NVIDIA Nemotron Nano V2 VL

NVIDIA

Abstract. We introduce Nemotron Nano V2 VL, the latest model of the Nemotron vision-language series designed for strong real-world document understanding, long video comprehension, and reasoning tasks. Nemotron Nano V2 VL delivers significant improvements over our previous model, Llama-3.1-Nemotron-Nano-VL-8B, across all vision and text domains through major enhancements in model architecture, datasets, and training recipes. Nemotron Nano V2 VL builds on Nemotron Nano V2, a hybrid Mamba-Transformer LLM, and innovative token reduction techniques to achieve higher inference throughput in long document and video scenarios. We are releasing model checkpoints in BF16, FP8, and FP4 formats and sharing large parts of our datasets, recipes and training code.

Model (BF16) | Model (FP8) | Model (NVFP4-QAD) | Dataset

1. Introduction

We introduce Nemotron Nano V2 VL, an efficient 12B vision–language model that achieves leading accuracy on OCRBench v2 (Fu et al., 2024a) private data leaderboard[1], along with strong performance in reasoning, document understanding, long-video comprehension, visual question answering, and STEM reasoning. Nemotron Nano V2 VL delivers substantial improvements over our previous model, Llama-3.1-Nemotron-Nano-VL-8B[2], driven by enhancements in model architecture, dataset composition, and training methodology. These gains stem from the inclusion of higher-quality reasoning data, expanded OCR datasets, and additional long-context datasets.

In addition to overall benchmark improvements, we extend the model's context length from 16K to 128K, enabling better handling of long videos and complex reasoning tasks. Consistent with our prior open-source efforts, we release the model weights, along with substantial portions of the training datasets, recipes, and codebase, to support continued research and development.

Nemotron Nano V2 VL builds on top of the Nemotron Nano V2 (NVIDIA et al., 2025) 12B reasoning LLM and RADIOv2.5 vision encoder (Heinrich et al., 2025). In addition, Nemotron Nano V2 VL adopts the multimodal fusion architecture, training recipe as well as data strategy similar to Eagle 2 and 2.5 (Li et al., 2025b; Chen et al., 2025a). We use the open-source Megatron (Shoeybi et al., 2019) framework to train the model in FP8 precision using Supervised Finetuning (SFT) across several vision and text domains, followed by additional SFT stages to further improve video understanding, long context performance, and recover text-only capabilities to achieve competitive results across many vision and text benchmarks.

Compared to Llama-3.1-Nemotron-Nano-VL-8B, the hybrid Mamba-Transformer architecture of the LLM offers 35% higher throughput in long multi-page document understanding scenarios. Additionally, we employ Efficient Video Sampling (EVS) (Bagrov et al., 2025) to accelerate throughput in video understanding use cases by 2x or more with minimal or no impact on accuracy.

Furthermore, Nemotron Nano V2 VL supports both reasoning-on and reasoning-off modes, with the former enabling extended reasoning for tasks that require more complex problem-solving. This

[1] https://99franklin.github.io/ocrbench_v2/
[2] https://huggingface.co/nvidia/Llama-3.1-Nemotron-Nano-VL-8B-V1

design enables a balanced trade-off between computational efficiency and task performance.

We are releasing our model weights on HuggingFace in BF16, FP8 and FP4 formats:

- Nemotron-Nano-12B-v2-VL: The final model weights after our multi-stage training recipe.
- Nemotron-Nano-12B-v2-VL-FP8: Quantized model weights in FP8 format
- Nemotron-Nano-12B-v2-VL-NVFP4-QAD Quantized model weights in FP4 format using Quantization-aware Distillation (QAD)

Additionally, we release a large portion of our SFT dataset and tooling:

- Nemotron VLM Dataset V2: A collection of over 8 million training samples.
- NVPDFTex: A custom LaTeX compiler toolchain to generate annotated OCR ground truth.

The remainder of this report is organized as follows: Section 2 describes the model architecture and input processing pipeline; Section 3 outlines the training recipe, datasets, and hyperparameters; and Section 4 presents comprehensive evaluations of the model across both multimodal and pure-text tasks.

2. Model Architecture

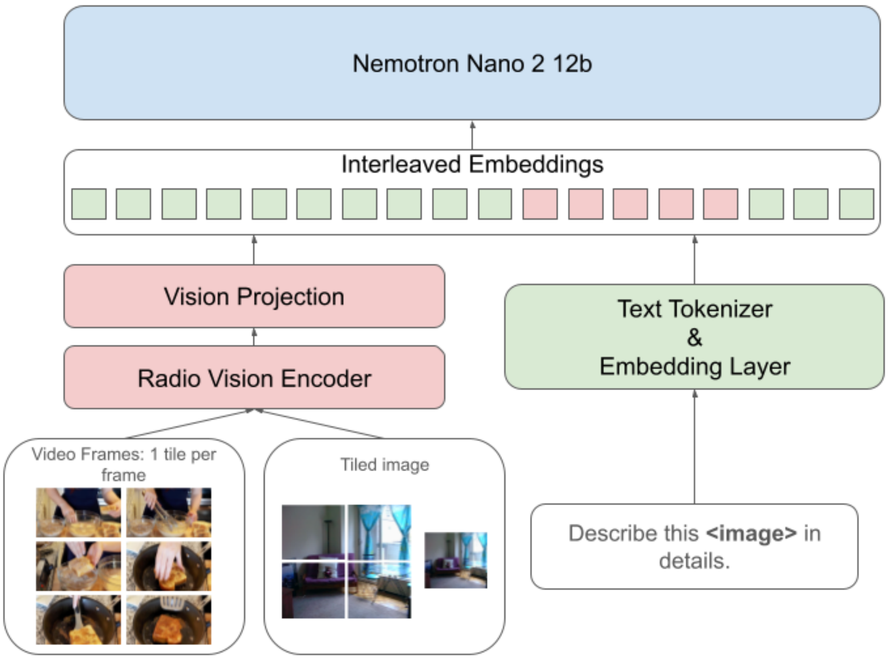


Figure 1 | Visualization of our VLM architecture. For images, we extract a dynamic number of tiles based on the image aspect ratio. For videos, we uniformly extract frames. Tiles and frames are resized to 512×512 pixels, and go through the RADIO vision encoder and an MLP connector. The image and text embeddings are interleaved, and fed to the Nemotron-Nano-12B-V2 LLM.

As illustrated in Figure 1, Nemotron Nano V2 VL consists of three modules: a vision encoder, an MLP projector, and a language model. We initialize the vision encoder using the c-RADIOv2-VLM-H version of the RADIOv2 vision encoder (Heinrich et al., 2025) and the language model with Nemotron-Nano-12B-V2 (NVIDIA et al., 2025).

Inspired by InternVL (Chen et al., 2024d), LLaVA-1.5 (Liu et al., 2024b) and Eagle (Li et al., 2025b; Chen et al., 2025a), we adopt a tiling strategy to handle varying image resolutions. First, each image is resized following the aspect ratio matching strategy employed by InternVL (Chen et al., 2024d) so that its width and height are multiples of s. Then it is divided into non-overlapping tiles of size $s \times s$. In this work, we set $s = 512$. With a patch size of 16, this results in 1024 visual tokens per tile. For scalability, we employ pixel shuffle with 2x downsampling to reduce the token count further to 256. During training, we set the maximum number of tiles to 12. Additionally, we use a single-tile thumbnail of the image to capture global image context. For video inputs, we limit each input frame to a single tile.

3. Training Recipe & Datasets

To preserve the base language model's text comprehension and reasoning abilities while improving its visual understanding, we adopt a multi-stage training approach as detailed below.

3.1. Stage 0

In this stage, we aim to warm up the MLP connector to establish cross-modal alignment between the language and vision domains. To this end, we freeze the vision encoder and language model weights and train only the MLP connector on a diverse multimodal subset of the Stage 1 SFT dataset (see Section 3.2), consisting of approximately 2.2 million samples (up to 36 billion tokens) spanning multiple tasks, including captioning, visual question answering, visual grounding, OCR, and document extraction.

3.2. SFT Stage 1: 16K context length

In this and all subsequent stages, we unfreeze all model components for training. In SFT Stage 1, the maximum sequence length is set to 16,384 tokens. This stage is trained on approximately 32.5 million samples (about 112.5 billion tokens). To preserve the text comprehension capabilities of the Nemotron-Nano-V2 (NVIDIA et al., 2025) LLM backbone, we incorporate a subset of the text reasoning data used in its Stage 1 SFT training, comprising approximately 6.5 million samples (around 40 billion tokens) spanning diverse domains and tasks such as mathematics, science, code, multilingual understanding, multi-turn dialogue, tool-use, and safety. In addition, we include multimodal datasets totaling 26 million samples (approximately 72 billion tokens) drawn from various tasks and sources, including:

1. **Image Captioning**: OpenImages (Kuznetsova et al., 2020), TextCaps (Sidorov et al., 2020), TextVQA (Singh et al., 2019), PixMo-cap (Deitke et al., 2024).
2. **Video Captioning**: Localized Narratives (Pont-Tuset et al., 2020), YouCook2 (Zhou et al., 2017), VaTeX (Wang et al., 2020a).
3. **General Visual QA**: TextVQA (Singh et al., 2019), VQAv2 (Goyal et al., 2017), OK-VQA (Marino et al., 2019), GQA (Hudson & Manning, 2019), CLEVR (Johnson et al., 2016), CLEVR-Math (Lindström & Abraham, 2022), TallyQA (Acharya et al., 2018), Dolly-15K (Conover et al., 2023), ScreenQA (Hsiao et al., 2025), VizWiz (Gurari et al., 2018), MapQA (Chang et al., 2022), ScienceQA (Lu et al., 2022), PMC-VQA (Zhang et al., 2024b), MetaMathQA (Yu et al., 2024), UniGeo (Chen et al., 2022), CMM-Math (Liu et al., 2024c), Geo-170K (Gao et al., 2025), VisualWebInstruct (Jia et al., 2025), LRV-Instruction (Liu et al., 2024a), OCR-VQA (Mishra et al., 2019), EST-VQA (Wang et al., 2020b), ST-VQA (Biten et al., 2019), PixMo-AskModelAnything (Deitke et al., 2024), ALLaVA-4v (Chen et al., 2024a), SLAKE

(Liu et al., 2021), VQA-RAD (Lau et al., 2018), DreamSim (Fu et al., 2023), Spot-the-Diff (Jhamtani & Berg-Kirkpatrick, 2018), NLVR2 (Suhr et al., 2019).
4. **Video QA**: CLEVRER (Yi et al., 2020), Perception Test (Pătrăucean et al., 2023), ALFRED (Shridhar et al., 2020), NextQA (Xiao et al., 2021), VCG+112K (Maaz et al., 2024).
5. **Visual Grounding**: RefCOCO (Kazemzadeh et al., 2014).
6. **OCR, Table & Document Extraction**: SynthDog-en (Kim et al., 2022), SynthTabNet (Nassar et al., 2022), DocLayNet (Pfitzmann et al., 2022), WebSight (Laurençon et al., 2024b), TabRecSet (Yang et al., 2023), FinTabNet (Zheng et al., 2020), PubTables-1M (Smock et al., 2021), TextOCR (Singh et al., 2021), HierText (Long et al., 2022), FUNSD (Jaume et al., 2019), CASIA-HWDB2 (Liu et al., 2011), RCTW-17 (Shi et al., 2018), ReCTS-19 (Liu et al., 2019), human-annotated CommonCrawl [3] samples, synthetically generated tables, arXiv paper annotations generated using the NVPDFTex[4] pipeline and translated to several other languages using mBART-large-50 (Tang et al., 2020), and multilingual Wikimedia[5] dumps.
7. **Document, Chart, Table and GUI QA**: ChartQA (Masry et al., 2022), InfoVQA (Mathew et al., 2021a), AI2D (Kembhavi et al., 2016), DocVQA (Mathew et al., 2021b), FigureQA (Kahou et al., 2018), ECD-10K (Yang et al., 2025b), ArXivQA (Li et al., 2024b), PlotQA (Methani et al., 2020), PixMo-Docs (Deitke et al., 2024), TabMWP (Lu et al., 2023), SlideVQA (Tanaka et al., 2023), Docmatix (Laurençon et al., 2024a), DocReason25K (Hu et al., 2024), UniChart (Masry et al., 2023), SimChart9K (Xia et al., 2024), MMTab (Zheng et al., 2024), VisText (Tang et al., 2023), ScreenQA (Hsiao et al., 2025), WaveUI-25K (AgentSea, 2024), as well as synthetic QA labels generated for FinTabNet (Zheng et al., 2020), HierText (Long et al., 2022) and CommonCrawl PDF samples transcribed using Nemo Retriever Parse[6] (Karmanov et al., 2025).
8. **Visual Grounding**: Visual7W (Zhu et al., 2016), OpenImages (Kuznetsova et al., 2020).
9. **Function Calling**: Glaive function calling (AI, 2023), xLAM-60K (Liu et al., 2024f).

We augment the corpus with both human-annotated reasoning traces and model-generated traces produced by Qwen2.5-VL-32B-Instruct (Qwen et al., 2025), GLM-4.1V, and GLM-4.5V (Hong et al., 2025) across multiple datasets to reinforce the extended reasoning ability of our model in reasoning-on mode. Additionally, for datasets lacking explicit QA labels, we generate synthetic question–answer pairs from existing OCR extractions or captions using LLMs from the Qwen2.5 (Qwen et al., 2025) and Qwen3 (Yang et al., 2025a) families. A large portion of the training data in this stage is released at Nemotron VLM Dataset V2.

3.3. SFT Stage 2: 49K context extension

In this stage, we extend the model's context length to 49,152 tokens to enhance its capability for multi-image and video understanding. The model is trained on approximately 11M samples (around 55B tokens), including a subset of the Stage 1 dataset. We experimented with varying proportions of Stage 1 data and found that a 25% reuse ratio offers a good balance between training efficiency and maintaining accuracy across text, vision, multi-frame and video benchmarks.

In addition to the reused Stage 1 subset, we curate video and multi-image datasets comprising approximately 1.4 million samples (around 17 billion tokens), covering a diverse range of tasks across several data sources, including: (1) **Video Classification**: Kinetics (Carreira & Zisserman, 2018); (2) **Dense Video Captioning**: YouCook2 (Zhou et al., 2017), HiREST (Zala et al., 2023),

[3] https://commoncrawl.org/
[4] https://github.com/NVIDIA-NeMo/Curator/tree/experimental/experimental/nvpdftex
[5] https://dumps.wikimedia.org/
[6] https://build.nvidia.com/nvidia/nemoretriever-parse

ActivityNet (Heilbron et al., 2015); (3) **Video Captioning**: EgoExoLearn (Huang et al., 2025b); (4) **Temporal Action Localization**: Breakfast Actions (Kuehne et al., 2014), Perception Test (Pătrăucean et al., 2023), HiREST (Zala et al., 2023), HACS Segment (Zhao et al., 2019), FineAction (Liu et al., 2022), Ego4D-MQ (Grauman et al., 2022), ActivityNet (Heilbron et al., 2015); (5) **Video Temporal Grounding**: YouCook2 (Zhou et al., 2017), QuerYD (Oncescu et al., 2021), MedVidQA (Gupta et al., 2022), Ego4D-NLQ (Grauman et al., 2022), DiDeMo (Hendricks et al., 2017); (6) **General Video QA**: LLaVA-Video-178K (Zhang et al., 2025c), Ego4D (Grauman et al., 2022), TVQA (Lei et al., 2019), Perception Test (Pătrăucean et al., 2023), NextQA (Xiao et al., 2021), EgoExoLearn (Huang et al., 2025b), CLEVRER (Yi et al., 2020), and relabeling of the following datasets with Qwen2.5-VL-72B-Instruct (Bai et al., 2025) into MCQ and open-ended questions: TAPOS (Shao et al., 2020), HC-STVG (Tang et al., 2021), EgoProceL (Bansal et al., 2022), CrossTask (Zhukov et al., 2019); (7) **Multi-page QA**: Synthetic multi-page QA data constructed from CommonCrawl PDF documents using Nemo Retriever Parse extractions; and (8) **Multi-image captions**: Mementos (Wang et al., 2024d).

We convert all the non-QA data into QA formats. For video classification, temporal action localization and temporal grounding data, we use template questions to generate QA pairs. For video captioning and multi-page OCR captions, we use existing LLM models from the Qwen2.5 family (Qwen et al., 2025) to synthesize both the questions and answers given the captions.

3.4. SFT stage 3: 49K text recovery

After SFT Stages 1 and 2, we observe a substantial drop in the LiveCodeBench score compared to the LLM backbone, despite including the text reasoning data from Nemotron Nano 2 (NVIDIA et al., 2025). To recover this loss, we introduce an additional SFT Stage 3 trained with a maximum sequence length of 49,152 using only code reasoning data totaling 1M samples or 15B tokens.

3.5. SFT stage 4: 300K context extension

Finally, we extend the model's context further and incorporate long-context data from the Stage 3 SFT stage of Nemotron Nano 2 (NVIDIA et al., 2025), accounting for around 74K samples or 12B tokens. The samples in this data are 160K tokens long on average, and we train with a maximum sequence length of 311,296 to accommodate the longest samples. We find that this stage helps improve the accuracy of the model in long-context benchmarks such as RULER (Hsieh et al., 2024).

3.6. Training details

At all stages, the model is trained with FP8 precision following a recipe similar to (NVIDIA et al., 2025) to accelerate training. The same configuration is applied to the LLM, vision encoder, and vision projection MLP, with the first and last layers of the LLM and the transformer blocks of the vision encoder kept in BF16. We did not observe any training instabilities with this setup, and both the training loss curve and benchmark scores closely match those of a full-BF16 model. Additionally, experiments keeping either the vision encoder or vision projection in BF16 did not yield a significant difference.

For video inputs to the model, we extract 2 frames per second, with a maximum of 128 frames for each video. If a video is longer than 64 seconds, we uniformly sample 128 frames instead.

As text-only, image and video samples vary significantly in sequence length, we find that sequence packing reduces training time by minimizing the number of padding tokens required for batching. We perform sequence packing online during training using a buffer containing several thousand

	Stage 0	Stage 1	Stage 2	Stage 3	Stage 4
Global Batch Size	1024	128			
Total Training iterations	2158	-	-	-	-
Linear Warmup Fraction	0.1				
Learning Rate	2×10^{-4}	2×10^{-5}			
Weight Decay	0.01	0.05			
Max Length	16384		49152		311296

Table 1 | Training hyperparameters for all stages

	Stage 0	Stage 1	Stage 2	Stage 3	Stage 4
# GPU nodes	32	64			
Training time (in hrs)	6	30	15	3.5	5.5

Table 2 | Hardware resources across training stages

samples. We employ the balance-aware data packing strategy described in (Li et al., 2025b).

To mitigate any bias towards shorter or longer sequences during training, we employ loss square-averaging, similar to InternVL (Chen et al., 2025b). We use the AdamW optimizer with β_1 and β_2 set to 0.9 and 0.999, respectively, and a cosine annealing schedule with a linear warmup. See Table 1 for an overview of the training hyperparameters.

Long Context Extension. For SFT stages 2, 3, and 4, we employ context parallelism in the LLM (Megatron Core, 2025). Context parallelism partitions the LLM input along the sequence dimension, mitigating out-of-memory issues at longer sequence lengths. We use 2-way and 8-way context parallelism for SFT stages 2–3 and stage 4, respectively. When using N-way context parallelism in the LLM, N replicas of the vision encoder and vision projection modules are instantiated. To efficiently utilize these replicas and further reduce GPU memory usage, we follow the approach of (Chen et al., 2024c) and split the vision encoder and projection inputs into N shards along the batch dimension. The N vision projection outputs are then gathered before being passed to the LLM.

Infrastructure. We train the model with the Megatron (Shoeybi et al., 2019) framework[7] using Transformer Engine[8] and the Megatron Energon[9] dataloader on NVIDIA H100 GPUs. Our training code is for large parts open-source. The training resources are summarized in Table 2.

Figure 2 | Overview of the training stages for the VLM along with the model context length and number of training tokens.

[7] https://github.com/NVIDIA/Megatron-LM
[8] https://github.com/NVIDIA/TransformerEngine
[9] https://github.com/NVIDIA/Megatron-Energon

4. Experiments

To comprehensively assess our model's capabilities, we evaluate it across a broad suite of multimodal benchmarks covering diverse tasks. In Section 4.1, we compare its performance with our previous-generation multimodal model, Llama-3.1-Nemotron-Nano-VL-8B, and with state-of-the-art multimodal models of similar scale. In Section 4.2, we demonstrate the importance of our multi-stage training strategy in preserving the text reasoning abilities of the LLM backbone. We also investigate reasoning budget control and present the model's behavior under different budget thresholds in Section 4.3. In Section 4.4, we investigate the efficiency gains achieved by applying Efficient Video Sampling (EVS) (Bagrov et al., 2025) to video inputs. Finally, we examine alternative approaches for processing image inputs in Section 4.5.

4.1. Multimodal Evaluations

We conduct a comprehensive evaluation of our model on 45 benchmarks over seven broad categories:

1. **General VQA**: MMBench V1.1 (Liu et al., 2024d), MMStar (Chen et al., 2024b), BLINK (Fu et al., 2024b), MUIRBench (Wang et al., 2024a), HallusionBench (Guan et al., 2024), ZeroBench (Roberts et al., 2025), CRPE (Wang et al., 2024c), POPE (Li et al., 2023), MME-RealWorld (Zhang et al., 2025b), RealWorldQA[10], MMT-Bench (Ying et al., 2024), R-Bench (Guo et al., 2025), WildVision (Lu et al., 2024b).
2. **STEM Reasoning**: MMMU (Yue et al., 2024), MMMU-Pro (Yue et al., 2025), MathVista-Mini (Lu et al., 2024a), MathVision (Wang et al., 2024b), MathVerse-Mini (Zhang et al., 2024a), DynaMath (Zou et al., 2025), LogicVista (Xiao et al., 2024), WeMath (Qiao et al., 2024)
3. **Document Understanding, OCR & Charts**: MMLongBench-Doc (Ma et al., 2024), OCRBench (Liu et al., 2024e), OCRBench-V2 (Fu et al., 2024a), ChartQA (Masry et al., 2022), RDTableBench (AI, 2025), AI2D (Kembhavi et al., 2016), TextVQA (Singh et al., 2019), DocVQA (Mathew et al., 2021b), InfoVQA (Mathew et al., 2021a), OCR-Reasoning (Huang et al., 2025a), VCR (Zhang et al., 2025a), SEED-Bench-2-Plus (Li et al., 2024a), CharXiv (Wang et al., 2024f)
4. **Visual Grounding & Spatial Reasoning**: TreeBench (Wang et al., 2025a), CV-Bench (Tong et al., 2024)
5. **GUI Understanding**: ScreenSpot (Cheng et al., 2024), ScreenSpot-v2 (Wu et al., 2024b), ScreenSpot Pro (Li et al., 2025a)
6. **Video Understanding**: LongVideoBench (Wu et al., 2024a), MLVU (Zhou et al., 2025), Video-MME (Fu et al., 2025)
7. **Multimodal Multilingual Understanding**: MTVQA (Tang et al., 2025), MMMB (Sun et al., 2025), Multilingual MMBench (Sun et al., 2025)

We use the VLMEvalKit (Duan et al., 2025)[11] framework for our evaluations with a vLLM (Kwon et al., 2023)[12] backend inference server. For the reasoning-off mode, we employ greedy decoding and cap the maximum number of generated tokens at 1,024 for all benchmarks except RDTableBench[13] where we use a limit of 16,384 tokens. For reasoning-on evaluations, we set the temperature to 0.6, top-p to 0.95, and the maximum output length to 16,384 tokens.

We present reasoning-off evaluation results on a subset of the benchmarks after each training stage in

[10] https://x.ai/news/grok-1.5v
[11] https://github.com/open-compass/VLMEvalKit
[12] https://github.com/vllm-project/vllm
[13] https://huggingface.co/datasets/reducto/rd-tablebench/tree/main

Task	Benchmark	Nemotron Nano V2 VL		InternVL3.5		GLM-4.5V		Qwen3-VL	
Size		12B	12B	14B	14B	106B (A12B)	106B (A12B)	8B	8B
Mode		Reasoning off	Reasoning on	Non-Thinking	Thinking	Non-Thinking	Thinking	Instruct	Thinking
General	MMBench V1.1 Dev (EN/ZH)	83.0/80.2	82.6/76.3	83.0*/82.3*	-	-	-	85.0/-	87.5/-
	MMStar	65.9	71.7	70.4	-	73.4	75.3	70.9	75.3
	BLINK (Val)	57.6	56.7	57.6	-	63.7	65.3	69.1	64.7
	MUIRBench	33.2	44.2	58.0	-	71.1	75.3	64.4	76.8
	HallusionBench	72.3	73.1	54.0	-	59.1	65.4	61.1	65.4
	ZeroBench (sub)	15.0	18.3	10.8*	-	21.9	23.4	22.8	18.6*
	CRPE (Relation)	71.3	64.3	76.6	-	-	-	71.7*	52.3*
	POPE	88.8	87.0	87.7	-	-	-	88.2*	86.2*
	MME-RealWorld (EN)	62.2	-	63.2	-	-	-	-	-
	RealWorldQA	76.2	72.2	70.5	-	-	-	71.5	73.5
	MMT-Bench (Val)	65.5	63.8	66.9*	-	-	-	-	-
	R-Bench (dis)	75.2	69.7	70.9	-	-	-	70.1*	69.3*
	WildVision (win rate)	16.0	20.2	73.0	-	-	-	75.0*	76.4*
STEM Reasoning	MMMU (val)	55.3	67.8	62.78*	73.3	68.4	75.4	69.6	74.1
	MMMU Pro	14.5	28.0	-	-	59.8	65.2	55.6	60.4
	MathVista-Mini	69.0	75.5	73.3*	80.5	78.2	84.6	77.2	81.4
	MathVision	31.5	53.6	-	59.9	52.5	65.6	53.9	62.7
	MathVerse-Mini (Vision-only)	34.3	58.2	41.75*	62.8	-	-	38.2*	68.7*
	Dynamath (worst case)	14.8	32.3	-	38.7	44.1	53.9	38.7*	-
	LogicVista	38.7	58.4	-	60.2	54.8	62.4	58.8*	59.3*
	WeMath	31.5	39.3	-	58.7	58.9	68.8	57.1*	-
Document Understanding, OCR & Charts	MMLongBench-Doc	32.1	-	-	-	41.1	44.7	47.9	48.0
	OCRBench	85.6	83.5	83.6	-	87.2	86.5	89.6	81.9
	OCRBenchV2 (EN/ZH)	62.0/44.2	54.8/39.8	-	-	-	-	65.4/61.2	63.9/59.2
	ChartQA (Test)	89.8	84.9	86.5	-	-	-	83.4*	-
	RDTableBench	67.8	57.4	-	-	-	-	82.4*	43.9*
	AI2D (Test)	87.2	84.7	85.1	-	-	-	85.7	84.9
	TextVQA (Val)	85.4	76.1	77.8	-	-	-	82.9*	-
	DocVQA (Test)	94.7	93.2	93.4	-	-	-	96.1	95.3
	InfoVQA (Test)	79.4	80.4	78.3	-	-	-	83.1	86.0
	OCR-Reasoning	21.0	33.9	-	-	-	-	39.3*	48.4*
	VCR-EN-Easy (EM/Jaccard)	71.8/80.0	-	93.4/97.7	-	-	-	91.8*/95.1*	87.4*/94.4*
	SEED-Bench-2-Plus	71.3	70.0	70.7	-	-	-	71.4*	69.9*
	CharXiv (RQ/DQ)	41.7/76.5	41.3/77.2	47.9/76.6	-	-	-	46.4/83.0	53.0/85.9
Visual Grounding & Spatial Reasoning	TreeBench	38.5	42.5	42.0*	-	47.9	50.1	26.9*	25.4*
	CV-Bench	81.0	78.3	80.1*	-	86.5	87.3	73.1*	79.5*
GUI	ScreenSpot	39.4	40.1	87.5	-	-	-	94.4	93.6
	ScreenSpot-v2	41.7	42.8	88.6	-	-	-	-	-
	ScreenSpot-Pro	4.8	5.5	-	-	-	-	54.6	46.6
Video Understanding	LongVideoBench	63.6	57.0	62.7	-	-	-	-	-
	MLVU (M-Avg)	73.6	-	72.1	-	-	-	-	-
	VideoMME (w/o sub)	66.0	63.0	67.9	-	74.3	74.6	71.4	71.8

Table 3 | Comparison of Nemotron Nano V2 VL with existing open-source multimodal models. All results marked with * were calculated in VLMEvalKit.

Table 4, along with a comparison to our previous generation multimodal model, Llama-3.1-Nemotron-Nano-VL-8B. We also compare our model against state-of-the-art open-source multimodal models of similar scale including InternVL3.5 (14B) (Wang et al., 2025b), GLM-4.5V (106B-A12B) (Hong et al., 2025) and Qwen3-VL (8B) (Yang et al., 2025a)[14] in Tables 3 and 5. Unless otherwise noted, we report the evaluation scores directly from the respective model reports. For benchmarks not covered therein, we independently evaluate the models using VLMEvalKit whenever possible.

Benchmark	Stage 0	SFT Stage 1: 16K context length	SFT Stage 2: 49K context extension	SFT stage 3: 49K text recovery	SFT stage 4: 300K context extension	Llama-3.1-Nemotron Nano-VL-8B
AI2D (Test)	67.6	87.1	87.1	**87.3**	87.2	85.0
ChartQA (Test)	70.9	89.9	90.0	**90.2**	89.8	86.3
DocVQA (Val)	79.1	**94.4**	94.3	94.2	**94.4**	91.2
InfoVQA (Val)	51.3	**80.2**	79.2	79.2	79.2	77.4
LongVideoBench	45.1	59.4	**63.6**	63.1	**63.6**	-
MMLongBench-DOC	10.75	29.2	32.0	30.8	**32.1**	-
MMMU (Val)	49.0	54.8	55.0	54.3	**55.3**	48.2
MathVista-Mini	53.1	67.7	**69.3**	69.2	69.0	-
OCRBench	61.4	84.8	85.3	85.4	**85.6**	83.9
OCRBench-V2 (CN)	18.3	42.9	43.4	43.4	**44.2**	37.9
OCRBench-V2 (EN)	38.3	**62.5**	**62.5**	61.8	62.0	60.1
TextVQA (Val)	76.7	**86.0**	85.0	85.2	85.4	-
Video-MME	36.3	57.6	65.8	65.4	**66.0**	54.7

Table 4 | Vision benchmarks for our previous-generation VLM, Llama-3.1-Nemotron-Nano-VL-8B, and after each training stage of Nemotron Nano V2 VL with reasoning-off.

Evaluation across training stages. Table 4 highlights the effectiveness of our long-context extension training introduced in SFT stages 2 and 4. We observe substantial gains on Video-MME (Fu et al., 2025) and MMLongBench-Doc (Ma et al., 2024) following SFT stage 2, and these improvements are retained in the final model after stage 4 training.

Comparison with Llama-3.1-Nemotron-Nano-VL-8B. As shown in Table 4, we observe consistent improvements across all benchmarks compared to Llama-3.1-Nemotron-Nano-VL-8B. We attribute these gains to a combination of factors, including an enhanced LLM backbone, expanded and higher-quality training datasets, and an improved training recipe.

4.2. Pure Text Evaluations

We conduct all pure-text evaluations using the NeMo-Skills[15] framework with a maximum output length of 32,768 tokens, temperature set to 0.6, and top-p of 0.95. We report Pass@1 average of 16 runs for AIME-2025; an average of 4 runs for MATH-500 (Lightman et al., 2023), GPQA-Diamond (Rein et al., 2023), LiveCodeBench (07/24 - 12/24) (Jain et al., 2024), IFEval (Zhou et al., 2023); and score of 1 run for SciCode (Tian et al., 2024) and RULER (Hsieh et al., 2024). For MMLU-Pro (Wang et al., 2024e), we report the accuracy on a 1000-sample subset.

Evaluation across training stages. We report the model's text evaluation scores after each training stage in Table 6. Comparing the results between stage 0 (where the LLM backbone remains

[14] https://github.com/QwenLM/Qwen3-VL
[15] https://github.com/NVIDIA-NeMo/Skills

Task	Benchmark	Nemotron Nano V2 VL Reasoning-off	InternVL3.5 Non-Thinking	GLM-4.5V	Qwen3-VL Instruct
Size		12B	14B	106B (A12B)	8B
MTVQA	Avg	24.3	34.2	22.0†	32.2*
MMMB	en	86.1	85.1	87.1†	85.4*
	zh	84.1	84.1	86.9†	82.5*
	pt	83.5	82.7	84.8†	81.5*
	ar	83.4	80.3	84.5†	80.3*
	tr	77.4	79.4	84.6†	78.7*
	ru	83.9	83.5	84.3†	81.9*
Multilingual MMBench	en	84.9	84.0	89.1†	85.5*
	zh	82.5	83.7	89.3†	85.6*
	pt	82.5	80.0	86.9†	82.5*
	ar	81.5	77.8	83.7†	79.0*
	tr	75.7	77.0	84.0†	79.0*
	ru	82.2	77.0	87.2†	81.3*

Table 5 | Comparison of Nemotron Nano V2 VL with SOTA multimodal models on multimodal multilingual benchmarks. All scores marked by * were reproduced by us using VLMEvalKit, and those marked with † were obtained from the InternVL3.5 (Wang et al., 2025b) technical report.

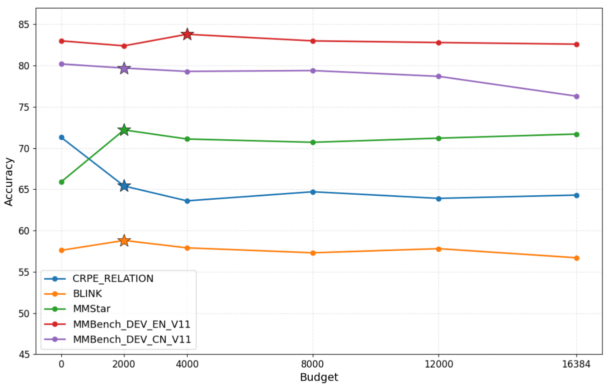
Benchmark	Stage 0: Pretraining	SFT Stage 1: 16K context length	SFT Stage 2: 49K context extension	SFT stage 3: 49K text recovery	SFT stage 4: 300K context extension
`MATH-500`	97.7	96.8	97.3	97.6	96.9
`AIME-25`	75.9	68.0	72.7	72.7	71.3
`GPQA`	65.0	60.9	63.0	60.6	64.1
`LiveCodeBench`	70.0	50.9	55.0	69.8	69.4
`IFEval_prompt_strict`	84.2	77.5	77.3	76.5	78.2
`IFEval_instruction_strict`	89.3	84.1	83.9	83.4	84.7
`SciCode_problem_accuracy`	7.5	5.0	6.9	5.0	6.9
`SciCode_subtask_accuracy`	22.3	17.5	14.9	17.2	17.6
`MMLU-Pro-1000`	77.8	75.2	75.8	76.7	77.1
`RULER`	77.9	8.8	17.4	21.5	72.1

Table 6 | Text benchmarks with reasoning on for the different stages. Our goal was to add vision capabilities with minimal impact to the text reasoning capabilities of the underlying LLM Nemotron-Nano-12B-V2. The text reasoning benchmarks of Stage 0 corresponds to the benchmarks results of the underlying LLM since the LLM is frozen during Stage 0. After Stage 1, we see a significant drop in text reasoning benhchmarks (eg. LiveCodeBench goes from 70 to 50.87) and long context benchmark (RULER goes from 77.91 to 8.80). The video long context extension (Stage 2) helps recover a little bit of the benchmark score, but we still observe very low LiveCodeBench (55.00) and RULER (17.39). We apply a code reasoning recovery stage (Stage 3), and a long context extension stage (Stage 4), to recover both benchmarks (LiveCodeBench of 69.44 and RULER of 72.12).

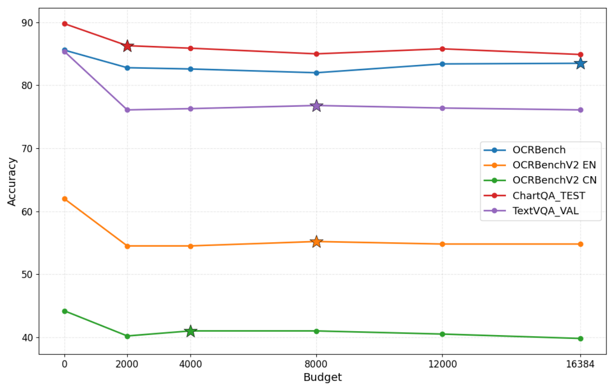
frozen) and SFT stage 1, we observe a significant drop in the LiveCodeBench score - from 70.0 to 50.87. To address this degradation without compromising vision performance, we explored several mitigation strategies that were unsuccessful, including augmenting the SFT stage 1 dataset with additional code reasoning examples and disabling loss scaling. Ultimately, we introduced an additional SFT stage 3 focused exclusively on code reasoning, which helped restore the LiveCodeBench score without affecting other benchmarks. As shown in Table 4, the vision benchmarks remain stable between SFT stage 2 and stage 3, and the final model largely preserves the text reasoning capabilities of the original LLM backbone across most tasks.

Furthermore, we see a significant improvement in the RULER score across SFT stages 2-4 following an initial drop after stage 1. These results further validate the effectiveness of our long-context training strategy.

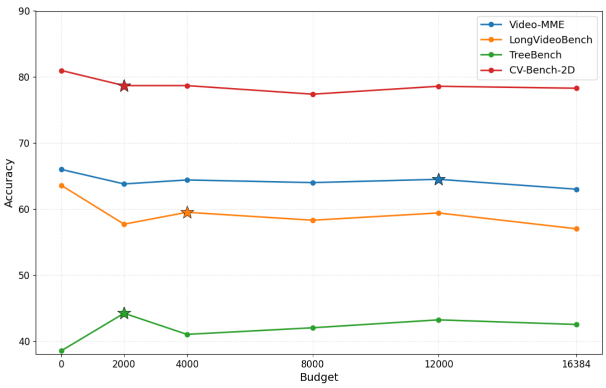
4.3. Reasoning Budget Control



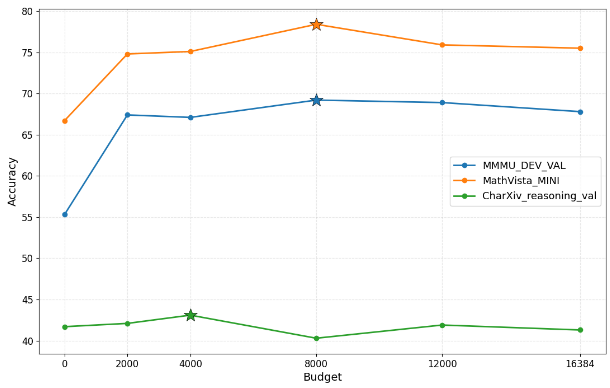
(a) General VQA



(b) Document, OCR & Chart Understanding



(c) Spatial & Video Understanding



(d) STEM & Chart Reasoning

Figure 3 | Effect of reasoning budget control at 2K, 4K, 8K, and 12K tokens across multiple tasks. A budget value of 0 corresponds to reasoning-off evaluations, while 16,384 denotes unrestricted reasoning-on evaluations with a maximum generation length of 16,384 tokens. The highest reasoning-on score (including the unrestricted case) is indicated with a ★ for each task.

Following Nemotron-Nano-V2 (NVIDIA et al., 2025), we experiment with varying reasoning budgets during inference. We evaluate the model's behavior under budgets of 2K, 4K, 8K, and 12K tokens, each with a 500-token grace period, as shown in Figure 3.

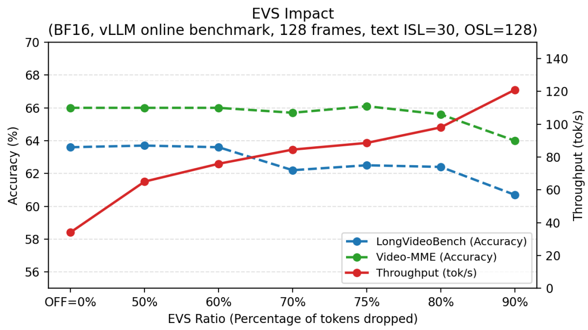
Our experiments indicate that tuning the reasoning budget can improve reasoning-on mode accuracy across multiple tasks, even in cases where the unrestricted reasoning-on score is lower than the reasoning-off score. These gains with budget control may arise from the early termination of malformed reasoning traces with repetition loops on out-of-distribution tasks, as well as the truncation of overly verbose reasoning chains for problems requiring minimal or straightforward reasoning.

4.4. Inference with Efficient Video Sampling

Building upon **Efficient Video Sampling (EVS)** (Bagrov et al., 2025), we integrate it directly into our video-processing pipeline. EVS reduces the number of visual tokens by identifying and pruning *temporally static patches* – spatial regions that remain nearly unchanged between consecutive frames, while preserving positional identity and semantic consistency. This enables our model to process substantially longer videos with lower latency and memory consumption, without requiring architectural changes or retraining.

We evaluate the model on two video benchmarks: **Video-MME** and **LongVideoBench**. Figure 4 presents EVS ablations for both BF16 and FP8 precision. The results demonstrate that EVS maintains strong performance on long-context video understanding tasks while significantly improving efficiency: as the EVS ratio increases, time-to-first-token (TTFT) decreases and throughput rises, with only a minor impact on accuracy.

EVS	LongVideoBench	Video-MME	TTFT (ms)	Throughput (tok/s)
OFF	63.6	66.0	4131	34
50%	63.7	66.0	2699	65
60%	63.6	66.0	2458	75
70%	62.2	65.7	2184	84
75%	62.5	66.1	2072	88
80%	62.4	65.6	1990	98
90%	60.7	64.0	1654	120



EVS	LongVideoBench	Video-MME	TTFT (ms)	Throughput (tok/s)
OFF	64.2	66.4	3436	51
50%	63.7	66.5	2384	80
60%	63.4	66.2	2223	85
70%	62.8	65.8	2000	95
75%	62.3	65.7	1840	103
80%	62.8	65.1	1717	103
90%	60.4	64.0	1567	132

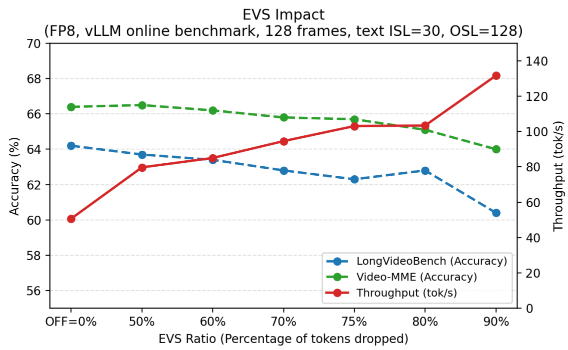


Figure 4 | EVS Ablation (RTX 6000 PRO SE, vLLM online benchmark, 128 frames, text ISL=30, OSL=128): top row shows BF16 results, bottom row shows FP8 results; left shows numeric tables (accuracy, time-TTFT, throughput), right shows corresponding visualizations.

4.5. Image Processing Ablations

We investigate an alternative approach to tiling for our input image processing pipeline. Instead of splitting the input image into non-overlapping tiles, we pass the entire image at native resolution to the vision encoder and MLP projector followed by convolutional token reduction for 4× sequence compression.

For each image processing variant, we train the model through Stages 0 and 1 of our full training recipe, excluding the text-only reasoning datasets from Stage 1. Table 7 compares these image processing strategies across a subset of multimodal benchmarks.

As shown in Columns 1 and 2, the native-resolution approach achieves comparable or even superior accuracy on several benchmarks. However, we observe a notable performance drop on OCRBench and OCRBench-V2 (English). Upon analysis, we found that the tiling algorithm occasionally applies large rescaling factors to smaller images to preserve aspect ratio. To isolate this effect, we conduct an additional experiment where we resize each image to match the size and aspect ratio that the tiling algorithm would have selected, without applying tiling. The results of this configuration are shown in Column 3 of Table 7, where we recover the performance drop on OCRBench. The gap on OCRBench-V2 (English), however, persists. We plan to further investigate strategies to address this gap in future work.

Benchmark	Tiling	Native Resolution	Native Resolution with tiling-size matching
AI2D (Test)	87.1	86.4	**87.8**
ChartQA (Test)	89.8	88.4	**90.3**
DocVQA (Val)	94.5	**95.1**	94.9
InfoVQA (Val)	80.2	**80.7**	79.0
MMMU (Val)	**56.8**	56.0	56.2
MathVista-Mini	69.7	**71.3**	71.2
OCRBench	84.5	82.8	**85.3**
OCRBench-V2 (CN)	40.5	**45.3**	42.7
OCRBench-V2 (EN)	**61.4**	57.6	57.6
TextVQA (Val)	85.6	84.6	**86.2**
Average	75.0	74.8	**75.1**

Table 7 | We compare our image tiling strategy with: 1) Native resolution image inputs to the vision encoder followed by convolutional token reduction 2) Native resolution image inputs with tiling-size matching where we resize the image to the size and aspect ratio the dynamic tiling algorithm would have picked, and then feed the resized image to the vision encoder followed by convolutional token merging. We ran the benchmarks on the last 10 saved checkpoints and, for each strategy, select the one with the highest average benchmark score.

4.6. Quantization

The model is trained with Transformer Engine's delayed-scaling FP8, using dynamic scaling factors computed from a running history of activation maxima across training iterations. By contrast, most downstream inference stacks (e.g. vLLM, TensorRT-LLM) assume static quantization with scaling factors fixed during a one-time calibration. To bridge this train–serve gap, we produce deployable checkpoints via post-training quantization (PTQ) and quantization-aware distillation (QAD) using software libraries TensorRT-Model-Optimizer and Megatron-LM. Unless otherwise noted, we quantize the language backbone - i.e., all linear layers, including both weights and activations - and retain the embedding layers, KV cache or others in higher precision. QAD is performed in BF16 to simulate lower-precision behavior. For FP8 we adopt the E4M3 format; we additionally provide NVFP4 variants from QAD.

PTQ We calibrate on 1,024 samples drawn from the training set and compute per-tensor static scales for weights and activations using the absolute amax aggregated over the calibration dataset.

The resulting FP8/NVFP4 checkpoints are directly usable in standard inference stacks such as vLLM.

QAD Because NVFP4 PTQ yields a small accuracy drop, we further improve quality by distilling a PTQ student from a BF16 teacher using a logit-matching loss (e.g. KL divergence) applied to the final model outputs only. Hyperparameters mirror SFT Stage 1, except we use a learning rate of 2×10^{-6}.

Table 8 summarizes the accuracy comparison across different quantization precisions and strategies. All evaluations are conducted within the vLLM framework under BF16, FP8, and NVFP4 runtime configurations. Minor discrepancies relative to previously reported baselines are attributable to variations in evaluation framework implementations.

Precision	AI2D	ChartQA	OCRBench	DocVQA-val	OCRBenchV2 English
BF16	87.21	89.68	854	94.22	61.74
FP8-PTQ	87.56	89.44	854	94.32	61.83
NVFP4-PTQ	86.37	88.84	863	92.38	60.88
NVFP4-QAD	87.14	89.96	851	93.95	61.94

Table 8 | Accuracy comparison across different precisions and tasks using vLLM backend.

5. Conclusion

In this work, we introduced Nemotron Nano V2 VL, an efficient 12B vision–language model built upon the Nemotron-Nano-V2 LLM. The model demonstrates substantial improvements in multimodal and text understanding, as well as reasoning capabilities, compared to its predecessor, Llama-3.1-Nemotron-Nano-VL-8B. We employed a multi-stage training strategy to enhance visual understanding while preserving the text comprehension abilities of the original backbone. We presented a comprehensive evaluation of the model across diverse tasks and modalities, along with investigations into efficient video sampling at inference and alternative image processing pipelines. Finally, we have open-sourced the model weights in BF16, FP8, and FP4 formats, along with a significant portion of our SFT dataset and associated tooling (see Section 1).

6. Contributors

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