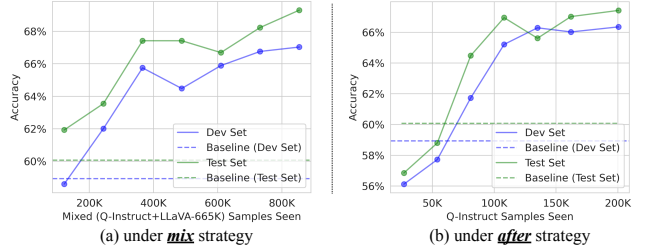
Table 4. Comparison of the low-level **Perception** ability between baseline MLLMs and **Q-Instruct-tuned** versions, on **LLVisionQA-test**.

Model (variant)	Q-Instruct Strategy	Yes-or-No $\uparrow$	What $\uparrow$	How $\uparrow$	Distortion $\uparrow$	Other $\uparrow$	I-C Distortion $\uparrow$	I-C Other $\uparrow$	Overall $\uparrow$
random guess	—	50.00%	28.48%	33.30%	37.24%	38.50%	39.13%	37.10%	37.94%
LLaVA-v1.5 (7B)	no (Baseline)	64.60%	59.22%	55.76%	47.98%	67.30%	58.90%	73.76%	60.07%
	(a) <i>mix</i> with high-level	78.65% $+14.05\%$	63.99% $+4.77\%$	63.79% $+8.03\%$	65.26% $+17.28\%$	68.97% $+1.67\%$	67.81% $+8.91\%$	79.47% $+5.71\%$	69.30% $+9.23\%$
	(b) <i>after</i> high-level	78.46% $+13.86\%$	63.34% $+4.12\%$	58.85% $+3.09\%$	60.46% $+12.48\%$	68.74% $+1.44\%$	69.52% $+10.62\%$	76.81% $+3.05\%$	67.42% $+7.35\%$
LLaVA-v1.5 (13B)	no (Baseline)	64.96%	64.86%	54.12%	53.55%	66.59%	58.90%	71.48%	61.40%
	(a) <i>mix</i> with high-level	77.19% $+13.23\%$	68.55% $+3.69\%$	65.43% $+11.31\%$	64.68% $+11.13\%$	71.12% $+4.43\%$	67.47% $+8.57\%$	85.55% $+14.07\%$	70.70% $+9.30\%$
	(b) <i>after</i> high-level	80.66% $+15.70\%$	67.25% $+2.39\%$	61.93% $+7.81\%$	66.03% $+12.48\%$	70.41% $+3.82\%$	69.86% $+10.96\%$	79.85% $+8.37\%$	70.43% $+9.03\%$
mPLUG-Owl-2	no (Baseline)	72.26%	55.53%	58.64%	52.59%	71.36%	58.90%	73.00%	62.68%
	(a) <i>mix</i> with high-level	78.47% $+6.21\%$	67.90% $+12.37\%$	63.37% $+4.73\%$	68.52% $+15.93\%$	68.02% $+3.34\%$	70.21% $+11.31\%$	77.57% $+4.57\%$	70.30% $+7.62\%$
	(b) <i>after</i> high-level	78.47% $+6.21\%$	60.74% $+5.21\%$	66.46% $+7.82\%$	63.34% $+10.75\%$	71.36% $\pm 0$	68.15% $+9.25\%$	77.95% $+4.95\%$	69.10% $+6.42\%$
InternLM-XComposer-VL	no (Baseline)	68.43%	62.04%	61.93%	56.81%	70.41%	57.53%	77.19%	64.35%
	(a) <i>mix</i> with high-level	78.65% $+10.22\%$	68.33% $+6.29\%$	66.26% $+4.33\%$	70.24% $+13.43\%$	71.12% $+0.81\%$	68.15% $+10.62\%$	77.95% $+0.76\%$	71.44% $+7.09\%$
	(b) <i>after</i> high-level	79.56% $+11.13\%$	64.64% $+2.60\%$	65.43% $+3.50\%$	64.30% $+7.49\%$	71.60% $+1.19\%$	66.44% $+8.91\%$	84.79% $+7.60\%$	70.37% $+6.02\%$

Table 5. Comparison of the low-level **Description** ability between baseline MLLMs and **Q-Instruct-tuned** versions, under the same prompt: “Describe and evaluate the quality of the image.”

Model (variant)	Q-Instruct Strategy	completeness	precision	relevance	sum
LLaVA-v1.5 (7B)	no (Baseline)	0.90	1.13	1.18	3.21
	(a) <i>mix</i> w/ high-level	<b>1.12</b>	<b>1.17</b>	<b>1.57</b>	<b>3.86</b>
	(b) <i>after</i> high-level	1.11	1.16	1.54	3.82
LLaVA-v1.5 (13B)	no (Baseline)	0.91	1.28	1.29	3.47
	(a) <i>mix</i> w/ high-level	<b>1.14</b>	<b>1.29</b>	1.58	<b>4.01</b>
	(b) <i>after</i> high-level	1.13	1.26	<b>1.61</b>	4.00
mPLUG-Owl-2	no (Baseline)	1.06	1.24	1.36	3.67
	(a) <i>mix</i> w/ high-level	<b>1.18</b>	<b>1.29</b>	<b>1.57</b>	<b>4.04</b>
	(b) <i>after</i> high-level	1.16	1.27	<b>1.57</b>	3.99
InternLM-XComposer-VL	no (Baseline)	1.03	1.26	1.27	3.56
	(a) <i>mix</i> w/ high-level	1.16	<b>1.35</b>	<b>1.63</b>	<b>4.14</b>
	(b) <i>after</i> high-level	<b>1.18</b>	1.34	1.62	<b>4.14</b>
Average Improvement		+0.17	+0.04	+0.31	+0.52

egy [53] to extract quality scores from MLLMs and evaluate their IQA ability, as listed in Tab. 6. Primarily, we notice the excellent performance on two “mostly seen” datasets. As we do not directly use any MOS values during training, this result suggests that we can effectively tune MLLMs to reach very high accuracy on IQA **without any numerical values** as supervision. This result by-side suggests the high reliability of the proposed datasets. The more exciting results are the huge improvements on “barely seen” (with a small proportion of images sampled into the **Q-Instruct**) and even “never seen” (cross-set) datasets. Considering the three “never seen” datasets [12, 27, 62] (with computer-generated images, artificially-degraded image, and even videos re-

Figure 6. Accuracy on MCQ questions with respect to data samples seen during training (in comparison with baseline), demonstrating the effectiveness of scaling up the **Q-Instruct** dataset.

spectively) have notable domain gap with the major part of the **Q-Instruct** dataset (mostly in-the-wild photographs), the +0.243 average SRCC gain on them demonstrates that the low-level instruction tuning can robustly improve low-level perception abilities of MLLMs on a broad domain.

### 6.3. Ablation Studies

Despite the main results for low-level visual instruction tuning, we also compare among several data variations during tuning on LLaVA-v1.5 (7B), analyzed as follows.

**#1: Effects of scaling up the Q-Instruct.** The first group of variations discuss the effects of data amount during low-level visual instruction tuning. As illustrated in Fig. 6, under either *mix* or *after* strategy, scaling up the **Q-Instruct** during training can continuously improve the low-level perceptual accuracy. Moreover, the results suggest that the per-

Table 6. Comparison of the **Quality Assessment (A3)** ability between baseline MLLMs and **Q-Instruct-tuned** versions, where “*Mostly Seen*” datasets denote those with the majority of their images sampled in the Q-Instruct, and “*Barely Seen*” represent those with only a small proportion (<20%) sampled. The “*Never Seen*” datasets have **zero** overlap with the **Q-Instruct**. Metrics are SRCC / PLCC.

Dataset Group		Mostly Seen		Barely Seen			Never Seen		
% of dataset seen during training		48.92%	95.26%	2.00%	17.11%	13.41%	0%	0%	0%
Model (variant)	Q-Instruct Strategy	KonIQ-10k	SPAQ	LIVE-FB	LIVE-irw	AGIQA-3K	CGIQA-6K	KADID-10K	KonViD-1k
NIQE	—	0.316 / 0.377	0.693 / 0.669	0.211 / 0.288	0.480 / 0.451	0.562 / 0.517	0.075 / 0.056	0.374 / 0.428	0.541 / 0.553
LLaVA-v1.5 (7B)	no (Baseline)	0.463 / 0.459	0.443 / 0.467	0.310 / 0.339	0.445 / 0.481	0.664 / 0.754	0.285 / 0.297	0.390 / 0.400	0.461 / 0.495
	(a) <i>mix</i> w/ high-level	0.809 / 0.852	0.880 / 0.883	0.377 / 0.436	0.800 / 0.806	0.724 / 0.828	0.521 / 0.535	0.688 / 0.695	0.766 / 0.717
	(b) <i>after</i> high-level	0.793 / 0.850	0.887 / 0.888	0.385 / 0.447	0.805 / 0.810	0.729 / 0.830	0.501 / 0.524	0.695 / 0.702	<b>0.780 / 0.731</b>
LLaVA-v1.5 (13B)	no (Baseline)	0.471 / 0.541	0.563 / 0.584	0.305 / 0.321	0.344 / 0.358	0.672 / 0.738	0.321 / 0.333	0.417 / 0.440	0.518 / 0.577
	(a) <i>mix</i> w/ high-level	0.732 / 0.787	0.858 / 0.848	0.371 / 0.463	0.629 / 0.701	0.709 / 0.814	0.471 / 0.488	0.627 / 0.626	0.720 / 0.733
	(b) <i>after</i> high-level	0.748 / 0.798	0.867 / 0.869	0.359 / 0.417	0.695 / 0.719	0.696 / 0.766	0.494 / 0.516	0.633 / 0.641	0.706 / 0.692
mPLUG-Owl-2	no (Baseline)	0.196 / 0.252	0.589 / 0.614	0.217 / 0.286	0.293 / 0.342	0.473 / 0.492	-0.024 / -0.032	0.541 / 0.546	0.409 / 0.442
	(a) <i>mix</i> w/ high-level	0.899 / 0.916	0.899 / <b>0.903</b>	0.432 / 0.545	0.829 / 0.822	0.743 / 0.806	<b>0.624 / 0.636</b>	0.698 / 0.676	0.693 / 0.663
	(b) <i>after</i> high-level	<b>0.911 / 0.921</b>	0.901 / 0.898	0.442 / <b>0.535</b>	<b>0.842 / 0.840</b>	0.700 / 0.763	0.572 / 0.578	0.682 / 0.683	0.769 / 0.721
InternLM-XComposer-VL	no (Baseline)	0.568 / 0.616	0.731 / 0.751	0.358 / 0.413	0.619 / 0.678	0.734 / 0.777	0.246 / 0.268	0.540 / 0.563	0.620 / 0.649
	(a) <i>mix</i> w/ high-level	0.874 / 0.892	<b>0.909</b> / 0.897	0.442 / 0.518	0.820 / 0.811	<b>0.785</b> / 0.830	0.391 / 0.411	<b>0.706 / 0.710</b>	0.739 / 0.702
	(b) <i>after</i> high-level	0.816 / 0.858	0.879 / 0.884	<b>0.443</b> / 0.510	0.771 / 0.801	0.772 / <b>0.847</b>	0.394 / 0.420	0.677 / 0.645	0.743 / 0.730
Average Improvement		+0.398/+0.392	+0.304/+0.280	+0.108/+0.144	+0.349/+0.324	+0.097/+0.120	+0.289/+0.297	+0.204/+0.185	+0.238/+0.170

Table 7. Comparison on low-level **Description** ability between **full Q-Instruct** and **only Q-Pathway** as low-level training dataset.

Q-Instruct Strategy	low-level dataset	completeness	precision	relevance	sum
no (Baseline)	None	0.90	1.13	1.18	3.21
(a) <i>mix</i> w/ high-level	only Q-Pathway	1.07	1.13	1.54	3.74
	full Q-Instruct	<b>1.12</b>	<b>1.17</b>	<b>1.57</b>	<b>3.86</b>
(b) <i>after</i> high-level	only Q-Pathway	1.02	1.12	<b>1.55</b>	3.69
	full Q-Instruct	<b>1.11</b>	<b>1.16</b>	1.54	<b>3.82</b>

Table 8. Comparison on low-level **Perception** ability (*test set*) between training with **full Q-Instruct** dataset and **only VQA** subset.

Q-Instruct Strategy	low-level dataset	Yes-or-No	What	How	Overall
no (Baseline)	None	64.6%	59.2%	55.8%	60.1%
(a) <i>mix</i> w/ high-level	only VQA subset	78.1%	61.5%	61.5%	67.6%
	full Q-Instruct	<b>78.7%</b>	<b>64.0%</b>	<b>63.8%</b>	<b>69.3%</b>
(b) <i>after</i> high-level	only VQA subset	77.9%	61.8%	56.8%	66.1%
	full Q-Instruct	<b>78.5%</b>	<b>63.3%</b>	<b>58.9%</b>	<b>67.4%</b>

formance of MLLMs is still not saturated even with the current 200K data scale, encouraging us to further unleash their vast underlying power on tackling low-level visual tasks.

**#2: Effects of joint training.** In the *low-level visual instruction tuning*, we combine different subsets together and train them jointly under one unified model. To validate its effectiveness, we compare this approach with traditional task-separate tuning, on both low-level description (Tab. 7) and question-answering (Tab. 8) capabilities. Both experiments indicate that a joint learning scheme can improve the accuracy on these abilities, especially when low-level data is independently used during tuning. While the different subsets in the **Q-Instruct** come from the same original human feedbacks, the improvement is cost-efficient, and inspires further explorations for *low-level visual instruction tuning* to expand to even more tasks, so as to further improve the low-level capabilities of these MLLMs.

**#3: Effects of high-level awareness.** While we notice generally on par abilities between the *mix* strategy and the *after* strategy, we further investigate the performance if we *re-*

Table 9. Comparison between the proposed two strategies (as in Sec. 5, and another variant that *replaces* high-level tuning into the low-level tuning, on their low-level **Perception** ability (*test set*).

Q-Instruct Strategy	Yes-or-No	What	How	Overall
no (Baseline)	64.6%	59.2%	55.8%	60.1%
<i>replace</i> high-level (not adopted)	75.0%	59.4%	56.4%	64.1%
<i>mix</i> with high-level (ours, strategy (a))	<b>78.7%</b>	<b>64.0%</b>	<b>63.8%</b>	<b>69.3%</b>
<i>after</i> high-level (ours, strategy (b))	<b>78.5%</b>	<b>63.3%</b>	<b>58.9%</b>	<b>67.4%</b>

*place* the second stage datasets into the **Q-Instruct**, while no high-level instruction tuning datasets are involved during training. As compared in Tab. 9, the “*replace*” strategy is notably worse than the two adopted strategies in Sec. 5, suggesting that fundamental high-level awareness is important on general low-level visual recognition for MLLMs.

## 7. Conclusion

Our work proposes the first-of-a-kind multi-modal datasets on low-level visual aspects, including the **Q-Pathway** with **58K** human *text* feedbacks, and the derived **Q-Instruct** with **200K** instruction-response pairs, to facilitate *low-level visual instruction tuning* for MLLMs. They allow MLLMs to significantly improve their question-answering accuracy related to low-level visual perception, and showcases the potential for providing more reliable low-level descriptions for images and eventually relieving human burdens on this task. Further, their IQA performance reveals an intriguing phenomenon, that pure *text-driven* instruction tuning can sufficiently align MLLMs with numerical quality scores, with impressive generalization on unseen types of visual inputs. In summary, our work has advanced a solid step forward on improving the low-level visual abilities of MLLMs, and we hope that our progresses and insights can encourage future explorations towards an eventual goal that foundation models understand the low-level visual world like a human.



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