Prediction of Negative Public Opinion Dissemination Trend on Social Media: An Improved Machine Learning Algorithm

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The widespread dissemination of negative public opinion on social media can have adverse effects. This study utilized word-to-vector (word2vec) to obtain word vectors and classified positive and negative public opinions using the bilateral long short-term memory (BiLSTM) algorithm. To predict the dissemination trend of negative public opinion on social media, the back-propagation neural network (BPNN) algorithm was selected and optimized by the improved sparrow search algorithm (ISSA). Public opinion data was collected from the "Wenzhou doctor injury" case for experiments. The results showed that the BiLSTM algorithm achieved a P-value of 0.9233, an R-value of 0.9164, and an F1-value of 0.9198 in sentiment classification, outperforming the convolutional neural network and long short-term memory algorithms. For Benchmark test functions, the ISSA demonstrated superior performance in optimization compared to the particle swarm optimization and sparrow search algorithm. In predicting the negative public opinion dissemination trend, the ISSA-BPNN algorithm yielded a mean square error of 845.12, a root-mean-square error of 29.07, and a mean absolute error of 21.56, surpassing support vector machine and other algorithms. These results validate the effectiveness of the method proposed in this study for predicting the dissemination trend of negative public opinion and its potential practical applications.

Povzetek: Članek obravnava napoved širjenja negativnega javnega mnenja na družbenih omrežjih z uporabo BiLSTM za analizo sentimenta in optimiziranega ISSA-BPNN za napoved trenda. Metoda dosega boljšo točnost in nižje napake kot primerjalni algoritmi na realnih podatkih iz družbenih omrežij.

1 Introduction

Network technology is developing rapidly, and social media is therefore constantly becoming popular. It has become a common practice for the public to stay informed about current events and express their opinions and thoughts on various social media platforms. Dealing with the vast amount of public opinion data and extracting valuable information from it has become a critical issue in current research [1]. The continuous generation and dissemination of negative public opinion on social media can disrupt the online environment's stability and adversely affect societal development [2]. Machine learning algorithms can identify negative public opinions by categorizing and analyzing public opinion data on social media and predicting future trends. Various methods have been employed to analyze social media opinion data [3]. Wang et al. [4] utilized a convolutional neural network (CNN) and bilateral long short-term memory (BiLSTM) to conduct sentiment analysis on online food safety public opinion, achieving an average accuracy of 94.12% and an F1 value of 94.61%. Liu et al. [5] used public opinion on a social media platform during the COVID-19 pandemic as a case study. They proposed a risk level grading model that combined analytic hierarchy process sort II and swing weighting, revealing a gradual decrease in public opinion risk over time after assessing it seven times from January 23 to April 8, 2020. He et al. [6] analyzed posts published on the Weibo platform in the six days following the 2022 Sichuan earthquake and discovered that emotional fluctuations were not only influenced by geographical region but also by the sentiment of the official Weibo accounts. Tan et al. [7] studied the evolution of netizens' sentiment regarding the anti-Extradition Law Amendment Bill campaign event in Hong Kong using a bidirectional encoder representation from transformers-latent dirichlet allocation hybrid model to track sentiment changes among netizens and opinion leaders during the incident, achieving an area under curve value of 99.6% in sentiment categorization. Areshey et al. [8] evaluated the effectiveness of bidirectional encoder representation from transformers (BERT), robustly optimized BERT pretraining approach (RoBERTa), a lite BERT (ALBERT), Distilled BERT (DistilBERT), and XLNet (generalized autoregressive pretraining for language understanding) in the sentiment classification task based on the Yelp reviews dataset. They found that the above methods achieved 97.40, 98.30, 97.20, 96.00, and 98.20, respectively. This study initially identified negative public opinion using a sentiment classification algorithm. Then, a back-propagation neural network (BPNN) prediction algorithm optimized by the improved sparrow search algorithm (ISSA) was developed to forecast the dissemination trend of negative public opinion on social media. Through experiments conducted using social media data, the effectiveness of the proposed method was validated, offering a new approach for processing and analyzing social media public opinion data in practical applications. This article provides some theoretical support for the monitoring and guidance of public opinion.

2 Prediction of negative public opinion dissemination trend

2.1 Sentiment classification of social media opinions

Social media opinions, as textual information, cannot be directly input into a classification model. Before sentiment categorization, the text must be converted into machine-readable language. This study used a word-to-vector (word2vec) model [9] to transform the text into word vectors. For the classification algorithm, the BiLSTM was selected [10]. Social media public opinion data is sequential data. The fermentation of a hot event involves public opinion over a relatively long period. When making predictions, the model needs to be able to "remember" information from a long time ago and establish connections. LSTM has shown strong performance in processing long sequence data and is commonly used in text classification [11]; however, it can only process sequence from front to back. BiLSTM, with its bidirectional structure, can effectively capture contextual information within a sentence to determine the sentiment category of the entire text. That is to say, when processing sequences, the model not only takes into account what happened before a certain moment but also what happened after that moment, enabling a more comprehensive and accurate analysis of the sentiment contained in the text. In the sentiment classification task, BiLSTM has also been applied to a certain extent [12]. Therefore, this paper employed the word2vec+BiLSTM approach for sentiment categorization of social media opinions.

For word vector x_t obtained from word2vec learning, LSTM is used to extract the feature information by three gate operations, as follows:

(1) Input gate i_t: $i_t = sig(w_{xi}x_t + w_{hi}h_{t-1} + b_i)$;

(2) Forget gate f_t: $f_t = sig(w_{xf}x_t + w_{hf}h_{t-1} + b_f)$;

(3) Output gate o_t: $o_t = sig(w_{xo}x_t + w_{ho}h_{t-1} + b_o)$.

In the above equations, w_{xi}, w_{hi}, w_{xf}, w_{hf}, w_{xo}, and w_{ho} are the weights of each layer, b_i, b_f, and b_o are the biases of each layer. Then, the candidate memory unit of the t-th cell is calculated:

$$\tilde{c}_t = \tanh(w_{x\tilde{c}}x_t + w_{h\tilde{c}}h_{t-1} + b_{\tilde{c}}),$$

where $w_{x\tilde{c}}$ and $w_{h\tilde{c}}$ are weights and $b_{\tilde{c}}$ is a bias. The state value of the memory cell at time t is calculated according to the above equation:

$$c_t = f_t \times c_{t-1} + i_t \times \tilde{c}_t.$$

The output of the LSTM is:

$$h_t = o_t \times \tanh(c_t).$$

The output of BiLSTM is obtained by splicing the output of the forward and backward LSTMs:

$$h_t = [\vec{h}_t, \overleftarrow{h}_t].$$

Finally, the probability result of each sentiment is obtained through a softmax layer to fulfill the sentiment categorization of texts.

2.2 Prediction algorithm for negative public opinion dissemination trend

2.2.1 Back-propagation neural network

After the sentiment classification of social media text data, predicting the number of negative public opinions within it can understand their dissemination trend. Various machine learning methods have been utilized for data prediction. The BPNN stands out for its robust nonlinear modeling capability and superior generalization performance in finance, industry, and other fields [13]. One of the advantages of BPNN lie in that it can learn extremely complex patterns through multi-level non-linear transformations of input features and quickly predict new data after training. The other advantage is that it is not sensitive to missing values in the input data or a certain degree of noise. Therefore, this study also introduced a negative public opinion dissemination trend prediction algorithm based on BPNN.

It is assumed that the input sample of BPNN is $x_1, x_2, \cdots, x_n$ and the hidden layer has l nodes. Its input and output can be written as:

$$H_j = \sum_{i=1}^{n} w_{ij}x_i,$$

$$t_j = f(H_j - a_j),$$

where w_{ij} is the weight from the input layer to the hidden layer, a_j is the threshold, and $f(x)$ is the activation function.

The output layer has m nodes, and its input and output can be written as:

$$o_k = \sum_{j=1}^{l} \mu_{jk}t_j,$$

$$y_k = f(o_k - b_k),$$

where μ_{jk} is the weight from the hidden layer to the output layer and b_k is the threshold value.

Subsequently, the BPNN constantly adjusts the weights and thresholds by back-propagating the error until it meets the specified criteria. Nevertheless, the initial weights and thresholds in BPNN will significantly impact the prediction results and speed. To prevent getting stuck in local optima and enhance the model's convergence speed, the BPNN can be improved with an intelligent algorithm to optimize the initial values.

2.2.2 Improved sparrow search algorithm

At present, intelligent algorithms such as genetic algorithm (GA) and particle swarm optimization (PSO) have been utilized to enhance BPNN [14]. The sparrow search algorithm (SSA) is a method that mimics the foraging behavior of sparrows [15], and its strong global search ability makes it easy to escape local optima. SSA has demonstrated superior convergence accuracy compared to methods such as GA. Compared with algorithms such as PSO, SSA has better core parameters, is easier to adjust and implement, and can find solutions of higher quality with fewer iterations. Hence, this study selected SSA and optimized it to achieve better performance in the parameter optimization of BPNN.

SSA was used to improve the BPNN. It is assumed that the SSA population size is n. In the d-dimensional space, the individual sparrow can be written as $x_{n,d}$ and the individual fitness is f. There is a pre-warning value $R(R \in [0,1])$ and a safety value $ST(ST \in [0.5,1])$. The location of the discoverer in the population is updated as:

$$X_{i,j}(t+1) = \begin{cases} X_{i,j}(t) e^{-\frac{i}{\alpha t_{max}}}, R < ST \\ X_{i,j}(t) + QL, R \geq ST \end{cases},$$

where Q denotes a random value obeying normal distribution, L is a matrix with a dimension of $l \times d$, whose elements are all 1, α is a random number in $(0,1]$, and t_{max} is the maximum number of iterations.

The position of the followers is updated as:

$$X_{i,j}(t+1) = \begin{cases} Qe^{\frac{X_w(t)-X_{i,j}(t)}{i^2}}, i > n/2 \\ X_{i,j}(t) + \left|X_{i,j}(t) - X_b(t)\right| A^* L, i \leq n/2 \end{cases},$$

where $X_w(t)$ is the current worst position, $X_b(t)$ is the current optimal position, and A is a matrix with a dimension of $l \times d$, whose element is either 1 or -1, $A^* = A^T(AA^T)^{-1}$.

The location of watchers is updated as:

$$X_{i,j}(t+1) = \begin{cases} X_b(t) + \beta\left|X_{i,j}(t) - X_b(t)\right|, f_i \neq f_b \\ X_{i,j}(t) + K\frac{\left|X_{i,j}(t)-X_w(t)\right|}{(f_i - f_w)+\varepsilon}, f_i = f_b \end{cases},$$

where β is the step size control parameter, f_i is the current individual fitness value, f_w is the current worst fitness, f_b is the current optimal fitness, and K is a random number in $[-1,1]$.

The individual positions are continuously updated according to the above equations until the maximum number of iterations is reached. To solve the problem that SSA is easy to converge prematurely, this paper developed the ISSA algorithm from the following two aspects.

(1) Tent chaos mapping

SSA uses random initialization, which may lead to uneven population distribution and limit the global search ability of the algorithm. Therefore, the population is initialized using Tent chaotic mapping [16] to improve the diversity of the population:

$$x_{i+1} = \begin{cases} \frac{x_i}{\alpha}, x_i \in [0, \alpha) \\ \frac{(1-x_i)}{(1-\alpha)}, x_i \in [\alpha 1,] \end{cases},$$

where $\alpha \in [0,1]$.

(2) $Lévy$ flight strategy

In the SSA, the update step size of the discoverer's position is relatively fixed, which may lead to low algorithm efficiency. Therefore, the SSA search capability is enhanced by adding the $Lévy$ flight strategy [17] to the discoverer position update equation:

$$X_{i,j}(t+1) = \begin{cases} X_{i,j}(t) e^{-\frac{i}{\alpha t_{max}}}, R < ST \\ X_{i,j}(t) + QL + Lévy(\delta) \cdot L, R \geq ST \end{cases},$$

$$Lévy(\delta) \sim \frac{u}{|v|^{1/2}},$$

$$u \sim N(0, \sigma_u^2), v \sim N(0, \sigma_v^2),$$

$$\sigma_u = \left\{\frac{\Gamma(1+\delta)\sin\left(\frac{\pi\delta}{2}\right)}{\Gamma\left[\frac{1+\delta}{2}\right]\delta \cdot 2^{\frac{(\delta-1)}{2}}}\right\}^{1/\delta}, \sigma_v = 1,$$

where u is a random number obeying $N(0, \sigma_u^2)$, v is a random number that obeys $(0, \sigma_v^2)$, and $\Gamma(\delta)$ is a Gamma function.

The Tent chaotic map can generate an initial population with a more uniform distribution and wider coverage, providing a good foundation for subsequent global search and effectively preventing premature convergence. The Lévy flight strategy can provide an adaptive step-size mechanism to achieve a good balance between global search and local search in the algorithm. In the initialization stage of ISSA, the Tent chaotic map is used to generate the initial population, providing a good starting point for global search. During the iteration process, the Lévy flight strategy is introduced, greatly enriching the search behavior. Therefore, in theory, ISSA can have a faster convergence and higher convergence accuracy than SSA.

The flowchart of the ISSA-BPNN algorithm for negative public opinion dissemination prediction is shown in Figure 1.

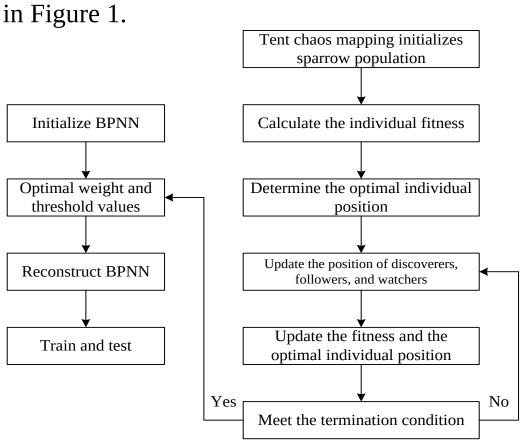

Figure 1: The ISSA-BPNN algorithm for negative public opinion dissemination prediction.

3 Experimental setup

3.1 Experimental settings

The experiments were conducted in a Windows 10 environment using Python 3.6. The parameters of the experimental model were all optimized through grid search. For sentiment categorization, the word vector dimension of the BiLSTM algorithm was set to 300, the Dropout was set to 0.5, the number of epochs was 25, and the batch size was set to 20. In predicting the dissemination trend of negative public opinion, the learning rate for the ISSA-BPNN algorithm was set to 0.01, the population size for ISSA was set to 30, the maximum number of iterations was set to 1,000, and the initial safety and pre-warning values were set to 0.6 and 0.2, respectively. The search range of the initial weights and thresholds of the BPNN was [-1, 1].

Crawler technology was used to crawl the comment data of three public opinion incidents, including a man in Wenzhou attacking a doctor, a college student abusing cats, and Heilongjiang coal mine accident, from the social media platform Sina Weibo as experimental data. The first incident is summarized as follows.

The incident that took place on July 19, 2024, at the First Affiliated Hospital of Wenzhou Medical University involved a heinous attack on a doctor. A man armed with a knife injured a doctor and subsequently jumped off the building. Tragically, the doctor could not be saved and succumbed to the injuries. It was revealed that the man who committed the assault was a family member of a patient. His wife had undergone surgical treatment in this hospital but was unsuccessful, which led to great resentment and dissatisfaction towards the hospital and the doctors. The doctor who lost his life was not the primary surgeon during the operation and was mistakenly targeted in this tragic incident.

The comment data of three events was preprocessed. Useless information such as English letters, spaces, and punctuation marks were removed from the text. Stop words were removed based on the stop word list of the Natural Language Processing Laboratory of Harbin Institute of Technology. The Jieba library was used to complete Chinese word segmentation. Then, the sentiment categories were manually labeled. The distribution of public opinion data for the three events is shown in Table 1.

Table 1: The experimental dataset.

	Positive public opinion	Negative public opinion
A man in Wenzhou attacking a doctor	9,832	10,584
A college student abusing cats	2,033	2,934
Heilongjiang coal mine accident	7,658	8,965

Taking the first event as an example, partial public opinions are shown in Table 2.

Table 2: Examples of public opinions.

Negative public opinion	Positive public opinion
Condemnation is of no use at all.	It is hoped that security measures can be implemented to strengthen the police-medical linkage to protect the safety of doctors and patients.
This kind of thing is sad, outrageous, and unmitigated. I hope that the protection of healthcare workers will be strengthened and that the perpetrators of crimes will be severely punished and will not be tolerated at all.	Hospitals should be a safe and harmonious environment, and it is vital to protect the safety of healthcare workers.
What is the reason? Why not trace? Why not publish the details? The doctor's life is gone. Why was he killed? Afraid to trace?	Where to find the benevolence of the doctors, the heart of justice cannot be sunk.
Why do the authorities only think of solutions when something bad happens?	Punish the perpetrators severely and maintain harmony between doctors and patients!
Why attack innocent people?	Resolutely defending doctors' dignity, safeguarding life's safety, and building a harmonious medical environment.

The sentiment classification experiments adopted the ten-fold cross-validation. The results were averaged and subjected to a statistical significance test. The 10,584 negative opinions were organized in chronological order, and the number of negative views per hour was taken as the experimental data, with the first 80% as the training set and the last 20% as the test set, which was used for the negative opinion dissemination trend prediction experiment. For the algorithm evaluation, the evaluation indicators of the sentiment classification effect are as follows.

(1) Precision

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

(2) Recall rate

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

(3) F1

$$F_1 = \frac{2PR}{P + R}$$

TP denotes the number of samples that are correctly predicted as positive. FP denotes the number of samples that are incorrectly predicted to be positive. FN denotes the number of samples that are incorrectly predicted to be negative.

The indicators for evaluating the effectiveness of predicting the trend in the dissemination of negative public opinion are as follows.

(1) Mean square error (MSE)

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(\hat{y}_i - y_i)^2$$

(2) Root mean square error (RMSE)

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(\hat{y}_i - y_i)^2}$$

(3) Mean absolute error (MAE)

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|(\hat{y}_i - y_i)|$$

(4) Mean absolute percentage error (MAPE)

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{\hat{y}_i - y_i}{y_i}\right| \times 100\%$$

In the above equations, $\hat{y}_i$ is the predicted result and y_i is the true value.

3.2 Results analysis

Based on Table 3, it is evident that the BiLSTM algorithm performed the best in sentiment classification of opinions on social media, and its differences with the CNN and LSTM algorithms were significant (P = 0.9233), showing an improvement of 0.1379 compared to the CNN algorithm and 0.0539 compared to the LSTM algorithm. Additionally, the BiLSTM algorithm exhibited an R-value of 0.9164, surpassing the CNN algorithm by 0.0439 and the LSTM algorithm by 0.027. The F1-value for the BiLSTM algorithm was 0.9198, showing an enhancement of 0.0931 compared to the CNN algorithm and 0.0405 compared to the LSTM algorithm. These results highlight that the BiLSTM algorithm could more comprehensively capture contextual information within the text.

Table 3: Comparison of sentiment categorization effectiveness.

	P	R	F1
CNN [18]	0.7854±0.0562	0.8725±0.0557	0.8267±0.0567
LSTM [19]	0.8694±0.0458	0.8894±0.0482	0.8793±0.0495
BiLSTM	0.9233±0.0517[ab]	0.9164±0.0521[ab]	0.9198±0.0552[ab]

Note: a: $p < 0.05$ compared to CNN; b: $p < 0.05$ compared to LSTM.

To evaluate the improvement effect of the ISSA on the BPNN algorithm, the PSO, SSA, and ISSA were compared using benchmark test functions (Table 4). The population size was set as 30, and 1,000 iterations was also set. The test results are shown in Table 5.

Table 4: Benchmark test function.

Test function	Range of value	Optimal solution
$\boldsymbol{F_1(x) = \sum_{i=1}^{n} x_i^2}$	[-100,100]	0
$\boldsymbol{F_2(x) = \sum_{i=1}^{n}\lvert x_i\rvert + \prod_{i=1}^{n}\lvert x_i\rvert}$	[-10,10]	0
$\boldsymbol{F_3(x) = \sum_{i=1}^{n}\left(\sum_{j=1}^{i} x_j\right)^2}$	[-100,100]	0
$\boldsymbol{F_4(x) = \sum_{i=1}^{n}\left[x_i^2 - 10\cos 2\pi x_i + 10\right]}$	[-5.12,5.12]	0
$\boldsymbol{F_5(x) = -20exp\left(-0.2\sqrt{\frac{1}{n}\sum_{i=1}^{n} x_i^2}\right) - exp\left(\frac{1}{n}\sum_{i=1}^{n}\cos 2\pi x_i\right) + 20 + e}$	[-32,32]	0

According to Table 5, when compared to the PSO algorithm, the optimization performance of the SSA was notably superior, showing enhanced accuracy and stability. Moreover, the comparison between the SSA and ISSA revealed that the ISSA demonstrated smaller mean and standard deviation values for each function solution, indicating that it could find optimal solutions more effectively. These results verified the effectiveness of the improvement made to the SSA.

Table 5: Test results.

		PSO	SSA	ISSA
$\boldsymbol{F_1}$	Mean value	1.1254×10^{4}	4.7415×10^{-7}	9.1254×10^{-47}
	Standard deviation	3.5214×10^{3}	1.9254×10^{-6}	4.5214×10^{-46}
$\boldsymbol{F_2}$	Mean value	4.5287×10^{2}	1.5214×10^{-3}	5.2179×10^{-18}
	Standard deviation	1.7154×10^{3}	6.5524×10^{-3}	1.6387×10^{-17}
$\boldsymbol{F_3}$	Mean value	4.1254×10^{4}	8.5413×10^{-6}	2.1596×10^{-34}
	Standard deviation	1.9524×10^{4}	3.5418×10^{-5}	1.6289×10^{-33}
$\boldsymbol{F_4}$	Mean value	2.8524×10^{2}	1.5248×10^{-2}	0
	Standard deviation	2.6145×10^{1}	7.5874×10^{-2}	0
$\boldsymbol{F_5}$	Mean value	1.6254×10^{1}	1.7415×10^{-4}	4.1297×10^{-16}
	Standard deviation	9.2541×10^{-1}	4.4652×10^{-4}	0

The convergence curves were given taking F_1 as an example (Figure 2). From the convergence curves in Figure 2, it can also be found that compared with the PSO algorithm and SSA, the ISSA required the fewest number of iterations. This indicated that the ISSA had not only higher accuracy but also a faster convergence speed and lower computational cost.

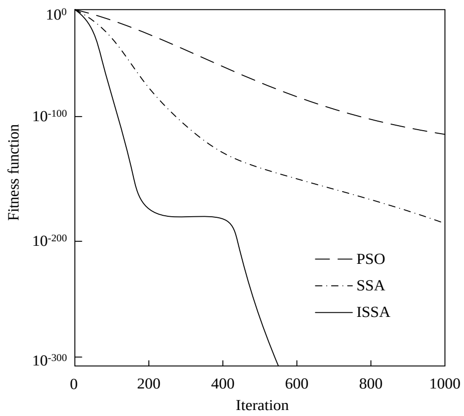

Figure 2: The convergence curves when the benchmark test function is F_1.

Then, the ISSA-BPNN algorithm was applied to predict the negative public opinion dissemination trend, and it was compared with other prediction algorithms (Table 6).

Table 6: Comparison of the effectiveness of predicting trends in the dissemination of negative public opinion.

	MSE	RMSE	MAE	MAPE
SVM [20]	1,685.52	41.06	156.25	8.97%
BPNN [21]	1,452.67	38.11	89.62	7.16%
PSO-BPNN [22]	1,251.52	35.38	45.85	5.09%
Transformer [23]	936.58	30.77	36.85	4.21%
ISSA-BPNN	845.14	29.07	21.56	

From Table 6, it can be observed that the SVM algorithm performed poorly in predicting the negative public opinion dissemination trend, with high errors. The MSE was 1,685.52, the RMSE was 41.06, the MAE was 156.25, and the MAPE was 8.97%. In contrast, the prediction performance of the BPNN algorithm showed significant improvement, indicating the reliability of choosing BPNN as the prediction model. When comparing several BPNN-based methods, it is evident that optimizations made by both PSO and ISSA contributed to the improved prediction performance of the BPNN. Specifically, the ISSA-BPNN algorithm demonstrated superior performance, with a MSE of 845.12, a RMSE of 29.07, a MAE of 21.56, and a MAPE of 3.67%, showing a 32.47% decrease, 17.83% decrease, 52.98% decrease, and 1.42% decrease compared to the PSO-BPNN algorithm. Moreover, compared with the Transformer algorithm, the ISSA-BPNN also had more advantages. These results validate the effectiveness of the ISSA-BPNN algorithm in forecasting negative public opinion dissemination trends and support its practical application.

While affirming its technical value, it is necessary to discuss the moral implications and potential abuses faced by the proposed method. In practical applications, the prediction of the spread trend of negative public opinion can provide services for the public sector's work such as public opinion guidance and crisis early warning, so as to intervene in a timely manner, ease contradictions, and maintain the stability of the online environment. However, if this technology is used for malicious purposes, such as public opinion manipulation, dissent suppression, and false propaganda, it may curtail freedom of speech and the public's right to know. Therefore, when using this technology, it is necessary to establish and improve relevant ethical constraints and regulatory mechanisms to avoid the abuse of technology and ensure that the use of technology is people-oriented.

4 Conclusion

In this study, the BiLSTM algorithm was used to classify public opinion sentiments and identify negative sentiments. Subsequently, an optimized machine learning approach, ISSA-BPNN, was developed to forecast the dissemination trend of negative public opinion on social media. Experimental results showed that the BiLSTM algorithm achieved an F1 value of 0.9198 for sentiment categorization, and the ISSA-BPNN algorithm outperformed SVM and other methods in predicting the spread of negative opinions. The proposed method demonstrates a great reliability, making it suitable for supervising public opinions on social media in real-world applications.

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