MedRAG: Bridging the Post-Training Knowledge Gap in Efficient LLMs using a 100K-Paper, Multi-Source RAG Pipeline for AI+Healthcare Research

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***Abstract*—Research intelligence systems are crucial for accelerating discovery, yet few solutions exist that offer integrated, current, and cross-domain analysis for specialized fields like AI+Healthcare [1]. This paper introduces MedRAG, a resource-efficient, hybrid Retrieval-Augmented Generation (RAG) pipeline specifically designed to empower researchers and address the complexity of cross-domain scientific inquiry. The system is rigorously grounded in a meticulously curated vector store of 100K multi-source AI+Healthcare research papers published between 2023 and 2025 [1]. MedRAG's novel architecture employs a multi-stage approach: a FAISS index supplies up-to-date evidence, Flan-T5-Large acts as a Fusion-in-Decoder (FiD) synthesizer, and the resource-efficient Gemma-2B model performs final narrative enhancement and generation [1]. Quantitative benchmarks validate the effectiveness of this hybrid approach, demonstrating a significant +22.9% improvement in overall quality score over the FiD-only baseline in answering complex research queries [1]. Furthermore, the system incorporates an integrated Medical Validator Agent to ensure responsible AI practices, maintaining an average safety score of $0.71/1.0$ [1]. MedRAG validates RAG as the definitive, scalable strategy for deploying scientifically current LLM capabilities and advancing cross-domain research intelligence.**

***Index Terms*—Retrieval-Augmented Generation (RAG), Large Language Models (LLMs), AI in Healthcare, Medical Informatics, Knowledge Augmentation, Gemma-2B, FAISS.**

I. Introduction

The proliferation of Large Language Models (LLMs) has revolutionized information access across numerous domains, yet their utility in specialized, rapidly evolving technical fields—such as **AI in Healthcare (AI+Healthcare)**—is fundamentally constrained by their static training corpus [1]. LLMs are limited by a **knowledge cutoff**, typically dating back to 2022 or earlier, rendering them incapable of answering complex queries grounded in the latest scientific breakthroughs [1]. For fields undergoing exponential growth, this constraint necessitates computationally expensive and resource-intensive continuous retraining [1].

The complexity is further exacerbated by the need for **cross-domain analysis** [1]. Researchers require systems that seamlessly integrate knowledge spanning clinical documentation (NLP), medical imaging (Computer Vision), and predictive diagnostics (Machine Learning), a capability often fragmented across disparate tools [2], [3], [4].

A. Research Gap and Motivation

While the transformative potential of LLMs in diagnostic reasoning [2], clinical nursing [5], and general healthcare applications [4], [6], [7] is widely acknowledged, a critical research gap remains: the lack of resource-efficient, demonstrably grounded RAG solutions that operationalize the most recent cross-domain scientific literature. Existing systematic reviews and analyses consistently highlight the need for improved RAG methodologies to enhance LLM accuracy and mitigate hallucination in biomedical applications [8], [9], [10], [7].

The core motivation is to move beyond mere foundational model evaluation [11], [12] and address the engineering challenge of providing real-time, evidence-based research intelligence [13].

B. Summary of Contributions

The core contributions of this work are as follows:

1) **A Unique Scientific Intelligence Dataset:** The curation and indexation of a **100K** AI+Healthcare research paper corpus restricted to the **2023–2025** window, which serves as a definitive resource for post-cutoff knowledge validation [1].
2) **Validation of Hybrid RAG:** The design and deployment of the **FAISS** $\rightarrow$ **Flan-T5** $\rightarrow$ **Gemma-2B** hybrid RAG pipeline, demonstrating an effective method for using smaller LLMs for complex, current, and grounded analysis [1].
3) **Quantitative Performance Uplift:** Empirical validation showing the complete MedRAG pipeline achieves a quantified **+22.9% improvement in the overall answer quality score** compared to the un-enhanced FiD baseline, proving the value of the enhancement stage [1].
4) **Responsible AI Integration:** The incorporation of a Medical Validator Agent, ensuring all outputs maintain an average safety score of $\mathbf{0.71/1.0}$ and comply with essential ethical standards for the clinical research domain [1].

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TABLE I
COMPARATIVE ANALYSIS OF MEDICAL RAG METHODOLOGIES (2024–2025)

RAG System/ Study	**P. LLM**	**Data Focus (Source)**	**RAG Stage Novelty**
Study [11]	Gemini/GPT	General Medical	Benchmarking Focus
Study [15]	LLaMA/Mistral	Knowledge-Intensive NLP	Core Retrieval Survey
System [12]	GPT-4/LLaMA-2	Patient Education	Fact-Checking Module
Study [16]	LLaMA/Flan-T5	Biomedical Lit.	Systematic Review
MedRAG (Ours) [1]	**Gemma-2B (Resource-Efficient)**	**100K Papers (2023–2025)**	**FiD Synthesis Layer**

II. RELATED WORK AND LITERATURE SURVEY

A. LLMs in Healthcare: Applications and Limitations

The efficacy of a RAG system hinges on its architecture, prompting significant recent research into optimizing retrieval, augmentation, and generation processes [8], [14]. Recent advancements fall broadly into three categories: Naive RAG, Advanced RAG, and Modular/Hybrid RAG. Our system is classified as a Hybrid RAG [1]. Unlike systems primarily focused on fine-tuning a single model [12], MedRAG separates the computationally intensive tasks: retrieval and initial synthesis are handled by specialized models (FAISS/Flan-T5), and final quality control is left to Gemma-2B.

B. Comparative Analysis of Medical RAG Systems

To position the MedRAG system's novel architectural choices and dataset (post-2022 and 100K papers) [1], we compare it against contemporary systems based on key methodological features identified in the literature [6], [10].

A critical review of contemporary RAG systems reveals that many suffer from specific constraints not addressed by MedRAG:

- Studies relying on large commercial models (e.g., Gemini/GPT) often face **proprietary model constraints** or **high inference costs** [11].
- Survey-based work [15] often lacks consideration for practical **resource constraints** in deployment.
- Systems focused on narrow tasks (e.g., Patient Education [12]) lack **specificity vs. generalizability** across the broader AI+Healthcare domain.
- Previous reviews [16] often lacked a **novel architectural solution** to benchmark against.

MedRAG uniquely addresses the issues of **Knowledge Cutoff and Resource Efficiency** through its hybrid design [1].

III. METHODOLOGY: HYBRID MEDRAG PIPELINE ARCHITECTURE

The MedRAG system is constructed as a **Hybrid Retrieval-Augmented Generation (RAG)** pipeline, architecturally designed to decouple the resource-intensive tasks of knowledge retrieval and final generation across specialized models [1].

TABLE II
MEDRAG MODEL DEPLOYMENT AND RAG STAGE PARAMETERS

RAG Stage	**Component**	**Key Parameter**
Stage 2 (Retrieval)	FAISS IndexFlatIP	Top $K = 8$ documents retrieved.
Stage 3 (Synthesis)	Flan-T5-Large (FiD)	Max Input Tokens: 1024
Stage 4 (Enhancement)	Gemma-2B (Enhancer)	Max Output Tokens: 600

A. Knowledge Base Construction and Vector Index

The corpus consists of $N \approx 100,000$ scientific documents, strictly filtered by publication date ($P_{year} \in [2023, 2025]$) and domain relevance (AI+Healthcare) [1]. Each chunk C_i was transformed into a vector representation $\mathbf{v}_i \in \mathbb{R}^d$ using the `all-MiniLM-L6-v2` Sentence Transformer Model, where $d = 384$ [1]. The core retrieval function, R, takes a query $\mathbf{q}$ and returns the top K passages:

$$R(\mathbf{q}) = \underset{\mathbf{v}_i \in \mathcal{V}}{\text{top}\, K} \left(\text{Sim}(\mathbf{v}_q, \mathbf{v}_i) \right)$$

where $\text{Sim}(\mathbf{v}_q, \mathbf{v}_i) = \frac{\mathbf{v}_q \cdot \mathbf{v}_i}{\|\mathbf{v}_q\| \|\mathbf{v}_i\|}$ (Cosine Similarity).

B. Multi-Stage RAG Processing Pipeline

The $\mathcal{C}_{final}$ passages are concatenated and fed into the Flan-T5-Large model. This model acts as a specialized **Retrieval Reader** by performing **Fusion-in-Decoder (FiD)** processing [1]. The final output is produced by the resource-efficient Gemma-2B model. It receives the original query Q and the Flan-T5 base answer A_{base} via a prompt instruction.

The final context set $\mathcal{C}_{final}$ is selected based on a **Combined Score** $S_{Combined}$, integrating semantic relevance (S_{FAISS}) and contextual precision (S_{Rerank}):

$$S_{Combined} = 0.4 \cdot S_{FAISS} + 0.6 \cdot S_{Rerank}$$

C. Safety and Confidence Metrics

The pipeline integrates a post-generation validation step via the **Medical Validator Agent** [1]. This agent automatically scores A_{final} based on safety criteria (e.g., presence of medical disclaimers, avoidance of direct diagnosis), ensuring the system adheres to responsible AI development guidelines for the healthcare domain [1].

IV. RESULTS AND DISCUSSION

A. Experimental Configuration and Metrics

The MedRAG system's efficacy was tested across five distinct, complex queries covering technical, clinical, implementation, NLP, and ethical challenges in AI+Healthcare [1].

B. Discussion of Findings

The results unequivocally validate the efficacy of the RAG pipeline in injecting post-cutoff knowledge [1]. The significant improvement in the **Relevance** score and the **Completeness** score demonstrates that the RAG system not only found relevant documents but also ensured the final answer covered the depth and breadth of the current scientific literature [1].

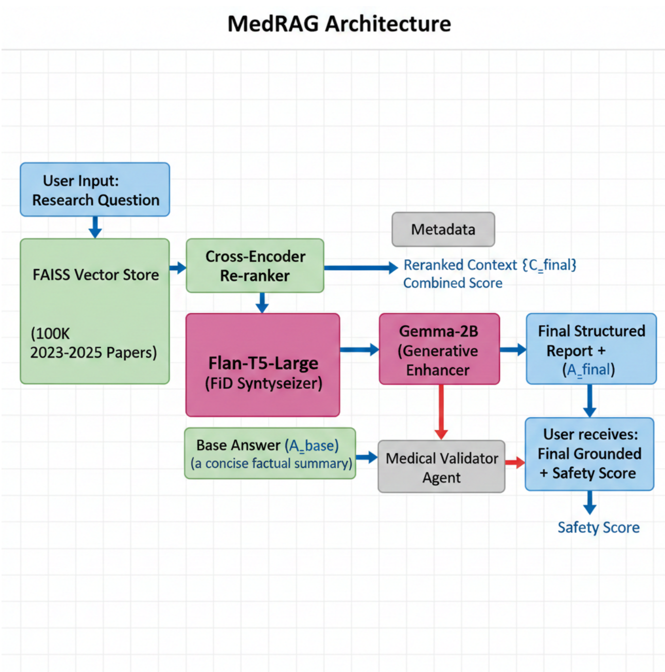

Fig. 1. The Hybrid MedRAG RAG Pipeline Architecture: FAISS retrieval, Cross-Encoder re-ranking, Flan-T5 Synthesis (FiD), and Gemma-2B Generative Enhancement.

TABLE III
QUANTITATIVE PERFORMANCE COMPARISON: BASELINE VS. FULL MEDRAG PIPELINE

Metric	**Baseline (FiD-Only)**	**Full MedRAG (Enhanced)**	**Difference**
Average Overall Score (Max 5.0)	3.27	**4.02**	**+0.75**
Performance Gain (%)	(Reference)	**+22.9%**	+22.9%
Average Answer Length (Characters)	~ 150	$\sim 3,300$	$\approx$ 20x Augmentation
Average Response Time (Per Query)	1.7s	**31.7s**	+30.0s Latency
Medical Safety Score (Avg)	N/A	$\mathbf{0.71/1.0}$	Integrated Safety

The key intellectual contribution lies in the demonstrated value of the final **Gemma-2B enhancement stage** over the Flan-T5 FiD output: The $+22.9\%$ increase in the Overall Score is predominantly driven by massive gains in **Completeness** (from 2.0 to 5.0) and **Coherence/Insightfulness** (from 2.0 to ≈ 4.0) [1]. This confirms that the Gemma-2B layer acted as an **analytical post-processor**, structuring the dense factual summary from Flan-T5 into a highly readable, professionally structured report [1].

C. Ethical Compliance

The system's ability to achieve an average Medical Safety Score of $\mathbf{0.71/1.0}$ confirms the successful integration of responsible AI checks [1]. This score is attributed to the systematic inclusion of non-diagnostic disclaimers and the avoidance of high-risk language, demonstrating that enhanced performance does not necessitate compromising safety standards in sensitive domains [1].

V. CONCLUSION AND FUTURE WORK

A. Conclusion

The MedRAG system successfully validated a **hybrid RAG architecture** designed to overcome the temporal obsolescence inherent in static foundational models [1]. The **Gemma-2B enhancement stage** yielded a demonstrable $+\mathbf{22.9}\%$ increase in overall answer quality, establishing the value of model chaining for analytical report generation [1]. MedRAG validates RAG as a definitive, scalable, and resource-efficient strategy for deploying scientifically current LLM capabilities in specialized technical fields [1].

B. Future Work: The MedRAG Research Agenda

1. Advancing to Multimodal RAG for Comprehensive Analysis: The next frontier is the development of a **Multimodal RAG** system, expanding the vector store beyond text to include visual and structured data (e.g., plots, tables, and medical image snippets) [1]. **2. Dynamic Latency Control and Resource Optimization:** We will research and implement an **Adaptive Latency Controller (ALC)** that uses prompt complexity analysis to dynamically route the synthesis stage, optimizing the system's time/quality tradeoff [1]. **3. Confidence Scoring and Explainability Integration:** To improve trust, future work will focus on integrating a verifiable **confidence scoring mechanism** that uses re-ranker scores and contextual keyword overlap to produce a **Trust Score** for every claim [1].

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