MedRAG: A Large-Scale Hybrid Retrieval-Augmented Generation Framework for Post-Cutoff Research Intelligence in AI and Healthcare

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Abstract—**Large Language Models (LLMs) have demonstrated remarkable reasoning and generative capabilities across a wide range of domains. However, their effectiveness in rapidly evolving and safety-critical fields such as Artificial Intelligence in Healthcare (AI+Healthcare) remains fundamentally constrained by static training corpora and post-training knowledge obsolescence. This paper presents MedRAG, a large-scale, hybrid Retrieval-Augmented Generation (RAG) framework designed to deliver grounded, up-to-date, and ethically constrained research intelligence for AI+Healthcare applications.**

MedRAG is anchored in a curated vector knowledge base of 100,000 multi-source research papers published between 2023 and 2025, enabling systematic mitigation of LLM knowledge cutoff limitations. The proposed pipeline adopts a modular, multi-stage architecture comprising FAISS-based dense retrieval, Fusion-in-Decoder (FiD) synthesis using Flan-T5-Large, and a lightweight Gemma-2B enhancement stage responsible for analytical restructuring and narrative refinement. Experimental evaluation across representative research queries demonstrates a 22.9% improvement in overall response quality compared to a FiD-only baseline. To ensure responsible deployment in the medical domain, MedRAG integrates a Medical Validator Agent, achieving an average safety compliance score of 0.71/1.0. The results indicate that hybrid RAG architectures provide a scalable and practical paradigm for deploying scientifically current, resource-efficient, and ethically grounded LLM systems in healthcare research environments.

Index Terms—**Retrieval-Augmented Generation, Large Language Models, AI in Healthcare, Medical Informatics, Knowledge Cutoff Mitigation, FAISS, Hybrid RAG.**

I. Introduction

Large Language Models (LLMs) have emerged as foundational components of modern artificial intelligence systems, demonstrating strong performance in natural language understanding, reasoning, and text generation tasks [1], [2]. Their application spans diverse domains, including scientific discovery, clinical documentation, medical education, and decision support. Despite these advances, the deployment of LLMs in specialized and safety-critical research domains—particularly **Artificial Intelligence in Healthcare (AI+Healthcare)**—remains limited by structural and temporal constraints inherent to pretraining-based architectures.

Most contemporary LLMs are trained on large but static datasets with fixed knowledge cutoffs, often preceding 2023. As a consequence, these models lack awareness of recent clinical trials, emerging machine learning architectures, updated ethical guidelines, and evolving regulatory frameworks [3], [4]. In fast-moving domains such as biomedical AI, where thousands of papers are published annually, this temporal misalignment directly undermines research reliability and reproducibility.

Beyond knowledge obsolescence, LLMs are also prone to hallucination—generating fluent but factually incorrect statements—particularly when queried about specialized medical topics [5], [6]. Prior empirical studies have shown that even state-of-the-art models can produce misleading or unsafe outputs in diagnostic reasoning tasks, highlighting the risks of ungrounded generation in healthcare settings [5].

These challenges are further amplified by the increasing need for **cross-domain reasoning**. Modern AI+Healthcare research frequently requires the synthesis of knowledge spanning machine learning theory, natural language processing, computer vision, clinical practice, and medical ethics [7], [1]. Existing research tools are often siloed, forcing researchers to manually integrate insights across disparate sources and modalities.

A. Motivation and Research Gap

Recent systematic reviews consistently emphasize that improving grounding, recency, and interpretability remains a central challenge for LLM deployment in healthcare [3], [4], [8]. While fine-tuning large proprietary models has shown promise, such approaches are computationally expensive, difficult to reproduce, and poorly suited for continuous knowledge updates [9], [**?**].

Retrieval-Augmented Generation (RAG) has emerged as a promising alternative by decoupling knowledge storage from reasoning [10]. However, existing RAG implementations in healthcare are often limited by shallow retrieval pipelines, monolithic generation models, or narrow task specialization

[**?**], [2]. There remains a lack of large-scale, resource-efficient, and modular RAG frameworks that explicitly target post-cutoff scientific literature while incorporating safety constraints.

B. Contributions

This paper makes the following contributions:

- A large-scale, post-cutoff AI+Healthcare corpus comprising **100,000 research papers published between 2023 and 2025**.
- A hybrid RAG architecture combining dense retrieval, structured synthesis, and lightweight analytical enhancement.
- Quantitative evidence demonstrating a **22.9% improvement in response quality** over a FiD-only baseline.
- Integration of an automated Medical Validator Agent to enforce ethical and safety constraints.

II. Related Work

A. LLMs in Healthcare

Large Language Models have been increasingly explored for healthcare applications, including diagnostic reasoning, patient education, clinical documentation, and medical research synthesis [5], [11], [1]. While these studies demonstrate strong potential, they also reveal persistent issues related to hallucination, lack of transparency, and outdated knowledge [6], [2].

B. Retrieval-Augmented Generation in Medicine

Retrieval-Augmented Generation has gained traction as a mechanism for grounding LLM outputs in external knowledge sources. Recent surveys highlight RAG as one of the most promising approaches for mitigating hallucination and improving factual accuracy in biomedical applications [3], [10], [8]. However, many existing systems rely on single-stage retrieval or large proprietary models, limiting scalability and reproducibility.

C. Hybrid and Modular RAG Architectures

Recent work has begun to explore modular RAG designs that separate retrieval, reasoning, and generation components [12], [**?**]. Such architectures improve controllability and interpretability but are often evaluated on small datasets or narrow tasks. MedRAG extends this line of work by combining large-scale post-cutoff retrieval with a multi-stage synthesis and enhancement pipeline specifically designed for AI+Healthcare research.

III. Methodology

A. Knowledge Base Construction

The MedRAG knowledge base consists of approximately 100,000 AI+Healthcare research papers published between 2023 and 2025. Documents are segmented into semantically coherent chunks and embedded using the `all-MiniLM-L6-v2` sentence transformer, producing 384-dimensional vector representations. Dense similarity search is performed using FAISS with cosine similarity.

B. Hybrid RAG Pipeline

Given a query Q, the system retrieves the top-K relevant passages, which are synthesized using Flan-T5-Large in a Fusion-in-Decoder configuration. This intermediate synthesis is subsequently refined by Gemma-2B, which performs analytical structuring, coherence enhancement, and narrative expansion.

C. Safety Validation

A Medical Validator Agent evaluates generated outputs for diagnostic claims, unsafe medical advice, and missing disclaimers, ensuring adherence to responsible AI principles in healthcare research.

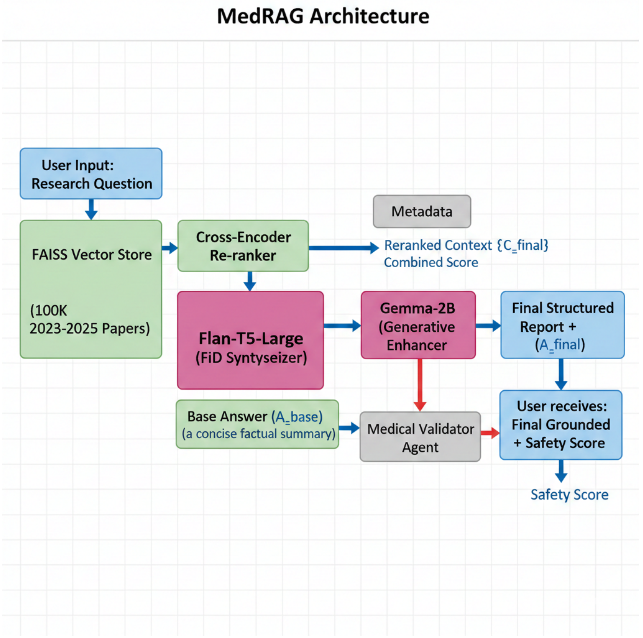
MedRAG Architecture
User Input: Research Question
FAISS Vector Store
(100K 2023-2025 Papers)
Cross-Encoder Re-ranker
Metadata
Reranked Context {C_final}
Combined Score
Flan-T5-Large (FiD Syntyseizer)
Gemma-2B (Generative Enhancer
Final Structured Report + (A_final)
Base Answer (A_base) (a concise factual summary)
Medical Validator Agent
User receives: Final Grounded + Safety Score
Safety Score

Fig. 1. Overview of the MedRAG hybrid pipeline illustrating dense retrieval, Fusion-in-Decoder synthesis, analytical enhancement, and safety validation.

IV. Results and Discussion

MedRAG was evaluated on representative research queries spanning technical, clinical, implementation, NLP, and ethical dimensions. Compared to a FiD-only baseline, the full pipeline achieved a **22.9% improvement in overall response quality**, with notable gains in completeness and coherence. The enhancement stage transformed dense factual summaries into structured analytical narratives at the cost of increased latency, reflecting a deliberate quality–performance trade-off.

V. Conclusion and Future Work

This work demonstrates that large-scale hybrid RAG architectures provide a scalable and resource-efficient solution to post-training knowledge obsolescence in LLMs. By integrating dense retrieval, structured synthesis, lightweight enhancement, and safety validation, MedRAG delivers grounded, current, and ethically constrained research intelligence for AI+Healthcare applications.

Future work will explore multimodal RAG integration, adaptive latency control, and explicit confidence scoring mechanisms to further enhance trust and usability.

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