TCM-Ladder: A Benchmark for Multimodal Question Answering on Traditional Chinese Medicine

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Abstract

Traditional Chinese Medicine (TCM), as an effective alternative medicine, has been receiving increasing attention. In recent years, the rapid development of large language models (LLMs) tailored for TCM has underscored the need for an objective and comprehensive evaluation framework to assess their performance on real-world tasks. However, existing evaluation datasets are limited in scope and primarily text-based, lacking a unified and standardized multimodal question-answering (QA) benchmark. To address this issue, we introduce **TCM-Ladder**, the first multimodal QA dataset specifically designed for evaluating large TCM language models. The dataset spans multiple core disciplines of TCM, including fundamental theory, diagnostics, herbal formulas, internal medicine, surgery, pharmacognosy, and pediatrics. In addition to textual content, TCM-Ladder incorporates various modalities such as images and videos. The datasets were constructed using a combination of automated and manual filtering processes and comprise **52,000+** questions in total. These questions include single-choice, multiple-choice, fill-in-the-blank, diagnostic dialogue, and visual comprehension tasks. We trained a reasoning model on TCM-Ladder and conducted comparative experiments against 9 state-of-the-art general domain and 5 leading TCM-specific LLMs to evaluate their performance on the datasets. Moreover, we propose **Ladder-Score**, an evaluation method specifically designed for TCM question answering that effectively assesses answer quality regarding terminology usage and semantic expression. To our knowledge, this is the first work to evaluate mainstream general domain and TCM-specific LLMs on a unified multimodal benchmark. The datasets and leaderboard are publicly available at `https://tcmladder.com` or `https://54.211.107.106` and will be continuously updated. The source code is available at `https://github.com/orangeshushu/TCM-Ladder`.

1 Introduction

The development of large language models tailored to the field of Traditional Chinese Medicine (TCM) [1, 2] has emerged as a significant research direction. Given the unique and intricate nature of the TCM knowledge system, the construction of intelligent tools specifically designed for this domain can substantially enhance the efficiency of medical students, clinicians, and researchers. Such models have the potential to facilitate accurate and timely access to specialized information for clinical decision-making, knowledge retrieval, and academic inquiry, thereby supporting effective reasoning and practical application within the TCM framework.

TCM diagnostic methods including inspection, auscultation and olfaction, inquiry, and palpation embody a representative process of multimodal information acquisition, integration, and reasoning [3]. Fundamentally, this diagnostic paradigm reflects the nature of multimodal fusion in clinical

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decision-making. However, existing large language models (LLMs) tailored for TCM still face notable limitations in real-world applications. These limitations are primarily manifested in their relatively small model scales, insufficient reasoning capacity, and the lack of deep integration of multimodal information. The acquisition of high-quality TCM data poses significant challenges, as it requires deep expertise in traditional medicine, sustained clinical data collection, and extensive manual annotation. Currently, most mainstream medical benchmark datasets [4, 5, 6, 7, 8] are predominantly focused on Western medicine and have yet to systematically address the core tasks unique to TCM, including syndrome differentiation, symptom-based diagnosis, and formula-herb matching. Furthermore, the training and evaluation of existing TCM large language models remain heavily reliant on unimodal textual data, neglecting other essential modalities that are widely utilized in clinical practice. These include diagnostic images (e.g., tongue and pulse), medicinal herb atlases, and structured case records. Such an overdependence on textual data severely constrains the models' ability to capture the holistic and multimodal nature of TCM knowledge, thereby impeding their performance in complex and realistic clinical scenarios.

Therefore, the construction of a standardized evaluation dataset for TCM that integrates text, images, audio, and structured data is of great importance. On one hand, such a dataset would enable a comprehensive and accurate assessment of existing LLMs in handling complex multimodal tasks, thereby providing a realistic reflection of their overall performance in clinical applications. On the other hand, a unified and standardized evaluation framework would facilitate fair and objective comparisons across different TCM-specific models, supporting continuous optimization and iterative improvement of model capabilities.

To address the aforementioned gaps, we propose **TCM-Ladder**, which, to the best of our knowledge, is the first large-scale multimodal dataset specifically designed for the training and evaluation of large language models in TCM. TCM-Ladder encompasses a wide spectrum of domain-specific knowledge, including fundamental TCM theories, diagnostics, formulae, pharmacology, clinical medicine, as well as visual modalities such as tongue images, herbal medicine illustrations, acupuncture, and tuina (therapeutic massage), thereby offering a comprehensive foundation for developing and benchmarking TCM-specific LLMs.

As illustrated in Figure 1, based on the TCM-Ladder dataset, we design a series of evaluation tasks to comprehensively assess the capabilities of TCM-specific large language models across multiple dimensions.We constructed a total of **21,326 high-quality questions** and **25,163 diagnostic long-text dialogues** based on domain-specific literature and publicly available databases across various subfields of TCM. In addition, we release a **visual dataset** comprising **6,061 images of medicinal herbs, 1,394 tongue images, 6,420 audio clips, and 49 videos**, forming a comprehensive multimodal foundation to support diverse evaluation tasks. All textual and visual data were independently reviewed and validated by certified TCM practitioners to ensure accuracy, clinical relevance, and authoritative quality. Subsequently, we benchmarked the performance of 9 state-of-the-art general domain LLMs[9, 10, 11, 12, 13, 14, 15, 16, 17] and 5 TCM-specific models[18, 19, 20] using the TCM-Ladder dataset. Additionally, we fine-tuned a GPT-4-based model, Bencao[21], and trained a Qwen2.5-7B [22] based reasoning model, which uses a training subset constructed from TCM-Ladder to support TCM-specific reasoning tasks.

Our contributions can be summarized as follows:

- We construct **TCM-Ladder**, a multimodal dataset designed for both training and evaluating TCM-specific and general domain LLMs. The dataset encompasses multiple TCM sub-disciplines and a variety of data modalities.
- We design a comprehensive set of tasks including single-choice questions, multiple-choice questions, fill-in-the-blank tasks, visual understanding tasks, and long-form question answering to evaluate models' reasoning abilities across different tasks.
- We introduce **Ladder-Score**, an evaluation metric that integrates TCM-specific terminology and LLM-assisted semantic scoring to assess term accuracy and reasoning quality in TCM question answering.
- We systematically evaluate the performance of several general domain and TCM-specific LLMs on TCM-Ladder. To our knowledge, this is the first work to conduct a comparative evaluation of diverse LLMs on a unified multimodal TCM dataset.

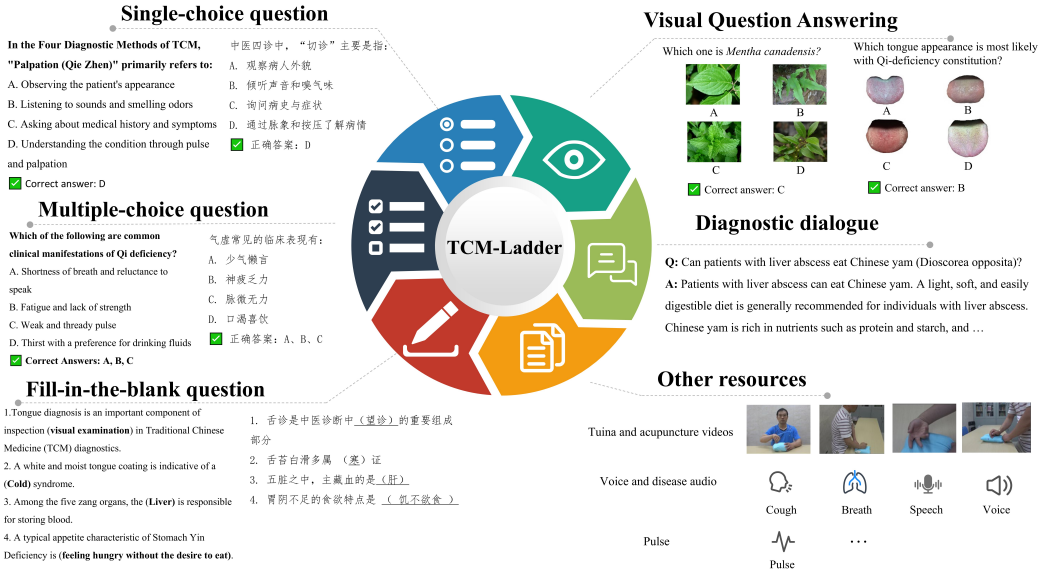

Figure 1: Overview of the architectural composition of TCM-Ladder. TCM-Ladder encompasses six task types aimed at evaluating the comprehensive capabilities of large language models in Traditional Chinese Medicine. These include: (1) single-choice questions, which assess basic knowledge recognition; (2) multiple-choice questions, designed to test the model's ability to integrate and reason over complex concepts; (3) long-form diagnostic question answering, which evaluates clinical reasoning based on detailed symptom descriptions and patient inquiries; (4) fill-in-the-blank tasks, which measure generative accuracy and contextual understanding without the aid of answer options; (5) image-based comprehension tasks, involving the interpretation of medicinal herb and tongue images to assess multimodal reasoning across visual and textual inputs; and (6) additional audio and video resources, such as diagnostic sounds, pulse recordings, and tuina (massage) videos, which support the development and evaluation of multimodal TCM models incorporating auditory and dynamic visual data.

- We develop an interactive data visualization website that not only presents evaluation results, but also allows researchers to explore existing data and contribute new entries, thereby providing a standardized, extensible, and multimodal infrastructure for future benchmarking of TCM-specific LLMs.

2 Related Works

In recent years, the expanding application of LLMs in medicine and the sciences has driven the progressive development of evaluation datasets tailored for TCM, evolving from modern medical domains to TCM-specific tasks, and from classification-based to generation-based paradigms. **Huatuo-26M**[23], released in 2020, remains the largest Chinese medical QA dataset, comprising over 26 million question–answer pairs sourced from online encyclopedias, medical knowledge bases, and telemedicine transcripts. Despite its scale, the dataset suffers from noisy labels, informal expressions, redundancy, and a lack of TCM-specific annotations, limiting its utility for TCM applications. **CBLUE**[24] introduced a standardized multi-task evaluation suite for Chinese biomedical NLP, covering named entity recognition, relation extraction,etc. **PromptCBLUE**[25] extended this framework via instruction tuning and prompt reformulation to facilitate few-shot and zero-shot evaluation. However, both benchmarks were designed around modern medical reasoning and do not reflect the unique logic or semantic structure of TCM diagnosis.

To address these gaps, **TCMBench**[26] compiled 5,473 structured questions from national TCM licensing examinations, providing a focused benchmark for foundational knowledge assessment. Nevertheless, it lacks multimodal input (e.g., tongue and pulse images) and real-world diagnostic reasoning tasks. **TCMEval-SDT**[27] introduced syndrome differentiation based on 300 clinical cases, evalu-

ating the model's reasoning over symptom–pathomechanism–syndrome chains. While it improved interpretability, its scale and disease diversity remain limited. Subsequently, **TCM-3CEval**[28] proposed a cognitive three-axis framework—basic knowledge, classical text comprehension, and clinical decision-making—enabling fine-grained cognitive evaluation. However, tasks were still text-only and often reduced the complexity of classical TCM literature to overly simplistic answers. **TCMD**[29] presented a human-annotated open-ended QA benchmark emphasizing reasoning and generation, though annotation costs limited its scale and case diversity. ShenNong_TCM_Dataset[30] adopted a novel approach, combining knowledge graphs with ChatGPT-based generation to create 110,000+ instruction–response pairs on herbal medicine and treatment plans. While valuable for instruction tuning, the absence of expert validation raises concerns over factual accuracy and stylistic fidelity. **CHBench**[31] introduced a safety-focused benchmark with 9,492 community-sourced questions, highlighting deficiencies in LLM reliability under ethically sensitive conditions. However, its scope remains narrow. **MedBench**[32] represents the most comprehensive Chinese medical LLM evaluation to date, integrating 20 datasets and over 300,000 questions across diverse tasks, including QA, clinical case analysis, diagnostic reasoning, and summarization. The platform supports dynamic sampling and randomized option ordering to prevent overfitting. However, access to API use is restricted due to data privacy concerns. Benchmarks like **CMB**[33] and **CMExam**[34] further extend to structured exam QA, offering high coverage but lacking realistic patient–physician interaction.

TCM-Ladder distinguishes itself from existing datasets in several key aspects. First, it establishes a large-scale, open-ended QA dataset that spans a wide range of TCM subfields, including basic theory, diagnostics, internal medicine, surgery, pediatrics, and pharmacology. This breadth enables more thorough and representative evaluation of TCM-specific LLMs across multiple knowledge domains. Second, TCM-Ladder integrates visual elements such as herbal medicine images and tongue diagnostics. This multimodal design reflects traditional TCM diagnostic practices, requiring LLMs to demonstrate both textual reasoning and visual understanding capabilities. Third, TCM-Ladder incorporates a variety of task formats. This comprehensive task structure facilitates an in-depth evaluation of the strengths and limitations of LLMs, providing guidance for the future development of TCM-specific models.

Table 1: Overview of TCM and Medical QA Datasets. En:English, Zh: Chinese.

Dataset	Format	TCM Coverage	Size	Source	Domain	Task	Verified	Language
Huatuo-26M	Text	✗	26M+	Online QA platforms and physician records	Medicine	QA, Dialogue	✗	Zh
CBLUE	Text	✗	13 subtasks	Clinical trials, EHRs, logs, textbooks	Biomedical	Classification, NER, RE, NLI	*Partial*	Zh
PromptCBLUE	Text	✗	11 prompt datasets	Prompt-formatted CBLUE	Biomedical	Same as CBLUE	✗	Zh
TCMD	Text	✓	1,500+	Professional TCM practitioners	TCM	NER, Term Normalization	✓	Zh
TCM-3CEval	Text	✓	4,000+	Expert-annotated multi-rater QA	TCM	QA	✓	Zh
ShenNong_TCM_Dataset	Text	✓	113,000	TCM knowledge graph GPT-3.5 assisted	TCM	Dialogue	✗	Zh
CMB	Text	*Partial*	280,839 MCQ, 74 consults	Textbooks, forums, exams	TCM	MCQ, Dialogue	✓	Zh
CMExam	Text	*Partial*	60,000+	TCM licensing exam	Medicine	MCQ, QA	*Partial*	Zh
CHBench	Text	*Partial*	9,492	Community health Q&A	Health	QA	✓	Zh
MedBench	Text	*Partial*	40,041	Clinical exam questions	Medicine	MCQ, QA	*Partial*	Zh
TCMBench	Text	✓	5,473	TCM licensing exam	TCM	QA	✗	Zh
TCM-Ladder (Ours)	Text, images, audio, video	✓	52,000+	Research, books, QA platforms	TCM	MCQ, FIB, QA, Dialogue, Image Understanding	✓	Zh & En

3 TCM-Ladder Dataset

3.1 Data Collection

We collected a question-answering dataset covering various domains of TCM, including several publicly available datasets previously published in academic literature under permissive licenses. For the textual data, we identified seven subfields: fundamental theory, diagnostics, herbal formulas, internal medicine, surgery, pharmacognosy, and pediatrics.

For the Chinese herbal medicine image data, we collected over 6,061 images of medicinal herbs based on the herb names referenced in The Pharmacology of Chinese Herbs[35]. The dataset comprises images sourced from publicly available online resources, as well as photographs we captured at

traditional Chinese medicine manufacturing facilities. Sample images and collection process are provided in **Appendix G**.

The clinical tongue images were collected by a tongue imaging device [14] at Shanghai University of Traditional Chinese Medicine. This device is designed for tongue diagnosis and provides stable and consistent lighting conditions during image acquisition. Another subset of the proprietary data was obtained from our previous work, the *iTongue* [36, 37] diagnostic software. All data collection procedures were approved by the institutional ethics review board. To protect the privacy of tongue image contributors, only a subset of tongue image patches and corresponding labels have been released.

The video data was recorded by faculty members from the Department of Acupuncture and Tuina at Shanghai University of Traditional Chinese Medicine. These instructional videos cover essential techniques, procedural explanations, and key operational steps. Audio and pulse diagnosis data were sourced from publicly available datasets referenced in academic publications[38, 39, 40, 41]. A detailed list is available in the supplementary materials. We manually filtered and removed samples with poor quality or missing information from the collected data.

3.2 Construction of the Dataset

The textual question-answering (QA) data consist of two parts. The first part comprises 5,000 TCM-related QA pairs manually written by licensed TCM practitioners under a standardized question design protocol (see **Appendix I**). To ensure answer accuracy, each question was independently reviewed and verified by two additional TCM physicians. The second part of the textual QA data was collected from publicly available sources, including the National Physician Qualification Examination of China and various open-access online resources. Detailed data sources and construction guidelines are provided in the **Appendix B**.

The visual question-answering (VQA) tasks were constructed through both manual annotation and automated generation based on existing knowledge bases. For the manually created subset, domain experts selected high-quality images from the Chinese herbal medicine image repository and generated corresponding questions based on each herb's name and medicinal properties. The automatically generated subset was produced through a procedural pipeline. For example, an image labeled as Astragalus membranaceus (Huangqi) was selected as the correct answer, while three distractor images were randomly sampled from the knowledge base. A question was then constructed using a predefined template library, such as "Which of the following images shows Huangqi?" The design of tongue image understanding tasks followed a similar approach. Details of the construction process and implementation code can be found in **Appendix G**.

3.3 Deduplication and Preprocessing

Detecting duplication and semantic similarity in the data is critical for both model evaluation and training, as it helps prevent evaluation failures and reduces the risk of overfitting caused by redundant content. Given the diverse sources of the original data, we conducted a comprehensive similarity detection process on the aggregated dataset and removed highly similar questions to enhance overall data quality. The methods employed included string edit distance[42], TF-IDF [43, 44] with cosine similarity, and BERT-based[45, 46] semantic encoding. Subsequently, all questions and answers were manually reviewed by two licensed physicians. The selection criteria and detailed experimental procedures are provided in **Appendix I**. Subsequently, we divided the dataset into three subsets: 10% for evaluation, 10% for validation, and 80% for training. To ensure balanced representation, each subset contains question-answer pairs spanning all subfields.

3.4 Dataset Statistics

Table 2 presents the statistics of all constructed question-answer pairs across different categories. The TCM-Ladder dataset comprises a total of 52,169 TCM-related QA instances, including 6,061 Chinese herbal medicine images and 1,394 annotated tongue image patches. The distribution of each data type is illustrated in Figure 2.

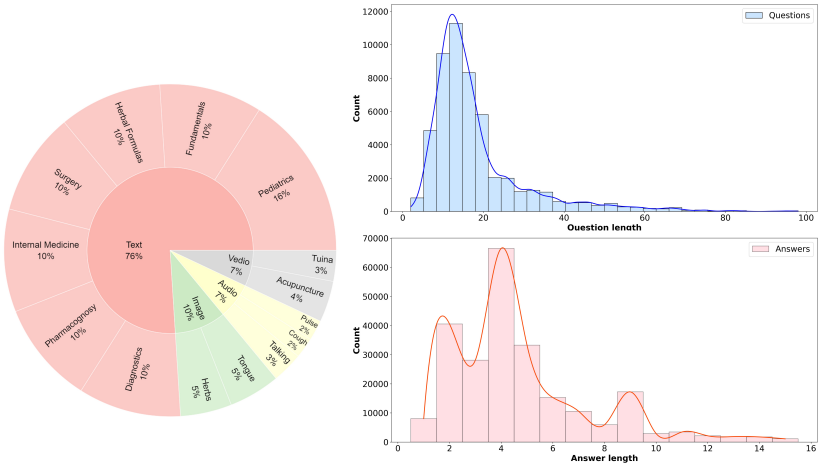

Figure 2: Data distribution and length statistics in TCM-Ladder. The left illustrates the dataset composition across text, image, and audio modalities, along with TCM subfields. The right plots show the distribution of question and answer lengths.

4 Ladder-Score

Evaluating free-form question answering presents notable challenges, as the responses are often descriptive and lack a predefined standard format. This issue is further exacerbated in the context of TCM diagnostic tasks, where large language models are capable of generating diverse and nuanced answers. Even when the expressions differ, the underlying responses may still be factually correct. Traditional evaluation metrics such as BLEU[47] and ROUGE[48] often fail to capture this semantic equivalence adequately. Recently proposed methods[49, 50, 51] employ instruction-tuned models to score candidate answers on a rubric-based scale. We propose a novel evaluation metric for TCM question answering, named **Ladder-Score**. This score comprises two components: *TermScore*, which assesses the accuracy and completeness of TCM terminology usage, and *SemanticScore*, derived from large language models to evaluate multiple aspects including logical consistency, semantic accuracy, comprehensiveness of knowledge, and fluency of expression. As shown in Equation 1, the Ladder-Score is a weighted combination of these two components:

Table 2: Statistics of the collected questions

Statistics	Number
Total questions	52,169
Total answers	238,867
Total subjects	7
Maximum question length	98
Maximum answer length	16
Average question length	18
Average answer length	5
Total images	7,455
Herbs visual questions	6,061
Tongue visual questions	1,394
Total videos	49
Total audios	6,420

$$\text{Ladder-Score} = \alpha \cdot \text{TermScore} + \beta \cdot \text{SemanticScore} \tag{1}$$

where $\alpha = 0.4$ and $\beta = 0.6$,which can be adjusted based on practical needs.

For details on the scoring criteria, terminology dictionary, and calculation examples, please refer to Appendix H.

5 Experiments

5.1 Experiment Setup

We evaluated 9 state-of-the-art general domain LLMs and 5 TCM-specific models on the TCM-Ladder dataset across five task settings: single-choice questions, multiple-choice questions, fill-in-

the-blank questions, image-based understanding, and long-form dialogue tasks. Evaluations were conducted under zero-shot settings, and models received only the task instructions as input. For single-choice and image understanding tasks, we used the Top-1 prediction accuracy[52] as the primary evaluation metric. For multiple-choice tasks, we adopted exact match accuracy to assess performance comprehensively. For fill-in-the-blank and long-form dialogue tasks, we evaluated models using metrics such as accuracy, BLEU[47], ROUGE[48], METEOR[53] and BERTScore[54].

5.2 Model Training

We trained two models using the TCM-Ladder dataset. The first is *Bencao*[21], an online model fine-tuned from ChatGPT, and the second is Ladder-base, which is built upon the pretrained *Qwen2.5-7B-Instruct*[55] model and enhanced with Group Relative Policy Optimization (GRPO)[56] to improve its reasoning capabilities. The Bencao model was trained on knowledge extracted from over 700 classical Chinese medicine books, none of which contained any question-answer pairs. Additionally, the training subset of TCM-Ladder was used as its knowledge base.

The GRPO stage for Ladder-base was conducted on two NVIDIA A100 PCIe GPUs (80GB each). The temperature and top-p sampling of Ladder-base were 0.7 and 0.8. Training was performed for 2 epochs with a group size of 6 and a batch size of 12, resulting in a total training time of approximately 60 hours. Model training and inference were implemented using HuggingFace Transformers, while the GRPO process was carried out using the TRL (Transformer Reinforcement Learning) library[57]. Details of the training process can be found in **Appendix C**.

5.3 Human Evaluation

We conducted a human evaluation on 20% of the TCM-Ladder test set. Due to the coverage of multiple subfields, establishing a reliable human upper bound poses a significant challenge, as accurately answering questions across all domains requires extensive interdisciplinary expertise. To investigate this issue, we recruited two licensed clinical TCM physicians, who were not involved in the original data annotation. Human evaluators were asked to select the correct answers based on the question stems and to identify the correct herbal medicine and tongue images. In terms of top-1 accuracy for answer retrieval, the human evaluators achieved a performance of 64%, which was approximately 4% lower than that of the best-performing model (*Bencao*). This suggests that LLMs may already possess strong comprehension capabilities in the domains of herbal medicine and tongue image recognition.

5.4 Main Results

5.4.1 Text-Based Single-Choice Question Answering

As shown in Figure 3, Ladder-base (ours) consistently outperforms other models across all subject areas, achieving the highest overall accuracy. Notably, its performance is especially strong in Pharmacognosy, Herbal Formulas, and Pediatrics, where exact match scores exceed 0.85. Our other model, Bencao (ours), also demonstrates robust performance, particularly in Diagnostics and Internal Medicine. Among the general domain LLMs, Gemini 2.5 Pro, Deepseek, and Tongyi Qwen show relatively stable accuracy across domains, with scores ranging from 0.65 to 0.75, though they still fall short compared to domain-specialized models. In contrast, Claude 3, GPT-4o mini, and Bentsao underperform, especially in the more clinically nuanced domains such as Surgery and Pediatrics, suggesting limited capability in handling complex, multi-faceted TCM tasks. These findings highlight the advantage of domain-specific fine-tuning and multi-source integration, as utilized in Ladder-base, for enhancing the accuracy and generalization of LLMs on structured TCM knowledge assessments.

5.4.2 Visual Question Answering

To further assess the models' capability in visual understanding tasks within Traditional Chinese Medicine (TCM), we evaluated 10 large language models (LLMs) on two image-based benchmarks: Herbs classification and Tongue image diagnosis. As illustrated in Figure 4, performance varies considerably across models. Among the evaluated models, Bencao (ours) achieves the highest accuracy in both tasks, with over 80% on herb recognition and above 65% on tongue classification, demonstrating strong multimodal understanding grounded in TCM-specific training. General domain

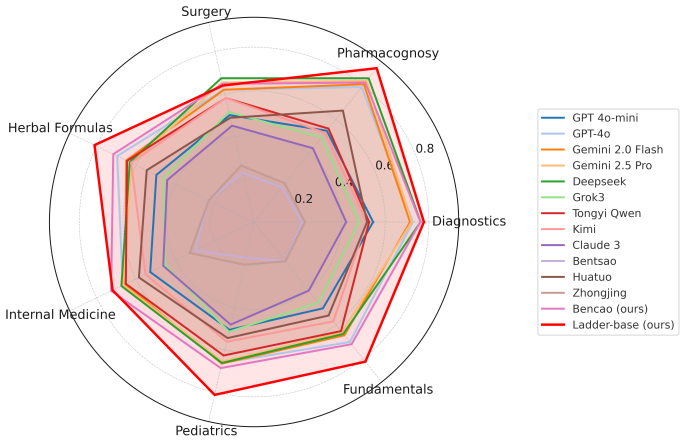

Figure 3: Performance of general-domain and TCM-specific language models on single and multiple-choice question answering tasks.

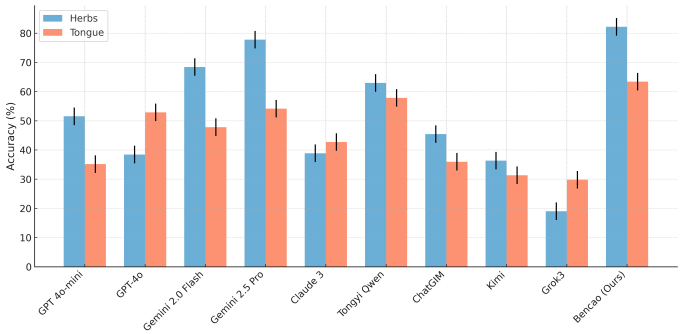

Figure 4: The performance of large language models on questions regarding Chinese herbal medicine and tongue images.

LLMs such as Gemini 2.5 Pro, Gemini 2.0 Flash, and Tongyi Qwen exhibit moderate performance, with herb classification accuracy around 65–75%, but show a relative drop in tongue image tasks (around 50–60%), likely due to the greater complexity and domain specificity of tongue diagnosis.

In contrast, models like GPT-4o, Claude 3, Kimi, and Grok3 demonstrate limited performance, particularly in the **tongue classification task**, where accuracies often fall below 40%. This reveals their insufficient visual comprehension of TCM-related imagery. It is worth noting that models such as Ladder-base and Zhongjing are not included in this figure, as they are not equipped with image understanding capabilities at this stage. Their current design focuses on structured text-based TCM evaluation and does not support visual input.

5.4.3 Diagnostic dialogue and Fill-in-the blank Questions

As shown in Table 3, in the diagnostic dialogue task, our model Ladder-base achieved the highest scores in BLEU-4 (0.0249), ROUGE-L (0.2431), and METEOR (0.2268), while also maintaining a strong Ladder-score (0.803). This indicates that Ladder-base generates answers with high lexical similarity, semantic accuracy, and alignment with TCM diagnostic logic. Notably, Tongyi Qwen achieved the best **Ladder-score (0.861)** and the highest METEOR (0.2328), showcasing its strength in generating fluently worded responses. Bencao (ours) achieved the best BERTScore (0.9663), reflecting its semantic closeness to gold references.

In the fill-in-the-blank task, Bencao significantly outperformed all other models, achieving the highest Exact Match Accuracy of 0.9034, followed by Tongyi Qwen (0.8786) and Deepseek (0.874). Our Ladder-base model also performed competitively with 0.8623 accuracy, further demonstrating its generalizability beyond free-form dialogue. Overall, the results demonstrate that Ladder-base excels

in structured diagnostic dialogue tasks, generating semantically accurate and logically coherent responses, while *Bencao* shows outstanding performance in fill-in-the-blank tasks, reflecting strong factual recall and precise terminology usage. Domain-specific models consistently outperform general domain LLMs, particularly in tasks that require accurate retrieval of structured TCM knowledge and professional terms.

Table 3: Performance Comparison on Diagnostic Dialogue and Fill-in-the-blank Tasks

	Diagnostic dialogue					Fill-in-the-blank
Model	**BLEU-4**	**ROUGE-L**	**METEOR**	**BERTScore**	**Ladder-score**	**Exact match accuracy**
GPT 4o-mini	0.0034	0.1125	0.119	0.9433	0.718	0.432
GPT-4o	0.0040	0.1447	0.2073	0.9620	0.828	0.514
Gemini 2.0 Flash	0.0067	0.1518	0.2155	0.9633	0.836	0.436
Gemini 2.5 Pro	0.0180	0.1353	0.2393	0.9605	0.859	0.7143
Deepseek	0.0047	0.1533	0.1293	0.9455	0.825	0.874
Grok3	0.0063	0.1751	0.1691	0.9526	0.686	0.6389
Tongyi Qwen	0.0225	0.1818	**0.2328**	0.9642	**0.861**	0.8786
Kimi	0.0100	0.1878	0.1586	0.9559	0.708	0.8378
Claude 3	0.0068	0.2267	0.2203	0.9561	0.756	0.489
Bentsao	0.0024	0.1135	0.1725	0.9531	0.613	0.162
Huatuo	0.0086	0.1375	0.1742	0.9635	0.855	0.2347
Zhongjing	0.0044	0.1951	0.1134	0.9539	0.573	0.2167
Bencao (ours)	0.0073	0.2156	0.2013	**0.9663**	0.791	**0.9034**
Ladder-base (ours)	**0.0249**	**0.2431**	0.2268	0.9549	0.803	0.8623

6 Application Website

In addition to releasing the raw dataset, we provide access to all TCM-Ladder data and leaderboard results through an interactive website (`https://tcmladder.com/`). This platform enables researchers to explore, verify, and contribute to the open-access data. We encourage the research community to submit additional data through the platform, and we intend to expand the dataset continuously as part of our ongoing efforts. Our objective is to establish a long-term and reliable data foundation for the training and evaluation TCM-specific LLMs.

7 Limitations and Societal Impact

Although TCM-Ladder encompasses question-answer pairs from multiple disciplines within TCM, its current scale remains insufficient to cover the full breadth of TCM knowledge. TCM diagnosis is inherently a multimodal process—textual information represents only one component. At present, the utilization of data related to tongue diagnosis, pulse diagnosis, and olfactory inspection remains limited, and these modalities require further supplementation and enrichment. Expanding and continuously updating the scope and scale of data included in TCM-Ladder will be a critical direction for future research.

8 Conclusion

We introduce **TCM-Ladder**, the first multimodal benchmark dataset designed explicitly for evaluating LLMs in the context of TCM. In addition, we propose a novel evaluation metric, Ladder-Score, which enables more precise analysis of the semantic alignment between candidate and reference answers. We conduct comprehensive experiments involving 9 state-of-the-art general domain and 5 TCM-specific LLMs, marking the first systematic comparison on a unified benchmark. Furthermore, we fine-tune two TCM-specific models using a subset of TCM-Ladder, and observe significant performance improvements over zero-shot baselines. Our work establishes a reproducible and extensible benchmark for TCM-specific, providing a foundation for future development and evaluation in this emerging research area.

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    Answer: [Yes]

    Justification:The detailed evaluation procedure of the large language models is described in **Section 5** and **Appendix F**.

    Guidelines:

    - The answer NA means that the core method development in this research does not involve LLMs as any important, original, or non-standard components.
    - Please refer to our LLM policy (`https://neurips.cc/Conferences/2025/LLM`) for what should or should not be described.