Shifting AI Efficiency From Model-Centric to Data-Centric Compression

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Project: Awesome-Token-level-Model-Compression

Abstract

The rapid advancement of large language models (LLMs) and multi-modal LLMs (MLLMs) has historically relied on model-centric scaling through increasing parameter counts from millions to hundreds of billions to drive performance gains. However, as we approach hardware limits on model size, the dominant computational bottleneck has fundamentally shifted to the quadratic cost of self-attention over long token sequences, now driven by ultra-long text contexts, high-resolution images, and extended videos. In this position paper, we argue that the focus of research for efficient AI is shifting from model-centric compression to data**centric compression**. We position token compression as the new frontier, which improves AI efficiency via reducing the number of tokens during model training or inference. Through comprehensive analysis, we first examine recent developments in long-context AI across various domains and establish a unified mathematical framework for existing model efficiency strategies, demonstrating why token compression represents a crucial paradigm shift in addressing long-context overhead. Subsequently, we systematically review the research landscape of token compression, analyzing its fundamental benefits and identifying its compelling advantages across diverse scenarios. Furthermore, we provide an in-depth analysis of current challenges in token compression research and outline promising future directions. Ultimately, our work aims to offer a fresh perspective on AI efficiency, synthesize existing research, and catalyze innovative developments to address the challenges that increasing context lengths pose to the AI community's advancement.

1 Introduction

The explosive growth of large language models (LLMs) [111, 131, 5, 52, 40, 152, 151, 95, 55] and their multi-modal extensions (MLLMs) [98, 96, 26, 25, 177, 138, 7, 29] over the past few years has driven remarkable gains in AI capabilities. Notably, this unprecedented progress has been largely achieved through increasing *model scale* across the field, with larger models consistently demonstrating superior performance in reasoning, knowledge acquisition, and task generalization. Indeed, the evolution from early language models with modest parameter counts, such as BERT (117M) [38], to today's state-of-the-art LLMs like Llama 4 [110], DeepSeek-R1 [55], and Qwen-3 [151] (100B+), demonstrates how each successive model iteration has delivered disproportionate performance improvements through sheer scale. Nevertheless, this relentless pursuit of enhanced

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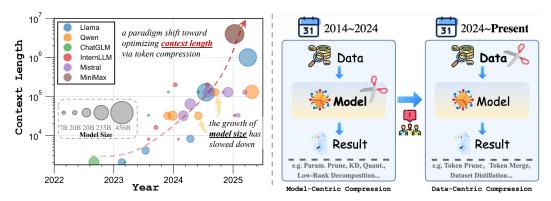


Figure 1: **The evolution of AI efficiency: from model-centric to data-centric compression.** From 2022 to 2024, AI model performance gains mainly came from scaling *model size*, directing efficiency research towards *model-centric compression*. By mid-2024, with model sizes approaching 1000B parameters, their growth has **slowed down**. Consequently, the focus has shifted to **expanding** *context length* to further enhance model capabilities. This paradigm shift necessitates a transition to *data-centric compression*, emphasizing context length reduction for model efficiency.

performance through increased model size comes at an ever-increasing computational cost. As a result, by early 2024, the dominant source of computational overhead was primarily attributed to the *linear growth in parameter count and associated memory requirements*.

In response to this scaling trend, the research community has developed numerous *model-centric compression* techniques. These include model quantization [153, 123], network pruning [58, 27], knowledge distillation [62, 50] and low-rank decomposition [159, 67]. These methods directly reduce computational overhead by decreasing model size, and were a natural response to the 2022 to 2024 era, when scaling up model size was the primary driver of performance gains.

As model sizes approach hardware limits, the pace of parameter growth is flattening. Meanwhile, a new computational challenge has emerged: the exponential growth in *token sequence lengths*. Figure 1 (left) clearly shows that while from 2022 to 2024, model size primarily drove computational costs, reaching around 1000B parameters before stagnating, from 2024 onward, the dominant factor has dramatically shifted to the staggering number of processed tokens, which continues to grow exponentially. This trend is evident across multiple domains: language models now process context lengths orders of magnitude longer than their predecessors [110, 151, 95], particularly with emerging technologies like long chain-of-thought reasoning [55] and multi-agent systems [57], vision models must handle increasingly high-resolution images [82, 177, 7] and longer videos [22, 101], and generative models are tasked with creating higher-resolution images [18, 78] and hour-long videos [12], requiring substantially more tokens and leading to overwhelming computational overhead. Consequently, by late 2024, the primary computational bottleneck has clearly shifted from model size to the *quadratic cost of attention mechanism over these extremely long token sequences*.

This unprecedented growth in sequence lengths has fundamentally shifted the computational bottleneck from model size to the quadratic cost of attention over long context sequences. Based on this observation, as illustrated in Figure 1 (right), we propose a critical position: **the AI community should shift its efficiency optimization paradigm from model-centric to data-centric compression**. Specifically, we advocate for token compression - a *data-centric compression* approach that directly reduces token redundancy in model inputs [51, 70, 88, 10, 11, 19]. Token compression methods address computational overhead by identifying and removing low-information tokens during processing, generally without modifying model architectures or even requiring retraining. Our detailed analysis in Section 3.3 demonstrates that token compression offers compelling advantages in terms of **universality, efficiency, and compatibility**, positioning it as a promising solution for enabling efficient next-generation LLMs and MLLMs.

Building upon these analyses, we make four key contributions in this position paper:

• Evolution of AI Efficiency: We analyze recent developments in long-context AI across various domains, revealing a critical transition from parameter-centric to context-centric computational bottlenecks that necessitates a paradigm shift in efficiency optimization.

- Unified Formulation of Model Efficiency: We establish a comprehensive mathematical formulation that unifies different perspectives on model efficiency, bridging architectural design, model-centric compression, and data-centric compression approaches through theoretical analysis.
- Systematic Review of Token Compression: We present a thorough investigation of token compression methods, constructing a unified framework to categorize diverse approaches while analyzing their benefits and trade-offs across different scenarios and tasks.
- Challenges and Future Directions: We provide an in-depth analysis of current challenges in token compression research and propose promising future directions, aiming to catalyze research efforts toward more efficient and effective compression methods.

2 Background

2.1 Token Overhead aross Various Domains

The field of artificial intelligence has witnessed remarkable advancements across multiple domains, including natural language processing, computer vision, and content generation. These developments have been largely driven by the introduction of the Transformer architecture [132], which has spawned a wide variety of models. As these domains evolve, we observe a significant increase in token sequence lengths across three main areas:

- Longer Context Length in Language Models Large language models (LLMs) [38, 131, 52, 95, 5, 152, 151, 111, 15] have demonstrated remarkable capabilities in natural language understanding and generation [174, 56]. The context length these models can handle has expanded dramatically from 2,048 tokens in early models like Llama 1 [131] to 10M tokens in recent iterations like Llama 4 Scout [110]. This expansion has led to the emergence of large reasoning models [55, 66, 64], which focus on complex multi-step problem solving through techniques like long chain-of-thought reasoning [94, 151, 21] and multi-agent collaboration [129, 24, 57].
- Higher Resolution and Longer Video Understanding Building on the success of LLMs, multimodal large language models (MLLMs) [85, 96, 97, 82, 6, 26, 25, 177] extend these capabilities by integrating vision and text processing [148]. The visual inputs these models process have evolved significantly from basic 224×224 resolution images in early models like LLaVA [98] to 4K ultrahigh-resolution images in InternVL3 [177] and 8K-frame videos in Video-XL-Pro [101], achieving remarkable performance in tasks involving images [7], videos [22], and multi-modal reasoning [140].
- More Complex Content in Generation Tasks The field of content generation has seen dramatic advancements, particularly with the application of Transformers to generative domains [116, 12, 89, 23]. Early diffusion models like Stable Diffusion [124] were limited to generating 512×512 resolution images. With Transformers being successfully applied to generative domains [116, 47, 12, 89], DiT-based models have dramatically advanced the field, producing high-quality 4K images in PixArt- Σ [18] and even hour-long videos in Sora [12]. These models capture complex dependencies across space and time, achieving remarkable results in high-fidelity content generation [78, 156, 133, 73].

While these advancements across domains have demonstrated outstanding performance, they now face significant efficiency challenges due to the *quadratic cost of attention mechanisms over extremely long token sequences*. This growing trend toward longer contexts—whether processing complex reasoning chains in language tasks, high-resolution images and longer videos in understanding tasks, or high-fidelity content in generation tasks—necessitates prioritizing research into model efficiency, particularly in addressing the computational overhead associated with increasing context lengths. Detailed statistical analysis of this trend is presented in the Appendix A.

2.2 Model Efficiency from Different Perspectives

Improving model efficiency has been a key goal in deep learning research. Given input data X and network parameters W, a neural network F produces output Y through the transformation:

$$\underbrace{\mathbf{Y}}_{\text{output}} = \underbrace{\mathbf{F}}_{\text{network}} (\underbrace{\mathbf{W}}_{\text{weights}}, \underbrace{\mathbf{X}}_{\text{input}})$$
 (1)

where model efficiency can be optimized from three perspectives: (I) Efficient Computation Architecture aims to design efficient neural architectures F [127, 119, 53], (II) Model-centric Compression

focuses on model weights **W** [62, 153, 83, 159], and (**III**) Data-centric Compression targets token sequences from input data **X** [122, 70, 10, 179, 19].

- (I) Efficient Computation Architecture (F) Since the computational efficiency of neural networks is determined by their architectural design, optimizing architectures represents a fundamental approach to enhance efficiency. Unlike traditional Transformer architectures with *quadratic* computational complexity $\mathcal{O}(n^2)$ in attention [132], where n is sequence length, recent innovations typically achieve *linear or sub-quadratic* scaling: (i) linear attention reformulates the attention mechanism to achieve linear complexity $\mathcal{O}(n)$, enabling efficient processing while maintaining model capacity [74, 127]; (ii) RWKV architecture integrates RNN-like linear scaling $\mathcal{O}(n)$ with transformer-like parallelism for efficient sequence processing [119, 42]; (iii) State Space Models like Mamba leverage structured state space modeling to achieve linear complexity $\mathcal{O}(n)$ while maintaining performance [53, 178]. While these architectural innovations improve efficiency significantly, they require complete model retraining, motivating the exploration of alternative approaches.
- (II) Model-centric Compression (W) As model parameters directly contribute to computational costs and memory usage, reducing parameter complexity serves as another essential strategy. Model compression can be regarded as model-centric compression, which transforms the original parameter set W to a reduced set W':

$$\mathbf{W}' = \mathbf{\Gamma}(\mathbf{W}), \text{ where } |\mathbf{W}'| < |\mathbf{W}|$$
 (2)

where Γ represents the compression operator and $|\cdot|$ denotes parameter size. Several key approaches have emerged: (i) network pruning removes redundant weights, reducing parameters and computation [106, 27]; (ii) model quantization reduces parameter precision from high-bit to low-bit representations [153, 123]; (iii) knowledge distillation transfers information from large models to compact ones [62, 50]; (iv) low-rank decomposition approximates weight matrices with lower-rank representations [159, 67]. With model sizes plateauing and context lengths growing, research focus has begun shifting from model-level to token-level compression strategies.

(III) Data-centric Compression (X) Different from *model-centric* compression, token compression represents a *data-centric* approach that directly reduces input complexity. Given input data represented as token set X, it produces a reduced representation X':

$$\mathbf{X}' = \mathbf{\Phi}(\mathbf{X}), \text{ where } |\mathbf{X}'| < |\mathbf{X}|$$
 (3)

where Φ is the token compression operator and $|\cdot|$ denotes token length. This approach complements model compression and has demonstrated significant effectiveness across computer vision [122, 10] and natural language processing [75, 70].

3 How Token Compression Drives Efficient and Effective Models

In this section, we begin with the research roadmap of data-centric compression (*i.e.*, token compression) in Section 3.1. Then, we comprehensively analyze the benefits of token compression during both training and inference stages in Section 3.2. Finally, we summarize five compelling advantages shared by existing token compression approaches in Section 3.3.

3.1 Research Roadmap - What Makes Token Compression Work?

Existing token compression methods fundamentally operate through a two-stage process: first, identifying tokens eligible for compression within the existing token sequence $\mathbf{X} = [\mathbf{x}_1, \mathbf{x}_2, \dots, \mathbf{x}_T]$ using carefully designed *compression criteria* through a scoring function $\mathcal{E}: \mathbf{X} \to \{s_t\}_{t=1}^T$, and then determining the precise handling of these tokens through specific *compression strategies* $\mathcal{P}: (\mathbf{X}, \{s_t\}_{t=1}^T) \to \mathbf{X}'$ that transform the original sequence into a compressed one where $|\mathbf{X}'| < |\mathbf{X}|$. Given that existing research primarily revolves around these two key components, we next systematically analyze their designs and review representative approaches across various scenarios.

Compression Criteria (\mathcal{E}) To determine which tokens should be compressed in sequence $\mathbf{X} = [\mathbf{x}_1, \mathbf{x}_2, \dots, \mathbf{x}_T]$, compression criteria employ scoring functions \mathcal{E} to evaluate each token's importance

or redundancy. Based on whether additional parameters are introduced into original models, these criteria can be categorized into two main approaches:

- (I) Parametric Methods employ auxiliary networks as scoring functions $\mathcal{E}_{\Delta\theta}: \mathbf{X} \to \{s_t\}_{t=1}^T$, introducing additional parameters $\Delta\theta$ beyond the original model parameters θ . These methods include: (i) training-aware approaches [122, 157, 87, 76] that optimize $\Delta\theta$ through training to learn scoring function $\mathcal{S}_{\Delta\theta}: \mathbf{X} \to \{s_t\}_{t=1}^T$, and (ii) training-free approaches [108, 172] that directly employ pre-trained networks as scoring function $\mathcal{S}_{\text{fixed}}: \mathbf{X} \to \{s_t\}_{t=1}^T$ without updating $\Delta\theta$.
- (II) Non-parametric Methods utilize parameter-free heuristics for token scoring without introducing extra parameters. These approaches can be categorized into: (i) inherent computation methods [90, 179, 19, 149, 48] that leverage model's internal calculations for token scoring $S_{\rm in}: \mathbf{A} \to \{s_t\}_{t=1}^T$, such as using attention weights $(s_t = \sum_{j=1}^T a_t^j)$, where a_t^j represents attention score between tokens), and (ii) external computation methods [9, 161, 39, 141, 102] that design additional metrics $S_{\rm ex}: \mathbf{Z} \to \mathbb{R}^{T \times T}$ to evaluate token relationships. For external methods, an additional function $g: \mathbf{X} \to \mathbf{Z}$ is introduced to compute intermediate features, where $\mathbf{Z} = g(\mathbf{X})$. The scoring function then operates on these features: $s_{i,j} = f(\mathbf{z}_i, \mathbf{z}_j)$, where f is a custom pairwise scoring function. A typical example is using cosine similarity, where g is an identity function and $s_{i,j} = \frac{\langle \mathbf{x}_i, \mathbf{x}_j \rangle}{\|\mathbf{x}_i\|_2 \|\mathbf{x}_j\|_2}$.

Compression Strategies (\mathcal{P}) To reduce sequence length while preserving critical information, compression strategies \mathcal{P} transform the original sequence based on token scores $\{s_t\}_{t=1}^T$. These strategies can be primarily categorized into two distinct approaches:

(I) Token Pruning directly discards less important tokens from the sequence based on their scores. These methods [122, 51, 70, 19] typically remove tokens with scores below a threshold, producing a compressed sequence:

$$\mathbf{X}' = \mathbf{X} \setminus \{ \mathbf{x}_t \mid s_t < \tau \} \tag{4}$$

where τ is a threshold determining token removal. Token pruning reduces computation through direct elimination but risks information loss, particularly for fine-grained tasks.

(II) Token Merging preserves information by combining semantically similar tokens [9, 90, 168, 11]. Given an input sequence $\mathbf{X} = \{\mathbf{x}_1, \dots, \mathbf{x}_T\}$ and a mapping $\pi : \{1, \dots, T\} \to \{1, \dots, M\}$ that assigns tokens to M merge groups based on their semantic relationships, this approach generates a compressed sequence $\mathbf{X}' = \{\mathbf{x}_1', \dots, \mathbf{x}_M'\}$ through weighted aggregation:

$$\mathbf{x}'_{m} = \sum_{t:\pi(t)=m} w_{t} \mathbf{x}_{t}, \quad w_{t} = \frac{s_{t}}{\sum_{t':\pi(t')=m} s_{t'}}$$
 (5)

where w_t represents importance weights. Token merging preserves information through weighted combinations of tokens, offering a more nuanced approach than direct elimination.

3.2 Training and Inference Targets - How Token Compression Benefits?

Training Stage Token compression techniques contribute to improving both the quality and efficiency of model training. These benefits can be broadly categorized into two aspects: *enhancing training quality* and *increasing training efficiency*.

- (I) Enhancing Training Quality Improvement in training quality can be achieved through methods such as *data augmentation* and *token selection*, which serve to increase data diversity and emphasize the most informative content, respectively.
- **Data augmentation** techniques have been widely adopted to enrich training datasets by introducing variability that enhances robustness and informativeness [35]. In computer vision, mixing or combining image tokens creates novel representations that elevate training effectiveness [162, 160]. This strategy has also been extended to synthetic datasets, where adaptive augmentation controls the informativeness of generated images [171, 81, 139]. Analogously, in natural language processing, augmenting text tokens through synonym replacement [142], contraction expansion [33], back-translation [17], and reformulation [60], supporting better generalization.
- **Token selection** focuses on filtering out low-quality tokens to refine training data quality [93, 80, 118, 145, 46, 84]. Common approaches include rule-based heuristics [121, 117], deduplication methods [80, 118, 1], and scoring strategies leveraging large language models [145, 46, 84, 146, 125].

Formally, consider a training batch $\mathcal{B} = \{\mathbf{X}_i\}_{i=1}^N$, where each $\mathbf{X}_i = [\mathbf{x}_{i,1}, \mathbf{x}_{i,2}, \dots, \mathbf{x}_{i,T}]$ is a token sequence of length T. A quality scoring function $q: \mathcal{T} \to \mathbb{R}$ assigns each token $\mathbf{x}_{i,j} \in \mathcal{T}$ a score reflecting its informativeness or relevance. Using a threshold τ , tokens with scores below τ are

filtered out via a mask \mathbf{m}_i : $m_{i,j} = \begin{cases} 1, & q(\mathbf{x}_{i,j}) \geq \tau \\ 0, & \text{otherwise} \end{cases}$. The filtered batch $\tilde{\mathcal{B}}$ consists of sequences:

$$\tilde{\mathbf{X}}_i = {\{\mathbf{x}_{i,j} \mid m_{i,j} = 1, \quad j = 1, \dots, T\}}.$$
 (6)

Training on these curated, high-quality tokens enables the model to concentrate on the most relevant information, reducing noise and redundancy, which enhances generalization and learning efficiency.

(II) Increasing Training Efficiency Token compression directly reduces the token length processed during training, addressing critical challenges associated with scaling large models [10, 28, 126, 150]. For Transformer architectures with sequence length reduced from n to m (m < n), the computational and memory benefits can be quantified as:

$$\frac{\Omega(\mathbf{X}')}{\Omega(\mathbf{X})} = \frac{\mathcal{O}(m^2 d)}{\mathcal{O}(n^2 d)} = \mathcal{O}\left(\frac{m^2}{n^2}\right), \quad \frac{\mathcal{M}(\mathbf{X}')}{\mathcal{M}(\mathbf{X})} \approx \frac{md}{nd} = \frac{m}{n},\tag{7}$$

where d is the embedding dimension, $\Omega(\cdot)$ represents the computational measure, and $\mathcal{M}(\cdot)$ denotes the memory measure. This quadratic reduction in computation and linear reduction in memory enable faster training iterations and larger batch sizes on fixed hardware resources.

Inference Stage Token compression methods can also enhance model inference efficiency through two key aspects: *decreasing computational complexity* and *reducing memory usage*.

- (I) Decreasing Computational Complexity Following patterns established in training, token compression achieves quadratic speedup in inference computations. Notably, many non-parametric compression methods [10, 72, 19] can be directly integrated into inference without additional training or architectural modifications, enabling immediate benefits across various domains [168, 144].
- (II) Reducing Memory Usage Token compression optimizes memory efficiency through two mechanisms: (i) computing memory reduction following the linear scaling pattern shown in training, and (ii) KV cache optimization for large language models [88, 14, 135, 134]. During autoregressive generation, each layer caches key and value states for attention computation, with memory growing with sequence length. For a sequence of length n compressed to length n, with n layers and hidden dimension n, the KV cache memory reduction is:

$$\frac{\mathcal{M}_{KV}(\mathbf{X}')}{\mathcal{M}_{KV}(\mathbf{X})} = \frac{2Lmd}{2Lnd} = \frac{m}{n},\tag{8}$$

where factor 2 accounts for both key and value states per layer.

These benefits are particularly crucial for real-time interactive systems, including UI agents [130], autonomous driving [45], and embodied AI [41], where efficient processing of continuous inputs under resource constraints is essential.

3.3 Compelling Advantages - Why Token Compression Matters?

Based on our comprehensive analysis of token compression techniques, we identify *five compelling advantages* that make them particularly promising:

- Universal Applicability: The redundancy of tokens exists consistently across modalities and tasks, making token compression possible in all kinds of settings.
- Dual-phase Efficiency: Token compression is capable of accelerating both model training and inference phases with minimal accuracy loss.
- Architectural Compatibility: Token compression is orthogonal to existing model compression and compression methods, making it is possible to be integrated seamlessly with existing compression techniques. Besides, it is friendly to the hardware and computer systems.
- Low Implementation Costs: Modern neural networks, such as transformers, is able to process tokens of different lengths. As a result, token compression can be done without introducing any training costs and data utilization.

• Quadratic Gains: The $\mathcal{O}(n^2)$ computation complexity of widely used self-attention indicates token compression can bring significant benefits in computation.

As AI development enters a new phase where context length becomes the primary bottleneck, the research focus of AI efficiency should shift towards data-centric compression through token compression, enabling more efficient and scalable AI systems.

4 Current Challenges

4.1 Performance Degradation

Methodological Bottlenecks. Attention scores play a crucial role across existing token compression approaches. For example, [CLS] token attention scores are used to select key visual tokens [120, 61, 167, 136, 59, 154, 103], while cross-modal guidance [69, 16, 128, 20, 150, 168] relies on text-vision attention scores. *But are attention scores truly reliable for deciding which tokens to keep?* Recent work [167, 143] reveals that attention scores can suffer from **position bias**. For instance, when using text-vision scores to retain visual tokens, those near the sequence end often get higher weights. In 2D image space, this biases retention toward the lower half or bottom-right corner. Clearly, it's unrealistic to assume the lower half of all images is more important. Such bias can significantly hurt compression performance. As shown in Figure 2, a comprehensive review and comparison of key studies [71, 144, 143, 169, 100, 102] confirms our hypothesis: even well-crafted attention-based methods can underperform simple random pruning or pooling. Detailed analysis is in Appendix B.

Inherent Limitations of Token Compression. Beyond performance degradation from methodological design, *does token compression face inherent limitations? Is it universally applicable across various tasks?* For multi-modal large language models, [143] shows most existing compression methods underperform on visual grounding tasks, with significant drops on benchmarks like RefCOCO [158]. In OCR-related parsing [155, 112], documents with dense layouts yield highly information-rich visual tokens. Compressing these risks severe information loss and degraded performance. Beyond vision, current methods also face inherent limits in other modalities. In Automatic Speech Recognition (ASR) and Automatic Speech Translation (AST) [3, 32], audio is encoded and then decoded into text using an MLLM [2, 30]. Audio tokens in ASR and AST are dense and temporally continuous. Pruning or merging them disrupts this continuity, leading to fragmented recognition or translation. Similarly, translation across languages in the text modality may suffer significant degradation under high compression ratios.

4.2 Suboptimal Token Representation

Most existing token compression methods fall into two categories: redundancy-based approaches that maximize information preservation between original (X) and compressed tokens (X') via $\max_{\mathcal{C}} I(\mathbf{X}; \mathbf{X}')$, and importance-based methods that ensure predictive sufficiency through $I(\mathbf{X}'; \mathbf{Y}) \geq I(\mathbf{X}; \mathbf{Y}) - \epsilon$ and ϵ is the bearable information loss. While effective in their respective objectives, we argue that these paradigms share a critical limitation: neither guarantees that the compressed tokens \mathbf{X}' form an **optimal representation** for downstream modeling. The redundancy-based framework, despite preserving maximal mutual information with \mathbf{X} , often retains tokens with reconstructive but low discriminative value. The importance-based framework, on the other hand, prioritizes maintaining predictive performance with respect to the target variable \mathbf{Y} , but often at the cost of introducing task-specific biases. By focusing solely on the preservation of information relevant to a predefined label, these methods may overlook the need to maintain stable structural and semantic patterns across the token sequence in \mathbf{X} that could enhance generalization across diverse downstream tasks. Consequently, both approaches risk producing token representations that are misaligned with the ultimate goal of effective and generalizable downstream modeling.

4.3 Fair Comparison

Rethinking FLOPs and Compression Ratios as Efficiency Metrics. Many token compression methods report speedup by estimating FLOPs reductions or directly using token compression ratios. *But do FLOPs or compression ratios truly reflect real acceleration?* Our analysis shows that, even with similar compression ratios or FLOPs, methods often vary significantly in runtime latency.

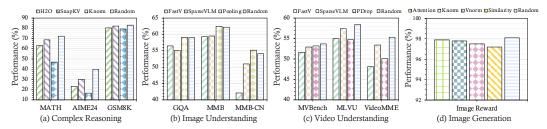


Figure 2: Empirical comparison of carefully designed token compression methods and random token dropping. Results demonstrate that in multiple scenarios, some meticulously engineered token compression methods surprisingly underperform compared to random token pruning.

Investigating further, we find: (i) Importance-based compression often uses attention scores [19, 168], but this can limit compatibility with efficient attention mechanisms like Flash Attention [37, 36], potentially contributing to the substantial discrepancy between FLOPs and actual runtime latency observed in some approaches. (ii) Some methods pursue high compression via progressive compression across layers [150], adding overhead that offsets the gains from token reduction. Thus, we argue that runtime latency should be prioritized in evaluations, as FLOP or token count reductions don't always yield real-world speedup.

Token Compression Evaluation: The Benchmarking Gap. Current token compression methods are primarily evaluated using general-purpose benchmarks, which are not tailored to capture the unique challenges of token compression. As a result, some benchmarks—such as ScienceQA [107] and VizWiz [8]—paradoxically show improved performance under certain compression settings, or minimal degradation across varying compression ratios. These observations defy intuition and suggest that existing benchmarks may fail to meaningfully reflect the trade-offs introduced by token compression. This discrepancy raises concerns about the validity of current evaluation practices. In particular, benchmarks that fail to penalize information loss introduced by compression may obscure meaningful differences between methods. Additionally, the lack of task diversity and compression-sensitive metrics further limits our understanding of how these methods behave in realistic scenarios. Without dedicated benchmarks, it remains unclear whether observed gains are due to genuine improvements in compression quality or artifacts of misaligned evaluation settings.

5 Future Works

5.1 Data-Model Centric Compression Co-Development

As AI systems continue to scale in both model complexity and context length, a promising direction for future research lies in the co-development of data-centric and model-centric compression strategies. Instead of treating these approaches independently, integrating them can yield synergistic benefits—enhancing overall efficiency while maintaining, or even improving, model performance. The most straightforward form of integration adopts a staged approach, where model-centric compression is applied first, followed by data-centric methods. For example, token compression techniques can be employed on models that have already undergone quantization, pruning, or distillation. More advanced approaches aim for mutual reinforcement between the two paradigms. From a data-centric perspective, analyzing the layer-wise evolution of token representations may reveal that certain layers contribute minimal changes. This insight can inform model-centric compression by identifying layers suitable for removal or more aggressive quantization. Conversely, gradient information or attention scores associated with the critical neurons retained after model pruning can also guide token selection in data-centric compression, helping to preserve only the most informative tokens.

5.2 Dedicated Benchmarks for Token Compression

Given the current limitations in evaluating data-centric token compression methods using general-purpose benchmarks, we envision the development of a dedicated benchmark specifically designed to evaluate them. Such a benchmark should comprehensively **span diverse domains**—including natural language processing, computer vision, and multi-modal tasks—and **incorporate task-specific challenges** particularly relevant to token compression, such as optical character recognition (OCR) parsing [112, 163] and automatic speech recognition (ASR) [32, 114]. Furthermore, it is essential

that this benchmark jointly **considers both task performance and latency**, as both are critical for real-world deployment. A well-rounded benchmark of this nature would enable more rigorous, fair, and holistic evaluation of token compression techniques, ultimately driving progress in this area.

6 Alternative Positions

While this paper promotes data-centric compression as a key strategy for advancing Efficient AI, it is equally important to recognize and engage with alternative viewpoints that challenge the feasibility, necessity, or overall effectiveness of this approach.

6.1 Model-Centric Compression as a Superior Alternative

Model-centric compression methods, such as *pruning* [106, 63, 58, 122, 68, 113], *quantization* [123, 137, 176, 153, 92, 43], and *knowledge distillation* [62, 166, 165, 115], have long been established as effective techniques for reducing model size and computational cost. Proponents argue that this paradigm is reliable for deployment in resource-constrained environments and maintains performance consistency. For example, pruning techniques such as DynamicViT [122] dynamically remove uninformative tokens during inference, reducing the computational load by up to 30–40% with minimal impact on accuracy. Proponents of this view claim that this approach achieves substantial speedups without discarding any original data. In contrast, data-centric methods that prune input tokens risk removing critical contextual information, which may degrade performance.

Counterargument. Although model-centric compression is effective, it faces scalability issues as models and datasets grow, requiring costly full retraining and processing of entire inputs. In contrast, data-centric compression reduces input complexity upfront, easing computational burdens. Some data-centric methods update only a small parameter subset [173, 99, 79], while others enable training-free deployment [9, 19, 88]. Combining both approaches can improve efficiency without sacrificing accuracy [4, 77], making data-centric methods a complement to model-centric techniques.

6.2 Advanced Model Architectures as a more Promising Direction

Another argument against data-centric compression is the continued advancement of model architectures that can inherently handle large datasets and long sequences more efficiently [54, 49, 119]. The development of transformer-based architectures, such as Vision Transformers [34], Swin Transformers [105], and large language models like GPT-3 [13], has shown significant improvements in both accuracy and scalability. These architectures integrate advanced techniques, such as hierarchical processing, self-attention mechanisms, and dynamic sparsity, enabling them to process large amounts of data efficiently. For example, Swin Transformers [105] utilize a window-based self-attention mechanism, which reduces the computational complexity of the standard attention mechanism, making it feasible to scale models to much larger datasets and sequences. Proponents of this view argue that as these advanced models continue to evolve, there may be less need for aggressive input compression, as these models are inherently better equipped to handle large-scale data directly.

Counterargument. Advanced model architectures offer strong performance but demand substantial computational resources, especially during training [110, 151, 111]. Data-centric compression reduces computational load early by simplifying input data, enabling more efficient training and inference without sacrificing accuracy. Techniques like token pruning and augmentation preserve or improve performance by focusing on informative data. Combined with advanced architectures, data-centric methods enhance efficiency and maintain high performance [46, 146], making them complementary rather than competitive.

7 Conclusion

In this position paper, we propose repositioning AI efficiency research by advocating a shift from model-centric to data-centric compression strategies, focusing on token compression to address long-context processing challenges. We first examine recent developments in long-context capabilities across various downstream scenarios, demonstrating how performance scaling has shifted from model size to context length, emphasizing the need for token compression to mitigate the impact of increasing context lengths. We then review approaches for improving model efficiency, with

emphasis on the research roadmap of data-centric compression (*i.e.*, token compression) and its potential benefits. After analyzing current challenges in token compression research, we propose promising future directions to inspire innovation in this emerging field. Our work aims to advance AI efficiency by providing a fresh perspective and catalyzing new research directions.

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A Trends in LLM Scaling: Parameters vs. Context Length

In this section, we provide a comprehensive analysis of the temporal progression of mainstream LLMs, documenting the growth trends in both parameter counts and context lengths. This analysis provides empirical support for our central thesis regarding the shift in computational bottlenecks from model parameters to context processing. As shown in Tables 1, 2, 3, 4, 5, 6, 7, and 8, both in text and vision domains, model size growth has significantly slowed, while context length continues to increase. This trend indicates that the focus of research for efficient AI is shifting from model-centric compression to data-centric compression.

B Comparison of Token Compression Methods and Random Token Dropping

In this section, we conduct a detailed analysis comparing carefully designed token compression methods with random token dropping (the simplest baseline for token compression). This analysis aims to support the arguments presented in Section 4.1, demonstrating that existing token compression techniques have certain performance limitations. Our experiments span across multiple domains, including: complex reasoning in the language domain, image and video understanding in the vision domain, and text-to-image generation in the AI content generation domain. This comprehensive approach allows us to evaluate the effectiveness of token compression methods across diverse AI tasks and modalities. Our findings underscore the need for more robust and effective approaches in token compression for LLMs, MLLMs, VideoLLMs, and DiTs, highlighting the importance of developing universally applicable compression strategies.

LLMs: Complex Reasoning We evaluated DeepSeek-R1-Distill-Llama-8B [55] on a suite of complex reasoning tasks, including MATH-500 [91], AIME24 [109], and GSM8K [31]. During the LLM's decoding phase, we enforced a fixed token budget (*e.g.*, 1024 tokens) for the KV cache and applied existing KV cache token dropping strategies such as H2O [170], SnapKV [88], KNorm [39], along with random dropping at regular intervals (*e.g.*, every 512 tokens).

Figure 2 (a) reveals a counterintuitive finding: existing KV cache token dropping strategies—including H2O, SnapKV, and KNorm—consistently underperform compared to simple random token dropping across complex math reasoning tasks. Most strikingly, on AIME24, random dropping even surpasses the second-best method (SnapKV) by a significant margin of 10% accuracy. Our findings yield two critical insights for the field: (i) We strongly suggest that random dropping should be included as a fundamental baseline in KV cache dropping studies, as it is frequently overlooked in current research despite its competitive performance; (ii) We hypothesize that random dropping's unexpected effectiveness may stem from its inherent property of preserving token distribution uniformity during auto-regressive decoding, thereby better maintaining semantic coherence and information integrity compared to deterministic dropping strategies. Our findings challenge the conventional wisdom that complex token dropping policies are inherently superior, while revealing fundamental gaps in current token importance modeling paradigms for KV cache management.

MLLMs: Image Understanding We conducted experiments on multiple widely used image understanding benchmarks (*e.g.*, GQA [65] and MMB [104]) using LLaVA-1.5-7B [98]. For all experiments, we uniformly retained 25% of the visual tokens, and benchmark evaluations were performed in accordance with the official evaluation scripts of LLaVA². In our experiments, we compared representative token compression methods, including FastV [19] and SparseVLM [168], along with two simple baselines: random token dropping and token-wise pooling.

As shown in Figure 2 (b), models employing random token dropping and token-wise pooling surprisingly outperform even some carefully designed methods. We hypothesize that the underlying reason lies in a key shared characteristic of random token dropping and token-wise pooling: **spatial uniformity**. This property effectively mitigates the issue of position bias (Sec. 4) inherent in attention-based token compression methods such as FastV. It also indirectly highlights the negative impact that position bias in attention scores can have on model performance. Therefore, we advocate for incorporating spatial uniformity as a key consideration in the design of token compression strategies.

²https://github.com/haotian-liu/LLaVA

VideoLLMs: Video Understanding We conducted comprehensive comparative experiments on LLaVA-OneVision-7B [82] across multiple video large language models (VideoLLMs) benchmarks, including MVBench [86], LongVideoBench [147], MLVU [175], and VideoMME [44]. Our study compares various token compression methods, specifically FastV [19], SparseVLM [168], and PDrop [150], with the token retention ratio set to R=15%. All evaluations were performed using the LMMs-Eval framework [164], ensuring consistency and reproducibility in our experimental setup³.

Figure 2 (c) reveals an unexpected result: even when retaining only 15% of visual tokens, random token dropping outperforms carefully designed token compression methods (e.g., FastV [19], SparseVLM [168], and PDrop [150]). This finding has two important implications: (i) Future token compression studies should include random token dropping as a baseline for comparative experiments; (ii) The design of token compression methods for VideoLLMs should prioritize achieving a uniform spatial and temporal distribution of tokens, potentially ensuring a more comprehensive representation of video information. We hypothesize that the success of random dropping may be attributed to its inherent ability to maintain this uniformity across the video sequence.

DiTs: Image Generation We conducted experiments on the widely-used DiT-based image generation model FLUX.1-dev [78], using the classic ToCa [179] method as an example. We set the cache cycle length to N=4 and the cache ratio to R=90%, meaning that only 10% of the tokens were computed at each cache step. We compared several classic token selection strategies, such as those based on maximum Attention, Key Norm (*i.e.*, Knorm), Value Norm (*i.e.*, Vnorm), and random selection. Surprisingly, all of these characteristic-based selection strategies yielded lower Image Reward scores than random selection.

Figure 2 (d) shows that random selection performs well in token compression for image generation tasks. To investigate the reasons behind this phenomenon, we designed a similarity-based token selection strategy: we first randomly selected 1% of the tokens as base tokens, and then selected the remaining 9% based on their highest similarity to the base tokens. This selection process resulted in the chosen tokens being clustered into one or a few similar types, leading to the worst generation quality. This suggests that redundancy exists among similar tokens, whereas random selection benefits from diversity, allowing the selected subset of tokens to carry richer and more varied information.

³https://github.com/LLaVA-VL/LLaVA-NeXT/blob/main/docs/LLaVA_OneVision.md

Table 1: **Qwen series model specifications.** Includes release dates, parameter counts, maximum context lengths, and Hugging Face links.

| Model Name | Release Date | Parameters | Maximum Context Length | Model Link |
|-------------------------|--------------|-------------------|-------------------------------|-------------------|
| Qwen-1.8B | Nov 30, 2023 | 1.8B | 32K | link |
| Qwen-7B | Aug 3, 2023 | 7B | 2K (Original), 8K (Updated) | link |
| Qwen-14B | Sep 25, 2023 | 14B | 8K | link |
| Qwen-72B | Nov 30, 2023 | 72B | 32K | link |
| Qwen1.5-0.5B | Early 2024 | 0.5B | 32K | link |
| Qwen1.5-1.8B | Early 2024 | 1.8B | 32K | link |
| Qwen1.5-4B | Early 2024 | 4B | 32K | link |
| Qwen1.5-7B | Early 2024 | 7B | 32K | link |
| Qwen1.5-14B | Early 2024 | 14B | 32K | link |
| Qwen1.5-32B | Early 2024 | 32B | 32K | link |
| Qwen1.5-72B | Early 2024 | 72B | 32K | link |
| Qwen1.5-110B | Early 2024 | 110B | 32K | link |
| Qwen1.5-MoE-A2.7B | Mar 28, 2024 | 14B | 32K | link |
| Qwen2-0.5B | Jun 6, 2024 | 0.5B | 32K | link |
| Qwen2-1.5B | Jun 6, 2024 | 1.5B | 32K | link |
| Qwen2-7B | Jun 6, 2024 | 7B | 32K (Base), 131K (Instruct) | link |
| Qwen2-57B-A14B | Jun 6, 2024 | 57B | 32K (Base), 64K (Instruct) | link |
| Qwen2-72B | Jun 6, 2024 | 72B | 32K (Base), 131K (Instruct) | link |
| Qwen2.5-0.5B | Sep 19, 2024 | 0.5B | 32K | link |
| Qwen2.5-1.5B | Sep 19, 2024 | 1.5B | 32K | link |
| Qwen2.5-3B | Sep 19, 2024 | 3B | 32K | link |
| Qwen2.5-7B | Sep 19, 2024 | 7B | 128K | link |
| Qwen2.5-14B | Sep 19, 2024 | 14B | 128K | link |
| Qwen2.5-32B | Sep 19, 2024 | 32B | 128K | link |
| Qwen2.5-72B | Sep 19, 2024 | 72B | 128K | link |
| Qwen2.5-7B-Instruct-1M | Jan 2025 | 7B | 1 M | link |
| Qwen2.5-14B-Instruct-1M | Jan 2025 | 14B | 1M | link |
| Qwen3-0.6B | Apr 29, 2025 | 0.6B | 32K | link |
| Qwen3-1.7B | Apr 29, 2025 | 1.7B | 32K | link |
| Qwen3-4B | Apr 29, 2025 | 4B | 32K | link |
| Qwen3-8B | Apr 29, 2025 | 8B | 131K | link |
| Qwen3-14B | Apr 29, 2025 | 14B | 131K | link |
| Qwen3-32B | Apr 29, 2025 | 32B | 131K | link |
| Qwen3-30B-A3B | Apr 29, 2025 | 30B | 131K | link |
| Qwen3-235B-A22B | Apr 29, 2025 | 235B | 131K | link |
| | | | | |

Table 2: **DeepSeek series model specifications.** Includes release dates, parameter counts, and maximum context lengths.

| Model Name | Release Date | Parameters | Context Length | Model Link |
|------------------------|-------------------|-----------------------------|----------------|------------|
| DeepSeek-Coder | November 2, 2023 | 1.3B/6.7B/33B | 16K tokens | link |
| DeepSeek-LLM | November 29, 2023 | 7B | 4096 tokens | link |
| DeepSeek-LLM | November 29, 2023 | 67B | 4096 tokens | link |
| DeepSeekMoE | January 11, 2024 | 16B total, 2.7B activated | 4096 tokens | link |
| DeepSeek-Math | April 2024 | 7B | 4096 tokens | link |
| DeepSeek-V2 | May 6, 2024 | 236B total, 21B activated | 128K tokens | link |
| DeepSeek-V2-Lite | May 16, 2024 | 16B total, 2.4B activated | 32K tokens | link |
| DeepSeek-Coder-V2 | June 17, 2024 | 236B total, 21B activated | 128K tokens | link |
| DeepSeek-Coder-V2-Lite | June 17, 2024 | 16B total, 2.4B activated | 128K tokens | link |
| DeepSeek-V2.5 | September 2024 | 236B total, 21B activated | 128K tokens | link |
| DeepSeek-V3 | December 26, 2024 | 671B total, 37B activated | 128K tokens | link |
| DeepSeek-R1-Zero | January 20, 2025 | 671B total, 37B activated | 128K tokens | link |
| DeepSeek-R1 | January 20, 2025 | 671B total, 37B activated | 128K tokens | link |
| DeepSeek-R1-Distill | January 20, 2025 | 1.5B, 7B, 8B, 14B, 32B, 70B | 32K tokens | link |
| DeepSeek-V3-0324 | March 2025 | 671B total, 37B activated | 128K tokens | link |

Table 3: **Llama series model specifications.** Details include release date, parameter count, context length, and Hugging Face model link.

| Model Name | Release Date | Parameters | Context Length | Model Link |
|---------------------------------|--------------------------------|---------------------------------|------------------------------|--------------|
| Llama 1 7B | February 24, 2023 | 7B | 2,048 tokens | link |
| Llama 1 13B | February 24, 2023 | 13B | 2,048 tokens | link |
| Llama 1 33B | February 24, 2023 | 33B | 2,048 tokens | link |
| Llama 1 65B | February 24, 2023 | 65B | 2,048 tokens | link |
| Llama 2 7B | July 18, 2023 | 7B | 4,096 tokens | link |
| Llama 2 13B | July 18, 2023 | 13B | 4,096 tokens | link |
| Llama 2 70B | July 18, 2023 | 70B | 4,096 tokens | link |
| Llama 3 8B | April 18, 2024 | 8B | 8,192 tokens | link |
| Llama 3 70B | April 18, 2024 | 70B | 8,192 tokens | link |
| Llama 3.1 8B | July 23, 2024 | 8B | 128,000 tokens | link |
| Llama 3.1 70B | July 23, 2024 | 70B | 128,000 tokens | link |
| Llama 3.1 405B | July 23, 2024 | 405B | 128,000 tokens | link |
| Llama 4 Scout | April 5, 2025 | 109B total / 17B active | 10M tokens | link |
| Llama 4 Maverick | April 5, 2025 | 400B total / 17B active | 1M tokens | link |
| Llama 3.1 405B Llama 4 Scout | July 23, 2024 April 5, 2025 | 405B 109B total / 17B active | 128,000 tokens 10M tokens | link link |

Table 4: **GLM series model specifications.** Includes release dates, parameter counts, maximum context lengths, and Hugging Face links.

| Model Name | Release Date | Parameters | Context Length | Model Link |
|-------------------|----------------|-------------------|-----------------------|------------|
| GLM-130B | August 2022 | 130B | 2,048 tokens | link |
| ChatGLM-6B | March 14, 2023 | 6.2B | 2,048 tokens | link |
| ChatGLM2-6B | June 25, 2023 | 6.2B | 32,768 tokens | link |
| ChatGLM2-6B-32K | July 2023 | 6.2B | 32,768 tokens | link |
| ChatGLM3-6B | October 2023 | 6.2B | 8,192 tokens | link |
| ChatGLM3-6B-32K | October 2023 | 6.2B | 32,768 tokens | link |
| ChatGLM3-6B-128K | November 2023 | 6.2B | 131,072 tokens | link |
| GLM-4-9B | May 2024 | 9B | 8,192 tokens | link |
| GLM-4-9B-Chat | May 2024 | 9B | 131,072 tokens | link |
| GLM-4-9B-Chat-1M | May 2024 | 9B | 1,048,576 tokens | link |

Table 5: **InternLM series model specifications.** Includes release dates, parameter counts, maximum context lengths, and Hugging Face links.

| Model Name | Release Date | Parameters | Context Length | Model Link |
|------------------------|--------------------|-------------------|------------------|------------|
| InternLM-7B | July 2023 | 7B | 8,000 tokens | link |
| InternLM-7B-Chat v1.1 | August 22, 2023 | 7B | 8,000 tokens | link |
| InternLM-20B | September 20, 2023 | 20B | 16,000 tokens | link |
| InternLM-20B-Chat | September 20, 2023 | 20B | 16,000 tokens | link |
| InternLM2-7B | January 17, 2024 | 7B | 200,000 tokens | link |
| InternLM2-20B | January 17, 2024 | 20B | 200,000 tokens | link |
| InternLM2.5-7B | July 3, 2024 | 7B | 200,000 tokens | link |
| InternLM2.5-7B-Chat-1M | July 2024 | 7B | 1,000,000 tokens | link |
| InternLM2.5-1.8B | August 1, 2024 | 1.8B | 200,000 tokens | link |
| InternLM2.5-20B | August 1, 2024 | 20B | 200,000 tokens | link |
| InternLM3-8B-Instruct | January 15, 2025 | 8B | 32768 tokens | link |

Table 6: **LLaVA series model specifications.** Includes release dates, backbone models, context lengths, and multimodal capabilities. si: single image; mi: multiple images; vid: video.

| Model Name | Release Date | LLM Backbone | Max Context | Image Resolution | Max Tokens | Model Link |
|----------------------|----------------|---------------------|-------------|-------------------------------|-------------------------------|------------|
| LLaVA-7B | April 2023 | Vicuna-7B | 2K | 224×224 | 256 | link |
| LLaVA-13B | April 2023 | Vicuna-13B | 2K | 224×224 | 256 | link |
| LLaVA-1.5-7B | October 2023 | Vicuna-7B-v1.5 | 4K | 336×336 | 576 | link |
| LLaVA-1.5-13B | October 2023 | Vicuna-13B-v1.5 | 4K | 336×336 | 576 | link |
| LLaVA-NeXT-7B | January 2024 | Mistral-7B | 8K | 336x{2x2,1x{2,3,4}, {2,3,4}x1 | 2880 | link |
| LLaVA-NeXT-7B | January 2024 | Vicuna-7B-v1.5 | 4K | 336x{2x2,1x{2,3,4}, {2,3,4}x1 | 2880 | link |
| LLaVA-NeXT-13B | January 2024 | Vicuna-13B-v1.5 | 4K | 336x{2x2,1x{2,3,4}, {2,3,4}x1 | 2880 | link |
| LLaVA-NeXT-34B | January 2024 N | ous-Hermes-2-Yi-34E | 3 4K | 336x{2x2,1x{2,3,4}, {2,3,4}x1 | 2880 | link |
| LLaVA-OneVision-0.5E | 3 August 2024 | Qwen2-0.5B | 32K | 336×336×[6,6] | 7290(si), 8748(mi), 6272(vid) | link |
| LLaVA-OneVision-7B | August 2024 | Qwen2-7B | 32K | 336×336×[6,6] | 7290(si), 8748(mi), 6272(vid) | link |
| LLaVA-OneVision-72B | August 2024 | Qwen2-72B | 32K | 336×336×[6,6] | 7290(si), 8748(mi), 6272(vid) | link |

Table 7: **InternVL series model specifications.** Includes release dates, backbone architectures, and multimodal capabilities.

| Model Name | Release Date | LLM Backbone | Max Context | Image Resolution | Max Tokens | Model Link |
|-----------------|--------------|-----------------------|-------------|---------------------------|------------|------------|
| InternVL-21B | Dec 2023 | Vicuna-7B | 2K | 224×224, 336×336, 448×448 | 1,024 | link |
| InternVL-27B | Dec 2023 | Vicuna-13B | 2K | 224×224, 336×336, 448×448 | 1,024 | link |
| InternVL1.5-26B | Apr 2024 | InternLM2-20B | 200K | 2688×2688 | 8,192 | link |
| InternVL2.5-1B | Dec 2024 | Qwen2.5-0.5B-Instruct | 32K | 2688×2688 | 8,192 | link |
| InternVL2.5-2B | Dec 2024 | Internlm2.5-1.8B-chat | 200K | 2688×2688 | 8,192 | link |
| InternVL2.5-4B | Dec 2024 | Qwen2.5-3B-Instruct | 32K | 2688×2688 | 8,192 | link |
| InternVL2.5-8B | Dec 2024 | Internlm2.5-7B-chat | 200K | 2688×2688 | 8,192 | link |
| InternVL2.5-26B | Dec 2024 | Internlm2.5-20B-chat | 200K | 2688×2688 | 8,192 | link |
| InternVL2.5-38B | Dec 2024 | Qwen2.5-32B-Instruct | 128K | 2688×2688 | 8,192 | link |
| InternVL2.5-78B | Dec 2024 | Qwen2.5-72B-Instruct | 128K | 2688×2688 | 8,192 | link |
| InternVL3-1B | Apr 2025 | Qwen2.5-0.5B | 32K | 2688×2688 | 32K | link |
| InternVL3-2B | Apr 2025 | Qwen2.5-1.5B | 32K | 2688×2688 | 32K | link |
| InternVL3-8B | Apr 2025 | Qwen2.5-7B | 128K | 2688×2688 | 32K | link |
| InternVL3-9B | Apr 2025 | InternLM3-8B | 32K | 2688×2688 | 32K | link |
| InternVL3-14B | Apr 2025 | Qwen2.5-14B | 128K | 2688×2688 | 32K | link |
| InternVL3-38B | Apr 2025 | Qwen2.5-32B | 128K | 2688×2688 | 32K | link |
| InternVL3-78B | Apr 2025 | Qwen2.5-72B | 128K | 2688×2688 | 32K | link |

Table 8: **Qwen-VL series model specifications.** Includes release dates, backbone architectures, and multimodal capabilities.

| Model Name | Release Date | LLM Backbone | Max Context | Image Resolution | Max Tokens | Model Link |
|----------------|--------------|--------------|-------------|----------------------------------|------------|------------|
| Qwen-VL-9.6B | Aug 2023 | Qwen-7B | 2K | 448×448 | 1,024 | link |
| Qwen2-VL-2B | Sep 2024 | Qwen2-1.5B | 32K | native resolution(max=2048×2048) | 16,384 | link |
| Qwen2-VL-7B | Sep 2024 | Qwen2-7B | 32K | native resolution(max=2048×2048) | 16,384 | link |
| Qwen2-VL-72B | Sep 2024 | Qwen2-72B | 32K | native resolution(max=2048×2048) | 16,384 | link |
| Qwen2.5-VL-3B | Feb 2025 | Qwen2.5-3B | 32K | native resolution(max=2048×2048) | 24,576 | link |
| Qwen2.5-VL-7B | Feb 2025 | Qwen2.5-7B | 128K | native resolution(max=2048×2048) | 24,576 | link |
| Qwen2.5-VL-72B | Feb 2025 | Qwen2.5-72B | 128K | native resolution(max=2048×2048) | 24,576 | link |