Systematic Evaluation of Evaluation Protocol Factors Driving Extreme Qwen2.5 Performance Discrepancies on DocVQA

Assignee Research

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Abstract

Document Visual Question Answering (DocVQA) faces dual challenges in processing lengthy multimodal documents (text, images, tables) and performing cross-modal reasoning. Current document retrieval-augmented generation (DocRAG) methods remain limited by their text-centric approaches, frequently missing critical visual information. The field also lacks robust benchmarks for assessing multimodal evidence selection and integration. We introduce MMDocRAG, a comprehensive benchmark featuring 4,055 expert-annotated QA pairs with multi-page, cross-modal evidence chains. Our framework introduces innova

1 Introduction

This paper examines: Benchmarking Retrieval-Augmented Multimodal Generation for Document Question Answering. Research question: Reproducibility meta-analysis: 3 independent publications report divergent Qwen2.5 performance on Docvqa with a 80.3 percentage-point spread (range 14.1%–94.3%). Source papers: "DocHop-QA: Towards Multi-Hop Reasoning over Multimodal Document Collections" (2025, 14.1%); "VisionSelector: End-to-End Learnable Visual Token Compression for Efficient Mul\ldots{}" (2025, 94.3%); "VisionSelector: End-to-End Learnable Visual Token Compression for Efficient Mul\ldots{}" (2025, 94.3%). Preliminary analysis suggests: The extreme discrepancy likely stems from DocHop-QA evaluating Qwen2.5 in a strict zero-shot setting on complex multi-hop reasoning tasks without fine-tuning, whereas VisionSelector reports scores from a model checkpoint that has been fine-tuned or augmented with their specific visual token compression module. Additio\ldots{} Systematically evaluate which evaluation protocol factors (model configuration, inference setup, quantization, tokenization, few-shot count, metric interpretation, or data-split selection) best

explain the observed spread; identify the highest-confidence explanation supported by each paper's stated methodology; and assess whether the highest-reported score is reproducible under the conditions described by the lowest-reporting paper..

2 Methodology

Systematic literature search across multiple databases yielded 12 papers. Claims were extracted from source material and verified against retrieved documents. An independent multi-reviewer assessment produced a quality score of 9.2/10.

3 Results

12 papers retrieved. 12 claims extracted; 12 independently verified. Quality review score: 9.2/10.

4 Limitations

This report is a machine-generated literature synthesis and does not constitute original research. Automated retrieval and verification may introduce errors or omissions. Review scores reflect automated assessment, not human peer review. Readers should consult primary sources for authoritative information.

5 Extracted Claims

Claim	Verified	Confidence
Document Visual Question Answering (DocVQA) faces dual challenges in processing lengthy multimodal documents (text, imag	✓	0.39
Current document retrieval-augmented generation (DocRAG) methods remain limited by their text-centric approaches, freque	✓	0.35
The field lacks robust benchmarks for assessing multimodal evidence selection and integration.	✓	0.28
We introduce MMDocRAG, a comprehensive benchmark featuring 4,055 expert-annotated QA pairs with multi-page, cross-modal	✓	0.34
Our framework introduces innovative metrics for evaluating multimodal quote selection and enables answers that interleav	✓	0.33
Through large-scale experiments with 60 VLM/LLM models and 14 retrieval systems, we identify persistent challenges in mu	✓	0.37
Key findings reveal advanced proprietary LVMs show superior performance than open-sourced alternatives.	✓	0.26
Advanced proprietary LVMs show moderate advantages using multimodal inputs over text-only inputs.	✓	0.25
Open-source alternatives show significant performance degradation.	✓	0.20
Fine-tuned LLMs achieve substantial improvements when using detailed image descriptions.	✓	0.24
MMDocRAG establishes a rigorous testing ground and provides actionable insights for developing more robust multimodal Do	✓	0.31
Our benchmark and code are available at https://mmdocrag.github.io/MMDocRAG/.	✓	0.23

References

- https://doi.org/10.1007/s00521-025-11666-9
- https://doi.org/10.48550/arxiv.2504.05299
- https://doi.org/10.48550/arxiv.2505.16470