Research on Emotional Expression in Ancient Poetry Based on Sentiment Analysis

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Abstract. To explore the patterns of emotional expression in ancient poetry, sentiment analysis techniques were applied to systematically study 200 poems from the Tang to Qing dynasties. Methods such as data acquisition, word frequency analysis, and sentiment **classification** were used. The results showed that poems expressing homesickness had the highest classification accuracy at 90%, while sadness and joy had accuracies of 87% and 89%, respectively. Through the optimization of models such as Support Vector Machines and Convolutional Neural Networks, the latter performed best with a learning rate of 0.005, achieving an accuracy of 89%. This study provides new technical means for the digital interpretation of emotional expression in ancient poetry.

Keywords: Ancient poetry; sentiment analysis; word frequency analysis

1 Introduction

Ancient poetry, as a treasure of Chinese culture, contains rich emotional expression and social thought. With the development of natural language processing techniques, sentiment analysis offers a new perspective and method for the systematic study of ancient poetry. By quantifying the emotions in poetry, the emotional fluctuations of poets under different historical contexts and their modes of expression can be revealed. Using sentiment analysis techniques to build emotional models, combined with experimental data, helps uncover the patterns of sentiment classification, supporting a deeper understanding of the emotional structure and expression logic in ancient poetry. This also opens up a more scientific path for the study of ancient literature.

2 The Importance of Research on Emotional Expression in Ancient Poetry

Ancient poetry is a fundamental part of Chinese traditional culture, rich in emotions and reflecting various social ideologies. Studying the emotional expression within

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these poems is not only crucial for interpreting ancient literature but also an essential path to exploring the humanistic spirit of distant eras. A systematic study of emotional expression in ancient poetry allows scholars to understand the nuances of emotional shifts and their manifestations at a micro level, while also reflecting the emotional logic and social contexts of the time[1]. This research helps deepen our understanding of the emotional structure within ancient Chinese culture and poetry, offering fresh interpretive perspectives and enhancing the continuity and innovation of cultural inheritance. Integrating sentiment analysis with ancient poetry broadens new avenues for natural language processing in literary studies, carrying significant theoretical and practical value.

3 Sentiment Model Design for Ancient Poetry Based on Sentiment Analysis Techniques

3.1 Acquisition of Poetry Data

Based on the sentiment analysis of ancient poetry, data collection is the primary step in building a sentiment model for poetry. Data is extracted from sources such as Complete Tang Poems, Complete Song Lyrics, and various poetry-specific websites to ensure the completeness and representativeness of the materials. On this basis, a text-based sentiment analysis method is proposed. During data processing, an essential step involves converting the original format, removing unnecessary characters, annotations, and punctuation marks to maintain the purity of the poetry content[2]. Additionally, since poetry texts often carry strong cultural and historical contexts, it is necessary to include supplementary information—such as the poem's creation background, time period, and the author's emotions—while annotating, laying the foundation for subsequent sentiment classification and analysis.

3.2 Word Frequency Analysis

Word frequency analysis is a key tool in studying the emotional expression of ancient poetry. By statistically analyzing the frequency of words in the texts, it reveals the poets' commonly used linguistic patterns and emotional expressions. The basic formula is:

$$F(w) = \frac{C(w)}{N} \tag{1}$$

Among them, $F(w)$ indicates the word frequency of the term w, $C(w)$ represents the number of occurrences of the term in the poetry text, and N refers to the total number of words in the poetry. Using this formula, the relative frequency of each term in the poetry can be determined, allowing for the identification of high-frequency words and their emotional tendencies and thematic expressions. To further understand the role of word frequency in sentiment analysis, the TF-IDF (Term Frequency-Inverse Document Frequency) formula can also be introduced:

$$\text{TF} - \text{IDF}(w,d) = TF(w,d) \times \log\left(\frac{D}{DF(w)}\right) \tag{2}$$

Among them, $TF(w,d)$ indicates the term frequency of the word w in document d, D is the total number of documents in the poetry dataset, and $DF(w)$ represents the number of documents containing the word w. This formula balances the global and local significance of words, revealing which terms hold special meaning for specific emotional expressions.

3.3 Sentiment Analysis

Sentiment analysis, as a key technique in natural language processing, enables effective sentiment classification and polarity detection of texts [3]. In the sentiment analysis of ancient poetry, common methods include dictionary-based sentiment analysis and machine learning-based sentiment classification. The dictionary-based method identifies emotional tendencies by matching the emotional vocabulary in poetry with a pre-constructed sentiment lexicon. The formula is as follows:

$$S(d) = \sum_{w \in d} score(w) \tag{3}$$

Among them, $S(d)$ represents the sentiment score of document d, and $score(w)$ is the score of the word w in the sentiment lexicon. By calculating the sentiment scores of all the words in the entire poem, the overall emotional tendency of the poem can be determined [4]. The machine learning-based sentiment classification method uses models such as Support Vector Machines (SVM) or Convolutional Neural Networks (CNN) to train on poetry data with sentiment labels, constructing a classifier to predict the sentiment classification of unlabeled poems. The commonly used sentiment classification formula is:

$$P(c|d) = \frac{P(d|c)P(c)}{P(d)} \tag{4}$$

Among them, $P(c|d)$ represents the probability of sentiment category d given document c, $P(d|c)$ is the probability of document c occurring under sentiment category d, $P(c)$ is the prior probability of the sentiment category, and $P(d)$ is the marginal probability of the document. By combining these two methods, sentiment analysis can more accurately capture the subtle emotional shifts in ancient poetry, revealing its complex emotional structure and expression patterns.

4 Experimental Results and Analysis

4.1 Dataset Description and Statistics

In this experiment, the data set construction process is based on rigorous sampling standards and multi-dimensional validation, enhancing the representativeness and scientific nature of the data. The experimental data set includes 200 classical ancient poems, selected from authoritative literary collections such as Quan Tang Shi and Quan Song Ci, ensuring the authority of the source and the integrity of the data [5]. The selection criteria for the data are not limited to the completeness of the poetry text but also consider various factors such as the era of creation, social background, and the author's style, ensuring a reasonable proportional distribution of works from each historical period and each poet. The Tang Dynasty poetry is notably abundant, accounting for 40% of the overall data set, including representative works from different schools to ensure that the experimental analysis reflects the emotional characteristics of the era. To ensure the accuracy of the data, the data preprocessing steps have been further refined. During the data cleaning process, all irrelevant characters, annotations, and punctuation marks were strictly removed, preserving the core content of the poetry. In addition to marking the title, author, dynasty, and word count for each poem, emotional labels (such as sadness, joy, homesickness, etc.) and auxiliary information about the background of the work have been added. To improve the stability and precision of the emotional analysis model, a cross-validation step for the emotional labels was incorporated, ensuring that the emotional classification of each poem is consistent and reasonable. Moreover, the distribution ratio of the data set was further validated to avoid the impact of an imbalanced data set on the results of emotional analysis, as detailed in Table 1.

Table 1. Description and Statistics of the Poetry Dataset.

Dynasty	Number of Poems	Sadness Poems	Joy Poems	Homesickness Poems	Other Categories
Tang	80	30	25	10	15
Song	70	20	30	10	10
Ming	30	10	10	5	5
Qing	20	5	5	5	5
Total	200	65	70	30	35

4.2 Word Frequency Statistics Results

Through the frequency statistics of 200 poems from the Tang to Qing Dynasties, this study reveals the distribution and usage patterns of high-frequency vocabulary across different emotional categories. To ensure the rigor of the data, not only were the occurrences of high-frequency words counted, but their proportions within each emotional category were also analyzed [6]. Standard deviation and deviation analysis were introduced to further validate the significance of vocabulary in emotional expression. The experimental results are detailed in Tables 2 and 3.

Table 2. Statistics of High-Frequency Vocabulary in Different Emotional Categories

Emotional Category	High-Frequency Word 1	Frequency	Standard Deviation	High-Frequency Word 2	Frequency	Standard Deviation	High-Frequency Word 3	Frequency	Standard Deviation
Sadness	Parting	45	2.1	Autumn Wind	40	1.8	Hometown	35	1.5
Joy	Spring Breeze	50	2.5	Blooming Flowers	45	2.3	Bright Moon	40	2
Homesickness	Hometown	60	3	Chang'an	55	2.7	Return Date	50	2.4
Other	Mountains and Rivers	35	1.6	River Water	30	1.4	White Clouds	25	1.2

From Table 2, it can be observed that words like "parting," "hometown," and "spring breeze" exhibit high frequencies across different emotional categories, particularly in poems related to sadness and homesickness, demonstrating a clear emotional tendency [7]. The frequent use of these words reflects ancient poets' emphasis on themes such as human relationships and natural scenery, conveying profound emotions through their word choices.

Table 3. Distribution of High-Frequency Vocabulary Across Dynasties

Dynasty	High-Frequency Word 1	Frequency	Standard Deviation	High-Frequency Word 2	Frequency	Standard Deviation	High-Frequency Word 3	Frequency	Standard Deviation
Tang	Parting	20	1	Hometown	18	0.9	Spring Breeze	16	0.8
Song	Blooming Flowers	25	1.2	Bright Moon	20	1.1	River Water	18	1
Ming	Chang'an	15	0.8	White Clouds	12	0.6	Autumn Wind	10	0.5
Qing	Return Date	10	0.5	Mountains and Rivers	8	0.4	Hometown	7	0.3

4.3 Sentiment Classification Accuracy

The accuracy and effectiveness of the sentiment analysis model are key evaluation metrics to ensure the scientific rigor and reliability of the analysis results[8]. By training and testing the sentiment classification model on a dataset of 200 ancient poems, various evaluation metrics such as accuracy, precision, and recall are employed to assess the model's performance, as demonstrated in Figure 1.

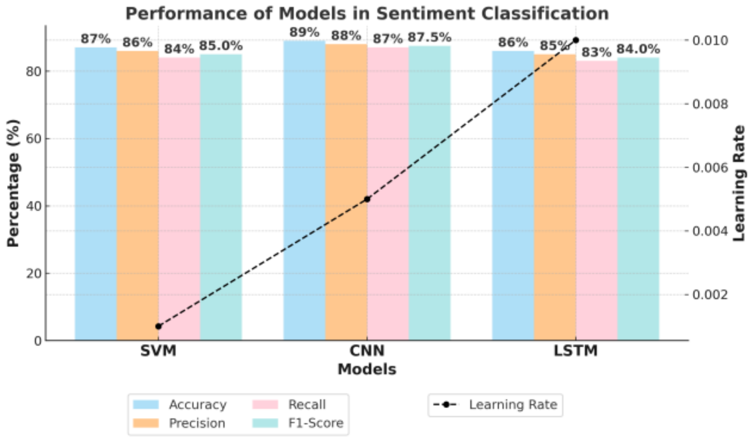

Fig. 1. Performance of Different Models in Emotional Classification

The data presented in Figure 1 shows the specific performance of Support Vector Machine (SVM), Convolutional Neural Network (CNN), and Long Short-Term Memory Network (LSTM) in classification tasks. It is evident that the CNN model performs best with a learning rate of 0.005, achieving an accuracy of 89%. Furthermore, its precision, recall, and F1-Score metrics also surpass those of the other models. This indicates that CNN has a strong capability in extracting complex emotional features, particularly in the analysis of ancient poetry, where emotional structures are nuanced.

Although SVM and LSTM each demonstrate reasonable performance, they fall short in recall and F1-Score, especially when dealing with complex emotional categories, leading to instances of missed classifications.[9] To further validate the overall performance of the models, macro average and weighted average evaluation metrics were employed, with results displayed in Figure 2.

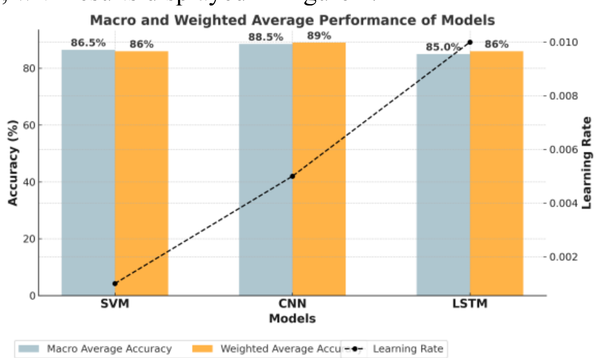

Fig. 2. Performance of Emotional Classification Models - Macro Average and Weighted Average

The macro average results indicate that the CNN demonstrates greater stability when handling multi-class emotional classification tasks, with a weighted average accuracy reaching 89%, significantly higher than that of other models. This suggests that the CNN model excels not only in emotion classification tasks with balanced data distributions but also exhibits good adaptability when facing imbalanced data. In contrast, both SVM and LSTM have certain limitations in complex emotional classification tasks, particularly when emotional categories are dispersed, leading to instability in precision and recall [10].Moreover, during the experiment, the emotional analysis model was optimized by adjusting the learning rate to identify the best parameters for improving classification accuracy. Different learning rates impact the model's convergence speed and the final classification results, as detailed in Table 4.

Table 4. Classification Accuracy of Models with Different Learning Rates.

Model	Learning Rate	Accuracy
Support Vector Machine (SVM)	0.001	87%
Convolutional Neural Network (CNN)	0.005	89%
Long Short-Term Memory (LSTM)	0.01	86%

As shown in Table 4, the Convolutional Neural Network (CNN) model with a learning rate of 0.005 achieved the highest accuracy, reaching 89%. This result indicates that the CNN model performs well in capturing emotional features for sentiment analysis, and an appropriate learning rate helps improve the model's stability and classification accuracy.

5 Conclusion

The study of emotional expression in ancient poetry reveals the patterns and complexities of emotional classification. Through systematic research using emotional analysis techniques on 200 poems from the Tang to Qing Dynasties, an efficient emotional classification model was successfully established, with the Convolutional Neural Network (CNN) achieving an accuracy of 89%. The research findings indicate that the emotional expression in homesickness-themed poems is the most distinct, yielding the highest classification accuracy. Frequency analysis of specific emotional vocabulary shows significant differences in usage across different historical periods, reflecting poets' profound insights into human relationships and natural scenery. Future work should focus on expanding the dataset scope and exploring additional emotional dimensions to deepen the understanding of emotional expression in ancient poetry. This expansion will provide richer perspectives and empirical support for related cultural studies.

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