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Research on the Value and Language Features of Chinese Language and Literature Texts Based on Text Mining Technology

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ABSTRACT

Sentiment analysis belongs to a classification technique with strong practical value, which can identify the hidden imagery in the text. In this paper, we study the sentiment tendency of words in Chinese language and literature texts, design a fuzzy ontology-based method for calculating textual sentiment tendency, build a textual sentiment tendency analysis model (SDNN) based on deep neural network and sentiment attention mechanism, and use the model in Chinese language and literature texts for empirical analysis. At 202 iterations, the Loss value of the SDNN model reaches the lowest value of 0.4626, and the corresponding accuracy, recall, and F1 values are 90.44%, 79.68%, and 84.72%, respectively, and tend to be stable. It indicates that the model has better classification performance and can be used in the task of analyzing the sentiment of Chinese language and literature texts. In addition, this paper explores the rhyme structure of character emotion vocabulary in Chinese language literary discourse, and takes Liu Zongyuan's related works as an example for empirical analysis of the model. The results show that Liu Zongyuan's emotion during his ten years in Yongzhou is generally in low, and the proportion of his negative emotion has been above 75%, which is reflected in the text vocabulary emotion is more sad than happy. This paper is of some significance for the study of the emotional tendency of vocabulary in Chinese language literary texts.

Keywords: Fuzzy ontology, emotional tendency, attention mechanism, SDNN model, feature extraction

1. Introduction

The unique flavor of poetry is the key to break through the shackles of time and space and infect people's hearts. Appreciation of poetic rhyme in Chinese language and literature is skillful, if you want to accurately grasp the aesthetic characteristics and artistic value of poetic works, and realize the unique flavor of poems, you have to adopt the way from the outside to the inside, from the shallow to the deep, and gradually complete the appreciation of the works. This requires readers to have a certain

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ability to appreciate the flavor of poetry, and to be able to understand the connotation of the work more quickly, deeply and thoroughly [1-3]. In the vast river of Chinese culture, ancient poetry, with its unique art form and profound emotional connotation, has become a treasure that has been handed down through the ages. It is not only a carrier for the literati to express their feelings and aspirations, but also a crystallization of the emotional memory of the Chinese nation. Every poem and every lyric coalesce the poets' heart and emotion, and they hold their feelings and thoughts about life, love, friendship, family and country, and other worldly conditions [4-6].

Poetry works in Chinese language and literature are loved by the people of China for their cohesive language and long rhythm. As a matter of fact, poetic works are not only a reflection of historical life, but also a key carrier of Chinese excellent traditional culture [7-8]. People's love for poetry is not only the favor of special literary genres, but also originates from the descendants' yearning for history, culture and the lives of the people before them. The beauty of poetry is either intuitive or implicit, and poetry appreciation is the process of excavating and realizing the charm of poetry. Appreciation of poetry rhyme in Chinese language and literature refers to the profound appreciation of poetry, with the help of knowledge and skills of language discipline, so that the appreciator can deeply understand the excellent traditional culture and grasp the unique charm of poetry [9-12]. Appreciation of poetry rhyme in Chinese language literature is an important way based on poetry appreciation and mining the humanistic spirit embedded in poetry, which not only has the function of guiding the readers to know the poetic works in depth and accurately grasp the connotation of the poems, but also helps the readers to broaden their horizons, enrich their knowledge, establish virtue and wisdom, and assists them to establish the correct aesthetic values of literature and to form a good sense of aesthetics and aesthetic interest, and to improve the appreciation taste, aesthetic realm and the ability to discover, feel and create beauty [13-15].

The appreciation of poetic rhyme in Chinese language and literature can be approached from several dimensions. In this process, people should not only pay attention to and analyze the external expression of the poems, but also appreciate the inner meaning of the poetic works. In this way, the appreciator can fully appreciate the flavor of poetry and feel the beauty of poetic works based on different levels [16-17]. In the practice of poetry appreciation, the appreciator should pay attention to the visual and auditory experiences presented by the poems, and appreciate the imagery used by the creators of the poems and the artistry of the works. When appreciating the inner meaning of poems, the appreciators need to have perspective thinking, to explore and appreciate the beauty of the meaning of poems through the surface content, and to deeply experience and understand the thoughts, emotions and creative techniques hidden in the poems. Poetry works with rich flavor often contain the creator's true feelings [18-20]. In the appreciation of poetry flavor in Chinese language literature, the appreciator should attach great importance to the ideological and emotional analysis of poetic works, pay attention to the hidden ideological connotation and emotional elements of the content of the work, and experience the unique flavor of poetry with the medium of love [21-22]. In the creation of literary and artistic works, creators often project their own thoughts and emotions into the works to give life and expressiveness to the works, and the same is true in the creation of poetic works [23]. Generally speaking, people can perceive and experience the creator's thoughts and feelings and understand the creator's inner world with the help of the content of the work by studying, analyzing, and comprehending the meaning of the poems in depth [24].

In this paper, based on the fuzzy ontology theory, the calculation method of lexical emotional tendency in Chinese language and literature text is designed. Then, combining BiGRU and CNN and introducing the mechanism of affective attention, the SDNN model for analyzing lexical affective tendency in Chinese language and literature texts is constructed.In order to verify the effectiveness of the model, it is compared with BiLSTM, BiGRU, BiGRU+CNN, etc. for the comparison of the accuracy rate, recall rate, F1 value and Loss value. In addition, the structure of affective flow and semantic rhyme structure in Chinese language literary texts are explored, and the SDNN model is used to analyze the word frequency and affective analysis of Liu Zongyuan's related literary works.

2. Fuzzy Logic Modeling and Feature Extraction for Lexical Emotional Propensity

2.1. Text data preprocessing

Text is usually expressed as a string, which expresses rich information, but cannot be directly used for sentiment analysis. Data preprocessing is a necessary stage of text sentiment tendency analysis, the main purpose is to process the massive unstructured data that cannot be recognized by the computer, so that it can meet the requirements of computer processing.

In this paper, the preprocessing of data can be done in the way of vector space model (VSM). Vector space is mostly utilized for natural language queries. Based on this, the query result can be processed as a small piece of information, then a certain information item in the vector space can be represented as:

$$D_j = (w_{j1}, w_{j2}, \cdots, w_{jn}) \tag{1}$$

In equation (1), n represents all the index items, and w_{jn} represents the weight of the index items within the information items.

Set D_j for the text item, k_i for the index item, k_i in D_j, the frequency of tf_{ij}, the inverse document rate of idf_i, the more the number of text items, the smaller the inverse document rate, the better the ability to distinguish between the words w, which for the calculation of the weight of the indexed items using the TD-IDF (Term Frequency-Inverse Document Frequency) method, which is calculated by the formula The formula is as follows:

$$w_{i,j} = tf_{i,j} * idf_i \tag{2}$$

where the expression for idf_i is as follows:

$$idf_i = \ln \frac{N}{n_i} \tag{3}$$

In equation (3), N represents all text items, and n_i is the number of information items in index k_i.

In order to make the data structured features more obvious, improve the formula for calculating the weight of index items, and the improved expression is as follows:

$$W(t,d) = \frac{tf(t,d) * \ln(N/n_i + 0.01)}{\sqrt{\sum_{t \in d} \left[tf(t,d) * \ln(N/n_i + 0.01) \right]^2}} \tag{4}$$

In summary, for the user model that needs to be queried, if through the VSM model can be represented as:

$$Q = (w_i, w_j, \cdots, w_n) \tag{5}$$

Therefore the vector similarity can be calculated using the matching degree model of user model Q and text D_j. The degree of similarity of these two vectors depends on the vector pinch angle, which is then calculated as follows:

$$\cos\theta = \frac{v_1 - v_2}{\| v_1 \| - \| v_2 \|} \tag{6}$$

Assuming that all index items k_i are independent of each other, the data preprocessing can be completed through the calculation of the above similarity measure, so that all the information of Chinese language literature text has structured characteristics, laying the foundation for the emotional semantic feature extraction of Chinese language literature text.

2.2. Fuzzy Ontology Based Textual Emotional Propensity Calculation

2.2.1. Fuzzy ontology. Fuzzy ontologies are constructed by introducing fuzzy logic from classical ontology concepts, which are able to express uncertain knowledge [25].

1) OntologyAn ontology is an illustration of a formal specification of a shared conceptual model, which includes knowledge within a domain as well as knowledge between multiple domains, enabling reuse of this knowledge. Databases and application software utilize ontologies to share domain knowledge. Ontology mainly consists of the following parts:

(1) Classes: the basic constituent elements of an ontology, abstractly describing things in the objective world, usually organized together using classification methods.

(2) Relationship: describes the binary relationship between class and class, such as: class inclusion relationship, attribute equivalence relationship.

(3) Function: describes that the first N-1 elements of a relationship determine the Nth element.

(4) Axiom: a description of a factual relationship, e.g., if a lion only eats meat, then it is a carnivore.

(5) Instance: a representation of a particular element, e.g., Li Hong is an instance of a student.

2) Fuzzy theory. The real world is full of fuzzy phenomena or fuzzy concepts that are not distinguishable in connotation and extension, while fuzzy set theory and fuzzy logic are used to manage imprecise and fuzzy knowledge.

(1) Fuzzy sets. Let A be a fuzzy set on the domain U, then $A=\{(x,S_A(x))\,|\,x\in U\}$, where S_A is a mapping from the domain U to the real closed interval [0, 1], i.e., $U\rightarrow[0,1]$, and call S_A the affiliation function, and $S_A(x)$ the degree of affiliation of element x in A.

From the above definition, it can be seen that a fuzzy set consists of elements and the degree of affiliation, while the degree of affiliation has is obtained from the affiliation function. The degree of affiliation describes the degree to which the element belongs to the fuzzy set relatively, the larger the degree of affiliation, the higher the degree to which the element belongs to the fuzzy set, and vice versa. When the degree of affiliation only takes 0 and 1, the fuzzy set degenerates into an ordinary set, while the affiliation function degenerates into its characteristic function.

(2) Affiliation function. The reasonableness or otherwise of the affiliation function directly affects the objective correctness of the fuzzy set. Since the design of the affiliation function is affected by the subjective will of people, it is impossible to give an absolutely correct function formula. So the affiliation function construction is generally as follows: example method, comparison method, empirical method and fuzzy statistical method.

(3) Fuzzy Logic. While ordinary sets are extended to fuzzy sets, operations based on ordinary sets are also applied to fuzzy sets by extension. For example, intersection, concatenation, negation and implication operations are represented on fuzzy sets as t-norm, t-conorm, negation function and implication function. Representative fuzzy logics are Lukasiewicz, Godel and Product. And these fuzzy logics are based on Zadeh fuzzy logic. The fuzzy logic operations are shown in Table 1.

Table 1. Fuzzy logic operations

Name	t-norm $\alpha\otimes\beta$	t-conorm $\alpha\ominus\beta$	negation - α	implication $\alpha\Rightarrow\beta$
Zadeh	$\min\{\alpha,\beta\}$	$\max\{\alpha,\beta\}$	$1-\alpha$	$\max\{1-\alpha,\beta\}$
Godel	$\min\{\alpha,\beta\}$	$\max\{\alpha,\beta\}$	$\begin{cases}1, & \alpha=0\\ 0, & \alpha>0\end{cases}$	$\begin{cases}1, & \alpha\le\beta\\ \beta, & \alpha>\beta\end{cases}$
Lukasiewicz	$\min\{\alpha+\beta-1,0\}$	$\min\{\alpha+\beta,1\}$	$1-\alpha$	$\min\{1-\alpha+\beta,1\}$
Product	$\alpha\cdot\beta$	$\alpha+\beta-\alpha\cdot\beta$	$\begin{cases}1, & \alpha=0\\ 0, & \alpha>0\end{cases}$	$\begin{cases}1, & \alpha\le\beta\\ \beta/\alpha, & \alpha>\beta\end{cases}$

3) Fuzzy Ontology. A fuzzy ontology is a quaternion $<X, C, Rxc, Rcc>$, where X is a set of objects, C is a set of concepts, and Rxc is a fuzzy relation: $X \times C \to [0,1]$, Rcc are relations between concepts.

Most of the current ontology creation tools are for deterministic knowledge, whereas most human knowledge is uncertain, and the degree of emotional disposition is even more representative of uncertain knowledge. In order to make uncertain knowledge well represented, it is necessary to represent fuzzy knowledge by introducing fuzzy logic and forming fuzzy ontology based on the framework of classical ontology.

2.2.2. Adverbs of degree and negative word processing:

1) Calculation of affective tendency of degree adverbs. The appearance of degree adverbs mainly brings about a change in the intensity of emotion, and the use of these degree adverbs can enrich the infectiousness of natural language, and degree adverbs can also be portrayed with an affiliation function, and the commonly used affiliation function for degree adverbs is:

$$S_{\text{Pole } A}(x) = (S_A(x))^4 \tag{7}$$

$$S_{\text{Very } A}(x) = (S_A(x))^2 \tag{8}$$

$$S_{\text{Quite } A}(x) = (S_A(x))^{1.22} \tag{9}$$

$$S_{\text{Compare } A}(x) = (S_A(x))^{0.8} \tag{10}$$

$$S_{\text{A little } A}(x) = (S_A(x))^{0.5} \tag{11}$$

$$S_{\text{A little bit } A}(x) = (S_A(x))^{0.25} \tag{12}$$

2) Calculation of emotional tendency of negative words. Words with negative meaning appear before emotion words, and their emotion category and intensity are changed. When the negative word appears in combination with emotion words alone, the polarity can be reversed operation, such as: unsatisfactory, not good and so on. However, when the negative word occurs in conjunction with degree adverbs and modifiers, a polarity judgment has to be made based on its position, e.g., "not very satisfactory, too unsatisfactory," etc.

According to the structure of the occurrence of the negative word (N), the adverb of degree (AD) and the emotive word (E), it can be roughly divided into two hierarchical structures, (N, AD, E) and (AD, N, E), e.g., "not very good", "very bad". Depending on the position of AD and N away from E, their tendency formulas are defined as the following two:

When the negative word is closer to the affective word than the degree adverb:

$$Emotion = Emotion_E * (-\alpha) Emotion_{AD} \tag{13}$$

When the adverb of degree is closer to the emotive word than the negative word:

$$Emotion = Emotion_E * (-\alpha) / Emotion_{AD} \tag{14}$$

Where $Emotion_R$ is the affective word polarity, using the difference between the positive and negative polarity of the affective word to indicate the overall affective tendency of the affective word, and $Emotion_{AD}$ is the degree of modification of the adverb of degree, which was determined using the degree of modifier identified in Hownet.

2.2.3. Sentence Sentiment Tendency Analysis Based on Weighted Approach. As the existence of emotion words makes the text with emotional tendency, the text can be divided into chapters, paragraphs, sentences, phrases and words according to the granularity refinement, and the higher text tendency is determined by the lower granularity emotional tendency, so it can be said that the text tendency of the sentence is determined by the emotion words or phrases that contain emotion words.

When analyzing the emotional tendency of Chinese language literature text, online comments can be broken down into sentences for emotional tendency analysis, and mainly focus on emotional words and phrases, and proffer a method to calculate the emotional tendency of a sentence by weighting and summing the emotional tendency values of emotional words and phrases in the sentence:

$$Emotion(S) = \sum_{i=1}^{n} \left[Emotion(word_i) \times W(word_i) \right] \tag{15}$$

Where S represents a sentence, $Emotion(word_i)$ is the affective tendency value of the phrase or affective word in which the difference between the positive and negative polarity of the affective word is utilized to represent the overall affective tendency of the affective word, and $W(word_i)$ is the weight of the phrase or affective word in the sentence and has $\sum_i W(word_i) = 1$.

Where $Emotion(word_i)$ must be calculated without neglecting the effect of degree adverbs and negatives on the sentence. Another influence on the emotional tendency of the sentence is the conjunction, and the general words that only have the meaning of connection do not affect the emotional tendency of the sentence, such as: and, and etc.. However, conjunctions with transitive meanings may have a great influence on the affective tendency of a sentence. Therefore, the weights of the emotional words and phrases in the sentence for the presence of transitive conjunctions are specified as follows:

$$W(word_i) = \begin{cases} \dfrac{2}{n_1 + n_2} & \text{Have a twist conjunctions} \\ \dfrac{1}{n_1 + n_2} & \text{No disjunctive conjunction} \end{cases} \tag{16}$$

where n_1 is the total number of sentiment words or phrases in the sentence and n_2 is the number of transitive clauses. When $n_2 = 0$, it is known that each emotion word or phrase has the same weight.

2.3. Affective Tendency Analysis Model for Chinese Language Literature Texts

2.3.1. Overall framework of the model. Aiming at the problem of lexical emotional tendency in Chinese language literature texts, this paper proposes a textual emotional tendency analysis model (SDNN) based on deep neural network and emotional attention mechanism. The overall framework structure of the model is shown in Figure 1, which is mainly composed of the following three parts:

1) Input layer. The attention mechanism is utilized to construct the sentiment word vector embedding matrix by using the sentiment words in the sentiment lexicon as the sentiment knowledge, so that the model can learn the deep-level sentiment semantic features under the guidance of the sentiment knowledge.

2) Neural network layer. In order to maintain the initial state of the text sequence information, the gated recurrent unit neural network is first used to receive the text word vector embedding matrix of the input layer to extract the sequence semantic features, and then the convolutional neural network is used to extract the local semantic features of the text, so as to realize the effective fusion of the text's sequence semantic features and the local semantic features to generate the deep-level emotion semantic features.

3) Output layer. For the deep-level emotional semantic features extracted by the model, the softmax classifier is used to judge the emotional tendency.

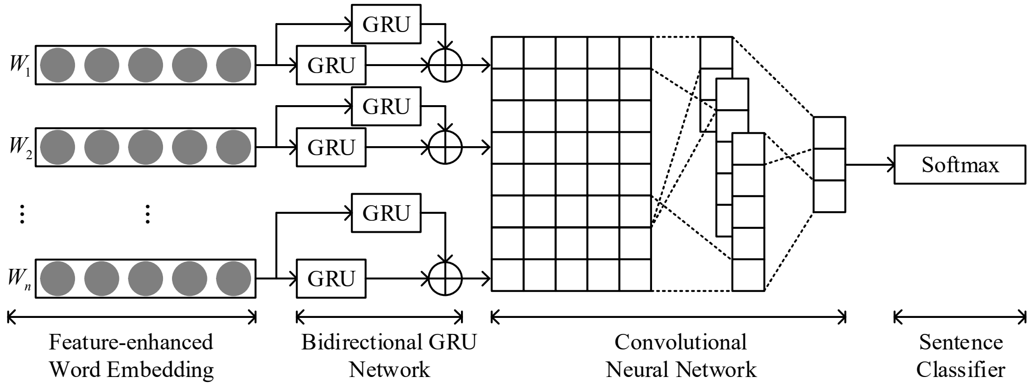


Fig. 1. The overall framework structure of the model

2.3.2. Emotional Attention Mechanisms:

1) Sentiment relation matrix. For a given input sentence $S=[s_1,s_1,\ldots,s_n]\in R^{1\times n}$ of length n, where s_i is the ith word in sentence S, and assuming that sentence S contains m emotion words, the model uses word2vec word vectors to convert the input sentence $S=[s_1,s_1,\ldots,s_n]\in R^{1\times n}$ into a contextual word embedding matrix $W^C=[w_1,w_2,\ldots,w_n]\in R^{n\times d}$, where d denotes the dimension of the word vector. Similarly, the sequence of emotion words in sentence S can be converted into an emotion word embedding matrix $W^S=\left[w_1^s,w_1^s,\ldots,w_m^s\right]\in R^{m\times d}$.

Sentiment words in text data largely determine the emotional inclination of that text. Therefore, firstly, the relationship matrix M^S between the emotion words and the sense of context words is designed, and the multiplication operation is applied to the context word embedding matrix W^C and the emotion word embedding matrix W^S, which is calculated as follows:

$$M^S=W^C\square\left(W^S\right)^T \tag{17}$$

where $\square$ denotes the multiplication operation of the matrix, $M^S\in R^{n\times m}$.

Next, define a matrix of sentiment words associated with context words X^S, which is computed as follows:

$$X^S=\left(W^C\right)^T\square M^S \tag{18}$$

where $X^S\in R^{d\times m}$. Similarly, the context word matrix X^C associated with a sentiment word can be obtained by doing an operation of the relation matrix M^S with the sentiment word embedding matrix W^S as follows:

$$X^C=\left(M^S\square W^S\right)^T \tag{19}$$

Of these, $X^C\in R^{d\times n}$.

2) Attention mechanism. In order to cope with complex contextual situations, this paper introduces the attention mechanism, which utilizes its characteristic of focusing on important semantic information in natural language processing to give more attention weight to clauses related to the overall emotional tendency and to reduce the attention weight of clauses not related to the overall emotional tendency [26]. The attention score function β is calculated as follows:

$$t_s=\frac{\sum_{i=1}^{m}X_i^s}{m} \tag{20}$$

$$\beta\left([X_i^c;t_s]\right)=u_s^T tanh\left(W_s[X_i^c;t_s]\right) \tag{21}$$

where t_s is the overall representation of the emotion word matrix X^s associated with the context word, and u_s^T and W_s denote the learnable weight matrices. Normalizing the attention score with the attention score function β, the attention weight of the ith word vector x_i^c in the context word matrix x^c associated with the emotion word can be obtained as shown in the following equation:

$$\alpha_i = \frac{\exp(\beta([X_i^c;t_s]))}{\sum_{i=1}^{n}\exp(\beta([X_i^c;t_s]))} \tag{22}$$

Finally, the i nd word vector x_i^c in the contextual word matrix x^c is multiplied with its corresponding attention weight α_i to obtain the word vector x_i for emotional feature enhancement:

$$x_i = \alpha_i X_i^c \tag{23}$$

After the above processing, the contextual word embedding matrix $W^c = [w_1, w_2, \cdots, w_n] \in R^{n\times d}$ is converted into an emotionally feature-enhanced contextual word embedding matrix $X = [x_1, x_2, \cdots, x_n] \in R^{n\times d}$, and the matrix X is used as an input to the neural network layer.

2.3.3. Deep Neural Networks. The neural network layer of the model in this paper receives the contextual word embedding matrix augmented with sentiment features from the input layer and furthermore extracts the deep sentiment semantic features from the text data. This section focuses on the structure and principles of gated recurrent unit neural networks (GRU) and the combination strategies of different deep neural networks [27].

1) GRU unit. The gating mechanism of the GRU unit mainly consists of a reset gate r_t and an update gate z_t. Among them, the reset gate r_t controls the state of the input information stream, and the reset gate z_t controls the effect of the input information stream on the state of the unit. It can be seen that the GRU unit effectively controls the state of the information flow through the gating mechanism. Taking the tth word x_t in the contextual word embedding matrix $X = [x_1, x_2, \ldots, x_n]$ for emotion feature enhancement as an example, the specific formula of GRU is as follows:

$$r_t = sigmoid\left(w_r \cdot |h_{t-1}, x_t|\right) \tag{24}$$

$$Z_t = sigmoid\left(w_z \cdot |h_{t-1}, x_t|\right) \tag{25}$$

$$\tilde{h}_t = tanh(W_{\tilde{h}} \cdot [r_t \odot h_{t-1}, x_t]) \tag{26}$$

$$h_t = (1 - z_t) \odot h_{t-1} + z_t \odot \tilde{h}_t \tag{27}$$

where $\odot$ denotes a dot-multiplication operation of a matrix, w_r, w_z and $w_{\tilde{h}}$ denote a learnable weight matrix, and h_t denotes a unit state value corresponding to x_t.

In the Bi-GRU layer, the forward GRU layer processes the text data word by word in the order of the input sequence as a way of obtaining the unit state value corresponding to each word, and the reverse GRU layer performs the same operation in the reverse order of the input sequence [28]. The calculation of the Bi-GRU unit state value is shown below:

$$\overrightarrow{h_t} = \overrightarrow{GRU}(x_t, \overrightarrow{h_{t-1}}) \tag{28}$$

$$\overleftarrow{h_t} = \overleftarrow{GRU}(x_t, \overleftarrow{h_{t-1}}) \tag{29}$$

$$h_t = \left[\overrightarrow{h_t} \oplus \overleftarrow{h_t}\right] \tag{30}$$

where $\overrightarrow{h_t}$ denotes the unit state value corresponding to forward $\overrightarrow{GRU}$, $\overleftarrow{h_t}$ denotes the unit state value corresponding to reverse $\overleftarrow{GRU}$, and $\oplus$ denotes the dot-add operation of the matrix. For the contextual word embedding matrix $x = [x_1, x_2, \cdots, x_n]$ is used as an input to the Bi-GRU layer, the

corresponding output of this layer is $H=[h_1,h_2,\cdots,h_n]$.
2) Combined GNN and GRU Strategy. In order to further learn the local semantic features of Chinese language and literature text, enrich the emotional feature representation of the text, and make the judgment of the emotional tendency of the text more accurate, this paper adopts convolutional neural network (CNN) to solve the problem of extracting the local semantic features of the text [29]. In order to combine the gated recurrent unit neural network and convolutional neural network effectively, the model in this chapter adopts the deep neural network combination strategy of Bi-GRU+CNN, i.e., the output of the input layer is first passed through the Bi-GRU layer to learn the sequential semantic features of the text, and then the output of the Bi-GRU layer is passed through the CNN layer to learn the local semantic features of the text.

Taking the output of Bi-GRUA $H=\left[h_1,h_2,\ldots,h_n\right]$ as an example, the CNN firstly slides the convolution in order to slide along the word sequence, and at the same time utilizes the convolution kernels with different widths to carry out the convolution operation on the data within the sliding window. The formula for the convolution operation is as follows:

$$c_i=f\left(H_{i:i+k}\cdot W_c+b_c\right) \tag{31}$$

where K denotes the width of the convolution kernel, f denotes the nonlinear activation function ReLU, W_c denotes the weight matrix of the convolution kernel, and b_c denotes the bias term. Each convolutional kernel corresponds to a linguistic feature detector, which extracts the local feature patterns of the n-gram at different granularities.The CNN applies convolutional kernels of different widths to each possible region of matrix $H=\left[h_1,h_2,\ldots,h_n\right]$ to generate feature map $C=\left[c_1,c_2,\ldots,c_{n_k}\right]$, where n_k denotes the total number of convolutional kernels of different widths. For each subgraph c_i in the feature graph $C=\left[c_1,c_2,\ldots,c_{n_k}\right]$, the CNN employs a maximum pooling layer to extract the most salient local semantic features in each subgraph c_i, which is computed as follows:

$$p_i=down\left(c_i\right) \tag{32}$$

where $down(\cdot)$ denotes the maximum pooling function. By the above, the pooling layer can extract the most important features in the local relations of different regions and generate a fixed-size vector (the vector size is equal to the total number of different-width convolutional kernels n_k). Finally, the CNN splices the output vectors of different width convolutional kernels corresponding to the pooling layer to generate the final text representation vector $S^*=\left[p_1,p_2,\ldots,p_{n_k\cdot n_{wid}}\right]$, where n_{wid} denotes the number of different width convolutional kernels.

Guided by the sentiment knowledge in the sentiment word embedding matrix, the deep neural network layer of the model in this chapter is able to extract the textual sequential semantic features and local semantic features that are closely related to the sentiment tendency, so that the classifier can more accurately complete the judgment of textual sentiment tendency.

2.3.4. Classifiers and Loss Functions. In order to accomplish the judgment of the sentiment tendency of the vocabulary of Chinese language and literature text, the model in this chapter inputs the text representation vector S^* of sentence S into the softmax classifier, predicts the probability distribution of the sentiment label of the sentence, and selects the sentiment label with the largest probability value as the sentiment polarity of sentence S. The specific calculation of the softmax classifier is as follows:

$$\tilde{y}=softmax(W_o^T s^*+b_o) \tag{33}$$

where $\tilde{y}$ denotes the probability value of the predicted sentiment label, and w_o^T and b_o denote the learnable parameters.

The cross-entropy loss function is used to train the model in this chapter in the following form:

$$J(\theta) = -\sum_{i=1}^{N}\sum_{j=1}^{C} y_i^j \log \tilde{y}_i^j + \lambda_r (\sum_{\theta \in \Theta} \theta^2) \tag{34}$$

where N denotes the size of the training set, c denotes the number of different types of sentiment labels, y denotes the true distribution of sentiment labels, λ_r denotes the coefficients of L_2 regularization, and θ denotes the set of parameters to be optimized during the training process. All the learnable parameters of the model in this chapter are optimized by stochastic gradient descent strategy, which is defined as:

$$\Theta = \Theta - \lambda_l \frac{\partial J(\theta)}{\partial \Theta} \tag{35}$$

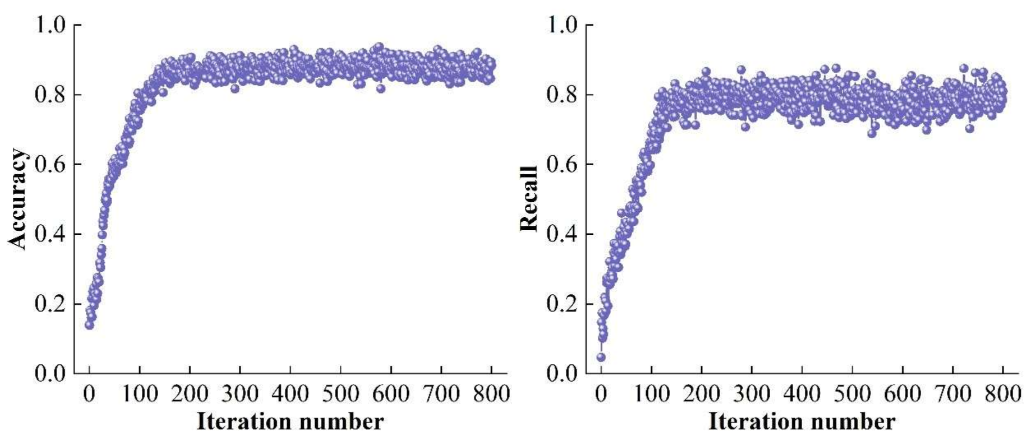
where λ_l denotes the learning rate.

3. Comparison and analysis of model application results

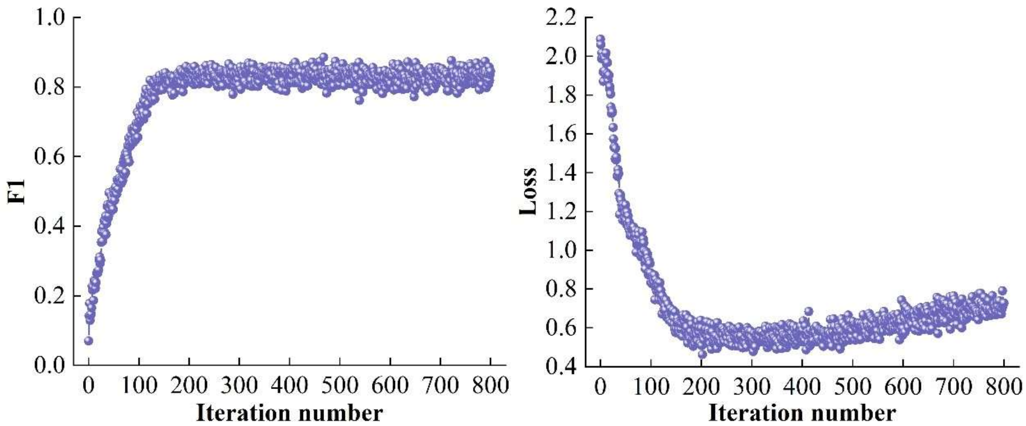
3.1. Experimental results of SDNN modeling

The experimental results of the SDNN model are shown in Fig. 2, and the corresponding accuracy, recall, F1 value, and Loss value of the model as the number of iterations gradually increases are shown in the four result plots from (a) to (d), respectively.

As can be seen from Fig. 2, the SDNN model achieves the lowest Loss value of 0.4626 at 202 iterations, and the corresponding accuracy, recall, and F1 values are relatively high, reaching 90.44%, 79.68%, and 84.72%, respectively, and tend to stabilize with the increase in the number of iterations. It can be concluded that the classification performance of the model is better compared with the classical model, which fully demonstrates that the model can realize the task of analyzing the sentiment of Chinese language and literature texts and achieve better results.



(a) Accuracy (b) Recall



(c) F1 (d) Loss

Fig. 2. Experimental results of SDNN model

3.2. Comparison and analysis of experimental results

The experimental comparison in this section is divided into two parts. Table 2 compares the results of the models trained using a one-way computation approach, aiming to validate the soundness of the selected GRU network. The comparison in Table 3, on the other hand, is the experimental results of the models trained using a bidirectional computation approach, which together validate the sentiment categorization effect of the given SDNN model (i.e., Bi-GRU+CNN+Attention model).

Comparing the experimental results of the models in Table 2, it can be found that the accuracy of sentiment classification of Chinese language and literature text vocabulary obtained using the unidirectional GRU network is up to 85.74%, which is an improvement of 4.48%, 2.10%, and 9.46%, respectively, compared with the results of the mainstream unidirectional models CNN, RCNN, and LSTM, which are all improved to a certain extent. Among them, CNN utilizes convolutional computation to obtain the representation of context words and aspect words, with fast computation speed, and has a great advantage in local feature mining of text.LSTM, on the other hand, can make up for the gradient defects of RNN to a certain extent, and extracts the text feature information selectively by adding a gating mechanism, which leads to the enhancement of the accuracy rate. This group of comparison experiments proves that the use of GRU network is effective, and lays the foundation for subsequent comparison experiments.

Table 2. Comparison of experimental results of classical unidirectional model

Models	Accuracy	Recall	F1 value	Loss
CNN	81.26%	73.54%	77.21%	0.6472
RCNN	83.64%	81.42%	82.52%	0.7105
LSTM	76.28%	68.76%	72.33%	0.6019
GRU	85.74%	78.03%	81.70%	0.5962

Comparing the experimental results of the first two models in Table 3, it can be found that the accuracy of lexical sentiment categorization of Chinese language and literature text obtained by using BiGRU can reach 86.45%, which is improved by 1.21% compared with the BiLSTM model. Among them, BiLSTM uses two long and short-term memory networks to extract the forward and backward features of the text respectively, and improves the performance of the model through feature fusion. The bidirectional gated recurrent unit neural network BiGRU model, on the other hand, by fusing the information in both directions to participate in the judgment of affective tendency, can effectively learn the semantic features of the text sequence that are closely related to affective tendency, and thus improve the effect of text sentiment analysis, thus proving the reasonableness of the selected BiGRU model.

At the same time, comparing the experimental results of the latter three models, it can be found that the accuracy of the BiGRU + CNN model for the lexical sentiment classification of Chinese language and literature texts reaches 88.53%, which is 2.08% higher than that of the single BiGRU model, which proves the effectiveness of the deep neural network combination strategy of GRU and CNN used in this paper, which can effectively integrate the sequential semantic features and local semantic features of the text to generate deep emotional semantic features. The accuracy of text sentiment classification obtained using the SDNN model can reach 90.87%, which is 4.42% and 2.34% higher than the results of the BiGRU model and BiGRU+CNN model without adding the sentiment attention mechanism, respectively. This is due to the fact that adding the attention mechanism layer on top of BiGRU+CNN can capture the internal correlation of text features and help the model optimize the feature vectors, which can effectively improve the performance of sentiment analysis and classification accuracy, thus proving the effectiveness of the method of adding the sentiment attention mechanism.

In addition, it can be found by comparing the results of multiple sets of models that the given SDNN model can obtain faster convergence of Loss values and higher recall, which further proves that the model can effectively improve the performance of the sentiment analysis of Chinese language and literature texts.

Table 3. Comparison of experimental results of classical bidirectional model

Models	Accuracy	Recall	F1 value	Loss
BiLSTM	85.26%	78.21%	81.58%	0.6345
BiGRU	86.45%	79.32%	82.73%	0.5734
BiGRU+CNN	88.53%	80.16%	84.14%	0.5219
SDNN	90.87%	80.73%	85.50%	0.4626

4. A Study of Emotional Vocabulary in Chinese Language Literature Texts

In order to further explore the characteristics of lexical emotional tendencies in Chinese language literary texts, this paper uses the constructed SDNN model as an emotion recognition tool to study the emotional vocabulary in the texts.

4.1. Rhythmic structure of emotional vocabulary

On the basis of the extraction of emotional features and identification of tendencies in Chinese language literary texts in the previous section, this study attempts to borrow the theory of coordinate axes in mathematics to construct a model of the rhyme structure of emotional resources in Chinese language literary texts.

4.1.1. The Structure of Emotional Flow in Chinese Language Literature Texts. The rhythmic structure of emotional vocabulary in literary discourse is like a river with undulating waves, which is the emotional flow of the discourse. The structure of emotional flow in Chinese language literary texts is shown in Fig. 3, in this model, the horizontal axis is an open axis, and 1, 2, 3a, 3b, 4, etc., on the top, represent the numbers of each emotional resource after relabeling. The vertical axis is the axis representing the extreme values, -3, -2, -1, 0, 1, 2, 3, etc., for each lexical resource. The extreme values may exceed -3 or 3 under the conditioning of graded modifiers. All implicit and explicit lexical resources form a zigzag arc by connecting the points after positioning them on the coordinate axis. From the dramatic and rapid change of positive and negative emotions in the emotional flow of the discourse, the dramatic psychological struggle and emotional change of the protagonist in the Chinese language literary text can be inferred. The main significance of this model, which starts with subjective quantification of emotional resources and ends with fuzzy visualization, is that it reflects the multimodality of emotions in Chinese language literary discourse, as well as provides a new perspective for recognizing and interpreting the emotional significance of Chinese language literary texts.

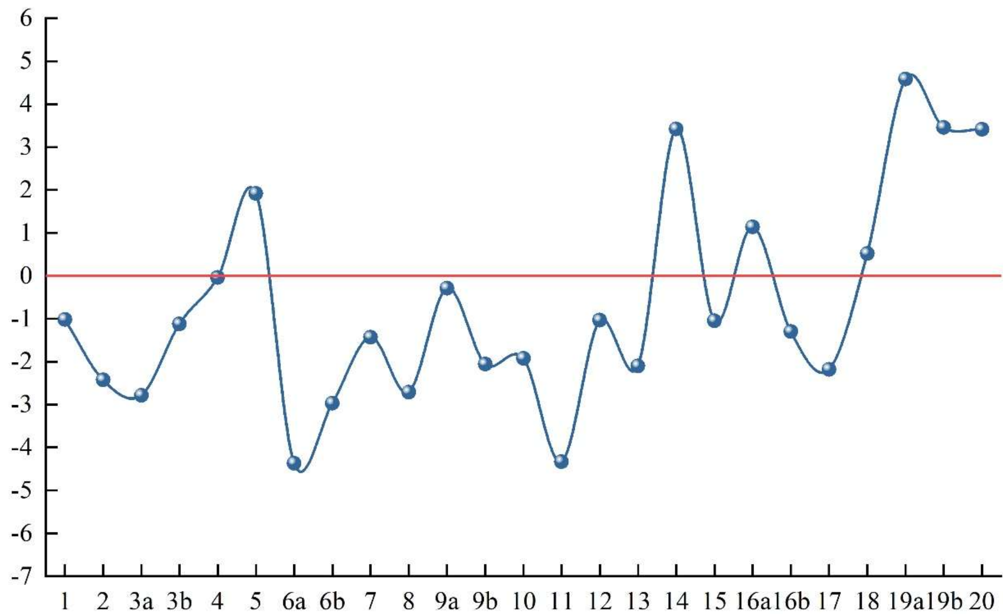


Fig. 3. The structure of emotion flow in Chinese literary texts

4.1.2. Semantic Rhyme Structure in Chinese Language Literature Texts. In order to explore how affective flow influences other indirect or neutral affective lexical resources to create the emotional atmosphere of the textual discourse, this paper further modifies the structural model of affective flow and obtains the semantic rhyme structure in the textual discourse of Chinese language literature as shown in Fig. 4, where the affective flow intersects with the horizontal axis to form a number of regions of varying sizes. Among them, each peak is a positive emotion domain and each valley is a negative emotion domain. The intersections of the emotion streams with the horizontal axis then mark the boundaries between the domains. In each of the rhyming domains, neutral affective textual resources are subject to the rendering of affective vocabulary, which creates the emotional atmosphere of the discourse. As a matter of fact, the semantic rhyme of a discourse is very complex because the rhyme domains of different characters will be intertwined. The interplay of the semantic rhymes, in turn, shapes the tone of the whole discourse.

There are 10 rhyme domains in Figure 4, including 5 positive emotion domains and 5 negative emotion domains. Obviously, the total area of the negative emotion domains is larger than that of the positive emotion domains, indicating that the emotional tone of this Chinese language literary text is predominantly pessimistic on the whole.

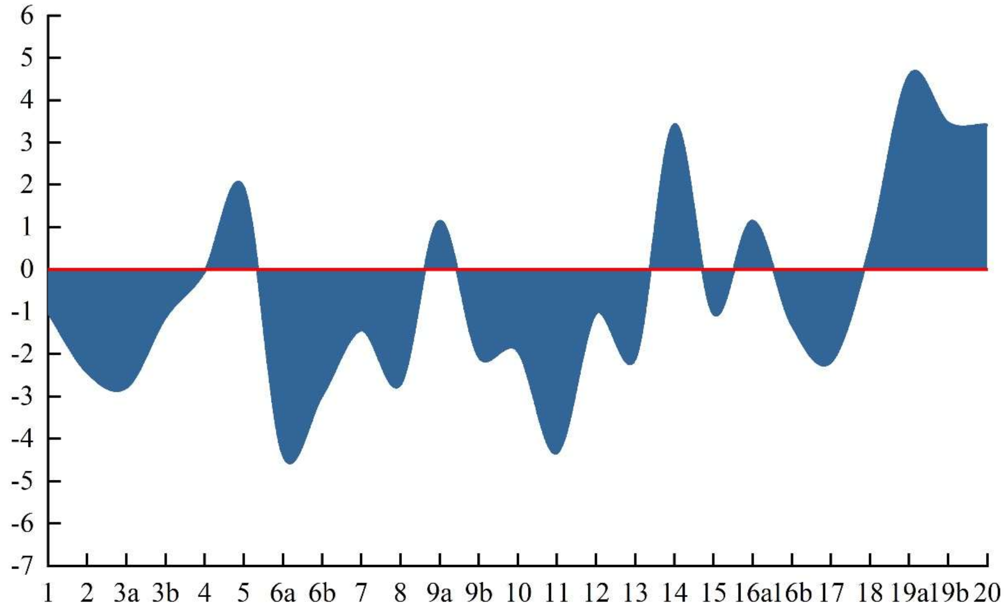


Fig. 4. Semantic rhyme structure in Chinese literary texts

4.2. Lexical Sentiment Analysis of Chinese Language Literature Texts

Taking Liu Zongyuan's literary works as an example, this section examines the emotional tendencies and their changes in the Chinese language literary works created by him through word frequency analysis and sentiment analysis.

4.2.1. Results of word frequency analysis. Using the standard word comparison table of landscape elements, 102 garden-related literary works created by Liu Zongyuan during his stay in Yongzhou, Hunan Province were screened on the basis of the place of creation and the place of description, and screened according to the word division and word frequency statistics of ROST CM6 software to get the word frequency situation of the literary works created during the five periods of his stay in 806~807, 808, 809~810, 811~814 and 815, and by classifying the high-frequency words into seven categories of aesthetic preference: sky view, earth view, water view, life view, architecture, garden view and scenery. The word frequency of literary works, and by classifying the high-frequency words into seven categories: sky view, earth view, water view, life view, architecture, garden view, and scenery, we get the change of Liu Zongyuan's aesthetic preference during his ten years in Yongzhou as shown in Fig. 5, which demonstrates his different preferences for the categorization of landscapes in different periods.

In landscape activities, Ryu primarily prefers earth and water views, while sky and life views come second. Between 806 and 807 and in 808, architecture was the main object of Liu's landscape activity, and his perception of sources other than garden scenes was relatively balanced. However, in the periods from 809 to 810 and from 811 to 814, water and earth scenes became the main objects of Liu Zongyuan's landscape activities. Especially in 809 to 810, there was a shift in Liu Zongyuan's aesthetic imagery, as he began to pay more attention to natural landscape sources and less to humanistic ones. This can be explained by the fact that he began to bring his landscape activities between the mountains and the waters, rather than just stopping at his residence. As for 815, landscapes and waterscapes were still his main aesthetic preferences, which may be related to the aesthetic habits he developed during his stay in Yongzhou.

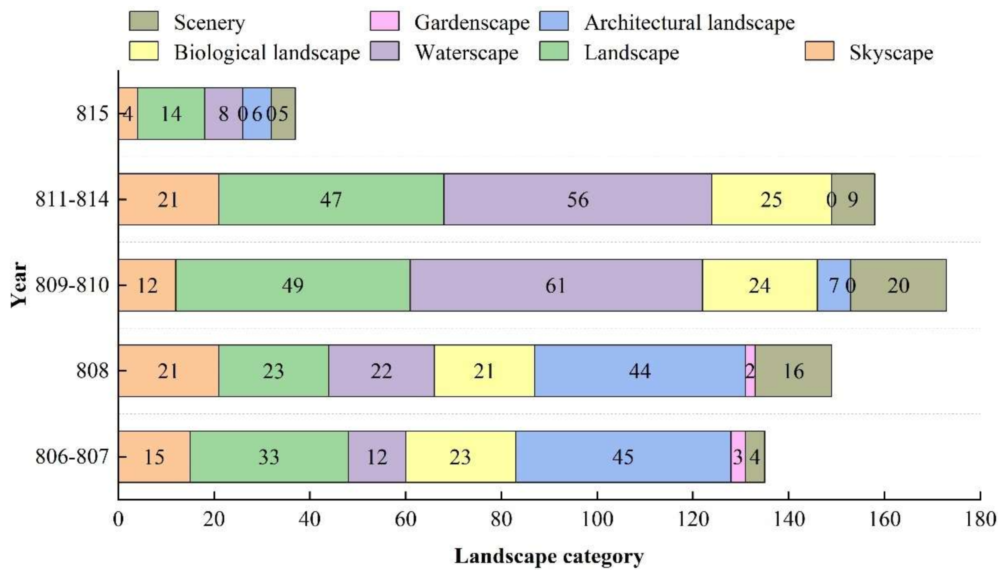


Fig. 5. Changes in Liu Zongyuan's aesthetic preferences during his ten years in Yongzhou

In addition, according to the word frequency analysis and landscape classification, it can be seen that Liu Zongyuan's aesthetic imagery has undergone significant changes in Yongzhou in the past ten years. He shifted from the small garden of his residence to the large garden between the mountains and rivers, and throughout the period, "Yuxi", "Longxing Temple", "house", "Xishan" and "Xiaoshui" were high-frequency words, which were not only landscape place names, but also landscape elements. In particular, "Yuxi" and "Longxing Temple" are two important places of residence in the transformation of his aesthetic imagery, which shows that Liu Zongyuan's landscape activities are centered on "houses" to explore everywhere.

4.2.2. Statistical results of sentiment analysis. On the basis of word frequency analysis, this paper utilizes the constructed lexical emotional tendency analysis model of Chinese language literary texts to analyze the emotions of 102 literary works created by Liu Zongyuan, and classifies his creative emotions into three categories: positive emotions, neutral emotions, and negative emotions, and finally obtains the changes of Liu Zongyuan's aesthetic emotions during the five periods from 806 to 815 as shown in Figure 6.

As can be seen from Figure 6, Liu Zongyuan's emotions during his ten years in Yongzhou were generally in the doldrums, and the proportion of his negative emotions was always above 75%, although both positive and negative emotions had ups and downs, they did not have any effect on the overall negative and pessimistic state of mind. Liu Zongyuan's mood during his ten years in Yongzhou was always in the doldrums, and even though his indulgence in landscapes improved, he was still more sad than happy in his writing.

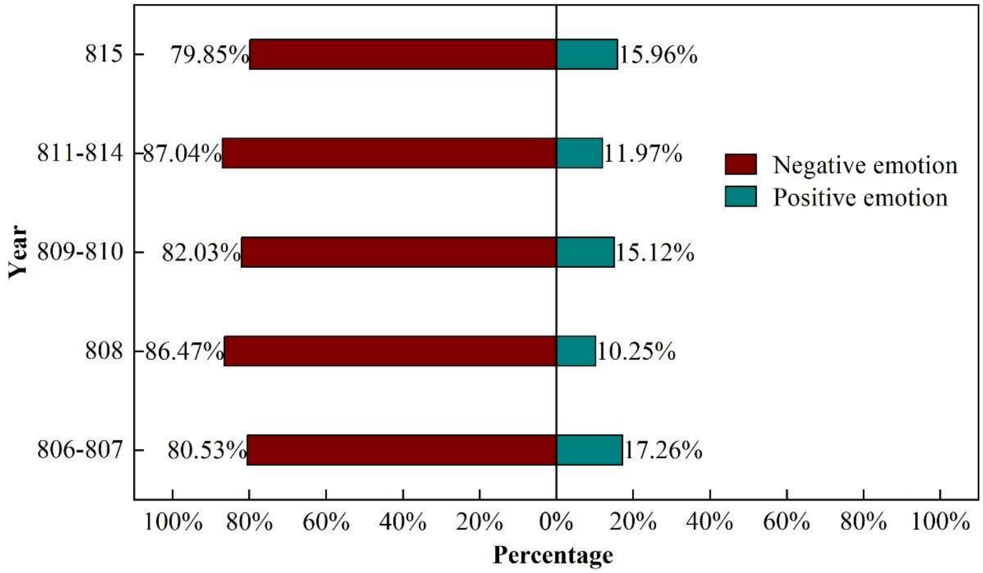


Fig. 6. The changes of Liu Zongyuan's aesthetic mood from 806 to 815

5. Conclusion

In this paper, the modeling of lexical affective tendency in Chinese language and literature text based on fuzzy ontology is realized, and SDNN, a textual affective tendency analysis model based on deep neural network and affective attention mechanism, is built and practically applied.

The SDNN model achieved the lowest Loss value of 0.4626 at 202 iterations, at which time the corresponding accuracy, recall, and F1 value reached 90.44%, 79.68%, and 84.72%, respectively, and gradually leveled off with the increase of iterations. It indicates that the SDNN model can be applied to the task of analyzing the sentiment of Chinese language and literature texts and achieve better classification results. Meanwhile, the accuracy of sentiment classification using unidirectional GRU network can reach 85.74%, which is 4.48%, 2.10% and 9.46% higher than the mainstream unidirectional models CNN, RCNN and LSTM, respectively, which proves the effectiveness of the use of GRU network in SDNN model. In addition, the sentiment classification accuracy using BiGRU+CNN model reaches 88.53%, which is an improvement of 2.08% with respect to the single BiGRU model, proving the effectiveness of the deep neural network combination strategy of GRU and CNN used in this paper. The accuracy of text sentiment classification obtained using the SDNN model is as high as 90.87%, which is improved by 4.42% and 2.34% compared to the results of the BiGRU model and BiGRU+CNN model without adding the sentiment attention mechanism, thus proving the effectiveness of the method of embedding the sentiment attention mechanism.

Subsequently, this paper quantitatively modeled the rhyme structure of lexical emotions in Chinese language literary texts through semantic assignment, constructed an emotion flow model and a semantic rhyme model, and the example text used has a total of 10 rhyme domains, including 5 positive emotion domains and 5 negative emotion domains, while the total area of negative emotion domains is larger than that of positive emotion domains, which means that the emotional tone of this Chinese language literary text is dominated by pessimism.

Finally, through the word frequency analysis and sentiment analysis of Liu Zongyuan's literary works, it can be seen that Liu Zongyuan's emotions during his ten years in Yongzhou were generally in the doldrums, and although there were some ups and downs in both positive and negative emotions, the overall negative and pessimistic were predominant, which was reflected in the text as being more pessimistic than joyful. This verifies the validity of this paper's SDNN model in the analysis of lexical emotional tendencies in Chinese language literary texts.

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