

Sid	Japanese POC Differential parsing in MLLM for rendering and parsing (Binary + Ocr)			Branch	Main
				Yash	feature_yash_attack1 feature_pb_injection3
	Framework LangGraph	env uv/conda	Python library	Sid	feature_sid_textonimage poc
				Ash	feature_ash_setup
Input	PDF [Finance, Education, Health]	60	75	94	90
Step 1	PDF Processing and extraction [PyMuPDF/ReportLab(Direct Binary Parsing)]	[Tesseract/Doclign(OCR)	[Llamaparser/Landing AI/deepseek/paddleocr(Agentic Document Extraction	[Gemini, Claude, Gpt] (MLLM)	Function/Tools calls
Step 2	C1 - Content extracted	C2	C3	C4	
Condition-> Any pdf	Summary, Domain, Intended Task, Sub Tasks, Evidence for task, Pre-conditions, effects, Field information, Contains -> images, tables, etc., B-box from step 1), Original Document Source (PPT, ARXIV ETC)	Task classification-> Classification/Generation(Reasoning based-> through llm)	Other metadata needed for Downstream manipulation	Prompt Needed	
Step 3	Planning	Attack Planning			
		Credit Application	Academic Exam	Hospital bill Claim	
Step 4	Injection	Injection Method			
	AI models like GEMINI have a hybrid document processing pipeline . It looks at both the text layer and the visual layer and then reasons over which one to respond for. For our attacks to work on GEMINI or Grok as well, we need to corrupt both for text and visual layer. For text - our already existing attacks, For visual - OCR based attacks	1) Binary injection 2) Adversarial Patch Injection (NOT MUCH USE UNLESS DEALING WITH VISION ENCODERS) Modern AI models use OCR based pipelines to extract text from screenshots 3) OCR Based Attacks (So that the document works on AI models like Gemini)	-> Byte level Injection -> Image injection BBOX, Entire page	3 Methods [Code-Glyph, Trap-Doc , Byte-Level Injection] 0 Methods https://anonymous.4open.science/r/adv_docVQA-E7C5/README.md	Prompt Needed Output: Attack information Enhance Counterfeit Answers Adversarial patch Simple TEXT WRITE
	python3 stage1.py --pdf mypdf.pdf	Extraction and parsing			
	python3 stage4.py --injection_method Trap-doc	Attack Injection			

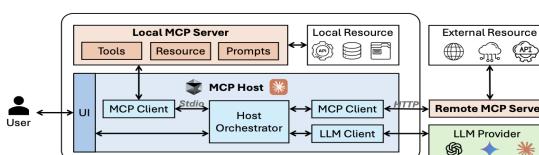
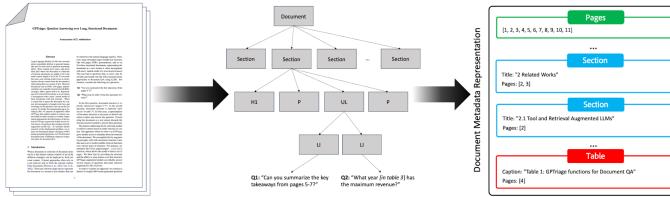


Figure 1: MCP architecture overview.

—OpenAI’s Preparedness Framework, Anthropic’s Responsible Scaling Policy, and GDM’s Frontier Safety Framework,

Input modality	Type	Number of tokens	Models
Plain text	Long-context	Linear increase	LongLoRA [4], LongLLaMA [5], YaRN [3]
	RAG	w/o Linear increase	Graph RAG [9], DISC-LawLLM [6], RAPTOR [19]
Pure vision	Single-page	w/o Linear increase	UniDoc [20], DocOwl [21], Vary [12], UReader [22], TextMonkey [10], LLaVA-NeXT [23], XC2-4KHD [24], InternVL-V1.5 [11]
	Multi-page	Linear increase	Hi-VT5 [14], GRAM [16], Fox [13], DocOwl2 [25], CREAM [26]
Text and images	Unlimited-page	w/o Linear increase	PDF-WuKong (Ours)

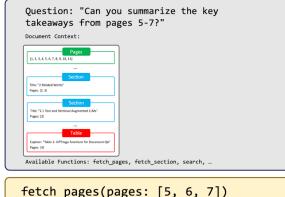
Step 1: Generate a structured metadata representation of the document.



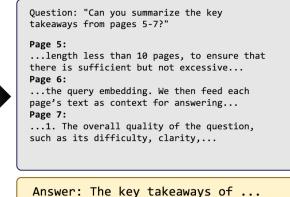
Document Metadata Representation



Step 2: LLM-based Triage
(frame selection/filling)



Step 3: Question answering
with selected context



https://raw.githubusercontent.com/adobe-research/pdftrifrage/main/docinstruct-v0/data/raw/hit_examples.csv