DeepSeek-OCR: Contexts Optical Compression

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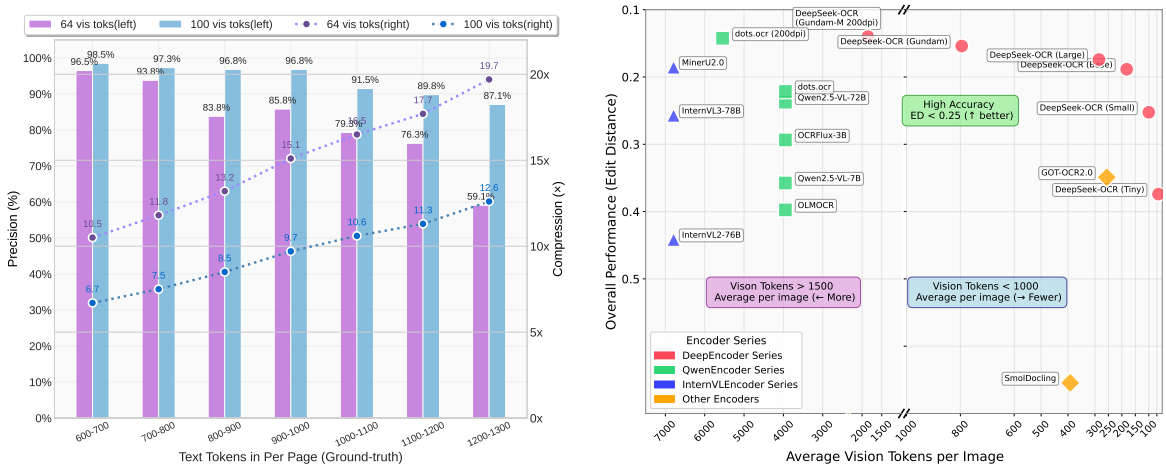
DeepSeek-AI

Abstract

We present DeepSeek-OCR as an initial investigation into the feasibility of compressing long contexts via optical 2D mapping. DeepSeek-OCR consists of two components: DeepEncoder and DeepSeek3B-MoE-A570M as the decoder. Specifically, DeepEncoder serves as the core engine, designed to maintain low activations under high-resolution input while achieving high compression ratios to ensure an optimal and manageable number of vision tokens. Experiments show that when the number of text tokens is within 10 times that of vision tokens (i.e., a compression ratio < 10×), the model can achieve decoding (OCR) precision of 97%. Even at a compression ratio of 20×, the OCR accuracy still remains at about 60%. This shows considerable promise for research areas such as historical long-context compression and memory forgetting mechanisms in LLMs. Beyond this, DeepSeek-OCR also demonstrates high practical value. On OmniDocBench, it surpasses GOT-OCR2.0 (256 tokens/page) using only 100 vision tokens, and outperforms MinerU2.0 (6000+ tokens per page on average) while utilizing fewer than 800 vision tokens. In production, DeepSeek-OCR can generate training data for LLMs/VLMs at a scale of 200k+ pages per day (a single A100-40G). Codes and model weights are publicly accessible at http://github.com/deepseek-ai/DeepSeek-OCR.



(a) Compression on Fox benchmark

(b) Performance on Omnidocbench

Figure 1 | Figure (a) shows the compression ratio (number of text tokens in ground truth/number of vision tokens model used) testing on Fox [21] benchmark; Figure (b) shows performance comparisons on OmniDocBench [27]. DeepSeek-OCR can achieve state-of-the-art performance among end-to-end models enjoying the fewest vision tokens.

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1. Introduction

Current Large Language Models (LLMs) face significant computational challenges when processing long textual content due to quadratic scaling with sequence length. We explore a potential solution: leveraging visual modality as an efficient compression medium for textual information. A single image containing document text can represent rich information using substantially fewer tokens than the equivalent digital text, suggesting that optical compression through vision tokens could achieve much higher compression ratios.

This insight motivates us to reexamine vision-language models (VLMs) from an LLM-centric perspective, focusing on how vision encoders can enhance LLMs' efficiency in processing textual information rather than basic VQA [12, 16, 24, 32, 41] what humans excel at. OCR tasks, as an intermediate modality bridging vision and language, provide an ideal testbed for this vision-text compression paradigm, as they establish a natural compression-decompression mapping between visual and textual representations while offering quantitative evaluation metrics.

Accordingly, we present DeepSeek-OCR, a VLM designed as a preliminary proof-of-concept for efficient vision-text compression. Our work makes three primary contributions:

First, we provide comprehensive quantitative analysis of vision-text token compression ratios. Our method achieves 96%+ OCR decoding precision at 9-10× text compression, ~90% at 10-12× compression, and ~60% at 20× compression on Fox [21] benchmarks featuring diverse document layouts (with actual accuracy being even higher when accounting for formatting differences between output and ground truth), as shown in Figure 1(a). The results demonstrate that compact language models can effectively learn to decode compressed visual representations, suggesting that larger LLMs could readily acquire similar capabilities through appropriate pretraining design.

Second, we introduce DeepEncoder, a novel architecture that maintains low activation memory and minimal vision tokens even with high-resolution inputs. It serially connects window attention and global attention encoder components through a 16× convolutional compressor. This design ensures that the window attention component processes a large number of vision tokens, while the compressor reduces vision tokens before they enter the dense global attention component, achieving effective memory and token compression.

Third, we develop DeepSeek-OCR based on DeepEncoder and DeepSeek3B-MoE [19, 20]. As shown in Figure 1(b), it achieves state-of-the-art performance within end-to-end models on OmniDocBench while using the fewest vision tokens. Additionally, we equip the model with capabilities for parsing charts, chemical formulas, simple geometric figures, and natural images to enhance its practical utility further. In production, DeepSeek-OCR can generate 33 million pages of data per day for LLMs or VLMs using 20 nodes (each with 8 A100-40G GPUs).

In summary, this work presents a preliminary exploration of using visual modality as an efficient compression medium for textual information processing in LLMs. Through DeepSeek-OCR, we demonstrate that vision-text compression can achieve significant token reduction (7-20×) for different historical context stages, offering a promising direction for addressing long-context challenges in large language models. Our quantitative analysis provides empirical guidelines for VLM token allocation optimization, while the proposed DeepEncoder architecture showcases practical feasibility with real-world deployment capabilities. Although focused on OCR as a proof-of-concept, this paradigm opens new possibilities for rethinking how vision and language modalities can be synergistically combined to enhance computational efficiency in large-scale text processing and agent systems.

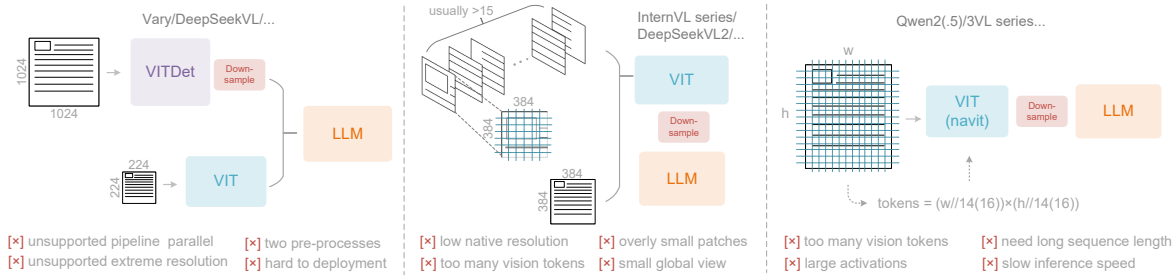

Figure 2 | Typical vision encoders in popular VLMs. Here are three types of encoders commonly used in current open-source VLMs, all of which suffer from their respective deficiencies.

2. Related Works

2.1. Typical Vision Encoders in VLMs

Current open-source VLMs employ three main types of vision encoders, as illustrated in Figure 2. The first type is a dual-tower architecture represented by Vary [36], which utilizes parallel SAM [17] encoder to increase visual vocabulary parameters for high-resolution image processing. While offering controllable parameters and activation memory, this approach suffers from significant drawbacks: it requires dual image preprocessing that complicates deployment and makes encoder pipeline parallelism challenging during training. The second type is tile-based method exemplified by InternVL2.0 [8], which processes images by dividing them into small tiles for parallel computation, reducing activation memory under high-resolution settings. Although capable of handling extremely high resolutions, this approach has notable limitations due to its typically low native encoder resolution (below 512×512), causing large images to be excessively fragmented and resulting in numerous vision tokens. The third type is adaptive resolution encoding represented by Qwen2-VL [35], which adopts the NaViT [10] paradigm to directly process full images through patch-based segmentation without tile parallelization. While this encoder can handle diverse resolutions flexibly, it faces substantial challenges with large images due to massive activation memory consumption that can cause GPU memory overflow, and sequence packing requires extremely long sequence lengths during training. Long vision tokens will slow down both prefill and generation phases of inference.

2.2. End-to-end OCR Models

OCR, particularly document parsing task, has been a highly active topic in the image-to-text domain. With the advancement of VLMs, a large number of end-to-end OCR models have emerged, fundamentally transforming the traditional pipeline architecture (which required separate detection and recognition expert models) by simplifying OCR systems. Nougat [6] first employs end-to-end framework for academic paper OCR on arXiv, demonstrating the potential of models in handling dense perception tasks. GOT-OCR2.0 [38] expands the scope of OCR2.0 to include more synthetic image parsing tasks and designs an OCR model with performance-efficiency trade-offs, further highlighting the potential of end-to-end OCR researches. Additionally, general vision models such as Qwen-VL series [35], InternVL series [8], and many their derivatives continuously enhance their document OCR capabilities to explore dense visual perception boundaries. However, a crucial research question that current models have not addressed is: *for a document containing 1000 words, how many vision tokens are at least needed for decoding?* This question holds significant importance for research in the principle that "*a picture is worth a thousand words.*"

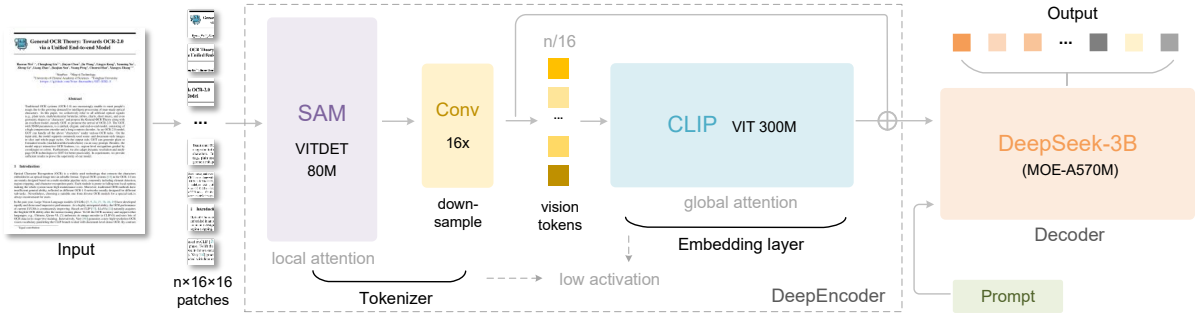

Figure 3 | The architecture of DeepSeek-OCR. DeepSeek-OCR consists of a DeepEncoder and a DeepSeek-3B-MoE decoder. DeepEncoder is the core of DeepSeek-OCR, comprising three components: a SAM [17] for perception dominated by window attention, a CLIP [29] for knowledge with dense global attention, and a 16× token compressor that bridges between them.

3. Methodology

3.1. Architecture

As shown in Figure 3, DeepSeek-OCR enjoys a unified end-to-end VLM architecture consisting of an encoder and a decoder. The encoder (namely DeepEncoder) is responsible for extracting image features and tokenizing as well as compressing visual representations. The decoder is used for generating the required result based on image tokens and prompts. DeepEncoder is approximately 380M in parameters, mainly composed of an 80M SAM-base [17] and a 300M CLIP-large [29] connected in series. The decoder adopts a 3B MoE [19, 20] architecture with 570M activated parameters. In the following paragraphs, we will delve into the model components, data engineering, and training skills.

3.2. DeepEncoder

To explore the feasibility of contexts optical compression, we need a vision encoder with the following features: 1.Capable of processing high resolutions; 2.Low activation at high resolutions; 3.Few vision tokens; 4.Support for multiple resolution inputs; 5. Moderate parameter count. However, as described in the Section 2.1, current open-source encoders cannot fully satisfy all these conditions. Therefore, we design a novel vision encoder ourselves, named DeepEncoder.

3.2.1. Architecture of DeepEncoder

DeepEncoder mainly consists of two components: a visual perception feature extraction component dominated by window attention, and a visual knowledge feature extraction component with dense global attention. To benefit from the pretraining gains of previous works, we use SAM-base (patch-size 16) and CLIP-large as the main architectures for the two components respectively. For CLIP, we remove the first patch embedding layer since its input is no longer images but output tokens from the previous pipeline. Between the two components, we borrow from Vary [36] and use a 2-layer convolutional module to perform 16× downsampling of vision tokens. Each convolutional layer has a kernel size of 3, stride of 2, padding of 1, and channels increase from 256 to 1024. Assuming we input a 1024×1024 image, the DeepEncoder will segment it into 1024/16×1024/16=4096 patch tokens. Since the first half of encoder is dominated by window attention and only 80M, the activation is acceptable. Before entering global attention,