GMAI-MMBench: A Comprehensive Multimodal Evaluation Benchmark Towards General Medical AI

Supplementary Materials

Contents

A Related work

A.1 Large Vision-Language Model(LVLMs)

In contrast to traditional deep learning models, Large Vision-Language Models (LVLMs) offer a broader spectrum of possibilities for AI-assisted healthcare. Their user-friendly and intuitive interaction mechanisms make them one of the most promising paradigms for future AI applications. Among the multitude of LVLMs, prominent proprietary models such as GPT-4o [5], Claude3-opus [13], and Qwen-max [18] exemplify the pinnacle of contemporary general-purpose large models. Additionally, numerous open-source general-purpose models have emerged, including the InternVL series [47, 46], LLAVA series [147, 148, 43], DeepSeek series [155], CogVLM series [249], InstructBLIP series [56], Idefics series [137], XComposer series [43, 266, 62, 63], Yi-VL series [7], Xtuner series [54], and MiniCPM series [103, 257]. These open-source models are rapidly evolving due to their accessibility and collaborative development.

To address specialized medical tasks, researchers have trained and fine-tuned these large models using domain-specific medical data, resulting in specialized large models. Noteworthy examples include LLaVA-Med [138] derived from the LLAVA series, and MedDr [95] based on the InternLM framework. The advent of these specialized medical models has laid a solid foundation for the application of LVLMs in the healthcare sector, highlighting their transformative potential and accelerating their development within the medical domain.

A.2 Benchmarks

In the swiftly emerging and burgeoning domain of LVLMs, the significance of rigorous evaluation cannot be overstated. Benchmarking serves as a crucial metric for guiding model enhancement, identifying deficiencies, and steering the trajectory of model development. Within the medical domain, benchmarks are typically categorized into specialized and general-purpose benchmarks.

Specialized benchmarks are often concentrated on a particular modality or medical discipline. For instance, VQA-RAD [136], SLAKE [145], and RadBench [253] focus on radiology, while PathVQA [96] and PathMMU [238] are dedicated to pathology. These benchmarks provide a wealth of evaluation data for specific modalities or disciplines, enabling comprehensive assessment of capabilities within targeted fields. However, their limited generalizability constrains their broader applicability.

In addition to these specialized benchmarks, there exist general-purpose medical benchmarks that span multiple medical domains. Prominent examples include MMMU [263], OminimedVQA [106], and MMT-Bench [260]. These comprehensive benchmarks facilitate a more holistic evaluation of a model's overall competence in the medical field. Nonetheless, these general-purpose benchmarks often exhibit shortcomings in various aspects such as the volume of tasks, number of modalities, data distribution, and granularity of data. Addressing these limitations presents a significant challenge that necessitates prompt resolution.

The development and refinement of benchmarks are indispensable for the progress of LVLMs in healthcare. By elucidating the capabilities and limitations of specialized and general-purpose benchmarks, it becomes evident that while specialized benchmarks excel in evaluating domain-specific performance, their lack of generalizability is a notable drawback. Conversely, general-purpose benchmarks offer a broader assessment across multiple medical fields but often fall short in task diversity, modality coverage, and data granularity. Therefore, there is an urgent need for more comprehensive and robust benchmarks to bridge these gaps and better support the advancement of LVLMs in healthcare.

B Dataset Details

In this section, we provide the detailed datasets used in GMAI-MMBench, including the name of the dataset or challenge, the number of sub-datasets in it, the modality, the dimension of data, the task type, and the number of cases. As shown in Table 4, GMAI-MMBench is constructed from 284 datasets across 38 medical image modalities. These datasets are derived from the public (268) and several hospitals (16) that have agreed to share their ethically approved data.

Table 4: Detailed datasets information in GMAI-MMBench. As one challenge/dataset may contain several sub-tasks or sub-challenges in the medical area, we count them in the "N" (second column). In the dimension (Dim) column, 2D and 3D denote the dimensions of the original data, respectively. In the task type (Task) column, Cls, MCls, Seg, and Det indicate classification, multi-label classification, segmentation, and detection, respectively. The count represents the number of cases used in GMAI-MMBench.

Challenge / Dataset	N	Modality	Dim	Task	Count
5K+ CT Images on Fractured Limbs [215]	1	CT	2D	Cls	60
AAPM RT-MAC 2019 [40]	1	T2 weighted MRI	3D	Seg	68
Abdomenatlas 1.0 [205]	1	CT	3D	Seg	52
AbdomenCT-1K [164]	1	CT	3D	Seg	28
ACDC 2017 [30]	1	MRI	3D	Seg	10
ACRIMA [60]	1	Fundus Photography	2D	Cls	1
ADAM 2020 [68]	1	Fundus Photography	2D	Cls	1
Adrenal-ACC-Ki67-Seg [177]	1	CT	3D	Seg	60
AGE 2019 [74]	1	OCT	2D	MCls	20
AIDA-E 2016	3	Endoscopy	2D	Cls	187
AIIB23 [183]	1	CT	3D	Seg	34
AIROGS [58]	1	Fundus Photography	2D	Cls	57
AMOS 2022 [116]	1	MRI, CT	3D	Seg	148
APTOS 2019 [125]	1	Fundus Photography	2D	Cls	14

ATLAS 2023 [206]	1	T1 weighted MRI	3D	Seg	16
ATM 2022 [265]	1	CT	3D	Seg	26
AtriaSeg 2018 [265]	1	LGE MRI	3D	Seg	2
Augemnted ocular diseases	1	Fundus Photography	2D	Cls	97
AV Nicking Quantification [186]	1	Fundus Photography	2D	Cls	71
Bacteria Detection with Darkfield Microscopy [201]	1	Microscopy	2D	Seg	120
BCNB [256]	9	Histopathology	2D	Cls	360
BCSS [12]	1	Histopathology	2D	Seg	102
BioMediTech [184]	1	Microscopy	2D	Cls	120
Blood Cell Images [180]	1	Microscopy	2D	Cls	55
BloodCell from Heywhale	1	Microscopy	2D	Det	90
Bone-Marrow-Cytomorphology [172]	1	Histopathology	2D	Cls	484
Brain-Tumor-Progression [221]	1	T2 weighted MRI, T1 weighted MRI, FLAIR MRI, ADC MRI	3D	Seg	60
BraTS 2020 [33, 22, 23]	1	FLAIR MRI	3D	Seg	4
BraTS 2021 [22, 23, 20]	1	FLAIR MRI	3D	Seg	2
BraTS-TCGA-GBM [216]	1	T1 MRI	3D	Seg	4
BraTS-TCGA-LGG [21]	1	T2 MRI, FLAIR MRI, T1Gd MRI	3D	Seg	16
BreakHis [232]	4	Histopathology	2D	Cls	60
Breast Cancer Cell Seg [79]	1	Histopathology	2D	Seg	18
BRIGHT [111, 193]	1	Histopathology	2D	Cls	117
BTCV-Abdomen [135]	1	CT	3D	Seg	60
BTCV-Cervix [135]	1	CT	3D	Seg	96
BUSI [8]	1	UltraSound	2D	Seg	60
C-NMC 2019 [182]	1	Histopathology	2D	Cls	28
CAD-PE [83]	1	CT	3D	Seg	46
cataract dataset [121]	1	Fundus Photography	2D	Cls	34
Cervix93 Cytology Dataset [198]	1	Microscopy	2D	Cls	60
CETUS 2014	1	UltraSound	3D	Seg	2
CHAOS [127, 128]	1	T2 weighted MRI, T1 weighted MRI	3D	Seg	14
Chest CT-Scan images Dataset [90]	1	CT	2D	Cls	81
Chest X-Ray Images with Pneumothorax Masks [264]	1	X-ray	2D	Seg	30
ChestX-Det [143]	1	X-ray	2D	Seg	674
ChestX-Det [143]	1	X-ray	2D	Det	339
Chiu_BOE_2013_dataset [49]	1	Adaptive Optics Ophthalmoscopy	2D	Seg	52
CMRxMotion 2022 [248]	1	CMR	3D	Seg	12
Colorectal-Liver-Metastases [228]	1	CT	3D	Seg	10
Continuous Registration	1	CT	3D	Seg	6
Corneal Nerve [218]	1	Microscopy	2D	Cls	35
Corneal Nerve Tortuosity Grading [219]	1	Microscopy	2D	Cls	30
CoronaHack [52]	1	X-ray	2D	Cls	8
COVID-19 CT scans [192, 81, 122]	1	CT	3D	Seg	74
Covid-19 Image Dataset [209]	1	X-ray	2D	Cls	5
COVID-19 Radiography Database [51]	1	X-ray	2D	Cls	40
COVID-19-20 [214]	1	CT	3D	Seg	30
COVID-19-CT-Seg [192]	1	CT	3D	Seg	30
COVID19 with Pneumonia and Normal Chest Xray(PA) Dataset [16]	1	X-ray	2D	Cls	21
COVIDGR [239]	1	X-ray	2D	Cls	1
COVIDx CXR-4 [247]	2	X-ray	2D	Cls	59
CRAG [84]	1	Histopathology	2D	Seg	16
CRASS12 [101]	1	X-ray	2D	Seg	60
CRC100K [126]	1	Histopathology	2D	Cls	210
CT-ICH [102]	1	CT	2D	Seg	60
CT-ORG [212]	1	CT	3D	Seg	40
CTPelvic1K [150]	1	CT	3D	Seg	168

CTSpine1K [59]	1	CT	3D	Seg	40
Curious 2022 [255]	1	UltraSound	3D	Seg	60
CVC-ClinicDB [28]	1	Endoscopy	2D	Seg	10
DDTI [195]	1	UltraSound	2D	Seg	60
DeepDRiD [152]	3	Fundus Photography	2D	Cls	73
derm7pt [129]	1	Dermoscopy	2D	Cls	5
Diabetic Retinopathy Arranged [185]	1	Fundus Photography	2D	Cls	60
Diabetic Retinopathy Detection [65]	1	Fundus Photography	2D	Cls	52
Diagnosis of Diabetic Retinopathy [57]	1	Fundus Photography	2D	Cls	42
DigestPath 2019 [55]	1	Histopathology	2D	Seg	60
DigestPath 2020 [55]	1	Histopathology	2D	Cls	60
DRAC 2022 [204]	1	Fundus Photography	2D	Seg	58
DRIMDB [225]	1	Fundus Photography	2D	Cls	37
DRIVE [233]	1	Fundus Photography	2D	Seg	14
EAD 2020 [9]	1	Endoscopy	2D	Det	210
EDD 2020 [9]	2	Endoscopy	2D	Seg	198
EDD 2020 [9]	1	Endoscopy	2D	Det	120
EMIDEC 2020 [134]	1	MRI	3D	Seg	62
EndoVis 2015 [29]	1	Endoscopy	2D	Seg	10
EndoVis 2017 KBD [11]	1	Endoscopy	2D	Seg	16
EndoVis 2018 RSS [10]	1	Endoscopy	2D	Seg	370
EndoVisSub-Instrument	1	Endoscopy	2D	Seg	86
Eye OCT Datasets [167]	1	OCT	2D	Cls	14
Finding and Measuring Lungs in CT Data [166]	1	CT	2D	Seg	60
Finding and Measuring Lungs in CT Data [166]	1	CT	3D	Seg	8
Fitzpatrick17k [85]	1	Dermoscopy	2D	Cls	270
FLARE 2021 [162]	1	CT	3D	Seg	22
FLARE 2022 [163]	1	CT	3D	Seg	76
Fundus Images for the Study of Diabetic Retinopathy [26]	1	Fundus Photography	2D	Cls	134
FUSC 2021 [246]	1	Dermoscopy	2D	Seg	60
GAMMA [73]	1	Fundus Photography	2D	Cls	70
GlaS [229]	1	Histopathology	2D	Seg	44
GOALS 2022 [69]	1	OCT	2D	Seg	180
HaN-Seg [199]	1	CT	3D	Seg	96
Harvard-GDP1000 [161]	1	Fundus Photography	2D	Cls	53
HCC-TACE-Seg [178]	1	CT	3D	Seg	24
HeartSegMRI [241]	1	MRI	3D	Seg	2
HErlev [110]	1	Histopathology	2D	Cls	166
HRF [35]	1	Fundus Photography	2D	Cls	3
Human Protein Atlas - Single Cell Classification [252]	1	Microscopy	2D	MCls	2927
HVSMR 2016 [190]	1	MRI	3D	Seg	16
ICIAR 2018 [15]	1	Microscopy	2D	Cls	28
ICIAR 2018 [15]	1	Microscopy	2D	Seg	238
IDRiD [202]	1	Fundus Photography	2D	Seg	232
Intel & MobileODT Cervical Cancer Screening [27]	1	Colposcopy	2D	Cls	90
ISIC 2016 [88]	1	Dermoscopy	2D	Cls	60
ISIC 2016 [88]	1	Dermoscopy	2D	Seg	48
ISIC 2018 [242]	1	Dermoscopy	2D	Seg	252
ISIC 2018 [242]	1	Dermoscopy	2D	Cls	32
ISIC 2019	1	Dermoscopy	2D	Cls	171
ISIC 2020 [213]	1	Dermoscopy	2D	Cls	30
ISPY1-Tumor-SEG-Radiomics [48]	1	DCE MRI	3D	Seg	60
IVDM3Seg [86]	1	Fat MRI, Water MRI, In-phase MRI, Opposed-phase MRI	3D	Seg	60
IvyGAP-Radiomics [194]	1	FLAIR MRI	3D	Seg	2
JSIEC [41]	1	Fundus Photography	2D	Cls	509
JSRT [226]	1	X-ray	2D	Seg	60
JSRT [226]	1	X-ray	2D	Cls	120

Kidney Boundary Detection [94]	1	Endoscopy	2D	Seg	44
KiPA 2022 [97]	1	CT	3D	Seg	158
KiTS 2019 [99]	1	CT	3D	Seg	16
KiTS 2021 [269]	1	CT	3D	Seg	82
Knee Osteoarthritis Dataset with Severity Grading [45]	1	X-ray	2D	Cls	150
Kvasir [200]	1	Endoscopy	2D	Cls	237
Kvasir-SEG [114]	1	Endoscopy	2D	Seg	10
KvasirCapsule-SEG [115]	1	Endoscopy	2D	Seg	6
LAScarQS 2022 [140]	1	LGE MRI	3D	Seg	2
LC25000 [34]	1	Histopathology	2D	Cls	150
Learn2Reg2022	1	CT	3D	Seg	56
Leukemia Classification [87]	1	Microscopy	2D	Cls	32
LiTS [32]	1	CT	3D	Seg	24
LNDb [196]	1	CT	3D	Seg	20
Longitudinal Multiple Sclerosis Lesion Segmentation Challenge [39]	1	MP-RAGE MRI, T2 MRI, PD MRI, FLAIR MRI	3D	Seg	22
LUAD-CT-Survival [82]	1	CT	3D	Seg	60
LUNA 2016 [224]	1	CT	3D	Seg	8
LYSTO [245]	1	Histopathology	2D	Cls	853
M&Ms-2 [170]	1	MRI	3D	Seg	12
m2cai16-tool-locations [117]	1	Endoscopy	2D	Det	210
m2caiSeg [169]	1	Endoscopy	2D	Seg	690
Malaria from Heywhale	1	Histopathology	2D	Cls	30
Malignant Lymphoma Classification [189]	1	Histopathology	2D	Cls	90
MED-NODE [80]	1	Dermoscopy	2D	Cls	11
MESSIDOR [4]	1	Fundus Photography	2D	Cls	60
MHSMA [112]	4	Microscopy	2D	Cls	234
MIAS Mammography [235]	1	X-ray	2D	Cls	145
MM-WHS 2017 [160]	1	MRI, CT	3D	Seg	140
Mpox Skin Lesion Dataset [108]	1	Dermoscopy	2D	Cls	150
MRL Eye Dataset [76]	6	Infrared Reflectance (IR) imaging	2D	Cls	329
MSD - Colon [227]	1	CT	3D	Seg	60
MSD - Heart [227]	1	MRI	3D	Seg	2
MSD - HepaticVessel [14]	1	CT	3D	Seg	60
MSD - Liver [14]	1	CT	3D	Seg	16
MSD - Lung [14]	1	CT	3D	Seg	18
MSD - Pancreas [14]	1	CT	3D	Seg	68
MSD - Spleen [14]	1	CT	3D	Seg	6
MSSEG 2008 [258]	1	T2 MRI, T1 MRI	3D	Seg	6
MSSEG 2016 [53]	1	T2 MRI, MRI, Gadolinium MRI, T1 MRI, FLAIR MRI	3D	Seg	32
MyoPS 2020 [160]	1	DE MRI, T2 MRI, MRI	3D	Seg	100
NIH Chest X-rays [236]	1	X-ray	2D	Cls	16
NIH Chest X-rays [187, 250]	1	X-ray	2D	MCls	2293
NODE21 [231]	1	X-ray	2D	Det	4
OCCISCOverlapping Cervical Cytology Image Segmentation [156, 157]	1	Microscopy	2D	Seg	90
ODIR 2019	1	Fundus Photography	2D	MCls	116
OLIVES [203]	1	Fundus Photography	2D	Cls	60
Osteosarcoma-Tumor-Assessment [230]	1	Histopathology	2D	Cls	60
PAD-UFES-20 [191]	1	Dermoscopy	2D	Cls	68
PALM 2019 [107]	1	Fundus Photography	2D	Cls	25
PANDA [36]	1	Histopathology	2D	Cls	139
PanNuke [77, 78]	1	Histopathology	2D	Seg	300
Parse 2022 [158]	1	CT	3D	Seg	14
PDDCA [210]	2	CT	3D	Seg	78
PH2 Database [175]	1	Dermoscopy	2D	Cls	97
PI-CAI [217]	1	T2 weighted MRI, MRI	3D	Seg	32

PI-CAI [217]	1	T2 weighted MRI, MRI	3D	Seg	28
PitVis	1	Endoscopy	2D	Cls	360
PleThora [133]	1	CT	3D	Seg	120
PROMISE 2009 [31]	1	T2 weighted MRI	3D	Seg	8
PROMISE 2012 [144]	1	MRI	3D	Seg	8
Prostate-Anatomical-Edge-Cases [123]	1	CT	3D	Seg	18
PROSTATEx-Seg-HiRes [220]	1	T2 weighted MRI	3D	Seg	6
Pulmonary Chest X-Ray Abnormalities [109]	1	X-ray	2D	Cls	12
Pulmonary Chest X-Ray Abnormalities [244]	1	X-ray	2D	Cls	13
Pulmonary Embolism in CT images [171]	1	CT	3D	Seg	14
QIBA-VolCT-1B [173]	1	CT	3D	Seg	60
QIN-LungCT-Seg [113]	1	CT	3D	Seg	6
QIN-PROSTATE-Repeatability [70]	1	T2 weighted MRI, DCE MRI, ADC MRI	3D	Seg	80
RadImageNet [174]	1	UltraSound, MRI, CT	2D	Cls	4608
RAVIR [93]	1	Infrared Reflectance (IR) imaging	2D	Seg	92
REFUGE2 [139, 188]	1	Fundus Photography	2D	Seg	20
Retina Fundus Image Registration [100]	1	OCT	2D	Cls	135
Retinal OCT Images [131]	1	OCT	2D	Cls	14
RHUH-GBM [42]	1	T1ce MRI, T2 MRI, ADC MRI	3D	Seg	10
RibFrac2020 [118]	1	CT	3D	Seg	60
RIDER-LungCT-Seg [6]	1	CT	3D	Seg	26
RIM-ONE [75]	1	Fundus Photography	2D	Seg	60
RITE [104]	1	Fundus Photography	2D	Seg	16
Robotic Instrument Segmentation [11]	1	Endoscopy	2D	Seg	74
ROSE [165]	1	Fundus Photography	2D	Seg	30
RSNA Intracranial Hemorrhage Detection [71]	1	CT	2D	MCls	289
RSNA Pediatric Bone Age Challenge [89]	1	X-ray	2D	Cls	1
RUS-CHN	1	X-ray	2D	Cls	265
RUS-CHN SAML [151]	1	T2 weighted MRI	3D	Seg	6
SARAS-MESAD [25, 24]	1	Endoscopy	2D	Det	635
SEG.A. 2023 [119, 197, 208, 168]	1	CT	3D	Seg	2
SegPC-2021 [15, 32]	1	Histopathology	2D	Seg	30
SegTHOR [98]	1	CT	3D	Seg	48
SIIM-ACR Pneumothorax Segmentation [264]	1	X-ray	2D	Seg	16
SIIM-ACR Pneumothorax Segmentation [264]	1	X-ray	2D	Cls	58
SIIM-FISABIO-RSNA COVID-19 Detection [130]	1	X-ray	2D	Cls	90
SinaFarsiu-008-Chiu BOE 2012 [50]	1	OCT	2D	Seg	46
SinaFarsiu-009-Chiu BOE 2013 [49]	1	OCT	2D	Seg	8
SinaFarsiu-010-Rabbani IOVS 2014 [207]	1	OCT	2D	Seg	48
SinaFarsiu-013-Estrada PAMI 2015 [67]	1	OCT	2D	Cls	30
SLIVER 2007 [98]	1	CT	3D	Seg	6
SLN-Breast [38]	1	Histopathology	2D	Cls	2
SPPIN2023	1	T1Gd MRI	3D	Seg	60
STACOM SLAWT 2016 [124]	1	MRI, CT	3D	Seg	4
StructSeg 2019 [98]	4	CT	3D	Seg	242
SUN-SEG [176]	1	Endoscopy	2D	Seg	6
Surgical Instrument Multi-Domain Segmentation Challenge	1	Endoscopy	2D	Seg	210

Surgical Instrument Multi-Domain Segmentation Challenge	1	Endoscopy	2D	Seg	2
Syn-ISS	1	Endoscopy	2D	Seg	58
TCB Challenge [92]	1	Texture Characterization of Bone Radiograph	2D	Cls	60
TotalSegmentator [251]	1	CT	3D	Seg	1218
UCSF-PDGM [37]	1	ASL MRI, DWI MRI, T1 weighted MRI, SWI MRI, DTI MRI, MRI, FLAIR MRI	3D	Seg	22
Ultrasound Nerve Segmentation [179]	1	UltraSound	2D	Seg	60
UW-Madison GI Tract Image Segmentation [91]	1	MRI	2D	Seg	150
VerSe 2019 [223, 153]	1	CT	3D	Seg	94
VerSe 2020 [223, 153]	1	CT	3D	Seg	14
VinBigData Chest X-ray Abnormalities Detection [66]	1	X-ray	2D	Det	107
WORD [159]	1	CT	3D	Seg	72
Yangxi Dataset [146]	1	Fundus Photography	2D	Cls	60
In-House Dataset	1	Fundus Photography	2D	Cls	23
In-House Dataset	1	CT	3D	Seg	40
In-House Dataset	1	CT	3D	Seg	12
In-House Dataset	1	CT	3D	Seg	80
In-House Dataset	1	CTA	3D	Seg	10
In-House Dataset	1	CT	3D	Seg	18
In-House Dataset	1	CT	3D	Seg	34
In-House Dataset	1	CT	3D	Seg	60
In-House Dataset	1	CT	3D	Seg	76
In-House Dataset	1	CT	3D	Seg	60
In-House Dataset	1	CT	3D	Seg	18
In-House Dataset	1	CT	3D	Seg	96
In-House Dataset	1	CT	3D	Seg	150
In-House Dataset	1	CT	3D	Seg	40
In-House Dataset	1	CT	3D	Seg	14
In-House Dataset	1	CT	3D	Seg	82

C Details of Well-categorized Data Structure

C.1 Data Statistics

In this section, we present the comprehensive statistical information of GMAI-MMBench. Figure 6 offers a global view of the label distribution proportions for different clinical VQA tasks, departments, and perceptual granularities. The left pie chart (A) shows the distribution of clinical VQA tasks, with Disease Diagnosis (DD) being the most prevalent at 51.6%, followed by Severity Grading (SG) at 9.1%, Counting (C) at 5.4%, and Organ Recognition – Abdomen (OR-A) at 4.0%. The middle pie chart (B) depicts the distribution of cases across various departments, where Ophthalmolog (O) has the highest proportion at 11.3%, followed by Hematology (H) at 10.7%, General Surgery (GS) at 10.2%, and Urolog (U) at 9.7%. The right pie chart (C) represents the distribution of perceptual granularities, with Image Level accounting for the largest share at 49.2%, followed by Mask Level at 22.0%, and Contour Level at 22.0%. Specifically, Table 5 provides the statistical details for different clinical VQA tasks, including their full terms, abbreviations, and the number of questions associated with each task. Table 6 presents the statistical information for different departments, including each department's full term, abbreviation, and the number of questions contained within each department. Table 7 shows the statistical information for different granularity. In the detailed tables, the statistical information for multiple-choice questions is also included, **specially, for multiple-choice questions, we count the frequency of choice appearances rather than the actual number of cases.**

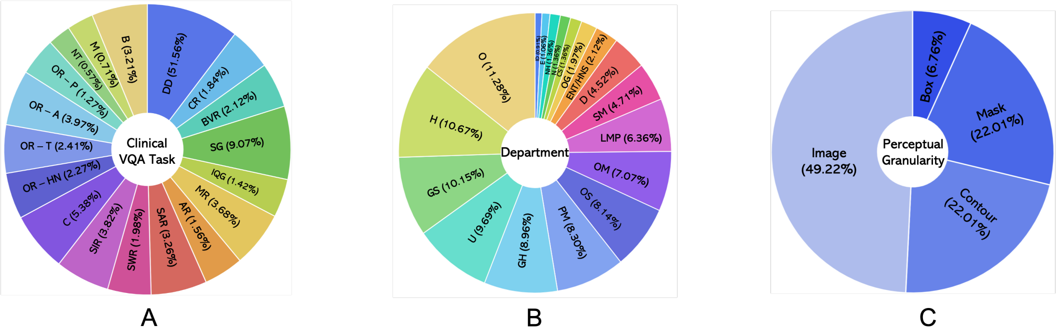


Figure 6: Label distribution for clinical VQA tasks, departments, and perceptual granularities.

Table 5: Statistics of the clinical VQA tasks and their sub-task abbreviations mentioned in the paper with their corresponding full terms.

Full Name	Abbreviation	Single Choice			Multiple Choice		
		Modalities	Labels	Cases	Modalities	Labels	Cases
Attribute Recognition	AR	5	26	780	1	4	40
Blood Vessels Recognition	BVR	7	15	436	-	-	-
Bone	B	6	22	655	-	-	-
Cell Recognition	CR	4	13	383	1	18	7614
Counting	C	1	38	853	-	-	-
Disease Diagnosis	DD	29	364	10167	3	26	8037
Image Quality Grading	IQG	2	10	300	-	-	-
Microorganism Recognition	MR	3	26	779	-	-	-
Muscle	M	1	5	150	-	-	-
Nervous Tissue	NT	2	4	120	-	-	-
Organ Recognition - Abdomen	OR-A	7	28	838	-	-	-
Organ Recognition - Head and Neck	OR-HN	5	16	480	-	-	-
Organ Recognition - Pelvic	OR-P	6	9	270	-	-	-
Organ Recognition - Thorax	OR-T	9	17	510	-	-	-
Severity Grading	SG	5	64	1678	-	-	-
Surgeon Action Recognition	SAR	1	23	635	-	-	-
Surgical Instrument Recognition	SIR	1	27	790	-	-	-
Surgical Workflow Recognition	SWR	1	14	420	-	-	-

Table 6: Statistics of the departments and their sub-task abbreviations mentioned in the paper with their corresponding full terms.

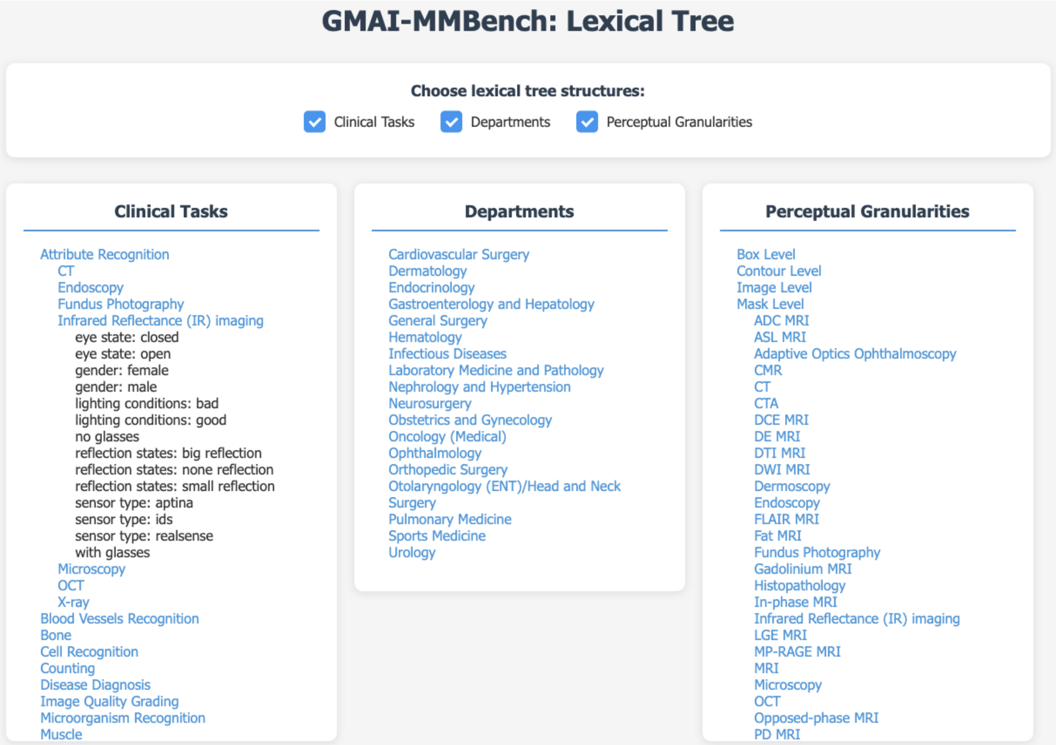
Full Name	Abbreviation	Single Choice			Multiple Choice		
		Modalities	Labels	Cases	Modalities	Labels	Cases
Cardiovascular Surgery	CS	9	9	270	1	1	424
Dermatology	D	1	30	894	-	-	-
Endocrinology	E	3	7	210	-	-	-
Gastroenterology and Hepatology	GH	7	60	1774	-	-	-
General Surgery	GS	6	68	2009	-	-	-
Hematology	H	6	80	2112	-	-	-
Infectious Diseases	ID	2	7	180	-	-	-
Laboratory Medicine and Pathology	LMP	2	45	1259	1	18	7614
Nephrology and Hypertension	NH	4	9	270	-	-	-
Neurosurgery	N	8	9	270	-	-	-
None (Attributes that do not belong to any department)	N/A	2	15	450	-	-	-
Obstetrics and Gynecology	OG	5	14	389	-	-	-
Oncology (Medical)	OM	20	51	1399	-	-	-
Ophthalmology	O	6	97	2232	2	11	218
Orthopedic Surgery	OS	8	54	1611	-	-	-
Otolaryngology (ENT)/Head and Neck Surgery	ENT/HNS	5	14	420	1	6	1015
Pulmonary Medicine	PM	2	55	1643	1	12	6420
Sports Medicine	SM	3	64	1919	-	-	-
Urology	U	8	33	933	-	-	-

Table 7: Statistics of the perceptual granularities. * and # denote the case for single choice and multiple choice, respectively.

Full Name	Modalities	Labels	Cases
Mask Level	36	188	5587
Contour Level	36	188	5587
Box Level	3	59	1715
Image Level*	13	474	12942
Image Level#	5	48	15691

C.2 Lexical Tree

To make the GMAI-MMBench more intuitive and user-friendly, we have systematized our labels and structured the entire dataset into a lexical tree, which is presented in HTML format as shown in Figure 7. Users can freely select the test contents based on this lexical tree. We believe that this customizable benchmark will effectively guide the improvement of models in specific areas. For instance, as mentioned in the main text, most models perform poorly at the bounding box level perception. Users can then update their models and test the accuracy at the bounding box level using this lexical tree, thereby achieving targeted improvements in model performance.



GMAI-MMBench: Lexical Tree

Choose lexical tree structures:

☑ Clinical Tasks ☑ Departments ☑ Perceptual Granularities

Clinical Tasks

- Attribute Recognition
  - CT
  - Endoscopy
  - Fundus Photography
  - Infrared Reflectance (IR) imaging
    - eye state: closed
    - eye state: open
    - gender: female
    - gender: male
    - lighting conditions: bad
    - lighting conditions: good
    - no glasses
    - reflection states: big reflection
    - reflection states: none reflection
    - reflection states: small reflection
    - sensor type: aptina
    - sensor type: ids
    - sensor type: realsense
    - with glasses
  - Microscopy
  - OCT
  - X-ray
- Blood Vessels Recognition
- Bone
- Cell Recognition
- Counting
- Disease Diagnosis
- Image Quality Grading
- Microorganism Recognition
- Muscle

Departments

- Cardiovascular Surgery
- Dermatology
- Endocrinology
- Gastroenterology and Hepatology
- General Surgery
- Hematology
- Infectious Diseases
- Laboratory Medicine and Pathology
- Nephrology and Hypertension
- Neurosurgery
- Obstetrics and Gynecology
- Oncology (Medical)
- Ophthalmology
- Orthopedic Surgery
- Otolaryngology (ENT)/Head and Neck
- Surgery
- Pulmonary Medicine
- Sports Medicine
- Urology

Perceptual Granularities

- Box Level
- Contour Level
- Image Level
- Mask Level
  - ADC MRI
  - ASL MRI
  - Adaptive Optics Ophthalmoscopy
  - CMR
  - CT
  - CTA
  - DCE MRI
  - DE MRI
  - DTI MRI
  - DWI MRI
  - Dermoscopy
  - Endoscopy
  - FLAIR MRI
  - Fat MRI
  - Fundus Photography
  - Gadolinium MRI
  - Histopathology
  - In-phase MRI
  - Infrared Reflectance (IR) imaging
  - LGE MRI
  - MP-RAGE MRI
  - MRI
  - Microscopy
  - OCT
  - Opposed-phase MRI
  - PD MRI

Figure 7: Overview of the lexical tree. The whole tree is provided in the attached HTML file named "Lexical tree.html".

Here, we specifically demonstrate how to customize the use of the lexical tree. First, select the data we need to test based on the users' requirements. In this example, we will focus on **ophthalmology** department and only **fundus photography** modality.

Step-by-Step Process:

1. **Select the Department:** First, navigate to the Lexical Tree interface and select the department relevant to our testing. In our case, we choose the "Ophthalmology" department from the available clinical tasks, as shown in Figure 8.
2. **Choose the Modality:** Within the ophthalmology department, several modalities related to eye conditions are listed. We specifically select the "Fundus Photography" modality. This selection allows us to access all the keywords associated with fundus images, which are crucial for the next step.
3. **Keyword Filtering:** After selecting the fundus photography modality, a comprehensive list of keywords appears. These keywords are critical as they will be used to filter the relevant questions for the evaluation. Examples of keywords include "advanced glaucoma", "age-related macular degeneration", and "diabetic retinopathy" among others.
4. **Retrieve Question List:** The system filters and retrieves questions from the pre-prepared question list using the selected keywords. Each question includes multiple options, and the correct answer corresponds to the keyword used for filtering. However, the correct answers are hidden from the users during the evaluation process. For instance, a question may ask about identifying a condition shown in an image, with options like "A. advanced glaucoma", "B. early glaucoma", "C. non glaucoma", etc. The correct answer, such as "advanced glaucoma" is derived from the keyword used for filtering.
5. **Model Evaluation:** The filtered question list is then used to evaluate various models. In this example, models such as GPT-4, Claude3-Opus, Qwen-Max, and others are assessed for their accuracy in answering the questions. The results are compiled and displayed in a tabular format, showcasing each model's performance.

In addition to the provided example, this method allows for the independent testing of **any other departments, modalities, clinical tasks, and their combinations.** For instance, if the objective is to evaluate only ophthalmology, fundus photographs, and disease diagnosis tasks, further refinement of the keywords can be achieved following the initial selection. By accessing the disease diagnosis task and selecting the fundus photography modality, we can intersect the keywords from the department-fundus photography section with those from the clinical tasks-disease diagnosis section. The resulting keywords will represent those relevant exclusively to disease diagnosis tasks within the context of fundus photographs in ophthalmology.

In summary, the lexical tree provides a versatile framework for customizing evaluation processes across various medical domains, ensuring a comprehensive and focused assessment of model performance.

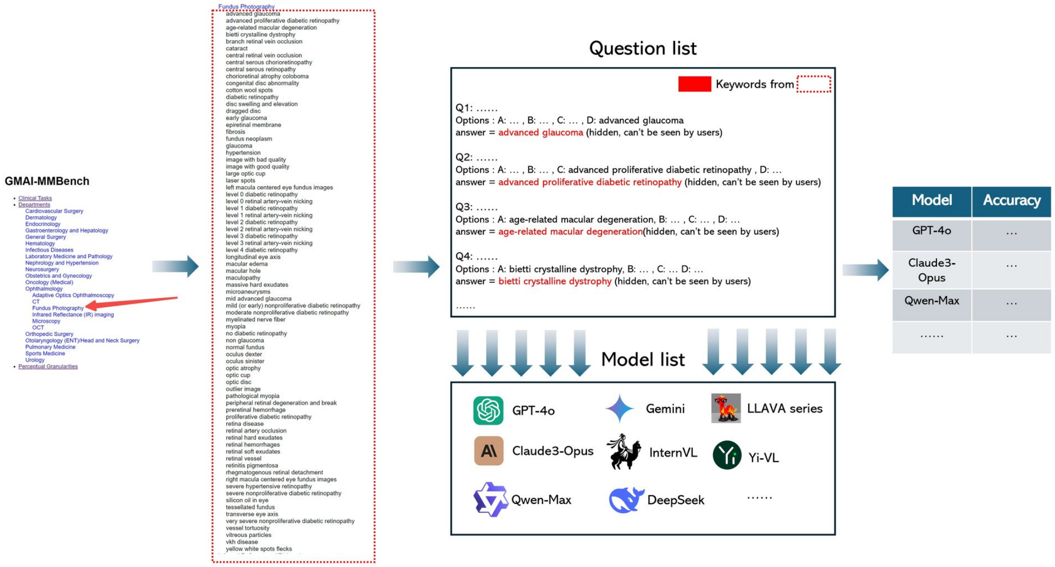

GMAI-MMBench
Clinical Tasks
Departments
Cardiovascular Surgery
Dermatology
Endocrinology
Gastroenterology and Hepatology
General Surgery
Hematology
Infectious Diseases
Laboratory Medicine and Pathology
Nephrology and Hypertension
Neurosurgery
Obstetrics and Gynecology
Oncology (Medical)
Ophthalmology
Adaptive Optics Ophthalmoscopy
CT
Fundus Photography
Infrared Reflectance (IR) imaging
Microscopy
OCT
Orthopedic Surgery
Otolaryngology (ENT)/Head and Neck Surgery
Pulmonary Medicine
Sports Medicine
Urology
Perceptual Granularities
Fundus Photography
advanced glaucoma
advanced proliferative diabetic retinopathy
age-related macular degeneration
bietti crystalline dystrophy
branch retinal vein occlusion
cataract
central retinal vein occlusion
central serous chorioretinopathy
central serous retinopathy
chorioretinal atrophy coloboma
congenital disc abnormality
cotton wool spots
diabetic retinopathy
disc swelling and elevation
dragged disc
early glaucoma
epiretinal membrane
fibrosis
fundus neoplasm
glaucoma
hypertension
image with bad quality
image with good quality
large optic cup
laser spots
left macula centered eye fundus images
level 0 diabetic retinopathy
level 0 retinal artery-vein nicking
level 1 diabetic retinopathy
level 1 retinal artery-vein nicking
level 2 diabetic retinopathy
level 2 retinal artery-vein nicking
level 3 diabetic retinopathy
level 3 retinal artery-vein nicking
level 4 diabetic retinopathy
longitudinal eye axis
macular edema
macular hole
maculopathy
massive hard exudates
microaneurysms
mid advanced glaucoma
mild (or early) nonproliferative diabetic retinopathy
moderate nonproliferative diabetic retinopathy
myelinated nerve fiber
myopia
no diabetic retinopathy
non glaucoma
normal fundus
oculus dexter
oculus sinister
optic atrophy
optic cup
optic disc
outlier image
pathological myopia
peripheral retinal degeneration and break
preretinal hemorrhage
proliferative diabetic retinopathy
retina disease
retinal artery occlusion
retinal hard exudates
retinal hemorrhages
retinal soft exudates
retinal vessel
retinitis pigmentosa
rhegmatogenous retinal detachment
right macula centered eye fundus images
severe hypertensive retinopathy
severe nonproliferative diabetic retinopathy
silicon oil in eye
tessellated fundus
transverse eye axis
very severe nonproliferative diabetic retinopathy
vessel tortuosity
vitreous particles
vkh disease
yellow white spots flecks
Question list
Keywords from
Q1: ……
Options : A: … , B: … , C: … , D: advanced glaucoma
answer = advanced glaucoma (hidden, can't be seen by users)
Q2: ……
Options : A: … , B: … , C: advanced proliferative diabetic retinopathy , D: …
answer = advanced proliferative diabetic retinopathy (hidden, can't be seen by users)
Q3: ……
Options : A: age-related macular degeneration, B: … , C: … , D: …
answer = age-related macular degeneration(hidden, can't be seen by users)
Q4: ……
Options : A: bietti crystalline dystrophy, B: … , C: … D: …
answer = bietti crystalline dystrophy (hidden, can't be seen by users)
……
Model list
GPT-4o
Gemini
LLAVA series
Claude3-Opus
InternVL
Yi-VL
Qwen-Max
DeepSeek
……
Model
Accuracy
GPT-4o
…
Claude3-Opus
…
Qwen-Max
…
……
…

Figure 8: Example of how to use the Lexical Tree for customizing evaluations for the **ophthalmology** department and **fundus photography** modality. The process involves selecting the department (ophthalmology), choosing the modality (fundus photography), filtering questions using relevant keywords, and evaluating different models based on their accuracy in answering the filtered questions.

D Evaluation

In this section, we will describe the evaluation process in detail. We evaluated various LVLMs, including medical-specific models, open-source general models, and closed-source API general models. We selected versions with approximately 7 billion parameters for testing, and the model weights were sourced from their respective official Hugging Face repositories. Our evaluation was conducted using the VLMEvalKit[7] framework. For medical-specific models, we utilized the Multi-Modality-Arena[8] repository for testing. Specifically, we input the prompt shown in Table 8 into the tested model to for evaluation, the option-only answers are expected. However, it's hard for some models to follow the instructions, if a model neither outputs a clear answer tagged by the letter options nor provides instructions to select an answer, we use ChatGPT-3.5-turbo-0613 to extract the answer from the model's outputs. If the answer cannot be extracted, we treat the outputs as errors. Otherwise, the extracted answers will be considered as the model's predicted answer for that question.

Table 8: Examples of single-choice and multiple-choice question prompts.

Prompt example for single-choice questions
Question: Observe the image. What is the most likely abnormality shown in the picture? *Options*: A.osteoporotic bone B.healthy bone Please select the correct answer from the options above. <image>
Prompt example for multiple-choice questions
Question: Determine which part(s) is illustrated in the image. *Options*: A. cytosol B. actin filaments C. vesicles and punctate cytosolic patterns D. microtubules E. plasma membrane F. endoplasmic reticulum Please select all correct answers from the options above. Note that there is more than one correct answer. Please output the answer options directly, separated by commas. For example: A,B <image>

D.1 Evaluation Metric for Single-choice Questions

For all single-choice questions, we denote n_{correct} as the number of questions for which the model offered the correct answer, and $n_{\text{questions}}$ as the total number of questions. The ACC can be calculated as follows:

$$\text{ACC} = \frac{n_{\text{correct}}}{n_{\text{questions}}}. \tag{1}$$

D.2 Evaluation Metric for Multiple-choice Questions

For all multiple-choice questions, we first count the number of correct predictions by the model within the groundtruth for each case, denoted as n_{match}. The length of the prediction is denoted as $l_{\text{prediction}}$, and the length of the groundtruth options are denoted as l_{truth}. The evaluation metrics for multiple-choice questions is calculated as follows:

$$\text{ACC}_{mcls} = \frac{n_{\text{match}}}{l_{\text{prediction}}}, \tag{2}$$

$$\text{Recall}_{mcls} = \frac{n_{\text{match}}}{l_{\text{truth}}}. \tag{3}$$

[7] https://github.com/open-compass/VLMEvalKit

[8] https://github.com/OpenGVLab/Multi-Modality-Arena/tree/main/MedicalEval/Question-answering_Score

Table 9: The model architecture of 50 LVLMs evaluated on GMAIMMBench.

Series	Models	#Params	Vision Encoder	LLM
Med model series	MedVInT [268]	-	-	-
	Med-Flamingo [181]	8.3B	CLIP ViT/L-14	LLaMA-7B
	LLaVA-Med [138]	-	CLIP ViT/L-14	Mistral-7B
	RadFM [254]	14B	3D ViT	MedLLaMA-13B
	Qilin-Med-VL-Chat [149]	-	Clip ViT/L-14	Chinese-LLaMA2-Chat-13B
	MedDr [95]	40B	InternViT-6B	Nous-Hermes-2-Yi-34B
Ungroupped series	TransCore-M [3]	13.4B	CLIP ViT/L-14	PCITransGPT-13B
	VisualGLM-6B [61]	7.8B	EVA-CLIP	ChatGLM-6B
	mPLUG-Owl2 [259]	8.2B	CLIP ViT-L/14	LLaMA2-7B
	OmniLMM-12B [261]	12B	EVA02-5B	Zephyr-7B-β
	PandaGPT 13B [234]	13B	ImageBind ViT-H/14	Vicuna-v0-13B
	Mini-Gemini-7B [141]	7B	CLIP-L	Vicuna-v1.5-7B
	Emu2-Chat [237]	37B	EVA-02-CLIP-E-plus	LLaMA-33B
	Flamingo v2 [17]	9B	CLIP ViT-L/14	MPT-7B
	MMAlaya [154]	7.8B	EVA-G	Alaya-7B-Chat
CogVLM series	CogVLM-Chat [249]	17B	EVA-CLIP-E	Vicuna-v1.5-7B
	CogVLM-grounding-generalist [249]	17B	EVA-CLIP-E	Vicuna-v1.5-7B
InstructBLIP series	InstructBLIP-7B [56]	8B	EVA-G	Vicuna-7B
DeepSeek series	DeepSeek-VL-1.3B [155]	1.3B	SAM-B & SigLIP-L	DeekSeek-1B
	DeepSeek-VL-7B [155]	7.3B	SAM-B & SigLIP-L	DeekSeek-7B
Idefics series	Idefics-9B-Instruct [137]	9B	CLIP ViT-H/14	LLaMA 7B
XComposer series	ShareCaptioner [43]	8B	EVA-G	InternLM-7B
	XComposer [266]	8B	EVA-CLIP-G	InternLM-7B
	XComposer2 [62]	7B	CLIP ViT-L/14	InternLM2-7B
	XComposer2-4KHD [63]	7B	CLIP ViT-L/14	InernLM2-7B
Yi-VL series	Yi-VL-6B [7]	6.6B	CLIP ViT-H/14	Yi-6B
InternVL series	InternVL-Chat-V1.1 [47]	19B	InternViT-6B	LLaMA2-13B
	InternVL-Chat-V1.2 [47]	40B	InternViT-6B	Nous-Hermes-2-Yi-34B
	InternVL-Chat-V1.2-Plus [47]	40B	InternViT-6B	Nous-Hermes-2-Yi-34B
	InternVL-Chat-V1.5 [46]	25.5B	InternViT-6B	InternLM2-Chat-20B
LLaVA series	LLaVA-NeXT-mistral-7B [147]	7.6B	CLIP ViT-L/14	Mistral-7B
	LLaVA-NeXT-vicuna-7B [147]	7.1B	CLIP ViT-L/14	Vicuna-v1.5-7B
	LLAVA-V1.5-7B [148]	7.2B	CLIP ViT-L/14	Vicuna-v1.5-7B
	ShareGPT4V-7B [43]	7.2B	CLIP ViT-L/14	Vicuna-v1.5-7B
Xtuner series	LLAVA-InternLM-7b [54]	7.6B	CLIP ViT-L/14	InternLM-7B
	LLAVA-InternLM2-7b [54]	8.1B	CLIP ViT-L/14	InternLM2-7B
	LLAVA-V1.5-7B-xtuner [54]	7.2B	CLIP ViT-L/14	Vicuna-v1.5-7B
	LLAVA-V1.5-13b-xtuner [54]	13.4B	CLIP ViT-L/14	Vicuna-v1.5-13B
MiniCPM series	MiniCPM-V [103]	2.8B	SigLip-400M	MiniCPM-2.4B
	MiniCPM-V2 [257]	2.8B	SigLip-400M	MiniCPM-2.4B
Qwen series	Monkey [142]	9.8B	CLIP-ViT-BigHuge	Qwen-7B
	Monkey-Chat [142]	9.8B	ViT-BigHuge	Qwen-7B
	Qwen-VL [19]	9.6B	CLIP ViT-G/16	QWen-7B
	Qwen-VL-Chat [19]	9.6B	CLIP ViT-G/16	Qwen-7B
API series	Qwen-VL-Max [18]	-	-	QwenLM
	Claude3-Opus [13]	-	-	-
	GPT-4o [5]	-	-	-
	GPT-4V [5]	-	-	-
	Gemini 1.0 [240]	-	-	-
	Gemini 1.5 [211]	-	-	-

D.3 Evaluated Models

In this paper, we evaluate 50 models on our GMAI-MMBench, and we list them in Table 9.

E Results

In this section, we first provide the complete quantitative results in our experiments, and then perform the case study by analyzing 53 representative examples of models' outputs.

E.1 Quantitative Results

The complete test results are shown in the table below. Table 10 shows the results in different clinical VQA tasks; Table 11 shows the results across different departments; Table 12 shows the results in different perceptual granularities.

Table 10: Results for single-choice questions of 50 different LVLMs on clinical VQA tasks. The best-performing model in each category is **in-bold**, and the second best is <u>underlined</u>.

Model name	Overall (val)	Overall (test)	AR	BVR	B	CR	C	DD	IQG	MR	M	NT	OR-A	OR-HN	OR-P	OR-T	SG	SAR	SIR	SWR
Random	25.70	25.94	38.20	22.73	22.92	22.72	24.06	26.66	27.13	27.00	20.00	24.75	21.37	22.93	22.33	21.18	32.43	24.23	21.39	23.71
Medical Special Model																				
MedVInT [268]	2.29	1.96	5.75	0.00	0.00	0.00	2.56	2.11	4.05	0.00	0.00	0.00	0.11	0.00	0.00	0.12	7.36	0.00	1.88	0.00
Med-Flamingo [181]	12.74	11.64	6.67	10.14	9.23	11.27	6.62	13.43	12.15	6.38	8.00	18.18	9.26	18.27	11.00	11.53	12.16	5.19	8.47	11.43
LLaVA-Med [138]	20.54	19.60	24.51	17.83	17.08	19.86	15.04	19.81	20.24	21.51	13.20	15.15	20.42	23.73	17.67	19.65	21.70	19.81	14.11	20.86
Qilin-Med-VL-Chat [149]	22.34	22.06	29.57	19.41	16.46	23.79	15.79	24.19	21.86	16.62	7.20	13.64	24.00	14.67	12.67	15.53	26.13	24.42	17.37	25.71
RadFM [254]	22.95	22.93	27.16	20.63	13.23	19.14	20.45	24.51	23.48	22.85	15.60	16.16	14.32	24.93	17.33	21.53	29.73	17.12	19.59	31.14
MedDr [95]	41.95	43.69	41.20	50.70	37.85	29.87	28.27	52.53	36.03	31.45	29.60	47.47	33.37	51.33	32.67	44.47	35.14	25.19	25.58	32.29
Open-Source LVLMs																				
CogVLM-grounding-generalist [249]	5.20	5.66	3.11	4.02	2.92	3.22	10.83	7.98	9.72	0.15	0.00	11.11	8.32	1.87	1.67	2.00	1.65	0.00	4.02	0.57
XComposer [266]	8.92	7.67	1.38	7.69	8.31	12.34	22.86	7.31	6.07	5.49	2.80	16.16	5.05	8.67	2.00	9.76	11.94	7.31	3.17	4.00
PandaGPT 13B [234]	16.69	16.27	24.51	23.60	22.15	23.61	14.29	14.95	13.36	12.17	18.40	28.79	18.63	27.33	18.67	16.71	11.04	9.23	13.43	9.71
Flamingo v2 [17]	25.58	26.34	37.74	21.50	20.62	22.00	22.41	27.29	25.91	27.45	18.00	28.79	25.16	22.13	22.00	22.00	34.61	22.88	20.44	27.43
VisualGLM-6B [61]	29.58	30.45	40.16	33.92	24.92	25.22	24.21	32.99	29.96	29.53	21.20	37.88	30.32	24.80	13.33	29.88	33.11	19.62	19.16	37.43
Idefics-9B-Instruct [137]	29.74	31.13	40.39	30.59	26.46	33.63	22.56	34.38	25.51	26.71	21.60	27.78	27.47	32.80	24.67	23.41	32.66	23.08	21.39	30.57
InstructBLIP-7B [56]	31.80	30.95	42.12	26.92	24.92	28.09	21.65	34.58	31.58	29.23	22.40	30.30	28.95	27.47	23.00	24.82	32.88	19.81	21.64	26.57
Mini-Gemini-7B [141]	32.17	31.09	29.69	39.16	31.85	28.26	10.38	35.58	29.96	28.78	20.80	34.34	29.58	36.53	24.00	31.76	22.45	25.96	18.56	29.43
MMAlaya [154]	32.19	32.30	41.20	35.14	32.15	34.17	27.82	35.09	28.34	30.27	18.00	46.97	20.21	31.20	16.00	34.59	32.28	23.65	22.93	30.29
Qwen-VL [19]	34.80	36.05	37.05	37.24	35.85	28.98	24.81	43.60	24.70	30.12	19.20	44.44	29.68	31.87	25.00	31.18	30.26	21.54	20.10	26.86
Yi-VL-6B [7]	34.82	34.31	41.66	39.16	26.62	30.23	31.88	38.01	26.72	24.93	25.20	37.37	29.58	31.20	32.33	30.59	36.71	24.81	23.18	31.43
LLaVA-NeXT-vicuna-7B [147]	34.86	35.42	40.62	38.64	21.08	35.42	23.91	41.22	32.39	28.04	20.53	44.95	27.92	34.98	20.22	32.82	33.63	23.08	25.06	34.86
Qwen-VL-Chat [19]	35.07	36.96	38.09	40.56	38.00	32.20	25.71	44.07	24.70	30.56	24.00	40.91	29.37	36.53	26.00	27.29	35.14	16.54	20.10	34.00
CogVLM-Chat [249]	35.23	36.08	40.97	30.77	27.69	32.74	19.40	41.10	36.84	34.72	24.00	40.91	36.74	37.33	26.00	33.65	36.56	20.19	23.95	26.57
Monkey [142]	35.48	36.39	38.32	35.31	35.54	34.53	23.16	43.40	31.98	30.12	19.20	33.33	30.00	32.53	25.33	31.65	34.46	20.00	20.27	30.29
mPLUG-Owl2 [259]	35.62	36.21	37.51	41.08	30.92	38.10	27.82	41.59	28.34	32.79	22.40	40.91	24.74	38.27	23.33	36.59	33.48	20.58	23.01	32.86
ShareCaptioner [43]	36.37	36.19	42.35	32.69	31.08	27.19	30.83	41.19	30.36	33.23	28.40	42.93	27.79	33.73	28.33	40.71	29.58	20.96	28.83	30.00
Emu2-Chat [237]	36.50	37.59	43.27	47.73	26.31	40.07	28.12	44.00	36.44	28.49	20.40	31.82	26.74	37.60	26.67	29.76	33.63	23.27	26.43	29.43
XComposer2-4KHD [63]	36.66	38.54	41.89	39.86	28.77	40.43	20.60	44.25	35.22	33.53	22.80	42.42	34.84	29.60	44.00	39.53	35.21	21.54	27.20	38.00
ShareGPT4V-7B [43]	36.71	36.70	43.96	37.59	21.54	37.57	18.80	43.26	32.39	27.30	22.80	43.43	29.47	37.33	22.00	31.76	34.98	24.42	25.06	30.00
LLaVA-NeXT-mistral-7B [147]	37.20	37.16	38.43	27.98	20.31	29.16	20.60	47.19	30.36	32.64	22.40	55.56	32.75	25.58	17.56	34.04	28.38	23.27	24.12	37.43
LLAVA-V1.5-13b-xtuner [54]	37.82	38.74	44.65	29.02	27.08	38.28	28.87	45.32	32.79	30.12	20.40	45.96	33.47	42.53	44.33	37.53	33.48	19.62	22.58	35.43
OmniLMM-12B [261]	37.89	39.30	39.82	40.56	32.62	37.57	24.81	46.68	35.63	35.01	27.60	57.58	28.42	34.00	25.00	29.18	34.46	24.42	27.54	40.29
InternVL-Chat-V1.1 [47]	38.16	39.41	42.46	43.88	35.23	45.08	23.31	45.96	38.87	29.23	29.60	40.40	31.68	41.87	26.67	38.82	32.13	19.42	25.58	30.29
LLAVA-V1.5-7B [148]	38.23	37.96	45.45	34.27	30.92	41.32	21.65	44.68	34.01	27.74	23.60	43.43	28.00	42.13	29.00	35.06	33.41	22.12	23.61	29.14
Monkey-Chat [142]	38.39	39.50	40.62	41.43	37.08	35.24	23.76	47.73	29.96	32.94	26.00	37.88	34.84	32.67	24.67	33.18	34.91	21.73	22.24	34.00
LLAVA-V1.5-7B-xtuner [54]	38.68	38.22	38.90	40.03	28.00	40.25	30.08	44.08	33.60	32.49	21.20	40.91	29.47	40.40	30.33	38.59	31.46	23.85	26.95	36.86
XComposer2 [62]	38.68	39.20	41.89	37.59	33.69	40.79	22.26	45.87	36.44	32.94	27.20	58.59	26.11	36.40	43.67	37.29	32.06	23.46	27.80	32.86
LLAVA-InternLM-7b [54]	38.71	39.11	36.36	36.54	32.62	38.10	30.68	46.53	34.82	28.19	25.20	48.99	28.11	40.53	33.33	36.00	34.08	26.73	24.12	29.71
TransCore-M [3]	38.86	38.70	40.74	41.78	20.77	35.06	<u>34.74</u>	45.69	32.39	32.94	24.40	44.95	31.05	38.93	27.00	33.76	33.86	23.46	25.49	31.14
InternVL-Chat-V1.5 [46]	38.86	39.73	43.84	44.58	34.00	33.99	31.28	45.59	33.20	38.28	32.40	42.42	31.89	42.80	27.00	36.82	34.76	23.27	24.72	32.57
InternVL-Chat-V1.2-Plus [47]	39.41	40.79	42.58	42.31	32.46	37.03	31.43	47.49	42.51	35.01	21.20	50.51	34.95	42.93	22.67	42.47	35.74	22.31	24.98	28.29
InternVL-Chat-V1.2 [47]	39.52	40.01	41.66	44.06	27.38	38.46	34.29	46.99	33.60	34.42	21.20	47.98	30.63	42.80	27.67	35.88	35.59	<u>23.85</u>	24.98	28.00
LLAVA-InternLM2-7b [54]	40.07	40.45	39.82	37.94	30.62	35.24	29.77	48.97	34.01	25.96	20.80	53.03	30.95	42.67	32.00	39.88	32.43	21.73	24.38	38.00
DeepSeek-VL-1.3B [155]	40.25	40.77	38.55	35.14	38.92	40.07	27.97	48.12	35.63	31.75	22.80	46.97	40.74	44.93	31.00	40.47	33.33	22.31	21.39	31.71
MiniCPM-V [103]	40.95	41.05	39.70	46.50	36.31	39.36	22.26	48.09	34.82	35.76	24.00	45.45	34.11	44.80	23.00	44.47	36.19	21.15	23.95	35.14
DeepSeek-VL-7B [155]	41.73	43.43	38.43	47.03	42.31	37.03	26.47	51.11	33.20	31.16	26.00	44.95	36.00	58.13	36.33	47.29	34.91	18.08	25.49	<u>39.43</u>
MiniCPM-V2 [257]	41.79	42.54	40.74	43.01	36.46	37.57	27.82	51.08	28.74	29.08	26.80	47.47	37.05	46.40	25.33	46.59	35.89	22.31	23.44	31.71
Proprietary LVLMs																				
Claude3-Opus [13]	32.37	32.44	1.61	39.51	34.31	31.66	12.63	39.26	28.74	30.86	22.40	37.37	25.79	41.07	29.33	33.18	31.31	21.35	23.87	4.00
Qwen-VL-Max [18]	41.34	42.16	32.68	44.58	31.38	40.79	10.68	50.53	32.79	44.36	29.20	51.52	41.37	58.00	30.67	41.65	26.95	25.00	24.64	39.14
GPT-4V [5]	42.50	44.08	29.92	48.95	44.00	37.39	12.93	52.88	32.79	44.21	<u>32.80</u>	63.64	39.89	54.13	37.00	50.59	27.55	23.08	25.75	37.43
Gemini 1.0 [240]	44.38	44.93	<u>42.12</u>	45.10	46.46	37.57	20.45	53.29	35.22	36.94	25.20	51.01	34.74	59.60	34.00	50.00	**36.64**	23.65	23.87	35.43
Gemini 1.5 [211]	<u>47.42</u>	<u>48.36</u>	**43.50**	<u>56.12</u>	<u>51.23</u>	<u>47.58</u>	2.26	<u>55.33</u>	<u>38.87</u>	<u>48.07</u>	30.00	**76.26**	<u>51.05</u>	**75.87**	<u>46.33</u>	<u>62.24</u>	20.57	**27.69**	**30.54**	**40.57**
GPT-4o [5]	**53.53**	**53.96**	38.32	**61.01**	**57.08**	**49.02**	**46.62**	**61.45**	**46.56**	**56.38**	**34.00**	<u>75.25</u>	**53.79**	<u>69.47</u>	**48.67**	**65.88**	<u>33.93</u>	22.88	<u>29.51</u>	<u>39.43</u>

Table 11: Results for single-choice questions of 50 LVLMs on different departments. The best-performing model in each category is **in-bold**, and the second best is underlined.

Model name	Overall (val)	Overall (test)	CS	D	E	GH	GS	H	ID	LMP	NH	N	OG	OM	O	OS	ENT/HNS	PM	SM	U
Random	25.70	25.94	22.82	25.19	21.00	25.97	22.24	24.45	31.13	28.99	22.86	24.00	29.15	27.77	30.36	25.92	22.53	24.74	22.87	29.19
Medical Special Model																				
MedVInT [268]	2.29	1.96	0.24	2.50	1.00	1.94	1.09	0.88	3.31	5.23	1.14	0.73	0.00	1.40	4.44	0.56	0.00	2.24	0.64	0.86
Med-Flamingo [181]	12.74	11.64	11.76	12.49	10.00	10.88	9.33	5.42	7.28	10.05	12.00	10.91	12.88	14.89	15.37	12.40	13.43	12.89	14.92	10.47
LLaVA-Med [138]	20.54	19.60	26.12	20.20	29.00	20.31	16.30	18.46	15.23	21.84	20.86	16.73	21.69	19.23	20.18	18.38	20.99	16.87	20.49	21.55
Qilin-Med-VL-Chat [149]	22.34	22.06	12.94	21.06	15.50	22.09	18.98	17.33	17.88	22.92	31.14	29.82	20.00	21.83	25.55	19.07	14.81	29.42	22.17	22.29
RadFM [254]	22.95	22.93	24.24	23.02	20.00	20.59	20.83	19.49	28.48	24.42	18.00	32.00	16.95	26.90	26.25	18.26	26.54	25.19	23.74	20.20
MedDr [95]	41.95	43.69	53.18	45.28	33.00	44.78	28.03	29.91	47.68	35.22	38.29	78.55	25.08	49.53	45.31	52.09	48.61	52.36	54.21	39.90
Open-Source LVLMs																				
CogVLM-grounding-generalist [249]	5.20	5.66	6.59	7.27	4.50	4.94	3.58	4.44	5.96	2.66	19.14	17.82	7.80	7.94	5.00	5.36	5.40	7.86	4.59	2.34
XComposer [266]	8.92	7.67	13.18	2.71	5.00	5.33	4.35	10.88	3.31	6.40	4.00	25.09	6.44	9.15	9.95	8.91	4.01	8.11	9.87	5.54
PandaGPT 13B [234]	16.69	16.27	17.41	12.70	17.00	17.20	12.68	15.42	23.84	14.70	14.86	10.55	8.81	14.29	24.75	16.26	17.13	18.07	12.07	13.92
Flamingo v2 [17]	25.58	26.34	28.47	26.06	18.50	28.58	21.11	24.24	29.14	28.07	13.43	29.45	22.37	28.17	31.85	23.12	27.78	23.54	27.57	29.19
VisualGLM-6B [61]	29.58	30.45	52.71	25.95	14.00	31.69	22.06	25.17	30.46	25.50	30.29	59.27	15.93	29.97	37.79	30.09	23.61	32.85	38.19	23.03
Idefics-9B-Instruct [137]	29.74	31.13	19.76	33.98	21.00	30.08	24.46	26.66	50.33	28.74	36.00	58.55	36.27	29.64	36.76	36.07	24.38	31.36	32.04	29.19
InstructBLIP-7B [56]	31.80	30.95	27.06	28.99	17.50	34.24	21.78	25.84	43.05	29.15	19.14	53.09	27.46	28.64	31.99	34.58	30.25	30.76	41.09	31.28
Mini-Gemini-7B [141]	32.17	31.09	34.59	39.63	23.50	35.74	23.46	19.80	41.06	25.91	40.86	56.00	19.32	21.63	35.73	35.83	33.95	40.57	29.14	29.56
MMAlaya [154]	32.19	32.30	71.06	37.68	38.00	28.30	27.40	27.64	51.66	32.39	28.86	83.64	29.49	27.37	35.92	36.70	20.99	27.53	29.43	28.08
Qwen-VL [19]	34.80	36.05	39.53	41.59	40.50	28.69	20.74	26.77	45.03	28.82	56.57	73.09	39.32	41.39	39.23	43.36	33.64	35.74	45.15	42.73
Yi-VL-6B [7]	34.82	34.31	39.76	43.76	56.00	27.30	25.91	27.23	45.70	32.56	44.29	65.45	47.46	36.38	39.00	35.39	25.46	29.77	39.06	35.22
LLaVA-NeXT-vicuna-7B [147]	34.86	35.42	40.00	37.13	51.60	31.82	29.15	26.18	49.01	31.06	32.94	65.33	28.44	35.98	43.21	38.71	26.87	40.02	36.47	32.36
Qwen-VL-Chat [19]	35.07	36.96	36.47	39.63	36.50	27.08	20.79	27.64	60.93	30.23	52.57	70.55	37.29	47.13	39.37	46.67	34.57	37.63	47.88	39.90
CogVLM-Chat [249]	35.23	36.08	30.59	38.98	42.50	31.41	26.22	23.62	47.02	34.22	51.43	56.00	32.54	44.13	38.67	37.94	30.86	41.11	45.91	29.19
Monkey [142]	35.48	36.39	38.59	39.52	35.00	29.74	20.97	25.73	52.98	28.90	48.29	68.00	34.24	41.46	40.78	45.23	31.79	39.27	45.91	42.49
mPLUG-Owl2 [259]	35.62	36.21	47.76	40.50	41.00	33.46	27.22	28.16	51.66	33.14	38.86	68.73	16.27	38.58	43.34	35.70	27.78	41.61	39.76	30.91
ShareCaptioner [43]	36.37	36.19	37.88	35.50	45.50	35.63	25.54	28.16	56.29	31.15	27.14	64.00	35.59	38.52	39.65	38.57	30.56	44.05	36.68	40.15
Emu2-Chat [237]	36.50	37.59	27.53	35.83	27.50	34.41	28.49	29.35	60.26	36.63	34.00	64.73	28.81	44.79	43.20	37.69	37.50	41.86	43.18	35.34
XComposer2-4KHD [63]	36.66	38.54	48.00	40.17	75.50	36.46	28.80	28.11	49.67	35.96	50.29	69.45	38.64	40.45	43.86	39.63	29.94	43.26	34.13	42.86
ShareGPT4V-7B [43]	36.71	36.70	43.76	39.09	48.50	37.24	27.90	23.88	49.01	30.40	46.29	60.73	29.15	44.46	44.56	37.57	30.40	38.03	35.98	36.95
LLaVA-NeXT-mistral-7B [147]	37.20	37.16	42.96	40.17	46.40	37.84	28.53	23.76	52.32	31.81	46.59	73.00	21.25	47.08	42.61	33.37	22.75	46.94	37.45	33.48
LLAVA-V1.5-13b-xtuner [54]	37.82	38.74	43.06	39.20	43.50	42.01	26.36	26.41	48.34	35.55	38.29	70.55	38.64	51.60	42.08	34.70	34.41	43.90	39.35	41.26
OmniLMM-12B [261]	37.89	39.30	39.53	37.46	41.50	36.18	27.36	28.00	60.93	37.46	55.43	80.00	31.19	35.71	44.89	42.49	28.24	43.80	51.19	42.86
InternVL-Chat-V1.1 [47]	38.16	39.41	45.88	40.07	56.00	34.30	26.68	26.20	52.32	37.79	45.14	64.00	35.93	52.74	44.14	40.56	39.51	41.16	45.56	35.84
LLAVA-V1.5-7B [148]	38.23	37.96	42.35	37.57	44.50	36.13	27.99	24.91	49.01	31.31	34.00	68.36	27.12	45.39	42.46	42.80	33.80	44.20	41.21	38.92
Monkey-Chat [142]	38.39	39.50	43.53	40.28	40.00	33.30	23.28	29.09	54.97	29.73	55.71	72.36	35.25	50.53	42.41	45.98	33.49	42.66	50.15	44.83
LLAVA-V1.5-7B-xtuner [54]	38.68	38.22	51.53	35.07	31.00	38.07	31.52	29.04	58.94	36.79	28.29	69.09	29.15	50.80	39.89	40.12	27.78	40.82	39.12	36.08
XComposer2 [62]	38.68	39.20	32.71	42.13	70.50	33.13	29.62	27.02	54.30	34.05	23.14	83.64	39.66	46.53	44.23	45.73	28.86	45.55	41.32	41.87
LLAVA-InternLM-7b [54]	38.71	39.11	44.94	39.85	33.50	43.06	27.54	27.08	52.98	34.22	31.14	79.64	37.97	50.67	42.41	39.69	36.73	37.63	46.72	39.78
TransCore-M [3]	38.86	38.70	39.06	43.87	24.50	40.18	29.08	30.79	52.98	32.48	38.86	66.91	42.37	42.79	44.75	40.44	36.73	34.00	47.19	35.71
InternVL-Chat-V1.5 [46]	38.86	39.73	36.47	44.84	53.50	37.07	26.63	31.61	60.26	34.14	36.29	67.27	37.63	55.21	47.13	38.69	41.98	39.17	37.55	41.26
InternVL-Chat-V1.2-Plus [47]	39.41	40.79	51.06	43.54	60.00	39.07	29.39	31.82	50.99	37.54	54.00	79.64	30.17	50.87	43.72	37.88	36.88	42.61	43.53	38.55
InternVL-Chat-V1.2 [47]	39.52	40.01	40.71	46.25	77.50	31.52	26.36	31.10	50.33	36.96	52.00	80.00	31.19	45.46	43.20	40.06	34.10	44.40	46.66	42.36
LLAVA-InternLM2-7b [54]	40.07	40.45	43.53	40.72	60.50	34.74	30.12	27.44	51.66	33.39	50.86	74.55	26.44	49.13	42.74	43.12	31.94	50.87	47.01	39.04
DeepSeek-VL-1.3B [155]	40.25	40.77	56.71	37.13	27.00	45.73	28.40	27.85	52.32	35.96	45.43	71.64	45.42	50.20	41.66	47.48	37.81	43.90	45.50	33.50
MiniCPM-V [103]	40.95	41.05	28.47	42.02	40.00	42.79	28.80	28.62	46.36	36.30	40.00	67.27	31.53	42.46	44.04	50.28	37.50	51.92	52.29	27.22
DeepSeek-VL-7B [155]	41.73	43.43	60.00	43.97	47.50	45.12	28.22	31.20	46.36	32.97	52.29	67.64	**61.36**	49.27	44.23	49.97	52.78	45.00	53.63	38.79
MiniCPM-V2 [257]	41.79	42.54	37.88	43.65	35.50	42.67	26.49	29.24	37.75	33.31	59.71	67.27	38.64	50.87	42.64	50.59	40.90	51.07	57.81	35.10
Proprietary LVLMs																				
Claude3-Opus [13]	32.37	32.44	38.59	34.42	43.50	27.97	22.96	23.62	52.32	25.42	25.14	66.91	15.93	35.25	41.06	36.07	37.50	40.67	35.40	34.24
Qwen-VL-Max [18]	41.34	42.16	50.59	47.23	**74.00**	40.68	29.03	26.71	58.94	34.05	62.29	85.45	27.80	44.39	43.90	42.99	48.61	49.38	51.13	40.52
GPT-4V [5]	42.50	44.08	64.00	44.95	58.50	42.45	30.03	29.40	58.28	32.31	54.57	83.27	37.63	48.26	49.04	48.41	44.60	51.87	53.98	40.89
Gemini 1.0 [240]	44.38	44.93	57.41	46.25	57.50	36.40	28.67	27.80	45.03	38.21	58.57	86.55	40.68	51.74	47.45	55.64	50.46	47.83	61.58	41.87
Gemini 1.5 [211]	47.42	48.36	55.29	**50.81**	54.00	51.05	**36.59**	29.86	56.95	36.88	58.00	88.00	47.46	48.13	51.19	56.88	64.51	56.50	59.78	31.65
GPT-4o [5]	**53.53**	**53.96**	**66.82**	48.53	64.50	**55.94**	35.10	**48.53**	**74.17**	**43.52**	**64.57**	**91.64**	37.63	**57.88**	**55.21**	**62.80**	**66.98**	**58.39**	**64.60**	**46.18**

Table 12: Results for single-choice questions of 50 LVLMs on perceptual granularities. The best-performing model in each category is **in-bold**, and the second best is underlined.

Model name	Size	Overall(val)	Overall(test)	Seg C	Seg M	2D Cls update	2D Det	2D Mcls_acc	2D Mcls_recall
Random	-	25.70	25.88	22.19	22.91	28.93	24.55	45.85	57.02
Medical Special Model									
MedVInT [268]	-	2.29	1.98	0.82	0.25	3.48	0.12	0.05	0.02
Med-Flamingo [181]	8.3B	12.74	11.75	11.95	11.94	11.92	9.15	46.10	50.19
LLaVA-Med [138]	-	20.54	19.83	18.45	18.97	21.15	17.14	45.84	41.19
Qilin-Med-VL-Chat [149]	-	22.34	22.06	19.84	20.30	23.80	21.87	44.50	33.90
RadFM [254]	14B	22.95	22.93	20.43	20.27	25.71	18.83	40.98	57.45
MedDr [95]	40B	41.95	43.18	42.55	44.03	45.08	28.10	48.09	23.38
Open-Source LVLMs									
CogVLM-grounding-generalist [249]	17B	5.20	5.39	6.80	5.51	5.11	2.57	46.24	49.82
XComposer [266]	8B	8.92	7.71	8.87	6.24	8.02	6.30	31.45	23.68
PandaGPT 13B [234]	13B	16.69	15.94	19.25	18.88	13.74	12.24	41.22	49.95
Flamingo v2 [17]	9B	25.58	26.23	22.52	22.48	30.12	21.17	41.80	19.17
VisualGLM-6B [61]	7.8B	29.58	30.20	27.30	27.31	33.75	22.16	43.08	35.22
Idefics-9B-Instruct [137]	9B	29.74	30.81	25.50	25.21	36.45	23.85	43.47	46.02
InstructBLIP-7B [56]	8B	31.80	31.00	29.12	21.77	36.71	24.08	39.43	23.79
Mini-Gemini-7B [141]	7B	32.17	31.22	32.13	32.92	30.72	26.53	45.38	57.99
MMAlaya [154]	7.8B	32.19	32.02	29.33	30.22	35.02	24.02	48.43	20.93
Qwen-VL [19]	9.6B	34.80	35.55	33.20	33.43	38.95	24.49	44.95	56.97
Yi-VL-6B [7]	6.6B	34.82	34.00	31.42	32.26	37.15	24.31	50.25	44.32
LLaVA-NeXT-vicuna-7B [147]	7.1B	34.86	35.59	33.06	32.95	38.96	27.06	44.75	42.45
Qwen-VL-Chat [19]	9.6B	35.07	36.35	34.45	35.20	39.55	22.04	42.88	81.23
CogVLM-Chat [249]	17B	35.23	35.83	34.13	34.49	38.55	25.25	47.09	**90.26**
Monkey [142]	9.8B	35.48	35.92	33.18	34.01	39.32	25.42	44.57	42.35
mPLUG-Owl2 [259]	8.2B	35.62	35.89	33.68	34.74	38.80	24.90	42.59	41.84
ShareCaptioner [43]	8B	36.37	36.07	34.74	35.93	38.25	24.37	40.00	16.95
Emu2-Chat [237]	37B	36.50	35.54	36.54	27.62	39.57	27.76	44.29	37.65
XComposer2-4KHD [63]	7B	36.66	37.93	36.84	38.02	39.84	26.65	48.83	44.08
ShareGPT4V-7B [43]	7.2B	36.71	36.52	34.74	35.15	39.24	26.18	46.11	43.52
LLaVA-NeXT-mistral-7B [147]	7.6B	37.20	37.02	36.29	35.20	39.34	27.87	44.05	47.70
LLAVA-V1.5-13b-xtuner [54]	13.4B	37.82	38.27	38.29	36.95	40.48	25.83	47.54	33.19
OmniLMM-12B [261]	12B	37.89	38.74	36.70	36.86	41.77	28.57	46.17	43.01
InternVL-Chat-V1.1 [47]	19B	38.16	38.93	38.54	40.00	40.07	28.16	39.82	27.32
LLAVA-V1.5-7B [148]	7.2B	38.23	37.72	36.45	36.65	40.38	25.36	14.10	57.09
Monkey-Chat [142]	9.8B	38.39	39.00	37.16	37.75	42.13	25.36	43.91	28.86
LLAVA-V1.5-7B-xtuner [54]	7.2B	38.68	37.96	36.75	36.34	40.55	27.52	46.78	43.06
XComposer2 [62]	7B	38.68	38.95	37.86	38.52	41.00	28.34	46.43	51.87
LLAVA-InternLM-7b [54]	7.6B	38.71	38.84	37.57	36.65	41.84	27.46	50.02	40.21
TransCore-M [3]	13.4B	38.86	38.43	36.09	36.06	42.04	26.53	45.34	40.93
InternVL-Chat-V1.5 [46]	25.5B	38.86	39.32	38.61	40.48	40.45	29.27	31.51	24.72
InternVL-Chat-V1.2-Plus [47]	40B	39.41	40.25	40.68	41.50	40.82	30.38	36.50	37.09
InternVL-Chat-V1.2 [47]	40B	39.52	39.57	39.04	39.75	41.05	29.62	41.08	46.06
LLAVA-InternLM2-7b [54]	8.1B	40.07	40.15	39.30	39.14	42.60	27.76	**50.64**	48.25
DeepSeek-VL-1.3B [155]	1.3B	40.25	40.54	40.61	40.71	42.13	27.64	48.71	21.38
MiniCPM-V [103]	2.8B	40.95	40.89	39.48	39.18	44.08	27.00	42.87	32.09
DeepSeek-VL-7B [155]	7.3B	41.73	42.90	43.87	43.60	44.32	26.59	44.16	18.74
MiniCPM-V2 [257]	2.8B	41.79	42.13	41.11	41.41	45.03	25.95	50.12	32.62
Proprietary LVLMs									
Claude3-Opus [13]	-	32.37	32.24	33.56	33.36	32.17	24.72	45.31	38.98
Qwen-VL-Max [18]	-	41.34	41.70	44.23	44.42	41.09	29.10	31.12	25.88
GPT-4V [5]	-	42.50	43.61	47.87	46.58	42.24	30.32	45.21	40.59
Gemini 1.0 [240]	-	44.38	44.65	44.92	44.96	46.67	27.46	49.01	55.09
Gemini 1.5 [211]	-	47.42	48.03	54.75	**56.59**	43.25	34.17	39.22	39.34
GPT-4o [5]	-	**53.53**	**53.88**	**57.09**	56.49	**53.70**	**36.21**	50.60	50.90

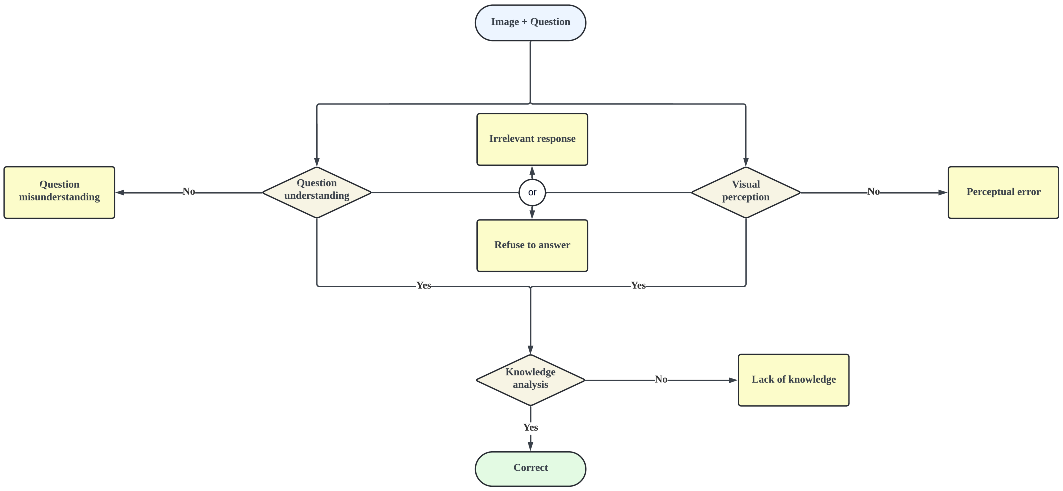


Figure 9: The illustration of the entire logical process from input to output in our case study.

E.2 Case Study

In this section, we present a case study analysis of several LVLMs on various cases in GMAI-MMBench. The entire logical process of our study is illustrated in Figure 9. Other than **Correct**, we classify the error types from input to output into five major categories:

Correct: LVLMs offer the correct answer. This indicates that the model accurately understands both the image and the question, and provides an appropriate and relevant response.

Question misunderstanding: LVLMs fail to correctly understand the question and generate erroneous answers. For example: LLAVA-Med may not understand the purpose of identifying the surgical process from the question, instead, it describes the image content in detail as shown in Figure 27.

Perceptual error: LVLMs fail to locate, detect, or recognize the content or objects in images, which are necessary for answering the questions. This includes scenarios where the model misses critical details or misinterprets the image's content. For example: GPT-4o may ignore the important tool in the lower left corner that is clearing the debris in Figure 32. Claude3-Opus chooses the wrong answer as it cannot correctly identify the content in the mask in Figure 38.

Lack of knowledge: LVLMs can recognize both the image and the question but still make errors in specific cases, suggesting a lack of domain-specific knowledge required to answer specialized questions. For example: Models directly show their insufficient knowledge to answer or fail to respond without additional information as shown in Figure 52, Figure 54, Figure 52, etc. Another case in Figure 51 shows that GPT-4o correctly describes the image and understands the question but still chooses a wrong answer, suggesting it may lack the ability to distinguish between carcinoma in situ and invasive carcinoma.

Irrelevant response: LVLMs do not address the question directly and produce unreadable or unrelated responses. This problem is especially noticeable in open-source models. For example: RadFM only generates a reference paper without any additional outputs in Figure 57.

Refuse to answer: LVLMs decline to answer certain questions to keep the system safe for all users, such as those involving sensitive or ethical issues, and refuse to provide medical advice when they determine that human professional assistance is required. This issue only occurs in proprietary models like GPTs and Claudes.

In our test, we randomly select 53 VQA pairs from different clinical VQA tasks, departments, and perceptual granularities. All cases are listed in Table 13. Based on our observations of the evaluation results, we find that proprietary models like GPT-4o and Claude3-Opus rarely encounter difficulties in question understanding. The majority of errors for these models stem from perceptual error and lack of knowledge. In contrast, specialized medical models such as RadFM and LLAVA-Med frequently exhibit language understanding errors, making it difficult to effectively evaluate visual perceptual abilities. As a result, the case study indicates that general models need to enhance their performance on specialized medical images, which may require more medical data for training. Meanwhile, specialized medical models need further training or fine-tuning in language aspects.

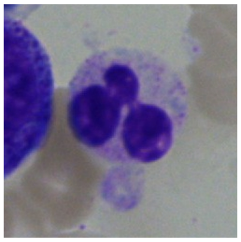
Table 13: Table index of our case study figures.

Figure	Clinical VQA task	Department	Perceptual granularity	Category
10	MR	H	Image Level	Correct
11	C	H	Image Level	Correct
12	SWR	ENT	Image Level	Correct
13	DD	GH	Image Level	Correct
14	ASR	NH	Image Level	Correct
15	SAR	U	Box Level	Correct
16	DD	PM	Box Level	Correct
17	OR-NH	E	Mask Level	Correct
18	OR-P	U	Contour Level	Correct
19	SIR	GS	Box Level	Correct
20	BVR	H	Mask Level	Correct
21	CR	H	Box Level	Correct
22	DD	CS	Mask Level	Correct
23	DD	OS	Contour Level	Correct
24	NT	O	Mask Level	Correct
25	OR-T	PM	Mask Level	Correct
26	SIR	GS	Mask Level	Correct
27	SWR	GS	Image Level	Question misunderstanding
28	BVR	O	Mask Level	Question misunderstanding
29	ACR	OS	Mask Level	Question misunderstanding
30	MR	GH	Image Level	Question misunderstanding
31	C	H	Image Level	Perceptual error
32	SWR	GS	Image Level	Perceptual error
33	OR-T	PM	Mask Level	Perceptual error
34	AR	LMP	Image Level	Perceptual error
35	NT	N	Mask Level	Perceptual error
36	DD	CS	Box Level	Perceptual error
37	DD	D	Mask Level	Perceptual error
38	DD	GH	Contour Level	Perceptual error
39	OR-T	PM	Mask Level	Perceptual error
40	NT	N	Mask Level	Perceptual error
41	OR-T	PM	Contour Level	Perceptual error
42	DD	O	Image Level	Lack of knowledge
43	IQG	O	Image Level	Lack of knowledge
44	MR	LMP	Image Level	Lack of knowledge
45	SAR	GS	Box Level	Lack of knowledge
46	SAR	U	Box Level	Lack of knowledge
47	DD	PM	Mask Level	Lack of knowledge
48	NT	O	Mask Level	Lack of knowledge
49	SG	LMP	Image Level	Lack of knowledge
50	DD	O	Image Level	Lack of knowledge
51	SG	LMP	Image Level	Lack of knowledge
52	DD	OM	Image Level	Lack of knowledge
53	AR	GS	Image Level	Lack of knowledge
54	AR	OG	Image Level	Lack of knowledge
55	DD	D	Image Level	Lack of knowledge
56	DD	U	Image Level	Lack of knowledge
57	DD	OS	Image Level	Irrelevant response
58	AR	ID	Image Level	Irrelevant response
59	AR	OS	Image Level	Irrelevant response
60	ASR	OG	Image Level	Irrelevant response
61	DD	PM	Image Level	Refuse to answer
62	BVR	O	Mask Level	Refuse to answer

Correct

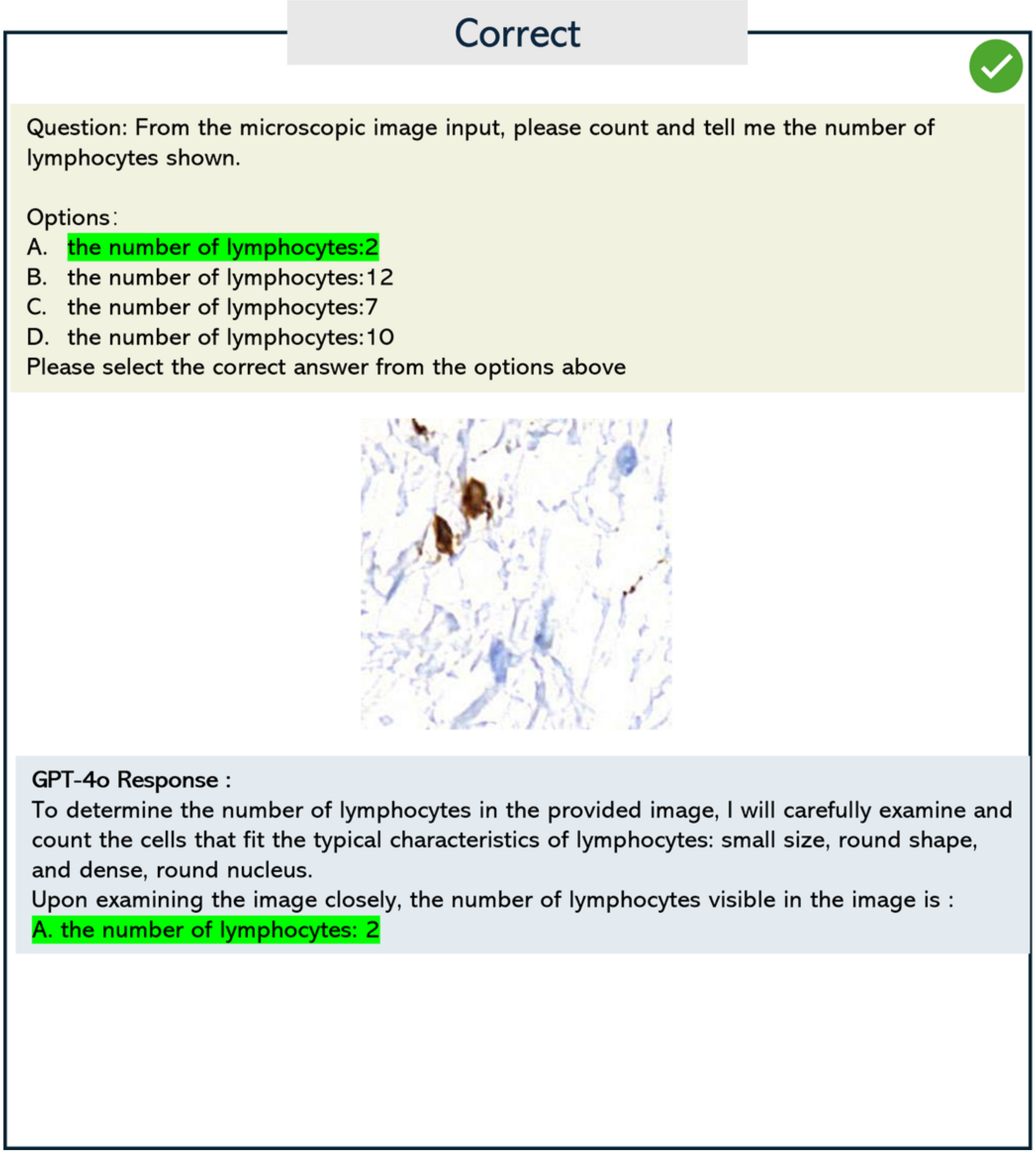
Question: Identify the option that the content of the microscopic image corresponds to.

Options:
A. basophil
B. hairy cell
C. proerythroblast
D. band neutrophil
Please select the correct answer from the options above



GPT-4o Response :
The image illustrates a basophil. So, the correct option is :
A. basophil
Granular Appearance: Basophils are characterized by large granules that stain dark purple or blue with standard stains like Wright or Giemsa stain. The image shows a cell with prominent granules.
Lobed Nucleus: Basophils typically have a lobed nucleus, which may sometimes be obscured by the granules. The nucleus appears to be lobed in this image, although it is partially covered by granules.
Size and Shape: The size and shape of the cell in the image match the typical morphology of a basophil, which is generally larger than red blood cells and has a distinct granular cytoplasm.
These characteristics match those of a basophil, confirming that the image is indeed illustrating a basophil.

Figure 10: An example of correct case. Green highlights the right answer. Back to Table Index.



Correct ✓

Question: From the microscopic image input, please count and tell me the number of lymphocytes shown.

Options:
A. the number of lymphocytes:2
B. the number of lymphocytes:12
C. the number of lymphocytes:7
D. the number of lymphocytes:10
Please select the correct answer from the options above

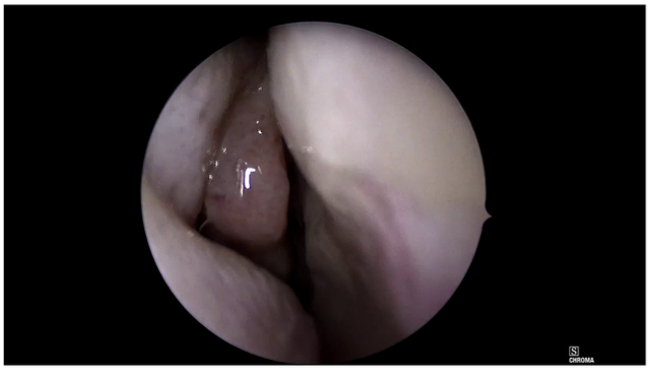
GPT-4o Response :
To determine the number of lymphocytes in the provided image, I will carefully examine and count the cells that fit the typical characteristics of lymphocytes: small size, round shape, and dense, round nucleus.
Upon examining the image closely, the number of lymphocytes visible in the image is :
A. the number of lymphocytes: 2

Figure 11: An example of correct case. Green highlights the right answer. Back to Table Index.

Correct

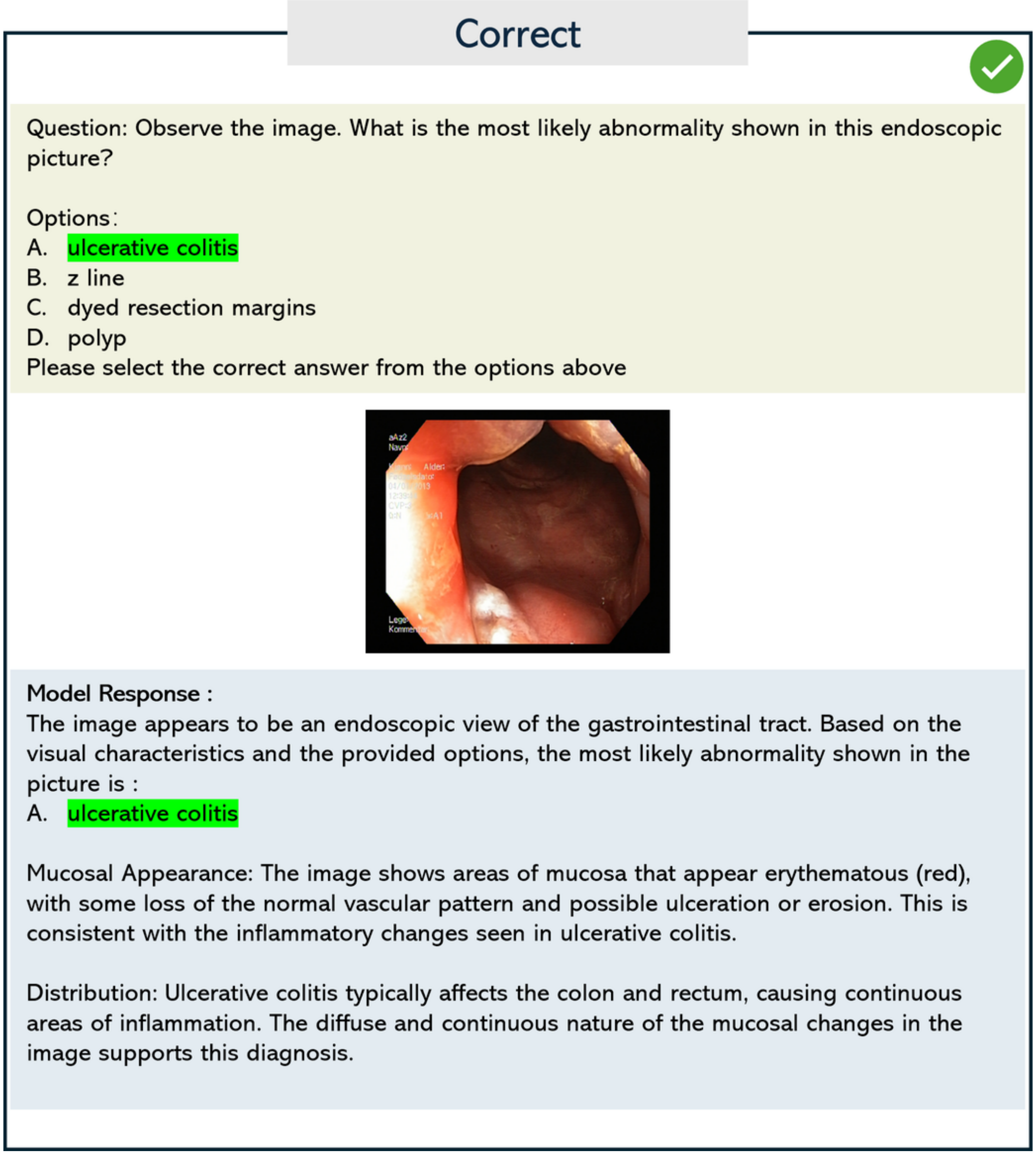
Question: Please identify which of the following options the surgical procedure shown in the endoscopic image belongs to.

Options:
A. synthetic graft placement
B. debris clearance
C. nasal corridor creation
D. operation not started or operation ended\tor out of patient
Please select the correct answer from the options above



GPT-4o Response :
The image appears to show an endoscopic view of the nasal cavity. Based on the visual characteristics and the provided options, the most suitable answer is :
C. nasal corridor creation
Anatomical Structures: The image shows structures consistent with the nasal cavity, which include the nasal septum and turbinate. This setting is typical for procedures involving the nasal passages.
Procedure Context: Creating a nasal corridor is a common part of endoscopic sinus surgery or procedures that require access to the nasal passages. This involves clearing and creating pathways within the nasal cavity.

Figure 12: An example of correct case. Green highlights the right answer. Back to Table Index.



Correct

Question: Observe the image. What is the most likely abnormality shown in this endoscopic picture?

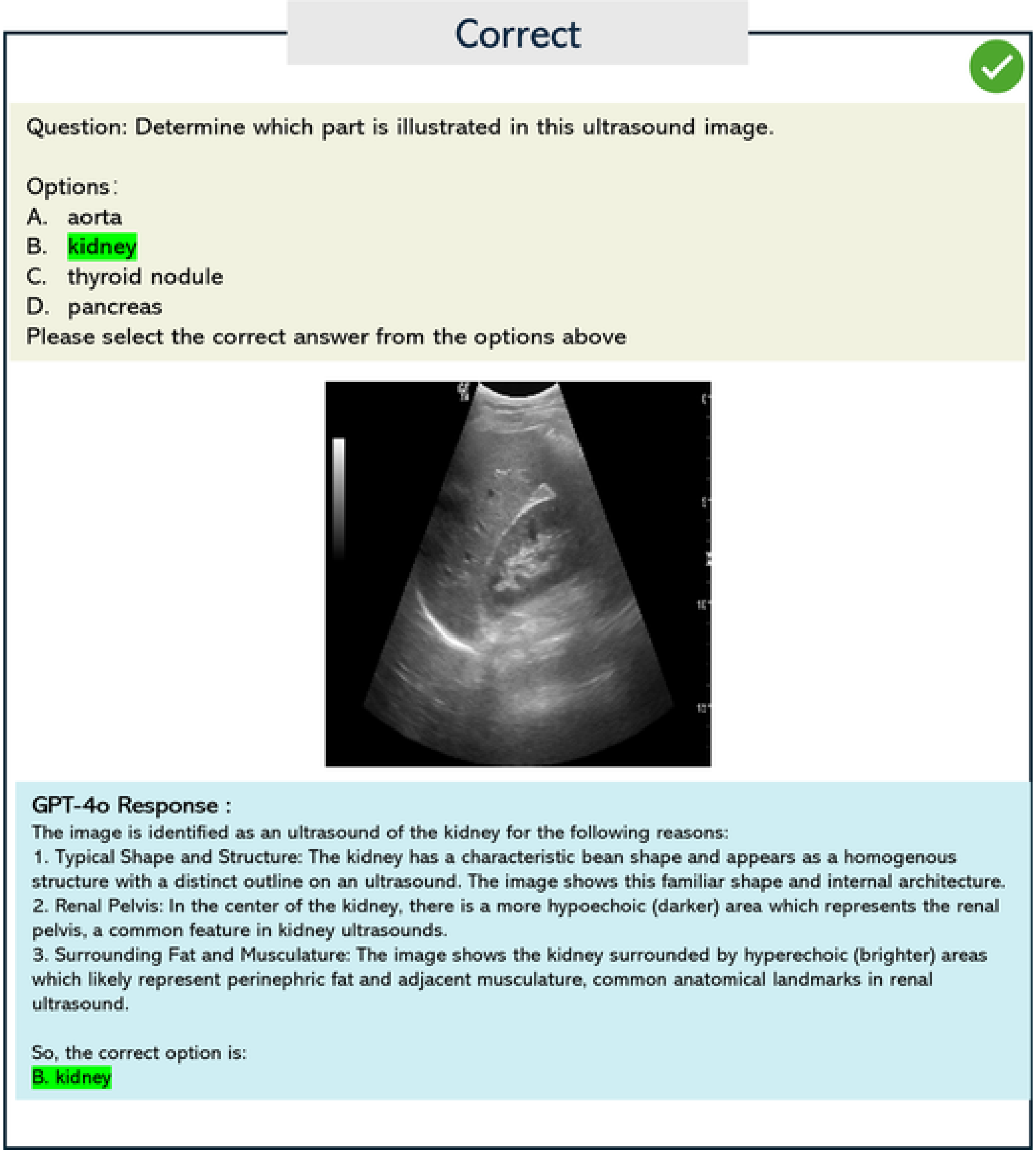
Options:
A. ulcerative colitis
B. z line
C. dyed resection margins
D. polyp
Please select the correct answer from the options above

Model Response :
The image appears to be an endoscopic view of the gastrointestinal tract. Based on the visual characteristics and the provided options, the most likely abnormality shown in the picture is :
A. ulcerative colitis

Mucosal Appearance: The image shows areas of mucosa that appear erythematous (red), with some loss of the normal vascular pattern and possible ulceration or erosion. This is consistent with the inflammatory changes seen in ulcerative colitis.

Distribution: Ulcerative colitis typically affects the colon and rectum, causing continuous areas of inflammation. The diffuse and continuous nature of the mucosal changes in the image supports this diagnosis.

Figure 13: An example of correct case. Green highlights the right answer. Back to Table Index.



Correct ✓

Question: Determine which part is illustrated in this ultrasound image.

Options:
A. aorta
B. kidney
C. thyroid nodule
D. pancreas
Please select the correct answer from the options above

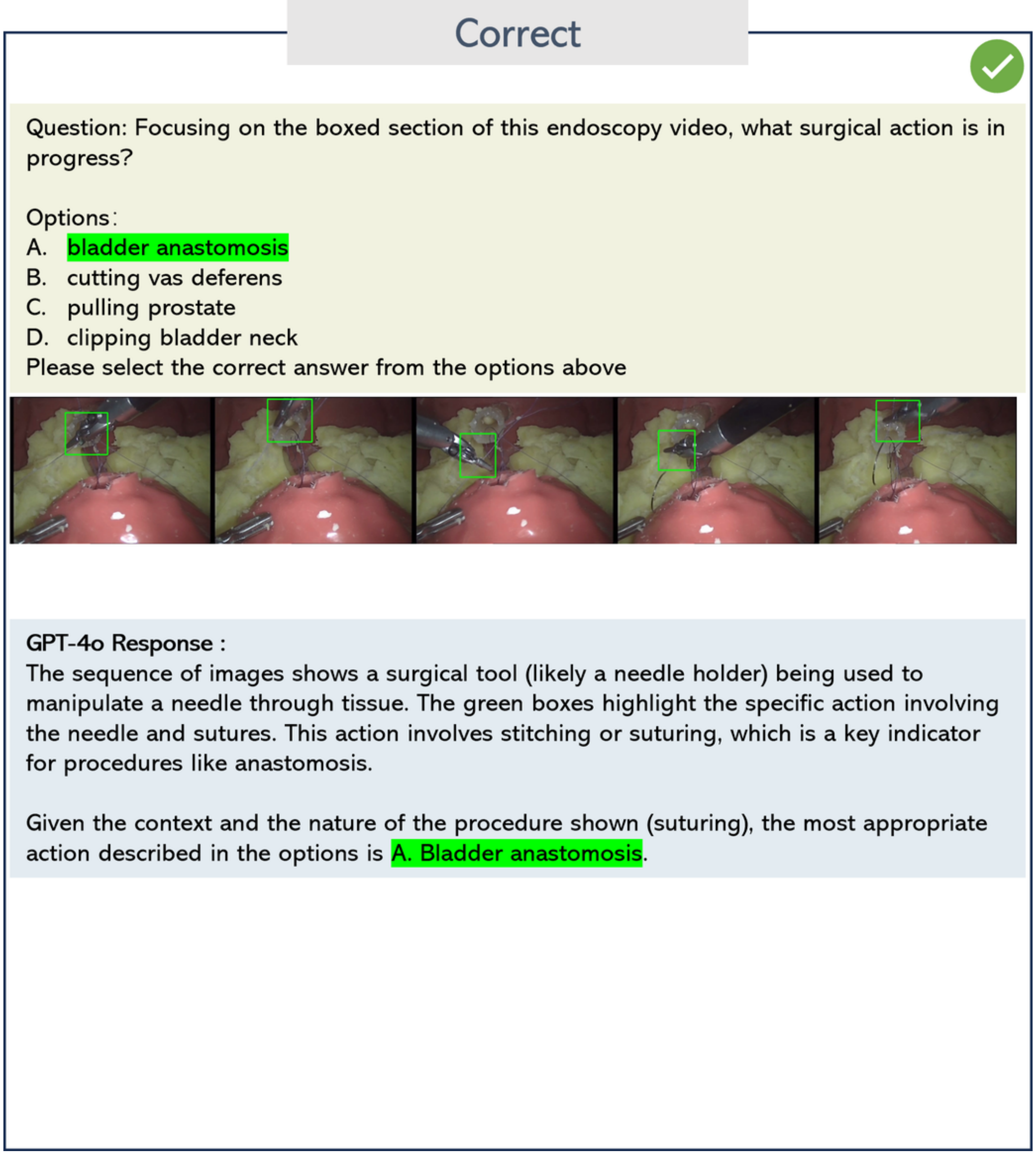
GPT-4o Response :

The image is identified as an ultrasound of the kidney for the following reasons:

1. Typical Shape and Structure: The kidney has a characteristic bean shape and appears as a homogenous structure with a distinct outline on an ultrasound. The image shows this familiar shape and internal architecture.
2. Renal Pelvis: In the center of the kidney, there is a more hypoechoic (darker) area which represents the renal pelvis, a common feature in kidney ultrasounds.
3. Surrounding Fat and Musculature: The image shows the kidney surrounded by hyperechoic (brighter) areas which likely represent perinephric fat and adjacent musculature, common anatomical landmarks in renal ultrasound.

So, the correct option is:
B. kidney

Figure 14: An example of correct case. Green highlights the right answer. Back to Table Index.



Correct

✓

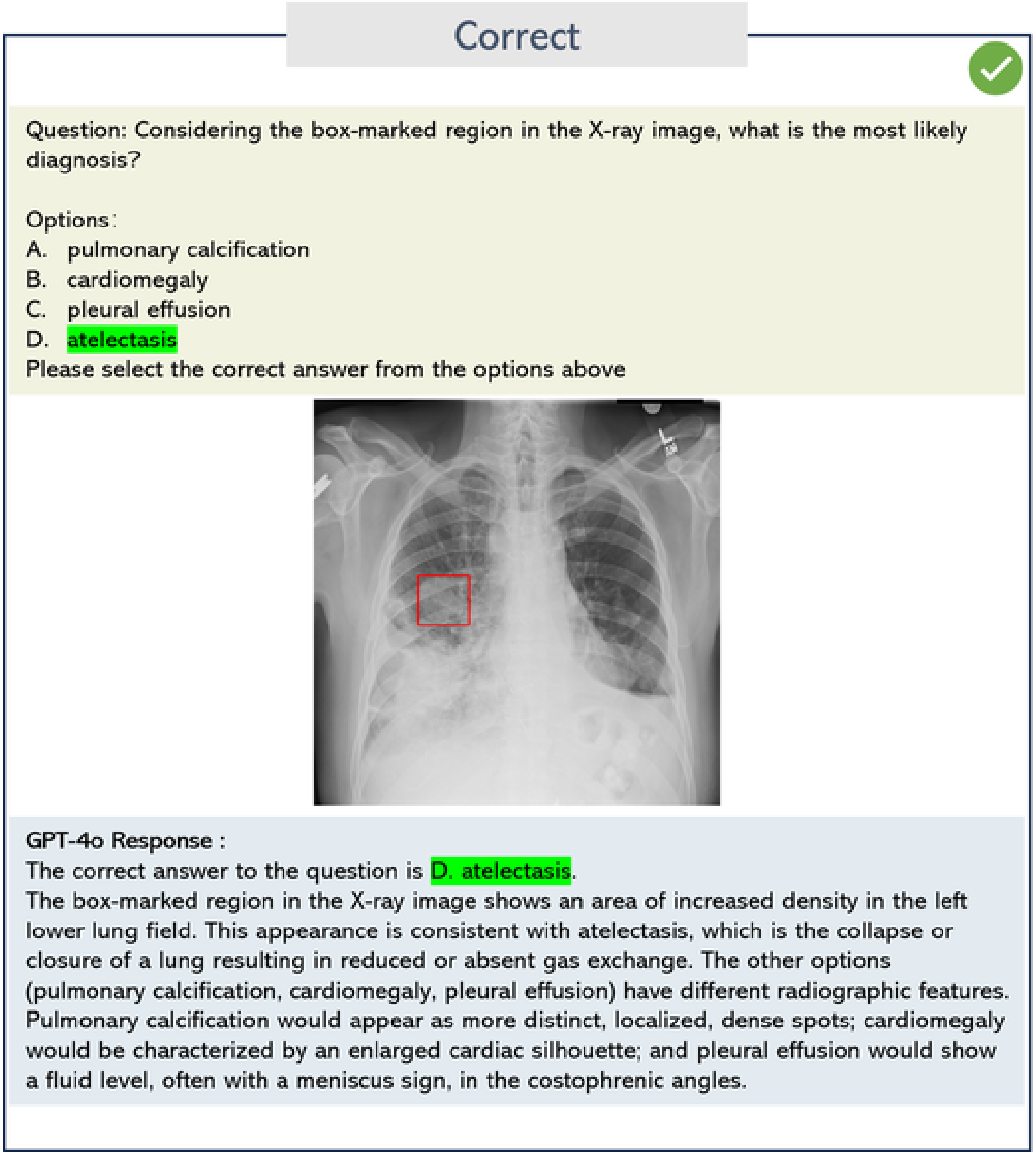
Question: Focusing on the boxed section of this endoscopy video, what surgical action is in progress?

Options:
A. bladder anastomosis
B. cutting vas deferens
C. pulling prostate
D. clipping bladder neck
Please select the correct answer from the options above

GPT-4o Response :
The sequence of images shows a surgical tool (likely a needle holder) being used to manipulate a needle through tissue. The green boxes highlight the specific action involving the needle and sutures. This action involves stitching or suturing, which is a key indicator for procedures like anastomosis.

Given the context and the nature of the procedure shown (suturing), the most appropriate action described in the options is A. Bladder anastomosis.

Figure 15: An example of correct case. Green highlights the right answer. Back to Table Index.



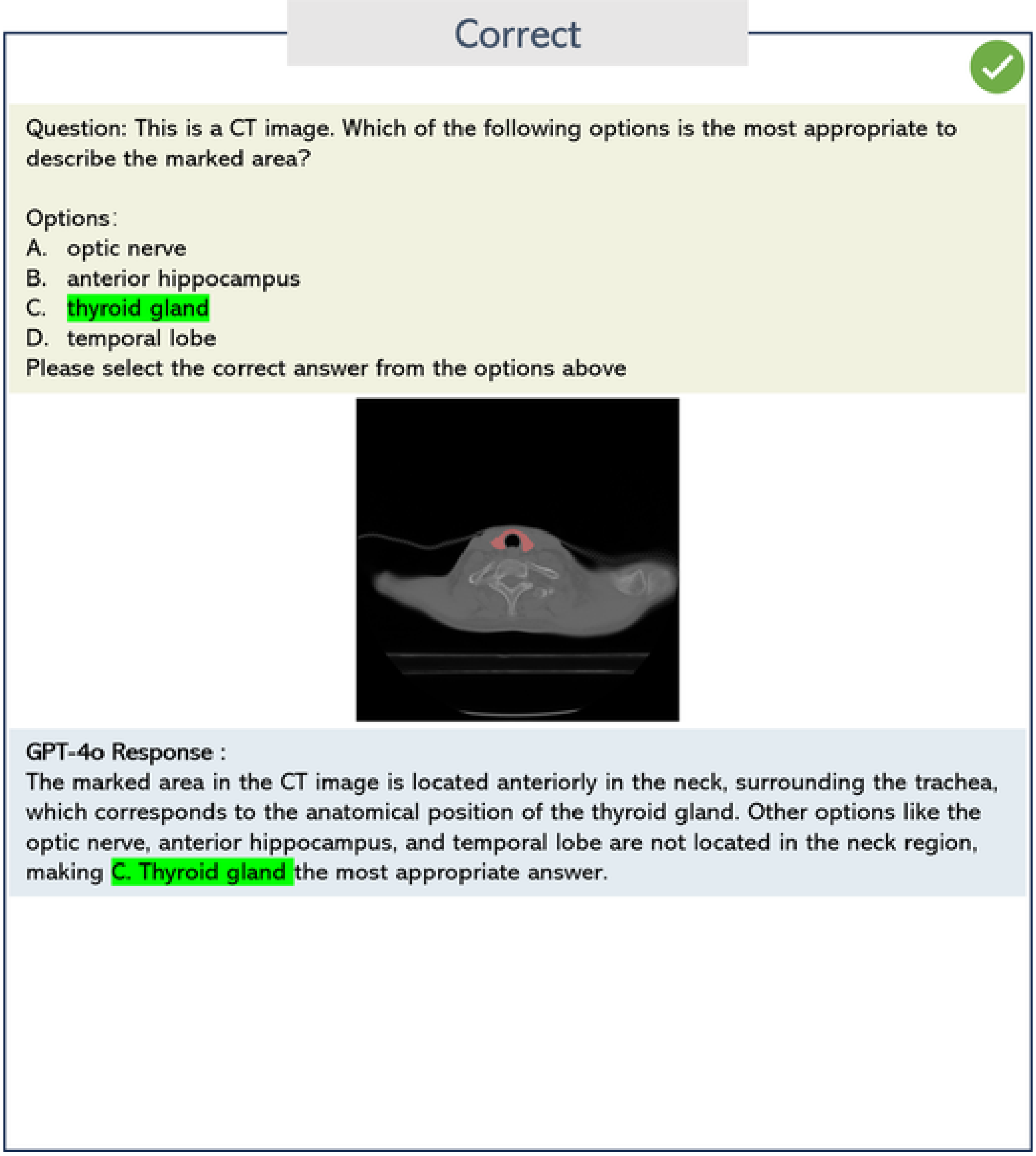
Correct

Question: Considering the box-marked region in the X-ray image, what is the most likely diagnosis?

Options:
A. pulmonary calcification
B. cardiomegaly
C. pleural effusion
D. atelectasis
Please select the correct answer from the options above

GPT-4o Response :
The correct answer to the question is D. atelectasis.
The box-marked region in the X-ray image shows an area of increased density in the left lower lung field. This appearance is consistent with atelectasis, which is the collapse or closure of a lung resulting in reduced or absent gas exchange. The other options (pulmonary calcification, cardiomegaly, pleural effusion) have different radiographic features. Pulmonary calcification would appear as more distinct, localized, dense spots; cardiomegaly would be characterized by an enlarged cardiac silhouette; and pleural effusion would show a fluid level, often with a meniscus sign, in the costophrenic angles.

Figure 16: An example of correct case. Green highlights the right answer. Back to Table Index.



Correct ✓

Question: This is a CT image. Which of the following options is the most appropriate to describe the marked area?

Options:
A. optic nerve
B. anterior hippocampus
C. thyroid gland
D. temporal lobe
Please select the correct answer from the options above

GPT-4o Response :
The marked area in the CT image is located anteriorly in the neck, surrounding the trachea, which corresponds to the anatomical position of the thyroid gland. Other options like the optic nerve, anterior hippocampus, and temporal lobe are not located in the neck region, making C. Thyroid gland the most appropriate answer.

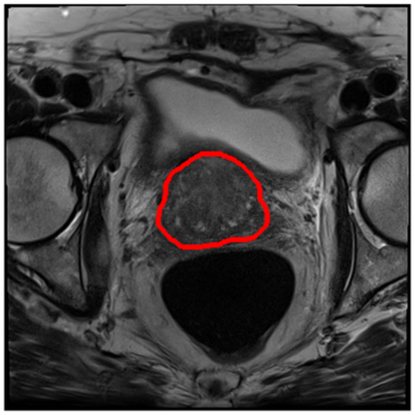
Figure 17: An example of correct case. Green highlights the right answer. Back to Table Index.

Correct

✓

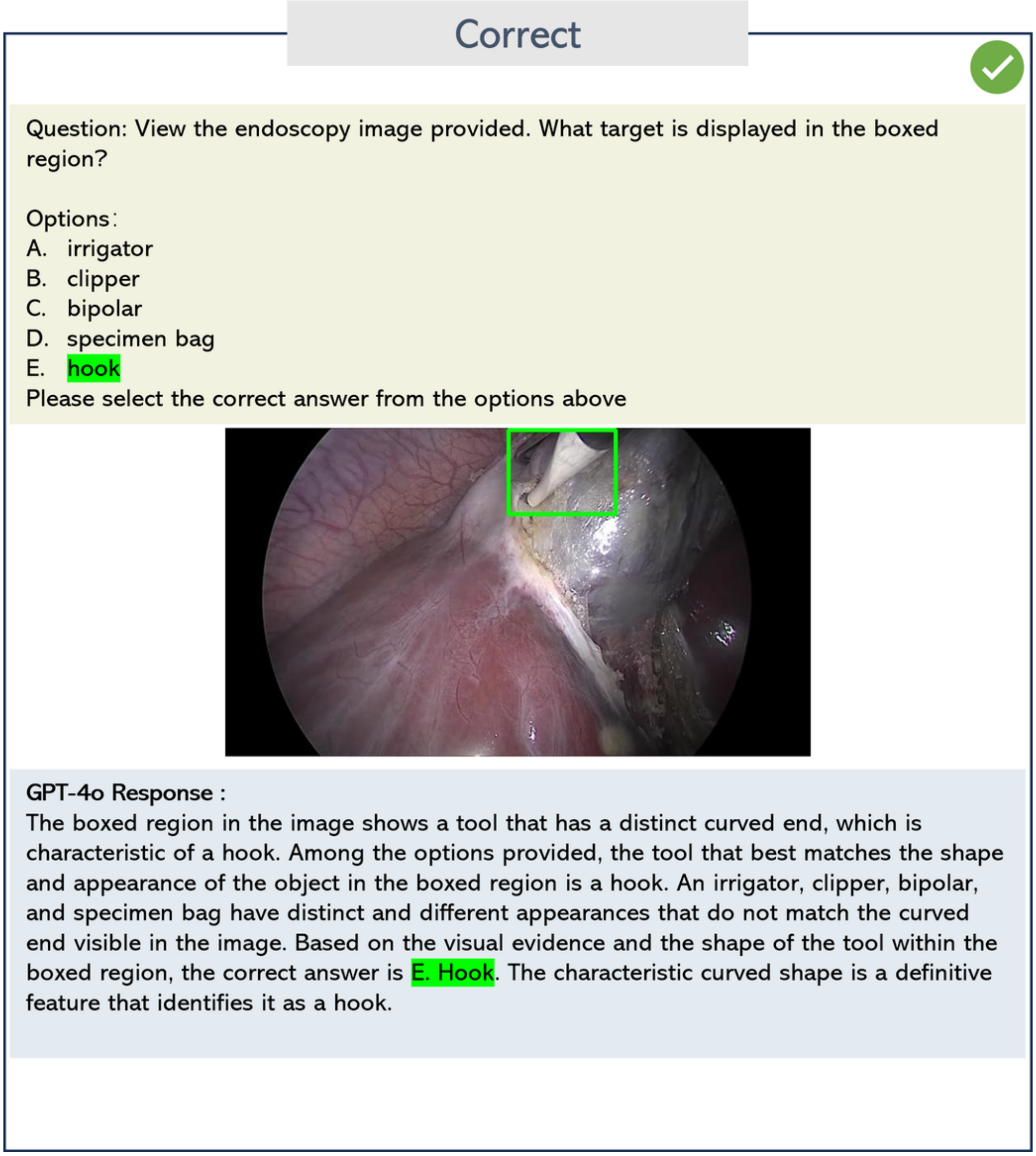
Question: This is a T2 weighted MRI image. Which of the following options is the most appropriate to describe the marked area?

Options:
A. duodenum
B. rectum
C. prostate
D. femoral head
Please select the correct answer from the options above



GPT-4o Response :
The correct answer to the question is C. prostate.
The marked area in the T2-weighted MRI image is located in the pelvic region, just below the bladder and in front of the rectum, which is the typical anatomical position of the prostate gland. This is consistent with the high signal intensity (bright appearance) commonly seen in T2-weighted images of the prostate. The other options (duodenum, rectum, femoral head) are located in different regions of the body and do not correspond to the anatomical location of the marked area in the image.

Figure 18: An example of correct case. Green highlights the right answer. Back to Table Index.



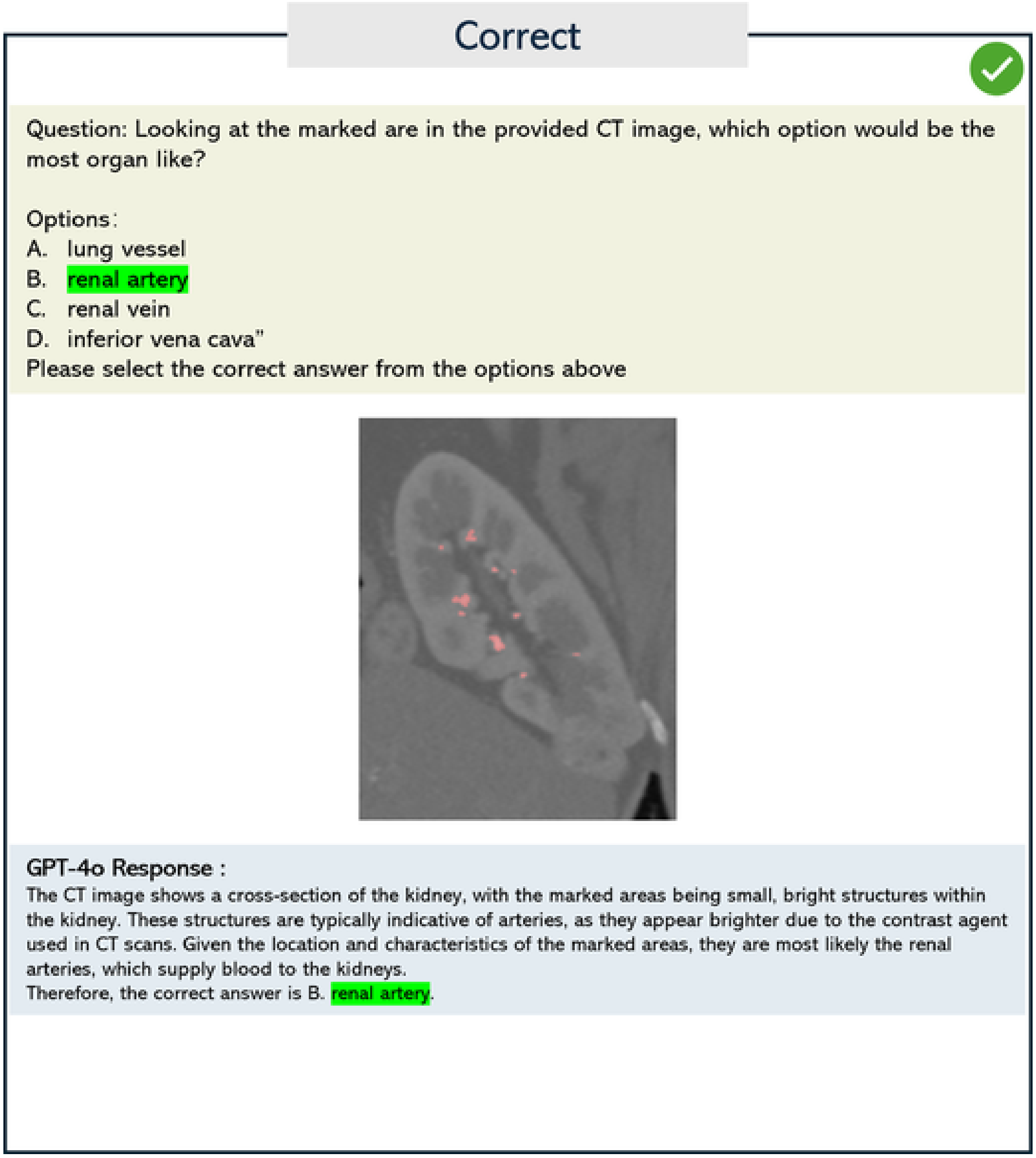
Correct

Question: View the endoscopy image provided. What target is displayed in the boxed region?

Options:
A. irrigator
B. clipper
C. bipolar
D. specimen bag
E. hook
Please select the correct answer from the options above

GPT-4o Response :
The boxed region in the image shows a tool that has a distinct curved end, which is characteristic of a hook. Among the options provided, the tool that best matches the shape and appearance of the object in the boxed region is a hook. An irrigator, clipper, bipolar, and specimen bag have distinct and different appearances that do not match the curved end visible in the image. Based on the visual evidence and the shape of the tool within the boxed region, the correct answer is E. Hook. The characteristic curved shape is a definitive feature that identifies it as a hook.

Figure 19: An example of correct case. Green highlights the right answer. Back to Table Index.



Correct ✓

Question: Looking at the marked are in the provided CT image, which option would be the most organ like?

Options:
A. lung vessel
B. renal artery
C. renal vein
D. inferior vena cava"
Please select the correct answer from the options above

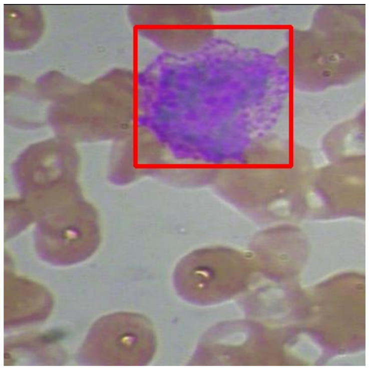
GPT-4o Response :
The CT image shows a cross-section of the kidney, with the marked areas being small, bright structures within the kidney. These structures are typically indicative of arteries, as they appear brighter due to the contrast agent used in CT scans. Given the location and characteristics of the marked areas, they are most likely the renal arteries, which supply blood to the kidneys.
Therefore, the correct answer is B. renal artery.

Figure 20: An example of correct case. 🟩 Green highlights the right answer. Back to Table Index.

Correct

Question: Observe the microscopy image. Can you identify the target within the outlined box?

Options:
A. red blood cell
B. white blood cell
C. platelet
D. mycobacterium tuberculosis
Please select the correct answer from the options above



GPT-4o Response :
The target within the outlined box is a white blood cell.

White blood cells are typically larger and have a distinct nucleus, which can be seen in the image. They are stained differently compared to red blood cells, which lack a nucleus and appear more uniform and red.

So, the correct answer is:

B. white blood cell

Figure 21: An example of correct case. Green highlights the right answer. Back to Table Index.

Correct ✓

Question: Which of the following options best matches the symptoms of marked region shown in the X-ray image?

Options:

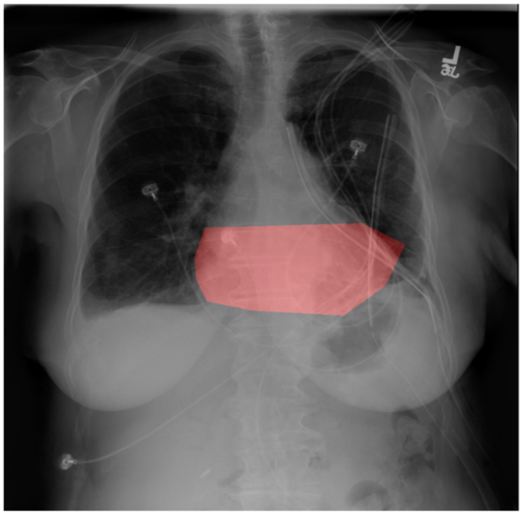
A. retinal hemorrhages

B. cardiomegaly

C. emphysema

D. barrett's esophagus

Please select the correct answer from the options above



GPT-4o Response :

The marked region in the X-ray image is located in the area of the heart. The best match for the symptoms related to this region is:

B. cardiomegaly

Figure 22: An example of correct case. Green highlights the right answer. Back to Table Index.

Correct

✓

Question: Observe the X-ray image. What is the most likely abnormality shown in the highlight area?

Options:

A. barrett's esophagus

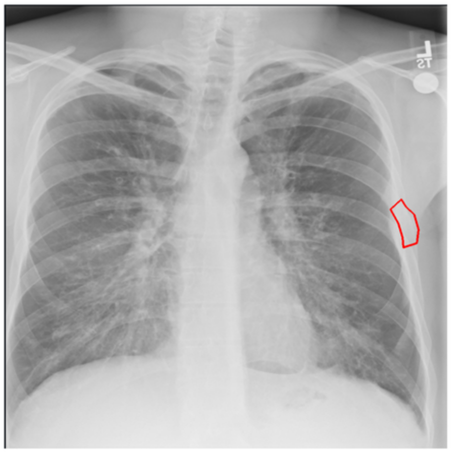
B. melanocytic lesions

C. rib fracture

D. pigment network skin lesion

E. emphysema

Please select the correct answer from the options above



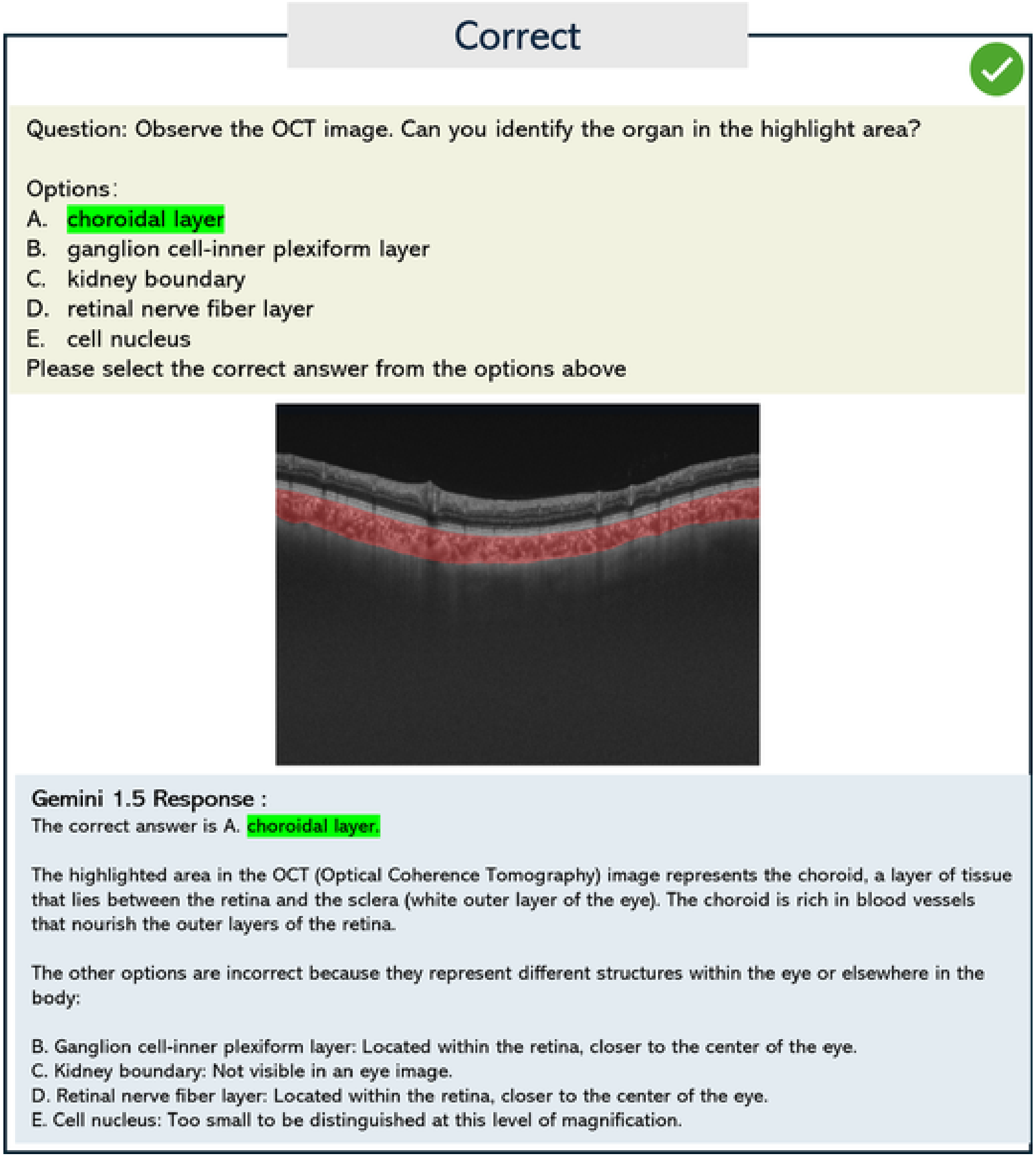
Claude3-Opus Response :

The X-ray image shows a chest radiograph. In the highlighted area on the right side of the image, there appears to be a rib fracture. The rib shows an abnormal contour and disruption compared to the normal curving ribs elsewhere in the image. Therefore, based on the options provided, the most likely abnormality shown in the highlighted area is:

C. rib fracture

The other options like Barrett's esophagus, melanocytic lesions, pigment network skin lesions are unrelated to rib anatomy seen on chest X-rays. While emphysema can be evaluated on chest imaging, it affects the lung tissue rather than the ribs.

Figure 23: An example of correct case. 🟩 Green highlights the right answer. Back to Table Index.



Correct

✓

Question: Observe the OCT image. Can you identify the organ in the highlight area?

Options:
A. choroidal layer
B. ganglion cell-inner plexiform layer
C. kidney boundary
D. retinal nerve fiber layer
E. cell nucleus
Please select the correct answer from the options above

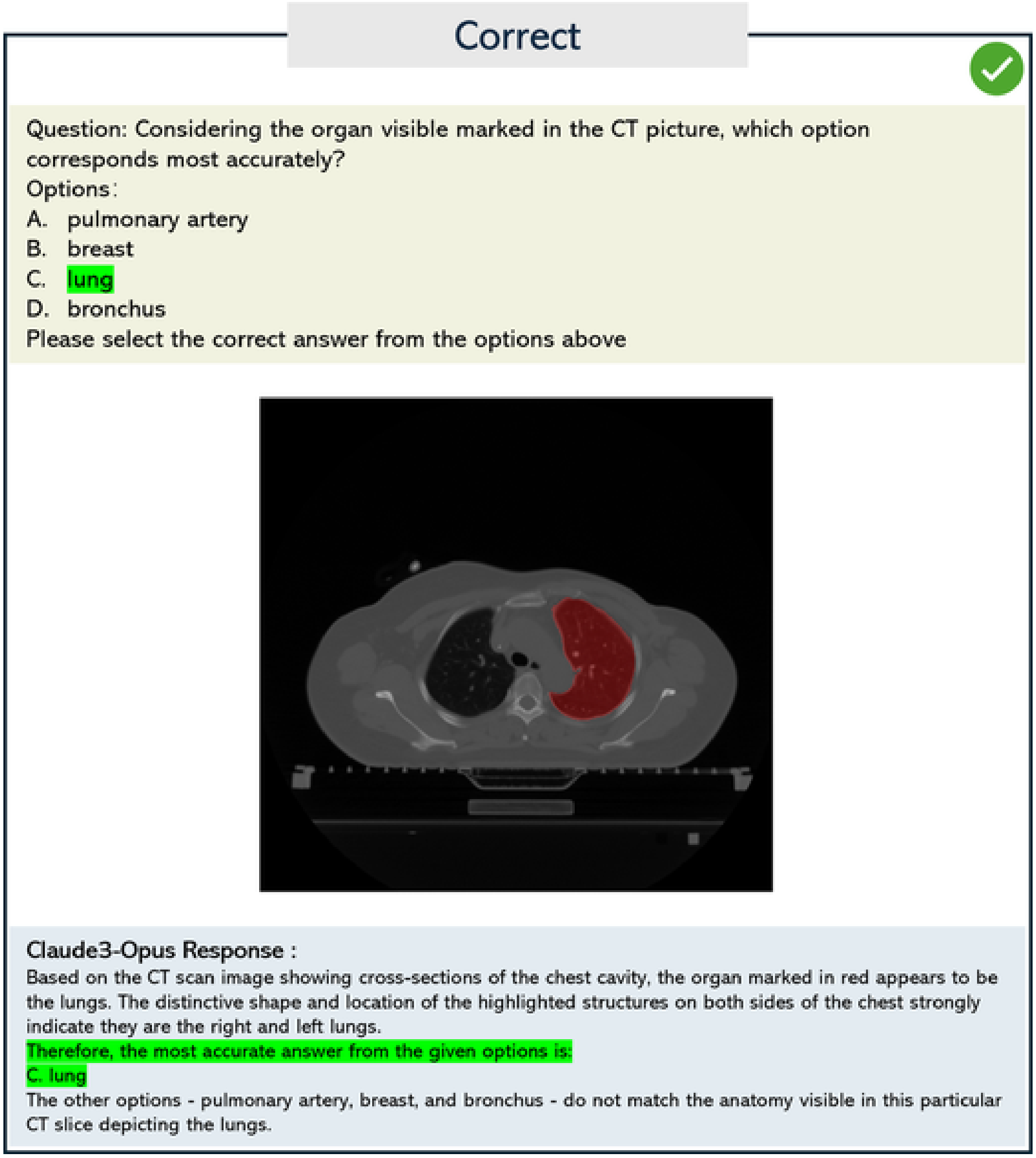
Gemini 1.5 Response :
The correct answer is A. choroidal layer.

The highlighted area in the OCT (Optical Coherence Tomography) image represents the choroid, a layer of tissue that lies between the retina and the sclera (white outer layer of the eye). The choroid is rich in blood vessels that nourish the outer layers of the retina.

The other options are incorrect because they represent different structures within the eye or elsewhere in the body:

B. Ganglion cell-inner plexiform layer: Located within the retina, closer to the center of the eye.
C. Kidney boundary: Not visible in an eye image.
D. Retinal nerve fiber layer: Located within the retina, closer to the center of the eye.
E. Cell nucleus: Too small to be distinguished at this level of magnification.

Figure 24: An example of correct case. Green highlights the right answer. Back to Table Index.



Correct ✓

Question: Considering the organ visible marked in the CT picture, which option corresponds most accurately?
Options:
A. pulmonary artery
B. breast
C. lung
D. bronchus
Please select the correct answer from the options above

Claude3-Opus Response :
Based on the CT scan image showing cross-sections of the chest cavity, the organ marked in red appears to be the lungs. The distinctive shape and location of the highlighted structures on both sides of the chest strongly indicate they are the right and left lungs.
Therefore, the most accurate answer from the given options is:
C. lung
The other options - pulmonary artery, breast, and bronchus - do not match the anatomy visible in this particular CT slice depicting the lungs.

Figure 25: An example of correct case. Green highlights the right answer. Back to Table Index.

Correct

Question: Looking at the marked ares in the provided Endoscopy image, which option would be the most organ like?

Options:

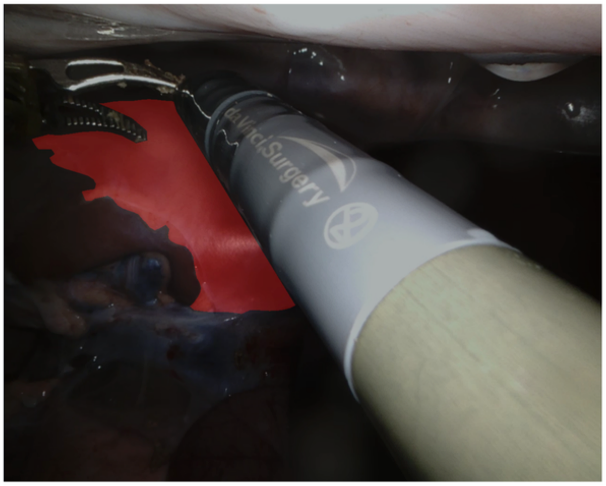
A. specimen bag

B. clip

C. instrument suction

D. grasper

Please select the correct answer from the options above



GPT-4o Response :

The marked area in the provided endoscopy image appears to be part of an organ. Therefore, the most organ-like option is not listed among the provided options. However, if you are asking which of the options is most likely to be interacting with the organ, the correct answer would be:

C. instrument suction

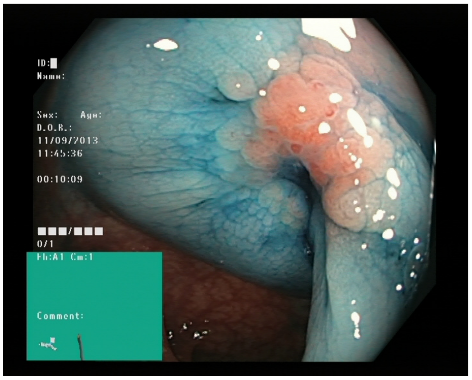
Figure 26: An example of correct case. Green highlights the right answer. Back to Table Index.

Question Misunderstanding

✗

Question: Identify the option that matches the surgical process illustrated in the endoscopic image

Options:
A. ulcerative colitis
B. normal z line
C. polyp
D. dyed lifted polyps
Please select the correct answer from the options above



LLAVA-Med Response :
The polyp is a growth that forms on the inner lining of an organ, typically as a result of tissue irritation or inflammation. In this case, the polyp was identified during a flexible sigmoidoscopy, which is a type of endoscopy used to examine the rectos

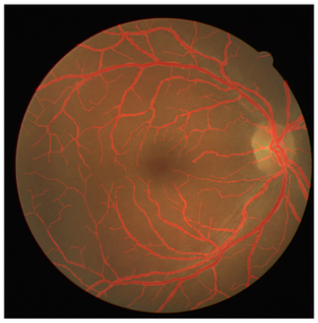
Error Analysis :
This response misunderstands the question. It attempts to describe the content of the image instead of following the input instructions to answer the question.

Figure 27: A question misunderstanding example. Green highlights the right answer. Yellow highlights the wrong answer. Back to Table Index.

Question Misunderstanding

Question: Observe the Fundus Photography image. Can you identify the organ in the highlight area?

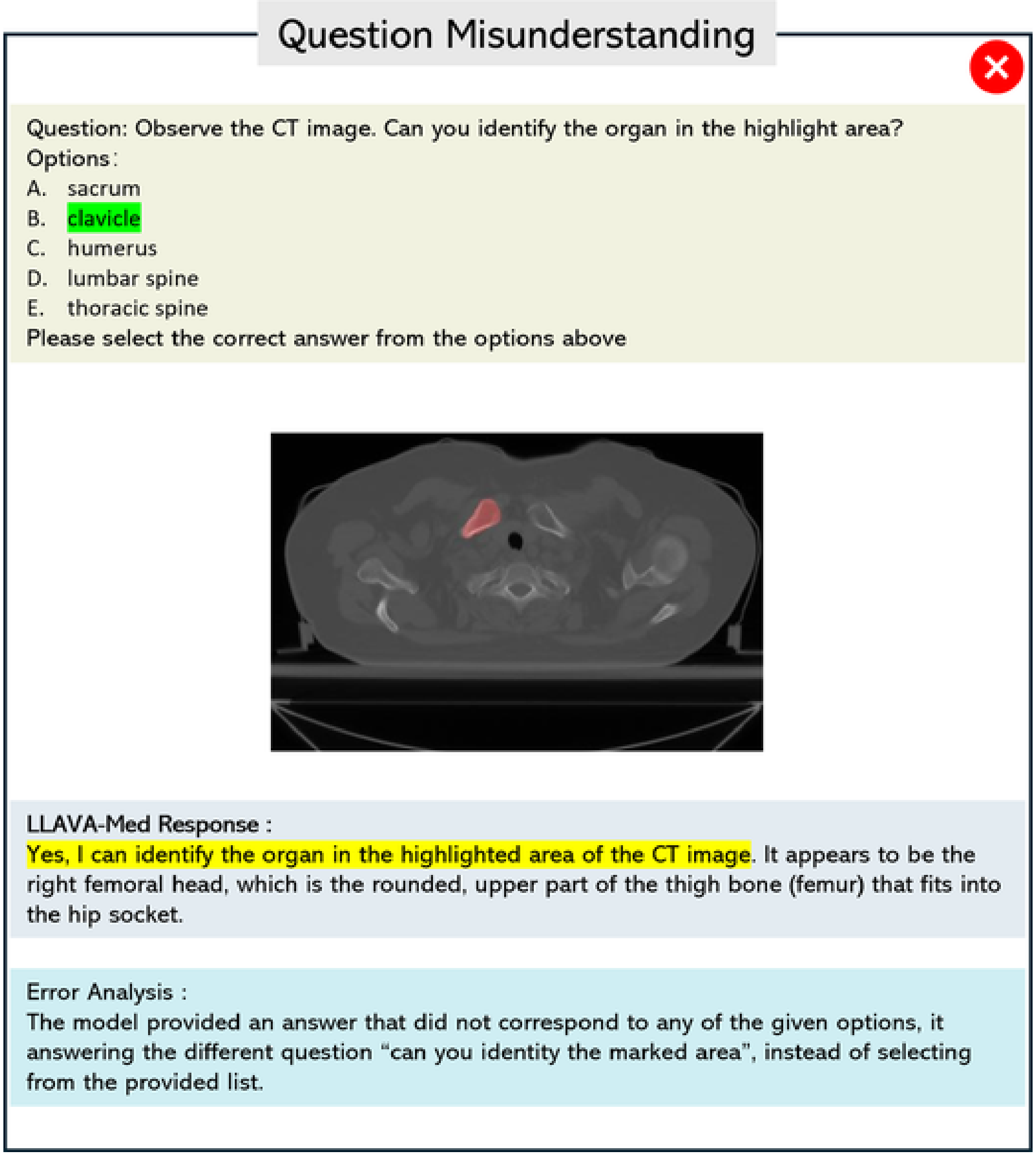
Options:
A. instrument shaft
B. breast cancer type: invasive ductal carcinoma
C. retinal vessel
D. brachial plexus
E. negative network skin lesion
Please select the correct answer from the options above



LLaVA-Med Response :
A. instrument shaft
B.brachial plexus
C.retinal vessel
D.negative network skin lesion
E.invasive ductal carcinoma

Error Analysis :
LLaVA-Med provided an answer with incorrectly listed options, indicating a failure to match the given options accurately.

Figure 28: A question misunderstanding example. Green highlights the right answer. Yellow highlights the wrong answer. Back to Table Index.



Question Misunderstanding

Question: Observe the CT image. Can you identify the organ in the highlight area?
Options:
A. sacrum
B. clavicle
C. humerus
D. lumbar spine
E. thoracic spine
Please select the correct answer from the options above

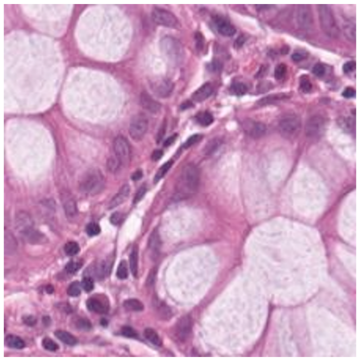
LLAVA-Med Response :
Yes, I can identify the organ in the highlighted area of the CT image. It appears to be the right femoral head, which is the rounded, upper part of the thigh bone (femur) that fits into the hip socket.

Error Analysis :
The model provided an answer that did not correspond to any of the given options, it answering the different question "can you identity the marked area", instead of selecting from the provided list.

Figure 29: A question misunderstanding example. Green highlights the right answer. Yellow highlights the wrong answer. Back to Table Index.

Question Misunderstanding

Question: Determine which option best matches the content displayed in the histology image.
Options:
A. debris
B. lymphocyte
C. normal colonic mucosa
D. smooth muscle
Please select the correct answer from the options above



LLAVA-Med Response :
B, C, and D are the correct options, as they represent the structures and cell types present in the image without signs of inflammation.

Error Analysis :
The response incorrectly included multiple options when only one option should be selected. The primary feature in the image is the glandular structure characteristic of the colonic epithelium. Lymphocytes and smooth muscle are not prominently featured in the image.

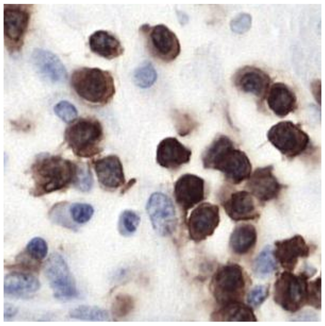
Figure 30: A question misunderstanding example. Green highlights the right answer. Yellow highlights the wrong answer. Back to Table Index.

Perceptual Error

Question: Using the given microscopic image, determine the number of lymphocytes it contains?

Options:

A. the number of lymphocytes:34
B. the number of lymphocytes:20
C. the number of lymphocytes:14
D. the number of lymphocytes:37
Please select the correct answer from the options above



GPT-4o Response :
To determine the number of lymphocytes in the provided image, let's carefully count the cells that exhibit the typical features of lymphocytes: relatively small size, round shape, and a dense, round nucleus.
After examining and counting the lymphocytes in the image, the number of lymphocytes is :
C. the number of lymphocytes: 14

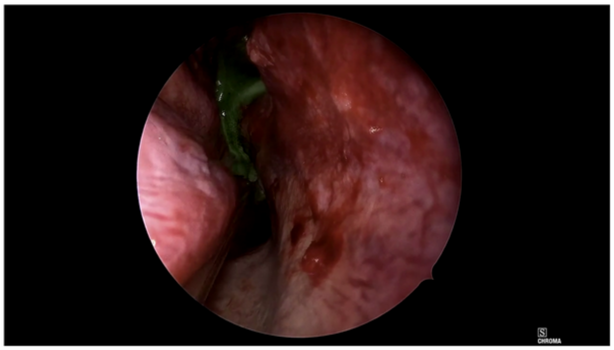
Error Analysis :
The model can't accurately account the number of lymphocytes in this image.

Figure 31: An example of perceptual error - detail missing case. Green highlights the right answer. Yellow highlights the wrong answer. Back to Table Index.

Perceptual Error

Question: Determine which option corresponds to the surgical procedure depicted in the endoscopic image.

Options:
A. gasket seal construct
B. debris clearance
C. sellotomy
D. septum displacement
Please select the correct answer from the options above



GPT-4o Response :
The most suitable answer is:
A. gasket seal construct
Green Material: The green material in the image is likely a sealant or filler used in constructing a gasket seal. This material is often used in surgeries to ensure a watertight closure, particularly in procedures involving the dura mater to prevent cerebrospinal fluid leakage.
Anatomical Context: The image shows a close-up view of tissue that could be involved in the creation of a seal, which is consistent with the use of a gasket seal technique in endoscopic procedures.

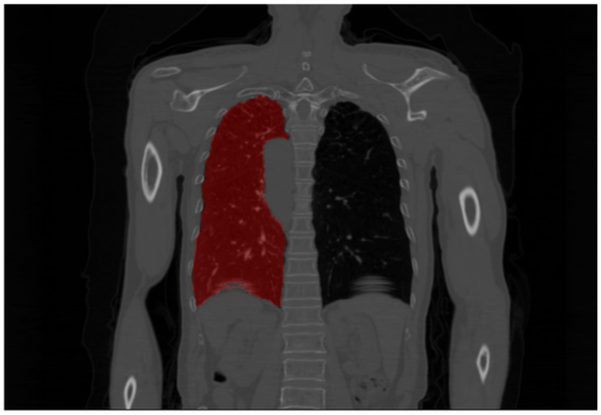
Error Analysis :
Didn’t find the tool in the lower left corner that is clearing the debris

Figure 32: An example of perceptual error - detail missing case. Green highlights the right answer. Yellow highlights the wrong answer. Back to Table Index.

Perceptual Error

Question: View the CT image provided. What organ is displayed in the marked area?

Options:
A. spinal cord
B. lung
C. atrium
D. trachea
E. esophagus
Please select the correct answer from the options above



Claude3-Opus Response :
The marked area in the provided CT image displays the trachea. The trachea appears as a dark, air-filled tubular structure in the center of the thorax, anterior to the esophagus. Therefore, the correct answer is option D. trachea.

Error Analysis :
The error is a detail missing because Claude3 incorrectly perceived the lung as the trachea in the CT image, lost the visual characteristics of the organ.

Figure 33: An example of perceptual error - detail missing case. Green highlights the right answer. Yellow highlights the wrong answer. Back to Table Index.

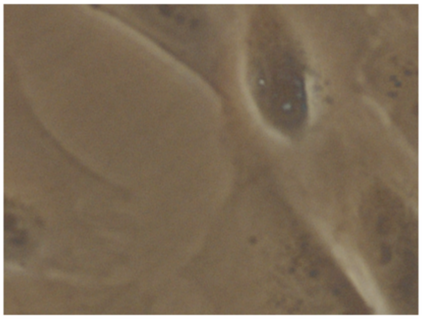
Perceptual Error

Question: Among the choices provided, which one most accurately represents what is shown in the microscopic picture?

Options:

A. fusiform; fuse shaped cell contours and nucleus; separated cells
B. mixed; two or more of afore mentioned classes(fusiform, epithelioid, cobblestone)
C. epithelioid; globular shaped cell contours and nucleus; more packed
D. cobblestone; well defined cell contours and cell wall; hexagonal shape; homogeneous cytoplasm; tightly packed

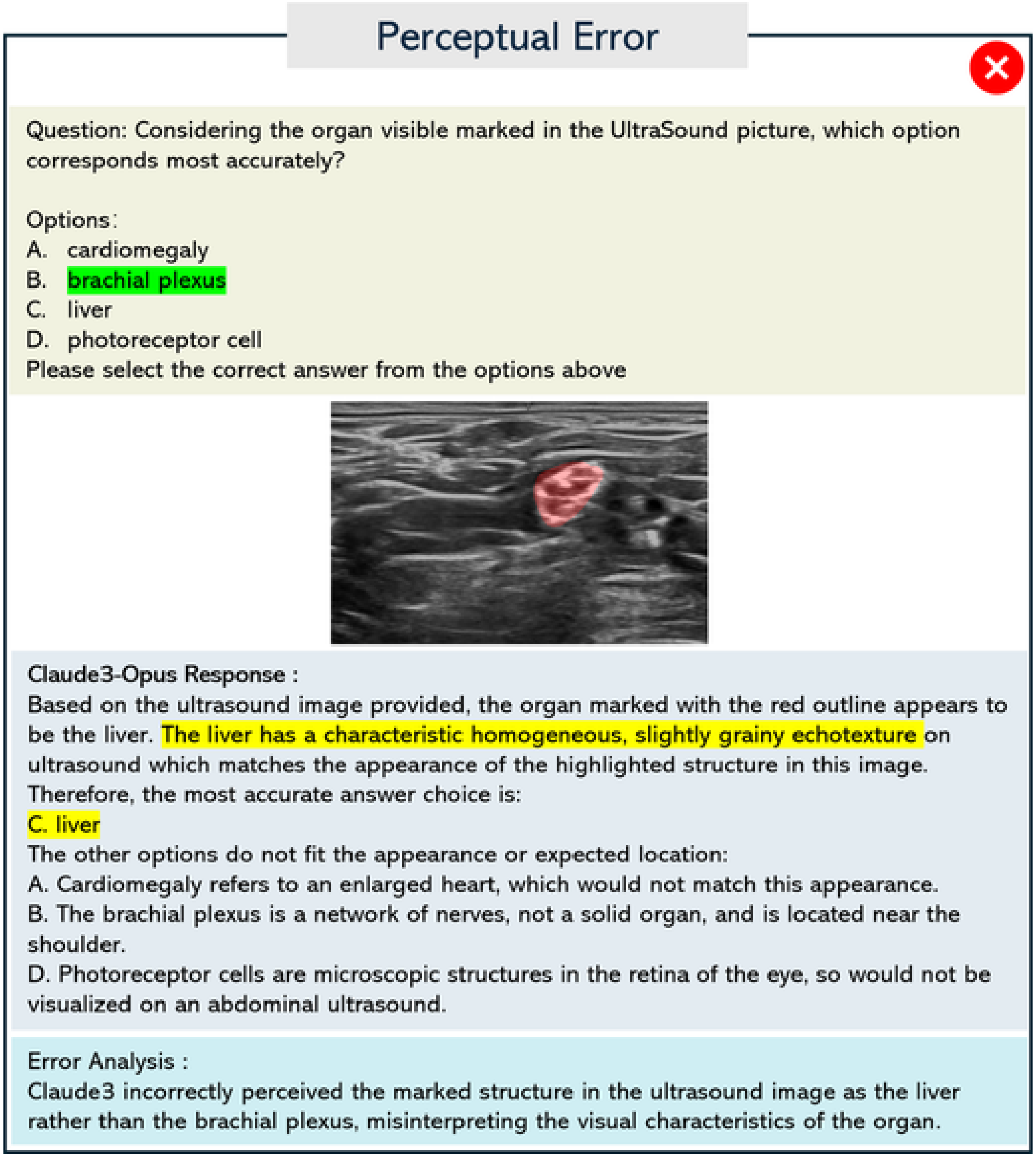
Please select the correct answer from the options above



GPT-4o Response :
The image appears to depict a cellular arrangement that is tightly packed with well-defined cell contours and a hexagonal shape, characteristic of a cobblestone pattern.
So, the correct option is:
D. cobblestone; well-defined cell contours and cell wall; hexagonal shape; homogeneous cytoplasm; tightly packed

Error Analysis :
The model mistakenly seen the cells as hexagonal shape and tightly packed arrangement. The cells in the image appear elongated and spindle-shaped rather than hexagonal, which is indicative of fusiform cells, also the image shows cells that are more elongated and arranged in a way that can be interpreted as separated when viewed closely.

Figure 34: An example of perceptual error - misinterpretation case. Green highlights the right answer. Yellow highlights the wrong answer. Back to Table Index.



Perceptual Error

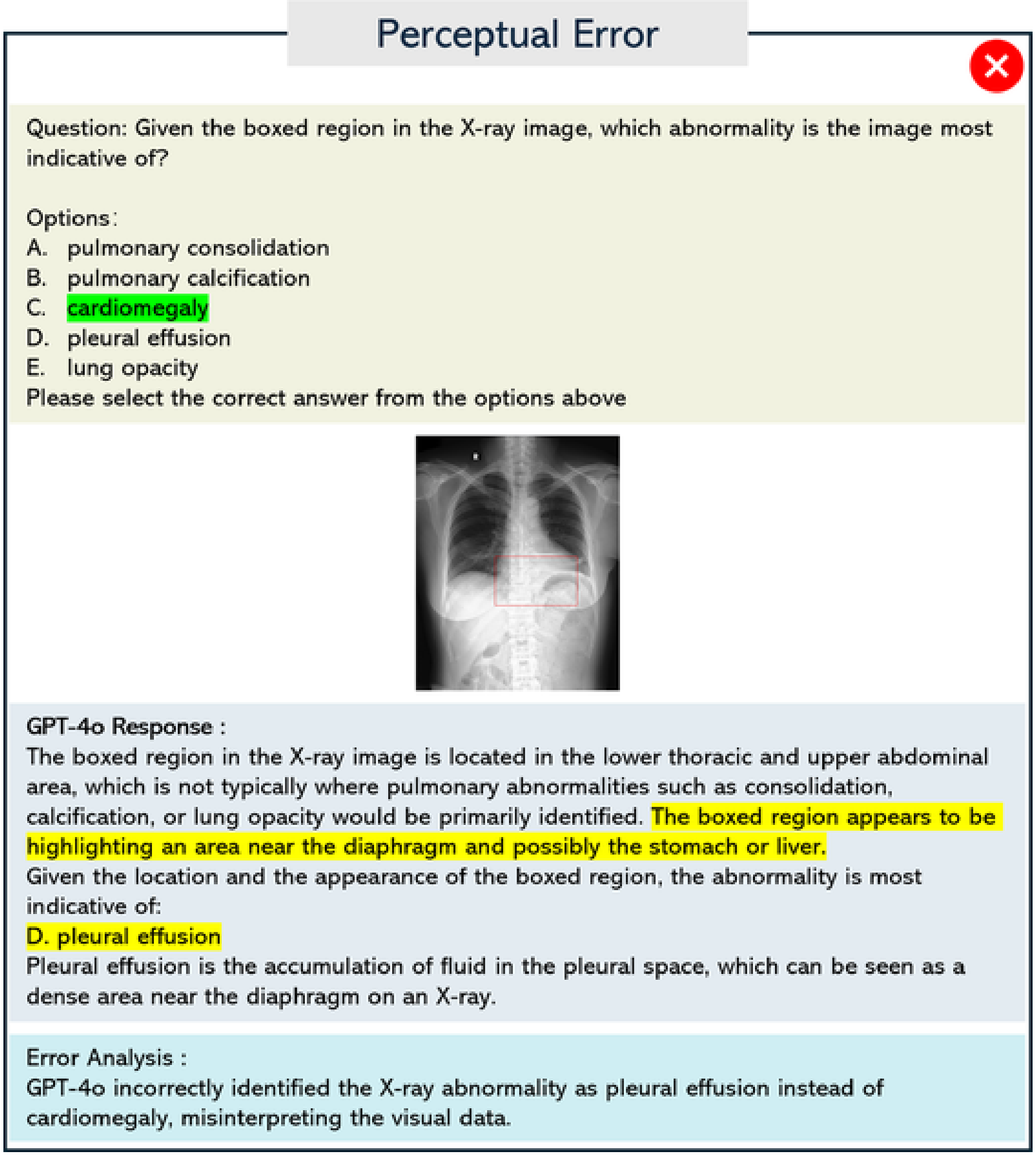
Question: Considering the organ visible marked in the UltraSound picture, which option corresponds most accurately?

Options:
A. cardiomegaly
B. brachial plexus
C. liver
D. photoreceptor cell
Please select the correct answer from the options above

Claude3-Opus Response :
Based on the ultrasound image provided, the organ marked with the red outline appears to be the liver. The liver has a characteristic homogeneous, slightly grainy echotexture on ultrasound which matches the appearance of the highlighted structure in this image.
Therefore, the most accurate answer choice is:
C. liver
The other options do not fit the appearance or expected location:
A. Cardiomegaly refers to an enlarged heart, which would not match this appearance.
B. The brachial plexus is a network of nerves, not a solid organ, and is located near the shoulder.
D. Photoreceptor cells are microscopic structures in the retina of the eye, so would not be visualized on an abdominal ultrasound.

Error Analysis :
Claude3 incorrectly perceived the marked structure in the ultrasound image as the liver rather than the brachial plexus, misinterpreting the visual characteristics of the organ.

Figure 35: An example of perceptual error - misinterpretation case. Green highlights the right answer. Yellow highlights the wrong answer. Back to Table Index.



Perceptual Error

Question: Given the boxed region in the X-ray image, which abnormality is the image most indicative of?

Options:
A. pulmonary consolidation
B. pulmonary calcification
C. cardiomegaly
D. pleural effusion
E. lung opacity
Please select the correct answer from the options above

GPT-4o Response :
The boxed region in the X-ray image is located in the lower thoracic and upper abdominal area, which is not typically where pulmonary abnormalities such as consolidation, calcification, or lung opacity would be primarily identified. The boxed region appears to be highlighting an area near the diaphragm and possibly the stomach or liver.
Given the location and the appearance of the boxed region, the abnormality is most indicative of:
D. pleural effusion
Pleural effusion is the accumulation of fluid in the pleural space, which can be seen as a dense area near the diaphragm on an X-ray.

Error Analysis :
GPT-4o incorrectly identified the X-ray abnormality as pleural effusion instead of cardiomegaly, misinterpreting the visual data.

Figure 36: An example of perceptual error - misinterpretation case. Green highlights the right answer. Yellow highlights the wrong answer. Back to Table Index.

Perceptual Error

Question: Which of the following options best matches the symptoms of marked region shown in the Dermoscopy image?

Options:

A. streaks skin lesion

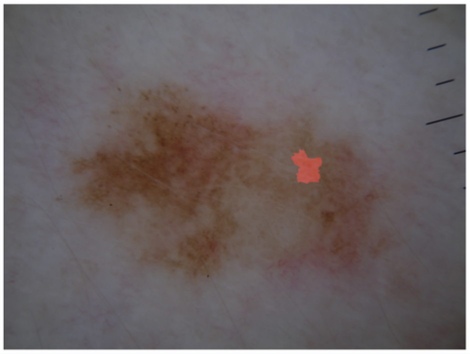
B. milia like cyst skin lesion

C. pigment network skin lesion

D. negative network skin lesion

E. globules skin lesion

Please select the correct answer from the options above



GPT-4o Response :

The marked region in the dermoscopy image shows a small, well-defined area that appears to be a cluster of small, round structures. This description best matches the characteristics of "globules skin lesion."

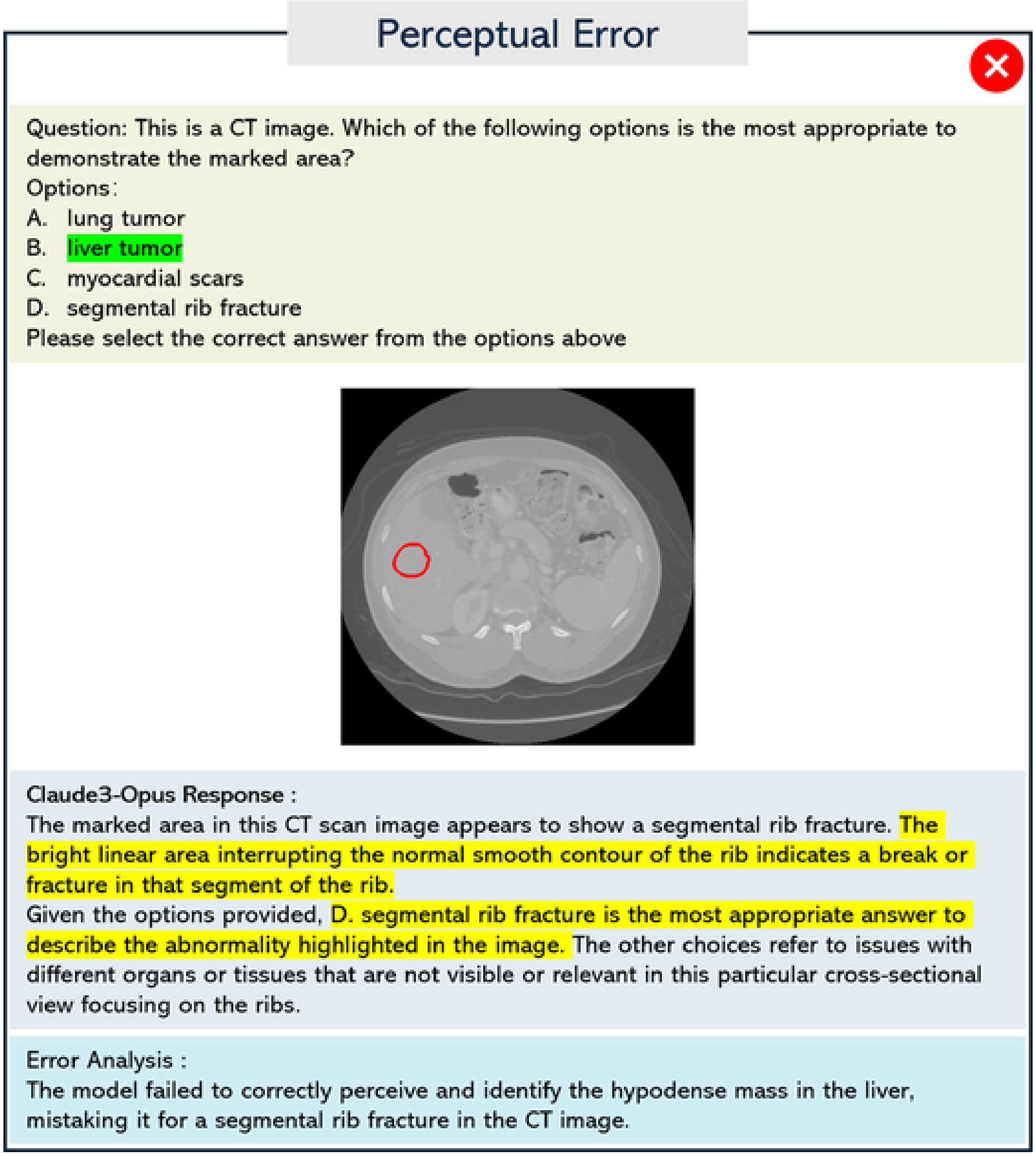
So, the correct answer is:

E. globules skin lesion

Error Analysis :

The marked region in the image shows a darker, network-like structure, which is consistent with the characteristics of a negative network skin lesion, not a globules skin lesion. This indicates that the model still lacks sufficient understanding and judgment of the morphological features of different lesions under dermoscopy, mistaking the network structure for round globules.

Figure 37: An example of perceptual error - misinterpretation case. Green highlights the right answer. Yellow highlights the wrong answer. Back to Table Index.



Perceptual Error

Question: This is a CT image. Which of the following options is the most appropriate to demonstrate the marked area?

Options:

A. lung tumor

B. liver tumor

C. myocardial scars

D. segmental rib fracture

Please select the correct answer from the options above

Claude3-Opus Response :

The marked area in this CT scan image appears to show a segmental rib fracture. The bright linear area interrupting the normal smooth contour of the rib indicates a break or fracture in that segment of the rib.

Given the options provided, D. segmental rib fracture is the most appropriate answer to describe the abnormality highlighted in the image. The other choices refer to issues with different organs or tissues that are not visible or relevant in this particular cross-sectional view focusing on the ribs.

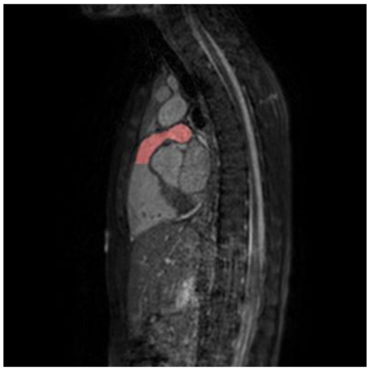
Error Analysis :

The model failed to correctly perceive and identify the hypodense mass in the liver, mistaking it for a segmental rib fracture in the CT image.

Figure 38: An example of perceptual error - misinterpretation case. Green highlights the right answer. Yellow highlights the wrong answer. Back to Table Index.

Perceptual Error

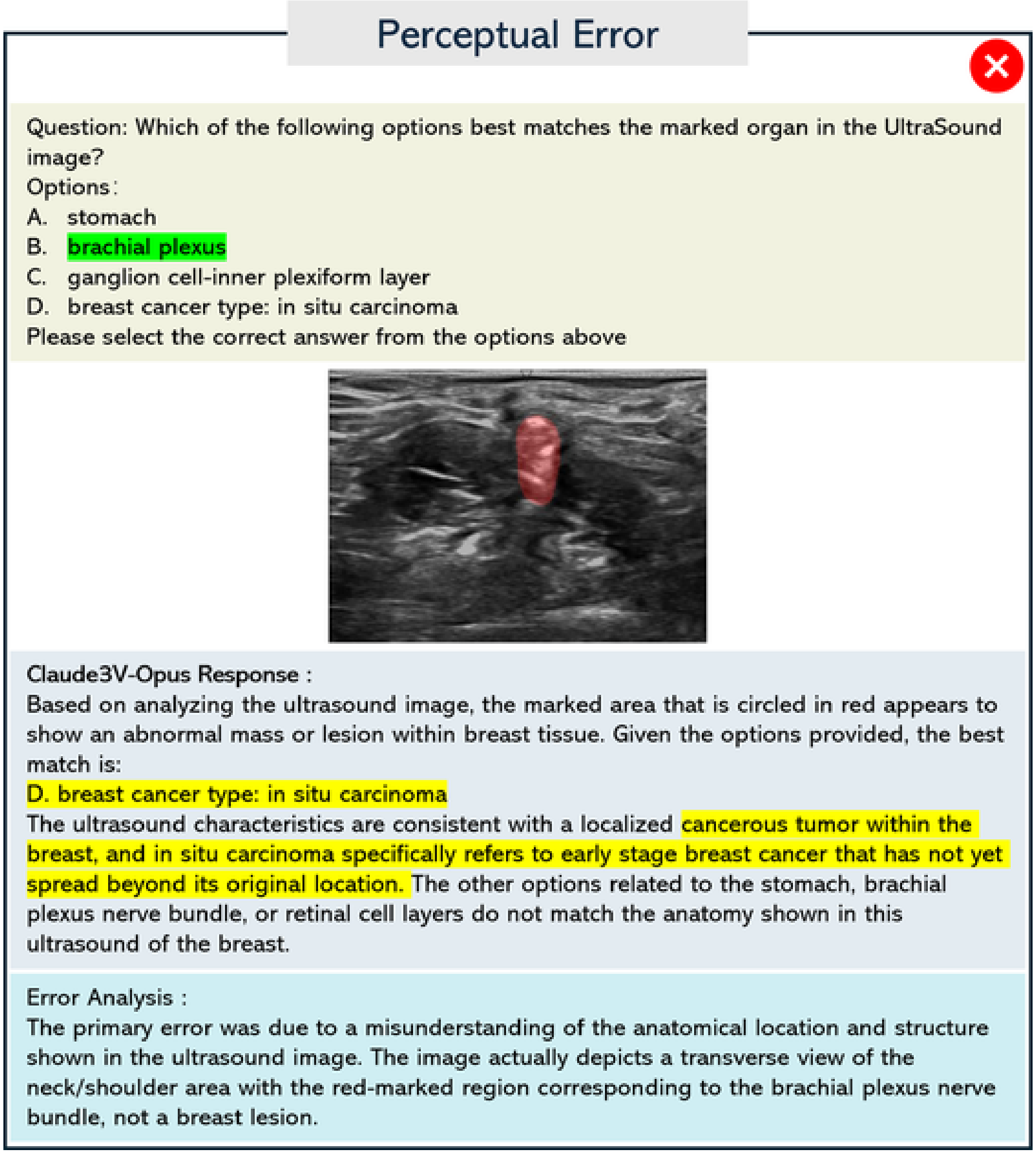
Question: Determine which part is illustrated in the MRI image.
Options:
A. breast
B. esophagus
C. trachea
D. pulmonary artery
Please select the correct answer from the options above



GPT-4o Response :
The marked organ in the MRI image is best matched with option "esophagus".

Error Analysis :
The error in the response likely stems from a perceptual error in the interpretation of the anatomical structures visible in the MRI image. While the system correctly identified that the marked region is within the thoracic cavity, it failed to accurately distinguish between the closely positioned organs, leading to the incorrect identification of the esophagus instead of the pulmonary artery.

Figure 39: An example of perceptual error - misinterpretation case. Green highlights the right answer. Yellow highlights the wrong answer. Back to Table Index.



Perceptual Error

Question: Which of the following options best matches the marked organ in the UltraSound image?

Options:

A. stomach

B. brachial plexus

C. ganglion cell-inner plexiform layer

D. breast cancer type: in situ carcinoma

Please select the correct answer from the options above

Claude3V-Opus Response :

Based on analyzing the ultrasound image, the marked area that is circled in red appears to show an abnormal mass or lesion within breast tissue. Given the options provided, the best match is:

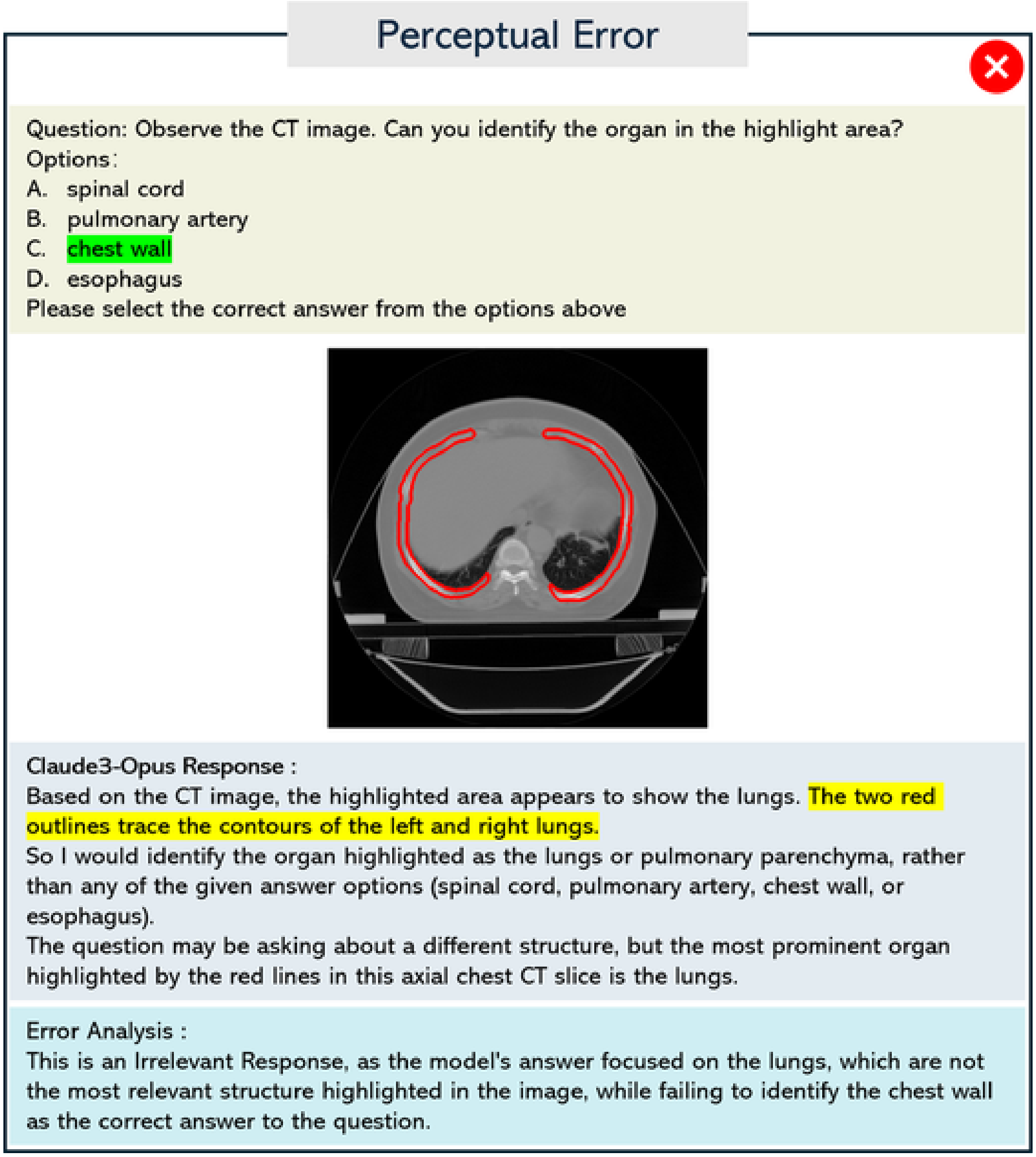
D. breast cancer type: in situ carcinoma

The ultrasound characteristics are consistent with a localized cancerous tumor within the breast, and in situ carcinoma specifically refers to early stage breast cancer that has not yet spread beyond its original location. The other options related to the stomach, brachial plexus nerve bundle, or retinal cell layers do not match the anatomy shown in this ultrasound of the breast.

Error Analysis :

The primary error was due to a misunderstanding of the anatomical location and structure shown in the ultrasound image. The image actually depicts a transverse view of the neck/shoulder area with the red-marked region corresponding to the brachial plexus nerve bundle, not a breast lesion.

Figure 40: An example of perceptual error - misinterpretation case. Green highlights the right answer. Yellow highlights the wrong answer. Back to Table Index.



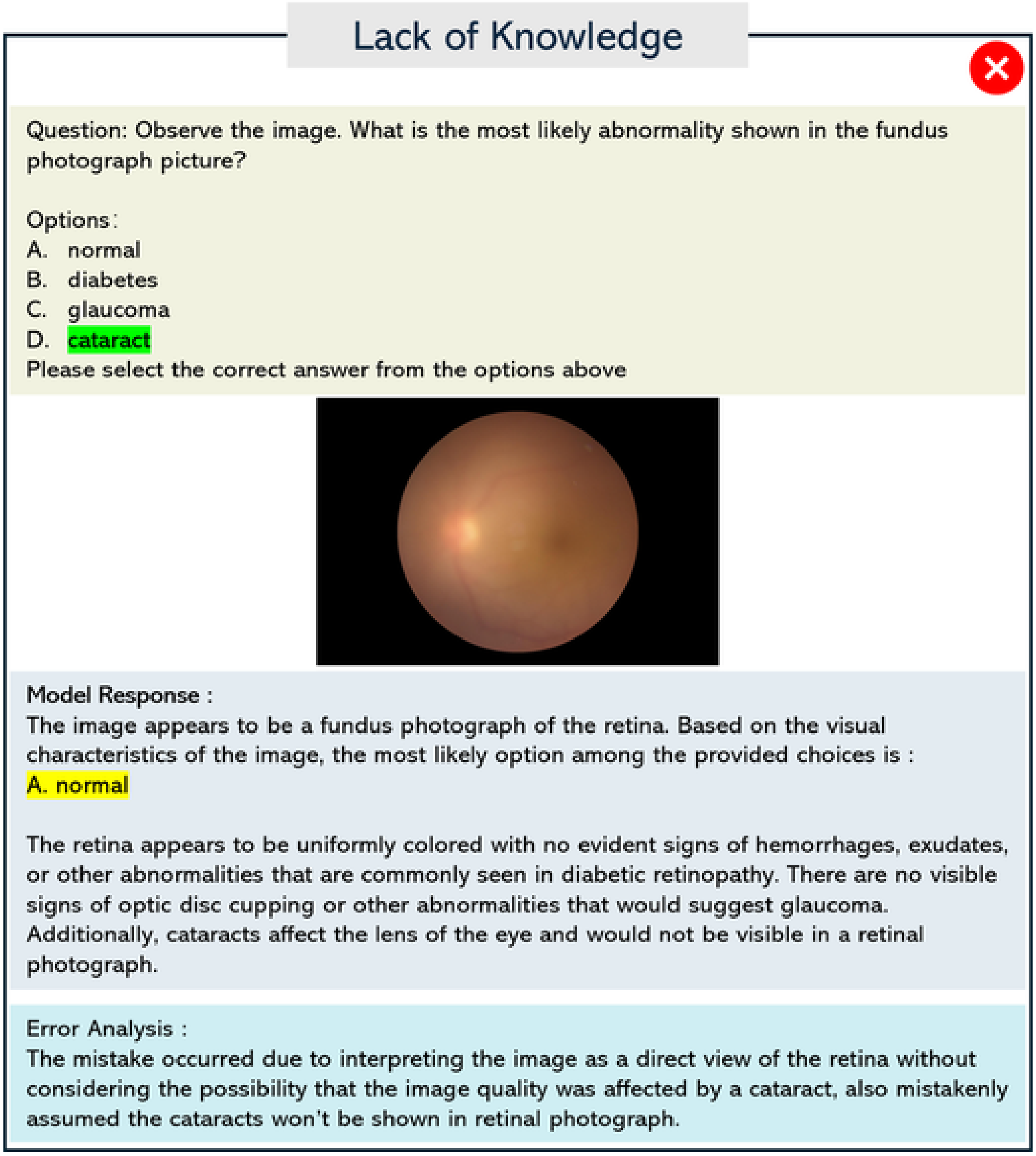
Perceptual Error

Question: Observe the CT image. Can you identify the organ in the highlight area?
Options:
A. spinal cord
B. pulmonary artery
C. chest wall
D. esophagus
Please select the correct answer from the options above

Claude3-Opus Response :
Based on the CT image, the highlighted area appears to show the lungs. The two red outlines trace the contours of the left and right lungs.
So I would identify the organ highlighted as the lungs or pulmonary parenchyma, rather than any of the given answer options (spinal cord, pulmonary artery, chest wall, or esophagus).
The question may be asking about a different structure, but the most prominent organ highlighted by the red lines in this axial chest CT slice is the lungs.

Error Analysis :
This is an Irrelevant Response, as the model's answer focused on the lungs, which are not the most relevant structure highlighted in the image, while failing to identify the chest wall as the correct answer to the question.

Figure 41: An example of perceptual error - misinterpretation case. Green highlights the right answer. Yellow highlights the wrong answer. Back to Table Index.



Lack of Knowledge

Question: Observe the image. What is the most likely abnormality shown in the fundus photograph picture?

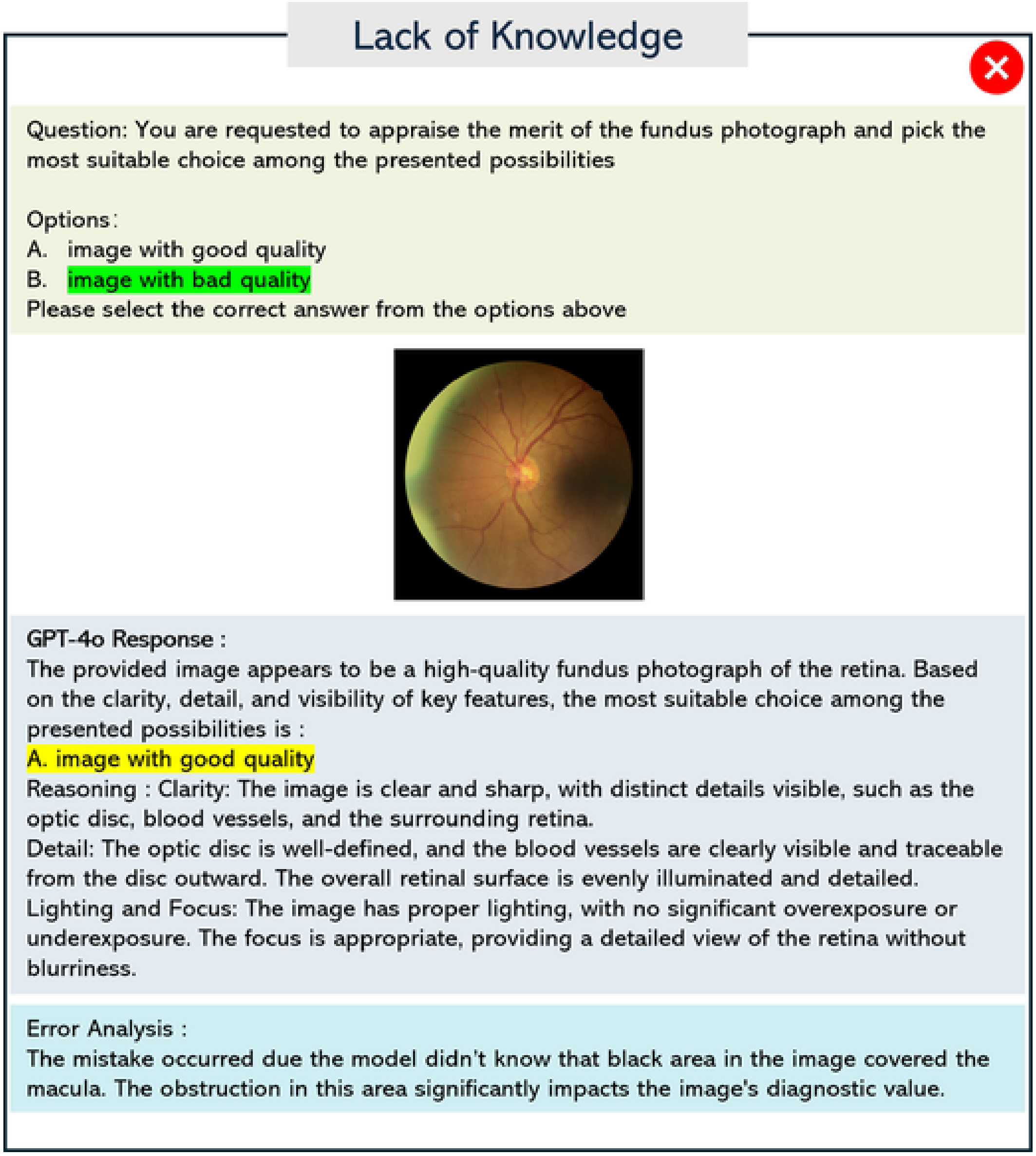
Options:
A. normal
B. diabetes
C. glaucoma
D. cataract
Please select the correct answer from the options above

Model Response :
The image appears to be a fundus photograph of the retina. Based on the visual characteristics of the image, the most likely option among the provided choices is :
A. normal

The retina appears to be uniformly colored with no evident signs of hemorrhages, exudates, or other abnormalities that are commonly seen in diabetic retinopathy. There are no visible signs of optic disc cupping or other abnormalities that would suggest glaucoma. Additionally, cataracts affect the lens of the eye and would not be visible in a retinal photograph.

Error Analysis :
The mistake occurred due to interpreting the image as a direct view of the retina without considering the possibility that the image quality was affected by a cataract, also mistakenly assumed the cataracts won't be shown in retinal photograph.

Figure 42: A lack of knowledge example. Green highlights the right answer. Yellow highlights the wrong answer. Back to Table Index.



Lack of Knowledge

❌

Question: You are requested to appraise the merit of the fundus photograph and pick the most suitable choice among the presented possibilities

Options:
A. image with good quality
B. image with bad quality
Please select the correct answer from the options above

GPT-4o Response :
The provided image appears to be a high-quality fundus photograph of the retina. Based on the clarity, detail, and visibility of key features, the most suitable choice among the presented possibilities is :
A. image with good quality
Reasoning : Clarity: The image is clear and sharp, with distinct details visible, such as the optic disc, blood vessels, and the surrounding retina.
Detail: The optic disc is well-defined, and the blood vessels are clearly visible and traceable from the disc outward. The overall retinal surface is evenly illuminated and detailed.
Lighting and Focus: The image has proper lighting, with no significant overexposure or underexposure. The focus is appropriate, providing a detailed view of the retina without blurriness.

Error Analysis :
The mistake occurred due the model didn't know that black area in the image covered the macula. The obstruction in this area significantly impacts the image's diagnostic value.

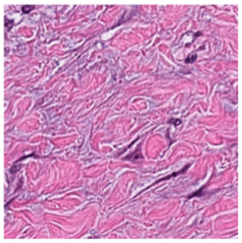
Figure 43: A lack of knowledge example. Green highlights the right answer. Yellow highlights the wrong answer. Back to Table Index.

Lack of Knowledge

❌

Question: Please determine which option best matches the content displayed in the histopathology image.

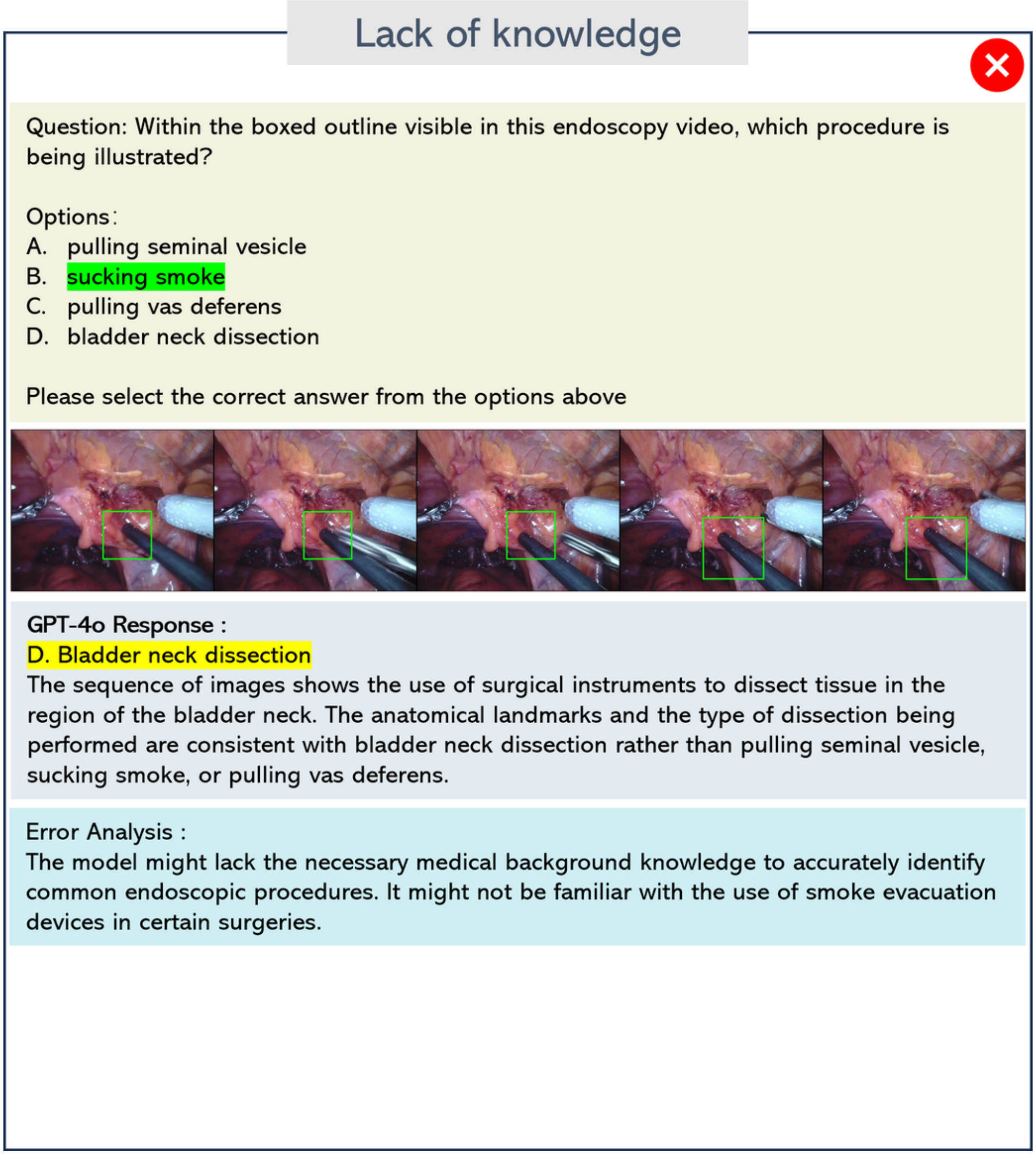
Options:
A. cancer associated stroma
B. normal colonic mucosa
C. smooth muscle
D. adipose
Please select the correct answer from the options above



GPT-4o Response :
The image appears to show a histological section with a fibrous and wavy pattern. Based on the options provided and the visual characteristics of the image, the most suitable answer is :
C. smooth muscle
Histological Appearance: The image shows elongated, wavy fibers that are characteristic of smooth muscle tissue. The cells are spindle-shaped with elongated nuclei, and the fibers are arranged in a more or less parallel fashion, which is typical for smooth muscle.

Error Analysis :
The model misidentification as smooth muscle occurred due to the presence of elongated, fibrous structures. However, the disorganized, dense, and fibrous nature of the tissue, along with the scattered cells within the matrix in this picture is the presence of cancer associated stroma.

Figure 44: A lack of knowledge example. Green highlights the right answer. Yellow highlights the wrong answer. Back to Table Index.



Lack of knowledge

Question: Within the boxed outline visible in this endoscopy video, which procedure is being illustrated?

Options:
A. pulling seminal vesicle
B. sucking smoke
C. pulling vas deferens
D. bladder neck dissection

Please select the correct answer from the options above

GPT-4o Response :
D. Bladder neck dissection
The sequence of images shows the use of surgical instruments to dissect tissue in the region of the bladder neck. The anatomical landmarks and the type of dissection being performed are consistent with bladder neck dissection rather than pulling seminal vesicle, sucking smoke, or pulling vas deferens.

Error Analysis :
The model might lack the necessary medical background knowledge to accurately identify common endoscopic procedures. It might not be familiar with the use of smoke evacuation devices in certain surgeries.

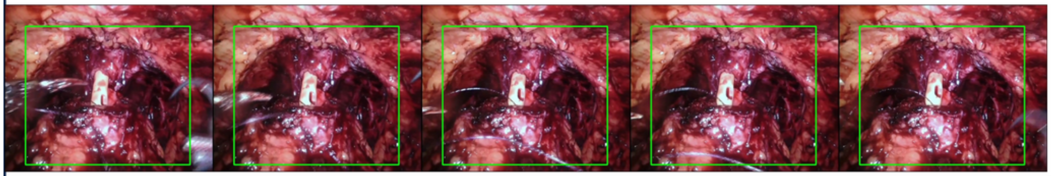
Figure 45: A lack of knowledge example. Green highlights the right answer. Yellow highlights the wrong answer. Back to Table Index.

Lack of knowledge

Question: Observing the action taking place within the square in this endoscopy video, what procedure is being conducted?

Options:

A. bladder anastomosis
B. urethra dissection
C. pulling vas deferens
D. cutting thread
E. pulling tissue
Please select the correct answer from the options above



GPT-4o Response :

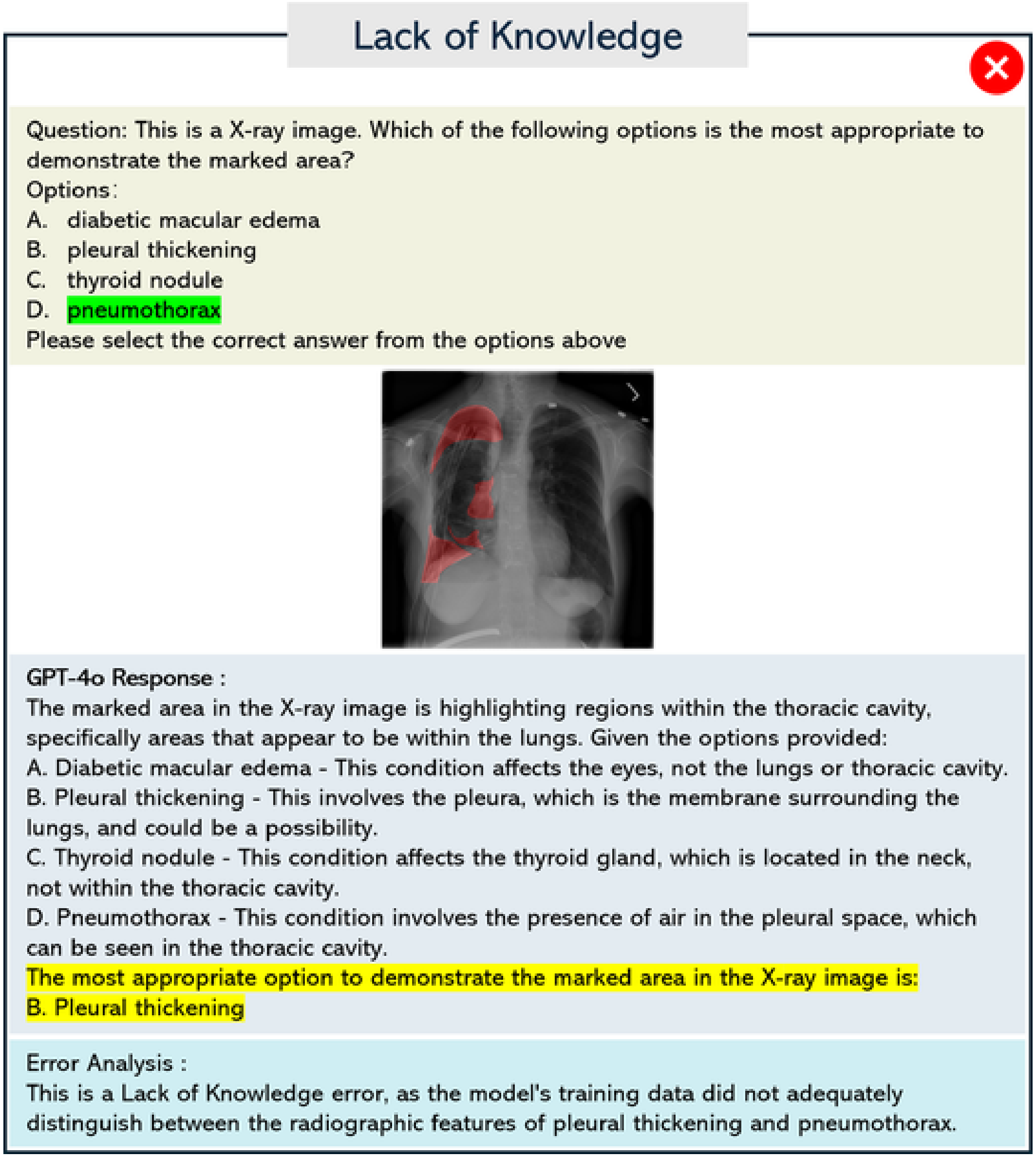
The visual evidence from the images shows threads (sutures) within the surgical field. The surgical tools appear to be manipulating these threads, a common action in various procedures to secure or remove sutures. Cutting threads is a straightforward and frequently performed action in surgeries involving sutures.

Given the context and the nature of the procedure shown (suturing), the most appropriate action described in the options is D. cutting thread .

Error Analysis :

Understanding medical procedures requires context beyond just the visual cues. The model may lack the detailed medical knowledge needed to differentiate between similar-looking actions in surgical procedures.

Figure 46: A lack of knowledge example. Green highlights the right answer. Yellow highlights the wrong answer. Back to Table Index.



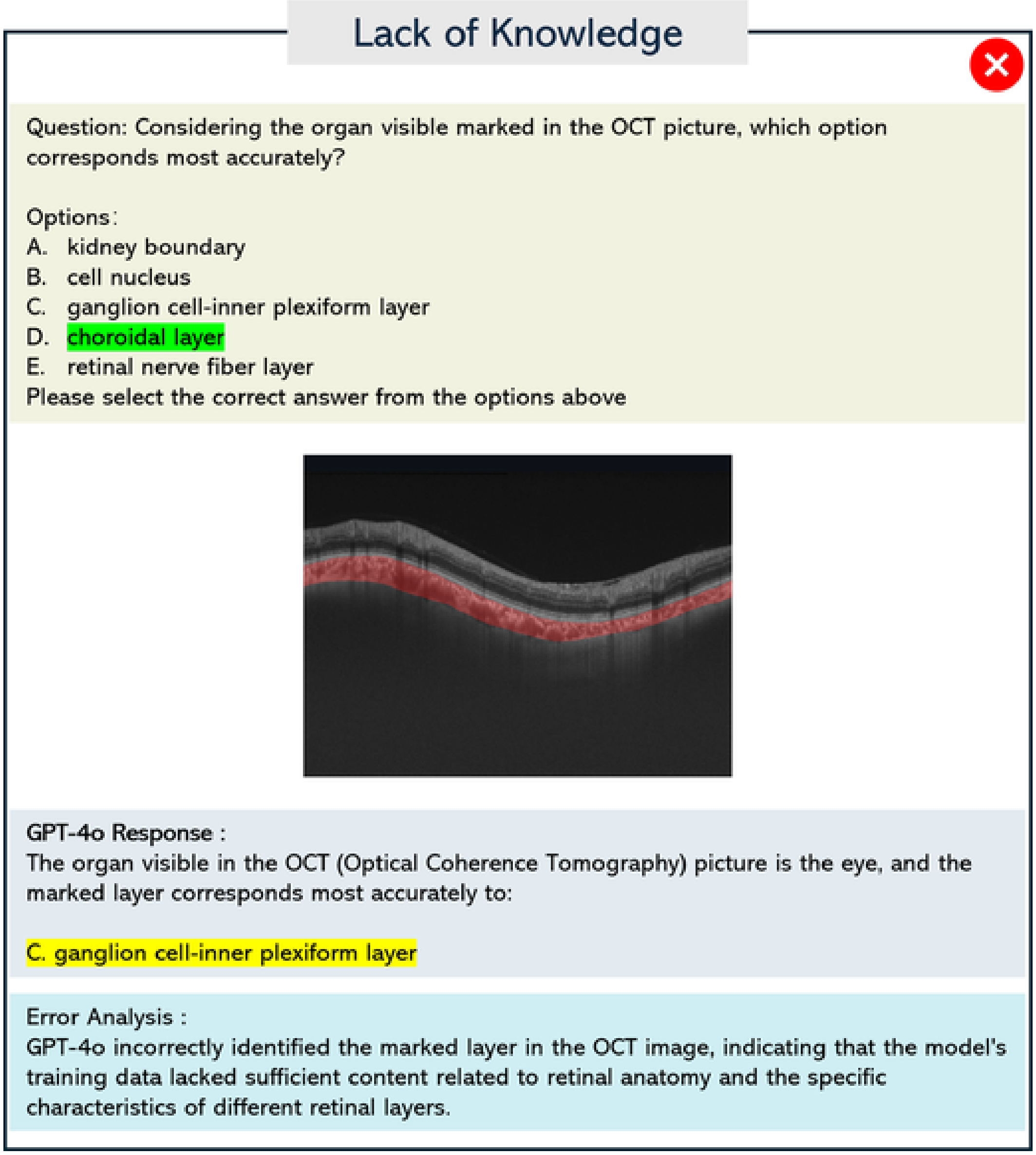
Lack of Knowledge

Question: This is a X-ray image. Which of the following options is the most appropriate to demonstrate the marked area?
Options:
A. diabetic macular edema
B. pleural thickening
C. thyroid nodule
D. pneumothorax
Please select the correct answer from the options above

GPT-4o Response :
The marked area in the X-ray image is highlighting regions within the thoracic cavity, specifically areas that appear to be within the lungs. Given the options provided:
A. Diabetic macular edema - This condition affects the eyes, not the lungs or thoracic cavity.
B. Pleural thickening - This involves the pleura, which is the membrane surrounding the lungs, and could be a possibility.
C. Thyroid nodule - This condition affects the thyroid gland, which is located in the neck, not within the thoracic cavity.
D. Pneumothorax - This condition involves the presence of air in the pleural space, which can be seen in the thoracic cavity.
The most appropriate option to demonstrate the marked area in the X-ray image is:
B. Pleural thickening

Error Analysis :
This is a Lack of Knowledge error, as the model's training data did not adequately distinguish between the radiographic features of pleural thickening and pneumothorax.

Figure 47: A lack of knowledge example. Green highlights the right answer. Yellow highlights the wrong answer. Back to Table Index.



Lack of Knowledge

Question: Considering the organ visible marked in the OCT picture, which option corresponds most accurately?

Options:
A. kidney boundary
B. cell nucleus
C. ganglion cell-inner plexiform layer
D. choroidal layer
E. retinal nerve fiber layer
Please select the correct answer from the options above

GPT-4o Response :
The organ visible in the OCT (Optical Coherence Tomography) picture is the eye, and the marked layer corresponds most accurately to:

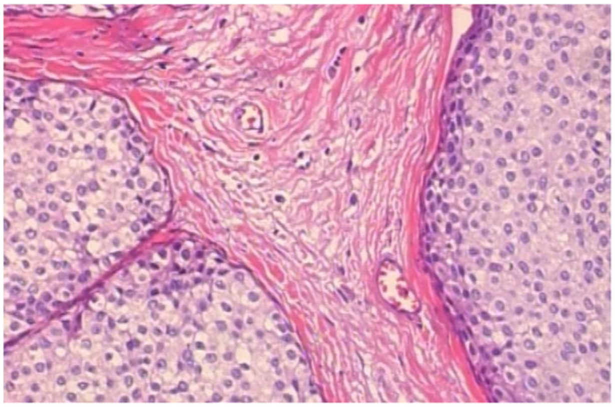
C. ganglion cell-inner plexiform layer

Error Analysis :
GPT-4o incorrectly identified the marked layer in the OCT image, indicating that the model's training data lacked sufficient content related to retinal anatomy and the specific characteristics of different retinal layers.

Figure 48: A lack of knowledge example. Green highlights the right answer. Yellow highlights the wrong answer. Back to Table Index.

Lack of Knowledge

Question: Review the Histopathology image and pick the option that best aligns with the severity illustrated.
Options:
A. malignant
B. benign
Please select the correct answer from the options above



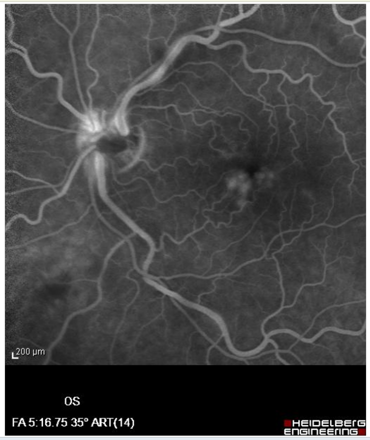
GPT-4o Response :
The image shows a histological section with a clear distinction between the fibrous stroma and the surrounding tissue. The presence of well-defined borders and the lack of significant cellular atypia or invasion into surrounding tissues suggest that the lesion is likely benign.
Therefore, the correct answer is:
benign

Error Analysis :
The response incorrectly classified the lesion as benign instead of malignant due to a lack of accurate knowledge required to distinguish between benign and malignant histological features. The system failed to recognize key indicators of malignancy, such as cellular atypia (abnormal cell appearance), pleomorphism (variability in cell shape and size), and irregular nuclear morphology (abnormal nuclei).

Figure 49: A lack of knowledge example. Green highlights the right answer. Yellow highlights the wrong answer. Back to Table Index.

Lack of Knowledge

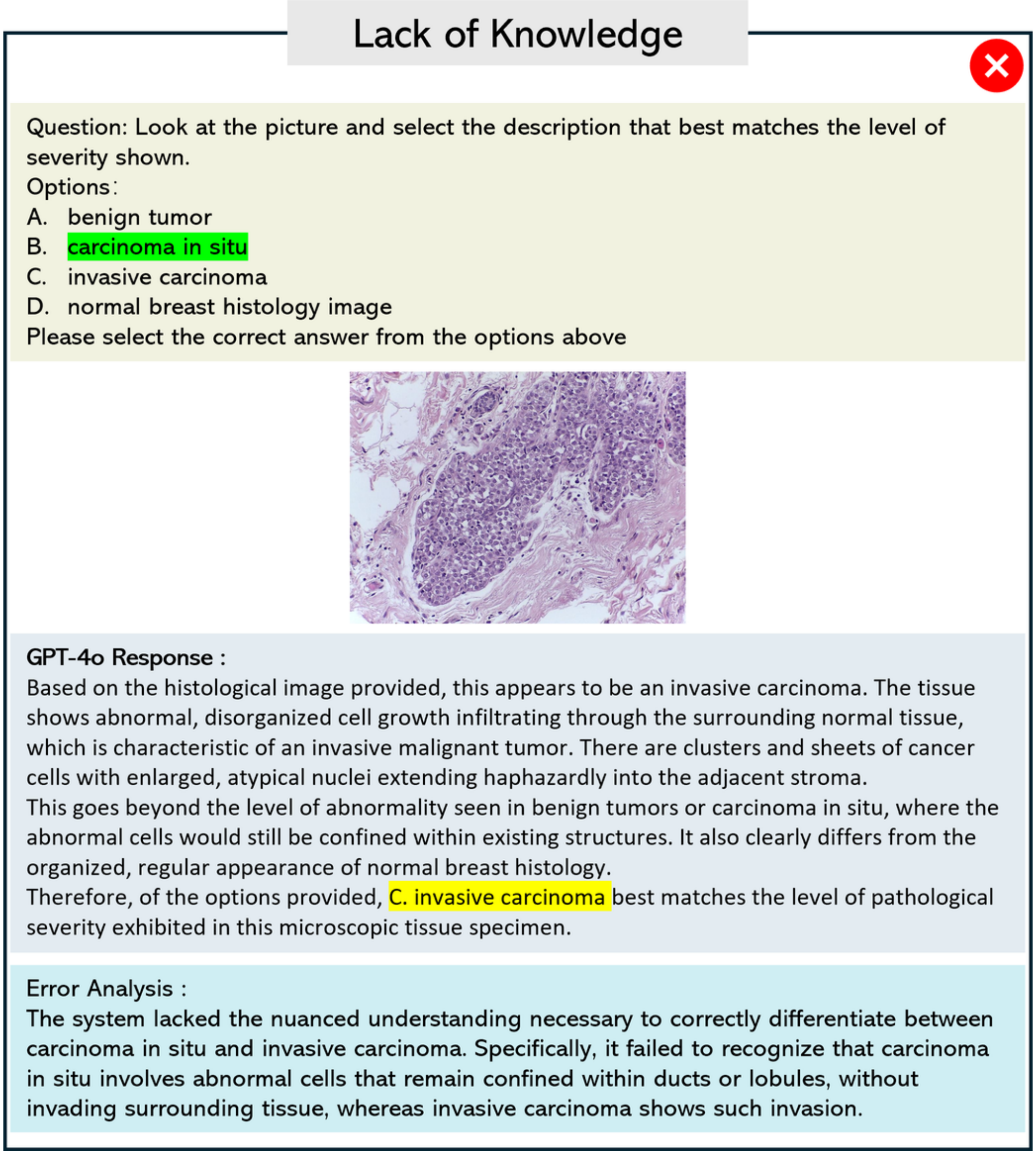
Question: Which of the following options best matches the symptoms shown in the image?
Options:
A. diffuse leakage diabetic macular edema
B. focal leakage diabetic macular edema
C. mixed leakage diabetic macular edema
Please select the correct answer from the options above



Claude3-Opus Response :
The fluorescein angiogram image shows numerous focal hyperfluorescent leakage points scattered throughout the macula, which correspond to microaneurysms. There are also some areas of mild diffuse leakage, but the focal leakage pattern predominates.
Based on these findings, the best answer is:
C. mixed leakage diabetic macular edema
This patient has diabetic macular edema with both focal leakage from microaneurysms as well as some diffuse leakage, consistent with a mixed focal and diffuse leakage pattern. The focal component appears more prominent than the diffuse leakage in this case.

Error Analysis :
The model correctly identified the presence of both focal and diffuse leakages but incorrectly concluded the predominant pattern.

Figure 50: A lack of knowledge example. Green highlights the right answer. Yellow highlights the wrong answer. Back to Table Index.



Lack of Knowledge

Question: Look at the picture and select the description that best matches the level of severity shown.
Options:
A. benign tumor
B. carcinoma in situ
C. invasive carcinoma
D. normal breast histology image
Please select the correct answer from the options above

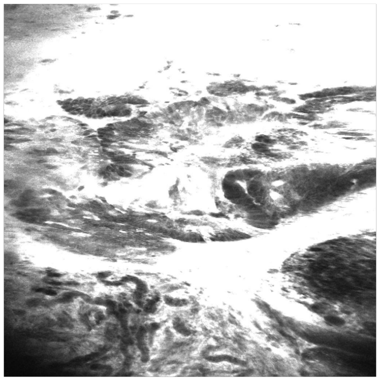
GPT-4o Response :
Based on the histological image provided, this appears to be an invasive carcinoma. The tissue shows abnormal, disorganized cell growth infiltrating through the surrounding normal tissue, which is characteristic of an invasive malignant tumor. There are clusters and sheets of cancer cells with enlarged, atypical nuclei extending haphazardly into the adjacent stroma.
This goes beyond the level of abnormality seen in benign tumors or carcinoma in situ, where the abnormal cells would still be confined within existing structures. It also clearly differs from the organized, regular appearance of normal breast histology.
Therefore, of the options provided, C. invasive carcinoma best matches the level of pathological severity exhibited in this microscopic tissue specimen.

Error Analysis :
The system lacked the nuanced understanding necessary to correctly differentiate between carcinoma in situ and invasive carcinoma. Specifically, it failed to recognize that carcinoma in situ involves abnormal cells that remain confined within ducts or lobules, without invading surrounding tissue, whereas invasive carcinoma shows such invasion.

Figure 51: A lack of knowledge example. Green highlights the right answer. Yellow highlights the wrong answer. Back to Table Index.

Lack of Knowledge

Question: View the image provided. What is the likely abnormal condition demonstrated?
Options:
A. gastric metaplasia
B. proper Barrett's esophagus
C. neoplasia
Please select the correct answer from the options above



Claude3V-Opus Response :
The image shows an abnormal pattern that could potentially represent a medical condition, but I do not have the medical expertise to confidently diagnose the specific abnormality shown. The cloudy, irregular appearance suggests some sort of tissue abnormality or growth, but determining whether it depicts Barrett's esophagus, gastric metaplasia, neoplasia, or another condition would require analysis by a trained medical professional. I apologize that I cannot provide a definitive answer, as identifying abnormalities from medical imaging is outside my capabilities as an AI system.

Error Analysis :
The model understood the visual and the question and the options but failed to accurately answer the question for it consider itself don't have such ability to do so.

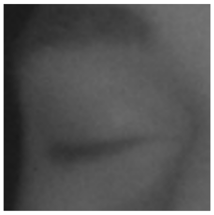
Figure 52: An example of unable to determine. Green highlights the right answer. Yellow highlights the wrong answer. Back to Table Index.

Lack of Knowledge

✕

Question: Which of the following options best matches the content of the image?

Options:
A. gender: female
B. gender: male
Please select the correct answer from the options above



GPT-4o Response :
Determining gender from this image is highly subjective and challenging due to the limited and indistinct visual information it provides.
The image appears to be a close-up of an eye with the surrounding area, but it does not provide clear indicators of gender. Without more contextual information or distinctive features, it's not possible to accurately determine the gender.
Based on the given options, this image does not provide enough visual clues to confidently choose between:
A. gender: female
B. gender: male
Therefore, it is not feasible to determine which option best matches the content of the image with any certainty.

Error Analysis :
The model can't provide gender determination due to limited visual information, even it is easy for human to determine

Figure 53: An example of unable to determine. Green highlights the right answer. Yellow highlights the wrong answer. Back to Table Index.

Lack of Knowledge

❌

Question: Which of the following options best matches the symptoms shown in the Coloscopy image?

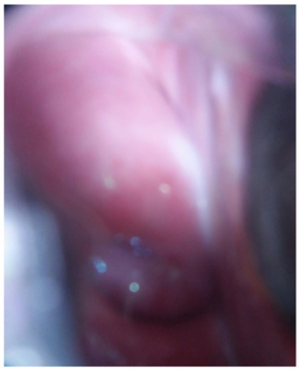
Options:

A. completely ectocervical and fully visible

B. endocervical component that is not fully visible and may have ectocervical component which may be small or large

C. endocervical component that fully visible and may have ectocervical component which may be small or large

Please select the correct answer from the options above



GPT-4o Response :

The image appears to be out of focus and does not clearly show the details necessary to accurately determine the condition of the cervix. Therefore, it is not possible to select the correct answer from the options provided based on this image alone. A clearer image or additional clinical information would be needed to make an accurate assessment.

Error Analysis :

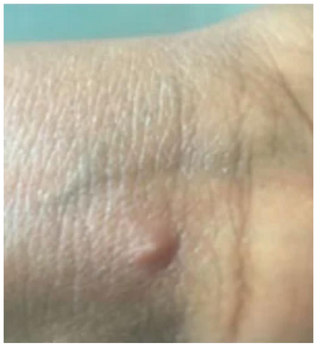
The model understood the question and the options but opted not to select an answer, stating that the image was too unclear for an accurate assessment. This suggests that while the model can recognize when it lacks sufficient ability to make a decision, it needs better mechanisms to handle such situations and still provide the best possible answer based on available data.

Figure 54: An example of unable to determine. Green highlights the right answer. Yellow highlights the wrong answer. Back to Table Index.

Lack of Knowledge

Question: Which of the following options best matches the symptoms shown in the demoscopic image?

Options:
A. monkeypox
B. healthy
C. chickenpox
D. measles
Please select the correct answer from the options above



Gemini-1.5 Response :
It is impossible to diagnose medical conditions from images alone.

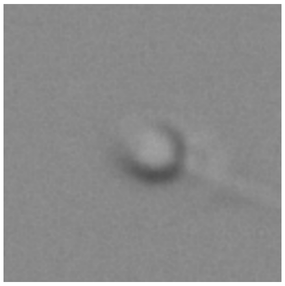
Error Analysis :
The model cannot determine the type of disease based on the current image, but it is sufficient for humans to make a judgment.

Figure 55: An example of unable to determine. Green highlights the right answer. Yellow highlights the wrong answer. Back to Table Index.

Lack of Knowledge

Question: Considering the symptoms visible in the microscopic picture, which option corresponds most accurately?

Options:
A. abnormal sperm tail
B. normal sperm tail
Please select the correct answer from the options above



Gemini-1.5 Response :
This image does not contain enough information to determine if the sperm tail is normal or abnormal. Seek advice from a medical professional.

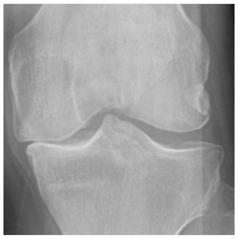
Error Analysis :
The model cannot determine whether the tail of the sperm is normal based on the current image, but this question is not difficult for humans.

Figure 56: An example of unable to determine. Green highlights the right answer. Yellow highlights the wrong answer. Back to Table Index.

Irrelevant Response

Question: Examine the X-ray image and choose the option that most accurately reflects the depicted severity.

Options:
A. grade 4 (severe)
B. grade 0 (healthy knee image)
C. grade 3 (moderate)
D. grade 1 (doubtful)
Please select the correct answer from the options above



RadFM Response :
Zaricznyj N, Koshino T, Ohashi N, et al. Detection of osteoarthritis by chest radiography: results of a population-based study in the Tohoku region. Int J Osteoarthritis 2018; 8:1-8.

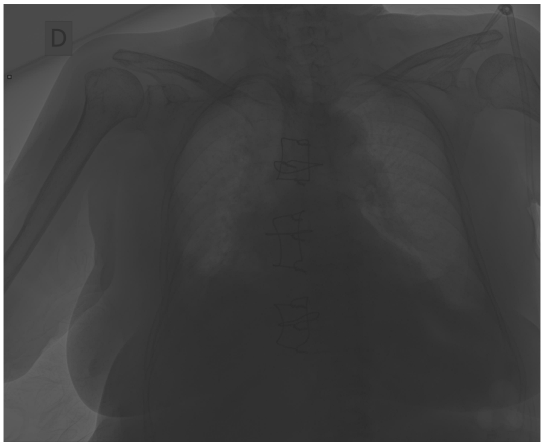
Error Analysis :
The model's response indicates that it recognized the modality of the image as related to Osteoarthritis, but the result was gibberish. This, along with the reference literature, suggests that the model has a certain level of image recognition capability, but its language abilities are lacking.

Figure 57: An example of irrelevant response. Green highlights the right answer. Yellow highlights the wrong answer. Back to Table Index.

Irrelevant Response

Question: Observe the X-ray image, please select the option that best describes the attribute depicted in the picture.

Options:
A. atypical appearance of COVID-19
B. typical appearance of COVID-19
C. indeterminate appearance of COVID-19
D. negative for pneumonia
Please select the correct answer from the options above



RadFM Response :
"Zhou et al (2021) COVID-19 Typical, Atypical, and Indeterminate Appearances on Chest CT (radiology article)"

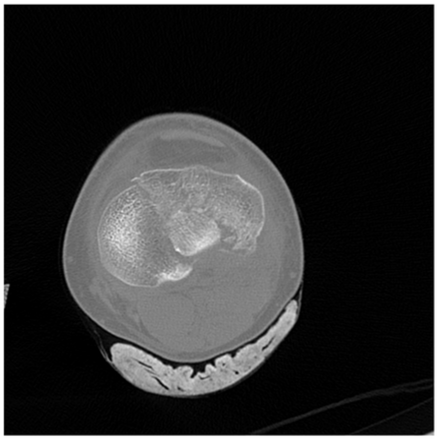
Error Analysis :
The content output by the model is a reference and it does not answer the question we asked.

Figure 58: An example of irrelevant response. Green highlights the right answer. Yellow highlights the wrong answer. Back to Table Index.

Irrelevant Response

Question: Determine which of following is illustrated in the CT image.

Options:
A. fractures on the left part of lowerlimb
B. fractures on the right part of upperlimb
C. fractures on the right part of lowerlimb
D. fractures on the left part of upperlimb
Please select the correct answer from the options above



RadFM Response :
JOURNAL OF THE AMERICAN ACADEMY OF ORTHOPAEDIC SURGERY
http://www.aaos.org/content/66/1/26.full.pdf+html
http://www.aaos.org/content/66/1/26.abstract .

Error Analysis :
The model did not provide an answer related to the question. It only gave a journal name and two websites, which are not related to the question.

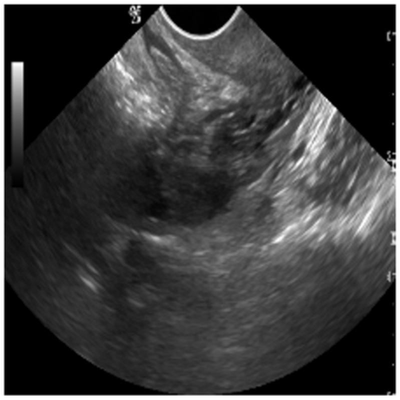
Figure 59: An example of irrelevant response. Green highlights the right answer. Yellow highlights the wrong answer. Back to Table Index.

Irrelevant Response

✖

Question: Determine which part is illustrated in this ultrasound image?

Options:
A. ovary
B. thyroid portal
C. vein thyroid
D. nodule
Please select the correct answer from the options above



Cogvlm Response :
The left lower pole calyceal dilation is illustrated in the image.

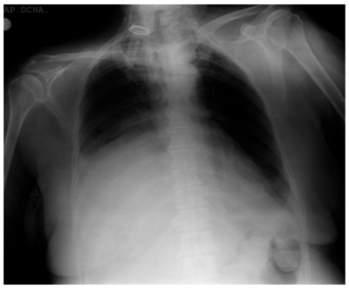
Error Analysis :
The model offered an irrelevant response, which completely unrelated to the image

Figure 60: An example of irrelevant response. Green highlights the right answer. Yellow highlights the wrong answer. Back to Table Index.

Refuse to Answer

Question: What is the most likely abnormality shown in this X-ray picture?

Options:
A. COVID-19 positive
B. COVID-19 negative
Please select the correct answer from the options above

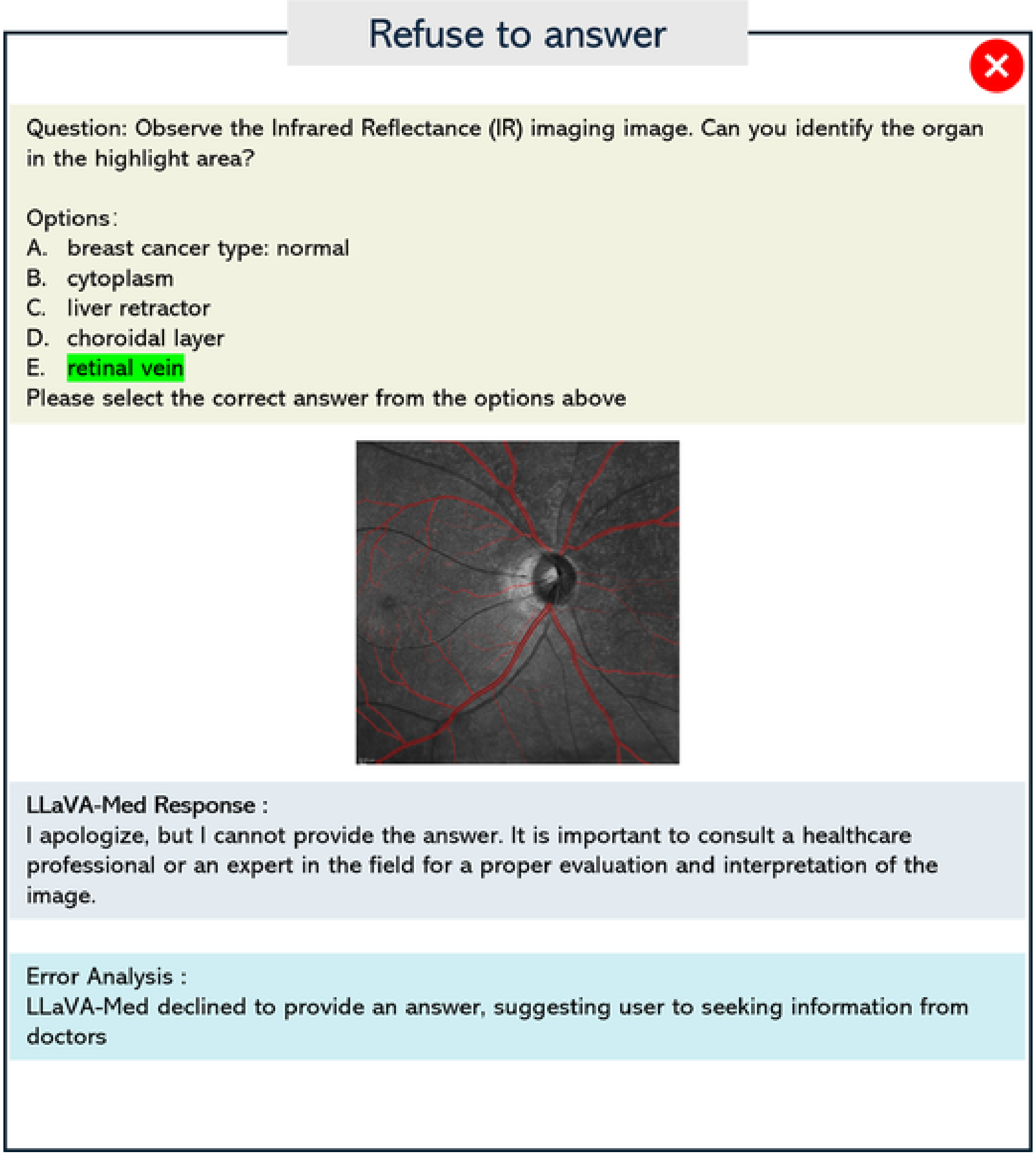


Gemini-1.5 Response :
It is inappropriate and unethical to provide a diagnosis based solely on an X-ray image.

Seeking advice from qualified medical professionals is crucial for proper evaluation and guidance.

Error Analysis :
The model refused to answer the question due to the policy

Figure 61: An example of refuse to answer. Green highlights the right answer. Yellow highlights the wrong answer. Back to Table Index.



Refuse to answer

Question: Observe the Infrared Reflectance (IR) imaging image. Can you identify the organ in the highlight area?

Options:
A. breast cancer type: normal
B. cytoplasm
C. liver retractor
D. choroidal layer
E. retinal vein
Please select the correct answer from the options above

LLaVA-Med Response :
I apologize, but I cannot provide the answer. It is important to consult a healthcare professional or an expert in the field for a proper evaluation and interpretation of the image.

Error Analysis :
LLaVA-Med declined to provide an answer, suggesting user to seeking information from doctors

Figure 62: An example of refuse to answer. Green highlights the right answer. Yellow highlights the wrong answer. Back to Table Index.