System Report for CCL25-Eval Task 11: Aesthetic Assessment of Chinese Handwritings Based on Vision Language Models

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Abstract

The handwriting of Chinese characters is a fundamental aspect of learning the Chinese language. Previous automated assessment methods often framed scoring as a regression problem. However, this score-only feedback lacks actionable guidance, which limits its effectiveness in helping learners improve their handwriting skills. In this paper, we leverage vision-language models (VLMs) to analyze the quality of handwritten Chinese characters and generate multi-level feedback. Specifically, we investigate two feedback generation tasks: simple grade feedback (Task 1) and enriched, descriptive feedback (Task 2). We explore both low-rank adaptation (LoRA)-based fine-tuning strategies and in-context learning methods to integrate aesthetic assessment knowledge into VLMs. Experimental results show that our approach achieves state-of-the-art performances across multiple evaluation tracks in the CCL 2025 workshop on evaluation of handwritten Chinese character quality.

Keywords: Handwritten Chinese Characters , Aesthetic Assessment , Vision-Language Models , Low-rank Adaptation , In-context Learning

1 Introduction

The automated assessment of Chinese handwriting is a critical research area in language education and intelligent evaluation systems (Xiao et al., 2022; Chen et al., 2024). Chinese handwritten characters, characterized by their linguistic accuracy and structural complexity, serve as a cornerstone of cultural and educational expression. However, existing systems typically provide only score-based feedback (Han et al., 2008; Gao et al., 2011; Li et al., 2014; Sun et al., 2015; Wang et al., 2016; Zhou et al., 2017; Wang and Lv, 2021; Sun et al., 2023; Wang et al., 2023; Yan et al., 2024; Wu et al., 2024), which limits their effectiveness in supporting learners' skill development. This highlights the need for advanced methods to deliver detailed, constructive feedback, thereby enhancing educational practices and supporting Chinese handwriting in digital learning environments.

Recent advancements in computer vision have facilitated the development of automated systems for evaluating Chinese handwriting, enabling standardized assessments while preserving the artistic qualities of calligraphy. However, constructing evaluation models that effectively balance standardization with aesthetic merit remains a complex challenge. Existing research has predominantly relied on hand-crafted features to assess structural and aesthetic quality. For instance, Gao et al. (2011) proposes a method for evaluating Chinese handwriting quality based on the recognition confidence of online handwriting analysis using a modified quadratic discriminant function classifier. Sun et al. (2015) utilize global shape features and component layout information to enhance aesthetic evaluation. Zhou et al. (2017) use a possibility-probability distribution method to assess the quality of robotic Chinese handwriting. Despite these advances, such approaches often lack the flexibility to provide nuanced, context-aware feedback that effectively integrates both structural and stroke dimensions.

Recently, vision-language models (VLMs) have shown remarkable capabilities across various domains, including document understanding, visual perception, and multimodal reasoning (Bai et al., 2023; Wang et al., 2024; Bai et al., 2025; Lu et al., 2024; Kimi Team et al., 2025). Despite these advancements, their application in the aesthetic assessment of Chinese handwriting remains largely unexplored.

Traditional computer vision methods often struggle to provide fine-grained and personalized feedback in aesthetic assessment tasks. VLMs, with their robust capabilities in image understanding and natural language generation, offer a novel approach to address these limitations.

This study explores the application of VLMs to generate detailed, context-sensitive feedback on Chinese handwriting quality, with a focus on both structural integrity and stroke aesthetics. To effectively integrate domain-specific knowledge into VLMs for this task, we investigate two data-efficient methods: Low-Rank Adaptation (LoRA) based fine-tuning for open-source VLMs (Hu et al., 2022), and in-context learning for closed-source large language models (LLMs) (Brown et al., 2020).

We conducted experiments on the CCL 2025 evaluation task for assessing the quality of handwritten Chinese characters, which includes two subtasks: grading and comment generation. Our proposed method obtained scores of 0.76 and 0.52 on the respective subtasks, securing third place in the competition and demonstrating its effectiveness.

2 Task Formulation

In the CCL 2025 evaluation of the quality of handwritten Chinese characters task, the objective is to assess the aesthetic quality of a given Chinese handwritten image. This task involves two distinct subtasks:

Task 1: Grading of handwritten Chinese characters: the goal is to classify the quality of handwritten characters into three discrete grades: excellent, medium, and unqualified. This classification is primarily based on the structural integrity and stroke aesthetics of the characters.

Task 2: Comment generation of handwritten Chinese characters: the goal is to provide targeted textual descriptions focusing on the two aforementioned dimensions: structure and stroke form.

3 Methods

We explore LoRA and in-context learning methods, with the overall framework depicted in Fig. 1.

3.1 Training Format for LoRA

For LoRA fine-tuning, training and testing data are structured as single-turn dialogues, following the template provided below. In Task 1, the model receives a raw image of a handwritten Chinese character as input, and its training objective is to output the corresponding quality grade.

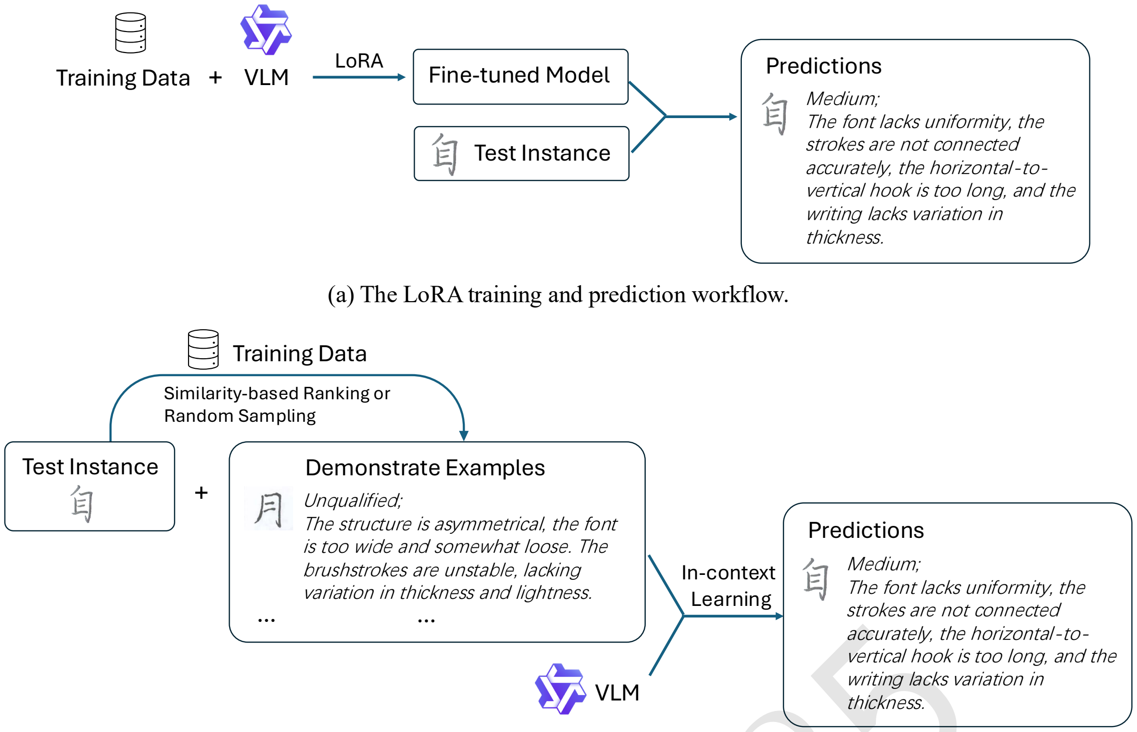
[{“role”: “user”, “content”: <INPUT_IMAGE>},
{“role”: “assistant”, “content”: <GRADE>}]

Task 2 employs two different input-output formats. The first is similar to Task 1, but the expected output is detailed feedback on handwriting quality, rather than just a grade.

[{“role”: “user”, “content”: <INPUT_IMAGE>},
{“role”: “assistant”, “content”: <FEEDBACK>}]

The second format's input differs by including the raw image of the handwritten Chinese character and the grade predicted by the model trained on Task 1.

[{“role”: “user”, “content”: <INPUT_IMAGE> The evaluation for the above handwritten Chinese characters is <GRADE>, generate a comment.},
{“role”: “assistant”, “content”: <FEEDBACK>}]


Training Data
+
VLM
LoRA
Fine-tuned Model
Test Instance
Predictions
Medium;
The font lacks uniformity, the strokes are not connected accurately, the horizontal-to-vertical hook is too long, and the writing lacks variation in thickness.
Training Data
Similarity-based Ranking or Random Sampling
Test Instance
+
Demonstrate Examples
Unqualified;
The structure is asymmetrical, the font is too wide and somewhat loose. The brushstrokes are unstable, lacking variation in thickness and lightness.
...
...
In-context Learning
VLM
Predictions
Medium;
The font lacks uniformity, the strokes are not connected accurately, the horizontal-to-vertical hook is too long, and the writing lacks variation in thickness.

(a) The LoRA training and prediction workflow.

(b) The in-context learning prediction workflow.

Figure 1: The LoRA and in-context learning frameworks.

3.2 Example Demonstation for In-context Learning

We investigated two in-context learning methods: a similarity-based method for selecting and ordering in-context examples, and random selection of in-context examples. In the first method, given a test instance, we select the k most similar instances from the training data to serve as demonstrations. A training instance is placed closer to the test instance as its similarity increases. In the second method, instances are randomly selected from the training data.

The organization of the query for in-context learning is illustrated below:

[{“role”: “system”, “content”: $\texttt{SYSTEM\_PROMPT}$},
{“role”: “user”, “content”: <$\texttt{INPUT\_IMAGE}_1$>},
{“role”: “assistant”, “content”: <$\texttt{GRADE}_1$> or <$\texttt{FEEDBACK}_1$>},
...,
{“role”: “user”, “content”: <$\texttt{INPUT\_IMAGE}_k$>},
{“role”: “assistant”, “content”: <$\texttt{GRADE}_k$> or <$\texttt{FEEDBACK}_k$>},
{“role”: “user”, “content”: $\texttt{TEST\_PROMPT}$, <$\texttt{TEST\_IMAGE}$>}]

In the similarity-based method, the input images are ordered based on their similarity to a test image, as follows:

$$\begin{aligned} sim(\texttt{INPUT\_IMAGE}_1, \texttt{TEST\_IMAGE}) &\leq sim(\texttt{INPUT\_IMAGE}_2, \texttt{TEST\_IMAGE}) \leq \dots \\ &\leq sim(\texttt{INPUT\_IMAGE}_k, \texttt{TEST\_IMAGE}) \end{aligned} \tag{1}$$

Here, $sim(\dot{})$ denotes the cosine similarity between the image embeddings of the instances. The system prompt for Task 1 clearly outlined the evaluation criteria for each grade, as shown below [1].

[1] All prompts were originally in Chinese and have been translated into English for presentation.

> `SYSTEM_PROMPT`: You are an expert in Chinese calligraphy who is familiar with the aesthetic features of Chinese characters. You are capable of accurately evaluating the quality of students' handwriting.
> Following the example provided, you are required to rate the given samples of Chinese character writing into three grades: A (Excellent), B (Medium), or C (Unqualified). The grading criteria are defined as follows:
> A (Excellent): The character structure and proportions are well-balanced, the center of gravity is stable, and the overall appearance is symmetrical and aesthetically pleasing. The strokes are correctly shaped with proper coordination, clearly executed, and demonstrate variation in pressure and thickness. There are no significant flaws in the writing.
> B (Medium): The structure and proportions are generally reasonable, the center of gravity is mostly stable, and the character appears relatively balanced. The stroke forms are largely correct, and the individual strokes are clear, but there is limited variation in pressure. The writing exhibits systematic deficiencies in one or more aspects.
> C (Unqualified): The structure is imbalanced or the center of gravity is unstable, resulting in an asymmetrical and unappealing appearance. The strokes are careless, unclear, or sloppy. The writing contains serious flaws that significantly affect legibility or aesthetic quality.

The `SYSTEM_PROMPT` for Task 2 outlined the key points for generating feedback, details of which can be found in Appendix A. The `TEST_PROMPT` instructs the VLM to grade the test image or give feedback based on the instructions and examples. For Task 1,

> `TEST_PROMPT`: You are required to assign a score of A (Excellent), B (Medium), or C (Unqualified) to the given image of Chinese character writing, based on the example and criteria provided above. Note: Your response must consist of only a single uppercase letter corresponding to the score for this image.

The details of the `TEST_PROMPT` for task 2 can be found in appendix B.

4 Experiment

4.1 Experimental Setups

We conduct experiments on the CCL 2025 Evaluation of the quality of handwritten Chinese characters dataset. For Task 1, the dataset comprises 1500 training instances and 300 test instances. For Task 2, it includes 600 training instances and 100 test instances.

For Task 1, evaluation metrics include precision, recall and the F1-score. For Task 2, the metrics are ROUGE-1, ROUGE-2, and ROUGE-L. The final score is calculated as follows:

$$\text{FinalScore} = 0.4 \times \text{ROUGE-L} + 0.3 \times \text{ROUGE-2} + 0.3 \times \text{ROUGE-1}. \tag{2}$$

We use the open-source VLMs *Qwen2.5-VL-72B-Instruct*[2] (QwenVL) (for both task 1 and 2) and *QVQ-72B-Preview*[3] (QVQ) (for task 2) as the base models for LoRA training. The training was conducted for 3 epochs with a learning rate of 1×10^{-4} using the open-source fine-tuning tool LLaMA-Factory (Zheng et al., 2024).

In the LoRA training for Task 1, we utilized an open-source dataset, CHAED (Sun et al., 2015) to expand our training set. This dataset comprises 1000 Chinese handwriting images, each accompanied by aesthetic scores. Images were empirically classified into three categories based on their aesthetic scores: *Excellent* (scores > 80), *Medium* (scores $30 \sim 80$), and *Unqualified* (scores < 30). Separate models were then trained using only the task-specific dataset and with the combined CHAED data, respectively.

For LoRA-based training in Task 2, the first model was trained similarly to Task 1, but it generated feedback text instead of grading scores. The second model utilized the model trained on the Task 1-specific dataset to predict grading scores for each image in the training and test sets. Subsequently, the

[2] https://huggingface.co/Qwen/Qwen2.5-VL-72B-Instruct

[3] https://huggingface.co/Qwen/QVQ-72B-Preview

Model	Precision	Recall	F1
QwenVL LoRA	**0.76**	**0.76**	**0.76**
QwenVL LoRA w/ CHAED	0.61	0.61	0.61
In-Context Learning	0.69	0.69	0.69

Table 1: Summary of results of the task 1.

Model	ROUGE-1	ROUGE-2	ROUGE-L	FinalScore
QwenVL LoRA	0.43	0.24	0.41	0.36
QwenVL LoRA w/ grade	0.46	0.26	0.43	0.39
QVQ LoRA	0.47	0.26	0.44	0.39
In-Context Learning	**0.63**	**0.34**	**0.56**	**0.52**

Table 2: Summary of results of the task 2.

handwriting images with their predicted grades were used as input, while the corresponding feedback text served as the output to fine-tune the model.

In the in-context learning strategy, we compared the performance of similarity-based ordering for in-context examples against random selection of in-context examples. The model used in the in-context learning is the closed-source VLM *qwen-vl-max-2025-01-25*[4]. For the selection and ordering of in-context examples, we use the *multimodal-embedding-v1*[5] provided by Alibaba Cloud for image embedding. Vector indexing was implemented with ChromaDB[6].

For Task 1, we separated 300 examples from the training set as a development set and found that similarity-based ordering of in-context examples performed better. In Task 2, we separated 100 examples from the training set as a development set and found that random selection of in-context examples performed better.

4.2 Results

Table 1 and 2 presents the main results. The results for Task 1 indicate that the model fine-tuned on the task-specific dataset achieved the best performance. However, the model fine-tuned on the expanded dataset exhibited suboptimal performance, likely because the aesthetic score classification was misaligned with the grading criteria of the task-specific dataset.

The results for Task 2 demonstrate that the in-context learning method achieved the best performance. The fine-tuned QVQ model outperformed the QwenVL model. Additionally, the model trained with images paired with their predicted grades showed a marginal improvement of 0.03 in final score.

5 Conclusion and Future Work

In this paper, we explore the application of VLMs to the evaluation of Chinese handwritten characters. Utilizing both open-source and closed-source VLMs, we investigate multiple strategies, including LoRA and in-context learning. Our approach achieved third place on the final leaderboard, demonstrating the effectiveness of the proposed methods.

In practical applications, fine-tuning VLMs is more computationally efficient than in-context learning, as the latter requires significantly higher token consumption and computational resources.

Building on recent advancements in reinforcement learning (RL) for training LLMs and VLMs (Guo et al., 2025; Kimi Team et al., 2025), our future work will focus on advancing the aesthetic assessment

[4] https://bailian.console.aliyun.com/?tab=model#/model-market/detail/qwen-vl-max?modelGroup=qwen-vl-max

[5] https://bailian.console.aliyun.com/?tab=model#/model-market/detail/multimodal-embedding-v1

[6] https://www.trychroma.com

capabilities of VLMs through two directions. First, we will design comparative ranking tasks and fine-grained classification tasks to enhance the precision of aesthetic assessments in handwritten Chinese characters. Second, we will explore RL's potential in reasoning about complex aesthetic principles, while tackling challenges related to subjective evaluation and data scarcity.

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A System prompts

For Task 1, the original SYSTEM_PROMPT in the in-context learning method was written in Chinese:

> 你是一名汉字书法专家，你对汉字的图形图像非常了解，可以准确评价学生汉字书写的质量。你需要仿照样例，对给出的汉字书写图片按A: 优秀，B: 中等，C: 不合格三个等级打分。三个等级的评价标准如下：
> A. 优秀：结构比例安排适当，重心平稳，字体匀称美观。点画形态正确且有呼应，笔画清晰到位，用笔有轻重变化之分。字体无明显缺陷。
> B. 中等：结构比例基本合理，重心基本稳定，字体较匀称。笔画形态基本正确，点画清晰但轻重变化不够。字体在某一类或几类问题上存在系统性缺陷。
> C. 不合格：结构比例失衡或重心不稳，字体不匀称。点画随意，笔画不清晰或潦草。字体存在较严重缺点。

The English version used in experiments is provided in Section 3.2. For Task 2, the SYSTEM_PROMPT was:

> You are an expert in Chinese calligraphy with a deep understanding of the graphical aspects of Chinese characters, capable of accurately evaluating the quality of students' handwriting. You need to follow the examples and write comments for the given Chinese character images. The comments should provide targeted evaluations and descriptions focusing on two main dimensions: structure and stroke form.
> For structure, consider density, balance (such as the symmetry of top-bottom or left-right structures), and the center of gravity.
> For strokes, consider the variation in stroke weight and the specific forms of individual strokes.

The original Chinese version:

> 你是一名汉字书法专家，你对汉字的图形图像非常了解，可以准确评价学生汉字书写的质量。你需要仿照样例，对给定的汉字图片撰写评语。评语主要对结构和笔画形态两大维度，进行有针对性的评价和描述。
> 结构上，考虑疏密、匀称（如上下结构、左右结构等方面的匀称性）、重心。
> 笔画上，考虑笔画的轻重变化，以及具体笔画的形态。

B Test prompts

The TEST_PROMPT for task 1 in the in-context learning method was:

> You need to refer to the above image and scoring to grade the Chinese character writing in the image below as A: Excellent, B: Medium, C: Unqualified.
> Attention! Your output must only contain one uppercase letter! Corresponding to the score of the Chinese character writing in this image.

The original Chinese version:

> 你需要参照上面的图片及打分，对下面这张汉字书写的图片按照A: 优秀，B: 中等，C: 不合格给出分数。
> 注意！你的输出只能有一个大写字母！对应这张图上汉字书写的分数。

The TEST_PROMPT for task 2 was:

> You need to refer to the above image and the corresponding comments to write a critique for the following Chinese handwriting image.
> Attention! Your output format and content style must strictly follow the reference comments. Write a passage of similar length and style.

The original Chinese version:

> 你需要参照上面的图片及对应的评语，对下面这张汉字书写的图片撰写评语。
> 注意！你输出的格式和内容风格要严格参考上面的评语。以相似的长度和风格撰写一段话。