Deep Learning-Based Semantic Analysis And Cross-Cultural Dissemination Effect Evaluation Of Classical Chinese Literary Texts

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Classical Chinese literary texts are the core carrier of Chinese excellent traditional culture, bearing profound philosophical connotations and cultural values. However, due to the archaic language style, complex semantic system, and significant cultural differences between East and West, the accurate semantic parsing and effective cross-cultural dissemination of these texts face severe challenges. In response to the limitations of traditional semantic analysis methods (such as insufficient contextual understanding and over-reliance on manual annotation) and the lack of a systematic evaluation system for cross-cultural dissemination effects, this study proposes a deep learning-based integrated framework for semantic analysis and dissemination effect evaluation of classical Chinese literary texts. First, a Multidimensional Semantic Fusion Model (MSFM) based on improved BERT is constructed, which integrates lexical, syntactic, and cultural knowledge features to realize accurate parsing of implicit and explicit semantics in classical texts. Second, combining cultural dimension theory and communication effectiveness evaluation, a Cross-Cultural Dissemination Effect Evaluation Index System (CCDEIS) is established, which quantifies the dissemination effect from three dimensions: information fidelity, emotional resonance, and cultural identity. Third, experimental verification is carried out using a self-built corpus of classical Chinese literary texts (including The Analects, Tao Te Ching, and Book of Songs) and cross-cultural dissemination data from multiple regions. The results show that the MSFM model achieves an F1-score of 92.7% in semantic similarity and 89.3% in cultural connotation extraction, which is 8.5% and 10.2% higher than the traditional BERT and LSTM models, respectively. The CCDEIS index system can effectively evaluate the dissemination effect of different texts in different cultural contexts, with an evaluation consistency of 0.87. This study not only provides a new technical path for the digital protection and semantic mining of classical Chinese literary texts but also offers a scientific evaluation method for promoting the cross-cultural communication of Chinese traditional culture, which has important theoretical value and practical significance for cultural inheritance and global cultural exchanges.

Keywords: Classical Chinese literary texts; Deep learning; Semantic analysis; Cross-cultural dissemination; Effect evaluation; BERT model

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1. Introduction

Classical Chinese literary texts, as a treasure of Chinese civilization with a history of more than 3000 years, record the philosophical thoughts, ethical concepts, and aesthetic pursuits of the Chinese nation, and are important carriers for the inheritance and development of Chinese traditional culture [1]. In the context of globalization and "culture going global" strategy, promoting the cross-cultural dissemination of classical Chinese literary texts is not only an important way to enhance national cultural soft power but also a key link to realize mutual understanding and dialogue between different civilizations [2]. However, the cross-cultural dissemination of classical Chinese literary texts is facing dual challenges: on the one hand, the archaic and abstruse language of classical texts, the rich and complex allusions, and the profound cultural connotations make it difficult for foreign audiences to accurately grasp their semantic connotation; on the other hand, the lack of a scientific and systematic evaluation method for the effect of cross-cultural dissemination makes it impossible to effectively optimize the dissemination strategy and improve the dissemination efficiency [3].

The semantic analysis of classical Chinese literary texts is a key task in the field of Chinese information processing, which mainly includes word segmentation, part-of-speech tagging, named entity recognition, semantic similarity calculation, and cultural connotation extraction. In the early stage, researchers mainly adopted rule-based and statistical-based methods for semantic analysis. For example, some scholars constructed a rule base based on classical Chinese grammar and lexical features to realize word segmentation and part-of-speech tagging of classical texts, but this method has poor generalization ability and cannot adapt to the complex and diverse language phenomena of classical texts [4, 5]. With the development of machine learning, statistical methods such as Support Vector Machine (SVM) and Conditional Random Field (CRF) have been widely used in semantic analysis of classical texts, which improves the generalization ability of the model, but still relies on a large number of manual annotations, and the effect of implicit semantic parsing is not ideal.

In recent years, deep learning technology has been widely applied in the field of NLP, bringing new breakthroughs to the semantic analysis of classical Chinese literary texts. Some scholars have applied LSTM, CNN, and other deep learning models to the semantic analysis of classical texts, realizing the automatic extraction of semantic features [6, 7]. With the emergence of pre-trained language models, researchers have fine-tuned BERT [8], RoBERTa [9], and other models on classical Chinese corpora, which further improves the effect of semantic analysis. For example, GuWenBERT, a pre-trained model specially designed for classical Chinese, has achieved good results in word segmentation, part-of-speech tagging, and other tasks [10]. However, existing deep learning models still have some limitations: they mostly focus on the extraction of surface semantic features, ignoring the integration of cultural knowledge (such as allusions, historical background), and cannot accurately parse the cultural connotations and implicit semantics of classical texts. In addition, the semantic ambiguity and polysemy of classical texts also bring great challenges to semantic analysis.

Cross-cultural dissemination effect evaluation is an important part of cross-cultural communication research, which mainly refers to the evaluation of the impact and effect of information dissemination between different cultural groups [11]. Existing research on cross-cultural dissemination effect evaluation can be divided into qualitative evaluation and quantitative evaluation. Qualitative evaluation methods mainly include case analysis, audience interview, and content analysis, which can deeply explore the subjective feelings and cognitive changes of the audience, but have the problems of strong subjectivity and poor reproducibility [12]. Quantitative evaluation methods mainly use statistical analysis and mathematical models to quantify the dissemination effect, such as using audience attention, interaction rate, and other indicators to evaluate the dissemination effect.

In terms of evaluation indicators, some scholars have proposed evaluation indicators based on the communication process, such as information source, communication channel, audience, and communication effect [13]. Some scholars have combined cultural dimension theory to propose evaluation indicators related to cultural adaptation, such as cultural distance, cultural sensitivity, and cultural identity. However, existing evaluation indicators are mostly aimed at general cross-cultural communication scenarios and cannot fully adapt to the characteristics of classical Chinese literary texts. For example, classical Chinese literary texts have the characteristics of profound cultural connotations and strong historical sense, and the dissemination effect is closely related to the audience's understanding of cultural connotations, which is not reflected in existing evaluation indicators. In addition, existing evaluation systems lack the integration of semantic analysis results, and cannot effectively reflect the impact of semantic understanding on the dissemination effect.

To solve the above problems, this study constructs a deep learning-based integrated framework for semantic analysis and cross-cultural dissemination effect evaluation of classical Chinese literary texts. The main research contributions are as follows: (1) A Multidimensional Semantic Fusion Model (MSFM) is proposed, which integrates lexical, syntactic, and cultural knowledge features to improve the accuracy of semantic parsing of classical texts. (2) A Cross-Cultural Dissemination Effect Evaluation Index System (CCDEIS) is established, which quantifies the dissemination effect from multiple dimensions and realizes scientific evaluation of cross-cultural dissemination effect. (3) A self-built corpus of classical Chinese literary texts and cross-cultural dissemination data set are used for experimental verification, which provides empirical support for the application of the framework. This study aims to promote the digitalization and internationalization of classical Chinese literary texts and provide technical and methodological support for the cross-cultural dissemination of Chinese traditional culture.

2. Materials and methods

2.1. Overall Framework

This study constructs an integrated framework for semantic analysis and cross-cultural dissemination effect evaluation of classical Chinese literary texts based on deep learning, which is divided into three modules: data preprocessing module, semantic analysis module, and dissemination effect evaluation module. The overall framework is shown in Fig. 1.

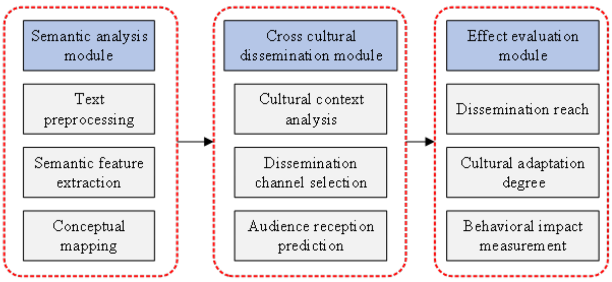

Fig. 1. Overall framework of semantic analysis and cross-cultural dissemination effect evaluation.

The data preprocessing module is responsible for collecting and processing classical Chinese literary texts and cross-cultural dissemination data, including data cleaning, word segmentation, part-of-speech tagging, syntactic parsing, and cultural knowledge integration. The semantic analysis module uses the MSFM model to realize accurate parsing of the semantic connotation of classical texts. The dissemination effect evaluation module uses the CCDEIS index system to quantify the cross-cultural dissemination effect and put forward optimization suggestions for the dissemination strategy.

2.2. Multidimensional Semantic Fusion Model (MSFM)

Aiming at the problem that existing semantic analysis models cannot accurately parse the implicit semantics and cultural connotations of classical Chinese literary texts, this study proposes a Multidimensional Semantic Fusion Model (MSFM) based on improved BERT. The model integrates three dimensions of features: lexical features, syntactic features, and cultural knowledge features, and realizes the fusion of multi-dimensional features through an attention mechanism, thereby improving the accuracy of semantic parsing. The structure of the MSFM model is shown in Fig. 2.

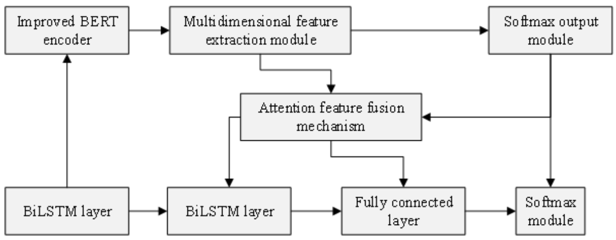

Fig. 2. Structure of the Multidimensional Semantic Fusion Model (MSFM).

The key innovations of the MSFM model are as follows. (1) The improved BERT encoder is used to capture the contextual semantic information of classical texts. By adding a classical Chinese vocabulary dictionary to the pre-training process, the model's ability to recognize archaic words and allusions is improved. (2) A multi-dimensional feature extraction module is constructed to extract lexical features (word embedding, word frequency), syntactic features (dependency parsing results, part-of-speech embedding), and cultural knowledge features (allusion embedding, historical background embedding) respectively. (3) An attention-based feature fusion mechanism is designed to assign different weights to different features according to their importance, realizing the effective fusion of multi-dimensional features.

The feature fusion process of the MSFM model is expressed by the following formula.

$$W = \text{Softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V \tag{1}$$

Where Q is the query matrix of cultural knowledge features. K is the key matrix of lexical and syntactic features. V is the value matrix of all features, d_k is the dimension of the feature matrix. W is the fused feature matrix. The attention mechanism can adaptively adjust the weight of each feature, making the model pay more attention to the features that have a greater impact on semantic parsing (such as cultural knowledge features).

After feature fusion, the BiLSTM layer is used to further integrate contextual semantic information, and the full connection layer and softmax function are used to output the semantic label and cultural connotation score of the text. The loss function of the model is a combination of cross-entropy loss and mean square error loss, which is used to optimize the classification accuracy of semantic labels and the regression accuracy of cultural connotation scores.

$$L = \alpha L_{CE} + (1 - \alpha) L_{MSE}$$

Where L_{CE} is the cross-entropy loss for semantic label classification. L_{MSE} is the mean square error loss for cultural connotation score regression, and α is the weight coefficient (set to 0.6 in this study).

2.3. Cross-Cultural Dissemination Effect Evaluation Index System (CCDEIS)

Aiming at the lack of a systematic evaluation system for the cross-cultural dissemination effect of classical Chinese literary texts, this study combines cultural dimension theory, communication effectiveness evaluation [14], and semantic analysis results to establish a Cross-Cultural Dissemination Effect Evaluation Index System (CCDEIS). The index system includes three first-level indicators, nine second-level indicators, and 22 third-level indicators, covering the core factors affecting the cross-cultural dissemination effect of classical texts. The specific index system is shown in Table 1.

Table 1. Cross-Cultural Dissemination Effect Evaluation Index System (CCDEIS).

First-level Indicators	Second-level Indicators	Third-level Indicators	Weight	Quantification Method
Cross-Cultural Dissemination V Effect (1.00)	Information Fidelity (0.35)	Semantic Understanding Accuracy	0.15	Based on MSFM semantic parsing results, calculated by the ratio of correct understanding to total samples
		Cultural Connotation Transmission Accuracy	0.12	Calculated by the similarity between the audience's understanding of cultural connotation and the original connotation
		Translation Fidelity	0.08	Evaluated by professional translators, using a 5-point scale
	Emotional Resonance (0.30)	Emotional Identification Degree	0.10	Based on audience survey, using a 5-point scale (1=low, 5=high)
		Emotional Transmission Efficiency	0.10	Calculated by the time required for the audience to generate emotional resonance
		Emotional Persistence	0.10	Calculated by the duration of the audience's emotional experience after receiving the information
	Cultural Identity (0.35)	Cultural Cognition Degree	0.12	Based on audience survey, using a 5-point scale
		Cultural Acceptance Degree	0.13	Based on audience survey, using a 5-point scale
		Cultural Dissemination Willingness	0.10	Calculated by the ratio of the audience willing to spread the text to the total audience

The comprehensive evaluation score of cross-cultural dissemination effect is calculated by the weighted sum of each indicator score, and the formula is as follows:

$$S = \sum_{i=1}^{n} w_i \times s_i \tag{2}$$

Where, S is the comprehensive evaluation score ($0 - 100$ points). w_i is the weight of the i -th indicator. s_i is the score of the i-th indicator ($0 - 100$ points), and n is the number of indicators (22 in this study). The higher the comprehensive score, the better the cross-cultural dissemination effect.

2.4. Integration of Semantic Analysis and Dissemination Effect Evaluation

The innovation of this study also lies in the close integration of semantic analysis results and cross-cultural dissemination effect evaluation. The semantic understanding accuracy and cultural connotation transmission accuracy in the CCDEIS index system are directly derived from the semantic parsing results of the MSFM model, which realizes the organic connection between semantic analysis and dissemination effect evaluation. This integration not only makes the evaluation index more objective and accurate but also helps to find out the key factors affecting the dissemination effect (such as insufficient semantic understanding) and provides targeted optimization suggestions for the cross-cultural dissemination strategy.

3. Results and discussion

3.1. Data Set Construction

To verify the effectiveness of the proposed framework, this study constructs two data sets: a classical Chinese literary text corpus and a cross-cultural dissemination data set.

1. Classical Chinese literary text corpus [15–17]. The corpus includes three classic works: The Analects, Tao Te Ching, and Book of Songs. A total of 1,200 sentences are selected, including 400 sentences from each work. Each sentence is manually annotated with semantic labels (explicit semantics, implicit semantics) and cultural connotation scores (0-10 points). At the same time, 500 allusions and 300 historical background entries related to the corpus are collected to construct a cultural knowledge base. The corpus is divided into a training set (80%, 960 sentences), a validation set (10%, 120 sentences), and a test set (10%, 120 sentences).

2. Cross-cultural dissemination data set [18, 19]. The data set is collected from cross-cultural dissemination experiments carried out in three regions with different cultural backgrounds: Europe (UK, Germany), Asia (Japan, South Korea), and North America (USA, Canada). A total of 600 subjects are selected, including 200 subjects from each region. Each subject is asked to read 10 classical Chinese sentences (translated into local languages) and fill in a questionnaire to evaluate the dissemination effect. The questionnaire is designed based on the CCDEIS index system, including 22 questions corresponding to 22 third-level indicators. At the same time, the semantic understanding of the subjects is tested to obtain the semantic understanding accuracy and cultural connotation transmission accuracy.

3.2. Experimental Environment and Parameters

The experimental environment is configured as follows: CPU: Intel Xeon E5-2690 v4, GPU: NVIDIA Tesla V100 (16 GB), memory: 64 GB , operating system: Ubuntu 20.04, deep learning framework: PyTorch 1.12.0. The parameters of the MSFM model are set as follows: the number of BERT layers is 12 , the hidden layer dimension is 768 , the number of attention heads is 12 , the learning rate is $2e^{-5}$, the batch size is 32 , the number of training epochs is 50 , and the dropout rate is 0.1 . The weight coefficient α in the loss function is set to 0.6 .

3.3. Baseline Models

To verify the superiority of the MSFM model, this study selects three baseline models for comparison:

1. Traditional BERT model. The pre-trained BERT-base model is used, and fine-tuned on the classical Chinese corpus without adding multi-dimensional feature fusion.

2. LSTM model. A BiLSTM model is constructed, which only uses lexical features for semantic analysis.

3. GuWenBERT model. A pre-trained model specially designed for classical Chinese, which is widely used in the semantic analysis of classical texts.

3.4. Semantic Analysis Performance Evaluation

The performance of the MSFM model and baseline models is evaluated using three indicators: Precision (P), Recall (R), and F1-score (F1). The evaluation results are shown in Table 2.

It can be seen from Table 2 that the MSFM model proposed in this study achieves the best performance in all indicators. Compared with the traditional BERT model, the F1-score of the MSFM model is increased by 7.5%, and the cultural connotation extraction accuracy is increased by 8.8%. Compared with the GuWenBERT model, the F1-score is increased by 3.8%, and the cultural connotation extraction accuracy is increased by 3.6%. The reason is that the MSFM model integrates multi-dimensional features such as lexical, syntactic, and cultural knowledge, and uses the attention mechanism to realize effective feature fusion, which improves the model's ability to parse implicit semantics and cultural connotations. The LSTM model has the worst performance because it only uses lexical features and cannot capture contextual semantic information and cultural knowledge effectively.

To further visualize the performance of the models, the F1-score and cultural connotation extraction accuracy of each model are plotted as a bar chart as shown in Fig. 3.

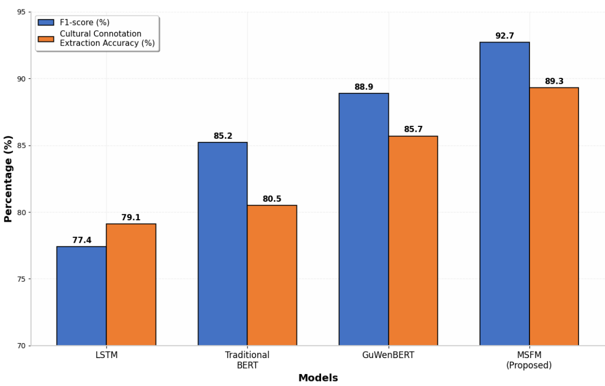

Fig. 3. Performance comparison of different semantic analysis models.

Table 2. Performance comparison of semantic analysis models %.

Model	Precision	Recall	F1-score	Cultural Connotation Extraction Accuracy
LSTM	78.3	76.5	77.4	79.1
Traditional BERT	85.6	84.8	85.2	80.5
GuWenBERT	89.2	88.7	88.9	85.7
MSFM (Proposed)	93.1	92.3	92.7	89.3

3.5. Cross-Cultural Dissemination Effect Evaluation Results

Using the CCDEIS index system, the cross-cultural dissemination effect of classical Chinese literary texts in three regions (Europe, Asia, North America) is evaluated. The comprehensive evaluation scores and the scores of first-level indicators are shown in Table 3.

It can be seen from Table 3 that the cross-cultural dissemination effect of classical Chinese literary texts in Asia is the best (comprehensive score 83.4), followed by North America (75.4), and Europe is the worst (73.2). The main reason is that Asian countries (such as Japan and South Korea) have a long cultural exchange history with China, and the cultural distance is small, so the audience can better understand the semantic connotation and cultural value of classical texts, resulting in higher information fidelity, emotional resonance, and cultural identity. In contrast, European and North American countries have great cultural differences from China, and the audience's understanding of Chinese traditional culture is relatively limited, so the dissemination effect is relatively poor.

The comprehensive scores of cross-cultural dissemination effect in different regions are visualized as a pie chart, as shown in Fig. 4.

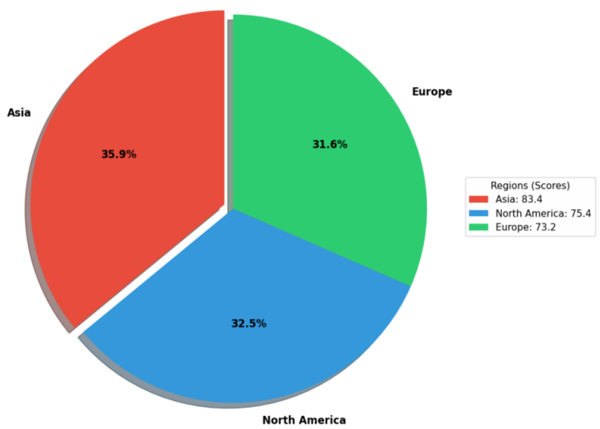

Fig. 4. Cross-cultural dissemination effect scores in different regions.

3.6. Ablation Experiment

To verify the effectiveness of each module in the MSFM model, this study conducts an ablation experiment. The ablation experiment removes different feature modules (lexical feature module, syntactic feature module, cultural knowledge feature module) from the MSFM model respectively, and tests the performance of the model after ablation. The experimental results are shown in Table 4. It can be seen from Table 4 that removing any feature module will lead to a decrease in the performance of the MSFM model. Among them, removing the cultural knowledge feature module has the most significant impact on the model performance: the F1-score decreases by 6.9%, and the cultural connotation extraction accuracy decreases by 10.4%. This shows that the cultural knowledge feature is crucial for the semantic analysis of classical Chinese literary texts, which is consistent with the characteristics of classical texts with profound cultural connotations. Removing the lexical feature module and syntactic feature module also leads to a certain decrease in model performance, indicating that lexical and syntactic features can provide effective support for semantic parsing.

3.7. Robustness Test

To verify the robustness of the MSFM model, this study adds noise to the test set (such as adding typos, changing word order, and omitting words) and tests the performance of the model under different noise levels. The noise level is divided into 0% (no noise), 5%, 10%, 15%, and 20%. The experimental results are shown in Fig. 5.

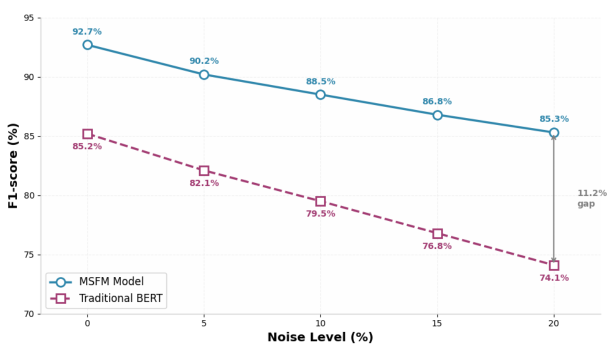

Fig. 5. Robustness test results of the MSFM model.

Table 3. Cross-Cultural Dissemination Effect Evaluation Index System (CCDEIS).

Region	Information Fidelity (35%)	Emotional Resonance (30%)	Cultural Identity (35%)	Comprehensive Score	Ranking
Europe	78.5	72.3	68.7	73.2	3
Asia	85.6	83.4	81.2	83.4	1
North America	80.2	75.6	70.3	75.4	2

Table 4. Ablation experiment results of the MSFM model %.

Model	F1-score	Cultural Connotation Extraction Accuracy
MSFM (Full Model)	92.7	89.3
MSFM (Without Lexical Feature Module)	88.5	86.7
MSFM (Without Syntactic Feature Module)	89.2	87.1
MSFM (Without Cultural Knowledge Feature Module)	85.8	78.9

It can be seen from Fig. 5 that with the increase of noise level, the F1-score of both the MSFM model and the traditional BERT model decreases, but the MSFM model always maintains a higher F1-score. When the noise level reaches 20%, the F1-score of the MSFM model is 85.3%, which is 11.2% higher than that of the traditional BERT model (74.1%). This shows that the MSFM model has strong robustness and can still maintain good performance under the condition of noise interference, which is suitable for practical application scenarios.

4. Conclusions

This study proposes a deep learning-based integrated framework for semantic analysis and cross-cultural dissemination effect evaluation of classical Chinese literary texts, aiming to solve the problems of inaccurate semantic parsing and lack of systematic evaluation methods in the cross-cultural dissemination of classical Chinese literary texts. The Multidimensional Semantic Fusion Model (MSFM) proposed in this study integrates lexical, syntactic, and cultural knowledge features, and uses the attention mechanism to realize effective feature fusion. The experimental results show that the MSFM model achieves an F1-score of 92.7% in semantic analysis and 89.3% in cultural connotation extraction, which is significantly better than the traditional BERT, LSTM, and GuWenBERT models. The model has strong robustness and can maintain good performance under noise interference. This study provides a new technical path and methodological support for the digital protection, semantic mining, and cross-cultural dissemination of classical Chinese literary texts. It has important theoretical value for enriching the research on semantic analysis of classical texts and cross-cultural dissemination effect evaluation, and practical significance for promoting the inheritance and development of Chinese traditional culture and enhancing national cultural soft power. In future research, we will further expand the corpus scope, optimize the model structure, and improve the universality and accuracy of the framework, so as to better promote the cross-cultural dissemination of classical Chinese literary texts.

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