

Retraction

Retracted: Network Media Public Opinion and Social Governance Supported by the Internet-of-Things Big Data

Security and Communication Networks

Received 10 October 2023; Accepted 10 October 2023; Published 11 October 2023

Copyright © 2023 Security and Communication Networks. This is an open access article distributed under the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

- (1) Discrepancies in scope
- (2) Discrepancies in the description of the research reported
- (3) Discrepancies between the availability of data and the research described
- (4) Inappropriate citations
- (5) Incoherent, meaningless and/or irrelevant content included in the article
- (6) Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

- [1] Y. Zhao and R. Miao, "Network Media Public Opinion and Social Governance Supported by the Internet-of-Things Big Data," *Security and Communication Networks*, vol. 2022, Article ID 2459815, 11 pages, 2022.

Research Article

Network Media Public Opinion and Social Governance Supported by the Internet-of-Things Big Data

Yixin Zhao¹ and Ruomu Miao ²

¹The Experimental High School Attached to Beijing Normal University, Beijing 100032, China

²School of Media and Communication, Shanghai Jiaotong University, Shanghai 200240, China

Correspondence should be addressed to Ruomu Miao; miaoruomu@sjtu.edu.cn

Received 28 June 2022; Accepted 21 July 2022; Published 17 August 2022

Academic Editor: Mohammad Ayoub Khan

Copyright © 2022 Yixin Zhao and Ruomu Miao. This is an open access article distributed under the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

The purpose is to make for the traditional Network Public Opinion (NPO) analysis methods' inadequacy in the era of big data and provide a sufficient decision-making basis for managers. Based on the Internet of Things (IoT) and big data, this work applies Natural Language Processing (NLP) to NPO analysis. Additionally, it takes the content of Microblog text format as the main collection target, constructs a big data collection tool, and establishes Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU), Deep Pyramid Convolutional Neural Network (DPCNN) based on Tensorflow and other deep learning models. It is also improved in combination with the characteristics of the model, and a new model is proposed. Finally, the performance of various models is compared and analyzed through experiments, and the path is proposed for the government to use big data to improve the ability to govern NPO and help social governance. The results show that the improved LSTM model can correctly classify the extracted Microblog text's emotion by as much as 80.00%. It improves the classification accuracy by nearly two percentage points under the ideal condition. Thus, by adding residual connection and attention mechanism, the model can extract the emotional features in the text better and improve the emotional discrimination ability. The public opinion of online media without effective control will have great security risks to social governance under the big data and IoT. The proposed method is of great help in analyzing NPO through the accurate analysis of Microblog text.

1. Introduction

Chen She Shi Jia [the biography of two peasant uprising leaders in the Qin dynasty (221 BC–207 BC)] mentioned, "Without digital communication, public opinion on major events could only be spread by word-of-mouth in ancient China." Even in modern traditional media, the speed of public opinion generation and dissemination seems to be expected and mostly under control [1–3]. Such a situation has been fundamentally changed since the twenty-first century with the rapid development of digital technology, the Internet, and big data technology, which has given birth to various new media. The emergence of new media has had a significant impact on the development of Network Public Opinion (NPO) [4, 5]. A circle of friends and a message Microblog might easily trigger NPO. Meanwhile, the speed

of NPO dissemination over the Internet is unexpected and hard to control. With the increase of Internet voice paths, everyone can be the disseminator and producer of network media. Various online media and NPO can find similar voices on the Internet. A massive amount of information can be excavated from public opinion [6, 7]. Therefore, relevant departments are under great pressure to control and guide NPO. In particular, the public opinion monitoring system can control and guide NPO from the root to avoid possible degeneration or fermentation [8, 9].

Hubert et al. [10] understood citizens' political preferences through emotional analysis of Twitter text data and predicted the popularity of Italian and French leaders and the results of Internet elections in 2011 and 2012. The results proved the correlation between social media and the results of traditional public surveys. Based on this, the future

development of some public events was predictable [10]. Li and Xu [11] analyzed the “1.16 school bus accident” through big data technology, used the Internet to collect NPO, and designed the network communication path map of the event [11]. Li et al. [12] analyzed the source of the development of Twitter NPO. They provided a way out of social media network data for NPO research and analysis [12]. Kostka [13] created a big data NPO analysis system, improved the information database into a distributed storage database, and proved that the system was effective [13]. Khalil et al. [14] used Twitter and web crawlers to obtain Hemagglutinin 1 Neuraminidase 1 (H1N1) influenza development data. They tracked the situation of H1N1 influenza [14]. Zaidi et al. [15] studied the Attribute-Based Access Control (ABAC) of web crawlers to facilitate unrestricted Microblog text data access [15]. Dang et al. [16] evaluated the network hot spots by cleaning the text of the NPO from the network, combining it with the domain dictionary and similarity calculation [16]. Mahmood and Qasim [17] used the Support Vector Machine (SVM) and Naive Bayes Model (NBM) to study NPO [17]. Huang [18] obtained Microblog and blog data through a web crawler and studied the classification of NPO texts by using the SVM model [18]. Liu et al. [19] analyzed the interaction between social media-based NPO analysis and government management. The outcome corroborated that through Big Data Analytics (BDA) technology, social media-based NPO analysis provided information support and data source for government management. BDA could be used to monitor and control NPO [19].

Scholars above have affirmed the important role of BDA in NPO spread and governance by studying NPO from the aspects of data acquisition, information analysis, and technology application. However, the existing method invests too much time, costs, and energy into NPO data information mining. Besides, their NPO prediction accuracy cannot be guaranteed. Deep Learning (DL) can improve the prediction accuracy but might get affected by many model parameters. To this end, after clarifying the research of BDA on NPO and considering NPO information acquisition, this work creates an improved DL NPO analysis system based on Tensorflow. The method proposed here is of great help to analyzing NPO through the accurate analysis of Microblog text, conducive to judging network media public opinion in the era of big data. It provides a research path for the management and decision-making of network media public opinion. The innovations of this work are as follows: first, given the problems and reasons for the current NPO governance, this work puts forward the improvement path of government NPO governance from the aspects of ideology, system, technology, and structure based on big data and the Internet of Things (IoT). The second is the innovation of research methods. With the help of the improved Long Short-Term Memory (LSTM) model, an NPO analysis system based on Tensorflow is established to explore new network media public opinion management paths.

Section 1 reviews the development and current situation of NPO and discusses the research on NPO governance by combining big data, and other information technology

means in and outside China. The analysis provides the research background for this work. Section 2, the research theory and method part, explains the propagation law of NPO, the application of Natural Language Processing (NLP) technology in NPO analysis, and the DL model, and establishes the NPO analysis system based on the LSTM optimization model. Then, Section 3 is the configuration of the model performance experiment environment. Section 4, the result analysis part analyzes the performance of the LSTM-based NPO analysis system and the classification results of Microblog text under the improved LSTM model. It also describes the construction of public opinion in online media and the path for the government to use big data to improve the ability to govern NPO and help social governance. Lastly, Section 5 is the conclusion, describing the research results, significance, deficiencies, and future research directions.

2. Research Theory and Method

2.1. Propagation Law of NPO under Network Media. In the context of the Internet, netizens express their understanding and views on various political and social phenomena online. In recent years, they have been able to talk freely about various national and social development issues by taking advantage of the Internet’s “everyone to everyone communication.” They can form a consensus quickly, ferment their emotions, induce action, and then affect society. Netizens’ willingness to express and sense of participation continued to rise, and they actively expressed their opinions on major media. On the one hand, the government strengthens network management and suppresses excessive extreme speech. On the other hand, the response speed of NPO has accelerated, and the government has initially formed the NPO monitoring and feedback from the central to the local. The main sources of NPO in network media include website news comments, Bulletin Board System (BBS), Really Simple Syndication (RSS), Oh, I Seek You (QICQ), Microsoft Network (MSN), Blog, and Microblog. Figure 1 lists the formation process of NPO caused by public events in network media.

Figure 1 shows the formation of NPO as a “linear process.” The opinion formed in each link is interrelated. Under normal circumstances, the NPO formation is a gradual process. When the stimulus-response mechanism appears, NPO will form an emergency mode. Stimulus is an emergency, and NPO is a reactant. Once an emergency occurs, it will spread rapidly on the Internet, causing a strong public response, and the expression of public opinion will be concentrated and intense. Ross et al. [20] analyzed the propagation law and causes of NPO and found that the hot cross-domain public opinion events on the network detonated rapidly. The empathy effect prompted netizens to reveal similar experiences. Unclosed public events triggered netizens to continue to ask questions, and human intervention intensified NPO propagation. There was a public opinion evacuation effect. The intervention of the government’s authority and the high-level society improved the public opinion guidance effect. As a result, the group

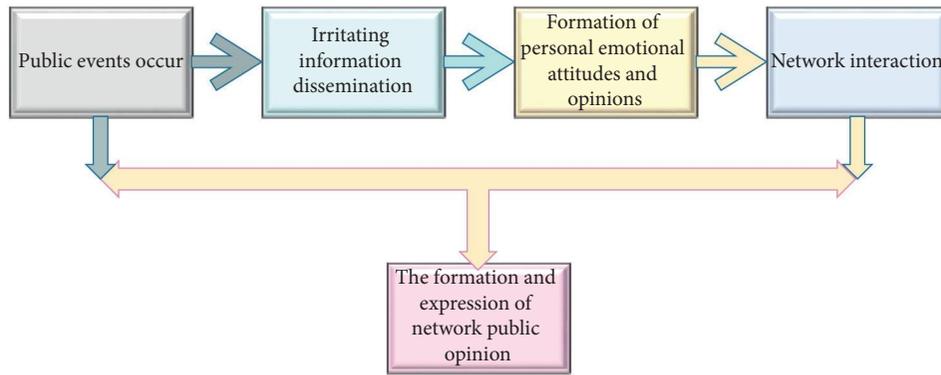


FIGURE 1: The formation process of NPO in network media.

polarization effect of the public opinion community intensified. Identifying the authenticity of network information became the knowledge of public opinion. Multiple attributions enhanced the voice of collaborative governance [20]. Table 1 details the propagation law of NPO caused by public events in network media.

The development of modern communication technology has greatly changed the mode and pattern of media communication. The development and maturity of the Global Satellite System have popularized personal electronic information products and improved network information transmission speed. A global mass communication pattern dominated by network media and supplemented by other technologies is taking shape. Figure 2 shows the network media's control relationship between IoT, BDA, and NPO.

In Figure 2, the internal motivation of NPO formation in network media includes interest demand and psychological force. Of these, the public's favorable demand is the driving source of NPO formation. The external motivation includes the function of the social environment and the force of NPO space in cyberspace. IoT and BDA are used to control and manage the NPO of network media. NPO evaluation needs to consider various factors and variables comprehensively. According to the above formation process, Table 2 explains the propagation laws and characteristics of NPO and the evaluation indexes of NPO.

2.2. Application of NLP Technology in NPO Analysis. The DL algorithm has pushed artificial intelligence (AI) to a higher level in recent years. NLP technology has seen broad applications in the network-indexing field. It includes new words mining on the Internet, ranking popular words on the Internet, and analyzing NPO and emotional bias using long and short sentences in the text. It also involves major social media platforms' topics and retrieval trends. These applications can help enterprises or individuals better understand the topics and events of public interest and count the development trend of topics and events. Ultimately, it helps the society make effective judgments and relevant governance. Accordingly, by researching, processing, and analyzing NPO text big data, this work summarizes the characteristics of text

expression under IoT and BDA. Specifically, it solves the technical challenges in NLP-related applications by exploring natural language's grammar logic and character vector representation. Then, the core technology chooses the deep semantic analysis to realize the application requirements of NPO text intelligent classification, intelligent text recommendation, and automatic generation of text information based on semantic understanding. The aim is to promote the social NPO governance from digitization and networking to intelligent development. Figure 3 depicts the application principle of NLP technology.

According to Figure 3, NLP works through machine learning (ML). ML systems store words and how they are combined like any other form of data. Phrases, sentences, and sometimes the book's contents are input into the ML engine, where grammatical rules, people's real language habits, or both are used for processing. Then, the computer uses the data to find the pattern and infer the next result. Notably, while Machine translation is a powerful NLP application, searching is one of the most common uses. Every time people search for content in Google or Bing search engine, they manually input data into the system. Upon clicking on a search result, the search engine interprets and confirms that it has found the correct result and uses this information to search better in the future. DL technology analyzes the semantic information of public opinion information and intelligently and accurately classifies the information. Then, it recommends relevant results and automatically generates concise main content of public opinion. The data acquisition module collects NPO texts in real-time and saves the text information to the database of the data storage layer. Simultaneously, the data-pre-processing module cleans and organizes the data according to the information processing needs. It classifies, summarizes, recommends texts, and extracts keywords through the NLP engine of the online computing module. Finally, the model results are saved to the database [21]. Further, NLP technology processes the Microblog texts. Figure 4 illustrates the application principle of NLP technology in NPO information collection.

Figure 4 first collects the NPO upon public event occurrence from major media websites as the learning samples

TABLE 1: The propagation law of NPO caused by public events in network media.

Propagation law	Features
Cross-domain hot NPO detonates quickly	Explosive transmission
Empathy drives netizens to support or expose similar experiences	Concealment of subject
The open loop incident triggered continuous attention and questioning from netizens	The fuzziness of information source
The law of round-the-clock, all media, real-time, and all channels of NPO communication is obvious	Interaction of netizens
Opinion leaders can sometimes even influence the direction of NPO	Directivity of opinions
The group polarization effect of the community of NPO intensifies	Significance of impact

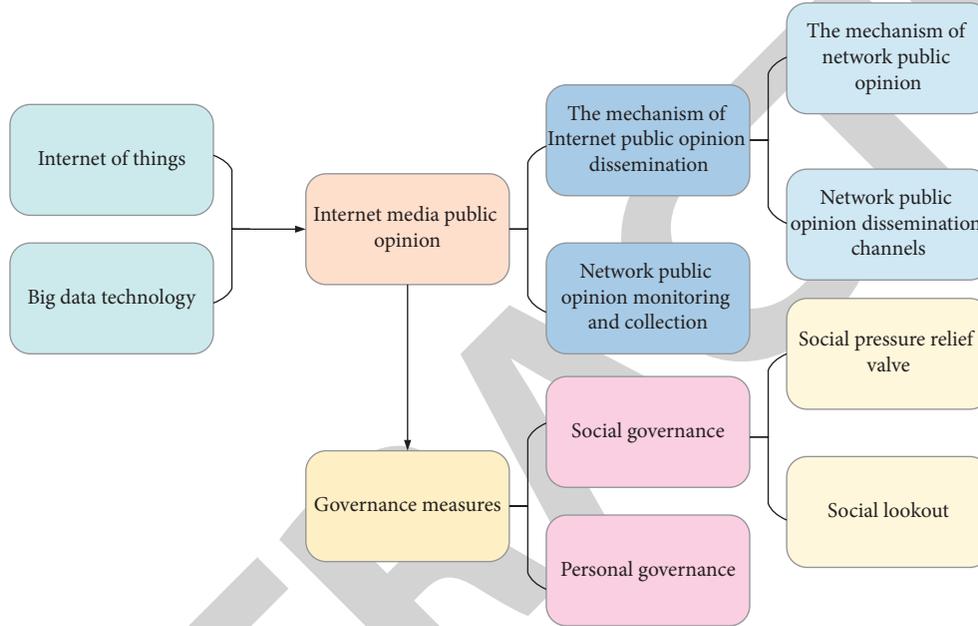


FIGURE 2: Control connection between IoT, BDA, and NPO in network media.

TABLE 2: Evaluation index of NPO.

Evaluation index	Detailed indexes
Propagation and diffusion	Changes in NPO information flow and regional distribution of network geography
Public concern	Forum, news, blog, and other channels' NPO information activity
Content sensitivity	Content sensitivity of NPO information
Attitude tendency	Attitude tendency of NPO information

of ML. Second, it inputs the sample features into the ML model to generate the NPO paragraph recognition model. Finally, the extracted features of the target NPO document are input into the ML model.

2.3. *Common DL Models.* Hochreiter and Schmidhuber proposed LSTM in their academic paper Long Short-Term Memory to solve the gradient disappearance in common DL models. The original LSTM has only an input gate and output gate. So far, a forget gate is also introduced into LSTM, an improved version of Gers in his book *Learning to Forget: Continual Prediction with LSTM*. Figure 5 draws an LSTM structure.

In Figure 5, the LSTM structure includes three gate structures. Essentially, they are the weights $\in [0, 1]$ and can be realized by the Sigmoid function. The cell represents the state of the current memory block and corresponds to the hidden layer neurons in the original Recurrent Neural Network (RNN). The white circles and functions represent the activation function (AF). There is a general standard for selecting AF. In particular, f is the AF of the gate structure. g denotes the AF of the cell input, and h indicates the AF of the cell output. Generally, the input gate, output gate, and forget gate choose the Sigmoid function as AF. The input and cell select the \tanh function for activation [22]. The specific calculation of the input gate, forget gate, and output gate are given in equations (1)–(3).

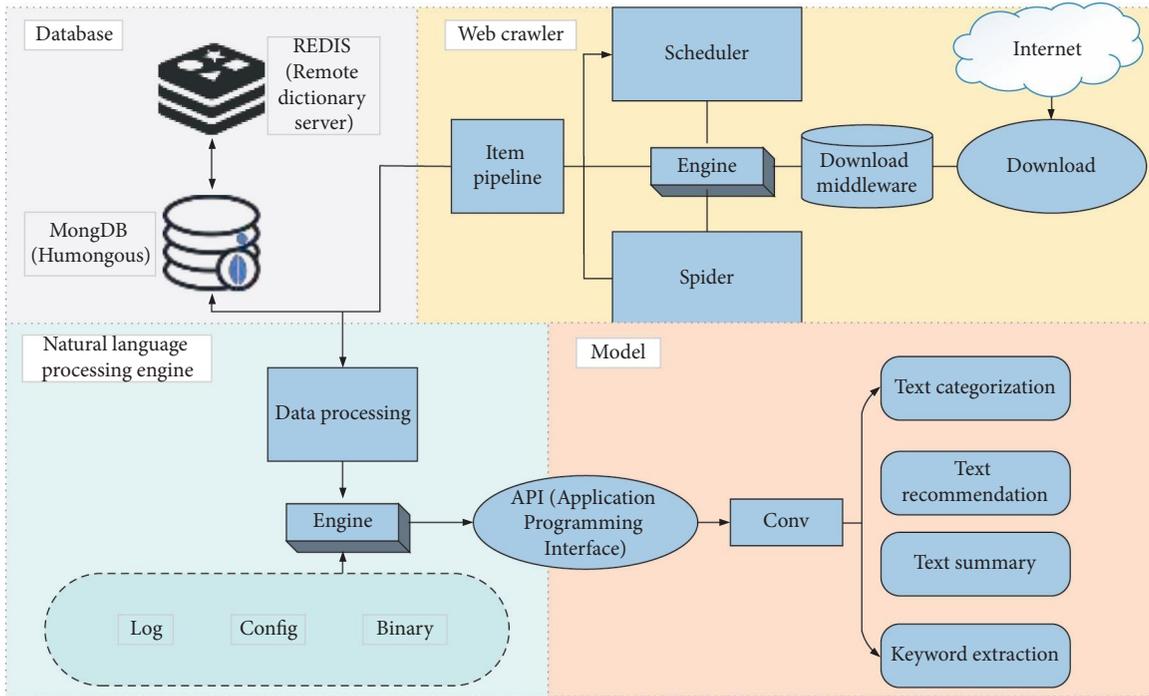


FIGURE 3: Application principle of NLP technology.

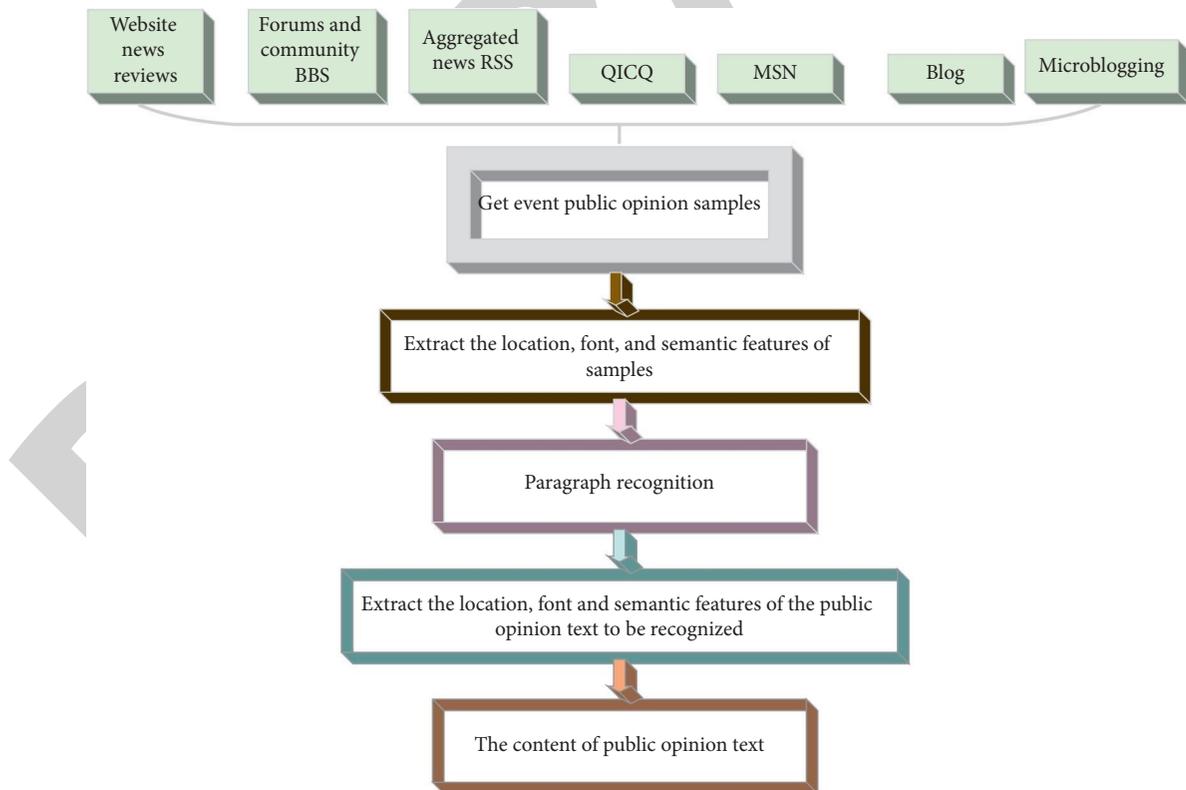


FIGURE 4: Application principle of NLP technology in NPO information collection.

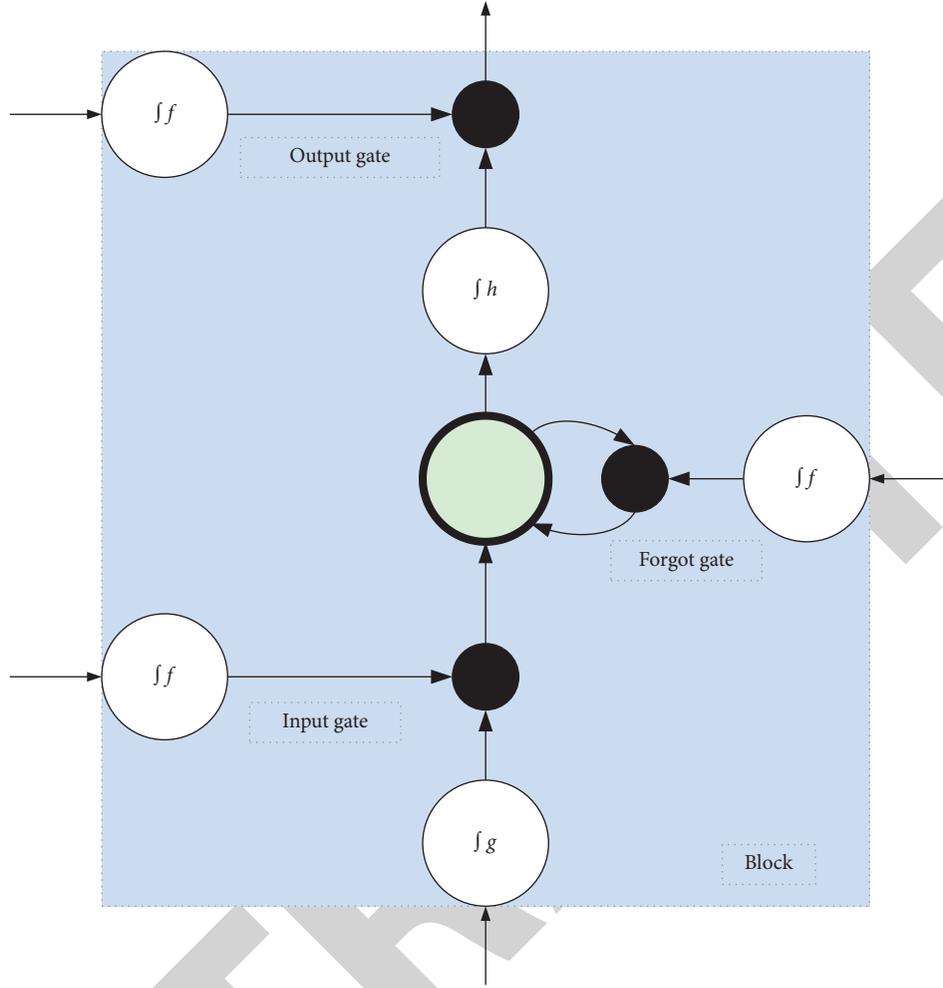


FIGURE 5: LSTM structure.

$$i_t = \text{sigmoid}(W_i \cdot [h_{t-1}, x_t] + b_i), \quad (1)$$

$$f_t = \text{sigmoid}(W_f \cdot [h_{t-1}, x_t] + b_f), \quad (2)$$

$$o_t = \text{sigmoid}(W_o \cdot [h_{t-1}, x_t] + b_o). \quad (3)$$

Here, i_t , f_t , and o_t are the output of the input gate, forget gate, and output gate, respectively. h_{t-1} represents the output of the previous moment. x_t is the input at the current moment. These two parameters enter the forget gate first to get the information with a smaller weight and then determine the information to be discarded: f_t . The output gate updates information as i_t that has a larger weight than the previous layer information. W and b mean the weight and threshold in each gate, respectively. Then, the forget gate discards the information through (2). Afterward, new information is added to the cell state. First, the information will be updated using the input gate, and then the new candidate cell information \tilde{C}_t will be obtained through a \tanh layer. The new candidate information may be updated to the new cell. The expression of candidate cell status reads:

$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] + b_C). \quad (4)$$

Next, the old cell information C_{t-1} is updated and converted into new cell information C_t . Here is the update rule: the forget gate determines what to discard in the old cell information. Then, the input gate calculates the candidate cell information \tilde{C} and adds it to get the new cell information C_t . The specific expression reads:

$$C_t = f_t \cdot C_{t-1} + i_t \cdot \tilde{C}_t. \quad (5)$$

Finally, h_{t-1} and x_t are inputted to judge the state characteristics of the output cell. Then, the input will pass through the Sigmoid layer in the output gate to determine the judgment conditions. As a result, a vector $\in [-1, 1]$ is obtained through the \tanh layer. Further, the vector is multiplied by the judgment conditions of the output gate to obtain the final output. The specific calculation reads:

$$h_t = o_t \cdot \tanh(C_t). \quad (6)$$

Additionally, the multilayer LSTM parameters are calculated by (7):

$$n \times 4[d_h(d_h + d_x) + d_h]. \quad (7)$$

In (7), n represents the number of layers of LSTM. d_x and d_h are the input and output dimensions. The LSTM has three gates, which are more complex than the direct calculation output. For experimental comparison, this work employs Gated Recurrent Unit (GRU). Figure 6 presents the GRU structure.

In Figure 6, R and Z are reset gate and update gate, respectively, and H is the update output of Z . Comparing Figures 5 and 6 reveal that GRU and LSTM have some similarities. Their differences are that GRU does not have the cell in LSTM but directly calculates the output. The update gate in GRU is similar to the fusion of the input gate and forget gate in LSTM. Observing the structure and the gate connected at the last moment shows that the forget gate in LSTM is actually divided into the update gate and reset gate in GRU [23]. The calculation process of GRU is detailed in equations (8) to (11):

$$R_t = \text{sigmoid}(W_r \cdot [h_{t-1}, x_t] + b_r), \quad (8)$$

$$Z_t = \text{sigmoid}(W_z \cdot [h_{t-1}, x_t] + b_z), \quad (9)$$

$$\tilde{H}_t = \tanh(W \cdot [x_t, h_{t-1} \odot R_t]), \quad (10)$$

$$H_t = (1 - Z_t) \odot H_{t-1} + Z_t \odot \tilde{H}_t. \quad (11)$$

Here, h_{t-1} and x_t are the output and input of the previous moment, respectively. The output of the current moment is H_t . Then, weighted-multiplication is performed on h_{t-1} and x_t and is activated by sigmoid to obtain the update gate Z_t and the reset gate R_t . The reset gate controls the previous state information to be written to the current candidate set \tilde{H}_t . W and b represent the weight and threshold in each information update, respectively.

2.4. Network Media NPO Analysis System Based on LSTM Neural Network (NN) Optimization Model. According to Section 2.3, the NN model supported by IoT and BDA is preliminarily analyzed. The commonly used DL frameworks TensorFlow and Pytorch also have some subtle differences in the implementation of LSTM. TensorFlow is the second-generation AI learning system developed by Google based on DistBelief. TensorFlow can be applied in many places, such as Speech Recognition (SR), Natural Language Understanding (NLU), and Computer Vision (CV). It can run on everything from smartphones to thousands of data center servers. However, there are still some problems in implementing LSTM on TensorFlow.

In practical application, the traditional computing platform cannot carry such a large amount of data computing of LSTM. Due to the massive amount of parameters and massive training data and reasoning test data, the training model and model reasoning have high-computational complexity. Thus, the power consumption is generated from the computing platform. Some researchers introduce the delta algorithm to accelerate hardware

calculation of sparse LSTM model. They used the numerical similarity of sequence data to construct and mine the sparsity of sequence data, reconstruct the LSTM model, and accelerate the algorithm. This method has obvious limitations in the scope of application. The hardware acceleration of LSTM model reconstruction based on the delta is complex and not conducive to hardware deployment. In this work, the sparsity of LSTM model parameter weights is improved. The specific improvement process is shown in Figure 7.

Figure 7 prunes the LSTM model by removing redundant parameters or setting them to 0. Since model training is based on floating-point numbers and consumes resources, K-Means Clustering (KMC) can be used to minimize parameters [24]. (9) reveals the specific calculation:

$$\arg \min \sum_{i=1}^k \sum_{w \in c_i} |w - c_i|^2. \quad (12)$$

In (9), w is the training parameter set. c_i denotes the parameter after classification. The weight data after pruning and quantization are greatly reduced for the point multiplication operation in LSTM. In order to transmit only effective weights, the weight data needs to be sparsely encoded. The trained network weights are trimmed into the sparse matrix, and then the nonzero weights are fine-tuned by the Fine-grained Structured Sparsity (FGSS) method. After the network weight is compressed, the data space and bandwidth are reduced by half. The sparse tensor core of the original network weight doubles the throughput of mathematical calculation by skipping zero. Against gradient disappearance, the residual connection is used to add 1 to the error reciprocal in the training process of the LSTM model. At this time, even if the original error reciprocal is tiny, the error can still be effectively back propagated to optimize the LSTM model. The proposed network media NPO analysis system based on LSTM using TensorFlow is portrayed in Figure 8.

In Figure 8, the LSTM NPO analysis system based on Tensorflow first inputs the search keywords. It obtains the event NPO information in the web crawler and stores the data in the database. Second, Tensorflow processes the data and uses the optimized LSTM model to analyze public opinion. In order to solve the long-term dependence problem in the LSTM, the residual connection is introduced. It combines the original word vector information with the extraction result of the model and is inputted to the attention layer. Finally, the classification result in the output layer is obtained.

3. Experimental Environment Configuration and Experimental Data Processing

This experiment uses Python, a programming language widely used in data processing and DL. The experiment is deployed under the Linux environment. The operating system chooses Ubuntu 18.04 with a 16 G Radom Access Memory (RAM), an Intel i7-9900k Central Processing Unit (CPU), and the GTX2080Ti Graphics Processing Unit (GPU). The DL framework is TensorFlow 2.0, and the

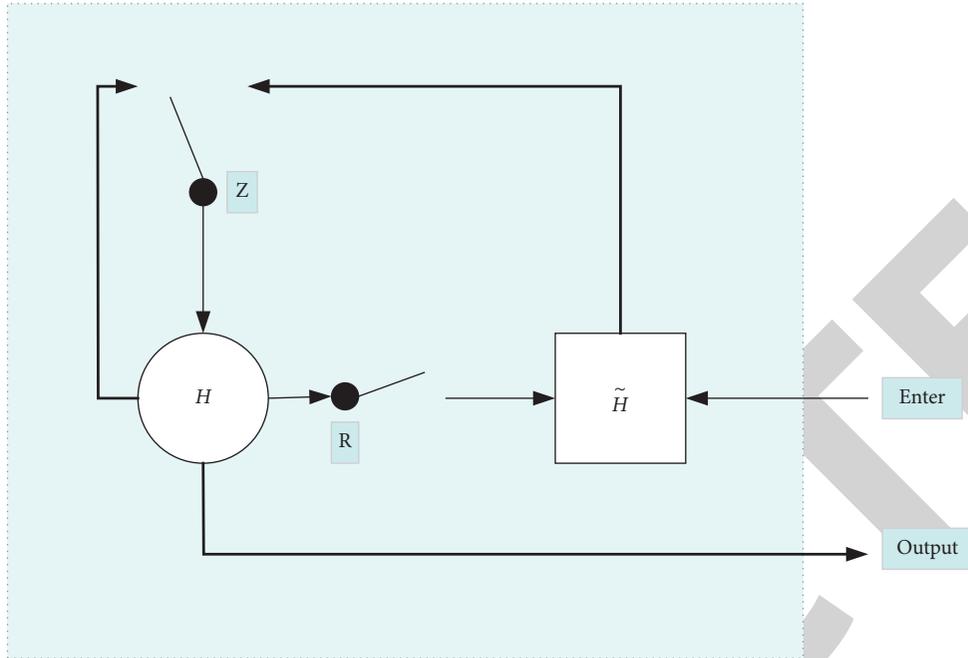


FIGURE 6: GRU structure.

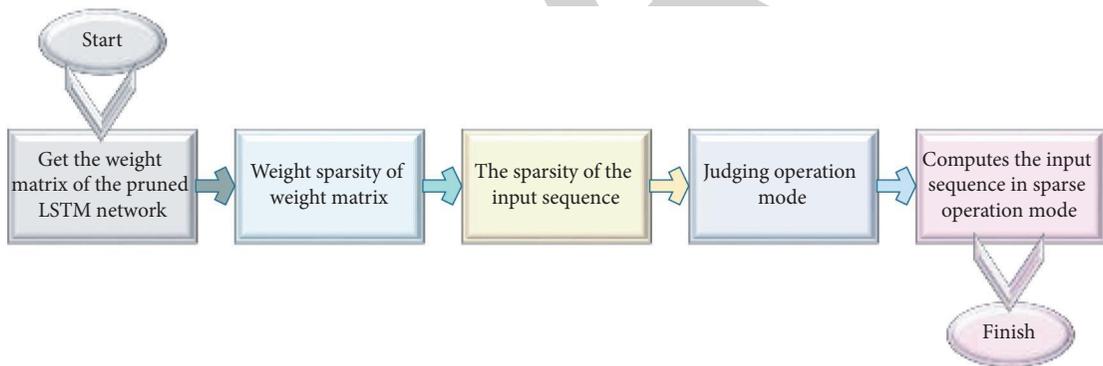


FIGURE 7: Improvement process of parameter weight sparsity of the LSTM model.

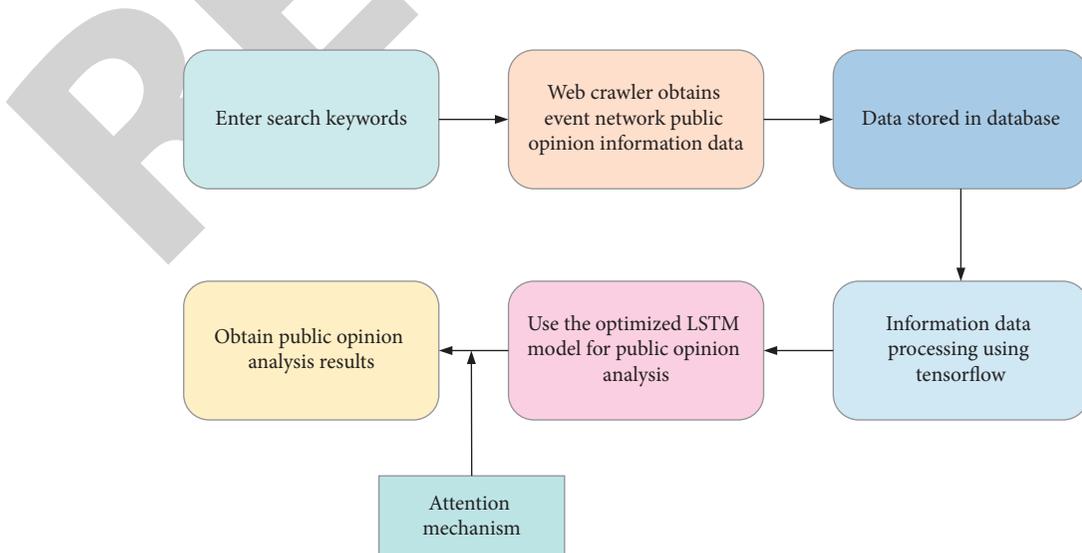


FIGURE 8: Network media NPO analysis system based on LSTM NN implemented on tensorflow.

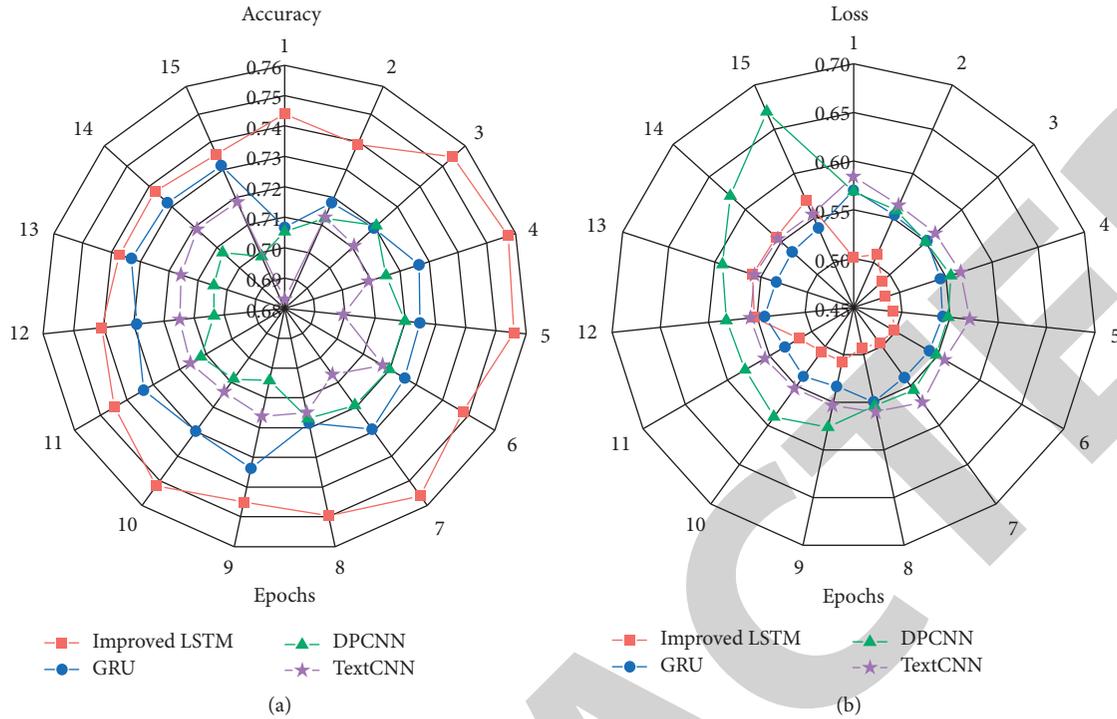


FIGURE 9: The analysis of the model results: (a) The accuracy of network media NPO analysis. (b) Loss rate of network media NPO analysis.

Integrated Drive Electronics (IDE) is PyCharm 2020. The experimental data training adopts the Microblog text data set, containing 100,000 Microblog texts and the corresponding emotional tendencies that predecessors have marked. Meaningless characters are removed. Redundant spaces are merged. Microblog expressions are retained. Some texts rendered meaningless after data cleaning will be removed from the data set.

4. Results Analysis

4.1. Result Analysis of DL Models. Shekhar et al. [25] applied LSTM to social media. LSTM network model can learn and accurately predict the language used in social media texts. The performance of different models was compared, reflecting the proposed model’s advantages [25]. Inspired by this, this section takes the Microblog text content as the primary research subject. Then, the performance is analyzed for the proposed LSTM-based network media NPO analysis system by comparing different DL models: LSTM, GRU, DPCNN, and Text Convolutional Neural Network (TextCNN). Each model’s characteristics are comparatively analyzed to put forward an improved LSTM model. Figure 9 plots the model analysis results. Figures 9(a) and 9(b) present the results of the accuracy and loss rate of network media NPO analysis, respectively.

According to Figure 9, the accuracy of the improved LSTM model is significantly higher than that of other models, and the loss rate is significantly lower than that of other models. The average accuracy of the improved LSTM, GRU, DPCNN, and TextCNN is 74.65%, 72.61%, 71.13%,

and 71.12%, respectively. Evidently, the prediction accuracy of DPCNN and TextCNN is similar. The average loss rate of the improved LSTM, GRU, DPCNN, and TextCNN is 51.52%, 54.29%, 57.64%, and 56.15%. The prediction accuracy of DPCNN and TextCNN is similar, but the loss is higher than the other two models. To sum up, the accuracy of the improved LSTM model is significantly higher than that of other models. In the ideal case, the accuracy can be improved by nearly two percentage points.

4.2. Emotional Analysis and Classification Results of Network Media NPO under the Improved LSTM Model. In this verification, the relevant information about “Lao Tan pickled cabbage bag is actually pickled in a pit” on the Microblog platform in March 2022 is used for data collection. Some texts are extracted for the improved LSTM-based network media NPO’s emotion analysis. “1” indicates a correct classification, and “0” is a wrong classification. Figure 10 describes the emotional classification results.

In Figure 10, the improved LSTM model correctly classifies the emotion of the extracted Microblog text by up to 80.00%, regardless of whether the extracted text fully interprets the keyword. Thus, the improved LSTM model has a good effect on analyzing NPO and emotion in network media.

In the Internet era, the smooth, practical, and good implementation of the network Mass Line is a test of the social public service level and social governance ability of the Communist Party of China (CPC) and the government. Applying BDA has made the NPO governance

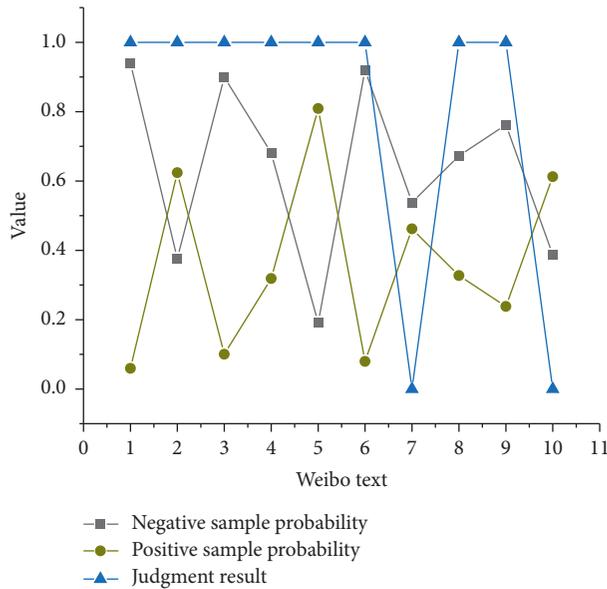


FIGURE 10: Model emotion classification results.

service more accurate and significantly improved the efficiency of social governance. A harmonious and healthy network Mass Line is an important means of contacting the masses, serving the masses, and innovating social governance. Netizens come from ordinary people, and from their Internet surfing behaviors come the NPO. Scientifically and flexibly using the Internet technology to understand NO and carry out work can help provide strong technical support for network information processing and analysis using BDA and AI. It enriches government network platforms' timely interaction and efficient communication with the citizens. Meanwhile, the government can find the difficulties and blind spots of social governance from many NOP and netizens' messages to create a new starting point for optimizing social governance. The key to using the Internet to improve social governance is to turn NPO into practical action. On the one hand, there is a need to gradually deepen the construction of the network platform and constantly perfect the official websites, Microblogs, and official accounts of the CPC and government. Simultaneously, the network interaction channels should be unblocked to ensure that NPO can provide an important decision and policy basis for the CPC and the government. On the other hand, it is imperative to explore new ways of government people interaction and actively respond to netizens' messages and public concerns. This way, the government can effectively offer timely feedback and deadline and address reasonable public demands. Only by asking about the people's plans can the state better serve the people. Lastly, utilizing the Internet can collect people's voices and emotions. BDA can help top-level design and policy implementation and continuously upgrade and optimize social governance concepts and capabilities. It is fair to say that people's happiness will be doubled, and a safer, more substantial, and reliable network environment will be envisioned in the future.

5. Conclusion

Under the background of IoT big data, this work analyzes the public opinion of online media. The performance of the proposed LSTM NPO analysis system based on TensorFlow is tested by comparing it with different DL models. The NPO and emotion classification of Microblog text by the improved LSTM model is verified based on the keyword "Lao Tan pickled cabbage bag is actually pickled in a pit" on the Microblog platform in March 2022. The results show that the average accuracy of the improved LSTM model is 74.65%, and the average loss rate is 51.52%. The improved LSTM model's accuracy is significantly higher than other models, and the loss is significantly lower. Therefore, the improved LSTM model can classify the emotion of the extracted Microblog text correctly, reaching as high as 80.00% accuracy. In the ideal case, the accuracy can be increased by nearly two percentage points. The results indicate that adding residual connection and attention mechanism can improve the model's emotional feature extraction ability and emotional discrimination ability in the text. The proposed method is of great help in analyzing NPO through Microblog texts. Lastly, some research pitfalls need future discussion. The sample size is too small to classify NOP and emotion in network media, and later research can expand the sample size. Moreover, with the continuous development of ML, the research on network media NPO also needs to be updated. Besides, since this work provides NPO keywords, researchers need to explore whether NLP technology can automatically extract the keywords of network media NPO in the future.

Data Availability

The data used to support the findings of this study are included within the article.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

References

- [1] C. Amatulli, M. De Angelis, G. Pino, and G. Guido, "An investigation of unsustainable luxury: how guilt drives negative word-of-mouth," *International Journal of Research in Marketing*, vol. 37, no. 4, pp. 821–836, 2020.
- [2] T. A. Manioudis and P. Bantimaroudis, "Hybrid salience: examining the role of traditional and digital media in the rise of the Greek radical left," *Journalism*, vol. 22, no. 4, pp. 1127–1144, 2021.
- [3] M. F. Y. Cheung and W. M. To, "The effect of consumer perceptions of the ethics of retailers on purchase behavior and word-of-mouth: the moderating role of ethical beliefs," *Journal of Business Ethics*, vol. 171, no. 4, pp. 771–788, 2021.
- [4] X. Han, J. Wang, M. Zhang, and X. Wang, "Using social media to mine and analyze public opinion related to COVID-19 in China," *International Journal of Environmental Research and Public Health*, vol. 17, no. 8, p. 2788, 2020.
- [5] M. Kaakinen, A. Sirola, I. Savolainen, and A. Oksanen, "Shared identity and shared information in social media:

- development and validation of the identity bubble reinforcement scale,” *Media Psychology*, vol. 23, no. 1, pp. 25–51, 2020.
- [6] S. C. McGregor, “Taking the temperature of the room,” *Public Opinion Quarterly*, vol. 84, no. S1, pp. 236–256, 2020.
- [7] K. Donovan, P. M. Kellstedt, E. M. Key, and M. J. Lebo, “Motivated reasoning, public opinion, and presidential approval,” *Political Behavior*, vol. 42, no. 4, pp. 1201–1221, 2020.
- [8] Z. Zhong, “Internet public opinion evolution in the COVID-19 event and coping strategies,” *Disaster Medicine and Public Health Preparedness*, vol. 15, no. 6, pp. e27–e33, 2021.
- [9] X. Ma, W. Liu, X. Zhou et al., “Evolution of online public opinion during meteorological disasters,” *Environmental Hazards*, vol. 19, no. 4, pp. 375–397, 2020.
- [10] R. B. Hubert, E. Estevez, A. Maguitman, and T. Janowski, “Analyzing and visualizing government-citizen interactions on Twitter to support public policy-making,” *Digital Government: Research and Practice*, vol. 1, no. 2, pp. 1–20, 2020.
- [11] J. Li and X. Xu, “A study of Big Data-based employees’ public opinion system construction,” *Journal of Industrial Integration and Management*, vol. 05, no. 02, pp. 225–233, 2020.
- [12] D. Li, Y. Zhang, and C. Li, “Mining public opinion on transportation systems based on social media data,” *Sustainability*, vol. 11, no. 15, p. 4016, 2019.
- [13] G. Kostka, “China’s social credit systems and public opinion: explaining high levels of approval,” *New Media & Society*, vol. 21, no. 7, pp. 1565–1593, 2019.
- [14] A. M. Khalil, R. Yoshida, T. Masatani, A. Takada, and M. Ozawa, “Variation in the HA antigenicity of A (H1N1) pdm09-related swine influenza viruses,” *Journal of General Virology*, vol. 102, no. 3, Article ID 001569, 2021.
- [15] S. Y. A. Zaidi, M. A. Shah, H. A. Khattak et al., “An attribute-based access control for IoT using blockchain and smart contracts,” *Sustainability*, vol. 13, no. 19, Article ID 10556, 2021.
- [16] N. C. Dang, M. N. Moreno-García, and F. De la Prieta, “Sentiment analysis based on deep learning: a comparative study,” *Electronics*, vol. 9, no. 3, p. 483, 2020.
- [17] S. A. Mahmood and Q. Q. Qasim, “Big data sentimental analysis using document to vector and optimized Support vector machine,” *UHD Journal of Science and Technology*, vol. 4, no. 1, pp. 18–28, 2020.
- [18] X. Huang, “Application analysis of AI reasoning engine in Microblog culture industry,” *Personal and Ubiquitous Computing*, vol. 24, no. 3, pp. 393–403, 2020.
- [19] S. Li, Z. Liu, and Y. Li, “Temporal and spatial evolution of online public sentiment on emergencies,” *Information Processing & Management*, vol. 57, no. 2, Article ID 102177, 2020.
- [20] B. Ross, L. Pilz, B. Cabrera, F. Brachten, G. Neubaum, and S. Stieglitz, “Are social bots a real threat? An agent-based model of the spiral of silence to analyse the impact of manipulative actors in social networks,” *European Journal of Information Systems*, vol. 28, no. 4, pp. 394–412, 2019.
- [21] Y. Kang, Z. Cai, C. W. Tan, Q. Huang, and H. Liu, “Natural language processing (NLP) in management research: a literature review,” *Journal of Management Analytics*, vol. 7, no. 2, pp. 139–172, 2020.
- [22] Z. Zhang, H. Luo, C. Wang, C. Gan, and Y. Xiang, “Automatic modulation classification using CNN-LSTM based dual-stream structure,” *IEEE Transactions on Vehicular Technology*, vol. 69, no. 11, pp. 13521–13531, 2020.
- [23] C. Hu, T. Ou, Y. Zhu, and L. Zhu, “GRU-type LARC strategy for precision motion control with accurate tracking error prediction,” *IEEE Transactions on Industrial Electronics*, vol. 68, no. 1, pp. 812–820, 2021.
- [24] A. K. Abasi, A. T. Khader, M. A. Al-Betar, S. Naim, Z. A. A. Alyasseri, and S. N. Makhadmeh, “A novel hybrid multi-verse optimizer with K-means for text documents clustering,” *Neural Computing & Applications*, vol. 32, no. 23, pp. 17703–17729, 2020.
- [25] S. Shekhar, D. K. Sharma, and M. M. S. Beg, “Language identification framework in code-mixed social media text based on quantum LSTM—the word belongs to which language?” *Modern Physics Letters B*, vol. 34, no. 06, Article ID 2050086, 2020.