

HeyDocAI

Radiology Report Explainer with Evidence-Backed Q&A

**INFO 7375 - Prompt Engineering for Generative AI
Generative AI Project - Final Report**

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1. Introduction

Radiology reports are critical medical documents but are often written in highly technical language that is difficult for patients and non-medical users to understand. Misinterpretation can lead to anxiety, misinformation, or incorrect assumptions about health conditions.

HeyDocAI is a Generative AI system designed to bridge this gap by:

- Translating radiology reports into plain English
- Extracting structured clinical information
- Answering user questions using evidence-backed retrieval

The system leverages **Retrieval-Augmented Generation (RAG)** and **Prompt Engineering** to ensure accuracy, transparency, and reliability.

This system is intended for **educational purposes only** and does not provide medical diagnosis or treatment advice.

2. Objectives

The primary objectives of this project are:

1. Build a real-world Generative AI application in the healthcare domain
2. Implement **Retrieval-Augmented Generation (RAG)** using a vector database
3. Design robust **prompt engineering workflows**
4. Provide evidence-backed answers with citations
5. Evaluate system performance using quantitative metrics

3. Core Generative AI Components Used

This project implements **two required components**:

3.1 Prompt Engineering

- System-level instructions defining assistant behavior
- Task-specific prompts:
 - Explanation (Simple / Normal / Clinician)
 - Structured extraction (JSON)
 - Evidence-based Q&A
- Context injection with retrieved evidence
- Guardrails for edge cases and hallucination prevention

3.2 Retrieval-Augmented Generation (RAG)

- Domain-specific knowledge base (radiology PDFs)
- Vector storage using Pinecone
- Semantic retrieval using OpenAI embeddings
- Evidence ranking and filtering before generation
- Citation formatting with source and page numbers

4. System Architecture

The system follows modular, evidence-first architecture.

Architecture Flow

- User inputs a radiology report or question via Streamlit UI
- Input is validated using guardrails
- RAG orchestration retrieves relevant evidence from Pinecone
- Evidence + context injected into prompts
- OpenAI LLM generates grounded responses
- Citations are displayed alongside answers

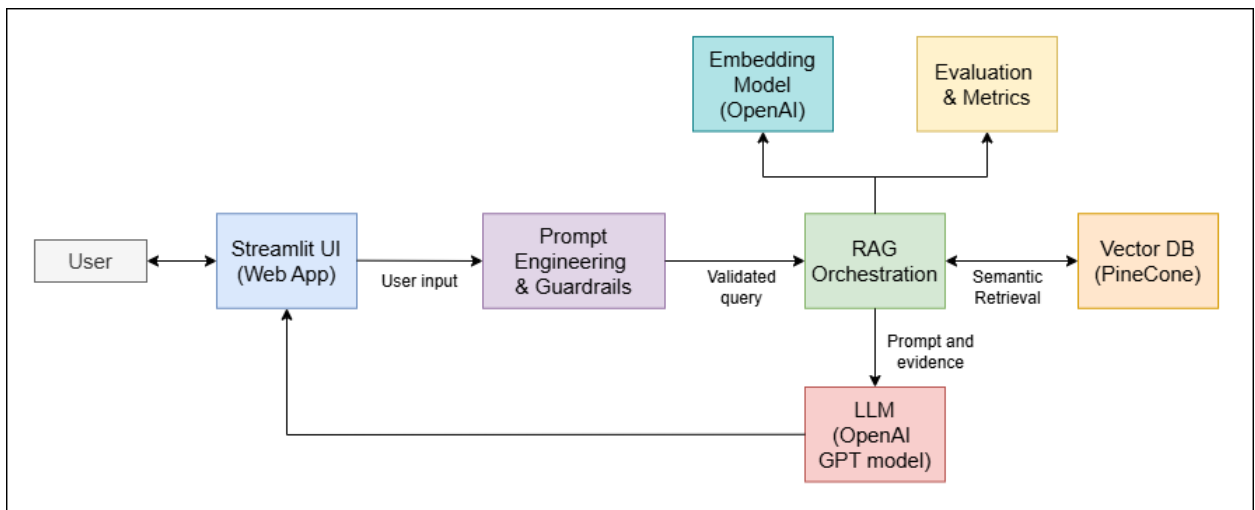


Figure 1. System Architecture Diagram

5. Knowledge Base Construction

The knowledge base consists of curated, authoritative radiology reference PDFs, including:

- Chest X-ray interpretation guides
- Thoracic imaging glossaries
- Lung pathology references (effusion, consolidation, pneumothorax)

Processing Steps

- PDF text extraction
- Page-level chunking
- Overlapping chunk strategy
- Embedding generation using OpenAI
- Storage in Pinecone vector database

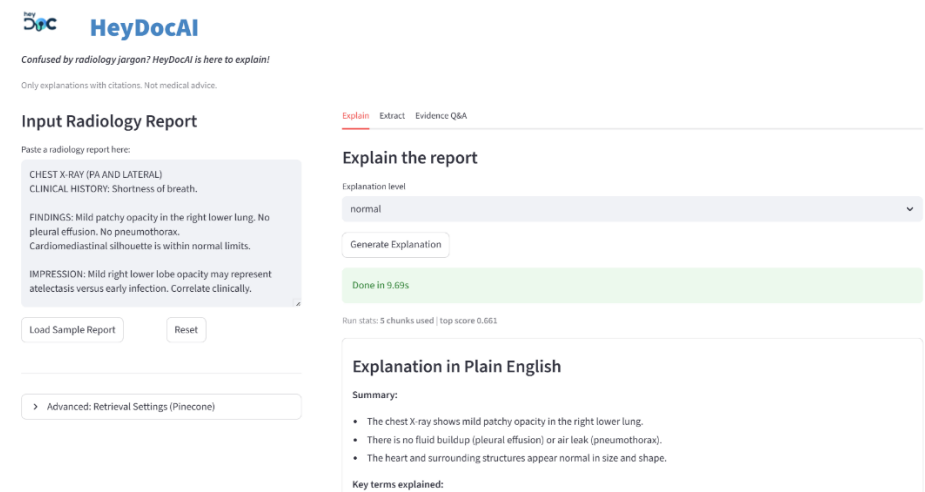
This enables precise semantic retrieval for downstream generation.

The screenshot shows a web browser at localhost:8501 displaying the HeyDocAI application. The interface includes a header with the HeyDocAI logo and a navigation bar with tabs for 'Explain', 'Extract', and 'Evidence Q&A'. The 'Explain' tab is active. On the left, there is a section titled 'Input Radiology Report' with a text area for pasting a report, a 'Load Sample Report' button, and a 'Reset' button. Below this is a yellow warning box that says 'Please provide a radiology report to analyze.' At the bottom, there is a link to 'Advanced: Retrieval Settings (Pinecone)'. On the right, the 'Explain the report' section features a dropdown menu for 'Explanation level' set to 'normal' and a 'Generate Explanation' button. The browser's address bar shows 'localhost:8501' and the top right corner has a 'Chat' button.

6. Application Features

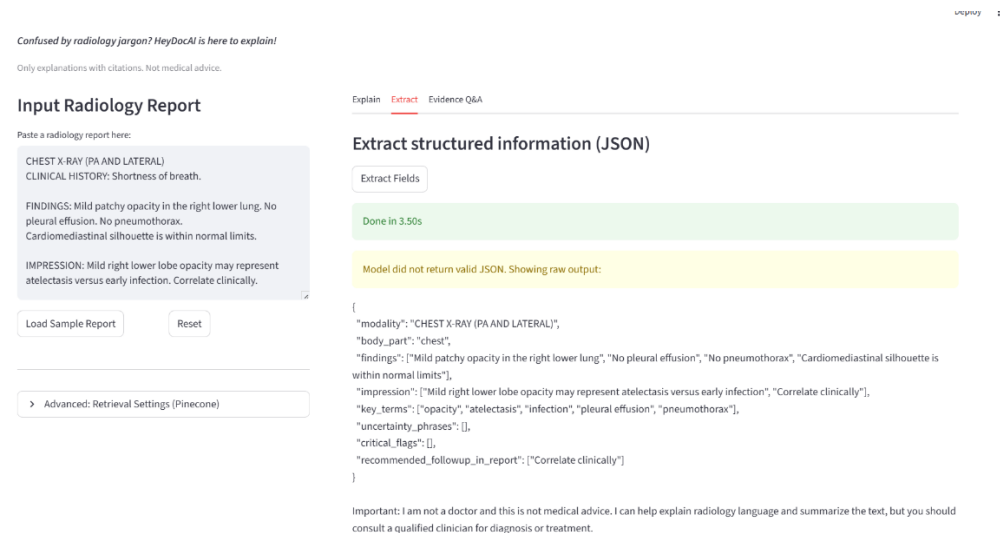
6.1 Explain Radiology Reports

- Converts reports into plain-English explanations
- Supports three explanation levels:
 - Simple (patient-friendly)
 - Normal
 - Clinician-oriented
- Displays retrieval statistics and citations



6.2 Structured Information Extraction

- Extracts findings, impressions, and key entities
- Outputs JSON and structured tables
- Useful for downstream clinical workflows



6.3 Evidence-Backed Q&A

- Users ask questions about the report
- Answers generated only if sufficient evidence is retrieved
- All responses include citations
- Chat history maintained for context



Confused by radiology jargon? HeyDocAI is here to explain!

Only explanations with citations. Not medical advice.

Input Radiology Report

Paste a radiology report here:

CHEST X-RAY (PA AND LATERAL)
CLINICAL HISTORY: Shortness of breath.

FINDINGS: Mild patchy opacity in the right lower lung. No pleural effusion. No pneumothorax. Cardiomediastinal silhouette is within normal limits.

IMPRESSION: Mild right lower lobe opacity may represent atelectasis versus early infection. Correlate clinically.

Load Sample Report

Reset

› Advanced: Retrieval Settings (Pinecone)

Explain Extract **Evidence Q&A**

Ask questions (answers must cite sources)

Suggested questions

Explain the impression

Is anything urgent?

Define key terms



Define key terms mentioned in this report (e.g., opacity, atelectasis, effusion).



Key Terms Defined:

- **Opacity:** In radiology, opacity refers to areas on an X-ray that appear denser than surrounding tissues, indicating potential abnormalities such as fluid, infection, or other pathological changes [1].
- **Atelectasis:** This term describes a partial or complete collapse of the lung, which can occur due to various reasons, including loss of negative pressure in the pleural space [2]. It may present as an area of increased opacity on imaging studies.
- **Effusion:** This term refers to the accumulation of fluid in the pleural space surrounding the lungs. In the report, it is noted that there is no pleural effusion present [1].

Supporting Bullets:

7. Guardrails and Safety Measures

To ensure reliability and ethical use, the system implements:

- Empty / invalid input validation
- Minimum similarity score thresholds
- “I don’t know” responses when evidence is insufficient
- Mandatory medical disclaimers
- Citation enforcement for generated answers

These measures significantly reduce hallucination risk.

8. Performance Evaluation

Automated evaluation was conducted using a standardized query set.

Metrics Measured

- Average response latency
- Evidence availability rate

- Citation coverage
- Citation coverage when evidence is available

Results Summary

- Average latency: ~4–5 seconds
- Evidence availability: ~90%
- Citation coverage (given evidence): **100%**

Snipped of eval/results.json:

```
"id": "q1_ggo_definition",
"type": "definition",
"question": "What does ground-glass opacity mean in a radiology report?",
"latency_sec": 12.714,
"retrieved_chunks_count": 5,
"citations_present": true,
"citations_ui": [
  "[1] thoracic_imaging_glossary_fleischner.pdf \u2014 page 35 (score: 0.600)",
  "[2] thoracic_imaging_glossary_fleischner.pdf \u2014 page 6 (score: 0.592)",
  "[3] thoracic_imaging_glossary_fleischner.pdf \u2014 page 9 (score: 0.576)",
  "[4] thoracic_imaging_glossary_fleischner.pdf \u2014 page 19 (score: 0.575)",
  "[5] thoracic_imaging_glossary_fleischner.pdf \u2014 page 47 (score: 0.560)"
],
"top_sources": [
  {
    "source": "thoracic_imaging_glossary_fleischner.pdf",
    "page": 35,
    "score": 0.6001
  },
  {
    "source": "thoracic_imaging_glossary_fleischner.pdf",
    "page": 6,
    "score": 0.5917
  }
]
```

9. Challenges and Solutions

Challenge 1: Hallucinated Medical Responses

Solution: Strict evidence validation and refusal to answer without sufficient retrieval.

Challenge 2: Overly Technical Explanations

Solution: Multi-level prompt templates tailored to user expertise.

Challenge 3: Long, Complex Radiology Documents

Solution: Chunking + overlap strategy with ranking and filtering.

10. Ethical Considerations

- No personal health data is stored
- No diagnosis or treatment recommendations
- Transparent citation of sources
- Bias minimized by grounding answers in trusted references
- Clear disclaimers shown in UI

11. Future Improvements

- Multimodal support (X-ray images + text)
- Expanded medical domains (CT, MRI, ultrasound)
- Improved ranking strategies (MMR, re-ranking models)
- Cloud deployment with authentication
- Multilingual support

12. Conclusion

HeyDocAI demonstrates how Generative AI can be safely and effectively applied in healthcare education. By combining **Prompt Engineering** with **Retrieval-Augmented Generation (RAG)**, the system delivers transparent, reliable, and user-friendly explanations of complex medical documents.

This project showcases a practical, real-world application of modern Generative AI techniques while addressing ethical and reliability concerns.

13. Appendix

- GitHub: <https://github.com/Ranjithnathk/HeyDoc-AI-RAG-Medical-Report-Explainer>
- Screenshots: docs/screens/
- Evaluation Results: eval/results.json
- Video Demonstration