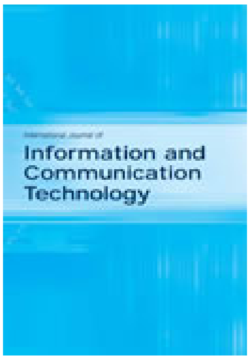
INDERSCIENCE PUBLISHERS
Linking academia, business and industry through research



International Journal of Information and Communication Technology

ISSN online: 1741-8070 - ISSN print: 1466-6642
https://www.inderscience.com/ijict

Exploration and analysis of online public opinion detection in digital economy based on deep learning

Min Qiu

Article History:

Received:	10 February 2025
Last revised:	20 February 2025
Accepted:	20 February 2025
Published online:	15 April 2025

Exploration and analysis of online public opinion detection in digital economy based on deep learning

Min Qiu

School of Economics and Management,
Hebi School of Engineering and Technology,
Henan University of Technology,
Hebi 458000, China
Email: qiumin0607@163.com

Abstract: With the booming development of digital economy, the internet has become an important platform for social emotions to converge. The detection of online public opinion is of vital importance to social stability. Focusing on the issue that current research cannot dynamically extract sentiment features, firstly, we use the dual-channel deep learning model to obtain the global and local sentiment features of the network comments respectively, enhance the sentiment features by the improved attention mechanism (EAM), and fuse the features to classify the sentiment of the public opinion using softmax. Subsequently, this paper classified the network opinion into levels and through the results of sentiment classification and combined with many indicators, a comprehensive calculation was carried out to obtain the public opinion detection level. Experimental outcome on two Twitter datasets show that the proposed method improves the weighted average F1 by 4.12–19.6%.

Keywords: web public opinion detection; deep learning; attention mechanism; text sentiment categorisation; opinion rating calculation.

Reference to this paper should be made as follows: Qiu, M. (2025) 'Exploration and analysis of online public opinion detection in digital economy based on deep learning', *Int. J. Information and Communication Technology*, Vol. 26, No. 7, pp.79–94.

Biographical notes: Min Qiu received her Master's degree from Henan University of Economics and Law in China in 2012. She is now an Associate Professor in Hebi School of Engineering and Technology, Henan University of Technology. Her research interests include machine learning, micro-economic theory and practice.

1 Introduction

Since the 18th Party Congress, the state has attached great importance to the development of digital economy. The network in the context of the digital economy serves as an important platform for information dissemination and communication, bringing together a huge amount of user-generated content (Kupriyanovsky et al., 2017). The current body of Internet users in our country is progressively younger, leading to a more heterogeneous online environment (Koch and Windsperger, 2017). Online media has become a medium for netizens to express and disseminate their opinions, and the unquantifiable data generated by people's online use poses a challenge to data processing (Xia et al., 2023), while the spread of negative emotions and rumours brought about by the dissemination of public opinion poses a challenge to the stability of the social order (Zhang et al., 2021a). If some online opinions with non-authenticity are not detected, they can bring great negative attitudes as well as emotions to the population, as well as show multiple adverse effects in terms of awareness and willingness, which can pose a serious threat to the security of the digital economy network (Khitskov et al., 2017). Therefore, it is very important to grasp online public opinion in time and correctly recognise its public opinion trend. This also greatly promotes the research of online public opinion detection.

Xian-Yi et al. (2010) conducted an in-depth exploration of the characteristics of online public opinion and risk warning subjects, and further constructed a social network public opinion detection model based on hierarchical network analysis and grey fuzzy theory, but the accuracy of detection was not high. Li and Zhu (2012) analysed the data of Baidu search terms and constructed a public opinion index for reflecting factors such as social happiness and stress, which provides effective methodological support for practical application scenarios. Liu et al. (2022) designed a set of public health public opinion event detection methods based on entropy weight method from the life cycle and evolution mechanism of online public opinion, and constructed a fuzzy comprehensive evaluation index system to accurately determine the detection level of online public opinion.

Early methods for detecting online public opinion were difficult to sift out key information from massive data and analyse it effectively, resulting in low detection efficiency. Machine learning-based research improves detection efficiency by counting social text features of online platforms. Chen et al. (2021) established a joint model containing public opinion detection and event element identification based on random forest selection features, but the detection effect is not satisfactory. Zhang et al. (2019) used a maximum entropy model based on traditional lexical and syntactic features to detect online public opinion, but the text features were not sufficiently extracted. Ala'm et al. (2023) used the BERT model to analyse the opinion sentiment of social text, and incorporated opinion sentiment into the hybrid support vector machine to realise the detection of false speech. Based on the machine learning method, the shallow semantic features are learned and the missing deeper semantic features have to be mined.

With the opening of the use of deep learning in natural language processing, deep neural network methods are gradually studied in the field of opinion detection. Hajek et al. (2020) proposed an opinion monitoring model based on the combination of convolutional neural network (CNN) and sentiment features, which can classify the opinion danger level of false comments and determine the trend of opinion. Ma et al. (2020) proposed a syntactic tree-based RNN opinion detection model, and the model was used to detect online opinions in a temporal sequence with a detection accuracy of 80.07%. Wankhade and Rao (2022) incorporated comprehensive feature information such as semantic and syntactic dependencies into vectors, which were then fed into BiLSTM to capture sentence information, thus realising opinion detection, but with large detection errors. Bhuvaneshwari et al. (2021) further explored the hybrid analysis and detection model of LSTM and CNN for online public opinion, which enables the acquisition of sequential information while also making full use of phrase chunks. Das et al. (2021) utilised a model combining GRU and attention mechanism to classify online public opinion emotions and achieved detection by calculating the emotional intensity of hotspot events. Verma et al. (2023) first utilised BERT-CNN to classify the opinion sentiment tendency, and then utilised the CRF model to extract the news elements, which improved the detection accuracy.

Focusing on the issue that the above research cannot dynamically extract sentiment features, which leads to unsatisfactory detection efficiency, a deep learning-based method for detecting online public opinion in digital economy is designed. Firstly, a two-channel deep learning-based sentiment analysis model for online public opinion is designed, which utilises BiLSTM and dynamic CNN shapes to obtain the global and local sentiment features of the comment text, respectively, and enhances the global and local sentiment features using the improved AM (EAM). EAM combines query and key together, and applies different weights to different keys to realise the selection tendency of value, thus making the model more concerned about the sentiment of the user's own comments. These features are subsequently fused to categorise opinion sentiment through a full connectivity layer. On this basis, this paper classifies online public opinion into four grades, and finally arrives at the online public opinion detection grades through the emotional tendency of the text comments under the topics and the number of likes and retweets, and combined with a number of indicators for comprehensive calculation. Experimental outcome on Twitter15 and Twitter16 datasets show that the designed method has a high weighted average accuracy and achieves accurate detection of online public opinion.

2 Relevant theoretical foundations

2.1 Convolutional neural network

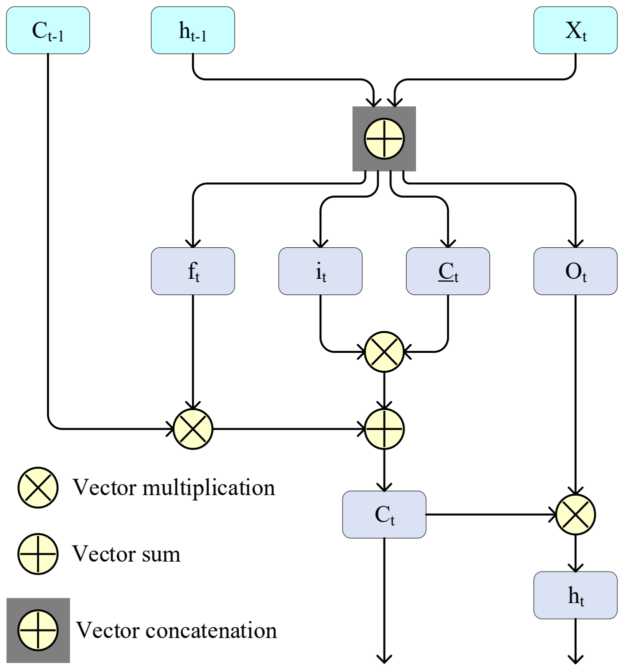
Machine learning methods require manual design of feature extractors, which not only requires significant domain knowledge and experience, but is often difficult to design effective features for complex data. In contrast, CNN can automatically learn different levels of features from raw data without manual hand design, which greatly improves the efficiency and accuracy of feature extraction (Gu et al., 2018). The biggest performance advantage of CNNs over neural networks such as BP neural networks (BPNNs) and recurrent neural networks (RNNs) is the ability of the CNN's convolutional layer to efficiently extract key features from the input data. Through convolutional operations, the network is able to capture localised features such as edges, textures, etc. and combine these features in deeper layers to recognise more complex patterns. This ability for automatic feature extraction allows CNNs to excel in processing data with a grid structure. CNN consists of an input level, a convolutional level, a pooling level, a fully connected level and an output level.

1 The convolutional level connects the input information of each neuron to the local sensation of the previous level, thus obtaining the local characteristics.

2 The pooling level extracts the locally significant features of each sub-region through the pooling function, and then the feature values of each sub-region are spliced together to obtain the final feature vector of the pooling level.

3 Fully connected level and output level. Classification is performed and results are output through Dropout operation and softmax logistic regression classifier (Khan et al., 2020) to avoid overfitting.

Figure 1 LSTM model structure (see online version for colours)



2.2 Long- and short-term memory recurrent neural network

LSTM is an improved RNN structure (Muzaffar and Afshari, 2019) that overcomes the problem of gradient vanishing that can occur in RNNs. Compared with CNN, LSTM is able to automatically learn the features of different time scales in the sequence data, and can adaptively adjust the parameters of gating to extract the most useful features, and its model structure is shown in Figure 1.

1 The forgetting gate f is used to control the information that needs to be forgotten in the unit state, at the moment t, the output value f_t of the forgetting gate is as follows:

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

where W_f is the weight matrix, h_{t-1} is the obscured level state value at moment $t - 1$, x_t is the input vector for t, and b_f is the bias vector.

2 The update gate is used to control the information that needs to be added in the cell state. Firstly the input gate i and the candidate cell state g are computed. The value i_t of the input gate and the candidate cell state g_t are as follows:

$$i_t = \sigma\left(W_i \cdot \left[h_{t-1}, x_t\right] + b_i\right) \tag{2}$$

$$g_t = \tanh\left(W_c \cdot \left[h_{i-1}, x_t\right] + b_c\right) \tag{3}$$

where tanh is the hyperbolic tangent function, W_i and W_c are weight matrices, b_i and b_c are bias vectors.

3 The output gate O calculates to obtain the output value o_t based on the input data x_t and h_{t-1}.

$$o_t = sigmoid\left(W_o \cdot \left[h_{t-1}, x_t\right] + b_o\right) \tag{4}$$

where W_o is the weight function and b_o is the bias vector.

Finally, based on o_t and the updated cell state, the obscured level state h_t is obtained and passed to the next LSTM cell.

$$h_t = o_t \odot \tanh\left(C_t\right) \tag{5}$$

2.3 BERT pre-trained language models

The BERT model has a complex but efficient structure and is capable of extracting rich feature representations from textual data. In stark contrast to unidirectional language models such as Word2Vec and GloVe, BERT employs a bi-directional architecture based on a Transformer encoder and a multi-head attention mechanism. BERT model has achieved significant performance improvements in NLP tasks (Min et al., 2023).

1 bi-directional encoding: the BERT model uses the encoder component of the transformer and residual linkage to complete deep bi-directional encoding of the input text, so as to capture various syntactic and semantic information in the text

2 self-supervised learning: pre-training through masked language models (MLM), which effectively utilises a large amount of unlabelled text data for feature learning

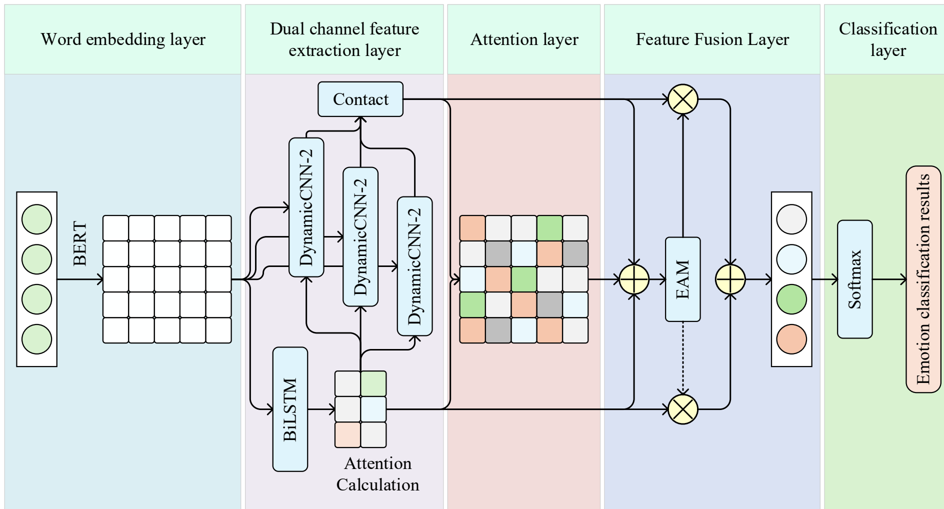
3 model fine-tuning: support model fine-tuning in specific downstream tasks, so that the network parameters can be better adapted to new application scenarios.

3 Sentiment analysis of online public opinion in digital economy based on improved CNN and BiLSTM

3.1 Constructing web comment text word vectors based on BERT

Digital economy online public opinion involves mostly textual data from Internet platforms, and existing deep learning-based sentiment analysis methods for online public opinion cannot dynamically extract sentiment features, resulting in inefficient detection. For this reason, this paper proposes a DCNN-BiLSTM-based sentiment analysis model for online public opinion, as shown in Figure 2. The word embedding layer generates dynamic word vectors through BERT. Then a two-channel neural network is designed, where the BiLSTM channel is used to extract the global features of the text, and the dynamic convolution channel is used to dynamically extract the local features of the text. The global and local features are also enhanced using EAM, and finally the feature fusion level is used to fuse the dual-channel features to capture the semantic interactions between the local and global affective features, and the fused affective feature representations are classified using the full connectivity level.

Figure 2 A DCNN-BiLSTM-based sentiment analysis model for online public opinion (see online version for colours)



The word embedding level maps each word to a high-dimensional vector space. In this paper, the text of online public opinion events is trained with the help of BERT model to generate word vectors with semantic information. The network text t consists of m sentences, i.e., $t = \{s_1, s_2, \ldots, s_m\}$, each consisting of n words, and the input sequence s. Then $s = \{w_1, w_2, \ldots, w_n\}$. For a given sentence $s = \{w_1, w_2, \ldots, w_n\}$, the input is formulated as a sequence $s = \{[CLS], w_1, w_2, \ldots, w_n, [SEP]\}$, with the [$CLS$] flag placed first in the sentence and the [SEP] flag used to separate the two input sentences. The BERT pre-training results in a vector representation of words $X = \{x_1, x_2, \ldots, x_n\}$, $x_i \in R^{d_{emb} \times 1}$, d_{emb} are the dimensions of the word vector.

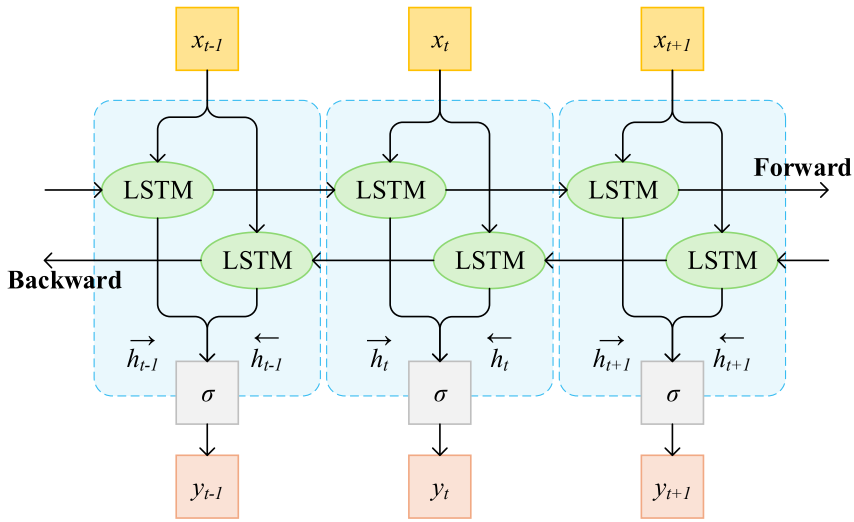
3.2 *Dual-channel text feature extraction based on improved CNN and BiLSTM*

The DCNN-BiLSTM model adopts a two-channel parallel feature extraction network, in which the improved CNN has a strong ability to extract shallow features of web text, but is not good at long distance modelling and is insensitive to the order of speech. To this end, the model is augmented with an improved BiLSTM to enhance the semantic understanding. The BiLSTM channel is used to extract the global sentiment information of the short text comments and to model the overall semantics for a better understanding of the text's sentiment tendencies.

1 BiLSTM channel. After obtaining the word vectors of the network text, it is difficult to achieve the desired results by training with a simple LSTM network because there may be some relationship between the respective contexts of the topics and comments, and the sentiment tendency can be more correctly responded only if all these relationships are taken into account. In this paper, BiLSTM is introduced to obtain the global sentiment information of text data, BiLSTM consists of two directional LSTMs, one processing the input sequence from front to back and one processing the input sequence from back to front. At each time step, the output of BiLSTM is a concatenation of the outputs of the forward and backward LSTMs. This

allows Bi-LSTM to better capture the semantic information in the sequence through the forward and backward information. The network structure of BiLSTM is shown in Figure 3.

Figure 3 The network structure of BiLSTM (see online version for colours)



From the above structure diagram, it can be seen that at any time step, the Bi-LSTM network model has forward and backward LSTM outputs. Their state formulas are shown in equations (6) and (7).

$$\vec{h}_t = LSTM\left(w_t, \vec{h}_{t-1}\right) \tag{6}$$

$$\overleftarrow{h}_t = LSTM\left(w_t, \overleftarrow{h}_{t-1}\right) \tag{7}$$

A sequence of text sentences $s = \{w_1, w_2, \ldots, w_n\}$ is passed into the forward and backward LSTM. The incoming forward LSTM is $\{w_1, w_2, \ldots, w_n\}$, which is denoted by $\vec{h}_t$, and the incoming backward LSTM is $(w_n, w_{n-1}, \ldots, w_1)$, which is denoted by $\overleftarrow{h}_t$. Subsequently, through the training of the hidden layer, the global opinion sentiment feature can be obtained, as shown in equation (8).

$$v^b = \tanh\left(W_{\vec{h}}\vec{h}_t + W_{\overleftarrow{h}}\overleftarrow{h}_t + b_y\right) \tag{8}$$

where $W_{\vec{h}}$ and $W_{\overleftarrow{h}}$ are the weight matrices of each layer connected to the previous hidden state, and b_y is the bias term. Y_t is the combination of the forward and backward output results at time t. Finally the result is passed to the subsequent DCNN channel. Finally, the results are passed into the DCNN channel.

2 DCNN channel: traditional CNNs share the same convolutional kernel when processing different input sequences, which affects the ability to extract emotional features from different sentences. To overcome this shortcoming, the proposed model in this chapter is inspired by the literature (Zhang et al., 2021b), and the dynamic convolutional network (DCNN) is improved for the two-channel of the

model in this chapter. Specifically, for different short text sequences, multiple parallel convolutional kernels are dynamically aggregated based on the global sentiment information extracted from the BiLSTM channel, i.e., different convolutional kernels are used for each input, and these different convolutional kernels are attentively weighted. This improvement allows the model to better capture the sentiment characteristics of different short text sequences, thus enhancing the performance of the model for sentiment analysis.

The global sentiment information extracted from the BiLSTM channel is used to generate weight vectors, and the parameters of the convolution kernel are dynamically adjusted to achieve the dynamic processing of sentiment features. Dynamic convolution is achieved using K parallel convolutional kernels $\{\tilde{W}_k, \tilde{b}_k\}$ which are dynamically aggregated $\tilde{W}$ for each input sequence X_i by means of a correlation attention $\pi_k(v^b)$, computed as follows:

$$v^c = Relu\left(\tilde{W}^T X_i + \tilde{b}\right) \tag{9}$$

$$\tilde{W} = \sum_{k=1}^{K} \pi_k\left(v^b\right) \tilde{W}_k \tag{10}$$

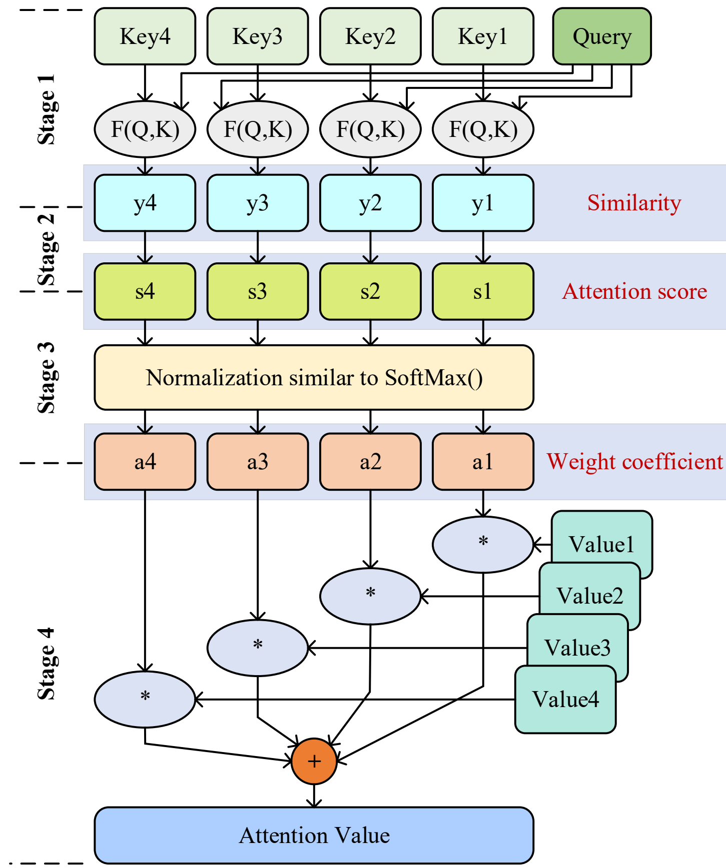
$$\tilde{a} = \sum_{k=1}^{K} \pi_k\left(v^a\right) \tilde{a}_k \tag{11}$$

The weight calculation function $\pi_k(v^b)$ plays a significant role in each text sequence, and its calculation process is as follows: firstly, the sentiment features extracted from the BiLSTM channel are pooled with the global average, then mapped to the K-dimensional space through two fully connected layers, and finally normalised by softmax. In this way, the K weight coefficients can be effectively assigned to K convolutional kernels, thus realising the dynamic convolutional feature extraction process. The design of this weighting function enables the model to better capture the semantic information in text sequences, which helps to improve the classification performance of the text task.

3.3 Feature enhancement based on improved attention mechanisms

After obtaining the global and local sentiment features of the web text, in order to enhance the sentiment features of the user's own speech, this paper introduces the improved AM (EAM) after the dual-channel feature extraction layer, respectively. Traditional AM pays more attention to the part related to keywords when processing information, while EAM reduces the influence of the sentiment of the topic itself and pays more attention to the sentiment of the user's own comments when processing user comments, the overall workflow is shown in Figure 4.

Figure 4 The overall workflow of EAM (see online version for colours)



EAM combines query and key through AM aggregation, applying different weights to different keys to achieve a selection preference for value. This approach is a better way to get the network to give lower weight to those talking points in user reviews. In this paper query corresponds to the topic words, key corresponds to the words in the user comments, and value corresponds to the DCNN-BiLSTM output. The details are that the method of calculating cosine similarity is chosen to calculate the similarity between the query and each key. Compared to traditional AM, EAM has an additional stage 2, where some way of converting similarity into a final attention score is chosen. The attention scores are then normalised by the softmax function to obtain the attention weight of each key-value, which is then multiplied by the value corresponding to each key and summed to obtain the final output result. The corresponding EAM weights and outputs are shown in equations (12) and (13), respectively.

$$\alpha(q, k_i) = softmax(a(q, k_i)) = \frac{\exp(a(q, k_i))}{\sum_{j=1}^{m} \exp(a(q, k_j))} \tag{12}$$

$$f(q, (k_1, v_1), \ldots, (k_m, v_m)) = \sum_{i=1}^{m} \alpha(q, k_i) v_i \tag{13}$$

The core of EAM lies in the choice of the representation of the attention scores (similarity between query and key), and in this paper, we adopt the method of calculating the cosine similarity between the two, as shown below.

$$a(q, k_i) = \cos(\theta) = \frac{q \cdot k_i}{\|q\| \times \|k_i\|} = \frac{\sum_{k=1}^{n} q_k \times k_{ik}}{\sqrt{\sum_{k=1}^{n} (q_k)^2} \times \sqrt{\sum_{k=1}^{n} (k_{ik})^2}} \tag{14}$$

3.4 Feature fusion and online opinion sentiment classification

The global and local features of DCNN-BiLSTM are fused, i.e., the simple corresponding elements are summed up, and then used as inputs to the EAM, which undergoes a sigmoid activation function and outputs the values from 0 to 1. This process is shown in Equation (15). With such a feature fusion and weight regulation mechanism, the model is able to dynamically adjust the weight of each feature according to the importance of the feature, thus improving the classification performance of the model.

$$Z = M(v^c \oplus v^b) \otimes v^c + (1 - M(v^c \oplus v^b)) \otimes v^b \tag{15}$$

where Z is the fusion feature, $\oplus$ is the sum of the corresponding elements, and $\otimes$ is the multiplication.

The EAM's Z-enhanced feature f is input to the classification layer for sentiment classification. The classification layer usually adopts a fully connected layer structure, and uses softmax function to downscale and classify the final fused sentiment representation. In addition, to reduce the overfitting phenomenon of the model, the Dropout method is applied to randomly discard some neuron connections with a certain probability, so as to improve the generalisation ability of the model. The specific formula is as follows:

$$Y = Dropout(W \cdot f + b) \tag{16}$$

$$\hat{Y} = softmax(Y) \tag{17}$$

where W and b are the weights and bias of the fully connected level, respectively; f is the feature vector output from the EAM feature enhancement layer; and Y is the feature vector processed by the Dropout method.

4 Sentiment analysis-based calculation of online public opinion detection levels for digital economy

The sentiment polarity of all user comments in the text of the digital economy network can be obtained by the DCNN-BiLSTM model in the previous chapter. The sentiment polarity of the user comments was categorised into positive, neutral and negative sentiments, along with information about the number of likes and retweets for each user comment. In this chapter, the sentiment level of a topic is calculated by using these three indicators of user comments. Then, the opinion detection level of the topic is calculated based on the number of readers, comments, sentiment and topic type, and the principle is shown in Figure 5.

1 Topic sentiment calculation. The sentiment of a topic is not only determined by the sentiment polarity of user comments under the topic, but also affected by the number of likes and retweets of other users under the comments. The two behaviours of liking and retweeting can reflect the degree of users' recognition and attention to the comments, thus indirectly affecting the sentiment degree of the topic. However, the degree of their influence on topic sentiment is different, so it is necessary to set different weight coefficients for liking and retweeting behaviours. Firstly, the sum of the affective tendency scores of all the comments under the topic was calculated. The average sentiment propensity score *Score* of the topic is then calculated based on the sum of the scores and the number of comments. To reduce the difference of the average affective tendency scores between different topics, the Sigmoid function is used to map the average affective tendency scores to the interval of (0, 100) to get the affectivity *E* of the hot search topics. The calculation of topic sentiment is shown below.

$$Score = \frac{1}{n}\sum_{i=1}^{n}\left(S_i + \alpha_1 l_i + \alpha_2 t_i\right) \tag{18}$$

$$E = \frac{100}{1 + e^{-Score}} \tag{19}$$

where S_i is the affective tendency score, l_i is the number of likes, t_i is the number of retweets, α_1 and α_2 are the weighting values of the number of likes and retweets, respectively, and n is the number of all comments under the topic.

2 Calculation of topic public opinion detection level. The degree of influence of online public opinion is not only affected by the nature of the event itself, but also by the scale of the event, the scope of influence, media coverage, and many other factors. This paper calculates the topic opinion detection level by using the topic's sentiment, reading volume, comment volume and other indicators. Topics with higher sentiment are less likely to be at risk and have lower detection levels. Topic Sentiment [0, 50) is considered a negative topic and [50, 100) is considered a positive topic. Whereas topic readership, comments, media coverage, etc. are quantitative and will affect the topic's public opinion situation, they will not change the topic's emotional polarity. When calculating the topic opinion detection rating, the opinion detection rating score $Score_{temp}$ is calculated first.

$$Score_{temp} = \begin{cases} \left(50 + (\beta_1 + \beta_2 + \beta_3)|E - 50|\right) * \beta_4, & E \in [0, 50) \\ \left(50 - (\beta_1 + \beta_2 + \beta_3)|E - 50|\right) * \beta_4, & E \in [50, 100] \end{cases} \tag{20}$$

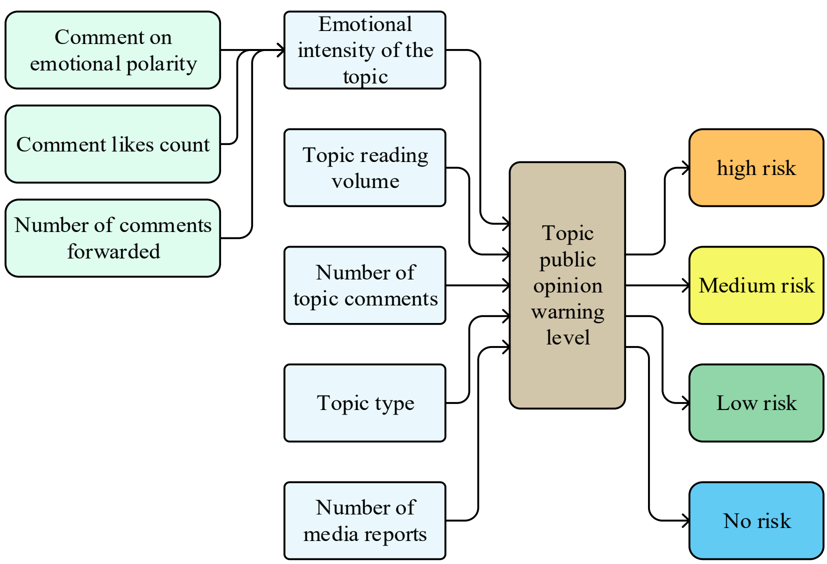
where β_1, β_2 and β_3 are the percentages of topic readership, comments, and media coverage, respectively, and a maximum limit needs to be set on these percentages to prevent these quantitative factors from having too great an impact. For example, β_1 is calculated as shown below, where m denotes the topic readership of the j^{th} topical search.

$$\beta_1 = \frac{m_j - \frac{1}{20}\sum_{i=1}^{20}(m_i)}{\frac{1}{20}\sum_{i=1}^{20}(m)} \tag{21}$$

After calculating $Score_{temp}$, you can map $Score_{temp}$ to the different grade labels as shown below:

$$Grade = \begin{cases} \text{without risk}, & Score_{temp} \in [80, 100] \\ \text{low risk}, & Score_{temp} \in [60, 80) \\ \text{medium risk}, & Score_{temp} \in [40, 60) \\ \text{high risk}, & Score_{temp} \in [0, 40) \end{cases} \tag{22}$$

Figure 5 The principle of the digital economy online public opinion detection (see online version for colours)



5 Experimental results and analyses

The experiments in this article are relied on two publicly available classic Twitter datasets: Twitter15 and Twitter16. The datasets contain 1,490 and 818 opinion source texts, respectively. Each source text in the dataset was labelled as no risk (W1), low risk (W2), medium risk (W3), and high risk (W4). More information on the two datasets is shown in Table 1, where Number is denoted by *N*. The experiments were conducted using 128 BiLSTM neurons with 50% dropout, dropout set to 0.5, Batch size of 64, 20 rounds of training and were trained using Adam optimiser and binary_crossentropy loss function. The experimental environment uses VSCode development tools written in Python-3.7 development language with pytorch-1.9.1 deep learning framework, operating system is Windows 64 and processor is Intel(R) Xeon(R) Gold 6230R CPU @2.10 GHz.

Table 1 Details of the Twitter15 and Twitter16 datasets

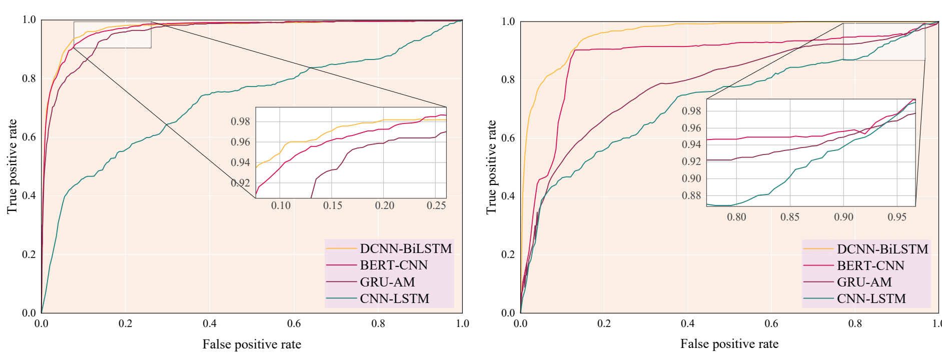
Dataset	*N of users*	*N of W1*	*N of W2*	*N of W3*	*N of W4*
Twitter15	276,663	374	370	372	374
Twitter16	173,487	205	205	207	201

To comprehensively validate the detection accuracy of the proposed method, this paper conducts comparative experiments with CNN-LSTM (Bhuvaneshwari et al., 2021), GRU-AM (Das et al., 2021), and BERT-CNN (Verma et al., 2023) on the two datasets, and the different models of the four public opinion risk levels' detection accuracies are shown in Table 2. On the Twitter15 dataset, for the W2 rank, the detection accuracy of DCNN-BiLSTM is 93.01%, which improves 16.17%, 8.5%, and 4.12% compared to CNN-LSTM, GRU-AM, and BERT-CNN, respectively. On the Twitter16 dataset, for the W3 rank, the detection accuracy of DCNN-BiLSTM is 91.69%, which is an improvement of 6.67–17.33% compared to the other three methods. DCNN-BiLSTM not only uses DCNN to extract local features of opinion sentiment, but also optimises AM so that the model pays more attention to the sentimentality of the user's own comments, which in turn improves the detection accuracy.

Table 2 Detection accuracy of four opinion risk levels with different models (%)

Method	*Twitter15*				*Twitter16*			
	W1	*W2*	*W3*	*W4*	*W1*	*W2*	*W3*	*W4*
CNN-LSTM	78.22	76.84	79.86	79.06	75.59	72.81	74.36	73.29
GRU-AM	82.05	84.51	83.69	82.93	80.65	79.52	78.69	80.41
BERT-CNN	87.23	88.89	89.03	89.31	85.21	84.53	85.02	86.19
DCNN-BiLSTM	95.61	93.01	94.95	94.46	89.34	90.65	91.69	90.59

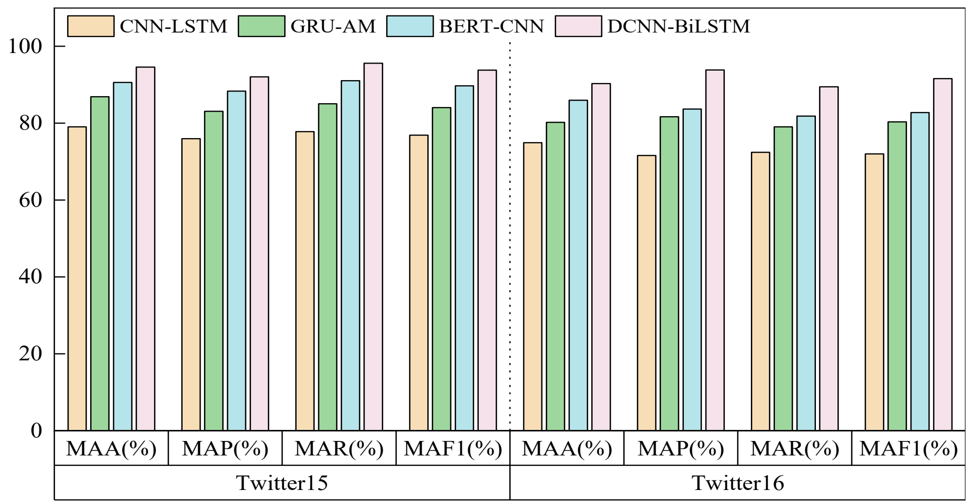
Figure 6 The ROC curves of different opinion monitoring methods, (a) comparison of ROC curves on dataset Twitter15 (b) comparison of ROC curves on dataset Twitter16 (see online version for colours)



(a) (b)

The ROC curves of different opinion monitoring methods on Twitter15 and Twitter16 are shown in Figure 6, AUC is the area under the ROC curve, and the closer the value is to 1, the better the detection performance. For the Twitter15 dataset, the AUC values of CNN-LSTM, GRU-AM and BERT-CNN and DCNN-BiLSTM are 0.7226, 0.9594, 0.9631 and 0.9746, respectively. Then comparing the performance of different methods on Twitter16, the AUC values of CNN-LSTM, GRU-AM and BERT-CNN and DCNN-BiLSTM are 0.9582, 0.8878, 0.8717 and 0.7226, respectively, so that the AUC value of DCNN-BiLSTM is the closest to 1, and it is the most effective in its detection. This is because DCNN-BiLSTM establishes a sentiment analysis model incorporating EMA on the basis of dual-channel feature extraction, and calculates the opinion risk monitoring level by combining multiple indicators such as topic sentiment, topic readership, comments, and the number of media reports, which greatly improves the detection efficiency.

Figure 7 The detection performance of each method on Twitter15 and Twitter16 dataset (see online version for colours)



In addition, this paper also evaluates the detection performance of each method on different datasets using the commonly used metrics Weighted Average Accuracy (MAA), Weighted Average Precision (MAP), Weighted Average Recall (MAR), and Weighted Average F1 (MAF1), as shown in Figure 7. On the two datasets, the MAA of DCNN-BiLSTM is 94.59% and 90.32%, respectively, which is at least 3.98% improvement compared to the other three methods. MAF1 is the reconciled mean of MAP and MAR, and provides a comprehensive picture of the strengths and weaknesses of the detection performance. On Twitter15 and Twitter16, the MAF1 of DCNN-BiLSTM is improved by 4.12%-19.6% over CNN-LSTM, GRU-AM and BERT-CNN. Taken together, DCNN-BiLSTM achieves excellent detection performance on the task of detecting online public opinion in digital economy.

6 Conclusions

Online public opinion in the context of digital economy involves a cluttered mass of data, so it is quite challenging to uncover potential public opinion from it and detect it accurately. For this reason, this paper explores a deep learning-based method for detecting online public opinion in the digital economy. Firstly, the BERT model is used to embed the representation of the comment text, and a dual-channel deep learning model is designed, with the BiLSTM channel for extracting global sentiment features and the DCNN channel for dynamically extracting local sentiment features. The multidimensional features are also augmented using EAM, followed by the fusion of dual-channel features, and the fused sentiment feature representations are classified using a fully connected layer. Based on this, this paper quantifies the topic opinion levels into four classes. Then this paper combined the results of the sentiment classification of the comment text, the readership of the topic, and the number of media reports to successively calculate the sentiment degree and opinion detection level of the topic, and finally arrived at the detection level of the topic. The experimental outcome on Twitter15 and Twitter16 datasets show that the weighted average accuracy of the proposed method is 94.59% and 90.32%, respectively, which has a greater degree of improvement than other methods, and can be better applied to the detection of online public opinion.

Although the designed method improves the accuracy of opinion detection, it has some shortcomings. The overall structure of the sentiment analysis part of the public opinion is more complex, resulting in longer training time. In addition, the information on the web is in various forms, including not only textual content, but also covering emoticons, pictures, videos and other forms, so the model is lacking in the analysis of multimodal data. Future research will focus on incorporating the analysis of multimodal data to improve the detection performance of the methods and to reduce the training and classification time.

Acknowledgements

This work is supported by the 2023 Institute of Engineering and Technology, Henan Polytechnic University university-level Humanities and Social Science Key Funding project (No. 2023-RWZZ-001), and 2024 Henan Province Science and technology development plan (Soft Science Research) Project (No. 242400410484).

Declarations

All authors declare that they have no conflicts of interest.

References

Ala'm, A-Z., Mora, A.M. and Faris, H. (2023) 'A multilingual spam reviews detection based on pre-trained word embedding and weighted swarm support vector machines', *IEEE Access*, Vol. 11, pp.72250–72271.

Bhuvaneshwari, P., Rao, A.N. and Robinson, Y.H. (2021) 'Spam review detection using self attention based CNN and bi-directional LSTM', *Multimedia Tools and Applications*, Vol. 80, No. 12, pp.18107–18124.

Chen, T., Yin, X., Peng, L. et al. (2021) 'Monitoring and recognizing enterprise public opinion from high-risk users based on user portrait and random forest algorithm', *Axioms*, Vol. 10, No. 2, p.106.

Das, A.K., Al Asif, A., Paul, A. et al. (2021) 'Bangla hate speech detection on social media using attention-based recurrent neural network', *Journal of Intelligent Systems*, Vol. 30, No. 1, pp.578–591.

Gu, J., Wang, Z., Kuen, J. et al. (2018) 'Recent advances in convolutional neural networks', *Pattern Recognition*, Vol. 77, pp.354–377.

Hajek, P., Barushka, A. and Munk, M. (2020) 'Fake consumer review detection using deep neural networks integrating word embeddings and emotion mining', *Neural Computing and Applications*, Vol. 32, No. 23, pp.17259–17274.

Khan, A., Sohail, A., Zahoora, U. et al. (2020) 'A survey of the recent architectures of deep convolutional neural networks', *Artificial Intelligence Review*, Vol. 53, pp.5455–5516.

Khitskov, E.A., Veretekhina, S.V., Medvedeva, A.V. et al. (2017) 'Digital transformation of society: problems entering in the digital economy', *Eurasian Journal of Analytical Chemistry*, Vol. 12, No. 5, pp.855–873.

Koch, T. and Windsperger, J. (2017) 'Seeing through the network: competitive advantage in the digital economy', *Journal of Organization Design*, Vol. 6, pp.1–30.

Kupriyanovsky, V., Sneps-Sneppe, M., Namiot, D. et al. (2017) 'Web of things and internet of things in the digital economy', *International Journal of Open Information Technologies*, Vol. 5, No. 5, pp.38–45.

Li, Z. and Zhu, T. (2012) 'A method of detecting online public opinions based on the query log of search engine', *International Journal of Networking and Virtual Organisations*, Vol. 10, Nos. 3–4, pp.260–274.

Liu, J., Liu, L., Tu, Y. et al. (2022) 'Multi-stage Internet public opinion risk grading analysis of public health emergencies: an empirical study on Microblog in COVID-19', *Information Processing & Management*, Vol. 59, No. 1, p.102796.

Ma, J., Gao, W., Joty, S. et al. (2020) 'An attention-based rumor detection model with tree-structured recursive neural networks', *ACM Transactions on Intelligent Systems and Technology (TIST)*, Vol. 11, No. 4, pp.1–28.

Min, B., Ross, H., Sulem, E. et al. (2023) 'Recent advances in natural language processing via large pre-trained language models: a survey', *ACM Computing Surveys*, Vol. 56, No. 2, pp.1–40.

Muzaffar, S. and Afshari, A. (2019) 'Short-term load forecasts using LSTM networks', *Energy Procedia*, Vol. 158, pp.2922–2927.

Verma, P.K., Agrawal, P., Madaan, V. et al. (2023) 'MCred: multi-modal message credibility for fake news detection using BERT and CNN', *Journal of Ambient Intelligence and Humanized Computing*, Vol. 14, No. 8, pp.10617–10629.

Wankhade, M. and Rao, A.C.S. (2022) 'Opinion analysis and aspect understanding during COVID-19 pandemic using BERT-Bi-LSTM ensemble method', *Scientific Reports*, Vol. 12, No. 1, p.17095.

Xia, L., Baghaie, S. and Sajadi, S.M. (2023) 'The digital economy: challenges and opportunities in the new era of technology and electronic communications', *Ain Shams Engineering Journal*, Vol. 15, No. 2, p.102411.

Xian-Yi, C., Ling-ling, Z., Qian, Z. et al. (2010) 'The framework of network public opinion monitoring and analyzing system based on semantic content identification', *Journal of Convergence Information Technology*, Vol. 5, No. 10, pp.1–5.

Zhang, M., Su, H. and Wen, J. (2021a) 'Analysis and mining of internet public opinion based on LDA subject classification', *Journal of Web Engineering*, Vol. 20, No. 8, pp.2457–2472.

Zhang, M., Zheng, R., Chen, J. et al. (2019) 'Emotional component analysis and forecast public opinion on micro-blog posts based on maximum entropy model', *Cluster Computing*, Vol. 22, pp.6295–6304.

Zhang, Z., Rao, Y., Lai, H. et al. (2021b) 'TADC: a topic-aware dynamic convolutional neural network for aspect extraction', *IEEE Transactions on Neural Networks and Learning Systems*, Vol. 34, No. 8, pp.3912–3924.