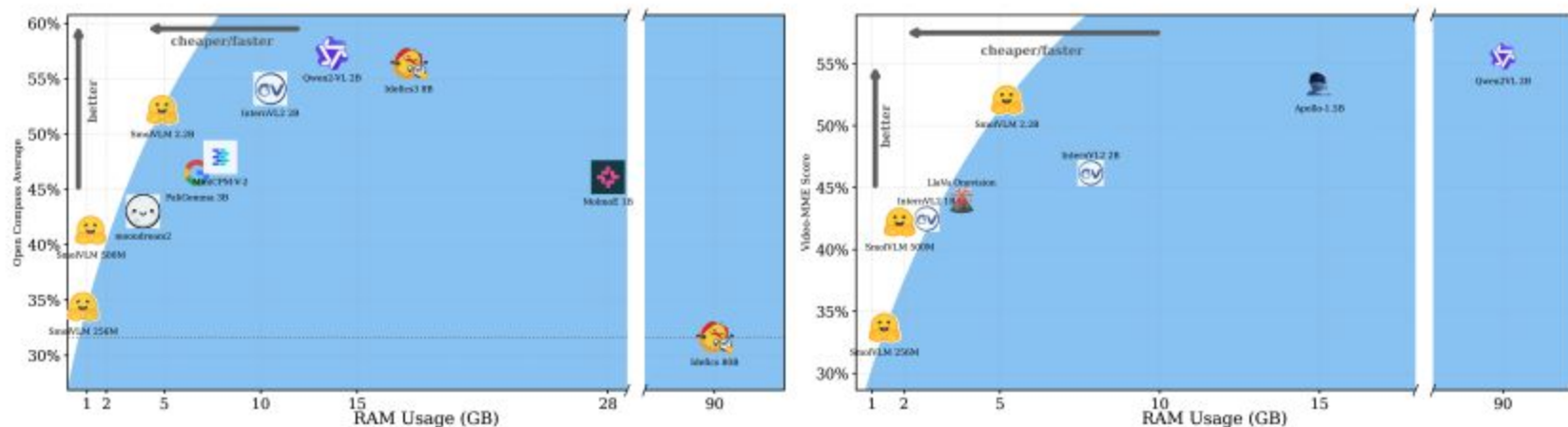


# SmolVLM: Redefining small and efficient multimodal models



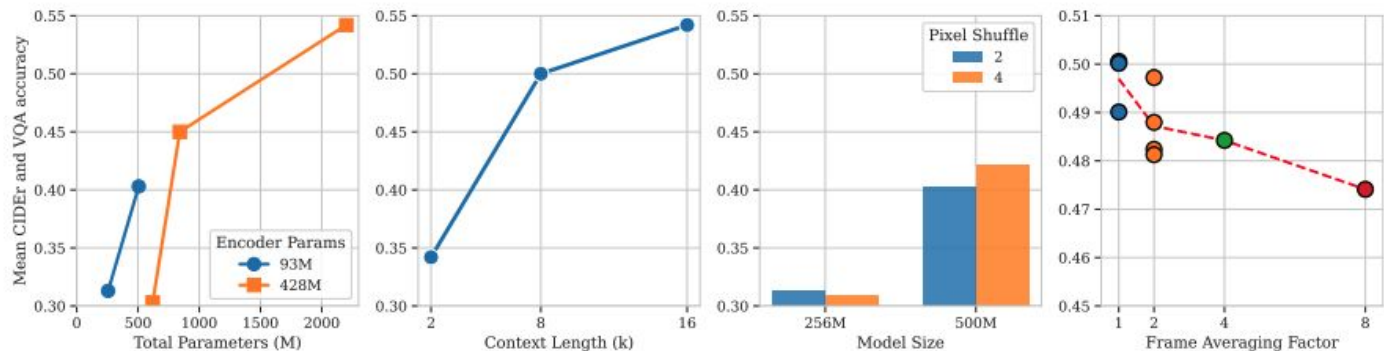
**Figure 1 | Smol yet Mighty:** comparison of SmolVLM with other state-of-the-art small VLM models. Image results are sourced from the OpenCompass OpenVLM leaderboard (Duan et al., 2024).

# Introduction

- Compact yet Powerful Models
- Efficient GPU Memory Usage
  - smallest model runs inference using less than 1GB GPU RAM
- Systematic Architectural Exploration
- Robust Video Understanding on Edge Devices
- Fully Open-source Resources
  - weights, datasets, code

# Architecture

- How to assign compute between vision and language towers?
  - Language Model : SmoLLM2 (135M, 360M, 1.7B)
  - Vision Model : SigLIP-B/16(93M), SigLIP-SO400M(428M)



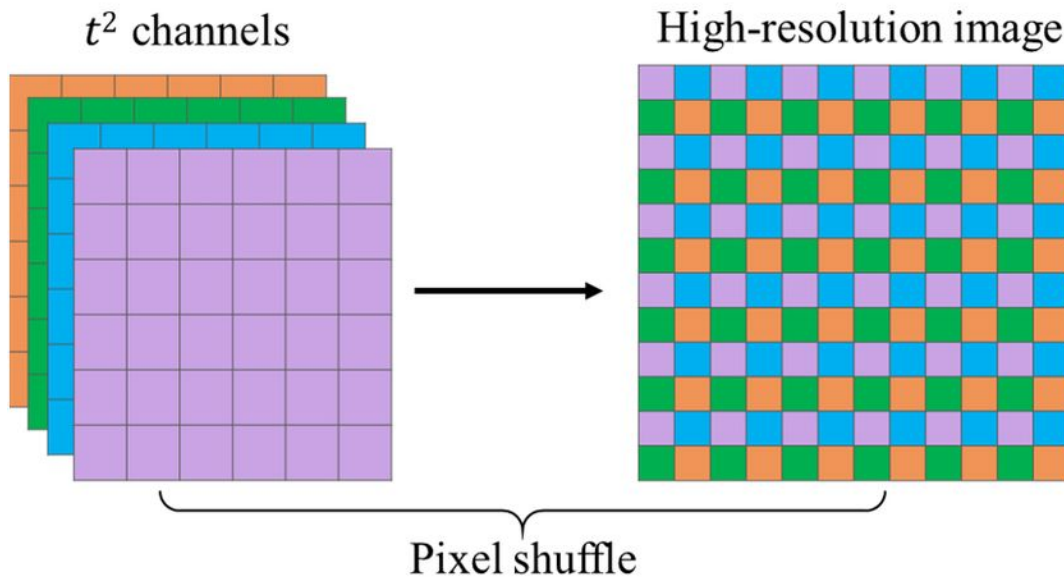
**Figure 3 | Performance analysis of SmoIVLM configurations.** (Left) Impact of vision encoder and language model sizes. Smaller language models (135M) benefit less from larger vision encoders (SigLIP-SO-400M, 428M) compared to SigLIP-B/16 (93M), while larger language models gain more from powerful encoders. (Middle-left) Performance significantly improves with increased context lengths (2k to 16k tokens). (Middle-right) Optimal pixel shuffle factor (PS=2 vs. PS=4) varies by model size. (Right) Frame averaging reduces video performance, with a rapid decline as more frames are averaged. Metrics average CIDEr (captioning) and accuracy (visual question answering).

# Architecture

- Context Length
  - RoPE
  - small model - 8k context length
  - large model - 16k context length

# Architecture

- How can we efficiently pass the images to the Language Model?
  - Pixel Shuffle



# Architecture

- How can we efficiently pass the images to the Language Model?
  - Sub image
    - resize to (512, 512), long edge
    - divide to 4 x 4
    - use whole resized image
    - one image to 17 images



# Architecture

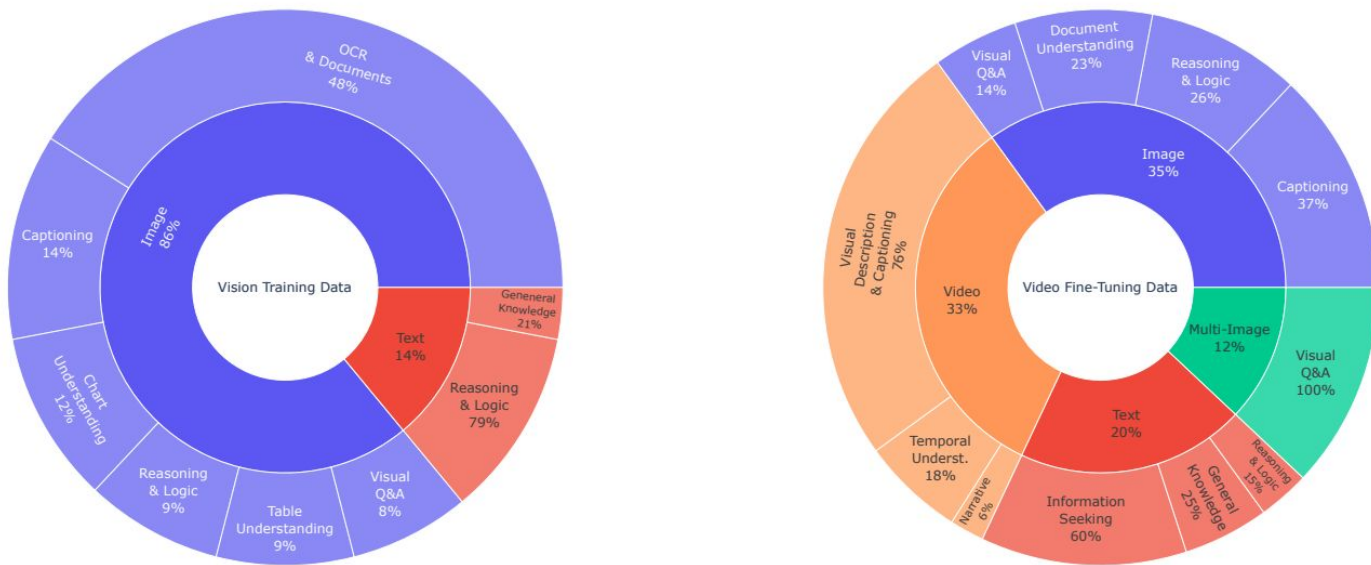
```
# Create input messages
messages = [
    {
        "role": "user",
        "content": [
            {"type": "image"},
            {"type": "image"},
            {"type": "text", "text": "Can you describe the two images?"}
        ]
    },
    {
        'role': 'Assistant',
        "content": [
            {'type': 'text', 'text': 'blah blah'},
        ],
    },
]
```



[illegible]

Assistant: blah blah&lt;end of utterance&gt;

# Dataset



**Figure 8 | Data Details.** Training dataset details for Vision (*Left*) and video (*Right*), broken down by modality and sub-categories.

# Dataset

- Training Dataset

- 2 stage : vision stage -> video stage

- vision stage

- new mixture of the datasets <https://arxiv.org/abs/2408.12637> to which added MathWriting <https://arxiv.org/abs/2404.10690>
      - The visual components comprise document understanding, captioning, and visual question answering (including 2% dedicated to multi-image reasoning), chart understanding, table understanding, and visual reasoning tasks.
      - To preserve the model's performance in text-based tasks, we retained a modest amount of general knowledge Q&A and text-based reasoning & logic problems, which incorporate mathematics and coding challenges.

# Dataset

- Training Dataset

- 2 stage : vision stage -> video stage

- video stage

- The video fine-tuning stage maintains 14% of text data and 33% of video to achieve optimal performance, following the learnings of Zohar et al. (2024b). For video, we sample visual description and captioning from LLaVA-video-178k (Zhang et al., 2024), Video-STAR (Zohar et al., 2024a), Vript (Yang et al., 2024), and ShareGPT4Video (Chen et al., 2023), temporal understanding from Vista-400k (Ren et al., 2024), and narrative comprehension from MovieChat (Song et al., 2024) and FineVideo (Farré et al., 2024). Multi-image data was sampled from M4-Instruct (Liu et al., 2024a) and Mammoth (Guo et al., 2024). The text samples were sourced from (Xu et al., 2024).

# Evaluation

Capability Benchmark		SmolVLM 256M	SmolVLM 500M	SmolVLM 2.2B	Efficient OS
Single-Image	OCRBench (Liu et al., 2024e) Character Recognition	52.6%	61.0%	72.9%	54.7% MolmoE-A1B-7B
	AI2D (Kembhavi et al., 2016) Science Diagrams	46.4%	59.2%	70.0%	71.0% MolmoE-A1B-7B
	ChartQA (Masry et al., 2022) Chart Understanding	55.6%	62.8%	68.7%	48.0% MolmoE-A1B-7B
	TextVQA (Singh et al., 2019) Text Understanding	50.2%	60.2%	73.0%	61.5% MolmoE-A1B-7B
	DocVQA (Mathew et al., 2021) Document Understanding	58.3%	70.5%	80.0%	77.7% MolmoE-A1B-7B
	ScienceQA (Lu et al., 2022) High-school Science	73.8%	80.0%	89.6%	87.5% MolmoE-A1B-7B
Multi-task	MMMU (Yue et al., 2024a) College-level Multidiscipline	29.0%	33.7%	42.0%	33.9% MolmoE-A1B-7B
	MathVista (Lu et al., 2024b) General Math Understanding	35.9%	40.1%	51.5%	37.6% MolmoE-A1B-7B
	MMStar (Chen et al., 2024a) Multidisciplinary Reasoning	34.6%	38.3%	46.0%	43.1% MolmoE-A1B-7B
Video	Video-MME (Fu et al., 2024) General Video Understanding	33.7%	42.2%	52.1%	45.0% InternVL2-2B
	MLVU (Zhou et al., 2024) MovieQA + MSRVTT-Cap	40.6%	47.3%	55.2%	48.2% InternVL2-2B
	MVBench (Li et al., 2024b) Multiview Reasoning	32.7%	39.7%	46.3%	60.2% InternVL2-2B
	WorldSense (Hong et al., 2025) Temporal + Physics	29.7%	30.6%	36.2%	32.4% Qwen2VL-7B
	TempCompass (Liu et al., 2024d) Temporal Understanding	43.1%	49.0%	53.7%	53.4% InternVL2-2B
Average	Across Benchmarks	44.0%	51.0%	59.8%	—
RAM Usage	Batch size = 1	0.8 GB	1.2 GB	4.9 GB	27.7 GB MolmoE-A1B-7B
	batch size = 64	15.0 GB	16.0 GB	49.9 GB	—

**Table 1 | Benchmark comparison of SmolVLM variants across vision-language tasks.** Performance of SmolVLM models at three scales (256M, 500M, and 2.2B parameters) compared to efficient open-source models on single-image, multi-task, and video benchmarks. SmolVLM models demonstrate strong accuracy while maintaining significantly lower RAM usage, highlighting their computational efficiency for resource-constrained multimodal scenarios.