New Compendium of a Myriad of Plants: A New Dataset Describing Ancient Chinese Plants

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Abstract

In ancient China, a variety of datasets depicted humanistic scenes, geographical features, and plants. However, these datasets, compiled long ago, often contain errors, lack comprehensiveness, and are inconsistent with modern realities. To meet current demands, we aim to expand and improve ancient datasets using large language model. Focusing on the *Great Compendium of Myriad Flowers*, an invaluable ancient plants dataset, we gather information on numerous previously excluded plants, carefully select and organize classical Chinese poetry and prose, and construct a comprehensive botanical encyclopedia knowledge system. Additionally, we collect ancient paintings and modern photographs of plants to enrich the dataset. Furthermore, we propose a novel multimodal plant classification model designed to integrate multimodal information from both classical and contemporary sources, enabling the extraction of plant-related information from classical Chinese poetry and prose. Extensive experiments demonstrate the importance of the proposed new ancient plants dataset, and also indicate the effectiveness of our proposed multimodal plant classification model.

1 Introduction

Classical Chinese texts are an essential carrier of Chinese civilization, documenting the rich knowledge accumulated over thousands of years in fields such as history, literature, medicine, agriculture, and astronomy. For example, the Compendium of Materia Medica (Zhou et al., 2024) (*Ben Cao Gang Mu*) recorded herbs, the Classic of Mountains and Seas (Liang et al., 2024) (*Shan Hai Jing*) depicted ancient humanistic scenes and geographical features, and the Great Compendium of Myriad Flowers (*Guang Qun Fang Pu*) documented ancient plants. However, these texts are ancient and mostly written in classical Chinese, which is highly concise and significantly different from modern Chinese, and are also inconsistent with modern realities in many aspects, thus posing considerable challenges for understanding and utilization.

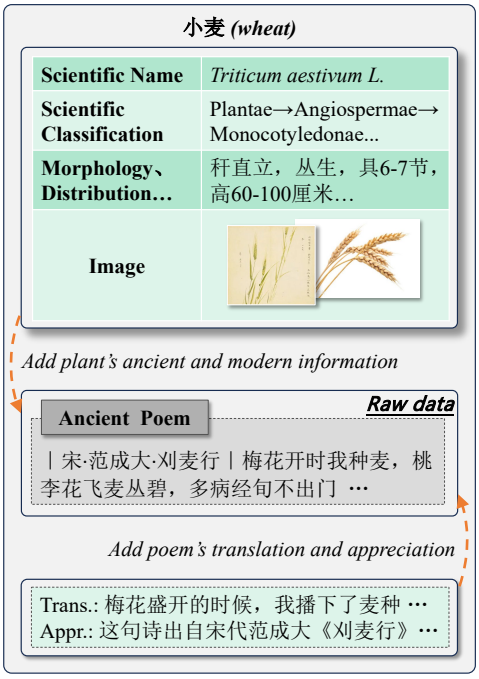


Figure 1: An example of our proposed dataset.

There have been some efforts to digitize these datasets and extract information from them (Yu et al., 2021; Xie et al., 2022; Feng et al., 2022; Tang et al., 2024a; Bao et al., 2025). Nevertheless, existing approaches often rely on shallow processing, such as basic digitization or tokenization (Liu et al., 2022; Yu et al., 2020; Tian and Guo, 2022), and struggle to handle the linguistic characteristics of classical Chinese (Zhou et al., 2023; Congcong et al., 2023; Zhang and Li, 2023a), including condensed syntax, polysemy, and implicit references. They also fail to fully capture the rich historical, cultural, and scientific contexts embedded in these texts (Mengcheng et al., 2023; Feng et al., 2024; Tang et al., 2024b), which can lead to superficial or even inaccurate interpretations. Moreover, the

scarcity of standardized, high-quality annotated datasets (Li et al., 2022; Cao et al., 2024b,a) further limits the ability of current methods to achieve deep semantic understanding and practical applicability.

Therefore, we plan to expand and improve upon ancient datasets and utilize LLM to construct a new dataset that describe ancient scenes and meet current demands. Specifically, in this study, we take the *Great Compendium of Myriad Flowers* (广群芳谱) dataset, which describes ancient plants, as our starting point.

The Great Compendium of Myriad Flowers is a highly valuable ancient botanical dataset. It covers various aspects of plants, including their growing environments, morphological characteristics, cultivation methods, offering extremely high reference value for ancient plant research. However, this dataset also has some notable shortcomings. The variety of plants included is not extensive enough. The number of classical literary works collected for each plant—which in our research specifically refers to classical Chinese poetry and prose—is limited and not systematically organized. Moreover, it lacks modern classification information and detailed encyclopedic knowledge about plants. Additionally, it does not contain ancient paintings depicting plants or modern plant photographs.

Therefore, based on the original dataset, we carry out extensive and in depth data collection work. As shown in Figure 1, we gather information on a large number of plants that are not previously included. We also carefully select and organize a sufficient amount of classical literary works for each plant. At the same time, by leveraging LLM together with manual verification, we accurately classify the plants according to modern standards and construct a comprehensive botanical encyclopedia knowledge system. In addition, we translate and appreciate classical literary works, building a bridge between the ancient and the modern. Furthermore, we make every effort to collect ancient paintings depicting each plant as well as modern plant photographs to enrich the content of the dataset and enhance its application value.

After successfully constructing the new dataset, we carry out comprehensive and meticulous data collection work. Ultimately, we collect information on a total of 780 plant species and 44,298 classical literary works related to plants, and supplement these textual data with a curated collection of 1,911 images from both ancient and modern sources to provide comprehensive visual references for further analysis.

This dataset integrates knowledge from multiple disciplines, providing rich resources for interdisciplinary research in digital humanities, while facilitating the digital organization and dissemination of classical literary works, paintings, and other cultural materials.

In addition, we propose a novel multimodal plant classification model that integrates both classical and modern sources to extract plant-related information from classical texts.Extensive experiments demonstrate both the value of the dataset and the effectiveness of the proposed model.

2 Related Work

In this section, we discuss two related topics: digitization of classical literature and information extraction from classical literature.

2.1 Digitization of Classical Literature

The digitization of classical literature involves applying digital technologies to process the content of classical literature, with a key step being the use of OCR (Optical Character Recognition) to identify the text (Chen, 2022).

Early approaches used statistical analysis to conduct research at the content level (Lingxiang and Xiting, 2006; Wei et al., 2014; Liu et al., 2020). Traditional machine learning and deep learning later used better representations to perform tasks including sentence segmentation, word segmentation, annotation, classification, and named entity recognition (Chen, 2024; Na, 2018; Yue et al., 2021; Qi et al., 2021; Ihnaini et al., 2024). Recently, the development of LLMs has attracted considerable attention from researchers. They use parameter-efficient fine-tuning to adapt LLMs for digitization tasks (Tian et al., 2021; Zhang and Li, 2023b; Si et al., 2024; Qi et al., 2025).

2.2 Information Extraction from Classical Literature

In the task of entity extraction from classical literature, entities that generally receive attention include personal names, place names, official titles, and temporal expressions (Yang and Dongbo, 2024).

Previous studies extracted the entities from pre-Qin literature such as Gong Yang Zhuan (Yafen, 2013; Dongbo et al., 2018; Mengcheng et al., 2023). Later, research further expanded to domain specific ancient literature (Chao and Wenbo, 2021; Feng

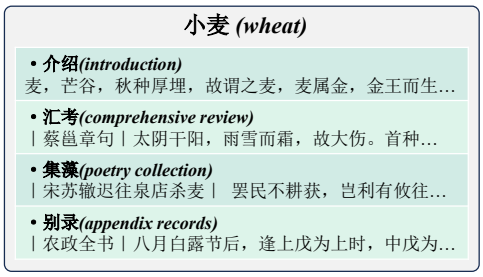


Figure 2: Content and organization of the original Great Compendium of Myriad Flowers dataset.

et al., 2024; Jing et al., 2022), as well as the extraction of information related to war from specific historical periods (Xuehan et al., 2021; Zhangchao et al., 2020). In addition, studies have also focused on agronomic classical literature, addressing knowledge related to crops and agricultural technologies (Na, 2021; Zheng et al., 2024). At the same time, numerous studies have focused on the construction of knowledge bases and knowledge graphs derived from classical literature through information extraction (Bolin et al., 2021; Liu et al., 2023b; Wang et al., 2023; Wei et al., 2024).

Different from previous works, we consider plant terms in classical Chinese, which often undergo de-entityization. Rather than serving as stable entity references, they are commonly used to project abstract meanings. This semantic property fundamentally distinguishes plant information extraction from standard entity centric tasks.

Thus, we expand and annotate the dataset based on the Great Compendium of Myriad Flowers to explore the extraction of plant imagery from classical literary works. By organizing and digitally presenting classical literary works, paintings, and other cultural materials, this dataset helps better inherit and promote the excellent traditional Chinese culture.

3 Dataset Construction

In this section, we give the description of data collection, annotation, and also give some statistics and analysis of our proposed dataset.

3.1 Original Data Collection

The *Great Compendium of Myriad Flowers* (广群芳谱) is a highly valuable ancient botanical dataset. Compiled by Wang Hao and others during the Qing Dynasty. It covers various aspects of plants, including their growing environments, morphological characteristics, cultivation methods, uses, as well as related classical literary works, myths, and legends, offering extremely high reference value for ancient plant research. As shown in Figure 2, for each plant in the dataset, the content record various information from classical literary works and literary references about the plant in ancient times. We manually extract plant information along with the corresponding classical literary works and references, and organize them into a unified schema for each plant from classical Chinese texts. Finally we obtain a high quality, structured basic dataset, laying a solid foundation for subsequent in depth research.

For this basic dataset, we adopt an organizational form centered around plants. Specifically, for each plant in the dataset, we treat it as an independent entry and attach in detail the corresponding classical literary works extracted precisely from original dataset after the plant entry.

3.2 Extended Data Collection

The original dataset has an obvious drawback: it contains too few plant species, with less than 500 different plants. To meet the needs of more extensive research and applications, we decide to expand the dataset.

First, we construct a list of commonly used plants based on the Catalogue of Life China[1]. The original list contains 47,474 plant species. Through the application of a scientific classification system and a category merging strategy, we consolidate this list to 1,923 commonly occurring plant species. The specific merging strategy is presented in the Appendix. Then, we manually collect possible candidate classical literary works corresponding to these plants from various classical Chinese anthologies[2].

Subsequently, as shown in Figure 3 (a), we design a three-stage framework to annotate the plant mentioned in classical literary work, using a dedicated model, LLM, and manual review. Specifically, we first train a dedicated model on historical data to generate a candidate plant list for each classical literary work. The LLM then, in a one shot manner without updating any model parameters (Zhang et al., 2024), selects the plant that best corresponds to each work, and the results are manually verified to produce the final mapping. During this process, we retain only entries that can

[1] http://www.sp2000.org.cn/

[2] https://www.gushiwen.cn/, http://gs.changrun.org/

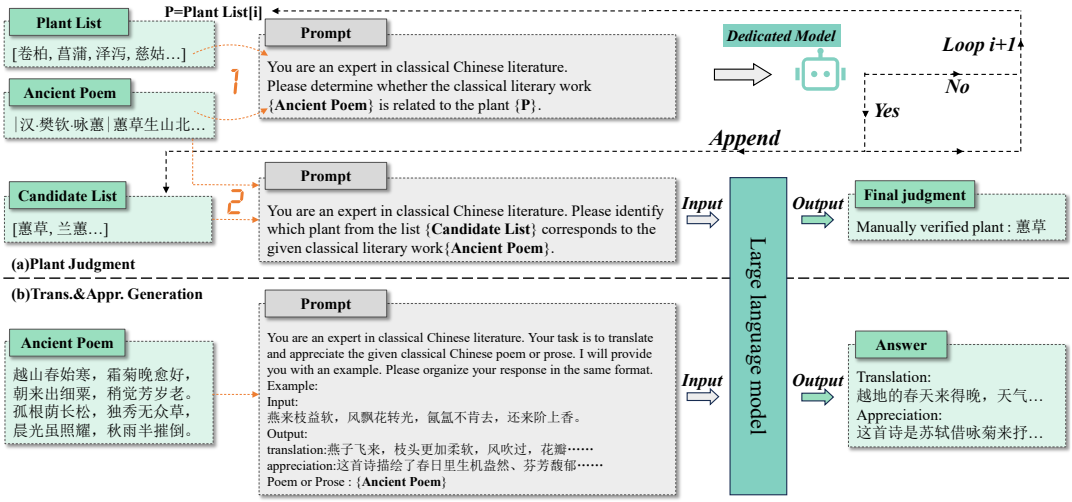


Figure 3: An example of (a) plant judgment, and (b) translation and appreciation generation.

be uniquely mapped to a single plant species.

3.3 Attributes Extraction

After completing the expansion and organization of the dataset, we extract relevant attributes for each plant and its corresponding classical literary works. These attributes include the encyclopedic knowledge of each plant, the translation and appreciation of each classical literary work, ancient paintings depicting each plant, and modern photographs of each plant.

Encyclopedic Information of Plants. Firstly, we retrieve the plant's entry from Wikipedia and other encyclopedic websites[3] and extract the required information, including the botanical name, scientific classification, morphological characteristics, planting situation, growth habits, and uses and organize these information into a fixed format. Then we leverage the classical literary works and related historical information recorded in original dataset to guide LLM to construct information of each plant's ancient morphological characteristics, planting situation, distribution.

Images of Plants. We collect ancient paintings depicting each plant, and modern photographs of each plant. For ancient paintings, we select works from historical atlases [4], these atlases contain a large number of ancient plant illustrations, which we manually collect and align with plant information. For modern photographs, during the process of collecting botanical information from the aforementioned encyclopedic websites, we also gather modern photographs from these sources.

[3] https://zh.wikipedia.org/

[4] https://www.shuge.org/view/jin_shi_kun_chong_cao_mu_zhuang/

Dataset	Original	Proposed	Growth
Plant	474	780	64.6%
Image	0	1,911	∞
Poet	821	3,072	274.2%
C_T	61	174	185.2%
C_L	10,604	44,298	317.7%

Table 1: Comparison between the proposed dataset and the original dataset. C_T and C_L mean Classical Chinese Text and Classical Literary Work.

Translation and Appreciation of classical literary works. As shown in Figure 3 (b), we employ a one-shot strategy to instruct the LLM to perform both translation and literary appreciation for each classical literary work in the dataset. The quality analysis of the translations and appreciations generated by the LLM is presented in the Appendix.

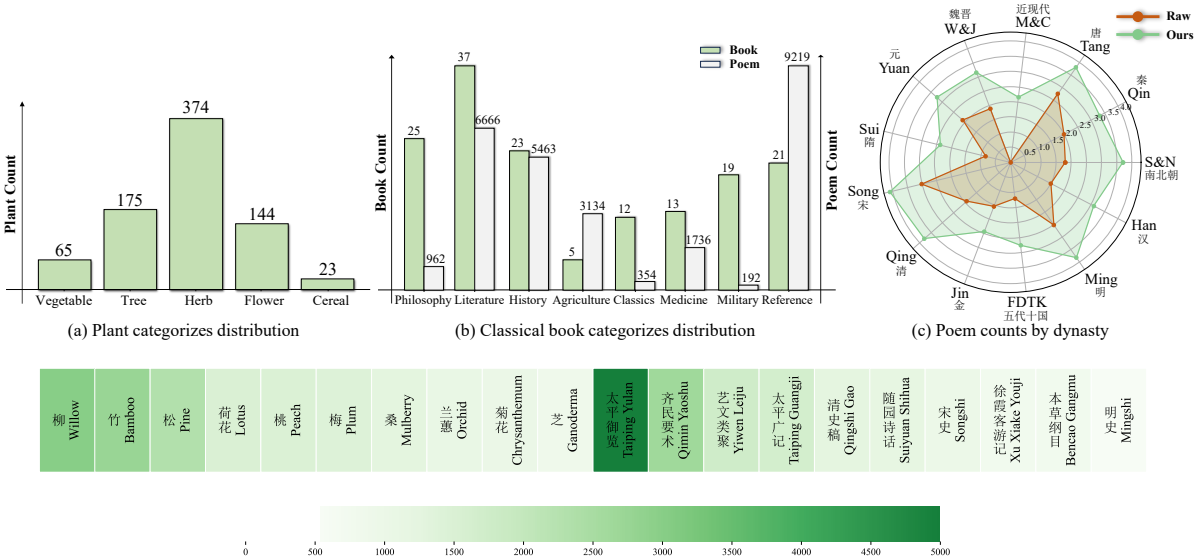
Figure 1 shows an example of an annotated data entry, which includes the original text and its corresponding labeled encyclopedic information, translation, appreciation, as well as modern and ancient images.

3.4 Statistics and Analysis

In this subsection, we give some statistics and analysis to evaluate the effective and importance of the proposed new dataset.

Overall Statistics

Table 1 demonstrates a basic comparison the proposed dataset and the original dataset. It is evident that the dataset has been significantly enriched in both diversity and volume. The data distribution



(a) Plant categorizes distribution (b) Classical book categorizes distribution (c) Poem counts by dynasty

(d) Top-10 most frequent plants and classical texts in the dataset

Figure 4: Overview of the dataset: (a) and (b) depict the distribution of plant species among major categories and the number of classical books and literary works across classical book categories. (c) shows the number of classical literary works from different dynasties before and after dataset expansion, where the values in the figure are log transformed. Here, W&J, S&N, FDTK, and M&C refer to the Wei-Jin period, the Southern and Northern Dynasties, the Five Dynasties and Ten Kingdoms, and the Modern and Contemporary period, respectively. (d) shows the top 10 plants and classical texts with the largest number of associated classical literary works in the dataset.

has been further balanced: while the number of plant species increases by less than twofold, the total number of classical literary works grows by more than four times. In addition, to integrate multimodal information from both historical and contemporary perspectives, we associate each plant species with ancient paintings and modern photographs. As a result, a total of 1,911 images are collected for 780 plant species.

Statistics of Plants

Figure 4 (a) demonstrates that the taxonomic diversity of plant species in our dataset, along with a balanced distribution across five predefined categories, ensuring adequate representation for conducting fine-grained studies within each category. In addition, the top 10 plant species depicted in Figure 4 (d) have the highest frequency of occurrence in classical Chinese texts. These plants are commonly found in China, especially in ancient China, and are frequently celebrated in classical literary works, such as willows, chrysanthemums, and orchids.

Statistics by Dynasty

As shown in Figure 4 (c), Chinese history is divided into 13 distinct periods, and we analyze the number of classical literary works from each.

The dataset is predominantly composed of works from the Tang (A.D. 618-907), Song (A.D. 960-1279), Ming (A.D. 1368-1644), and Qing (A.D. 1636-1912) dynasties. These periods provide rich material and can serve as focal points for more in-depth research focused on specific dynasties when needed. Focusing on the trends of specific dynasties allows for more in-depth exploration of their unique cultural characteristics.

Statistics by Classical Chinese Text

As shown in Figure 4 (b) and (d), we conduct a statistical analysis of classical Chinese texts by category and report the ten most frequently occurring texts in the dataset.

From the Figure 4(b), our dataset covers a wide range of classical Chinese texts across diverse categories, ensuring rich textual diversity and capturing the cultural and historical contexts of plants. Figure 4(d) further shows that these texts span multiple historical periods, from the Song to the Qing Dynasty, and include various genres such as historical records, reference works, essay collections, and ancient novels. This diversity enables a comprehensive analysis of the dissemination and evolution of plant classification knowledge across different historical periods and cultural domains.

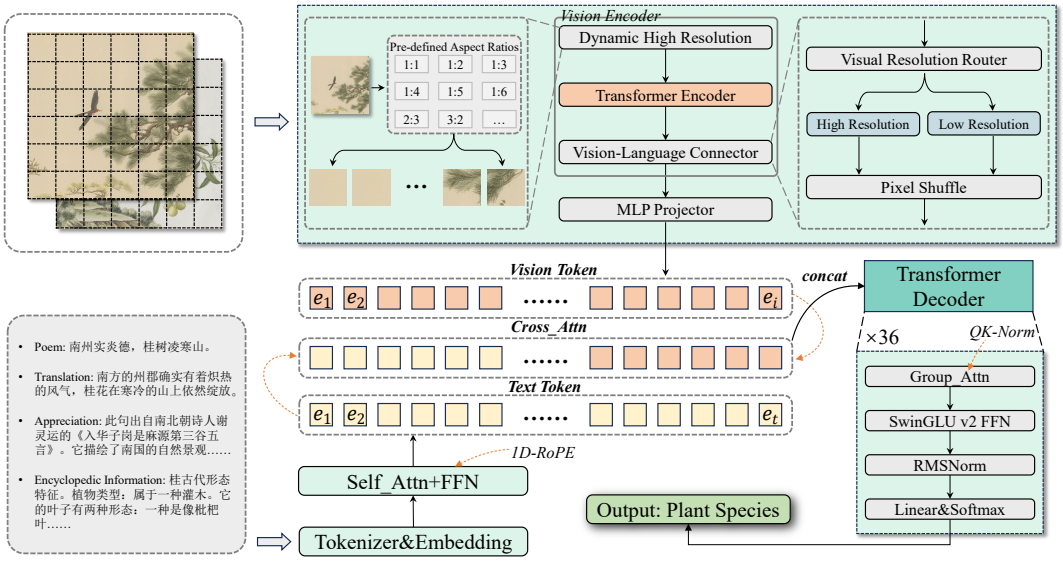


Figure 5: Overview of proposed multimodal plant classification model.

4 Multimodal Plant Classification Model

After collecting and constructing the new dataset, to verify the effectiveness of the dataset we have built, we propose a novel *plant multi-class classification* task based on classical literary works. The input of this task consists of classical literary work and images that depict the content of these classical literary work, while the output is the plant corresponding to the given classical literary work.

As shown in Figure 5, we propose a multimodal fusion model. This model can integrate textual information from classical literary work and image information to simultaneously predict the plant corresponding to the classical literary work.

4.1 Text Representation

Given an input text sequence $W = w_1, \ldots, w_t$ from classical literary work, we first tokenize the sequence and using an embedding matrix, thereby obtaining the hidden vector representations $H = h_1, \ldots, h_t$:

$$H = Embedding(w_1, \ldots, w_t) \quad (1)$$

Since the input consists of a sequential textual structure, we incorporate positional information via 1D-RoPE, which enables the model to capture relative token positions effectively. This sequence is then passed through a multi-layer self attention, combined with feed forward network at each layer, to generate context aware textual representations:

$$E_t = FFN(Self_Attn(h_1, \ldots, h_t)) \quad (2)$$

4.2 Visual Representation

Given an input image, we first apply dynamic high resolution processing to divide it into multiple fixed size patches $P = p_1, \ldots, p_i$. For patches that may contain critical information, we preserve their high resolution to avoid the loss of fine details. These patches are then fed into the ViT (Dosovitskiy et al., 2021), whose core architecture is built upon the transformer encoder.

After obtaining the visual representations encoded by the ViT, we further adopt the visual resolution router (ViR) (Wang et al., 2025) technique to improve the inference efficiency of the model. The key idea is to evaluate the semantic complexity of each patch: regions containing rich or fine-grained information are preserved with more tokens to avoid semantic loss, while redundant or relatively simple regions are compressed into fewer tokens. This adaptive resolution routing strategy effectively reduces inference latency while maintaining semantic integrity, thereby striking a balance between efficiency and accuracy.

After all patches are processed by the above module, they are flattened and mapped into a vector space. These vectors are then fed into two MLPs to project them into the same dimensional space as the text embeddings.

$$E_v = MLP(VisionEncoder(p_1, \ldots, p_i)) \quad (3)$$

4.3 Multimodal Transformer

In the previous representations for both text and visual inputs, text tokens and visual patches share

the same embedding dimension. The model then leverages cross attention to fuse information across modalities, after which the fused representations are concatenated and fed into a stack of transformer decoders for further processing.

$$\begin{aligned} E_t', E_v' &= Cross_Attn(E_t, E_v) \\ y &= Decoder(Concat(E_t', E_v')) \end{aligned} \tag{4}$$

It is worth noting that in the GQA component of our model, we adopt QK normalization (Henry et al., 2020). Before computing attention, both queries and keys are normalized to prevent large variations in magnitude from affecting the attention scores. This improves the stability of training and helps the model better align information across different modalities.

As a result, the model becomes more adept at capturing the relationships between space and time when processing images, text, or videos, thereby boosting its overall understanding ability.

4.4 Training

The goal of the proposed model is to maximize the output plant name P_n probability given the input classical literary work, its associated textual information W, and visual information P. Here, we use h_m to represent multimodal input. Therefore, we optimize the negative log-likelihood loss function:

$$\begin{aligned} \mathbf{h}_m &= \{W, P\} \\ \mathcal{L}_{\text{mpc}} &= -\frac{1}{N} \sum_{(P_n, h_m) \in \tau}^{N} \log P(P_n^{(i)} \mid \mathbf{h}_m^{(i)}; \theta) \end{aligned} \tag{5}$$

where θ is the model parameters, and (P_n, h_m) is a (plant, multimodal information) pair in training set τ, then:

$$\begin{aligned} &\log P(P_n \mid \mathbf{h}_{\text{m}}; \theta) \\ &= \frac{1}{N} \sum_{i=1}^{N} \log P(P_n^i | P_n^1, \ldots, P_n^{i-1}, h_m; \theta) \end{aligned} \tag{6}$$

where $P(P_n^i | P_n^1, \ldots, P_n^{i-1}, h_m; \theta)$ is calculated by the model.

5 Experiments

In this section, we introduce our experimental setup, showcase the experimental results, and analyze the impact of various factors on the experimental outcomes.

Method	P.	R.	F1.
Rule	0.4428	0.3855	0.4122
GPT-5	0.6880	0.6990	0.6934
MT5-base	0.3988	0.3404	0.3672
Llama2-7B	0.5711	0.5246	0.5468
Qwen2-7B	0.5497	0.5406	0.5451
Mengcheng et al.	0.8040	0.7232	0.7651
Kang et al.	0.7670	0.7680	0.7680
Tang et al.	0.8035	0.7619	0.7824
Blouin et al.	0.5553	0.6127	0.5826
Ours	**0.8020**	**0.7893**	**0.7956**

Table 2: Comparison with baselines.

5.1 Setting

We randomly divide the proposed new dataset into a training set, a validation set, and a testing set, with a split ratio of 8:1:1. We employ InternVL3_5-8B[5] and fine-tune its parameters for our classical literary works plant classification model. We select the best model by early stopping using the eval loss on the validation dataset. The model parameters are optimized by AdamW(Loshchilov and Hutter, 2019) with a learning rate of 5e-5. The batch size is 8. Our experiments are carried out with an Nvidia RTX 4090 GPU. In evaluation, we calculate the Precision and Recall, and use F1 score as the final evaluation metric for classical literary works plant recognition.

5.2 Main Results

As show in Table 2, we conduct experimental comparisons on multiple baseline models, along with a rule-based experiment. The input consists solely of classical literary works. Among these baselines: *Rule* refers to rule-based matching, where semantic similarity analysis[6] is directly conducted between classical Chinese poetry and plant names; *Llama3-8B* (Touvron et al., 2023), *MT5-base* (Xue et al., 2021), *Qwen2-7B* (Yang et al., 2024) have all been pre-trained on large scale Chinese corpora and strike a practical balance between model capacity and computational efficiency, providing sufficient representational power, which enables them to be effectively adapted to our task.

Since our work is the first to address plant classification in Classical Chinese, there are no base-

[5] https://huggingface.co/OpenGVLab/InternVL3_5-8B-HF

[6] https://huggingface.co/BAAI/bge-large-zh-v1.5

Method	P.	R.	F1.
Classical Literary Work	0.5497	0.5406	0.5451
+Translation	0.7134	0.6897	0.7014
+Appreciation	0.7117	0.7109	0.7113
+Encyclopedic	0.7244	0.7383	0.7313
+The Above Three	0.7742	0.7794	0.7768
+Image	0.7251	0.7160	0.7205
+*ALL*	**0.8020**	**0.7893**	**0.7956**

Table 3: Results of different factors.

Method	P.	R.	F1.
Llava-v1.6-7b	0.6524	0.6553	0.6538
Qwen2.5-VL-7b	0.8104	0.7694	0.7894
MiniCPM-V-2_6	0.7146	0.6871	0.7006
Gemma-3-4b-it	0.6996	0.7011	0.7003
Ours	0.8020	0.7893	0.7956

Table 4: Performance on different multimodal models.

lines specific to the domain for direct comparison. Therefore, we select state of the art information extraction models (Mengcheng et al., 2023; Kang et al., 2024; Feng et al., 2024; Blouin et al., 2024) developed for other Classical Chinese tasks as our baselines, we adopt them for our plant classification task.

From the experimental results, it is evident that simple rule-based methods struggle to achieve satisfactory performance, indicating their limited capability in handling complex linguistic patterns. In contrast, approaches based on large models, particularly fine-tuned models, can yield superior results.

Furthermore, our proposed multimodal fusion method achieves the highest performance, significantly outperforming all baseline models ($p < 0.05$). Additionally, compared with other works on information extraction from various types of ancient texts, our model consistently outperforms their results.

5.3 Impact of Different Factors

Table 3 shows the comprehensive results of the experiments by analyzing the impact of different factors. From the experimental results, it is clear that translation information, literary appreciation content, and encyclopedic knowledge all play significant roles in the classification task, offering substantial performance improvements compared to using literary work information alone. This demonstrates that providing translation and appreciation, helps the model better understand semantic content and capture subtler associations between text and plant entities, reducing ambiguity inherent in classical expressions. Moreover, by incorporating unified visual information, we effectively alleviate the difficulty of understanding classical Chinese. Ultimately, we find that integrating all types of information into a multimodal large model yields the best classification results. These results confirm that a multimodal approach is essential for maximizing performance in complex plant classification task.

5.4 Influence of Multimodal Models

To comprehensively evaluate the performance of multimodal models in plant classification tasks, we conducted a series of experiments using various well known multimodal large models, including *LLaVA* (Liu et al., 2023a), *Qwen2.5* (Bai et al., 2025), *MiniCPM* (Yao et al., 2024), and *Gemma3* (Team et al., 2025). The experimental results are presented in Table 4.

When comparing the results of these multimodal models with single modal baselines, we observe that all multimodal models achieve significant improvements. This not only validates the effectiveness of our proposed multimodal model but also indicates that incorporating additional information such as images can significantly assist in plant classification tasks. The multimodal information provides a more comprehensive view of the plants, enabling the model to make more accurate and reliable classifications.

6 Conclusion

In this study, we aim to expand and improve ancient datasets using LLM. Focusing on the Great Compendium of Myriad Flowers, we gather information on numerous previously excluded plants, carefully select and organize ancient poetic and literary materials, and construct a comprehensive botanical encyclopedia knowledge system. Additionally, we collect ancient paintings and modern plant photographs to enrich the dataset. Furthermore, we propose a novel multimodal plant classification model designed to integrate multimodal information from both classical and contemporary sources, enabling the extraction of plant-related information from classical Chinese poetry and prose. Extensive experiments demonstrate the importance and effectiveness of the proposed dataset and method. More detailed analysis can be found in Appendix.

Limitations

Although this study has achieved certain results, there are still limitations and multiple directions for expansion. In terms of data, the current ancient poetic dataset is limited in scale and the content related to plants it covers is not comprehensive enough, making it difficult for the model to generalize to classical Chinese texts beyond poetry and affecting the depth and breadth with which the model can extract plant information from literary works.

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A Similarity Analysis among Plant, Text and Image

Table 5 presents the similarity metrics within our dataset, including three perspectives: text–image similarity, plant–image similarity, and ancient–modern (i.e., anc. and mod.) image similarity. These metrics are designed to evaluate how well the textual descriptions align with the corresponding visual representations, how closely plant-related information is reflected in images, and how consistent ancient illustrations are when compared with their modern counterparts.

To compute these similarities, we adapt CLIP (Radford et al., 2021), a large scale pre-trained neural network model that jointly encodes images and text into a shared embedding space. The semantic similarity between an image and its associated text or other image is then computed as the cosine similarity between their respective embeddings. We calculate the similarity for all pairs in the dataset and then compute the mean of these values to obtain a global measure of the dataset. By leveraging its powerful cross modal alignment capabilities, CLIP allows us to quantitatively assess the degree of semantic consistency across different modalities in our dataset, thus providing an important reference for evaluating data quality and guiding downstream tasks.

Source	Target	Similarity
Image	Plant	0.3604
Image	Text	0.3716
Anc.Image	Mod.Image	0.4182

Table 5: Results of similarity analysis.

Latin name	Chinese name
Astragalus aksuensis	阿克苏黄芪
Astragalus albicans	革果黄芪
Astragalus alopecias	长尾黄芪
Lagerstroemia stenophylla	狭叶紫薇
Lagerstroemia subcostata	南紫薇
Lagerstroemia venusta	西双紫薇

Table 6: An example of original data.

B Strategy of Plant List Merging

In the data augmentation stage, we find that the raw plant list obtained from the Catalogue of Life China contains too many entries, and we need to reduce the list size to meet our requirements. Table 6 shows a portion of the original data. In the full dataset, many entries exhibit similar patterns, where a single plant species appears under multiple fine-grained taxonomic categories.

Therefore, we adopt a rule-driven merging strategy based on botanical naming conventions. In botanical taxonomy, the Latin scientific name of a plant follows a binomial nomenclature, where the first term denotes the genus, and the subsequent term specify the species (Turland et al., 2018).

Leveraging this convention, we perform plant list merging at the genus level. Specifically, for each plant entry, the Latin name is tokenized using whitespace delimiters, and the first token is extracted as the genus identifier. All entries sharing the same genus are then grouped and merged into a single category. For example, the data shown in the table are merged into Astragalus and Lagerstroemia.

This deterministic rule enables the consolidation of multiple fine-grained species level records into a unified genus level representation.

The proposed rule-based strategy is fully unsupervised, does not rely on external taxonomic databases, and ensures high interpretability and reproducibility. By reducing fine-grained taxonomic redundancy while preserving core taxonomic structure, this approach effectively decreases the size of the plant list and improves its suitability for related data augmentation tasks. Based on the collected raw classical poems from multiple sources, we perform deduplication, and the final dataset retains only plants that are associated with more than 10 classical poems.

C Influence of Dynasties and Categories

Table 7 presents the classification performance across different plant categories. Overall, the model performs relatively well on trees and cereals, indicating strong classification ability for these categories. In contrast, the performance on flowers is comparatively lower, reflecting the fact that flowers are often described metaphorically in classical texts, which increases the difficulty of identification. Moreover, for vegetables and grasses, the results show a certain degree of imbalance: while the model achieves high precision in some cases, it is accompanied by relatively low recall, suggesting missed detections. In general, the model demonstrates strong performance on more straightforward categories, whereas categories with more implicit

Attribute	Herb	Tree	Flower	Vegetable	Cereal	ALL
Pre_Qin	1.0000	-	1.0000	-	1.0000	1.0000
Han	-	-	1.0000	-	0.8000	0.8333
W&J	1.0000	1.0000	0.7500	-	1.0000	0.8947
S&N	-	-	1.0000	-	0.6000	0.7778
Sui	-	1.0000	1.0000	-	1.0000	0.9286
Tang	1.0000	0.6667	0.8043	-	0.9333	0.8267
FDTK	1.0000	1.0000	0.6667	-	-	0.7500
Song	0.7500	0.8000	0.7983	1.0000	1.0000	0.8205
Jin	-	-	1.0000	-	-	1.0000
Yuan	-	1.0000	0.7273	-	1.0000	0.7895
Ming	0.6000	0.8000	0.6905	1.0000	1.0000	0.7193
Qing	-	-	0.9091	-	1.0000	0.9286
M&C	-	-	0.6667	-	-	0.6667
ALL	0.7500	0.8276	0.7868	1.0000	0.9385	0.8207

Table 7: Results of different dynasties and categories.

Translation					
Score	$Expert_1$	$Expert_2$	$Expert_3$	$Expert_4$	Consistency
Faithfulness	1.200	1.685	1.805	1.815	0.603
Accuracy	1.310	1.595	1.760	1.780	0.638
Fluency	1.445	1.690	1.960	1.970	0.645
Appreciation					
Score	$Expert_1$	$Expert_2$	$Expert_3$	$Expert_4$	Consistency
Faithfulness	1.655	1.64	1.97	1.965	0.694
Accuracy	1.315	1.775	1.855	1.74	0.589
Fluency	1.835	1.920	2.000	1.985	0.878

Table 8: Human evaluation of LLM generated translations and appreciations

or metaphorical expressions remain challenging.

Finally, we analyze the performance of our proposed model on different plant categories across various historical periods, with the results presented in Table 7. From these results, we can observe that classical literary works from periods such as the Yuan and Ming dynasties often employ more subtle and nuanced metaphors to describe plants, making information extraction more challenging. At the same time, the results reveal the aesthetic preferences of poets in different eras, showing which plant species are more frequently celebrated or symbolically emphasized in their works. This analysis not only highlights the temporal variations in literary representation but also provides insights into the cultural and ecological significance of specific plants throughout Chinese history.

D Evaluation of LLM Generated Translations and Appreciations

To evaluate the quality of the LLM generated translations and literary appreciations, we invite four domain experts—one PhD student and three Master's students—to conduct an assessment. Following prior work on Classical Chinese processing (Jiang et al., 2023), we adopt three evaluation dimensions—faithfulness, accuracy, and fluency—to systematically examine the generated results. We use the AvgAgr metric (Wiebe et al., 2005) to measure inter annotator agreement.

The evaluation scheme is based on classical Chinese poems and their corresponding translations or appreciations, using the following scoring rubric:

- 0: completely not conforming (relevance below 30%)
- 1: basically conforming (relevance between 30% and 60%)

Case	Label	Literary Work	+ALL
渊明岂但隐逸人，渊明素怀诸葛志， 清香不独占秋天，菊潭一滴三千岁。 Tao Yuanming, more than a recluse, bore Zhuge Liang's ambition. Chrysanthemums bloom beyond autumn, their scent endures millennia.	菊花 Chrys.	菊花 ✓ Chrys.	菊花 ✓ Chrys.
春风满面喜津津，纵有痴拳不忍嗔， 窃恐意观安注脚，笑他何事与何人。 Spring breeze brings delight, foolish blows stir no wrath. I fear his thoughts chase notes, laughing at nothing, with no one.	含笑 Michelia	菊花 ✗ Chrys.	含笑 ✓ Michelia
六出玉盘金屈卮，青瑶丛里出花枝， 清香自信高群品，故与江梅相并时。 Six jade plates, golden cup, a flower blooms from green clusters. Fragrance rivals the finest, blooming with the river plum.	水仙 Narcissus	山矾花✗ Ixora	水仙✓ Narcissus

Table 9: Case analysis.

- 2: mostly conforming (relevance above 60%)

Based on the results of human evaluation presented in Table 8, the translations and appreciations generated by the LLM exhibit several notable advantages.

In terms of translation, firstly, regarding fidelity, although there are some variations in the scores given by different experts, the overall relatively high scores suggest that the LLM generated translations can capture the core essence of the original classical Chinese poems. Secondly, for accuracy, the scores imply that the translations are able to precisely transfer the semantic and cultural information from the original poems. Finally, in terms of fluency, the high scores across the board show that the generated translations read smoothly and naturally.

As for the appreciations, the high fidelity scores demonstrate that the LLM can generate analyses that are closely related to the original poems. Moreover, the extremely high fluency scores for appreciations imply that the generated content is well organized and logically coherent, with a high level of language proficiency, which enhances the readability and persuasiveness of the appreciations.

E Case Study

Table 9 presents three examples of classical Chinese texts from our dataset, along with the results of plant classification under two settings: using the raw input, and combining all annotation information. Through these examples, we can clearly observe the varying levels of difficulty involved in extracting plant-related information from classical Chinese texts.

Firstly, when the text explicitly states the plant being described, even the simplest baseline methods are capable of correctly identifying the target plant.

However, this is not always the case. For instance, in the second example, classical texts often introduce other plants as contrasts or foils, which can easily mislead the model and result in incorrect classification.

Furthermore, in third example, the description of plants frequently relies on metaphors, allusions, and deep cultural background knowledge. Such implicit expressions pose an even greater challenge for accurate classification, as they require a certain level of cultural understanding.

F Prompt Template

We design the prompt by jointly incorporating role specification, explicit capability guidance, and out-

put space constraints, enabling the model to perform more robust, interpretable, and controllable reasoning in the task of plant classification from Classical Chinese texts.

The prompt template used for plant classification is as follows:

Role

- You are an expert in plant information extraction for Classical Chinese.
- Your task is to extract the plant described in Classical Chinese texts.

Skills

- Auxiliary information includes translations of Classical Chinese, literary appreciation, related encyclopedic knowledge, and images.
- You should combine the above information to carefully analyze the connotations of the Classical Chinese and make accurate judgments.

Constraints

- Your answer must select only from the candidate plant list:{plant_list}
- Only provide the plant name, without any other characters.

Input information: {text + image}

G Statement

We will release the dataset, along with the training code and model configurations, as open source upon acceptance of the paper.