

HeyDocAI

Radiology Report Explainer with Evidence-Backed Q&A

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

Done by Ranjithnath Karunanidhi

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

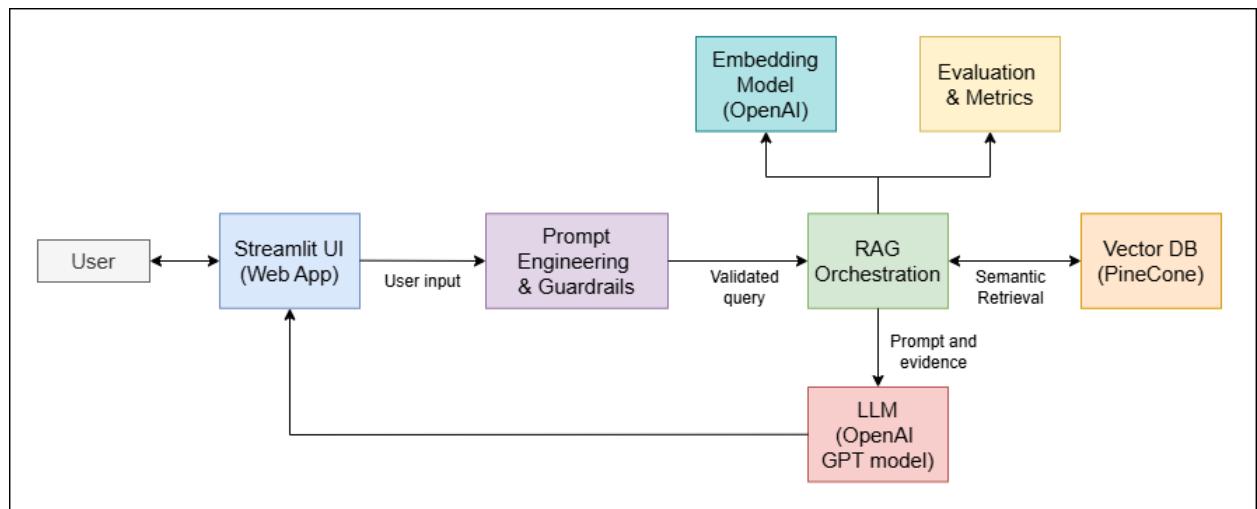


Figure 1. System Architecture Diagram

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 the HeyDocAI web application running locally at localhost:8501. The interface includes a navigation bar with icons for search, star, user, and more, along with a 'Deploy' button. The main header features the 'heyDoc AI' logo and the text 'HeyDocAI'. Below the header, a sub-header reads 'Confused by radiology jargon? HeyDocAI is here to explain!'. A note states 'Only explanations with citations. Not medical advice.' The main content area has three tabs: 'Explain' (which is active), 'Extract', and 'Evidence Q&A'. On the left, there's an 'Input Radiology Report' section with a text input field, a 'Load Sample Report' button, and a 'Reset' button. On the right, there's an 'Explain the report' section with an 'Explanation level' dropdown set to 'normal' and a 'Generate Explanation' button. A yellow callout box at the bottom left says 'Please provide a radiology report to analyze.' At the bottom, there's a link to 'Advanced: Retrieval Settings (Pinecone)'.

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

The screenshot shows the HeyDocAI web application. At the top, there's a logo with a blue 'D' and the text 'HeyDocAI'. Below it, a message says 'Confused by radiology jargon? HeyDocAI is here to explain!'. A note below that says 'Only explanations with citations. Not medical advice.' The main area has two tabs: 'Explain' (which is active) and 'Extract'. Under 'Explain', there's a dropdown for 'Explanation level' set to 'normal'. A button 'Generate Explanation' is visible. A green bar at the bottom indicates 'Done in 9.69s'. Below this, a summary section says 'Run stats: 5 chunks used | top score 0.661'. The 'Explanation in Plain English' section contains a summary and a list of findings. The findings list includes: 'The chest X-ray shows mild patchy opacity in the right lower lung.', 'There is no fluid buildup (pleural effusion) or air leak (pneumothorax).', and 'The heart and surrounding structures appear normal in size and shape.' A 'Key terms explained:' section is also present.

6.2 Structured Information Extraction

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

This screenshot shows the 'Extract' tab of the HeyDocAI interface. It has a similar layout to the 'Explain' page, with a message about radiology jargon, a note about medical advice, and an 'Input Radiology Report' section where users can paste their report. The 'Extract Fields' button is visible. A green bar at the bottom indicates 'Done in 3.50s'. Below this, a message says 'Model did not return valid JSON. Showing raw output:'. The raw JSON output is displayed in a code block:

```
[{"modality": "CHEST X-RAY (PA AND LATERAL)", "body_part": "chest", "findings": ["Mild patchy opacity in the right lower lung", "No pleural effusion", "No pneumothorax", "Cardiomeastinal silhouette is within normal limits"], "impression": ["Mild right lower lobe opacity may represent atelectasis versus early infection", "Correlate clinically"], "key_terms": ["opacity", "atelectasis", "infection", "pleural effusion", "pneumothorax"], "uncertainty_phrases": [], "critical_flags": [], "recommended_followup_in_report": ["Correlate clinically"]}]
```

At the bottom, a note reads: 'Important: I am not a doctor and this is not medical advice. I can help explain radiology language and summarize the text, but you should consult a qualified clinician for diagnosis or treatment.'

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

The screenshot shows the HeyDocAI web application. At the top, there's a logo with 'hey' and 'Doc' and the text 'HeyDocAI'. Below it, a subtext says 'Confused by radiology jargon? HeyDocAI is here to explain!'. A note below that says 'Only explanations with citations. Not medical advice.' The main area has tabs: 'Explain', 'Extract', and 'Evidence Q&A' (which is underlined in red). On the left, there's a section titled 'Input Radiology Report' with a text input field containing a sample radiology report. This report includes findings from a chest X-ray and an impression. Buttons for 'Load Sample Report' and 'Reset' are below the input field. To the right, under 'Ask questions (answers must cite sources)', there are three buttons: 'Explain the impression', 'Is anything urgent?', and 'Define key terms'. Below these buttons is a callout box with a magnifying glass icon and the text 'Define key terms mentioned in this report (e.g., opacity, atelectasis, effusion.)'. Another callout box below it has a book icon and the text 'Key Terms Defined:' followed by a bulleted list explaining three medical terms: Opacity, Atelectasis, and Effusion.

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