IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received 27 September 2024, accepted 26 October 2024, date of publication 29 October 2024, date of current version 6 November 2024.

Digital Object Identifier 10.1109/ACCESS.2024.3487752

RESEARCH ARTICLE

DIBTBL: A Novel Text Sentiment Analysis Model Based on an Improved Swarm Intelligence Algorithm and Deep Learning

GUANGYU MU[1,2], LI DAI[1], XIURONG LI[3], XIAOQING JU[1], YING CHEN[1], AND JIAXIU DAI[1]

[1]School of Management Science and Information Engineering, Jilin University of Finance and Economics, Changchun 130000, China
[2]Laboratory of Financial Technology of Jilin Province, Changchun 130000, China
[3]Faculty of Information Technology, Beijing University of Technology, Beijing 100124, China

Corresponding author: Xiurong Li (xiurong_li@bjut.edu.cn)

This work was supported in part by the National Social Science Fund of China under Grant 19BJY246, in part by the Natural Science Fund Project of the Science and Technology Department of Jilin Province under Grant 20240101361JC, and in part by the Think Tank Fund Project of Jilin Science and Technology Association.

ABSTRACT Analyzing and understanding emotional expressions in user comments is a crucial and complex task in business. Conducting text sentiment analysis is of great significance. This paper constructs a novel DIBTBL model that integrates an extended sentiment dictionary, an improved swarm intelligence algorithm, and deep learning techniques to accurately capture and analyze user emotions. Firstly, this paper expands the sentiment dictionary to extract emotion feature words from the review text. Secondly, the BERT model embeds these emotional feature words and pre-processed text into high-dimensional semantic space to obtain richer semantic representations and improve sentiment classification performance. Then, the TextCNN-BiLSTM feature extraction model is established to balance the grasping ability of local and global features. Fourthly, this paper innovatively improves the swarm intelligence algorithm BWO to optimize the parameters of the TextCNN-BiLSTM. Finally, MLP is employed for sentiment classification. The experimental data is crawled from Ctrip, China's largest hotel booking website. In the comparative experiment, the proposed model achieves a higher accuracy than TBL, DTBL, BTBL, and IBTBL by 2.94%, 2.44%, 1.64%, and 0.66%, respectively. In addition, we compare the proposed model with seven advanced models in the open dataset waimai_10k. The experimental results indicate that this model outperforms all the other models, with an average improvement in accuracy of 8.21%. The study offers precise insights into user sentiment, assisting companies in better understanding and meeting customer needs.

INDEX TERMS Sentiment analysis, deep learning, text features, algorithm optimization, algorithm improvement.

I. INTRODUCTION

Social network platforms have become one of the primary channels for consumers to communicate and share information. Whether it is an online shopping experience, product evaluation, or service feedback, netizens can share and discuss on the platforms [1], [2]. Social media platforms in the business sector, such as Taobao, Pinduoduo, Meituan, and Ctrip, enable consumers to express their opinions and emotions through text [3], [4], [5]. Analysis of review texts in the business field can assist companies in gaining a deeper understanding of customer perceptions, evaluating the competitive market, enhancing product and service quality, and making informed business decisions [6]. Therefore, it is significant to conduct sentiment analysis on comments in the business field.

Sentiment analysis is a technique in natural language processing (NLP) aimed at identifying and quantifying emotions

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

expressed in text [7]. This method determines the emotional tendency of the text by analyzing language features, word choice, context, and other information. Typically, the analysis usually classifies the text into positive, negative, or neutral categories [8], [9]. Applying sentiment analysis in business can assist companies in better understanding the emotional inclinations of consumers. The analysis results can be used to customize marketing strategies, enhance services and products, improve customer satisfaction and loyalty, boost market competitiveness, and achieve sustainable development. In the business context, positive and negative emotional feedback is often associated with customer satisfaction, experience, and suggestions regarding offerings. This feedback is crucial for evaluating and improving the quality of products and services [10], [11]. However, neutral comments have no apparent emotional color. They are usually simple statements of facts and lack constructive opinions, making it difficult to provide targeted improvement direction for the enterprise. Therefore, this paper's review text also analyzes positive and negative emotions in business.

Previous studies use sentiment dictionaries and machine learning to analyze text sentiment [12], [13]. The sentiment dictionary aims to simplify the process by evaluating the sentiment of comments through word segmentation and matching them to a specific dictionary [14]. The machine learning method can utilize particular algorithms to extract features and achieve more effective emotion classification [15]. Although these two methods are commonly used, limitations gradually emerge, such as insufficient capture of semantic information and contextual relevance in text [16]. Extensive research has shown that using deep learning models for text sentiment analysis can yield superior results to traditional methods because deep learning models have high nonlinearity and powerful representation learning ability [17], [18]. The deep learning method can comprehensively capture text features and deeply understand the semantics and context of the text through multi-level neural network structures. In the end, better performance in emotion analysis tasks is achieved.

Even if a deep learning model with good performance is used to improve sentiment analysis accuracy, it still ignores the remote semantic relationships of emotional features. When analyzing longer text, the model may not fully consider the context between words, which could lead to potentially biased sentiment analysis results. Additionally, optimizing the parameters of deep learning models is a crucial issue [19]. Traditional methods may trap the model in a local solution or overfit. Therefore, it is essential to use a swarm intelligence algorithm to optimize the model's parameters, improve its generalization ability, and enhance accuracy [20]. As a new swarm intelligence algorithm, the Beluga Whale Optimization (BWO) algorithm is inspired by beluga whales' behavior in group cooperative hunting and survival [21]. The algorithm boasts a wide global search range, rapid convergence speed, and simple implementation. The BWO has succeeded in various optimization problems, such as function optimization, parameter optimization, and neural network training, and has obtained excellent optimization results. However, the BWO algorithm is prone to local optimization when solving complex optimization problems [22]. Thus, it is essential to enhance the BWO algorithm.

In summary, previous sentiment analysis models need improvement in capturing emotionally charged words in text data, which is the motivation for writing this paper:

(1) Establishing a sentiment dictionary to extract emotional features is necessary to improve text sentiment analysis accuracy and effectiveness.

(2) Building a deep learning model is indispensable to solving the problem of capturing local features and long-term dependencies in text sentiment analysis.

(3) A swarm intelligence optimization algorithm is selected to optimize the deep learning model to assist the model in finding the best hyperparameter settings. The optimization algorithm is improved to optimize the model's generalization ability and effectively deal with the overfitting problem.

This paper presents a text sentiment analysis model integrating a sentiment dictionary, BERT, TextCNN, and BiLSTM with the improved BWO. The main contributions of this paper are as follows:

(1) A sentiment dictionary for the business field is established and used to extract the emotional features from texts.

(2) The TextCNN-BiLSTM two-channel feature extraction model is designed. TextCNN is utilized to extract local features from the text, while BiLSTM is employed to capture long-term dependency and semantic information. The features from these two components are combined to prevent loss of information.

(3) Improve the BWO algorithm to avoid falling into local optimal and overfitting. The IBWO is also utilized to optimize the parameters of the TextCNN-BiLSTM model.

II. LITERATURE REVIEW

Currently, researchers utilize two primary methods for sentiment analysis: the technique based on a sentiment dictionary and the approach based on supervised learning, which includes machine learning and deep learning.

A. SENTIMENT ANALYSIS BASED ON SENTIMENT DICTIONARY

One of the simplest methods of sentiment dictionary analysis entails matching the words in a comment with a sentiment dictionary. The sentiment score is computed by applying grammatical rules to ascertain the overall sentiment expressed in the comment [23], [24]. Standard Chinese and English emotion dictionaries include SentiSense [25], SenticNet5 [26], WordNet-Affect [27], Dalian University of Technology Emotion Vocabulary Ontology [28], CNKI Emotion Dictionary [29], and Tsinghua University Li Jun Chinese Dictionary [30]. Although sentiment dictionaries are widely used to assess emotions in social media settings, existing emotion vocabularies often lack coverage of crucial domain-specific emotion words.

Constructing domain sentiment dictionaries is essential in text mining and natural language processing. Many fields lack a specific sentiment dictionary, so many scholars have created their own. Badhakavi [31] expanded the domain-specific sentiment dictionary and utilized it for sentiment feature extraction. He argued that current vocabularies were static, whereas text on social media was dynamic. Thus, it is inadequate for extracting practical document representation features. Zhao used TF-IDF to prioritize emotion-related words based on their importance [32]. Then, they adjusted the significance of words in the expanded SO-PMI word set and integrated it with an essential sentiment dictionary created by the Dalian Institute of Technology and the HowNet Sentiment Dictionary. Furthermore, they revised the calculation rules for the emotional intensity of sentences based on interrogative and exclamatory sentence structures. Zhang classified e-commerce text comments based on keywords, evaluation objects, and emotional resources using a specialized emotional dictionary [33]. Hui [34] utilized corpus and semantic knowledge base to extract seed words from a large-scale online public opinion corpus and combined them with existing sentiment dictionaries to expand the list of emotion words. The experiment demonstrated that the newly constructed dictionary has good accuracy and reliability.

Sentiment dictionaries have limitations due to their restricted coverage and difficulty keeping up with language changes [35]. They often provide only the emotional color of words and fail to capture the overall emotional tendency of a sentence or text. As a result, sentiment dictionaries are usually combined with deep learning to handle complex sentiment expressions and improve the effectiveness of emotion analysis [36], [37], [38].

B. SENTIMENT ANALYSIS BASED ON SUPERVISED LEARNING

Supervised learning utilizes labeled data to train a model and predict sentiment categories based on the input text. Specific algorithms and techniques used in supervised learning include machine learning and deep learning.

The core idea behind the machine learning-based sentiment analysis model is to transform textual data into a digital format understandable to machines. This process involves manually partitioning labeled raw data into training and test sets. A model with customized parameters from the training set is then used to classify emotions. Diop and Iqbal [39] conducted a comparative study on the sentiment dictionary used in text sentiment analysis and the supervised machine learning model. The experimental results proved that machine learning results were slightly better [39]. Sharma and Dey performed sentiment analysis on online movie review datasets [40]. They compared feature selection using machine learning methods and found that Support Vector Machine (SVM) outperformed other methods in classification. Jagdale [41] selected Naive Bayes (NB) and SVM for sentiment analysis of six product reviews from Amazon. Experimental results indicated that both models achieved an average accuracy of 90%. However, the latter model's accuracy was 4.63% lower than the former. Because of its simplicity, the machine learning model has found extensive application in text sentiment analysis [42]. However, machine learning models cannot generalize and face numerous challenges when dealing with NLP tasks, such as ambiguity, polysemy, language variation, and context issues.

Deep learning algorithms outperform sentiment dictionaries and traditional machine learning algorithms in text sentiment analysis, especially when trained on large corpora. The main reason is that deep learning models can better capture the complexity and diversity of languages and make significant progress on classification tasks. A text sentiment analysis model was evaluated in a comparison experiment conducted by Q. et al. [43]. The deep learning model was compared with NB, Decision Tree (DT), SVM, and other machine learning models. The accuracy of the deep learning model was 96.41%, whereas the other models had less than 90% accuracy. Popular deep learning models, such as GRU, TextCNN, and LSTM, have superior performance [44]. LSTM is primarily proposed to tackle the issue of capturing distant dependencies. It is excellent at understanding context and can automatically learn text features [45]. However, LSTM only considers information preceding the present moment, which needs to be improved for tasks like sentiment analysis that necessitate grasping the overall context of a text. On the other hand, BiLSTM has apparent advantages in text emotion classification. BiLSTM can take into account the information before and after the current moment at the same time to better grasp the semantic and contextual relations of the text [46], [47]. Scholars have found that BiLSTM mainly captures global information and long-distance dependency on text. In the meantime, its ability to acquire local features is relatively weak, which may lead to a lack of specific details in the model. Researchers addressed the above shortcomings by combining BiLSTM with models that extract local text features, such as GRU [48] and TextCNN [49]. Rhanoui et al. [50] conducted a comparative study involving CNN, LSTM, and BiLSTM models and their combinations. The findings indicated that the CNN-BiLSTM model achieved superior accuracy to individual CNN, LSTM, and BiLSTM models. To extract richer text emotional features, Jia et al. [51] used a combination model to extract various text semantic and grammatical features. BERT was used to generate text word embedding, and then the resulting feature representations were input into TextCNN, BiLSTM, and BiGRU. Experiments showed that the proposed combined model outperformed the baseline model in extracting text emotion features, integrating local and global information, and achieving the best classification performance.

Deep learning algorithms excel in tasks like text sentiment analysis but suffer from long operation times, high complexity, excessive adjusting parameters, and sensitivity to those parameters. Researchers started exploring implementing swarm intelligence optimization algorithms to address these issues. The Particle swarm optimization (PSO) algorithm is utilized to optimize the parameters of the emergency public opinion prediction model for short texts, improving the model's prediction accuracy [52]. PSO and Harris Hawk Optimization (HHO) algorithms are employed to optimize the parameters of support vector regression (SVR). Test results demonstrate that HHO-SVR yields superior prediction performance [53]. Zhong et al. [21] tested the effectiveness of the proposed BWO and compared the statistical results with 15 other population intelligent optimization algorithms, such as PSO and Genetic Algorithm (GA). The results indicated that BWO ranked first in the extendibility analysis of the benchmark function in the comparative group of intelligent optimization algorithms.

III. METHOD

A. EXPANDED SENTIMENT DICTIONARY

A sentiment dictionary contains emotional words and their corresponding polarities, providing a tool for sentiment analysis to identify the predominant emotional tone in textual content. This paper consolidates four resources: the Dalian Science and Technology Dictionary, Tsinghua University Chinese Words for Praise and Criticism, Taiwan University Chinese Emotion Polarity Dictionary, and CNKI.com Emotion Dictionary. This paper removes duplicate content, adds words from the business field and common words for praise and criticism in modern online networks, and creates an expanded dictionary. The paper employs the dictionary to pinpoint essential sentiment-bearing words within the text. By extracting these keywords, we can better capture the text's emotional content, enhancing the accuracy and reliability of sentiment analysis.

We extract sentiment features using a sentiment dictionary before feeding the text into the BERT model. Each word in the review text is given a weight based on its value in the sentiment dictionary. Positive emotion words are assigned a weight of +1, while negative emotion words are given a weight of −1. This method allows us to create a sequence of emotional features for each comment. For instance, when we analyze the comment "Absolutely loved the product! It is amazing and works perfectly," the resulting sequence of sentiment features obtained is [0, 1, 0, 0, 1, 0, 1]. We then input this sequence and the text into the BERT model for training. This approach enables the model to consider the context of words and integrate emotional information, significantly improving the model's performance.

For sentiment analysis using only sentiment dictionaries, the sentiment value for each word in the comment text that matches the sentiment dictionary can be calculated as:

$$s_i = \sum\nolimits_{i=1}^{n} w_i \cdot f_i \tag{1}$$

In formula (1), n represents the total number of emotion words in the sentiment dictionary, and f_i represents the frequency of occurrence of the ith emotion word in the text. Based on the value of s_i, we can determine the emotional tendency of the comment text. If $s_i > 0$, the comment is positive; if $s_i \leq 0$, the comment is negative.

B. WORD EMBEDDING

The word embedding layer is critical in text sentiment analysis by converting the words or subwords in the input text into dense vector representations. This layer allows the neural network to better understand and process the text semantics. Bidirectional Encoder Representations from Transformers (BERT) is a pre-trained language model. Its word embedding layer uses WordPiece embedding technology to segment words or subwords in input text into fixed-size word fragments. The model generates word vectors for each word fragment, which contain semantic information capturing the context and meaning of the word or subword in context. When the model receives a text sentence, it transforms the words into embeddings. Fig. 1 shows two types of character tokens: CLStoken and SEPtoken. CLStoken is typically used to gather global information. SEPtoken represents the separation and suspension of sentences. Their output includes token embeddings, segment embeddings, and position embeddings. Word embeddings correspond to text words and match a set domain word list. Downstream classification tasks can utilize output features.

This paper proposes a modification to the existing models to improve the accuracy of text sentiment analysis. Specifically, it suggests passing the output vector of BERT to the TextCNN-BiLSTM model. This approach is chosen because fine-tuning BERT requires significant computing resources and time, especially when dealing with large datasets. The proposed method allows for quicker experimental iterations at a reduced computational cost, thus facilitating the rapid verification of our hypothesis. Furthermore, combining BERT's output with TextCNN and BiLSTM leverages the strengths of each model: TextCNN excels at capturing local features, while BiLSTM is adept at capturing sequence information. This combination may prove more effective than solely fine-tuning a BERT variant.

C. FEATURE EXTRACTION

1) TEXT CONVOLUTIONAL NEURAL NETWORK

TextCNN is a variation of CNN, a convolutional neural network model designed explicitly for text classification. It can simultaneously use filters of various sizes to extract features of different dimensions from the text, thus obtaining representative features. The TextCNN model comprises convolution, pooling, and classification layers. The core of TextCNN is the convolutional layer, which is crucial for extracting diverse textual features using a range of one-dimensional convolutional kernels of different sizes. The calculation formula is as follows:

$$h_i = tanh(w_{i(x,y)} * c_{(x,y)} + b_i) \tag{2}$$

where tanh is the activation function, w_i represents the weight of the filter input node corresponding to the ith node in the output matrix, and (x, y) represents the node's value. In the filter, b_i represents the offset corresponding to the ith node.

$$P_i = \max(h_i) \tag{3}$$

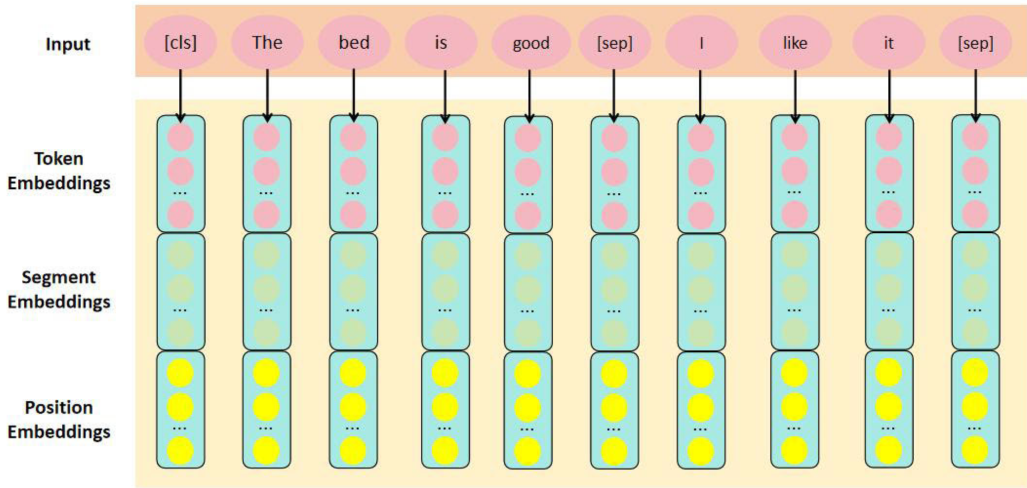

FIGURE 1. **BERT embedding layer.**

Finally, the result of the pooling operation P_i passes into the output layer. The softmax function calculates the prediction probability for achieving binary sentiment classification.

$$p\left(y \mid P_i, w_s, b_s\right) = \text{softmax}(P_i * w_s + b_s) \tag{4}$$

where w_s represents the weight, b_s represents the bias item, and softmax is the activation function.

2) BIDIRECTIONAL LONG SHORT-TERM MEMORY

LSTM comprises multiple homogeneous cells that retain information over extended periods by continually updating their internal states. A single-layer Bidirectional LSTM (BiLSTM) consists of two LSTMs: one processes the input sequence from front to back, while the other processes it from back to front. Then, the outputs of the two LSTMs are concatenated. Fig. 2 illustrates how BiLSTM operates. The forward LSTM and the reverse LSTM generate a result vector after five-time steps, which are combined to create the final BiLSTM output. Specifically, taking forward LSTM as an example, the following formulas are used to calculate the hidden state and cell state of each time step of the forward LSTM, as well as the output of the final BiLSTM:

$$f_t = \sigma\left(\mathcal{W}_f\left(x_t, \overrightarrow{h_{t-1}}\right) + b_t\right) \tag{5}$$

$$i_t = \sigma\left(\mathcal{W}_f\left(x_t, \overrightarrow{h_{t-1}}\right) + b_i\right) \tag{6}$$

$$o_t = \sigma\left(\mathcal{W}_o x_t + V_o \overrightarrow{h_{t-1}} + b_o\right) \tag{7}$$

$$\hat{c}_t = \tanh\left(\mathcal{W}_c\left(x_t, \overrightarrow{h_{t-1}}\right) + b_c\right) \tag{8}$$

$$c_t = i_t \widehat{c}_t + f_t c_{t-1} \tag{9}$$

$$\overrightarrow{h_t} = o_t \cdot \tanh\left(c_t\right) \tag{10}$$

$$b_t = \left[\overrightarrow{h_t}, \overleftarrow{h_t}\right] \tag{11}$$

The forgetting, input, and output gate states are represented by f_t, i_t, and o_t, respectively. At time t, x_t represents the input of the tth LSTM unit, and $\overrightarrow{h_{t-1}}$ represents the output of the previous LSTM unit. W and b correspond to the weight matrix of the gate and the biased vector, respectively, while σ represents the sigmoid activation function. The forget gate f_t determines which information from the input state x_t is passed to the previous hidden state $\overrightarrow{h_{t-1}}$ and what information should be discarded. It then stores the updated information in the next memory unit. The $\hat{c}_t$ represents the state of the LSTM unit at time t. It updates the information using the input gate and the tanh activation function to calculate the updated information. BiLSTM's output b_t is stitched together from hidden states in two directions.

3) TextCNN-BiLSTM

The TextCNN-BiLSTM model utilizes TextCNN to extract local features and BiLSTM to capture the global semantic information of the text. The fused features are then input into the subsequent classifier for classification. This approach enables the model to consider both local features and context information in the text, thereby improving its ability to understand and represent the text and enhancing its performance in tasks such as text classification and sentiment analysis.

D. BELUGA WHALE OPTIMIZATION (BWO) ALGORITHM

The BWO algorithm was introduced as a meta-heuristic optimization algorithm in 2022. The BWO algorithm demonstrates good adaptability in addressing various optimization problems. Compared to other optimization algorithms, the parameter setting for BWO is relatively simple and usually does not require extensive adjustment, making it more convenient [21]. The BWO algorithm involves: exploration, development, and whale drop. In the BWO algorithm, the

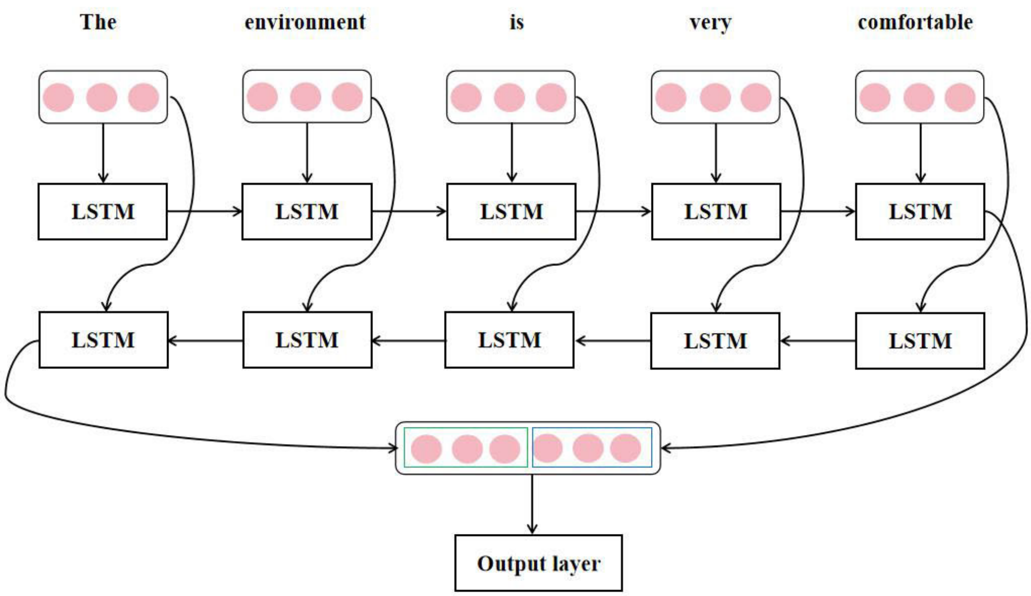

FIGURE 2. BiLSTM operating diagram.

choice of the exploration and development stages depends on the balance factor B_f. The expression for the balance factor is as follows.

$$B_f = B_0 * (1 - \frac{t}{2T}) \tag{12}$$

B_0 is a random number in the range of (0,1), which will change in each iteration. With the increase in the number of iterations, the fluctuation range of B_f gradually decreases from (0,1) to (0,0.5). t is the current number of iterations, and T is the maximum. The population is in the exploration stage when the balance factor $B_f > 0.5$. When the balance factor $B_f \leq 0.5$, the population is in the development stage.

1) EXPLORATION PHASE

The exploration phase of BWO is initiated by studying the swimming behavior of beluga whales (13), as shown at the bottom of the next page.

$X_{i,j}^{t+1}$ represents the new position of the ith Beluga whale in the j dimension, $P_j(j = 1, 2, \cdots, d)$ represents the random integer selected from the d dimension, and represents the position of the ith Beluga whale in the P_j dimension. $X_{r,p1}^t$ represents the present position of any r Beluga whale. r_1 and r_2 are random numbers in the range (0,1). The sine and cosine functions simulate the mirror image change of a Beluga whale swimming, and is an integer.

2) DEVELOPMENT PHASE

The BWO algorithm draws inspiration from the cooperative foraging and movement behaviors observed in beluga whales, utilizing Levy flights to update positions and improve convergence.

$$X_i^{t+1} = r_3 X_{\text{best}}^t - r_4 X_i^t + C_1 * \text{Levy}\left(X_r^t - X_i^t\right) \tag{14}$$

$$C_1 = 2r_4\left(1 - \frac{t}{T}\right) \tag{15}$$

$$\text{Levy} = 0.05\frac{\mu\sigma}{|v|^{1/\beta}} \tag{16}$$

$$\sigma = \left(\frac{\Gamma(1+\beta) * \sin\left(\frac{\pi\beta}{2}\right)}{\Gamma\left(\frac{1+\beta}{2}\right) * \beta * 2^{(\beta-1)/2}}\right)^{1/\beta} \tag{17}$$

where r_3 and r_4 are random numbers in the range of (0,1), X_i^{t+1} and X_i^t indicate the updated and current position of the ith Beluga whale. X_r^t is the current position of any r Beluga whale. X_{best}^t indicates the best Beluga location. C_1 and Levy are random jump intensity and Levy flight function. β is 1.5, and $\Gamma()$ is the gamma function.

3) WHALE DROP STAGE

In the natural environment, beluga whales face threats from other living beings, such as being captured or hunted for food. To help protect the population, we track the location of beluga whales and monitor their migration patterns.

$$X_i^{t+1} = r_5 X_i^t - r_6 X_r^t + r_7 X_{\text{step}} \tag{18}$$

$$X_{\text{step}} = (u_b - l_b)^{-C_2 * \frac{t}{T}} \tag{19}$$

$$C_2 = 2nW_f \tag{20}$$

$$\text{W}_f = 0.1 - \frac{0.05\,t}{T} \tag{21}$$

where r_5 and r_6 are random numbers in the range of (0,1), X_{step} represents the step length of the fall of the Beluga whale, u_b and l_b are the upper and lower bounds of the variables, C_2 is the step factor, and W_f is the fall probability of the Beluga whale.

E. IMPROVED BELUGA WHALE OPTIMIZATION (IBWO) ALGORITHM

The BWO algorithm is known for its simple structure, fast computation speed, and effective global optimization convergence. However, as the iterations progress, the individuals in the population tend to converge toward the global optimum, leading to reduced diversity. This tendency creates challenges in avoiding local optima and can reduce calculation accuracy. Considering the limitations of the BWO algorithm, this paper proposes the following improvements.

1) INITIALIZE THE POPULATION

The current population initialization methods lack diversity, leading to an initial population covering only some areas of the problem space. The first issue may result in individuals being too closely grouped in certain regions, limiting the algorithm's ability to find the best solution. Another challenge is the need for more helpful information for a specific problem, which may result in many low-quality individuals in the initial population, affecting the speed and efficiency of the algorithm's convergence. Therefore, improving the population initialization method is crucial for algorithm performance. The algorithm's enhancement involves increasing diversity, avoiding local optimizations, and utilizing heuristic information.

In this paper, we utilize the Tent chaotic mapping strategy to enhance the population initialization stage of BWO. The Tent chaotic mapping exhibits chaotic properties and can generate sequences with high randomness and uncertainty. This randomness is beneficial in increasing the diversity of population initialization, enabling the initial population to cover the problem space better and thereby expanding the algorithm's search breadth. Introducing chaos-induced randomness can effectively mitigate the clustering phenomenon, allowing the algorithm to explore the entire solution space more thoroughly. The Tent chaotic map can be fine-tuned and optimized to align with specific problem characteristics. Properly adjusting the chaotic map's parameters makes the initially generated population more likely to encompass high-quality individuals, thus enhancing the algorithm's convergence speed and search efficiency. Its function is as follows:

$$\mathrm{X}_{n+1}=\begin{cases}\mathrm{x}_n/0.5, & 0\le x_n<0.5\\ (1-\mathrm{x}_n)/0.5, & 0.5\le x_n\le 1\end{cases} \tag{22}$$

The initial function based on tent mapping is:

$$X_{i,d}^{t}=l_b+(u_b-l_b)*H_{i,d}^{t} \tag{23}$$

where d represents the sequence number of chaotic variables, equivalent to the individual's dimension in the algorithm, and $\mathrm{H}_{\mathrm{i,d}}^{\mathrm{t}}$ represents the chaotic sequence obtained after iterating t times.

2) UPDATE THE BALANCE FACTOR

The balance factor $\mathrm{B_f}$ measures the equilibrium between the exploration and production stages in a process, influencing the balance of global and local search capabilities. However, the current $\mathrm{B_f}$ is adjusted according to static rules and does not dynamically adapt to the problem's complexity or the search space's characteristics when the search progresses. The above procedure may lead to the algorithm getting stuck in local optimal solutions. Additionally, $\mathrm{B_f}$ may not effectively balance algorithms' exploration and exploitation processes. When the balance factor is too high, the algorithm tends to focus on known solution spaces and neglects to explore new ones. However, when the balance factor is too low, the algorithm is more inclined to explore new solutions and may neglect the development of known solutions.

This study adjusts the balance factor using periodic variations of the sine function to maintain equilibrium between exploration and exploitation during the search process. This method dynamically adapts as the number of iterations increases, effectively guiding the algorithm's search direction. It introduces periodic fluctuations between exploration and development stages, enhancing algorithmic diversity and robustness. The updated formula is presented below:

$$B_f=\frac{1}{2}(1+\sin(\frac{2\pi t}{T})) \tag{24}$$

This formula causes the balance factor to fluctuate between 0 and 1, increasing the algorithm's variety and explorability during iteration.

F. MODEL CONSTRUCTION

This paper constructs a hybrid DBIBTB model for text sentiment analysis. The model's architecture is illustrated in Fig. 3. The approach comprises the following steps:

1) TEXT PREPROCESSING

The review dataset undergoes cleaning, word segmentation, stop word filtering, outlier processing, and manual annotation to produce preprocessed data used as input variables for the subsequent model.

2) SENTIMENT FEATURE EXTRACTION

A generalized sentiment dictionary is created to extract emotion feature words from text data, capturing emotion information and preparing for subsequent analysis.

$$\begin{cases}X_{i,j}^{t+1}=X_{i,pj}^{t}+\left(X_{r,p1}^{t}-X_{i,pj}^{t}\right)(1+r_1)\sin(2\pi r_2), j=2n\\ X_{i,j}^{t+1}=X_{i,pj}^{t}+\left(X_{r,p1}^{t}-X_{i,pj}^{t}\right)(1+r_1)\cos(2\pi r_2), j=2n+1\end{cases} \tag{13}$$

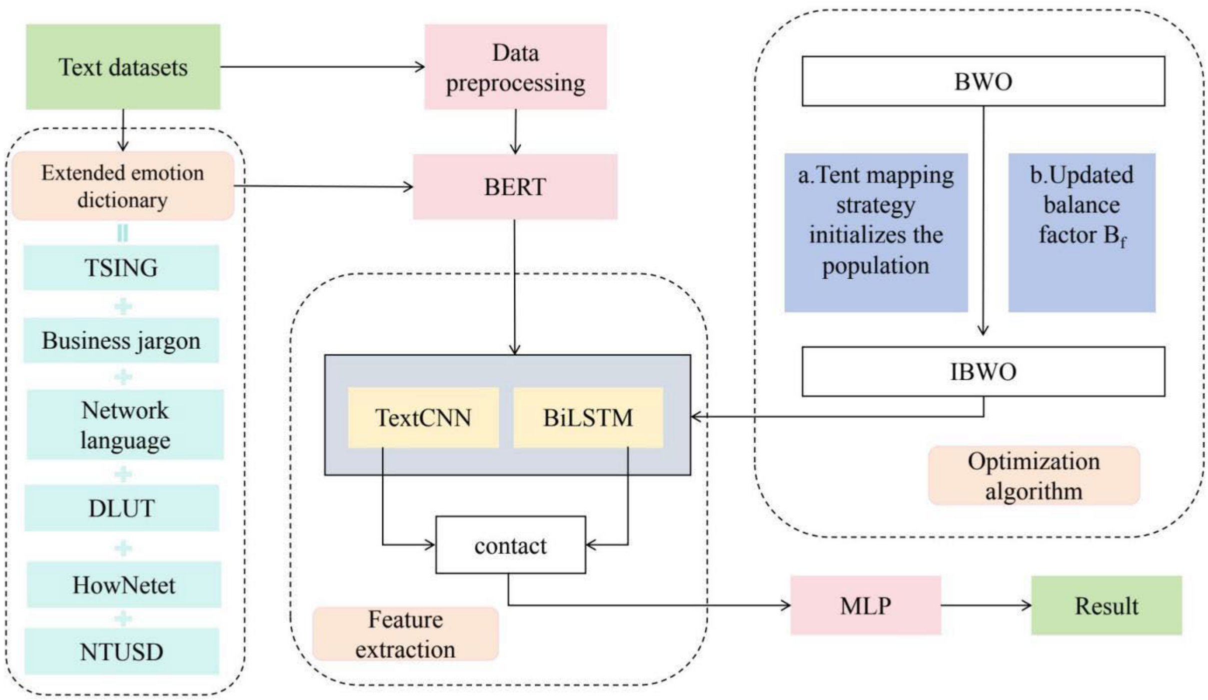

FIGURE 3. DBIBTB model framework.

3) BERT EMBEDDING

The pre-trained BERT model integrates the extracted emotion feature words with the preprocessed text, converting them into a word vector representation.

4) TWO-CHANNEL FEATURE EXTRACTION

A two-channel TextCNN-BiLSTM model is designed for extracting text features. TextCNN extracts local semantic features, while BiLSTM captures contextual global semantic features.

5) OPTIMIZATION MODEL

To further enhance the model's performance, we employ an improved Beluga Whale Optimization (IBWO) to adjust and optimize the feature extraction model's parameters.

6) SENTIMENT CLASSIFICATION

MLP is used to classify semantic features and conduct text sentiment analysis.

IV. EXPERIMENTAL ANALYSIS

A. DATA ACQUISITION

To investigate the impact of sentiment analysis in the business sector, we utilize accurate data from the Ctrip website to validate the method proposed in this paper. Ctrip is a prominent online travel service provider in China with over 90 million members who use the platform for hotel reservations, reviews, special inquiries, and other services. The website generates a large volume of review data. For this study, we collect 38,578 customer reviews of hotels from the website using Octopus and randomly selected 15,000 reviews to create a sentiment analysis dataset. The dataset consists of 10,000 positive reviews and 5,000 negative reviews. The dataset is partitioned into training and testing sets using an 8:2 ratio to assess the proposed model in this study.

B. EVALUATION INDEX

In text sentiment analysis, the accuracy rate, precision rate, recall rate, and F1 value are chosen as evaluation metrics because they comprehensively assess the model's performance. The accuracy rate measures the overall correct classification and is useful when the categories are evenly distributed. However, in sentiment analysis, the distribution of positive and negative emotions may be uneven, making accuracy and recall rates important. The accuracy rate assesses the model's accuracy in predicting positive emotions. In contrast, the recall rate focuses on the proportion of positive emotions captured by the model, ensuring crucial emotional information is not overlooked. The F1 value, as the harmonic average of precision and recall rates, is especially suitable for unbalanced data and provides a comprehensive view of the model's performance in both emotions. Using these metrics together allows for a more thorough assessment of the strengths and weaknesses of sentiment analysis models, leading to improved effectiveness in practical applications. The symbols in formula (25) - (27) are explained in Table 1.

TABLE 1. Meaning of symbols.

Symbol	Meaning
TP	The number of positive samples predicted correctly.
FP	The number of genuinely negative samples is incorrectly predicted as positive.
TN	The number of negative samples predicted correctly.
FN	The number of actually positive samples is mispredicted as negative samples.

(1) Accuracy Rate (Acc). This represents the percentage of total samples that predict the correct outcome.

$$\mathrm{Acc} = \frac{\mathrm{TP}+\mathrm{TN}}{\mathrm{TP}+\mathrm{FP}+\mathrm{TN}+\mathrm{FN}} \tag{25}$$

(2) Precision Rate (Pre). This indicates the accuracy of positive sample predictions. A higher Pre value indicates fewer false detections.

$$\mathrm{Pre} = \frac{\mathrm{TP}}{\mathrm{TP}+\mathrm{FP}} \tag{26}$$

(3) Recall Rate (Rec). This measures the coverage of predicted positive samples in the actual positive sample. A higher R-value indicates fewer missed samples.

$$\mathrm{Rec} = \frac{\mathrm{TP}}{\mathrm{TP}+\mathrm{FPN}} \tag{27}$$

(4) F1 Value. This metric simultaneously considers accuracy and recall rates to achieve a balanced performance.

$$\mathrm{F1} = \frac{2 * \mathrm{Pre} * \mathrm{R}}{\mathrm{Tre}+\mathrm{R}} \tag{28}$$

V. ANALYSIS OF EXPERIMENTAL RESULTS

This paper uses single and hybrid models to analyze text sentiment and make comparisons.

A. COMPARATIVE EXPERIMENTS OF SINGLE MODELS

In a single model comparison experiment, three types of models are selected: sentiment dictionary (general sentiment dictionary, extended sentiment dictionary), machine learning (SVM, NB, RF), and deep learning (GRU, TextCNN, LSTM, BiLSTM). Among the machine and deep learning types, four types use a fundamental bag of words model for word embedding. Table 2 presents the sentiment analysis results for nine single models using hotel review data. The experimental results indicate the following analysis.

Firstly, this study compared the extended sentiment dictionary with the general emotion dictionary. The results indicate that the accuracy rate of the extended emotion dictionary improved by 6.84%, the precision rate improved by 5.66%, the recall rate improved by 1.17%, and the F1 value improved by 3.56%. These findings demonstrate the effectiveness and necessity of constructing an extended sentiment dictionary specifically for business.

Secondly, the average accuracy rate, precision rate, recall rate, and F1 value of machine learning are 0.7755, 0.7521, 0.8899, and 0.8148. In contrast, the average accuracy rate, precision rate, recall rate, and F1 value of deep learning exceed 0.8000, 0.7997, 0.8735, and 0.8349. The results indicate that deep learning tends to outperform traditional machine learning approaches in the context of text sentiment analysis. Deep learning excels in feature learning, context comprehension, and handling complex relationships, enabling it to capture emotional information in the text more accurately.

Thirdly, compared with the deep learning model, the TextCNN model is better than GRU regarding local feature extraction among the deep learning models. The former's accuracy, precision, recall rate, and F1 values are 0.92%, 4.55%, 3.75%, and 4.17% higher than the latter's. TextCNN uses multiple convolution kernels of different sizes to carry out text convolution operations, effectively capturing local features of various lengths. On the other hand, due to the design of its gating mechanism, GRU is relatively weak in modeling long-distance dependence and capturing local features of different lengths. In the context of global feature extraction, BiLSTM is better than LSTM because it can capture information from the global context more effectively. By introducing backpropagation into the sequence model, BiLSTM can simultaneously consider each time step's past and future context information, better capturing the overall sequence's features.

Table 3 presents the experimental results comparing using BERT for word embedding with not using BERT before deep learning for sentiment analysis. The implementation of BERT has resulted in a considerable enhancement in performance. After integrating BERT into the GRU model, the accuracy rate, precision rate, recall rate, and F1 value increased by 8.75%, 12.18%, 3.78%, and 7.98%, respectively. When BERT was incorporated into the TextCNN model, the accuracy rate, precision rate, recall rate, and F1 value improved by 9.68%, 7.56%, 0.41%, and 3.98%, respectively. Upon adding BERT to the LSTM model, the accuracy rate, precision rate, recall rate, and F1 value rose by 8.63%, 11.26%, 0.92%, and

TABLE 2. Comparison results of single models.

Type	model	Acc	Pre	Rec	F1
Sentiment dictionary	General sentiment dictionary	0.7576	0.7379	0.8841	0.8044
	Extended sentiment dictionary	0.8094	0.7797	0.8945	0.8331
Machine learning	SVM	0.7194	0.7042	0.8876	0.7853
	NB	0.8076	0.7774	0.8952	0.8321
	RF	0.7997	0.7748	0.8871	0.8271
Deep learning	GRU	0.8096	0.7863	0.8497	0.8167
	TextCNN	0.8171	0.8221	0.8816	0.8508
	LSTM	0.8185	0.7924	0.8741	0.8312
	BiLSTM	0.8219	0.7983	0.8889	0.8411

6.09%, respectively. Finally, in the BiLSTM model, BERT led to increases of 9.10% in accuracy rate, 11.88% in precision rate, 0.92% in recall rate, and 6.39% in F1 value. BERT is a deep two-way language model based on Transformer architecture, enabling a thorough understanding and representation of words and contexts and enhanced comprehension of word meanings in various contexts. Additionally, BERT can be pre-trained on extensive datasets to capture more comprehensive language knowledge and contextual information.

This paper utilized the Octopus software available on the carbon trading platform (https://tanguanjia.bjx.com.cn/) to gather 1164 articles related to carbon trading. After filtering out irrelevant information, 1094 practical texts are identified. Table 2 presents four examples of carbon trading financial news per year.

B. COMPARISON EXPERIMENTS OF HYBRID MODELS

The experimental comparison in the previous section reveals that using BERT for word embedding before applying deep learning techniques leads to improved performance. As a result, all the hybrid models introduced in this paper are based on BERT word vectors. Here is an overview of these hybrid models:

1) GBL

After embedding BERT words into the comment text, they are input into the GRU-BILSTM model. GRU and BiLSTM extract local and global features from the text, respectively.

2) DGBL

The extended sentiment dictionary extracts words with emotional features from the review text. The emotional feature words are embedded with BERT words and then input with the pre-processed text into the GRU-BiLSTM model. GRU and BiLSTM extract local and global features from the text, respectively.

3) TBL

After tokenizing words with BERT, the comment text is input into the TextCNN-BiLSTM model. TextCNN extracts local text features, while BiLSTM captures the global semantic information of the text sequence.

4) DTBL

The extended sentiment dictionary extracts words with emotional features from the review text. The emotional feature words are embedded with BERT words and then input with the pre-processed text into the TextCNN-BiLSTM model. TextCNN and BiLSTM extract local and global features from the text, respectively.

5) BTBL

After embedding BERT words into the comment text, input the TextCNN-BILSTM model optimized by BWO. TextCNN and BiLSTM extract local and global features from the text, respectively.

6) DBTBL

Emotion feature words are extracted from the comment text using the extended sentiment dictionary, and then the extracted emotion feature words and the pre-processed text are embedded with BERT words and input into the BWO-optimized TextCNN-BiLSTM model. TextCNN and BiLSTM extract local and global features from the text, respectively.

TABLE 3. Sentimental dictionary.

Model	Acc	Pre	Rec	F1
GRU	0.8096	0.7863	0.8497	0.8167
BERT-GRU	0.8805	0.8821	0.8819	0.8819
TextCNN	0.8171	0.8221	0.8816	0.8508
BERT-TextCNN	0.8962	0.8843	0.8853	0.8847
LSTM	0.8185	0.7924	0.8741	0.8312
BERT-LSTM	0.8892	0.8817	0.8822	0.8819
BiLSTM	0.8219	0.7983	0.8889	0.8411
BERT-BiLSTM	0.8967	0.8932	0.8967	0.8949

7) IBTBL

After embedding BERT words into the comment text, input the TextCNN-BiLSTM model optimized by IBWO. TextCNN and BiLSTM extract local and global features from the text, respectively.

8) DIBTBL

The model described in this paper extracts emotion feature words from the comment text using the extended sentiment dictionary. These extracted emotion feature words and the pre-processed text are embedded with BERT words and then input into the IBWO-optimized TextCNN-BiLSTM model. TextCNN and BiLSTM extract local and global features from the text, respectively.

Table 4 shows the evaluation criteria results for each model, with the optimal experimental outcomes highlighted in bold. Also, to illustrate the complexity of the hybrid model in this study, we add the running time of the model in the last column.

Table 4 shows that the accuracy, precision, recall rates, and F1 value of TBL increased by 1.14%, 1.24%, 0.73%, and 2.14% compared to GBL, respectively. These results suggest that opting for TextCNN over GRU for local feature extraction and combining it with the global feature extraction method BiLSTM yields better performance.

Through pairwise comparison, we can see that the accuracy rate, precision rate, recall rate, and F1 value of DGBL are 1.14%, 1.76%, 1.24%, and 1.52% higher than those of GBL. Similarly, the accuracy rate, precision rate, recall rate, and F1 value of DTBL are 0.49%, 2.1%, 1.07%, and 0.50% higher than those of TBL. Additionally, the accuracy rate, precision rate, recall rate, and F1 value of DBTBL are 0.76%, 0.35%, 1.87%, and 1.12%, higher than those of BTBL, and the accuracy rate, precision rate, recall rate, and F1 value of DIBTBL are 0.66%, 0.23%, 1.20%, and 0.71% higher than those of BTBL, respectively. These enhancements imply that the extended sentiment dictionary not only aids in capturing crucial emotional information from the text but also assists the model in more accurately classifying emotions, ultimately leading to improved overall classification performance.

The accuracy rate, precision rate, recall rate, and F1 value of BTBL increased by 1.28%, 2.43%, 1.08%, and 0.69%, respectively, compared with TBL. Similarly, the accuracy rate, precision rate, recall rate, and F1 value of DBTBL increased by 1.54%, 0.69%, 1.88%, and 1.31%, respectively, compared with DTBL. Using the BWO swarm intelligence algorithm to optimize model parameters significantly improves performance. With the BWO algorithm, the model can efficiently adjust parameters during learning and adapting to data, enhancing its performance and predictive accuracy. These results underscore the effectiveness and potential of BWO in optimizing machine learning models, particularly in strengthening the performance of complex models.

The accuracy rate, precision rate, recall rate, and F1 value of IBTBL increased by 0.98%, 0.48%, 1.85%, and 1.17% respectively compared with BTBL. Similarly, the accuracy rate, precision rate, recall rate, and F1 value of DIBTBL increased by 0.87%, 0.36%, 1.18%, and 0.76%, respectively, compared with DBTBL. The improved BWO algorithm allows for more effective parameter space exploration and helps find better model parameter configurations. As a result, this enhances the model's overall performance and prediction accuracy across different tasks.

Comparing the run times of hybrid models gives us a better understanding of their efficiency. While the DIBTBL model proposed in this paper has a slightly longer running time, the increase is acceptable from a time-cost perspective, especially when considering the significant improvement in the accuracy and capability of the model in sentiment analysis.

TABLE 4. Comparison results of hybrid models.

Model	Acc	Pre	Rec	F1	Running Time (Second)
GBL	0.9586	0.9542	0.9524	0.9532	2938
DGBL	0.9696	0.9710	0.9643	0.9676	3102
TBL	0.9695	0.9661	0.9594	0.9727	3025
DTBL	0.9743	0.9862	0.9697	0.9776	3235
BTBL	0.9819	0.9896	0.9698	0.9795	3462
DBTBL	0.9894	0.9931	0.9880	0.9905	3619
IBTBL	0.9915	0.9944	0.9878	0.9910	4584
DIBTBL	**0.9981**	**0.9967**	**0.9997**	**0.9981**	4760

TABLE 5. Comparative results of waimai_10k emotion analysis.

Model	Acc	Pre	Rec	F1
XLNet-RCNN [54]	0.9180	0.9170	0.9180	0.9180
Qinglan Wei [55]	0.7872	0.8268	0.7263	0.7733
ET_s_BG+p [56]	0.8430	0.8395	0.8835	0.8598
ALBERT-SACR [57]	0.8880	0.8810	0.7690	0.82.10
KSCB [58]	0.8962	—	0.8943	0.8951
CG-BERT [59]	0.8901	—	—	0.7834
SpikeBERT [60]	0.8966	—	—	—
DIBTBL（Ours)	**0.9459**	**0.9367**	**0.9261**	**0.9272**

Therefore, the extension of the operating time is warranted, especially when striving for improved performance.

C. COMPARISON WITH EXISTING MODELS

This paper evaluates the performance of the proposed model by comparing it with models created by scholars in recent years using the waimai_10k dataset, a public Chinese sentiment analysis dataset for text sentiment classification. The waimai_10k dataset is sourced from user reviews collected by the Meituan Food Delivery platform and consists of 4,001 positive and 7,987 negative emotional data points.

According to Table 5, the evaluation metrics for the model presented in this paper outperform those of other models. These findings indicate that the DIBTBL model is more accurate and efficient in handling text sentiment analysis tasks than existing methods, positively impacting research and applications in this field. Additionally, this further confirms the effectiveness of the IBWO optimization algorithm in model design. Our model can adapt to and learn from complex text emotional expression and improve performance.

VI. CONCLUSIONS, RECOMMENDATIONS AND FUTURE WORK

A. CONCLUSION

This paper constructs a hybrid text sentiment analysis model called DIBTBL. It combines an extended sentiment dictionary, a deep learning method, and an improved optimization algorithm to improve the accuracy and effectiveness of sentiment analysis for business reviews. Comparative analysis allows us to draw the following conclusions:

Firstly, The effectiveness of a sentimental dictionary is crucial in extracting emotional features from text and can significantly improve the accuracy of sentiment classification. By creating a sentiment dictionary specific to the business domain, the model can capture essential emotional words more accurately and identify and quantify the sentiment in comments, leading to better performance in sentiment analysis.

Secondly, The advantages of the TextCNN-BiLSTM model lie in its ability to effectively extract text features by combining TextCNN and BiLSTM. TextCNN excels at capturing local text features, while BiLSTM effectively extracts global text dependencies. The combined use of these two methods enhances the model's capacity to grasp the semantic information of text, boosting its proficiency in handling long text, especially in capturing distant semantic relationships and emotional features.

Thirdly, The Beluga Whale Optimization algorithm (BWO) is crucial in optimizing model parameters. By utilizing the BWO algorithm, the model can more effectively explore the parameter space to find an improved configuration, enhancing generalization ability and prediction accuracy. The BWO algorithm's global search capability prevents the model from being trapped in local optimality, thereby boosting its performance on complex datasets.

Fourthly, The improved BWO algorithm further enhances the model's performance. By avoiding local optimization, the IBWO algorithm enhances the model's global optimization ability, making it more robust and efficient in processing text for sentiment analysis tasks. Applying the IBWO algorithm can significantly improve the model's prediction accuracy, particularly when handling large and complex datasets.

In summary, the accuracy of text sentiment analysis dramatically depends on the effectiveness of the sentiment dictionary used. Developing specific business domain sentiment dictionaries can significantly enhance sentiment classification. Furthermore, combining TextCNN and BiLSTM is crucial for extracting features, and their synergy improves the model's ability to comprehend semantic information in text. When dealing with complex datasets, the BWO and IBWO are vital for optimizing model parameters and substantially improving the model's generalization ability and prediction accuracy. Therefore, the quality of the sentiment dictionary is paramount. Simultaneously, the combination of the model structure TextCNN-BiLSTM and the optimization algorithm BWO and IBWO are equally important, forming an effective mixed text sentiment analysis model.

B. RECOMMENDATIONS

Using sentiment analysis, marketers can better understand consumers' emotional attitudes toward products, services, or brands, enabling them to create personalized marketing strategies. Sentiment analysis also helps marketers identify positive and negative emotions, optimize marketing content and communication channels, understand competitors' market performance, and build emotional connections and brand loyalty with consumers. Ultimately, this will enhance the long-term value of the brand.

Sentiment analysis can offer valuable insight into how users feel about products, including their satisfaction, preferences, and dissatisfaction. Product managers and research and development teams can leverage this information to enhance product design, functionality, and user experience. By understanding users' emotional needs and addressing potential issues, businesses can drive innovation, improve competitiveness, and expand their market share. Additionally, analyzing competitors' emotional feedback can provide estimable opinions for product improvement. Promptly addressing inverse suggestions and taking proactive measures can help maintain a positive product image. This feedback can also adjust market positioning and target user groups more effectively.

The customer service team should promptly address customer feedback and resolve their issues positively to enhance customer satisfaction. By understanding customers' emotions, we can tailor our service solutions to meet their needs and preferences and foster loyalty. Moreover, we should continuously improve our service process and quality based on customer feedback to enhance their experience and satisfaction, ultimately establishing a solid brand reputation. Protecting our brand image and converting them into positive experiences is essential. We should also develop various communication channels, train our team to be emotionally intelligent, and create customer emotion profiles to better understand their preferences and past issues, allowing us to provide more personalized service.

Senior management can utilize sentiment analysis to comprehend consumers' emotional attitudes towards the brand, leading to an assessment of the brand's reputation and image in the market. This analysis can also unveil emotional trends and keywords in review text, which can help identify consumer preferences and changes in needs. Top management can facilitate timely corporate strategy and product planning adjustments to capitalize on market opportunities. Additionally, it also allows for an analysis of competitors' emotional expression and market performance in reviews, which helps understand their strengths and weaknesses and aids in developing targeted competitive strategies to maintain market competitiveness. Furthermore, sentiment analysis can uncover consumer dissatisfaction with products, services, or brands, enabling timely actions to address these issues and prevent a negative impact on the company's image. Finally, by leveraging consumer emotional feedback, products and services can be continuously enhanced, improving customer experience and satisfaction, increasing customer loyalty, and positive word-of-mouth.

C. FUTURE WORK

The sentiment analysis model presented in this paper has delivered impressive results in recognizing sentiments in business reviews. However, sentiment analysis, as a continuously evolving research area, still offers considerable potential for improvement. Incorporating images, audio, and video could provide valuable insights for future research. This multimodal method can enhance sentiment analysis capabilities, enabling businesses to make informed decisions and improve user interactions.

REFERENCES

[1] M. Stilinovic and J. Hutchinson, "Living in media and the era of regulation: Policy and internet during a pandemic," *Policy Internet*, vol. 13, no. 3, pp. 338–344, Sep. 2021, doi: 10.1002/poi3.271.

[2] H.-T. Tseng, "Shaping path of trust: The role of information credibility, social support, information sharing and perceived privacy risk in social commerce," *Inf. Technol. People*, vol. 36, no. 2, pp. 683–700, Mar. 2022, doi: 10.1108/itp-07-2021-0564.

[3] H. B. Abdalla and L. Wang, "Evaluating Chinese potential e-commerce websites based on analytic hierarchy process," *Int. J. Adv. Comput. Sci. Appl.*, vol. 12, no. 9, pp. 170–176, 2021, doi: 10.14569/ijacsa.2021.0120921.

[4] C. Zhang, J. Jiang, H. Jin, and T. Chen, "The impact of COVID-19 on consumers' psychological behavior based on data mining for online user comments in the catering industry in China," *Int. J. Environ. Res. Public Health*, vol. 18, no. 8, p. 4178, Apr. 2021, doi: 10.3390/ijerph18084178.

[5] Z. Gan, "Research on service quality of travel e-commerce based on online review mining—A case study of ctrip," *China Collective Economy*, vol. 13, pp. 71–73, Jan. 2020. [Online]. Available: https://kns.cnki.net/kcms2/article/abstract?v=5iIAKlsf9WB755LMxg9PlW2-zrrq6ryDTos4SCxmubgR9WCcDqMuu97OzLpctBlYVZ2fmw5bKkOQ6kiF0f2FfQuDBBR0ipFAn7WDcF5EEHfUab3yxtN2O7mHvGGxXTAgBIsmcyxKgQ1DjSAzI7T0P8laH6g0zpnx6vqlkss0KT6GkmokXRjGng==&uniplatform=NZKPT&language=CHS

[6] S. Putatunda, A. Bhowmik, G. Thiruvenkadam, and R. Ghosh, "A BERT based ensemble approach for sentiment classification of customer reviews and its application to nudge marketing in e-commerce," Nov. 2023, *arXiv:2311.10782*.

[7] A. Nguyen, A. Longa, M. Luca, J. Kaul, and G. Lopez, "Emotion analysis using multilayered networks for graphical representation of tweets," *IEEE Access*, vol. 10, pp. 99467–99478, 2022, doi: 10.1109/ACCESS.2022.3207161.

[8] N. Ajmeera and P. Kamakshi, "Hamiltonian deep neural network fostered sentiment analysis approach on product reviews," *Signal, Image Video Process.*, vol. 18, no. 4, pp. 3483–3494, Feb. 2024, doi: 10.1007/s11760-024-03014-6.

[9] O. Grljević and Z. Bosnjak, "Sentiment analysis of customer data," *Strategic Manage.*, vol. 23, no. 3, pp. 38–49, 2018, doi: 10.5937/straman1803038g.

[10] R. G. Bilro, S. M. C. Loureiro, and J. Guerreiro, "Exploring online customer engagement with hospitality products and its relationship with involvement, emotional states, experience and brand advocacy," *J. Hospitality Marketing Manage.*, vol. 28, no. 2, pp. 147–171, Feb. 2019, doi: 10.1080/19368623.2018.1506375.

[11] T. Fernandes and F. Fernandes, "Sharing dissatisfaction online: Analyzing the nature and predictors of hotel guests negative reviews," *J. Hospitality Marketing Manage.*, vol. 27, no. 2, pp. 127–150, Aug. 2017, doi: 10.1080/19368623.2017.1337540.

[12] F. Z. Xing, F. Pallucchini, and E. Cambria, "Cognitive-inspired domain adaptation of sentiment lexicons," *Inf. Process. Manage.*, vol. 56, no. 3, pp. 554–564, May 2019, doi: 10.1016/j.ipm.2018.11.002.

[13] K. Kumar, B. S. Harish, and H. K. Darshan, "Sentiment analysis on IMDb movie reviews using hybrid feature extraction method," *Int. J. Interact. Multimedia Artif. Intell.*, vol. 5, no. 5, p. 109, 2019, doi: 10.9781/ijimai.2018.12.005.

[14] 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.

[15] Z. Nanli, Z. Ping, L. Weiguo, and C. Meng, "Sentiment analysis: A literature review," in *Proc. Int. Symp. Manage. Technol. (ISMOT)*, Nov. 2012, pp. 572–576. [Online]. Available: https://ieeexplore.ieee.org/document/6679538

[16] W. Medhat, A. Hassan, and H. Korashy, "Sentiment analysis algorithms and applications: A survey," *Ain Shams Eng. J.*, vol. 5, no. 4, pp. 1093–1113, Dec. 2014, doi: 10.1016/j.asej.2014.04.011.

[17] N. Bai, F. Meng, X. Rui, and Z. Wang, "Rumour detection based on graph convolutional neural net," *IEEE Access*, vol. 9, pp. 21686–21693, 2021, doi: 10.1109/ACCESS.2021.3050563.

[18] P. Liang, "The research on Chinese sentiment classification using recurrent neural network and convolutional neural network," M.S. thesis, Univ. Hunan, Changsha, China, 2017. [Online]. Available: https://kns.cnki.net/kcms2/article/abstract?v=5iAKlsf9WDI5ZkBRMx3UsA3g-DOWeu_tn4riE8pxJ4v1bzn7Zc8a_6oShyhBVfbpxtzanpo6Sc3n0Wxrx7qczGUkYIDREyPdCWEvncs5y8IV0CU2RtdsSCgmLYk7y8BhGmRkJTAzojUIAM2581nT_L1SqveCh3EdQpxWCh_yJighV20gqCdeqqkufsBInZ&uniplatform=NZKPT&language=CHS

[19] G. Mu, J. Li, Z. Liao, and Z. Yang, "An enhanced IHHO-LSTM model for predicting online public opinion trends in public health emergencies," *Sage Open*, vol. 14, no. 2, Apr. 2024, Art. no. 21582440241257681, doi: 10.1177/21582440241257681.

[20] G. Mu, L. Dai, X. Ju, Y. Chen, and X. Huang, "MS-IHHO-LSTM: Carbon price prediction model of multi-source data based on improved swarm intelligence algorithm and deep learning method," *IEEE Access*, vol. 12, pp. 80754–80769, 2024, doi: 10.1109/ACCESS.2024.3409822.

[21] C. Zhong, G. Li, and Z. Meng, "Beluga whale optimization: A novel nature-inspired metaheuristic algorithm," *Knowl.-Based Syst.*, vol. 251, Sep. 2022, Art. no. 109215, doi: 10.1016/j.knosys.2022.109215.

[22] M. H. Hassan, S. Kamel, F. Jurado, M. Ebeed, and M. F. Elnaggar, "Economic load dispatch solution of large-scale power systems using an enhanced Beluga whale optimizer," *Alexandria Eng. J.*, vol. 72, pp. 573–591, Jun. 2023, doi: 10.1016/j.aej.2023.04.002.

[23] M. Taboada, J. Brooke, M. Tofiloski, K. Voll, and M. Stede, "Lexicon-based methods for sentiment analysis," *Comput. Linguistics*, vol. 37, no. 2, pp. 267–307, Jun. 2011, doi: 10.1162/coli_a_00049.

[24] G. Mu, N. Gao, Y. Wang, and L. Dai, "A stock price prediction model based on investor sentiment and optimized deep learning," *IEEE Access*, vol. 11, pp. 51353–51367, 2023, doi: 10.1109/ACCESS.2023.3278790.

[25] J. Carrillo, L. Plaza, and P. Gerv'as, "SentiSense: An easily scalable concept-based affective lexicon for sentiment analysis," in *Proc. LREC*, May 2012, pp. 3562–3567.

[26] E. Cambria, S. Poria, D. Hazarika, and K. Kwok, "SenticNet 5: Discovering conceptual primitives for sentiment analysis by means of context embeddings," in *Proc. AAAI Conf. Artif. Intell.*, Apr. 2018, vol. 32, no. 1, pp. 1–8, doi: 10.1609/aaai.v32i1.11559.

[27] C. Strapparava and A. Valitutti, "WordNet affect: An affective extension of WordNet," in *Proc. 4th Int. Conf. Lang. Resour. Eval.*, May 2004, pp. 1083–1086. [Online]. Available: http://www.lrec-conf.org/proceedings/lrec2004/pdf/369.pdf

[28] J. Chen, "The construction and application of Chinese emotion word ontology," M.S. thesis, Dalian Univ. Technol., Dalian, China, 2009. [Online]. Available: https://kns.cnki.net/kcms2/article/abstract?v=5iIAKlsf9WBPbXm879TItnsHcGeOF0SFRaDbd-O1wB1YO7lvGVGL3w9HWh5il0NGdo-Q2GiXRFUONBe91Y4B6WULplBdADKmtAjrq-zcrD5oamIi0q8VLmYGVDjpOhpP5eFdFRn–9kG8770moJPZjTlFyk0mTK4SXEva98oIaXb5c1QHhRC3Q==&uniplatform=NZKPT&language=CHS

[29] F. Xianghua, L. Guo, G. Yanyan, and W. Zhiqiang, "Multi-aspect sentiment analysis for Chinese online social reviews based on topic modeling and HowNet lexicon," *Knowl.-Based Syst.*, vol. 37, pp. 186–195, Jan. 2013, doi: 10.1016/j.knosys.2012.08.003.

[30] X. Zeng, C. Yang, C. Tu, Z. Liu, and M. Sun, "Chinese LIWC lexicon expansion via hierarchical classification of word embeddings with sememe attention," in *Proc. AAAI Conf. Artif. Intell.*, Apr. 2018, vol. 32, no. 1, pp. 1–8, doi: 10.1609/aaai.v32i1.11982.

[31] A. Bandhakavi, N. Wiratunga, D. Padmanabhan, and S. Massie, "Lexicon based feature extraction for emotion text classification," *Pattern Recognit. Lett.*, vol. 93, pp. 133–142, Jul. 2017, doi: 10.1016/j.patrec.2016.12.009.

[32] C. Zhao, P. Zhang, J. Liu, J. Wang, and J. Zhang, ''Research on domain emotion dictionary construction method based on improved SO-PMI algorithm,'' in *Proc. 5th Int. Conf. Natural Language Process. Inf. Retr.*, Dec. 2021, pp. 18–23, doi: 10.1145/3508230.3508233.

[33] Y. Zhang, J.-Y. Sun, L. Meng, and Y. Liu, ''Sentiment analysis of e-commerce text reviews based on sentiment dictionary,'' in *Proc. IEEE Int. Conf. Artif. Intell. Comput. Appl. (ICAICA)*, Jun. 2020, pp. 1346–1350, doi: 10.1109/ICAICA50127.2020.9182441.

[34] F. Hui, ''Research on the construction of emergency network public opinion emotional dictionary based on emotional feature extraction algorithm,'' *Frontiers Psychol.*, vol. 13, Apr. 2022, Art. no. 857769, doi: 10.3389/fpsyg.2022.857769.

[35] Z. He, ''Text sentiment analysis based on multi-layer bi-directional LSTM with a trapezoidal structure,'' *Intell. Autom. Soft Comput.*, vol. 37, no. 1, pp. 639–654, Jan. 2023, doi: 10.32604/iasc.2023.035352.

[36] H. Wang and D. Zhao, ''Emotion analysis of microblog based on emotion dictionary and bi-GRU,'' in *Proc. Asia–Pacific Conf. Image Process., Electron. Comput. (IPEC)*, Apr. 2020, pp. 197–200, doi: 10.1109/IPEC49694.2020.9115194.

[37] J. Khan, N. Ahmad, S. Khalid, F. Ali, and Y. Lee, ''Sentiment and context-aware hybrid DNN with attention for text sentiment classification,'' *IEEE Access*, vol. 11, pp. 28162–28179, 2023, doi: 10.1109/ACCESS.2023.3259107.

[38] L. Yang, Y. Li, J. Wang, and R. S. Sherratt, ''Sentiment analysis for e-commerce product reviews in Chinese based on sentiment lexicon and deep learning,'' *IEEE Access*, vol. 8, pp. 23522–23530, 2020, doi: 10.1109/ACCESS.2020.2969854.

[39] M. Diop and R. Iqbal, ''Comparative study of sentiment analysis with product reviews using machine learning and lexicon-based approaches,'' *SMU Data Sci. Rev.*, vol. 1, no. 4, p. 7, 2018. [Online]. Available: https://scholar.smu.edu/cgi/viewcontent.cgi?article=1051&context=datasciencereview

[40] A. Sharma and S. Dey, ''A comparative study of feature selection and machine learning techniques for sentiment analysis,'' in *Proc. ACM Res. Appl. Comput. Symp.*, Oct. 2012, pp. 1–7, doi: 10.1145/2401603.2401605.

[41] R. S. Jagdale, V. S. Shirsat, and S. N. Deshmukh, ''Sentiment analysis on product reviews using machine learning techniques,'' in *Cognitive Informatics and Soft Computing*. Singapore: Springer, Aug. 2018, pp. 639–647, doi: 10.1007/978-981-13-0617-4_61.

[42] P. K. Jain, R. Pamula, and G. Srivastava, ''A systematic literature review on machine learning applications for consumer sentiment analysis using online reviews,'' *Comput. Sci. Rev.*, vol. 41, Aug. 2021, Art. no. 100413, doi: 10.1016/j.cosrev.2021.100413.

[43] S. Q. Et. al, ''A comparison of machine learning techniques for sentiment analysis,'' *Turkish J. Comput. Math. Educ. (TURCOMAT)*, vol. 12, no. 3, pp. 1738–1744, Apr. 2021, doi: 10.17762/turcomat.v12i3.999.

[44] A. Yadav and D. K. Vishwakarma, ''Sentiment analysis using deep learning architectures: A review,'' *Artif. Intell. Rev.*, vol. 53, no. 6, pp. 4335–4385, Dec. 2019, doi: 10.1007/s10462-019-09794-5.

[45] D. G. S. N. Murthy, S. Rao Allu, B. Andhavarapu, and M. B. M. Bagadi, ''Text based sentiment analysis using LSTM,'' *Int. J. Eng. Res.*, vol. 9, no. 5, May 2020, doi: 10.17577/ijertv9is050290.

[46] G. Xu, Y. Meng, X. Qiu, Z. Yu, and X. Wu, ''Sentiment analysis of comment texts based on BiLSTM,'' *IEEE Access*, vol. 7, pp. 51522–51532, 2019, doi: 10.1109/ACCESS.2019.2909919.

[47] M. Arbane, R. Benlamri, Y. Brik, and A. D. Alahmar, ''Social media-based COVID-19 sentiment classification model using bi-LSTM,'' *Exp. Syst. Appl.*, vol. 212, Feb. 2023, Art. no. 118710, doi: 10.1016/j.eswa.2022.118710.

[48] B. S. Ainapure, R. N. Pise, P. Reddy, B. Appasani, A. Srinivasulu, M. S. Khan, and N. Bizon, ''Sentiment analysis of COVID-19 tweets using deep learning and lexicon-based approaches,'' *Sustainability*, vol. 15, no. 3, p. 2573, Jan. 2023, doi: 10.3390/su15032573.

[49] C. Wu, Y. Zhang, S. Lu, and G. Xu, ''Short text sentiment analysis based on multiple attention mechanisms and TextCNN-BiLSTM,'' in *Proc. IEEE 13th Int. Conf. Electron. Inf. Emergency Commun. (ICEIEC)*, vol. 40, Jul. 2023, pp. 124–128, doi: 10.1109/iceiec58029.2023.10199931.

[50] M. Rhanoui, M. Mikram, S. Yousfi, and S. Barzali, ''A CNN-BiLSTM model for document-level sentiment analysis,'' *Mach. Learn. Knowl. Extraction*, vol. 1, no. 3, pp. 832–847, Jul. 2019, doi: 10.3390/make1030048.

[51] K. Jia, F. Meng, J. Liang, and P. Gong, ''Text sentiment analysis based on BERT-CBLBGA,'' *Comput. Electr. Eng.*, vol. 112, Dec. 2023, Art. no. 109019, doi: 10.1016/j.compeleceng.2023.109019.

[52] G. Mu, Z. Liao, J. Li, N. Qin, and Z. Yang, ''IPSO-LSTM hybrid model for predicting online public opinion trends in emergencies,'' *PLoS ONE*, vol. 18, no. 10, Oct. 2023, Art. no. e0292677, doi: 10.1371/journal.pone.0292677.

[53] A. Malik, Y. Tikhamarine, S. S. Sammen, S. I. Abba, and S. Shahid, ''Prediction of meteorological drought by using hybrid support vector regression optimized with HHO versus PSO algorithms,'' *Environ. Sci. Pollut. Res.*, vol. 28, no. 29, pp. 39139–39158, Mar. 2021, doi: 10.1007/s11356-021-13445-0.

[54] L. Pan, C. Zeng, H. Zhang, C. Wen, R. Hao, and P. He, ''Text sentiment analysis method combining generalized autoregressive pre-training language model and recurrent convolutional neural network,'' *J. Comput. Appl.*, vol. 42, no. 4, pp. 1115–51108, 2022. [Online]. Available: https://link.cnki.net/urlid/51.1307.TP.20210906.1654.002

[55] Q. Wei, Y. He, and J. Song, ''An adaptive automatic construction algorithm for sentiment dictionaries based on semantic rules,'' *J. Beijing Univ. Aeronaut. Astronaut.*, pp. 1–11, Mar. 2024, doi: 10.13700/j.bh.1001-5965.2023.0367.

[56] Y. Xiu, X. Liu, J. Qiu, T. Qu, J. Liu, and Y. Bian, ''A method of sentiment analysis and visualized interaction based on ernie-tiny and BiGRU,'' *Appl. Sci.*, vol. 13, no. 10, p. 5961, May 2023, doi: 10.3390/app13105961.

[57] S. Hou, X. Zhao, N. Liu, X. Shi, Y. Wang, and G. Zhang, ''Self-adaptive context reasoning mechanism for text sentiment analysis,'' in *Proc. Int. Conf. Web Inf. Syst. Appl.*, in Lecture Notes in Computer Science, Jan. 2022, pp. 194–205, doi: 10.1007/978-3-031-20309-1_17.

[58] W. Jiang, K. Zhou, C. Xiong, G. Du, C. Ou, and J. Zhang, ''KSCB: A novel unsupervised method for text sentiment analysis,'' *Appl. Intell.*, vol. 53, no. 1, pp. 301–311, Apr. 2022, doi: 10.1007/s10489-022-03389-4.

[59] F. Cao and X. Huang, ''Performance analysis of aspect-level sentiment classification task based on different deep learning models,'' *PeerJ Comput. Sci.*, vol. 9, p. e1578, Oct. 2023, doi: 10.7717/peerj-cs.1578.

[60] C. Lv, T. Li, J. Xu, C. Gu, Z. Ling, C. Zhang, X. Zheng, and X. Huang, ''SpikeBERT: A language spikformer learned from BERT with knowledge distillation,'' 2023, *arXiv:2308.15122*.

GUANGYU MU received the bachelor's degree in computer science from Jilin Engineering University, in 1994, the master's degree in computer science from Jilin University, in 2004, and the Ph.D. degree in computer science from Jilin University, in 2011. She is currently a Professor and a faculty with the School of Management Science and Information Engineering, and the Director of the Institute of Economic Information Management, Jilin University of Finance and Economics. She is a peer reviewer of China National Social Science Fund projects, an expert on Humanities and Social Science Fund Projects of the Ministry of Education of China, and an Expert on the Outstanding Contribution of Jilin Province. Her research interests include information resource management, data mining, and financial engineering.

LI DAI received the Engineering degree, in 2021. She is currently pursuing the master's degree in management science and engineering with the School of Management Science and Information Engineering, Jilin University of Finance and Economics. Her current research interests include NLP, financial market forecasting, and green finance. She won the second-class scholarship and the Academic Advanced Individual title at school.

YING CHEN received the Engineering degree, in 2023. She is currently pursuing the master's degree in management science and engineering with the School of Management Science and Information Engineering, Jilin University of Finance and Economics. Her current research interests include deep learning based data mining and NLP. She won a third-class scholarship in the school.

XIURONG LI received the bachelor's degree in computer science from Jilin Engineering University, in 1994, and the master's degree in computer science from Beijing University of Technology, in 2005. She is currently an Associate Professor and a faculty with Beijing University of Technology. Her research interests include cryptography and information security.

XIAOQING JU received the Engineering degree, in 2023. She is currently pursuing the master's degree in electronic information with the School of Management Science and Information Engineering, Jilin University of Finance and Economics. Her current research interests include multimodal fusion and false information detection. She won a third-class scholarship.

JIAXIU DAI received the Engineering degree, in 2024. She is currently pursuing the master's degree in electronic information with the School of Management Science and Information Engineering, Jilin University of Finance and Economics. Her current research interest includes fake news detection. She won a third-class scholarship.