DrVD-Bench: Do Vision-Language Models Reason Like Human Doctors in Medical Image Diagnosis?

Tianhong Zhou[1*] **Yin Xu**[1*] **Yingtao Zhu**[1*] **Chuxi Xiao**[1]
Haiyang Bian[2†] **Lei Wei**[1†] **Xuegong Zhang**[1]
[1]Tsinghua University
[2]Alibaba Cloud Computing

Abstract

Vision–language models (VLMs) exhibit strong zero-shot generalization on natural images and show early promise in interpretable medical image analysis. However, existing benchmarks do not systematically evaluate whether these models truly reason like human clinicians or merely imitate superficial patterns. To address this gap, we propose DrVD-Bench, the first multimodal benchmark for clinical visual reasoning. DrVD-Bench consists of three modules: *Visual Evidence Comprehension*, *Reasoning Trajectory Assessment*, and *Report Generation Evaluation*, comprising a total of 7,789 image–question pairs. Our benchmark covers 20 task types, 17 diagnostic categories, and five imaging modalities—CT, MRI, ultrasound, radiography, and pathology. DrVD-Bench is explicitly structured to reflect the clinical reasoning workflow from modality recognition to lesion identification and diagnosis. We benchmark 19 VLMs, including general-purpose and medical-specific, open-source and proprietary models, and observe that performance drops sharply as reasoning complexity increases. While some models begin to exhibit traces of human-like reasoning, they often still rely on shortcut correlations rather than grounded visual understanding. DrVD-Bench offers a rigorous and structured evaluation framework to guide the development of clinically trustworthy VLMs.
Dataset: Kaggle, Hugging Face **Code:** GitHub

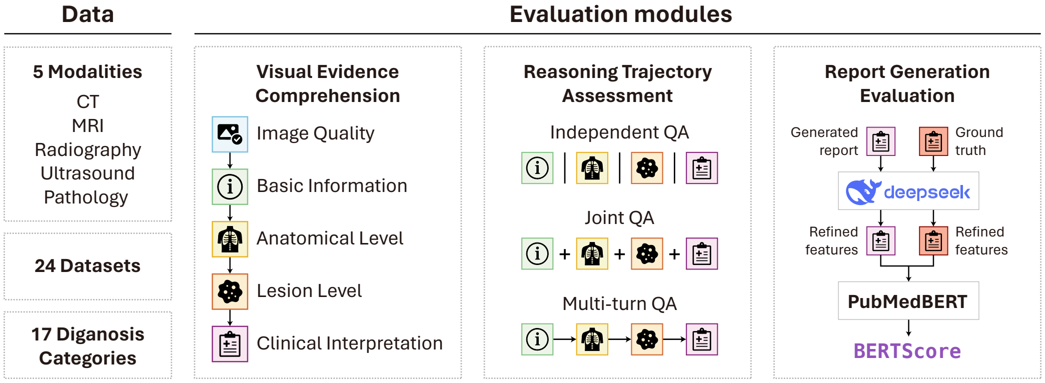

Figure 1: Overview of the DrVD-Bench

[*]Equal contribution.
[†]Corresponding authors: bianhaiyang.bhy@alibaba-inc.com, weilei92@tsinghua.edu.cn

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1 Introduction

The lack of interpretability in AI-driven diagnostic systems has long been a critical barrier to their adoption in clinical practice [87, 36]. Vision-Language Models (VLMs) [29, 18, 14, 27, 74, 35, 90] offer a promising direction toward interpretable medical AI, as they can generate outputs that mimic the stepwise clinical reasoning process of physicians [72, 13, 66]. In clinical settings, physicians arrive at diagnosis by progressively integrating information across multiple levels—ranging from basic image features to anatomical structures and lesion characteristics—before synthesizing this evidence step-by-step into a clinical diagnostic report. Despite the increasing adoption of VLMs in analyzing medical images, there exists no benchmark that systematically evaluates whether these models follow a similar reasoning trajectory or merely rely on memorized patterns and spurious shortcuts.

To address this gap, we introduce DrVD-Bench (Doctor-like Visual Diagnosis Benchmark), the first benchmark explicitly designed to evaluate the understanding and reasoning capabilities of VLMs in medical image analysis. DrVD-Bench comprises three complementary modules: (i) *Visual Evidence Comprehension*, containing 4,480 high-quality image–question pairs structured to mirror the each step of clinical reasoning, assessing how well models identify essential visual cues and generate diagnoses; (ii) *Reasoning Trajectory Assessment*, consisting of 487 images with 3,321 question–answer turns that emulate the progressive reasoning process of clinicians and evaluate whether models reason step by step or rely on shortcuts; and (iii) *Report Generation Evaluation*, comprising 475 questions aimed at assessing holistic understanding through free-form clinical report generation.

Modules 1 and 2 are explicitly designed to reflect the clinical reasoning workflow—from modality recognition to anatomical localization, lesion characterization, and final diagnosis. This workflow is defined as follows:

- **Level 0: Image Quality Assessment** — Detecting artifacts or noise; typically handled during acquisition.
- **Level 1: Basic Information Extraction** — Identifying modality, body region, view, etc.; often available as metadata in clinical settings.
- **Level 2: Anatomy-Level Recognition** — Recognizing and localizing anatomical structures (e.g., organs, tissues).
- **Level 3: Lesion-Level Identification** — Detecting, localizing, and describing abnormalities such as lesions or fractures.
- **Level 4: Clinical Interpretation** — Integrating visual findings to produce a diagnosis or generate a structured report.

By organizing tasks into stepwise levels, DrVD-Bench enables fine-grained analysis of VLM performance—not only in terms of final diagnostic predictions, but also in their capacity to extract intermediate visual evidence and engage in coherent reasoning. This structure allows us to examine whether models genuinely analyze medical images by identifying key visual cues and reasoning in a step-by-step manner, akin to human clinicians. In the *Visual Evidence Comprehension* module, we introduce specially designed *organ erasure* and *lesion erasure* tasks, which compel models to rely on visible image content rather than memorized associations, thereby mitigating potential information leakage from pretraining. The *Reasoning Trajectory Assessment* module includes three distinct QA formats—*Independent QA*, *Joint QA*, and *Multi-turn QA*, —with the latter specifically enforcing a stepwise reasoning pattern that mirrors clinical workflows. Except for this module, all other stages adopt an independent QA format, where each question is presented in isolation without shared context. Finally, unlike previous benchmarks that limit report generation to specific modalities [41, 75, 93] such as radiographs or CT scans, our *Report Generation Evaluation* module introduces a setting to assess models' holistic understanding across diverse imaging modalities.

We evaluated 19 publicly available VLMs, including both general purpose and medical-specific models (see Table 3). Our key findings are summarized as follows:

- **Reasoning performance declines with task complexity:** VLMs perform well on low-level visual tasks such as modality or view recognition, but their accuracy drops substantially on higher-level tasks involving anatomical understanding, lesion localization, and diagnosis.

- **Correct answers without supporting evidence:** Many models achieve higher diagnostic accuracy than their performance on lesion-level tasks, suggesting they can produce correct diagnoses without fully understanding or localizing the supporting visual evidence.
- **Limited capacity for stepwise clinical reasoning:** Models perform best when provided with all questions at once (Joint QA), but struggle in Multi-turn QA, suggesting difficulty with maintaining dialogue state and reasoning trajectories.
- **Hallucinations in report generation:** In free-form generation tasks, models often produce plausible but unsupported statements, revealing challenges in grounding clinical language in image evidence.
- **Smaller, specialized models can compete:** While larger and newer models generally perform better, domain-optimized models demonstrate strong performance relative to their scale, highlighting the value of medical-specific alignment.

2 Related Works

2.1 Vision-Language Models

Modern vision-language models (VLMs) build upon the reasoning capabilities and world knowledge of large language models (LLMs) by aligning visual inputs with the textual domain [90]. For instance, LLaVA [45] introduces a multi-layer perceptron (MLP)[59] to bridge a vision encoder (e.g., CLIP [62]) with a language model backbone, enabling the system to perform tasks such as interpreting scientific figures [82] and understanding cartoons [47]. VLMs have also been adapted for the medical domain [42, 89, 39]. For example, LLaVA-Med [39], derived from LLaVA, is fine-tuned on medical data to adapt the model for healthcare-specific tasks. Although VLMs have shown impressive performance on general visual reasoning tasks [16, 88, 32, 51], it remains uncertain whether they truly comprehend medical images or merely rely on prior knowledge and pattern matching [17, 77, 60, 37].

2.2 Medical VLM Benchmarks

The application of VLMs in medicine demands benchmarks with broad coverage and fine-grained, clinically relevant evaluation. However, most existing benchmarks remain narrow in scope (see Table 1), typically limited to single modalities or task types. For example, PathMMU [73], VQA-RAD [38], and PMC-VQA [92] focus primarily on visual question answering (VQA) within specific imaging domains, limiting generalizability and diagnostic depth.

Recent benchmarks introduce hierarchical structures [58, 85, 31], but these do not align with the stepwise nature of clinical reasoning. GMAI-MMBench [85], for instance, organizes questions by perceptual complexity rather than reasoning stages. OmniMedVQA [31] covers diverse tasks like modality recognition and diagnosis but lacks a clinically grounded task progression, grouping questions only by type. As a result, current benchmarks fall short in evaluating whether VLMs reason like clinicians. A critical gap remains: we lack a benchmark that not only measures answer correctness but also reveals how and why models succeed or fail—essential for assessing clinical reasoning ability.

Table 1: Comparison of Medical VLM Benchmarks

Benchmark	Imaging modalities	Task hierarchy	Clinical reasoning	Task types
VQA-RAD[38]	Radiography, CT	✗	✗	VQA
SLAKE[44]	Radiography, CT, MRI	✗	✗	VQA
PMC-VQA [92]	CT, MRI, and others	✗	✗	VQA
Rad-ReStruct [58]	Radiography	✓	✗	VQA
GMAI-MMBench[85]	CT, MRI, Radiography, Ultrasound, Pathology	✓	✗	VQA
PathMMU[73]	Pathology	✗	✗	VQA
OmniMedVQA[31]	12 modalities	✓	✗	VQA
CARES[79]	16 modalities	✗	✗	VQA
MultiMedEval[68]	$\geq$ 11 modalities	✗	✗	VQA, open QA, and others
DrVD-Bench	5 modalities	✓ (stepwise)	✓	VQA, report generation

3 Design of DrVD-Bench

3.1 Overview

We propose DrVD-Bench, a multi-scale benchmark for systematically evaluating vision–language models (VLMs) in the medical domain. Inspired by the diagnostic workflow of clinicians, DrVD-Bench defines a three-module framework that evaluates VLMs from three aspects: (i) Reliability in visual evidence extraction; (ii) Ability in stepwise clinical reasoning; and (iii) Comprehensive understanding of medical image-revealed by the ability in report generation. Representative examples are shown in Figure 2.

DrVD-Bench comprises three modules: (1) **Visual Evidence Comprehension**, containing 4,480 expert-curated image–question pairs across 16 tasks, structured by the depth of clinical reasoning, from the superficial modality recognition to the deep lesion-level identification and diagnosis. To reduce reliance on shortcuts, we introduce **organ** and **lesion erasure** tasks that force models to reason from visible evidence. (2) **Reasoning Trajectory Assessment**, with 3,321 QA turns on 487 images, evaluates whether models reason step by step using three prompting formats: **Joint QA**, **Independent QA**, and **Multi-turn QA**. (3) **Report Generation Evaluation**, spanning all the five modalities, it contains 475 questions aimed at assessing holistic understanding through free-form clinical report generation. See Appendix A.2 for the detailed composition of our benchmark.

Together, these components enable fine-grained analysis of VLMs' clinical visual understanding and diagnostic reasoning.

3.2 Dataset Collection and Task Construction

3.2.1 Data Collection

This study systematically aggregates multi-modal medical images (CT, MRI, ultrasound, X-ray, and pathology) from 24 publicly available datasets and online repositories (See Table 8 in Appendix A). These sources encompass a wide range of imaging scales, including panoramic, organ-level, and histopathological views. Only images with a resolution of at least 256 × 256 are retained to ensure sufficient visual clarity for structural and anatomical interpretation;

3.2.2 Task Overview

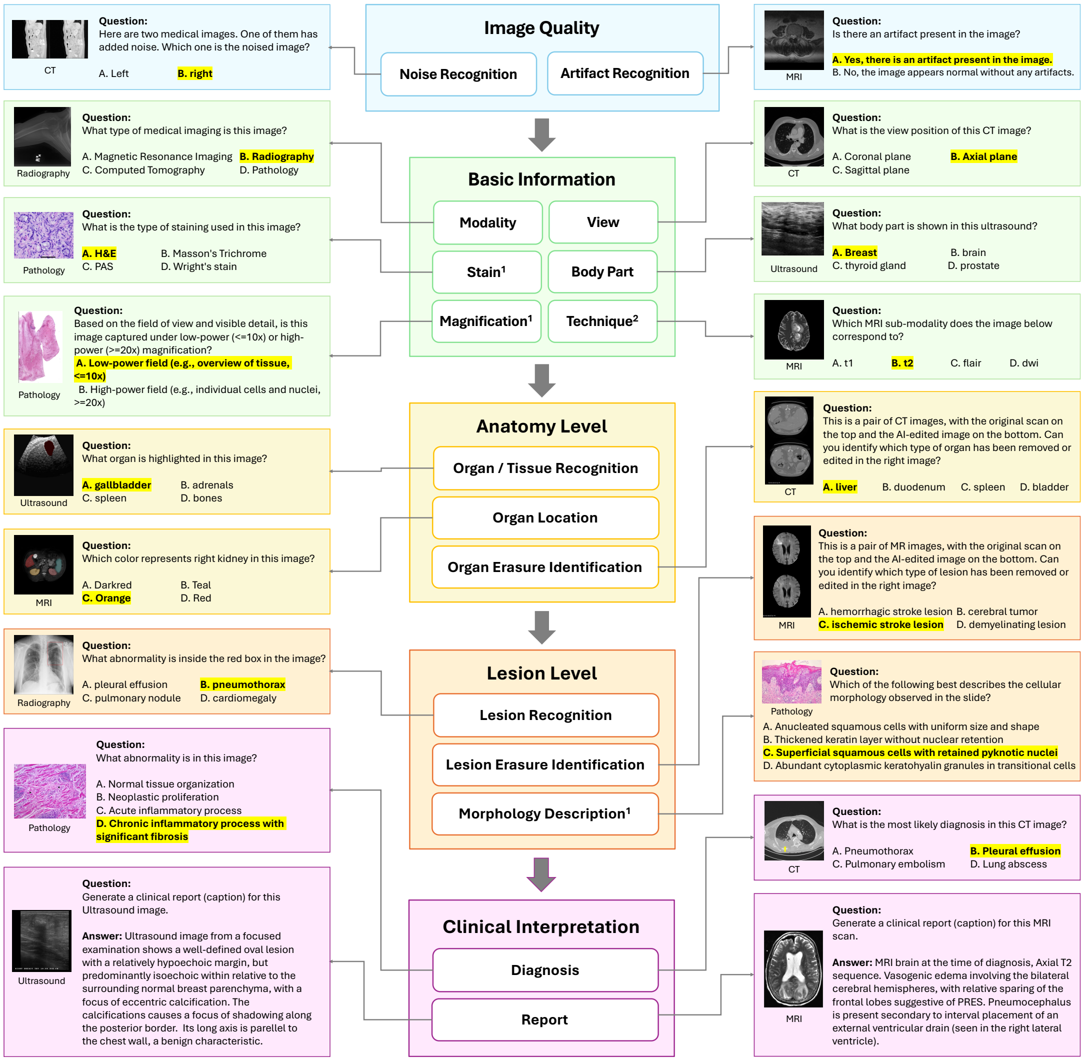
To enable fine-grained evaluation of models' intermediate reasoning in medical image analysis, DrVD-Bench organizes all QA tasks (except report generation) into a five-level hierarchy that mirrors the cognitive stages of clinical diagnosis. Each level targets a distinct reasoning step:

- **Level 0 (Image Quality):** noise and artifact detection.
- **Level 1 (Basic Information):** modality, view, body part, magnification, stain, and imaging technique recognition.
- **Level 2 (Anatomy Level):** organ/tissue identification, localization, and organ-erasure detection.
- **Level 3 (Lesion Level):** lesion recognition, lesion-erasure detection, and morphological description.
- **Level 4 (Clinical Interpretation):** diagnostic classification.

The *Visual Evidence Comprehension* module includes tasks from all levels, with each image paired with a single QA focused on one aspect of visual understanding. In contrast, the *Reasoning Trajectory Assessment* module evaluates multi-level reasoning per image by combining one task from each level (e.g., modality, body part, organ, lesion, diagnosis). It offers three prompting formats: **Joint QA** presents all questions at once; **Independent QA** asks them sequentially; and **Multi-turn QA** incorporates the model's prior response into subsequent prompts, simulating stepwise reasoning.

3.2.3 Dataset and QA Pair Construction

To support diverse evaluation objectives, we employ task-specific dataset construction strategies. For noise robustness, we simulate modality-specific clinical noise at three PSNR levels—15, 25, and 35



Question:
Here are two medical images. One of them has added noise. Which one is the noised image?
A. Left B. right

Question:
What type of medical imaging is this image?
A. Magnetic Resonance Imaging B. Radiography
C. Computed Tomography D. Pathology

Question:
What is the type of staining used in this image?
A. H&E B. Masson's Trichrome
C. PAS D. Wright's stain

Question:
Based on the field of view and visible detail, is this image captured under low-power (<=10x) or high-power (>=20x) magnification?
A. Low-power field (e.g., overview of tissue, <=10x)
B. High-power field (e.g., individual cells and nuclei, >=20x)

Question:
What organ is highlighted in this image?
A. gallbladder B. adrenals
C. spleen D. bones

Question:
Which color represents right kidney in this image?
A. Darkred B. Teal
C. Orange D. Red

Question:
What abnormality is inside the red box in the image?
A. pleural effusion B. pneumothorax
C. pulmonary nodule D. cardiomegaly

Question:
What abnormality is in this image?
A. Normal tissue organization
B. Neoplastic proliferation
C. Acute inflammatory process
D. Chronic inflammatory process with significant fibrosis

Question:
Generate a clinical report (caption) for this Ultrasound image.

Answer: Ultrasound image from a focused examination shows a well-defined oval lesion with a relatively hypoechoic margin, but predominantly isoechoic within relative to the surrounding normal breast parenchyma, with a focus of eccentric calcification. The calcifications causes a focus of shadowing along the posterior border. Its long axis is parellel to the chest wall, a benign characteristic.

Question:
Is there an artifact present in the image?
A. Yes, there is an artifact present in the image.
B. No, the image appears normal without any artifacts.

Question:
What is the view position of this CT image?
A. Coronal plane B. Axial plane
C. Sagittal plane

Question:
What body part is shown in this ultrasound?
A. Breast B. brain
C. thyroid gland D. prostate

Question:
Which MRI sub-modality does the image below correspond to?
A. t1 B. t2 C. flair D. dwi

Question:
This is a pair of CT images, with the original scan on the top and the AI-edited image on the bottom. Can you identify which type of organ has been removed or edited in the right image?
A. liver B. duodenum C. spleen D. bladder

Question:
This is a pair of MR images, with the original scan on the top and the AI-edited image on the bottom. Can you identify which type of lesion has been removed or edited in the right image?
A. hemorrhagic stroke lesion B. cerebral tumor
C. ischemic stroke lesion D. demyelinating lesion

Question:
Which of the following best describes the cellular morphology observed in the slide?
A. Anucleated squamous cells with uniform size and shape
B. Thickened keratin layer without nuclear retention
C. Superficial squamous cells with retained pyknotic nuclei
D. Abundant cytoplasmic keratohyalin granules in transitional cells

Question:
What is the most likely diagnosis in this CT image?
A. Pneumothorax B. Pleural effusion
C. Pulmonary embolism D. Lung abscess

Question:
Generate a clinical report (caption) for this MRI scan.

Answer: MRI brain at the time of diagnosis, Axial T2 sequence. Vasogenic edema involving the bilateral cerebral hemispheres, with relative sparing of the frontal lobes suggestive of PRES. Pneumocephalus is present secondary to interval placement of an external ventricular drain (seen in the right lateral ventricle).

Figure 2: Hierarchical five-level evaluation framework for medical imaging diagnostics. Representative tasks—spanning CT, MRI, ultrasound, radiography, and pathology—are shown alongside their corresponding stage in the clinical reasoning cascade. Tasks labeled with [1] are exclusive to pathology, and those with [2] are exclusive to MRI.

dB—representing severe, moderate, and mild interference per clinical standards. Recognition and localization tasks include bounding box and region annotations for relevant anatomical or pathological areas. To assess sensitivity to local visual cues, we introduce an erasure task: using the Bailian high-throughput image platform, targeted anatomical or lesion regions are digitally removed while preserving structural continuity. All modified images are manually verified to ensure artifact-free erasure and reliable evaluation of visual evidence dependence.

The *Reasoning Trajectory Assessment* module builds on the *Visual Evidence Comprehension* question format but varies in structure and prompting. Independent QA pairs one image with multiple questions at different reasoning levels. Joint QA bundles sub-questions from multiple levels into a single prompt for simultaneous response. Multi-turn QA sequentially passes earlier responses into higher-level questions, simulating stepwise reasoning (See Appendix Figure 12).

For *Report Generation Evaluation*, we frame the task as medical captioning, using curated ground-truth references from PubMedVision [15] and PathMMU [73] that provide detailed clinical explanations.

All QA pairs are authored by physicians based on task objectives (e.g., modality recognition, localization, diagnosis) and span both closed-form and open-ended formats. Each is blind-reviewed by a senior clinician to ensure clinical relevance, visual grounding, and diagnostic realism. Distractors are carefully curated to remain plausible, and all questions are self-contained, unambiguous, and visually answerable. Data distribution is summarized in Table 2.

4 Experiments

4.1 Experiment Setup

In this study, we evaluated a total of 19 models (Table 3), including general-purpose open-source models, proprietary models accessed via API calls, and fine-tuned medical vision models. The parameter sizes of open-source models range from 7B to 72B. All experiments were conducted under a standardized zero-shot evaluation framework using system prompts on 8×NVIDIA A100 GPUs (80GB each). This setup ensures consistent and fair comparisons across different model architectures while maintaining reliable performance benchmarking.

Table 2: Statistics of DrVD-Bench

Category	**Metric**	**Count**
Module 1: Visual Evidence Comprehension		
Total QA pairs		4,480
Level 0: Image Quality	QA pairs	591
Level 1: Basic Information	QA pairs	1,400
Level 2: Anatomy	QA pairs	1,151
Level 3: Lesion	QA pairs	890
Level 4: Clinical Interpretation	QA pairs	923
Module 2: Reasoning Trajectory Assessment		
Total images		487
Independent QA	QA pairs	2,347
Joint QA	QA pairs	487
Multi-turn QA	QA pairs	487
CT/MRI/Radiography/US	images each	100
Pathology	images	87
Module 3: Report Generation Evaluation		
Open-ended QA pairs		475
Global Dataset Statistics		
Total QA pairs (all modules)		7,789
Organ/Tissue classes		38
Lesion classes		27
Diagnosis categories		17

Table 3: VLMs benchmarked in our study

Model	**Developer**	**Year**
Proprietary		
GPT-4o[54]	OpenAI	2024.11
GPT-o1[55]	OpenAI	2024.12
GPT-o3[53]	OpenAI	2025.04
Gemini 2.5 Pro[25]	Google	2025.03
Grok-3[78]	xAI	2025.02
Doubao1.5-VisionPro [11]	ByteDance	2025.01
Claude 3.7 Sonnet[4]	Anthropic	2025.02
Open-source		
Qwen2.5-VL [6]	Alibaba	2025.01
Phi-4 14B [1]	Microsoft	2024.12
GLM-4V [23]	Tsinghua	2024.06
Janus-Pro-7B [19]	DeepSeek	2025.01
Medical-specific		
HuatuoGPT-Vision-34B [15]	CUHK	2024.06
HealthGPT-L14B [42]	ZJU	2025.02
RadFM-14B [76]	PJLAB	2023.12
LLaVA-Med-7B [39]	Microsoft	2024.04

4.2 Evaluation

In DrVD-Bench, we use accuracy to evaluate multiple-choice tasks, each with a single correct answer. If the model's output conforms to the expected format, we directly compare it with the ground truth to determine correctness. For responses that deviate from the format, we apply DeepSeek-V3 [43] to extract the selected option. If extraction fails, the answer is marked as incorrect (See Appendix D). All results are averaged over five independent runs to ensure robustness. Accuracy is computed per question and then averaged within each level to obtain level-specific scores.

For open-ended tasks such as report generation, we employ DeepSeek-V3 [43] to extract key features from both the model's response and the reference text. We then adopt BERTScore [91] with PubMedBERT [26] to capture biomedical semantics of the generated data. To enable consistent comparison, we normalize BERTScore using the baseline (See Appendix B) and best-performing model. Let s_{model} be the model's BERTScore, s_{baseline} the score of an irrelevant response, and s_{best}

the highest score observed. The normalized score is:

$$\text{Normalized BERTScore} = \frac{s_{\text{model}} - s_{\text{baseline}}}{s_{\text{best}} - s_{\text{baseline}}}$$

In addition, to further evaluate factual consistency and hallucination in report generation, we incorporate FActScore [50] as a complementary metric. FActScore first extracts atomic-level clinical facts from both the reference and generated reports using DeepSeek-v3, followed by fact-level matching with GPT-4o. We compute two indicators: recall, which measures the proportion of true facts correctly captured by the model, and specificity, which measures the proportion of generated facts supported by the reference. Low recall and specificity respectively reflect insufficient factual coverage and the presence of hallucinated content.

5 Results Analysis

5.1 Models' Performance on Visual Evidence Comprehension

5.1.1 Models Perform Differently Across Task Levels

Table 4 presents the evaluation results for CT modality tasks, with results for other modalities provided in Appendix B. Across all models, we observe a consistent decline in performance as the reasoning level increases. While most models perform well on basic recognition tasks such as identifying the imaging modality or view, their accuracy drops markedly on tasks requiring organ-level understanding, and declines even further on lesion-level reasoning. For instance, GPT-o3 achieves 86% accuracy on Basic Information tasks, decreases to 66% on Organ-Level tasks, and further falls to 41% on Lesion-Level tasks. This trend reflects a clear gap between surface-level visual parsing and clinically meaningful reasoning. As tasks increasingly demand multi-step inference and integration of both global context and local features, model performance becomes less stable and less reliable. These results highlight the limitations of current VLMs in replicating the fine-grained, layered reasoning processes central to clinical diagnosis.

Table 4: **Accuracy of different VLMs across different task levels.** The best-performing scores are highlighted in **red**, and the second-best in **blue**. Due to the large number of tasks across imaging modalities, we only present the performance of different models on task levels here. Results for the detailed subtasks among five modalities (CT, MRI, Ultrasound, Radiography, and Pathology) are provided in Appendix B. These are recognition subtasks across reasoning levels.

Model	Image Quality	Basic Info	Anatomy Level	Lesion Level	Diagnosis
Random	49	29	27	25	24
Proprietary					
GPT-4o	68	84	57	50	54
GPT-o1	56	71	44	37	39
GPT-o3	69	**86**	**66**	41	48
Claude 3.7 Sonnet	68	83	60	42	48
Gemini 2.5 Pro	**76**	**88**	**65**	52	54
Grok-3	63	78	56	45	51
Doubao-VisionPro	63	82	52	**59**	52
Qwen-VL-MAX	65	78	54	**56**	53
Open-source					
Qwen2.5-VL-72B	65	77	54	**56**	52
LLaVA-1.6-34B	61	60	38	49	46
Qwen2.5-VL-32B	61	73	51	48	**56**
Phi-4-14B	**70**	68	39	44	47
GLM-4V-9B	65	70	43	32	36
Qwen2.5-VL-7B	68	69	41	45	38
Janus-Pro-7B	59	68	44	39	**56**
Medical-specific					
HuaTuoGPT-Vision-34B	61	85	58	54	**59**
HealthGPT-L14B	56	77	46	41	53
RadFM-14B	52	61	33	38	31
LLaVA-Med-7B	52	49	34	32	29

5.1.2 Overdiagnosis without Understanding

Notably, as shown in Table 4, many models perform better on diagnosis tasks than on lesion recognition, revealing a disconnect between output accuracy and reasoning fidelity. In other words, models can produce clinically plausible diagnostic results without actually identifying the supporting lesion evidence, a phenomenon we term "overdiagnosis without understanding".

This gap likely stems from biases in training data. Most VLMs are trained on image–report pairs that provide final diagnoses (e.g., "pneumonia", "fracture") but omit intermediate steps such as lesion localization or characterization. As a result, models tend to learn global pattern-to-label mappings, bypassing the step-by-step reasoning process that underpins clinical decision-making.

The issue becomes especially pronounced in zero-shot settings that demand fine-grained lesion-level reasoning. As shown in Table 11 (Appendix B), in CT lesion erasure detection, GPT-o3 and Gemini 2.5 Pro perform worse than random (19% and 16%, respectively), and achieve only 28% accuracy on lesion-level tasks—indicating a failure to recognize missing lesion evidence. Yet, on CT diagnosis tasks, they attain substantially higher accuracy (52% and 71%, respectively). This stark discrepancy suggests that diagnostic conclusions can be produced without properly grounding in anatomically or lesion-relevant visual features.

This behavior raises fundamental concerns about the reliability and clinical validity of current models. Despite producing seemingly accurate outputs, many models struggle with evidence-based reasoning, especially when visual grounding is essential to safe and explainable diagnosis.

5.2 Models Prefer Global Context over Step-by-Step Clinical Reasoning

Our benchmark reveals a clear performance hierarchy across the three reasoning settings (Table 5): Joint QA achieves the best overall results, followed by Independent QA, while Multi-turn QA performs the worst. In the Joint QA setting, where the model receives the full sequence of questions at once, it can reason more effectively by integrating global context and avoiding cumulative errors. Independent QA, where each question is asked separately without memory of previous turns, provides more stable but fragmented reasoning, leading to limited performance in higher-order tasks such as lesion identification and diagnosis. Surprisingly, Multi-turn QA—which retains previous questions and answers to simulate a realistic step-by-step clinical reasoning process—results in the weakest performance. This suggests that current models struggle with managing dialogue state and are vulnerable to propagating errors over turns. Overall, these findings indicate that today's VLMs benefit more from static, comprehensive context than from dynamic, trajectory-based reasoning.

To further verify this, we conducted a controlled experiment to isolate the effect of error accumulation from other factors such as missing image references or prompt formatting. We designed three conditions:

(1) **Baseline** — the model reasons based on its own previous answers;

(2) **Insert-Correct** — lower-level answers are replaced with ground-truth labels;

(3) **Insert-Error** — lower-level answers are replaced with random incorrect labels.

As shown in Table 6, results on three representative models (Qwen2.5-VL-72B, Claude 3.7 Sonnet, and GPT-4o) reveal that diagnosis accuracy improves notably when earlier answers are corrected (e.g., +28 for Qwen) and drops when errors are inserted (–15). Intermediate tasks (Body Part and Organ) change only slightly (±6%), suggesting that dependencies intensify at deeper reasoning stages. These results confirm that cumulative errors—rather than prompt design or forgetting—are the main cause of performance degradation in multi-turn reasoning.

5.3 Hallucinations and Reasoning Errors in Clinical Report Generation

Figure 9 and Table 17 (Appendix B) shows the report scores of various models across five imaging modalities. Gemini 2.5 Pro, HuatuoGPT, and Claude 3.7 Sonnet demonstrate strong performance across multiple modalities, with leading overall scores. Figure 3 further illustrates the performance of the highest-scoring model, Gemini 2.5 Pro, under different scenarios: examples A and B are high-scoring cases that successfully identify key lesions and generate structured descriptions, but still exhibit occasional diagnostic errors or hallucinations. In contrast, example C is a low-scoring

Table 5: **Performance across modality, bodypart, organ, lesion, and diagnosis (recognition subtasks across levels in module 1).** Each cell shows accuracy in the format: **Independent/Multi-turn/Joint**. The highest value(s) are **bolded**, second highest are underlined. Missing values are shown as –.

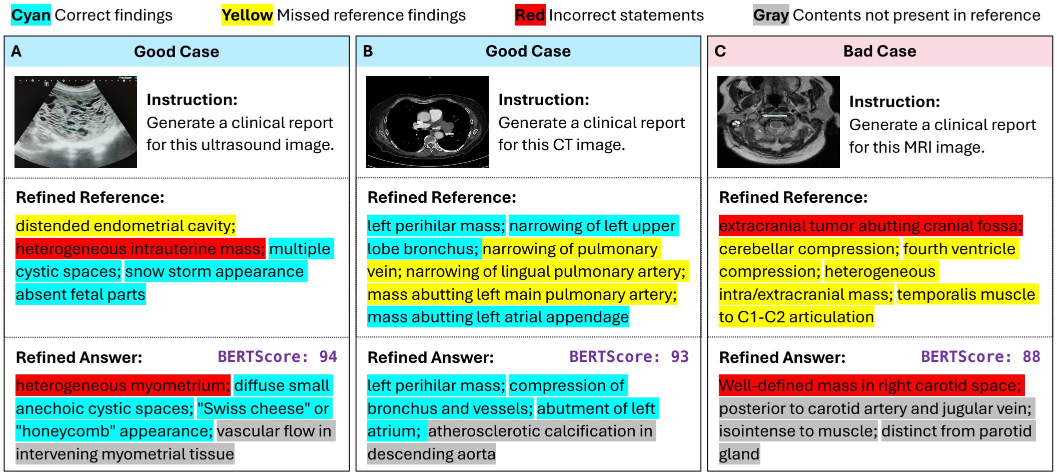
Model	Modality	Bodypart	Organ	Lesion	Diagnosis
GPT-4o	**99/99/99**	**86**/85/–	58/55/**65**	45/45/**54**	40/40/**41**
Claude	**99/99/99**	82/**83**/–	53/52/**70**	38/36/**51**	33/30/**38**
Gemini 2.5 Pro	**100/100**/99	**90**/78/–	62/47/**76**	51/38/**61**	48/35/**55**
Qwen2.5-VL-72B	**99/99/99**	**85/85**/–	57/56/**68**	44/**47/47**	36/34/**38**
Grok-3	**99/99/99**	**87**/59/–	56/37/**62**	38/20/**46**	33/18/**35**

Table 6: **Impact of low-level answer accuracy on multi-turn QA performance.** Each cell shows accuracy under three conditions: **Baseline/Insert-Correct/Insert-Error**. The highest value(s) are **bolded**, and the second highest are underlined.

Model	Modality	Body Part	Organ	Lesion	Diagnosis
Qwen2.5-VL-72B	**99/99/99**	**85**/84/84	57/**58**/55	47/**60**/43	37/**65**/22
Claude 3.7 Sonnet	**99/99/99**	83/**84**/77	**52**/52/46	36/**50**/32	30/**60**/19
GPT-4o	**99/99/99**	85/**86**/85	**55**/55/54	45/**52**/44	40/**67**/33

case, where most of the generated content consists of hallucinated findings unrelated to the reference diagnosis. These results suggest that while current models have made noticeable progress in medical image-based reasoning and diagnosis, they still struggle to fully eliminate inaccuracies and hallucinations during the reasoning process, limiting their clinical reliability.

To quantify this issue, we evaluate four representative models—Gemini 2.5 Pro, HuaTuoGPT-Vision-34B, Qwen2.5-VL-72B, and Claude 3.7 Sonnet—using FActScore. As shown in Table 7, all models exhibit low recall and low specificity, indicating that they capture only a small fraction of clinically relevant facts while generating substantial hallucinated content unrelated to the reference reports or underlying images. These findings further demonstrate that factual consistency remains a key bottleneck for current VLMs in clinical report generation.



Instruction:
Generate a clinical report for this ultrasound image.

Refined Reference:
distended endometrial cavity; heterogeneous intrauterine mass; multiple cystic spaces; snow storm appearance absent fetal parts

Refined Answer: BERTScore: 94
heterogeneous myometrium; diffuse small anechoic cystic spaces; "Swiss cheese" or "honeycomb" appearance; vascular flow in intervening myometrial tissue

Instruction:
Generate a clinical report for this CT image.

Refined Reference:
left perihilar mass; narrowing of left upper lobe bronchus; narrowing of pulmonary vein; narrowing of lingual pulmonary artery; mass abutting left main pulmonary artery; mass abutting left atrial appendage

Refined Answer: BERTScore: 93
left perihilar mass; compression of bronchus and vessels; abutment of left atrium; atherosclerotic calcification in descending aorta

Instruction:
Generate a clinical report for this MRI image.

Refined Reference:
extracranial tumor abutting cranial fossa; cerebellar compression; fourth ventricle compression; heterogeneous intra/extracranial mass; temporalis muscle to C1-C2 articulation

Refined Answer: BERTScore: 88
Well-defined mass in right carotid space; posterior to carotid artery and jugular vein; isointense to muscle; distinct from parotid gland

Figure 3: Report generation examples of Gemini 2.5 Pro. A and B represent high-scoring examples, while C represents bad-scoring examples

5.4 Bigger, Newer, or Specialized: Factors Drive Model Performance

Model performance on DrVD-Bench is shaped by both scale and recency. Large proprietary models such as Gemini 2.5 Pro and GPT-o3 lead the overall leaderboard, confirming the advantages of

Table 7: **FActScore results: factual consistency of clinical report generation.** Recall measures the coverage of true facts, while specificity reflects the proportion of generated facts supported by the reference report. Low values indicate persistent hallucination issues across models.

Model	**Recall (std)**	**Specificity (std)**
Gemini 2.5 Pro	0.13 (0.16)	0.07 (0.10)
Claude 3.7 Sonnet	0.06 (0.11)	0.03 (0.05)
Qwen2.5-VL-7B	0.08 (0.13)	0.05 (0.09)
HuatuoGPT-Vision-34B	0.13 (0.16)	0.09 (0.17)

scale—especially for complex reasoning and fine-grained visual tasks. Meanwhile, newer models consistently outperform older ones at similar sizes (Figure 4), highlighting the impact of improved architectures, training pipelines, and data quality on overall effectiveness.

Yet scale and recency are not the whole story. While proprietary models dominate, open-source models like Qwen2.5-VL-72B perform competitively despite having fewer parameters. More notably, HuaTuoGPT-Vision-34B achieves the second-highest accuracy with fewer than half the parameters of top-tier models. Its success demonstrates that domain-specific optimization—when aligned with medical structure and semantics—can enable smaller models to rival or even surpass larger general-purpose systems in clinical reasoning.

6 Conclusion

We present DrVD-Bench, a hierarchical, multimodal benchmark designed to assess whether VLMs reason like human clinicians. Covering five imaging modalities, 20 task types, and 7,789 QA pairs, DrVD-Bench captures the full spectrum of clinical visual reasoning—from basic information tasks like modality recognition to lesion identification and diagnosis. While many VLMs perform well on surface-level recognition tasks, their accuracy drops sharply as reasoning complexity increases. Notably, some models generate plausible diagnoses without correctly identifying supporting visual evidence, revealing a disconnect between diagnostic output and evidence-based understanding. By explicitly targeting intermediate reasoning steps and simulating clinical workflows, DrVD-Bench shows that current VLMs show early signs of clinical reasoning, but still far from truly interpreting medical images like human doctors. Our benchmark offers a structured foundation for developing clinically reliable and visually grounded medical AI systems.

7 Limitations

Although DrVD-Bench is clinically inspired, it remains a controlled evaluation without real-world patient context (e.g., notes, disease progression), limiting its reflection of actual diagnostic workflows. Thus, results should not be overinterpreted for clinical translation, and future refinements should better capture real-world complexity.

As DrVD-Bench uses public datasets, some recent models may have seen parts of them during pre-training, leading to potential train–test overlap and affecting performance trends. Besides, given current VLM limitations, selecting one "most informative" 2D slice from 3D or 4D volumes is a practical compromise but remains a common constraint. Moreover, most training datasets (Table 10 in Appendix A) originate from large institutions, underrepresenting minority groups and smaller or resource-limited hospitals. Future benchmarks should better control data leakage, enable volumetric reasoning, and reduce data bias to improve fairness and generalizability.

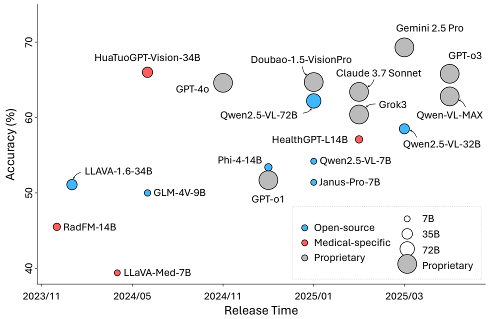


Figure 4: Performance of VLMs on DrVD-Bench visual evidence comprehension tasks across different scales and recencies.

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A Technical Appendices and Supplementary Material

A.1 Dataset Availability

DrVD-Bench is publicly available at the following links:

- **Kaggle**: `https://www.kaggle.com/datasets/tianhongzhou/drvd-bench`
- **Hugging Face**: `https://huggingface.co/datasets/jerry1565/DrVD-Bench`

The code used to conduct our experiments is released at `https://github.com/Jerry-Boss/DrVD-Bench`.

A.2 Detailed Composition of Our Benchmark

In this section, we describe the task compositions and dataset usage in more detail. Our benchmark contains 3 modules, Module 1 (Visual Evidence Comprehension) contains 4480 QA pairs, Module 2 (Reasoning Trajectory Assessment) contains 3321 QAs, and Module 3 (Report Generation Evaluation) contains 475 questions (See Figure 5). The compositions of Module 1 is illustrated in Figure 6, and that of Module 2 is illustrated in Figure 7. The levels and tasks of Module 1 are listed in detail in Table 9.

Tasks of Module 2 (Reasoning Trajectory Assessment) are adapted from Module 1 (Visual Evidence Comprehension), But they are differently organized. They are organized into 3 forms using different prompts (See Appendix C). Notably, there are 4 questions per Joint QA, and 5 questions per Multi-turn QA.

In Joint QA, the number of answer options is carefully designed to reduce prompt-induced information leakage. Both modality and organ questions contain 4 options each, while lesion and diagnosis questions are expanded to 8 options (i.e., 4×2), mitigating the information leak from our prompts.

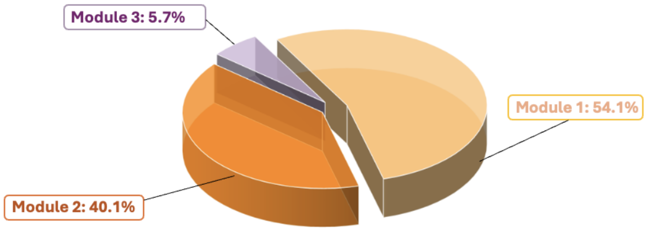


Figure 5: Diagram for the composition of our benchmark, which contains 3 modules

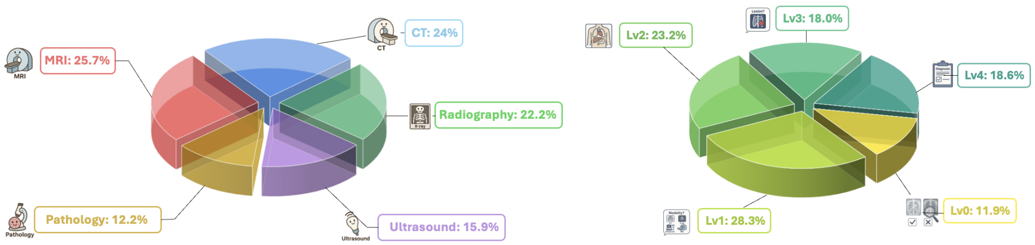


Figure 6: Diagram for the composition of Module 1. Module 1 spans all five modalities, and is designed to contain tasks of five levels

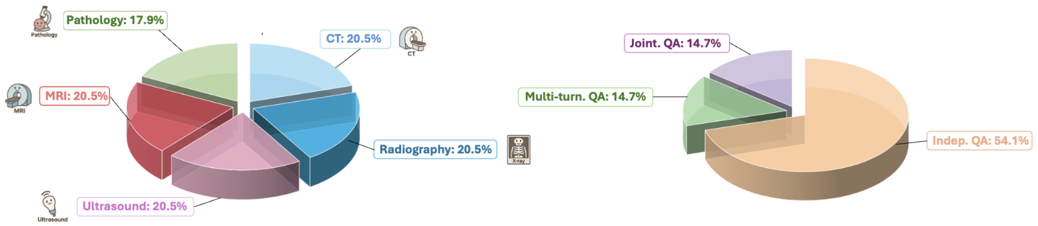


Figure 7: Diagram for the composition of Module 2. Module 2 contains three parts: Independent QA, Joint QA and Multi-turn QA.

Table 8: Datasets used in DrVD-Bench, organized by imaging modality.

Modality	**Dataset Name**
Radiography (X-ray)	MIMIC-CXR v4[34] MURA[64] VinDr-SpineXR[52] Panoramic Dental Radiography / Tufts Dental Dataset[56] SA-Med2D-20M [84] RSNA-Pneumonia[3]
CT	SA-Med2D-20M [84] AMOS 2022 [33] DeepLesion[81] CT-RATE[28] PubMedVision [15] LiTS (Liver Tumor Segmentation)[10] COVID-CTset [63] CTPelvic1k [46] CT-ORG [65] StructSeg2019-subtask1 [70] KiTS 2021 [30] LNDb [57] MSD-Liver [5, 71] COVID-19-20 [67]
MRI	TotalSegmentator MRI[21] BraTS 2020[49, 7, 8] BraTS 2021 [49, 7, 8] PI-CAI [69] LLD-MMRI [48] MICCAI 2024 CARE MyoPS++ [94, 40, 61, 22] ISPY1-Tumor-SEG-Radiomics[20]
Ultrasound	BUSI[2] CardiacUDA[83] CuRIOUS2022[80, 9] TG3K [24] Abdominal Ultrasound Images [12] Annotated Ultrasound Liver Images [86]
Pathology	PathMMU[73]

Table 9: Task QA numbers in Module 1 (continued on next page)

Modality	**Level**	**Task**	**Number**
CT	Image Quality	Noise Recognition	100
		Artifact Recognition	100
	Basic Information	Modality	100
		View	100
		Body Part	100
	Anatomy Level	Organ Recognition	100
		Organ Location	99
		Organ Erasure Identification	98
	Lesion Level	Lesion Recognition	95
		Lesion Erasure Identification	100
	Clinical Interpretation	Report	100
		Diagnosis	90
Radiography	Image Quality	Noise Recognition	100
		Artifact Recognition	61
	Basic Information	Modality	100
		View	100
		Body Part	100
	Anatomy Level	Organ Recognition	100
		Organ Location	100
		Organ Erasure Identification	68
	Lesion Level	Lesion Recognition	95
		Lesion Erasure Identification	100
	Clinical Interpretation	Report	100
		Diagnosis	100
Ultrasound	Image Quality	Artifact Recognition	46
	Basic Information	Modality	100
		Body Part	100
	Anatomy Level	Organ Recognition	100
		Organ Erasure Identification	100
	Lesion Level	Lesion Recognition	100
		Lesion Erasure Identification	100
	Clinical Interpretation	Report	75
		Diagnosis	63
Pathology	Basic Information	Stain	100
		Magnification	100
	Anatomy Level	Organ/Tissue Recognition	100
	Lesion Level	Morphology Description	100
	Clinical Interpretation	Report	100
		Diagnosis	100

(continued)

Modality	Level	Task	Number
MRI	Image Quality	Noise Recognition	100
		Artifact Recognition	84
	Basic Information	Modality	100
		View	100
		Technique	100
		Body Part	100
	Anatomy Level	Organ Recognition	100
		Organ Location	86
		Organ Erasure Identification	100
	Lesion Level	Lesion Recognition	100
		Lesion Erasure Identification	100
	Clinical Interpretation	Report	100
		Diagnosis	95

Table 10: Training datasets for medical-Specific VLMs. List of domain-specific vision–language models and their corresponding medical training datasets.

Medical-specific VLM	Medical training datasets
HuatuoGPT-Vision-34B	PubMedVision
HealthGPT-L14B	PubMedVision, LLaVA-Med, PathVQA, MIMIC-CXR-VQA, SLAKE, VQA-RAD
RadFM-14B	Rad3D-series, MPx-series, PMC-Inline, PMC-CaseReport, VinDr-Mammo, VinDr-SpineXR, VinDr-PCXR, PMC-OA, PMC-VQA, VQA-RAD, SLAKE, MIMIC-CXR, VinDr-CXR, NIH ChestXray14, CheXpert, Covid-CXR2, NLM-TB, Object-CXR, OpenI
LLaVA-Med-7B	PMC-15M

B Detailed Results

In this section, we show our benchmark results in detail.

For Module 1 (Visual Evidence Comprehension), the result for CT is in Table 11; the result for Radiography is in Table 12; the result for MRI is in Table 13; the result for Ultrasound is in Table 14; the result for Pathology is in Table 15.

We also analyzed model performance across different imaging modalities (Figure 8). VLMs perform best on Pathology and worst on Ultrasound. The strong results in Pathology may stem from the fact that we did not use whole-slide images; instead, human annotators selected diagnostically relevant regions and zoomed in, effectively reducing task complexity. In contrast, Ultrasound poses a unique challenge due to its inherently dynamic nature—clinical interpretation typically relies on real-time video sequences rather than static frames, making single-image reasoning considerably more difficult.

We evaluated the performance of different models on the report generation task by comparing their outputs against clinically relevant references (See Figure 9 and Table 17). The performance differences across modalities is minimal.

To establish a baseline, we introduced a set of medically plausible but image-irrelevant texts and computed their BERTScores against the ground-truth references. Each reference was paired with a randomly selected sentence from the list below, and the resulting BERTScore served as the normalization baseline:

- No focal consolidation is seen. However, based on clinical history, the findings may suggest a prior episode of viral gastroenteritis.
- There is no acute intracranial hemorrhage. The patient's recent weight loss should be evaluated further with laboratory studies.
- No pulmonary embolism is identified. The patient's chronic insomnia is unlikely to be explained by these imaging findings.
- Normal appearance of abdominal organs. Note: elevated serum calcium should be correlated with parathyroid hormone levels.
- No significant degenerative changes are observed. Patient's dizziness may be related to recent changes in medication dosage.
- Imaging of the chest is unremarkable. Recommend thyroid function tests given the history of fatigue and cold intolerance.
- No mass lesion is detected. Given the positive ANA, autoimmune evaluation is advised.
- The study is negative for acute pathology. Further investigation is warranted for the reported night sweats and low-grade fever.
- No obstructive uropathy is evident. Patient's lab findings of hematuria require correlation with urine cytology.
- Brain MRI is within normal limits. Symptoms of memory loss may be functional in origin or related to recent psychosocial stressors.

Table 11: **Results of different VLMs across different VQA tasks in visual evidence tasks for the CT modality.** The best-performing scores are bolded, and the second-best are underlined.

Model	Image Quality			Basic Information				Organ Level				Lesion Level			Clinical Interpretation
	Overall	Artifact	Noise	Overall	Modality	Bodypart	View	Overall	Recognition	Location	Erasure	Overall	Recognition	Erasure	Diagnosis
Random	48	51	45	30	25	27	39	29	29	27	30	26	25	26	24
Proprietary															
GPT-4o	72	52	92	89	**100**	85	92	50	60	46	44	38	39	36	67
GPT-o1	62	51	72	86	94	78	87	35	39	34	33	29	30	27	46
GPT-o3	80	65	94	**94**	**100**	90	**92**	**70**	**76**	**77**	56	28	37	19	52
Claude 3.7 Sonnet	75	52	97	84	**100**	84	**92**	47	60	46	36	29	28	29	46
Gemini 2.5 Pro	**82**	64	**99**	93	**100**	88	**92**	67	67	73	**62**	28	39	16	71
Grok-3	65	54	76	66	**100**	88	43	44	58	33	41	35	36	33	58
Doubao1.5-VisionPro	78	**68**	87	90	98	81	90	50	59	52	38	**55**	**61**	**49**	59
Qwen-VL-MAX	74	61	87	87	**100**	85	89	54	55	58	49	45	42	47	68
Open-source															
Qwen2.5-VL-72B	75	59	90	88	**100**	87	89	54	57	61	45	45	42	47	69
LLaVA-1.6-34B	62	53	70	72	80	85	51	32	42	16	38	43	41	45	54
Qwen2.5-VL-32B	59	50	68	88	97	80	86	45	48	41	47	39	46	32	68
Phi-4-14B	75	50	**99**	67	99	76	57	36	45	27	36	41	35	46	64
GLM-4V-9B	66	49	83	74	86	83	52	36	44	27	36	33	29	36	38
Qwen2.5-VL-7B	71	57	84	76	**100**	79	73	37	40	34	36	40	42	38	39
Janus-Pro-7B	71	52	90	82	94	88	63	37	45	32	34	41	40	42	**73**
Medical-specific															
HuaTuoGPT-Vision-34B	67	60	74	**94**	**100**	**91**	**92**	52	63	48	44	33	47	33	68
HealthGPT-L14B	51	49	53	84	**100**	90	84	38	52	30	32	32	41	22	72
RadFM-14B	52	47	56	72	92	56	67	30	39	29	22	44	45	42	35
LLaVA-Med-7B	57	53	60	55	82	57	26	33	32	36	32	34	33	35	30

Table 12: **Results of different VLMs across different VQA tasks in visual evidence tasks for the radiography modality.** The best-performing scores are **bolded**, and the second-best are underlined.

Model	Image Quality			Basic Information				Organ Level				Lesion Level			Clinical Interpretation
	Overall	Artifact	Noise	Overall	Modality	Bodypart	View	Overall	Recognition	Location	Erasure	Overall	Recognition	Erasure	Diagnosis
Random	49	51	46	27	29	25	28	30	18	44	27	25	28	22	21
Proprietary															
GPT-4o	69	70	67	92	**100**	95	81	59	46	79	53	36	45	27	27
GPT-o1	60	61	59	82	91	74	81	51	49	57	48	33	40	25	18
GPT-o3	72	74	69	92	**100**	**98**	79	76	80	**94**	53	33	41	25	24
Claude 3.7 Sonnet	62	62	61	**95**	**100**	91	**93**	66	81	65	53	38	47	28	36
Gemini 2.5 Pro	**79**	70	**88**	88	**100**	97	68	71	80	89	43	**53**	**57**	**48**	25
Grok-3	64	72	55	91	99	85	90	55	37	74	53	32	36	28	32
Doubao-VisionPro	53	44	61	90	**100**	89	82	60	**84**	77	18	37	43	30	42
Qwen-VL-MAX	66	68	64	85	**100**	93	63	71	80	78	**56**	37	37	36	27
Open-source															
Qwen2.5-VL-72B	65	63	67	76	**100**	63	64	70	79	78	52	41	48	34	28
LLaVA-1.6-34B	62	72	51	69	96	65	46	37	38	62	10	25	27	23	31
Qwen2.5-VL-32B	64	62	66	67	**100**	63	37	68	75	78	52	33	38	27	29
Phi-4-14B	77	70	84	75	**100**	90	34	43	39	73	16	31	34	27	37
GLM-4V-9B	66	64	68	81	**100**	89	53	50	56	66	28	28	29	26	20
Qwen2.5-VL-7B	75	**78**	72	73	98	89	33	46	53	61	25	33	36	30	37
Janus-Pro-7B	57	46	67	73	99	88	33	39	37	73	6	33	35	30	24
Medical-specific															
HuaTuoGPT-Vision-34B	63	66	59	81	**100**	63	79	58	67	75	32	35	42	28	37
HealthGPT-L14B	60	70	49	75	98	60	68	39	32	66	19	32	37	27	34
RadFM-14B	60	70	49	66	72	58	68	39	34	51	31	24	17	30	**44**
LLaVA-Med-7B	51	49	52	51	70	51	32	44	28	60	44	28	25	31	24

Table 13: **Results of different VLMs across different VQA tasks in visual evidence tasks for the MRI modality.** The best-performing scores are **bolded**, and the second-best are underlined.

Model	Image Quality			Basic Information				Organ Level				Lesion Level			Clinical Interpretation
	Overall	Artifact	Noise	Overall	Modality	Bodypart	Imaging	Overall	Recognition	Location	Erasure	Overall	Recognition	Erasure	Diagnosis
Random	49	55	42	27	21	29	24	34	24	22	29	20	28	25	30
Proprietary															
GPT-4o	66	51	80	72	**100**	68	55	66	52	**66**	45	46	58	53	57
GPT-o1	50	33	67	56	78	46	36	65	35	38	29	38	44	46	40
GPT-o3	62	40	84	76	**100**	69	62	71	53	**66**	**49**	43	51	50	48
Claude 3.7 Sonnet	**70**	54	86	65	**100**	56	43	60	49	56	38	53	56	61	43
Gemini 2.5 Pro	**70**	45	**94**	**80**	99	**74**	**81**	67	**54**	58	46	**57**	55	55	57
Grok-3	60	45	75	64	98	65	37	55	51	64	35	53	50	51	50
Doubao-VisionPro	62	56	68	64	99	53	45	60	46	61	38	40	**61**	54	45
Qwen-VL-MAX	62	45	79	61	96	58	37	54	43	48	36	46	**65**	68	60
Open-source															
Qwen2.5-VL-72B	65	50	79	63	96	60	40	54	46	54	36	49	67	**71**	58
LLaVA-1.6-34B	62	50	74	46	57	43	29	56	35	36	24	45	**68**	60	**76**
Qwen2.5-VL-32B	60	49	71	62	91	60	39	57	44	45	38	48	63	61	70
Phi-4-14B	66	43	88	55	97	47	25	51	31	33	24	36	57	49	44
GLM-4V-9B	65	50	79	50	93	55	17	34	39	39	30	47	35	29	37
Qwen2.5-VL-7B	62	45	78	51	95	52	24	34	42	49	29	47	54	46	39
Janus-Pro-7B	59	38	79	57	87	68	22	50	43	45	44	40	36	31	**79**
Medical-specific															
HuaTuoGPT-Vision-34B	57	40	73	77	**100**	70	65	**73**	49	63	36	47	**68**	67	67
HealthGPT-L14B	60	**67**	53	61	98	63	25	58	43	50	35	43	54	54	42
RadFM-14B	46	50	42	49	94	31	38	33	43	58	32	40	55	50	35
LLaVA-Med-7B	51	59	43	43	71	34	28	38	25	31	17	27	36	34	32

Table 14: **Results of different VLMs across different VQA tasks in visual evidence tasks for the ultrasound modality.** The best-performing scores are **bolded**, and the second-best are underlined.

Model	Image Quality	Basic Information			Organ Level			Lesion Level			Clinical Interpretation
	Artifact	Overall	Modality	Bodypart	Overall	Recognition	Erasure	Overall	Recognition	Erasure	Diagnosis
Random	53	25	22	27	24	23	25	22	23	20	20
Proprietary											
GPT-4o	50	76	99	53	44	37	51	54	76	31	62
GPT-o1	35	61	89	32	35	27	43	35	44	26	43
GPT-o3	46	**82**	99	**65**	46	36	55	36	36	36	48
Claude 3.7 Sonnet	48	71	**100**	41	**54**	**46**	**61**	28	36	19	49
Gemini 2.5 Pro	50	81	**100**	61	48	40	56	59	58	59	51
Grok-3	**54**	75	98	52	45	36	54	53	74	32	**64**
Doubao-VisionPro	48	71	**100**	42	35	31	39	**83**	**87**	**78**	49
Qwen-VL-MAX	39	67	98	35	37	33	40	69	76	62	52
Open-source											
Qwen2.5-VL-72B	30	66	98	33	36	33	38	63	74	52	46
LLaVA-1.6-34B	50	54	77	31	32	22	42	58	83	32	51
Qwen2.5-VL-32B	50	59	94	24	32	28	36	34	36	32	52
Phi-4-14B	37	66	95	36	26	25	27	43	49	36	41
GLM-4V-9B	50	75	**100**	49	29	30	28	17	23	10	33
Qwen2.5-VL-7B	50	47	92	2	30	32	28	46	36	56	25
Janus-Pro-7B	15	69	98	40	30	29	30	26	47	4	60
Medical-specific											
HuaTuoGPT-Vision-34B	46	**82**	98	**65**	44	33	55	64	63	64	**64**
HealthGPT-L14B	50	67	94	40	35	36	34	25	4	45	51
RadFM-14B	50	47	60	33	20	25	14	36	60	12	11
LLaVA-Med-7B	44	50	58	41	23	21	25	31	30	32	30

Table 15: **Results of different VLMs across different VQA tasks in visual evidence tasks for the pathology modality.** The best-performing scores are **bolded**, and the second-best are underlined.

Model	Basic Information			Organ Level	Lesion Level	Clinical Interpretation
	Overall	Magnification	Stain	Recognition	Morphology	Diagnosis
Random	34	46	21	30	23	25
Proprietary						
GPT-4o	88	88	88	80	62	57
GPT-o1	72	73	71	65	43	50
GPT-o3	88	89	87	83	56	66
Claude 3.7 Sonnet	94	96	91	83	61	**67**
Gemini 2.5 Pro	**96**	**99**	**93**	**86**	63	**67**
Grok-3	83	83	83	83	55	49
Doubao-VisionPro	93	94	91	69	58	63
Qwen-VL-MAX	86	84	87	65	63	58
Open-source						
Qwen2.5-VL-72B	86	85	87	66	64	59
LLaVA-1.6-34B	60	56	63	53	51	49
Qwen2.5-VL-32B	88	89	87	66	**69**	59
Phi-4-14B	69	65	72	59	46	47
GLM-4V-9B	69	73	65	61	48	51
Qwen2.5-VL-7B	89	93	84	50	50	50
Janus-Pro-7B	58	70	46	73	57	44
Medical-specific						
HuaTuoGPT-Vision-34B	93	93	**93**	**86**	61	57
HealthGPT-L14B	91	93	89	75	64	64
RadFM-14B	73	60	85	32	33	30
LLaVA-Med-7B	47	56	38	43	32	27

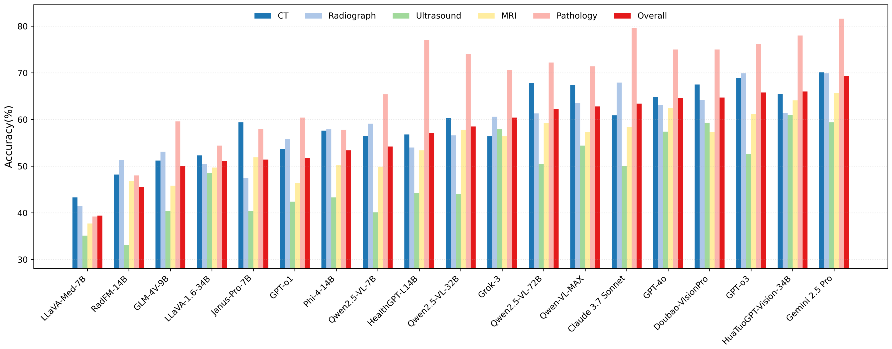


Figure 8: Performance of VLMs across five medical imaging modalities in visual evidence tasks, sorted by overall accuracy.

Table 16: **Performance of VLMs across five medical imaging modalities in visual evidence tasks.** The best-performing scores are **bolded**, and the second-best are underlined.

Model	CT	Radiography	Ultrasound	MRI	Pathology	Overall
			Proprietary			
GPT-4o	64.8	63.1	57.4	62.5	75	64.6
GPT-o1	53.7	55.8	42.4	46.4	60.4	51.7
GPT-o3	68.9	**69.9**	52.6	61.2	76.2	65.8
Claude 3.7 Sonnet	60.9	67.9	50	58.4	79.6	63.4
Gemini 2.5 Pro	**70.1**	**69.9**	59.4	**65.7**	**81.6**	**69.3**
Grok-3	56.4	60.6	58	56.4	70.6	60.4
Doubao-1.5-VisionPro	67.5	64.2	59.3	57.3	75	64.7
Qwen-VL-MAX	67.4	63.5	54.4	57.3	71.4	62.8
			Open-source			
Qwen2.5-VL-72B	67.8	61.3	50.5	59.2	72.2	62.2
LLaVA-1.6-34B	52.3	50.5	48.5	49.7	54.4	51.1
Qwen2.5-VL-32B	60.3	56.6	44	57.8	74	58.5
Phi-4-14B	57.6	57.9	43.3	50.2	57.8	53.4
GLM-4V-9B	51.2	53.1	40.4	45.8	59.6	50.0
Qwen2.5-VL-7B	56.5	59.1	40.1	49.9	65.4	54.2
Janus-Pro-7B	59.4	47.5	40.4	51.9	58	51.4
			Medical-specific			
HuaTuoGPT-Vision-34B	65.5	61.4	**61**	64.1	78	66
HealthGPT-L14B	56.8	54	44.3	53.4	77	57.1
RadFM-14B	48.2	51.3	33.1	46.8	48	45.5
LLaVA-Med-7B	43.3	41.5	35.1	37.7	39.2	39.4

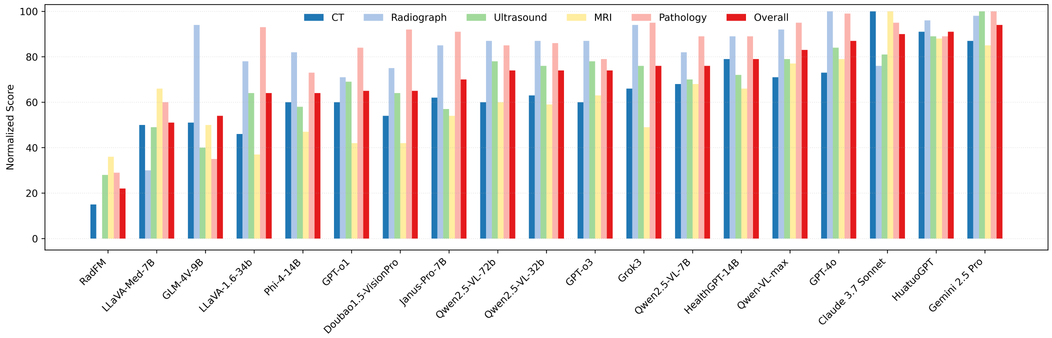


Figure 9: Normalized scores of report generation across five imaging modalities (sorted by overall scores).

Table 17: **BERTScore performance of vision-language models across five imaging modalities.** Best-performing scores are bolded, and second-best scores are underlined. Models follow visual grouping.

Model	CT	Radiography	Ultrasound	MRI	Pathology	Overall
Proprietary						
GPT-4o	73/89.42	**100/92.09**	84/89.98	79/89.11	99/90.20	87/90.16
GPT-o1	60/88.96	71/90.79	69/89.39	42/87.90	84/89.69	65/89.35
GPT-o3	60/88.97	87/91.52	78/89.73	63/88.60	79/89.52	74/89.67
Claude 3.7 Sonnet	**100/90.35**	76/91.02	81/89.85	**100/89.80**	95/90.08	90/90.22
Gemini 2.5 Pro	87/89.89	98/91.98	**100/90.61**	85/89.30	**100/90.25**	**94/90.41**
Grok3	66/88.90	94/91.07	76/89.35	49/87.52	95/89.99	76/89.77
Doubao1.5-VisionPro	54/87.67	75/89.76	64/88.91	42/87.45	92/89.73	65/88.70
Qwen-VL-max	71/89.71	92/91.01	79/89.62	77/89.38	95/89.84	83/89.91
Open-source						
Qwen2.5-VL-72b	60/87.85	87/89.99	78/89.53	60/87.50	85/89.71	74/88.92
LLaVA-1.6-34b	46/85.32	78/88.66	64/88.34	37/86.76	93/89.81	64/87.78
Qwen2.5-VL-32b	63/88.26	87/89.99	76/89.31	59/87.43	86/89.72	74/88.94
Phi-4-14B	60/87.84	82/89.12	58/87.46	47/87.04	73/88.26	64/87.74
GLM-4V-9B	51/86.37	94/91.05	40/86.36	50/87.23	35/85.48	54/87.30
Qwen2.5-VL-7B	68/88.98	82/89.12	70/88.91	68/88.61	89/89.88	76/89.50
Janus-Pro-7B	62/88.15	85/89.79	58/87.10	54/87.28	91/89.89	70/88.84
Medical-specific						
HuatuoGPT	91/91.40	96/91.65	89/89.06	88/88.38	89/89.37	91/90.94
HealthGPT-14B	79/90.08	89/88.79	72/88.26	66/88.09	89/89.08	79/88.86
RadFM	15/81.46	0/80.00	29/82.85	36/83.64	29/82.87	22/82.17
LLaVA-Med-7B	50/85.04	30/83.01	49/84.94	66/88.09	60/86.01	51/85.13

C Prompts

In this section, we present the exact prompts used in our experiments. To ensure model compliance, particularly with recent models that may reject clinical queries, all prompts are framed within an educational context.

C.1 Multiple-Choice Problems

System prompt:
You are a helpful assistant participating in an educational visual reasoning task. Always follow the instructions strictly.

User prompt:
Question: { }

Options:
A) { }
B) { }
C) { }
D) { }

Instructions:
Choose the SINGLE best answer by replying with one capital letter (A–D). Do not explain. Do not add extra text.

C.2 Independent QA

You are participating in an educational exercise based on visual information.

Below is an image typically used in medical training, followed by a question.

Question: { }

Options:
A) { }
B) { }
C) { }
D) { }

Instructions: Based only on the visible structures and general anatomical knowledge, choose the most appropriate answer by replying with a single capital letter (A, B, C, or D). Do not explain your reasoning.

C.3 Joint QA

System prompt:
You are participating in a step-by-step medical reasoning diagnosis task based on interpretation of a medical image.

User prompt:
Please answer the following four questions sequentially. Each question builds upon the reasoning of the previous one. Carefully analyze the image and select the most appropriate answer at each step. For each question, choose one capital letter (A, B, C, or D). Do not skip any step.

1. What imaging modality is used in this image?
Options:
A. { }
B. { }
C. { }
D. { }

2. Which organ appears to be abnormal in this image?
Options:
A. { }
B. { }

C. { }
D. { }

3. Based on the abnormal organ, what lesion or finding is most clearly visible?
Options:
A. { }
B. { }
C. { }
D. { }
E. { }
F. { }
G. { }
H. { }

4. Considering all the above findings, what is the most likely diagnosis?
Options:
A. { }
B. { }
C. { }
D. { }
E. { }
F. { }
G. { }
H. { }

Instructions:
Please reply with your four selected letters in order, separated by commas (e.g., A,C,B,A). Do not provide explanations.

C.4 Multi-turn QA

System prompt:
You are an expert medical AI. You will answer several step-by-step questions about the same medical image. Respond with one capital letter (A–H).

User (Round 1):
(with image)
1. What imaging modality is used in this image?
Options: A) CT B) MRI C) Ultrasound D) Radiography

Assistant:
A

User:
`[Same image QA record]` 1. What imaging modality is used in this image?

Assistant:
CT

User (Round 2):
2. Which organ is shown in this medical image?
Options: A) Liver B) Pancreas C) Spleen D) Kidney

Assistant:
A

User:
`[Same image QA record]` 2. Which organ is shown in this medical image?

Assistant:
Liver

User (Round 3):
3. What lesion is visible in this image?
Options: A) Target sign B) Hepatic steatosis C) Pancreatic pseudocyst D) Splenic infarct

Assistant:
A

User (Round 4):
4. What is the most likely diagnosis?
Options: A) Crohn's disease B) Acute pancreatitis C) Splenic rupture D) Diverticulitis

C.5 Report Generation

System prompt:
Generate a clinical report based on the image. This is used solely for educational purposes.

User prompt:
Generate a clinical report based on the image. Limit your output to no more than 500 words. *(with image)*
`{question}`

C.6 Key Feature Extraction in Generated Reports

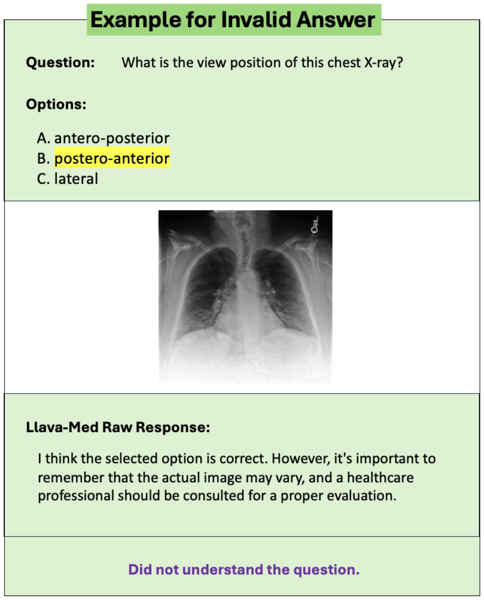
Given the following description of a medical image, extract only clinically relevant information that can be visually determined from the image. This includes both **normal findings** (e.g., "no lung opacity", "normal heart size") and **abnormal findings** (e.g., "fracture", "tumor mass"). Exclude any details that cannot be inferred from the image itself (e.g., patient history, lab values).

Input: `{text}`

Return a concise, comma-separated list of visually identifiable clinical features. Do not include any irrelevant words or phrases, do not include explanations.

D Examples for Model Response

In this section, we provide examples of model responses. For multiple-choice questions, models are required to respond with a single capital letter (A, B, C, or D) corresponding to their selected answer. If the response does not follow this format, we perform automatic answer extraction using DeepSeek-V3 [43]. If no valid answer can be extracted, the response is considered *incorrect*.



Example for Invalid Answer

Question: What is the view position of this chest X-ray?

Options:

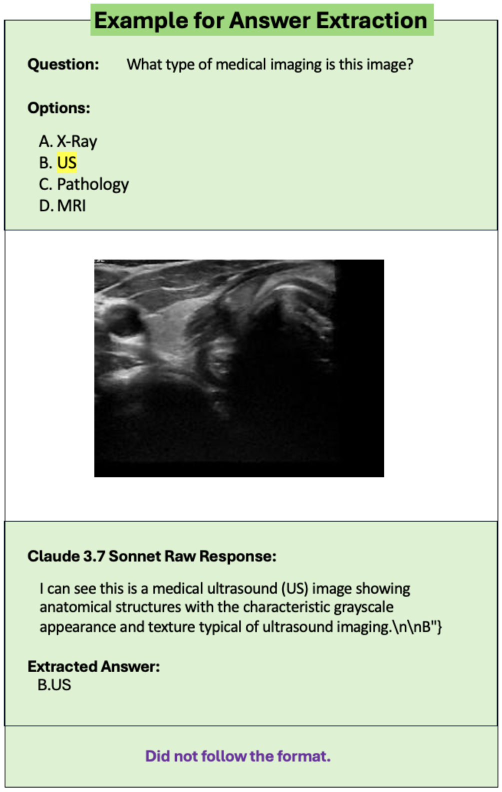
A. antero-posterior
B. postero-anterior
C. lateral

Llava-Med Raw Response:

I think the selected option is correct. However, it's important to remember that the actual image may vary, and a healthcare professional should be consulted for a proper evaluation.

Did not understand the question.

Figure 10: An example of an invalid answer, which is marked as *wrong*. The option highlighted in yellow is the correct answer.



Example for Answer Extraction

Question: What type of medical imaging is this image?

Options:

A. X-Ray
B. US
C. Pathology
D. MRI

Claude 3.7 Sonnet Raw Response:

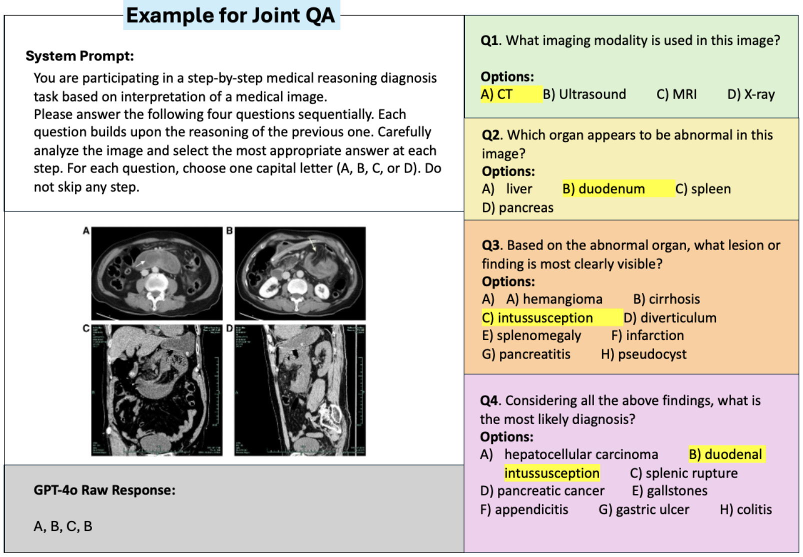
I can see this is a medical ultrasound (US) image showing anatomical structures with the characteristic grayscale appearance and texture typical of ultrasound imaging.\n\nB"}

Extracted Answer:
B.US

Did not follow the format.

Figure 11: An example of a valid but unformatted answer, which is still marked as *correct*. The option highlighted in yellow indicates the correct answer.

We provide an example of Joint QA below. The formats of Independent QA and Multi-turn QA are similar and thus omitted. Both Independent and Multi-turn QA present questions sequentially; however, in Independent QA, each answer is given without memory of prior interactions, whereas in Multi-turn QA, the model retains memory of previous questions and answers, simulating a step-by-step reasoning process.



Example for Joint QA

System Prompt:

You are participating in a step-by-step medical reasoning diagnosis task based on interpretation of a medical image.
Please answer the following four questions sequentially. Each question builds upon the reasoning of the previous one. Carefully analyze the image and select the most appropriate answer at each step. For each question, choose one capital letter (A, B, C, or D). Do not skip any step.

GPT-4o Raw Response:

A, B, C, B

Q1. What imaging modality is used in this image?

Options:
A) CT B) Ultrasound C) MRI D) X-ray

Q2. Which organ appears to be abnormal in this image?
Options:
A) liver B) duodenum C) spleen
D) pancreas

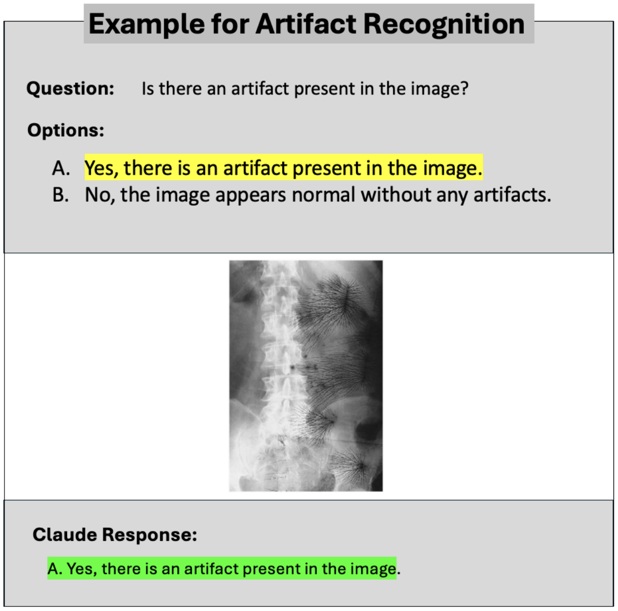
Q3. Based on the abnormal organ, what lesion or finding is most clearly visible?
Options:
A) A) hemangioma B) cirrhosis
C) intussusception D) diverticulum
E) splenomegaly F) infarction
G) pancreatitis H) pseudocyst

Q4. Considering all the above findings, what is the most likely diagnosis?
Options:
A) hepatocellular carcinoma B) duodenal intussusception C) splenic rupture
D) pancreatic cancer E) gallstones
F) appendicitis G) gastric ulcer H) colitis

Figure 12: An example of Joint QA, in which the model answers four questions from different reasoning levels simultaneously. The option highlighted in yellow indicates the correct answer.

E Examples of Tasks

This section provides detailed examples of our tasks. Choices highlighted in yellow represent the ground truth. In the responses, correct answers are highlighted in green, while incorrect ones are highlighted in red.



Example for Artifact Recognition

Question: Is there an artifact present in the image?

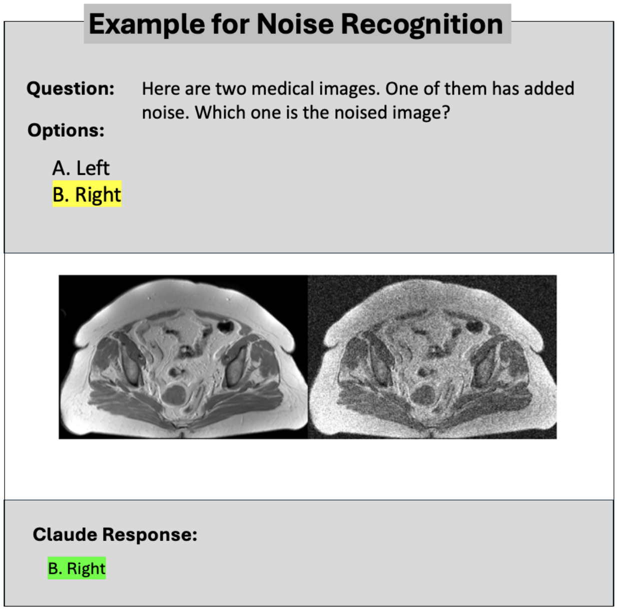
Options:

A. Yes, there is an artifact present in the image.
B. No, the image appears normal without any artifacts.

Claude Response:

A. Yes, there is an artifact present in the image.

Figure 13: Example for Artifact Recognition



Example for Noise Recognition

Question: Here are two medical images. One of them has added noise. Which one is the noised image?

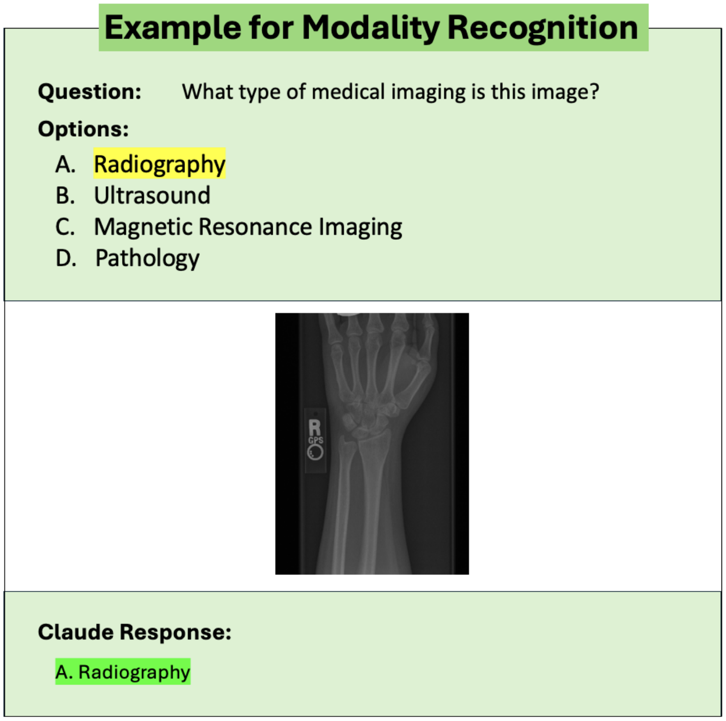
Options:

A. Left
B. Right

Claude Response:

B. Right

Figure 14: Example for Noise Recognition



Example for Modality Recognition

Question: What type of medical imaging is this image?

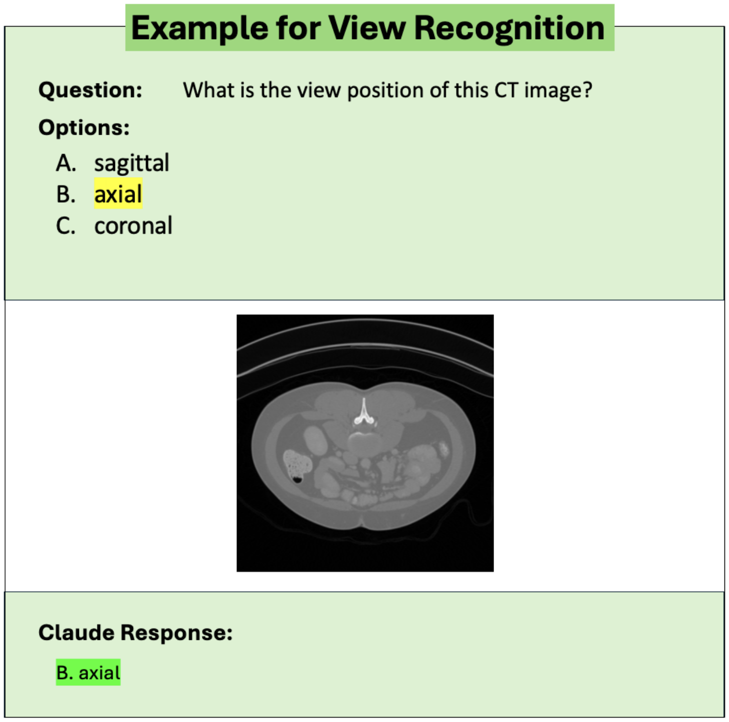
Options:

A. Radiography
B. Ultrasound
C. Magnetic Resonance Imaging
D. Pathology

Claude Response:

A. Radiography

Figure 15: Example for Modality Recognition



Example for View Recognition

Question: What is the view position of this CT image?

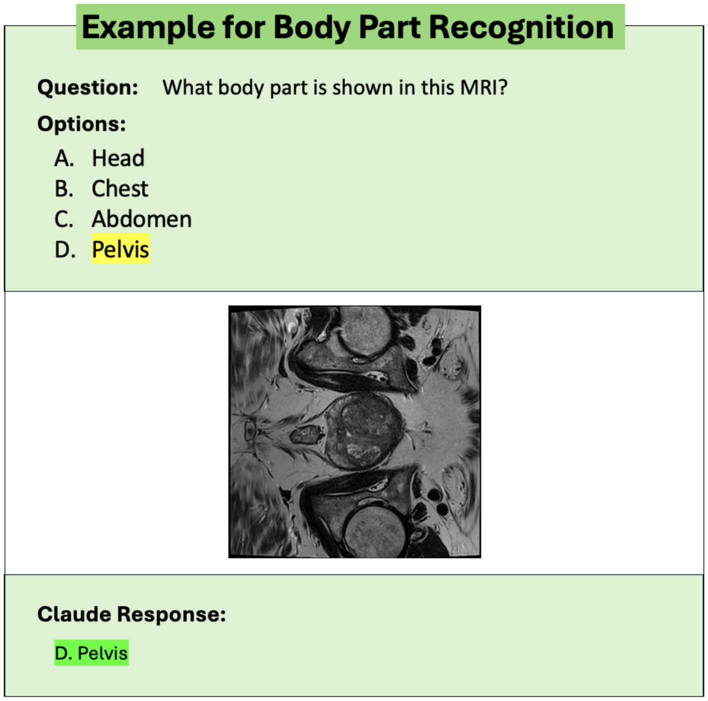
Options:

A. sagittal
B. axial
C. coronal

Claude Response:

B. axial

Figure 16: Example for View Recognition



Example for Body Part Recognition

Question: What body part is shown in this MRI?

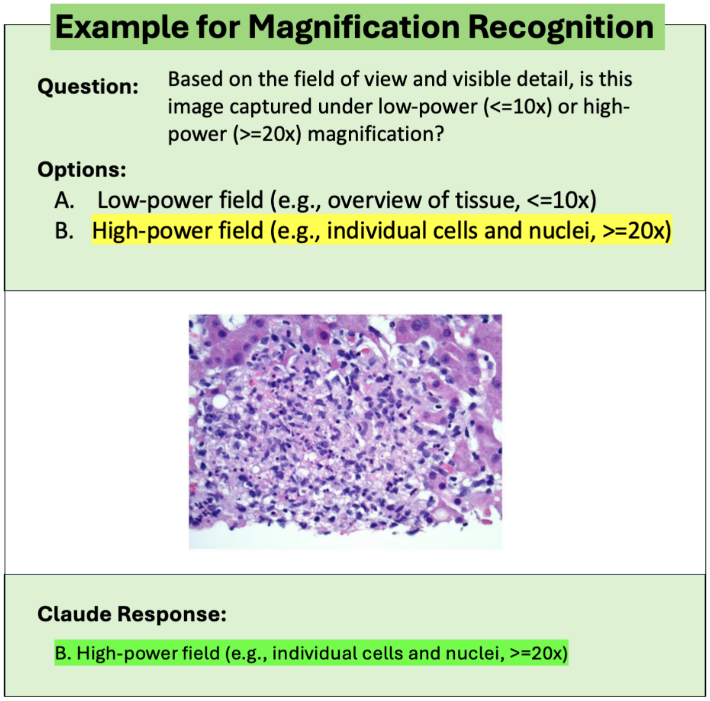
Options:

A. Head
B. Chest
C. Abdomen
D. Pelvis

Claude Response:

D. Pelvis

Figure 17: Example for Body Part Recognition



Example for Magnification Recognition

Question: Based on the field of view and visible detail, is this image captured under low-power (<=10x) or high-power (>=20x) magnification?

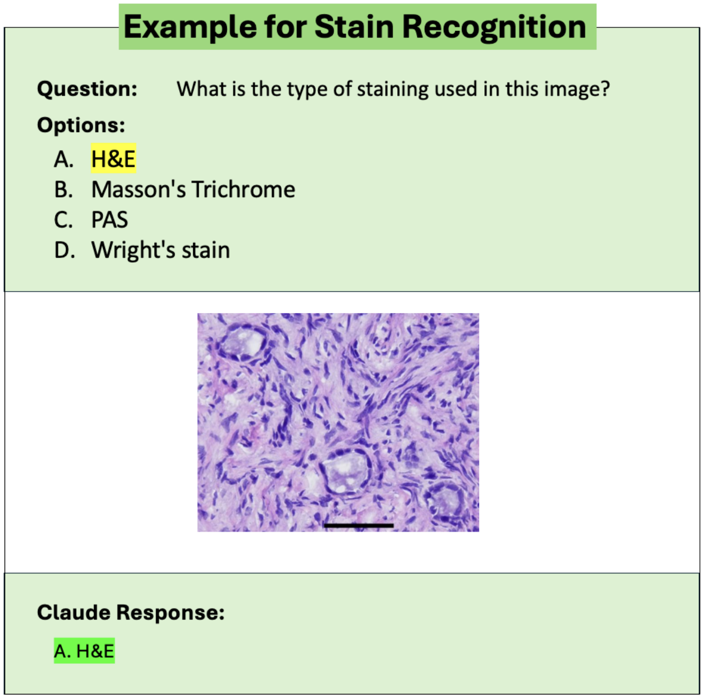
Options:

A. Low-power field (e.g., overview of tissue, <=10x)
B. High-power field (e.g., individual cells and nuclei, >=20x)

Claude Response:

B. High-power field (e.g., individual cells and nuclei, >=20x)

Figure 18: Example for Magnification Recognition



Example for Stain Recognition

Question: What is the type of staining used in this image?

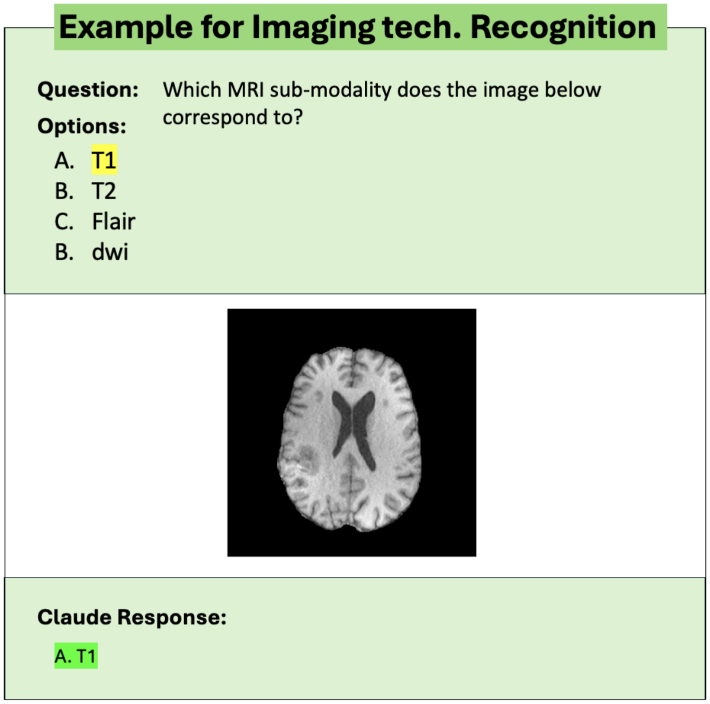
Options:

A. H&E
B. Masson's Trichrome
C. PAS
D. Wright's stain

Claude Response:

A. H&E

Figure 19: Example for Stain Recognition



Example for Imaging tech. Recognition

Question: Which MRI sub-modality does the image below correspond to?

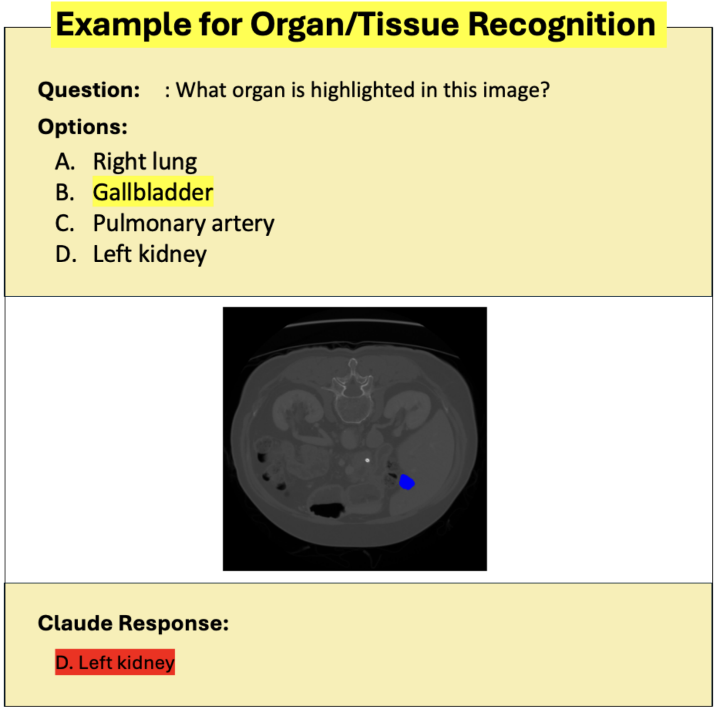
Options:

A. T1
B. T2
C. Flair
B. dwi

Claude Response:

A. T1

Figure 20: Example for Imaging Technique Recognition



Example for Organ/Tissue Recognition

Question: : What organ is highlighted in this image?

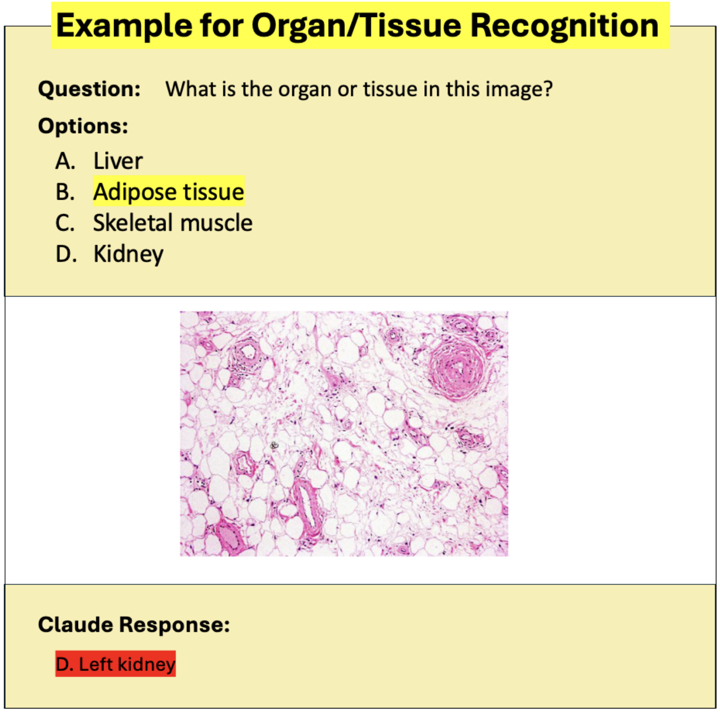
Options:

A. Right lung
B. Gallbladder
C. Pulmonary artery
D. Left kidney

Claude Response:

D. Left kidney

Figure 21: Example for Organ Recognition



Example for Organ/Tissue Recognition

Question: What is the organ or tissue in this image?

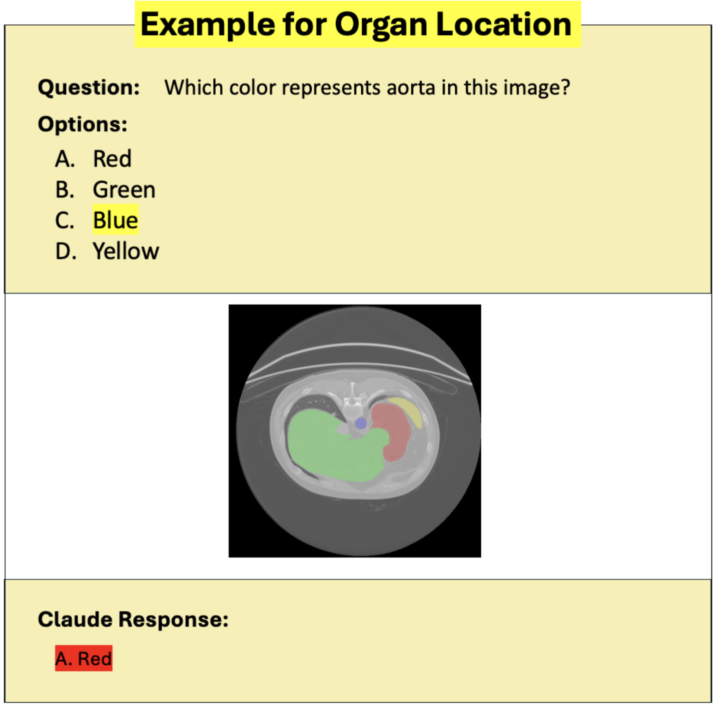
Options:

A. Liver
B. Adipose tissue
C. Skeletal muscle
D. Kidney

Claude Response:

D. Left kidney

Figure 22: Example for Tissue Recognition



Example for Organ Location

Question: Which color represents aorta in this image?

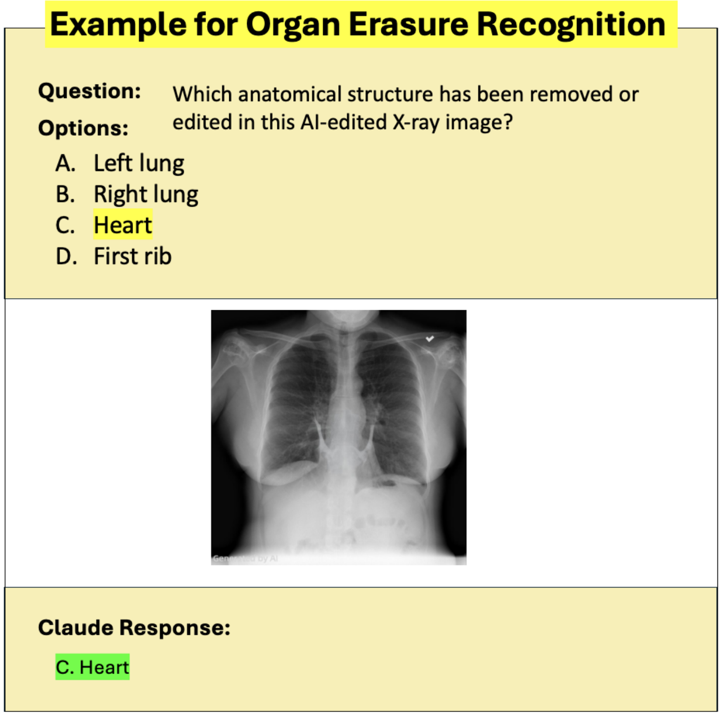
Options:

A. Red
B. Green
C. Blue
D. Yellow

Claude Response:

A. Red

Figure 23: Example for Organ Location



Example for Organ Erasure Recognition

Question: Which anatomical structure has been removed or edited in this AI-edited X-ray image?

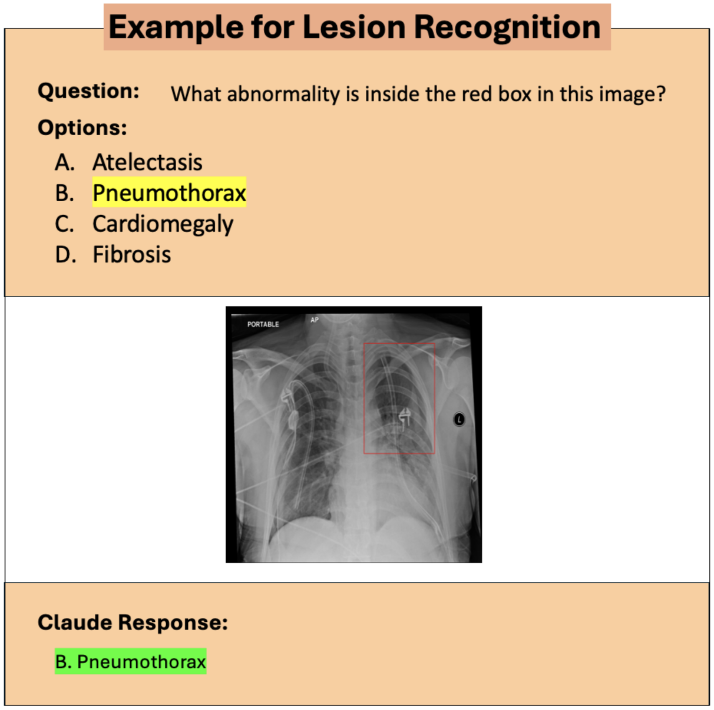
Options:

A. Left lung
B. Right lung
C. Heart
D. First rib

Claude Response:

C. Heart

Figure 24: Example for Organ Erasure Recognition



Example for Lesion Recognition

Question: What abnormality is inside the red box in this image?

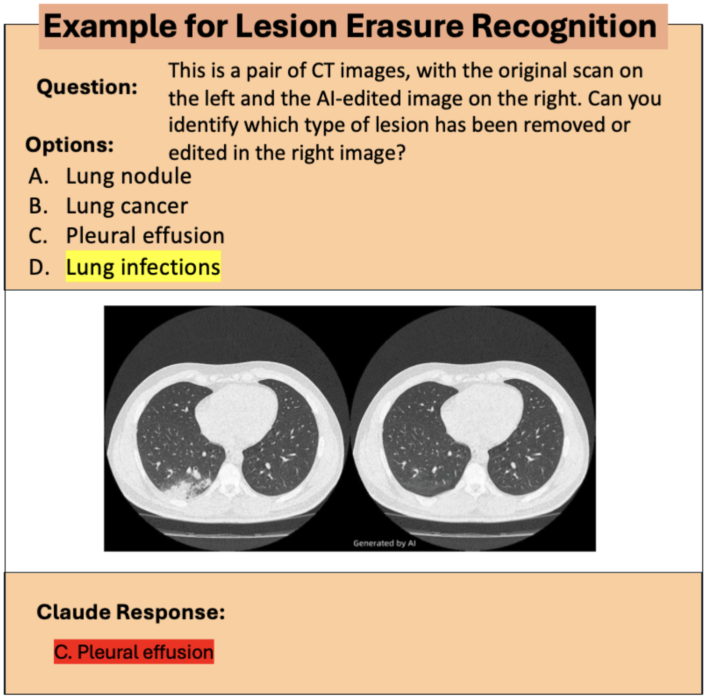
Options:

A. Atelectasis
B. Pneumothorax
C. Cardiomegaly
D. Fibrosis

Claude Response:

B. Pneumothorax

Figure 25: Example for Lesion Recognition



Example for Lesion Erasure Recognition

Question: This is a pair of CT images, with the original scan on the left and the AI-edited image on the right. Can you identify which type of lesion has been removed or edited in the right image?

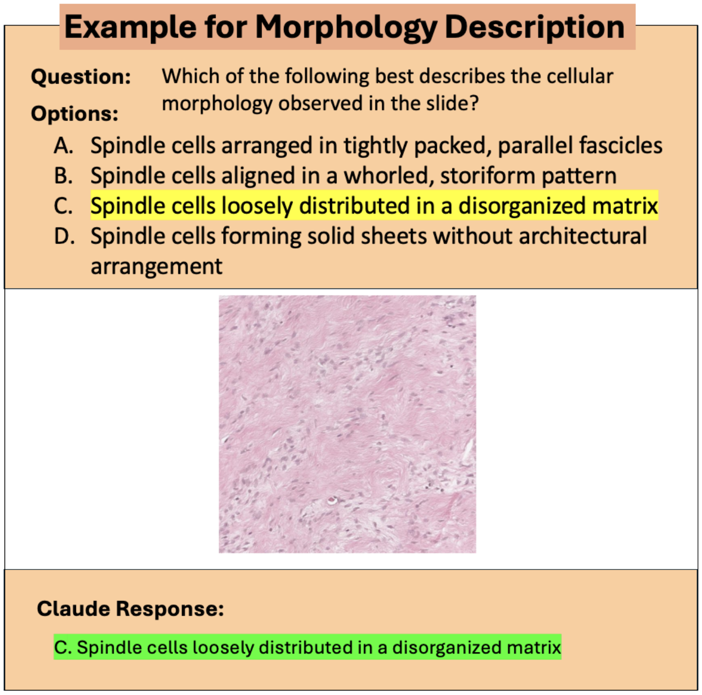
Options:

A. Lung nodule
B. Lung cancer
C. Pleural effusion
D. Lung infections

Claude Response:

C. Pleural effusion

Figure 26: Example for Lesion Erasure Recognition



Example for Morphology Description

Question: Which of the following best describes the cellular morphology observed in the slide?

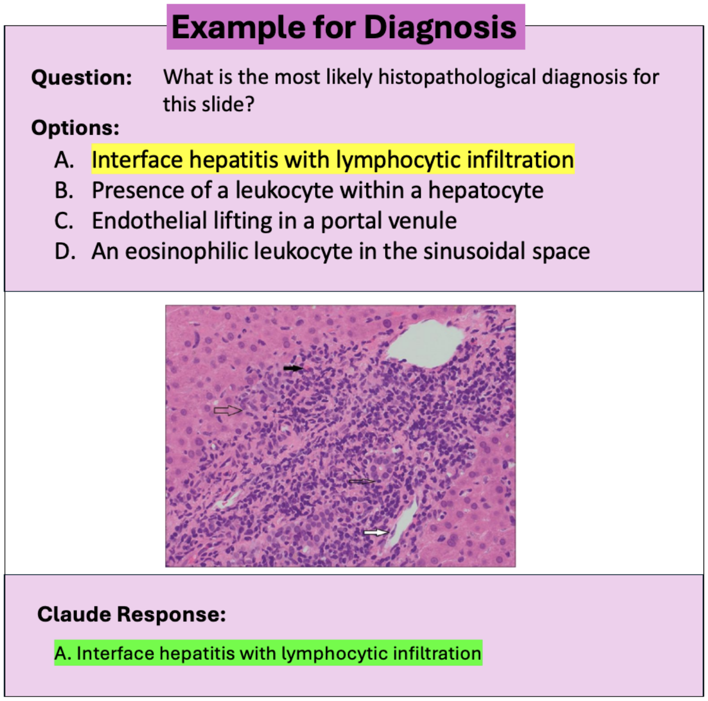
Options:

A. Spindle cells arranged in tightly packed, parallel fascicles
B. Spindle cells aligned in a whorled, storiform pattern
C. Spindle cells loosely distributed in a disorganized matrix
D. Spindle cells forming solid sheets without architectural arrangement

Claude Response:

C. Spindle cells loosely distributed in a disorganized matrix

Figure 27: Example for Morphology Description



Example for Diagnosis

Question: What is the most likely histopathological diagnosis for this slide?

Options:

A. Interface hepatitis with lymphocytic infiltration
B. Presence of a leukocyte within a hepatocyte
C. Endothelial lifting in a portal venule
D. An eosinophilic leukocyte in the sinusoidal space

Claude Response:

A. Interface hepatitis with lymphocytic infiltration

Figure 28: Example for Diagnosis

NeurIPS Paper Checklist

1. **Claims**

   Question: Do the main claims made in the abstract and introduction accurately reflect the paper's contributions and scope?

   Answer: [Yes]

   Justification: Yes, please refer to the Abstract and Introduction of this paper for details.

   Guidelines:

   - The answer NA means that the abstract and introduction do not include the claims made in the paper.
   - The abstract and/or introduction should clearly state the claims made, including the contributions made in the paper and important assumptions and limitations. A No or NA answer to this question will not be perceived well by the reviewers.
   - The claims made should match theoretical and experimental results, and reflect how much the results can be expected to generalize to other settings.
   - It is fine to include aspirational goals as motivation as long as it is clear that these goals are not attained by the paper.

2. **Limitations**

   Question: Does the paper discuss the Limitations of the work performed by the authors?

   Answer: [Yes]

   Justification: Yes, please refer to the Limitation section of this paper for details.

   Guidelines:

   - The answer NA means that the paper has no limitation while the answer No means that the paper has limitations, but those are not discussed in the paper.
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   - The paper should point out any strong assumptions and how robust the results are to violations of these assumptions (e.g., independence assumptions, noiseless settings, model well-specification, asymptotic approximations only holding locally). The authors should reflect on how these assumptions might be violated in practice and what the implications would be.
   - The authors should reflect on the scope of the claims made, e.g., if the approach was only tested on a few datasets or with a few runs. In general, empirical results often depend on implicit assumptions, which should be articulated.
   - The authors should reflect on the factors that influence the performance of the approach. For example, a facial recognition algorithm may perform poorly when image resolution is low or images are taken in low lighting. Or a speech-to-text system might not be used reliably to provide closed captions for online lectures because it fails to handle technical jargon.
   - The authors should discuss the computational efficiency of the proposed algorithms and how they scale with dataset size.
   - If applicable, the authors should discuss possible limitations of their approach to address problems of privacy and fairness.
   - While the authors might fear that complete honesty about limitations might be used by reviewers as grounds for rejection, a worse outcome might be that reviewers discover limitations that aren't acknowledged in the paper. The authors should use their best judgment and recognize that individual actions in favor of transparency play an important role in developing norms that preserve the integrity of the community. Reviewers will be specifically instructed to not penalize honesty concerning limitations.

3. **Theory assumptions and proofs**

   Question: For each theoretical result, does the paper provide the full set of assumptions and a complete (and correct) proof?

   Answer: [NA]

Justification: This paper introduces a benchmark and does not propose any theoretical results or formal proofs. Therefore, the question about theoretical assumptions and proofs does not apply.

Guidelines:

- The answer NA means that the paper does not include theoretical results.
- All the theorems, formulas, and proofs in the paper should be numbered and cross-referenced.
- All assumptions should be clearly stated or referenced in the statement of any theorems.
- The proofs can either appear in the main paper or the supplemental material, but if they appear in the supplemental material, the authors are encouraged to provide a short proof sketch to provide intuition.
- Inversely, any informal proof provided in the core of the paper should be complemented by formal proofs provided in appendix or supplemental material.
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