WikiSeeker: Rethinking the Role of Vision-Language Models in Knowledge-Based Visual Question Answering

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Abstract

Multi-modal Retrieval-Augmented Generation (RAG) has emerged as a highly effective paradigm for Knowledge-Based Visual Question Answering (KB-VQA). Despite recent advancements, prevailing methods still primarily depend on images as the retrieval key, and often overlook or misplace the role of Vision-Language Models (VLMs), thereby failing to leverage their potential fully. In this paper, we introduce WikiSeeker, a novel multi-modal RAG framework that bridges these gaps by proposing a multi-modal retriever and redefining the role of VLMs. Rather than serving merely as answer generators, we assign VLMs two specialized agents: a Refiner and an Inspector. The Refiner utilizes the capability of VLMs to rewrite the textual query according to the input image, significantly improving the performance of the multimodal retriever. The Inspector facilitates a decoupled generation strategy by selectively routing reliable retrieved context to another LLM for answer generation, while relying on the VLM's internal knowledge when retrieval is unreliable. Extensive experiments on EVQA, InfoSeek, and M2KR demonstrate that WikiSeeker achieves state-of-the-art performance, with substantial improvements in both retrieval accuracy and answer quality. Our code will be released on https://github.com/zhuyjan/WikiSeeker.

1 Introduction

Retrieval-Augmented Generation (RAG) has been extensively validated as an effective paradigm for addressing Knowledge-Based Visual Question Answering (KB-VQA) (Yan and Xie, 2024; Yang et al., 2025; Cocchi et al., 2025), which necessitates external context or information not present in the image. Such progress is closely intertwined with the broader evolution of autonomous agents (Wang et al., 2025a) and aligned reasoning models (Wang et al., 2025b), as well as rapid developments in fine-grained multi-modal visual perception (Zhu et al., 2026; Chen et al., 2025; Xue et al., 2022). As illustrated in Figure 1(A), existing methods typically utilize the query image as the retrieval key to obtain relevant documents from a knowledge base. These retrieved documents are then concatenated with the input query and passed to an answer generator to produce the final response. However, existing approaches under this paradigm suffer from the following two critical limitations:

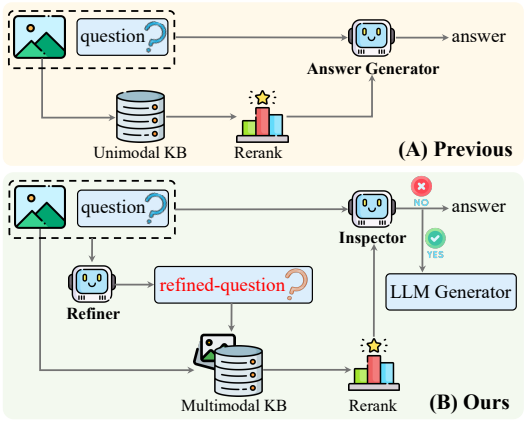

Figure 1: The overall architecture of WikiSeeker in comparison with previous methods. (A) Existing methods typically rely on visual-only retrieval and employ the VLM only as the answer generator. (B) Our proposed WikiSeeker conducts multi-modal retrieval and redefines the VLM as a Refiner and an Inspector.

Visual-Only Retrieval. Most prior methods rely on a visual-only retrieval strategy (Yan and Xie, 2024; Yang et al., 2025; Tian et al., 2025), in which the retrieval key is restricted to the query image. This design overlooks the semantic information contained in the user's textual query during the retrieval stage, often resulting in irrelevant results when the visual content is ambiguous.

Misplaced VLM Role. In multimodal RAG systems, VLMs are typically used solely as answer

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generators (Caffagni et al., 2024; Yang et al., 2025; Yan and Xie, 2024). However, our empirical analysis shows that VLMs are less effective than textual Large Language Models (LLMs) at summarization and extracting correct answers from the retrieved context, as illustrated in Table 2. Consequently, existing methods fail to fully leverage the potential of VLMs within multimodal RAG systems.

To address these limitations, we introduce WikiSeeker, a novel multi-modal RAG framework as illustrated in Figure 1(B). To tackle the first issue of the visual-only retrieval, we propose a multi-modal knowledge base that allows textual queries to participate in the retrieval process. Furthermore, to resolve the misplaced role of VLMs, instead of using the VLM as a generic answer generator, we reposition it into two specialized agents:

Refiner: The VLM leverages visual cues to rewrite the original question, generating a more specific query that explicitly captures visual entities and better aligns with the user's intent.

Inspector: After retrieval, the VLM evaluates whether the retrieved context is sufficient to answer the question. If the inspection passes, the refined query is routed to an LLM generator to produce the final answer; otherwise, the VLM answers directly using its internal parametric knowledge.

In summary, our main contributions can be mainly summarized as follows:

- We propose a multi-modal knowledge base and introduce a weighted dense retrieval strategy that flexibly integrates visual and textual features for multi-modal retrieval.
- We introduce a novel architecture that employs VLMs as specialized agents. Specifically, we design a Reinforcement Learning (RL)-based Refiner that leverages visual cues to rewrite the original question, and an Inspector to validate retrieved context.
- Extensive experiments on three widely used benchmarks including EVQA, InfoSeek and M2KR demonstrate that WikiSeeker outperforms existing methods across all main metrics, achieving state-of-the-art performance.

2 Related Work

2.1 KB-VQA

Knowledge-Based VQA (KB-VQA) requires external sense or world knowledge beyond visual recognition. Early benchmarks such as KVQA, FVQA, and KB-VQA (Shah et al., 2019; Wang et al., 2017b,a) were designed to target knowledge-intensive questions, but the required knowledge in these datasets is completely "closed". Subsequent datasets like OK-VQA (Marino et al., 2019) significantly expanded the scale and visual-semantic diversity. Moreover, A-OKVQA (Schwenk et al., 2022) models perform reasoning rather than simple fact retrieval to answer questions.

Recent works have introduced more challenging benchmarks that integrate encyclopedic knowledge with extensive multimodal information, specifically E-VQA and InfoSeek (Mensink et al., 2023; Chen et al., 2023). Furthermore, M2KR (Lin et al., 2024) unifies multiple visual knowledge retrieval tasks into a comprehensive framework. Our work achieves better performance on these challenging benchmarks compared to existing methods.

2.2 Multi-modal RAG

Multi-modal Retrieval-Augmented Generation (RAG) is effective to address the limited knowledge coverage and hallucination issues of multi-modal large language models (MLLMs) on KB-VQA by incorporating external knowledge bases. Wiki-LLaVA (Caffagni et al., 2024) firstly proposed a hierarchical retrieval pipeline to achieve effective retrieval. EchoSight (Yan and Xie, 2024) and OMGM (Yang et al., 2025) focus on implementing and enhancing multimodal rerankers to improve both retrieval and generation performance. Addressing the challenge of noise, LLM-RA (Jian et al., 2024) and RoRA-VLM (Qi et al., 2024) employ LLM-based and similarity-based methods, respectively, to filter irrelevant information from queries and retrieved results.

Moving towards more autonomous systems, mR^{2}AG (Zhang et al., 2024) and ReflectiVA (Cocchi et al., 2025) introduce reflection mechanisms into the RAG system, allowing models to dynamically decide whether external knowledge is necessary and identify which retrieved content is valid, thereby enhancing accuracy. To further resolve knowledge source reliability, CoRe-MMRAG (Tian et al., 2025) proposes a cross-source reconciliation framework that addresses inconsistencies between parametric and retrieved knowledge, as well as misalignments between visual and textual modalities, through a four-stage integration pipeline. Most recently, MI-RAG (Choi et al., 2025) firstly introduced an iterative framework to KB-VQA, enabling the progressive refine-

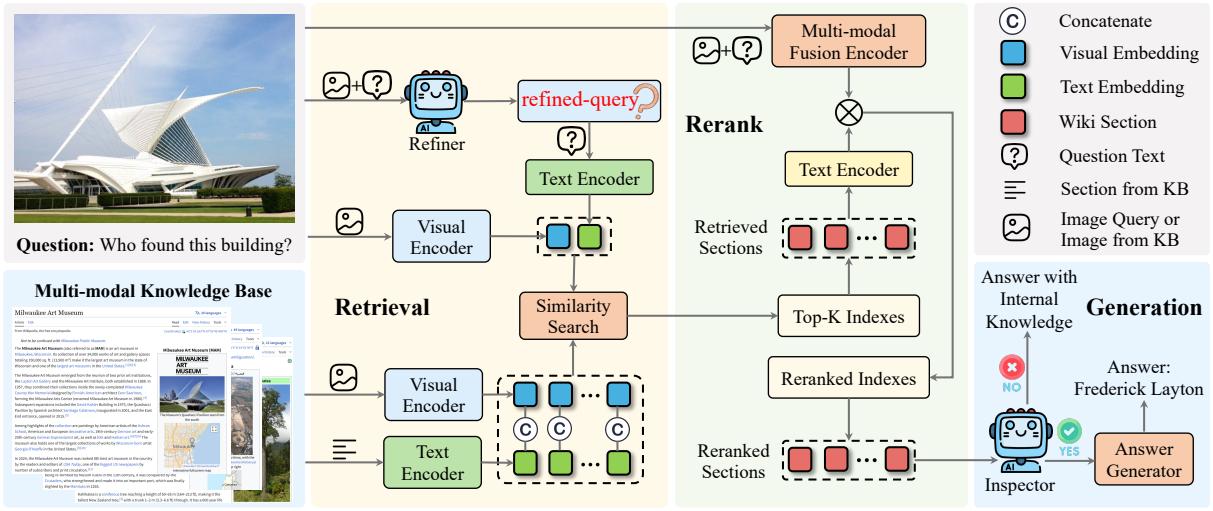

Figure 2: The overall architecture of WikiSeeker. We employ VLMs as specialized agents rather than just generators. The pipeline consists of three stages: (1) Retrieval: A VLM-based Refiner expands the initial question with visual semantics. We then perform dense retrieval by concatenating visual and textual embeddings to match against a pre-constructed multi-modal knowledge base. (2) Rerank: A multi-modal reranker filters the top relevant candidate sections. (3) Generation: A VLM-based Inspector evaluates the sufficiency of the retrieved context. It dynamically routes the query: valid contexts are processed by Answer Generator (path "YES"), while insufficient contexts trigger the Inspector to answer using internal parametric knowledge (path "NO").

ment of retrieval and reasoning. Distinct from these approaches, our work focuses on repositioning VLMs within the Multi-modal RAG framework, aiming to fully leverage their potential in both retrieval and generation stages.

2.3 Reinforcement Learning

RL methods were introduced to LLM tuning through RL from human feedback (RLHF) via Proximal Policy Optimization (Ouyang et al., 2022). However, PPO requires multiple rounds of LLM optimization, making it challenging to implement. To simplify RL-based tuning, methods such as Direct Preference Optimization (DPO) (Rafailov et al., 2023) and SimPO (Meng et al., 2024) have been proposed. Group Relative Policy Optimization (GRPO) (Shao et al., 2024) removes the need for a critic model entirely by utilizing the average reward of a group of outputs as the baseline, which is utilized to train our Refiner.

3 Methodology

To address the limitations of current multi-modal RAG systems, we propose WikiSeeker as illustrated in Figure 2. WikiSeeker performs multi-modal retrieval and redefines the VLM as a Refiner and an Inspector. The Refiner leverages the VLM's capabilities to rewrite and expand the original question based on the query image. Following refinement, the system performs dense retrieval using a multi-modal embedding strategy. Specifically, the refined text query and input image are encoded separately and then concatenated to form a unified query embedding. This embedding is matched against an index of our knowledge base, which consists of similarly concatenated embeddings of knowledge base (KB) images and section texts. After retrieving the top candidates, we employ a multi-modal reranker to filter for the most relevant sections. Finally, the Inspector evaluates whether the retrieved information is sufficient and consistent. If the inspection passes, the answer generator produces the final response; otherwise, it answers directly using its internal knowledge.

3.1 Multi-modal Dense Retrieval

Multi-modal Index Construction. Unlike previous approaches (Yan and Xie, 2024; Yang et al., 2025) that construct indices based on isolated images or coarse-grained article-level summaries, we construct a fine-grained Knowledge Base (KB) composed of aligned <image, section> pairs. For every image I_{kb} in the source data, we identify its corresponding textual section T_{kb}. To ensure semantic density and fix length variations, we employ an LLM to summarize excessively long sections. For images that correspond to missing content or low-information sections (e.g., reference lists), we

substitute T_{kb} with the abstract section of the article. We then utilize a visual encoder Φ_{vis} and a textual encoder Φ_{text} to generate the index vector $\mathbf{v}_i$ by directly concatenating the visual and textual embeddings of the i-th entry:

$$\mathbf{v}_i = \text{Concat}\left[\Phi_{\text{vis}}(I_{kb}), \Phi_{\text{text}}(T_{kb})\right]. \quad (1)$$

Embedding and Retrieval. To fuse the modalities and flexibly control the semantic contribution of each modality, we employ a weighted concatenation strategy. We introduce a hyperparameter $\alpha \in [0, 1]$ to control the relative importance of visual and textual features. During the retrieval phase, given an input query image I_q and the refined question T_q, the weighted multi-modal embedding vector $\mathbf{v}_q$ is defined as:

$$\mathbf{v}_q = \text{Concat}\left[\alpha \cdot \Phi_{\text{vis}}(I_q), (1-\alpha) \cdot \Phi_{\text{text}}(T_q)\right]. \quad (2)$$

We then compute the cosine similarity between the query and all entries in the knowledge base to retrieve the top-k most relevant sections. The retrieval set $\mathcal{S}_{\text{ret}}$ is obtained as follows:

$$\mathcal{S}_{\text{ret}} = \left\{ s_i = \left\langle \frac{\mathbf{v}_q \cdot \mathbf{v}_i}{||\mathbf{v}_q|| \cdot ||\mathbf{v}_i||} \right\rangle, i = 1, \ldots, N \right\}_{\text{top-}k}, \quad (3)$$

where $\mathbf{v}_i$ represents the multi-modal vector of the i-th entry in the knowledge base.

In Knowledge-Based Visual Question Answering (KB-VQA), user queries are characteristically concise and abstract. This inherent ambiguity often introduces excessive noise during the multimodal retrieval process, thereby significantly degrading retrieval quality. To mitigate this, we propose a VLM Refiner that leverages visual cues to rewrite and expand user queries. Unlike traditional approaches that rely on supervised fine-tuning with expensive human-annotated query pairs, our framework adopts a Reinforcement Learning (RL) paradigm. This allows the model to autonomously discover optimal query refinement strategies by interacting with the retrieval system and receiving feedback based on retrieval performance.

3.2 VLM as Refiner

Reasoning-Enhanced Generation To promote a deeper understanding of the visual content, we enforce a structured generation process. Instead of directly producing a refined query, the model is encouraged to first generate a chain-of-thought (CoT) (Wei et al., 2022) reasoning sequence enclosed in <think> tags, followed by the final output

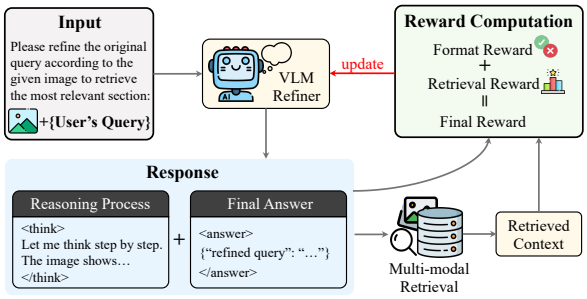

Figure 3: The training pipeline of the VLM Refiner via Reinforcement Learning. The refined query is used to retrieve information from the multimodal knowledge base. VLM's response is used to compute the structure-based format reward, while the retrieved context is used to compute the rank-based retrieval reward. The combined reward is finally used to update the model through the GRPO algorithm.

in <answer> tags. This mechanism enhances the robustness and interpretability of the query refinement process through explicit visual reasoning.

Optimization via GRPO We optimize the VLM policy π_θ using Group Relative Policy Optimization (GRPO) (Shao et al., 2024). For each query q, GRPO samples a group of G outputs $\{o_1, \ldots, o_G\}$ from the old policy $\pi_{\theta_{\text{old}}}$. The optimization objective can be defined as:

$$\mathcal{J}_{\text{GRPO}}(\theta) = \mathbb{E}_{q\sim\mathcal{D},\, \{o_i\}_{i=1}^{G}\sim\pi_{\theta_{\text{old}}}} \left[\frac{1}{G} \sum_{i=1}^{G} \Big(\min\big(\rho_i A_i, \text{clip}(\rho_i, 1-\epsilon, 1+\epsilon)\, A_i\big) - \beta\, \mathbb{D}_{\text{KL}}\big(\pi_\theta \,\|\, \pi_{\text{ref}}\big) \Big) \right], \quad (4)$$

where ϵ and β are hyper-parameters, and $\rho_i = \frac{\pi_\theta(o_i|I,q)}{\pi_{\theta_{\text{old}}}(o_i|I,q)}$ is the probability ratio. Crucially, A_i is the advantage, computed using the group of rewards $\{r_1, r_2, \ldots, r_G\}$ corresponding to the outputs within each group:

$$A_i = \frac{r_i - \text{mean}(\{r_1, r_2, \ldots, r_G\})}{\text{std}(\{r_1, r_2, \ldots, r_G\})}. \quad (5)$$

Reward Function Design Inspired by DeepRetrieval (Jiang et al., 2025), the reward signal r_i for the i-th generated output o_i, is composed of two distinct components: retrieval reward $r_{\text{retrieval}}(o_i)$ and format reward $r_{\text{format}}(o_i)$. Formally, the total reward is defined as:

$$r_i = r_{\text{retrieval}}(o_i) + r_{\text{format}}(o_i). \quad (6)$$

The format reward measures the syntactic correctness of the generated text. We check both the presence and the correct ordering of the XML-style

tags. In addition, the content inside <answer> must be a valid and parseable JSON object that includes the required key. A positive score of +1 is assigned when the output fully satisfies these constraints, whereas any structural violation results in a substantial penalty of -4. For the retrieval reward, we per-

hit rank	$[1, 5]$	$[6, 10]$	$[11, 20]$	$[21, 50]$	$[51, 100]$	$[101, 200]$
reward	+4	+3.5	+3	+1	+0.5	+0.1

Table 1: The discrete mapping of retrieval rewards based on the hit rank.

form multimodal retrieval using the refined query generated by the VLM together with the image query. We obtain the top 200 retrieved Wikipedia entities, and if the ground-truth entity is hit, a reward is assigned based on the criteria defined in Table 1. Otherwise, a penalty of -2.5 is applied.

3.3 VLM as Inspector

Method	Ratio=0	Ratio=0.3	Ratio=0.7	Ratio=1.0
QwenVL(I+T)	**22.75**	41.26	68.99	88.46
QwenVL(T)	19.44	41.75	70.82	91.10
LLaMA	18.51	40.48	**70.88**	92.99
Qwen	19.77	**42.52**	70.80	**93.45**

Table 2: VQA performance comparison under different signal-to-noise ratios. The ratio indicates the proportion of correct sections in the input context. QwenVL(I+T) and QwenVL(T) denote Qwen2.5-VL with and without image input, respectively. More detailed experimental results can be found in Table 15 in Appendix C.2.

Existing KB-VQA methods (Yang et al., 2025; Caffagni et al., 2024) typically use VLMs as answer generators. However, our empirical analysis shows that VLMs are less effective than LLMs at leveraging retrieved context to answer questions. As illustrated in Table 2, we compare Qwen2.5-VL-7B (with and without image input) against two strong text-only baselines: LLaMA3.1-8B (Dubey et al., 2024) and Qwen2.5-7B. As shown in the table, as retrieval performance gradually improves, starting from 0.3, the performance of QwenVL with image input consistently falls below that of all text-only models. This suggests that in KB-VQA task where the answer is contained in text evidence, visual tokens from the query image often behave as noise rather than helpful context and may distract the model from leveraging the retrieved information.

Based on this observation, we propose a decoupled generation strategy that explicitly separates visual perception from textual reading comprehension. In our framework, an LLM is responsible for precise answer extraction, while the VLM functions as an inspector to validate the retrieved context and provide the answer using its internal parametric knowledge if the inspection is not passed.

The Inspector ($\mathcal{M}_{\text{ins}}$) takes the query image I_q, the question Q, and the reranked sections $\mathcal{S}_{\text{rerank}}$ as input. Its goal is to determine whether the retrieved context is sufficient to answer the question and consistent with the visual evidence. Formally, the inspection process can be formulated as:

$$(s, A_{\text{internal}}) = \mathcal{M}_{\text{ins}}(I_q, Q, \mathcal{S}_{\text{rerank}}), \quad (7)$$

where $s \in \{\text{PASS}, \text{FAIL}\}$ denotes the decision result, indicating whether the inspection is passed, and A_{internal} represents the answer generated directly by the VLM using its parametric knowledge.

If the context passes inspection ($s = \text{PASS}$), we rely on the retrieved context and use a text-only LLM ($\mathcal{M}_{\text{gen}}$) to generate the final answer A. If inspection fails ($s = \text{FAIL}$), we instead select the VLM's answer. This process can be expressed as:

$$A = \begin{cases} \mathcal{M}_{\text{gen}}(Q, \mathcal{S}_{\text{rerank}}), & \text{if } s = \text{PASS} \\ A_{\text{internal}}, & \text{if } s = \text{FAIL} \end{cases}. \quad (8)$$

4 Experiments

4.1 Datasets and Metrics

We conduct our experiments on three widely used KB-VQA benchmarks: Encyclopedic VQA (EVQA), InfoSeek and M2KR. The detailed dataset information and setup can be found in Appendix. Performance evaluation is conducted along two dimensions. The retrieval performance is measured using Recall@K and Pseudo Recall@K. For question-answering performance, each dataset adopts its own official evaluation metric. Specifically, EVQA is evaluated using the BEM score (Zhang et al., 2019), while InfoSeek uses both the standard and relaxed VQA Accuracy (Antol et al., 2015; Methani et al., 2020).

4.2 Implementation Details

We evaluate WikiSeeker against several state-of-the-art multi-modal RAG frameworks for KB-VQA, including Wiki-LLaVA (Yang et al., 2025), EchoSight (Yan and Xie, 2024), ReflectiVA(Cocchi et al., 2025), and OMGM (Yang et al., 2025), among others. We directly use the reranker from

Method	E-VQA				InfoSeek			
	R@1	R@5	R@10	R@20	R@1	R@5	R@10	R@20
CLIP I-T	3.3	7.7	12.1	16.5	32.0	54.0	61.6	68.2
Wiki-LLaVA	3.3	-	9.9	13.2	36.9	-	66.1	71.9
LLM-RA	-	-	-	-	47.3	53.8	-	-
mR^{2}AG	-	-	-	-	38.0	-	65.0	71.0
ReflectiVA	15.6	36.1	-	49.8	56.1	77.6	-	86.4
EchoSight	36.5	47.9	48.8	48.8	53.2	74.0	77.4	77.9
CoRe-MMRAG	13.3	31.3	41.0	-	45.6	67.1	73.0	-
OMGM	42.8	55.7	58.1	58.7	64.0	80.8	83.6	84.8
WikiSeeker (ours)								
w/o. Refiner	28.0	37.2	40.9	43.4	53.5	74.6	77.8	78.5
w. Refiner	**44.1**	**59.9**	**62.1**	**62.3**	**67.0**	**83.7**	**86.9**	**87.7**

Table 3: Retrieval results on the E-VQA test set and InfoSeek validation set. "w/o. Refiner" and "w. Refiner" indicate whether the input query is expanded by Refiner. Best results are highlighted in bold.

Method	E-VQA (M2KR)					OKVQA-GS (M2KR)					OVEN (M2KR)			
	R@1	R@5	R@10	PR@5	PR@20	R@1	R@5	R@10	PR@5	PR@20	R@1	R@5	R@10	R@20
CLIP	3.3	7.7	12.1	10.4	-	-	-	-	5.7	-	-	22.0	-	-
FLMR	-	-	-	-	-	-	-	-	68.1	-	-	40.5	-	-
PreFLMR														
w/o. Refiner	40.4	62.5	70.2	72.2	78.0	13.8	30.5	39.3	67.5	86.6	31.1	64.2	76.5	85.2
w. Refiner	**43.1**	**65.3**	**73.2**	**72.5**	**79.9**	**20.7**	**41.5**	**51.1**	**77.5**	**91.6**	**42.8**	**69.7**	**78.8**	**86.9**

Table 4: Retrieval performance on M2KR benchmark. "w/o. Refiner" and "w. Refiner" indicate whether the input query is expanded by Refiner. Best results are highlighted in bold.

EchoSight and keep its weights frozen throughout the experiments. After the reranking stage, only the top-1 section is selected. We then apply bge-reranker-v2-m3 (Chen et al., 2024) to perform text reranking over the entire article corresponding to that section, and the resulting top-1 section is used as the context for generation. All fine-tuning processes were conducted using the LlamaFactory framework (Zheng et al., 2024) to enable efficient LLM fine-tuning. All experiments are conducted on 4 NVIDIA A800 40GB SXM4 GPUs.

Retriever We utilize EVA-CLIP-8B (Sun et al., 2023) to encode visual inputs (both query image and KB reference images) and Qwen3-Embedding-0.6B (Zhang et al., 2025) to encode textual inputs (refined question and KB sections). To generate the unified representation for both the input query and the <image, section> entries in the knowledge base, we extract the pooled features from the final layer of each encoder and concatenate them. For efficient large-scale indexing and retrieval, we leverage the FAISS library (Johnson et al., 2019), employing cosine similarity as the distance metric to identify the top-ranked candidates.

Refiner We implement the Refiner using Qwen2.5-VL-3B-Instruct (Bai et al., 2025b), optimized via the GRPO algorithm within the HybridFlow (Verl) framework (Sheng et al., 2025). To construct RL training datasets for EVQA and InfoSeek, we first perform retrieval on the respective training sets using our multi-modal retriever. We then sample training queries according to the rank of the ground-truth entity (hit rank). The specific sampling distribution is detailed in Table 5, resulting in a dataset of 7,000 samples for each benchmark.

hit rank	$[1, 5]$	$[6, 10]$	$[11, 20]$	$[21, 200]$	miss
EVQA	500	1000	1000	2500	2000
InfoSeek	0	500	1000	2500	3000

Table 5: The sampling distribution based on retrieval hit rank used to construct the RL datasets.

For the EVQA split in M2KR benchmark, we directly deploy the Refiner trained on the standard EVQA dataset without further tuning. However, for the OKVQA and OVEN (Hu et al., 2023) splits, we utilize the PreFLMR retriever and train on the corresponding training splits provided by M2KR. Regarding hyperparameters, we set the global batch size to 32 and the learning rate to 1×10^{-6}. The vision tower of the VLM remains frozen during the training process. For the GRPO configuration, we

Method	Generator Model	Gen. FT	Ret. FT	E-VQA	InfoSeek		
					Unseen-Q	Unseen-E	Overall
RoRA-VLM	LLaVA-1.5-7B	✓	✗	20.29	27.34	25.10	26.9
Wiki-LLaVA	LLaVA-1.5-7B	✓	✗	21.8	30.1	27.8	28.9
LLM-RA	BLIP2-Flan-T5XL	✓	✓	-	26.12	20.90	23.14
EchoSight	Mistral-7B | LLaMA3-8B	✗	✓	41.8	-	-	31.3
mR^{2}AG	LLaVA-1.5-7B	✓	✓	-	40.6	39.8	40.2
ReflectiVA	LLaVA-MORE-8B	✓	✓	35.5	40.4	39.8	40.1
OMGM	LLaVA-1.5-7B	✓	✓	50.17	43.46	43.53	43.49
WikiSeeker (ours)	Qwen3-VL-8B-Instruct	✗	✓	51.81	38.7	37.69	38.19
	Qwen2.5-7B-Instruct	✗	✓	52.97	35.99	34.93	35.46
	Inspector+Qwen2.5-7B-Instruct	✓	✓	**55.62**	**43.82**	**45.64**	**44.72**

Table 6: VQA accuracy comparison with the baselines. Gen. FT and Ret. FT indicate whether the generator and retriever of the method were fine-tuned, respectively. Best results are highlighted in bold.

set the group size to 5 and the rollout temperature to 0.7, training the model for a total of 600 steps.

Answer Generator We choose Qwen2.5-7B-Instruct (Yang et al., 2024) as the LLM Generator and fine-tune separate models tailored to each dataset. For InfoSeek, we construct a training set of 13,640 samples using the original ground-truth answers as supervision targets. For EVQA, we employ an auxiliary LLM to enrich the ground-truth answers with more descriptive responses, resulting in a dataset of 10,000 samples.

Inspector We initialize the Inspector with Qwen3-VL-8B-Instruct (Bai et al., 2025a) and fine-tune it on a mixed dataset of 38,000 samples derived from the training splits of both datasets. The model is fine-tuned to generate structured JSON outputs. If the retrieved context matches the gold section, the sample is labeled {"pass": "true"}. Otherwise, it is labeled {"pass": "false"}, and the Inspector is supervised to generate the ground-truth answer using its internal parametric knowledge. More details can be found in Appendix C.3 and Figure 8.

4.3 Main Results

Retrieval Results. Table 3 presents a comparative analysis of retrieval performance on the EVQA and InfoSeek datasets. The results demonstrate that using refined queries for multimodal retrieval provides a substantial performance improvement over using the original queries, establishing the state-of-the-art (SOTA) results across all evaluated metrics. To further validate the generalizability of our approach, we report results on the M2KR benchmark in Table 4. Building upon the strong PreFLMR (Lin et al., 2024) baseline, integrating our Refiner consistently improves retrieval accuracy on the EVQA, OKVQA-GS, and OVEN splits. Notably, the enriched queries enable PreFLMR to achieve SOTA performance on all splits across all metrics, with Recall@1 exhibiting impressive gains of 6.9 percentage points on OKVQA-GS and 11.7 percentage points on OVEN, respectively.

VQA Results. Table 6 presents a comprehensive comparison of VQA accuracy between WikiSeeker and existing state-of-the-art methods. Under the zero-shot setting, our approach already surpasses the previous SOTA on the EVQA dataset. The performance is further improved when combining the proposed Inspector with a fine-tuned Qwen2.5-7B-Instruct generator. Overall, our method achieves the best results on both datasets, with particularly notable improvements on EVQA, where it exceeds the previous best method by a substantial margin of 5.45 percentage points. We attribute these significant gains to our two core contributions: the Refiner, which substantially enhances retrieval quality, and the Inspector, which equips the generator with visual understanding while preserving the LLM's superior information-extraction capabilities.

4.4 Ablation Study

To comprehensively evaluate WikiSeeker and the contribution of each component, we carry out extensive experiments focusing on both retrieval and overall question-answering performance.

Component analysis of WikiSeeker. To isolate the impact of our core modules, we conduct an ablation study as summarized in Table 7. We first es-

tablish a baseline model that performs multimodal retrieval using the original, unrefined query and employs a fine-tuned Qwen2.5-7B-Instruct as the answer generator without inspection. It can be found that integrating the Refiner leads to substantial improvements, boosting accuracy by 11.57% on EVQA and 11.79% on InfoSeek. This significant improvement indicates that the enhanced retrieval quality provided by the Refiner is the primary factor driving final KB-VQA performance. Moreover, introducing the Inspector consistently yields additional gains, regardless of whether the input query is refined. These consistent improvements further validate the effectiveness of our decoupled generation strategy.

Refiner	Inspector	E-VQA	InfoSeek
✗	✗	42.35	31.68
✗	✓	46.28	33.29
✓	✗	53.92	43.47
✓	✓	**55.62**	**44.72**

Table 7: The ablation study on the impact of Refiner and Inspector on the VQA results.

Effect of Refiner. We conduct a comparative analysis to validate that the performance gains of the Refiner in WikiSeeker. As detailed in Table 8, we compare our refinement method against several strong baselines. We employ Qwen2.5-VL-7B-Instruct to generate both the Image Caption and Zs Expansion variants, prompt can be refered to Appendix D. The results indicate that zero-shot expansion provides a moderate improvement over the original query, demonstrating the importance of refining textual queries in KB-VQA tasks. Notably, our WikiSeeker Refiner, although built on a smaller 3B model, achieves substantial performance gains across all metrics and thereby highlights the effectiveness of our reinforcement learning strategy.

Method	R@1	R@5	R@10	R@20
Original Query	14.59	29.43	37.14	43.35
Image Caption	16.11	31.58	37.81	42.93
Zs Expansion	18.78	34.88	42.4	47.79
Zs Expansion+Caption	18.34	34.88	42.15	47.81
WikiSeeker Refiner	**25.45**	**44.48**	**52.42**	**57.98**

Table 8: Impact of different query formulation strategies on EVQA retrieval performance.

Analysis of Decoupled Generation Strategy. In this analysis, we utilize VLM to denote Qwen3-VL-8B-Instruct (Bai et al., 2025a) and LLM to denote Qwen2.5-7B-Instruct (Yang et al., 2024). To evaluate the effectiveness of the decoupled generation strategy, we first conduct an oracle analysis on the EVQA dataset, as shown in Table 9. In this table, "Decoupled" refers to the strategy in which successfully retrieved entries are explicitly routed to the LLM, while retrieval failures are routed to the VLM. We observe that this hybrid design yields substantial performance gains, regardless of whether the generators are fine-tuned. Building on this observation, Table 10 presents the comparative results of our proposed Inspector. "Oracle Ensemble" is defined as the union of correct predictions from both the VLM and LLM, representing the theoretical upper bound of the decoupled strategy. As shown in the table, LLM generation with Inspector achieves 55.62% accuracy on EVQA and 44.72% on InfoSeek, surpassing the strongest fine-tuned baselines and clearly demonstrating the effectiveness of the Inspector within WikiSeeker.

Setting	Generator	Strategy	Accuracy(%)
Zero-shot	VLM	VLM-only	51.81
	LLM	LLM-only	52.97
	VLM + LLM	Decoupled	**54.48**
Fine-tuned	VLM	VLM-only	52.59
	LLM	LLM-only	53.92
	VLM + LLM	Decoupled	**56.34**

Table 9: Oracle analysis of the decoupled generation strategy on the EVQA dataset.

Method	FT	EVQA	InfoSeek
VLM	✗	51.81	38.19
LLM	✗	52.97	35.46
VLM	✓	52.59	44.06
LLM	✓	53.92	43.47
LLM + Inspector	✓	**55.62**	**44.72**
Oracle Ensemble	✓	58.87	47.28

Table 10: Ablation study on the effectiveness of the WikiSeeker Inspector on EVQA and InfoSeek.

5 Conclusion

In this work, we have proposed the WikiSeeker, a multi-modal RAG framework for KB-VQA, which implements a multi-modal retriever and redefines the role of vision-language models (VLMs). Specifically, we assign VLMs two specialized agents: a reinforcement learning–optimized Refiner for query expansion and an Inspector for retrieved

context validation. The refined query produced by the Refiner is utilized alongside the input image to facilitate robust multi-modal retrieval. Furthermore, the Inspector plays a central role in our decoupled generation strategy by effectively integrating the context summarization capabilities of large language models (LLMs) with the visual reasoning strengths of VLMs. Extensive experiments on the EVQA, InfoSeek, and M2KR benchmarks confirm that WikiSeeker achieves state-of-the-art performance, demonstrating significant improvements in both retrieval accuracy and answer generation. These findings provide valuable insights for designing effective multi-modal retrieval systems in future research on KB-VQA tasks.

Limitations

While WikiSeeker achieves strong performance, several directions remain for further improvement. First, our current decoupled generation strategy adopts a hard routing rule: instances with successful retrieval are handled by the LLM, whereas retrieval failures are handled by the VLM. Our experiments suggest that this routing mechanism is not necessarily optimal. More effective collaboration between LLM and VLM under a decoupled design therefore warrants further investigation. Second, WikiSeeker currently supports only single-pass retrieval and cannot address multi-hop questions. Incorporating iterative retrieval mechanisms and training multi-step reasoning and answering via reinforcement learning constitutes a promising direction for future work.

Ethical Statement

The datasets Encyclopedic VQA (EVQA), InfoSeek, and M2KR , and the models (including the Qwen2.5-VL, Qwen3-VL, and Qwen2.5-Instruct series) employed in this study are all open-source, thereby incurring no risks associated with licensing. Furthermore, as our research is centered on the Knowledge-Based Visual Question Answering (KB-VQA) domain, it does not entail risks pertaining to human ethics and values.

Acknowledgments

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References

Stanislaw Antol, Aishwarya Agrawal, Jiasen Lu, Margaret Mitchell, Dhruv Batra, C Lawrence Zitnick, and Devi Parikh. 2015. Vqa: Visual question answering. In *Proceedings of the IEEE International Conference on Computer Vision (ICCV)*, pages 2425–2433.

Shuai Bai, Yuxuan Cai, Ruizhe Chen, Keqin Chen, Xionghui Chen, Zesen Cheng, Lianghao Deng, Wei Ding, Chang Gao, Chunjiang Ge, Wenbin Ge, Zhifang Guo, Qidong Huang, Jie Huang, Fei Huang, Binyuan Hui, Shutong Jiang, Zhaohai Li, Mingsheng Li, and 45 others. 2025a. Qwen3-vl technical report. *arXiv preprint arXiv:2511.21631*.

Shuai Bai, Keqin Chen, Xuejing Liu, Jialin Wang, Wenbin Ge, Sibo Song, Kai Dang, Peng Wang, Shijie Wang, Jun Tang, and 1 others. 2025b. Qwen2. 5-vl technical report. *arXiv preprint arXiv:2502.13923*.

Davide Caffagni, Federico Cocchi, Nicholas Moratelli, Sara Sarto, Marcella Cornia, Lorenzo Baraldi, and Rita Cucchiara. 2024. Wiki-llava: Hierarchical retrieval-augmented generation for multimodal llms. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPRW)*, pages 1818–1826.

Jianlv Chen, Shitao Xiao, Peitian Zhang, Kun Luo, Defu Lian, and Zheng Liu. 2024. Bge m3-embedding: Multi-lingual, multi-functionality, multi-granularity text embeddings through self-knowledge distillation. *arXiv preprint arXiv:2402.03216*.

Lin Chen, Yingjian Zhu, Qi Yang, Xin Niu, Kun Ding, and Shiming Xiang. 2025. Sam-mi: A mask-injected framework for enhancing open-vocabulary semantic segmentation with sam. *arXiv preprint arXiv:2511.20027*.

Yang Chen, Hexiang Hu, Yi Luan, Haitian Sun, Soravit Changpinyo, Alan Ritter, and Ming-Wei Chang. 2023. Can pre-trained vision and language models answer visual information-seeking questions? In *Proceedings of the 2023 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pages 14948–14968.

Changin Choi, Wonseok Lee, Jungmin Ko, and Wonjong Rhee. 2025. Multimodal iterative rag for knowledge-intensive visual question answering. *arXiv preprint arXiv:2509.00798*.

Federico Cocchi, Nicholas Moratelli, Marcella Cornia, Lorenzo Baraldi, and Rita Cucchiara. 2025. Augmenting multimodal llms with self-reflective tokens for knowledge-based visual question answering. In *Proceedings of the Computer Vision and Pattern Recognition Conference (CVPR)*, pages 9199–9209.

Abhimanyu Dubey, Abhinav Jauhri, Abhinav Pandey, Abhishek Kadian, Ahmad Al-Dahle, Aiesha Letman, Akhil Mathur, Alan Schelten, Amy Yang, Angela Fan, and 1 others. 2024. The llama 3 herd of models. *arXiv e-prints*, pages arXiv–2407.

Hexiang Hu, Yi Luan, Yang Chen, Urvashi Khandelwal, Mandar Joshi, Kenton Lee, Kristina Toutanova, and Ming-Wei Chang. 2023. Open-domain visual entity recognition: Towards recognizing millions of wikipedia entities. In *Proceedings of the IEEE/CVF International Conference on Computer Vision (ICCV)*, pages 12065–12075.

Pu Jian, Donglei Yu, and Jiajun Zhang. 2024. Large language models know what is key visual entity: An LLM-assisted multimodal retrieval for VQA. In *Proceedings of the 2024 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pages 10939–10956.

Pengcheng Jiang, Jiacheng Lin, Lang Cao, Runchu Tian, SeongKu Kang, Zifeng Wang, Jimeng Sun, and Jiawei Han. 2025. Deepretrieval: Hacking real search engines and retrievers with large language models via reinforcement learning. *arXiv preprint arXiv:2503.00223*.

Jeff Johnson, Matthijs Douze, and Hervé Jégou. 2019. Billion-scale similarity search with gpus. *IEEE Transactions on Big Data*, 7(3):535–547.

Weizhe Lin, Jingbiao Mei, Jinghong Chen, and Bill Byrne. 2024. PreFLMR: Scaling up fine-grained late-interaction multi-modal retrievers. In *Proceedings of the 62nd Annual Meeting of the Association for Computational Linguistics (ACL)*, pages 5294–5316.

Kenneth Marino, Mohammad Rastegari, Ali Farhadi, and Roozbeh Mottaghi. 2019. Ok-vqa: A visual question answering benchmark requiring external knowledge. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 3195–3204.

Yu Meng, Mengzhou Xia, and Danqi Chen. 2024. Simpo: Simple preference optimization with a reference-free reward. *Advances in Neural Information Processing Systems (NeurIPS)*, 37:124198–124235.

Thomas Mensink, Jasper Uijlings, Lluis Castrejon, Arushi Goel, Felipe Cadar, Howard Zhou, Fei Sha, André Araujo, and Vittorio Ferrari. 2023. Encyclopedic vqa: Visual questions about detailed properties of fine-grained categories. In *Proceedings of the IEEE/CVF International Conference on Computer Vision (ICCV)*, pages 3113–3124.

Nitesh Methani, Pritha Ganguly, Mitesh M Khapra, and Pratyush Kumar. 2020. Plotqa: Reasoning over scientific plots. In *Proceedings of the IEEE/CVF Winter Conference on Applications of Computer Vision (WACV)*, pages 1527–1536.

Long Ouyang, Jeffrey Wu, Xu Jiang, Diogo Almeida, Carroll Wainwright, Pamela Mishkin, Chong Zhang, Sandhini Agarwal, Katarina Slama, Alex Ray, and 1 others. 2022. Training language models to follow instructions with human feedback. *Advances in Neural Information Processing Systems (NeurIPS)*, 35:27730–27744.

Jingyuan Qi, Zhiyang Xu, Rulin Shao, Yang Chen, Jin Di, Yu Cheng, Qifan Wang, and Lifu Huang. 2024. Rora-vlm: Robust retrieval-augmented vision language models. *arXiv preprint arXiv:2410.08876*.

Rafael Rafailov, Archit Sharma, Eric Mitchell, Christopher D Manning, Stefano Ermon, and Chelsea Finn. 2023. Direct preference optimization: Your language model is secretly a reward model. *Advances in Neural Information Processing Systems (NeurIPS)*, 36:53728–53741.

Dustin Schwenk, Apoorv Khandelwal, Christopher Clark, Kenneth Marino, and Roozbeh Mottaghi. 2022. A-okvqa: A benchmark for visual question answering using world knowledge. In *European Conference on Computer Vision (ECCV)*, pages 146–162. Springer.

Sanket Shah, Anand Mishra, Naganand Yadati, and Partha Pratim Talukdar. 2019. Kvqa: Knowledge-aware visual question answering. In *Proceedings of the AAAI Conference on Artificial Intelligence (AAAI)*, volume 33, pages 8876–8884.

Zhihong Shao, Peiyi Wang, Qihao Zhu, Runxin Xu, Junxiao Song, Xiao Bi, Haowei Zhang, Mingchuan Zhang, YK Li, Yang Wu, and 1 others. 2024. Deepseekmath: Pushing the limits of mathematical reasoning in open language models. *arXiv preprint arXiv:2402.03300*.

Guangming Sheng, Chi Zhang, Zilingfeng Ye, Xibin Wu, Wang Zhang, Ru Zhang, Yanghua Peng, Haibin Lin, and Chuan Wu. 2025. Hybridflow: A flexible and efficient rlhf framework. In *Proceedings of the Twentieth European Conference on Computer Systems (ECCS)*, pages 1279–1297.

Quan Sun, Yuxin Fang, Ledell Wu, Xinlong Wang, and Yue Cao. 2023. Eva-clip: Improved training techniques for clip at scale. *arXiv preprint arXiv:2303.15389*.

Yang Tian, Fan Liu, Jingyuan Zhang, V. W., Yupeng Hu, and Liqiang Nie. 2025. CoRe-MMRAG: Cross-source knowledge reconciliation for multimodal RAG. In *Proceedings of the 63rd Annual Meeting of the Association for Computational Linguistics (ACL)*, pages 32967–32982.

Peng Wang, Qi Wu, Chunhua Shen, Anthony Dick, and Anton Van Den Henge. 2017a. Explicit knowledge-based reasoning for visual question answering. In *Proceedings of the 26th International Joint Conference on Artificial Intelligence (IJCAI)*, pages 1290–1296.

Peng Wang, Qi Wu, Chunhua Shen, Anthony Dick, and Anton Van Den Hengel. 2017b. Fvqa: Fact-based visual question answering. *IEEE Transactions on Pattern Analysis and Machine Intelligence (TPAMI)*, 40(10):2413–2427.

Xinming Wang, Jian Xu, Aslan H Feng, Yi Chen, Haiyang Guo, Fei Zhu, Yuanqi Shao, Minsi Ren, Hongzhu Yi, Sheng Lian, and 1 others. 2025a. The hitchhiker's guide to autonomous research: A survey of scientific agents. *TechRxiv.August 07, 2025. DOI:10.36227/techrxiv175459840.02185500/V1*.

Xinming Wang, Jian Xu, Bin Yu, Sheng Lian, Hongzhu Yi, Yi Chen, Yingjian Zhu, Boran Wang, Hongming Yang, Han Hu, and 1 others. 2025b. Mr-align: Metareasoning informed factuality alignment for large reasoning models. *arXiv preprint arXiv:2510.24794*.

Jason Wei, Xuezhi Wang, Dale Schuurmans, Maarten Bosma, Fei Xia, Ed Chi, Quoc V Le, Denny Zhou, and 1 others. 2022. Chain-of-thought prompting elicits reasoning in large language models. *Advances in Neural Information Processing Systems (NeurIPS)*, 35:24824–24837.

Xiaojun Xue, Chunxia Zhang, Zhendong Niu, and Xindong Wu. 2022. Multi-level attention map network for multimodal sentiment analysis. *IEEE Transactions on Knowledge and Data Engineering*, 35(5):5105–5118.

Yibin Yan and Weidi Xie. 2024. EchoSight: Advancing visual-language models with Wiki knowledge. In *Findings of the Association for Computational Linguistics: EMNLP 2024 (EMNLP)*, pages 1538–1551.

An Yang, Baosong Yang, Binyuan Hui, Bo Zheng, Bowen Yu, Chang Zhou, Chengpeng Li, Chengyuan Li, Dayiheng Liu, Fei Huang, Guanting Dong, Haoran Wei, Huan Lin, Jialong Tang, Jialin Wang, Jian Yang, Jianhong Tu, Jianwei Zhang, Jianxin Ma, and 40 others. 2024. Qwen2 technical report. *arXiv preprint arXiv:2407.10671*.

Wei Yang, Jingjing Fu, Rui Wang, Jinyu Wang, Lei Song, and Jiang Bian. 2025. OMGM: Orchestrate multiple granularities and modalities for efficient multimodal retrieval. In *Proceedings of the 63rd Annual Meeting of the Association for Computational Linguistics (ACL)*, pages 24545–24563.

Tao Zhang, Ziqi Zhang, Zongyang Ma, Yuxin Chen, Zhongang Qi, Chunfeng Yuan, Bing Li, Junfu Pu, Yuxuan Zhao, Zehua Xie, and 1 others. 2024. mr $\hat{2}$ ag: Multimodal retrieval-reflection-augmented generation for knowledge-based vqa. *arXiv preprint arXiv:2411.15041*.

Tianyi Zhang, Varsha Kishore, Felix Wu, Kilian Q Weinberger, and Yoav Artzi. 2019. Bertscore: Evaluating text generation with bert. *arXiv preprint arXiv:1904.09675*.

Yanzhao Zhang, Mingxin Li, Dingkun Long, Xin Zhang, Huan Lin, Baosong Yang, Pengjun Xie, An Yang, Dayiheng Liu, Junyang Lin, and 1 others. 2025. Qwen3 embedding: Advancing text embedding and reranking through foundation models. *arXiv preprint arXiv:2506.05176*.

Yaowei Zheng, Richong Zhang, Junhao Zhang, Yanhan Ye, Zheyan Luo, Zhangchi Feng, and Yongqiang Ma. 2024. Llamafactory: Unified efficient fine-tuning of 100+ language models. In *Proceedings of the 62nd Annual Meeting of the Association for Computational Linguistics (ACL)*.

Yingjian Zhu, Ying Wang, Yuyang Hong, Ruohao Guo, Kun Ding, Xin Gu, Bin Fan, and Shiming Xiang. 2026. Seavis: Sound-enhanced association for online audio-visual instance segmentation. *arXiv preprint arXiv:2603.01431*.

Appendix

A Dataset Details

Encyclopedic VQA dataset serves as a rigorous benchmark for knowledge-intensive visual reasoning, comprising approximately 1 million VQA samples derived from 221,000 unique question-answer pairs. These samples are centered around 16.7k distinct fine-grained entities, with visual data sourced from the iNaturalist 2021 and Google Landmarks Dataset V2. To facilitate evidence-based answering, the dataset is coupled with a comprehensive, controlled knowledge base consisting of 2 million Wikipedia articles from the WikiWeb2M corpus, each enriched with supporting images to provide necessary context. While the full dataset encompasses both single-hop and complex multi-hop reasoning tasks, this study focuses exclusively on the single-hop subset and utilizes the officially released 2M knowledge base to evaluate the model's capability in retrieving and synthesizing external encyclopedic information for precise visual recognition and fact-based answering.

InfoSeek benchmark is a large-scale dataset designed to challenge models in visual information seeking across a diverse spectrum of more than 11,000 visual entities derived from the OVEN framework. To balance the need for extensive training data with the necessity for rigorous evaluation, the dataset is structured into a massive automatically generated training set containing 1.3 million questions and a high-quality, human-annotated evaluation set comprising 8.9 thousand samples. Since the original 6-million-entity knowledge base was not publicly released, we adhere to the experimental protocols established by EchoSight, by utilizing their released 100,000-entity knowledge base filtered from Wikipedia. This ensures a consistent and fair comparison within the research community, specifically focusing on the model's ability to retrieve relevant encyclopedic evidence and generalize to both seen and unseen entities in a real-world information-seeking context.

M2KR benchmark is a comprehensive training and evaluation framework designed to foster the development of general-purpose multimodal retrievers by repurposing nine diverse vision-and-language datasets into a consistent, uniform retrieval format. This benchmark suite encompasses three fundamental task types: Image-to-Text (I2T), Question-to-Text (Q2T), and the more complex Image-Question-to-Text (IQ2T), which requires a model to jointly synthesize visual and textual information to accurately retrieve relevant documents. In our experimental framework, we concentrate on these knowledge-intensive IQ2T subtasks, specifically utilizing high-quality datasets such as E-VQA for its focus on fine-grained entity properties and specialized domain knowledge, OKVQA for its requirement of outside world knowledge, and OVEN for its emphasis on open-domain visual entity recognition. By standardizing these datasets with task-specific prompting instructions, M2KR provides a robust environment for evaluating a retriever's ability to navigate large-scale external knowledge bases, such as the WikiWeb2M corpus, ensuring that models can effectively bridge the gap between complex visual understanding and factual knowledge retrieval.

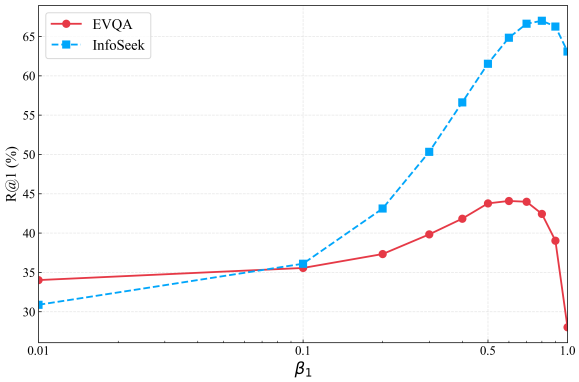


Figure 4: Impact of the multi-modal rerank stage weight β_1 on the final retrieval accuracy (R@1). The x-axis (log scale) represents the weight assigned to the initial retrieval similarity score, where $\beta_1 = 1.0$ indicates using only the retrieval score without reranking. The results show that a hybrid scoring mechanism yields the best performance, with optimal weights of 0.6 for EVQA and 0.8 for InfoSeek.

B Parameter Searching

B.1 Retrieval Modality Weight

To determine the optimal fusion ratio between visual and textual modalities, we conduct a two-stage parameter search for the weighting hyperparameter α. As depicted in the left panel of Figure 5, the coarse-grained search across the full range $\alpha \in [0, 1]$ reveals a distinct performance peak around 0.6. This trend confirms that the proposed hybrid retrieval strategy significantly outperforms uni-modal approaches (where $\alpha = 0$ or $\alpha = 1$). Furthermore, the results indicate a preference for visual semantics, as the performance drops more

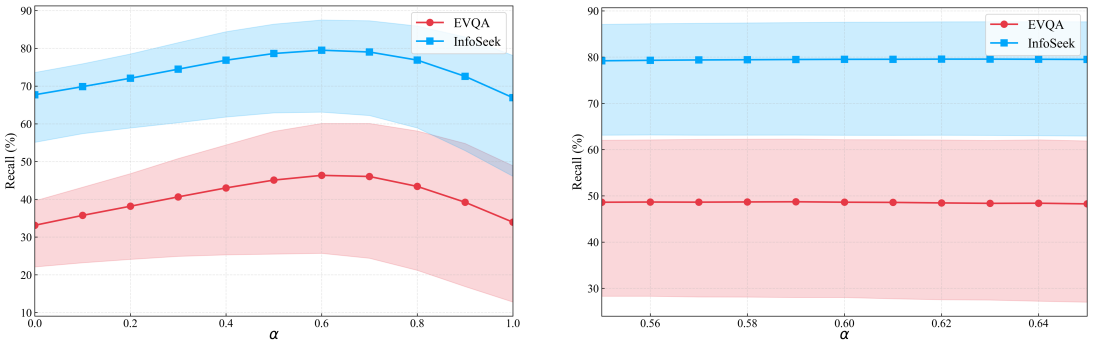


Figure 5: Impact of the modality weighting hyperparameter α on retrieval performance using refined queries. Left: Coarse-grained search across the full range $\alpha \in [0, 1]$, demonstrating that multi-modal retrieval outperforms uni-modal baselines. Right: Fine-grained search within the interval $[0.55, 0.65]$ to identify the precise optimal weights. The central markers denote the average recall (mean of R@1, R@5, R@10, and R@20), while the shaded areas indicate the performance range between the lower bound (R@1) and the upper bound (R@20).

sharply when $\alpha < 0.5$ compared to $\alpha > 0.5$. To pinpoint the exact optimal configuration, we perform a fine-grained grid search within the interval $[0.55, 0.65]$ with a step size of 0.01, as shown in the right panel of Figure 5. Based on the peak recall values observed in this refined search space, we set the optimal hyperparameters as $\alpha = 0.59$ for EVQA and $\alpha = 0.63$ for InfoSeek.

B.2 Multi-modal Rerank Stage Weight

To effectively aggregate the global semantic matching capability of the dense retriever and the local discriminative power of the multi-modal reranker, we introduce a hyperparameter β_1 to balance their respective scores. Specifically, the final ranking score is a weighted sum where β_1 controls the contribution of the initial retrieval cosine similarity, and $1 - \beta_1$ controls the contribution of the reranking score. Notably, setting $\beta_1 = 1.0$ is equivalent to using the raw retrieval score exclusively (i.e., disabling the reranker).

Figure 4 illustrates the sensitivity of the Top-1 Recall (R@1) to varying β_1 values on both EVQA and InfoSeek datasets. We observe a consistent trend where performance improves as β_1 increases from extremely low values (0.01), suggesting that the reranker's score alone is insufficient and requires the global context provided by the retrieval score as an anchor. The performance peaks when a balanced integration is achieved—specifically at $\beta_1 = 0.6$ for EVQA and $\beta_1 = 0.8$ for InfoSeek. Beyond these optimal points, particularly as β_1 approaches 1.0, the performance drops, confirming that the multi-modal reranker provides critical fine-grained filtering that the dense retriever alone cannot achieve.

B.3 Textual Rerank Stage Weight

Following the multi-modal reranking phase, we isolate the top-ranked candidate section and retrieve its corresponding full Wikipedia article. To further pinpoint the precise evidence, we apply a textual reranker to score all sections within this article. The final selection of the top-1 section is determined by a weighted fusion of the initial multi-modal reranking score and the intra-article textual reranking score, controlled by the hyperparameter β_2.

Figure 6 illustrates the impact of β_2 on the final retrieval accuracy (Recall@1). We observe that performance initially improves as β_2 increases from 0, indicating that incorporating fine-grained textual verification helps filter out noise within the candidate article. However, the performance peaks at $\beta_2 = 0.2$ for both EVQA (53.92%) and InfoSeek (43.47%) and subsequently declines as the weight increases further. This trend suggests that while local textual coherence is a valuable auxiliary signal, the global semantic alignment captured by the multi-modal reranker remains the primary indicator of relevance. Excessive reliance on the textual score dilutes this global context, leading to suboptimal retrieval. Consequently, we set $\beta_2 = 0.2$ as the default configuration for our framework.

C More Experimental Details

C.1 More details on M2KR benchmark

To provide a comprehensive evaluation of WikiSeeker's generalization capabilities, we present fine-grained retrieval results on the EVQA, OKVQA, and OVEN splits of the M2KR benchmark. We extend the evaluation metrics to cover a

Dataset	PASS Samples	FAIL Samples
EVQA	3,000	5,000
InfoSeek	15,000	15,000
Total	**18,000**	**20,000**

Table 11: Distribution of the training data used for fine-tuning the Inspector module. "PASS" samples represent successful retrieval cases where the context is sufficient, while "FAIL" samples represent cases where the Inspector must rely on internal parametric knowledge.

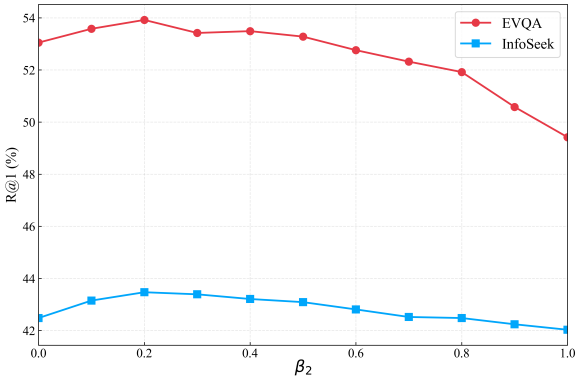


Figure 6: Impact of the textual rerank stage weight β_2 on the final context retrieval accuracy (Recall@1). The results demonstrate that a moderate incorporation of textual reranking scores ($\beta_2 = 0.2$) yields the optimal performance for both EVQA and InfoSeek datasets.

wider range of retrieval depths (up to $K = 100$ or $K = 500$) to analyze both top-rank precision and long-tail coverage.

Performance on EVQA. As detailed in Table 12, integrating the Refiner yields consistent performance improvements across all metrics for the EVQA split. The gains are observed in both standard Recall and Pseudo Recall, indicating that the refined queries help identify not only the ground-truth sections but also semantically equivalent candidates that may have been missed by the baseline.

Performance on OKVQA. Table 13 presents the results on the OKVQA split. The improvements here are particularly pronounced. The Refiner boosts Pseudo Recall@1 from 42.01% to 57.91% and Recall@1 from 13.77% to 20.69%. These substantial margins suggest that the visual-only baseline often fails to capture the necessary commonsense knowledge required by OKVQA, whereas our query refinement successfully bridges this semantic gap, significantly enhancing the relevance of top-ranked results.

Performance on OVEN. Finally, we report the performance on the OVEN split in Table 14. Since OVEN is an entity-centric open-domain dataset, precise immediate retrieval is critical. Our method achieves a remarkable gain in Recall@1, increasing from 31.09% to 42.75%. Furthermore, the performance advantage persists even at extended retrieval depths (Recall@500), demonstrating that WikiSeeker effectively enriches the candidate pool with correct entities even in challenging search scenarios.

C.2 More details about Limitations of VLMs as Answer Generators

In the main text, we discussed the limitations of VLMs as answer generators compared to LLMs when provided with textual context. Table 15 provides the complete set of results for this experiment across the full spectrum of Signal-to-Noise Ratios (SNR), ranging from 0 (completely irrelevant context) to 1.0 (oracle context). The experimental results are entirely consistent with the analysis presented in the main text.

C.3 Training Dataset of Inspector

To equip the Inspector with the robust capability to discriminate between sufficient and insufficient contexts, we construct a comprehensive instruction-tuning dataset comprising 38,000 samples derived from the training splits of both EVQA and InfoSeek benchmarks. As outlined in Table 11, this dataset is carefully balanced between positive ("PASS") samples, where the retrieved context contains the necessary evidence, and negative ("FAIL") samples, where the Inspector determines the context is inadequate and must rely on its internal parametric knowledge. Specifically, we aggregate 8,000 samples from EVQA (3,000 PASS and 5,000 FAIL) and 30,000 samples from InfoSeek (15,000 PASS and 15,000 FAIL) to ensure diversity in visual complexity and question types.

The data labeling process employs distinct strategies for each benchmark to accommodate differences in annotation availability. For EVQA, which provides explicit ground-truth section annotations, we label a retrieved context as "PASS" if the top-ranked section matches the ground truth; otherwise, it is labeled as "FAIL," where we employ an auxiliary LLM to expand the short ground-truth answer into a descriptive sentence to serve as the VLM's target response. In contrast, since InfoSeek lacks granular section annotations and only

Method	Pseudo Recall@K						Recall@K					
	1	5	10	20	50	100	1	5	10	20	50	100
w/o. Refiner	51.20	72.24	78.72	83.44	88.37	90.93	40.40	62.53	70.24	78.03	86.05	91.09
w. Refiner	**51.57**	**72.48**	**79.20**	**84.32**	**88.91**	**91.07**	**43.12**	**65.25**	**73.17**	**79.95**	**87.01**	**91.25**

Table 12: Detailed retrieval performance comparison on the EVQA split of the M2KR benchmark.

Method	Pseudo Recall@K						Recall@K					
	1	5	10	20	50	100	1	5	10	20	50	100
w/o. Refiner	42.01	67.52	78.02	86.64	94.11	96.87	13.77	30.52	39.34	49.56	63.79	71.68
w. Refiner	**57.91**	**77.55**	**85.32**	**91.58**	**96.43**	**98.18**	**20.69**	**41.48**	**51.15**	**61.57**	**72.65**	**79.45**

Table 13: Detailed retrieval performance comparison on the OKVQA split of the M2KR benchmark.

Method	Recall@K						
	1	5	10	20	50	100	500
w/o. Refiner	31.09	64.18	76.46	85.25	92.52	95.21	97.97
w. Refiner	**42.75**	**69.71**	**78.85**	**86.89**	**92.73**	**95.72**	**98.34**

Table 14: Detailed retrieval performance on the OVEN split of the M2KR benchmark.

provides ground-truth entities, we implement a rigorous proxy validation strategy. We consider a retrieved context valid ("PASS") only if it successfully recalls the ground-truth entity and simultaneously enables a zero-shot LLM generator to derive the correct answer. Samples failing these dual criteria are categorized as "FAIL," thereby ensuring high-quality supervision for the Inspector's validation mechanism.

C.4 Efficiency Analysis

In this section, we discuss the training and inference efficiency of our framework. Regarding training efficiency, our approach is designed to be computationally lean. For the Refiner, we utilize GRPO, which eliminates the need for a value model required by standard PPO algorithms, thereby reducing memory usage and computational overhead during the RL training phase. Furthermore, the fine-tuning of our Generator and Inspector is implemented via the efficient LLaMA-Factory framework, ensuring optimized parameter updates with minimal resource consumption.

To evaluate inference efficiency, we conducted a comparative study on the M2KR EVQA split. We benchmarked WikiSeeker against two baselines: the direct generation method (LLaVA-1.5-7B) and the one-step multimodal RAG method (PreFLMR). We measured three key metrics: Average Retrieval Time, Average Inference Time, and VQA Performance. The results are summarized in Table 16.

As shown in Table 16, compared to PreFLMR, our framework demonstrates faster retrieval speeds, even accounting for the additional step of VLM-based query refinement. While the total inference time exhibits a marginal increase due to the multi-agent architecture, WikiSeeker achieves substantial improvements in VQA performance, significantly surpassing both LLaVA-1.5-7B and PreFLMR. These results demonstrate that our framework offers a highly favorable trade-off, achieving SOTA performance while maintaining competitive efficiency.

C.5 Evaluation of the Inspector Module

To substantiate its reliability, we measure the Inspector's performance as a standalone binary classification process based on Equation 7. We conducted a comprehensive evaluation on the EVQA test set. The Inspector's performance in determining whether re-ranked sections are relevant (PASS/-FAIL) is summarized in the confusion matrix in Table 17.

The Inspector achieves an overall routing accuracy of 82.1%, demonstrating its proficiency in validating retrieved context. Notably, the False Negative (FN) rate is higher than the False Positive (FP) rate (12.34% vs. 5.60%), reflecting a conservative routing strategy. Comparing the two failure modes, the consequences of an FP result are particularly detrimental, as they feed noisy or irrelevant context to a text-only LLM, directly leading to hallucinations. In contrast, FN scenarios represent a much safer failure mode: the query is simply routed back to the VLM (Inspector). As specified in our Inspector prompt (Figure 8), the VLM in this

Method	Signal-to-Noise Ratio										
	0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	Oracle
Qwen2.5-VL-7B (I+T)	**22.75**	**28.27**	**35.45**	41.26	48.27	55.10	61.68	68.99	74.99	81.79	88.46
Qwen2.5-VL-7B (Text-only)	19.44	27.18	34.91	41.75	49.20	56.13	62.93	70.82	77.33	84.42	91.10
LLaMA3-8B	18.51	25.81	33.90	40.48	48.80	55.92	63.12	**70.88**	**78.08**	**85.37**	92.99
Qwen2.5-7B	19.77	26.17	34.42	**42.52**	**49.31**	**56.53**	**63.37**	70.80	77.77	85.18	**93.45**

Table 15: Full VQA performance comparison under different Signal-to-Noise Ratios. The ratio represents the proportion of correct sections mixed into the input context. "Qwen2.5-VL-7B (I+T)" denotes the standard multimodal setting, while "(Text-only)" denotes the same model with the image input removed. The best result for each ratio is highlighted in bold.

Method	Avg. Ret. Time	Avg. Inf. Time	VQA Result
LLaVA-1.5-7B	-	1.432	17.00
PreFLMR	0.984	2.196	54.45
WikiSeeker (Ours)	0.915	2.417	65.87

Table 16: Inference efficiency comparison on the M2KR EVQA split.

	Ground Truth: PASS	Ground Truth: FAIL
Predicted: PASS	TP: 1,274 (26.82%)	FP: 264 (5.60%)
Predicted: FAIL	FN: 586 (12.34%)	TN: 2,626 (55.28%)

Table 17: Confusion matrix of the Inspector's routing decisions on the EVQA test set.

path still retains access to both the input image and the retrieved context. Given the VLM's robust internal parametric knowledge and visual reasoning capabilities, it remains highly likely to produce a correct answer.

D Prompt Used in WikiSeeker

In this section, we provide a detailed overview of the prompts employed across the various modules of WikiSeeker to facilitate reproducibility. The system prompt and reasoning instructions for the Refiner, designed to expand user queries using visual semantics, are presented in Figure 7. The prompt for the Inspector, which is tasked with determining the consistency and sufficiency of the retrieved context, is illustrated in Figure 8.

For the LLM Generator, we adopt prompt templates that are largely consistent with those used in the OMGM. The specific prompts tailored for the EVQA and InfoSeek datasets are shown in Figure 9 and Figure 10, respectively. Regarding data processing and knowledge base construction, Figure 11 displays the prompt used to expand short ground-truth answers into natural sentences for constructing the Inspector's training data. Figure 12 depicts the prompt applied to concisely summarize excessively long Wikipedia sections during the construction of our multi-modal knowledge base. Finally, Figure 13 outlines the specific prompts utilized for the image captioning and zero-shot query expansion variants in our ablation studies.

E Case Study

To intuitively demonstrate the mechanisms behind WikiSeeker's performance improvements, we provide qualitative visualizations of our two core modules: the Refiner and the Inspector.

Analysis of the Refiner. Figure 14 presents five representative examples illustrating the Refiner's workflow. In these scenarios, the original user queries are often too vague or implicit (e.g., "What is the street address of this facility?") to retrieve the correct documents directly, resulting in irrelevant top-1 retrieval results. However, through an explicit reasoning process, the Refiner effectively identifies key visual entities—such as the "Roue de Paris" or the "white-breasted nuthatch"—and incorporates them into an expanded search query. This query expansion allows the Vision-Language Model to actively participate in the retrieval phase, thereby making it significantly easier to retrieve the correct entity.

Analysis of the Decoupled Generation Strategy. Figure 15 validates the effectiveness of our decoupled generation strategy and the Inspector's routing logic. We compare the responses of a text-only LLM (Qwen2.5-7B-Instruct) and a VLM (Qwen3-VL-8B-Instruct) against our WikiSeeker framework.

- The **left column** displays cases where the retrieval is successful (contexts marked in green). Here, the correct answer is explicitly contained within the text (underlined). In these instances, the LLM demonstrates superior reading comprehension, correctly extracting the answer, whereas the VLM fails

WikiSeeker Refiner Prompt.

System Prompt:

Character Introduction

You are an expert in generating queries for encyclopedic retrieval. You first think about the reasoning process in the mind and then provide the user with the answer. Given a question about the given image <image>, your task is to retain the original query while expanding it with additional relevant information derived from both the visual content and world knowledge, to retrieve documents that best answer the question.

Response Format

Show your work in <think> </think> tags. Your final response must be in JSON format within <answer> </answer> tags. For example,

```
<answer>
{
    "query": "...."
}
</answer>.
```

User Prompt:

Here's the user query: **{Query}** Assistant: Let me think step by step. <think>

Figure 7: Prompt of WikiSeeker Refiner.

WikiSeeker Inspector Prompt.

System Prompt:

Character Introduction

You are an assistant to determine the consistency and completeness of the provided context in relation to a question and an image <image>. You will receive a question and a retrieved context. Follow these steps:

1. Check if the context is consistent with both the image and the question.
2. Determine if the context contains the answer to the question.

Response Format

If both conditions are satisfied, respond with:

```
{
    "pass": "true"
}
```

If either condition is not satisfied, respond with:

```
{
    "pass": "false",
    "answer": "predicted answer"
}
```

Be concise and ensure your responses are in JSON format.

User Prompt:

Question: **{Query}**

Retrieved Context: **{Context}**

Figure 8: Prompt of WikiSeeker Inspector.

WikiSeeker Generator Prompt on EVQA.

System Prompt:

You are a helpful assistant for answering encyclopedic questions.If the context does not contain the information required to answer the question, you should answer the question using internal model knowledge.

User Prompt:

Context: **{Context}**
Question: **{Question}**
The answer is:

Figure 9: Prompt of WikiSeeker Generator on EVQA.

WikiSeeker Generator Prompt on InfoSeek.

System Prompt:

You are a helpful assistant for answering encyclopedic questions. Do not answer anything else.If you need to answer questions about numbers or time, please output the corresponding numerical format directly.If the context does not contain the information required to answer the question, you should answer the question using internal model knowledge.

User Prompt:

Context: **{Context}**
Question: **{Question}**
Just answer the questions , no explanations needed. Short answer is:

Figure 10: Prompt of WikiSeeker Generator on InfoSeek.

to focus on the textual evidence. Our Inspector correctly validates these contexts (PASS) and routes the query to the LLM Generator (marked as Gen"), ensuring accuracy.

- The **right column** illustrates retrieval failures (contexts marked in red). Without relevant external knowledge, the LLM hallucinates or fails to answer. In contrast, the VLM successfully answers these questions by leveraging its internal parametric knowledge and visual understanding. Crucially, our Inspector detects the insufficiency of the retrieved context (FAIL) and intervenes by providing the answer directly (marked as Ins"), effectively preventing the propagation of retrieval errors.

Prompt for GT answer expansion.

System Prompt:

Character Introduction

Given a question and its short answer, expand the answer into a complete sentence while keeping the original answer intact. Expand the answer into a natural, complete sentence that includes the original answer.

Response Format

Return your response in JSON format. Output format:

```
{
    "expanded_answer": "your expanded sentence here"
}
```

User Prompt:

Question: **{question}** Original Answer: **{original answer}**

Figure 11: Prompt for GT answer expansion.

Prompt designed for summarizing extended Wikipedia sections.

System Prompt:

Summarize the following Wikipedia section concisely while preserving key information.

User Prompt:

Article: **{title}**
Section: **{section title}**
Content: **{section text}**
Provide a concise summary:

Figure 12: Prompt designed for summarizing extended Wikipedia sections.

Prompt for image caption and zero-shot query expansion.

System Prompt:

Character Introduction

You are an expert in generating queries for encyclopedic retrieval. Given a question about the given image, you should:
1. Concisely caption the image which is most relevant to the question.
2. Retain the original query while expanding it with additional relevant information derived from both the visual content and world knowledge, to retrieve documents that best answer the question.

Response Format

Your final response must be in JSON format. For example:

```
{
    "caption": "...",
    "query": "..."
}
```

User Prompt:

Here's the user query: **{query}**

Figure 13: Prompt for image caption and zero-shot query expansion.

Question: What is the street address of this facility?

Retrieved Top 1: Ferris wheel ✗

Reasoning: The image shows the Roue de Paris (Paris Wheel) at the Port de la Villette in Paris, France. This is an observation wheel located at the Jardin des Tuileries, which is part of the Louvre Museum complex. The address of the Port de la Villette is 75000 Paris. In summary, the facility is the Roue de Paris (Paris Wheel) at the Port de la Villette in Paris, France.

Refined Question: What is the street address of the Roue de Paris (Paris Wheel) at the Port de la Villette in Paris, France?

Retrieved Top 1: Roue de Paris ✓

Question: What is the closest parent taxonomy of this bird?

Retrieved Top 1: Brown-headed nuthatch ✗

Reasoning: The image shows a white-breasted nuthatch (Sitta carolinensis). This bird belongs to the Family Sittidae, which is part of the order Passeriformes. The closest parent taxonomy to this bird would be the order Passeriformes. Based on this analysis, I can generate the following expanded query: "What is the closest parent taxonomy of the white-breasted nuthatch?" With this expanded query, I can now proceed to retrieve relevant documents.

Refined Question: What is the closest parent taxonomy of the white-breasted nuthatch?

Retrieved Top 1: White-breasted nuthatch ✓

Question: What is the brand of this vehicle?

Retrieved Top 1: Ferrari 458 ✗

Reasoning: The image shows a McLaren Sports Car. To confirm this, I'll consider the visible features such as the logo, design, and the context of the vehicle being a sports car. The McLaren logo is distinctive, and the car's aerodynamic design is characteristic of McLaren vehicles.

Refined Question: What is the brand of the McLaren Sports Car shown in the image?

Retrieved Top 1: McLaren 12C ✓

Question: What is the oldest age of this animal?

Retrieved Top 1: Bear ✗

Reasoning: The image shows a red panda, also known as a lesser panda. Red pandas are native to the forests of western China and are not considered a threatened specie……, they are likely to reach adulthood at around 2-3 years old and live for several years thereafter

Refined Question: What is the estimated lifespan of a red panda?

Retrieved Top 1: Red panda ✓

Question: Which city or region does this building locate in?

Retrieved Top 1: Lycée Fénelon, Paris ✗

Reasoning: The building in the image is the Hôtel de Soubise, which is located in Paris. It is situated at 12 rue de Varenne, in the 7th arrondissement of Paris. This hotel was originally built in the mid-16th century as part of the Hôtel des Tournelles but later expanded to include the current structure. The building served as the residence of the French kings and also housed the Ministry of Finance from 1804 until 1971.

Refined Question: Which city or region does the Hôtel de Soubise locate in?

Retrieved Top 1: Hôtel de Soubise ✓

Figure 14: Qualitative examples demonstrating the effectiveness of the Refiner. For each case, the original user query fails to retrieve the correct entity (marked with ✗). The Refiner analyzes the image through a chain-of-thought reasoning process to generate a refined query, which successfully retrieves the ground-truth entity (marked with ✓).

Question: What is a cultivar of this plant?

Context: Daucus carota, whose common names include wild carrot, ……Domesticated carrots are cultivars of a subspecies, Daucus carota subsp. sativus.

LLM: A cultivar of this plant is a domesticated carrot.

VLM: Daucus carota subsp.sativus

Ours: A cultivar of this plant is a domesticated carrot. (Gen)

Question: What is dark brown to black on this butterfly?

Context: Upperside: Male velvety black, female very dark brown, suffused with bluish in……on the underside the ground colour is distinctly ochraceous brown.

LLM: The ground color of this butterfly is dark brown to black.

VLM: The dark brown to black parts of the butterfly are its upperside wings.

Ours: Its wings. (Ins)

Question: What type of white butterfly eats this plant?

Context: The species that grow with Arabidopsis lyrata are Senecio obovatus……by many herbivores such as the cabbage white butterfly, Pieris brassicae.

LLM: The type of white butterfly that eats this plant is the cabbage white butterfly.

VLM: Pieris brassicae

Ours: The type of white butterfly that eats this plant is the cabbage white butterfly. (Gen)

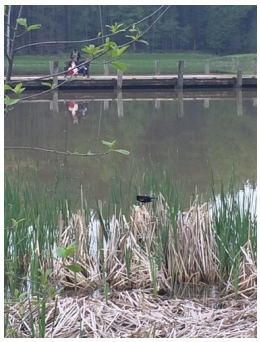
Question: In what country is this tree native?

Context: Vachellia tortuosa, the twisted acacia , poponax or huisachillo, is …… It is found in tropical and desert habitats, such as the Rio Grande Valley, Central Mexican Plateau, and Colombian Tatacoa Desert.

LLM: This tree is native to Colombia.

VLM: It is native to Australia.

Ours: This tree is native to Australia. (Ins)



Question: What is a sign of threat among males in this bird?

Context: These markings are vital in the defense of the territory……, the spots on the wings are …… than as carotenoids.

LLM: A sign of threat among males in this bird is indicated by the spots on the wings.

VLM: Presence of spots.

Ours: A sign of threat among males in this bird is indicated by the spots on the wings. (Gen)

Question: Of all the flycatcher species that breed in the united states, this bird has what?

Context: The eastern wood pewee (Contopus virens) is a small tyrant flycatcher from ……distinguished most easily by their calls.

LLM: Of all the flycatcher species that breed in the United States, this bird has the largest range.

VLM: The longest migration.

Ours: It has the longest migration. (Ins)

Figure 15: Visualization of the decoupled generation strategy enabled by the Inspector. **Left (Green Context):** Scenarios where retrieval is accurate. The relevant evidence is underlined. The LLM accurately extracts the answer, whereas the VLM fails. The Inspector validates the context and routes the query to the LLM Generator (indicated by "Gen"). **Right (Red Context):** Scenarios where retrieval fails. The LLM cannot answer correctly due to missing information, but the VLM correctly answers using internal parametric knowledge. The Inspector detects the retrieval failure and provides the answer directly (indicated by "Ins").