CultureVLM: Characterizing and Improving Cultural Understanding of Vision-Language Models for over 100 Countries

Anonymous CVPR submission

Paper ID 00006

Abstract

Vision-language models (VLMs) have advanced human-AI interaction but struggle with cultural understanding, often misinterpreting symbols, gestures, and artifacts due to biases in predominantly Western-centric training data. In this paper, we construct CultureVerse, a large-scale multimodal benchmark covering 19,682 *cultural concepts,* 188 *countries/regions,* 15 *cultural topics, and* 3 *question types, with the aim of characterizing and improving VLMs' multicultural understanding capabilities. Then, we propose CultureVLM, a series of VLMs fine-tuned on our dataset to achieve significant performance improvement in cultural understanding. Our evaluation of* 16 *models reveals significant disparities, with a stronger performance in Western concepts and weaker results in African and Asian contexts. Fine-tuning on our CultureVerse enhances cultural perception, demonstrating cross-cultural, cross-continent, and cross-dataset generalization without sacrificing performance on models' general VLM benchmarks. We further present insights on cultural generalization and forgetting. We hope that this work could lay the foundation for more equitable and culturally aware multimodal AI systems.*

1. Introduction

Vision-language models (VLMs) have achieved great performance in various tasks, such as visual question answering and captioning [6, 20, 33, 46, 55, 57]. Meanwhile, one of the most vital aspects of human experience, cultural understanding, which encompasses language, cultural values, social norms, culinary practices, and artistic expressions–remains a challenging area for these models [3, 59].

Challenges. Cultural understanding is essential for AI systems intended for global deployment, as it enables them to interact appropriately and sensitively with users of diverse cultural, ethnic, and social backgrounds. However, current VLMs often struggle to grasp the deeper cultural meanings embedded in symbols and artifacts. For instance, a VLM may identify an eagle as merely a bird, overlooking its symbolic significance as a national emblem representing the spirit and identity of the United States. Similarly, the lotus flower is not only a plant, but a profound symbol of purity and spiritual enlightenment in Indian culture. Gestures present an even more complex challenge: the "OK" hand gesture, which conveys a positive meaning in North American countries, is interpreted as offensive in countries such as Brazil and Turkey [35]. Misinterpretations of culturally significant symbols can lead to misunderstandings and even cause offense.

These challenges partially stem from inherent biases and limitations in VLMs' training data: *1) Skewed Domain Coverage.* Pre-training images and texts predominantly feature *generic* daily scenes or natural settings, often lacking coverage of *culturally specific* artifacts, traditions, beliefs, and historical sites. Models may fail to interpret culturally significant symbols, particularly those from underrepresented regions. *2) English-centric Data and Western Bias.* The texts for pre-training VLMs is primarily sourced from English content [21, 39], which predominantly represents high-resource cultures, resulting in a Western Bias [15, 61]. This limits the models' understanding of diverse cultures, especially those in the global south [13].

Addressing these challenges is crucial for developing culturally aware AI systems that can engage effectively and respectfully with global users. Although there have been efforts to build culturally aware LLMs through data collection [13, 27, 52], improving VLMs for cultural understanding remains in its infancy. VLMs require multimodal input–both texts and images–making the collection or generation of culturally rich training data even more challenging, especially for low-resource cultures. From the *benchmarking* perspective, existing datasets for VLMs [41, 50] usually rely on human annotators for data curation. These datasets are limited in scale, often lack sufficient regional and national representation, and may not capture deep cultural relevance. From the *modeling* perspective, there is a lack of work aimed at building culturally aware VLMs, a significant obstacle to AI equity for underrepresented cultures.

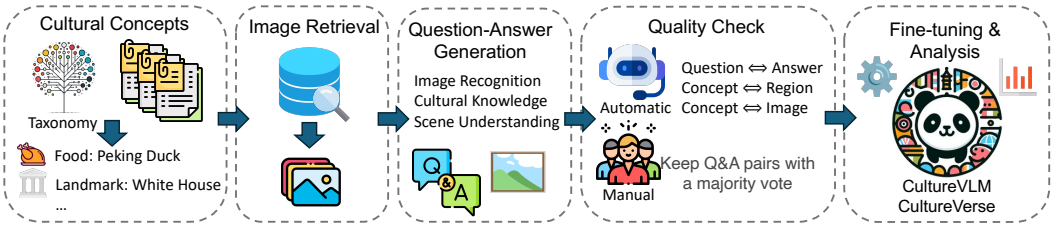


Figure 1. Our pipeline to build CultureVerse and CultureVLM.

This Work. We take the first step toward advancing cultural understanding in VLMs through both comprehensive benchmarking and targeted model improvements. To achieve this, we construct CultureVerse, a large-scale multimodal dataset to evaluate and enhance the multicultural capabilities of VLMs. Our flexible pipeline (Figure 1) can easily integrate additional languages and cultures, ensuring adaptability and inclusiveness. Our work lays a solid foundation for developing more equitable AI systems that address the needs of developing nations, ethnic minorities, and underrepresented cultures. The key findings are as follows.

- **Disparity in Cultural Understanding**: *All* VLMs show highly consistent regional disparities in cultural understanding, with the highest cultural understanding for the Americas, followed by Europe and Oceania, and the weakest understanding for Asia and Africa.
- **Training for Enhanced Cultural Perception**: Fine-tuning effectively enhances the cultural perception of VLMs, narrowing the gaps in cultural understanding across different regions and categories without significantly compromising the model's general capabilities.
- **Model and Data Scale Enhance Cultural Understanding**: Cultural understanding is generally positively correlated with model size, though not absolutely, as demonstrated by the Llama 3.2-11B model achieving performance comparable to that of Qwen 2-72B. Regarding fine-tuning, larger training datasets lead to more significant improvements, but gains slow as data grows.
- **Generalization across Cultures, Concepts, Continent, and Datasets**: Due to the inherent correlations between cultures of different regions and types, fine-tuning for cultural understanding exhibits reasonable generalization across different cultures, concepts, continents, and even datasets, showing great potential to improve cultural understanding via generalization research.

Contributions. Our contributions are as follows:

- **Large-scale Dataset.** We present CultureVerse, a massive scale benchmark consisting of $19,682$ cultural concepts and $228,053$ samples, covering 3 tasks, 188 countries or regions, and 15 cultural topics. The test set includes $11,085$ widely recognized concepts and their corresponding $31,382$ samples.
- **Comprehensive Evaluation.** We evaluate a wide range of cultural concepts across 16 open-source and proprietary models of varying scales.
- **Improvement of Multimodal Cultural Understanding.** We present CultureVLM, which includes a flexible and cost-effective data collection and construction process and a series of VLMs fine-tuned on our dataset. Experimental results demonstrate that our models enhance cultural understanding while maintaining general capabilities and exhibiting a degree of generalization abilities.

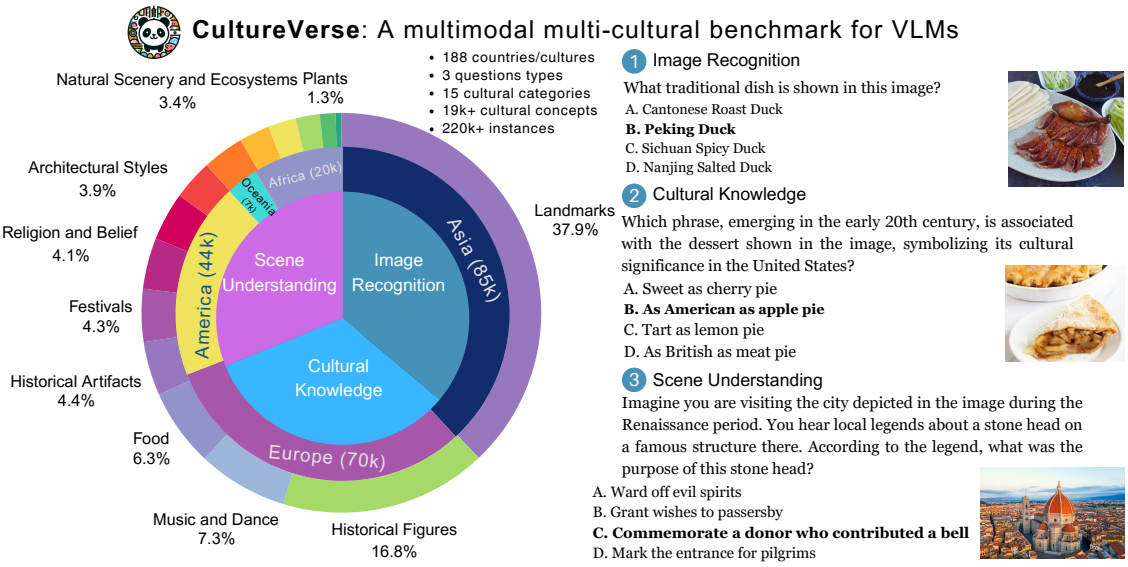
2. CultureVerse: A Scalable Benchmark for VLM Cultural Understanding

Collecting reliable large-scale culture datasets presents two key challenges: *Diversity* and *Scalability*. Achieving comprehensive coverage is especially difficult for *culturally diverse* topics, particularly for underrepresented groups in the Global South. The construction and annotation of such datasets would typically require substantial human expertise from various countries and ethnic groups, resulting in poor scalability and high costs. Existing cultural benchmarks for VLMs usually lack adequate representation of diverse regions and communities, and often reflect a bias towards dominant cultures [31, 44, 50].

To overcome these limitations, we introduce a scalable data collection pipeline that integrates automated web crawling for *scalability* and *diversity* with expert human annotation for *reliability*. As shown in Figure 1, our pipeline consists of three stages: tangible cultural concept collection (2.1), question-answer generation (2.2), and quality assurance (B.1). This hybrid approach ensures that our dataset captures a wide spectrum of cultural contexts while maintaining high standards of data quality and relevance. At the same time, this pipeline is more scalable (B.2) compared to existing methods, regardless of concepts, language, country, region, or image. More details and analyses are in B.3.

2.1. Tangible Cultural Concept Collection

To construct a comprehensive set of cultural concepts, a common approach is to employ a bottom-up strategy that retrieves specialized knowledge from open web documents. For example, Fung et al. [16] begin with an initial set of cultural topics (e.g., education, marriage customs, and



(a) The Distribution of Cultural Concepts in CultureVerse **(b) Examples of Different Types of Questions**

Figure 2. Overview of CultureVerse. In total, there are over 220k instances and 19k cultural concepts for training and evaluation, respectively, composed of 3 different types of questions from 188 countries.

holiday traditions), collect relevant Wikipedia documents, and expand their scope through linked connections. However, many resulting documents primarily describe general, abstract, or high-level concepts, such as `Renaissance Art` or `Mediterranean cuisine`, which often lack specific, unambiguous visual representations.

Concept Construction. To overcome this issue, we adopt a top-down approach, starting with 15 predefined cultural categories of tangible cultural concepts such as food, festivals, landmarks, and performing arts, as shown in Table 2. These categories are chosen to capture culturally distinctive and visually recognizable elements suitable for image retrieval and analysis. We then use GPT-4o to process all relevant Wikipedia documents, extracting conceptual entities that align with the 15 predefined categories. To ensure the quality and specificity of the extracted entities, we implement a 3-step filtering process on the extracted conceptual entities: 1) *Entity Consolidation.* We unified duplicate entities, merging those that are identical or differ solely by case, and eliminated entities with formatting issues or irregularities; 2) *Frequency-based Thresholding.* We retained only entities that appeared at least twice across the documents from a given country, ensuring that the concepts are well-recognized within their cultural context; 3) *Entity Refinement.* We filtered out overly abstract or generic entities such as `Imperial Cuisine` and those lacking distinct regional specificity such as `Steak` using additional judgment by GPT-4o. Through this refined process, we curated a collection of over $19,682$ cultural concepts from 188 countries, as shown in Table 10. Our pipeline ensures that the selected concepts are diverse and recognizable, relevant for evaluating VLMs in understanding global cultural diversity.

Image Retrieval. Using these concepts and their corresponding countries, we scrape images from Google Images for each cultural concept[1], obtaining five images for each concept. The first image was reserved for the test set and for human quality assessment, while the remaining four images were used for the training set. Images larger than 10MB were compressed to ensure compatibility with typical input requirements of VLMs.

2.2. Question-Answer Generation

We designed three levels of VQA tasks to assess and improve the multicultural knowledge of VLMs:

Image Recognition Questions evaluate models' ability to identify cultural concepts in images. Accurate identification of such concepts is fundamental to retrieving relevant cultural knowledge. Given an image and a cultural concept, models answer questions like "What dish is in the image?"

Cultural Knowledge Questions further evaluate model's deeper understanding of the cultural background associated with the concepts. For each concept, we generated comprehensive descriptions, including aspects like location, characteristics, history, and cultural significance. Subsequently, we instruct GPT-4o to formulate a question based on the introduction and the image to probe this cultural knowledge without directly naming the concept in the question. These questions require the model to identify cultural concepts and apply various levels of reasoning, drawing on relevant cultural knowledge to provide accurate answers.

[1] All images are only used for research purpose.

Scene Understanding Questions are designed to assess the model's ability to interpret, interact, and respond within culturally specific contexts, rather than simply recalling factual information as in the previous two categories. We curate scenarios with cultural elements or characteristics depicted in the images, providing context cues that challenge the VLMs to make contextually appropriate choices. Using the detailed introductions of the previous steps, we prompt GPT-4o to generate scenario-based understanding questions. These questions require the model to not only recognize cultural concepts but also apply contextual reasoning based on the associated cultural knowledge.

3. Experiments

3.1. Main Results on CultureVerse

We evaluate our benchmark on 14 open-source and 2 proprietary VLMs. The experimental setup is in C. As shown in Figure 3, our main findings are as follows:

- **Task Characteristics**: Cultural Scene Understanding Outperforms Recognition. (D.1)
- **Regional Disparities**: Better Performance in Western Cultures. (D.2)
- **Category Characteristics**: Weak Understanding of History and Landmarks. (D.3)
- **Performance Variability from Model Level**: Although larger models tend to demonstrate better performance, size alone is not the determining factor. (D.4)
- **Direct Answer v.s. Stepwise Reasoning**: Stepwise reasoning does not improve cultural recognition and, in most cases, significantly impairs performance. (D.5)

More detailed results are in Appendix D.

3.2. Training CultureVLM

We fine-tuned three models: LLaVA-1.5, Phi-3-Vision, and LLaMa-3.2-Vision, with the results presented in Figure 4b. Cultural knowledge, in contrast to reasoning tasks such as mathematics and coding, is relatively easier to enhance as a form of memory-based perception. Consequently, all four models achieved consistent and substantial improvements, reaching performance levels comparable to those of closed-source models. We also performed ablation studies to analyze the impact of fine-tuning data size (E.1) and decoding temperatures (E.2).

3.3. Generalization and Robustness

To evaluate the generalizability of VLMs in multicultural contexts, we partitioned the training data by continents (Americas, Asia, Europe, Africa, Oceania) and fine-tuned LLaVA-1.5-7B [33] separately on each subset. Table 5 in the appendix illustrates the performance of each model trained on specific continental data and tested in all regions, and Figure 6 shows the aggregated results.

Intra- and Inter-continent Generalization. The diagonal values represent cases where the model was trained and evaluated on data from the same continent, consistently yielding the highest scores. Notably, Asia achieved the best performance (90.8), followed closely by Europe and the Americas (90.5), indicating strong regional specialization. Furthermore, the off-diagonal values reveal models' ability to generalize across regions. Although cross-region scores are generally lower, the model still exhibits reasonable transferability. Fine-tuning on Oceania, however, resulted in the lowest average performance drop, from 85.2 to 75.0, suggesting a distinct data distribution for this region.

Robustness across Concepts. We grouped the 15 concepts into 3 main classes: *Cultural Heritage and Traditions* (CHT), *History and Landmarks* (HL), and *Natural Environment and Local Resources* (NELR) using GPT-4o. We then conducted training in each group and evaluated on all groups. The specific category mappings are in Appendix B. As shown in Figure 6 (right), models generally perform the best when trained and evaluated within the same category (in-distribution). The model fine-tuned on HL exhibits greater generalization, achieving an average performance of 87.8, compared to NELR (84.3). High off-diagonal scores, such as CultureVLM-HL's 87.2 when tested on CHT, indicate substantial cross-category knowledge transfer, particularly between culturally related classes.

Cross-dataset Generalization. We also evaluated the generalization ability of CultureVLM for cultural reasoning on other datasets. As shown in Figure 8, we tested LLaVA-1.5-7B on CVQA [50] before and after fine-tuning. It is evident that our CultureVLM achieves improvements across most countries and cultures (7% improvement on average), which can be attributed to the comprehensive coverage of our dataset across global nations and cultures, indicating the potential of CultureVerse for cultural research.

Catastrophic Forgetting. Through evaluations on the common VQA benchmarks, we have also found that our method possesses a strong ability to resist catastrophic forgetting. This further demonstrates the strong robustness of our CultureVLM series of models. More details are in E.3.

4. Conclusion

We constructed CultureVerse, a comprehensive multimodal benchmark to characterize the multicultural understanding of VLMs. Extensive evaluation shows significant performance disparities across regions and tasks, highlighting VLMs' strong biases towards Western cultural contexts and their weaker performance in underrepresented regions like Africa and Asia. Using supervised fine-tuning in CultureVerse, we demonstrated effective enhancements in cultural perception and cross-cultural generalization. Our findings underscore the importance of culturally diverse training data and provide actionable insights to improve VLMs.

References

[1] Mohammad Amin Abbasi, Arash Ghafouri, Mahdi Firouzmandi, Hassan Naderi, and Behrouz Minaei Bidgoli. Persianllama: Towards building first persian large language model. *arXiv:2312.15713*, 2023. 9

[2] Marah Abdin, Sam Ade Jacobs, Ammar Ahmad Awan, Jyoti Aneja, Ahmed Awadallah, Hany Awadalla, Nguyen Bach, Amit Bahree, Arash Bakhtiari, Harkirat Behl, et al. Phi-3 technical report: A highly capable language model locally on your phone. *arXiv:2404.14219*, 2024. 10

[3] Muhammad Farid Adilazuarda, Sagnik Mukherjee, Pradhyumna Lavania, Siddhant Singh, Ashutosh Dwivedi, Alham Fikri Aji, Jacki O'Neill, Ashutosh Modi, and Monojit Choudhury. Towards measuring and modeling" culture" in llms: A survey. *arXiv:2403.15412*, 2024. 1

[4] Vibhor Agarwal, Yiqiao Jin, Mohit Chandra, Munmun De Choudhury, Srijan Kumar, and Nishanth Sastry. Medhalu: Hallucinations in responses to healthcare queries by large language models. *arXiv:2409.19492*, 2024. 13

[5] Pravesh Agrawal, Szymon Antoniak, Emma Bou Hanna, Baptiste Bout, Devendra Chaplot, Jessica Chudnovsky, Diogo Costa, Baudouin De Monicault, Saurabh Garg, Theophile Gervet, et al. Pixtral 12b. *arXiv:2410.07073*, 2024. 10

[6] Anthropic. Claude 3.5 sonnet, 2024. 1

[7] Arjun Appadurai. Modernity at large: Cultural dimensions of globalization. *U of Minnesota P*, 1996. 17

[8] Zechen Bai, Pichao Wang, Tianjun Xiao, Tong He, Zongbo Han, Zheng Zhang, and Mike Zheng Shou. Hallucination of multimodal large language models: A survey. *arXiv:2404.18930*, 2024. 13

[9] Mehar Bhatia, Sahithya Ravi, Aditya Chinchure, Eunjeong Hwang, and Vered Shwartz. From local concepts to universals: Evaluating the multicultural understanding of vision-language models. *arXiv:2407.00263*, 2024. 9, 10

[10] Y Cao, L Zhou, S Lee, L Cabello, M Chen, and D Hershcovich. Assessing cross-cultural alignment between chatgpt and human societies: An empirical study. arxiv. *Preprint posted online on March*, 31, 2023. 8

[11] Alex J Chan, José Luis Redondo García, Fabrizio Silvestri, Colm O'Donnel, and Konstantina Palla. Harmonizing global voices: Culturally-aware models for enhanced content moderation. *arXiv:2312.02401*, 2023. 9

[12] Zhe Chen, Jiannan Wu, Wenhai Wang, Weijie Su, Guo Chen, Sen Xing, Muyan Zhong, Qinglong Zhang, Xizhou Zhu, Lewei Lu, Bin Li, Ping Luo, Tong Lu, Yu Qiao, and Jifeng Dai. Internvl: Scaling up vision foundation models and aligning for generic visual-linguistic tasks. *arXiv:2312.14238*, 2023. 10

[13] Yu Ying Chiu, Liwei Jiang, Bill Yuchen Lin, Chan Young Park, Shuyue Stella Li, Sahithya Ravi, Mehar Bhatia, Maria Antoniak, Yulia Tsvetkov, Vered Shwartz, et al. Culturalbench: a robust, diverse and challenging benchmark on measuring the (lack of) cultural knowledge of llms. *arXiv:2410.02677*, 2024. 1, 10

[14] LMDeploy Contributors. Lmdeploy: A toolkit for compressing, deploying, and serving llm. https://github.com/InternLM/lmdeploy, 2023. 10

[15] Chengyuan Deng, Yiqun Duan, Xin Jin, Heng Chang, Yijun Tian, Han Liu, Henry Peng Zou, Yiqiao Jin, Yijia Xiao, Yichen Wang, et al. Deconstructing the ethics of large language models from long-standing issues to new-emerging dilemmas. *arXiv:2406.05392*, 2024. 1

[16] Yi Fung, Ruining Zhao, Jae Doo, Chenkai Sun, and Heng Ji. Massively multi-cultural knowledge acquisition & lm benchmarking. *arXiv:2402.09369*, 2024. 2, 8

[17] Yi R Fung, Tuhin Chakraborty, Hao Guo, Owen Rambow, Smaranda Muresan, and Heng Ji. Normsage: Multi-lingual multi-cultural norm discovery from conversations on-the-fly. *arXiv:2210.08604*, 2022. 8

[18] Michael Minkov Geert Hofstede, Gert Jan Hofstede. *Cultures and Organizations: Software of the Mind, Third Edition*. McGraw Hill Professional, https://books.google.co.uk/books?id=7bYWmwEACAAJ, 2010. 8

[19] Team GLM, Aohan Zeng, Bin Xu, Bowen Wang, Chenhui Zhang, Da Yin, Diego Rojas, Guanyu Feng, Hanlin Zhao, Hanyu Lai, Hao Yu, Hongning Wang, Jiadai Sun, Jiajie Zhang, Jiale Cheng, Jiayi Gui, Jie Tang, Jing Zhang, Juanzi Li, Lei Zhao, Lindong Wu, Lucen Zhong, Mingdao Liu, Minlie Huang, Peng Zhang, Qinkai Zheng, Rui Lu, Shuaiqi Duan, Shudan Zhang, Shulin Cao, Shuxun Yang, Weng Lam Tam, Wenyi Zhao, Xiao Liu, Xiao Xia, Xiaohan Zhang, Xiaotao Gu, Xin Lv, Xinghan Liu, Xinyi Liu, Xinyue Yang, Xixuan Song, Xunkai Zhang, Yifan An, Yifan Xu, Yilin Niu, Yuantao Yang, Yueyan Li, Yushi Bai, Yuxiao Dong, Zehan Qi, Zhaoyu Wang, Zhen Yang, Zhengxiao Du, Zhenyu Hou, and Zihan Wang. Chatglm: A family of large language models from glm-130b to glm-4 all tools, 2024. 10

[20] Aaron Hurst, Adam Lerer, Adam P Goucher, Adam Perelman, Aditya Ramesh, Aidan Clark, AJ Ostrow, Akila Welihinda, Alan Hayes, Alec Radford, et al. Gpt-4o system card. *arXiv:2410.21276*, 2024. 1

[21] Yiqiao Jin, Mohit Chandra, Gaurav Verma, Yibo Hu, Munmun De Choudhury, and Srijan Kumar. Better to ask in english: Cross-lingual evaluation of large language models for healthcare queries. In *Web Conference*, pages 2627–2638, 2024. 1

[22] Yiqiao Jin, Minje Choi, Gaurav Verma, Jindong Wang, and Srijan Kumar. Mm-soc: Benchmarking multimodal large language models in social media platforms. In *ACL*, 2024. 10

[23] Rebecca L Johnson, Giada Pistilli, Natalia Menédez-González, Leslye Denisse Dias Duran, Enrico Panai, Julija Kalpokiene, and Donald Jay Bertulfo. The ghost in the machine has an american accent: value conflict in gpt-3. *arXiv:2203.07785*, 2022. 8

[24] James Kirkpatrick, Razvan Pascanu, Neil Rabinowitz, Joel Veness, Guillaume Desjardins, Andrei A Rusu, Kieran Milan, John Quan, Tiago Ramalho, Agnieszka Grabska-Barwinska, et al. Overcoming catastrophic forgetting in neural networks. *PNAS*, 114(13):3521–3526, 2017. 14

[25] Woosuk Kwon, Zhuohan Li, Siyuan Zhuang, Ying Sheng, Lianmin Zheng, Cody Hao Yu, Joseph E. Gonzalez, Hao

Zhang, and Ion Stoica. Efficient memory management for large language model serving with pagedattention. In *SIGOPS*, 2023. 11

[26] Bo Li, Yuanhan Zhang, Dong Guo, Renrui Zhang, Feng Li, Hao Zhang, Kaichen Zhang, Peiyuan Zhang, Yanwei Li, Ziwei Liu, et al. Llava-onevision: Easy visual task transfer. *arXiv:2408.03326*, 2024. 10

[27] Cheng Li, Mengzhou Chen, Jindong Wang, Sunayana Sitaram, and Xing Xie. Culturellm: Incorporating cultural differences into large language models. In *NeurIPS*, 2024. 1, 8, 9, 17

[28] Cheng Li, Damien Teney, Linyi Yang, Qingsong Wen, Xing Xie, and Jindong Wang. Culturepark: Boosting cross-cultural understanding in large language models. In *NeurIPS*, 2024. 8, 9

[29] Yen-Ting Lin and Yun-Nung Chen. Taiwan llm: Bridging the linguistic divide with a culturally aligned language model. *arXiv:2311.17487*, 2023. 9

[30] Chen Cecilia Liu, Fajri Koto, Timothy Baldwin, and Iryna Gurevych. Are multilingual llms culturally-diverse reasoners? an investigation into multicultural proverbs and sayings. *arXiv:2309.08591*, 2023. 8

[31] Fangyu Liu, Emanuele Bugliarello, Edoardo Maria Ponti, Siva Reddy, Nigel Collier, and Desmond Elliott. Visually grounded reasoning across languages and cultures. *arXiv:2109.13238*, 2021. 2, 9

[32] Haotian Liu, Chunyuan Li, Yuheng Li, and Yong Jae Lee. Improved baselines with visual instruction tuning. In *CVPR*, pages 26296–26306, 2024. 10

[33] Haotian Liu, Chunyuan Li, Qingyang Wu, and Yong Jae Lee. Visual instruction tuning. *NeurIPS*, 36, 2024. 1, 4, 10

[34] Reem I Masoud, Ziquan Liu, Martin Ferianc, Philip Treleaven, and Miguel Rodrigues. Cultural alignment in large language models: An explanatory analysis based on hofstede's cultural dimensions. *arXiv:2309.12342*, 2023. 8

[35] Noha Medhat. 8 normal signs and gestures that can be offensive in the middle east. *StepFeed*, 2015. Retrieved 25 February 2019. 1

[36] Meta. Llama 3.2. *https://ai.meta.com/blog/llama-3-2-connect-2024-vision-edge-mobile-devices*, 2024. 10

[37] Cas Mudde. The 2012 stein rokkan lecture: Three decades of popu list radical right parties in western europe: so what? In *The Populist Radical Right*, pages 545–558. Routledge, 2016. 8

[38] Junho Myung, Nayeon Lee, Yi Zhou, Jiho Jin, Rifki Afina Putri, Dimosthenis Antypas, Hsuvas Borkakoty, Eunsu Kim, Carla Perez-Almendros, Abinew Ali Ayele, et al. Blend: A benchmark for llms on everyday knowledge in diverse cultures and languages. *arXiv:2406.09948*, 2024. 17

[39] Tarek Naous, Michael J Ryan, Anton Lavrouk, Mohit Chandra, and Wei Xu. Readme++: Benchmarking multilingual language models for multi-domain readability assessment. In *EMNLP*, 2023. 1

[40] Tarek Naous, Michael J Ryan, and Wei Xu. Having beer after prayer? measuring cultural bias in large language models. *arXiv:2305.14456*, 2023. 8

[41] Shravan Nayak, Kanishk Jain, Rabiul Awal, Siva Reddy, Sjoerd van Steenkiste, Lisa Anne Hendricks, Karolina Stańczak, and Aishwarya Agrawal. Benchmarking vision language models for cultural understanding. *arXiv:2407.10920*, 2024. 1, 9

[42] Tuan-Phong Nguyen, Simon Razniewski, Aparna Varde, and Gerhard Weikum. Extracting cultural commonsense knowledge at scale. In *Web Conference*, pages 1907–1917, 2023. 8

[43] Xuan-Phi Nguyen, Wenxuan Zhang, Xin Li, Mahani Aljunied, Qingyu Tan, Liying Cheng, Guanzheng Chen, Yue Deng, Sen Yang, Chaoqun Liu, et al. Seallms–large language models for southeast asia. *arXiv:2312.00738*, 2023. 9

[44] Sejoon Oh, Yiqiao Jin, Megha Sharma, Donghyun Kim, Eric Ma, Gaurav Verma, and Srijan Kumar. Uniguard: Towards universal safety guardrails for jailbreak attacks on multimodal large language models. *arXiv preprint arXiv:2411.01703*, 2024. 2

[45] OpenAI. Gpt-4o, 2024. 10

[46] OpenAI. Gpt-4v, 2024. 1

[47] Kunat Pipatanakul, Phatrasek Jirabovonvisut, Potsawee Manakul, Sittipong Sripaisarnmongkol, Ruangsak Patomwong, Pathomporn Chokchainant, and Kasima Tharnpipitchai. Typhoon: Thai large language models. *arXiv:2312.13951*, 2023. 9

[48] Ramon Pires, Hugo Abonizio, Thales Sales Almeida, and Rodrigo Nogueira. Sabiá: Portuguese large language models. In *Brazilian Conference on Intelligent Systems*, pages 226–240. Springer, 2023. 9

[49] Abhinav Rao, Akhila Yerukola, Vishwa Shah, Katharina Reinecke, and Maarten Sap. Normad: A benchmark for measuring the cultural adaptability of large language models. *arXiv:2404.12464*, 2024. 8

[50] David Romero, Chenyang Lyu, Haryo Akbarianto Wibowo, Teresa Lynn, Injy Hamed, Aditya Nanda Kishore, Aishik Mandal, Alina Dragonetti, Artem Abzaliev, Atnafu Lambebo Tonja, et al. Cvqa: Culturally-diverse multilingual visual question answering benchmark. *arXiv:2406.05967*, 2024. 1, 2, 4, 9, 10, 16

[51] Tanik Saikh, Tirthankar Ghosal, Amish Mittal, Asif Ekbal, and Pushpak Bhattacharyya. Scienceqa: a novel resource for question answering on scholarly articles. *International Journal on Digital Libraries*, 23(3):289–301, 2022. 14

[52] Weiyan Shi, Ryan Li, Yutong Zhang, Caleb Ziems, Raya Horesh, Rogério Abreu de Paula, Diyi Yang, et al. Culturebank: An online community-driven knowledge base towards culturally aware language technologies. *arXiv:2404.15238*, 2024. 1, 8

[53] Amanpreet Singh, Vivek Natarajan, Meet Shah, Yu Jiang, Xinlei Chen, Dhruv Batra, Devi Parikh, and Marcus Rohrbach. Towards vqa models that can read. In *CVPR*, pages 8317–8326, 2019. 14

[54] World Values Survey. World values survey. https://www.worldvaluessurvey.org/wvs.jsp, 2022. 8

[55] Gemini Team, Rohan Anil, Sebastian Borgeaud, Yonghui Wu, Jean-Baptiste Alayrac, Jiahui Yu, Radu Soricut, Johan Schalkwyk, Andrew M Dai, Anja Hauth, et al.

Gemini: a family of highly capable multimodal models. *arXiv:2312.11805*, 2023. 1, 10

[56] SM Tonmoy, SM Zaman, Vinija Jain, Anku Rani, Vipula Rawte, Aman Chadha, and Amitava Das. A comprehensive survey of hallucination mitigation techniques in large language models. *arXiv:2401.01313*, 2024. 13

[57] Peng Wang, Shuai Bai, Sinan Tan, Shijie Wang, Zhihao Fan, Jinze Bai, Keqin Chen, Xuejing Liu, Jialin Wang, Wenbin Ge, et al. Qwen2-vl: Enhancing vision-language model's perception of the world at any resolution. *arXiv:2409.12191*, 2024. 1, 10

[58] Wenxuan Wang, Wenxiang Jiao, Jingyuan Huang, Ruyi Dai, Jen-tse Huang, Zhaopeng Tu, and Michael R Lyu. Not all countries celebrate thanksgiving: On the cultural dominance in large language models. *arXiv:2310.12481*, 2023. 8

[59] Genta Indra Winata, Frederikus Hudi, Patrick Amadeus Irawan, David Anugraha, Rifki Afina Putri, Yutong Wang, Adam Nohejl, Ubaidillah Ariq Prathama, Nedjma Ousidhoum, Afifa Amriani, et al. Worldcuisines: A massive-scale benchmark for multilingual and multicultural visual question answering on global cuisines. *arXiv:2410.12705*, 2024. 1

[60] Yuan Yao, Tianyu Yu, Ao Zhang, Chongyi Wang, Junbo Cui, Hongji Zhu, Tianchi Cai, Haoyu Li, Weilin Zhao, Zhihui He, et al. Minicpm-v: A gpt-4v level mllm on your phone. *arXiv:2408.01800*, 2024. 10

[61] Alex Young. Western theory, global world: Western bias in international theory. *Harvard International Review*, pages 29–31, 2014. 1

[62] Wenlong Zhao, Debanjan Mondal, Niket Tandon, Danica Dillion, Kurt Gray, and Yuling Gu. Worldvaluesbench: A large-scale benchmark dataset for multi-cultural value awareness of language models. *arXiv:2404.16308*, 2024. 8

Appendix
CultureVLM: Characterizing and Improving Cultural Understanding of Vision-Language Models for over 100 Countries

Contents

A Related Work 8

B Details of the CultureVerse Dataset 9
B.1. Quality Assurance . . . 10
B.2. Scalability . . . 10
B.3. Analysis of CultureVerse . . . 10

C Experiment Setup 10

D Detailed Main Results 11
D.1. Task Characteristics: Cultural Awareness Outpaces Image and Detail Recognition . . . 11
D.2. Regional Disparities: Better Performance in Western Cultures . . . 11
D.3. Category Characteristics: Weak Understanding of History and Landmarks . . . 12
D.4. Performance Variability from Model Level . . . 12
D.5. Direct Answer v.s. Stepwise Reasoning . . . 13

E Detailed Fine-tuning Results 13
E.1. Impact of Data Sizes . . . 13
E.2. Impact of Decoding Temperatures . . . 14
E.3. Catastrophic Forgetting . . . 14

F. Details of Human Annotation 15
F.1. Statistics of Human Annotators and the Process . . . 15
F.2. Accuracy of Human Annotation . . . 16

G Limitations 16

H Case Study 17

I. Prompt List 19

A. Related Work

Cultural Bias in LLMs and VLMs. Recent research has increasingly focused on cultural biases present in large language models (LLMs). Johnson et al. [23] investigated conflicts between model outputs and input values and found that GPT-3's responses often aligned more closely with dominant U.S. cultural norms. Similarly, Naous et al. [40] observed a bias toward Western cultural perspectives in models processing Arabic text. The Cultural Alignment Test (CAT), based on Hofstede's cultural dimensions framework [18], was used to evaluate the cultural alignment of models like ChatGPT and Bard across various regions, showing that GPT-4 exhibited the strongest alignment with U.S. values [34]. Additionally, Cao et al. [10] found that, while ChatGPT was well-aligned with American cultural values, it struggled to represent other cultures accurately, especially when responding to English prompts. Liu et al. [30] further reported that multilingual LLMs showed limited proficiency in reasoning with proverbs and revealed a "culture gap" in translation tasks.

Datasets and Models for Cultural Understanding. Most of the research used existing datasets as cultural datasets. Wang et al. [58] introduced a benchmark based on the World Values Survey (WVS) [54] and the Political Culture and Trust (PCT) dataset [37]. Subsequent works include the Cultural Alignment Test [34], NORMSAGE [17], WorldValueBench [62], and NORMAD [49], each drawing on various existing datasets. Other sources include CultureAtlas [16] and MAPS [30], which collected data from Wikimedia, while Candle [42] and CultureBank [52] gathered data from social media platforms, including TikTok and Reddit. In contrast, there is a growing trend toward automatic data augmentation such as [27, 28]. A strand of

Dataset	Country	Concept	Image	Question	Multi.
MaRVL [31]	5	454	4,914	5,670	✗
CVQA [50]	28	-	4,560	9,044	✗
CulturalVQA [41]	11	-	2,328	2,328	✗
GlobalRG [9]	50/15	-	3,591	-	✓
CultureVerse	188	11,085	11,085	31,382	✓
w/ Train Set	188	19,682	74,959	196,673	✓

Table 1. Comparison of various cultural datasets with features. 'Multi.' indicates whether the dataset provides multi-faceted questions rather than just one single type.

research focuses on training cultural-specific LLMs by assembling large-scale pre-training datasets, followed by fine-tuning to enhance alignment [1, 11, 29, 43, 47, 48]. Instead of relying on massive data collection, Li et al. [27, 28] proposed cost-efficient approaches to fine-tuning cultural-specific models by data augmentation.

Unlike LLMs, training data are significantly more difficult to obtain for VLMs. The research in VLMs' cultural bias is still preliminary, with most efforts in *manual* data collection [9, 31, 41, 50]. MaRVL [31] introduced a protocol for building an ImageNet-style hierarchy that represents a wider range of languages and cultures. CVQA [50] proposed a culturally diverse multilingual visual question-answering benchmark designed to encompass a wide variety of languages and cultural contexts, engaging native speakers and cultural experts in the data collection process. CulturalVQA [41] developed a visual question-answering benchmark focused on evaluating VLMs ' understanding of culturally diverse, geographically specific content. GlobalRG [9] presents two challenging tasks: retrieval across cultural universals and culturally specific visual grounding.

However, these datasets are often limited in size, lack sufficient regional and national representation. More critically, at the model level, there has been no significant effort to develop culturally aware VLMs, posing a major barrier to AI equity for underrepresented cultures. By systematically constructing datasets and models through *tangible concepts*, we achieve both *reduced manual effort* and ensured *scalability*. Table 1 shows the key difference between our benchmark and existing multimodal cultural datasets.

B. Details of the CultureVerse Dataset

Table 2 shows the definition of cultural concepts in our dataset. Table 10 shows the number of concepts in different countries from the evaluation set. In total, we have $11,085$ evaluation samples and $19,682$ training samples from 188 countries/regions.

Overall Category	**Category**	**Example Description**
Cultural Heritage and Traditions	Festivals	Unique festival celebration scenes
	Traditional Clothing	Ethnic clothing, festival attire
	Handicrafts and Artifacts	Ethnic handicrafts, traditional handmade items
	Music and Dance	Traditional musical instruments, dance scenes
	Religion and Belief	Temples and churches, religious ceremonies
	Entertainment and Performing Arts	Theater performances, street performers
History and Landmarks	Famous Landmarks	Famous historical sites, buildings
	Historical Artifacts	Museum collections, ancient relics
	Historical Figures	Portraits of historical figures, statues
	Architectural Styles	Traditional architecture, modern landmark buildings
Natural Environment and Local Resources	Food	Local specialty dishes, traditional festival foods
	Plants	Unique flowers, crops in a certain area
	Animals	Unique wild animals, livestock in a certain area
	Natural Scenery and Ecosystems	Unique natural landscapes, ecological reserves
	Markets and Shopping Traditions	Local markets, specialty shops

Table 2. Collected concepts, their overall categories, and descriptions in the dataset.

B.1. Quality Assurance

To ensure the integrity of the dataset, we conduct a comprehensive manual quality check on each cultural concept, along with its corresponding images and questions. Specifically, we employ human annotators (details are shown in Appendix F) to inspect three main components:

- **Image-Concept Alignment.** We assessed whether each cultural concept accurately represents the culture of its respective country or region and is either unique to or widely recognized within that. We started with frequency analysis and leverage GPT-4o for preliminary screening, effectively filtering out less desirable data and significantly reducing the manual review workload.
- **Image Quality Check.** We checked the image quality and ensured that the cultural concept is accurately presented in the image.
- **Question & Answer Validation.** We verified that all three generated questions are reasonable, clear, logically sound, and have a single correct answer. Annotators refined the questions and answer options by removing redundant information and resolving any ambiguities to maintain clarity and accuracy.

Following the quality assurance process, we utilized human annotations for the evaluation set of CultureVerse while applying the automated annotation pipeline to the larger training set. With over 98% of the evaluation set samples correctly annotated by the automated process, we conclude that the pipeline is highly effective. Any remaining erroneous or challenging samples that could not be refined were filtered out to maintain the dataset's high quality. Additional details on annotator accuracy are in Appendix F.2.

B.2. Scalability

Our approach to constructing multimodal cultural datasets is notably more scalable and comprehensive than existing methods. Existing ones mostly rely on manual efforts to search for cultural concepts, retrieve images, and formulate questions, significantly increasing human efforts beyond quality check [13, 22, 50]. This manual process typically results in limited or biased coverage due to the limited scope of cultural concepts explored. For example, some datasets [9] cover only a dozen countries, with approximately 40 cultural concepts for each country.

In contrast, our work is the first to advance the number of specific cultural concepts to the scale of tens of thousands and to extend coverage to approximately two hundred countries/regions, as shown in Table 10. Additionally, our dataset construction process allows for further large-scale expansion, including the retrieval of more images and the synthesis of various types of QAs, such as open-ended QAs, multiple-choice QAs, and reasoning QAs. Our work provides a potential data source for enhancing the multicultural knowledge of VLM models.

B.3. Analysis of CultureVerse

Figure 2(a) illustrates the distribution of three tasks (Section 2.2), 5 continents (188 countries, with North and South America combined into America) and 15 cultural topics in CultureVerse. Since cultural concepts are collected at the country level, regions with more countries, such as Asia and Europe, naturally yield larger datasets. Detailed counts of countries and concepts are provided in the Appendix 10. Detailed statistics of the concepts are provided in Table 1. Compared to recent multi-model culture datasets, CultureVerse is driven by *tangible, presentable cultural concepts*, achieving an order of magnitude increase in the number of regions, images, and questions. This expansion advances multimodal and multicultural research beyond a limited set of countries, moving toward truly global, inclusive cultural integration. Figure 2(b) shows examples of three questions associated with one concept, clearly demonstrating that different question types aim to evaluate different abilities.

C. Experiment Setup

Data Split. To ensure robust evaluation, we partition CultureVerse into training/test sets for all countries/regions, allowing us to assess transferability between regions. We select more common cultural concepts from the entire dataset for the test set, which underwent manual quality checks, while the training set includes all cultural concepts. We ensured that the images in training and test sets did not overlap to prevent data leakage.

Evaluation Models. We conduct evaluations on the following models: (a) open-source models including LLaVA-1.5 [32], LLaVA-1.6-Mistral-7B-Instruct [33], LLaVA-OneVision [26], LLaMA-3.2-Vision [36], Qwen2-VL [57], InternVL-2 [12], Phi-3-Vision [2], MiniCPM-Llama3-V-2.5 [60], GLM-4V [19], Pixtral 12B [5]; (b) proprietary models such as GPT-4o [45], Gemini-1.5-Pro [55].

Evaluation Setup. We report accuracy, in line with previous works [33]. For all multiple-choice questions, we employ greedy search decoding for deterministic predictions. For LLaVA-1.5, LLaMA-3.2-Vision and InternVL-2, we use lmdeploy [14]

for inference acceleration. For other models, we use vllm [25] for the acceleration of inference. For models before and after fine-tuning, we use the same acceleration toolkit to prevent potential impact. The number of questions differs across the three tasks. This is because generating questions for cultural knowledge and scenario reasoning is more complex, and in some cases, GPT-4o refused to provide answers, making it impossible to generate valid questions. For image recognition questions, we directly use the questions and options as prompts. For cultural knowledge and scene understanding questions, we employ stepwise reasoning prompts to facilitate the reasoning explanation. The prompts are available in the Appendix I. For all proprietary models, we utilize the default hyper-parameters, setting the temperature to 0 and the max tokens to 1,024. For all open-source models, do_sample is set to False, max_gen_len is set to 512, and the temperature is set to 0.01.

Training Setup. We use the official train ing scripts of LLaVA[2], Phi[3], and LLaMA[4] for model training, largely adhering to the original hyperparameters, except for appropriately adjusting the batch size to accommodate the GPU memory capacity. For LLaVA-1.5, a learning rate of 2×10^{-5} is used, with no weight decay applied (0.0). The learning rate followed a cosine schedule, gradually increasing during the initial phase with a warmup ratio of 0.03. For Phi-3, we use a learning rate of 4×10^{-5} and a weight decay of 0.01. A linear learning rate scheduler is utilized, with 50 warmup steps to stabilize the early training stage. For LLaMA-3.2, fine-tuning is conducted using a learning rate of 1×10^{-5} with no weight decay (0.0). A multiplicative learning rate decay is applied after each epoch, with a gamma value of 0.85. The batch sizes are set to 64, 16 and 32 respectively. All models are trained for one epoch on the training set and fully fine-tuned on 4×A100 80GB GPUs. For the training data, although we do not conduct large-scale human annotation, we synthesize the data using only concepts that passed either GPT-4o or human quality assurance, significantly improving the accuracy of the dataset. The prompts used for GPT quality check can be found in the Appendix I.

D. Detailed Main Results

Detailed results on different tasks, continents, and cultural categories can be found in Table 3.

D.1. Task Characteristics: Cultural Awareness Outpaces Image and Detail Recognition

From the task perspective, we observe that image recognition and cultural knowledge questions pose challenges comparable for VLMs. *Image recognition* tests VLMs' ability to identify culturally specific objects or concepts, which relies heavily on diverse and relevant image data. For instance, recognizing traditional foods like *kimchi* from Korea, or regional attire such as a *sari* from India, requires the model to have encountered similar image-text pairs in its training data. In contrast, cultural knowledge questions assess the model's understanding of broader cultural elements based on text-based training. For example, asking about the significance of a festival like *Diwali* or the symbolism of a *red envelope* during Lunar New Year taps into the model's text-based memory, which tends to be richer due to the abundance of internet text data. Interestingly, in the *scene understanding* task, which integrates images with contextual background (e.g., a Japanese tea ceremony scene or a Brazilian Carnival parade), VLMs tend to generate culturally appropriate responses, avoiding inappropriate or culturally insensitive outputs. This can be attributed to the model's inherent multicultural awareness and its alignment with ethical and harm-reduction training.

D.2. Regional Disparities: Better Performance in Western Cultures

A dominant *regional disparity* is observed among all models: VLMs demonstrate the strongest cultural understanding of the Americas, followed by Europe and Oceania. This trend reflects the dominance of English data centered around the Global North, leading to a disproportionate focus on Western cultural content. North America's relatively homogenous cultural landscape, combined with fewer countries, contributes to better model performance. In contrast, Asia and Africa show significantly weaker results, likely due to the scarcity of digitized, English-language data and the high cultural diversity in these regions. For instance, Asia consists of many countries with distinct and complex cultural contexts, such as those from East Asia, South Asia, and Southeast Asia, both within and across nations. Although Asia has the most data in CultureVerse (see Figure 2), the models struggle to capture the intra-regional and inter-regional cultural nuances, resulting in suboptimal performance.

[2] https://github.com/haotian-liu/LLaVA.
[3] https://github.com/microsoft/Phi-3CookBook.
[4] https://github.com/meta-llama/llama-recipes/blob/main/recipes/quickstart/finetuning/finetune_vision_model.md.

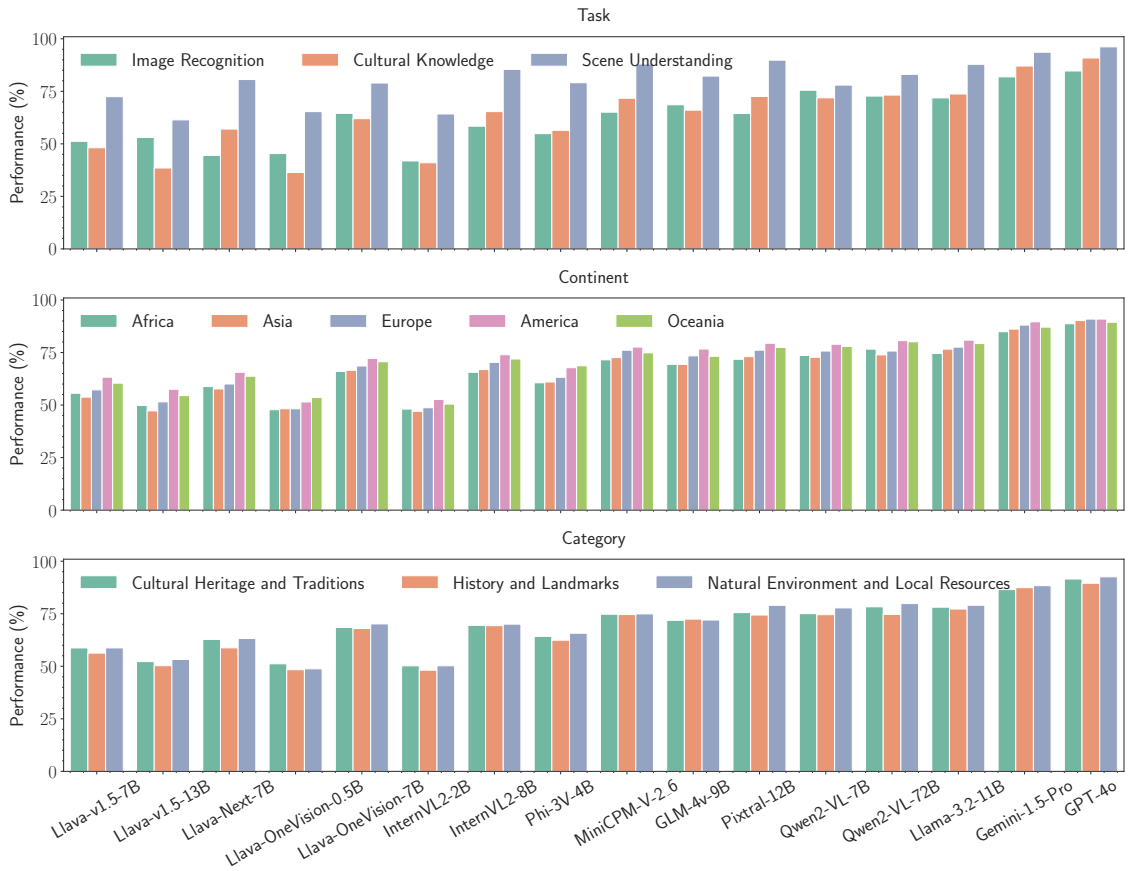
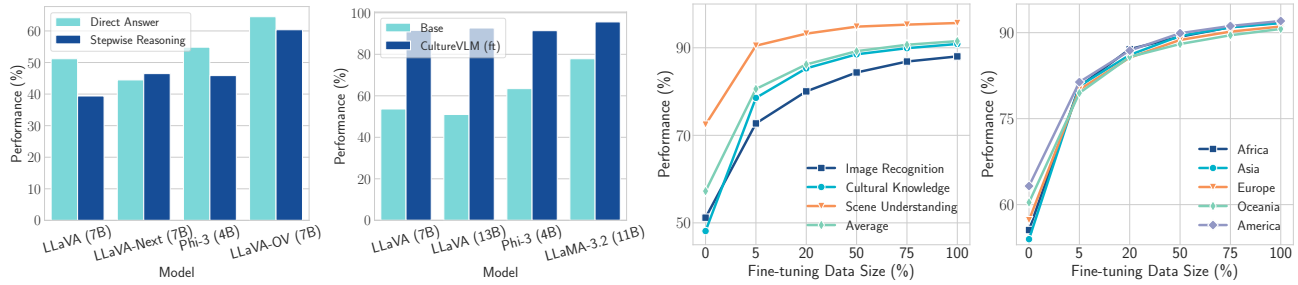


Figure 3. Accuracy of different models on three tasks (upper), five regions (middle), and three categories of concepts (lower).



(a) Direct v.s. reasoning (b) Fine-tuning results (c) Cultural concepts (d) Continents

Figure 4. Results and analysis of CultureVLM by fine-tuning on our CultureVerse.

D.3. Category Characteristics: Weak Understanding of History and Landmarks

VLMs generally exhibit weaker recognition and understanding of cultural concepts related to history and landmarks. The primary reason is the relatively limited internet data available on historical figures and landmarks. Additionally, recognizing a landmark typically requires training data that includes images from multiple perspectives to form a comprehensive, three-dimensional understanding.

D.4. Performance Variability from Model Level

Proprietary models continue to outperform open-source counterparts, with GPT-4o achieving the best results. Although larger models tend to demonstrate better performance, size alone is not the determining factor. For example, the size variations of LLaVA-1.5 and Qwen2-VL show similar performance. Cultural knowledge often resides in model's memory, an aspect overlooked in VLMs development. Thus, smaller models (e.g. Phi-3-Vision) with comparable training data can already

exhibit strong cultural understanding when using similar training data as larger models.

D.5. Direct Answer v.s. Stepwise Reasoning

For image recognition tasks, we compare two prompt methods: 1) the model directly identifies and outputs the cultural concept, and 2) first provides a detailed description of the image and then analyzes and compares the options to reach a final answer. As shown in Figure 4a, we find that stepwise reasoning does not improve cultural recognition and, in most cases, significantly *impair* performance. Upon analyzing the answers, we observe that VLMs frequently exhibit hallucinations [4, 8, 56] during step-by-step explanations, as shown in the example in Figure 9. This poor robustness suggests that while VLMs may have encountered similar images during training and associated them with certain concepts, they may lack a deeper understanding of the details and components that make up those concepts.

Model	Task			Continent					Category		
	Image Recognition	Cultural Knowledge	Scene Reasoning	Africa	Asia	Europe	America	Oceania	CHT	HL	NELR
Open-Source Models											
LLaVA-v1.5 7B	51.19	48.13	72.44	55.62	53.78	57.24	63.27	60.41	58.73	56.27	58.75
LLaVA-v1.5 13B	53.05	38.51	61.40	49.83	47.23	51.52	57.53	54.51	52.21	50.28	53.24
LLaVA-NeXT-v1.6 7B	44.48	57.03	80.61	58.80	57.67	60.03	65.61	63.72	62.78	58.77	63.22
LLaVA-OneVision 0.5B	45.38	36.40	65.33	47.80	48.24	48.23	51.48	53.59	51.19	48.38	48.79
LLaVA-OneVision 7B	64.50	61.98	78.94	66.00	66.53	68.59	72.20	70.63	68.50	67.98	70.17
InternVL2 2B	41.86	40.99	64.22	48.10	47.01	48.73	52.67	50.46	50.22	48.15	50.24
InternVL2 8B	58.40	65.34	85.43	65.58	66.89	70.32	73.94	71.92	69.47	69.34	70.05
Phi-3-vision 4B	54.85	56.43	79.09	60.60	60.99	63.21	67.78	68.69	64.22	62.40	65.73
MiniCPM-V-2_6 8B	65.07	71.69	88.00	71.52	72.59	76.10	77.60	74.86	74.77	74.62	74.93
GLM-4V 9B	68.59	66.03	82.25	69.38	69.34	73.41	76.67	73.20	71.86	72.45	72.02
Pixtral 12B	64.43	72.56	89.82	71.79	73.04	76.12	79.41	77.44	75.56	74.39	79.02
Qwen2-VL 7B	75.51	71.90	77.96	73.59	72.73	75.71	78.93	77.90	75.05	74.57	77.78
Qwen2-VL 72B	72.73	73.20	83.05	76.62	73.87	75.71	80.66	80.11	78.30	74.69	79.84
LLaMA-3.2-Vision 11B	71.87	73.72	87.86	74.55	76.62	77.57	80.90	79.28	78.12	77.24	79.04
Proprietary Models											
Gemini-1.5-Pro	81.88	87.03	93.60	84.91	86.14	88.06	89.62	87.08	86.50	87.43	88.36
GPT-4o	84.67	90.86	96.16	88.69	90.22	90.91	90.92	89.41	91.53	89.50	92.58

Table 3. Zero-shot accuracy on open-source and proprietary models across three tasks, five continents, and three categories. CHT denotes *Cultural Heritage and Traditions*; HL denotes *History and Landmarks*; and NELR denotes *Natural Environment and Local Resources*.

E. Detailed Fine-tuning Results

The detailed results of the fine-tuned models are shown in Table 4. Detailed results on the generalization of the fine-tuned model in different regions and for different categories can be found in Table 5 and Table 6. Detailed results of the models before and after fine-tuning on the general VQA benchmark are shown in Table 7.

Model	Task			Continent					Category		
	Image Recognition	Cultural Knowledge	Scene Reasoning	Africa	Asia	Europe	America	Oceania	CHT	HL	NELR
LLaVA-v1.5 7B	88.03	90.87	95.66	91.68	91.61	91.02	91.91	90.61	92.58	90.98	91.70
LLaVA-v1.5 13B	89.72	92.20	96.09	92.68	92.37	92.59	93.05	92.73	93.17	92.40	92.60
Phi-3-vision 4B	87.53	90.84	95.77	90.80	91.56	91.41	90.91	91.16	92.83	90.50	92.35
LLaMA-3.2-Vision 11B	89.13	91.49	96.20	91.99	92.24	91.82	93.08	91.34	93.20	91.78	92.50

Table 4. Performance of fine-tuned models across three tasks, five continents, and three categories. CHT denotes *Cultural Heritage and Traditions*; HL denotes *History and Landmarks*; and NELR denotes *Natural Environment and Local Resources*.

E.1. Impact of Data Sizes

We vary the number of fine-tuning examples within $[5\%, 20\%, 50\%, 75\%, 100\%]$ to examine the effects of training data sizes on the final results. As shown in Figure 4c and 4d, the model's performance decreases as the training data is reduced.

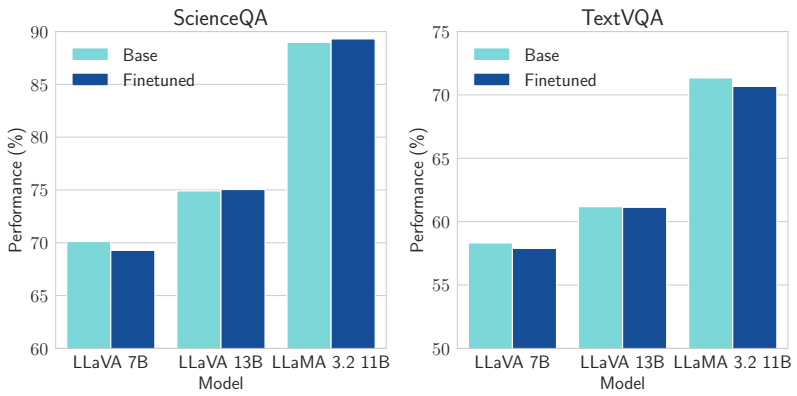


Figure 5. Performance of open-source and proprietary models on general VQA datasets. *Base* refers to the original model, while *Finetuned* refers to the model adapted using our CultureVerse. The comparable performance across both versions suggests that finetuning on our dataset preserves the models' natural language understanding and commonsense reasoning abilities.

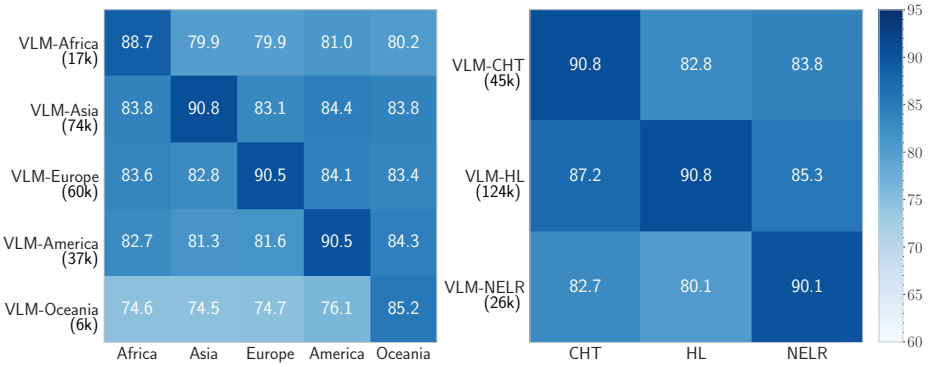


Figure 6. Generalization and Robustness. **Left**: Performance of CultureVLM (y-axis) evaluated across data from different continents (x-axis). CultureVLM achieves the highest performance for in-distribution settings, while still demonstrating strong generalizability for out-of-domain settings. **Right**: CultureVLM fine-tuned with data under different categories of CultureVerse (x-axis) and evaluated across various categories (y-axis). CHT denotes *Cultural Heritage and Traditions*; HL denotes *History and Landmarks*; and NELR denotes *Natural Environment and Local Resources*.

However, the decline is minimal, indicating that even a small amount of training data can effectively enhance the model's multicultural awareness.

E.2. Impact of Decoding Temperatures

We evaluate the performance of the original models and CultureVLMs under different temperature and decoding settings, as shown in Figure 7. It can be observed that VLMs perform better when the temperature is lower and decoding diversity is reduced. However, when the temperature reaches 1.0, there is a noticeable and expected decline in performance.

E.3. Catastrophic Forgetting

Catastrophic forgetting [24] refers to the phenomenon where a model loses previously learned knowledge when trained on new information, especially when the new data diverges significantly from the pretraining data. This can be especially problematic in cultural knowledge acquisition, as it may cause the model to compromise essential commonsense knowledge in favor of culture-specific details.

To assess this, we evaluate the models on standard VQA benchmarks, including ScienceQA [51] and TextVQA [53] to determine if the process of acquiring cultural knowledge inadvertently diminishes their grasp of general commonsense concepts. The results in Figure 5 reveal that our fine-tuned CultureVLM merely influences general VLM tasks, indicating the versatility of the solution.

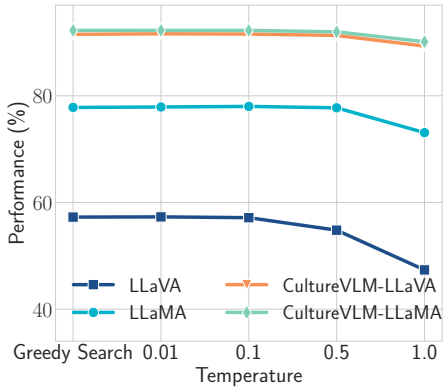


Figure 7. Impact of different decoding temperatures on performance

Task	Model	Total	Africa	Asia	Europe	America	Oceania
Image Recognition	LLaVA-v1.5-7B-Africa	72.73	85.79	72.69	70.54	71.37	69.74
	LLaVA-v1.5-7B-America	75.84	75.35	73.24	72.52	86.00	76.05
	LLaVA-v1.5-7B-Asia	80.20	75.78	88.62	75.04	75.84	75.26
	LLaVA-v1.5-7B-Europe	79.34	77.61	75.64	86.89	75.62	76.05
	LLaVA-v1.5-7B-Oceania	64.51	64.05	63.14	63.60	65.28	83.95
Cultural Knowledge	LLaVA-v1.5-7B-Africa	78.54	86.77	75.82	78.28	80.38	79.42
	LLaVA-v1.5-7B-America	81.85	79.29	78.33	80.45	90.78	85.22
	LLaVA-v1.5-7B-Asia	84.42	81.25	88.76	81.27	82.90	83.77
	LLaVA-v1.5-7B-Europe	84.12	80.52	80.20	90.43	83.15	81.74
	LLaVA-v1.5-7B-Oceania	73.78	73.16	72.38	73.91	75.03	81.16
Scene Understanding	LLaVA-v1.5-7B-Africa	91.29	93.63	91.06	90.87	91.41	91.41
	LLaVA-v1.5-7B-America	92.70	93.40	92.24	91.85	94.81	91.69
	LLaVA-v1.5-7B-Asia	94.16	94.44	95.11	92.92	94.52	92.52
	LLaVA-v1.5-7B-Europe	93.26	92.71	92.64	94.08	93.45	92.52
	LLaVA-v1.5-7B-Oceania	87.54	86.57	88.08	86.55	88.11	90.58

Table 5. Accuracy across different continents for each fine-tuned model.

Task	Model	Total	Cultural Heritage and Traditions	History and Landmarks	Natural Environment and Local Resources
Image Recognition	LLaVA-v1.5-7B-CHT	77.91	88.58	74.36	77.48
	LLaVA-v1.5-7B-HL	84.76	81.57	86.89	80.25
	LLaVA-v1.5-7B-NELR	73.46	74.89	69.18	89.88
Cultural Knowledge	LLaVA-v1.5-7B-CHT	83.29	88.53	81.71	82.16
	LLaVA-v1.5-7B-HL	87.99	84.91	90.58	82.03
	LLaVA-v1.5-7B-NELR	81.17	80.71	79.91	86.84
Scene Understanding	LLaVA-v1.5-7B-CHT	92.96	95.27	92.45	91.73
	LLaVA-v1.5-7B-HL	94.77	95.23	94.90	93.62
	LLaVA-v1.5-7B-NELR	91.85	92.58	91.16	93.62

Table 6. Accuracy across different categories for each fine-tuned model.

F. Details of Human Annotation

F.1. Statistics of Human Annotators and the Process

Table 8 shows the statistics of human annotators in our study. In total, through the contractor company, we hired 10 expert annotators whose ages are between 20 and 36 with at least a bachelor's degree. Most of them are within the non-AI areas such as education, specific languages, and history. When assigning the annotation job, we asked each annotator to label the correctness, consistency, and relatedness of our questions and answers. Specifically, correctness refers to the correctness of the generated questions and answers, consistency refers to the consistency between the questions, answers, and the concepts, and relatedness aims to make sure that the concepts and generated questions are related to each other. We asked the annotators not only to make judgement based on their experience but also to manually check the results via Google search and other

Dataset	Model	Base	Finetuned
ScienceQA	LLaVA 7B	70.12	69.28
	LLaVA 13B	74.91	75.04
	LLaMA 3.2 11B	88.97	89.30
TextVQA	LLaVA 7B FT	58.32	57.89
	LLaVA 13B FT	61.18	61.13
	LLaMA 3.2 11B	71.34	70.67

Table 7. Performance of models before and after fine-tuning on general VQA datasets. *Base* refers to the original model, while *Finetuned* refers to the model adapted using our CultureVerse. The comparable performance across both versions suggests that finetuning on our dataset preserves the models' natural language understanding and commonsense reasoning abilities.

Age	%	Degree	%	Major
20-25	50%	Bachelor	50%	Education; Specific languages; Computer science;
26-36	50%	Master	50%	Communication; Public relation; History

Table 8. Statistics of the human annotators to validate CultureVerse.

search engines. Each instance is labeled by two experts and then verified by another to ensure correctness. All annotation operations are performed following local laws and regulations to ensure fairness, equity, and accountability.

F.2. Accuracy of Human Annotation

Table 9 shows the precision of human annotators in our generated questions. We then filter out all the wrong questions and only retain the correct ones. It is surprising that automatically generated questions can achieve high accuracy, indicating the promising future of the adoption of advanced AI models like GPT-4o for data collection and annotation.

Check Item	Accuracy
Concept-Region Alignment	98.25%
Concept-Image Alignment	99.49%
Image Recognition Question-Answer Correctness	98.61%
Cultural Knowledge Question-Answer Correctness	96.52%
Scene Understanding Question-Answer Correctness	93.18%

Table 9. Accuracy of CultureVerse based on the human annotations.

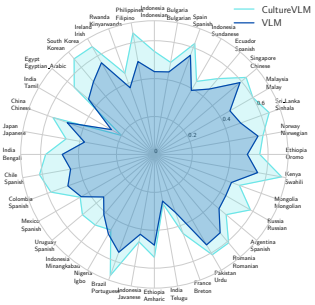


Figure 8. Results on CVQA [50].

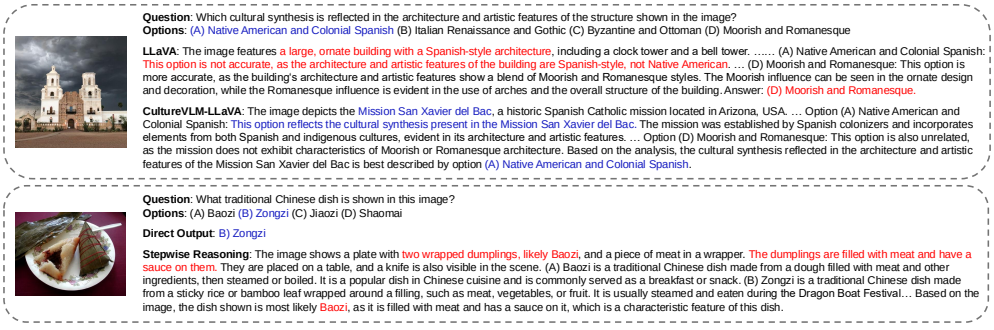


Figure 9. Case study on the effect of fine-tuning and prompt variations.

G. Limitations

First, while we use languages as proxies for cultural boundaries in the development of CultureVLM, we acknowledge that language alone does not capture the full complexity of culture. This simplification was made to address challenges in defining

cultural contexts, inspired by previous research [7, 27, 38]. Our pipeline and approach remain flexible to incorporate additional languages and cultures. Second, we acknowledge that the current dataset lacks multilingual support. Most foundational models currently exhibit weak multilingual capabilities, so fine-tuning on multilingual cultural data is less effective than on English data [27]. Therefore, the English data provided currently is also timely and valuable to our community. Third, due to resource constraint cost, we limit our fine-tuning experiments to the current set of models. Evaluating a wider range of models could yield further insight. The current CultureVerse only contains multiple-choice questions. Exploring open-ended questions could also offer additional avenues for assessment. Our data and models will be released to the public after ethical reviews.

H. Case Study

Figure 9 shows the responses of LLaVA and CultureVLM. We incorporate extensive explanations into the training data, enriching CultureVLM with substantial knowledge that enhances its cultural recognition and understanding ability.

Below, we present examples from CultureVerse representing three different countries. Each example includes a cultural concept, country, category, image recognition question, cultural knowledge question, and scene understanding question.

Concept: Peking Opera
Country: China
Category: Music and Dance

Image Recognition:
Question: What traditional Chinese performance is shown in this image?
Options: (A) Henan Opera (B) Peking Opera (C) Kunqu Opera (D) Yue Opera
Ground truth: **(B) Peking Opera**

Cultural Knowledge:
Question: Which musical instrument is traditionally associated with accompanying the theatrical art form depicted in the image?
Options: (A) Guzheng (B) Pipa (C) Jinghu (D) Dizi
Ground truth: **(C) Jinghu**

Scene Understanding:
Question: In a theatrical performance known for its vibrant costumes and symbolic gestures, what might the intricate face paint and elaborate attire of a character symbolize?
Options: (A) The character's age and wisdom (B) The character's social status and role (C) The weather conditions in the story (D) The importance of technology in the narrative
Ground truth: **(B) The character's social status and role**

Concept: Florence Cathedral
Country: Italy
Category: Famous Landmarks

Image Recognition:
Question: What famous cathedral is shown in this image?
Options: (A) St. Peter's Basilica (B) Milan Cathedral (C) Florence Cathedral (D) Siena Cathedral
Ground truth: **(C) Florence Cathedral**

Cultural Knowledge:
Question: Which renowned architect was responsible for engineering the innovative dome of the structure shown in the image?
Options: (A) Leon Battista Alberti (B) Filippo Brunelleschi (C) Giorgio Vasari (D) Michelangelo Buonarroti
Ground truth: **(B) Filippo Brunelleschi**

Scene Understanding:
Question: Imagine you are visiting the city depicted in the image during the Renaissance period. You hear local legends about a stone head on a famous structure there. According to the legend, what was the purpose of this stone head?
Options: (A) To ward off evil spirits (B) To grant wishes to passersby (C) To commemorate a donor who contributed a bell (D) To mark the entrance for pilgrims
Ground truth: **(C) To commemorate a donor who contributed a bell**

Concept: Pha That Luang
Country: Lao People's Democratic Republic
Category: Famous Landmarks

Image Recognition:
Question: What famous structure is shown in this image?
Options: (A) Wat Arun (B) Angkor Wat (C) Pha That Luang (D) Shwedagon Pagoda
Ground truth: **(C) Pha That Luang**

Cultural Knowledge:
Question: The structure shown in the image, originally built as a Hindu temple, underwent major reconstruction during the reign of which historical figure when Buddhism gained prominence in the region?
Options: (A) King Jayavarman VII (B) King Setthathirath (C) King Anawrahta (D) King Ramkhamhaeng
Ground truth: **(B) King Setthathirath**

Scene Understanding:
Question: Imagine you are attending a festival at the site shown in the image, which is considered one of the most significant Buddhist celebrations in the country. During this event, which of the following cultural practices would you most likely observe that emphasizes the religious and national significance of this site?
Options: (A) A parade featuring traditional music and dance (B) A ceremony honoring ancient Hindu deities (C) A cooking contest of traditional Lao dishes (D) A fireworks display celebrating the lunar new year
Ground truth: **(A) A parade featuring traditional music and dance**

I. Prompt List

```
Concept: {concept}
Country: {country}
Class: {class_}

Please determine whether "{concept}" is a kind of {class_} that can reflect {country}
culture and whether it can serve as a symbol of {country} culture (unique and very famous
within {country}, and not commonly seen in other parts of the world).
Additionally, the symbol should not be a broad category that includes various specific items
, but rather a distinct and indivisible entity, such as a specific dance form, a famous
individual's photograph, a renowned landmark, etc.

Here are some counterexamples:
- Broad concepts like "fast food" (which includes burgers, fries, etc.), "traditional
Chinese instruments" (which include guzheng, erhu, etc.) "Dance" (which include jazz dance,
Square dancing, etc.) are not acceptable due to their lack of a unified visual marker.
- Concept itself is the wrong word, such as "...", "N/A".
- Concept exists in many regions, such as "pork", "duck" or "grapes" (which might be a
specialty or staple in certain countries but is quite common in many places. However,
specific concepts like "peking duck" or "schweinshaxe" would be correct).

Please provide your short explanation and include your answer (Yes/No) into <<<>>>. For
example, if you think "{concept}" is a specific and indivisible symbol of {country} culture,
 please write <<<Yes>>>.
```

1. Prompt of concept judgement.

```
Please extract cultural elements from the given wikipedia document that can represent {
country} culture or are very famous in {country}, including the following categories:

### Categories
- Food: e.g., local specialty dishes, traditional festival foods.
- Plants: e.g., unique flowers, crops in {country}.
- Animals: e.g., unique wild animals, livestock in {country}.
- Famous Landmarks: e.g., famous historical sites, buildings.
- Festivals: e.g., unique festival celebration scenes.
- Historical Artifacts: e.g., museum collections, ancient relics.
- Historical Figures: e.g., portraits of historical figures, statues.
- Traditional Clothing: e.g., ethnic clothing, festival attire.
- Architectural Styles: e.g., traditional architecture, modern landmark buildings.
- Handicrafts and Artifacts: e.g., ethnic handicrafts, traditional handmade items.
- Music and Dance: e.g., traditional musical instruments, dance scenes.
- Religion and Belief: e.g., temples and churches, religious ceremonies.
- Natural Scenery and Ecosystems: e.g., unique natural landscapes, ecological reserves.
- Markets and Shopping Traditions: e.g., local markets, specialty shops.
- Entertainment and Performing Arts: e.g., theater performances, street performers.

Please note that not all categories may be included in the document. Only list the most
famous cultural elements, with a total not exceeding 10. For categories without famous
elements, use 'NA' to indicate. Directly output in the format "Category: [Element1, Element2
, ...]", for example:

### Cultural Elements
- Food: [Food 1], [Food 2], ...
- Plants: NA
- Music and Dance: [Musical Instrument 1], [Dance Scene 2], ...
```

```
The following is the wikipedia document.
### Wikipedia Document
{wikipedia}
```

2. Prompt for extracting cultural concept entities from Wikipedia documents.

```
This is the {concept} of {country}. Your task is to generate a multiple-choice question that
 asks the user to identify what is shown in the image. Use the following format for your
question:
- Question: [Your Question] Options: (A) [Option 1] (B) [Option 2] (C) [Option 3] (D) [
Option 4]

For example, if the image shows a Peking Duck of China, the question and options should look
 like this:
- Question: What traditional dish is shown in this image? Options: (A) Cantonese Roast Duck
(B) Peking Duck (C) Sichuan Spicy Duck (D) Nanjing Salted Duck

If the image shows the Erhu of China:
- Question: What musical instrument is shown in this image? Options: (A) Pipa (B) Erhu (C)
Sanxian (D) Yangqin

If the image shows the White House of US:
- Question: What famous American building is shown in this image? Options: (A) The Capitol (
B) The White House (C) The Lincoln Memorial (D) The Supreme Court Building

Ensure that "{concept}" should be included in one of the options. Ensure that the options
are plausible but only one is the correct answer. The incorrect options should be similar
enough to the correct one to create a challenge, but not so similar that they cause any
potential ambiguity.
```

3. Prompt for generating scene recognition questions.

```
Please provide a detailed introduction of {concept} of {country}, including information such
 as: Location and Features (where it is found or originates from, what makes it unique);
Time period (when it was created or became significant); History (historical background and
development, or any significant events); Cultural significance (cultural Context in {country
}, modern-day significance); Stories or Legends (Any stories, legends, or folklore
associated with {concept}).

Use the following format for your introduction:
Introduction of {concept}: [Detailed Introduction of {concept}]

Here are two examples:

Introduction of Peking Duck: Peking Duck is a famous Chinese dish that originated in Beijing
 during the Imperial era. The dish dates back to the Yuan Dynasty (1271-1368) and became a
staple in the Ming Dynasty (1368-1644). Traditionally, Peking Duck is known for its thin,
crispy skin and is served with pancakes, hoisin sauce, and scallions. The preparation
involves inflating the duck to separate the skin from the fat, marinating it, and roasting
it in a closed or hung oven. It is considered a national dish of China and a symbol of
Chinese culinary art.

Introduction of The White House: The White House, located at 1600 Pennsylvania Avenue NW in
Washington, D.C., is the official residence and workplace of the President of the United
States. Construction began in 1792 and was completed in 1800. The building was designed by
Irish-born architect James Hoban in the neoclassical style. It has been the residence of
every U.S. president since John Adams. The White House has undergone several renovations and
 expansions, including the addition of the West Wing and the Oval Office. It is a symbol of
the U.S. government and a site of significant historical events.
```

```
Now please provide the introduction for {concept}.
Introduction of {concept}:
```

4. Prompt for generating the introduction of cultural concept.

```
This public image shows the "{concept}" of {country}. Generate a multiple-choice question
based on this image and the introduction of {concept}. Provide the correct answer
immediately following the question.

Ensure the question delves into deeper cultural knowledge but does not directly name the {
concept}. The options should be somewhat confusing to increase the difficulty, but there
must be only one correct answer. Users can only answer based on the image, so don't mention
any "introduction" or "{concept}" in the question. Use the following format for your
generated question:
- Question: [Your Question] Options: (A) [Option 1] (B) [Option 2] (C) [Option 3] (D) [
Option 4]
- Answer: (X) [Option X]

Here are two examples:

Image: Peking Duck
Introduction of Peking Duck: Peking Duck is a famous Chinese dish that originated in Beijing
 during the Imperial era. The dish dates back to the Yuan Dynasty (1271-1368) and became a
staple in the Ming Dynasty (1368-1644). Traditionally, Peking Duck is known for its thin,
crispy skin and is served with pancakes, hoisin sauce, and scallions. The preparation
involves inflating the duck to separate the skin from the fat, marinating it, and roasting
it in a closed or hung oven. It is considered a national dish of China and a symbol of
Chinese culinary art.

- Question: During which dynasty did the dish shown in the image become a staple in the
cuisine of its country? Options: (A) Tang Dynasty (B) Song Dynasty (C) Ming Dynasty (D) Qing
 Dynasty
- Answer: (C) Ming Dynasty


Image: The White House
Introduction of The White House: The White House, located at 1600 Pennsylvania Avenue NW in
Washington, D.C., is the official residence and workplace of the President of the United
States. Construction began in 1792 and was completed in 1800. The building was designed by
Irish-born architect James Hoban in the neoclassical style. It has been the residence of
every U.S. president since John Adams. The White House has undergone several renovations and
 expansions, including the addition of the West Wing and the Oval Office. It is a symbol of
the U.S. government and a site of significant historical events.

- Question: Who was the architect responsible for designing the building shown in the image?
 Options: (A) James Hoban (B) Benjamin Latrobe (C) Thomas Jefferson (D) Charles Bulfinch
- Answer: (A) James Hoban


Now please generate the question for the Image: {concept} of {country}
{introduction}
```

5. Prompt for generating cultural knowledge questions based on the introduction of cultural concepts.

```
This public image shows the "{concept}" of {country}. Generate a visual reasoning multiple-
choice question based on this image and the introduction of {concept}. Provide the correct
answer and reason immediately following the question.
```

```
Here are some requirements:
- The question must describe a specific scenario crafted to test deeper cultural
understanding without directly naming {concept}. The scenario can be related to cultural
background, regional characteristics, historical legends, or etiquette and customs, etc.
- The question needs to be related to the image but does not need to describe the content of
 the image.
- Ensure the question requires the user to recognize the image and use relevant knowledge to
 answer through reasoning based on the scenario provided. Users can only answer based on the
 image, so don't mention any "introduction" or "{concept}" in the question.

Use the following format for your introduction and question:
- Question: [Your Scenario-based Question] Options: (A) [Option 1] (B) [Option 2] (C) [
Option 3] (D) [Option 4]
- Answer: (X) [Option X]
- Reason: [Your Reason for the Answer]

Here are two examples:

Image: Peking Duck
Introduction of Peking Duck: Peking Duck is a famous Chinese dish that originated in Beijing
 during the Imperial era. The dish dates back to the Yuan Dynasty (1271-1368) and became a
staple in the Ming Dynasty (1368-1644). Traditionally, Peking Duck is known for its thin,
crispy skin and is served with pancakes, hoisin sauce, and scallions. The preparation
involves inflating the duck to separate the skin from the fat, marinating it, and roasting
it in a closed or hung oven. This meticulous process ensures the skin becomes crispy while
the meat remains tender. Peking Duck is often carved in front of diners and served in three
stages: the skin, the meat, and a broth made from the bones. It is considered a national
dish of {country} and a symbol of Chinese culinary art. Peking Duck has also been a part of
many state banquets and diplomatic events, symbolizing Chinese hospitality and culinary
excellence.

- Question: During a state banquet featuring the dish in the image, which aspect of its
presentation is most likely emphasized to symbolize Chinese culinary excellence and
hospitality? Options: (A) The use of exotic spices (B) The serving of the duck with rice (C)
 The incorporation of seafood (D) The carving of the duck in front of diners
- Answer: (D) The carving of the duck in front of diners
- Reason: The traditional carving of Peking Duck in front of diners highlights the skill
involved in its preparation and serves as a symbol of Chinese culinary excellence and
hospitality.


Image: The White House
Introduction of The White House: The White House, located at 1600 Pennsylvania Avenue NW in
Washington, D.C., is the official residence and workplace of the President of the United
States. Construction began in 1792 and was completed in 1800. The building was designed by
Irish-born architect James Hoban in the neoclassical style, featuring a white-painted Aquia
Creek sandstone exterior. It has been the residence of every U.S. president since John Adams
. The White House has undergone several renovations and expansions, including the addition
of the West Wing, East Wing, and the Oval Office. The building's iconic appearance and
historical significance make it a symbol of the U.S. government and a site of significant
historical events. The White House has been the location of many important decisions,
meetings with foreign dignitaries, and addresses to the nation. It also serves as a museum
of American history, housing numerous artifacts and pieces of art. The White House is not
only a residence but also a working office, with various staff members ensuring the smooth
operation of the executive branch of the U.S. government.

- Question: During a critical diplomatic event, the President is scheduled to meet with
```

```
several foreign dignitaries to discuss global climate initiatives. As depicted in the image,
 which room inside the building is most likely to be used for this high-level diplomatic
meeting? Options: (A) The Lincoln Bedroom (B) The Oval Office (C) The White House Kitchen (D
) The East Room
- Answer: (B) The Oval Office
- Reason: The Oval Office is traditionally used for important meetings and discussions,
making it the most likely choice for a high-level diplomatic meeting with foreign
dignitaries.


Now please generate the question for the Image: {concept} of {country}
{introduction}
```

6. Prompt for generating scene reasoning questions based on the introduction of cultural concepts.

```
(Hint: This image shows the {concept} of {country}.)

Here is a question about this image:
{question}

First, describe the image in detail and analyze its features. Then, analyze the
characteristics of the four options and compare each one with the features of the image.
Finally, provide your final answer. Please include your answer into (). For example, if you
choose A, please write (A).
```

7. Prompt for generating knowledge-based reasoning response to image recognition questions in training set.

```
(Hint: This image shows the {concept} of {country}. {introduction})

Here is a question about this image:
{question}

First, provide a detailed description and identification of the image, analyzing its
features. Then, conduct a comprehensive analysis of the question and four options based on
the Hint and your knowledge. Finally, present the final answer.

Please refrain from explicitly mentioning the "Hint" in your response, as these are for your
 discreet knowledge and not provided by the question. Please include your answer into ().
For example, if you choose A, please write (A).

Response:
```

8. Prompt for generating knowledge-based reasoning response to cultural knowledge / scene reasoning questions in training set.

```
Here is a question about this image:
Question: {question} Options: {options}

First, describe and identify the image. Then, analyze the question and all four options in
detail. Finally, provide the answer, indicating your final choice in parentheses. For
example, if you choose A, please write (A).
```

9. Prompt for stepwise reasoning in the evaluation of CultureVerse.

Country	Concept	Country	Concept	Country	Concept
SUM of Concepts	**19,682**	Sri Lanka	90	Samoa	30
India	1,430	Democratic People's Republic of Korea	90	Turkmenistan	27
United States of America	1,411	Saudi Arabia	87	Qatar	26
Italy	661	Lithuania	86	Guyana	26
China	545	Malta	86	Kuwait	25
Mexico	524	Uzbekistan	84	Paraguay	24
Japan	522	Algeria	83	Sudan	24
Philippines	465	Lebanon	79	Angola	24
Indonesia	400	Nigeria	78	Fiji	24
France	374	Colombia	78	Seychelles	23
Russian Federation	328	Austria	77	Lesotho	22
Greece	300	Cyprus	75	Barbados	21
Germany	273	Mongolia	74	Dominica	21
Egypt	272	Cuba	73	Mauritius	20
Armenia	259	Bosnia and Herzegovina	72	Maldives	19
Australia	254	Ecuador	71	Niger	18
Spain	249	Slovakia	65	Zambia	18
Georgia	245	Iceland	65	Antigua and Barbuda	17
Brazil	239	Luxembourg	65	Saint Lucia	16
Canada	231	Iraq	62	Eswatini	16
Thailand	228	Ghana	61	Bahrain	15
Myanmar	226	Albania	60	Papua New Guinea	15
Ireland	220	Uruguay	60	Kazakhstan	15
Pakistan	218	Montenegro	60	Tuvalu	14
Nepal	216	Uganda	58	Liechtenstein	14
New Zealand	209	Chile	56	Côte d'Ivoire	14
Portugal	199	Senegal	56	Suriname	13
Ukraine	197	United Republic of Tanzania	56	Bahamas	12
Malaysia	189	United Arab Emirates	56	Eritrea	12
Bangladesh	188	Guatemala	54	Mozambique	12
Peru	188	Latvia	53	Burundi	11
Poland	186	Yemen	52	Marshall Islands	11
Bulgaria	182	Afghanistan	51	Honduras	11
United Kingdom of Great Britain and Northern Ireland	176	Belarus	50	San Marino	11
Croatia	176	Benin	50	Liberia	11
Serbia	172	Oman	50	Tajikistan	11
Romania	167	Dominican Republic	49	Solomon Islands	10
Ethiopia	155	Tunisia	48	Comoros	9
Cambodia	154	Trinidad and Tobago	48	Nauru	9
Netherlands	151	El Salvador	47	Vanuatu	8
Denmark	142	Monaco	47	Kiribati	8
Lao People's Democratic Republic	141	Mali	46	Timor-Leste	8
South Africa	138	Kenya	45	Grenada	8
Argentina	134	Estonia	45	Sierra Leone	7
Republic of Korea	132	Haiti	44	Rwanda	7
Czechia	130	Jamaica	43	Guinea	7
Bhutan	130	Belize	42	Libya	7
Azerbaijan	129	Plurinational State of Bolivia	41	Andorra	7
Morocco	126	Congo	40	Gambia	7
Norway	120	Namibia	39	Burkina Faso	7
Sweden	112	Somalia	39	South Sudan	5
Finland	112	Nicaragua	38	Gabon	5
Israel	109	Kyrgyzstan	36	Togo	4
Türkiye	109	Bolivarian Republic of Venezuela	35	Malawi	4
Viet Nam	109	Madagascar	35	Saint Kitts and Nevis	4
Hungary	101	Republic of Moldova	34	Djibouti	4
Ethnic_and_religiou_groups	94	Zimbabwe	33	Saint Vincent and the Grenadines	3
North Macedonia	94	Jordan	33	Central African Republic	3
Slovenia	93	Tonga	32	Chad	2
Islamic Republic of Iran	93	Botswana	32	Mauritania	2
Switzerland	93	Cameroon	31	Panama	1
Singapore	93	Costa Rica	31	Federated States of Micronesia	1
Belgium	91	Democratic Republic of the Congo	31	Equatorial Guinea	1

Table 10. Number of cultural concepts of different countries or regions