

LLaVA-OneVision-1.5: Fully Open Framework for Democratized Multimodal Training

LLaVA-OneVision Community Contributors

Abstract

We present LLaVA-OneVision-1.5, a novel family of Large Multimodal Models (LMMs) that achieve state-of-the-art performance with significantly reduced computational and financial costs. Different from the existing works, LLaVA-OneVision-1.5 provides an open, efficient, and reproducible framework for building high-quality vision-language models entirely from scratch. The LLaVA-OneVision-1.5 release comprises three primary components: **(1) Large-Scale Curated Datasets:** We construct an 85M concept-balanced pretraining dataset LLaVA-OneVision-1.5-Mid-Traning and a meticulously curated 26M instruction dataset LLaVA-OneVision-1.5-Instruct, collectively encompassing 64B compressed multimodal tokens. **(2) Efficient Training Framework:** We develop a complete end-to-end efficient training framework leveraging an offline parallel data packing strategy to facilitate the training of LLaVA-OneVision-1.5 within a \$16,000 budget. **(3) State-of-the-art Performance:** Experimental results demonstrate that LLaVA-OneVision-1.5 yields exceptionally competitive performance across a broad range of downstream tasks. Specifically, LLaVA-OneVision-1.5-8B outperforms Qwen2.5-VL-7B on 18 of 27 benchmarks, and LLaVA-OneVision-1.5-4B surpasses Qwen2.5-VL-3B on all 27 benchmarks. We anticipate releasing LLaVA-OneVision-1.5-RL shortly and encourage the community to await further updates.

- ⌚ **Code** <https://github.com/EvolvingLMMs-Lab/LLaVA-OneVision-1.5>
- 👉 **Models** <https://huggingface.co/1mms-lab/LLaVA-OneVision-1.5-8B-Instruct>
- 👉 **Pretrain data** <https://huggingface.co/datasets/1mms-lab/LLaVA-One-Vision-1.5-Mid-Training-85M>
- 👉 **Instruct data** <https://huggingface.co/datasets/1mms-lab/LLaVA-OneVision-1.5-Insturct-Data>

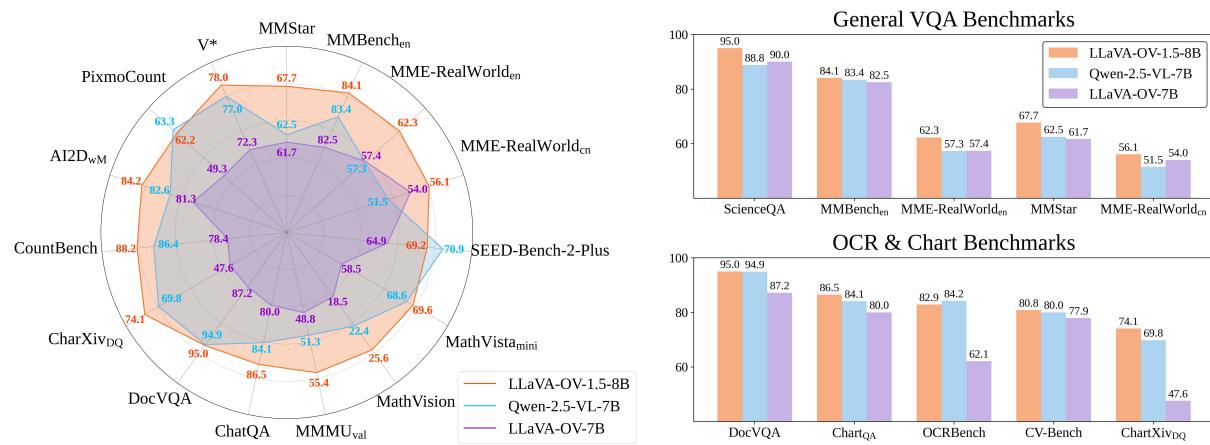


Figure 1 Performance of LLava-OV-1.5-8B across multiple benchmarks.

1 Introduction

Recent advancements in Large Multimodal Models (LMMs) have demonstrated remarkable capabilities in multimodal understanding and reasoning (Comanici et al., 2025; Guo et al., 2025; Zhu et al., 2025). These developments enable artificial intelligence applications to effectively comprehend and analyze images, charts, and PDF documents. However, the most performant models remain proprietary, with neither their training data nor source code publicly available. Consequently, the broader research community lacks crucial insights into how such high-performing LMMs can be built from scratch.

To reduce barriers for community development, several research efforts have attempted to reproduce the capabilities of proprietary models using open architectures. Early efforts such as LLaVA (Liu et al., 2023), LLaVA-Next (Liu et al., 2024b), and LLaVA-OneVision (Li et al., 2025a) provided fully open training data and code, but their performance now falls substantially behind that of current state-of-the-art models (Bai et al., 2025; Zhu et al., 2025). More recent works have pushed the boundary: Molmo (Deitke et al., 2025) released model weights, datasets, and source code, enabling the community to train LMMs from scratch. Through careful architectural choices, a refined training pipeline, and high-quality data, Molmo achieves near-parity with GPT-4V on both academic benchmarks and user preference evaluations. Open-Qwen2VL (Wang et al., 2025) introduces a 2B-parameter model pre-trained on only 0.36% of 1.4T multimodal tokens in Qwen2-VL, while outperforming Qwen2-VL-2B across various multimodal benchmarks. Despite these advances, the performance gap between open-source and proprietary models continues to widen as the field of LMMs rapidly evolves. Current open-source models are still constrained by substantial computational demands and suboptimal training efficiency.

To overcome the aforementioned limitations, we introduce LLaVA-OneVision-1.5, a fully open-source family of LMMs, extending the LLaVA series (Li et al., 2025a) to achieve superior performance with limited computational cost. Specifically, LLaVA-OneVision-1.5 adopts RICE-ViT (Xie et al., 2025) as the vision encoder, enabling native-resolution adaptation and fine-grained visual understanding based on stronger region-level semantic representation. Building upon LLaVA-OneVision (Li et al., 2025a), LLaVA-OneVision-1.5 adopts a three-stage training pipeline: (Stage-1) Language-Image Alignment, (Stage-1.5) High-Quality Knowledge Learning, and (Stage-2) Visual Instruction Tuning. Notably, we find that simply scaling data at the mid-training stage alone can produce state-of-the-art LMMs, eliminating the need for complex training paradigms. To foster open research, we release all assets to the community, including LLaVA-OneVision-1.5-Mid-Traning and LLaVA-OneVision-1.5-Instruct datasets, the training framework, and model checkpoints (LLaVA-OneVision-1.5-Base and LLaVA-OneVision-1.5-Instruct). In summary, our contributions are as follows:

- **Large Multimodal Models.** We propose LLaVA-OneVision-1.5 a family of fully open-source large multimodal models that achieve superior performance across multiple multimodal benchmarks compared to Qwen2.5-VL.
- **Large-Scale Datasets.** We construct an 85M concept-balanced pre-training dataset LLaVA-OneVision-1.5-Mid-Traning and a meticulously curated 26M instruction dataset LLaVA-OneVision-1.5-Instruct, jointly forming 64B compacted multimodal tokens.
- **Efficient Training Framework.** We develop a complete end-to-end training framework that employs an offline parallel data packing strategy to optimize cost-effectiveness, enabling the training of LLaVA-OneVision-1.5 within a \$16,000 compute budget.
- **Open-Source Release.** We release all assets to the public including LLaVA-OneVision-1.5-

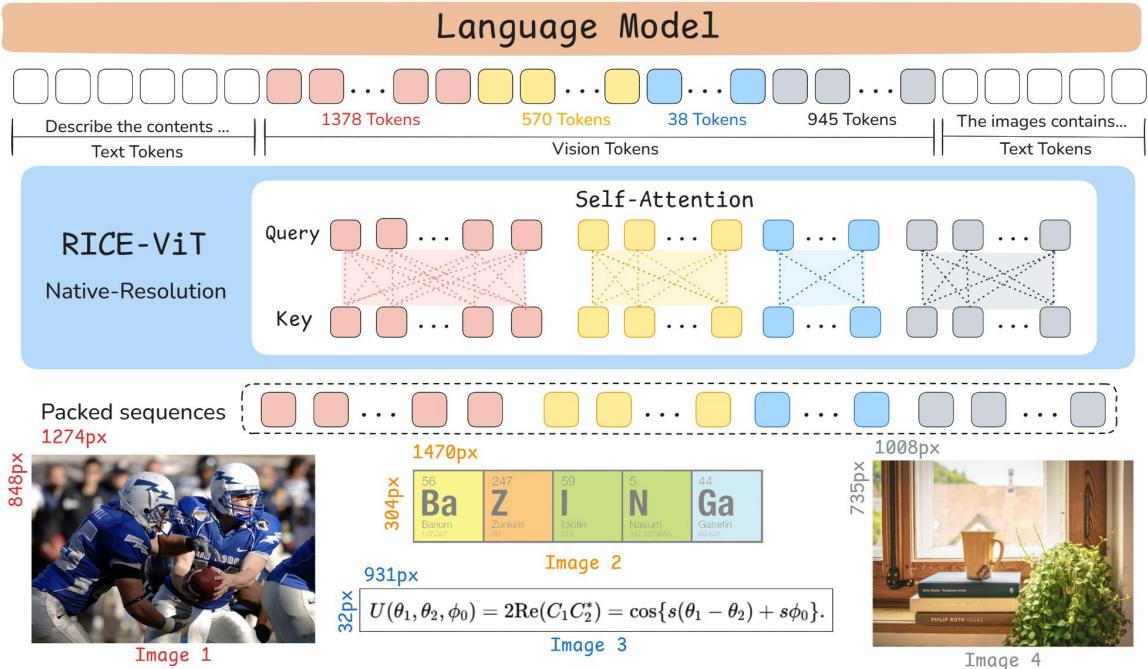


Figure 2 Overall architecture of LLaVA-OneVision-1.5. The framework integrates a pre-trained vision encoder with a language model decoder. The vision encoder adopts 2D RoPE for native-resolution processing and incorporates region-aware attention to enhance local semantic modeling. During pretraining, both object regions and OCR regions are jointly modeled to inject fine-grained text understanding capability. A lightweight projector maps visual features into the LLM embedding space, and the [CLS] token is preserved to retain global semantic capacity during multimodal alignment.

Mid-Traning and LLaVA-OneVision-1.5-Instruct dataset, training framework, and the model checkpoints (LLaVA-OneVision-1.5-Base and LLaVA-OneVision-1.5-Instruct).

2 Architecture

2.1 Overall Architecture

The overall architecture of LLaVA-OneVision-1.5 is illustrated in Fig. 2. LLaVA-OneVision-1.5 retains the “ViT–MLP–LLM” paradigm of the LLaVA series, comprising three core modules:

- **Vision Encoder:** The vision encoder is responsible for extracting rich and semantically meaningful visual representations from input images, which serve as the foundation for multimodal alignment and downstream reasoning. Unlike previous works (Wang et al., 2024b; Bai et al., 2025) that adopt SigLIP (Zhai et al., 2023) or DFN (Fang et al., 2023), LLaVA-OneVision-1.5 integrates our recently proposed cluster discrimination model RICE-ViT (Xie et al., 2025) to improve region-aware visual and OCR capabilities.
- **Projector:** The projector bridges the modality gap between the vision encoder and the large language model by mapping visual embeddings into the text embedding space of the LLM. Following Qwen2.5-VL (Bai et al., 2025), we first group spatially adjacent sets of four patch features, which are then concatenated and passed through a two-layer multi-layer perceptron to map them into the text embedding space of the LLM.

- **Large Language Model:** The large language model acts as the reasoning and generation core of the architecture. After receiving the projected multimodal embeddings, the LLM integrates visual information with linguistic context to perform complex reasoning, instruction following, and natural language generation. The LLaVA-OneVision-1.5 series utilize Qwen3 (Team, 2025) as the language backbone to significantly enhance performance on downstream tasks.

This modular design follows the LLaVA framework but incorporates more efficient training recipes and carefully selected encoders, enabling superior cost-effectiveness and scalability.

2.2 Vision Encoder via Region-Aware Cluster Discrimination

Fine-grained visual semantics are essential for dense prediction tasks such as grounding, OCR, and segmentation. Although large-scale vision–language contrastive models like CLIP (Radford et al., 2021) and SigLIP (Zhai et al., 2023) demonstrate strong performance through global vision–language alignment, they fail to capture the similarity structure of training data or the local region-level semantics within images. This shortcoming stems from instance-wise contrastive learning, which treats all instances as negatives regardless of their semantic similarity and represents each instance solely with a single global embedding.

To overcome these limitations, our LLaVA-OneVision-1.5 leverages the RICE-ViT (Xie et al., 2025) as its vision encoder, enabling precise multimodal alignment and enriched region-level representation. RICE-ViT enhances both object-centric and OCR capabilities by introducing a unified region cluster discrimination loss, trained on 450M images and 2.4B candidate regions. Its design combines a region-aware attention mechanism for local semantic modeling with 2D rotary positional encoding, which naturally supports variable input resolutions without requiring resolution-specific fine-tuning, unlike models such as Qwen2-VL (Wang et al., 2024b) and InternVL 2.5 (Chen et al., 2024b).

We integrate this pretrained encoder with a language model through joint training, yielding a streamlined multimodal pipeline. Compared to SigLIP2 (Tschannen et al., 2025), which depends on multiple specialized losses (SILC, TIPS, LocCa, and Sigmoid), our method adopts a single cluster discrimination loss that simultaneously strengthens general understanding, OCR, and localization. This unified formulation provides an elegant, computationally efficient solution that matches SigLIP2’s performance while substantially reducing architectural complexity and training overhead.

3 Data

3.1 Pre-Training Dataset

We use the LLaVA-1.5 558K (Liu et al., 2024a) to align the visual features into the word embedding space of LLMs. After that, LLaVA-OneVision-1.5 is underpinned by a large-scale multimodal dataset LLaVA-OneVision-1.5-Mid-Traning, which contains 85 million high-quality image-text pairs (20M in Chinese and 65M in English). The data of LLaVA-OneVision-1.5-Mid-Traning are from a wide range of sources: COYO-700M (Byeon et al., 2022), Obelics (Laurençon et al., 2023), DataComp-1B (Gadre et al., 2023), LAION-CN (Zhang et al., 2022), ImageNet-21K (Russakovsky et al., 2015), SAM-1B (Kirillov et al., 2023), MINT (Wang et al., 2024c), and Zero250M (Xie et al., 2023). To enrich the diversity of our pretraining data, we introduce a concept-balanced sampling strategy inspired by MetaCLIP (Xu et al., 2024). Unlike MetaCLIP, which depends on raw captions for concept matching and struggles with caption-free or interleaved datasets (e.g., SAM-1B, ImageNet-

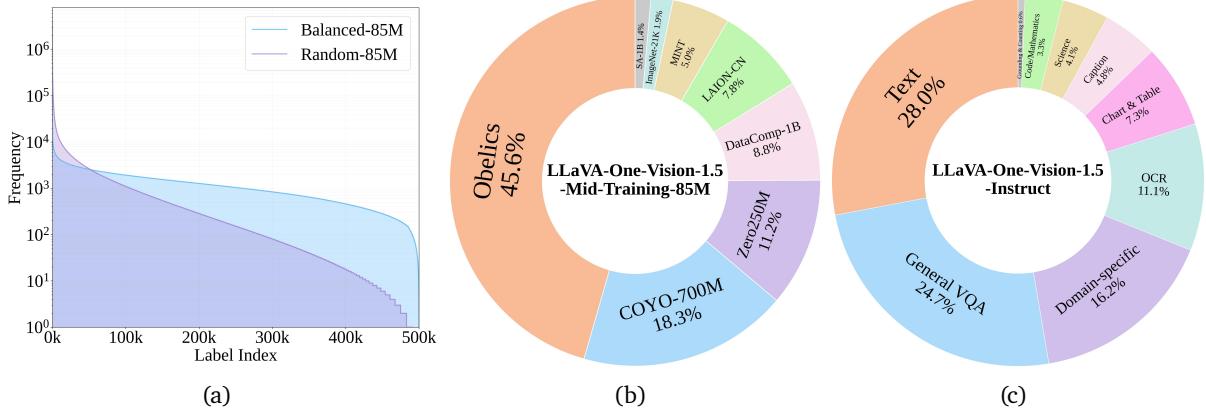


Figure 3 (a) The vocabulary coverage proportion in the LLaVA-OneVision-1.5-Mid-Traning dataset before and after concept balancing. (b) Distribution of data sources within the LLaVA-OneVision-1.5-Mid-Traning dataset. (c) Distribution of data sources within the LLaVA-OneVision-1.5-Instruct.

21K, and Obelics), our method reduces reliance on caption quality, such as the brief and incomplete annotations common in COYO-700M. Instead, we adopt a feature-based matching approach that coarsely groups image sources. Specifically, using the pretrained MetaCLIP-H/14-Full-CC2.5B encoders (Xu et al., 2024), we project both images and MetaCLIP’s 500K concept entries into a shared embedding space. Since MetaCLIP embeddings are already concept-balanced, this enables effective similarity-based concept induction: for each image, we retrieve its top-K nearest concept embeddings to construct refined pseudo-captions that enhance semantic alignment.

Top-K Concept Assignment and Balance Sampling. Given an image set $\mathcal{I} = \{i_0, i_1, \dots, i_N\}$ and a concept vocabulary set $\mathcal{V} = \{v_0, v_1, \dots, v_M\}$, we first utilize the image encoder Φ_v and text encoder Φ_t to extract the image embeddings $\mathcal{E}_i = \{\Phi_v(i), i \in \mathcal{I}\}$ and concept embeddings $\mathcal{E}_t = \{\Phi_t(v), v \in \mathcal{V}\}$. Then we assign each image with the top- k nearest concepts based on the cosine similarity of the L2-normalized image and concept embeddings. After that, following MetaCLIP (Xu et al., 2024), we weight each image by the inverse frequencies of its concepts and then sample images based on the normalized image weights. This inverse-frequency methodology promotes a more balanced concept distribution, without relying on original captions, which may be noisy or missing. This process yields 85M images with balanced concepts. Subsequently, we apply a powerful captioner to produce English and Chinese captions for these images, followed by a validity filter to eliminate duplicates and excessively lengthy outputs. Ultimately, we establish an 85M concept-balanced mid-training dataset. The distribution of data sources of the LLaVA-OneVision-1.5-Mid-Traning dataset is illustrated in Fig. 3(b).

3.2 Instruction Dataset

Visual instruction tuning (Liu et al., 2023) is vital for enabling LMMs to understand and follow visual instructions, and its effectiveness hinges on the quality of the instruction datasets. To this end, we construct the LLaVA-OneVision-1.5-Instruct dataset by aggregating a wide range of instruction-tuning datasets from diverse sources. The data are carefully curated to ensure balanced coverage across seven categories: Caption, Chart & Table, Code & Math, Domain-specific, General VQA, Grounding & Counting, OCR, and Science. The resulting corpus comprises 26 million samples, with Fig. 3(c) showing the proportional distribution across categories.

Table 1 Performance comparison across vision-language models on various benchmarks grouped by task type. All scores are reported as accuracy percentages unless otherwise specified.

Benchmark	LLaVA-OV-1.5 8B	Qwen2.5-VL 7B	LLaVA-OV-1.5 4B	Qwen2.5-VL 3B	LLaVA-OV 7B
General VQA	MMSStar	67.7	62.5	64.9	55.9
	MMBench _{en}	84.1	83.4	84.2	78.0
	MMBench _{cn}	81.0	81.6	76.9	74.6
	MME-RealWorld _{en}	62.3	57.3	61.6	51.6
	MME-RealWorld _{cn}	56.1	51.5	49.6	45.4
	SeedBench _{image}	77.3	77.5	76.6	74.8
	CV-Bench	80.8	80.0	77.2	71.5
	ScienceQA	95.0	88.8	93.6	83.3
	SEED-Bench-2-Plus	69.2	70.9	68.9	68.6
	RealWorldQA	68.1	68.5	67.8	60.0
Avg.		74.2	72.2	72.1	66.4
Reasoning	MathVista _{mini}	69.6	68.6	67.9	60.2
	WeMath	33.6	33.3	24.9	18.4
	MathVision	25.6	22.4	24.2	21.3
	MMMU _{val}	55.4	51.3	52.7	46.4
	MMMU-Pro _{standard}	37.4	36.3	35.3	31.1
	MMMU-Pro _{vision}	25.2	32.8	25.4	21.3
	Avg.	41.1	40.8	38.4	33.1
					31.5
OCR & Chart	ChartQA	86.5	84.1	87.1	83.4
	CharXiv _{DQ}	74.1	69.8	63.8	58.2
	DocVQA	95.0	94.9	94.4	92.7
	OCRBench	82.9	84.2	80.0	79.2
	AI2D _{w M}	84.2	82.6	83.6	78.6
	AI2D _{w/o M}	94.1	93.4	93.3	90.7
	InfoVQA	78.4	81.7	76.1	75.6
	Avg.	85.0	84.4	82.6	79.8
Others	PixmoCount	62.2	63.3	52.2	50.9
	CountBench	88.2	86.4	79.8	72.5
	VL-RewardBench	46.7	49.7	48.2	42.1
	V*	78.0	77.0	74.9	69.6
	Avg.	68.8	69.1	63.8	58.8
					61.1

4 Training Strategy

4.1 Training Pipeline

Following LLaVA-OneVision (Li et al., 2025a), LLaVA-OneVision-1.5 undergoes three distinct learning stages to enable LLM for multimodal capabilities:

- **Stage-1: Language-Image Alignment.** The stage aims to pretrain the projection layer with the LLaVA-1.5 558K to align the visual features into the word embedding space of LLMs.
- **Stage-1.5: High-Quality Knowledge Learning.** Building on the language-image alignment stage, we introduce the high-quality knowledge learning stage to strike a balance between computational efficiency and injecting new knowledge into LMMs. In this stage, we transition to full-parameter training of all modules using the LLaVA-OneVision-1.5-Mid-Traning dataset.
- **Stage-2: Visual Instruction Tuning.** To enable LMMs to handle a diverse range of visual tasks with desired responses, we continue full-parameter training with the proposed LLaVA-OneVision-1.5-Instruct as well as the FineVision (Face, 2025) dataset.

4.2 Infrastructure

Load Balancing via Data Packing. A major source of training inefficiency arises from padding, where batch samples are standardized by adding padding tokens. This results in significant computational overhead and poor GPU utilization, particularly with heterogeneous multimodal data. To mitigate this, we propose an offline parallel data packing method that consolidates multiple shorter samples into packed sequences during preprocessing. Our approach employs hash buckets to handle large-scale data efficiently and leverages multi-threaded, strategy-aware batching to control packing success rate, sample count, and batch composition. Unlike online packing, which operates dynamically at runtime, our method processes entire datasets or large contiguous chunks offline, ensuring uniform output lengths. This yields up to an $11\times$ compression ratio on 85 million pretraining samples, substantially improving efficiency.

Hybrid Parallelism Framework. We adopt AIAK-Training-LLM¹ built upon Megatron-LM (Shoeybi et al., 2019) as our training framework. Its transformer engine and specialized optimizations enable efficient mid-training of LLaVA-OneVision-1.5-8B with a context length of 8K. By leveraging distributed optimizer parallelism and uniform recomputation, the mid-training process is conducted at native resolution on 85 million captions using $128 \times$ A800 GPUs over 3.7 days.

5 Experiments

5.1 Overall Performance

We use LMMS-Eval Zhang et al. (2024) with the default prompt to evaluate the performance of LLaVA-OneVision-1.5 across multiple benchmarks in four categories of downstream tasks:(1) General Visual Question Answering (VQA): MMStar (Chen et al., 2024a), MMEBench series (Fu et al., 2023), MME-RealWorld series (Zhang et al., 2025), SeedBench (Li et al., 2024b), Seed-Bench-2-Plus (Li et al., 2024a), CV-Bench (Tong et al., 2024), and RealWorldQA (Corp., 2024). (2) Multimodal Reasoning: MathVista (Lu et al., 2024), WeMath (Qiao et al., 2025), MathVision (Wang et al., 2024a), MMMU (Yue et al., 2024), and MMMU-Pro series (Yue et al., 2025).(3) OCR & Chart Understanding: ChartQA (Masry et al., 2022), CharXiv (Wang et al., 2024d), DocVQA (Mathew et al., 2021), OCRCBench (Liu et al., 2024c), AI2D (Kembhavi et al., 2016), and InfoVQA (Mathew et al., 2022).(4) Others: PixmoCount (Deitke et al., 2025), CountBench (Paiss et al., 2023), VL-RewardBench (Li et al., 2025b), and V* (Wu and Xie, 2024). As shown in Tab. 1, LLaVA-OneVision-1.5-8B surpasses Qwen2.5-VL-7B on 18 of 27 benchmarks and LLaVA-OneVision-1.5-4B surpasses Qwen2.5-VL-3B on 27 of 27 benchmarks.

5.2 General Visual Question Answering

As detailed in Tab. 1, we evaluate the general visual question answering capability of LLaVA-OneVision-1.5 across multiple benchmarks, and LLaVA-OneVision-1.5-8B demonstrates superior performance on MMStar (67.7), MMBench_{en} (84.1), MME-RealWorld_{en} (62.3), MME-RealWorld_{cn} (56.1), CV-Bench (80.8), and ScienceQA (95.0). Besides, LLaVA-OneVision-1.5 also presents comparable performance on MMBench_{cn} (81.0), SeedBench_{image} (77.3), SEED-Bench-2-Plus (69.2), and RealWorldQA (68.1).

¹AIAK-Training-LLM: Baidu Cloud’s optimized Megatron-LM

Table 2 Comparison of RICE-ViT with other vision encoders using the LLaVA-NeXT framework. All models are evaluated using identical configurations: Qwen2.5-7B as the language model, LLaVA-NeXT training data, and the same training pipeline. To ensure fair comparison, we adopt LLaVA-NeXT’s tiling strategy (up to $2 \times 2 + 1$ tiles) for handling high-resolution images, as many vision encoders do not support native resolution processing.

Model Configuration		OCR & Document Understanding							General Vision Understanding								
Method	Vision Tower	InfoVQA	DocVQA	ChartQA	TextVQA	OCRBench	OCRBenchV2	LiveXivVQA	OQR Avg	A12D	MMB ^{EN}	MME _{Cog}	MME _{Per}	POPE	RealworldQA	MMStar	Other Avg
CLIP	ViT-L-14-336px	38.9	75.2	66.5	62.5	52.5	23.0	47.4	52.3	73.2	74.6	48.0	75.6	88.8	63.7	49.0	67.6
MLCD	ViT-L-14-336px	43.5	76.5	67.8	61.7	53.1	24.0	48.4	53.6	77.0	76.4	54.1	79.9	88.7	61.1	51.0	69.7
AIMv2	ViT-L-14-336px	35.4	77.2	72.7	65.9	57.2	23.9	47.3	54.2	75.4	78.6	48.3	75.0	88.4	62.2	50.2	68.3
RICE-ViT	ViT-L-14-336px	45.2	79.2	72.3	65.9	57.5	24.1	48.9	56.2	77.9	76.6	54.6	80.7	88.5	63.1	51.8	70.5
DFN5B	ViT-H-14-378px	38.6	70.9	64.4	59.4	47.3	21.9	46.2	49.8	73.5	73.4	45.8	76.9	88.6	59.9	49.1	66.7
SigLIP	ViT-SO400M-14-384px	41.4	76.7	69.3	64.7	55.4	24.0	48.4	54.3	76.2	77.0	46.1	79.9	88.8	63.7	47.3	68.4
SigLIPv2	ViT-SO400M-14-384px	43.7	79.1	70.2	66.2	58.7	25.4	48.6	56.0	77.0	77.1	46.6	80.4	89.3	63.4	52.8	69.5
RICE-ViT	ViT-L-14-378px	48.1	82.6	75.1	66.2	58.8	25.8	49.5	58.0	76.5	77.6	54.1	79.0	89.1	62.9	51.2	70.1
SigLIPv2	ViT-SO400M-16-560px	50.2	86.2	77.4	70.2	62.7	26.5	52.9	60.9	77.0	76.5	53.5	79.9	89.3	68.2	53.1	71.1
RICE-ViT	ViT-L-14-560px	53.2	87.4	78.1	69.0	60.7	26.1	53.0	61.1	76.9	78.6	56.3	79.3	88.9	65.1	50.5	70.8
Qwen-ViT from Qwen2.5-VL 7B	ViT-H-14-560px	55.9	85.8	78.8	73.7	66.2	26.8	53.4	62.9	78.8	78.4	62.0	80.8	88.6	64.2	55.0	72.5
RICE-ViT from OV-1.5 3B	ViT-L-14-560px	53.7	87.1	81.9	73.8	73.3	30.4	53.6	64.8	80.3	79.6	58.6	82.2	89.0	67.3	56.6	73.4

5.3 Multimodal Reasoning

LLaVA-OneVision-1.5 exhibits superior multimodal reasoning capabilities compared to Qwen2.5-VL. Specifically, LLaVA-OneVision-1.5-4B outperforms Qwen2.5-VL-3B on all evaluated benchmarks, leading in MathVista_{mini} (67.9), WeMath (24.9), MathVision (24.2), MMMU_{val} (52.7), MMMU-Pro_{standard} (35.3), and MMMU-Pro_{vision} (25.4). Notably, LLaVA-OneVision-1.5-4B surpasses LLaVA-OneVision-7B across all benchmarks. Compared with Qwen2.5-VL-7B, LLaVA-OneVision-1.5-8B also demonstrates gains of 1.0%, 0.3%, 3.2%, 4.1%, and 1.1% on MatchVista_{mini}, WeMath, MathVision, MMMU_{val}, and MMMU-Pro_{standard}.

5.4 OCR & Chart Understanding

The interpretation of visual data, including documents and charts, requires a sophisticated array of skills from multimodal large language models, ranging from low-level Optical Character Recognition (OCR) to high-level semantic reasoning. To thoroughly evaluate these capabilities, we assess LLaVA-OneVision-1.5 across seven challenging benchmarks. LLaVA-OneVision-1.5-8B demonstrates robust outcomes on ChartQA (86.5), CharXiv_{DQ} (74.1), DocVQA (95.0), AI2D_{w M} (84.2), and AI2D_{w/o M} (94.1). Notably, LLaVA-OneVision-1.5-4B outperforms Qwen2.5-VL-3B on all seven benchmarks.

5.5 Others

To further elucidate the capabilities of LLaVA-OneVision-1.5, we extend our evaluation to include PixmoCount, CountBench, VL-RewardBench, and V*. LLaVA-OneVision-1.5-8B records scores of 62.2 on PixmoCount, 88.2 on CountBench, 46.7 on VL-RewardBench, and 78.0 on V*, demonstrating proficiency in counting, visual perception, and visual grounding, on par with Qwen2.5-VL-7B.

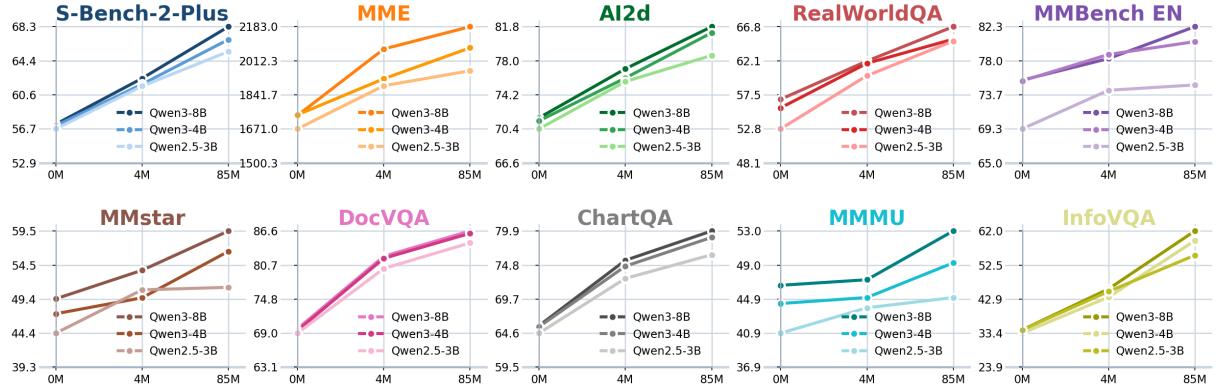


Figure 4 Performance comparison across different mid-training data scales on various benchmarks. Models initially undergo pre-training on LLaVA-558K and are then subjected to mid-training at different data scales (4M, 85M), followed by fine-tuning using the LLaVA-NeXT (Liu et al., 2024b) SFT framework. 0M denotes native pre-training without the mid-training stage.

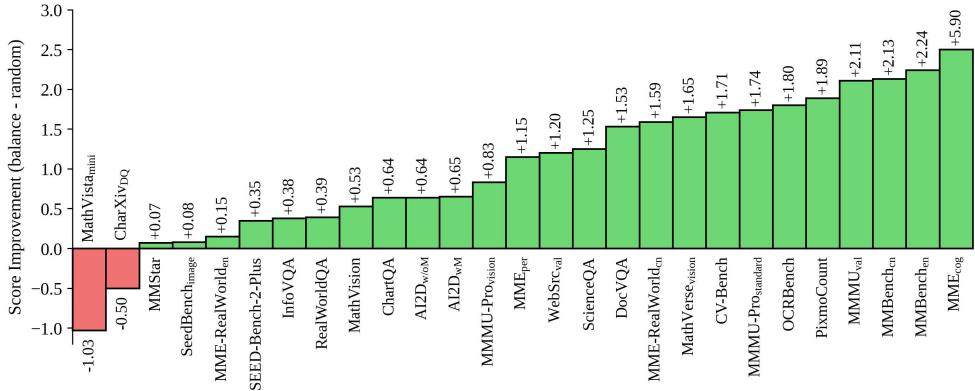


Figure 5 Experimental results using 2M blanced and unbalanced mid-training samples (LLaVA-NeXT-780k as the SFT data) show that using a balanced mid-training dataset yields consistent improvements over a random sampling strategy.

5.6 Ablation Study

5.6.1 Comparison of Different Vision Encoders

In Tab. 2, we evaluate various vision encoders, CLIP (Radford et al., 2021), MLCD (An et al., 2024), AIMv2 (Fini et al., 2025), DFN (Fang et al., 2023), SigLIP (Zhai et al., 2023), SigLIPv2 (Tschannen et al., 2025), and RICE-ViT (Xie et al., 2025), within the LLaVA-NeXT framework. At a resolution of 336 pixels, RICE-ViT surpasses CLIP across all benchmarks, achieving significant gains in InfoVQA (+6.3%) and OCRBench (+5.0%). It also demonstrates significant improvements in document understanding compared to AIMv2. At 378 pixels, RICE-ViT outperforms computationally intensive models such as SigLIPv2 in 9 of 14 benchmarks, notably in InfoVQA (+4.4%), DocVQA (+3.5%), and ChartQA (+4.9%). These results position RICE-ViT as a leading vision encoder, enhancing OCR capabilities and providing robust visual understanding, crucial for applications requiring advanced document analysis and visual reasoning. In addition, we further compare the performance of RICE-ViT with that of Qwen-ViT after incorporating LMM training, where RICE-ViT is derived from LLaVA-OneVision-1.5-3B and Qwen-ViT is derived from Qwen2.5-VL-7B. In the areas of OCR & Document Understanding and General Vision Understanding, RICE-ViT demonstrates average performance improvements of 1.9% and 0.9% compared to Qwen-ViT.

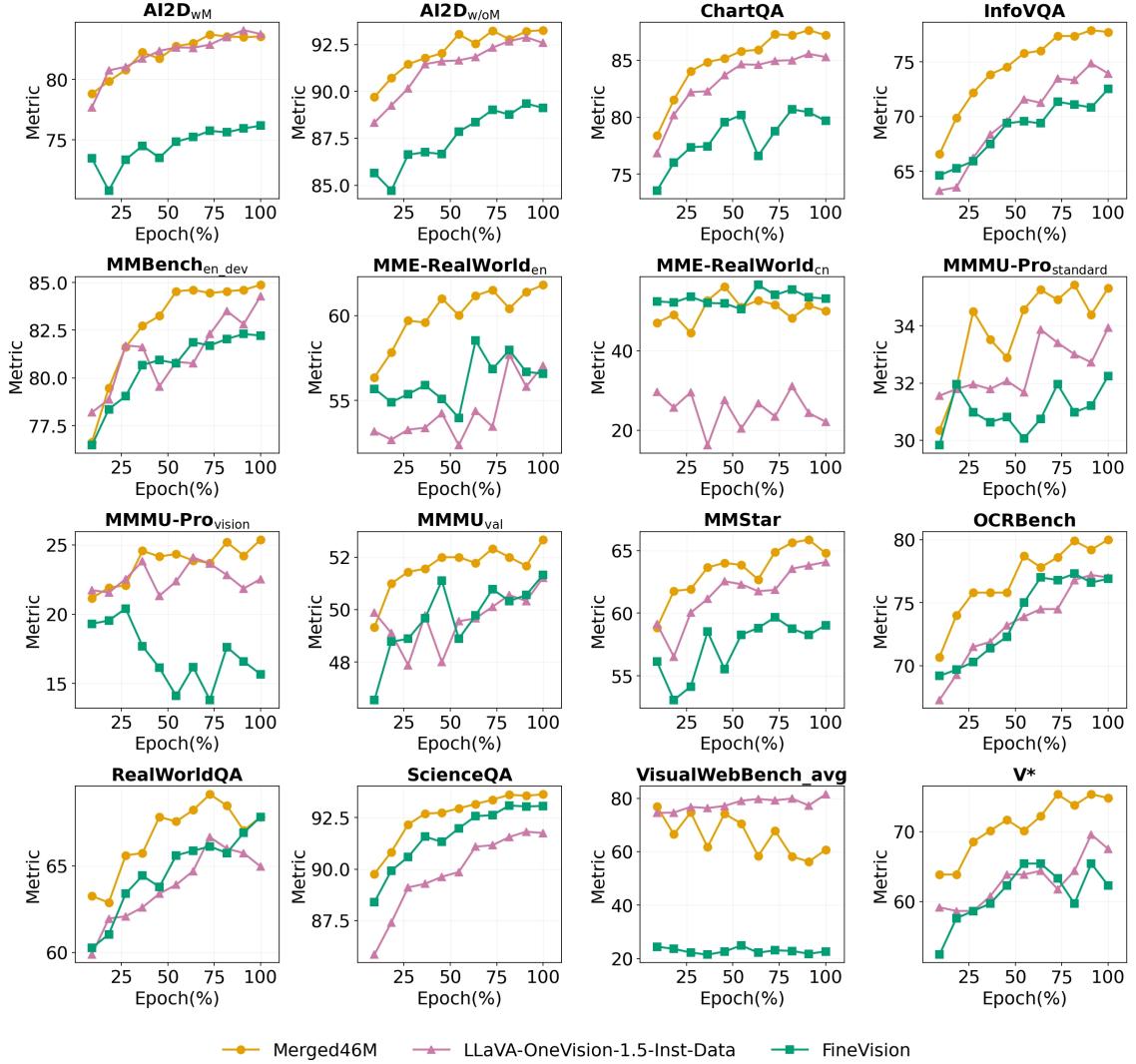


Figure 6 Performance comparison of three datasets (Merge46M, FineVision, and LLaVA-OneVision-1.5-Inst-Data) across 16 benchmarks during the SFT phase, demonstrating the superiority of Merge46M on most benchmarks.

5.6.2 Mid-Training Data Scaling

As depicted in Fig. 4, we present the performance of three different LMMs trained with various scales of mid-training data across ten distinct benchmarks. Employing LLaVA-558K for language-image alignment and standard LLaVA-Next instruction tuning, our findings indicate that scaling the data volume during the high-quality knowledge learning phase consistently enhances model performance across all benchmarks. These results not only underscore the high quality and scalability of the proposed LLaVA-OneVision-1.5-Mid-Traning dataset but also confirm the efficacy of data scaling in improving the performance of LMMs.

5.6.3 Effectiveness of Concept Balance

Fig. 3(a) illustrates that after implementing concept balancing, LLaVA-OneVision-1.5-Mid-Traning exhibits a smoother distribution, thereby enhancing the model’s capability to assimilate a more comprehensive set of knowledge. To further validate the effect of concept balance, we conducted a comparative analysis of models trained on 2M concept-balanced data versus those trained on

2M data obtained through random sampling. As indicated in Fig. 5, the concept-balanced 2M data set demonstrates superior performance in 25 of 27 evaluated downstream benchmarks.

5.6.4 Instruction Data Quality and Scaling

To enhance performance across diverse VQA tasks, we compile 124 types of instruction data (LLaVA-OneVision-1.5-Inst-Data) for SFT training. We further scale the model capabilities by deduplicating and merging the recently proposed FineVision dataset (HuggingFaceM4, 2025), resulting in the Merged46M SFT dataset. To maintain consistent training steps, we double the batch size for Merged46M due to its larger scale. Fig. 6 shows performance comparisons on 16 benchmarks during SFT using three datasets: LLaVA-OneVision-1.5-Inst-Data, FineVision, and Merged46M. LLaVA-OneVision-1.5-Inst-Data achieves performance comparable to FineVision, while the Merged46M dataset delivers the best results across nearly all benchmarks.

6 Conclusions

In this work, we introduce LLaVA-OneVision-1.5, a family of large multimodal models that establishes a new paradigm for constructing high-performance vision-language systems with improved efficiency and reproducibility. We demonstrate the feasibility of training competitive multimodal models from scratch under strict constraints. Our contributions are threefold: a large-scale, curated multimodal dataset; an efficient end-to-end training framework operable under a limited budget; and extensive empirical results demonstrating state-of-the-art performance across diverse benchmarks. The model excels particularly in resource-constrained settings, surpassing strong baselines such as Qwen2.5-VL-7B. This study underscores how open and efficient frameworks can drive progress in multimodal AI, democratizing access to state-of-the-art performance. We envision LLaVA-OneVision-1.5 as a foundational resource that empowers the community to build specialized applications and develop more powerful LMMs across diverse tasks through continued scaling.

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A LLaVA-OV-1.5 vs. Qwen2.5-VL with Same LLM

To enable a fair comparison with Qwen2.5-VL, we train LLaVA-Onevision-1.5-3B based on Qwen2.5-3B-Instruct. As shown in Fig. 7, LLaVA-Onevision-1.5-3B also demonstrates superior performance, achieving better results on 17 out of 27 downstream benchmarks.

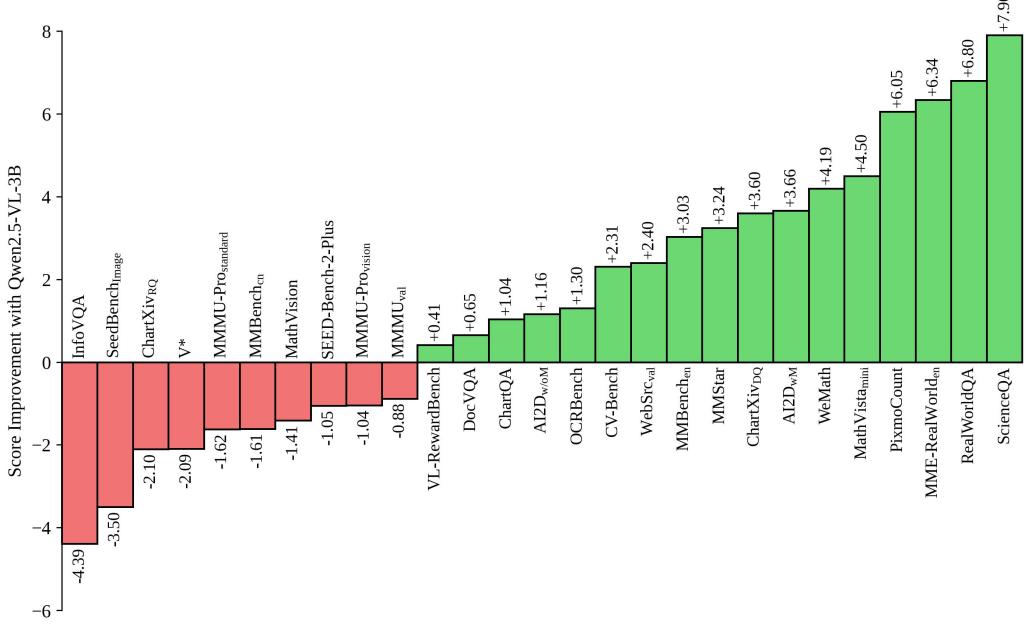


Figure 7 Comparison between LLaVA-OV-1.5-3B and Qwen2.5-VL-3B model on public datasets using the same LLM for both evaluations.

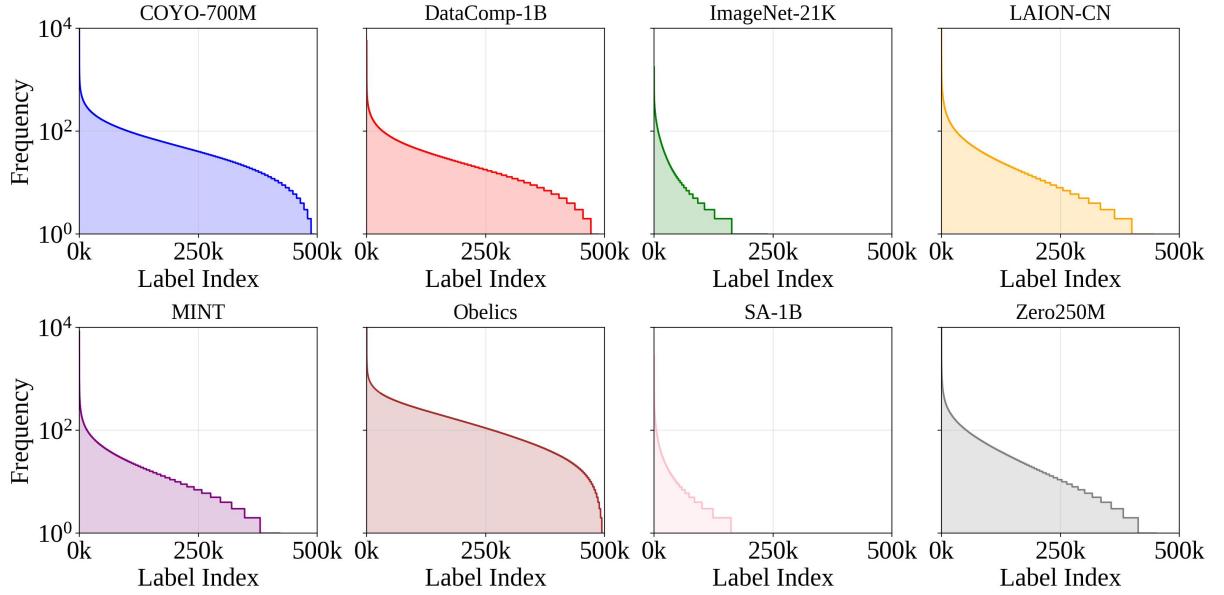


Figure 8 Original concept distributions across eight common vision datasets used in the LLaVA-OneVision-1.5-Mid-Traning dataset.

B Mid-Training Data: Concept Distribution and Top 50 Topics

Fig. 8 presents the raw concept distributions across eight common vision datasets used in the LLaVA-OneVision-1.5-Mid-Traning dataset. All sources exhibit a pronounced long-tail bias, indicating that the original data are far from comprehensive. Obelics displays the broadest and most uniform distribution (slowest tail decay), while others, such as ImageNet-21K and SA-1B, cover fewer concepts with higher frequency concentration. To characterize the semantic space of the mid-training mixture, we apply topic modeling to associated texts and extract the 50 most salient topics (Tab. 3). These span diverse domains, including wildlife, apparel, cuisine, interiors, engineering, electronics, healthcare, WebUI, and cultural activities, offering an interpretable summary of data coverage. This analysis confirms Obelics as the most comprehensive source and highlights coverage gaps in other datasets, informing subsequent data curation.

Table 3 Topic Modeling Results (50 Topics)

Concept	Related words
Wildlife	feathers, wildlife, beak, branch, birds, habitat, scales, plumage, claws, feather, behavior, spots, watchers, snout, species, creature, paws, limbs, flight, drawing
Jewelry and Aviation	jewelry, beads, airplane, aircraft, aviation, plane, sparkle, bracelet, flight, stones, elegance, pendant, accessory, loop, diamonds, gemstones, gemstone, pearl, landing, shine
Internet Humor	humor, phrase, eco, baby, parents, sustainability, frustration, references, meme, sentiment, surprise, mother, farm, disney, twist, internet, cartoonish, novelty, reaction, drawing
Education and Learning	slide, educators, learners, bullet, education, learning, classroom, study, math, guide, student, resource, writing, textbook, skills, problem, publisher, question, list, questions
Watches and Accessories	case, strap, watch, wristwatch, hour, brim, crown, markers, dial, barrel, numerals, grip, accessory, clock, luxury, gun, minute, buckle, rifle, stitching
Gaming and Sports	games, gamers, baseball, armor, jerseys, fi, franchise, sword, basketball, horror, competition, sport, court, gaming, anime, athleticism, readiness, arena, athletes, flames
Certification and Professionalism	stamp, clients, certification, seal, colleagues, stamps, standards, calligraphy, headshot, friendliness, compliance, certifications, profiles, mark, envelope, creases, impression, identification, trustworthiness, german
Vehicles and Racing	seat, wheel, tires, grille, truck, license, headlights, speed, driver, track, rims, quarter, mirrors, race, seats, racing, train, transportation, three-quarter, windshield
Architectural and Mechanical Plans	grooves, architects, drawings, plan, drawing, tire, hub, roller, wheel, tread, plans, coaster, distances, blueprint, 2023, rubber, planners, amusement, skateboard, traction

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Table 3 – continued from previous page

Concept	Related words
Ceremonies and Achievement	achievement, pride, ceremony, award, trophy, university, campus, awards, skeleton, victory, graduation, bones, success, achievements, alumni, casino, medal, certificate, dinosaur, tuxedo
Portraiture and Makeup	finger, eyebrows, jawline, cheek, makeup, cheeks, portraiture, index, nails, individual, strands, thumb, beer, cheekbones, brow, bangs, ear, shot, stubble, creases
Software and Development	software, computer, developers, options, system, user, code, management, file, version, application, menu, fields, input, process, arrows, programming, files, 3d, interfaces
Pets and Footwear	dog, footwear, owners, cat, shoe, laces, toe, sole, heel, paws, tongue, sneakers, soles, mesh, ankle, rubber, foot, dogs, toes, straps
Typography and Design	sans, gradients, letter, variations, symbolism, forms, spacing, thickness, variation, meaning, bold, alignment, curves, designers, representation, emotions, rectangle, curve, knowledge, trademark
Cuisine and Cooking	cooks, meal, ingredients, dish, freshness, vegetables, cooking, sauce, fruit, slices, pieces, herbs, spoon, meat, cuisine, crispy, slice, rice, fruits, chocolate
Home Interiors	coffee, lamp, shelf, living, vase, bedroom, cabinet, pillows, comfort, rug, countertop, cup, homeowners, sofa, pillow, cabinets, counter, flooring, couch, shade
Skincare and Packaging	skincare, liquid, lid, wine, container, ingredients, tube, supplements, screw, premium, luxury, benefits, transparency, labeling, jar, solutions, supplement, powder, oil, spray
Childhood and Holidays	parents, toy, holiday, baby, gift, toys, polka, kids, christmas, decorations, ribbon, bear, caregivers, fun, charm, decoration, greeting, rabbit, birthday, dot
Social Interactions	pen, smiles, postures, mid-20th-century, discussion, celebrity, hairstyles, collage, interactions, collaboration, jackets, notebook, -century, fourth, gestures, cinema, teamwork, interview, ties, plaid
Literature and Romance	love, spine, intimacy, works, couple, publisher, affection, novel, romance, proximity, moments, bond, hardcover, 19th-century, pages, edition, poetry, drama, collection, covers
Inspirational Quotes	quote, self, positivity, inspiration, resilience, philosophy, quotes, hope, help, introspection, journey, phrase, attribution, things, weight, motivation, freedom, contemplation, love, vulnerability

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Table 3 – continued from previous page

Concept	Related words
Waterside Leisure	beach, shore, ripples, relaxation, sand, roofs, boat, sea, pool, bridge, shoreline, turquoise, landscapes, boats, river, lake, deck, skyline, trunks, leisure
Engineering and Mechanics	component, engineers, holes, mechanics, diy, engineering, technicians, screws, hardware, hole, specifications, wires, electronics, manufacturers, steel, manufacturing, manufacturer, circuit, grip, ends
Retail and Pricing	price, package, shoppers, 10, barcode, promotion, pack, store, 20, sale, 100, tag, info, shipping, 50, medication, 30, sales, discount, quantity
Technology and Innovation	innovation, network, lightning, connectivity, bolt, globe, connections, nodes, ideas, cloud, gears, communication, networks, bulb, intelligence, integration, lightbulb, concept, telecommunications, networking
Industrial and Manufacturing	workers, machine, machinery, manufacturing, storage, safety, fish, facility, factory, workshop, pipes, warehouse, maintenance, logistics, task, site, fins, warning, steel, production
Trust and Publication	trust, shield, reliability, studies, china, stakeholders, clients, partners, publication, translation, institution, publisher, public, tradition, scholars, formality, stability, organizations, strength, academics
Healthcare and Fitness	healthcare, fitness, patients, training, wellness, exercise, hospital, practice, gym, strength, clinic, muscles, shirtless, support, lab, treatment, stethoscope, muscle, weight, doctor
Museum Artifacts	motifs, sculpture, bronze, museum, statue, coin, folds, engravings, artifacts, skull, scroll, item, carvings, coins, gallery, pedestal, scratches, artifact, elegance, artwork
Dining and Hospitality	tables, restaurant, café, experience, spot, counter, customers, seating, locals, diners, drinks, shop, establishment, patrons, menu, casual, fixtures, hats, market, drink
Real Estate	estate, tiles, homeowners, shrubs, bathroom, lawn, railings, bushes, porch, property, driveway, staircase, bricks, houses, panes, yard, homebuyers, neighborhood, chimney, concrete
Music and Geography	guitar, musicians, concert, instrument, instruments, country, artist, strings, regions, musician, roads, singer, drum, song, locations, geography, land, performers, performances, maps
Entomology and Containers	lid, antennae, container, insect, butterfly, spots, shell, spines, wing, ridges, candle, storage, rim, insects, hairs, abdomen, entomology, bee, iridescent, observation

Continued on next page

Table 3 – continued from previous page

Concept	Related words
Apparel Design	apparel, pocket, neckline, pockets, waist, garment, fit, cuffs, zipper, hip, belt, tag, straps, torso, cotton, crew, seams, hem, hood, knee
Crafting and DIY	crafters, craft, supplies, crafts, diy, artists, projects, creativity, lab, textiles, textile, laboratory, project, pieces, motifs, stationery, pencil, thread, tactile, workspace
Data and Chemistry	graph, comparison, values, axis, trends, analysis, chart, x-, analysts, market, chemistry, metrics, chemical, visualization, graphs, 2d, years, investors, axes, groups
Electronic Devices	devices, smartphone, computer, keyboard, laptop, lens, monitor, cable, indicator, case, audio, keys, speaker, tablet, usb, ports, security, workspace, electronics, solutions
Recreation and Law	police, law, sheet, superhero, notes, golf, enforcement, club, course, officer, officers, cape, notation, copyright, costume, security, piano, personnel, swing, musicians
Web and UI	navigation, app, user, header, links, webpage, search, smartphone, screenshot, web, options, link, yuan, tabs, battery, url, post, site, menu, email
Space and Music Media	moon, earth, exploration, record, wonder, vinyl, planet, purples, astronomy, records, sphere, thirds, crescent, two-thirds, landmasses, herbarium, rocket, oceans, cloud, magic
Business and Finance Documents	bullet, info, finance, header, management, money, address, documents, topics, question, headers, description, list, headings, job, email, fields, slide, dollar, newspaper
Weddings and Traditions	wedding, lace, embroidery, dance, festival, dresses, indian, traditions, bouquet, occasion, gown, couple, bride, costumes, couples, weddings, outfits, tradition, headscarf, veil
Transportation and Fiction	horse, ship, bike, mystery, bicycle, soldiers, handlebars, thriller, hull, motorcycle, crime, smoke, genre, rider, genres, cyclists, drama, horses, war, dramas
Botany and Gardening	stems, veins, cluster, stem, blooms, bloom, gardeners, soil, gardening, tips, clusters, bark, buds, trunk, stamens, botany, canopy, blossoms, fishing, droplets
Vast Landscapes	terrain, peaks, landscapes, desert, expanse, slopes, range, formations, vastness, isolation, grandeur, peak, hikers, valley, stones, mist, appeals, earth, slope, awe
Biological Diagrams	diagram, arrows, biology, research, documentation, anatomy, cell, diagrams, purposes, cells, blood, flow, study, emergency, specimen, scientists, tissue, understanding, measurements, response

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Table 3 – continued from previous page

Concept	Related words
Religious Architecture	carvings, grandeur, church, robe, dome, reverence, christian, robes, temple, site, statue, landmark, spires, arches, european, towers, statues, arch, castle, spire
Time and Health Data	dates, days, calendar, pm, masks, covid-19, times, info, week, month, ray, pandemic, schedule, daily, 1st, sunday, flyer, dna, 2020, helix
Public Speaking	speech, bubble, press, speaker, podium, politics, pin, government, formality, communication, mark, bubbles, microphones, announcement, lapel, u.s., gesture, exclamation, gravity, gestures
Urban Streetscape	signage, mid-morning, -morning, sidewalk, pavement, parking, pole, traffic, hotel, poles, store, locals, awning, lot, streetlights, pedestrians, station, residents, storefront, japan

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