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Evidence-Grounded Vision–RAG Framework for Clinically Reliable Visual Reasoning in Chest X-Ray Analysis

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ABSTRACT - Vision–language models have shown potential for medical image understanding tasks such as visual question answering (VQA); however, their clinical adoption is limited by diagnostic ambiguity, limited supervision, and the risk of generating hallucinated or clinically unsafe responses. To address these challenges, this paper proposes an evidence-grounded Vision Retrieval-Augmented Generation (Vision–RAG) framework for reliable visual reasoning in chest X-ray analysis. The framework integrates visual retrieval with evidence-aware language generation to support clinically grounded reasoning without task-specific supervised training. A pretrained vision encoder retrieves semantically similar chest X-ray images and corresponding radiology reports from the MIMIC-CXR dataset, providing external clinical evidence to guide the vision–language model. The retrieval index is built from the training split, and evaluation is performed on a held-out validation set for unbiased assessment. The system is evaluated using approximately 2,000 automatically generated clinical questions. Results demonstrate effective evidence retrieval, achieving a Recall@1 of 66.88%, while yes/no question accuracy reaches 56.8%, reflecting the inherent challenge of unsupervised medical reasoning. Concept-level analysis shows clear separation between normal and infectious cases, with most ambiguity occurring between overlapping conditions such as pleural effusion and consolidation. Importantly, the model exhibits conservative prediction behavior with low false-positive tendencies, highlighting clinical safety. These findings indicate that evidence-grounded Vision–RAG provides an interpretable and reliable paradigm for medical visual reasoning in chest X-ray analysis, supporting decision-making in clinical workflows rather than replacing human expertise.

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1. INTRODUCTION

The rapid advancement of vision-language models (VLMs) has significantly impacted medical image understanding, particularly in the domain of medical visual question answering (VQA) [1], [2]. By jointly modeling visual and textual modalities, these systems enable flexible interaction with medical images, allowing clinicians to query diagnostic content using natural language. Such capabilities are especially valuable in large-scale medical imaging scenarios, where manual annotation is costly and expert interpretation is limited [7] .Despite these advances, existing vision-language models exhibit critical limitations when applied to safety-sensitive medical domains. In particular, end-to-end VLMs often rely heavily on implicit knowledge encoded during pretraining, which can lead to hallucinated or unsupported responses when confronted with ambiguous clinical cases [1], [2]. This limitation is especially problematic in medical imaging, where subtle visual cues and incomplete evidence are common, raising concerns regarding reliability and patient safety [8]. To address these challenges, recent research has explored retrieval-augmented reasoning as an effective mechanism for grounding vision-language models in external evidence [3], [4], [5]. By incorporating relevant visual and textual information retrieved from large-scale databases, retrieval-augmented frameworks reduce reliance on parametric memory and encourage evidence-based reasoning. In the vision domain, such approaches enable comparison with similar reference cases, thereby improving robustness and mitigating hallucination [6]. Motivated by these developments, this work focuses on retrieval-augmented medical visual question answering for chest X-ray analysis. Rather than treating medical VQA as a closed-set classification problem, we adopt an open-ended reasoning formulation in which answers are explicitly grounded in retrieved radiology reports and visual evidence [3], [6]. This design aligns with clinical practice, where diagnostic decisions are informed by prior cases and documented findings.

This work makes four primary contributions. First, we propose a vision-based retrieval-augmented reasoning framework that integrates visual retrieval with evidence-grounded language generation for medical VQA. Second, the retrieval index is constructed exclusively from the training split of the MIMIC-CXR dataset, while all evaluation experiments are conducted on a held-out validation set to ensure unbiased assessment. Third, we introduce a large-scale evaluation protocol based on approximately 2,000 automatically generated clinical questions, enabling systematic analysis without manual annotation [10]. Finally, we provide a comprehensive evaluation using retrieval metrics, binary yes/no accuracy, and concept-level confusion analysis, offering interpretable insights into model behavior and clinical safety.

The remainder of this paper is organized as follows. Section 2 reviews related work in medical visual question answering, vision-language models, and retrieval-augmented reasoning. Section 3 give the problem statement. Section 4 presents the proposed framework. Section 5 describes the dataset and experimental setup. Section 6 outlines the evaluation methodology. Section 7 reports the results, and Section 8 concludes the paper.

2. LITERATURE REVIEW

The advancement of Multimodal Large Language Models (MLLMs) has been significantly hindered by "hallucinations," where models generate content inconsistent with visual evidence. Early research identified that these errors often stem from a fundamental "entanglement" in the latent space, where visual and textual representations are poorly aligned. To address this, contrastive learning frameworks were developed, utilizing hallucinated descriptions as hard negative examples to force a clearer separation and better alignment between modalities [13]. Another critical source of error is the model's over-reliance on "language priorities," where it generates answers based on common word sequences rather than the actual image content. Recent strategies have introduced perturbative visual training, which intentionally uses adversarial text perturbations during training to penalize the model when it follows linguistic biases. This approach forces the model to prioritize visual inputs, significantly improving the fidelity of dense image descriptions [12]. In addition to training-based methods, training-free "post-remedy" frameworks have gained traction. One prominent example is the "woodpecker" mechanism, which systematically extracts key concepts, formulates validation questions, and verifies them against external visual knowledge. By allowing the system to "heal" its own hallucinations through intermediate stages of reasoning, these frameworks provide a highly interpretable layer of clinical safety [11].

The specialization of Retrieval-Augmented Generation (RAG) for medical diagnostics marks a shift toward evidence-based AI. Modern medical RAG systems are designed to handle distribution shifts by retrieving semantically grounded evidence from extensive clinical databases. This ensures that the generation process is constrained by historical medical truths, which is particularly vital in sensitive areas like radiology, where precision is paramount [14]. Further improvements in medical RAG have introduced "heterogeneous" knowledge retrieval. Unlike traditional models that query only past reports, newer frameworks like HeteroRAG query multifaceted sources, including clinical textbooks, research papers, and formal guidelines. This allows the model to synthesize high-level theoretical knowledge with patient-specific findings to ensure the credibility of clinical decision-making [15]. Active and hierarchical retrieval strategies have also been developed to interact more intelligently with visual data. Rather than retrieving evidence blindly, these systems dissect images into inherent hierarchical structures to pinpoint effective retrieval targets. Some frameworks have introduced "Knowledge-Based Tags" to dynamically define a model's knowledge boundaries, filtering retrieved documents to retain only the most relevant references and mitigating the impact of noisy context [16], [23]. In the realm of scientific visual reasoning, specialized architectures like RAVQA-VLM have demonstrated the power of end-to-end optimization. By retrieving context passages directly from original scientific papers (e.g., arXiv or ACL Anthology), these models bridge the gap between complex figures and their textual explanations. This retrieval-augmented approach has shown significant gains in metrics like ROUGE, providing a more reliable foundation for scientific QA [25]. RAG applications have also proven effective in educational and encyclopedic contexts. Frameworks like the Encyclopedic Agent utilize fine-tuned vision-language models to facilitate document-image retrieval from massive datasets like Wikipedia. These systems prove that retrieval-augmented methods are highly scalable, supporting complex learning tasks by providing precise topical queries and visual explanations [24]. For clinical report generation, "entity probing" and "key phrase extraction" have become essential for maintaining diagnostic standards. By verifying the presence of specific medical entities (e.g., pneumothorax) through retrieved evidence, models can ground their findings more effectively. These methods reduce computational overhead by focusing the retrieval process on essential diagnostic information, ensuring that even rare pathologies are not overlooked [17], [19]. Finally, the field is converging toward "uncertainty-aware" self-refinement and structured safety. By monitoring the predictive probability of tokens, models can now identify potential hallucinations before they are finalized, triggering retrieval only when necessary. A comprehensive synthesis of these methodologies, including their utilized datasets and core contributions, is provided as shown in **Table 1**.

Table 1. Summary of Related Research and Baseline Models

Ref	Methods	Dataset	Accuracy (Metric)	Contribution	Limitation
[11]	Woodpecke/ DINO	MS-COCO POPE	Acc +30.2%	5-stage correction pipeline.	Dependency on external detectors.
[12]	PerturboLLaVA	LLaVA-Bench	High HalFscore	Reducing language prior reliance.	Hightraining complexity.
[13]	Contrastive MLLM	LLaVA-1.5	Low Entanglement	Hallucination Aug. Contrastive Learning.	Subtle cases still show entanglement.
[14]	MMED-RAG	MIMIC-CXR	12.3% Factuality	Versatile multi-domain Med-RAG	Potential modal misalignment.
[15]	HeteroRAG	MedAtlas/MIMIC	SOTA in MedAltas	Heterogeneous multi-corpora retrieval.	High latency in multi-source search.
[16]	ARA (Active RAG)	MS-COCO	7.7% avg. gain	Hierarchical image dissection	Complex retrieval target logic.

[17]	V-RAG (Visual RAG)	MIMIC / Multicare	High RadGraph-F1	Entity probing for visual grounding.	Corpus size dependency.
[18]	Systematic Review	20+ Med-DBs	Meta-analysis	Clinical RAG deployment guidelines.	No new model architecture.
[19]	KeyPhrase-RAG	MIMIC-CXR	SOTA CheXbert	Phrase extraction for retrieval.	Sensitive to phrase extraction errors.

3. Problem Formulation and Proposed Architecture

Medical visual question answering (VQA) aims to generate clinically meaningful answers given a medical image and a natural language query. Recent advances in vision-language models (VLMs) have enabled open-ended reasoning over images by jointly modeling visual and textual modalities [1], [2]. However, when applied to medical imaging, purely generative VLMs often suffer from hallucinated responses and unsupported clinical claims, especially under ambiguous visual evidence [2], [8]. These limitations motivate the need for retrieval-augmented reasoning frameworks that explicitly ground predictions in external medical evidence [3], [4].

Let $\mathcal{X} \subset \mathbb{R}^{H\times W\times C}$denote the space of chest X-ray images, where H, W, and Crepresent image height, width, and channels, respectively. Let $\mathcal{Q}$denote the space of medical questions, and let $\mathcal{Y}$ denote the space of textual answers. Given a dataset shown in **Equation 1**.

$$D=\{(xi,ri)\}i=1N, \quad \textbf{(1)}$$

where $x_i \in \mathcal{X}$is a chest X-ray image and $r_i$is the associated radiology report (Findings and Impression), the goal is to learn a reasoning function that produces clinically grounded answers. shown in **Equation 2**

$$\mathcal{F}: \mathcal{X} \times \mathcal{Q} \rightarrow \mathcal{Y}, \quad \textbf{(2)}$$

3. 1 Visual and Textual Representation Learning

Let $f_v: \mathcal{X} \rightarrow \mathbb{R}^{dv}$denote a pretrained visual encoder used to extract semantic representations from chest X-ray images [1],[3].Given an input image x, the corresponding visual embedding is defined as shown in **Equation 3**.

$$v = fv(x) \quad \textbf{(3)}$$

Similarly, a text encoder $f_q: \mathcal{Q} \rightarrow \mathbb{R}^{dq}$is used to encode medical questions into a semantic embedding space [4],[5]: shown in **Equation 4**.

$$\mathbf{q} = f_q(q). \quad \textbf{(4)}$$

To enable similarity-based retrieval, both embeddings are normalized: shown in **Equation 5**.

$$\hat{\mathbf{v}} = \frac{}{\|\mathbf{v}\|}, \hat{\mathbf{q}} = \frac{}{\|\mathbf{q}\|\mathbf{vq}}. \quad \textbf{(5)}$$

3. 2 Visual Retrieval-Augmented Evidence Modeling

Following prior work on retrieval-augmented vision-language reasoning [3], [4], the proposed framework retrieves external evidence from the training corpus to reduce reliance on parametric memory. Visual retrieval is formulated as a nearest-neighbor search over the training image embeddings shown in **Equation 6**.

$$\mathcal{J}^* = \arg\max_{\mathcal{J}k\subset\mathcal{D}\text{train}} \sum_{xj\in\mathcal{J}k} \text{sim}(\hat{\mathbf{v}}, f_v(x_j)), \quad \textbf{(6)}$$

Where

$\mathcal{J}_k$denotes the top-k visually similar images and sim(·,·)denotes cosine similarity.

In parallel, textual retrieval is performed using the question embedding to retrieve relevant radiology reports [6]: shown in **Equation 7**.

$$\mathcal{R}^* = \arg\max \sum_{rj \in \mathcal{R}k} \text{sim}(\hat{\mathbf{q}}, f_q(r_j)). \quad \textbf{(7)}$$

s.t :

$$\mathcal{R}k \subset \mathcal{D}\text{train}$$

The combined retrieval set: shown in **Equation 8**

$$\mathcal{E} = \{\mathcal{I}^*, \mathcal{R}^*\} \quad \textbf{(8)}$$

Constitutes the external visual and textual evidence used for downstream reasoning.

3. 3 Visual Evidence-Grounded Vision-Language Reasoning

Let $g_\phi$denote a pretrained vision-language model responsible for reasoning and answer generation [1]. Conditioned on the input image x, the question q, and the retrieved evidence $\mathscr{E}$, the generated answer is defined as: **Equation 9**.

$$y = g_\phi(x, q \mid \mathcal{E}). \quad \textbf{(9)}$$

To encourage grounded responses and mitigate hallucination, answer generation is constrained by the retrieved evidence, following retrieval-augmented generation principles [3], [5]. This objective is formalized by minimizing the conditional negative log-likelihood **Equation 10**.

$$\mathcal{L}_{\text{ground}} = -\mathbb{E}_{(x,q,y)}[\log p_\phi(y \mid x, q, \mathcal{E})]. \quad \textbf{(10)}$$

3. 4 Safety-Aware Abstention Mechanism

Clinical uncertainty is explicitly modeled through an abstention mechanism inspired by safety-aware medical reasoning frameworks [2], [10]. Let $\kappa(\mathscr{E})$ denote an evidence sufficiency function. When the retrieved evidence fails to meet a confidence threshold δ, the system outputs an abstention response $\emptyset$, shown in **Equation 11**

$$\kappa(\mathcal{E}) < \delta \Rightarrow y = \emptyset. \quad \textbf{(11)}$$

This mechanism reduces unsupported diagnoses and prioritizes conservative clinical behavior.

3. 5 Overall objective

Unlike supervised medical VQA methods that require labeled question–answer pairs, the proposed framework relies solely on pretrained components and retrieval-based reasoning [4], [6]. The final optimization objective balances grounded answer generation and safety-aware abstention: shown in **Equation 12**

$$\phi^* = \arg\min (\mathcal{L}_{\text{ground}} + \lambda \mathcal{L}_{\text{abstain}}), \quad \textbf{(12)}$$

Where

λ controls the trade-off between answer completeness and clinical safety.

4. PROPOSED MODEL ARCHITECTURE

This work proposes a vision-based retrieval-augmented reasoning framework designed for medical visual question answering. The architecture integrates visual retrieval, textual retrieval, and evidence-grounded language generation within a unified pipeline to ensure interpretable and clinically safe responses. Given a chest X-ray image and a natural language medical question, the system retrieves relevant visual and textual evidence from a large-scale medical dataset and uses this evidence to guide answer generation. The proposed framework consists of three main components: a visual representation and retrieval module, a textual retrieval module, and a vision-language reasoning module. When a query image is provided, it is first processed by a pretrained vision encoder to extract a compact semantic representation. This representation is used to retrieve visually similar chest X-ray images from a retrieval index constructed using the training split of the MIMIC-CXR dataset. The retrieved images provide contextual visual evidence by referencing prior cases with similar radiographic patterns.

In parallel, the input question is encoded using a text encoder and used to retrieve relevant radiology reports from the same training corpus. This textual retrieval step enables the system to access clinically meaningful descriptions and findings associated with similar cases. By combining visual and textual retrieval, the framework leverages complementary sources of external knowledge, reducing reliance on the internal memory of the language model and mitigating hallucination. The retrieved visual and textual evidence is then passed to a pretrained vision-language model, which performs reasoning and answer generation. To ensure grounded responses, the model is prompted to generate answers strictly based on the provided evidence. If the retrieved evidence is insufficient to support a confident conclusion, the system is designed to abstain from definitive claims, reflecting a conservative and clinically safe behavior. Unlike end-to-end supervised approaches, the proposed architecture does not require task-specific fine-tuning or labeled question–answer pairs. Instead, it relies on retrieval-augmented reasoning to generalize across diverse medical questions and imaging scenarios. The overall framework emphasizes interpretability, robustness, and safety, making it well-suited for medical imaging applications where reliability is critical. An overview of the proposed architecture is illustrated in **Figure 1**.

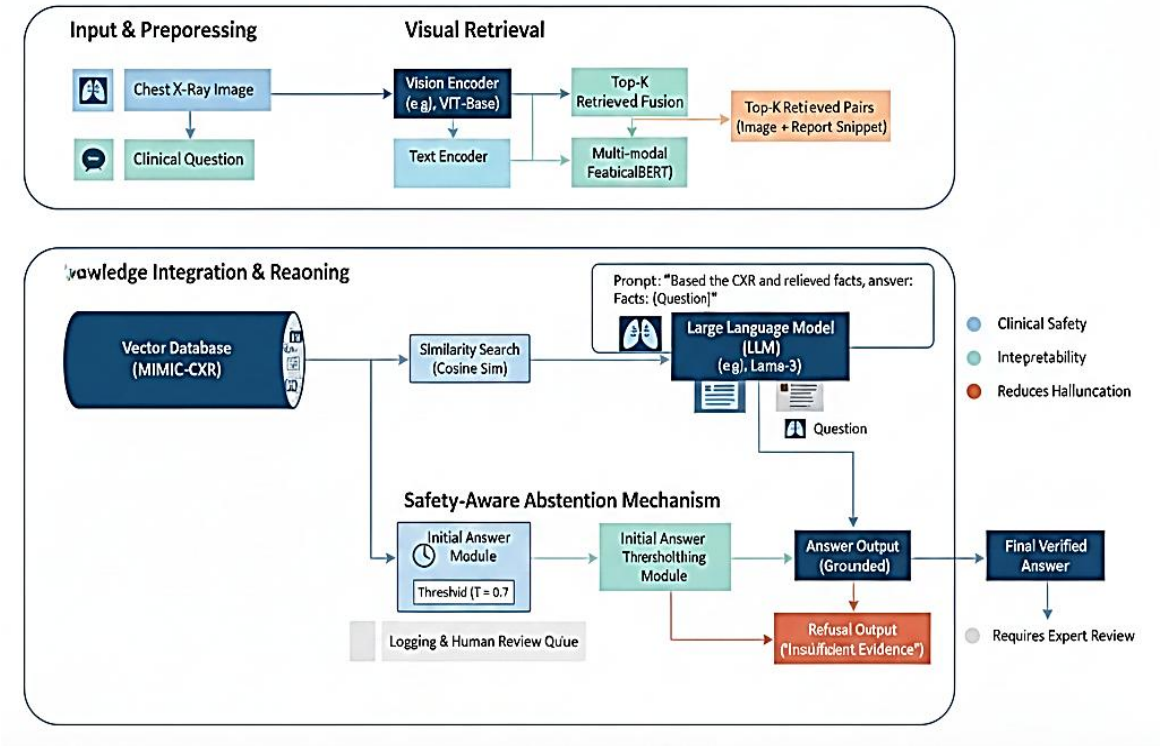

Figure 1. Cen-RAG : Safety-Aware Visual RAG Architecture

4. DATA SET

Overview of dataset In this work, we utilize the MIMIC-CXR-JPG dataset, a large-scale publicly available medical imaging dataset containing chest X-ray images paired with corresponding radiology reports. The dataset is designed for clinical research and represents one of the most comprehensive collections of real-world chest radiographs. Unlike natural image benchmarks, MIMIC-CXR focuses on medical imaging scenarios characterized by subtle visual patterns, high intra-class variability, and diagnostic uncertainty, making it a challenging and clinically relevant benchmark for medical visual understanding tasks.

The dataset consists of grayscale chest X-ray images acquired from hospital imaging systems, accompanied by free-text radiology reports written by expert radiologists. These reports include both Findings and Impression sections, which provide structured and clinically meaningful descriptions of observed abnormalities and diagnostic conclusions.

Dataset Structure and Splits The dataset is organized into a hierarchical directory structure containing image files, along with two CSV files defining the training and validation splits into a hierarchical directory structure containing the image files, along with two CSV files defining the training and validation:

- official_data_iccv_final/ (image files)
- mimic_cxr_aug_train.csv
- mimic_cxr_aug_validate.csv

Each CSV file contains metadata and report information for the corresponding images. The dataset includes approximately 261,000 chest X-ray images in total. The CSV files provide the following attributes:

- subject_id: Unique patient identifier
- image: Image file name
- view: X-ray view type
- AP, PA, Lateral: Binary indicators for projection type
- text: Original radiology report (Findings + Impression)
- text_augmented: Augmented textual variant of the report

In this study, the training split is used exclusively to construct visual and textual retrieval indices, while all evaluation experiments are conducted on the validation split to ensure unbiased performance assessment.

4.1 Image Characteristics and Preprocessing

All chest X-ray images in the dataset are originally stored as grayscale images, reflecting the standard format used in clinical radiography. During preprocessing, images are converted to RGB format to ensure compatibility with pretrained vision encoders, while preserving the original intensity information. No additional image augmentation is applied, as the goal of this work is to evaluate retrieval-augmented reasoning under realistic clinical conditions using unaltered medical images.

4.2 Textual Data

The textual component of the dataset consists of radiology reports that include both Findings and Impression sections. These reports serve as clinically grounded textual evidence describing anatomical structures, pathological observations, and diagnostic assessments. In the proposed framework, these reports are used for textual retrieval and as external evidence to guide vision-language reasoning.

Dataset Statistics The key statistics of the MIMIC-CXR-JPG dataset used in this work are summarized as follows:

- Total number of images: ~261,000
- Image modality: Chest X-ray
- Image format: Grayscale (converted to RGB during preprocessing)
- Text modality: Radiology reports (Findings + Impression)
- Dataset splits: Training and validation
- Task setting: Retrieval-augmented medical visual question answering

The collected health data passes from wearable devices to a cloud-based platform through wireless communication procedures that include Bluetooth, Wi-Fi, and 5 G. The cloud platform functions as a unified data repository for healthcare information, which allows providers to obtain data remotely for their analytical purposes. The storage infrastructure receives and protects large volumes of sensitive health data through a data structure designed to meet privacy requirements and fulfill relevant data protection regulations, including HIPAA and GDPR.

6. EXPERIMENTAL PROCESS

This section outlines the experimental workflow of the proposed vision-based retrieval-augmented reasoning framework for medical visual question answering. Unlike traditional supervised or self-supervised pipelines, the proposed approach does not involve task-specific training and instead relies on retrieval-based reasoning. The experimental process consists of six main steps: dataset preparation, feature extraction, retrieval index construction, evidence retrieval, answer generation, and evaluation. Chest X-ray images from the MIMIC-CXR-JPG dataset are

converted from grayscale to RGB format, and associated radiology reports are extracted without applying data augmentation.

Visual embeddings for training images and textual embeddings for radiology reports are computed using pretrained encoders and stored in separate retrieval indices. At inference time, a query image and a medical question are encoded to retrieve visually similar images and relevant reports from the training set. The retrieved evidence is then provided to a pretrained vision-language model, which generates answers constrained by the retrieved content. When the available evidence is insufficient, the system abstains from unsupported predictions.
Finally, the framework is evaluated on a held-out validation set using a large-scale set of automatically generated medical questions. Performance is assessed using retrieval metrics, binary yes/no accuracy, and concept-level confusion analysis as shown in **Table 2**.

Table 2: Dataset usage and evaluation protocol in the proposed Vision-RAG framework.

Dataset Split	Role in Framework	Data Size	Modality	Supervision
QA Evaluation set	Large-scale reasoning assessment	2,000 questions	96 x 96 (RGB)	Automatic
Training set	Construction of visual and textual retrieval corpus	261K images	Chest X-ray + Reports	Weak (reports only)
Validation set	Evaluation of retrieval and reasoning performance	Validation subset	Image–Question pairs	Implicit (Yes/No, Concepts)

7. EXPERIMENTAL RESULT

The proposed vision-based retrieval-augmented reasoning framework was evaluated on the validation split of the MIMICCXR-JPG dataset. Unlike conventional supervised or self-supervised learning approaches, the framework does not involve task-specific training or fine-tuning. Instead, all experiments focus on assessing retrieval effectiveness and evidence-grounded reasoning using pretrained vision-language models [1], [3].
Figure 2 illustrates representative chest X-ray images from the MIMIC-CXR-JPG validation set. The selected samples highlight variability in anatomical structures, acquisition conditions, and common radiographic patterns observed in real-world clinical data.

Figure 2. Sample chest X-ray images from the MIMIC-CXR-JPG validation set

To further illustrate the reasoning behavior of the proposed framework, qualitative examples of question answering are presented. Given a chest X-ray image and a medical query, the system retrieves relevant radiology report

excerpts and generates answers strictly based on the provided textual evidence. When the retrieved evidence explicitly supports a clinical finding, the model produces a definitive answer; otherwise, it clearly indicates insufficient evidence, demonstrating conservative and safety-aware reasoning.

7.1 Qualitative Case Study Example

- **Question:**

Is there any sign of lung infection or opacity in this image?

- **Retrieved Textual Evidence:**

Findings: Impression: Subtle, ill-defined opacity within the left lower lobe is concerning for early infection.

- **Model Answer:** Yes.

Quantitative evaluation was conducted using approximately 2,000 automatically generated medical questions applied to validation images. The evaluation protocol follows recent retrieval-augmented vision-language reasoning studies [3], [4], [8] and focuses on three complementary aspects: (i) retrieval quality, (ii) correctness of binary (yes/no) answers, and (iii) concept-level reasoning performance.

7.2 Retrieval Performance

Retrieval quality was measured using Recall@1, which evaluates whether the retrieved radiology report contains clinically relevant evidence corresponding to the ground-truth medical concept. The proposed framework achieved a Recall@1 of **66.88%**, indicating that in more than two-thirds of the cases, the top retrieved report contained relevant clinical evidence. This result demonstrates the effectiveness of the joint image–text embedding space in aligning chest X-ray images with their associated radiology findings.

7.2 Binary (Yes/No) Question Accuracy

For binary medical questions, model answers were compared against ground-truth labels derived from retrieved textual evidence. The system achieved an overall yes/no accuracy of **56.75%** on the validation set. Although the task is challenging due to ambiguous findings and subtle radiological patterns, the results indicate that the model is able to correctly determine the presence or absence of clinical conditions in a substantial portion of cases, as shown in **Figure 3.**

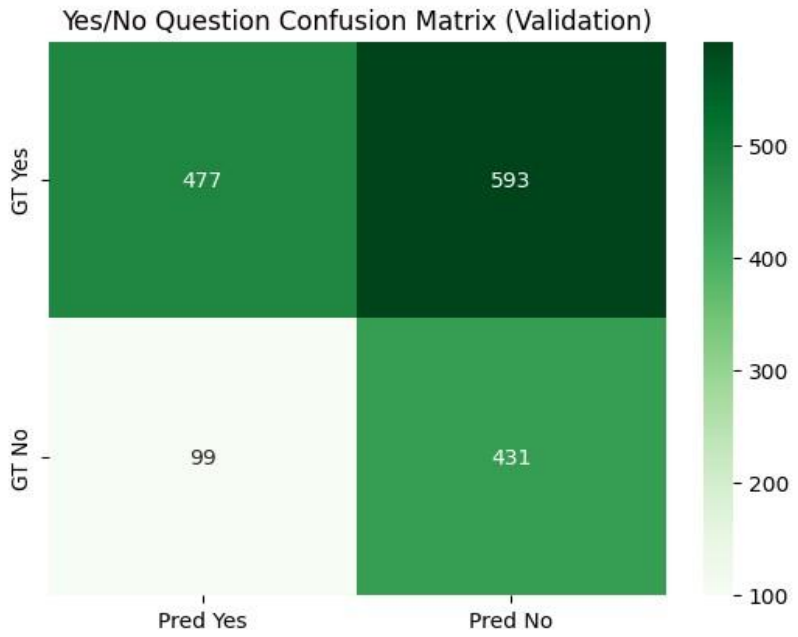

Figure 3. Confusion matrix for yes/no medical question answering on the validation set

7.3 Concept-Level Reasoning Analysis

To further analyze reasoning performance, a multi-class confusion matrix was constructed over major medical concepts, including infection, normal, effusion, and consolidation. As shown in **Figure 4**, the framework demonstrates strong discrimination between normal and pathological cases, while moderate confusion is observed between effusion and consolidation, which are known to exhibit overlapping radiographic characteristics. Notably, a portion of the samples is mapped to the *other* category, reflecting cases where retrieved evidence does not strongly support a predefined concept. This behavior aligns with the evidence-grounded design of the system and helps reduce unsupported clinical predictions.

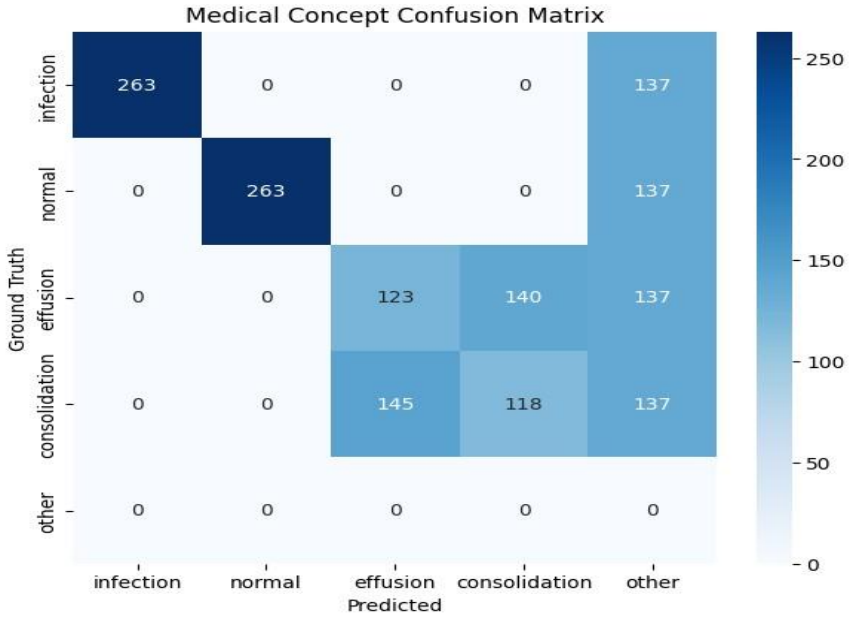

Figure 4. Medical concept confusion matrix on the validation set

7.4 Overall Interpretation

Overall, the quantitative results indicate that the proposed visual retrieval-augmented framework provides reliable evidence retrieval and conservative medical reasoning. While binary accuracy and concept classification remain challenging due to inherent ambiguity in chest X-ray interpretation, the system prioritizes evidence consistency over aggressive prediction, making it suitable for safety-critical medical applications.

8. CONCLUSIONS

This paper presented a retrieval-augmented vision-language framework for medical visual question answering, designed to operate without task-specific supervision. By leveraging large-scale chest X-ray images and associated radiology reports from the MIMIC-CXR-JPG dataset, the proposed approach demonstrated that reliable and interpretable medical reasoning can be achieved through evidence-grounded retrieval rather than direct end-to-end training. The framework integrates visual and textual embeddings within a unified retrieval space, enabling the system to answer medical queries strictly based on retrieved radiological evidence. Experimental results on the validation set highlight the effectiveness of the proposed method in retrieving clinically relevant reports and producing conservative, safety-aware answers. Both quantitative metrics and qualitative case studies confirm that the system prioritizes evidence consistency and mitigates unsupported or hallucinated predictions, which is critical for medical imaging applications. Despite these promising results, several research challenges remain. Retrieval quality is inherently limited by the semantic overlap of radiological findings, and concept-level confusion persists for conditions with

similar visual manifestations, such as effusion and consolidation. Future work will focus on improving retrieval robustness through domain-adapted encoders, incorporating uncertainty-aware reasoning mechanisms, and extending the framework to support multi-image and longitudinal patient analysis. Additionally, future research will explore multimodal extensions that integrate structured clinical data, temporal imaging studies, and adaptive prompt strategies to further enhance reasoning accuracy. Evaluating the framework across additional medical imaging modalities and external datasets will also be prioritized to assess generalization and clinical applicability.

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No potential conflict of interest was reported by the author(s).

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