MC-CoT: A Modular Collaborative CoT Framework for Zero-shot Medical-VQA with LLM and MLLM Integration

Lai Wei¹, Wenkai Wang¹, Xiaoyu Shen², Yu Xie³, Zhihao Fan⁴, Xiaojin Zhang¹, Zhongyu Wei⁵ and Wei Chen^{1*}

¹Huazhong University of Science and Technology, ²Eastern Institute of Technology, ³Purple Mountain Laboratories, ⁴Alibaba Inc., ⁵Fudan University

Abstract

In recent advancements, multimodal large language models (MLLMs) have been fine-tuned on specific medical image datasets to address medical visual question answering (Med-VQA) tasks. However, this common approach of task-specific fine-tuning is costly and necessitates separate models for each downstream task, limiting the exploration of zero-shot capabilities. In this paper, we introduce MC-CoT, a modular cross-modal collaboration Chainof-Thought (CoT) framework designed to enhance the zero-shot performance of MLLMs in Med-VQA by leveraging large language models (LLMs). MC-CoT improves reasoning and information extraction by integrating medical knowledge and task-specific guidance, where LLM provides various complex medical reasoning chains and MLLM provides various observations of medical images based on instructions of the LLM. Our experiments on datasets such as SLAKE, VQA-RAD, and PATH-VQA show that MC-CoT surpasses standalone MLLMs and various multimodality CoT frameworks in recall rate and accuracy. These findings highlight the importance of incorporating background information and detailed guidance in addressing complex zero-shot Med-VQA tasks. Our code is available at https: //github.com/thomaswei-cn/MC-CoT.

1 Introduction

The recent development of large language models (LLMs) (Achiam et al., 2023; Reid et al., 2024; Touvron et al., 2023), especially multimodal large language models (MLLMs) (Zhu et al., 2023; Liu et al., 2024b), has garnered significant attention in the medical visual question answering (Med-VQA) task (He et al., 2020; Liu et al., 2021; Zhang et al., 2023b). By pre-training on extensive pairs of medical images and text and then fine-tuning on specific Med-VQA datasets, these models (Moor et al.,

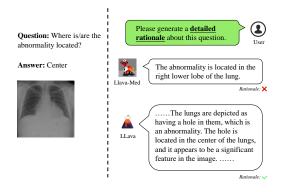


Figure 1: The ability of instruction-following for open source multimodal large language models in the medical field is severely degraded.

2023; Li et al., 2024) have achieved promising results. However, this approach adheres to the conventional *pre-training and fine-tuning* paradigm, requiring dedicated models for different task or dataset, thereby consuming substantial resources and limiting scalability, as shown in Figure 1.

Med-VQA is a complex and challenging multimodal task (Lin et al., 2023) that necessitates extensive medical knowledge in areas such as anatomy, pathology, and clinical medicine to accurately interpret the rich and specialized content of medical images, including X-rays, CT scans, and MRI scans. Additionally, this task requires sophisticated multimodal reasoning abilities (Zhang et al., 2023c) to integrate and analyze data spanning visual, textual, and other formats. These abilities encompass advanced modality fusion, contextual understanding, and language processing, all crucial for delivering precise and clinically relevant answers. However, the capability of LLMs or MLLMS to perform Med-VQA tasks without task-specific fine-tuning or zero-shot capabilities, along with their proficiency in multimodal reasoning on medical images, remains largely unexplored.

Inspired by recent research on intelligent sys-

^{*}Corresponding author. Email:lemuria_chen@hust.edu.cn

tems in the medical field driven by LLMs in purely textual modalities (Bao et al., 2023; Tang et al., 2023; Fan et al., 2024), this paper presents an extensive study on a multi-modality reasoning framework tailored for medical imaging question answering. We introduce MC-CoT, a Modular Collaborative Chain-of-Thought framework designed to enhance the zero-shot performance of MLLMs on Med-VQA tasks. MC-CoT integrates LLMs into the problem-solving process, utilizing their extensive knowledge and robust chainof-thought (CoT) reasoning capabilities to guide the analysis and response generation. Specifically, MC-CoT comprises three pre-designed image feature extraction modules—Pathology, Radiology, and Anatomy. Each module targets specific aspects of the images, designed to process particular tasks related to its focus area and generate informed responses based on the image data. Within these modules, the LLM first evaluates the input task, supplying essential background knowledge and strategic guidance to the MLLM, which then produces the final output. When faced with a new problem, MC-CoT leverages the LLM to dissect the issue, activating one or more of its specialized modules based on the problem's requirements. Each module is assigned specific tasks, after which the LLM synthesizes the outputs from the engaged modules to formulate a cohesive and comprehensive final answer.

We evaluate MC-CoT's performance on three diverse Med-VQA datasets: PATH-VQA, VQA-RAD, and SLAKE, comparing it against baseline visual CoT methods and other collaborative frameworks. Our experiments demonstrate that MC-CoT consistently outperforms existing approaches in terms of answer accuracy and recall of key information. The framework's effectiveness is verified across different MLLM and LLM combinations, highlighting its broad applicability. Further analysis reveals the significant impact of key processes within MC-CoT, such as image captioning, LLM-guided reasoning, and answer summarization. These findings suggest that MC-CoT offers a promising approach for enhancing the zero-shot capabilities of MLLMs in Med-VQA tasks by effectively integrating domain-specific knowledge and guided reasoning.

In summary, our paper makes the following two key contributions:

• We propose MC-CoT, a novel framework that

- enhances the zero-shot performance of Multimodal Large Language Models (MLLMs) on Med-VQA tasks.
- We conduct comprehensive experiments on diverse Med-VQA datasets, our extensive analysis demonstrates MC-CoT's broad applicability and provides insights into the impact of key processes and specialized modules, offering directions for future optimization in Med-VQA systems.

2 Related Works

2.1 Medical Visual Question Answering

Prior to the development of Med-VQA, research in medical question answering focused on text-based datasets (Jin et al., 2019; Pal et al., 2022; Chen et al., 2023a,d,c) which facilitated advancements in medical natural language processing. The Med-VQA task involves answering questions about medical images, which can provide clinicians with more fine-grained references. Early work primarily viewed Med-VQA as a classification problem (Eslami et al., 2021; Li et al., 2023; Gong et al., 2022; Do et al., 2021; Zhang et al., 2023a), achieving high accuracy on small datasets, but struggled with the diverse expressions of real-world questions.

Recently, training MLLMs with image-text pairs for downstream tasks has become the preferred approach, leading researchers to adopt generative methods for Med-VQA (Chen et al., 2024; Van Sonsbeek et al., 2023).

2.2 Multimodal Prompting Methods

As LLMs and MLLMs gain popularity, effective prompting techniques have become essential to fully leverage their capabilities. These approaches generally fall into three categories: zeroshot prompting (Kojima et al., 2022; Wan et al., 2023), few-shot prompting (Brown et al., 2020; Dong et al., 2022; Min et al., 2022), and other methods like ToT (Yao et al., 2024) and GoT (Besta et al., 2024; Zheng et al., 2024).

In multimodal domains, various prompting techniques have emerged. MM-CoT (Zhang et al., 2023c), CCoT (Mitra et al., 2024), and the Cantor framework (Gao et al., 2024) rely exclusively on MLLMs. MM-CoT uses a two-stage approach: generating rationales based on ground truth before producing the final answer. Similarly, CCoT generates a scene graph to aid reasoning. Cantor con-

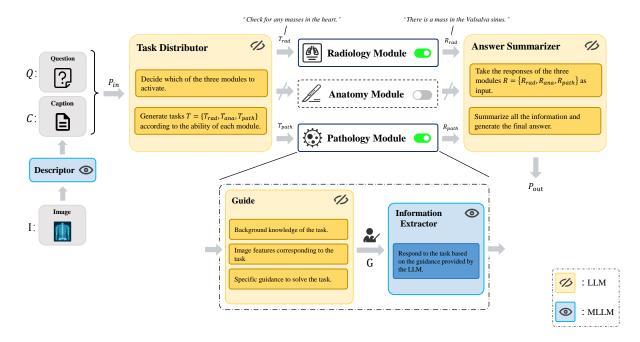


Figure 2: The schematic diagram of the MC-CoT framework.

structs modular structures for problem decomposition.

DDCoT (Zheng et al., 2023), on the other hand, uses LLM to assist MLLM by breaking the original question into sub-questions to form a reasoning process.

2.3 Multi-modal Large Language Models

Multimodal Large Language Models (Chowdhery et al., 2023; Li et al., 2022; Radford et al., 2021) capitalize on the cognitive abilities of LLMs to enhance reasoning in tasks that require both visual and textual understanding, such as Visual Question Answering (VQA) (Antol et al., 2015; Hudson and Manning, 2019; Marino et al., 2019). These models typically bridge pre-trained visual representations with pre-trained LLMs through additional layers, enabling them to exhibit visual perception abilities comparable to those of humans, along with some degree of logical reasoning.

Despite their potential, the number of MLLMs specifically tailored for the medical domain remains limited. Among the available open-source models, LLaVA-Med and Med-Flamingo (Moor et al., 2023) stand out, but they are constrained by their relatively small parameter sizes. This limitation results in significant shortcomings in their logical reasoning and instruction-following capabilities, especially when compared to other open-source MLLMs.

Nevertheless, while recent open-source MLLMs such as LLaVA-1.5 (Liu et al., 2024a) and DeepSeek-VL (Lu et al., 2024) have made substantial strides in improving instruction execution and image perception, they still face considerable challenges in the medical domain due to the lack of domain-specific knowledge.

3 Method

There are various ways to cooperate MLLM with LLM. Studies like DDCoT and IdealGPT(You et al., 2023) have shown that leveraging LLM to decompose tasks effectively enhances reasoning in general domain VQA. Based on this idea, we equipped the MC-CoT framework with three specialized modules, each with clearly defined functions, to guide the LLM in decomposing problems along the aspects that each module focuses on.

Additionally, although general-domain MLLMs have demonstrated impressive reasoning abilities on tasks such as ScienceQA (Saikh et al., 2022; Schwenk et al., 2022), they struggle to interpret medical images like doctors due to their limited medical knowledge and weak medical reasoning abilities. Therefore, we consider leveraging LLMs to provide guidance, compensating for the deficiencies of MLLMs in reasoning abilities.

In general, as shown in Figure 2, our MC-CoT framework is divided into three stages: *Module*

Symbol	Meaning
\overline{Q}	Question
C	Caption of the image
I	Image
G	Guide generated by LLM
P_{in}, P_{out}	Input and output of the whole framework
$T_{rad}, T_{ana}, T_{path}$	Tasks assigned to the radiology, anatomy and pathology module
$R_{rad}, R_{ana}, R_{path}$	Responses to the task from the radiology, anatomy and pathology module

Table 1: Explanation of the meanings behind the symbols used.

Activation and Task Assignment, Modular Medical Image Feature Extraction, and Answer Generation. The symbols and their meanings used in this paper to illustrate the frameworks are shown in the table 1. The specific prompts are illustrated in Appendix C.

3.1 Module Activation and Task Assignment

Inspired by (Chen et al., 2023b), the goal of this stage is to determine the problem-solving approach based on the problem scenario and assign specific tasks to each module. Given the LLM's strong reasoning abilities and extensive background knowledge, we chose to use the LLM to complete the aforementioned process. However, since the LLM cannot directly interpret images, providing only the question (Q) might lead the LLM to make random guesses about the image content based on the question's context, which could negatively impact the subsequent reasoning process. Therefore, we also include an image caption (C) as input to further narrow down the scope of the question.

Specifically, we use the prompt Please provide a detailed description of the features you believe are relevant to the question to instruct the MLLM to generate a simple and objective description of the image, referred to as C. The MC-CoT then combines C with the original question Q to form $P_{in} = \{Q, C\}$, which is then input into the LLM. In the LLM, we applied the CoT method to improve the quality of its output. It first generates a rationale, then selects and activates the appropriate modules, and finally generates tasks $T = \{T_{rad}, T_{ana}, T_{path}\}$ for each activated module.

3.2 Modular Medical Image Feature Extraction

This stage is equipped with three modules, each with distinct capabilities and responsibilities:

Radiology Module: Determine the appropri-

ate imaging modality, identify the imaging plane, locate the lesion, and analyze the color/contrast characteristics to differentiate tissue types and abnormalities.

Anatomy Module: Identify the organ or anatomical structure involved and provide detailed information on the anatomical position and relations of the lesion within the body.

Pathology Module: Consider the number of lesions and their clinical significance, and provide a reasonable explanation for the phenomenon using pathology knowledge.

Based on the tasks $T = \{T_{rad}, T_{ana}, T_{path}\}$ provided by the Module Activation and Task Assignment module, MC-CoT utilizes these three specialized modules to extract and analyze information from the image. Since we are discussing the zero-shot capabilities of MLLM, we use a general-domain MLLM to extract additional information from the image.

To tackle the lack of medical background in general-domain MLLM, each module incorporates an LLM-based process. Using the task from the preceding module, we input the following instructions into the LLM:

- Please use your medical knowledge to provide a guide on how to solve the task.
- You need to explain the features that the image may contain based on the task, and how to give the right answer from the perspective of the picture.

These instructions prompt the LLM to analyze the task and provide a detailed guide G. Additionally, we remind the LLM:

 Remember you are teaching a rookie to read a medical image. So make sure you break down medical or biological terms into intuitive descriptions, especially terms related to image features.

This reminder ensures that the LLM's response minimizes the use of complex medical terminology and makes the explanation more accessible.

 You cannot give your speculation on the final answer.

This reminder instructs the LLM to remain neutral and avoid making assumptions about the final answer.

This process above provides guidance and relevant background information to the MLLM, enabling it to focus on specific features of the image to better complete the task. Subsequently, the MLLM takes $\{I, T_x, G\}$ as input, extracts information from the image based on the guidance, and outputs the final answer.

3.3 Answer Generation:

The last module is responsible for logical reasoning based on the question and synthesizing all supplementary information extracted from the image $R = \{R_{path}, R_{ana}, R_{rad}\}$ by three specialized modules , along with the image's caption C, to ultimately provide an answer.

MC-CoT uses an LLM to complete this process. To further enhance the logical reasoning ability of LLM, we require LLM to generate a reasoning process before outputting the final answer.

4 Experiment Setup

4.1 Datasets

We evaluated MC-CoT's performance on three Med-VQA datasets. All three datasets include open-ended questions (e.g., why, what, how, where) and closed-ended questions (mostly yes/no). The ground truth for open-ended questions primarily consists of single nouns or phrases, such as "Chest" or "Lung Cancer."

Basic information about the datasets is summarized in Table 2.

• PATH-VQA This is a pathology image dataset. It includes 4,998 images paired with 32,799 QA pairs. Each image is linked to questions about location, shape, color, and appearance. Answers require not just image analysis but also integration with pathological knowledge to derive conclusions.

- VQA-RAD It features 3,515 cliniciancreated QA pairs and 315 radiology images, evenly distributed among the head, chest, and abdomen. The questions cover 11 categories: abnormalities, modalities, organ systems, color, count, object/condition presence, size, plane location reasoning, and others.
- SLAKE It contains 642 radiology images and over 7,000 QA pairs, featuring diverse modalities across body parts like the brain, neck, chest, abdomen, and pelvis. Additionally, SLAKE is bilingual with English and Chinese, but our experiments used only the English data.

The ultimate goal of developing a Med-VQA system is to answer user questions about a medical image in natural language. To align with this goal, we conducted experiments using only openended questions from the test sets of the datasets mentioned.

Dataset	Images	QA pairs	#
VQA-RAD	0.3k	3.5k	949
PATH-VQA	5k	32.8k	625
SLAKE	0.7k	14k	645

Table 2: Basic information about the dataset used for evaluation. # represents the number of open-ended QA pairs in the test sets used in our experiments.

4.2 MC-COT Settings

For MLLM selection, LLaVA-1.5-7B was used in the primary experiments and analysis, with its precision set to fp16. To verify the broad applicability of our MC-CoT framework, we also conducted supplementary experiments using DeepSeek-VL-7B-chat(Lu et al., 2024), Qwen-VL-Chat(Bai et al., 2023), and Qwen-VL-Max.

For LLM selection, GPT-3.5 was used in the main experiments within the MC-CoT framework. In supplementary experiments, we tested GLM-4-9B-Chat(GLM et al., 2024), Qwen2-72B-Instruct(Yang et al., 2024), and Deepseek-V2(DeepSeek-AI et al., 2024), respectively.

4.3 Model Comparison

To further explore the capabilities of the MC-CoT framework, we compared it with other frameworks, including two simple and intuitive MLLM-LLM

	PATH-VQA		VQA-RAD		SLAKE		Avg.			
	Recall	Acc.	Recall	Acc.	Recall	Acc.	Recall	Acc.		
MLLM alone										
Only*	44.89	26.19	51.31	32.53	69.96	52.09	55.39	36.94		
PS-Prompting(2023)	42.86	10.35	48.19	12.82	60.19	23.62	50.41	15.60		
Cantor-med**	43.41	26.83	49.96	25.29	61.74	26.20	51.70	26.11		
CCoT(2024)	47.76	26.93	53.41	32.35	67.35	47.96	56.17	35.75		
Visual CoT(2024)	44.92	27.20	51.13	31.05	66.05	47.08	54.03	35.11		
MMCoT(2023c)	47.64	27.89	52.93	31.51	68.30	51.73	56.29	37.04		
	LLM & MLLM									
DDCoT(2023)	38.96	37.17	47.95	35.09	66.07	47.55	50.99	39.94		
QD Cap.(2024)	37.45	21.39	45.40	25.78	62.55	45.37	48.47	30.85		
IdealGPT(2023)	42.19	19.04	50.48	27.50	66.06	44.75	52.91	30.43		
QVix(2023)	49.59	34.88	53.31	32.56	68.05	48.11	56.98	38.52		
FCCoT	46.07	26.83	51.91	27.08	65.04	38.76	54.34	30.89		
IICoT	48.92	36.43	54.02	35.65	67.68	46.15	56.87	39.41		
MC-CoT (Ours)	49.90	45.07	57.06	38.25	69.82	54.88	58.93	46.07		

Table 3: Using LLaVA-1.5-7B as the MLLM and GPT-3.5 as the LLM, we compared the performance of multiple frameworks across 3 datasets. In this table, Only* means using LLaVA-1.5-7B only. Cantor-med** is a framework obtained by replacing the four original modules in Cantor with three modules from MC-CoT.

collaborative CoT frameworks we designed: IICoT and FCCoT.

IICoT The name IICoT stands for Information-Instruction Chain-of-Thought, which refers to using an LLM to supplement the current problem context with background information and provide guidance for solving the problem. The MLLM then follows this guidance to answer the question.

FCCOT The name FCCoT stands for Flaw-Check Chain-of-Thought, which refers to first using an MLLM to generate an analysis of the problem, then using both the LLM and MLLM to check for flaws in the reasoning, factual information, and other aspects of the analysis. Finally, the MLLM revises its analysis and re-generates the answer.

Details about these two frameworks can be found in the appendix B.

For the *Question-Driven Image Captions as Prompts* (Özdemir and Akagündüz, 2024) method, which we refer to as QD Cap., we use the MLLM to generate image captions and the LLM as the QA model to provide answers.

Furthermore, for a fairer comparison, we replaced the four general-purpose expert modules in Cantor with the three medical expert modules from the MC-CoT.

4.4 Evaluation Metrics

We proposed two evaluation methods: one is an automated evaluation metric, and the other is a model-based metric.

Automated Evaluation Since the ground truth answers in our dataset are single nouns or phrases, we believe that the presence of key words from the correct answers in model-generated responses indicates that the model has focused on essential information.

Thus, we calculate the *recall* rate of correct answers within the generated responses to assess the model's ability to concentrate on key information in the question context.

Model-based Evaluation Considering that the same medical concept can be expressed in different ways, a simple string comparison is insufficient. Instead, we use an LLM to assess the conceptual overlap between the generated answers and the ground truth to evaluate the *accuracy*.

We utilize Deepseek-V2 to rate the model's responses on a scale of 1 to 4, with 1 being the worst and 4 the best, and the final scores are scaled to a maximum of 100 points.

The implementation details of the evaluation and the prompts we used can be found in Appendix D.

	PATH-VQA Recall Acc.		VQA-	RAD	SLA	KE	Avg.	
			Recall	Acc.	Recall	Acc.	Recall	Acc.
MC-CoT(w/o caption)	48.71	39.95	56.02	33.02	68.23	48.84	57.65	40.60
MC-CoT(w/o guide)	49.11	32.64	55.65	31.30	69.93	52.61	58.23	38.85
MC-CoT(MLLM summarize)	49.82	28.21	56.37	29.40	69.99	49.46	58.73	35.69
MC-CoT	49.90	45.07	57.06	38.25	69.82	54.88	58.93	46.07

Table 4: The impact of key processes on the effectiveness of the MC-CoT framework.

5 Experiment Results

5.1 Comparison with other CoT frameworks

Improvements in Correctness The experimental results in Table 3 demonstrate that the MC-CoT framework surpasses most baseline methods in terms of the *recall* rate of correct answers. This indicates that the MC-CoT framework is more effective in capturing the key information present in the question's context, allowing the model to provide more accurate responses.

In terms of *accuracy*, the MC-CoT framework consistently outperforms LLaVA-1.5-7B and all other CoT frameworks evaluated in this study. The results indicate that MC-CoT has enhanced the model's zero-shot capability on the Med-VQA task. It also demonstrates that providing necessary background knowledge and guidance to MLLMs can improve their performance to a certain extent, which offers a direction for future research.

Effectiveness Across Different LLM and MLLM Combinations We experimented with different LLM and MLLM pairings to explore the broad applicability of MC-CoT. Table 5 shows the results of supplementary experiments conducted using various MLLMs paired with GPT-3.5. The results demonstrate that regardless of the underlying architecture or parameter size of the MLLM, the MC-CoT framework consistently improves the correctness of generated answers.

Table 6 presents the results of pairing different LLMs with LLaVA-1.5-7B. Similarly, whether compared to directly using LLaVA from Table 3 or other LLM-MLLM collaborative frameworks in the experiments, MC-CoT consistently achieved the highest average accuracy.

This consistency across different models indicates that M3 is highly adaptable and capable of enhancing performance across various model combinations.

Importantly, the generalizability of the MC-CoT framework shows that its design principles can be

effectively applied to models of different sizes and architectures. This means that MC-CoT does not overly depend on specific model configurations, making it versatile and scalable for Med-VQA.

5.2 Impact of Key Processes

Table 4 clearly demonstrates the impact of key steps at each stage of the MC-CoT framework.

Captions Help the LLM to Grasp the Context The comparison results show that using the image caption along with the question as input achieved higher accuracy than using the question alone. This indicates that effectively conveying visual information can enhance the LLM's understanding and reasoning abilities.

LLM-Guided Approach Enhances Accuracy, Especially on Challenging Datasets Compared to directly using the MLLM to complete the assigned task, the LLM-guided approach improved the overall accuracy.

Additionally, by observing the degree of accuracy decline, we found that providing guidance has a more significant impact on more challenging datasets such as PATH-VQA and VQA-RAD.

LLM Summarization Boosts Performance Due to limitations in input length and model capability, the LLM was better able to summarize the collected information and provide answers through reasoning. In our experimental results, using the LLM to summarize answers indeed improved the overall efficiency of the MC-CoT framework.

This division of roles between LLM and MLLM optimized their respective strengths, resulting in a better solution for handling complex open-ended Med-VQA problems.

5.3 Impact of Modules

As shown in Figure 3, the complete MC-CoT framework achieves the highest average *accuracy* and average *recall* across the three datasets.

The extent of accuracy decline suggests that the radiology module within the MC-CoT framework

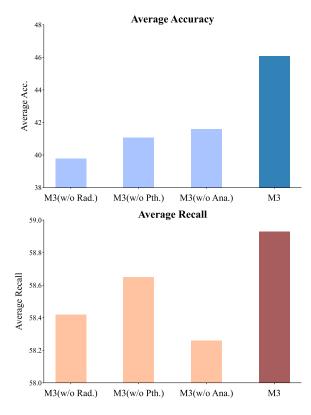


Figure 3: The impact of the 3 modules on the effectiveness of the MC-CoT framework.

contributes the most to the *accuracy* of the answers. This implies that determining the imaging modality in advance is crucial when analyzing medical images, as different imaging modalities may highlight different features of the target.

In terms of average *recall*, the anatomy module is the most important. This indicates that identifying which body part or organ system is relevant to the question is critical for capturing key information.

5.4 Case study

The detailed visual comparison of the output obtained using the MC-CoT framework, the output from other CoT frameworks, and the output from using MLLM alone can be found in Appendix E.

Figure 12 presents a case from the PATH-VQA dataset. Due to the unique nature of the PATH-VQA dataset, where the answers cannot be directly derived from the images but require reasoning based on pathological knowledge, models without access to background knowledge can only provide a vague answer, such as *positively charged protein* (highlighted in yellow). In contrast, with DDCoT and MC-CoT, the LLM considered the underlying process behind the question and either proposed

guiding questions or directly provided guidance, allowing the answer to be refined to *histone proteins* (highlighted in blue).

Figure 13 highlights the importance of captions. While the LLM Guide approach offers instructions for distinguishing different MRI image weights, it lacks targeted guidance due to the LLM's lack of prior knowledge of the image. In contrast, the MC-CoT framework generates a caption for the image initially, which narrows the problem scope and enhances guidance relevance.

In this case, LLaVA-1.5-7B initially lacked knowledge about MRI weights but successfully identified the liver in the image, allowing GPT-3.5 to generate more specific guidance. Eventually, LLaVA-1.5-7B learned from the instructions and provided the correct answer.

Finally, in the example shown in Figure 14, most CoT frameworks fail to comprehend the question (highlighted in yellow). The DDCoT framework, however, assumes that sub-question 1 does not require any reliance on visual information and directly provides an answer based on commonsense reasoning from the LLM. However, for serious medical issues, we do not want the model to draw conclusions based on common sense and experience.

Among these methods, only the MC-CoT framework points out the characteristics of the hemidiaphragm as well as the liver and guides the MLLM to search for the corresponding structures in the image for verification (highlighted in blue). Clearly, the reasoning process of the MC-CoT framework is more rigorous.

6 Conclusion

The paper explores Med-VQA tasks with openended questions by experimenting with various CoT frameworks, investigating the feasibility of enhancing MLLM's zero-shot capabilities without the need for pretraining or fine-tuning. We introduce MC-CoT, a modular approach that examines problems from multiple angles and uses LLM to supply the necessary background knowledge and solutions for MLLM to address the tasks effectively. MC-CoT outperforms both directly use MLLM and several popular CoT frameworks, including MMCoT and DDCoT, in terms of recall rate and accuracy. Furthermore, MC-CoT exhibits strong generalizability, maintaining its effectiveness across various LLM and MLLM combinations.

Limitation

While the MC-CoT framework demonstrates significant improvements in enhancing MLLM's zero-shot performance on Med-VQA tasks, it is not without limitations.

Firstly, the three modules we designed—anatomy, pathology, and radiology—have only been validated on open-ended questions in the PATH-VQA, VQA-RAD, and SLAKE datasets. When encountering new problems, a substantial redesign of the modules and their associated prompts may be required.

Moreover, the effectiveness of the MC-CoT framework heavily relies on the quality of the prompts provided by the LLM to guide the MLLM. Crafting prompts that effectively guide the model without overly restricting its reasoning can be challenging and may require significant domain expertise. Additionally, the LLM itself must possess sufficient medical knowledge.

Currently, the framework only considers imagebased information, without incorporating other clinical symptoms such as patient history, which is crucial for real-world applications. Integrating more comprehensive patient data could enhance the framework's performance but would also introduce additional complexity.

Lastly, our evaluation metrics are tailored to Med-VQA and may not fully capture the nuances of real-world medical diagnostic reasoning. As application scenarios change, further research will be necessary to develop evaluation methods that better reflect clinical utility.

References

- Josh Achiam, Steven Adler, Sandhini Agarwal, Lama Ahmad, Ilge Akkaya, Florencia Leoni Aleman, Diogo Almeida, Janko Altenschmidt, Sam Altman, Shyamal Anadkat, et al. 2023. Gpt-4 technical report. arXiv preprint arXiv:2303.08774.
- Stanislaw Antol, Aishwarya Agrawal, Jiasen Lu, Margaret Mitchell, Dhruv Batra, C Lawrence Zitnick, and Devi Parikh. 2015. Vqa: Visual question answering. In *Proceedings of the IEEE international conference on computer vision*, pages 2425–2433.
- Jinze Bai, Shuai Bai, Shusheng Yang, Shijie Wang, Sinan Tan, Peng Wang, Junyang Lin, Chang Zhou, and Jingren Zhou. 2023. Qwen-vl: A frontier large vision-language model with versatile abilities. *arXiv* preprint arXiv:2308.12966.
- Zhijie Bao, Wei Chen, Shengze Xiao, Kuang Ren, Jiaao Wu, Cheng Zhong, Jiajie Peng, Xuanjing Huang, and

- Zhongyu Wei. 2023. Disc-medllm: Bridging general large language models and real-world medical consultation. *arXiv preprint arXiv:2308.14346*.
- Maciej Besta, Nils Blach, Ales Kubicek, Robert Gerstenberger, Michal Podstawski, Lukas Gianinazzi, Joanna Gajda, Tomasz Lehmann, Hubert Niewiadomski, Piotr Nyczyk, et al. 2024. Graph of thoughts: Solving elaborate problems with large language models. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 38, pages 17682–17690.
- Tom Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared D Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, et al. 2020. Language models are few-shot learners. *Advances in neural information processing systems*, 33:1877–1901.
- Jiawei Chen, Dingkang Yang, Yue Jiang, Yuxuan Lei, and Lihua Zhang. 2024. Miss: A generative pretraining and finetuning approach for med-vqa. *arXiv* preprint arXiv:2401.05163.
- Wei Chen, Zhiwei Li, Hongyi Fang, Qianyuan Yao, Cheng Zhong, Jianye Hao, Qi Zhang, Xuanjing Huang, Jiajie Peng, and Zhongyu Wei. 2023a. A benchmark for automatic medical consultation system: frameworks, tasks and datasets. *Bioinformatics*, 39(1):btac817.
- Wei Chen, Qiushi Wang, Zefei Long, Xianyin Zhang, Zhongtian Lu, Bingxuan Li, Siyuan Wang, Jiarong Xu, Xiang Bai, Xuanjing Huang, et al. 2023b. Disc-finllm: A chinese financial large language model based on multiple experts fine-tuning. *arXiv* preprint *arXiv*:2310.15205.
- Wei Chen, Shiqi Wei, Zhongyu Wei, and Xuan-Jing Huang. 2023c. Knse: A knowledge-aware natural language inference framework for dialogue symptom status recognition. In *Findings of the Association for Computational Linguistics: ACL 2023*, pages 10278–10286.
- Wei Chen, Cheng Zhong, Jiajie Peng, and Zhongyu Wei. 2023d. Dxformer: a decoupled automatic diagnostic system based on decoder—encoder transformer with dense symptom representations. *Bioinformatics*, 39(1):btac744.
- Aakanksha Chowdhery, Sharan Narang, Jacob Devlin, Maarten Bosma, Gaurav Mishra, Adam Roberts, Paul Barham, Hyung Won Chung, Charles Sutton, Sebastian Gehrmann, et al. 2023. Palm: Scaling language modeling with pathways. *Journal of Machine Learning Research*, 24(240):1–113.
- DeepSeek-AI, Aixin Liu, Bei Feng, Bin Wang, Bingxuan Wang, Bo Liu, Chenggang Zhao, Chengqi Dengr, Chong Ruan, Damai Dai, Daya Guo, Dejian Yang, Deli Chen, Dongjie Ji, Erhang Li, Fangyun Lin, Fuli Luo, Guangbo Hao, Guanting Chen, Guowei Li, H. Zhang, Hanwei Xu, Hao Yang, Haowei Zhang, Honghui Ding, Huajian Xin, Huazuo Gao, Hui Li,

- Hui Qu, J. L. Cai, Jian Liang, Jianzhong Guo, Jiaqi Ni, Jiashi Li, Jin Chen, Jingyang Yuan, Junjie Qiu, Junxiao Song, Kai Dong, Kaige Gao, Kang Guan, Lean Wang, Lecong Zhang, Lei Xu, Leyi Xia, Liang Zhao, Liyue Zhang, Meng Li, Miaojun Wang, Mingchuan Zhang, Minghua Zhang, Minghui Tang, Mingming Li, Ning Tian, Panpan Huang, Peiyi Wang, Peng Zhang, Qihao Zhu, Qinyu Chen, Qiushi Du, R. J. Chen, R. L. Jin, Ruiqi Ge, Ruizhe Pan, Runxin Xu, Ruyi Chen, S. S. Li, Shanghao Lu, Shangyan Zhou, Shanhuang Chen, Shaoqing Wu, Shengfeng Ye, Shirong Ma, Shiyu Wang, Shuang Zhou, Shuiping Yu, Shunfeng Zhou, Size Zheng, T. Wang, Tian Pei, Tian Yuan, Tianyu Sun, W. L. Xiao, Wangding Zeng, Wei An, Wen Liu, Wenfeng Liang, Wenjun Gao, Wentao Zhang, X. Q. Li, Xiangyue Jin, Xianzu Wang, Xiao Bi, Xiaodong Liu, Xiaohan Wang, Xiaojin Shen, Xiaokang Chen, Xiaosha Chen, Xiaotao Nie, Xiaowen Sun, Xiaoxiang Wang, Xin Liu, Xin Xie, Xingkai Yu, Xinnan Song, Xinyi Zhou, Xinyu Yang, Xuan Lu, Xuecheng Su, Y. Wu, Y. K. Li, Y. X. Wei, Y. X. Zhu, Yanhong Xu, Yanping Huang, Yao Li, Yao Zhao, Yaofeng Sun, Yaohui Li, Yaohui Wang, Yi Zheng, Yichao Zhang, Yiliang Xiong, Yilong Zhao, Ying He, Ying Tang, Yishi Piao, Yixin Dong, Yixuan Tan, Yiyuan Liu, Yongji Wang, Yongqiang Guo, Yuchen Zhu, Yuduan Wang, Yuheng Zou, Yukun Zha, Yunxian Ma, Yuting Yan, Yuxiang You, Yuxuan Liu, Z. Z. Ren, Zehui Ren, Zhangli Sha, Zhe Fu, Zhen Huang, Zhen Zhang, Zhenda Xie, Zhewen Hao, Zhihong Shao, Zhiniu Wen, Zhipeng Xu, Zhongyu Zhang, Zhuoshu Li, Zihan Wang, Zihui Gu, Zilin Li, and Ziwei Xie. 2024. Deepseek-v2: A strong, economical, and efficient mixture-of-experts language model. *Preprint*, arXiv:2405.04434.
- Tuong Do, Binh X Nguyen, Erman Tjiputra, Minh Tran, Quang D Tran, and Anh Nguyen. 2021. Multiple meta-model quantifying for medical visual question answering. In *Medical Image Computing and Computer Assisted Intervention–MICCAI 2021: 24th International Conference, Strasbourg, France, September 27–October 1, 2021, Proceedings, Part V 24*, pages 64–74. Springer.
- Qingxiu Dong, Lei Li, Damai Dai, Ce Zheng, Zhiyong Wu, Baobao Chang, Xu Sun, Jingjing Xu, and Zhifang Sui. 2022. A survey on in-context learning. *arXiv preprint arXiv:2301.00234*.
- Sedigheh Eslami, Gerard de Melo, and Christoph Meinel. 2021. Does clip benefit visual question answering in the medical domain as much as it does in the general domain? arXiv preprint arXiv:2112.13906.
- Zhihao Fan, Jialong Tang, Wei Chen, Siyuan Wang, Zhongyu Wei, Jun Xi, Fei Huang, and Jingren Zhou. 2024. Ai hospital: Interactive evaluation and collaboration of llms as intern doctors for clinical diagnosis. *arXiv preprint arXiv:2402.09742*.
- Timin Gao, Peixian Chen, Mengdan Zhang, Chaoyou Fu, Yunhang Shen, Yan Zhang, Shengchuan Zhang, Xiawu Zheng, Xing Sun, Liujuan Cao, et al. 2024.

- Cantor: Inspiring multimodal chain-of-thought of mllm. *arXiv preprint arXiv:2404.16033*.
- Team GLM, Aohan Zeng, Bin Xu, Bowen Wang, Chenhui Zhang, Da Yin, Diego Rojas, Guanyu Feng, Hanlin Zhao, Hanyu Lai, et al. 2024. Chatglm: A family of large language models from glm-130b to glm-4 all tools. *arXiv preprint arXiv:2406.12793*.
- Haifan Gong, Guanqi Chen, Mingzhi Mao, Zhen Li, and Guanbin Li. 2022. Vqamix: Conditional triplet mixup for medical visual question answering. *IEEE Transactions on Medical Imaging*, 41(11):3332–3343.
- Xuehai He, Yichen Zhang, Luntian Mou, Eric Xing, and Pengtao Xie. 2020. Pathvqa: 30000+ questions for medical visual question answering. *arXiv* preprint *arXiv*:2003.10286.
- Drew A Hudson and Christopher D Manning. 2019. Gqa: A new dataset for real-world visual reasoning and compositional question answering. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, pages 6700–6709.
- Qiao Jin, Bhuwan Dhingra, Zhengping Liu, William W Cohen, and Xinghua Lu. 2019. Pubmedqa: A dataset for biomedical research question answering. *arXiv* preprint arXiv:1909.06146.
- Takeshi Kojima, Shixiang Shane Gu, Machel Reid, Yutaka Matsuo, and Yusuke Iwasawa. 2022. Large language models are zero-shot reasoners. *Advances in neural information processing systems*, 35:22199–22213.
- Chunyuan Li, Cliff Wong, Sheng Zhang, Naoto Usuyama, Haotian Liu, Jianwei Yang, Tristan Naumann, Hoifung Poon, and Jianfeng Gao. 2024. Llavamed: Training a large language-and-vision assistant for biomedicine in one day. *Advances in Neural Information Processing Systems*, 36.
- Junnan Li, Dongxu Li, Caiming Xiong, and Steven Hoi. 2022. Blip: Bootstrapping language-image pretraining for unified vision-language understanding and generation. In *International conference on machine learning*, pages 12888–12900. PMLR.
- Pengfei Li, Gang Liu, Lin Tan, Jinying Liao, and Shenjun Zhong. 2023. Self-supervised vision-language pretraining for medial visual question answering. In 2023 IEEE 20th International Symposium on Biomedical Imaging (ISBI), pages 1–5. IEEE.
- Zhihong Lin, Donghao Zhang, Qingyi Tao, Danli Shi, Gholamreza Haffari, Qi Wu, Mingguang He, and Zongyuan Ge. 2023. Medical visual question answering: A survey. *Artificial Intelligence in Medicine*, 143:102611.
- Bo Liu, Li-Ming Zhan, Li Xu, Lin Ma, Yan Yang, and Xiao-Ming Wu. 2021. Slake: A semantically-labeled knowledge-enhanced dataset for medical visual question answering. In 2021 IEEE 18th International

- Symposium on Biomedical Imaging (ISBI), pages 1650–1654. IEEE.
- Haotian Liu, Chunyuan Li, Yuheng Li, and Yong Jae Lee. 2024a. Improved baselines with visual instruction tuning. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 26296–26306.
- Haotian Liu, Chunyuan Li, Qingyang Wu, and Yong Jae Lee. 2024b. Visual instruction tuning. *Advances in neural information processing systems*, 36.
- Haoyu Lu, Wen Liu, Bo Zhang, Bingxuan Wang, Kai Dong, Bo Liu, Jingxiang Sun, Tongzheng Ren, Zhuoshu Li, Yaofeng Sun, et al. 2024. Deepseek-vl: towards real-world vision-language understanding. *arXiv preprint arXiv:2403.05525*.
- Kenneth Marino, Mohammad Rastegari, Ali Farhadi, and Roozbeh Mottaghi. 2019. Ok-vqa: A visual question answering benchmark requiring external knowledge. In *Proceedings of the IEEE/cvf conference* on computer vision and pattern recognition, pages 3195–3204.
- Sewon Min, Xinxi Lyu, Ari Holtzman, Mikel Artetxe, Mike Lewis, Hannaneh Hajishirzi, and Luke Zettlemoyer. 2022. Rethinking the role of demonstrations: What makes in-context learning work? *arXiv* preprint arXiv:2202.12837.
- Chancharik Mitra, Brandon Huang, Trevor Darrell, and Roei Herzig. 2024. Compositional chain-of-thought prompting for large multimodal models. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 14420–14431.
- Michael Moor, Qian Huang, Shirley Wu, Michihiro Yasunaga, Yash Dalmia, Jure Leskovec, Cyril Zakka, Eduardo Pontes Reis, and Pranav Rajpurkar. 2023. Med-flamingo: a multimodal medical few-shot learner. In *Machine Learning for Health (ML4H)*, pages 353–367. PMLR.
- Övgü Özdemir and Erdem Akagündüz. 2024. Enhancing visual question answering through question-driven image captions as prompts. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 1562–1571.
- Ankit Pal, Logesh Kumar Umapathi, and Malaikannan Sankarasubbu. 2022. Medmcqa: A large-scale multi-subject multi-choice dataset for medical domain question answering. In *Conference on health, inference, and learning*, pages 248–260. PMLR.
- Alec Radford, Jong Wook Kim, Chris Hallacy, Aditya Ramesh, Gabriel Goh, Sandhini Agarwal, Girish Sastry, Amanda Askell, Pamela Mishkin, Jack Clark, et al. 2021. Learning transferable visual models from natural language supervision. In *International conference on machine learning*, pages 8748–8763. PMLR.

- Machel Reid, Nikolay Savinov, Denis Teplyashin, Dmitry Lepikhin, Timothy Lillicrap, Jean-baptiste Alayrac, Radu Soricut, Angeliki Lazaridou, Orhan Firat, Julian Schrittwieser, et al. 2024. Gemini 1.5: Unlocking multimodal understanding across millions of tokens of context. arXiv preprint arXiv:2403.05530.
- Tanik Saikh, Tirthankar Ghosal, Amish Mittal, Asif Ekbal, and Pushpak Bhattacharyya. 2022. Scienceqa: A novel resource for question answering on scholarly articles. *International Journal on Digital Libraries*, 23(3):289–301.
- Dustin Schwenk, Apoorv Khandelwal, Christopher Clark, Kenneth Marino, and Roozbeh Mottaghi. 2022. A-okvqa: A benchmark for visual question answering using world knowledge. In *European conference on computer vision*, pages 146–162. Springer.
- Hao Shao, Shengju Qian, Han Xiao, Guanglu Song, Zhuofan Zong, Letian Wang, Yu Liu, and Hongsheng Li. 2024. Visual cot: Unleashing chain-of-thought reasoning in multi-modal language models. arXiv preprint arXiv:2403.16999.
- Xiangru Tang, Anni Zou, Zhuosheng Zhang, Yilun Zhao, Xingyao Zhang, Arman Cohan, and Mark Gerstein. 2023. Medagents: Large language models as collaborators for zero-shot medical reasoning. *arXiv* preprint arXiv:2311.10537.
- Hugo Touvron, Thibaut Lavril, Gautier Izacard, Xavier Martinet, Marie-Anne Lachaux, Timothée Lacroix, Baptiste Rozière, Naman Goyal, Eric Hambro, Faisal Azhar, et al. 2023. Llama: Open and efficient foundation language models. *arXiv preprint arXiv:2302.13971*.
- Tom Van Sonsbeek, Mohammad Mahdi Derakhshani, Ivona Najdenkoska, Cees GM Snoek, and Marcel Worring. 2023. Open-ended medical visual question answering through prefix tuning of language models. In *International Conference on Medical Image Computing and Computer-Assisted Intervention*, pages 726–736. Springer.
- Xingchen Wan, Ruoxi Sun, Hanjun Dai, Sercan O Arik, and Tomas Pfister. 2023. Better zero-shot reasoning with self-adaptive prompting. *arXiv preprint arXiv:2305.14106*.
- Lei Wang, Wanyu Xu, Yihuai Lan, Zhiqiang Hu, Yunshi Lan, Roy Ka-Wei Lee, and Ee-Peng Lim. 2023. Planand-solve prompting: Improving zero-shot chain-of-thought reasoning by large language models. *arXiv* preprint arXiv:2305.04091.
- An Yang, Baosong Yang, Binyuan Hui, Bo Zheng, Bowen Yu, Chang Zhou, Chengpeng Li, Chengyuan Li, Dayiheng Liu, Fei Huang, Guanting Dong, Haoran Wei, Huan Lin, Jialong Tang, Jialin Wang, Jian Yang, Jianhong Tu, Jianwei Zhang, Jianxin Ma, Jin Xu, Jingren Zhou, Jinze Bai, Jinzheng He, Junyang Lin, Kai Dang, Keming Lu, Keqin Chen, Kexin Yang, Mei Li, Mingfeng Xue, Na Ni, Pei Zhang, Peng Wang, Ru Peng, Rui Men, Ruize Gao, Runji Lin,

Shijie Wang, Shuai Bai, Sinan Tan, Tianhang Zhu, Tianhao Li, Tianyu Liu, Wenbin Ge, Xiaodong Deng, Xiaohuan Zhou, Xingzhang Ren, Xinyu Zhang, Xipin Wei, Xuancheng Ren, Yang Fan, Yang Yao, Yichang Zhang, Yu Wan, Yunfei Chu, Yuqiong Liu, Zeyu Cui, Zhenru Zhang, and Zhihao Fan. 2024. Qwen2 technical report. *arXiv preprint arXiv:2407.10671*.

Kaiwen Yang, Tao Shen, Xinmei Tian, Xiubo Geng, Chongyang Tao, Dacheng Tao, and Tianyi Zhou. 2023. Good questions help zero-shot image reasoning. arXiv preprint arXiv:2312.01598.

Shunyu Yao, Dian Yu, Jeffrey Zhao, Izhak Shafran, Tom Griffiths, Yuan Cao, and Karthik Narasimhan. 2024. Tree of thoughts: Deliberate problem solving with large language models. *Advances in Neural Information Processing Systems*, 36.

Haoxuan You, Rui Sun, Zhecan Wang, Long Chen, Gengyu Wang, Hammad A Ayyubi, Kai-Wei Chang, and Shih-Fu Chang. 2023. Idealgpt: Iteratively decomposing vision and language reasoning via large language models. *arXiv preprint arXiv:2305.14985*.

Sheng Zhang, Yanbo Xu, Naoto Usuyama, Hanwen Xu, Jaspreet Bagga, Robert Tinn, Sam Preston, Rajesh Rao, Mu Wei, Naveen Valluri, et al. 2023a. Biomedclip: a multimodal biomedical foundation model pretrained from fifteen million scientific image-text pairs. arXiv preprint arXiv:2303.00915.

Xiaoman Zhang, Chaoyi Wu, Ziheng Zhao, Weixiong Lin, Ya Zhang, Yanfeng Wang, and Weidi Xie. 2023b. Pmc-vqa: Visual instruction tuning for medical visual question answering. *arXiv* preprint *arXiv*:2305.10415.

Zhuosheng Zhang, Aston Zhang, Mu Li, Hai Zhao, George Karypis, and Alex Smola. 2023c. Multimodal chain-of-thought reasoning in language models. arXiv preprint arXiv:2302.00923.

Ge Zheng, Bin Yang, Jiajin Tang, Hong-Yu Zhou, and Sibei Yang. 2023. Ddcot: Duty-distinct chain-of-thought prompting for multimodal reasoning in language models. *Advances in Neural Information Processing Systems*, 36:5168–5191.

Li Zheng, Hao Fei, Fei Li, Bobo Li, Lizi Liao, Donghong Ji, and Chong Teng. 2024. Reverse multichoice dialogue commonsense inference with graph-of-thought. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 38, pages 19688–19696.

Deyao Zhu, Jun Chen, Xiaoqian Shen, Xiang Li, and Mohamed Elhoseiny. 2023. Minigpt-4: Enhancing vision-language understanding with advanced large language models. *arXiv preprint arXiv:2304.10592*.

A Supplementary Experiments

In the supplementary experiments, we used different combinations of LLMs and MLLMs.

Table 5 presents the results of experiments where we paired two 7B MLLMs (Qwen-VL-Chat and Deepseek-VL-7B) and one MLLM with a larger scale of parameter (Qwen-VL-Max) with GPT-3.5.

Table 6 shows experiment results using the GLM-4-9B-Chat, the Qwen2-72B-Instruct, and the Deepseek-V2 model, which has capabilities comparable to GPT-4, all paired with LLaVA-1.5-7B.

B Frameworks Designed for Comparison

IICoT This framework consists of one LLM process and one MLLM process, as depicted in Figure 4. In the first stage, the LLM only takes the text-based question as input. We use the same prompt as in the Modular Medical Image Feature Extraction step of the MC-CoT to have the LLM provide supplementary information and guidance to the MLLM. The MLLM then follows the LLM's instructions to complete the task. Specifically, the MLLM step here adopts the same approach as MM-CoT to generate a more accurate final answer. This involves first using the MLLM to output a rationale, and then re-inputting this rationale into a new MLLM step to generate the final answer.

FCCoT This framework employs both an LLM and an MLLM to check for flaws in the MLLM's output. The structure is illustrated in Figure 5. Initially, the MLLM provides an answer and a reasoning process based on the question. However, due to the limitations of the MLLM, this reasoning process may contain flaws. Potential flaws include factual inaccuracies, reasoning errors, and errors caused by a lack of background knowledge. We introduce an additional MLLM process to correct factual errors by verifying that the original reasoning aligns with the entities depicted in the image. The LLM is used to correct reasoning flaws and highlight any missing background knowledge. Finally, based on all the supplementary information, the MLLM regenerates the reasoning process and the answer.

C Prompts Used in MC-CoT

The effectiveness of the MC-CoT framework largely depends on carefully designed prompts that guide the model through various stages. Below are examples of the prompts used in the MC-CoT framework:

 Figure 6 shows the prompt used to guide the MLLM in generating image descriptions.

	PATH-VQA		VQA-	RAD	SLA	KE	Avg.				
	Recall	Acc.	Recall	Acc.	Recall	Acc.	Recall	Acc.			
Qwen-VL-Chat with GPT-3.5											
Only	43.92	25.87	53.60	31.65	68.91	51.47	55.48	36.33			
Visual CoT	44.90	19.95	51.88	22.48	69.56	44.34	55.45	28.92			
DDCoT	46.66	34.08	56.15	32.35	70.28	48.63	57.70	38.35			
MC-CoT (Ours)	50.02	35.52	57.72	32.17	70.19	51.73	59.31	39.81			
	Deepseek-VL-7B with GPT-3.5										
Only	42.55	25.49	51.96	29.29	68.65	54.57	54.39	36.45			
Visual CoT	47.52	31.15	55.84	33.61	72.54	51.68	58.63	38.81			
DDCoT	47.26	31.95	55.99	29.22	70.57	45.94	57.94	35.70			
MC-CoT (Ours)	49.44	35.47	58.83	31.96	72.81	52.71	60.36	40.05			
Qwen-VL-Max with GPT-3.5											
Only	46.15	30.56	58.82	38.88	73.40	59.33	59.46	42.92			
Visual CoT	43.20	21.87	52.94	30.28	67.77	52.04	54.64	34.73			
DDCoT	47.60	32.32	57.49	34.46	70.75	50.59	58.61	39.12			
MC-CoT (Ours)	51.05	38.67	60.16	38.88	71.35	54.99	60.85	44.18			

Table 5: Using different MLLMs to validate the effectiveness of the MC-CoT framework.

	PATH-VQA		VQA-	-RAD	SLA	KE	Avg.				
	Recall	Acc.	Recall	Acc.	Recall	Acc.	Recall	Acc.			
LLaVA-v1.5-7B with GLM-4-9B-Chat											
QVix	49.37	34.88	54.49	32.07	69.20	48.06	57.69	38.34			
DDCoT	49.47	22.13	54.16	24.31	67.34	36.43	56.99	27.62			
IICoT	49.51	40.00	55.64	33.83	68.62	43.26	57.92	39.03			
MC-CoT (Ours)	52.40	42.08	58.55	40.96	71.20	54.68	60.72	45.91			
LLaVA-v1.5-7B with Qwen2-72B-Instruct											
QVix	49.29	31.31	53.40	31.61	69.36	48.79	57.35	37.24			
DDCoT	44.79	29.87	50.88	28.94	65.95	44.65	53.87	34.49			
IICoT	50.04	36.91	55.42	32.81	68.38	49.10	57.95	39.61			
MC-CoT (Ours)	48.97	36.21	54.97	38.32	69.08	54.50	57.67	43.01			
	LLaVA-v1.5-7B with Deepseek-V2										
QVix	49.13	33.71	53.44	31.89	69.01	49.04	57.19	38.21			
DDCoT	39.45	30.77	45.99	28.21	60.35	37.57	48.59	32.18			
IICoT	47.91	36.91	55.40	33.09	69.37	46.51	57.56	38.84			
MC-CoT (Ours)	49.87	49.17	56.52	48.93	70.71	60.31	59.03	52.80			

Table 6: Using different LLMs to validate the effectiveness of the MC-CoT framework.

- Figure 7 shows the prompt used to guide the LLM in assigning questions to three specially designed modules.
- Figure 8 shows the prompt used to guide the LLM in providing necessary background information and problem-solving guidance.
- Figure 9 shows the prompt used to guide the MLLM in following instructions and completing tasks.
- Figure 10 shows the prompt used to guide the LLM in generating the final answer.

These prompts are designed to ensure that the model can accurately understand the problem, effectively extract information from the image, and generate precise and comprehensive answers.

D Evaluation Details

We use Deepseek-V2 to assess the *accuracy* of the model-generated answers.

Given that the same medical concept can be expressed in various ways, we have developed a scoring system based on the degree of conceptual overlap.

In this system, 1 point represents a refusal to answer or a completely incorrect answer, while 4 points indicate complete conceptual accuracy. Since we found that the model often provides multiple guesses when uncertain, which is undesirable, we assign 2 points to answers with multiple guesses and 3 points to answers with minor conceptual deviations.

We provide the correct answer along with the model-generated answer to Deepseek-V2 and use the prompt shown in Figure D to instruct it to evaluate the model-generated answers. Finally, the scores were scaled to 100 points.

On the other hand, for *recall* calculation, since both MC-CoT and DDCoT include a rationale in their final outputs, which significantly increases the length of the answers, it would be unfair to calculate *recall* based on this. Therefore, when calculating *recall*, we excluded the rationale of MC-CoT and DDCoT and used only their final answers for the calculation.

E Example Cases

Through specific case analyses, we can more intuitively understand the advantages of the MC-

CoT framework in handling open-ended Med-VQA tasks.

Figure 12 shows a case from the PATH-VQA dataset, where the MC-CoT framework successfully generated an accurate answer through the reasoning process of the LLM.

Figure 13 shows a case from the SLAKE dataset, where the MC-CoT framework helped the LLM better understand the context of the question by generating an image description and providing targeted guidance.

Figure 14 shows a case from the VQA-RAD dataset, where the MC-CoT framework, with the guidance provided by the LLM, was able to accurately identify and interpret key features in the pathological image.

These cases demonstrate the effectiveness and potential of the MC-CoT framework in handling complex and open-ended medical visual question-answering tasks.

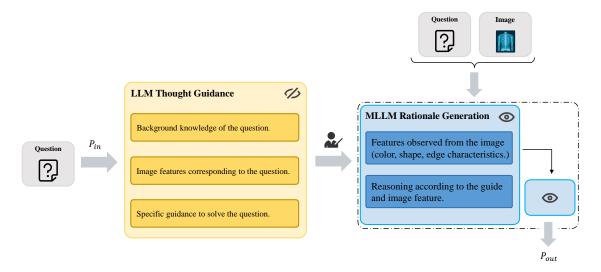


Figure 4: The schematic diagram of the IICoT framework.

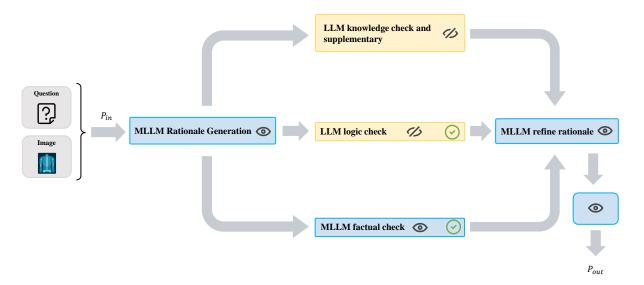


Figure 5: The schematic diagram of the FCCoT framework.

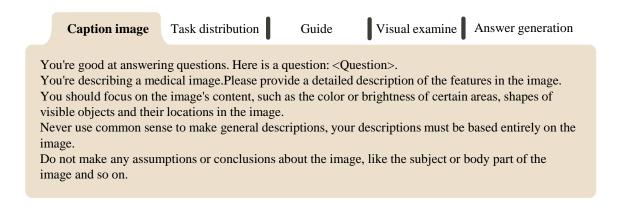


Figure 6: The prompt used to instruct MLLM generate a caption about the image.

Caption image Task distribution Guide Visual examine Answer generation

You are a advanced question-answering agent equipped with 3 specialized modules to aid in analyzing and responding to questions about medical images:

1. Radiology Module:

Abilities:

- 1) Determine the appropriate imaging modality (e.g., CT, MRI, Ultrasound).
- 2) Identify the imaging plane (e.g., axial, sagittal, coronal).
- 3) Pinpoint the position of the lesion within the image.
- 4) Analyze the color/contrast characteristics on the imaging study to differentiate tissue types and abnormalities.

When this module is required, specify your request as: 'Radiology Module: <specific task or information to extract>.'

2. Anatomy Module:

Abilities:

- 1) Identify the organ or anatomical structure involved.
- 2) Provide detailed information on the anatomical position and relations of the lesion within the body.

When you need this module, specify your request as: 'Anatomy Module: <specific task or information to extract>.'

3. Pathology Module:

hilities

- 1) Consider the number of lesions and their clinical significance.
- Provide a reasonable explanation for the phenomenon in combination with pathology knowledge.

When information from this module is needed, specify your request as: \"Pathology Module: <specific task or information to extract>.

When faced with a question about an image, which will be accompanied by a description that might not cover all its details, your task is to:

- Provide a rationale for your approach to answering the question, explaining how you will use the information from the image and the modules to form a comprehensive answer.
- Assign specific tasks to each module as needed, based on their capabilities, to gather additional
 information essential for answering the question accurately.

Your response should be structured as follows:

Answer: [Rationale: Your explanation of how you plan to approach the question, including any initial insights based on the question and image description provided. Explain how the modules' input will complement this information.]

Modules' tasks (if applicable):

- Radiology Module: [Clearly list in detail the tasks that need to be completed by the radiology module.]
- Anatomy Module: [Clearly list in detail the tasks that need to be completed by the anatomy module.]
- 3. Pathology Module: [Clearly list in detail the tasks that need to be completed by the pathology module 1

Ensure your response adheres to this format to systematically address the question using the available modules or direct analysis as appropriate.

Please refer to the prompts and examples above to help me solve the following problem:<Question> Here is a description of the related medical image: <Caption>

Figure 7: The prompt used to instruct LLM to distribute task to 3 carefully designed modules.

Visual examine Answer generation Task distribution Guide Caption image Here is a question based on a medical image: <Question>

In order to answer the question correctly, you are assigned to complete the following task: <Task> You cannot see the image, please use your medical knowledge to provide a guide on how to solve the task.

Points to note:

- 1. You need to explain the features that the image may contain based on the task, and how to give the right answer from the perspective of the picture.
- 2. Remember you are teaching a rookie to read a medical image. So make sure you break down medical or biological terms into intuitive descriptions, especially terms related to image features.
- 3. You cannot give your speculation on the final answer.

Figure 8: The prompt used to instruct LLM to give necessary background infomation as well as a guide on solving the problem.

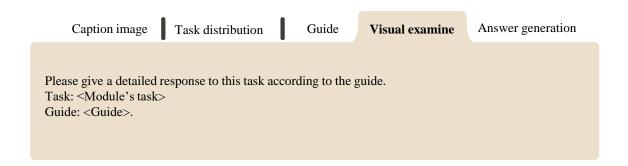


Figure 9: The prompt used to instruct MLLM to follow the guide and finish the assigned task.

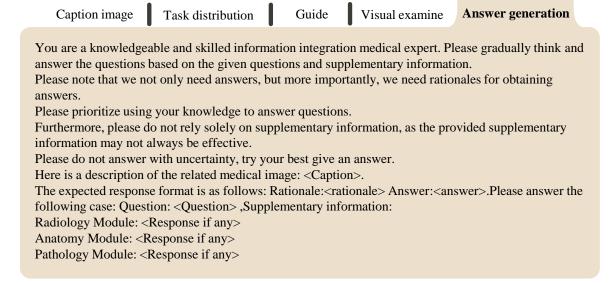


Figure 10: The prompt used to instruct LLM to generate the final answer.

Accuracy

You're an expert in evaluating <Dataset's name> dataset answers. Your task is to evaluate the predict answer generated by a Multimodal model. Every generated answer will be paired with a correct answer, consider the correct answer as a gold standard. You need to rate the generated answer from 1 to 4 according to the following criteria:

- 1: No answer is given, or the generated answer is referring totally different thing, imaging type or body part from the correct answer, or the generated answer is simply restating the information the question has given.
- 2: The generated answer includes multiple guesses, among which there is the correct answer or part of the correct answer, though wrong answers may also be mentioned.
- 3: The generated answer only contains part of the correct answer or just an aspect of the correct answer, with no wrong answers included.
- 4: The generated answer is identical to the correct answer.

Remember, the question is just for reference, when rating the answer, do not consider the relation between the generated answer and the question or the context.

And since you can not see the image, please consider that the image only show exactly what the correct answer tells you.

Now, here is a question based on some medical images: <Question>, and the correct answer is <Answer>.

Please follow the instructions above and evaluate the generated answer: <Generated Answer>
Your output should include your reason and be in the exact same format as "Result:[Your rating]"

Figure 11: The prompt used to instruct Deepseek-V2 to evaluate the answers according to the given criteria.

Examples in PATH-VQA

What are positively charged, thus allowing the compaction of the negatively charged DNA?



Only

Answer: The positively charged proteins are the ones that allow the compaction of the negatively charged DNA.



MMCoT

Rationale: The positively charged proteins are essential for the compaction of the negatively charged DNA. These proteins, known as histones, help to organize and package the DNA tota a compact structure called a nucleosome. The positively charged histones interact with the negatively charged DNA, creating a stable and compact structure that is essential for proper gene expression and regulation.

Answer: The positively charged proteins are essential for the compaction of the negatively charged DNA.

DDCoT

Sub-questions:

- 1. What particles are positively charged?
- 2. What is the process of compaction of negatively charged DNA?

Sub-answer1: Protons are positively charged particles.

Sub-answer2: DNA compaction is facilitated by histone proteins in a process called chromatin packaging.

......

Answer: Histone proteins are positively charged, thus allowing the compaction of the negatively charged DNA.



QVix

Answer: In the image, there are positively charged structures, such as the blue and purple proteins, that are involved in compacting the negatively charged DNA. These positively charged structures interact with the negatively charged DNA through various molecular interactions, such as electrostatic forces and hydrogen bonding. The spatial arrangement of the positively charged elements in the image suggests that they are arranged in a way that helps to bring the DNA molecules closer together, thus facilitating compaction. This arrangement allows for the efficient packaging of the DNA within the cell, which is essential for maintaining the stability and integrity of the genetic material.



М3

Pathology module's tasks:

- Consider the significance of the positively charged components in compacting DNA.
- 2. Offer a scientific explanation based on pathology knowledge regarding the role of positively charged elements in DNA compaction.

Guide:

Positively charged elements, such as histone proteins, are responsible for compacting DNA into a structure known as chromatin. Histones are proteins that have a high content of positively charged amino acids, such as lysine and arginine. These positively charged amino acids interact with the negatively charged phosphate groups in the DNA backbone, allowing the histones to bind to the DNA and wrap it around themselves.

This binding of histones to DNA helps in the compaction of DNA into a more condensed structure, which is essential for packaging the long DNA molecules into the small space of the cell nucleus. This compaction also plays a role in regulating gene expression, as the accessibility of DNA to transcription factors and other regulatory proteins is influenced by the degree of compaction.

MLLM's response:

In the image, the DNA is shown wrapped around a protein structure, which is a histone. Histones are positively charged proteins that play a crucial role in compacting DNA into a structure known as chromatin......

Answer Generation: The positively charged components that allow for the compaction of the negatively charged DNA are histone proteins.

Figure 12: A specific example of the PATH-VQA dataset.

Examples in SLAKE

What is the mr weighting in this image?



Only

Answer: 100



MMCoT

Rationale: In the image, the mr weighting is a medical imaging technique that allows for a detailed view of the internal organs and structures of the body.The mr weighting in the image provides a clear view of the internal organs, such as the liver, spleen, and pancreas, as well as the surrounding tissues and structures. This type of imaging is particularly useful for medical professionals in diagnosing and monitoring various health conditions, as it provides a non-invasive and detailed view of the body's internal workings.

Answer: The mr weighting in the image is a medical imaging technique that allows for a detailed view of the internal organs and structures of the body.



Sub-questions:

1. What are the common types of MR weightings used in medical imaging?

2. Is there any specific feature or characteristic in the image that can help identify the MR weighting?

Sub-answer1: T1-weighted, T2-weighted, proton density-weighted.

Sub-answer2: The presence of the abdominal area in the image suggests that the image is likely an MR weighting.

.....

Answer: Without further specific features or characteristics visible in the image that can directly indicate the MR weighting, it is not possible to determine the exact MR weighting solely based on the information provided.



LLM Guide

To determine the MR weighting in an image, a rookie should look for specific features that are characteristic of T1-weighted and T2-weighted images.

- 1. In a T1-weighted image, structures with high fat content appear bright, while in a T2-weighted image, fluid-filled structures appear bright.
- 2. Tissues with high water content, such as cerebrospinal fluid, appear bright in T2-weighted images.
- 3. Bone appears dark in both T1 and T2-weighted images.

....

Answer: The mr weighting in this image is T2-weighted MRI.



M3

Caption: The mr weighting in this image is the liver.

Radiology module's task:

1. Analyze the characteristics of the liver in the MRI to identify the MR weighting (T1-weighted, T2-weighted, etc.).

Guide:

To analyze the liver in the MRI image, we can look for the following features:

- 1. T1-weighted images typically show fat as bright and water as dark. The liver appears as a homogeneous structure with moderate signal intensity.
- 2. T2-weighted images show fat as dark and water as bright.

MLLM's response:

The imaging modality used in the image is MRI (Magnetic Resonance Imaging). The MR weighting used in the image is T1-weighted, as the liver appears as a homogeneous structure with moderate signal intensity.

Answer Generation: The MR weighting in this image is T1-weighted



Figure 13: A specific example of the SLAKE dataset.

Examples in VQA-RAD

What is located immediately inferior to the right hemidiaphragm?



Only Answer: Lung



Visual CoT

Thought: The right hemidiaphragm is located in the lower part of the chest. The diaphragm is a muscle that separates the chest and abdominal cavities. The diaphragm is a key muscle in breathing.

Answer: The right hemidiaphragm is located immediately inferior to the right hemidiaphragm.



DDCoT

Sub-questions:

1. What is the anatomical structure located immediately inferior to the right hemidianhrasm?

Sub-answer1: The liver is located immediately inferior to the right hemidiaphragm



Answer: The liver is located immediately inferior to the right hemidiaphragm.

QVix

Answer: The right hemidiaphragm is located in the lower part of the chest, and it is situated below the right lung. The right lung is a part of the respiratory system, and it is responsible for the exchange of oxygen and carbon dioxide between the air and the blood. The right hemidiaphragm is a muscular structure that helps in the process of breathing by contracting and expanding to move air in and out of the lungs.



Anatomy module's tasks:

- 1. Identify the organ or anatomical structure located immediately inferior to the right hemidiaphragm.
- 2. Provide detailed information on the anatomical position and relations of the identified structure within the body.

Guide:

Tho

The right hemidiaphragm is a dome-shaped muscle that separates the thoracic cavity from the abdominal cavity. It plays a crucial role in the process of breathing. Immediately inferior to the right hemidiaphragm lies the liver. The liver is the largest solid organ in the body and is located in the right upper quadrant of the abdomen.

In a medical image, the liver appears as a large, reddish-brown organ with a smooth texture. It is situated just below the right hemidiaphragm and is closely related to other structures in the abdominal cavity, such as the gallbladder, stomach, and intestines.

When analyzing a medical image to identify the structure located inferior to the right hemidiaphragm, it is important to look for a large, solid organ with a distinct shape and position in the right upper quadrant of the abdomen. The liver's unique appearance and location make it easily recognizable in imaging studies such as ultrasound, CT scans, or MRI scans.

.....

MLLM's response:

Answer Generation: The structure located immediately inferior to the right hemidiaphragm is the liver.



Figure 14: A specific example of the VQA-RAD dataset.