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Research on Emotional Analysis and Emotional Color Extraction Algorithm of Chinese Language and Literature Based on Emotional Computing

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Abstract: - In China, the emotional response of diverse cultural bearers, including literature, movies, and other media, frequently mirrors the country's cultural improvement. Consequently, emotional analysis of the text and paintings may be used to examine the cultural evolution, determine its growth dynamics, and sort out its context. The project aims to investigate how well sophisticated affective computing performs in identifying and analyzing the emotional aspects of traditional Chinese literature and language. The study selects the Double Channel based Self-organized Residual Network-50 V2 (DC-SoResNet 50V2) algorithm based on a combination of deep learning algorithms and further improving the (DC-SoResNet 50V2) algorithm using Emperor penguin Colony optimizer (EPCO). Moreover, the color image and text features from traditional Chinese literature are extracted using hummingbird-based term frequency-inverse document frequency (HB-TF-IDF) and Stochastic Color Harmony Algorithm (SCHA). Comparisons are made between the proposed and standard approaches using the training and test sets, respectively. The training time of the proposed approach is stable at around 25.1 s, while the test time is steady at about 18.5 s. The emotion identification accuracy of the proposed method achieved average of 99.11 and 99.23% in testing and training sets for the entire datasets, respectively. Comprehensive analysis of classic literary works can be possible with the help of this research, which offers fresh viewpoints and theoretical references.

Keywords: Optimization, Deep learning, Emotion, Chinese language, literature, traditional culture, and Quality Education.

1. INTRODUCTION

Emotional analysis involves the computational examination of text, speech, or other forms of communication to identify, classify, and understand the underlying emotions expressed [1-3]. In emotion analysis, researchers aim to go beyond mere polarity and explore the complexity of human emotions, including happiness, sadness, anger, fear, and more subtle variations [4]. It includes recognizing linguistic patterns, contextual cues, and cultural nuances that influence the expression of emotions in communication. By understanding the emotional content of a text, businesses can tailor their products and services to meet consumer needs better[5]. Emotional computing, as a field, seeks to bridge the gap between human emotions and computer systems, enabling machines to understand, respond to, and generate dynamic content [6]. In the case of Chinese, this involves linguistic challenges to cultural and contextual considerations unique to the Chinese-speaking world [7]. Researchers explore various methods to capture the essence of emotions expressed through language, from emotion analysis to emotion detection and categorization [8]. Emotion detection (ED) has emerged as a crucial area of focus within NLP, attracting considerable attention from researchers due to its wide-ranging applications. Researchers explore diverse methodologies, including machine learning models, deep neural networks, and sentiment analysis techniques, to develop robust algorithms that effectively detect emotions from text [9-10].

According to Xu et al. [11], building a Weibo-based emotion dictionary involves combining ground theory and semi-automated methods to generate a comprehensive set of emotion categories and associated terms. The advantage lies in its ability to capture a wide range of emotions expressed on Weibo and improve the performance of sentiment analysis. A Chinese Positive Emotion Database (CPED) has been established to address the lack of standardized inducing materials for extensive positive emotions by Zhang, Y et al. [12]. Additionally, 113 features extracted from PPG and GSR signals were utilized in an SVM classifier. Bashir et al. [13] proposed a deep learning (DL) approach for emotion classification using UNED. The dataset facilitates research in emotion detection for Urdu text, enabling the evaluation of machine learning and DL techniques for emotion classification. Lian et al. [14] addressed real-world facial emotion recognition challenges by focusing on the authenticity of predictions generated by different facial areas. Han, J. and Geng, X. [15] examined student attitudes to online learning technologies (SAOLT) within a technology-enhanced learning (TEL) framework during the COVID-19 pandemic.

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Analyzing data from 7210 Chinese undergraduate students, perceived instructional support was positively associated with a deep attitude toward online learning technologies while negatively affecting surface attitude. These findings contribute to the understanding of SAOLT and provide pedagogical insights to promote the effective use of online learning technologies, thereby improving the quality of learning in TEL environments. This study puts forward a Chinese literary emotional analysis model based on the combined deep learning and optimization approach for learners' learning experience texts and paintings. The main contribution of this research is summarized as follows.:

- The computation of emotion from the Chinese language and traditional literature is analyzed using the proposed DC-SoResNet 50V2 method.
- Chinese traditional literature includes paintings and text. Features are extracted from the data using HB-TF-IDF and SCHA methods for both text and image data.
- Experiments show that the classification speed of this method is lower than that of earlier methods. Also, the proposed model classifies the learning experience text and image information in multiple levels to improve the performance of learners' emotional analysis and provide more effective support for teaching design and management.

The rest of the paper is organized as follows: Section 2 covers the proposed strategy and each stage of the procedure in depth. Section 3 contains the dataset utilized and the outcomes of the technique's implementation and assessments. Section 5 covers the conclusion and final views at the end.

2. PROPOSED METHODOLOGY

The Chinese Traditional Painting (CTP) dataset" and "COCO-CN" dataset are used in the proposed approach, which focuses on analyzing the use of color at a professional and emotional level in the paintings and text of Chinese traditional and literature. This study first collected the data, which was then filtered and analyzed. The pre-processed data is given to the feature extraction part to separate the significant features from the text and colored paintings for adequate classification.

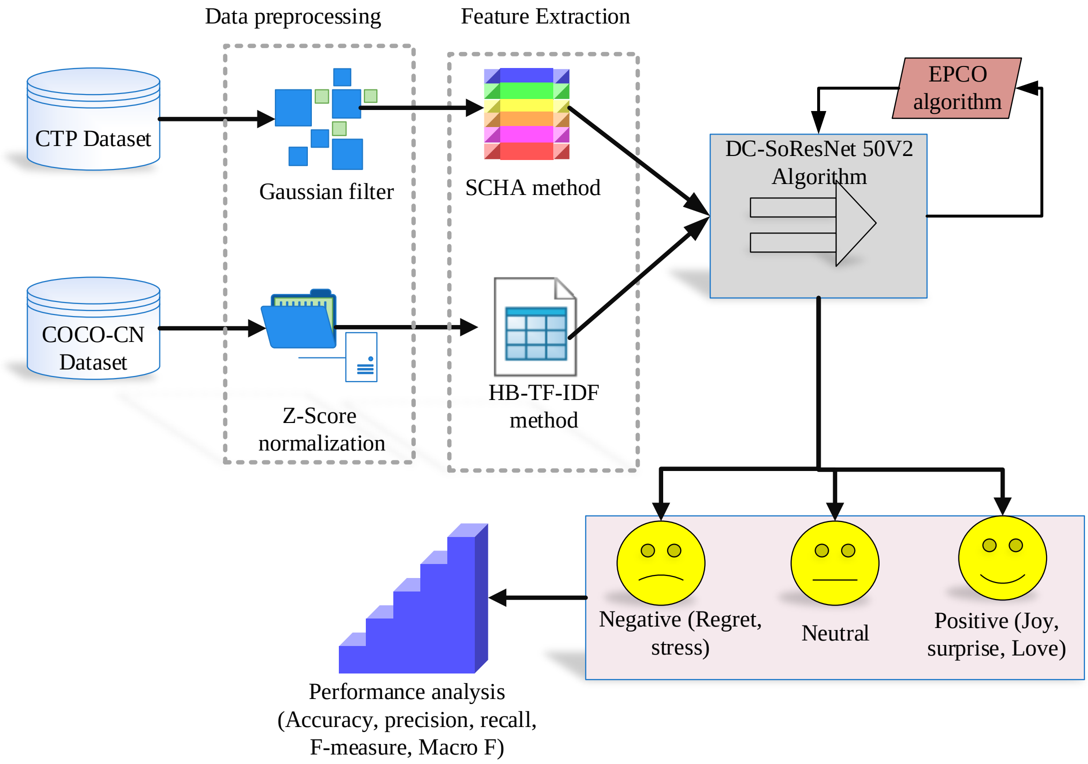

Fig.1. Proposed framework of emotional analysis for Chinese language and literature

The HB-TF-IDF method is used to extract the features from the Chinese traditional text data, and the SCHA method is used to remove the features using the color extraction function. DC-SoResNet 50V2 was used in this study to classify the data according to the emotional traits shown in the images and text. Finally, the performance of the proposed approach is validated for the practical analysis of quality education in Chinese vocational and regular classes.

4.1. Data pre-processing

Two types of Chinese datasets, text, and paintings, were collected for this study. Following acquiring data from traditional Chinese literature, this study used a Gaussian and Z-score normalization to filter and analyze the data.

$$G_a(u,v) = \frac{1}{2\pi\delta^2} e^{-\frac{u^2+v^2}{2\delta^2}} \tag{1}$$

Where, u is denoted as the U coordinate value and v is denoted as V coordinate value, π is the constant value and the standard deviation is represented as δ. These techniques eliminate unnecessary data and bring the artwork's natural look back. The text data is normalized using Z-score normalization and expressed in eqn. (2),

$$m' = \frac{m - \overline{B}}{\delta_B} \tag{2}$$

Where, m and m' is denoted as the ole and new entry of each data, δ_B and $\overline{B}$ is the standard deviation and mean of the data, respectively. This will decrease the effect of errors and increase the predictive abilities of the proposed model.

4.2. Feature Extraction

Two methods are used in the feature extraction part: the HB-TF-IDF and SCHA methods. The HB-TF-IDF method is used for the text and literature data extraction, and SCHA is used for the color feature extraction of Chinese paintings and images.

a) HB-TF-IDF

The HB-TF-IDF method is the combination of hummingbird optimization with the TF-IDF approach. The TF-IDF method is highly effective for large amounts of data, yet it needs to improve its performance in terms of semantic meaning consideration. Thus, the performance of the hummingbird optimization algorithm fitness function is added to the TF-IDF algorithm, and a new HB-TF-IDF-based feature extraction model is developed. TF determines the frequency of words in a text, and IDF determines the frequency of a word in the file. TF and IDF scores are computed separately. The term's importance is expressed in an article as the product of these two values. A vector including the most pertinent terms is generated to get the ultimate collection of top-performing characteristics. The measure of TF-IDF is expressed using eqn. (3),

$$TF - IDF(word) = \frac{N.Count(word)}{\ln\left(\frac{N}{M+1}\right) * \sum_{i=1}^{M} count(word_i^t)} \tag{3}$$

Where, the variables M and N represent the number of tests and the total number of core texts, respectively, that include the word. In TF-IDF, the weight of the keyword is optimized using the fitness function of the hummingbird algorithm. Initialize the population size, utmost iteration, and limits for upper and lower boundaries to the algorithm. Compute the best features based on the flight skills of hummingbirds. In each population, the best features are searching using the exploration and exploitation function using eqn. (4) and (5),

$$H_i(t+1) = w_{i,j}(t) + b * d * (w_i(t) - w_{i,j}(t)) \quad ,b \in n(0,1) \tag{4}$$

$$H_i(t+1) = w_{i,j}(t) + b * d * w_i(t) \quad ,b \in n(0,1) \tag{5}$$

The value of keywords weight is updated in HB-TF-IDF using eqn. (6),

$$W_i(t+1) = \begin{cases} W_i(t) & if\,(W_i(t)) \le H_i(t+1)) \\ H_i(t) & f\,(W_i(t)) > H_i(t+1)) \end{cases} \tag{6}$$

Where, the source of keyword weight is denoted as $w_{i,j}(t)$ at the t^{th} iteration and $w_i(t)$ is the targeted optimized weights of the keywords in TF-IDF model, d is the dimension. Finally, the best features are extracted from the HB-TF-IDF method.

b) SCHA method

In this study, the SCHA algorithm combines the Stochastic paint algorithm and the Color Harmony algorithm to extract color from traditional Chinese literature and language datasets. Initialize the total number of pre-processed Chinese painting data in the SCHA algorithm using eqn. (7)

$$p_{i,0} = p_{\min} + r * (p_{\max} - p_{\min}), \quad i = 0,1....n \tag{7}$$

Where $p_{i,0}$ is the first color of the i^{th} data, the upper and lower limit of the design is represented as $p_{\max}$ and $p_{\min}$. An integer having a range of [0, 1] is called a r. the number of colors or variables is represented by n. The average number of colors in the search space is measured when the initial set of colors is acquired, and its diversity is either above or equal to the initial variation threshold value. Since harmonic colors aren't specific hues, various colors are chosen, blended, and created using eqn. (8),

$$p^1(a,b) = r_1.p(x_a,b) + p\,(y_a,b) \begin{array}{l} a\,i = 0,1....nc \\ b\,i = 0,1....n \end{array} \tag{8}$$

Where $p(x_a,b)$ and $p\,(y_a,b)$ are the components of the newly updated hue circle colors, where p^1 is the product of a random set of integers as r_1 and r_2. As a result of the task, colors are arranged in ascending order by matching goal functions. Ultimately, it is divided into three equal groups: primary, which is the best; secondary, which is fair; and tertiary, which is the poorest. If the new color's attractiveness index is higher than the old one after evaluation, a new color gets substituted for the old one. The optimization cycle ends when several iterations have been completed. A new process is planned if the condition is not fulfilled; if it is, the process ends, and the best solution is provided.

4.3. EPCO based DC-SoResNet 50V2 algorithm

The DC-SoResNet 50V2 combines deep learning algorithms such as self-organized mapping and the ResNet 50V2 algorithm. The parameters of the DC-SoResNet 50V2 algorithm are optimized using the EPCO model. The DC-SoResNet 50V2 design involves batch normalization at first, then an activation function, a fully connected layer that is self-organized mapping, and weight updates using EPCO. Next, this is carried out the ReLU activation function and batch normalization. EPCO was used to tune the weights after the activation function. The primary distinction between the proposed architecture and the DC-SoResNet 50V2 architecture is to activate the weight layers prior rather than subsequently. To create an identity connection, DC-SoResNet 50V2 was designed to eliminate nonlinearity, which clears a path from the input to the output. Before the weights are multiplied, version 2 of the ResNet component performs the activation mechanism and batch normalization. Given that the dimensions of the input and output differ, the residual block function is defined as follows in Eqn (9).

$$z = f\,(y, \{S_i\}) + S_u y \tag{9}$$

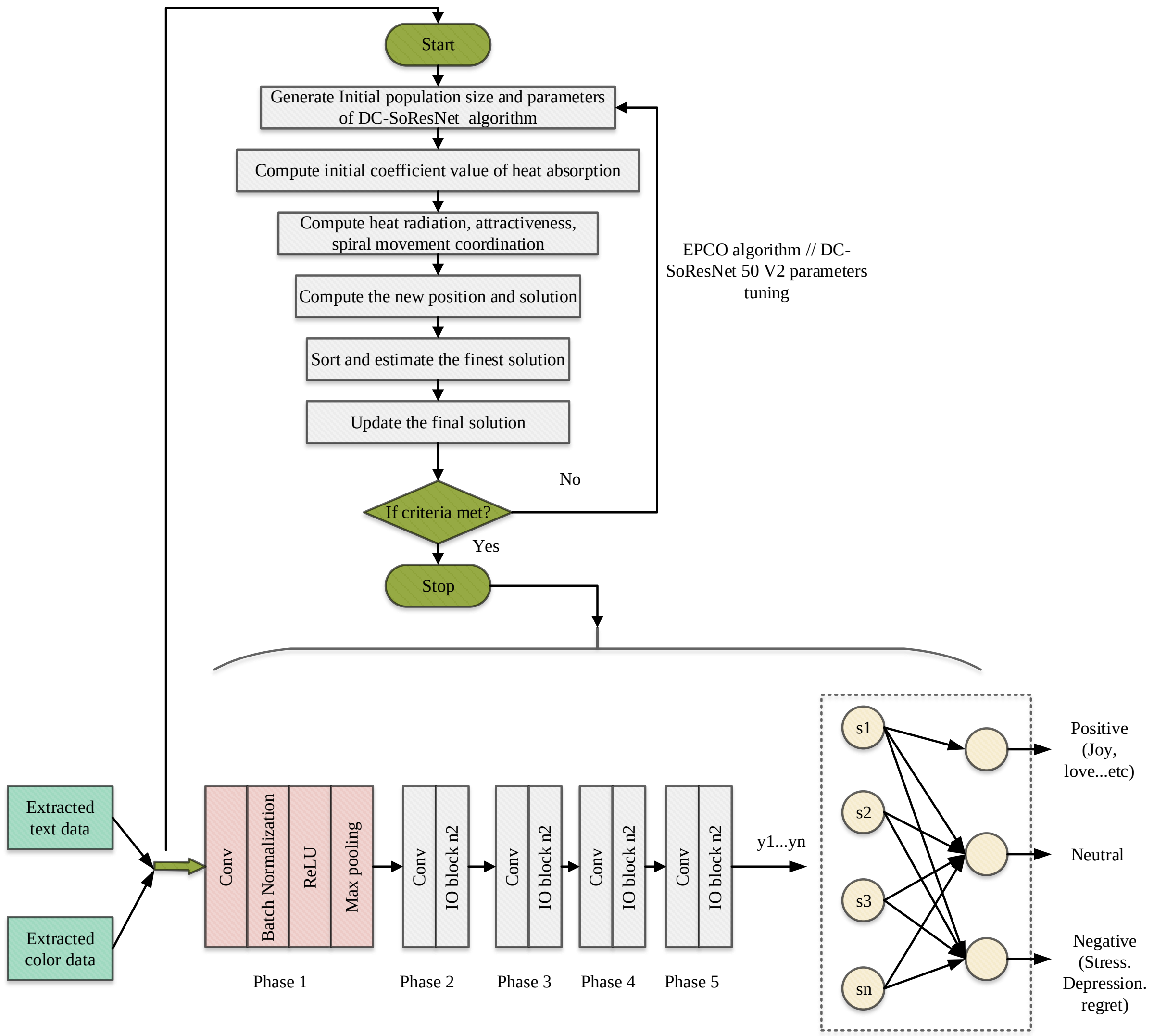

Fig.2 Proposed EPCO based DC-SoResNet 50V2 algorithm for Chinese literature emotion analysis

Where y is the input picture, S is the pre-trained EPCO weights, and f is is the residual block function. Change the dimensions and DC-SoResNet 50V2 yields significantly improved outcomes while the residual block function performs block mapping with zero additional paddings. The self-organized mapping functions are applied for the connected layer by initializing the random weights and learning rate values. Estimate the Euclidian distance using eqn. (10)

$$d(i) = \sum (S_{iji} - y_i)^2 \qquad \begin{matrix} i = 1,2,a \\ j = 1,2\ldots b \end{matrix} \tag{10}$$

When $d(i)$ is the smallest, identify index j, which will be the chosen index. Next, determine the new weight for each j that is in a particular neighborhood of j as well as for all i.

$$S_{iji}(new) = S_{iji}(old) + \alpha\left(y_i - S_{iji}(old)\right) \tag{10}$$

Furthermore, the learning rule is updated and terminates the criteria for the final emotion analysis. Identity mappings produced from additional layers will allow data to pass across the network, decreasing training error and enabling any layer to function as an original input. Here, the parameters of the proposed DC-SoResNet 50V2 algorithm are optimized using the EPCO algorithm.

a) EPCO algorithm

The behavior of emperor penguins led to the development of a brand-new metaheuristic algorithm known as Emperor Penguins optimization. Set the initial values for each EP's location and hyperparameter population size. Heat radiation, attraction, and spiral movement conditions are used to run the optimization. Each hyperparameter radiates heat in the initial population and is attracted to each other by the absorption coefficient. Every hyperparameter is assumed to have the same body surface area. Eqn (11) is used to evaluate the impact of heat radiation and adjust the parameters.

$$E_p = N\beta\varepsilon P_a^4 \tag{11}$$

Where E_p is the parameter tuning rate per second. The Stefan-Boltzmann constant is β , the parameter's plumage emissivity is ε , and the absolute condition make up the total size of the parameter is P_a . System surface and size effects are disregarded since the hyperparameter considers the whole adjustment range. The DC-SoResNet 50V2 parameter tweaking is likely linear. Penguin attractiveness is determined by the number of values in the difference between two hyperparameters. Longer distances have a lower value, whereas shorter distances yield more value. Eqn (12) provides an estimate of the hyperparameter tuning attractiveness.

$$E_p = N\beta\varepsilon P_a^4 e^{-\mu g} \tag{12}$$

If the two hyperparameter values are taken into account as l and m. Higher values for the optimized hyperparameter are required when the tuning function is conducted. The spiral movement functions here from to l and m. During the absorption phase, the hyperparameters' spiral movement is non-monotonic and displays a uniform variance distribution. Equation (13) is used to assess the coordinated optimization movement.

$$\begin{aligned} u_g &= y e^{z\frac{1}{z}\ln\left[(1-E_a)e^{z\tan^{-1}\frac{v_l}{u_m}}+E_a{}^{y\tan^{-1}\frac{v_l}{u_m}}\right]} \cos\left[\frac{1}{z}\ln\left[(1-E_a)e^{z\tan^{-1}\frac{v_l}{u_m}}+E_a{}^{y\tan^{-1}\frac{v_l}{u_m}}\right]\right] \\ v_g &= y e^{z\frac{1}{z}\ln\left[(1-E_a)e^{y\tan^{-1}\frac{v_l}{u_m}}+E_a{}^{z\tan^{-1}\frac{v_l}{u_m}}\right]} \sin\left[\frac{1}{z}\ln\left[(1-E_a)e^{z\tan^{-1}\frac{v_l}{u_m}}+E_a{}^{y\tan^{-1}\frac{v_l}{u_m}}\right]\right] \end{aligned} \tag{13}$$

The spiral-like movement may get monotonous due to the fixed angle information. It is better not to avoid traveling the same old circular route. Thus, to increase diversity, a random element must be included. This way, the hyperparameter will move in a spiral pattern before being appended to a random vector and relocated. One may think of the following as the equation:

$$\text{Previous equation } (14) + \beta\varepsilon_u \tag{14}$$

where ε is the mutation factor influencing the path change and β is a random vector. The recommended optimization technique yields the best possible result if the conditions are satisfied. If not, the initial action is where it starts.

3. RESULT AND DISCUSSION

This article's experiments use the "COCO-CN" and "Chinese Traditional Painting" datasets. There are 1000 content photos and 100 style images in the Chinese Traditional Painting dataset for style transfer. Most content photographs are photorealistic sceneries from places south of the Yangtze River, including mountains, lakes, rivers, bridges, and buildings. In addition to sights from China, it has stunning images of the Grand Canyon, the Rhine, Yellow Stone, the Alps, and other locations. There are many different kinds of traditional Chinese paintings in the content photos. COCO-CN is a multilingual image description dataset with handwritten Chinese phrases and tags. It is another one. The new dataset may be applied to various cross-lingual applications, such as picture labeling, captioning, and extraction.

3.1. Performance Metrics

A classifier's effectiveness is often gauged using a few assessment metrics. Accuracy, recall, precision, F-measure, and macro-F are the performance assessment indicators frequently employed in categorizing Chinese literature and language. The ratio of related documents recovered to the total associated data is known as the recall rate. In contrast, the ratio of related data retrieved to the entire data returned is the precision rate. The most popular technique for calculating the overall classification impact is the F-measure. Macro-F, the arithmetic mean of the performance metrics of each data instance, assesses the overall effectiveness of categorization.

$$R_e = \frac{x}{x+y} \tag{15}$$

$$P_r = \frac{x}{x+z} \tag{16}$$

$$F_m = \frac{2 * P_r * R_e}{P_r + R_e} \tag{17}$$

$$Macro_f = \frac{1}{N} \sum_{e,r,m \in emotions} F_m \tag{18}$$

where y is the number of data that are incorrectly classified but actually belong in a specific classification, z is the number of data that are correctly categorized but not included in a particular class, and x is the number of data that are correctly classified.

3.2. Performance analysis

The comparison shows that the combination of HB-TF-IDF, SCHA, and EPCO -based DC-SoResNet 50V2 approach yields the most outstanding performance in this article. Specifically, how much better the proposed strategy performed in terms of performance measures for both the training and testing sets of data than the present methods such as ON-LSTM [16], ELECTRA-attend-BiLSTM [17], AttBiLSTM [18], CNN_Text_Word2vec [19] and Seq2Seq -RNN-CNN [20].

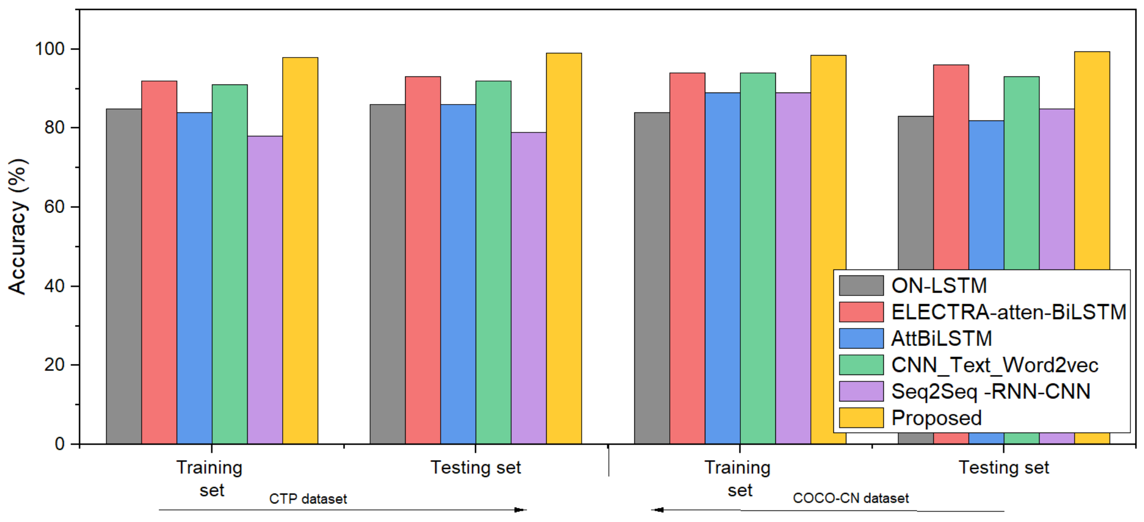

Fig.3 Performance comparison of accuracy for training and testing set of both datasets

The proposed method may enhance by at least 6.5% over existing algorithms, as seen in Figure 3, by providing 98.23% and 98.11% accuracy for CTP and COCO-CN on the training dataset. It's remarkable that at least 7.36% greater than others, its Precision, Recall, F1, and Macro-F measures are among the highest. In summary, fig. 4-7 illustrates how the proposed approach, when compared to ON-LSTM [16], ELECTRA-attend-BiLSTM [17], AttBiLSTM [18], CNN_Text_Word2vec [19], and Seq2Seq -RNN-CNN [20] techniques, are obtained a noticeably higher emotion predicting performance. The proposed method may achieve 99.23% and 99.2% accuracy for CTP and COCO-CN, respectively, on the test dataset, as shown in Figure 3. It is an enhancement of at least 5.6% over other techniques. It's remarkable that at least 3.56% greater than others, its Precision, Recall, F1 measure and Macro-F measure are likewise at the top, as shown in Fig. 4-7. Therefore, on the test dataset, the proposed approach obtained an emotion forecasting performance that is noticeably superior to ON-LSTM [16], ELECTRA-attend-BiLSTM [17], AttBiLSTM [18], CNN_Text_Word2vec [19], and Seq2Seq -RNN-CNN [20].

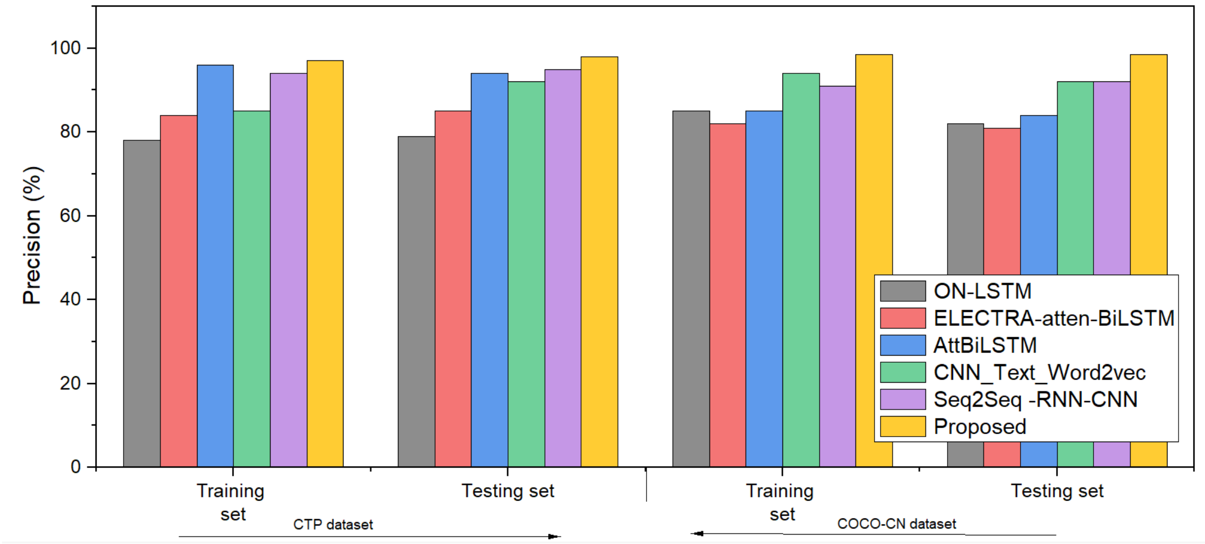

Fig.4 Performance comparison of precision for training and testing set of both datasets

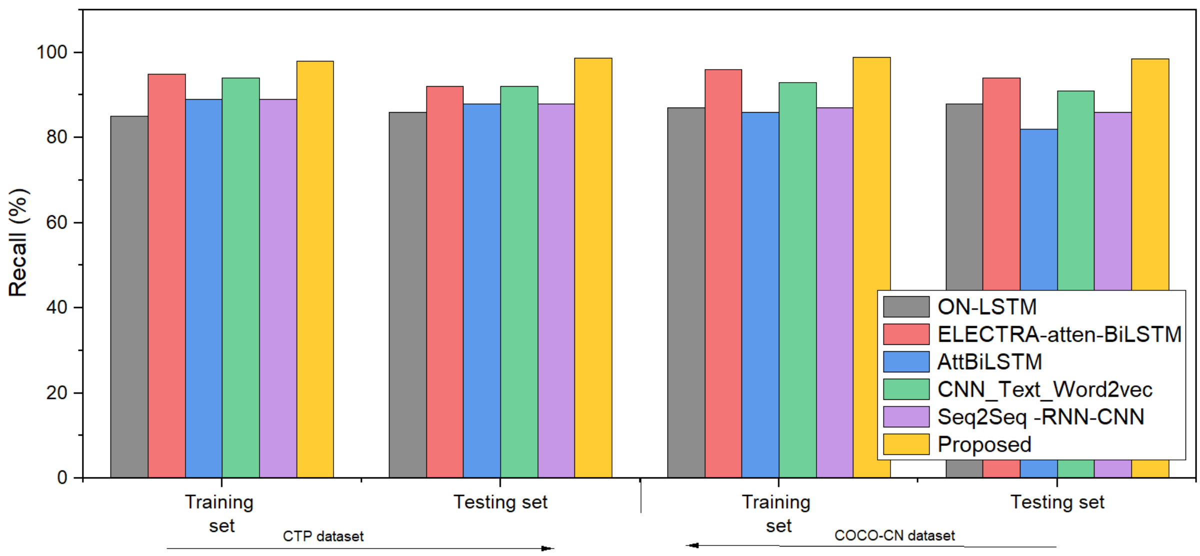

Fig.5 Performance comparison of Recall for training and testing set of both datasets

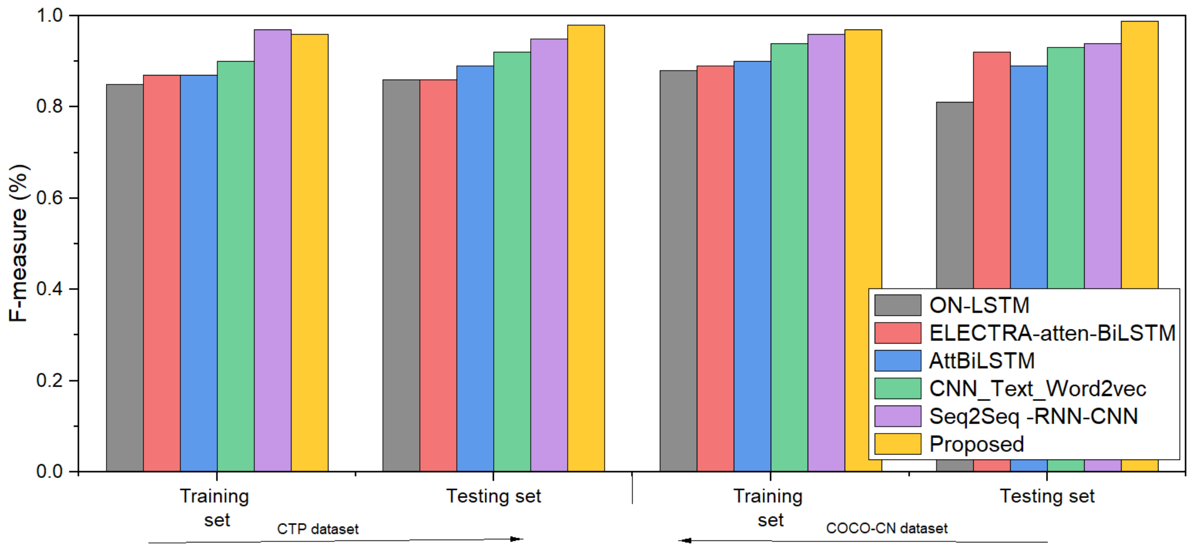

Fig.6 Performance comparison of F-measure for training and testing set of both datasets

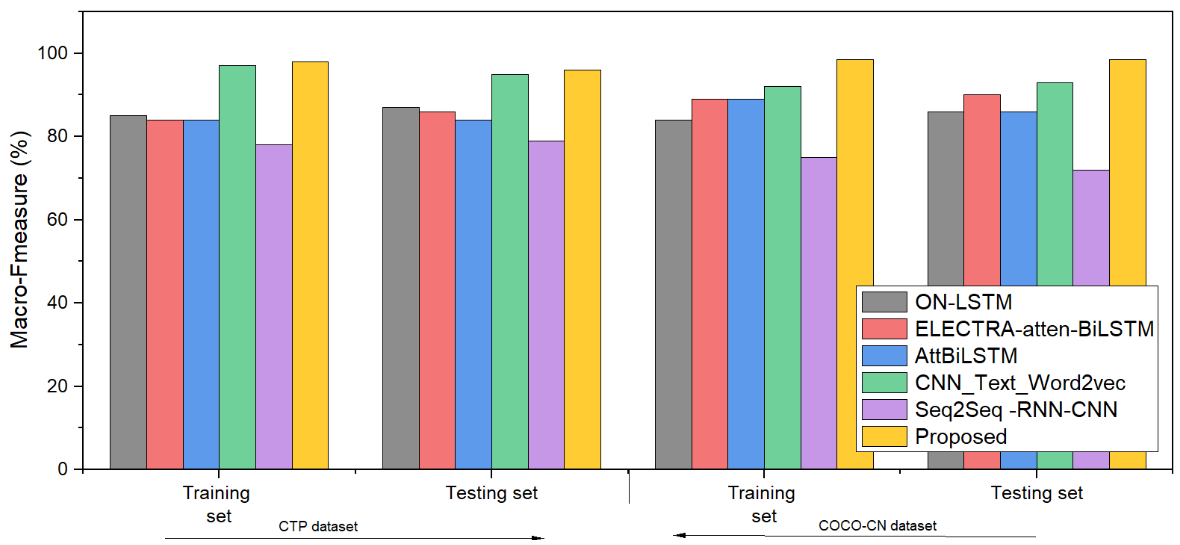

Fig.7 Performance comparison of F-measure for training and testing set of both datasets

Furthermore, all methods need time durations that rapidly reduce initially, then tend to maintain over periods; this indicates that the algorithms converge. Specifically, the proposed strategy needs 25.1 seconds for training and 18.5 seconds for testing, significantly less than existing algorithms. Due to its faster algorithm convergence and improved capacity for generalization, the suggested method produces forecasts in a shorter amount of time. Thus, the analysis shows that the proposed method has achieved finest performance and it will highly useful for the quality education of Chinese by estimating the emotion of students and teachers.

4. CONCLUSION

Many decades of precipitation have molded Chinese growth, creating distinctive visual features. The same images can express joy and grief on different levels, while others portray different emotions. In this article, we proposed an innovative approach based on the Culture Technology idea to extract emotions using SCHA-based feature extraction and EPCO-based DC-SoResNet 50V2 with HB-TF-IDF and color extraction from a collection of Chinese heritage paintings and literature. According to the experimental results, this study's proposed emotion analysis method dramatically improves the accuracy of Chinese literary emotion recognition compared to the conventional intelligent analysis method. Increased performance measures like high accuracy, precision, recall, F-measure, Macro F-measure, and convergence rate demonstrate it. The suggested approach's test time is steady at around 18.5 s, while its training time is stable at about 25.1 s. The proposed method's emotion recognition accuracy averaged 99.11 and 99.23% in the testing and training sets for the whole dataset. Among the many elements influencing the feelings a painting evokes, we considered literary texts and painting colors in this study. At the same time, it is true that the proposed strategy functions effectively without other factors, such as additional elements that often elicit an emotion, including texture, composition, subject matter, and so on. Considering these elements in addition to color might enhance the ability to extract more accurate emotions. As a result, the study of painting elements like texture and composition is necessary. Using these elements, we will investigate how to extract emotions from additional paintings and videos.

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