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Improved Danmaku Emotion Analysis and Its Application Based on Bi-LSTM Model

SHAOKANG WANG [1], YIHAO CHEN [1], HONGJUN MING [2], HAI HUANG [1], LINGXIAN MI [3], AND ZENGYI SHI [3]

[1] School of Information and Communication Engineering, Beijing University of Posts and Telecommunications, Beijing 100876, China
[2] School of Software, Beijing University of Posts and Telecommunications, Beijing 100876, China
[3] International School, Beijing University of Posts and Telecommunications, Beijing 100876, China

Corresponding author: Hai Huang (huanghai@bupt.edu.cn)

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ABSTRACT With the rapid development of social media, danmaku video provides a platform for users to communicate online. To some extent, danmaku video provides emotional timing information and an innovative method to analyze video data. In the age of big data, studying the characteristics of danmaku and its emotional tendencies can not only help us understand the psychological characteristics of users but also feedback the effective information of users to video platforms, which can help the platforms optimize related short video recommendations so that it can provide a more accurate solution for the selection of audiences during video production. However, danmaku is different from traditional comments. Current emotion classification methods are only suitable for two-dimensional classification which are not suitable for danmaku emotion analysis. Aiming at the problems such as the colloquialism, diversity, spelling errors, structural non-linearity informal language on the Internet, diversity of social topics, and context dependency of emotion analysis of the danmaku data, this paper proposes an improved emotion analysis model based on Bi-LSTM model to classify the further four-dimensional emotions of Pleasure, Anger, Sorrow and Joy. Furthermore, we add tags such as comment time and user name to the danmaku information. Experimental results show that the improved model has higher Accuracy, Recall, Precision, and F1-Score under the same conditions compared with the CNN and SVM. The classification effect of improved model is close to the SOTA. Experimental results also show that the improved model can be effectively applied to the analysis of irregular danmaku emotion.

INDEX TERMS Danmaku, emotion analysis, emotion classification, Bi-LSTM.

I. INTRODUCTION

In recent years, emotion analysis research has entered a period with rapid growth, and has gradually become a hot spot in academic research. The network media has abundant emotional symbols and abundant emotional colors. The network informal language (NIL) has become the mainstream. Network new words are emerging one after another, and the subject is generalized [12], [13]. Online social texts exist in rich social contexts, with short text lengths and incomplete information. The unique characteristics of network media have brought great challenges to the accuracy of traditional text sentiment calculation methods.

Emotion analysis is the process of analyzing, processing, summarizing, and reasoning on subjective texts with emotional colors. With the ability of emotion analysis, the natural language text with subjective description can be automatically judged on the positive and negative tendencies of the text and the corresponding results are given [14]. It is widely used in comment analysis and decision-making, e-commerce comment classification and public opinion monitoring.

Indiana University scholars use the mood analysis tool provided by Google to predict the Dow Jones Industrial Index from 9.7 million messages, with an accuracy rate of 87% [30], [34]. Based on 45 million online shopping data per month and combined with the popular reviews of products mined on social networks, Wal-Mart developed the machine learning semantic search engine Polaris, which increased the number of online shoppers by 10% to 15% and increased sales by more than one billion dollars. Wall Street's Derwent Capital Markets company analyzes global 340 million Weibo account messages and judges people's emotions [45], [59].

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People always buy stocks when they are happy, and they sell stocks when they are anxious, so the company decided to buy or sell the stock based on people's emotion. The company achieved a 7% yield in the first quarter. At present, online social media contains rich information about online users' emotions, and has become the best resource for countries and enterprises to understand the emotions and opinions of netizens.

In recent years, danmaku culture has developed rapidly. As a new type of information carrier, danmaku has become an indispensable part of people's daily life, communication, and entertainment [1], [2]. More and more people use danmaku to communicate with others on the Internet. Whether in the process of watching videos or watching live broadcasting, danmaku plays an indispensable role in people's communication [2]. The development of the danmaku is based on the development of video. Since Google acquired YouTube in 2006, YouTube has entered the global people's vision. With the growth of YouTube, more and more people explore the business opportunities in videos, which drives the development of video websites around the world. Danmaku video originated from NICONICO animation, which is a Japanese danmaku video-sharing website. Moreover, danmaku video quickly spread to the whole world. Typical danmaku video websites in China include bilibili, Tencent Video, etc.

Danmaku and comments are used in people's interactions. However, the difference between danmaku and comments is that danmaku can greatly improve the interaction between people [3]. Because the danmaku is timely, it can instantly display the content sent by the user on the screen at a specific time point in the video, and it can better show the sender's thoughts, moods, and other information at that time. The appearance of the danmaku allows the audience to exchange views with more people and get more responses from them, instead of focusing on the first few pages of the comment list. Besides, the audience of the danmaku video is younger [4]. In many video websites and APP that use danmaku, the young people occupy the main body in the user group, and the consumption level of young people is higher than that of the average audience group. Research on danmaku has also a high commercial value. Studying the characteristics of danmaku and its emotional tendency has great practical value [5]. It feedbacks the effective information of users to video platforms, which can help the platforms improve live streaming technologies and optimize short video recommendations so that it can provide a more accurate solution for the selection of audiences during short video production. As a new network video mode, danmaku video is recognized by more and more users, but now few scholars have begun to pay attention to danmaku and use danmaku as data for research and analysis [6].

Considering the above background, how to utilize the features of danmaku to improve or design an emotion analysis model, how to investigate the dynamic changes in multi-dimensional emotion in danmaku, and how to apply the emotion analysis to video platform are new challenges in emotion analysis and evaluation [15]. In this paper, based on mining the danmaku data in semantic layers and statistics analyzing users' emotional characteristics, an emotion analysis model of danmaku reviews is constituted. We processed the danmaku data, including filtering, word segmentation, removing stop words, and constructing word vectors. The paper proposes an improved method based on Bi-LSTM model to extract emotion features to analyze danmaku video content. This machine learning algorithms is a hot research topic in emotion analysis that can improve the generalization performance of emotion classification. Therefore, the results of this study are of significance and have practical value in video analysis and video recommendations.

The main contributions of this paper could be summarized in the following three aspects.

- Firstly, we propose an improved method based on Bi-LSTM model that can identify and classify the four-dimensional emotion of danmaku messages.
- Additionally, we achieve the analysis of danmaku data, obtain the dynamic changing trend of the number of danmaku messages and their timestamps, and obtain the time distribution of four-dimensional emotion of danmaku messages namely Pleasure, Anger, Sorrow and Joy.
- Furthermore, we dig deep into the practical value and commercial value of danmaku, offering a whole new idea for short video production and video recommendations.

II. RECENT DEVELOPMENTS ABOUT DANMAKU EMOTION ANALYSIS

In recent years, with the rapid development of danmaku, more and more researches incline to the direction of danmaku, mainly including the analysis of user motivation and behavior, public communication, emotion analysis, recommendation, data mining based on danmaku and so on.

In the aspect of neural networks and optimization methods, X. Luo et al theoretically analyze the characteristics of an AMNLF model and presents detailed empirical studies regarding its performance on nine HiDS matrices from industrial applications currently in use [7], [9]. In the aspect of Recommenders Algorithms, X. Luo et al carefully investigates eight extended SGD algorithms to propose eight novel LF models and adopt the principle of Hessian-free optimization. They successfully avoid the direct manipulation of a Hessian matrix by employing the efficiently obtainable product between its Gauss-Newton approximation and an arbitrary vector [8], [10]. In the aspect of user motivation and behavior, Chong Tong and others adopted a content analysis method to analyze the danmaku information from bilibili video website and they reckoned that the danmaku motivation of the users mainly includes three types information demand, entertainment demand and social demand [42]. Based on this, 14 kinds of behaviors, such as teasing, slogans, chanting, and formation arrangement of comments, are derived. In the aspect of emotion analysis, Qing Hong et al others acquired, preprocessed and analyzed the danmaku data [37]. By introducing the user's emotional indexes and using them as the user's feature for unsupervised classification, they improved the traditional K-Means algorithm and introduced DTW to calculate the distance of the user's emotional distribution. And they also proposed a user classification algorithm based on emotion analysis of danmaku data to realize the analysis of danmaku data and the classification of danmaku users. Yangyang Zheng and others used the sentence-level emotion analysis method to establish the danmaku emotion analysis model based on the emotion dictionary and extracted the emotional words and calculated the emotional value of the comment texts, and by analyzing combined with the time series, obtained the emotional information contained in the danmaku data in the network online videos. In the aspect of recommendation based on danmaku, Xuqiang Zhuang analyzed the LSTM network model and AT-LSTM model based on attention mechanism and proposed a SIS-LSTM emotion analysis model combining video importance score and LSTM network model, and finally effectively detected the highlights in the video. Yang Deng and others proposed an emotion recognition algorithm of video clips based on danmaku text, which was used as the recommendation basis of video clips; at the same time, according to the relationship of emotional dependence between video clips, they recommended the relative video clips, and the experimental results showed that this model can be effectively used for the emotion analysis of irregular texts with complex information [38]. In the aspect of data mining, Ming He used data mining technology to systematically analyze and quantify the new characteristics of danmaku data, such as multi-peak and herding effect to create the model; given the uncertainty of online-video popularity prediction of danmaku function, Ming He proposed a multi-factor popularity probability prediction model and constructed a deep hybrid model for large-scale image classification.

It can be seen from the research of current scholars that the danmaku and a real-time text review corresponding to the video time point have become the main means to study online videos with various related research contents and it is also mature in some aspects [16]. However, in recent years, most of the researches focus on the animation, TV series, and other aspects on the danmaku video websites. Few scholars apply related technologies to sports events, and there are few related researches in this field. Most of the research only studies the distribution of the danmaku with the whole view and get the general data about the video, but fails to combine the single user with the danmaku data they sent to get the information about the specific user [17]. At the same time, we find that it's much simpler to do sentiment analysis but very hard to carry out emotion analysis. The next level of sentiment analysis is in the field of intent analysis where few researchers have been working on mining out intent from the chunk of text, which seems of very high business value. Besides, it is also a new attempt to apply the emotion analysis of the danmaku to the improvement of the video platform, the guidance of the subsequent short video production, and the recommendation of the video audience. This paper proposes an improved danmaku emotion analysis model based on Bi-LSTM model to classify the further four-dimensional emotions of Pleasure, Anger, Sorrow and Joy.

This paper is devoted to the problems mentioned above using Tencent Video's danmaku as data set for data mining and natural language processing, improving Bi-LSTM model, and applying to emotion analysis. Because of the large number, multiple categories and high quality of the NBA games, this paper takes this as the starting point to analyze. Considering the characteristics of the danmaku, this paper adopts the two-way long, and short-term memory network model based on the emotion analysis method of machine learning, and the experiment proves that it can be better applied.

III. EMOTION ANALYSIS MODEL OF DANMAKU

A. SOURCE AND METHOD OF OBTAINING DANMAKU DATA

The experimental data comes from the NBA videos in Tencent Video. The data is obtained by crawling with Python. The experiment saves the data (danmaku text and related content) returned by the network request every time you watch a video by referring to the Python requests module. Since each request can return a maximum of 8000 danmaku text data, the maximum number of requests can be obtained through a relevant interface open on the Tencent Video website, and then it is traversed to obtain the desirable danmaku data set for each video.

B. DANMAKU DATA PREPROCESSING

After studying the data set, we found that most of the length of danmaku text is not less than five and there is no reference value for a danmaku less than five in length. Therefore, we use the program to read each danmaku and remove data that is less than five in length. The danmaku retained after being processed by the program is the object of our further research.

In terms of word segmentation, we chose pkuseg, the open-source word segmentation tool of Peking University, as the word segmentation tool. Pkuseg is a multi-domain Chinese word segmentation toolkit developed by Peking University based on the paper [54]. It is simple and easy to use, supports segmentation in segmented fields, and effectively improves the accuracy of segmentation. Compared with jieba and THULAC, pkuseg has shown good performance. Therefore, we choose it as a tool for our word segmentation [22].

As can be seen from TABLE 1, after processing by the pkuseg tool, the long text in the danmaku is well divided into several short words [23]. The next step is to get word vectors from these short words.

The danmaku data obtained by crawling contains a piece of useless data. For example, some shorter texts do not

TABLE 1. Proprocessed Danmaku data.

COMMENTS	Time	User Name
我/的/詹皇	38	归来见我
看个/球/有/什么/能喷的/地方？	44	柯南。
讨厌/格林	70	柳宗元的小吉
第二次/被横扫/哈哈	45	JuneDay
哈登/最帅	40	菉
勇士/已经/夺得/总冠军	51	Anonyme
勇士/赢了	49	新亚口腔
詹姆斯/尽力了	52	乖乖睡了
裁判/这么/帮忙/都输了	49	榛子
勇士/总冠军	47	塞翁失马

contain emotions or some meaningless sentences. Therefore, to obtain high-quality data, the crawled data must first pass through Filtering, word segmentation, etc. The Word2Vec model is used to obtain the word vector in the experiment. Word2Vec is one of the methods of Word Embedding, and its purpose is to convert unstructured words into computable structured vectors. It is an important step in transforming realistic problems in artificial intelligence into mathematics. It solves the problem that classifiers are not good at dealing with discrete data, and it also plays a role in expanding features to a certain extent. Word2Vec will consider the context, so compared with the traditional Embedding method, Word2Vec has better results, faster speed, and strong generality. It relies on the Skip-Gram word-jumping model for unsupervised learning training using large-scale danmaku corpora to obtain word vectors.

Assume that the size of the dictionary index set V is |V|, and V = 0, 1 . . . |V| − 1. Given a text sequence of length T, the word at the time step t is w(t). When the time window size is m, the word-jumping model needs to maximize the probability of generating all background words for any given central word

$$\prod_{\mathrm{t}=1}^{T} \prod_{-m\leq j\leq m, j\neq 0} P\left(w^{t+j} \middle| w^{(t)}\right) \tag{1}$$

The maximum likelihood estimation of the above formula is equivalent to minimizing the following loss functions:

$$-\frac{1}{T}\prod_{\mathrm{t}=1}^{T} \prod_{-m\leq j\leq m, j\neq 0} \log_{P\left(w^{t+j} \middle| w^{(t)}\right)} \tag{2}$$

The conditional probability of background words generated by given central words in loss function can be defined by softmax function.

When training the model, each iteration is actually to use these gradients to iterate the vectors of the central words and background words in the subsequence. At the end of the training, we get the vector sum of the two groups of words as the center word (v_i) and the background word (u_i) for any index word 'i' in the dictionary. In the text processing application of danmaku data, the central word vector is obtained by using the skip word model.

C. EMOTION ANALYSIS BASED ON BI-LSTM MODEL

Most of the existing emotion classification models are comment-based classification models, which have two categories: emotion dictionary and machine learning [11]. There are many machine learning methods such as support vector machine (SVM) or improve Naive Bayes and clustering. However, the emotion dictionary method needs a rich emotion lexicon as its support. The result depends on the artificially designed emotion dictionary and judgment rules, and the adaptability is poor. It can be found that there are fewer results based on danmaku in machine learning. To improve the classification accuracy, we try to construct an improved model of the Bi-LSTM model to classify the danmaku text.

The full name of LSTM is Long Short-Term Memory, which is a type of RNN (Recurrent Neural Network). The reason why LSTM is effective is because of the characteristics of its design structure, which can capture long-distance dependencies, so it is very suitable for processing sequential text data [29]. To combine the representations of words into the representations of sentences, you can use the method of adding, that is, adding all the representations of words, or averaging. But these methods do not take into account the order of words in the sentence. For example, the sentence "I don't think he is good", the word "no" is a negation of "good", that is, the emotional polarity of the sentence is derogatory [25]–[27]. Because the LSTM can learn what information to remember and what information to forget through the training process, using the LSTM model can better capture long-distance dependency.

There are three main stages in the LSTM:

1. Forget stage. This stage is mainly to selectively forget the input from the previous node. In short, it means "forget the unimportant, remember the important". By calculating z^f (f represents forget) as a forget gate, to control the previous state needs c^{t-1} to be left and which needs to be forgotten.

2. Select Memory Stage. Selectively "remember" the input. Select memory for inputx^t. It is important to keep a record of what is important, and less to remember. The current input is represented by z calculated earlier. The selected gating signal is controlled by z^i ('i' stands for information). Add the results obtained in the previous two steps to get transmitted to the next state c^t.

3. Output stage. To control by z^o, this stage will determine which outputs will be taken as the current state. Also, the results obtained in the previous statez^o are scaled (changed by a tanh activation function).

In FIGURE 1, the LSTM model consists of X_t(input time), C_t(cell state), $\tilde{C}_t$ (temporary cell state), h_t(hidden state), f_t (forgetting gate), i_t(memory gate) and O_t(output gate). The calculation process of LSTM can be summarized as follows [16]: by forgetting the information in the cell state and memorizing new information, the useful information for the subsequent calculation can be transmitted, while the useless information is discarded, and the hidden state h_t will be output at each step, in which the forgetting, memory and output

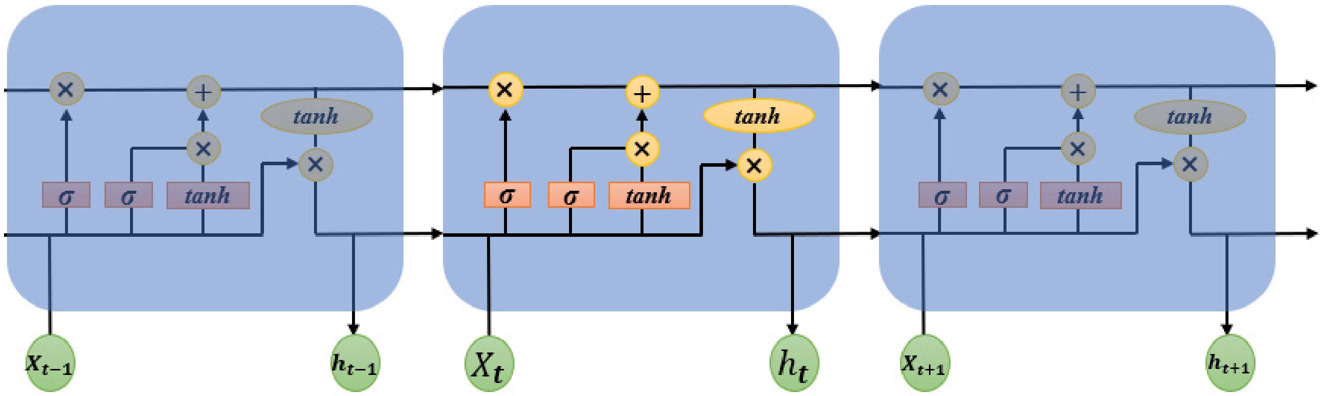


FIGURE 1. The overall framework of LSTM.

are calculated by the hidden state h_{t-1} of the previous time and the current input X_t, the forgetting gate f_t, the memory gate i_t and the output gate O_t to control [18], [19].

Forgetting gate is used to select the information to be forgotten. The input is the implicit state of the previous time h_{t-1} and the input of the current time X_t. The forgetting gate f_t is obtained by the following formula [51].

W_f is the weight of the forgetting gate. b_f is the offset of the forgetting gate. σ is an activation function.

$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] + b_f\right) \tag{3}$$

Memory gate is used to select the information to be remembered. The input is the same as the input when calculating the forgetting gate. It is the implicit state of the previous moment h_{t-1} and the input at the current moment X_t. The output of the memory gate i_t and temporary cell state $\tilde{C}_t$ is calculated by the following formula [20], [24].

W_i is the weight of the input gate. b_i is the offset of the input gate. σ is the activation function. W_C is the weight of the cell state. b_C is the offset of the cell state.

$$i_t = \sigma\left(W_i \cdot [h_{t-1}, x_t] + b_i\right) \tag{4}$$
$$\tilde{C}_t = \tanh\left(W_C * [h_{t-1}, x_t] + b_C\right) \tag{5}$$

Cell state at the current time. The input is the cell state at the previous time C_{t-1} and the memory gate i^t, forgetting gate f_t and temporary cell state $\tilde{C}_t$ calculated by (3)-(5). The cell state output at the current time C_t is obtained by the following formula.

$$C_t = f_t \cdot C_{t-1} + i_t \cdot \tilde{C}_t \tag{6}$$

The output gate and the hidden layer state at the current time, the input is the hidden state at the previous time h_{t-1}, the input at the current time X_t and the cell state at the current time C_t, and the output gate O_t and the current hidden state h_t are obtained by the following formula.

W_o is the weight of the output gate. b_o is the offset of the output gate. σ is an activation function.

$$O_t = \sigma\left(W_o * [h_{t-1}, x_t] + b_o\right) \tag{7}$$
$$h_t = O_t \cdot \tanh\left(C_t\right) \tag{8}$$

Through the repeated calculation of steps (3)-(8), the hidden layer state sequence $\{h_0, h_1, \ldots, h_{n-1}\}$ with the same sentence length after word segmentation can be obtained. However, there is a problem in modeling sentences with LSTM, which can't encode the information from the back to the front. For example, this ball is extremely terrible. "Extremely" is a modification of the word "terrible". This information cannot be obtained by using LSTM. To solve this problem, we adopt and improve Bi-LSTM model. The full name of Bi-LSTM is Bi-directional Long Short-Term Memory, which is composed of forward LSTM and backward LSTM. For example, we code the sentence "I like Kobe" as shown in FIGURE 2.

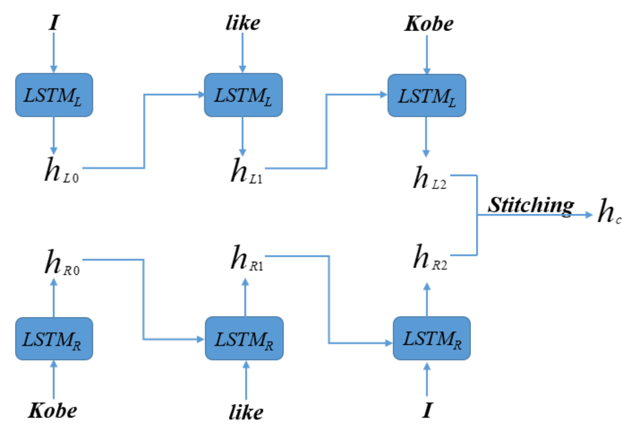


FIGURE 2. Encoding process and Vector stitching.

The forward LSTM inputs "I", "like", "Kobe" to get three vectors, the backward LSTM inputs "Kobe", "like", "I" to get three vectors, and finally splices the forward and backward hidden vectors to get h_0, h_1, h_2. For the task of emotion classification, the sentences we use are usually h_{L2} and h_{R2}. Because it contains all the forward and backward information, as shown in the figure below.

D. THE FLOW OF THE BI-LSTM ALGORITHM

1. Define the input function and read the training set, test set data, and classification labels from the specified location.

Perform processing such as mixing and repetition on the read data and return to the processed data set [49].

2. Define the model processing function, find the index of the words in the training set and the test set from the word vector set, and then randomly remove the neurons in the neural network to prevent the network from overfitting. Use the LSTMBlockFusedCell function in the RNN class in Tensorflow to build the main part of the Bi-LSTM network, and randomly remove the neurons in the network again. Calculate the loss function, construct evaluation indicators, train the network in training mode, and evaluate the specified indicators in test mode [50].

3. Build the input handles of the training set and test set, configure the training and test mode parameters, transfer the training set and model to the estimator high-level API in Tensorflow, and perform the training.

4. Call the trained model to process the test set data, write the predicted results to the corresponding file, and calculate the accuracy rate, callback rate, and other indicators.

According to the approximate emotional distribution of the obtained danmaku, we decided not to use the existing mainstream emotional classification, but to define four types of emotional sets as follows:

- Pleasure: a feeling of enjoyment or satisfaction, or something that produces this feeling. Pleasure is a kind of feeling, including appreciation, admiration, love, worship, etc. In the danmaku, it shows "Curry's invincible three-pointer!", "Curry is the strongest" and so on.
- Anger: indignation, questioning, extreme antipathy to social phenomena, other people's encounter or even unrelated matters, a tense and unpleasant mood, etc. In the danmaku, it appears that "Durant didn't do anything when Curry won the championship."
- Sorrow: sadness, regret, helplessness, etc. It is opposed to Joy, optimism, happiness. In the danmaku, it appears that "Distressed James.", "James is always second." and so on.
- Joy: happiness, excitement, etc. Joy is a kind of happiness in the human spirit, a kind of spiritual satisfaction and a very comfortable feeling felt from the inside out. It refers to a happy state of people. "Congratulations to the Cavaliers champion" "champion!" and so on.

After statistics, these four emotional categories can cover most danmaku of the sports events [31].

Many of the existing research results are based on the existing corpus. It is undeniable that the existing corpus has been sorted out and used by many scholars and is relatively complete [32]. However, after our investigation, we found that most of the existing corpora are traditional comments. Although they are rich and perfect, they are quite different from danmaku. To get the accuracy of the experiment, we decided to build our corpus, and through modifying the model, after the accuracy of the model reaches a certain index, we will continue to add the classified test data into the training set to enrich the training set and improve its quantity and quality [33]. There will inevitably be errors in the process of experiment, but they account for a relatively small proportion. With the increase of data, we can reduce the proportion of errors.

At the same time, we will add as many user features as possible to the training model, which will help us to get more information, conduct more extensive analysis, and draw more comprehensive and useful conclusions.

IV. THE EXPERIMENTAL RESULTS AND ITS APPLICATION

A. DATA RESULTS

We take the 2010 NBA Finals in Tencent Video as an example and deal with it by improving the Bi-LSTM model. The results of user emotion classification are shown in TABLE 2.

In the data of 7127 pieces of danmaku in 2018 NBA Finals, 1761 pieces of danmaku have emotional tendency to be 'Sorrow', 1306 pieces of danmaku have emotional tendency to be 'Joy', 2318 pieces of danmaku have emotional tendency to be 'angry', and 1742 pieces of danmaku have emotional tendency to be 'Pleasure'. The classification statistics are shown in FIGURE 3.

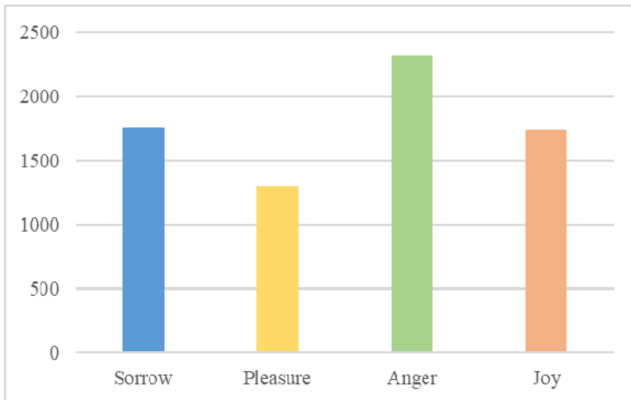


FIGURE 3. Danmaku emotion classification statistics.

B. COMPARATIVE EXPERIMENT WITH CNN AND ITS VISUALIZATION

Through statistical analysis, the four performance indexes of Accuracy, Recall, Precision, and F1-Score (as shown in FIGURE 4) in the model used in the experiment are higher than they in the CNN-Convolutional Neural Networks model [21]. Through the experimental analysis, based on the above comparison, the improved emotion analysis model based on the Bi-LSTM model has a better effect on the emotion analysis of danmaku data in sports events.

C. COMPARATIVE EXPERIMENT WITH SVM

SVM is difficult to train large-scale data and cannot directly support multi-classification [43]. Since LSTM can maintain long term memory, it well overcomes the shortcomings of averaging the word vector of each sentence in SVM classification and losing the order information between sentence words, retaining the semantic information between words

TABLE 2. Danmaku emotion classification and label table.

Classification	COMMENTS	Time	User Name
Joy	我的詹皇	38	归来见我
Anger	看个球有什么能喷的地方？	44	柯南。
Anger	讨厌格林	70	柳宗元的小吉
Pleasure	第二次被横扫哈哈	45	JuneDay
Joy	哈登最帅	40	苿
Pleasure	勇士已经夺得总冠军	51	Anonyme
Pleasure	勇士赢了	49	新亚口腔
Sorrow	詹姆斯尽力了	52	乖乖睡了
Sorrow	裁判这么帮忙都输了	49	榛子
Pleasure	勇士总冠军	47	塞翁失马

TABLE 3. Comparison of the accuracy of Bi-LSTM and CNN.

Test set serial number	1	2	3	4	5	6	7	8	9	10
CNN	0.54	0.58	0.56	0.54	0.69	0.71	0.48	0.46	0.53	0.54
Bi-LSTM	0.90	0.91	0.89	0.87	0.93	0.92	0.88	0.89	0.93	0.90

TABLE 4. Precision comparison between Bi-LSTM and CNN.

Emotion	Sorrow	Pleasure	Anger	Joy
CNN	0.6320	0.3960	0.7520	0.6280
Bi-LSTM	0.8720	0.8160	0.9120	0.8760

TABLE 5. Recall comparison between Bi-LSTM and CNN.

Emotion	Sorrow	Pleasure	Anger	Joy
CNN	0.6270	0.5470	0.5449	0.7072
Bi-LSTM	0.8385	0.8831	0.8413	0.9202

TABLE 6. F1-Score comparison between Bi-LSTM and CNN.

Emotion	Sorrow	Pleasure	Anger	Joy
CNN	0..6295	0.4594	0.6319	0.6653
Bi-LSTM	0.8549	0.8482	0.8752	0.8975

(such as Word order information, context information, etc), and through the complex nonlinear calculation to better extract the hidden emotional information in the word vector. Bi-LSTM model sentiment classification accuracy rate is above 90%, while SVM classification accuracy rate is about 80%. Using Bi-LSTM model accuracy rate is much higher than SVM method, showing very good results in emotion analysis.

D. COMPARATIVE EXPERIMENT WITH SOTA

Compared with CNN and SVM, the Bi-LSTM model shows good performance in this experiment. However, compared with the current SOTA (State of the Arts) model in the field of sentiment analysis, there are still some deficiencies [55]–[60]. The following is illustrated with TABLES.

It can be seen from the above table that the Bi-LSTM model mentioned in this paper has a certain gap in Accuracy, Recall, F1-Score and other indicators compared with SOTA. The reason for the difference in accuracy should be attributed to the insufficient number of samples in the training set, and the quality is also a factor limiting the accuracy. In terms of recall, the Bi-LSTM model is superior to the CNN-LSTM model [58] on an average level. In terms of F1-Score, the Bi-LSTM model far exceeds the two types of models proposed by the papers [59], [60]. In summary, compared with

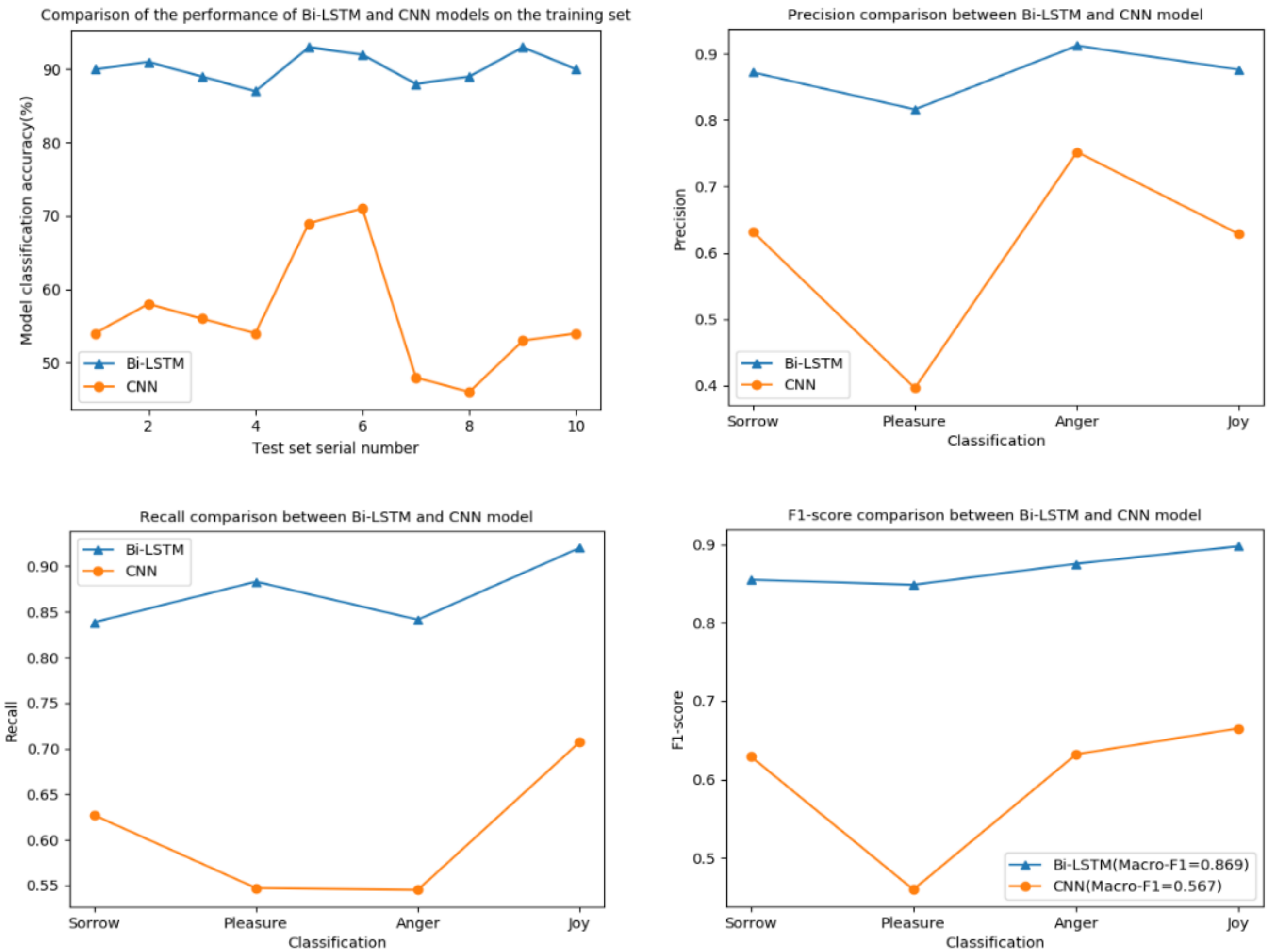


FIGURE 4. Visualized compare of Accuracy, Precision, Recall and F1-Score between CNN and improved Bi-LSTM model.

TABLE 7. Accuracy comparison with SOTA.

Data	Model	Accuracy
IMDb	BCN+Char+CoVe	0.918
NBA 2018	Bi-LSTM	0.902
SST-2 Binary classification	CNN-RNF-LSTM	0.900
chinanews	BERT	0.948

the SOTA, the Bi-LSTM model proposed in this paper has a certain gap in some indicators, such as accuracy and recall. But it performs very well on the F1-Score indicator. The LSTM model has certain improvements over the previous models. This experiment is mainly an attempt to use the new data of danmaku. Later research may try to use a better model such as Bert model for research.

E. APPLICATION OF THE EMOTION ANALYSIS MODEL

After analyzing the number, content, emotion they express, the time when the danmaku was added, user name and other labels of the danmaku, this experiment considers applying the improved model to the following aspects: according to the classification results, analyzing users' experience of the event content, emotional information retrieval and induction, and mastering the trend of public opinions so that we can get the audience's opinions on live streaming technology and

TABLE 8. Recall comparison with SOTA.

Data	Model	Recall
NBA 2018	Bi-LSTM	0.87
ASTD	CNN-LSTM	0.62
chinanews	BERT	0.94

TABLE 9. F1-Score comparison with SOTA.

Data	Model	F1-Score
NBA 2018	Bi-LSTM	0.87
SemEval	LSTMs+CNNs ensemble with multiple conv.ops	0.69
chinanews	BERT	0.85

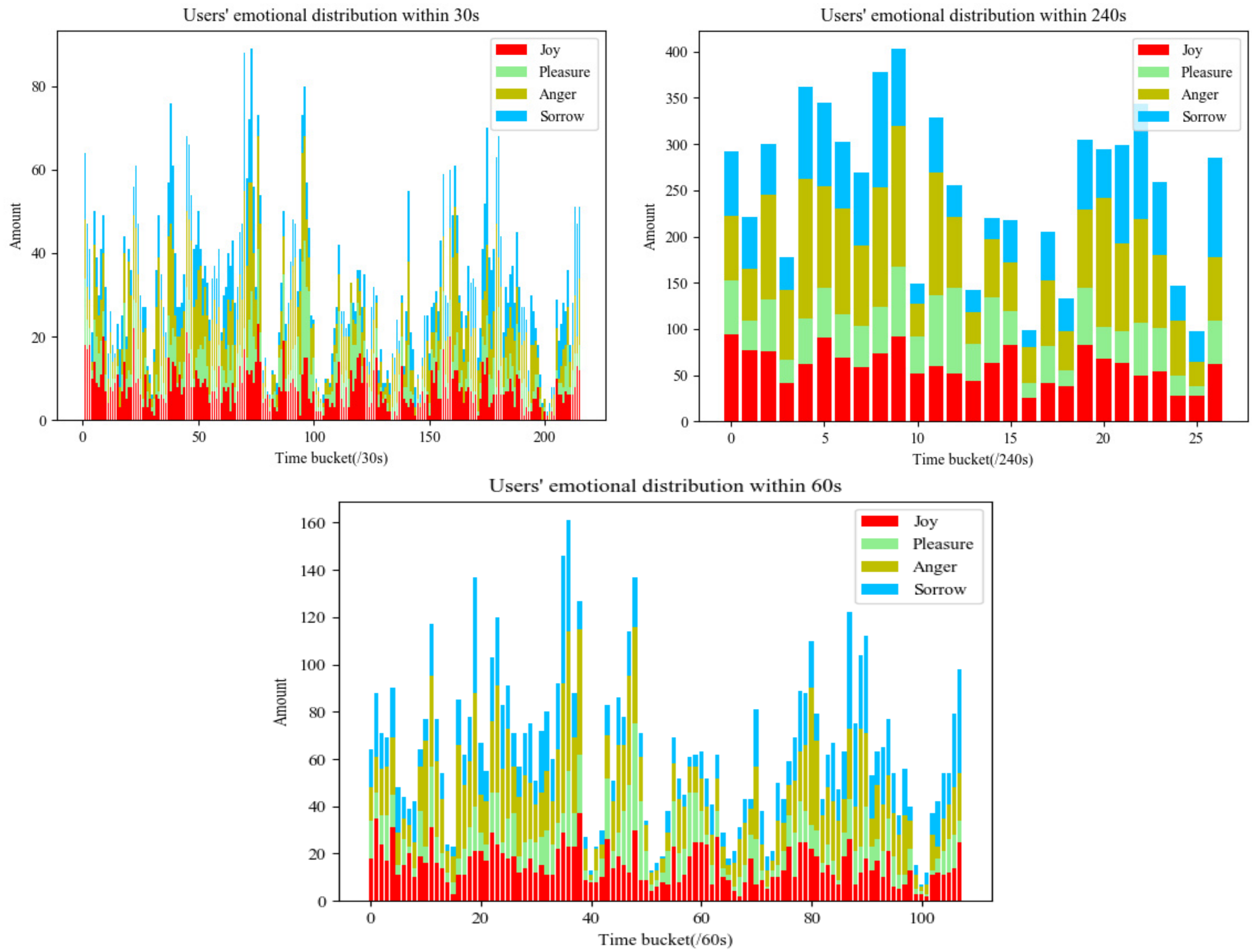


FIGURE 5. Emotion distribution of users every period of 30 seconds, 60 seconds and 240 seconds.

the ability of sportscasters of the video platforms, including but not limited to the level of delay and the ability of sportscasters [35]. And we can establish a scoring mechanism to score for the platform, to facilitate the timely feedback and improvement of live streaming platform. It provides the basis of different angles for short-video cutting and recommendation [36]. Whether the current video content is wonderful or brilliant is measured by the number and content of danmaku in a period time. When there are a large number of danmaku in a certain period time and the emotion of those danmaku content is strong enough, the video content in this period time is regarded as being more wonderful than others [39]–[41]. We can find the moment with high visual attraction whether the audience wants to praise it or abuse it, and then the video clip will be fed back to the platform, which is helpful to improve the efficiency of the platform's massive video cutting. By analyzing the existing danmaku information and video data at the same time, we can identify the wonderful video clips from the whole video. When the users watch the video, they can choose to watch the highlights of the video to improve their watching experience [44], [45].

We find that the emotion of the audience in sports events will change many times in a short time due to the changes in video content. To provide more accurate recommendations, we need to select a suitable period to reflect the user's emotion. If the selected period is too short, the number of danmaku will be small, and the distribution of emotion is not obvious so that the emotional distribution may always be maintained at a relatively average level, which is not easy to analyze and draw conclusions. If the selected time is too long, the number of bullet screens will be more, but the situation of sports events may change many times in a long period time, and the emotion expressed in the audience's danmaku will also subsequently change many times. When recommending, the long video makes the audience difficult to grasp the video theme and emotion, which is not conducive to recommend to the users [46]–[48]. After a large number of data analysis and comparison, as shown in FIGURE 5 with the number and classification distribution diagram of danmaku in every 30s, 60s and 240s period, we found that the video separated by 60s has high-quality content of danmaku and obvious centralized distribution of the number of danmaku, which can accurately reflect the emotional distribution of the users. At the same time, it can be seen from the acquired data of danmaku that the video with a duration of about 6500s contains about 6800 danmaku, with an average of 1.046 per second.

From the above discussion, we have formulated a video cutting rule that if the number of four emotional types of danmaku sent out by the audience exceeds 90 in every 60 seconds, the video clip is considered to be of considerable appreciation. The recommendation rule is that we stipulate that the video clip is considered to be more wonderful if the number of danmaku with Pleasure or Joy emotion tendency by the audience exceeds 60 within every 60s.

According to QuestMobile data, 4 out of every 10 mobile Internet users use a short video, which the time using short-video has taken up 7.5% of the total time of using mobile Internet. As for the definition of a short video, it generally refers to the video content with playback time less than 5 minutes. And the standard of the current mainstream video platform-ByteDance for short video is 4 minutes. This figure is also concluded by ByteDance after analyzing the works of domestic mainstream short video PGC. ByteDance thinks that 4 minutes is the most mainstream time of short video and the most suitable time for playing. The establishment of short-video standards is closely related to the positioning and the target population of the platform. For the ByteDance of PGC, it is more desirable to describe a story completely, and 4 minutes is more appropriate. The model we proposed is based on the sports video, so we use four short videos with the length of 60s of each as a group to perform mixed cutting, and the synthesized short videos with a length of 4 minutes are recommended to users.

By analyzing the content and emotion of the danmaku in the videos, we can get the main content of the video and the preferences of the users by the danmaku [52], [53]. From the perspective of the danmaku, we can build a user short video recommendation model, to achieve more accurate video recommendation. At the same time, we can also speculate the characteristics of all kinds of users, and provide a reference for the platform to provide more personalized content recommendations for users.

V. CONCLUSION

In this paper, the acquisition, processing, and deep-seated analysis algorithm of the danmaku data of sports events are introduced in detail, and an improved danmaku emotion analysis model based on the Bi-LSTM model is proposed. The model algorithm can better classify and analyze the emotional tendency of the users in the sports events. The experimental results show that the improved model can do well in analyzing the complex emotional characteristics of irregular text and the applicability of danmaku in the field of video emotion analysis, and add user information, time and other labels to the relative danmaku at the same time. Based on this paper, there are other research directions in the future. For example, the release time of the danmaku can be used to study whether the user's attention, emotional data, and the content of the danmaku will show special changing rules over time from the video starts to be published on the network. The abnormal points can be detected by algorithm research. Through the monitoring of the abnormal points of the danmaku, we can analyze whether the athletes in the relevant sports events have new or special dynamics, which results in a great change in the frequency or state of the user sending the danmaku. It can improve and optimize the video clip recommendation algorithm based on danmaku emotion analysis, and provide solutions for video platforms to provide better watching experience for users to absorb more users using their platforms.

In the age of big data, data collection, processing, analysis, and mining become more and more important. Danmaku, this new type of text data, provides us with a new direction and a new challenge in the field of natural language processing. Cognitive computing provides new capabilities for big data analysis, understands natural language and human communication styles, generates and evaluates results based on data cognition and reasoning, and continuously learns and cognitively evolves through human-computer interaction and result modification. Cognitive computing is a process of information processing. There are paradigms such as symbolism, connectionism, and activism. It has strong vitality and moves toward computationalism. The mechanism of affective cognition is the theoretical basis of innovative affective computing methods. The affective computing method is a technical means to verify the theory of affective cognition. The practice of cognitive computing technology in the era of big data is forcing the advance of cognitive science.

REFERENCES

[1] Q. Bai, Q. V. Hu, L. Ge, and L. He, "Stories that big danmaku data can tell as a new media," *IEEE Access*, vol. 7, pp. 53509–53519, 2019.

[2] Y. He and T. Y. Tang, "Recommending highlights in anime movies: Mining the real-time user comments 'DanMaKu,'" in *Proc. Intell. Syst. Conf. (IntelliSys)*, London, U.K., Sep. 2017, pp. 319–322.

[3] J. Leng, J. Zhu, X. Wang, and X. Gu, "Identifying the potential of Danmaku video from eye gaze data," in *Proc. IEEE 16th Int. Conf. Adv. Learn. Technol. (ICALT)*, Austin, TX, USA, Jul. 2016, pp. 288–292.

[4] Z. Chen, Y. Tang, Z. Zhang, C. Zhang, and L. Wang, "Sentiment-aware short text classification based on convolutional neural network and attention," in *Proc. IEEE 31st Int. Conf. Tools with Artif. Intell. (ICTAI)*, Portland, OR, USA, Nov. 2019, pp. 1172–1179.

[5] 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.

[6] Y. Sun, J. Li, Y. Zhen, Y. Tang, Q. Hu, and L. He, "USee: An online-offline hybird Danmaku social system," in *Proc. IEEE 22nd Int. Conf. Comput. Supported Cooperat. Work Design (CSCWD)*, Nanjing, China, May 2018, pp. 253–258.

[7] X. Luo, M. Zhou, S. Li, L. Hu, and M. Shang, "Non-negativity constrained missing data estimation for high-dimensional and sparse matrices from industrial applications," *IEEE Trans. Cybern.*, vol. 50, no. 5, pp. 1844–1855, May 2020, doi: 10.1109/TCYB.2019.2894283.

[8] X. Luo, D. Wang, M. Zhou, and H. Yuan, "Latent factor-based recommenders relying on extended stochastic gradient descent algorithms," *IEEE Trans. Syst., Man, Cybern. Syst.*, early access, Jan. 3, 2019, doi: 10.1109/TSMC.2018.2884191.

[9] D. Wu, X. Luo, M. Shang, Y. He, G. Wang, and M. Zhou, "A deep latent factor model for high-dimensional and sparse matrices in recommender systems," *IEEE Trans. Syst., Man, Cybern. Syst.*, early access, Aug. 15, 2019, doi: 10.1109/TSMC.2019.2931393.

[10] X. Luo, M. Zhou, S. Li, Y. Xia, Z.-H. You, Q. Zhu, and H. Leung, "Incorporation of efficient second-order solvers into latent factor models for accurate prediction of missing QoS data," *IEEE Trans. Cybern.*, vol. 48, no. 4, pp. 1216–1228, Apr. 2018, doi: 10.1109/TCYB.2017.2685521.

[11] S. Gao, M. Zhou, Y. Wang, J. Cheng, H. Yachi, and J. Wang, "Dendritic neuron model with effective learning algorithms for classification, approximation, and prediction," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 30, no. 2, pp. 601–614, Feb. 2019, doi: 10.1109/TNNLS.2018.2846646.

[12] N. Zerari, M. Chemachema, and N. Essounbouli, "Neural network based adaptive tracking control for a class of pure feedback nonlinear systems with input saturation," *IEEE/CAA J. Automatica Sinica*, vol. 6, no. 1, pp. 278–290, Jan. 2019, doi: 10.1109/JAS.2018.7511255.

[13] Y. Ouyang, L. Dong, L. Xue, and C. Sun, "Adaptive control based on neural networks for an uncertain 2-DOF helicopter system with input deadzone and output constraints," *IEEE/CAA J. Automatica Sinica*, vol. 6, no. 3, pp. 807–815, May 2019, doi: 10.1109/JAS.2019.1911495.

[14] M. Shang, X. Luo, Z. Liu, J. Chen, Y. Yuan, and M. Zhou, "Randomized latent factor model for high-dimensional and sparse matrices from industrial applications," *IEEE/CAA J. Automatica Sinica*, vol. 6, no. 1, pp. 131–141, Jan. 2019, doi: 10.1109/JAS.2018.7511189.

[15] J. Niu, S. Li, S. Mo, S. Yang, and B. Fan, "Affective content analysis of online video clips with live comments in Chinese," in *Proc. IEEE SmartWorld, Ubiquitous Intell. Comput., Adv. Trusted Comput., Scalable Comput. Commun., Cloud Big Data Comput., Internet People Smart City Innov. (SmartWorld/SCALCOM/UIC/ATC/CBDCom/IOP/SCI)*, Guangzhou, China, Oct. 2018, pp. 849–856.

[16] X. Yang, W. Binglu, H. Junjie, and L. Shuwen, "Natural language processing in 'Bullet Screen' application," in *Proc. Int. Conf. Service Syst. Service Manage.*, Dalian, China, 2017, pp. 1–6.

[17] S. Djamasbi, A. Hall-Phillips, Z. Liu, W. Li, and J. Bian, "Social viewing, bullet screen, and user experience: A first look," in *Proc. 49th Hawaii Int. Conf. Syst. Sci. (HICSS)*, Koloa, HI, USA, Jan. 2016, pp. 648–657.

[18] Y. Luan and S. Lin, "Research on text classification based on CNN and LSTM," in *Proc. IEEE Int. Conf. Artif. Intell. Comput. Appl. (ICAICA)*, Dalian, China, Mar. 2019, pp. 352–355.

[19] C. Li, G. Zhan, and Z. Li, "News text classification based on improved Bi-LSTM-CNN," in *Proc. 9th Int. Conf. Inf. Technol. Med. Educ. (ITME)*, Hangzhou, China, Oct. 2018, pp. 890–893.

[20] J. Wang and Z. Cao, "Chinese text sentiment analysis using LSTM network based on l2 and Nadam," in *Proc. IEEE 17th Int. Conf. Commun. Technol. (ICCT)*, Chengdu, China, Oct. 2017, pp. 1891–1895.

[21] J. Zhang, Y. Li, J. Tian, and T. Li, "LSTM-CNN hybrid model for text classification," in *Proc. IEEE 3rd Adv. Inf. Technol., Electron. Autom. Control Conf. (IAEAC)*, Chongqing, China, Oct. 2018, pp. 1675–1680.

[22] C.-G. Lim and H.-J. Choi, "LSTM-based model for extracting temporal relations from Korean text," in *Proc. IEEE Int. Conf. Big Data Smart Comput. (BigComp)*, Shanghai, China, Jan. 2018, pp. 666–668.

[23] L. Skovajsova, "Long short-term memory description and its application in text processing," in *Proc. Commun. Inf. Technol. (KIT)*, Vysoké Tatry, Slovakia, Oct. 2017, pp. 1–4.

[24] M.-H. Su, C.-H. Wu, K.-Y. Huang, and Q.-B. Hong, "LSTM-based text emotion recognition using semantic and emotional word vectors," in *Proc. 1st Asian Conf. Affect. Comput. Intell. Interact. (ACII Asia)*, Beijing, China, May 2018, pp. 1–6.

[25] M. Gumilang and A. Purwarianti, "Experiments on character and word level features for text classification using deep neural network," in *Proc. 3rd Int. Conf. Informat. Comput. (ICIC)*, Palembang, Indonesia, Oct. 2018, pp. 1–6.

[26] Y. Woldemariam, "Sentiment analysis in a cross-media analysis framework," in *Proc. IEEE Int. Conf. Big Data Anal. (ICBDA)*, Hangzhou, China, Mar. 2016, pp. 1–5.

[27] J. Ding, H. Sun, X. Wang, and X. Liu, "Entity-level sentiment analysis of issue comments," in *Proc. 3rd Int. Workshop Emotion Awareness Softw. Eng. SEmotion*, Gothenburg, Sweden, 2018, pp. 7–13.

[28] Q. Li, S. Shah, R. Fang, A. Nourbakhsh, and X. Liu, "Tweet sentiment analysis by incorporating sentiment-specific word embedding and weighted text features," in *Proc. IEEE/WIC/ACM Int. Conf. Web Intell. (WI)*, Omaha, NE, USA, Oct. 2016, pp. 568–571.

[29] J. Li and L. Qiu, "A sentiment analysis method of short texts in microblog," in *Proc. IEEE Int. Conf. Comput. Sci. Eng. (CSE) IEEE Int. Conf. Embedded Ubiquitous Comput. (EUC)*, Guangzhou, China, Jul. 2017, pp. 776–779.

[30] V. Ramanathan and T. Meyyappan, "Twitter text mining for sentiment analysis on people's feedback about oman tourism," in *Proc. 4th MEC Int. Conf. Big Data Smart City (ICBDSC)*, Muscat, Oman, Jan. 2019, pp. 1–5.

[31] W. Zongyue and Q. Sujuan, "A sentiment analysis method of Chinese specialized field short commentary," in *Proc. 3rd IEEE Int. Conf. Comput. Commun. (ICCC)*, Chengdu, China, Dec. 2017, pp. 2528–2531.

[32] J. S. Lee, D. Zuba, and Y. Pang, "Sentiment analysis of Chinese product reviews using gated recurrent unit," in *Proc. IEEE 5th Int. Conf. Big Data Comput. Service Appl. (BigDataService)*, Newark, CA, USA, Apr. 2019, pp. 173–181.

[33] M. Al-Amin, M. S. Islam, and S. Das Uzzal, "Sentiment analysis of bengali comments with Word2 Vec and sentiment information of words," in *Proc. Int. Conf. Electr., Comput. Commun. Eng. (ECCE)*, Cox's Bazar, Feb. 2017, pp. 186–190.

[34] V. Prakruthi, D. Sindhu, and D. S. Anupama Kumar, "Real time sentiment analysis of Twitter posts," in *Proc. 3rd Int. Conf. Comput. Syst. Inf. Technol. Sustain. Solutions (CSITSS)*, Bengaluru, India, Dec. 2018, pp. 29–34.

[35] S. Nabil, J. Elbouhdidi, and M. Yassin, "Recommendation system based on data analysis-application on tweets sentiment analysis," in *Proc. IEEE 5th Int. Congr. Inf. Sci. Technol. (CiSt)*, Marrakech, Morocco, Oct. 2018, pp. 155–160.

[36] S. Sun, F. Wang, and L. He, "Movie summarization using bullet screen comments," *Multimedia Tools Appl.*, vol. 77, no. 7, pp. 9093–9110, Apr. 2018.

[37] H. Qing, W. Siyao, and Z. Qinpei, "Video user group classification based on barrage comments sentiment analysis and clustering algorithms," *Comput. Eng. Sci.*, vol. 282, no. 6, pp. 173–187, 2018.

[38] D. Yang, Z. Chenxi, and L. Jiangfeng, "Video shot recommendation model based on emotion analysis using time-sync comments," *J. Comput. Appl.*, vol. 4, pp. 157–162, 2017.

[39] E. Boiy and M.-F. Moens, "A machine learning approach to sentiment analysis in multilingual Web texts," *Inf. Retr.*, vol. 12, no. 5, pp. 526–558, Oct. 2009.

[40] S. M. Liu and J.-H. Chen, "A multi-label classification based approach for sentiment classification," *Expert Syst. Appl.*, vol. 42, no. 3, pp. 1083–1093, Feb. 2015.

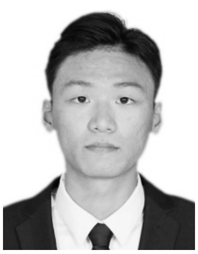
[41] K. Ravi and V. Ravi, "A survey on opinion mining and sentiment analysis: Tasks, approaches and applications," *Knowl.-Based Syst.*, vol. 89, pp. 14–46, Nov. 2015.

[42] T. Chong and Z. Yuxiang, "Exploring users' motivations and behaviors on Danmaku video sharing Websites: A content analysis," *Library Forum*, vol. 39, no. 6, pp. 80–89, 2019.

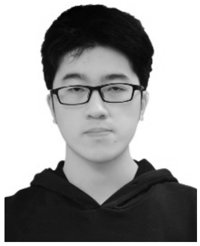
[43] A. S. Manek, P. D. Shenoy, M. C. Mohan, and V. K. R, "Aspect term extraction for sentiment analysis in large movie reviews using gini index feature selection method and SVM classifier," *World Wide Web*, vol. 20, no. 2, pp. 135–154, Mar. 2017.

[44] J. Wei, J. Liao, Z. Yang, S. Wang, and Q. Zhao, "BiLSTM with multi-polarity orthogonal attention for implicit sentiment analysis," *Neurocomputing*, vol. 383, pp. 165–173, Mar. 2020.

[45] H. Saif, Y. He, M. Fernandez, and H. Alani, "Contextual semantics for sentiment analysis of Twitter," *Inf. Process. Manage.*, vol. 52, no. 1, pp. 5–19, Jan. 2016.
[46] T. Chen, R. Xu, Y. He, and X. Wang, "Improving sentiment analysis via sentence type classification using BiLSTM-CRF and CNN," *Expert Syst. Appl.*, vol. 72, pp. 221–230, Apr. 2017.
[47] F. Wan, "Sentiment analysis of Weibo comments based on deep neural network," in *Proc. Int. Conf. Commun., Inf. Syst. Comput. Eng. (CISCE)*, Jul. 2019, pp. 626–630.
[48] W. Liu, Z. Wang, X. Liu, N. Zeng, Y. Liu, and F. E. Alsaadi, "A survey of deep neural network architectures and their applications," *Neurocomputing*, vol. 234, pp. 11–26, Apr. 2017.
[49] J. Schmidhuber, "Deep learning in neural networks: An overview," *Neural Netw.*, vol. 61, pp. 85–117, Jan. 2015.
[50] S. Kiritchenko, X. Zhu, and S. M. Mohammad, "Sentiment analysis of short informal texts," *J. Artif. Intell. Res.*, vol. 50, pp. 723–762, Aug. 2014.
[51] S. Hochreiter and J. Schmidhuber, "Long short-term memory," *Neural Comput.*, vol. 9, no. 8, pp. 1735–1780, 1997.
[52] C. Quan and F. Ren, "A blog emotion corpus for emotional expression analysis in chinese," *Comput. Speech Lang.*, vol. 24, no. 4, pp. 726–749, Oct. 2010.
[53] F. Jia and C.-C. Chen, "Emotional characteristics and time series analysis of Internet public opinion participants based on emotional feature words," *Int. J. Adv. Robotic Syst.*, vol. 17, no. 1, pp. 1–11, 2020.
[54] R. Luo, J. Xu, Y. Zhang, X. Ren, and X. Sun, "PKUSEG: A toolkit for multi-domain chinese word segmentation," 2019, *arXiv:1906.11455*. [Online]. Available: http://arxiv.org/abs/1906.11455
[55] B. Sun, L. Yang, P. Dong, W. Zhang, J. Dong, and C. Young, "Super characters: A conversion from sentiment classification to image classification," 2018, *arXiv:1810.07653*. [Online]. Available: http://arxiv.org/abs/1810.07653
[56] B. McCann, J. Bradbury, C. Xiong, and R. Socher, "Learned in translation: Contextualized word vectors," in *Proc. Adv. Neural Inf. Process. Syst.*, 2017, pp. 6294–6305.
[57] Y. Yang, "Convolutional neural networks with recurrent neural filters," 2018, *arXiv:1808.09315*. [Online]. Available: http://arxiv.org/abs/1808.09315
[58] I. Abu Farha and W. Magdy, "Mazajak: An online arabic sentiment analyser," in *Proc. 4th Arabic Natural Lang. Process. Workshop*, 2019, pp. 192–198.
[59] M. Cliche, "BB_twtr at SemEval-2017 task 4: Twitter sentiment analysis with CNNs and LSTMs," 2017, *arXiv:1704.06125*. [Online]. Available: http://arxiv.org/abs/1704.06125
[60] C. Baziotis, N. Pelekis, and C. Doulkeridis, "DataStories at SemEval-2017 task 4: Deep LSTM with attention for message-level and topic-based sentiment analysis," in *Proc. 11th Int. Workshop Semantic Eval. (SemEval-)*, 2017, pp. 747–754.



SHAOKANG WANG is currently pursuing the bachelor's degree in information and communication engineering with the Beijing University of Posts and Telecommunications. His research interest includes natural language processing.



YIHAO CHEN is currently pursuing the bachelor's degree in information and communication engineering with the Beijing University of Posts and Telecommunications. His research interests include natural language processing and algorithm research.

HONGJUN MING is currently pursuing the bachelor's degree in software engineering with the Beijing University of Posts and Telecommunications. His research interest includes algorithm research.

HAI HUANG received the Ph.D. degree from Beihang University. He was a Postdoctoral Researcher with the State Key Laboratory of Virtual Reality Technology and Systems. He is currently an Assistant Professor of information and communication engineering with the Beijing University of Posts and Telecommunications. His research interests include virtual reality and pattern recognition.

LINGXIAN MI is currently pursuing the bachelor's degree in telecommunications engineering with management with the Beijing University of Posts and Telecommunications. Her research interest includes natural language processing.

ZENGYI SHI is currently pursuing the bachelor's degree in telecommunications engineering with management with the Beijing University of Posts and Telecommunications. Her research interest includes natural language processing.