IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received 23 May 2024, accepted 31 May 2024, date of publication 6 June 2024, date of current version 14 June 2024.

Digital Object Identifier 10.1109/ACCESS.2024.3410281

RESEARCH ARTICLE

Research on the Cultivation of Practical English Talents Based on a Big Data-Driven Model and Sentiment Dictionary Analysis

QIUWEI FANG
Guizhou Medical University, Guiyang, Guizhou 550025, China
e-mail: qiuweifang2024@163.com

ABSTRACT Amidst the ongoing wave of economic globalization, the societal demand for English proficiency is escalating, particularly for individuals adept in practical applications of the language. Recognizing the pivotal role of English reading as a cornerstone in language acquisition, there arises a need for personalized approaches tailored to individual interests, thereby necessitating an in-depth analysis of text emotions. Addressing the challenges in text classification within English reading courses, this study presents a novel method for text emotion analysis. Integrating sentiment dictionaries with BI-GRU networks, the proposed approach significantly enhances the efficiency of text emotion recognition while simultaneously fostering students' engagement. By segmenting the emotion dictionary based on polarity and extracting pertinent features, the study amalgamates these with BI-GRU features at the feature level. This fusion facilitates emotion classification within reading texts through sophisticated activation functions. Notably, the precision of recognizing positive, negative, and neutral emotions reaches an impressive 92.5%, marking a notable improvement over methods devoid of dictionary feature integration. This framework offers novel insights for future English reading material development and intelligent learning strategies to bolster student enthusiasm and chart a promising trajectory for cultivating practical English talents.

INDEX TERMS Sentiment dictionary, English teaching, teaching methods, BI-GRU.

I. INTRODUCTION

Globalization has swept the whole world these years, bringing tremendous opportunities and challenges to all countries and regions. On the one hand, countries worldwide have cooperated and exchanged in various fields such as economics, politics, society, science, and technology, and the interdependence and mutual penetration between countries have become increasingly close [1]. Especially in the economic field, countries' goods and consulting services can freely circulate in the global market, and the national financial system has developed into an interdependent trade and investment system. In this context, the importance of foreign languages has also been highlighted [2]. In developing information capital brought about by globalization, governments of all countries regard education as a significant factor in ensuring national economic creativity and competitiveness. In other words, governments worldwide increasingly regard education policies as countermeasures to participate in global competition and cooperation. In the globalization process, English, as the universal language, has played a pivotal role in promoting the experiment and reform of the whole society, resolving social and political conflicts, and allocating economic resources and political rights. Therefore, various countries have carried out multiple reforms in English teaching to improve their people's English learning ability [3].

The increasing demand in society for English professionals makes it necessary for countries worldwide to combine closely with practical applications to determine the goal of cultivating practical English talents. As the primary place for training English talents, universities should have theoretical and research-oriented talents and transmit modern technology management and application-oriented talents to

The associate editor coordinating the review of this manuscript and approving it for publication was Senthil Kumar.

the front line of social production [4]. At present, it is evident that pure English talents cannot meet the needs of the society. How to cultivate talents with unique advantages in English is the direction that colleges and universities should determine in the future. It isn't easy to obtain employment because there are too many English professionals on the one hand, and the other hand, in terms of school training, they only focus on quantity, not quality. Students' knowledge structure cannot match that of enterprises' employers. From these two aspects alone, if English majors want to adapt to the development of the economy and society, college English education should clarify the requirements of enterprises and institutions for English skills and carry out targeted training. In the process of cultivating English talents, how to ensure student's interest in learning, especially in practical application, and how to intelligently arrange the reading text of the boring natural life scenes needs to be realized by more intelligent means to realize teaching according to their aptitude [5] truly.

In addition to understanding the essential operations and teaching of English, such as listening, speaking, reading, and writing, practical English talents should also understand the theme of the learning materials. Reading, as the primary way of English learning, is also an essential course for practical English talent training. They can understand the emotion they want to express only by correctly commenting on the English materials' emotional theme [6]. Follow-up learning can only be carried out after accurately grasping the emotion of the reading text. It can also help the training unit refine and arrange the reading materials, improve students' learning interests, and complete the training of practical English talents. Today, with the development of deep learning and intelligent pattern recognition, it is possible to intelligently classify emotions according to text content and help students improve their interest in learning. Considering the learning needs of practical English talents in reading and the tiresome reading process, this paper proposes a text emotion classification framework based on data-driven dictionary model and combined with in-depth learning method to help schools arrange reading materials reasonably when cultivating English talents. The specific contributions of this paper are as follows:

1. According to the emotional classification requirements of the reading course text in the training of English talents, this paper uses the sentiment dictionary to complete the text feature extraction;
2. Using the BI-GRU network to extract text features and sentiment dictionary features to complete feature fusion, the average recognition rate of positive, negative and neutral in the text reaches 92.5%;
3. According to the text sentiment classification results of the proposed model, the teachers were invited to rearrange the reading course text, the positive ones were selected for learning, and student satisfaction was greatly improved.

The remainder of this paper is organized as follows: in Section II, related works for sentiment dictionary and machine learning-based methods for the text classification are introduced; in Section III, the sentiment dictionary and Bi-GRU feature extraction are described for the sentiment analysis model construction; Section IV gives the experiment and result analysis of the sentiment classification and practical test; In Section V, we discuss the result and what should be paid for the English talent training; Conclusion is presented at last.

II. RELATED WORKS

A. TEXT SENTIMENT ANALYSIS BASED ON DICTIONARY PATTERN MATCHING

Sentimental dictionary analysis is a classic and most developed statistical probability analysis method. It uses mathematical and statistical methods to count the emotional values of all polar words in the document and takes the results as the total emotional memory. The sentiment dictionary summarizes the words related to emotion, indicates the emotion category and polarity of each word, and grades it according to the intensity of emotion. The text analysis is based on a sentiment dictionary to collect all the words with emotional polarity in a text and sum them mathematically to obtain the ultimate value [7]. In the research of sentiment dictionaries, there are ways to combine rules with dictionaries and dictionaries with machine learning. Jia and Li [8] calculate the emotional intensity of different emotional categories of Weibo by combining sentimental dictionaries and semantic rules to achieve emotional classification. Wang et al. [9] combined with the sentiment dictionary, extracted the emotion keywords in the education news, calculated the weight of each clause according to the corresponding rules, obtained the weighted sum of each clause, and analyzed the emotional tendency of the whole education news to determine the positive and negative classification of the education news. Xu et al. [10] realized the emotion classification of text by using the extended sentiment dictionary and the designed emotion scoring rules. Li et al. [11] put forward an emotional analysis method of bullet screen comments based on the sentiment dictionary and Naive Bayes, which is very helpful for monitoring the overall emotional tendency of bullet screen videos and predicting their popularity. Lu and Wu [12] proposed a sentiment analysis method for movie review text based on sentiment dictionary and machine learning support vector machine classification technology, which proved that this method has higher accuracy of emotion classification than the method based on an essential sentiment dictionary. Wu et al. [13] proposed two methods to enhance neuroaffective classification using affective words. A large number of experiments on three benchmark data sets have verified the effectiveness of this method.

It can be seen that today, with the continuous development of machine learning, there is little research on the method of using sentiment dictionary alone; instead, more use of sentiment dictionary features and then put these contents into the corresponding deep learning and machine learning models to complete high-precision text sentiment analysis.

B. RESEARCH ON TEXT SENTIMENT ANALYSIS BASED ON MACHINE LEARNING

Concerning sentiment analysis, machine learning is one of experimental research's most widely used tools. This method is divided into supervised, semi-supervised and unsupervised machine learning algorithms according to the text processing. The main supervised learning technologies include SVM, KNN, NB and maximum entropy. The supervised learning method needs to train the text classifier by using the manually labeled data as the training set, then input the test set text into the trained classifier and continuously tune it to achieve good results. Mano et al. [14] designed a comprehensive framework for emotional analysis based on naive Bayes and genetic algorithms. Pang and Lee [15] and others studied the performance of emotional polarity classification based on the film review corpus by comparing it with SVM, naive Bayes, maximum entropy, and other methods. Through experimental verification, the accuracy of the SVM classifier is better than that of the other two methods. Semi-supervised learning discards the shortcomings of both methods and minimizes the work of manual annotation of the corpus. Based on the semi-supervised learning method, Mohammad et al. [16] proposed a model of a small amount of manual labeling and active learning, which solved the cross-language polarity classification problem in machine translation. The unsupervised learning method, also known as clustering, is a method that does not need to label the corpus, and its representative algorithm is the K-means algorithm. Turney [17], based on an unsupervised learning algorithm, classifies comments into two emotional types: support and non-support. The experimental results in four fields show that the average accuracy rate is 74%. In the direction of natural language processing (NLP), word vector is the intermediate of training using the neural network model and the core of the deep learning model. In 2003, Bengio and Senécal [18] proposed a probability function based on a neural network, considering the probability distribution of word sequences and the context of each word, and obtained good experimental results by training two text corpora. The improvement of the neural network domain system is accompanied by the introduction and application of new word vector tools, such as Google's open-source word2vec. In 2018, Li et al. [19] used a large Chinese corpus to train and provide a variety of Chinese word vectors based on the word2vec algorithm. With the explosive increase of corpus, the RNN [20] has become the main deep learning model and is widely used in affective analysis tasks. The cyclic neural network has the characteristics of memory and parameter sharing and has great advantages over the irregular features of text sequences. The main improved models include Bi-RNN, LSTM [21] and other structures. Kim [22] et al. proposed a simple convolution neural network based on a convolution neural network in the training process of word vectors, which effectively improved feature extraction efficiency and emotion classification accuracy.

To sum up, text analysis research based on deep learning and machine learning has become the focus of the study at this stage, and the corresponding problems have been solved by processing different text morphemes. Improving the emotion recognition rate in English text classification and ensuring the accuracy of information users receive are more important. The method based on machine learning needs to annotate the text data and establish the feature engineering. At the same time, the short text length is too short, resulting in the sparse structure of data features and ambiguity. On the contrary, the sentiment dictionary method does not need to label data but is limited by the construction quality of the sentiment dictionary. Although the result of the neural network is good, it is subject to the quantity and quality of text annotation. Therefore, the research focus of this kind of problem is to fuse the information features of a sentiment dictionary, reasonably conduct text vectorization modeling, and give full play to deep network feature extraction ability.

III. MODEL ESTABLISHMENT FOR THE TEXT ANALYSIS

A. CONSTRUCTION AND OPTIMIZATION OF SENTIMENT DICTIONARY

The usual processing method of a sentiment dictionary is to set the interval value to judge the summation result. If the result of summation is greater than 0, it will be judged as a positive emotion; If the result is equal to 0, it is a neutral emotion; If the result is less than 0, it is a negative emotion. The emotion dictionary classification method is simple. Assuming that the emotion words to be analyzed are all included in the dictionary, the emotion classification results will also be very significant according to the polarity and weight. The discrimination rules are shown in equation (1), where $w_{ord}d_i$ stands for emotional words, $\mathrm{w_i}$ is the weight of the corresponding label of emotion words [23].

$$\text{sentiment orientation} = \begin{cases} positive, \sum_{i=1}^{m} word_i \times w_i > 0 \\ neural, \sum_{i=1}^{m} word_i \times w_i = 0 \\ negative, \sum_{i=1}^{m} word_i \times w_i < 0 \end{cases} \tag{1}$$

Because the words that are not included in the emotion dictionary will be lost, which will have a certain impact on the judgment of the emotional polarity of the text; therefore, in the process of emotion classification research, the dictionary must collect as many positive, neutral and negative emotion words as possible. The construction of the sentiment dictionary is divided into two parts: The first part mainly carries out the operations of de-duplication, word segmentation, and de-duplication of the corpus, which can be done with the help of word segmentation tools. The second part is mainly about the TF - IDF high-frequency words training on the processed corpus, the high-frequency words and essential seed words training through the word vector model, the screening of the strength seed word set through Euclidean distance calculation, and the strength calculation of the candidate words through the constraint set; The emotion value of candidate words is calculated with the help of emotion seed word set, and finally the establishment of emotion model is realized through dictionary optimization. The specific flow chart is shown in Figure 1 [24]:

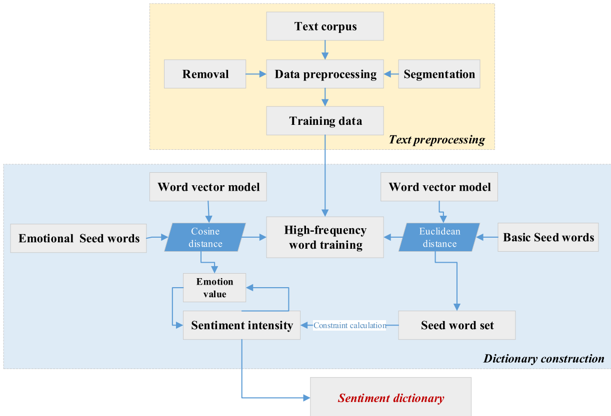

FIGURE 1. **The flow of the sentiment dictionary construction.**

Compared with the classical word vector model, the BERT model has good dynamic characteristics and can solve the problem of polysemy. To mine the semantic information contained in words, with the help of the course text corpus, words can be mapped into high-dimensional continuous word vector space through the BERT model [25]. BERT is a deep learning model for sentence-level data processing. Its design aims to comprehensively understand and represent vocabulary in sentences through the bidirectional encoder of the Transformer model. The model utilizes bidirectional learning mechanisms to effectively capture contextual relationships and semantic information between words in the text, thereby generating word embeddings with rich semantic representations. In natural language processing, the BERT model is widely used in tasks such as text classification, named entity recognition, question-answering systems, etc. Its powerful sentence-level representation ability supports solving complex natural language understanding problems. In this paper, we set different seed word sets and calculate candidate words' emotional polarity and intensity. When calculating the distance, we use equations (2) - (5) to constrain:

$$Sent(Nword) = Count + Load + Conmean \tag{2}$$

$$Count = C_0/\left(C_1 + T_{\text{cout}}\right) \tag{3}$$

$$Load = C_2/T_{\text{load}} \tag{4}$$

$$Conmean = \sum\nolimits_{T_i}\left(\frac{T_{\text{mean}}}{\text{Diw}_{[T_i]}}\right) \tag{5}$$

where: C_0, C_1, C_2 is a constant that can be set and revised according to the value update; $T_{\text{count}}, T_{\text{load}}, T_i$ is related to the setting of threshold T. Send(Nword) is the emotional intensity of the candidate word, and the emotional tendency of the candidate word is divided by calculating the emotional difference between the candidate word and the nearest cosine distance.

B. EMOTION CLASSIFICATION NETWORK BASED ON EMOTION DICTIONARY FEATURES

The RNN method is widely used in text emotion classification because it can remember the attributes in different time states in the sequence. Text analysis is a common time series. In theory, RNN can model infinitely long series. In practical applications, gradient dispersion and over-fitting often exist. To solve these problems, the gate mechanism was born. LSTM and GRU are representatives of the gate mechanism [25]. Compared with LSTM, GRU has two main differences: first, its structure is relatively simple and its calculation speed is faster; Secondly, due to the few parameters, it has a more substantial generalization effect for small sample data sets. It can not only perfectly simulate problems involving multiple input variables but also be used to deal with time series prediction problems [26]. It can be seen from the figure that the network structure of GRU is more straightforward. It only contains two gate control units: reset gate and update gate, which correspond to rt and zt in Figure 2. The reset gate is responsible for controlling the degree of neglect of historical status information, and the update gate changes the update speed of status information according to the amount of historical status information in the current state.

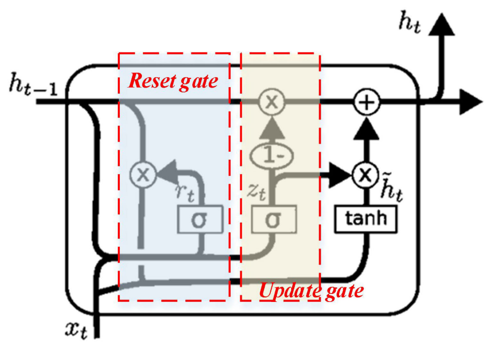

FIGURE 2. **The cell of the GRU.**

Although GRU can solve the gradient vanishing problem in RNN network and improve the convergence speed of the network based on LSTM, in a unidirectional neural network structure such as GRU, the neuron state is always transmitted from the front to the back, and the time characteristics of the future moment information are not considered [27]. Therefore, Bi-GRU is used for modeling in this paper to improve the recognition accuracy. The calculation method of the Bi-GRU model is shown in equation (6) - (8):

$$\overrightarrow{h}^t = \text{GRU}\left(x_t, \overrightarrow{h}^{t-1}\right) \tag{6}$$

$${}^t\bar{h} = GRU\left(x_t, {}^{t-1}\bar{h}\right) \tag{7}$$

$$O^t = \overrightarrow{W}^t \overrightarrow{h}^t + {}^t\text{W}^t\text{h} + b_t \tag{8}$$

where $\overrightarrow{h}^t$ represents the forward hidden state, $^{t}\bar{h}$ is the backward hidden state, $\overrightarrow{W}^t$ is the weight matrix, x_t is the input at time step t. The fusion of emotion dictionary features and Bi-GRU features is realized at the feature level to improve the overall accuracy of model recognition. The framework of the proposed method is shown in Figure 3:

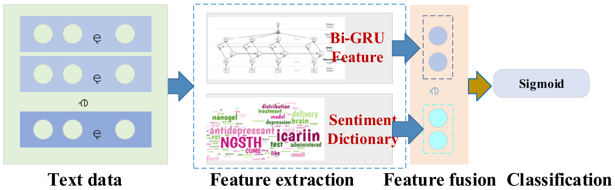

FIGURE 3. The framework of emotion classification network based on sentiment dictionary features.

The emotion classification method delineated in this paper, specifically tailored for the reading texts of college-level English learners, is graphically represented in Figure 3. The process commences with text data preprocessing, a crucial step wherein sentiment dictionary features and BI-GRU features are meticulously extracted.

Subsequently, these two sets of features are harmoniously fused, leveraging their strengths to enrich the classification process. This fusion enhances the depth of analysis and ensures a more comprehensive understanding of the nuanced emotional context within the text.

Finally, the culmination of this process is applying a sigmoid activation function, which serves as the pivotal mechanism for text classification. Through its iterative computations, the activation function effectively delineates the emotional polarity embedded within the text, thus enabling accurate and nuanced classification outcomes.

IV. EXPERIMENT RESULT AND ANALYSIS

After completing the model building, this paper classifies the After completing the model construction, this article classifies the emotions of articles in English reading courses based on the characteristics of the courses learned and invited relevant teachers to evaluate their true values. Due to the large amount of reading text, it is challenging to complete the classification of all content. Therefore, in this article, the first and last parts of the article that are most relevant to the content theme were selected for analysis. More than 100 relevant text data were obtained for analysis and classified according to the classic positive, negative, and neutral sentiment dictionaries. The average length of each paragraph is 300-500 words, which reflects the article's theme well. While setting up the label, we invited three teachers who have taught the course for over five years to refine and annotate the data. Three experienced teachers will analyze the sentiment of these data, and two or more with the same evaluation will be directly used as standard labels for three different teachers. In other situations, they will be re-evaluated until all labels are labeled. Three teachers independently review this process to ensure the validity of the labels. According to the characteristics of deep learning, this paper selects precision, recall and F1 scores to evaluate the model's performance. The index can be got from equations (9) - (11):

$$P = \frac{TP}{TP + FP} \tag{9}$$

$$R = \frac{TP}{TP + FN} \tag{10}$$

$$F1 = \frac{2 \times P \times R}{P + R} \tag{11}$$

where TP is the true positive, FP is the false positive and FN represents the false negative.

A. THE RESULT FOR THE SENTIMENT CLASSIFICATION

According to the characteristics of the sentiment dictionary and the feature analysis characteristics of the reading text, the classic positive, negative and neutral emotions are used in the classification of the sentiment dictionary, and three types of statistical indicators are counted. The results are shown in Figure 4:

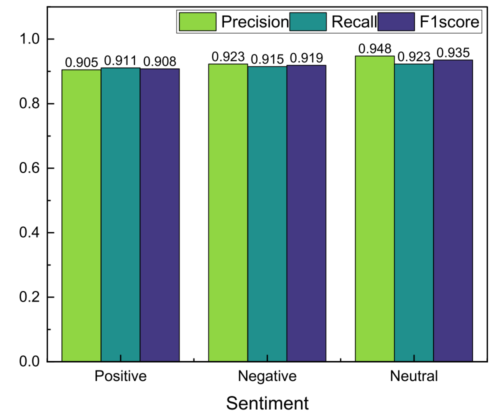

FIGURE 4. The result for the proposed framework.

As shown in Figure 4, the sentiment classification network based on the sentiment dictionary and Bi-GRU features proposed has a good recognition rate for three types of emotions, and the recognition precision of all kinds of emotions exceeds 90%. At the same time, its F1-score results show that this method can balance precision and recall well to achieve more moderate and accurate text emotion judgment. The fusion of sentiment dictionary features in the proposed method is the key of the algorithm, so to better explain the role of sentiment dictionary, we trained the model for adding sentiment dictionary, and the results are shown in Figure 5:

According to the comparison of results in Figure 5, it can be seen that after adding the sentiment dictionary feature, its various indicators have improved, so the sentiment dictionary feature plays an important role in improving the performance of the text model.

B. RESULT FOR THE METHOD COMPARISON

To better verify the performance of the neural network proposed for fusing sentiment dictionary features, this paper selects TextCNN, LSTM and other methods that are widely used in the field of text sentiment recognition for actual

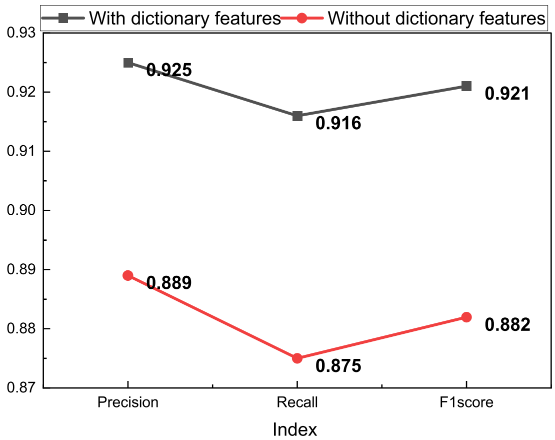

FIGURE 5. The result for the sentiment classification with and without dictionary features.

testing and comparison, and the results are shown in Figure 6 and Figure 7:

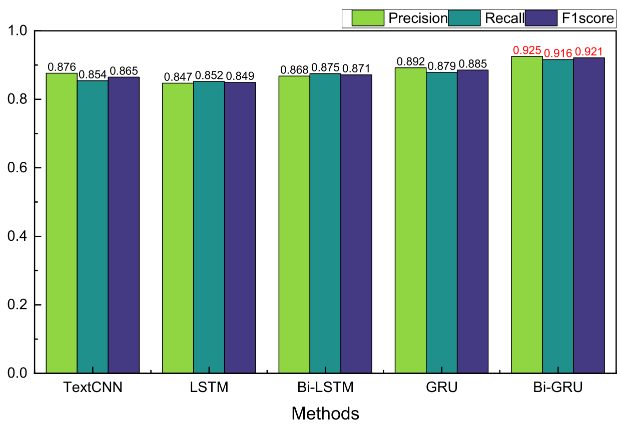

FIGURE 6. The comparison result for the method with dictionary features.

Figure 6 shows the average precision and recall of the three types of emotion after adding the sentiment dictionary feature. After adding the sentiment dictionary feature simultaneously, the Bi-GRU method has obvious advantages in the classification after feature fusion. It can be seen that the reset gate and update gate do not reduce the calculation accuracy while improving the calculation performance of the model itself.

Figure 7 shows that Bi-GRU has a robust feature extraction ability and can complete the emotion classification task without adding sentiment dictionary features. Still, it can directly complete feature extraction using different model methods. By comparing the function of sentiment dictionary features, that is, comparing the average classification results of the same cluster in Figures 6 and 7, we can find that sentiment dictionary features can significantly promote the emotion classification ability of the model. Therefore, in future research on such problems, enriching the types of emotion dictionaries, improving the polarity, etc., can significantly promote text analysis.

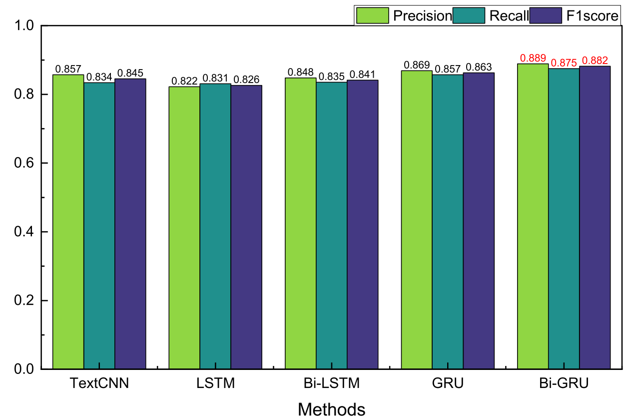

FIGURE 7. The comparison result for the method without dictionary features.

C. THE PRACTICAL TEST FOR THE PROPOSED FRAMEWORK

To better validate the performance of the method proposed in this article, in addition to training and analyzing the model on historical data, practical application tests were also conducted. Based on the model proposed in this article, the applied articles in English reading classes were sentiment-classified, and the texts with strong positivity were found. The teacher was asked to rearrange the original texts, changing the order of the texts without modifying the actual content. Five positive text materials were selected and 50 students were invited to read and learn. These 50 students did not change this type of text, so they participated in corresponding testing experiments after briefly familiarizing themselves with the system. They conducted an emotional understanding of the five texts they read and compared them with actual methods to evaluate the effectiveness of the proposed method in practical applications. The specific results are shown in Figure 8:

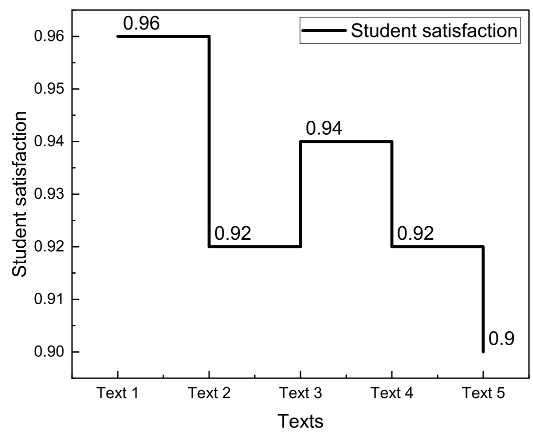

FIGURE 8. The student satisfaction in the practical test.

Figure 8 shows that after the text optimization, students' satisfaction with the course has improved significantly. Before the adjustment, students' satisfaction with these texts and courses is lower than 90%. After the content rearrangement, the overall satisfaction has improved. It can be seen that for talent training, in addition to paying attention to the study of basic knowledge, we should also grasp the overall emotional characteristics to ensure students' enthusiasm.

V. DISCUSSION

English reading plays a pivotal role in training English talents, and enhancing efficiency in comprehending text materials is paramount for improving learning outcomes. Arranging texts based on their emotional characteristics can significantly boost students' interest in reading. To address these needs, this paper proposes an automatic emotion classification framework for English text reading, which integrates emotional dictionary features and Bi-GRU features to enhance the efficiency of emotion classification. In traditional text emotion analysis, Tang et al. [28] improved analysis by incorporating user and product information into the word embedding and pooling layers. Similarly, Chen et al. [29] enhanced classification performance by incorporating time information into a sequence model and extracting features through a one-dimensional convolutional neural network. These approaches underscore the importance of feature types and fusion methods in improving classification accuracy, suggesting that extracting additional text features in future research may offer a more cost-effective strategy than increasing network complexity.

Beyond mastering fundamental English skills, such as listening, speaking, reading, and writing, practical English talents should also be adept at recognizing emotions in learning materials to enhance learning efficiency and foster holistic development [30]. To achieve this, colleges should prioritize practical activities aligned with societal needs, such as English contests, speech and debate competitions, and large-scale English events. Teachers can assess students' performance in these activities to gauge their practical English abilities accurately [31]. Furthermore, extracurricular English interest activities like dubbing and drama performances can stimulate students' enthusiasm for English and hone their practical skills, contributing to cultivating practical talents [32]. Leveraging the advantages of the Internet of Things, big data, and artificial intelligence throughout the educational process holds immense promise for nurturing practical talents in the future.

VI. CONCLUSION

Aiming at the tiresome problem of reading courses in cultivating practical English talents, this paper proposes a text emotion classification method that combines the characteristics of an emotion dictionary to enhance student's learning interest and speed up the talent training cycle. The text classification framework proposed in this paper establishes the emotion dictionary according to the text characteristics and extracts the corresponding emotion features. On this basis, the BI-GRU network is used to fuse the text features and emotion dictionary features, and the goal is finally achieved, which is to improve the precision of emotion classification. The results show that the accuracy of text emotion classification is improved by 3.6% after adding emotion dictionary features. At the same time, when comparing methods in this paper, using the classic TextCNN, LSTM, and other methods to complete text emotion classification, the overall recognition rate of the network is improved by adding emotion dictionary features. This provides a new idea for future text classification emotion analysis research.

In the training process of practical English talents, in addition to enhancing the ability to read text, the methods proposed in this paper will be transferred in speech recognition in the future to improve students' oral ability is also an important direction for future development.

ACKNOWLEDGMENT

The author received no specific funding for this study.

CONFLICTS OF INTEREST

The author declares that there are no conflicts of interest.

FUNDING STATEMENT

The study received no funding.

REFERENCES

[1] F. Junqiang, "Study on the practical path of building a community with a shared future for mankind," *Int. J. Frontiers Sociol.*, vol. 5, no. 9, pp. 75–80, 2023, doi: 10.25236/ijfs.2023.050913.

[2] A. Laoli, O. Dakhi, and M. M. Zagoto, "The application of lesson study in improving the quality of English teaching," *Edukatif, Jurnal Ilmu Pendidikan*, vol. 4, no. 2, pp. 2238–2246, Feb. 2022, doi: 10.31004/edukatif.v4i2.2434.

[3] F. Lengkoan and P. L. Hampp, "Imitation technique in learning English at English education department Universitas Negeri Manado," *Jurnal Pendidikan Bahasa Inggris Indonesia*, vol. 10, no. 1, pp. 48–53, Mar. 2022, doi: 10.23887/jpbi.v10i1.668.

[4] D. P. Tatipang, M. J. Manuas, C. N. Wuntu, O. A. Rorintulus, and F. Lengkoan, "EFL students' perceptions of the effective English teacher characteristics," *Jurnal Pendidikan Bahasa Inggris undiksha*, vol. 10, no. 1, pp. 23–30, Aug. 2022, doi: 10.23887/jpbi.v10i1.45709.

[5] H. Liu, C. Yan, and J. Fu, "Exploring livestream English teaching anxiety in the Chinese context: An ecological perspective," *Teaching Teacher Educ.*, vol. 111, Mar. 2022, Art. no. 103620, doi: 10.1016/j.tate.2021.103620.

[6] B. Mandasari and D. Aminatun, "Investigating teachers' belief and practices toward digital media of English learning during COVID-19 pandemic," *English Rev., J. English Educ.*, vol. 10, no. 2, pp. 475–484, Jun. 2022, doi: 10.25134/erjee.v10i2.6248.

[7] A. Mengelkamp, K. Koch, and M. Schumann, "Creating sentiment dictionaries: Process model and quantitative study for credit risk," in *Proc. Eur. Conf. Social Media*, 2022, vol. 9, no. 1, pp. 121–129, doi: 10.34190/ecsm.9.1.167.

[8] K. Jia and Z. Li, "Chinese micro-blog sentiment classification based on emotion dictionary and semantic rules," in *Proc. Int. Conf. Comput. Inf. Big Data Appl. (CIBDA)*, Guiyang, China, Apr. 2020, pp. 309–312, doi: 10.1109/CIBDA50819.2020.00076.

[9] B. Wang, L. Gao, T. An, M. Meng, and T. Zhang, "A method of educational news classification based on emotional dictionary," in *Proc. Chin. Control Decis. Conf. (CCDC)*, Shenyang, China, Jun. 2018, pp. 3547–3551, doi: 10.1109/CCDC.2018.8407737.

[10] G. Xu, Z. Yu, H. Yao, F. Li, Y. Meng, and X. Wu, "Chinese text sentiment analysis based on extended sentiment dictionary," *IEEE Access*, vol. 7, pp. 43749–43762, 2019, doi: 10.1109/ACCESS.2019.2907772.

[11] Z. Li, R. Li, and G. Jin, "Sentiment analysis of danmaku videos based on Naïve Bayes and sentiment dictionary," *IEEE Access*, vol. 8, pp. 75073–75084, 2020, doi: 10.1109/access.2020.2986582.

[12] K. Lu and J. Wu, "Sentiment analysis of film review texts based on sentiment dictionary and SVM," in *Proc. 3rd Int. Conf. Innov. Artif. Intell.*, Suzhou, China, Mar. 2019, pp. 73–77, doi: 10.1145/3319921.3319966.

[13] C. Wu, F. Wu, J. Liu, Y. Huang, and X. Xie, "Sentiment lexicon enhanced neural sentiment classification," in *Proc. 28th ACM Int. Conf. Inf. Knowl. Manage.*, Beijing, China, Nov. 2019, pp. 1091–1100, doi: 10.1145/3357384.3357973.

[14] L. Y. Mano, B. S. Faiçal, V. P. Gonçalves, G. Pessin, P. H. Gomes, A. C. P. L. F. de Carvalho, and J. Ueyama, "An intelligent and generic approach for detecting human emotions: A case study with facial expressions," *Soft Comput.*, vol. 24, no. 11, pp. 8467–8479, Jun. 2020, doi: 10.1007/s00500-019-04411-7.

[15] B. Pang and L. Lee, "A sentimental education: Sentiment analysis using subjectivity summarization based on minimum cuts," in *Proc. 42nd Annu. Meeting Assoc. Comput. Linguistics*, 2004, pp. 271–278, doi: 10.3115/1218955.1218990.

[16] M. S. Hajmohammadi, R. Ibrahim, A. Selamat, and H. Fujita, "Combination of active learning and self-training for cross-lingual sentiment classification with density analysis of unlabelled samples," *Inf. Sci.*, vol. 317, pp. 67–77, Oct. 2015, doi: 10.1016/j.ins.2015.04.003.

[17] P. D. Turney, "Thumbs up or thumbs down: Semantic orientation applied to unsupervised classification of reviews," in *Proc. 40th Annu. Meeting Assoc. Comput. Linguistics*, 2001, pp. 417–424, doi: 10.3115/1073083.1073153.

[18] Y. Bengio and J.-S. Senecal, "Adaptive importance sampling to accelerate training of a neural probabilistic language model," *IEEE Trans. Neural Netw.*, vol. 19, no. 4, pp. 713–722, Apr. 2008, doi: 10.1109/TNN.2007.912312.

[19] S. Li, Z. Zhao, R. Hu, W. Li, T. Liu, and X. Du, "Analogical reasoning on Chinese morphological and semantic relations," in *Proc. 56th Annu. Meeting Assoc. Comput. Linguistics*, 2018, pp. 138–143, doi: 10.18653/v1/p18-2023.

[20] A. Sherstinsky, "Fundamentals of recurrent neural network (RNN) and long short-term memory (LSTM) network," *Phys. D, Nonlinear Phenomena*, vol. 404, Mar. 2020, Art. no. 132306, doi: 10.1016/j.physd.2019.132306.

[21] X. Shi, Z. Wang, H. Zhao, S. Qiu, R. Liu, F. Lin, and K. Tang, "Threshold-free phase segmentation and zero velocity detection for gait analysis using foot-mounted inertial sensors," *IEEE Trans. Human-Mach. Syst.*, vol. 53, no. 1, pp. 176–186, Feb. 2023, doi: 10.1109/THMS.2022.3228515.

[22] Y. Kim, "Convolutional neural networks for sentence classification," in *Proc. Conf. Empirical Methods Natural Lang. Process. (EMNLP)*, 2014, pp. 1746–1751, doi: 10.3115/v1/d14-1181.

[23] W. Ren, H. Zhang, and M. Chen, "A method of domain dictionary construction for electric vehicles disassembly," *Entropy*, vol. 24, no. 3, p. 363, Mar. 2022, doi: 10.3390/e24030363.

[24] B. Zhang, Y. Hu, D. Xu, M. Li, and M. Li, "SKG-learning: A deep learning model for sentiment knowledge graph construction in social networks," *Neural Comput. Appl.*, vol. 34, no. 13, pp. 11015–11034, Jul. 2022, doi: 10.1007/s00521-022-07028-4.

[25] N. J. Prottasha, A. A. Sami, M. Kowsher, S. A. Murad, A. K. Bairagi, M. Masud, and M. Baz, "Transfer learning for sentiment analysis using BERT based supervised fine-tuning," *Sensors*, vol. 22, no. 11, p. 4157, May 2022, doi: 10.3390/s22114157.

[26] D. Wang and K. Mao, "Multimodal object classification using bidirectional gated recurrent unit networks," in *Proc. IEEE 3rd Int. Conf. Data Sci. Cyberspace (DSC)*, Jun. 2018, pp. 685–690, doi: 10.1109/DSC.2018.00109.

[27] J. Chung, C. Gulcehre, K. Cho, and Y. Bengio, "Empirical evaluation of gated recurrent neural networks on sequence modeling," 2014, *arXiv:1412.3555*.

[28] D. Tang, B. Qin, and T. Liu, "Learning semantic representations of users and products for document level sentiment classification," in *Proc. 53rd Annu. Meeting Assoc. Comput. Linguistics 7th Int. Joint Conf. Natural Lang. Process.*, Beijing, China, 2015, pp. 1014–1023, doi: 10.3115/v1/p15-1098.

[29] T. Chen, R. Xu, Y. He, Y. Xia, and X. Wang, "Learning user and product distributed representations using a sequence model for sentiment analysis," *IEEE Comput. Intell. Mag.*, vol. 11, no. 3, pp. 34–44, Aug. 2016, doi: 10.1109/MCI.2016.2572539.

[30] W. Gao, "Practical teaching strategies for college English based on the output-driven hypothesis," *J. Contemp. Educ. Res.*, vol. 6, no. 2, pp. 70–74, Jan. 2022, doi: 10.26689/jcer.v6i2.3565.

[31] Z. Yang, "Application and exploration of VR and AI technology in college English teaching," *Adv. Multimedia*, vol. 2022, pp. 1–10, Jul. 2022, doi: 10.1155/2022/1810177.

[32] Y. Kong, "A practical study of the cultivation of innovative foreign language talents in colleges and universities," *Theory Pract. Lang. Stud.*, vol. 8, no. 7, p. 866, Jul. 2018, doi: 10.17507/tpls.0807.19.

QIUWEI FANG was born in Guiding, Guizhou, China, in 1986. She received the degree from Guizhou University, in 2015. Since 2015, she has been with Guizhou Medical University. Her research interests include Chinese–English translation, English–Chinese translation, and college English teaching.