

RAVENEA: A Benchmark for Multimodal Retrieval-Augmented Visual Culture Understanding

Jiaang Li^{1†*} Yifei Yuan^{1,2‡} Wenyan Li¹ Mohammad Aliannejadi³
 Daniel Hershcovich¹ Anders Søgaard¹ Ivan Vulic⁴
 Wexuan Zhang⁵ Paul Pu Liang⁶ Yang Deng^{7‡} Serge Belongie^{1‡}

¹University of Copenhagen ²ETH Zürich ³University of Amsterdam
⁴University of Cambridge ⁵Singapore University of Technology and Design
⁶Massachusetts Institute of Technology ⁷Singapore Management University

Abstract

As vision-language models (VLMs) become increasingly integrated into daily life, the need for accurate visual culture understanding is becoming critical. Yet, these models frequently fall short in interpreting cultural nuances effectively. Prior work has demonstrated the effectiveness of retrieval-augmented generation (RAG) in enhancing cultural understanding in text-only settings, while its application in multimodal scenarios remains underexplored. To bridge this gap, we introduce RAVENEA (Retrieval-Augmented Visual culturE uNdErstAnding), a new benchmark designed to advance visual culture understanding through retrieval, focusing on two tasks: culture-focused visual question answering (cVQA) and culture-informed image captioning (cIC). RAVENEA extends existing datasets by integrating over 10,000 Wikipedia documents curated and ranked by human annotators. With RAVENEA, we train and evaluate seven multimodal retrievers for each image query, and measure the downstream impact of retrieval-augmented inputs across fourteen state-of-the-art VLMs. Our results show that lightweight VLMs, when augmented with culture-aware retrieval, outperform their non-augmented counterparts (by at least 3.2% absolute on cVQA and 6.2% absolute on cIC). This highlights the value of retrieval-augmented methods and culturally inclusive benchmarks for multimodal understanding.

-  **Website** <https://jiaangli.github.io/RAVENEA/>
-  **Code** <https://github.com/yfyuan01/RAVENEA>
-  **Data** <https://huggingface.co/datasets/jaagli/ravenea>

1 Introduction

Vision-language models (VLMs) are increasingly deployed in real-world applications, from education to assistive technologies [1, 2, 3, 4], where understanding not only visual content but also the surrounding cultural context is crucial. Despite achieving impressive performance on general tasks [5, 6, 7, 8], VLMs often struggle to capture cultural nuances, such as traditions, symbols, and region-specific practices that require external, culturally grounded knowledge [9, 10, 11, 12]. For example, as shown in Figure 1, a VLM may incorrectly identify the season of a festival scene as ‘Autumn’, overlooking that the image depicts Kyoto’s Gion Festival, which occurs in July and corresponds to

*Project Lead.

†Equal contribution.

‡Principal senior advisor.

‘Summer’. A promising approach to address this limitation is the integration of external knowledge through retrieval-augmented generation (RAG) [13], which has shown success in improving cultural awareness in language models [14, 15]. However, prior work in the culture domain has predominantly been confined to text-only settings. Meanwhile, existing culture-related multimodal datasets primarily focus on evaluating VLM outputs on culturally oriented tasks, with limited emphasis on the integration of external cultural knowledge. As a result, the potential of RAG to improve multimodal cultural understanding remains underexplored.

To bridge the gap, we introduce RAVENEA (**R**etrieval-**A**ugmented **V**isual cultur**E** **u****N****d****E**rt**A**nding), a *manually curated* dataset designed to evaluate cultural understanding in VLMs with retrieval support. We construct RAVENEA based on two existing datasets: CVQA [16], which includes culturally relevant visual questions and corresponding answers, and CCUB [17], offering culturally contextualized captions to foster inclusivity in text-to-image generation⁴. For each instance drawn from the source datasets, we append a set of Wikipedia documents that have been **human-ranked** based on their cultural relevance to the associated image. This curation effort, designed to ensure broad cultural representation, contains data related to **eight** countries and spans **eleven** diverse categories, comprising more than **1,800** images and **10,000 human-ranked** documents. RAVENEA thus provides a retrieval-augmented benchmark for evaluating cultural sensitivity in multimodal retrievers, and further allows for assessing how well VLMs integrate and make use of retrieved cultural context. Specifically, we focus on two culturally grounded tasks: (i) **culture-focused visual question answering (cVQA)** and (ii) **culture-informed image captioning (cIC)**. We select these two tasks for their centrality in assessing cultural understanding in VLMs—question answering tests context-aware reasoning, while captioning evaluates generation sensitivity to cultural nuances.

With RAVENEA, we first train and evaluate seven multimodal retrievers that use both visual and textual inputs to retrieve Wikipedia documents for a given query image based on their cultural relevance. Then, we evaluate a diverse set of state-of-the-art (SOTA) VLMs, including GPT-4.1 [18], LLaVA-OneVision-7B [19], Pixtral [20], Phi-4 Multimodal [21], the Gemma3 family [22], the Qwen2.5-VL family [23], the InternVL3 family [24], and the Deepseek-VL2 family [25], each with and without multimodal retrieval, to assess the impact of retrieval augmentation on cultural understanding. Our dataset provides a testbed for assessing the cultural relevance capabilities of multimodal retrievers and the effectiveness of VLMs in consuming and using such retrieved cultural context.

Our contributions and key findings include:

- **RAVENEA benchmark:** We introduce RAVENEA, the first benchmark aimed at evaluating VLMs and multimodal retrieval in leveraging external knowledge for visual culture understanding. It comprises a diverse, large-scale collection of human-curated, culturally related documents linked to images from eight countries across eleven categories, enabling evaluation on two tasks: culture-focused visual question answering and culture-informed image captioning. (Section 3)
- **Cultural grounding annotations enhance multi-modal retrieval:** We evaluate seven retrievers that integrate visual and textual cues to retrieve culturally relevant documents. We find fine-tuning retrievers on culture-targeted annotations leads to marked gains in retrieval accuracy, highlighting the value of explicit cultural supervision. (Section 6.3)
- **Benefits of culture-aware retrieval:** Culture-aware retrieval boosts task performance across VLMs, with lightweight models showing the greatest improvement. This suggests that such retrieval can seamlessly integrate into downstream VLM tasks, enhancing their performance. (Section 5.2)

⁴We reuse the cultural captions from CCUB as ground-truth references for the inverse task, image-to-text generation, specifically for culture-aware image captioning.

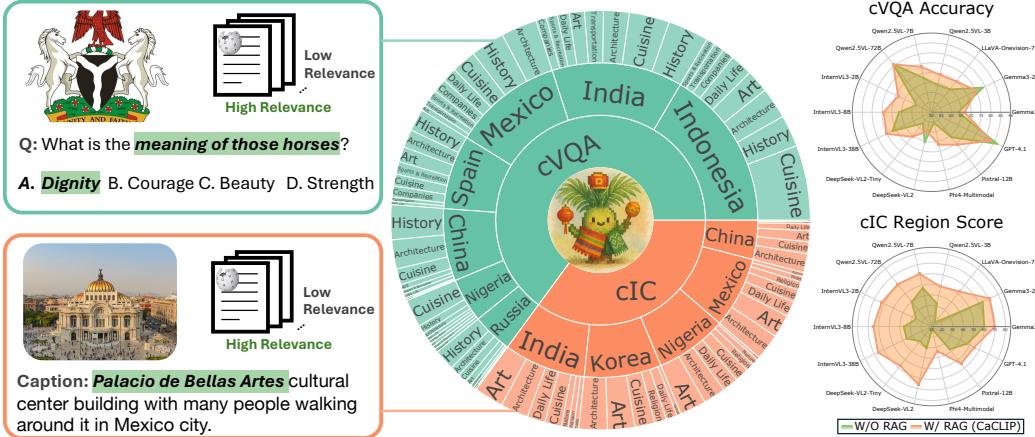


Figure 2: **RAVENEA**: A Multimodal Retrieval-Augmented Visual culture uNdErstAnding dataset. **Left**: Examples of cVQA and cIC tasks. **Middle**: Geographic and categorical distribution of cultural references. **Right**: Performance comparison of 14 VLMs, evaluated with and without integration of our culture-aware retriever. Here, CaCLIP="culture-aware CLIP-L/14@224px".

- **Cross-cultural variation:** Evaluation across eight countries reveals that VLMs exhibit distinct cultural preferences, with each model favoring different regional contexts—suggesting model-specific cultural biases. (Section 6.2)

2 Related Work

Retrieval augmentation for cultural understanding. Retrieval augmentation has demonstrated significant efficacy for culture-related NLP tasks [26, 27, 28]. Prior work uses sources like the World Values Survey for cultural question answering [14, 29], or retrieves web and knowledge base content to enhance cultural contextualization [15]. In multimodal settings, however, cultural retrieval remains underexplored. While some approaches retrieve culture-relevant images to fine-tune VLMs [10], they require additional training. In contrast, our method introduces a plug-and-play retrieval system that enriches cultural grounding at inference time without modifying the base model.

Vision-language culture datasets. Several recent studies examine cultural understanding in VLMs through multicultural VQA [30, 9], cuisine recognition [31, 32], and concept-based image retrieval [33]. Others benchmark cultural entity recognition using Wikipedia-based prompts [34] or curate culture-specific image sets for value-based tasks [29]. While these efforts highlight current VLM limitations, they often rely on static, manually curated datasets. A natural extension to address these deficiencies is through culture-relevant multimodal retrieval—an area lacking dedicated datasets. Our work specifically aims to fill this critical research gap.

3 RAVENEA Dataset

We construct our dataset by building culturally relevant document lists for each image in two existing culture-grounded datasets: CVQA [16], a widely used dataset for culture-focused VQA, and CCUB [17], a dataset designed to mitigate cultural bias in text-to-image generation with culturally contextualized captions. To ensure broad geographic and cultural coverage, we curate a diverse subset comprising images from seven countries in CVQA: China, Nigeria, Russia, Spain, Mexico, India, and Indonesia, and all five countries in CCUB: China, Korea, India, Mexico, and Nigeria (see Figure 2). After that, we separate the dataset construction process into three critical stages shown in Figure 3.

3.1 Dataset Construction

Data collection. The data collection process consists of two main steps: **(i) culture-related captioning** and **(ii) document retrieval**. For **culture-related captioning**, we generate culturally grounded

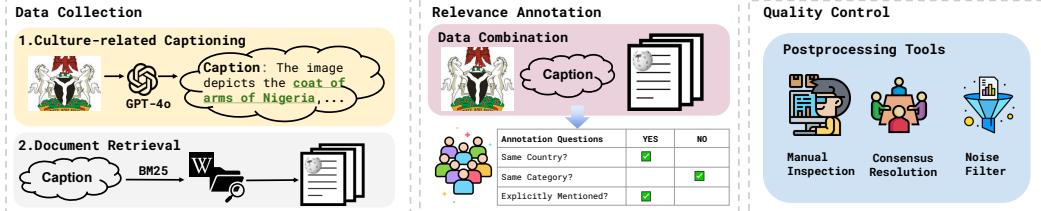


Figure 3: **RAVENEA construction pipeline.** **Left:** A two-stage retrieval process to match each image with relevant documents. **Middle:** Decomposition of cultural relevance into three interpretable dimensions to improve human annotation. **Right:** Postprocessing methods for quality control.

captions for each image to facilitate more effective attachment of relevant documents. Since the CVQA lacks captions and the CCUB provides only brief descriptions, we employ GPT-4o to generate richer, culturally informative captions (see the prompt example in Table 10). For **document retrieval**, we first conduct a coarse filtering using the generated cultural captions as queries for a BM25 [35] retriever to extract the semantically relevant documents from a large-scale corpus comprising over six million English Wikipedia documents⁵. To mitigate the impact of inaccurate captions and ensure precise document relevance, we then perform human annotation on the retrieved documents.

Relevance annotation. Based on the initial BM25 retrieval results, we refine the cultural relevance label of retrieved documents via human annotation. For each image-caption pair, annotators are presented with the top 10 Wikipedia documents retrieved by BM25. They are asked to assess whether each document provides meaningful background or contextual information that is relevant to the culture described in the caption or the image (see Appendix K). Specifically, we decomposed cultural relevance into three interpretable and independently verifiable dimensions: **Country association**: *Is the topic of the Wikipedia article associated with the same country as the image and its caption?* **Topic alignment**: *Does the topic of the Wikipedia article align with the semantic category of the image and its caption?* **Explicit visual representation**: *Is the topic of the Wikipedia article explicitly mentioned or visually represented in the image and its caption?* Each dimension is framed as a binary (True / False) question to reduce ambiguity and improve annotation consistency. However, for the **country association** dimension (the first listed), we introduce an additional label, "Cannot be determined", to handle cases where this association is unclear from the annotator's perspective. Additionally, annotators are also instructed to include the title and URL of any relevant Wikipedia article they believe is missing from the top-10 retrieved results. These manually suggested articles are treated as the most cultural references closely related to the given image (see details in Appendix G).

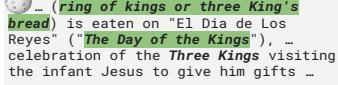
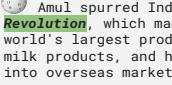
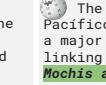
Quality control. To ensure the quality and consistency of our annotations, we implement several quality control methods. First of all, prior to the annotation process, all annotators are required to carefully review a detailed instruction file outlining the relevance criteria and annotation guidelines. To ensure proper understanding of the guidelines, annotators are required to complete a mock annotation test and correctly answer all questions before proceeding with the actual annotation tasks (see Figure 14). We also perform an additional quality check on a subset of the dataset. Specifically, for each selected countries, we employ an additional local quality checker who is tasked with manually reviewing the annotations to verify their accuracy and adherence to the guidelines. The quality checker reviews a random sample of annotated items, focusing on both the relevance labels and the justification behind any edge cases, such as borderline relevance or use of the "Cannot be determined" label. If inconsistencies or deviations from the annotation guidelines are identified, the affected samples are flagged for re-annotation. The overall acceptance rate from the meta quality checkers is 98.2%. The inter-annotator agreement (IAA) Cohen's Kappa (κ) [36] between the meta checker and annotator on the sampled annotations is 0.83.

Table 1: **Statistics of the RAVENEA dataset.** The dataset is constructed by curating existing sources and augmenting them with over 10,000 wiki-derived documents to broaden cultural knowledge coverage and enhance content diversity.

Dataset	Images	Documents	Pairs	Questions	Captions
CVQA	1,213	8,319	12,130	2,331	-
CCUB	655	4,441	6,550	-	655
RAVENEA	1,868	11,580	18,680	2,331	655

⁵<https://huggingface.co/datasets/wikimedia/wikipedia>

cVQA

<p>Q: What is the name of the dish shown in the image?</p> <p>A. Day of the Dead Cake B. Pan de muerto C. Three Kings cake D. Fruit cake</p> <p></p> <p></p> <p>W/O RAG: B ✗ With CaCLIP: C ✓</p>	<p>Q: Which revolution of India is this brand associated with?</p> <p>A. Golden B. Green C. White D. Yellow</p> <p></p> <p></p> <p>W/O RAG: A ✗ With CaCLIP: C ✓</p>	<p>Q: Between which Mexican states is the train route shown in the image?</p> <p>A. Chihuahua and Veracruz B. Chihuahua and Sinaloa C. Michoacán and Sinaloa D. Chihuahua and Sonora</p> <p></p> <p></p> <p>W/O RAG: D ✗ With CaCLIP: B ✓</p>
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cIC

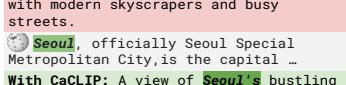
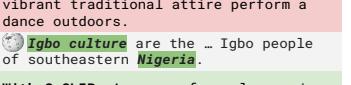
 <p>W/O RAG: A bustling cityscape at dusk with modern skyscrapers and busy streets.</p> <p></p> <p>With CaCLIP: A view of Seoul's bustling downtown area during twilight, showcasing its modern architecture and busy streets.</p>	 <p>W/O RAG: A bustling plaza in front of an ornate building with a golden dome, surrounded by people and greenery.</p> <p></p> <p>With CaCLIP: A view of the Palacio de Bellas Artes in Mexico City, showcasing its grand architecture and bustling surroundings.</p>	 <p>W/O RAG: Three individuals wearing vibrant traditional attire perform a dance outdoors.</p> <p></p> <p>With CaCLIP: A group of people wearing colorful traditional Igbo attire perform the Egedege dance at an event.</p>
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Figure 4: Examples demonstrating the impact of CaCLIP Wikipedia retrieval integration on cVQA and cIC tasks using DeepseekVL2-Tiny. When augmented with culture-aware retrieval, the model exhibits enhanced sensitivity to cultural context.

3.2 Dataset Statistics

We present the statistics of our dataset in Table 1. The dataset comprises a total of **1,868** culturally diverse images, with approximately **65%** originating from CVQA and the remaining **35%** from CCUB. Each image is paired with a GPT-4o-generated cultural caption, as well as the top-10 ranked Wikipedia documents retrieved via a cultural relevance scoring pipeline (Figure 3), yielding a total of **18,680** image-document pairs (see illustrated examples in Figure 4). The collection spans **eight** countries and encompasses a broad spectrum of cultural domains, such as traditional attire, festivals, architecture, cuisine, and social practices (see more statistics in Appendix E).

4 Culture-aware Multimodal Retriever

Leveraging the RAVENEA dataset, we train and evaluate seven multimodal retrievers to retrieve culturally relevant Wikipedia documents using both visual and textual inputs. We fine-tune five representative models—spanning both generative and discriminative paradigms—to optimize multimodal document retrieval. Performance is evaluated using standard retrieval metrics, including Mean Reciprocal Rank (MRR) [37], Precision@k (P@k) [38], and Normalized Discounted Cumulative Gain (nDCG@k) [39], where $k \in \{1, 3, 5\}$. We integrate responses from three annotation questions per data point into a continuous scale ranging from -3 to 3 , where higher values indicate stronger cultural relevance. We fine-tune a VisualBERT-based [40, 41] reranker following standard BERT-style setups [42], and adapt two multimodal generators—VL-T5 [43] and LLaVA-OneVision-7B [19]—for end-to-end document retrieval [44, 45, 46]. To enhance cultural awareness in the contrastive retrieval, we introduce Culture-Aware Contrastive (CAC) learning, a supervised learning framework compatible with both CLIP and SigLIP architectures. We denote the culture-aware fine-tuned versions of CLIP-L/14@224px and SigLIP2-SO/14@384px using CAC as CaCLIP and CaSigLIP2, respectively.

4.1 Culture-aware Contrastive Learning

Given an image I_i associated with T textual descriptions $\{D_{i1}, D_{i2}, \dots, D_{iT}\}$, each document D_{it} is annotated with a binary label $y_{it} \in \{0, 1\}$, where $y_{it} = 1$ indicates cultural relevance and

Table 2: **Performance with different retriever models.** Fine-tuned contrastive models consistently outperform their frozen counterparts across tasks. Here, "CaSigLIP"=Culture-aware SigLIP2-SO/14@384px, and "CaCLIP"=Culture-aware CLIP-L/14@224px. Models in gray are frozen.

Method	MRR \uparrow	P@1 \uparrow	P@3 \uparrow	P@5 \uparrow	nDCG@1 \uparrow	nDCG@3 \uparrow	nDCG@5 \uparrow
SigLIP2-SO/14@384px	66.71	50.42	40.14	34.25	58.85	62.43	67.50
CLIP-L/14@224px	70.76	54.58	43.47	36.58	62.54	67.25	72.43
VisualBERT	59.66	42.50	35.97	32.75	51.29	55.49	62.29
VL-T5	55.53	35.42	34.03	31.42	45.21	53.18	59.62
LLaVA-OneVision-7B	54.15	36.20	31.83	28.69	45.85	50.82	56.74
CaSigLIP2 (ours)	69.35	54.17	43.47	36.50	61.98	66.75	71.98
CaCLIP (ours)	78.34	65.42	49.44	39.50	72.25	75.22	79.32

$y_{it} = 0$ indicates irrelevance. For each image–text pair (I_i, D_{it}) , we employ a shared vision-language encoder—such as CLIP—to obtain modality-specific representations: $\mathbf{E}_{I_i} = \mathcal{E}_V(I_i)$ for the visual input and $\mathbf{E}_{D_{it}} = \mathcal{E}_L(D_{it})$ for the textual input. We then compute the cosine similarity score s_{it} between \mathbf{E}_{I_i} and each corresponding $\mathbf{E}_{D_{it}}$, resulting in a similarity vector $\mathbf{S}_i = [s_{i1}, s_{i2}, \dots, s_{iT}]$.

Culture-awareness classification now amounts to:

$$\mathcal{L}_{\text{Culture Classify}} = -\frac{1}{B \cdot T} \sum_{i=1}^B \sum_{j=1}^T [y_{ij} \log \sigma(s_{ij}) + (1 - y_{ij}) \log(1 - \sigma(s_{ij}))], \quad (1)$$

where B is the number of images; $\sigma(\cdot)$ denotes the sigmoid function.

To prioritize culturally relevant descriptions in the ranking, we apply a margin ranking loss between all pairs of descriptions with differing cultural relevance. For each image I_i , we compare all pairs (D_{ij}, D_{ik}) such that $y_{ij} = 1$ and $y_{ik} = 0$, and encourage the model to assign a higher similarity score to the relevant description. The ranking loss is defined as:

$$\mathcal{L}_{\text{Rank}} = \frac{1}{B} \sum_{i=1}^B \sum_{\substack{j,k=1 \\ y_{ij}=1, y_{ik}=0}}^T \max(0, \delta - (s_{ij} - s_{ik})), \quad (2)$$

To mitigate the risk of overly similar positive text embeddings for the same image, we introduce a penalty that encourages intra-modal diversity among textual representations. We apply a diversity-promoting loss that forces the similarity between different text embeddings to be reduced while keeping each embedding highly similar to itself. Specifically, the penalty is formulated using an exponential function to emphasize the dissimilarity between embeddings:

$$\mathcal{L}_{\text{Diversity}} (\mathbf{S}_i) = - \sum_{t=1}^T \log \left(\frac{\exp(s_{it})}{\sum_{j=1}^T \exp(s_{ij})} \right) \quad (3)$$

Then we can get the culture-aware contrastive loss:

$$\mathcal{L}_{\text{CAC}} = \frac{1}{3} (\mathcal{L}_{\text{Culture Classify}} + \mathcal{L}_{\text{Rank}} + \mathcal{L}_{\text{Diversity}}). \quad (4)$$

4.2 Multimodal Retrieval Results

We perform a comprehensive evaluation of both frozen and fine-tuned retrievers, and present the results in Table 2. We find that fine-tuned models, particularly those based on contrastive learning, consistently outperform their frozen counterparts. For instance, CaCLIP achieves a substantial improvement in P@1, rising from 54.58% to 65.42%, and sets a new SOTA across all evaluation metrics. Although SigLIP2-SO/14@384px also benefits from fine-tuning, the performance gains are comparatively modest. In contrast, models such as LLaVA-OneVision-7B, VL-T5, and VisualBERT lag behind after fine-tuning, even underperforming relative to frozen baselines. This underperformance likely stems from the fact that models such as LLaVA-OneVision-7B and VisualBERT were originally pretrained for generative tasks with different objectives, whereas CLIP-L/14@224px and SigLIP2-SO/14@384px were explicitly trained for similarity-based alignment, providing them with a structural advantage in retrieval settings.

5 Multimodal Retrieval-augmented Visual Culture Understanding

We then evaluate the effectiveness of these retrievers with 14 SOTA VLMs, spanning a diverse set of architectures. We conduct experiments on two downstream tasks: **cVQA** and **cIC**, respectively.

5.1 Experimental Setup

Models. We benchmark open and closed-weight SOTA VLMs on RAVENEA, leveraging various retrievers against non-RAG baselines, assessing retrieval effectiveness across models of different sizes. The open-weight models include LLaVA-OneVision-7B [19], Pixtral-12B [20], Phi-4 Multimodal-Instruct [21], Gemma3-4B-Instruct and 27B-Instruct [22], Qwen2.5-VL-Instruct (3B, 7B, 72B⁶) [23], InternVL3 (2B, 8B, 38B) [24], and Deepseek-VL2 variants (Tiny and Base) [25]. For the closed models, we adopt GPT-4.1 [18] (accessed on 2025/04/14)⁷.

Evaluation metrics. For the cVQA task, we use accuracy as the primary evaluation metric, which measures the proportion of correctly predicted answers. For the cIC task, we employ several evaluation metrics including ROUGE-L [48], CIDEr [49], BERTScore [50], and CLIPScore [51], to assess the alignment between generated and reference captions across lexical, syntactic, and embedding-based levels. To further evaluate the cultural relevance and human-perceived quality, we conduct a human evaluation study. We employed four researchers to select the most accurate caption from 14 VLMs (see details in Appendix I and L), and find a significant mismatch between automatic metric scores and human judgments of cultural appropriateness (see Table 3). To bridge this gap, we further introduce **RegionScore**, a novel evaluation metric designed to quantify cultural grounding (see details in Appendix H and Table 9). It measures how well captions identify the correct country names tied to cultural elements, adding geographic and cultural specificity in image captioning.

Table 3: Kendall’s τ rank correlation [47] between automatic metrics and human judgments for the **CCUB** task. Statistically significant correlations ($p < 0.05$) are marked with \checkmark . Our proposed metrics correlate stronger with human evaluation than the others.

Rouge-L [48]	CIDEr [49]	BERTScore [50]	CLIPScore [51]	RegionScore (ours)
-0.172 ✗	-0.316 ✗	-0.011 ✗	0.139 ✗	0.442 \checkmark

5.2 Overall Performance

We present the main results in Table 4. The results demonstrate the efficacy of incorporating culture-aware retrieval augmentation. Employing fine-tuned retrievers yields substantial performance gains over both non-RAG and frozen retrievers baselines. Specifically, the CaCLIP achieves the highest average performance across both tasks, improves the accuracy for cVQA from 67.7% to 71.5%, and substantially improving the RegionScore for cIC from 40.2% to 58.1%. While CLIP-L/14@224px also offers improvements, fine-tuning consistently unlocks further potential. Furthermore, in the **cVQA task**, among all evaluated models, GPT-4.1 achieves the highest accuracy (86.8%) without RAG. Within the category of open-weight models, Qwen2.5-VL-72B leads with an accuracy of 81.0%. For lightweight models ($\leq 8B$ parameters), Qwen2.5-VL-7B achieves the best performance without RAG, reaching 67.7%. However, incorporating a CaCLIP significantly boosts performance, which enables InternVL3-8B to achieve 74.2% and outperform Qwen2.5-VL-7B by 0.6% with identical reranking. Notably, across multiple model families, augmenting the smallest variant with CaCLIP consistently elevates its performance to match or even exceed that of the next larger model tier. In the **cIC task**, with culture-aware contrastive learning, CaCLIP demonstrates substantial gains in identifying the culture in country-level of visual content, especially when built on top of VLMs with strong vision-language priors. It achieves the highest average RegionScore (58.1%) among the six reranking methods evaluated, with peak performance reaching 76.3% on the Gemma3-4B backbone. CaCLIP achieves leading the scores on 9 of 14 diverse suits of VLMs. This result underscores CaCLIP’s robustness and adaptability, particularly in culture-aware image captioning and retrieval tasks that demand fine-grained multimodal alignment.

⁶Due to computational constraints, we use the quantized version Qwen2.5-VL-Instruct-72B-AWQ.

⁷Knowledge cutoff: June 1, 2024; <https://platform.openai.com/docs/models/gpt-4.1>

Table 4: **cVQA and cIC Performance w/ and w/o RAG.** Models in gray are frozen retrievers. Results are colored as **Best**. VLMs augmented with finetuned retriever generally perform better.

Retriever	Average	Open Weights										Closed Weights		
		DeepSeek-VL2-Tiny	DeepSeek-VL2	Qwen2.5-VL-3B	Qwen2.5-VL-7B	InternVL3-2B	InternVL3-8B	InternVL3-38B	Gemma3-4B	Gemma3-27B	Phi4-Multimodal	Pixtral-12B	LLaVA-OneVision-7B	GPT-4.1
<i>cVQA Accuracy</i> ↑														
W/O RAG	67.7	57.1	65.5	64.2	67.7	81.0	58.4	66.5	71.9	63.6	78.7	55.5	66.1	64.8
SigLIP2-SO/14@384px	67.2	58.7	55.8	63.9	67.7	77.1	62.3	68.4	71.9	60.7	71.9	62.6	69.4	67.1
CLIP-L/14@224px	70.6	64.2	56.1	67.7	73.2	79.0	68.1	71.0	76.1	66.1	74.5	69.4	71.0	69.7
Finetuned Models														
VisualBERT	67.1	58.7	59.4	66.5	68.4	77.1	61.3	66.1	71.9	60.7	73.6	63.2	66.5	63.9
VL-T5	65.8	56.5	61.3	62.9	69.4	77.1	60.3	66.8	70.3	55.8	74.2	61.0	61.0	61.9
LLaVA-OneVision-7B	67.8	60.0	61.3	64.8	71.3	80.7	61.3	64.8	73.9	62.3	73.6	62.6	67.4	63.9
CaSigLIP2 (ours)	69.8	62.6	58.7	67.1	72.3	77.7	65.8	72.6	75.8	64.2	75.5	64.2	70.7	69.4
CaCLIP (ours)	71.5	65.8	60.0	69.4	73.6	81.0	68.7	74.2	75.2	66.8	75.2	66.8	71.0	70.0
<i>cIC RegionScore</i> ↑														
W/O RAG	40.2	31.3	36.3	36.3	48.8	47.5	27.5	37.5	22.5	67.5	62.5	10.0	35.0	18.8
SigLIP2-SO/14@384px	52.5	50.0	56.3	36.3	57.5	53.8	58.8	56.3	61.3	70.0	66.3	30.0	53.8	41.3
CLIP-L/14@224px	55.4	56.3	63.8	41.3	66.3	60.0	61.3	62.5	67.5	70.0	70.0	31.3	55.0	47.5
Finetuned Models														
VisualBERT	56.3	58.8	63.8	41.3	58.8	62.5	61.3	61.3	66.3	71.3	70.0	30.0	58.8	45.0
VL-T5	55.4	60.0	65.0	41.3	62.5	66.3	62.5	58.8	67.5	71.3	68.8	30.0	61.3	40.0
LLaVA-OneVision-7B	56.0	60.0	65.0	40.0	60.0	62.5	61.3	62.5	66.3	71.3	71.3	28.8	57.5	47.5
CaSigLIP2 (ours)	56.3	57.5	65.0	36.3	61.3	63.8	58.8	61.3	67.5	71.3	70.0	27.5	57.5	46.3
CaCLIP (ours)	58.1	60.0	67.5	42.5	65.0	65.0	62.5	60.0	70.0	76.3	75.0	27.5	62.5	52.5

6 Analysis and Further Discussion

Culture-aware retrieval augmentation substantially benefits VLMs across both cVQA and cIC tasks, compared to their no-RAG counterparts. In this section, we explore the margin of the improvement, cultural preference and the effectiveness of cultural annotation.

6.1 Scaling Models Yields Diminishing or Negative Returns across Retrievers

In the **cVQA task**, within the same VLM family, performance differences between RAG and non-RAG approaches exhibit non-monotonic trends as model size scales. For all four model families, larger models show marginal or even negative returns from RAG integration. What's more, sensitivity to RAG varies across model families. Notably, DeepSeek-VL2 demonstrates the most pronounced performance gap: the smallest model benefits from RAG with an average improvement of approximately +5%, whereas the largest model in the same family suffers

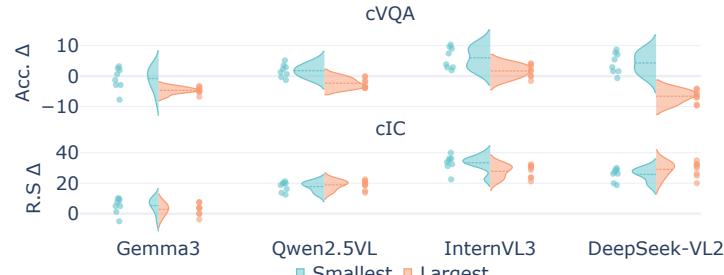


Figure 5: **Performance improvements for smallest and largest models per family with multimodal retrievers.** Scaling models yields marginal gains with various retrievers, even negative effects in both cVQA and cIC tasks. "ACC." denotes accuracy; "R.S." refers to the RegionScore; "Δ" represents the change incorporated with RAG compared to the non-RAG baseline.

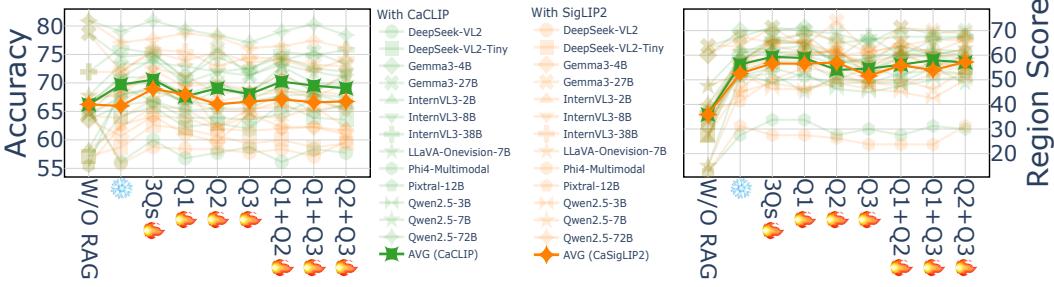


Figure 7: **Ablation for different annotation questions.** Combining all three culture-relevant annotation questions yields the best performance.

a degradation of around -6% on average. In the **cIC task**, the effectiveness of RAG exhibits a consistent trend with respect to model scale within a given model family. Across all four model families evaluated, larger models tend to benefit less—or at most comparably—from the integration of RAG, suggesting diminishing returns at higher capacity. Among them, Gemma3 models show the smallest relative improvement, achieving approximately a +7% performance gain on average, whereas InternVL3 models yield the highest benefit, with performance gains reaching up to +30%.

6.2 Differences across Countries

We evaluate all models using CaCLIP across a range of countries for both tasks, as shown in Figure 6. In the cVQA setting, most VLMs exhibit substantially diminished performance on culture-specific questions regarding Nigeria and Indonesia, in contrast to their performance on questions under other national contexts. Interestingly, questions related to Spanish culture reveal high inter-model variance, with accuracy differentials reaching up to 35%, underscoring significant discrepancies in cultural representation across models. In the cIC task, VLMs consistently underperform on images and documents associated with Indian cultural contexts, while achieving the highest RegionScores on Korean culture-related inputs. Model performance on Indian culture is particularly volatile, indicating inconsistent cultural grounding across architectures. By comparison, Korean and Chinese cultural inputs yield more stable performance across models, suggesting entrenched model-specific preferences in cultural alignment (see more results in Appendix J).

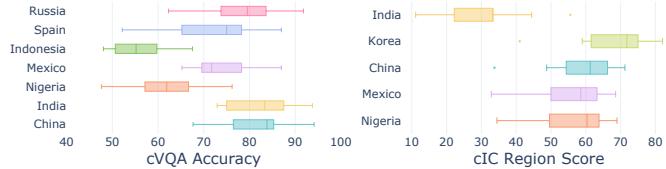


Figure 6: **Performance of 14 VLMs with CaCLIP across different countries.** Despite the integration of CaCLIP, disparities in model performance persist across countries.

6.3 Ablation Study on Annotation Questions

We further perform ablation studies across diverse combinations of annotation questions to assess their impact on downstream performance. Specifically, we evaluate 13 open-weight VLMs equipped with either CaSigLIP or CaCLIP, each trained on datasets constructed using varying subsets of culture-relevant annotations. From Figure 7, we can observe that leveraging all three questions (Q1 regarding country association; Q2 for topic alignment; Q3 for visual representation fidelity) yields the strongest performance on both cVQA and cIC tasks. For the cVQA task, we find Q1 provides the most significant benefit to CaSigLIP, whereas CaCLIP gains more from Q2. Among all pairwise combinations, the joint supervision from Q1 (country associations) and Q2 (topic alignment) proves slightly more effective than other pairs. In the cIC task, both CaSigLIP and CaCLIP achieve better performance improvements when trained with data derived from Q1, compared to other single-question sets. For pairwise combinations, CaCLIP benefits most from the Q1+Q3 combination, while CaSigLIP shows a clear preference for the Q2+Q3 setup.

7 Conclusion

We introduce RAVNEA, a novel benchmark dataset designed to comprehensively evaluate the cultural sensitivity of diverse multimodal retrievers across 14 SOTA VLMs. The benchmark consists of culturally contextualized queries and image captions from eight countries, curated and paired with Wikipedia passages ranked by human annotators based on their cultural relevance. Our findings highlight the potential of RAG for visual cultural understanding, particularly when lightweight VLMs are enhanced with culturally-aware multimodal retrievers such as CaCLIP, which consistently outperform their non-augmented counterparts – with the caveat that the largest models in each VLM family often exhibit diminishing returns when integrated with RAG. Notably, the inclusion of culture-sensitive questions during data annotation significantly improves effectiveness of multimodal retrievers and enhances performance in downstream tasks.

8 Acknowledgment

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A Limitations

While RAVNEA establishes a solid foundation for advancing the study of visual culture understanding with retrieval augmentation, it has three limitations that warrant future attention. First, due to budgetary constraints, the dataset’s cultural scope is currently limited to eight countries and eleven categories. Although this selection introduces meaningful diversity, it does not comprehensively represent the global spectrum of cultural perspectives, particularly those of underrepresented or marginalized communities. Second, our use of Wikipedia as the primary external knowledge source introduces inherent biases and may lack the depth, plurality, and contextual richness necessary for nuanced cultural interpretation. Finally, due to resource limitations, we were unable to include certain proprietary VLMs that require paid APIs, such as Gemini 2.5 Pro [52] and Claude Opus 3.7 [53]. We hypothesize that their performance would be comparable to GPT-4.1, which was included in our evaluation, but this remains an open empirical question.

B Future Directions

Our work opens several avenues for advancing visual culture understanding in multimodal models. First, expanding RAVNEA to include more countries, cultural categories, and diverse knowledge sources, beyond Wikipedia, would improve coverage and reduce institutional bias. Second, future benchmarks could include richer tasks beyond CVQA and cIC, such as culture-grounded object recognition, historical retrieval, and symbolic interpretation, to better capture cultural semantics. Third, our results suggest a need for culturally-aware evaluation metrics, particularly for text generation. The limited effectiveness of retrieval augmentation in larger models also warrants further study, especially regarding how cultural knowledge is integrated and utilized. Together, these directions aim to support the development of more culturally-sensitive and globally robust vision-language models.

C Ethics Statement

This work focuses on improving the cultural awareness of VLMs through retrieval-augmented methods. All data used in the construction of the RAVNEA benchmark were sourced from publicly available datasets and Wikipedia, a community-curated open-access knowledge base. To protect individual privacy, we apply automated face detection and blur all identifiable faces in images prior to release. To mitigate cultural bias and ensure broad representation, the benchmark includes images and documents spanning eight countries and eleven cultural domains, curated and annotated by a diverse group of annotators. We provide detailed documentation of the annotation process and guidelines to support transparency and reproducibility. While enhancing cultural understanding is a central goal of this work, we acknowledge that culture is inherently complex, dynamic, and context-dependent. Consequently, the benchmark cannot capture the full richness of any cultural context. Finally, this work does not involve any personally identifiable information (PII), biometric data, or sensitive attributes. All human annotators were compensated fairly, and data annotation adhered to ethical guidelines for responsible research.

D Experimental Details for Multi-modal Retrievers

Dataset. We integrate responses from three annotation questions per data point into a continuous scale ranging from -3 to 3 , where higher values indicate stronger cultural relevance. To ensure fair evaluation across regions, we adopt the train-validation-test split strategy from class-imbalance loss [54], yielding an approximate 85-5-10 data split. This setup guarantees that validation and test sets contain a balanced set of images per country (Figure 8), thereby mitigating evaluation bias from skewed geographic distributions. During training, we employ random cropping for images as a sample-level augmentation to normalize the distribution of training instances across countries, further mitigating region-specific sampling biases.

Hyperparameters. In this work, we adopt different sets of hyperparameters as VisualBERT, VL-T5, LLaVA-OneVision-7B, CLIP-L/14@224px, SigLIP2-SO/14@384px. For VisualBERT, VL-T5, and LLaVA-OneVision-7B we follow the setting in [44, 45, 46]. We show the training hyperparameters in

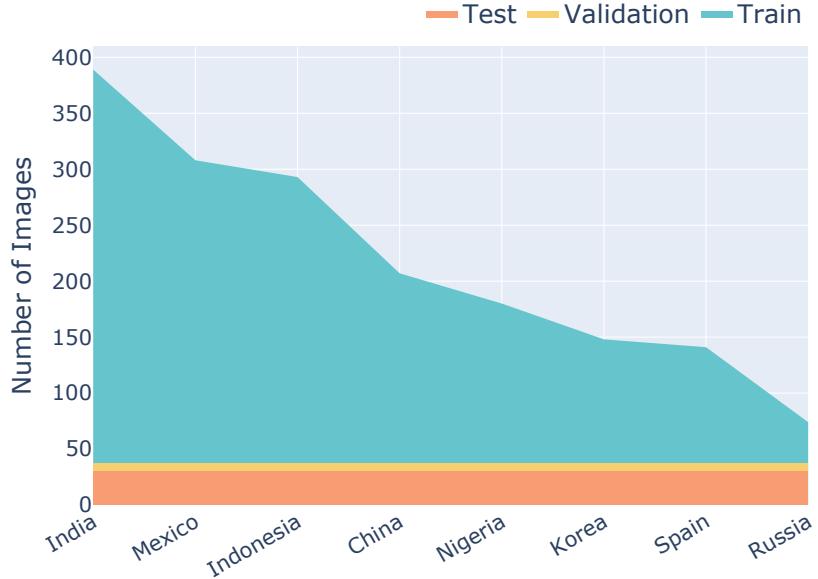


Figure 8: Data distributions across eight countries. Restrict the dataset to the images paired with at least one document annotated by human raters as culturally relevant.

Table 5: Hyperparameters for finetuning on five models.

Hyperparameters	VisualBERT	VL-T5	LLaVA-OneVision-7B	CLIP-L/14@224px	SigLIP2-SO/14@384px
batch size	32	128	4	64	64
lr	2e-4	1e-4	1e-4	1e-5	1e-5
lr warmup ratio	-	0.1	-	-	-
weight decay	-	-	-	-	-
Max Epoch	100	20	10	50	50
Patience	10	10	3	5	5
early stopping			Yes		
optimizer			AdamW		
Using LORA	-	-	Yes	-	-

rerankering experiments for all models in Table 5. All experiments are conducted using a maximum of 2 Nvidia H100 GPUs.

E Data Statistics

Table 6: Statistics of images in each country.

India	Mexico	Indonesia	China	Nigeria	Korea	Spain	Russia
408	349	309	303	223	151	142	77

We then apply cryptographic hashing (SHA-256) to identify and remove duplicate images, resulting in a cleaner and more distinct cultural image set. Consequently, RAVENEA comprises images collected from eight countries across four continents, spanning eleven distinct categories. The distribution of images by country and by category is detailed in Tables 6 and 7, respectively.

F Evaluation of VLMs

For closed-weight model, GPT-4.1, we directly call the corresponding API. For open-source models, we use vllm [55]. During the evaluation, to ensure the stability of the results, we set the temperature

Table 7: Statistics of images in each category.

Architecture	Cuisine	History	Art	Daily Life	Companies	Sports & Recreation	Transportation	Religion	Nature	Tools
403	402	278	275	185	80	73	68	52	31	21

parameter to 0.0 and the maximum output length to 256. All open-weight models are listed in Table 8. To avoid the impact of the length the retrieved content, we use the first 256 words in the top-1 Wikipedia document.

Table 8: Model details: Hugging Face model names.

Model	Hugging Face Model Name
LLaVA-OneVision-7B [19]	llava-hf/llava-onevision-qwen2-7b-ov-hf
Phi-4-Multimodal [21]	microsoft/Phi-4-multimodal-instruct
Pixtral [20]	mistral-community/pixtral-12b
Qwen2.5VL family [23]	Qwen/Qwen2.5-VL-3B-Instruct Qwen/Qwen2.5-VL-7B-Instruct Qwen/Qwen2.5-VL-72B-Instruct-AWQ
DeepSeek-VL2 family [25]	deepseek-ai/deepseek-vl2 deepseek-ai/deepseek-vl2-tiny
InternVL3 family [24]	OpenGVLab/InternVL3-2B OpenGVLab/InternVL3-8B OpenGVLab/InternVL3-38B
Gemma3 family [22]	google/gemma-3-4b-it google/gemma-3-27b-it

G Annotation Details

Based on the initial BM25 retrieval results, we refine the cultural relevance label of retrieved documents via human annotation. We found that directly asking annotators to rate overall cultural relevance on a continuous scale (e.g., 0–10) led to unreliable and inconsistent labels. This difficulty arises from several factors: (1) the semantic meaning of intermediate scores is ambiguous, (2) annotators tended to overemphasize a few salient visual elements [56], and (3) small numerical differences (e.g., between 5 and 6) often fail to reflect meaningful distinctions, especially given the cognitive load of processing lengthy Wikipedia documents, resulting in intra-annotator variance even on repeated examples. Instead, given an image–caption–document triplet, we decomposed cultural relevance into three interpretable and independently verifiable dimensions: **country association**, **topic alignment**, and **explicit visual representation**.

Prior to the annotation process, all annotators are required to carefully review a detailed instruction file outlining the relevance criteria and annotation guidelines. To ensure proper understanding of the guidelines, annotators are required to complete a mock annotation test and correctly answer all questions before proceeding with the actual annotation tasks. For each image-caption pair, annotators are presented with the top 10 Wikipedia documents retrieved by BM25. They are asked to assess whether each article provides meaningful background or contextual information that is directly relevant to the cultural elements described in the caption or depicted in the image.

H A New Metric: *RegionScore*

To evaluate the extent to which captions reference specific geopolitical regions, we introduce a **RegionScore**. This metric measures whether a caption contains explicit references to a country or its common demonym. N be the total number of samples. PRED_i denote predicted captions for the i -th sample. C_i be the country name associated with the i -th sample. $\text{Adj}(C_i)$ denote the set of adjectives or demonym associated with C_i . $T_i = \{C_i\} \cup \text{Adj}(C_i)$ denote the set of region-related

terms for the i -th sample. We define binary indicators for each sample:

$$\delta_i^{\text{pred}} = \begin{cases} 1 & \text{if any } t \in \mathcal{T}_i \text{ appears in } \text{PRED}_i \\ 0 & \text{otherwise} \end{cases} \quad (5)$$

The RegionScore for predicted captions are then computed as:

$$\text{RegionScore}_{\text{PRED}} = \frac{1}{N} \sum_{i=1}^N \delta_i^{\text{pred}} \quad (6)$$

These scores reflect the proportion of captions that include explicit regional identifiers. A higher score indicates stronger region-awareness in the captioning. For the ground truth in CCUB dataset, the $\text{RegionScore}_{\text{GT}} = 99\%$.

I Details of Human Evaluation in the cIC Task

We randomly sample 10 images and generate captions using 14 vision-language models (VLMs) under three configurations: CaCLIP, CLIP, and a no-retrieval baseline, yielding 420 captions in total. Four expert annotators participated in the evaluation. For each image, they were presented with caption triplets—one per retrieval configuration—and asked to assess approximately 35 such triplets each. Annotators are instructed to select the caption that most accurately and appropriately reflects the cultural context depicted. To evaluate annotation consistency, we randomly sample 30 triplets and assign them to a fifth expert annotator. Inter-annotator agreement (IAA) between this annotator and the original four, measured using Cohen’s κ , is 0.595.

J Additional Results

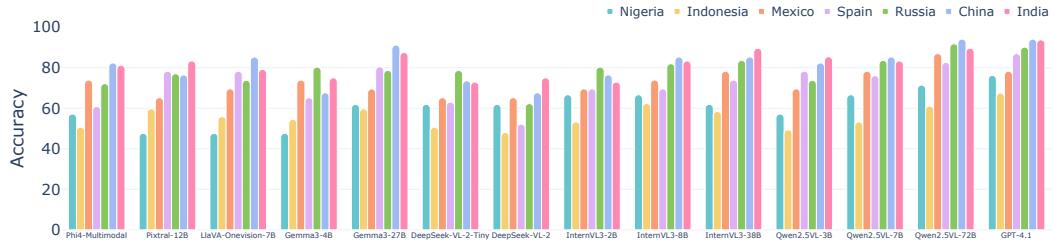


Figure 9: Performance of the 14 VLMs equipped with CaCLIP in cVQA task.

As illustrated in Figures 9 and 10, the models exhibit diverse cultural preferences. Notably, most models achieve relatively stronger performance on Chinese and Indian cultural contexts in the cVQA task, and on Chinese and Korean contexts in the cIC task. We report the CIDEr, ROUGE-L,

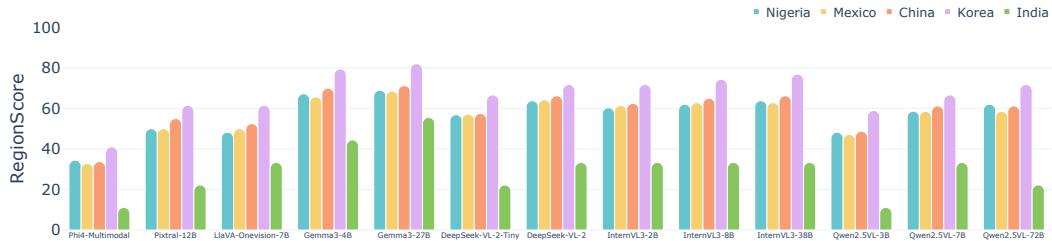


Figure 10: Performance of the 14 VLMs equipped with CaCLIP in cIC task.

BERTScore, and CLIPScore metrics for 14 VLMs on the cIC task in Table 9.

As shown in Figures 12 and 11, VLMs demonstrate varying degrees of performance shifts across cultural contexts in both the cIC and cVQA tasks. In the cIC setting, most fine-tuned retrievers yield

Table 9: Four metrics comparison of RAG and Non-RAG methods for CCUB task.

Method	Average	Open Weights												Closed Weights	
		DeepSeek-VL2-Tiny	DeepSeek-VL2	Qwen2.5-VL-3B	Qwen2.5-VL-7B	Qwen2.5-VL-72B	InternVL3-2B	InternVL3-38B	Gemma3-4B	Gemma3-27B	Phi4-Multimodal	Pixtral-12B	LLaVA-OneVision-7B	GPT-4.1	
<i>CCUBRouge-L</i>															
W/O RAG	18.3	18.7	18.2	21.8	18.2	16.5	17.8	19.6	19.8	16.7	15.9	20.6	15.4	21.4	19.6
Frozen Models															
SigLIP2-SO/14@384px	18.0	20.0	19.1	23.8	17.2	14.9	19.2	17.4	17.5	15.1	14.9	23.1	14.0	23.6	17.0
CLIP-L/14@224px	18.1	20.9	18.5	23.0	16.8	14.5	18.3	17.2	17.5	15.1	15.8	22.4	14.4	24.7	16.1
Finetuned Models															
VisualBERT	18.6	19.5	18.3	22.5	16.8	14.8	17.4	17.4	16.9	15.0	16.0	22.5	14.8	24.3	19.0
VL-T5	17.6	19.0	18.1	23.1	17.9	14.4	18.2	17.2	16.9	14.7	15.4	20.8	13.8	23.5	17.4
LLaVA-OneVision-7B	17.3	18.4	17.7	23.0	17.2	14.5	17.6	16.4	17.1	14.6	15.0	20.9	13.1	22.8	17.3
SigLIP2-SO/14@384px	18.4	19.3	19.2	24.5	18.5	14.8	18.4	18.2	17.2	15.2	16.4	22.2	14.3	23.5	18.9
CLIP-L/14@224px	18.1	19.6	18.6	23.9	17.1	14.7	18.0	17.3	17.7	16.0	16.3	21.5	13.7	24.2	17.0
<i>CCUBCIDEr</i>															
W/O RAG	28.1	30.0	27.2	49.2	22.9	16.9	10.5	18.6	35.8	11.2	10.1	49.1	16.7	47.4	34.4
Frozen Models															
SigLIP2-SO/14@384px	25.2	39.2	20.5	58.5	16.9	7.6	12.4	7.1	6.3	4.7	6.1	62.0	10.1	51.4	17.2
CLIP-L/14@224px	23.8	40.9	18.8	59.6	13.0	6.2	9.6	7.8	4.8	4.7	6.6	56.3	11.1	49.7	14.6
Finetuned Models															
VisualBERT	26.1	40.2	24.0	60.9	16.3	8.2	10.0	7.5	5.1	6.4	10.2	51.1	15.1	49.5	24.4
VL-T5	24.5	37.0	20.6	51.1	16.0	7.3	10.2	5.0	4.0	6.8	7.5	52.5	10.3	48.4	21.6
LLaVA-OneVision-7B	21.7	38.8	18.5	62.6	13.2	4.8	8.4	5.7	3.4	5.7	4.5	48.9	11.4	42.2	17.6
SigLIP2-SO/14@384px	28.2	40.2	22.8	64.7	17.8	8.4	9.7	5.8	4.4	4.7	7.7	62.3	13.2	54.8	26.5
CLIP-L/14@224px	24.6	35.4	22.1	61.5	15.7	8.9	9.9	6.5	5.8	5.8	7.8	53.1	11.2	51.7	18.3
<i>CCUBBERTScore</i>															
W/O RAG	54.7	55.4	55.6	55.6	55.7	54.2	52.5	54.5	55.4	54.1	54.8	53.5	52.7	56.6	56.8
Frozen Models															
SigLIP2-SO/14@384px	54.9	57.2	56.4	57.9	55.2	53.0	55.1	54.8	55.0	52.4	54.0	56.9	52.6	58.7	54.8
CLIP-L/14@224px	54.8	57.6	56.2	57.7	54.8	52.4	54.8	55.1	55.3	52.6	53.7	55.9	52.5	59.4	54.6
Finetuned Models															
VisualBERT	54.8	57.1	56.5	57.6	54.9	52.8	54.6	54.9	54.4	52.1	53.8	55.7	52.8	58.5	56.2
VL-T5	54.2	56.7	56.0	58.1	54.9	52.6	53.9	54.0	54.4	52.0	53.4	54.4	52.1	57.8	55.7
LLaVA-OneVision-7B	54.2	56.6	55.5	58.2	54.5	52.1	53.9	54.2	54.6	51.6	53.3	55.0	51.8	58.3	54.9
SigLIP2-SO/14@384px	55.2	57.4	57.1	57.9	55.7	53.2	54.7	55.2	54.9	52.5	54.2	56.8	52.6	58.7	56.7
CLIP-L/14@224px	55.0	57.0	56.5	58.2	54.8	53.2	54.6	55.3	55.3	52.9	54.2	56.0	52.3	59.3	55.4
<i>CCUBCLIPScore</i>															
W/O RAG	19.1	19.1	18.8	19.6	18.3	18.2	18.4	18.7	19.2	18.4	18.4	20.2	18.5	20.2	18.7
Frozen Models															
SigLIP2-SO/14@384px	19.1	19.3	19.0	19.9	18.9	18.8	19.1	18.8	18.7	18.6	18.5	20.5	18.8	20.0	18.6
CLIP-L/14@224px	19.0	19.2	19.0	20.0	19.0	18.5	19.2	18.8	18.6	18.8	18.4	20.4	18.5	19.6	18.3
Finetuned Models															
VisualBERT	19.1	19.1	18.9	20.2	18.9	18.9	19.1	18.9	18.8	18.5	18.6	20.3	18.7	19.9	18.5
VL-T5	19.1	19.4	19.1	19.9	19.0	18.8	19.0	19.1	18.7	18.5	18.7	20.4	18.7	19.9	18.4
LLaVA-OneVision-7B	19.1	19.3	18.9	20.1	18.9	18.7	19.3	18.9	18.6	18.5	18.6	20.4	18.8	19.7	18.6
SigLIP2-SO/14@384px	19.1	19.2	18.9	20.1	18.8	18.6	19.1	19.0	18.5	18.6	18.5	20.4	18.8	19.8	18.5
CLIP-L/14@224px	19.0	19.2	18.9	20.0	19.1	18.6	19.2	18.9	18.7	18.6	18.4	20.1	18.8	19.7	18.6

noticeable improvements over their original counterparts, indicating the effectiveness of retrieval adaptation. Performance on the cVQA task reveals more nuanced outcomes. While fine-tuned retrievers generally exhibit large performance improvement compared to non-RAG baselines, certain countries, such as Spain and Indonesia, experience exhibit diminishing returns. These discrepancies may stem from the limited presence of culturally representative visual content in the training data. Although targeted image augmentation strategies were employed to alleviate this imbalance, the results suggest that data distribution remains a significant bottleneck. Understanding and addressing

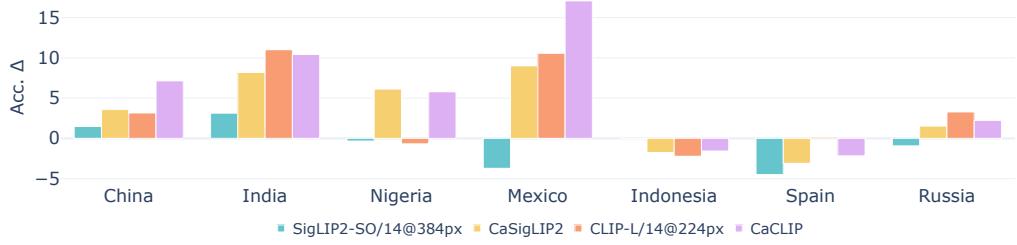


Figure 11: Average improvement across 14 VLMs in different countries with 4 retrievers for cVQA task.

such cross-cultural performance disparities in multimodal tasks like cVQA will be an important direction for future work.

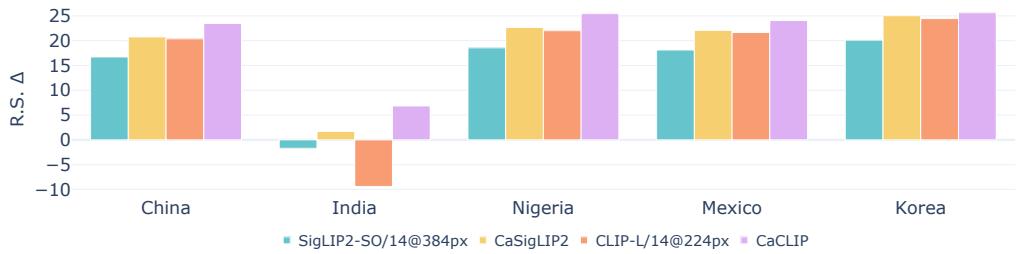


Figure 12: Average improvement across 14 VLMs in different countries with 4 retrievers in cIC task.

K Human Annotation & Evaluation Interface

The annotation interface are shown in Figure 14 and 15. The interface for human evaluation in cIC task is shown in Figure 13.

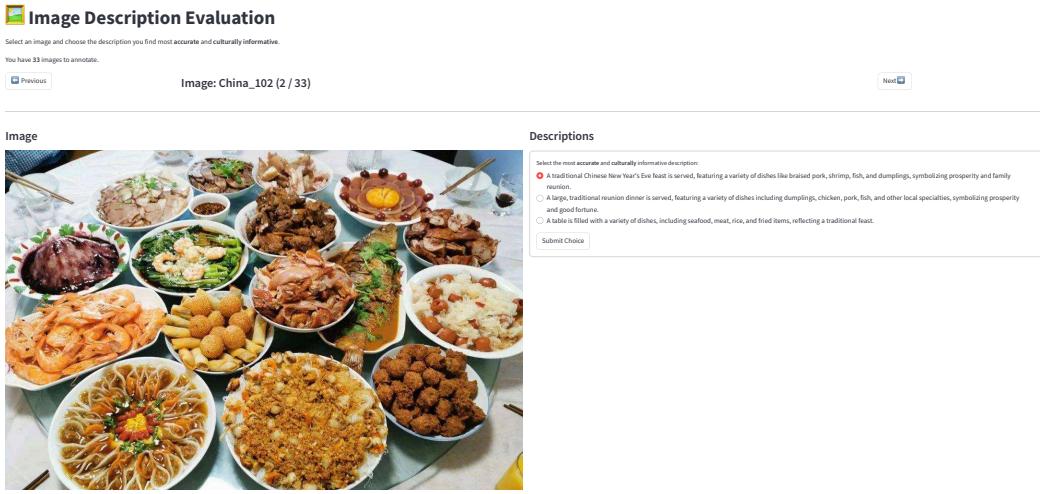


Figure 13: Human evaluation interface for cIC task.

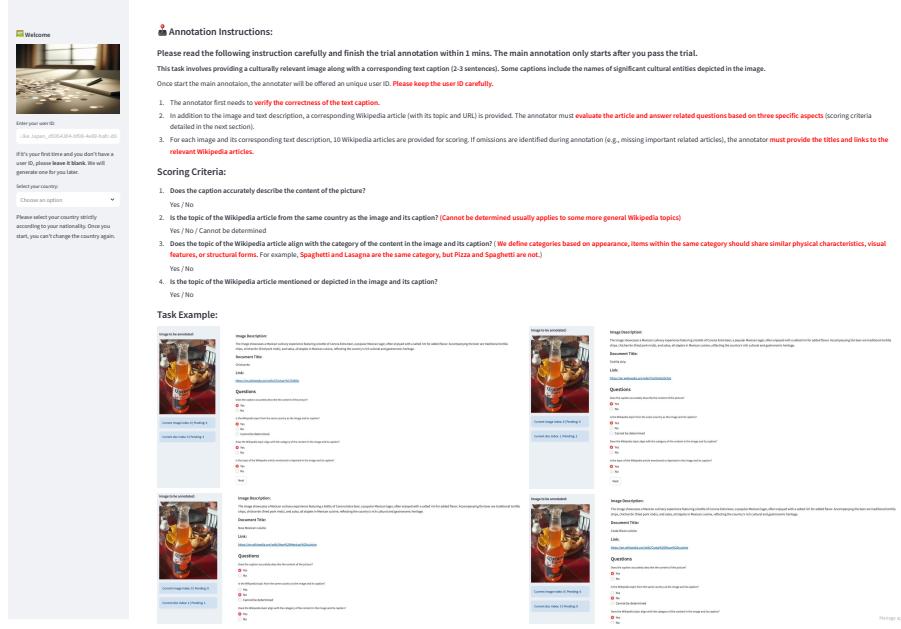


Figure 14: Human annotation instructions.

Image Description:
Sushi, a traditional Japanese delicacy, showcases a harmonious blend of fresh ingredients, meticulous preparation, and cultural artistry. It is a celebrated symbol of Japanese cuisine worldwide.

Image Description Verification
7 Does the description (not Wikipedia document here) accurately describe the content of the picture?
 Yes
 No
 Cannot be determined

Document Title:
Sushi

Link:
<https://en.wikipedia.org/w/index.php?title=Sushi&oldid=981111111>

Questions
7 Is the topic of the Wikipedia article from the same country as the image and its caption?
 Yes
 No
 Cannot be determined
7 Does topic of the Wikipedia article align with the category of the content in the image and its caption?
 Yes
 No
7 Is the topic of the Wikipedia article mentioned or depicted in the image and its caption?
 Yes
 No

(a) Annotation interface (1).

Image Description:
Sushi, a traditional Japanese delicacy, showcases a harmonious blend of fresh ingredients, meticulous preparation, and cultural artistry. It is a celebrated symbol of Japanese cuisine worldwide.

Missing Wiki Documents Form:
Are there any missing wiki documents? If so, please provide the details below. If not, just click the 'Submit' button.
Enter the URL(s), if there are several urls, use commas to split, like url1,url2
 https://en.wikipedia.org/wiki/Sushi
Enter the Title(s), if there are several titles, use commas to split, like Big Ben1, Big Ben2
 Big Ben

(b) Annotation interface (2).

Figure 15: Human annotation interfaces.

L Correlation between Automatic Metrics and Human Judgments

To assess the correlation between human preferences and automatic evaluation metrics, we compute Kendall’s Tau rank correlation. Human annotations are segmented according to the output chunks produced by corresponding 14 VLMs with each retriever variant (CaCLIP-based, CLIP-based, and non-RAG). Within each segment, we calculate the selection winning ratio for each retrieval method, yielding a human preference vector formed by concatenating these ratios across all evaluation instances. For the automatic evaluation, we extract BERTScore, CIDEr, ROUGE-L, and CLIPScore

Table 10: Prompt example for generating captions used to retrieve the Wiki documents.

Prompt for data collection
<p>GPT-4o SYSTEM: Default USER:</p>  <p>Generate a culture related caption given the image with around 2 sentences. Please include the name of the thing shown in the picture within the caption if it's strongly related to the culture. Name the three most culturally relevant entities in the image and attach the name at the end. Follow the format of: caption. entity name1; entity name2; entity name3.</p>

for each corresponding retrieval variant and VLM. These scores are similarly concatenated into a metric-based vector. Finally, we compute Kendall’s Tau between the human and metric vectors to quantify the consistency between automatic rankings and human judgments.

M Prompts

The prompts that we used to collect the documents and two downstream tasks were designed to ensure consistency across different models. One prompt example for cultural caption generation is shown in Table 10. The prompts for both with and without retrieval augmentation for VLMs are shown in Table 12 and 11.

Table 11: **Prompt examples without RAG.** Multimodal prompt samples with interleaved image are shown for both CVQA and CCUB tasks.

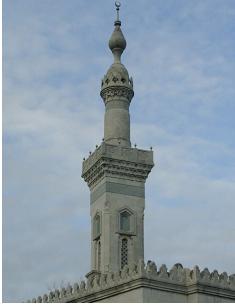
CVQA task	CCUB task
<p>SYSTEM: You are a helpful assistant. USER:</p>  <p>Answer the following multiple choice question. The last line of your response must be of the following format: Answer: \$LETTER (without quotes) where LETTER is one of ABCD.</p> <p>Question: Which city is famous for such artwork?</p> <ul style="list-style-type: none"> A) Zhejiang Yiwu B) Jingdezhen, Jiangxi C) Datong, Shanxi D) Zibo, Shandong 	<p>SYSTEM: You are a helpful assistant. USER:</p>  <p>Write a concise, one-sentence caption for the given image. The generated caption must contain the visual content and culturally relevant elements of the image. Avoid explicit references to the image itself (e.g., "This image shows...", "Pictured here is...", "In this photograph..."). Do not generate multiple options.</p>

Table 12: **Prompt examples with RAG.** Multimodal prompt samples with interleaved image are shown for both CVQA and CCUB tasks.

CVQA task	CCUB task
<p>SYSTEM: You are a helpful assistant. USER:</p>  <p>Answer the following multiple choice question. The last line of your response must be of the following format: Answer: \$LETTER(without quotes) where LETTER is one of ABCD. The scope of the question is strictly limited to the given image. However, please analyze and incorporate information from both the image and the following document to answer the question.</p> <p>Document: Buildings and structures Buildings about 800 - Borobudur temple in Java completed. 802 Haeinsa of Korea, is constructed. Palace of Charlemagne in Aachen, Carolingian Empire completed (begun about 790). The Palatine Chapel still stands. At Oviedo in the Kingdom of Asturias Cámara Santa constructed. First reconstruction of Oviedo Cathedral begun by Tioda. 815 - Second Temple of Somnath built in the Pratihara Empire, India. 816 - Reims Cathedral begun. 810s - Chapel of San Zeno in Santa Prassede, Rome decorated. 818 - Old Cologne Cathedral built....</p> <p>Question: What is the name of the square where the cathedral and the statue of the image are located? A) Riego Square B) Trascorras Square C) The square of Alfonso II the Chaste D) The Fontan square </p>	<p>SYSTEM: You are a helpful assistant. USER:</p>  <p>Write a concise, one-sentence caption for the given image. The generated caption must contain the visual content and culturally relevant elements of the image. Avoid explicit references to the image itself (e.g., "This image shows...", "Pictured here is...", "In this photograph..."). Do not generate multiple options. Please consider the following context: Architecture of Nigeria was historically influenced by environmental conditions as well as social and cultural factors. The coming of missionaries and political changes brought about by colonialism precipitated a change in architectural style and utility of buildings. A Gothic revival style was adopted for early churches built in the colony of Lagos. A one or two storey timber house building made with pre-fabricated material components and designed with the influence of classic antiquity styles served as mission house for the missionaries...</p>