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Proposal of a Comprehensive Evaluation Model for the Cultural Value of Tang Dynasty Literary Works Based on CNN and Text Features

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Abstract As a treasure of Chinese culture, Tang Dynasty literature carries rich cultural values, but lacks a systematic evaluation model. Traditional evaluation methods are highly subjective and difficult to comprehensively reflect the multidimensional value of Tang Dynasty literature. This study constructs a comprehensive evaluation model of the cultural value of Tang Dynasty literary works based on the improved Transformer model, and realizes the automatic evaluation of the cultural value of Tang Dynasty literary works through the technical improvements of the feature participle layer, the output participle CLS Token and the Pre-Norm structure. The study establishes an evaluation system containing 21 evaluation indexes from six aspects: historical dimension, ideological dimension, artistic dimension, humanistic dimension, cultural inheritance dimension and social function dimension. The experiment uses 1200 sample data, of which 1000 are used for training and 200 for testing. The results show that the improved Transformer model achieves an accuracy of 85% on the test set, with a precision of 1.0 and an F1 score of 0.862, which is better than the traditional CNN model and LSTM model. In further validation experiments, the model achieves an overall prediction accuracy of 92.65%, which is significantly higher than the CNN model's 80.65% and the LSTM model's 80.01%. Factor analysis showed that the cumulative variance contribution rate of the six main factors reached 83.79%, which can comprehensively reflect the cultural value of Tang Dynasty literary works. This study provides an objective and efficient quantitative method for evaluating the cultural value of Tang Dynasty literary works.

Index Terms Transformer model, Tang Dynasty literature, cultural value evaluation, attention mechanism, factor analysis, deep learning

I. Introduction

Tang Dynasty literature is the product of Chinese history when the feudal society reached the highest peak and began to fall from the highest peak, which became an extremely important link in the process of development of the literary tradition, and has an extremely important position in the history of literature [1]. From the general tendency and style, Tang Dynasty literature is full of passion, more idealistic, rich in romanticism, more lyrical, more open and outgoing without being conservative and too rational, as if it is a creative young man full of vigor and imagination, full of vitality and romantic atmosphere, which can give people the power of inspiration [2], [3]. This is the fundamental reason why Tang literature is the most attractive and infectious [4]. As far as the internal development of literature is concerned, Tang literature is the best inheritance of the literary tradition of the previous generation, absorbing the essence, eliminating the dross, absorbing and absorbing, and benefiting from many masters, showing a strong self-confidence and a broad-mindedness of mind [5], [6]. Tang Dynasty literature is the golden age in the history of Chinese literature, review and analyze the experience of literary development in this period, and view its position in the whole literary tradition, which will be of great benefit to today's literary construction and even cultural construction [7].

Cultural value is a social product, a property of things that satisfy individual cultural needs [8]. Deeper, from the perspective of culture, cultural value is expressed as the kernel of culture, as the affirmative or negative intention of culture, representing the basic interest of a certain culture, and is the directionality of the beauty and goodness of a culture [9]. From the human point of view, cultural value is expressed as “human meaning”, that is to say, to satisfy the purpose and needs of human beings, to construct the cultural psychological structure of human beings, to internalize the hereditary social psychology, to contribute to the construction and development of the society, and to produce “social meaning” [10], [11]. By comprehensively evaluating the cultural value of Tang Dynasty literature, corresponding countermeasures can be proposed for its planning and construction [12].

Literary works of the Tang Dynasty are the bright pearls in the treasure house of Chinese civilization, condensing the political wisdom, cultural essence and artistic achievements of ancient Chinese society. As the golden period of Chinese literary development, Tang literature has become an important window for the study of Chinese traditional culture with its rich ideological connotation, unique artistic style and far-reaching historical influence. The cultural value of literary works is embodied in multiple dimensions, including its realistic reproduction of historical events and comprehensive coverage of all social classes, as well as its profound revelation of the complexity of human nature and in-depth exploration of the philosophy of life, while also demonstrating achievements in artistic innovation and stylistic renewal. However, traditional evaluation of literary works often relies on subjective judgments of experts and lacks systematic and standardized evaluation methods, making it difficult to comprehensively and objectively capture the multi-dimensional cultural value of literary works. Especially in the context of the big data era, how to use modern technical means to efficiently and accurately evaluate the value of massive Tang Dynasty literary works has become an important topic in the field of literary research. Currently, artificial intelligence technology, especially deep learning methods, has made significant progress in the field of text analysis, providing a new technical path for the cultural value evaluation of Tang Dynasty literary works. Among them, the Transformer model, by virtue of its powerful self-attention mechanism and parallel processing capability, shows excellent performance in natural language processing tasks and provides technical possibilities for processing complex literary texts. Based on this, constructing a comprehensive evaluation model that combines deep learning technology and literary evaluation expertise is of great significance in promoting the scientific and precise study of Tang Dynasty literature.

This study proposes a comprehensive evaluation model for the cultural value of Tang Dynasty literary works based on the improved Transformer model. First, the core components of the Transformer model including the attention mechanism, multi-head attention mechanism, location coding, residual network and normalization are deeply analyzed. Then, the original Transformer model is improved in three aspects to address the characteristics of Tang Dynasty literary works data: first, a feature partition layer is introduced to process category features and numeric features separately to capture inter-feature relationships and importance; second, an output partition CLS Token is added to globally aggregate features across all the partition information to avoid bias of specific data on the results; Third, the Pre-Norm variant structure is used to front-load the normalization layer to improve the model training efficiency. In the construction of the evaluation system, a comprehensive evaluation system containing 21 evaluation indexes was established from six aspects, namely, historical dimension, ideological dimension, artistic dimension, humanistic dimension, cultural heritage dimension and social function dimension. Through factor analysis, the six main factors that could explain 83.79% of the total variance were extracted, and the comprehensive scoring function was constructed accordingly. Finally, the superior performance of the proposed model in the task of recognizing the cultural value of Tang Dynasty literary works is verified through comparison experiments with CNN model and LSTM model.

II. Evaluation model based on an improved Transformer model

II. A. Transformer Neural Network

II. A. 1) Attention mechanisms

The mechanism of attention is inspired by discoveries in the field of neuroscience. During the processing of information, the human brain engages in selective focusing, i.e., it pays more attention to certain specific inputs and ignores those that are not relevant. Certain neurons are able to respond more dramatically to specific input signals, while responses to other signals are relatively weakened or even inhibited. The sources of information cues can be divided into two broad categories: involuntary and autonomous sources. In the attention mechanism, autonomous cues are often called "Query", and the input data from the environment is called "Value", and each value is assigned a "Key" as an identifier for non-autonomous cues. This process, which uses the pairing of the query and the key, filters out the value that best fits the query (sensory input information) through the mechanism of focusing attention to achieve effective screening and processing of information [13]. The principle of the attention mechanism is shown in Figure 1.

Linear transformation of the input can obtain three matrices Q (query), K (key), and V (value), respectively. The calculation process of attention can be divided into four steps: in the first step, the dot product of Q (query) and K (key) is performed to obtain the correlation vector of word vectors with all word vectors. In the second step, the result of the dot product is normalized with the aim of reducing the gradient value so that it cannot be too large. In the third step, the result is mapped into the interval $[0,1]$ using the Softmax function. In the fourth step, the mapped results are used as weights to perform weighted averaging on the V (value) matrix to obtain the output of the input word vectors.

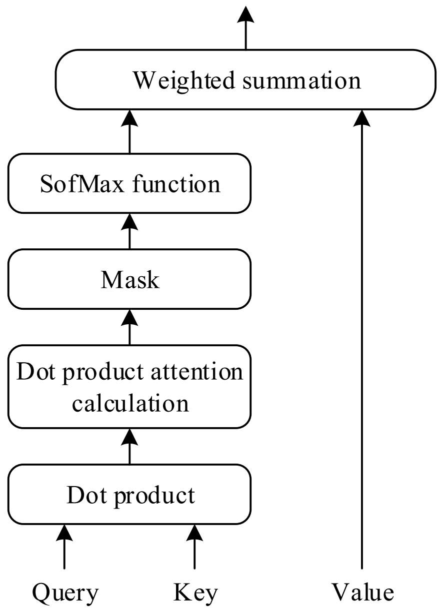

Figure 1: The principle of the attention mechanism

The process can be expressed as:

$$Attention(Q,K,V) = soft\max\left(\frac{QK^T}{\sqrt{d_k}}\right)V \tag{1}$$

where d_k is the row dimension of the Q and K matrices.

II. A. 2) Multi-attention mechanisms

The mechanism of multi-head attention is a combination of multiple self-attention. Instead of a simple superposition of multiple self-attention, in multi-head attention, multiple self-attention matrices are stitched together for parallel computation. The method uses several different linear projections to transform Q (query), K (key), and V (value), and then employs parallel processing in turn feeds into the attention aggregation. Each output is processed by a specific attention focusing mechanism, which is figuratively called a "head" [14]. The multi-head attention process is shown in Figure 2. The multi-head attention mechanism allows the model to focus on information from different locations and different representation subspaces at the same time, which improves the training effect of the model.

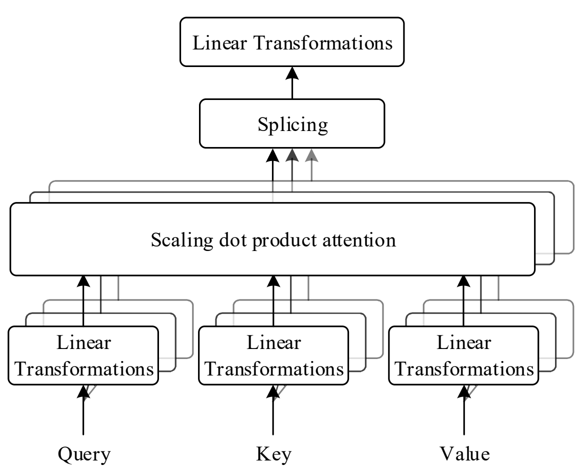

Figure 2: Multi-head attention mechanism diagram

II. A. 3) Position coding

In the model, for position coding, sine and cosine functions of different frequencies are used. The position coding equation is shown below:

$$PE(t,2i)=\sin\left(\frac{pos}{10000^{\frac{2i}{d_{model}}}}\right) \tag{2}$$

$$PE(t,2i+1)=\cos\left(\frac{pos}{10000^{\frac{2i}{d_{model}}}}\right) \tag{3}$$

where pos denotes the absolute position $(pos=0,1,2...)$. The d_{model} denotes the dimension of the word vector, i denotes the i th dimension of the word vector, and the $2i$ and $2i+1$ distributions denote the parity of the features.

II. A. 4) Residual networks

The structure of the residual network is shown in Fig. 3, where the input x jumps directly to the output over some specific layers, which can be visualized as “jump connections”. It can be seen that with the use of jump connections, what is learned in certain layers changes. The Residual Network (ResNet) is used to solve the problem of gradient degradation due to the depth of the layers, by allowing the gradient to propagate back to the lower layers using paths established by jump connections. From the figure, it can be assured that ResNet is allowing the model to learn constant mappings, i.e. mappings that pass directly from input to output without any transformations [15]. This ensures that the original features of the input signal are maintained as the depth of the network is increased, without losing or degrading this information.

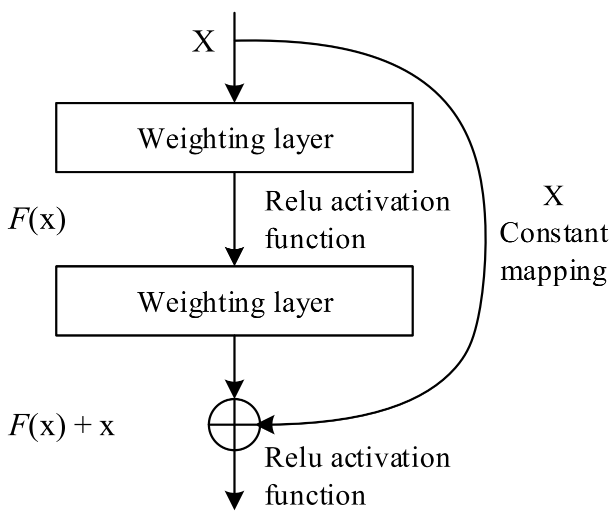

Figure 3: Residual network structure

II. A. 5) Normalization

In the Transformer structure, normalization is used simultaneously between the self-attentive and fully connected modules for training. The central role of normalization is to adjust all the hidden variables in the model so that they are close to or conform to the standard form of normal distribution. This process eliminates the unit differences and enhances the compactness and concentration of the data, thus making the model more efficient and stable in processing the data. The normalization formula is as follows:

$$u_j=\frac{1}{m}\sum_{i}^{m}x_{ij} \tag{4}$$

$$\sigma_j^2 = \frac{1}{m}\sum_{i}^{m}(x_{ji} - u_j)^2 \tag{5}$$

$$LayerNorm(x) = \frac{x_{ij} - u_j}{\sqrt{\sigma_j^2 + \varepsilon}} \tag{6}$$

where x_{ij} is the value of the i th row and j th column of the output matrix, μ is the mean of the j th column of the output matrix, and σ is the column variance of the output matrix. Subtract all the elements of the columns from the mean of the columns and divide by the standard deviation of the columns to finally get the normalized result. ε is a non-zero parameter, the role is to avoid the denominator is zero.

Normalization is mainly divided into two categories, batch normalization (BN) and layer normalization (LN). Where batch normalization involves first calculating a small batch of data and then using those statistics to normalize that batch, layer normalization does not depend on the size of the batch and is calculated on a single sample.

II. A. 6) Masking Multiple Attention

The decoder consists of three sub-layers, two of which are similar to the encoder, the multi-head attention layer and the feed-forward neural network layer. The decoder also has a unique sublayer, the masked multi-head attention layer. In the masked multi-head attention layer, in order to satisfy the condition that the encoder can only obtain the current information and cannot predict the future information, it is necessary to mask some of the data. In practice, an additional masking transformation is performed on each sequence. This transformation generates a square matrix whose dimension is greater than the length of any sequence. In the matrix, the values in the upper triangular positions are all 0, while the values in the remaining positions are set to an extremely large negative value or $-\infty$. The masking operation is accomplished by applying this matrix to each sequence.

II. B.Model Improvement for Tang Dynasty Literary Works Data

Traditional Transformer models simply take categorical feature embeddings and convert them to contextual embeddings through the Transformer model, and subsequently connect numerical features to them to produce results through a multilayer perceptual machine. However, the exclusion of numeric features from the table problem will prevent the Transformer model from achieving the same level of sophistication in this problem as in the field of natural language processing.

II. B. 1) Feature Segmentation Layer

The data of Tang Dynasty literary works are processed by feature discretization to uplift each feature and generate corresponding weight vectors. These weight vectors capture the relationship and importance between features. Feature disambiguation separates category features and numeric features as two parts of the input. Each dimension of the numeric features is multiplied with the corresponding weight vector $W_j^{(num)}$ and a bias b_j is added. This encodes the numerical features and preserves their information. The categorical features are processed as follows: for the categorical features, first a solo thermal encoding is performed, and then the encoded vector is multiplied by the matrix of weight vectors $W_j^{(cat)}$ and the bias b_j is added. This converts the category features into a continuous vector representation. After feature processing, all converted vectors are stacked together to form the final feature representation.

For the input x transformed into an embedding $T \in \mathbb{R}^{k\times d}$, the computation is as follows:

$$T_j = b_j + f_j(x_j) \in \mathbb{R}^d \quad f_j : x_j \to \mathbb{R}^d \tag{7}$$

where b_j is the j th feature and e_j^T is the unique heat vector of the corresponding category of features, computed as follows:

$$T_j^{(num)} = b_j^{(num)} + x_j^{(num)} \cdot W_j^{(num)} \in \mathbb{R}^d \tag{8}$$

$$T_j^{(cat)} = b_j^{(cat)} + e_j^T W_j^{(cat)} \in \mathbb{R}^d \tag{9}$$

$$T = stack\left[T_1^{(num)},\cdots,T_{k^{(num)}}^{(num)},\cdots,T_1^{(cat)},\cdots,T_{k^{(cat)}}^{(cat)}\right] \in \mathbb{R}^{k\times d} \tag{10}$$

II. B. 2) Output Split CLS Token

The usage of output participle CLSToken originates from the field of natural language processing and is equally applicable when facing problems. The basic idea is that, after embedding the features, an output participle CLSToken is attached to the features, which makes a global feature aggregation of the information of all the other participles, and does not need to be based on the training data itself, which effectively avoids the bias of the specific data in the data on the results. At the same time, CLSToken uses a fixed positional encoding that is fixed at the beginning of the sequence, which also effectively avoids the interference of positional encoding. In this way, the categorical embedding and numerical embedding can be effectively captured with relevance and contextual information through the Transformer module. After that, the CLS disambiguation embeddings of the contextual context will be used as inputs to the subsequent MLP classifiers to produce the output of the final model.

$$T0 = stack\left[\left[CLS\right], T\right] \tag{11}$$

II. B. 3) Transformer module

In the Transformer module, a Pre-Norm variant is used, where two normalization layers are added before the multi-head self-attention module and the feed-forward neural network, and in more in-depth model training, the Pre-Norm variant demonstrates a higher efficiency compared to the initial Transformer model Post-Norm construction, the Pre-Norm structure as shown in Figure 4. The final CLS disambiguation is used to represent the output with the following mathematical expression:

$$\hat{y} = Linear\left(ReLU\left(LayerNorm\left(T_L^{[CLS]}\right)\right)\right) \tag{12}$$

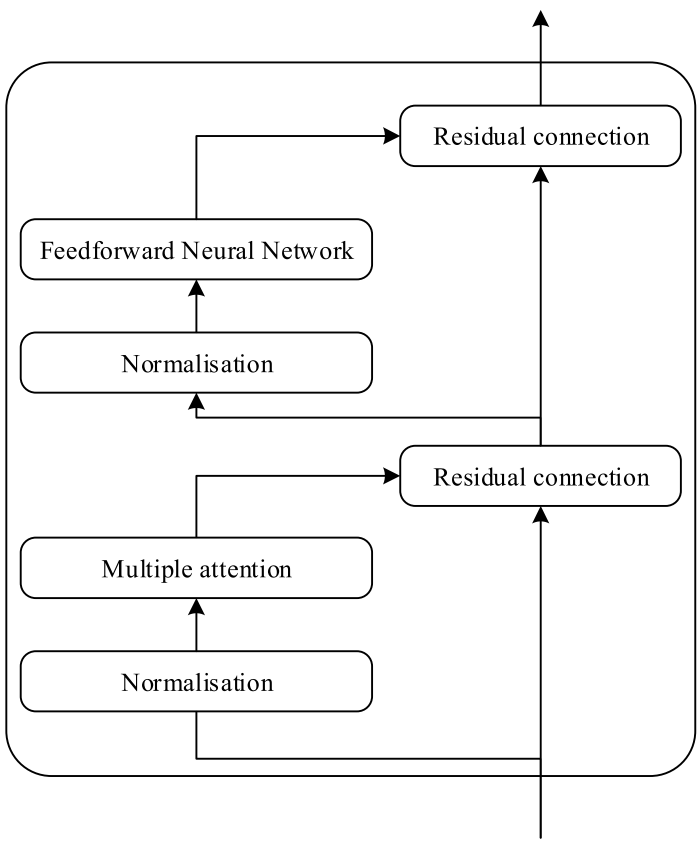

Figure 4: Pre-Norm Structure Diagram

III. Experiments and discussion of results

III. A. Evaluation of the Cultural Value of Tang Dynasty Literary Works

III. A. 1) Sample Selection and Calculation

The cultural value of Tang Dynasty literary works profoundly reflects the ideological, political, religious and humanistic style of Tang Dynasty society. Therefore, this paper divides them into six core dimensions, namely, historical dimension, ideological dimension, artistic dimension, humanistic dimension, cultural inheritance dimension and social function dimension, with a total of 21 evaluation indexes: truthfulness of historical events, coverage of social strata, relevance of economy and people's livelihood, reproducibility of folklore, depth of fusion of Confucianism, Buddhism and Taoism, revelation of the complexity of human nature, exploration of the philosophy of life, strength of social criticism, and innovativeness of language, Intentional originality, structural sophistication, musicality, stylistic innovation, emotional universality, group consciousness construction, gender perspective value, influence of later literature, cross-cultural dissemination power, modern interpretation space, moral education function, cultural symbolism, and the composition of cultural value indexes of Tang Dynasty literary works is shown in Table 1.

The sample size of factor analysis method should be more than 5 times of the variables, the variables in this paper are 21, and some data of Tang Dynasty literary works are selected, and the sample size is more than 5 times of the variables. The preliminary calculation and processing of the organized data. The regression estimation method is used to analyze the data for missing values and supplement the missing values of the data. Adopting emotional universality and group consciousness construction is not the bigger the better, it should be at a reasonable level, so Z-Score data standardization is done for these two indicators.

Table 1: The cultural value of literature works in tang dynasty

Index category	Index name	Index code
Historical dimension	Historical events	A1
	Social stratification	A2
	Economic wellbeing	A3
	The reappearance of folk customs	A4
Thought dimension	The fusion depth of the Confucianism	A5
	Disclosure of human complexity	A6
	Philosophy of life	A7
	Social criticism	A8
Artistic dimension	Language innovation	A9
	originality	A10
	Structural ingenuity	A11
	Musical performance	A12
	Creative contribution	A13
Cultural dimension	Emotional universality	A14
	Group consciousness construction	A15
	Gender perspective value	A16
Cultural inheritance dimension	afterinfluence	A17
	Cross-cultural communication	A18
	Modern interpretation space	A19
Social function dimension	Moral education	A20
	Cultural symbolic significance	A21

III. A. 2) Factor analysis applicability test

The applicability test of factor analysis method is shown in Table 2. According to the table, it can be seen that the standardized calculation results with other data for KMO test and Bartlett sphericity test. The KMO test value of 0.653>0.6 indicates that the information overlap between the sample variables is fair, and a more satisfactory factor analysis model can be derived, so the sample data can be factor analyzed. The significance in Bartlett's test of sphericity is 0.000<0.001, which indicates that the hypothesis that the variables are not related is rejected, and at the same time it indicates that there is a strong correlation between the variables, so this sample data can be analyzed for factor analysis.

Table 2: Factor analysis applicability test

KMO and bartlett test		
KMO sampling availability number		0.653
Bartlett sphericity test	Approximate card	2503.162
	Freedom	223
	Significance	0.000

III. A. 3) Principal factor extraction

The results of total variance interpretation are shown in Table 3. The variance of the first principal component accounts for 31.824% of all principal component methods, and the cumulative contribution of the variance of the first 6 principal components reaches 83.79%, so using the first 6 principal components is sufficient to describe the cultural value of Tang Dynasty literary works. Therefore, we extract the first 6 factors as principal factors.

Table 3: The total variance explains the result

Constituent	Initial eigenvalue			Extracting the load of the load			Rotational load squared		
	Total	Percentage of variance	Cumulation%	Total	Percentage of variance	Cumulation%	Total	Percentage of variance	Cumulation%
1	6.683	31.824	31.824	6.683	31.824	31.824	5.412	25.771	25.771
2	3.975	18.929	50.753	3.975	18.929	50.753	4.177	19.890	45.661
3	2.32	11.048	61.801	2.32	11.048	61.801	2.117	10.081	55.742
4	1.896	9.029	70.83	1.896	9.029	70.83	1.992	9.486	65.228
5	1.511	7.195	78.025	1.511	7.195	78.025	1.974	9.400	74.628
6	1.211	5.767	83.792	1.211	5.767	83.79	1.924	9.162	83.79
7	0.974	4.638	88.43						
8	0.697	3.319	91.749						
9	0.578	2.752	94.501						
10	0.393	1.871	96.372						
11	0.203	0.967	97.339						
12	0.158	0.752	98.091						
13	0.122	0.581	98.672						
14	0.103	0.490	99.162						
15	0.075	0.357	99.519						
16	0.046	0.219	99.738						
17	0.025	0.119	99.857						
18	0.015	0.071	99.928						
19	0.009	0.043	99.971						
20	0.004	0.019	99.99						
21	0.002	0.010	100						

The results of the fragmentation plot are shown in Figure 5. The gravel plot is used to show the importance of each factor more intuitively, the horizontal axis indicates the serial number of the factor, and the vertical axis indicates the magnitude of the eigenvalue, the factors can be directly observed by arranging the factors according to the eigenvalue in order from the largest to the smallest, and a large slope indicates that the corresponding eigenvalue plays a more obvious role and has a larger impact. A relatively gentle slope indicates that the eigenvalues play a weaker role and have less influence. As can be seen from the above gravel plot, the first 6 factors are in the stage of large slope and the eigenvalues are all less than 1. The last 15 factors are relatively smooth, so it is sufficient to consider the first 6 eigenvalues.

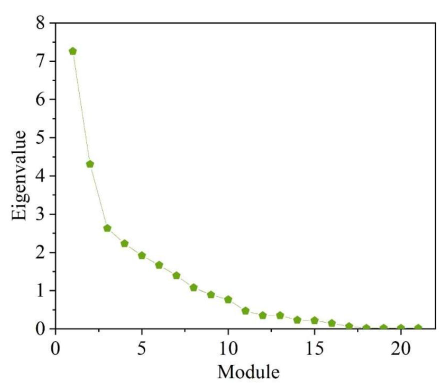

Figure 5: Gravel chart results

The rotated component matrix is shown in Table 4. The maximum variance method was utilized to rotate the factors to obtain the rotated factor loading matrix, which reflects the loading of each factor in each variable, i.e., the degree of influence of each factor on each variable. It can make each factor have a clear meaning of cultural value. The higher the absolute value of the factor loadings, the higher the correlation between the original variables and the common factors. It is basically categorized into the following six factors: the first factor, which is mainly composed of the degree of reproduction of folk customs and styles, the authenticity of historical events, the degree of coverage of social strata, the relevance of economy and livelihood, the space of modern interpretation, and the depth of integration of Confucianism, Buddhism and Taoism. The second factor is mainly composed of emotional universality, musical performance, structural sophistication, and group consciousness construction. The third factor is mainly composed of cultural significance, contribution to stylistic innovation, and moral edification. The fourth factor is mainly composed of intentional originality and later literary influence. The fifth factor, mainly consists of philosophical exploration of life, linguistic innovativeness, and the value of gender perspective. The sixth factor is mainly composed of the revelation of the complexity of human nature, the originality of intention, and the strength of social criticism.

Table 4: The component matrix after rotation

	Component 1	Component 2	Component 3	Component 4	Component 5	Component 6
A1	0.969	-0.074	0.043	0.084	0.131	0.024
A4	0.964	-0.113	0.123	0.073	0.028	0.091
A2	0.928	0.189	0.185	0.054	-0.039	0.136
A3	0.923	0.285	0.152	-0.034	0.034	0.06
A5	0.801	0.48	0.077	0.018	-0.008	-0.209
A19	0.728	-0.212	0.218	0.333	-0.23	-0.033
A14	-0.034	-0.93	-0.133	-0.074	-0.076	0.016
A11	0.08	0.857	0.142	-0.022	-0.256	-0.092
A12	0.059	0.855	0.131	0.008	-0.303	-0.051
A15	-0.064	-0.852	-0.103	-0.072	-0.085	-0.131
A21	0.394	0.012	0.839	0.096	0.041	0.053
A13	0.281	0.364	0.785	-0.002	-0.1	0.021
A20	-0.025	0.152	0.707	0.094	0.122	-0.002
A18	0.1	0.035	0.106	0.947	-0.009	0.039
A17	0.124	0.081	0.06	0.941	-0.034	0.132
A7	-0.048	-0.088	0.191	-0.064	0.819	0.151
A9	-0.065	-0.412	0.001	-0.018	0.733	0.136
A16	0.47	0.303	-0.187	0.06	0.594	-0.021
A6	-0.175	-0.067	-0.11	0.121	0.139	0.801
A10	0.302	-0.299	0.098	0.072	0.325	0.748
A8	0.188	0.422	0.203	-0.006	-0.063	0.726

III. A. 4) Calculating the factor score function

The matrix of component score coefficients is shown in Table 5. From the table, the percentage of variance of each factor to the total cumulative variance contribution was used to calculate the composite score function Y. The formula is shown below:

Y composite score = 37.66%Y1 + 22.21%Y2 + 13.39%Y3 + 10.65%%Y4 + 8.73%Y5 + 6.91%Y

III. B. Analysis and validation of model identification results

III. B. 1) Analysis of experimental results

In this section, some Tang poems are selected to be analyzed and judged, and the dataset has a total of 1,200 samples, of which 1,000 are training set and 200 are testing set. The training dataset is dedicated to the training process of the model, while the test dataset is used to evaluate the performance and accuracy of the model. Therefore, we explore and validate the efficacy of the model by evaluating the accuracy of the model in the test set. The confusion matrix scale diagram is shown in Fig. 6.

Table 5: Component score coefficient matrix

	Component 1	Component 2	Component 3	Component 4	Component 5	Component 6
A1	0.211	-0.044	-0.074	-0.011	0.045	-0.02
A2	0.178	0.004	-0.012	-0.055	-0.055	0.063
A3	0.181	0.041	-0.042	-0.086	0.01	0.029
A4	0.203	-0.071	-0.037	-0.029	-0.038	0.023
A5	0.152	0.099	-0.073	-0.022	0.059	-0.137
A11	-0.011	0.197	-0.01	-0.03	-0.062	-0.011
A12	-0.025	0.201	-0.006	-0.011	-0.091	0.02
A13	-0.022	0.004	0.396	-0.071	-0.037	-0.005
A16	0.093	0.149	-0.204	0.061	0.379	-0.121
A17	-0.03	0.026	-0.044	0.502	0.003	-0.005
A18	-0.046	0.007	-0.019	0.507	0.043	-0.065
A19	0.133	-0.133	0.05	0.116	-0.162	-0.03
A6	-0.042	0.02	-0.09	0.015	-0.052	0.451
A7	-0.051	0.032	0.111	-0.023	0.463	-0.052
A8	-0.004	0.099	0.014	-0.087	-0.142	0.434
A9	-0.019	-0.041	0.038	0.011	0.375	-0.047
A10	0.038	-0.078	0.015	-0.022	0.02	0.373
A20	-0.102	-0.018	0.396	0.014	0.101	-0.062
A21	-0.01	-0.081	0.429	-0.026	0.003	-0.04
A14	0.038	-0.258	0.022	-0.05	-0.146	0.021
A15	0.026	-0.242	0.048	-0.031	-0.108	-0.051

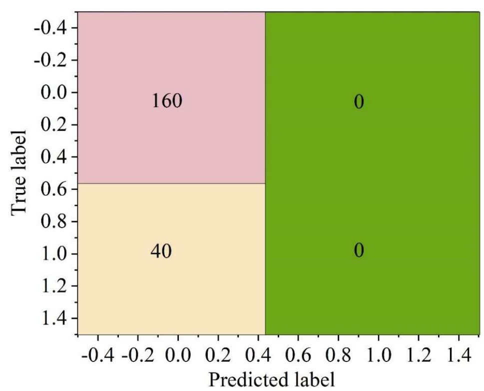

Figure 6: Confusion matrix scale

where the accuracy of the test set is 0.85, precision is 1.0, recall is 0.8, and F1 score is 0.862. The ROC plot is shown in Fig. 7.

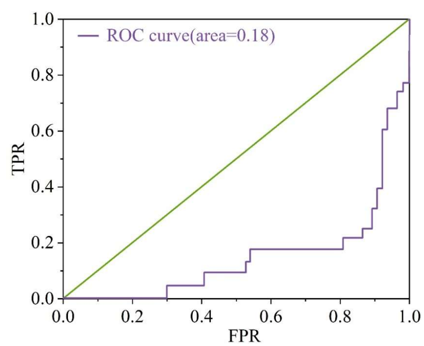

Figure 7: ROC graph

III. B. 2) Model performance comparison

In order to deeply verify the significant performance advantages of the Transformer-based cultural value recognition model for Tang Dynasty literary works proposed in this paper, we purposely choose two representative deep learning models, such as the convolutional neural network (CNN) model and the long-short-term memory (LSTM) model, with which we conduct exhaustive experimental comparisons. By comparing with other neural network structures, such as fully connected networks or deep learning models, the CNN and LSTM models show significant advantages. Therefore, if the Transformer corporate financial fraud recognition model proposed in this paper demonstrates significant advantages in performance comparison with CNN and LSTM models, it will strongly confirm the superior performance of this model in corporate financial fraud recognition task. After several rounds of fine tuning of the model structure and hyperparameters, the CNN model architecture with excellent performance in recognizing the cultural values of Tang Dynasty literary works is established: it consists of a single input layer, three 1D convolutional layers connected in series, two fully-connected layers, and one output layer. All convolutional layers use a 3x3 filter and the step size of the convolutional operation is fixed to 1. The model consists of three sequentially stacked convolutional layers with corresponding channel numbers of 121, 262, and 134, respectively. Two fully-connected layers with 80 and 1 neuron, respectively, are subsequently connected, and the output layer is designed to be a single neuron for output. In the model design, ReLU activation function is specially chosen for the convolutional and fully connected layers, and Sigmoid activation function is also adopted for the output layer. After rigorous optimization, the most effective corporate financial crisis prediction model identified was based on an LSTM architecture, with the network architecture clearly defined as a single input layer, a single LSTM unit layer, and an output layer design. In the design, 160 neurons were selected to construct the LSTM layer and the ReLU activation function was used. The architectural design with a single output neuron and selected Sigmoid activation function. Secondly, all using the same dataset, after 100 rounds of network iterations, we evaluated the prediction performance of the CNN model, the LSTM model, and the Transformer model, respectively, and the total prediction accuracies of each model are shown in Table 6. Through the final comprehensive evaluation of the total prediction accuracy, the Transformer model outperforms the CNN model, which in turn outperforms the LSTM model. After in-depth validation, the Transformer-based cultural value recognition model for Tang Dynasty literary works proposed in this paper shows significant superior performance with a total prediction accuracy of 92.65%.

Table 6: The overall accuracy of the models is accurate

	CNN model	LSTM model	Ours
Total accuracy	80.65%	80.01%	92.65%

III. B. 3) Applying analytical tests

In order to further test the ability of Transformer's deep learning model in recognizing the cultural value of Tang Dynasty literary works, this paper selects 1000 samples as the dataset, of which 750 are the training set and 250 are the test set. Among them, there are 179 articles with low cultural value and 821 articles with high cultural value. The training dataset is dedicated to the training process of the model, while the test dataset is used to evaluate the performance and accuracy of the model. Therefore, we explored and validated the efficacy of the model by evaluating the accuracy of the model in the test set. The confusion matrix of the test set is shown in Fig. 8 and the ROC curve of the test set is shown in Fig. 9.

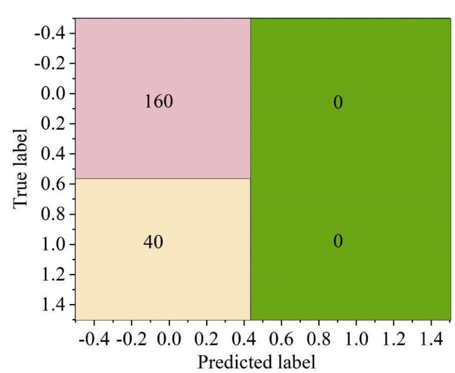

Figure 8: The confusion matrix of the test set

where the test set has an accuracy of 0.95, a precision of 1.0, a recall of 0.95, and an F1 score of 1.

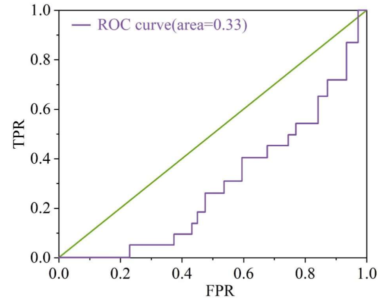

Figure 9: ROC curve of the test set

IV. Conclusion

The comprehensive evaluation model of cultural value of Tang Dynasty literary works based on the improved Transformer model has outstanding predictive ability. The model significantly improves the evaluation of the cultural value of Tang Dynasty literary works through three key technological improvements: feature partition layer, output partition CLS Token and Pre-Norm structure. The experimental results demonstrate that the improved Transformer model has a total prediction accuracy of 92.65%, which is significantly ahead of the CNN model's 80.65% and the LSTM model's 80.01%, and exhibits an accuracy of 85%, an accuracy of 1.0, and an F1 score of 0.862 on the test set. Factor analysis revealed that the cultural value of Tang Dynasty literary works can be expressed by six main factors with a cumulative variance contribution of 83.79%, covering multiple dimensions such as historical authenticity, artistic innovation, and cultural inheritance. These six main factors are composed of different evaluation indexes, such as the first factor mainly includes the degree of folklore reproduction, the authenticity of historical events and the degree of social class coverage, etc., while the second factor is composed of emotional universality, musical performance and structural subtlety. The comprehensive scoring function Y=37.66%Y1+22.21%Y2+13.39%Y3+10.65%%Y4+ 8.73%Y5+6.91%Y6 accurately reflects the weight contribution of each factor. This model provides an objective quantitative tool for assessing the cultural value of Tang Dynasty literary works, effectively reduces the subjective bias of traditional evaluation methods, and introduces a new technical path and methodological support for the field of ancient literature research.

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