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Constructing the Public Opinion Crisis Prediction Model Using CNN and LSTM Techniques Based on Social Network Mining

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Abstract

This research endeavors to address the persistent dissemination of public opinion within social networks, mitigate the propagation of inappropriate content on these platforms, and enhance the overall service quality of social networks. To achieve these objectives, Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM) techniques are employed in this research to develop a predictive model for anticipating public opinion crises in social network mining. This model furnishes users with a valuable reference for subsequent decision-making processes. The initial phase of this research involves the collection of user behavior data from social networks using IoT technologies, serving as the basis for extensive big data analysis and neural network research. Subsequently, a social network text categorization model is constructed by amalgamating the Convolutional Neural Network-Long Short-Term Memory (CNN-LSTM) architecture, elucidating the training procedures of deep learning methodologies within CNN and LSTM networks. The effectiveness of this approach is subsequently validated through comparisons with other deep learning techniques. Based on the obtained results and findings, the CNN-LSTM model demonstrates a noteworthy accuracy rate of 92.19% and an exceptionally low loss value of 0.4075. Of particular significance is the classification accuracy of the CNN-LSTM algorithm within social network datasets, which surpasses that of alternative algorithms, including CNN (by 6.31%), LSTM (by 4.43%), RNN (by 3.51%), Transformer (by 40.29%), and Generative Adversarial Network (GAN) (by 4.49%). This underscores the effectiveness of the CNN-LSTM algorithm in the realm of social network text classification.

Keywords

Convolutional Neural Network, Deep Learning, Inappropriate Remarks, Internet of Things, Long Short-Term Memory, Social Network.

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I. Introduction

The market for intelligent hardware in China has witnessed a rapid expansion. The infusion of intelligence into hardware components has enabled seamless connectivity, fostering the realization of Internet service integration. This has given rise to a distinctive architectural paradigm known as 'cloud + terminal', which effectively harnesses the potential of big data [1] ,[2]. Foundational elements of this platform, including software and hardware components, are characterized by emerging technologies such as intelligent sensor interconnectivity, human-computer interaction, innovative display technologies, and advanced capabilities for processing large-scale data. In their pursuit of cutting-edge designs, materials, and hardware processes, social networks are increasingly focusing on developing new intelligent terminal products and service network applications. This is accomplished by seamlessly integrating intelligent hardware via applications [3]. The field of social network analysis, utilizing deep learning and the Internet of Things (IoT), has emerged as an increasingly significant area of research. The development of IoT has led to enhanced production efficiency due to the evolution of information networks. However, a substantial opportunity may be overlooked if one merely considers the value of social networks from a communication standpoint. Social networks exert a deeper influence on understanding and engagement than traditional social networks, significantly impacting various facets

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of human civilization to a greater extent than their conventional counterparts [4]. The IoT is well-positioned to effectively monitor interactive data within social networks, particularly given individuals' abundant sharing of interactive data. When intervention is warranted, IoT technology can support users in optimizing social networking applications by offering insights into usage patterns of application software [5]. Within the domain of deep learning, developers have the capacity to construct intricate neural network models capable of identifying and evaluating extensive information from social media. This is accomplished by utilizing expansive and reliable datasets [6]-[8], enhancing the potential for precise analysis and comprehension of social network data.

The primary objective of this research is to address the persistent challenges associated with the propagation of public opinions and inappropriate content within social networks. Additionally, it aims to enhance the overall service quality of social networks. To achieve these goals, this paper leverages deep learning and IoT technologies to intelligently identify and mitigate inappropriate comments within social networks. Initially, IoT technology is employed to amass user behavior data from social networks, laying the foundation for subsequent big data analysis and neural network research. Subsequently, the training procedures of deep learning techniques, specifically Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM), are elucidated. A social network text classification model that integrates CNN and LSTM methodologies is established. Finally, a comparative analysis of the performance of various deep learning techniques is conducted to validate the effectiveness of the proposed algorithm.

The paper is structured into five sections. Section 1 serves as the introduction, providing insights into the research background of social network analysis based on deep learning and IoT. Furthermore, it outlines the research methodology and paper's structure. Section 2 comprises a literature review, presenting theoretical research pertaining to IoT applications and exploring the application of deep learning within social networks. It also expounds on the process of integrating IoT with social networks. Section 3, the model section, introduces the CNN and LSTM algorithms and details the establishment of a social network text classification model that amalgamates both techniques. Section 4 encompasses the results and discussion, wherein the paper elucidates the dataset used for experimentation and evaluates the performance of the social network text classification model that integrates CNN and LSTM. Finally, Section 5 concludes the paper, providing a comprehensive summary of the research conducted herein. It further discusses the achieved results and encountered limitations while outlining prospects for future research endeavors.

II. Literature Review

Al-Garadi et al. conducted a research study employing the social network analysis methodology to investigate variations in communicative language within the context of theoretical research concerning the IoT in the realm of social networks. They established a correlation between the intensity of communicative language and the distribution of languages, positing that the emergence of social networks has transformed the Internet into a social force that exerts a significant influence on interpersonal relationships [9]. Khalil et al. contended that online communication media share a common attribute in reinforcing existing social models while expanding the reach of social networks. These media enable users to engage in active communication for predefined periods without supplanting other communication tools [10]. Additionally, Andronie et al. argued that emerging technologies had heightened the prevalence of networked social behaviors [11]. With the aid of these novel technologies, individuals are redefining the mode of network interaction, giving rise to a new form of network society. Deep learning, as an influential approach, has proven effective in addressing a multitude of intricate challenges and has demonstrated remarkable efficacy in diverse domains, including object detection, speech recognition, and language translation. Rahman et al. applied machine learning techniques to analyze the emotions conveyed in social network texts. They employed a noise reduction autoencoder for text feature extraction and emotion classification, with experimental results highlighting the proficiency of machine learning in emotional data analysis [12].

The advent of novel technologies has afforded individuals the opportunity to reshape the social structure and interaction modalities within networks. Deep learning has emerged as a potent tool for tackling complex challenges, enabling target detection, speech recognition, and language translation. In the context of social network alignment, Vinayakumar et al. delved into the alignment processes utilized by dynamic social network users and proposed a dynamic social network model based on the depth sequence model. Their extensive experiments, conducted with real data, revealed a substantial 10% enhancement in the alignment effect by utilizing the dynamic social network model [13]. Humayun et al. aimed to generate user-matching scores through deep learning, employing CNN to map features derived from grid data logged by users in social networks. Their findings affirmed the heightened matching accuracy achieved through this approach [14]. Lv et al. conducted research focused on the extraction of public opinion information from social networks using deep learning-based techniques [15]. Khan and colleagues investigated the application of deep learning in social network surveillance and developed social computing to enhance the safety of social network environments [16]. Siboni et al. integrated deep self-coding and network representation learning while collecting implicit semantic data from the network to construct a social network information recommendation model [17]. Experimental results indicated that implicit social network information more accurately identifies user connections compared to explicit semantic information. Sarker explored the capacity of CNNs and LSTM networks to categorize public opinions and emotions within social networks, leveraging deep learning techniques for public opinion classification within these networks [18]. In another study, Yu et al. employed a web crawler to collect login information from Facebook and Twitter users, pre-processed the experimental data, and applied a deep learning algorithm for identity recognition. Research findings demonstrated that deep learning surpasses conventional identification algorithms, highlighting its potential benefits within the realm of social networks [19]. Furthermore, text mining technology can analyze textual content, identify user behaviors and characteristics, investigate social media connections, and create user profiles, emphasizing its relevance and utility within the domain of social network analysis.

Social media data has been harnessed for various urban planning and tourism analysis applications. Muñoz et al. (2022) employed social media data to extract insights into tourist characteristics, laying the groundwork for urban planning and tourism analysis [20]. Leveraging the vast reservoir of user-generated content, social media data provides valuable glimpses into tourists' preferences, interests, and behaviors. This resource facilitates an enhanced comprehension of tourist behavior patterns and demands, thereby enabling the development of more precisely targeted strategies for urban planning and tourism decision-making. In the domain of hotel reviews, the utilization of attention-based emotion prediction models has exhibited promise. Arroni et al. (2023) implemented an attention-based model to forecast sentiment in tweets pertaining to Las Vegas hotels. The study reported a similarity score of 0.64121 with actual hotel rankings, underscoring the model's efficacy in sentiment analysis [21]. This approach can aid hotel managers in gaining insights into customer sentiment feedback, swiftly identifying, and addressing issues, and ultimately elevating service quality.

In summary, notwithstanding the substantial theoretical and practical strides made by researchers in China and other nations, shallow learning methodologies continue to predominate in natural language processing research and applications. The integration of CNN or deep learning techniques for text training and classification remains relatively limited. Embracing the realm of deep learning and IoT-based social network analysis, however, offers the potential for a more comprehensive and reliable information source, serving as a valuable asset to inform subsequent decision-making processes for users. While extant research has predominantly focused on the exploration of changes in communication language, particularly in the context of language variation in communication, it has not delved deeply into social media discourse or discourse characteristics linked to public opinion crises. These research perspectives may fall short in providing adequate insights and solutions to tackle the challenges posed by public opinion crises. These identified limitations and gaps serve as the impetus and focal point of the present study. The objective of this paper is to develop a predictive model capable of addressing public opinion crises within social networks. The paper harnesses CNN and LSTM technologies to enhance the accuracy and efficacy of the public opinion crisis prediction model. CNN excels at capturing local patterns and features within textual data, while LSTM adeptly models and analyzes temporal dependencies within textual data. By synergistically deploying these two techniques, the paper aims to construct a model proficient in extracting pertinent features from social network user behavior data and accurately classifying and forecasting public opinion crises.

A. Integration of IoT Technology and Social Network

The IoT represents an extensive network, expanding its reach by amalgamating diverse information-sensing devices into the network infrastructure. This convergence empowers the IoT to comprehend the perpetual interconnectedness of people, machinery, and objects across all temporal and spatial dimensions [22]. The amalgamation of IoT and Artificial Intelligence (AI) into the concept of Artificial Intelligence of Things (AIoT) is poised to usher in a multitude of innovative applications and guide future trends. On one hand, the amalgamation of IoT devices with AI technologies enables the realization of intelligent production processes and automation control. For instance, within the manufacturing sector, AIoT has the capability to oversee device operational statuses, gather production data, and employ machine learning algorithms for comprehensive analysis and optimization. This, in turn, facilitates heightened efficiency in production scheduling and enhanced quality control. On the other hand, AIoT holds the potential to exert a transformative influence on various domains, including urban management, transportation, and healthcare. For instance, through the integration of IoT sensing devices with AI algorithms, AIoT can pave the way for smart transportation systems, ultimately streamlining traffic patterns and ameliorating congestion. In the healthcare domain, AIoT can be harnessed for health monitoring and remote medical services, affording individuals personalized health management and timely access to medical assistance. In summary, the amalgamation of IoT and AI into AIoT stands poised to significantly augment efficiency and the degree of intelligence across various sectors. This amalgamation heralds fresh prospects for the establishment of more intelligent and interconnected systems, ultimately fostering improved outcomes and enhancing quality of life.

The IoT can be envisaged as an extension and amplification of the conventional Internet, constituting its core and foundational underpinning. It encompasses a broad spectrum of devices and commodities designed for communication and the exchange of information. Within this context, the IoT denotes a network that establishes connections between diverse objects and the Internet, thereby enabling seamless information exchange and communication through well-established protocols. This exchange is facilitated by information sensing devices such as radio frequency identification (RFID), infrared sensors, global positioning systems, and laser scanners, which empower intelligent object identification, positioning, tracking, monitoring, and management. The overarching architecture of the IoT is visually depicted in Fig. 1.

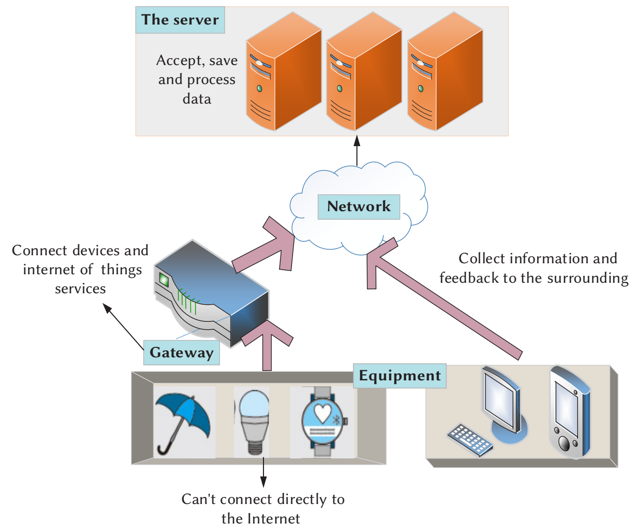

Fig. 1 Overall architecture of IoT. (Source: self-drawn by the author, icon source: Visio and https://www.iconfont.cn/).

The IoT, as illustrated in Fig. 1, operates within a meticulously structured framework comprising hardware, networking infrastructure, and cloud computing components. The seamless interconnection between the IoT and the broader Internet ecosystem is made possible by integrating pivotal IoT technologies. At the heart of the IoT's intricately layered architecture resides the sensor network, which harnesses cutting-edge two-dimensional code and RFID technology to discern and engage with a diverse array of interconnected entities. The application network, functioning as the ingress and egress control terminal, affords accessibility through an array of devices, including but not limited to mobile phones and other compatible interfaces. Conversely, the transmission network serves as the backbone for data dissemination and computation, capitalizing on the established infrastructure of the Internet, as well as conventional mediums such as radio and television networks, communication networks, and emerging next-generation networks. It is very important to underscore that each facet of social networking applications hinges on advanced hardware replete with specialized coding, differentiating between an extensive spectrum of devices, spanning from stereos to mobile phones. Through the judicious deployment of IoT, this paper attains its predefined objectives, concurrently harnessing data to elevate product quality and gain deeper insights into prevailing usage patterns within the realm of social media. A comprehensive elucidation of the operational workflow of the IoT is thoughtfully presented in Fig. 2.

As delineated in Fig. 2, an IoT device is thoughtfully equipped with both network and sensor modules, thus endowing it with the capability to seamlessly upload data to and retrieve data from the cloud server. Significantly, the cloud server serves as the central hub for orchestrating the management of intelligent hardware components. The network infrastructure emerges as the linchpin, facilitating the transmission and computation of data, thereby enabling effective control and interaction with the application network. The application network's input/output control terminal, which functions as the gateway to access its functionalities, exhibits compatibility with a multitude of established devices, including but not limited to mobile phones, personal computers (PCs), and other compatible terminals. In this context, it is paramount to underscore the pivotal role played by the IoT in the aggregation of user activity data extracted from social networks. This comprehensive data corpus serves as the foundation for conducting meticulous text data mining and analysis, empowering the various components of social networks to make well-informed judgments. For a deeper comprehension of IoT and social networks convergence, this paper presents the research findings concisely summarized in Table I.

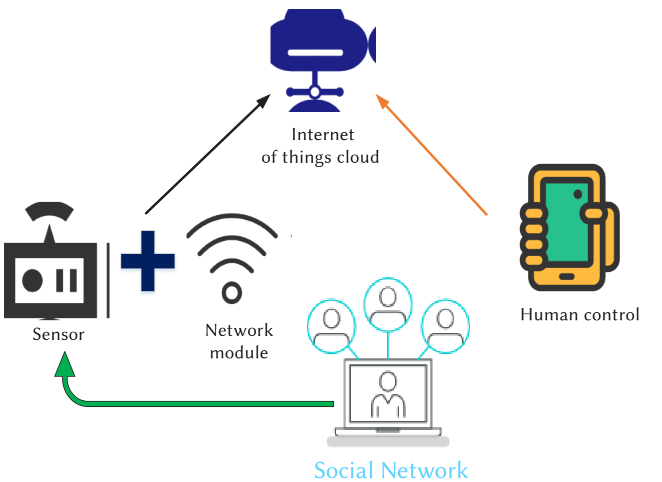

Fig. 2 The operation process of IoT. (Source: self-drawn by the author, icon source: Visio and https://www.iconfont.cn/).

TABLE I. Discussions on the Integration Technology of IoT Technology and Social Network

Research scholar	Specification
Wang, Wang, Li, Leung & Taleb (2020) [23]	Based on the social network, the sharing of things in the IoT is realized.
Lombardi, Pascale & Santaniello (2021) [24]	Social IoT realizes resource sharing and service between objects.
Gupta & Quamara (2020) [25]	The Architecture of Social IoT
Javaid & Khan (2021) [26]	A research method and model with social network characteristics is formed to realize the network application of the IoT, adopting the social network model, using the social relations among people, people and things, things, and things.

III. Research Model

A. CNN Algorithm

CNN, short for Convolutional Neural Network, represents a multi-layer perceptron explicitly designed for the extraction of localized features from images. It accomplishes this task through the implementation of convolution and pooling techniques. In stark contrast to fully connected neural networks, CNN is distinguished by three key attributes: localized perception, weight sharing, and the deployment of multiple convolution kernels. The process of localized perception hinges on the coordinated operation of upper neurons and convolution kernels. Their collaborative effort is directed toward the extraction of localized features from the input data originating from lower neurons, leading to the creation of a novel feature map. Weight sharing is a fundamental strategy employed to ensure that features are systematically extracted from the same feature graph. This technique serves to curtail the proliferation of network parameters by relying on a shared set of convolution kernels within the same feature graph. Furthermore, to encompass a broader spectrum of image information, a multi-convolution kernel conducts convolution operations on a feature map, employing multiple convolution kernels for the purpose. The structural organization of CNN is thoughtfully depicted in Fig. 3.

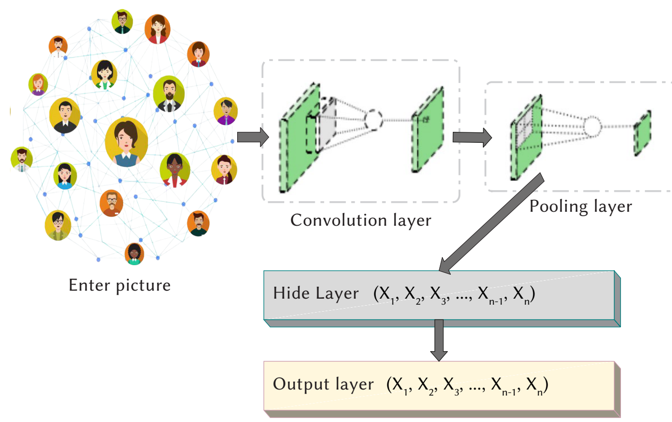

Fig. 3 CNN structure. (Source: self-drawn by the author, icon source: Visio and https://www.iconfont.cn/).

The foundational architectural framework of the CNN, as depicted in Fig. 3, comprises five principal layers: the input layer, convolution layer, pooling layer, fully connected layer, and output layer. Commencing with the input layer, it serves as the recipient of data, arriving in the configuration of an image pixel array. The convolution layer shoulders the responsibility of isolating local features from the input image. Subsequently, the pooling layer undertakes the task of transforming the extracted data features into a linear format, employing a down-sampling technique. This transformation yields data points that are subsequently transmitted to the output layer, which ultimately generates the desired results [27] , [28]. Mathematically, the operation of the convolution layer is succinctly expressed as shown in (1):

$$y_{mn} = f\left(\sum_{j=0}^{Q-1}\sum_{j=0}^{P-1} x_{m+i,n+j} w_{ij} + b\right), 0 \le m < M, 0 \le n < N \tag{1}$$

In Equation (1), $x_{m+i,n+j}$ is the pixel size of the input image, and y_{mn} is the output data of convolution operation. b is the offset, $P \times Q$ is the size of the convolution kernel, and w_{ij} is the value of the convolution kernel in (i, j). M and N are the sizes of the input image on $P \times Q$. Equation (2) and (3) show the excitation function:

$$Softmax(x) = \frac{e^{x^i}}{\sum_i e^{x^l}} \tag{2}$$

$$ReLU(x) = \max(0, x) = \begin{cases} 0, x < 0 \\ x \ \ x > 0 \end{cases} \tag{3}$$

The image size after convolution is shown in Equation (4):

$$N = \frac{W-F+2P}{S} + 1 \tag{4}$$

In Equation (4), W is the extracted data size, F is the size of the convolution kernel, P is the number of padding data columns at the edge of the original data, and S is the moving step size. Equation (5) shows the pooling operation:

$$a^l = pool(a^{l-1}) \tag{5}$$

In Equation (5), *pool* represents the process of reducing the size of input data by pooling area *k* and pooling standard, and a^{l-1} is the input tensor obtained by edge filling of the convolution input data matrix.

Equation (6) shows the output of the full connection layer:

$$a^l = \sigma(z^l) = \sigma(W^l a^{l-1} + b^l) \tag{6}$$

In Equation (6), b^l is the threshold of the fully connected layer l, and σ is the activation function. In the training process of CNN, the forward propagation is shown in (7)(8)(9):

$$z^{(l)} = W^{(L)} \cdot a^{(l-1)} + b^{(l)} \tag{7}$$

$$a^{(l)} = f_l(z^{(l)}) \tag{8}$$

$$x = a^{(0)} \rightarrow z^{(1)} \rightarrow a^{(1)} \rightarrow z^{(2)} \rightarrow a^{(2)} \rightarrow \cdots \rightarrow z^{(l)} \rightarrow a^{(l)} \tag{9}$$

In Equations (7)(8)(9), l is the number of layers of the CNN, L is the number of neurons, $W^{(L)}$ is the weight, $b^{(l)}$ is the bias, $a^{(l)}$ represents the network prediction output of the forward operation, $z^{(l)}$ is the input of the l-layer neuron, and $f_l(\cdot)$ is the activation function. Equation (10) shows the difference between the test value and the average value of the backward propagation output:

$$\delta^l = \frac{\partial J(W,b,x,y)}{\partial a^l} \odot \sigma'(z^l) \tag{10}$$

In Equation (10), J (W, b, x, y) is the variance, z^l is the input of l-layer neurons, a^l is the output of l-layer neurons, and $\sigma'(\cdot)$ directs the number operation. The process of updating the parameters (W, b) by gradient descent of the weights and offset vectors of the l-layer network is shown in (11)(12)(13):

$$\delta^l = (W^{(l+1)})^T \cdot \delta^{(l-1)} \odot \sigma'(z^l) \tag{11}$$

$$\frac{\partial J(W,b,x,y)}{\partial W^l} = \delta^l (a^{l-1})^T \tag{12}$$

$$\frac{\partial J(W,b,x,y)}{\partial b^l} = \delta^l \tag{13}$$

In Equation (11), the gradient calculation of the weight and the offset vector can be obtained, as shown in Equations (12) and (13). Then, all parameters (W, b) are updated using random gradient descent to complete the feedback operation [29].

B. Neural Network Algorithm for LSTM

The LSTM network stands apart from other deep learning architectures due to its distinctive unit state mechanism. It exercises selective information transmission through the utilization of a gate structure, enabling the incorporation or removal of data from the cell state. This operation generally entails the application of a sigmoid neural network layer in conjunction with point-wise multiplication procedures [30]. The structural arrangement of the LSTM neural networks is delineated in Fig. 4:

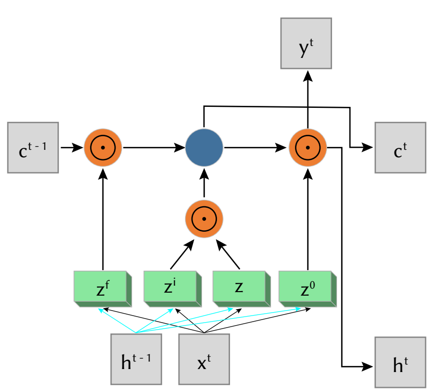

Fig. 4 Neural network structure of LSTM (Source: self-drawn by the author).

The LSTM neural network structure illustrated in Fig. 4 comprises two LSTM units, each featuring three gate structures: the input gate, the forgetting gate, and the output gate. The primary function of these 'gates' is to regulate and update the cell state within the network. The forgetting gate employs the *sigmoid* activation function to evaluate whether specific cell state information should be retained or forgotten. The input gate, in conjunction with the *tanh* layer, is responsible for storing and preserving cell information, while the output gate facilitates the output of pertinent information. The sigmoid activation function plays a pivotal role in determining particular aspects of the output unit state. Subsequently, the *tanh* layer is employed to manipulate the cell state, and the final output value is derived as the product of the *sigmoid* layer and the *tanh* layer. The equations governing the LSTM network are delineated in (14)(15)(16)(17):

$$z = \tanh\,(w \cdot [x^t, h^{t-1}] + b) \tag{14}$$

$$z^i = \sigma(w^i \cdot [x^t, h^{t-1}] + b^i) \tag{15}$$

$$z^f = \sigma(w^f \cdot [x^t, h^{t-1}] + b^f) \tag{16}$$

$$z^o = \sigma(w^o \cdot [x^t, h^{t-1}] + b^o) \tag{17}$$

z^i, z^f and z^0 are values converted into [0,1] by *sigmoid* layer, z is values converted into [−1,1] by *tanh* layer. b^i, b^f and b^0 are corresponding thresholds. The forgetting gate reads x^t and h^{t-1}, and decides which historical information to forget according to the current input information, and finally gets z. When the information is stored in the cell, the sigmoid layer determines the updated value, the tanh layer creates a new candidate value vector, and z is added to the state to update the cell state information of the sigmoid layer and tanh layer. The output h^{t-1} at the last moment, and the current data input x^t get z through the input gate. Then update the old cell state, and c^{t-1} is updated to c^t. The old state is multiplied by z^f and the information that is determined to be discarded is discarded. Then $z^i *$ z is added to generate new candidate values. According to the degree of the decision to update each cell state, the process of obtaining the temporary state c^t at the current moment through the unit state is changed. Finally, the output value determines which part of the cell state is output by running the *sigmoid* layer. Then, the cell state is processed by *tanh* layer and multiplied by the output of *sigmoid* gate, and the result is converted into numerical value by *tanh* activation function as the input signal. The final output determines the output port, the output h^{t-1} at the last moment, and the current data input x^t, and z^0 is obtained through the output gate, and the final output h^t is obtained by combining the cell states c^t and z^0 of the current cell. Through the *tanh* layer, the c^t obtained in the previous stage is scaled down. After obtaining the hidden layer state h^t, the output y^t and W' are often obtained by changing h^t as the output weight matrix [31], [32], the internal training process of LSTM is shown in (18)(19)(20).

$$c^t = z^f * c^{t-1} + z^i * z \tag{18}$$

$$h^t = z^o * \tanh\,(c^t) \tag{19}$$

$$y^t = \sigma(W' h^t) \tag{20}$$

C. Construction of a Social Network Text Classification Model Based on CNN and LSTM

Deep learning and IoT technology are used to identify and intelligently manage inappropriate comments on social networks to avoid public opinion crises. A social network text categorization model using CNN-LSTM and CNN is shown in Fig. 5.

In Fig. 5, initially, IoT technology is employed to gather social media user behavior data, encompassing users' activities such as posts, comments, likes, and shares on social networks. Subsequently, the assembled social media text data undergoes a pre-processing phase, which encompasses tasks such as text cleansing, tokenization, and the elimination of stop-words. These operations are undertaken to

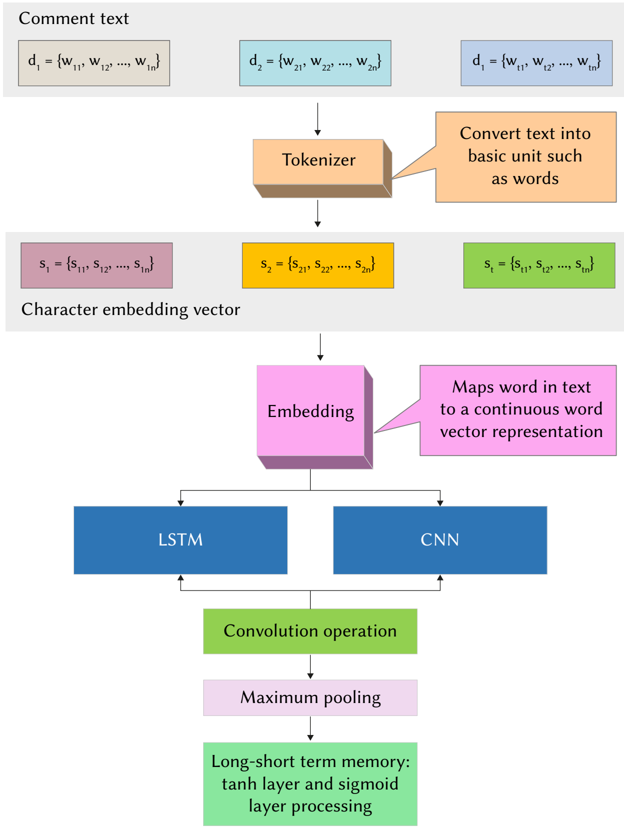

Fig. 5 Social network text classification model of CNN-LSTM network. (Source: self-drawn by the author).

transform the raw textual content into a format amenable for utilization as input within the model. The text cleaning phase involves the removal of noise, special characters, and unnecessary formatting from the text. This helps ensure that the text data input to the model is clean and consistently formatted. Tokenization is the process of segmenting the original text into words or tokens. This means converting the text into basic units, which are words or tokens, that the model can understand. This process aids the model in understanding the structure of the text. Stop words refer to words that frequently appear in the text but typically do not carry important information (e.g., "the," "is," "in"). In this step, stop words are removed to reduce the dimensionality and noise of the text data. Secondly, Word2Vec, a word embedding model, is used to map each word to a continuous word vector representation. This enables the capture of semantic relationships between words. The embedding layer is a crucial component used to map words in the text to continuous word vector representations. This helps the model understand the semantic relationships and contextual information between words. Word2Vec is a commonly used embedding model that transforms each word into a high-dimensional vector to capture the semantic similarity between words. This enables the model to better understand the meaning and associations of words in the text. In the initial layer of the model, a convolutional layer is employed to perform feature extraction. This layer conducts local feature extraction on the input sequence using sliding windows. Multiple convolutional kernels of various sizes can be utilized to capture features at different scales. In the subsequent layer of the model, an LSTM layer is utilized to capture long-term dependencies within the sequence effectively. The LSTM layer is well-suited for handling sequential data and incorporates a memory mechanism to retain crucial information. The output features from both the CNN and LSTM layers are then combined through a weighted sum. Following this, the fused features are fed into a fully connected layer for the purpose of classification, resulting in the prediction of the text's category. Subsequently, the model is trained using annotated training data, and the model parameters are updated through the backpropagation algorithm. To expedite convergence during this process, the Adam optimization algorithm can be employed. Once the model has been trained and evaluated, it can be utilized to predict and classify new social media text. As users post new content or comments on social networks, the constructed model can be employed to determine whether it falls within the category of a public opinion crisis. Based on the model's predictions, users can make informed decisions, which may include removing or revising inappropriate remarks or responding promptly to public sentiments.

The algorithm pseudocode for the social network text classification model based on the CNN-LSTM network is presented in Table 2.

TABLE II. Algorithm, Pseudocode of Social Network Text Classification Model, Based on CNN-LSTM Network

Step	**Algorithm Pseudocode**
Step 1: Data pre-processing; assume that the steps of data pre-processing and division into the training set and test set have been completed	import numpy as np from TensorFlow. Keras. Models import Sequential from tensorflow. Keras.layers import Embedding, Conv1D, MaxPooling1D, LSTM, Dense
Step2: Define the model	model = Sequential() model.add(Embedding(input_dim=vocab_size, output_dim=embedding_dim, input_length=max_length)) model.add(Conv1D(filters=num_filters, kernel_size=filter_size, activation='relu')) model.add(MaxPooling1D(pool_size=pool_size)) model.add(LSTM(units=lstm_units)) model.add(Dense(units=num_classes, activation='softmax'))
Step3: Compile the model	model.compile(loss='categorical_crossentropy', optimizer='adam', metrics=['accuracy'])
Step4: Model training	model.fit(train_data, train_labels, epochs=num_epochs, batch_size=batch_size)
Step5: Model evaluation	loss, accuracy = model.evaluate(test_data, test_labels)
Step6: Model application	predictions = model.predict(new_data)
Step7: Result analysis	—
Step8: Analyze and compare the results as needed	—
Step9: Complete the model building and evaluation process	—

IV. Results and Discussion

A. Experimental System Construction and Model Performance Evaluation

The experimental hardware environment comprises an Intel® Core™ i5-7200U CPU @ 2.50GHz. The software environment is Windows 10. The deep learning framework utilized is Keras, with the underlying deep learning framework being TensorFlow. The implementation is performed using the Python programming language with 20 iterations.

To evaluate the performance of the social network text classification model of the CNN-LSTM network, the study adopted a random split to divide the dataset into two parts, resulting in 70% of the data being used as the training set and 30% as the testing set. The purpose of splitting the dataset is to use the training set for parameter estimation when building the model and to evaluate the model's performance on the testing set. The accuracy, precision, recall rate, F1 value, and loss value are used for evaluation [33], as shown in (21)(22)(23)(24)(25):

$$Accuracy = \frac{TP+TN}{TP+FN+FP+TN} \tag{21}$$

$$Precision = \frac{TP}{TP+FP} \tag{22}$$

$$Recall = \frac{TP}{TP+FN} \tag{23}$$

$$F_1 = \frac{2*Precision*Recall}{Precision+Recal} \tag{24}$$

$$Loss = -\frac{1}{n}\sum_{i=1}^{n}\sum y^{(i)} log\hat{y}^{(i)} \tag{25}$$

In the context of the experimental evaluation, True Positive (TP) denotes the number of positive samples accurately identified, while True Negative (TN) represents the number of negative samples correctly classified. False Positive (FP) indicates the count of negative samples incorrectly identified as positive, and False Negative (FN) refers to the number of positive samples mistakenly classified as negative. The variable n represents the total number of training samples, $y^{(i)}$ corresponds to the actual (real) value, and $\hat{y}^{(i)}$ stands for the predicted value.

B. Experimental Data

The data extraction process primarily centered on the identification of specific keywords, including "network civility," "universities," "economy," "internal spiritual conflict," "culture," "New Year's Day," "Spring Festival," "Lantern Festival," "consumer rights," and various others. These keywords served as the focal points in assembling the research dataset for this paper. It is noteworthy that most of the Weibo comments comprising this dataset are characterized by brevity and conciseness. Specifically, there were 8,833 texts containing up to 30 Chinese characters, 9,799 texts with up to 40 Chinese characters, and 10,687 texts containing up to 100 Chinese characters. Furthermore, it is imperative to underscore that these comments exhibit colloquial expressions, and they may feature diverse emoji representations. Given these distinct attributes of the comment data, the experiment necessitated meticulous consideration of feature extraction integrity when selecting the appropriate text vectorization algorithm. Additionally, a denoising procedure was applied to eliminate extraneous comment elements, such as superfluous words, phrases, and punctuation marks. As a result of this data refinement process, a total of 7,368 comments were retained for inclusion in this paper. This corpus comprises 3,425 comments categorized as offensive remarks and 3,943 comments falling under the category of other comments.

C. Hyperparameter Settings

In the course of constructing the model, the learning rate assumes a critical role in governing the step size for updating model parameters, with a predetermined value of 0.001 being employed. Concurrently, the batch size, which dictates the quantity of samples utilized for parameter updates in each iterative step, was set at 128. In configuring the model's architecture, the word embedding dimension was established at 150, while the maximum permissible length for text sequences was defined as 380 characters. The convolutional layer featured 256 filters employing a kernel size of 5, while the pooling layer incorporated a window size of 2. The LSTM layer was equipped with 64 units, and the fully connected layer had an output category count of 16. Model training spanned 25 epochs to achieve the desired convergence.

D. Evaluation Performance of Social Network Text Classification Model Combining CNN-LSTM

Within the framework of the CNN-LSTM network algorithm, predicated on the theoretical underpinnings and the model's training regimen, the aforementioned text datasets were categorized into two distinct groups, denoted as Data1 and Data2. The specific outcomes of the model's classification process are graphically illustrated in Fig. 6:

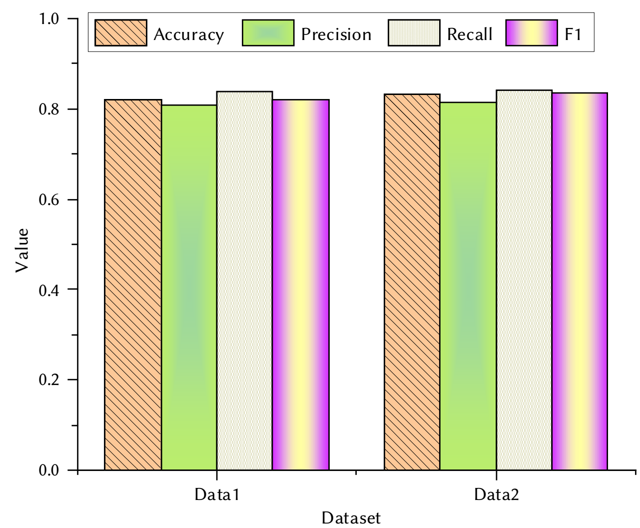

Fig. 6 Classification results based on Data1 and Data2 in this paper. (Source: self-drawn by the author).

Through a meticulous comparative examination of the Data1 and Data2 datasets, Fig. 6 effectively delineates that the model introduced in this scholarly work exhibits a nominal degree of divergence concerning its classification and evaluation metrics when applied to the two distinct datasets. Specifically, the performance metric for the social network text classification model, predicated on the CNN-LSTM network architecture, attains a value of 0.8217 when applied to Data1 and registers at 0.8315 for Data2. It is noteworthy that the Data2 model manifests an enhanced classification performance, denoting a 1.19% amelioration relative to its Data1 counterpart. Thus, it becomes apparent that the CNN's influence on the outcome becomes discernible, particularly in connection with the convolutional block encompassing the pooling operation, as the model interacts with the sequence data within the dataset. The experimental findings elucidating the performance of the CNN-LSTM network-based social network text categorization model is graphically depicted in Fig. 7.

In Fig. 7, the CNN-LSTM model demonstrates a commendable accuracy rate of 92.19% while concurrently achieving a relatively low loss value of 0.4075. Notably, when the CNN-LSTM model processes a solitary convolution block preceding each pooling operation, its performance registers a notable enhancement of 2.62%, concomitant with a substantial reduction of 16.11% in its loss value. Conversely, upon configuring the CNN-LSTM model to process three convolution blocks preceding each pooling operation, an even more substantial performance improvement of 4.43% is observed, accompanied by a notable loss reduction of 24.29%. These outcomes illuminate that the CNN-LSTM model's capacity is not profoundly influenced by the number of network layers it encompasses. An excessive increase in network layers may potentially lead to network degradation, ultimately detrimentally impacting the model's overall performance.

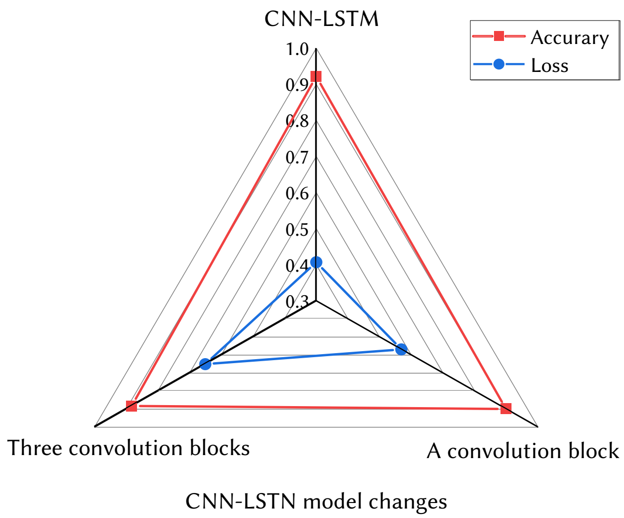

Fig. 7 Experimental effect of social network text classification model of CNN-LSTM network. (Source: self-drawn by the author).

E. Effectiveness Analysis of CNN-LSTM Algorithm in Social Network Text Classification

To substantiate the efficacy of the CNN-LSTM algorithm, this research undertakes a comparative assessment against independent CNN, LSTM, RNN, Transformer, and Generative Adversarial Network (GAN) algorithms employed for the task of social network text classification. The classification outcomes of these diverse algorithms on social network datasets are thoughtfully presented in Fig. 8.

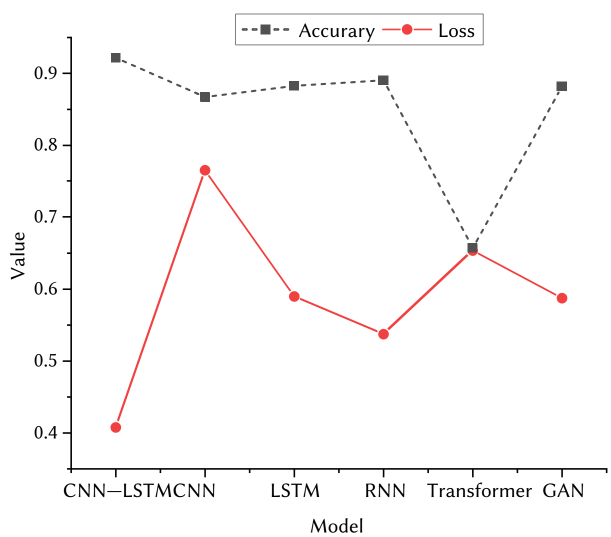

Fig. 8 Classification results of different algorithms in social network data sets. (Source: self-drawn by the author).

Fig. 8 provides a comprehensive comparative analysis of various deep learning algorithms, with CNN-LSTM emerging as the frontrunner, exhibiting the highest accuracy rate and the lowest loss rate within the context of this paper. Specifically, when applied to social network datasets, the CNN algorithm attains a classification accuracy of 86.72% alongside a loss value of 0.7653. The LSTM methodology achieves a commendable classification accuracy of 88.28%, accompanied by a loss value of 0.5898 on social network datasets. In contrast, the RNN algorithm impressively registers a classification accuracy of 89.06% while maintaining a relatively low loss value of 0.5373 on social network datasets. Notably, while demonstrating a reasonable classification accuracy of 65.71%, the Transformer algorithm corresponds to a loss value of 0.6535 on social network datasets. Furthermore, the GAN algorithm notably achieves a classification accuracy of 88.23% alongside a loss value of 0.5874 when operating on social network datasets. Conversely, the CNN-LSTM algorithm consistently outperforms the CNN algorithm, LSTM methodology, RNN algorithm, Transformer algorithm, and GAN algorithm in terms of classification accuracy when confronted with the intricacies of social network datasets. These compelling results underscore the remarkable efficacy and aptitude of the CNN-LSTM algorithm for the task of social network text categorization. The variation in classification performance across different datasets is thoughtfully presented in Fig. 9.

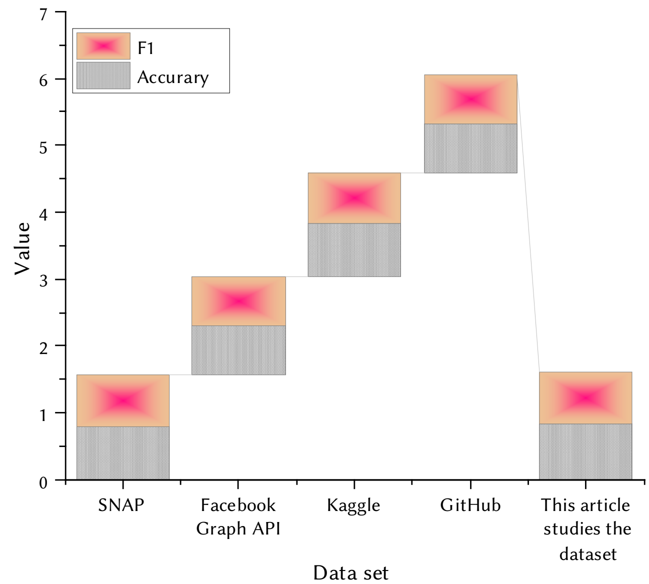

Fig. 9 Classification Effect of the Model Under Different Data Sets. (Source: self-drawn by the author).

Fig. 9 meticulously outlines the model's classification performance across distinct datasets. Notably, the dataset employed within the scope of this paper attains the highest level of accuracy, impressively reaching 84.29%. The Stanford Network Analysis Project (SNAP) dataset exhibits a commendable accuracy rate of 80.09%. Meanwhile, the accuracy for the Facebook Graph API dataset and the Kaggle dataset stands at 74.57% and 79.14%, respectively. The GitHub dataset yields an accuracy of 73.86%. It is noteworthy that the dataset utilized in this paper consistently demonstrates superior performance, not only in terms of accuracy but also in the F1 score metric. Equally noteworthy is the SNAP dataset, which also showcases commendable results in accuracy and F1 score. The remaining datasets, while still demonstrating noteworthy performance, exhibit slightly lower accuracy rates and F1 scores in comparison.

F. Discussion

This paper utilized LSTM and CNN, two deep learning techniques, to construct a predictive model for public opinion crises. Compared to standalone models such as CNN, LSTM, RNN, GAN, Transformer, etc., the CNN-LSTM model proposed in this paper demonstrates the highest accuracy and the lowest loss rate, achieving a significant advantage. The accuracy and reliability of the model have also been thoroughly validated in the experiments. The results indicate its outstanding performance in crisis prediction tasks. Furthermore, the consistent performance of the model on different datasets suggests its stability and robustness. These findings align with the research conducted by Kang et al. (2020), where it was observed that LSTM-based methods exhibited the capability to effectively address imbalanced datasets, subsequently leading to enhanced classification performance [34]. Consequently, given the inclusion of LSTM as a pivotal component in this paper, it is reasonable to anticipate favorable outcomes when dealing with opinion data within the context of social networks. Furthermore, the attention mechanism introduced by He et al. (2022) for fine-grained text classification introduces the prospect of information exchange between sentences and keywords during the text classification process. This innovative mechanism has the potential to bolster the model's comprehension and classification proficiency when handling social media text [35]. Additionally, Dang et al. (2020) conducted research that employed deep learning techniques for the analysis of question texts, achieving an impressive F-score of 80.20% within the specific text length range of 50 to 100 words [36]. Given the typically concise nature of text in social networks, these findings bear relevance to the present study. As the model presented in this paper is tailored for social network mining, it may encounter shorter text segments or sentences. Therefore, it is conceivable that the model in this paper may demonstrate similar effectiveness in the realm of social media text analysis. In addition, Saxena et al.'s (2023) research involves link prediction, which is the task of determining whether a connection will exist between two entities in a network, primarily applied in social network analysis, biological networks, and other network science domains. The study used a combination of network centrality and graph convolutional networks, enhancing model accuracy by selecting nodes with high betweenness centrality for model training [37]. This research provides a robust approach to link prediction and thoroughly discusses its performance in both experimental and theoretical aspects. Arroni et al. (2023) proposed a simpler attention-based model that utilizes a transformer architecture to predict sentiment expressed in tweets about Las Vegas hotels, comparing its performance with traditional sentiment analysis methods. Experimental results demonstrated the outstanding predictive performance of their model [38]. Although these two studies focus on different areas than the present paper, they also leverage deep learning techniques and have achieved significant results in different application domains, which is relevant to the discussion of the effectiveness and potential of social network text classification tasks in this paper. In summary, the CNN-LSTM model in this paper exhibits outstanding performance in handling social network text classification tasks, providing powerful tools and methods for predicting and managing public sentiment crises.

V. Conclusion

This paper harnessed the capabilities of the IoT and a web crawler to amass a corpus of 11,238 comments originating from the trending entertainment topics on the Weibo social networking platform. The primary objective was to discern and intelligently manage inappropriate comments within the realm of social networks, thereby proactively averting potential public opinion crises that could arise from the dissemination of such objectionable content. The performance of our social network text classification model, which amalgamates the CNN-LSTM network, underwent comprehensive evaluation, encompassing various metrics such as accuracy rate, precision, recall rate, F1 score, and loss value. The research outcomes revealed minimal disparities in classification across distinct data sets and assessment criteria when comparing the CNN-LSTM network with alternative models for social network text classification. Notably, the CNN-LSTM model exhibited an impressive accuracy rate of 92.19% along with a commendably low loss value of 0.4075. Intriguingly, our model's performance exhibited a diminishing trend as the number of network layers increased, thereby indicating that the network's efficacy is not significantly influenced by layer count. Additionally, the CNN-LSTM algorithm outperformed several other deep learning algorithms, underscoring its preeminence in the domain of social network text classification. When juxtaposed with the CNN algorithm, our CNN-LSTM algorithm showcased a noteworthy 6.31% enhancement in accuracy. Similarly, when compared to the LSTM algorithm, the CNN-LSTM algorithm demonstrated a commendable 4.43% increase in classification accuracy. Furthermore, it surpassed the RNN algorithm by 3.51%, the Transformer algorithm by a substantial 40.29%, and the GAN algorithm by 4.49% when applied to social network data sets. These compelling findings unequivocally validate the efficacy of the CNN-LSTM algorithm in the domain of social network text classification. The principal research findings presented in this paper carry substantial practical implications for the application of deep learning techniques in the context of managing social network crises and processing high-dimensional data. These findings furnish valuable tools and methodologies for social network governance and data analytics, which, in turn, can significantly contribute to the enhancement of social network services and the overall quality of decision-making processes.

Nonetheless, it is imperative to acknowledge certain caveats associated with this research. The ever-expanding landscape of social networks may have introduced unaccounted-for nuances and unrepresented social network datasets, potentially affecting the generalizability and robustness of our experiment's findings. Furthermore, our acquisition of the hot search comment dataset from microblog public opinion sources relied on a combination of web crawling and manual screening. Consequently, the dataset this paper compiled may be afflicted by incomplete coverage, which could potentially introduce biases into our overall results. The experiments and tests carried out in this paper were conducted within a simulated computer environment. Therefore, disparities may exist between our experimental outcomes and real-world results. The evolution of information technology and ongoing updates to filtering techniques may compel malicious actors to employ diverse countermeasures aimed at circumventing information filtering while disseminating their content. Thus, future research should prioritize developing and applying novel information filtering methods integrated with deep learning technology to tackle the multifaceted challenges posed by social networks. By establishing a comprehensive social network dataset for deep learning application research, this paper can pioneer advancements in filtering methodologies for mining public opinion information, thereby fortifying network security and enhancing information filtering within the dynamic landscape of social media.

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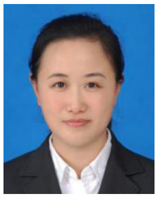

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