

TEMMED-BENCH: EVALUATING TEMPORAL MEDICAL IMAGE REASONING IN VISION-LANGUAGE MODELS

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<https://TemMedBench.github.io>

ABSTRACT

Existing medical reasoning benchmarks for vision-language models primarily focus on analyzing a patient’s condition based on an image from a *single* visit. However, this setting deviates significantly from real-world clinical practice, where doctors typically refer to a patient’s historical conditions to provide a comprehensive assessment by tracking their changes over time. In this paper, we introduce TEMMED-BENCH, the first benchmark designed for analyzing changes in patients’ conditions between different clinical visits, which challenges large vision-language models (LVLMs) to reason over **temporal medical images**. TEMMED-BENCH consists of a test set comprising three tasks – visual question-answering (VQA), report generation, and image-pair selection – and a supplementary knowledge corpus of over 17,000 instances. With TEMMED-BENCH, we conduct an evaluation of twelve LVLMs, comprising six proprietary and six open-source models. Our results show that most LVLMs lack the ability to analyze patients’ condition changes over temporal medical images, and a large proportion perform only at a random-guessing level in the closed-book setting. In contrast, GPT o3, o4-mini and Claude 3.5 Sonnet demonstrate comparatively decent performance, though they have yet to reach the desired level. To enhance the tracking of condition changes, we explore augmenting the input with both retrieved visual and textual modalities in the medical domain. We also show that multi-modal retrieval augmentation yields notably higher performance gains than no retrieval and textual retrieval alone across most models on our benchmark, with the VQA task showing an average improvement of 2.59%. Overall, we compose a benchmark grounded on real-world clinical practice, and it reveals LVLMs’ limitations in temporal medical image reasoning, as well as highlighting the use of multi-modal retrieval augmentation as a potentially promising direction worth exploring to address this challenge.

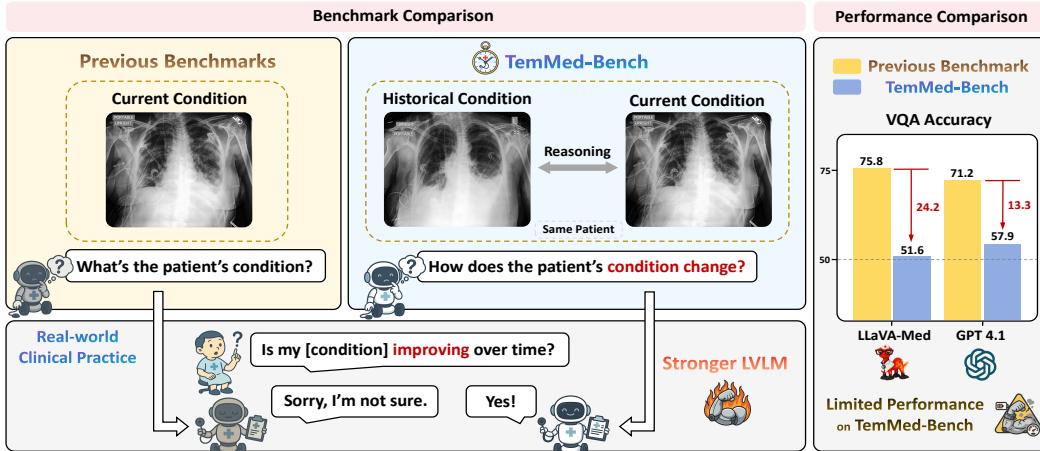


Figure 1: An example from TEMMED-BENCH. Previous benchmarks (Johnson et al., 2019; Hu et al., 2024) mainly focused on analyzing a single-visit image. However, real-world clinical practice requires doctors to monitor changes in patients’ conditions over time. The previous benchmark in the rightmost chart is a VQA variant (Xia et al., 2025) of the MIMIC-CXR dataset (Johnson et al., 2019).

Benchmarks	Task	Historical Conditions	Multi-Image Input
VQA-RAD (Lau et al., 2018)	VQA	✗	✗
SLAKE (Liu et al., 2021)	VQA	✗	✗
PathVQA (He et al., 2020)	VQA	✗	✗
PMC-VQA (Zhang et al., 2024)	VQA	✗	✗
PubMedVision (Chen et al., 2024)	VQA	✗	✗
OmniMedVQA (Hu et al., 2024)	VQA	✗	✗
Harvard-FairVLMed (Luo et al., 2024)	Report	✗	✗
IU-Xray (Demner-Fushman et al., 2015)	Report	✗	✗
CheXpert Plus (Chambon et al., 2024)	Report	✗	✗
MIMIC-CXR (Johnson et al., 2019)	VQA + Report	✗	✗
TEMMED-BENCH (Ours)	VQA+Report+Image-pair	✓	✓

Table 1: Comparison with previous works. TEMMED-BENCH focuses on evaluating LVLMs in temporal reasoning over multiple medical images. VQA: visual question answering; Report: report generation; Image-pair: image-pair selection.

1 INTRODUCTION

With the recent developments in Large Vision-Language Models (LVLMs), Medical LVLMs (Med-LVLMs) have shown promise for diagnostic tasks such as disease detection, therapeutic planning, and clinical guidance (Li et al., 2023; Chen et al., 2024; Lin et al., 2025). When evaluating Med-LVLMs, prior benchmarks have suffered from limited modality diversity (Lau et al., 2018; Liu et al., 2021; He et al., 2020), small scale (Lau et al., 2018; Liu et al., 2021; He et al., 2020; Demner-Fushman et al., 2015), and restricted task formats (Zhang et al., 2024; Luo et al., 2024). Although some efforts have mitigated these issues (Hu et al., 2024; Johnson et al., 2019; Chambon et al., 2024), existing benchmarks still share a common limitation: they analyze a patient’s condition based on a single-visit image. We argue that this limitation prevents the evaluation of Med-LVLMs from capturing real-world clinical practice, where doctors rely on patients’ medical histories to comprehensively assess current conditions and track changes over time, as illustrated in Figure 1. This real-world scenario challenges Med-LVLMs to possess strong reasoning abilities over temporal medical images, a capability largely overlooked in previous works.

To address this limitation, we introduce TEMMED-BENCH, the first multimodal benchmark that challenges LVLMs to reason over temporal medical images. Specifically, each sample in TEMMED-BENCH contains images from two different clinical visits of the same patient, requiring the model to analyze the changes in the patient’s condition over time. As summarized in Table 1, TEMMED-BENCH features three primary highlights. (1) *Temporal reasoning focus*: Each sample in TEMMED-BENCH includes historical condition information, which challenges models to analyze changes in patient conditions over time. (2) *Multi-image input*: Each sample in TEMMED-BENCH contains multiple images from different visits as input, emphasizing the need for models to process and reason over multiple images. (3) *Diverse task suite*: TEMMED-BENCH comprises three tasks, including VQA, report generation, and image-pair selection. Additionally, TEMMED-BENCH includes a knowledge corpus with more than 17,000 instances to support retrieval-augmented generation (RAG), each comprising two images and one corresponding report of condition changes.

We conducted extensive experiments on TEMMED-BENCH to evaluate six proprietary and six open-source LVLMs. In addition to closed-book evaluation, we also benchmark whether and how LVLMs benefit from retrieval augmentation on TEMMED-BENCH. Beyond augmenting the input with retrieved textual information (Tao et al., 2024; Kumar & Marttinen, 2025; Sun et al., 2025; Xia et al., 2024; 2025), we further explore augmenting the input with both retrieved visual and textual modalities in the medical domain, which remains unexplored.

For the closed-book evaluation, experimental results show that most LVLMs lack the ability to analyze changes in patients’ conditions across temporal medical images. In the VQA task, GPT-4o-mini and Claude 3.5 Sonnet achieved accuracies of 79.15% and 69.90%, respectively, while most LVLMs scored below 60%. For the more challenging tasks of report generation and image-pair selection, all LVLMs underperformed, with the highest average BLEU, ROUGE-L, and METEOR score at 20.67

for report generation and a top accuracy of 39.33% for image-pair selection in a three-option setting. These results reveal a fundamental gap in current LVLM training, i.e., lack of focus on temporal image reasoning.

For the retrieval augmentation evaluation, experimental results demonstrate that augmenting input with both visual and textual information substantially boosts performance for most models compared to text-only augmentation. Notably, HealthGPT (Lin et al., 2025) exhibits an accuracy improvement of over 10% in the VQA task when augmented with multi-modal retrieved information. These results confirm that multi-modal retrieval augmentation provides more relevant medical information by retrieving images with similar conditions, highlighting its potential for input augmentation in the medical domain. In addition, we found that while previous benchmarks emphasize pattern recognition and matching for a single-visit image, which can be easily hacked by directly taking top-1 retrieved result as the answer, TEMMED-BENCH is more robust to it due to its reasoning attribute. Further discussion can be found in Appendix C.1.

The main contributions of this paper are as follows: (1) We propose TEMMED-BENCH, the first benchmark that focuses on evaluating the temporal reasoning ability of LVLMs over medical images. (2) Comprehensive evaluation of mainstream LVLMs on the three tasks in our benchmark reveals their limitations in temporal reasoning over medical images. (3) We explore multi-modal RAG for the medical domain, and highlight the effectiveness of retrieving multi-modal information to boost the performance of Med-LVLMs.

2 TEMMED-BENCH

2.1 BENCHMARK OVERVIEW

The key statistics of TEMMED-BENCH are shown in Table 2. TEMMED-BENCH consists of a test set and a knowledge corpus. The test set comprises three tasks: visual question answering (VQA), report generation, and image-pair selection. The formulations of these tasks are as follows:

VQA: An LVLM \mathcal{M} takes a historical image i_h , a current image i_c , and a textual question q describing the condition change as input, and is required to output a binary answer of "yes" or "no".

Report Generation: \mathcal{M} takes i_h , i_c , and a textual task instruction q_{inst} as input, and is required to output a report that analyzes the changes in condition between these two images.

Image-pair Selection: \mathcal{M} is given three image pairs – I_A ($[i_{h1}, i_{c1}]$), I_B ($[i_{h2}, i_{c2}]$), and I_C ($[i_{h3}, i_{c3}]$) – along with a textual question q , and is required to output the choice of A, B, or C that best matches the medical statement in q .

Besides, each instance in the knowledge corpus follows the format of an image pair (i_h , i_c) with its corresponding condition change report t .

2.2 KEY OBSERVATION & RAW DATA COLLECTION

TEMMED-BENCH is built upon a key observation regarding existing medical report generation datasets: while these datasets typically assign each report to a single visit, some reports actually include sentences that describe changes in a patient’s condition, rather than just the condition at that visit. More specifically, consider the following examples. If a sentence contains phrases such as "*mild* atelectasis", "*moderate* atelectasis", or "*severe* atelectasis", where the adjectives quantitatively describe the condition, we refer to it as a *single-visit description sentence*. In contrast, if a sentence contains phrases such as "*persistent* atelectasis", "*worsening* atelectasis", or "*atelectasis has improved*", where the adjectives indicate a change in condition, we refer to it as a *condition change description sentence*. Obviously, reports with condition change description sentences reflect that the doctor considered both current and previous conditions, not just information from a single visit.

Statistic (#)	Questions	Images	Choice
VQA	2,000	2	2
Report	1,000	2	-
Image-pair	862	6	3
Corpus	17,144	2	-

Table 2: Key statistics of TEMMED-BENCH. VQA: visual question answering; Report: report generation; Image-pair: image-pair selection. Corpus: knowledge corpus.

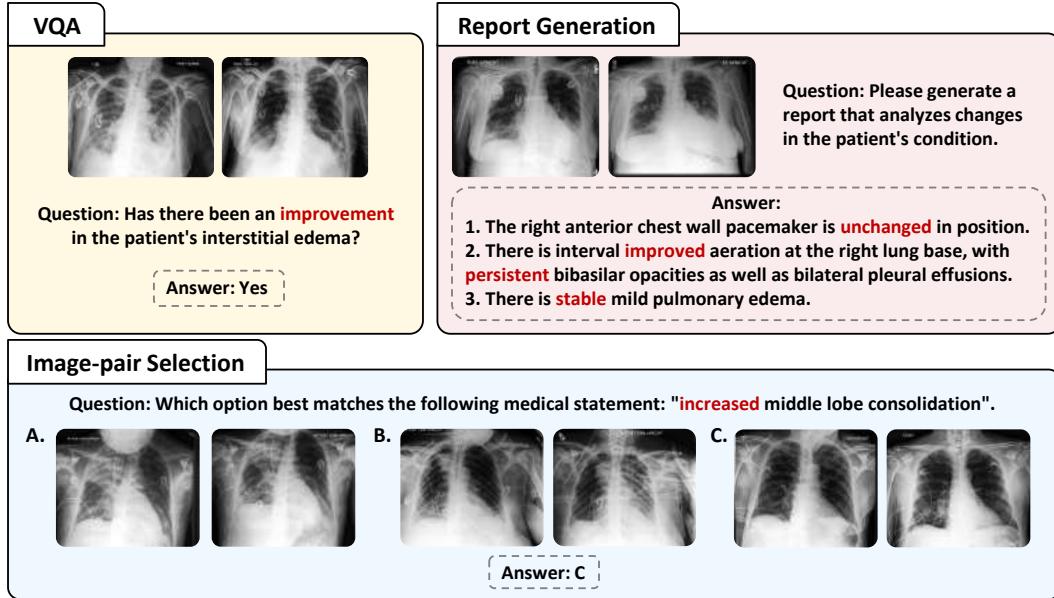


Figure 2: Examples of the three tasks in TEMMED-BENCH. Each question in these tasks is designed to challenge LLMs’ ability to analyze condition changes, providing a comprehensive evaluation of their temporal medical image reasoning ability.

The raw data for our benchmark are collected from the CheXpert Plus dataset (Chambon et al., 2024). We first collect reports in which every sentence is a condition change description sentence. For implementation, we select a set of keywords that are commonly used to describe condition changes, such as *increase*, *worsen*, and *stable*. We then use regular expressions to identify sentences containing at least one of these keywords (in any tense) as condition change description sentences. Next, we collect reports in which every sentence is a condition change description sentence as our target reports, and retrieve the corresponding frontal view image for each report as the current condition image. After identifying these target reports, we leverage the *patient_report_date_order* attribute in the CheXpert Plus dataset to track the historical visits of the same patient for each report. For each target report, we consider the most recent prior visit as the most relevant historical reference, and select the frontal view image from that visit as the historical condition image. In this way, a total of 18,144 instances were collected, each consisting of a pair of images and a report, with each sentence in the report describing condition changes observed between the images. More details on the data collection method can be found in Appendix A.1, and further discussion is provided in Appendix C.2.

2.3 TASK DATA COLLECTION

We randomly selected 1,000 instances as the test set and used the remaining instances as the knowledge corpus. Based on the test set instances, we constructed three tasks: VQA, report generation, and image-pair selection. Since the raw data has already been formatted for report generation, no additional processing is required for this task. Examples of the three tasks are shown in Figure 2.

VQA Task Construction As illustrated in § 2.1, our VQA task adopts a binary setting, with "yes" or "no" as answers. To construct the VQA data, we leverage GPT-4o (OpenAI, 2024) to rephrase each report into question-answer pairs, following Li et al. (2023); Zhang et al. (2024); Xia et al. (2024). Specifically, each report is first segmented into individual sentences. Since each sentence in the reports is a condition change description sentence, it can be rephrased as a question that asks whether the patient’s condition has changed. Then, all of these sentences are fed into GPT-4o to create VQA data with "yes" or "no" answers. To balance answer distribution, we prompt GPT-4o to generate roughly equal numbers of "yes" and "no" questions. Additionally, each instance is manually reviewed to ensure that the questions target condition changes and the answers align with the truth in the report. More details of the construction process and quality control are provided in Appendix A.2.

Image-pair Selection Task Construction Our image-pair selection task adopts a three-option setting, with "A", "B", or "C" as answers. Unlike conventional multiple-choice question-answering

tasks (Lau et al., 2018; Zhang et al., 2024; Hu et al., 2024), where each question consists of a target image and several textual options, our image-pair selection task is more vision-centric, with the options being image pairs, and the model is asked to choose the image pair that best matches a target medical statement. This task requires the model to analyze three image pairs at a time, which demands a high level of multi-image processing and reasoning abilities. For the data construction of this task, we first select a set of keywords that are often used to describe condition changes (KW_C), e.g., *persist*, *improve*, and *decrease*, as well as a set of pathology keywords (KW_P) that frequently occur in the reports (Chambon et al., 2024), e.g., *atelectasis*, *edema*, and *effusion*. We observe that most statements describing condition changes in the reports match the following regular expression:

$$[KW_C]_{(\text{in any tense})} + 0 \sim 4 \text{ attributives} + [KW_P]$$

For example, "*improving mild cardiogenic edema*" and "*decrease in left pleural effusion*". Using this regular expression, we can assign multiple condition change statements to each image pair. Subsequently, for each condition change statement in each image pair, we construct an image-pair selection sample, where the specific condition change statement serves as the target medical statement in the question, and the corresponding image pair serves as the correct option. To generate incorrect options, we randomly sample image pairs with the same pathology but reflect a different condition change, thereby ensuring that only one option matches the target medical statement. For more details on the keywords and construction examples, please refer to Appendix A.3.

3 MULTI-MODAL RETRIEVAL AUGMENTATION

3.1 PROBLEM FORMULATION

In the medical domain, medical reports serve as a commonly used knowledge corpus for *text-only retrieval augmentation* (Tao et al., 2024; Xia et al., 2024; 2025; Sun et al., 2025). Formally, given a query tuple $\mathbf{Query} = (\mathbf{i}_h, \mathbf{i}_c, \mathbf{q})$ composed of a historical image, a current image, and a textual question, the retriever \mathcal{R} retrieves a set of relevant textual medical reports $\mathbf{T} = [\mathbf{t}_1, \mathbf{t}_2, \dots, \mathbf{t}_N]$ from a knowledge corpus \mathcal{C} . The LVLM \mathcal{M} then takes $(\mathbf{Query}, \mathbf{T})$ as input for answer generation.

In our work, we explore a more challenging yet promising setting of *multi-modal retrieval augmentation*. As discussed in § 2, we use the collected image pairs and their condition change reports as our knowledge corpus. Formally, given a \mathbf{Query} , the retriever \mathcal{R} returns a set of relevant medical images and their corresponding reports $(\mathbf{I}_h, \mathbf{I}_c, \mathbf{T}) = [(\mathbf{i}_{h_1}, \mathbf{i}_{c_1}, \mathbf{t}_1), (\mathbf{i}_{h_2}, \mathbf{i}_{c_2}, \mathbf{t}_2), \dots, (\mathbf{i}_{h_N}, \mathbf{i}_{c_N}, \mathbf{t}_N)]$ from \mathcal{C} . \mathcal{M} then takes $(\mathbf{Query}, \mathbf{I}_h, \mathbf{I}_c, \mathbf{T})$ as input and generates the final answer.

3.2 PAIRWISE IMAGE RETRIEVAL

Existing cross-modal retrieval methods typically focus on calculating feature similarity between the target image and the reports in the knowledge corpus (Tao et al., 2024; Xia et al., 2024; 2025; Sun et al., 2025). Given an image i and a report t , the similarity score is computed as follows:

$$\text{Score} = \text{Sim}(\text{Enc}_i(\mathbf{i}), \text{Enc}_t(\mathbf{t})), \quad (1)$$

where Enc_i and Enc_t denote the image and text encoder models, respectively, and Sim denotes cosine similarity. However, this method does not fit with TEMMED-BENCH, since the reports in TEMMED-BENCH describe the condition changes between the historical image and the current image. Therefore, the report feature does not align with a single image, but rather with an image pair.

For retrieval augmentation in TEMMED-BENCH, we aim to retrieve instances whose condition changes are similar to those of the target images. To retrieve higher-quality data, we propose a pairwise image retrieval method. Specifically, given a target image pair $(\mathbf{i}_h, \mathbf{i}_c)$ and an instance $(\mathbf{i}_h^*, \mathbf{i}_c^*, \mathbf{t}^*)$ from the knowledge corpus, the pairwise image similarity score is computed as follows:

$$\text{Score} = \text{Sim}(\text{Enc}_i(\mathbf{i}_h), \text{Enc}_i(\mathbf{i}_h^*)) + \text{Sim}(\text{Enc}_i(\mathbf{i}_c), \text{Enc}_i(\mathbf{i}_c^*)), \quad (2)$$

where the two terms ensure that the historical and current images of the retrieved instance are similar to their counterparts in the target image pair, respectively, while their joint evaluation ensures that the condition changes are similar. Then, image pairs with high similarity scores, along with their corresponding reports, are used as the retrieved instances.

Model	Params	VQA		Report Generation				Image Selection
		Acc _[50]	F1 _[50]	BLEU	ROUGE-L	METEOR	Avg.	Acc _[33.3]
<i>Open-Source LVLMs</i>								
LLaVA-Med*	7B	51.65	35.23	9.85	6.51	7.10	7.82	/
HuatuoGPT-Vision*	7B	53.00	41.65	7.00	6.54	18.30	10.61	33.29
HealthGPT*	14B	46.30	43.49	11.61	9.26	18.70	13.19	33.64
Qwen2.5-VL	7B	59.90	57.60	12.13	10.46	18.34	13.64	33.87
Llama3.2-Vision	11B	45.65	45.48	8.57	7.94	15.77	10.76	33.06
LLaVA-OneVision	7B	63.90	62.12	5.18	6.07	13.10	8.12	32.83
<i>Proprietary LVLMs</i>								
Gemini 2.5 Flash	/	47.30	47.30	20.23	14.19	22.79	19.07	39.33
Claude 3.5 Sonnet	/	69.90	69.49	17.17	14.01	24.91	18.70	33.53
GPT 4o	/	51.65	47.16	12.74	12.32	23.46	16.17	32.60
GPT 4.1	/	57.90	57.51	9.81	11.67	22.6	14.69	35.38
GPT o4-mini	/	79.15	78.94	20.54	15.75	25.71	20.67	35.03
GPT o3	/	64.40	64.40	16.99	13.71	25.77	18.82	38.05

Table 3: Evaluation results on TEMMED-BENCH in the closed-book setting. Highest and second-highest scores for each task are highlighted in red and blue, respectively. Models marked with superscript * indicate medical LVLMs. Square-bracketed subscripts denote random-guess scores.

In contrast to the VQA and report generation tasks, the implementation of retrieval augmentation for the image-pair selection task requires some special handling. For more details, please refer to Appendix B.2.

4 EXPERIMENTS

4.1 EXPERIMENTAL SETUP

We evaluate 12 popular LVLMs on TEMMED-BENCH, comprising 6 proprietary and 6 open-source models. Among the open-source models, 3 are medical LVLMs.

- **Proprietary models:** GPT o3 (OpenAI, 2025b), GPT o4-mini (OpenAI, 2025b), GPT 4.1 (OpenAI, 2025a), GPT 4o (OpenAI, 2024), Claude 3.5 Sonnet (Anthropic, 2024), and Gemini 2.5 Flash (Google, 2025).
- **Open-source models:** LLaVA-Med (7B) (Li et al., 2023), HuatuoGPT-Vision (7B) (Chen et al., 2024), HealthGPT (14B) (Lin et al., 2025), Qwen2.5-VL (7B) (Team, 2025), Llama3.2-Vision (11B) (Meta AI, 2024), and LLaVA-OneVision (7B) (Li et al., 2024).

Evaluation Setup For VQA, we use accuracy and F1 score as metrics. For report generation, following Jing et al. (2018) and Xia et al. (2025), we use BLEU (Papineni et al., 2002), ROUGE-L (Lin, 2004), and METEOR (Banerjee & Lavie, 2005). For image-pair selection, accuracy is used. Detailed evaluation prompts for closed-book and RAG scenarios can be found in Appendix B.1.

4.2 MAIN RESULTS

The evaluation results in the closed-book setting are shown in Table 3. Our TEMMED-BENCH clearly reveals the limitations of current LVLMs in temporal medical image reasoning. Most LVLMs perform at around the random guess level in the VQA and image-pair selection tasks, and achieve relatively low average scores in the report generation task. Moreover, the results highlight several noteworthy observations which we further discuss below. Additional analysis can be found in Appendix C.3.

Importance of Reasoning Ability Among these results, the reasoning model GPT o4-mini achieves outstanding performance. It achieves the highest performance in both VQA and report generation tasks, with its VQA accuracy surpassing that of the second-highest model by 10%, and also shows relatively high performance in the image-pair selection task. These results suggest that, for TEMMED-BENCH, advanced image reasoning is a key capability for effectively addressing these tasks. Given

Model	VQA		Report Generation				Image Selection Acc
	Acc	F1	BLEU	ROUGE-L	METEOR	Avg.	
<i>Open-Source LVLMs</i>							
LLaVA-Med *	51.65	35.23	9.85	6.51	7.10	7.82	/
+ Text-only RAG	54.45 _{+2.80}	41.71 _{+6.48}	17.51	13.35	17.76	16.21 _{+8.39}	/
+ Multi-Modal RAG	56.00 _{+4.35}	44.70 _{+9.47}	12.70	10.74	17.16	13.53 _{+5.71}	/
HuatuoGPT-Vision *	53.00	41.65	7.00	6.54	18.30	10.61	33.29
+ Text-only RAG	59.50 _{+6.50}	52.50 _{+10.85}	8.12	7.53	20.63	12.09 _{+1.48}	-
+ Multi-Modal RAG	61.75 _{+8.75}	56.73 _{+15.08}	9.50	9.07	21.81	13.46 _{+2.85}	32.02 _{-1.27}
HealthGPT *	46.30	43.49	11.61	9.26	18.70	13.19	33.64
+ Text-only RAG	59.05 _{+12.75}	57.13 _{+13.64}	13.46	10.50	20.68	14.88 _{+1.69}	-
+ Multi-Modal RAG	69.90 _{+23.60}	68.71 _{+25.22}	14.96	11.46	20.42	15.61 _{+2.42}	33.53 _{-0.11}
Qwen2.5-VL	59.90	57.60	12.13	10.46	18.34	13.64	33.87
+ Text-only RAG	63.15 _{+3.25}	60.26 _{+2.66}	12.80	12.33	22.12	15.75 _{+2.11}	-
+ Multi-Modal RAG	65.35 _{+5.45}	63.03 _{+5.43}	13.26	12.43	21.69	15.79 _{+2.15}	35.15 _{+1.28}
Llama3.2-Vision	45.65	45.48	8.57	7.94	15.77	10.76	33.06
+ Text-only RAG	63.05 _{+17.40}	58.76 _{+13.28}	12.46	10.86	20.13	14.48 _{+3.72}	-
+ Multi-Modal RAG	64.10 _{+18.45}	60.52 _{+15.04}	14.26	12.37	21.45	16.03 _{+5.27}	35.15 _{+2.09}
LLaVA-OneVision	63.90	62.12	5.18	6.07	13.10	8.12	32.83
+ Text-only RAG	78.25 _{+14.35}	78.21 _{+16.09}	9.30	9.12	19.81	12.74 _{-4.63}	-
+ Multi-Modal RAG	78.65 _{+14.75}	78.35 _{+16.23}	11.36	10.15	20.27	13.93 _{+5.81}	33.64 _{+0.81}
<i>Proprietary LVLMs</i>							
Gemini 2.5 Flash	47.30	47.30	20.23	14.19	22.79	19.07	39.33
+ Text-only RAG	49.95 _{+2.65}	49.20 _{+1.90}	22.88	17.27	22.98	21.04 _{+1.97}	-
+ Multi-Modal RAG	51.40 _{+4.10}	50.54 _{+3.24}	23.49	21.48	23.17	22.71 _{+3.64}	40.26 _{+0.93}
Claude 3.5 Sonnet	69.90	69.49	17.17	14.01	24.91	18.70	33.53
+ Text-only RAG	66.25 _{-3.65}	65.50 _{+3.99}	20.58	16.73	27.27	21.53 _{+2.83}	-
+ Multi-Modal RAG	74.15 _{+4.25}	73.95 _{+4.46}	22.35	17.83	26.44	22.21 _{+3.51}	37.35 _{+3.82}
GPT 4o	51.65	47.16	12.74	12.32	23.46	16.17	32.60
+ Text-only RAG	60.10 _{+8.45}	59.57 _{+12.41}	21.06	17.17	26.74	21.66 _{+5.48}	-
+ Multi-Modal RAG	64.85 _{+13.20}	64.42 _{+17.26}	23.79	19.14	26.80	23.24 _{+7.07}	34.69 _{+2.09}
GPT 4.1	57.90	57.51	9.81	11.67	22.6	14.69	35.38
+ Text-only RAG	58.50 _{+0.60}	58.30 _{+0.79}	17.07	15.57	27.48	20.04 _{+5.35}	-
+ Multi-Modal RAG	58.60 _{+0.70}	58.55 _{+1.04}	19.03	16.56	28.07	21.22 _{+6.53}	33.87 _{-1.51}
GPT o4-mini	79.15	78.94	20.54	15.75	25.71	20.67	35.03
+ Text-only RAG	81.80 _{+2.65}	81.78 _{+2.84}	24.77	19.42	27.99	24.06 _{+3.39}	-
+ Multi-Modal RAG	77.80 _{-1.35}	77.69 _{-1.25}	24.30	19.06	26.46	23.27 _{+2.61}	34.69 _{-0.34}
GPT o3	64.40	64.40	16.99	13.71	25.77	18.82	38.05
+ Text-only RAG	66.65 _{+2.25}	66.60 _{+2.20}	18.89	15.33	26.84	20.35 _{+1.53}	-
+ Multi-Modal RAG	65.65 _{+1.25}	65.60 _{+1.20}	18.72	15.20	27.16	20.44 _{+1.61}	39.56 _{+1.51}

Table 4: Evaluation results on TEMMED-BENCH with text-only and multi-modal retrieval augmentation (using top-1 retrieval). The highest and second-highest scores for each model in each task are highlighted in red and blue, respectively. Relative performance changes compared to the closed-book setting are shown as subscripts, with red indicating gains and blue indicating drops.

that changes in medical image features across different visits are often subtle, our findings further underscore the importance of fine-grained visual reasoning in this context.

Comparison between Proprietary and Open-Source LVLMs By comparing the performance of proprietary and open-source LVLMs on TEMMED-BENCH, we observed that proprietary LVLMs consistently achieve the best results across all tasks. Notably, in report generation, all proprietary LVLMs outperform the best open-source models, likely due to their superior language organization. For the VQA task, some open-source LVLMs achieve comparable performance to several proprietary models, with LLaVA-OneVision reaching 63.9% accuracy and Qwen2.5-VL achieving 59.9%. However, there is still a gap compared to GPT o4-mini and Claude 3.5 Sonnet.

Degradation of Medical LVLMs To our surprise, among open-source models, medical LVLMs do not show better performance compared to general-domain LVLMs, with the report generation task and image-pair selection task achieving nearly the same performance on average, and even worse performance on the VQA task. A similar observation was also reported by Hu et al. (2024). Such findings reflect the lack of robustness and generalizability of current medical LVLMs, and reveals that prevailing medical knowledge fine-tuning schemes often erode the broad reasoning abilities inherited from general-domain pre-training. This underscores the need to develop adaptation frameworks that preserve general reasoning capabilities while reliably incorporating domain expertise.

Retrieval Method	Acc	F1
Text-only RAG		
Image-to-Text	58.90	56.77
Image-to-Image	58.15	55.95
Pairwise Image	59.05	57.13
Multi-Modal RAG		
Image-to-Text	65.75	64.19
Image-to-Image	68.45	67.17
Pairwise Image	69.90	68.71

Table 5: Ablation study. We evaluate the performance of HealthGPT with different retrieval methods, including image-to-text, image-to-image, and pairwise image retrieval. The pairwise image retrieval method demonstrates the best performance among these methods.

4.3 MAIN RESULTS WITH RETRIEVAL-AUGMENTATION

The evaluation results in Table 4 demonstrate that multi-modal retrieval augmentation generally yields greater performance improvements across most models compared to text-only retrieval augmentation. Notably, compared to their text-only counterparts, HealthGPT, Claude 3.5 Sonnet, and GPT-4o demonstrate substantial gains in the multi-modal setting, with increases in VQA accuracy of 10.85%, 7.90%, and 4.75%, and improvements in report generation average score of 0.73, 0.68, and 1.59, respectively. Additional noteworthy observations are as follows.

Comparison between Open-Source and Proprietary LVLMs with Retrieval Augmentation. We noticed that open-source LVLMs exhibit a notably high performance gain in the VQA task after using retrieval augmentation. Specifically, HealthGPT, Llama3.2-Vision and LLaVA-OneVision show an increase of 23.60%, 18.45%, and 14.75% in VQA accuracy under multi-modal retrieval augmentation, respectively, compared to the closed-book setting. This makes some open-source LVLMs perform competitively with proprietary LVLMs in VQA. However, the performance of open-source LVLMs in the report generation and image-pair selection tasks still lags behind that of proprietary LVLMs, indicating that proprietary LVLMs still have an advantage in tasks requiring advanced language organization skills and strong multi-image processing capabilities.

Challenges of Leveraging Retrieved Information in the Image-pair Selection Task Although most LVLMs exhibit significant performance gains with retrieval augmentation, the improvement is less pronounced in the image-pair selection task, with several LVLMs even exhibiting a decrease in performance. We argue that this highlights the unique challenges of leveraging retrieved information in this specific task. Unlike the other two tasks, which involve only a single target image pair and require the model merely to compare the retrieved information with that pair to determine its usefulness, the image-pair selection task involves three target pairs. Consequently, the model must align the retrieved information with three separate pairs, splitting its attention and reconciling potentially conflicting cues, which substantially amplifies retrieval noise. The relatively complicated logic for retrieval augmentation in this setting underscores the need for advanced methods to improve LVLMs’ ability to utilize retrieved information in such multifaceted scenarios.

4.4 ANALYSIS OF MULTI-MODAL RETRIEVAL AUGMENTATION

To further investigate the optimal settings for multi-modal retrieval augmentation, we use HealthGPT on the VQA task as an illustrative case. Additional experiments on proprietary model GPT 4o are presented in Appendix C.4.

Ablation Study on Retrieval Methods Table 5 presents the ablation studies comparing the proposed pairwise image retrieval method with conventional image-to-text and image-to-image retrieval methods. Given a target image pair (i_h, i_c) and an instance from the knowledge corpus (i_h^*, i_c^*, t^*), the image-to-text retrieval computes the similarity score between i_c and t^* , whereas the image-to-image retrieval computes the similarity score between i_c and i_c^* . Results indicate that

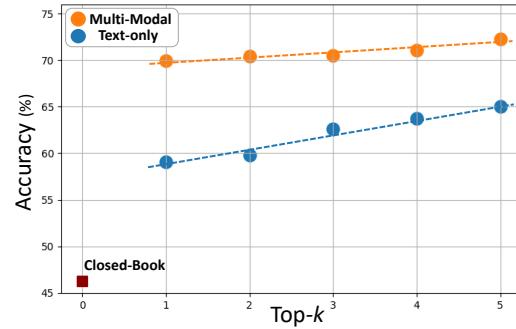


Figure 3: Results of top-1 to top-5 retrieval augmentation HealthGPT. The orange line indicates multi-modal retrieval augmentation, while the blue line indicates text-only retrieval augmentation. The red square shows model performance without retrieval augmentation.

pairwise image retrieval achieved the highest performance, primarily due to two factors. First, for image-to-text retrieval, the report feature in TEMMED-BENCH does not correspond to a single image, as the report describes condition changes between two images. Consequently, directly calculating the feature similarity between the report and a single image introduces bias. Second, image-to-image retrieval relies solely on the similarity of current-visit images, ensuring similarity in current conditions between the target and retrieved instances, but does not guarantee similarity in condition changes. Therefore, in TEMMED-BENCH, only by considering both historical and current images during retrieval and ensuring similarity in both, can retrieved instances reflect similar condition changes.

Impact of Top- k Retrieval Augmentation To further analyze the impact of varying top- k retrievals on augmentation performance, we conducted experiments to evaluate the performance of LVLMs under top-1 to top-5 retrieval augmentation settings, as shown in Figure 3. Notably, multi-modal retrieval augmentation consistently outperforms text-only retrieval augmentation across top-1 to top-5 settings, further confirming the effectiveness of incorporating multi-modal retrieved information in enhancing LVLM performance in the medical domain.

5 RELATED WORK

5.1 MEDICAL VISION-LANGUAGE BENCHMARKS

Medical Vision-Language Models (Med-LVLMs) have recently shown great promise in medical diagnostics, prompting interest in developing more advanced models (Li et al., 2023; Chen et al., 2024; Lin et al., 2025). For their evaluation, early benchmarks such as VQA-RAD (Lau et al., 2018), SLAKE (Liu et al., 2021), and PathVQA (He et al., 2020) focused on visual question-answering (VQA) but are limited by modality diversity and dataset size. More recent efforts (Zhang et al., 2024; Chen et al., 2024; Hu et al., 2024) have introduced larger VQA datasets with varied modalities. In addition, some studies (Luo et al., 2024; Bustos et al., 2020; Demner-Fushman et al., 2015; Chambon et al., 2024; Johnson et al., 2019) have built benchmarks for the report generation task, which present greater challenges for models in terms of long-form language generation, going beyond simple, short-sentence responses (Jing et al., 2018; Chen et al., 2020). However, these benchmarks all focus on analyzing a patient’s condition based on a single-visit image. In contrast, TEMMED-BENCH focuses on reasoning over temporal medical images from different clinical visits.

5.2 MULTI-MODAL RETRIEVAL AUGMENTATION

Retrieval-Augmented Generation (RAG) has been proposed as an effective approach to address the inherent limitations of language models (Lewis et al., 2020). In the general domain, multi-modal knowledge retrieval has been widely studied to enhance generative models (Chen et al., 2022; Liu et al., 2023; Zhao et al., 2023; Yasunaga et al., 2023; Cui et al., 2024; Sharifmoghaddam et al., 2025). Recent benchmarks designed to evaluate multi-modal retrieval augmentation (Hu et al., 2025; Liu et al., 2025) further highlight the value of visual information retrieval for vision-centric tasks. However, in the medical domain, existing works mainly focus on performing retrieval augmentation using text-only information (Tao et al., 2024; Kumar & Marttinen, 2025; Sun et al., 2025; Xia et al., 2024; 2025). Whether multi-modal retrieval augmentation is useful in this domain remains unexplored. Our work addresses this gap.

6 CONCLUSION

In this work, we introduce TEMMED-BENCH, a benchmark specifically designed to evaluate LVLMs’ ability to reason over temporal medical images, by letting LVLMs track changes in patients’ conditions between different clinical visits. We extend our benchmark to three tasks and release a knowledge corpus with over 17,000 instances. Through the evaluation of six proprietary and six open-source LVLMs, our findings highlight the limitations of current LVLMs in performing temporal reasoning with medical images. Furthermore, we investigate and validate the potential of multi-modal retrieval augmentation in the medical domain, emphasizing the efficacy of leveraging multi-modal information retrieval to enhance the performance of Med-LVLMs. Our work provides an evaluation that better reflects real-world clinical practice, guiding Med-LVLM development toward actual clinical needs.

ETHICS STATEMENT

We used LLMs to assist in improving grammar, clarity, and wording in parts of this work. We also used LLMs to generate data only by perturbing or converting existing text, and all LLM outputs were human-checked. The models were not used to create new data. Therefore, these uses do not raise trustworthiness concerns. Apart from the above, all ideas, analyses, and conclusions were developed solely by the authors.

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A DATA COLLECTION DETAILS

A.1 RAW DATA COLLECTION

For raw data collection, we select a set of keywords commonly used to describe condition changes and then apply regular expressions to identify sentences that contain at least one of these keywords (in any tense) as condition change description sentences.

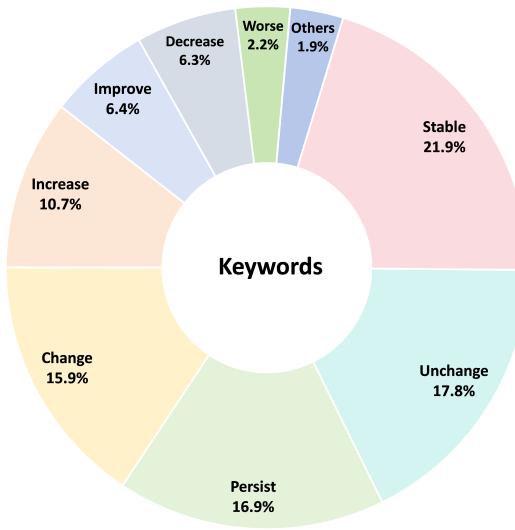


Figure 4: Keywords distribution.

The selected keywords are: `["stable", "unchange", "change", "persist", "increase", "decrease", "improve", "worsen", "thicken", "thin", "progress", "deteriorate", "reduce", "resolve", "exacerbate"]`. The distribution of keywords in the collected instances is shown in Figure 4.

A.2 VQA DATA CONSTRUCTION

Construction Process To construct VQA data, we use GPT-4o to rephrase each sentence in our selected reports into a question-answer pair. The following is the prompt for this process, with `{ANSWER}` set to *Yes* for half of the data and *No* for the other half. Table 6 shows an example of how a report is converted into multiple VQA items.

Prompts for VQA Data Construction

You are a professional medical expert. I will provide you with a sentence from a medical report. Please generate a question with the answer '`{ANSWER}`' based on the provided sentence.

The question should focus on the content that indicates a change in the patient's condition. The subject of the question should be the medical image or the patient, not the report. Please include only the question and answer in your response.

Below are the given sentence: `{SENTENCES}`

Report:

1. Lines and tubes unchanged. 2. Stable pulmonary edema. 3. Small, slightly decreased aeration of the right lung. 4. Increased right pleural effusion is possible. 5. Increased thickening of the left parietal pleura, consistent with increased effusion, possibly loculated.

Sentences:

[sentence 1] Lines and tubes **unchanged**.

[sentence 2] **Stable** pulmonary edema.

[sentence 3] Small, slightly **decreased** aeration of the right lung.

[sentence 4] **Increased** right pleural effusion is possible.

[sentence 5] **Increased thickening** of the left parietal pleura, consistent with increased effusion, possibly loculated.

Question-Answer Pair:**[QA 1]**

Q: Were there any changes in the placement of lines and tubes? | A: No.

[QA 2]

Q: Is the pulmonary edema in the patient stable? | A: Yes.

[QA 3]

Q: Has the aeration of the right lung increased? | A: No.

[QA 4]

Q: Has the right pleural effusion decreased? | A: No.

[QA 5]

Q: Have the medical images revealed an increased thickening of the left parietal pleura? | A: Yes.

Table 6: An example of VQA data construction

Quality Control As our dataset for the VQA task is constructed using AI tools, we perform human evaluation to ensure its quality. For each question-answer pair, we manually assess whether the question targets a condition change and whether the answer is consistent with the ground truth described in the report. We find that nearly all answers are consistent with the report. However, 214 out of 2,000 questions (10.7%) do not target a condition change. We manually correct these question-answer pairs.

A.3 IMAGE-PAIR SELECTION DATA CONSTRUCTION

For image-pair selection data construction, the keywords for describing condition changes (KW_C) and the pathology keywords (KW_P) are listed in Table 7. The selection of KW_P is based on the frequently occurring pathology labels in the reports (Chambon et al., 2024).

Figure 5 shows an example of how to construct data for the image-pair selection task. We use regular expressions to associate medical statements with each image pair. The incorrect options are selected from image pairs with the same pathology but different changes in condition.

Regular Expression: $[KW_C]_{(\text{in any tense})} + 0 \sim 4 \text{ attributives} + [KW_P]$

KW_C : ["stable", "unchange", "persist", "increase", "decrease", "improve", "worsen", "thicken", "thin", "progress", "deteriorate", "reduce", "resolve", "exacerbate"]

KW_P : ["atelectasis", "cardiomegaly", "consolidation", "edema", "cardiomedastinum", "fracture", "lesion", "opacity", "effusion", "pneumonia", "pneumothorax"]

Table 7: Keyword selection for image-pair selection data construction

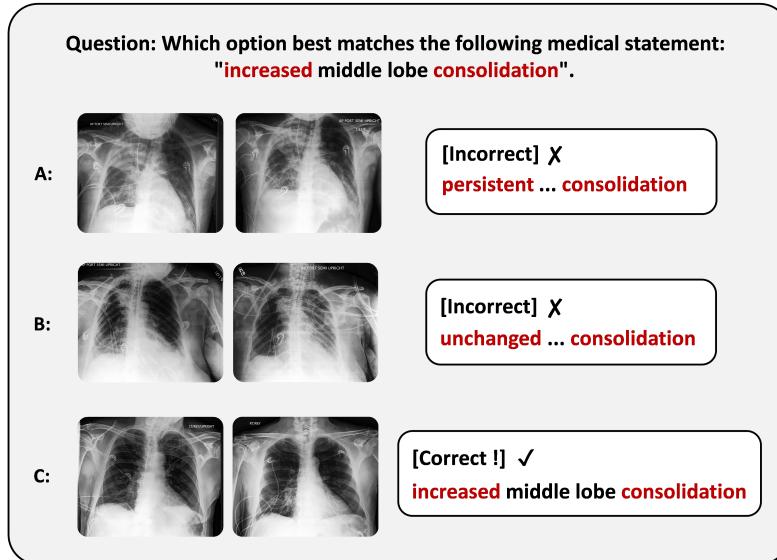


Figure 5: An example of image-pair selection data construction

B EXPERIMENT SETTING DETAILS

B.1 EVALUATION PROMPTS

The following are the evaluation prompts for TEMMED-BENCH, where <image> denotes the image placeholder.

Prompts for VQA Task (Closed-book)

Last visit image: <image>

Current visit image: <image>

You are a professional radiologist. You are provided with two X-ray images from the same patient. The first image is from the last visit, and the second image is from the current visit.

I will ask you a question about the change in condition between the last and current visit of this patient. Please answer the question based on the two images and choose from the following two options: [Yes, No]. Please only include your final choice of 'Yes' or 'No' in your response.

Question: {VQA_QUESTION}

Prompts for VQA Task (Text-only RAG)

You are a professional radiologist. You are provided with a reference X-ray image report:

Report: {RAG_REPORT}

Please learn how to track changes in the patient's condition based on this example.

Now, you are given two new X-ray images from another patient:

Last visit image: <image>

Current visit image: <image>

The first new image is from the last visit, and the second new image is from the current visit. I will ask you a question about the change in condition between the last and current visit of this patient. Note that the diagnostic information from the reference report should not be directly used for diagnosis but only as a reference for comparison.

Please answer the question based on the two new images and choose from the following two options: [Yes, No]. Please only include your final choice of 'Yes' or 'No' in your response.

Question: {VQA_QUESTION}

Prompts for VQA Task (Multi-Modal RAG)

You are a professional radiologist. You are provided with two reference X-ray images from the same patient, along with the corresponding report for the current visit image:

Last visit image: <image>

Current visit image: <image>

Report for the current visit image: {RAG_REPORT}

Please learn how to analyze X-ray images and track changes in the patient's condition based on this example.

Now, you are given two new X-ray images from another patient:

Last visit image: <image>

Current visit image: <image>

The first new image is from the last visit, and the second new image is from the current visit. I will ask you a question about the change in condition between the last and current visit of this patient. Note that the diagnostic information from the reference images and report should not be directly used for diagnosis but only as a reference for comparison.

Please answer the question based on the two new images and choose from the following two options: [Yes, No]. Please only include your final choice of 'Yes' or 'No' in your response.

Question: {VQA_QUESTION}

Prompts for Report Generation Task (Closed-book)

Last visit image: <image>

Current visit image: <image>

You are a professional radiologist. You are provided with two X-ray images from the same patient. The first image is from the last visit, and the second image is from the current visit.

Please generate a report for the current visit image. You should consider the last visit image to analyze the changes in the patient's condition in your report. Please only include the content of the report in your response.

Prompts for Report Generation Task (Text-only RAG)

You are a professional radiologist. You are provided with a reference X-ray image report:

Report: {RAG_REPORT}

Please learn how to track changes in the patient's condition and generate reports based on this example.

Now, you are given two new X-ray images from another patient:

Last visit image: <image>

Current visit image: <image>

The first new image is from the last visit, and the second new image is from the current visit. Please generate a report for the new current visit image. You should consider the new last visit image to analyze the changes in the patient's condition in your report.

Note that the diagnostic information from the reference report should not be directly used for diagnosis but only as a reference for comparison. Please only include the content of the report in your response.

Prompts for Report Generation Task (Multi-Modal RAG)

You are a professional radiologist. You are provided with two reference X-ray images from the same patient, along with the corresponding report for the current visit image:

Last visit image: <image>

Current visit image: <image>

Report for the current visit image: {RAG_REPORT}

Please learn how to analyze X-ray images, track changes in the patient's condition, and generate reports based on this example.

Now, you are given two new X-ray images from another patient:

Last visit image: <image>

Current visit image: <image>

The first new image is from the last visit, and the second new image is from the current visit. Please generate a report for the new current visit image. You should consider the new last visit image to analyze the changes in the patient's condition in your report.

Note that the diagnostic information from the reference images and report should not be directly used for diagnosis but only as a reference for comparison. Please only include the content of the report in your response.

Prompts for Image-pair Selection Task (Closed-book)

A:

Last visit image: <image>

Current visit image: <image>

B:

Last visit image: <image>

Current visit image: <image>

C:

Last visit image: <image>

Current visit image: <image>

You are a professional radiologist. You are provided with three pairs of X-ray images. Each pair contains two X-ray images from the same patient. The first image in each pair is from the last visit, and the second one is from the current visit. Your task is to choose one of the options, based on the condition change from the last to the current visit, that best matches the following medical statement: '{MEDICAL_STATEMENT}'.

Please provide your answer by selecting the corresponding letter from the given choices.
Please provide your final answer in the format: 'My answer is [option]' at the end of your response.

Prompts for Image-pair Selection Task (Multi-Modal RAG)

You are a professional radiologist. You are provided with two reference X-ray images from the same patient, along with the corresponding report:

Last visit image: <image>

Current visit image: <image>

Report: {RAG_REPORT}

Please learn how to analyze X-ray images and track changes in the patient’s condition based on this example.

Now, you are provided with three pairs of X-ray images:

A:

Last visit image: <image>

Current visit image: <image>

B:

Last visit image: <image>

Current visit image: <image>

C:

Last visit image: <image>

Current visit image: <image>

Each pair contains two X-ray images from the same patient. The first image in each pair is from the last visit, and the second one is from the current visit. Your task is to choose one of the options, based on the condition change from the last to the current visit, that best matches the following medical statement: '[MEDICAL_STATEMENT]’.

Please provide your answer by selecting the corresponding letter from the given choices. Please provide your final answer in the format: ‘My answer is [option]’ at the end of your response.

B.2 RETRIEVAL AUGMENTATION FOR THE IMAGE-PAIR SELECTION TASK

For the image-pair selection task, the input format differs significantly from the other two tasks: there are three target image-pairs rather than one, and it is unknown which pair is the correct answer. This setting prevents us from using image features to retrieve instances that match the medical statement in the question. Therefore, we adopt a text-to-text retrieval approach. Specifically, we represent the medical statement in the question and each report in the knowledge corpus using their corresponding TF-IDF embeddings. The relevance score between the medical statement med_s and each report t is then computed as follows:

$$Score = \text{Sim}(\text{TF-IDF}(med_s), \text{TF-IDF}(t)), \quad (3)$$

where TF-IDF denotes TF-IDF embedding function, and Sim denotes cosine similarity. The retrieved report, along with its corresponding historical image and current image, is then used as a retrieved instance.

Additionally, We argue that, in the image-pair selection task, text-only retrieval augmentation is not meaningful. In this setting, there are three target image-pairs, and the retrieved report simply describes a condition similar to that in the medical statement of the question. Without the images corresponding to the retrieved report, this report merely restates the information already present in the medical statement. As a result, the model cannot effectively make use of the retrieved report. Only when the corresponding images are provided can the model compare each target image-pair with the retrieved image-pair, thereby making meaningful use of the retrieved report.

C ADDITIONAL DISCUSSION

C.1 DISCUSSION ON THE TOP-1 RETRIEVAL HACK

Benchmarks	Model	Report Generation			
		BLEU	ROUGE-L	METEOR	Avg.
IU-Xray	MMed-RAG	31.38	25.59	32.43	29.80
	Top-1 Retrieval Hack	31.61	26.68	31.79	30.03
MIMIC-CXR	MMed-RAG	23.25	12.34	20.47	18.69
	Top-1 Retrieval Hack	26.16	19.99	25.28	23.81
TEMMED-BENCH (Ours)	HealthGPT (fine-tuned)	25.34	27.45	26.45	26.41
	Top-1 Retrieval Hack	24.24	22.11	24.15	23.50

Table 8: Evaluation results of top-1 retrieval hack. For each benchmark, the higher score is highlighted in red, and the lower score is highlighted in blue.

The evaluation results of the top-1 retrieval hack are shown in Table 8. We report the score for the top-1 retrieval hack, where the top-1 retrieved report is used directly as the answer. We also evaluate the performance of the model, which has already been fine-tuned on each benchmark, in the text-only retrieval augmentation setting. For the IU-Xray (Demner-Fushman et al., 2015) and MIMIC-CXR (Johnson et al., 2019) benchmarks, we use the RAG-based model MMed-RAG (Xia et al., 2025), while for TEMMED-BENCH, we fine-tune HealthGPT (Lin et al., 2025) on our knowledge corpus and use it for experiments.

Experimental results indicate that, on IU-Xray and MIMIC-CXR, simply taking the top-1 retrieved report as the answer even outperforms the fine-tuned models in the retrieval-augmented setting. However, TEMMED-BENCH is more robust to this hack. We argue that this is because previous benchmarks are conducted in a single-visit image analysis setting, which place more emphasis on pattern recognition and matching. Therefore, the demand for reasoning based on retrieved information to arrive at the answer is not high. In contrast, TEMMED-BENCH, due to its emphasis on reasoning, encourages models to leverage the retrieved information to perform reasoning over images, rather than simply copying or rephrasing the retrieved information, making it more robust to this hack.

C.2 DISCUSSION ON THE DATA COLLECTION

Right Input		Random Historical Image		Random Current Image	
Acc	F1	Acc	F1	Acc	F1
79.15	78.94	59.20 _{-19.95}	58.74 _{-20.20}	54.15 _{-25.00}	53.97 _{-24.97}

Table 9: Evaluation results of GPT o4-mini under the random historical image and random current image settings. Relative performance changes compared to the right input setting are shown as subscripts, with blue indicating drops.

To ensure the effectiveness of our data collection method, we conduct two additional experiments. Given the strong performance of GPT o4-mini on the VQA task, we select this setting as our baseline. Specifically, in the *Random Historical Image* experiment, we replace the historical image in each data sample with a random image; in the *Random Current Image* experiment, we replace the current image in each data sample with a random image.

As shown in Table 9, experimental results demonstrate that either replacing the historical image or replacing the current image leads to a significant decrease in performance. The model’s performance drops to less than 60%, which is close to the level of random guessing. This indicates that both the collected historical and current images are essential for the model to achieve optimal performance, suggesting that our data collection method is effective.

	Retrieval Method	HealthGPT		GPT 4o	
		Acc	F1	Acc	F1
Text-only RAG	Image-to-Text	58.90	56.77	57.90	57.46
	Image-to-Image	58.15	55.95	60.05	59.54
	Pairwise Image	59.05	57.13	60.10	59.57
Multi-Modal RAG	Image-to-Text	65.75	64.19	61.60	61.09
	Image-to-Image	68.45	67.17	64.35	63.81
	Pairwise Image	69.90	68.71	64.85	64.42

Table 10: Ablation study on GPT 4o and HealthGPT. The pairwise image retrieval method demonstrates the best performance on both models.

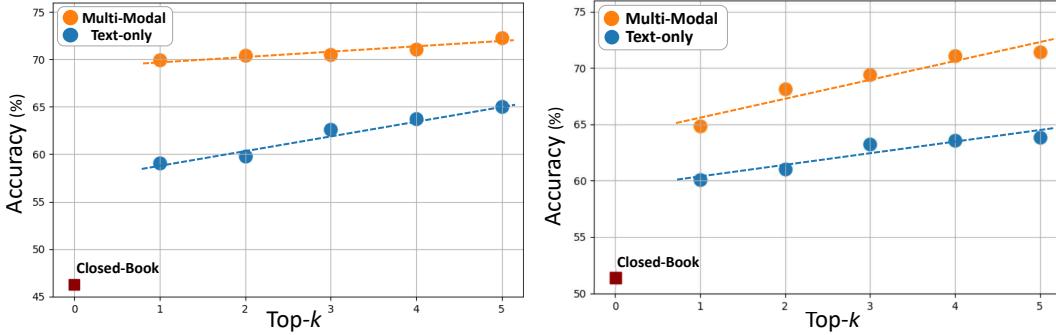


Figure 6: Results of top-1 to top-5 retrieval augmentation on HealthGPT (left) and GPT 4o (right). The orange line indicates multi-modal retrieval augmentation, while the blue line indicates text-only retrieval augmentation. The red square shows model performance without retrieval augmentation.

C.3 DISCUSSION ON MODEL PERFORMANCE

Low F1 Scores of LVLMs in the Closed-Book Setting For the evaluation results shown in Table 3, We noticed that the F1 score of LLaVA-Med is much lower than 50%, being only 35.23%. This is because LLaVA-Med tends to consistently output "Yes" when it is unable to answer a question, rather than randomly guessing between "Yes" and "No". As a result, the model's output exhibits a highly imbalanced class distribution, which leads to the low F1 score.

Performance Gains of LVLMs with Retrieval Augmentation Based on the retrieval augmentation results in Table 4, we noticed that, for the VQA task, the performance gains of some open-source LVLMs are greater than those of proprietary LVLMs. Take HealthGPT and GPT-4o as examples. Although HealthGPT performs worse than GPT-4o under the closed-book setting, after adding Multi-Modal RAG, HealthGPT achieves 69.90% accuracy, even outperforming GPT-4o's 64.85% accuracy. We believe that this may be attributable to the limited ability of most LVLMs to analyze condition changes, whereas proprietary LVLMs tend to rely more on their own knowledge when incorporating retrieved information.

We evaluated the performance of the models when answering questions based solely on the retrieved information. More specifically, we prompted the models to answer the questions based only on the retrieved information without being given target images. We found that when they fully trust the retrieved information, HealthGPT and GPT-4o achieve 68.40% and 69.55% accuracy, respectively. These results indicate that GPT-4o refuses to trust the retrieved information for part of the questions in Multi-Modal RAG experiment, and since its own knowledge is limited in analyzing condition changes, this reliance on its own knowledge redirects GPT-4o to the wrong answer. In contrast, HealthGPT tends to rely more on the retrieved knowledge, leading to relatively higher performance. This observation further underscores the need to enhance LVLMs' capacity to analyze changes in the patients' conditions and to make informed judgments on whether to trust retrieved information or to rely on their own knowledge.

C.4 ADDITIONAL ANALYSIS OF MULTI-MODAL RETRIEVAL AUGMENTATION

Ablation Study on Retrieval Methods Table 10 presents ablation studies of different retrieval methods for two models. The results indicate that pairwise image retrieval achieves the highest performance on both the proprietary model GPT-4o and the open-source model HealthGPT.

Impact of Top- k Retrieval Augmentation Figure 6 shows the performance of GPT-4o and HealthGPT across top-1 to top-5 retrieval augmentation settings. For both models, multi-modal retrieval augmentation consistently outperforms text-only retrieval augmentation. Furthermore, by comparing the performance improvement from top-1 to top-5, we observe that GPT-4o demonstrates a significantly higher increase in accuracy (6.6%) compared to HealthGPT (2.37%). These results suggest that LVLMs with superior multi-image processing capabilities derive greater benefits from an increased number of retrieved instances, underscoring the importance of enhancing multi-image processing ability to fully leverage multi-modal retrieved information.