



Application of edge computing combined with deep learning model in the dynamic evolution of network public opinion in emergencies

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Abstract

The aim is to clarify the evolution mechanism of Network Public Opinion (NPO) in public emergencies. This work makes up for the insufficient semantic understanding in NPO-oriented emotion analysis and tries to maintain social harmony and stability. The combination of the Edge Computing (EC) and Deep Learning (DL) model is applied to the NPO-oriented Emotion Recognition Model (ERM). Firstly, the NPO on public emergencies is introduced. Secondly, three types of NPO emergencies are selected as research cases. An emotional rule system is established based on the One-Class Classification (OCC) model as emotional standards. The word embedding representation method represents the preprocessed Weibo text data. Convolutional Neural Network (CNN) is used as the classifier. The NPO-oriented ERM is implemented on CNN and verified through comparative experiments after the CNN's hyperparameters are adjusted. The research results show that the text annotation of the NPO based on OCC emotion rules can obtain better recognition performance. Additionally, the recognition effect of the improved CNN is significantly higher than the Support Vector Machine (SVM) in traditional Machine Learning (ML). This work realizes the technological innovation of automatic emotion recognition of NPO groups and provides a basis for the relevant government agencies to handle the NPO in public emergencies scientifically.

Keywords Deep learning · Public emergency · Network public opinion · Emotion recognition · CNN

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1 Introduction

1.1 Research background and motivations

The Internet and information technologies are widely used, such as in Smart Mobile Devices (SMDs), helping expand the Online Social Networks (OSNs). Thus, OSNs have become the most inclusive way of socializing globally and replacing the traditional social networks. As a result, OSNs greatly impact traditional social communication and information dissemination modes.

With the vigorous development of the new media industry, SMDs have been given many features, including Artificial Intelligence (AI), networking, virtualization, and openness. On the one hand, SMDs can facilitate people publish information actively rather than receiving them passively, such as by releasing news and live webcasts anytime and anywhere. SMDs can well combine the new media technology with OSNs to acquire information resources at the fastest speed [1, 2]. On the other hand, when public emergencies occur, OSNs offer netizens with convenient, anonymous, virtual, and inexpensive real-time services. People can express their opinions, attitudes, and emotions using SMDs [3]. The revolution of information dissemination methods broke agenda-setting, information inspecting, and information sharing mechanisms in the traditional media era. It allows offline public events to be quickly disseminated. Network Public Opinions (NPOs) affect the scientific handling of emergencies and can easily trigger new public opinion events, affecting social harmony and stability [4–6]. Therefore, NPO is the continuation of actual public opinion on the Internet, and NPO has become the focus of public opinion in modern society. Internet rumors caused by the Corona Virus Disease 2019 (COVID-19) are increasing. As the China-US dispute continues to extend, tensions in international public opinion are increasing. Given the above background, this work starts by detecting NPO during the COVID-19 pandemic. Scholars worldwide have analyzed the emotion classification or emotion tendency of NPO from the aspects of semantic emotion dictionary or from statistical Natural Language Processing (NLP). However, problems exist, such as insufficient semantic understanding of emergencies and only focusing on emotion dictionaries. Thus, the difficulty of NPO-oriented emotion classification lies in understanding the semantic information in OSNs. Using Data Mining (DM) and NLP technologies to mine information from massive amounts of text data and improve classification accuracy is also a primary concern. Jiang et al. [7] proposed a new model of short-text relationships for extracting opinion topics from OSNs. The model extracted the text features of OSN and communication patterns among individuals. Then, a dynamic version of the short-text relationship model was proposed to capture the evolution of NPOs. The results show that, compared with the benchmark method, the proposed models could use OSN data features to gain meaningful NPO. It could also effectively obtain the evolution of public attention at different stages of the COVID-19 pandemic. Monitoring NPOs could correctly guide the NPO on agricultural products and prevent the spread of negative NPO in time, reducing the negative impact of NPO hotspot events. Liu et al.

[8] developed a big data-based NPO monitoring system for agricultural products. The model could collect, process, and analyze data in time, discover and track hot topics, and calculate and visualize the polarity of NPOs. Wu et al. [9] proposed an Ortony-Clore-Collins (OCC) model and a Convolutional Neural Network (CNN)-based NPO summarization method for Chinese Weibo systems. The proposed method was tested using real-world Weibo data. Then, the accuracy of manual emotion annotation was compared using OCC-based emotion classification rules. Experimental results analyzing three real Weibo datasets demonstrate the effectiveness of the proposed method.

Many specialized research institutions provide reliable data for experts and scholars in the NPO field through data collection, statistics, and analysis. However, the existing literature on NPO mainly focuses on the dissemination of NPO. There are few in-depth studies on the evolution of NPOs in public emergencies. The evolution of NPOs has not yet formed a certain scientific framework, and previously, the research contents and methods are not perfect.

1.2 Research objectives

Therefore, this work intends to combine Edge Computing (CC) with Deep Learning (DL) model to identify NPOs in public emergencies, classify emotions in NPO, and summarize the general features of NPOs in public emergencies from the macro level. The main contribution and innovation lie in establishing the NPO-oriented Emotion Recognition Model (ERM) from the perspective of emotional cognition and the DL method. Based on the induction mechanism of One-Class Classification (OCC) emotional cognition, the OCC emotional rules of NPO in public emergencies are designed from the perspective of emotional cognition. Hence, the NPO-oriented group emotional classification method is innovated. This work is organized as follows. Firstly, Chapter 1 introduces the development background of Internet technology and the new media industry. The recent related research work is introduced in Chapter 2. Then, Chapter 3 combines NPO and emotional rules, designs the model, and maps the emotional categories. Chapter 4 analyzes the influence data of the NPO-oriented ERM. In Chapter 5, the conclusion is drawn after the summary through the analysis and comparison of the result data. The research has practical application value for applying the DL model in the dynamic evolution of NPO in public emergencies.

2 Literature review

Many scholars have researched DL and NPO in public emergencies. Jain et al. [10] analyzed the consumer emotion toward online comments and compared and analyzed the usefulness and applicability of online comments through a systematic literature review. This research was of great significance to service providers in formulating management strategies for consumers to choose on-demand services. Peng et al. [11] studied the NPO-oriented Early Warning Model (EWM) for

major emergencies, fully considered the development features and communication features, and built an NPO-oriented early warning index system including four primary indicators and 13 secondary indicators. The results showed that the index system and early warning model were feasible and could provide a reference for the related NPO research. Jain et al. [12] investigated the service recommendation model based on the multi-tag integration strategy and designed a predictive recommendation method. The designed method could predict consumer recommendations in travel and tourism. Compared with other binary classification methods, the proposed model achieved higher accuracy in using various evaluation measures. Qiang et al. [13] conducted bibliometric analysis and research on NPO and explored the knowledge base and hot trends from a quantitative perspective. They searched 1385 related papers and conducted a bibliometric mapping analysis on them. The research results indicate that early warning information could be extracted from big data-based NPO to achieve in-depth analysis and accurate prediction of NOP. The results could improve NPO-oriented decision-making ability.

To sum up, with the arrival of the big data era, Big Data Technology (BDT) is widely used in various fields. To some extent, it is fair to say that BDT is the research frontier. Combining EC with the DL model to analyze the NPO in public emergencies can further improve the NPO-oriented decision-making ability. The accuracy of evaluation and prediction can also be improved.

3 Research model

3.1 NPO on public emergencies

NPO on public emergencies means that netizens express their opinions and emotional attitudes on public emergencies, such as natural disasters and accidents, on OSNs including Weibo, Douyin, and WeChat. In particular, making NPO on public emergencies impartial involves government regulation. Rumors can easily follow some large-scale public emergencies, thus becoming very challenging to handle. This work dissects NPO factors from four dimensions: the subject, the object, the NPO itself, and the media of NPO.

1. The subject: In general, the government and Netizens are the subjects of NPO in public emergencies. The personal qualities and cultural values of Netizens will have an impact on the development of NPO. Unfairness or hatred towards the rich can easily cause extreme NPOs. Meanwhile, the government's response time, measures, and follow-up on the dynamics of the public emergencies all play an important role. Surely, well-handled public emergencies help NPO develop in a positive direction.
2. The object: Public emergencies are the objects of NPO on public emergencies, and they are also the root cause and stimulus of NPO. The stimulus of NPO mainly includes the nature, duration, and sensitivity of the emergency. Meanwhile, complex social relationships also complicate public emergencies. NPO also diverts the Netizens' attention to public emergencies. Sensitive topics, official

- corruption, social injustice, and morality issues are likely to trigger more serious NPOs among Netizens with long and negative social emotions.
3. NPO itself: The expression, emotions, and attitudes of Netizens' NPO during public emergencies are characterized by timeliness, massive scale, diverse forms, and different incentives. Netizens' understanding abilities also differ greatly. While guiding the NPO, the government should fully consider the information dissemination form to attract the attention of netizens in a positive direction [14, 15].
 4. The media: The mass media is an important part of NPO dissemination. Especially in the new media era, traditional media are also gaining a foothold online. The higher the reporting efficiency and the more agendas, the more it can meet the needs of Netizens and promote the sound development of NPO. Various OSNs have further increased Netizens' enthusiasm to discuss, making information dissemination faster and wider while also facilitating malicious and false information to be released online [16, 17]. Therefore, disseminating big data over the Internet has greatly promoted NPO development. However, at the same time, it has also increased the difficulty of handling NPO.

3.2 Design of emotional rules of NPO based upon OCC model

3.2.1 Cognitive mechanism of the OCC model

The One-Class Classification (OCC) model is a classic structure of emotional cognition. It is widely used in emotional modeling, and its emotional and cognitive mechanism is shown in Fig. 1. In the OCC model, emotions are generated by evaluating

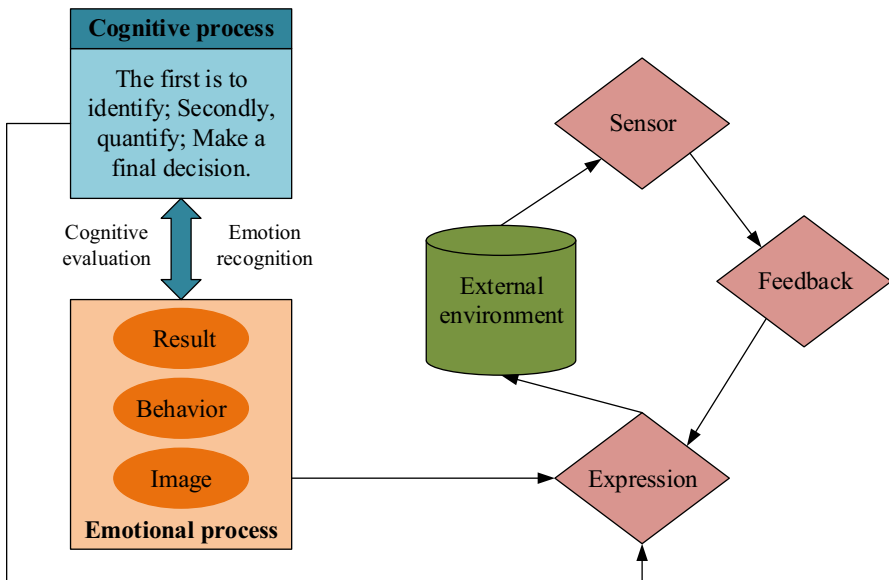


Fig. 1 Emotional and cognitive mechanism of the OCC model

the cognitive process results, and the generation process is specifically divided into classification, quantification, mapping, and expression [18].

Classification: In the OCC model, the evaluation is determined by three components: the result of the event, the behavior of the object, and the image of the object. Before evaluation, the impact of these three components on information recipients is classified and evaluated. Subject evaluation assigns the highest weight to the goal and focuses on the result of the event. Object behavior evaluation assigns the highest weight to the code of conduct. Object evaluation assigns the highest weight to the attitude of the evaluation subject towards the object [19, 20].

Quantification: Three factors (satisfaction with the event's outcome, attitude towards the event object, and the normativeness of the object behavior) will have a certain impact on the intensity of emotion classification [21, 22]. Hence, the intensity of these variables is determined by the hierarchical structure of the subject evaluation index.

Mapping: The OCC model provides 22 kinds of synthetic emotions, and researchers will map these 22 kinds of emotions into corresponding dimensions. For example, facial expression research will map six emotions: happiness, disappointment, surprise, sadness, fear, and anger.

Expression: Information received by the recipient must be expressed. Common expressions ways include physical behavior, words, and facial expressions. Mostly, the NPO-oriented emotion analysis is based on the Weibo text. Therefore, the OCC model classifies NPO emotions per the tone of comments, the text's semantics, and the sentences' logical relationship.

3.2.2 Emotional category mapping of NPO based on the OCC model

Based on DL and OCC emotion rules, this work builds an NPO-oriented ERM based on the DL algorithm by factoring in positive, negative, and neutral emotions. Specifically, it focuses on the emotional tendency of Netizens' opinions evolution on public emergencies. Therefore, the specific case texts and emotions are combined based on the actual background of public emergencies. In many public emergencies, most comments or opinions are directed at the emergencies themselves or people. Therefore, the types of emotions related to them in the OCC model are deleted. Finally, eight basic emotion types are selected: happy for others, admiration, reproach, gratitude, regret, hate, love, and anger. At the same time, these eight basic emotion types map into positive and negative emotions in the DL algorithm to be defined as neutral emotions. The classification of NPO and emotion in public emergencies are given in Fig. 2.

According to Fig. 2, 9-dimensional emotional space is constructed. Then an emotional variable is assigned to each NPO text, as shown below:

$$\text{Emotions} = [e_{\text{happy-for}}, e_{\text{pity}}, e_{\text{admiration}}, e_{\text{reproach}}, e_{\text{gratitude}}, e_{\text{anger}}, e_{\text{love}}, e_{\text{hate}}, e_{\text{other}}] \quad (1)$$

Here, $e[0,1]$ is the value of each dimension of emotion, and e_{other} is the emotion expressed by the comment text of the NPO of emergencies, and it does not belong to these eight emotion categories.

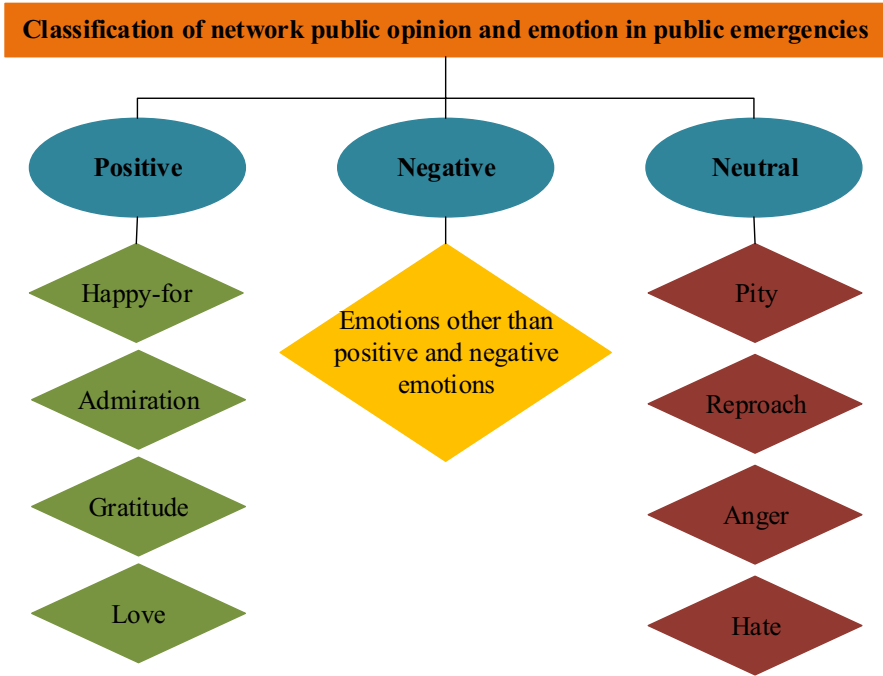


Fig. 2 Emotional category mapping of NPO

The three types of emotional rules for public emergencies mapped out based on the OCC emotional rules can be expressed as:

$$\begin{aligned} \text{Emotion(positive)} = & \text{Emotion(happy - for)} \cup \text{Emotion(admiration)} \\ & \cup \text{Emotion(gratitude)} \cup \text{Emotion(love)} \end{aligned} \quad (2)$$

$$\begin{aligned} \text{Emotion(negative)} = & \text{Emotion(pity)} \cup \text{Emotion(reproach)} \\ & \cup \text{Emotion(anger)} \cup \text{Emotion(hate)} \end{aligned} \quad (3)$$

3.3 Recognition of emotional rules of NPO based on DL

CNN is a deep feedforward network that combines a classifier and features extractor to input the image. Then, a set of feature vectors will appear after multiple feature learning. The meaning of this group of vectors is very close to the image. Finally, this group of feature vectors is input into the classifier for classification and recognition tasks. CNN generally comprises a down-sampling layer, an input layer, a convolutional layer, an output layer, and a fully connected layer. It is used in abstract recognition.

In emotion recognition of the NPO in public emergencies, CNN is used as the emotion classifier to calculate the vector-matrix of the Weibo text after the text

representation. Then, the emotion of the Weibo text can be predicted. The structure of the CNN-based network emotion classifier designed herein includes a convolutional layer and a pooling layer. Each convolutional layer in CNN has a pooling layer that can calculate part of the maximum or average value. The feature resolution can be significantly reduced because of the particularity of the second extracting feature of CNN. Then the effect of network emotion classification can be improved.

The loss function cross-entropy is used to evaluate the quality of the proposed NPO-oriented ERM. The cross-entropy loss function is defined as follows:

$$J_{(\theta)} = -\frac{1}{n} \sum_{i=1}^n y^{(i)} \log(h_{\theta}(x^{(i)})) + (1 - y^{(i)}) \log(1 - h_{\theta}(x^{(i)})) \quad (4)$$

$h_{\theta}(x^{(i)})$ represents the distribution of predicted probability. y is the actual probability distribution. There are three classification situations, and the three types of emotions: positive, negative, and neutral, are set to three label vectors: [1,0,0], [0,0,1], and [0,1,0], respectively.

Training CNN is to modify and reduce the cross-entropy loss function continuously. As long as TensorFlow has one graph describing each computing unit, it can effectively adjust the cross-entropy loss function through the Backpropagation (BP) algorithm. The mini-batch Gradient Descent Method (GDM) minimizes the cross-entropy loss function for a part of the sample data variables at a certain learning rate.

The effectiveness of the proposed NPO-oriented ERM is measured by accuracy. The specific calculation reads:

$$\text{accuracy} = n_{\text{correct}}/n_{\text{total}} \quad (5)$$

n_{total} is the number of all Weibo comments on the public emergency. n_{correct} denotes the number of correctly classified Weibo comments on the public emergency.

4 Experimental design and performance evaluation

4.1 Experimental materials

According to the nature and development of emergencies, three cases are selected. Sina Weibo is used as the collection platform, including some keywords, and the period of emergencies is the time interval for crawling. Application Programming Interface (API) crawler is used to crawl the Weibo data using JAVA based on Eclipse and Mysql databases. After crawling the relevant case data, some dirty data are filtered and cleaned, such as "forwarding Weibo" and URLs. After filtering and cleaning, let the projects that understand and do not understand the OCC emotion rules form the emotion classification and labeling of the Weibo information text of the NPO. Then, a case database of NPO for public emergencies is formed.

4.2 Experimental environment

The data set of public emergency cases is "Tianjin Explosion Incident," the number is TJ_812, the actual data captured is 24/9/19, and the valid data are 23,154 pieces. The number of "Hangzhou Nanny Arson Incident" is HZ_Arson, the actual data captured are 8,969 pieces, and the valid data are 4,652 pieces. The number of "Theater High Altitude Area Defense (THAAD)'s entry into Korea" is SK_THAAD. The actual data captured are 65,647 pieces, and the valid data are 16,889 pieces. The labeled data set is divided into a training set and a test set by 9:1.

4.3 Parameters setting

The initial hyperparameters of the proposed NPO-oriented ERM are set below. The dimension of the word vector is 300, and the convolution kernel size is 2, 3, and 4. The Dropout is 0.5, the L2 norm is 0, the mini-batch is 32, and the number of convolution kernels is 100, 100, and 100. The training iteration is 200/500/200, and the initial accuracy of the model for public emergencies TJ_812, HZ_Arson, and SK_THAAD is 84.68%, 68.84%, and 84.93%, respectively.

4.4 Performance evaluation

The word vector dimension is determined according to the actual emotion of the text information on the public emergencies. It is set to 100, 200, 300, 400, and 500 without changing other hyperparameters and variables. Then, the model is trained. The impact of the word vector dimension on the proposed NPO-oriented ERM is explained in Fig. 3.

Figure 3 suggests that when dimension=200, the model's emotion recognition accuracy for "THAAD's entry into Korea incident" and "Hangzhou nanny arson incident" is the highest. When dimension=400, "Tianjin explosion incident" accuracy is the highest. Thus, careful consideration implies that the accuracy of emotion recognition is higher word vector dimension is 200.

Each row of the convolution kernel is the vector dimension of the word. Three types of convolution kernels of different sizes are combined to verify the influence of the convolution kernel size and number on the NPO-oriented ERM. The size of each convolution kernel for the experiment is set to 1, 2, 3; 2, 3, 4; 3, 4, 5; 4, 5, 6; and 5, 6, 7. The number of convolution kernels is set to 100, 200, 300, 400, and 500, respectively, and the training is performed. The influence of the size and the number of convolution kernels on the proposed NPO-oriented ERM are compared in Fig. 4 and Fig. 5, respectively.

As Fig. 4 presents, the accuracy of the three types of events, the "THAAD entering South Korea incident," the "Hangzhou nanny arson incident," and the "Tianjin explosion incident," has relatively small differences under different convolution kernel sizes. However, when the convolution kernel size is 1, 2, and 3, the accuracy for three events is the highest.

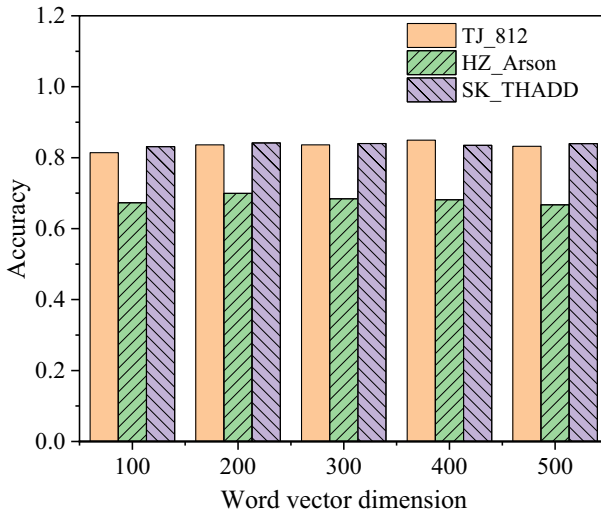


Fig. 3 The impact of word vector dimensions on the proposed NPO-oriented ERM

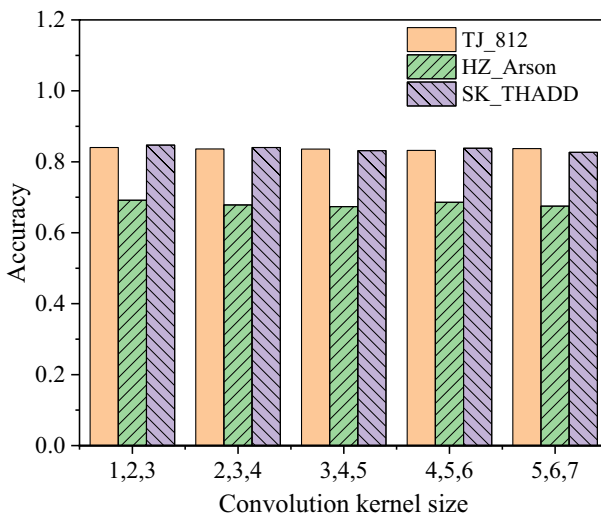


Fig. 4 The influence of the convolution kernel size on the NPO-oriented ERM

Figure 5 shows that when the number of convolution kernels is 300, the classification effect of "Hangzhou nanny arson incident" and "Tianjin explosion incident" is the best. When the number of convolution kernels is 200, the classification effect of "THAAD enters Korea incident" is the best. Thus, when the number of convolution kernels is 300, the model's emotion recognition effect on NPO is the best.

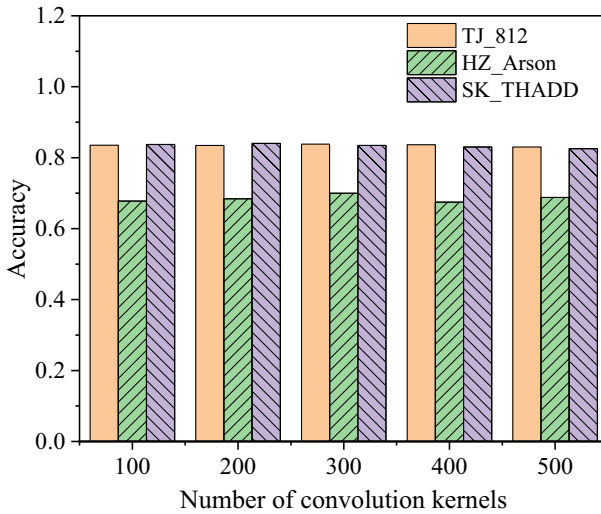


Fig. 5 The influence of the number of convolution kernels on the NPO-oriented ERM

Dropout can prevent network overfitting. The influence of Dropout on the proposed NPO-oriented ERM is described in Fig. 6.

Figure 6 indicates that when Dropout=0.6, the classification effect of "Tianjin bombing incident" and "THAAD entering Korea incident" is the best. When Dropout=0.3, the "Hangzhou nanny arson incident" recognition effect is the best. When the Dropout value is 0.8 and 0.9, too many neurons are output, leading to

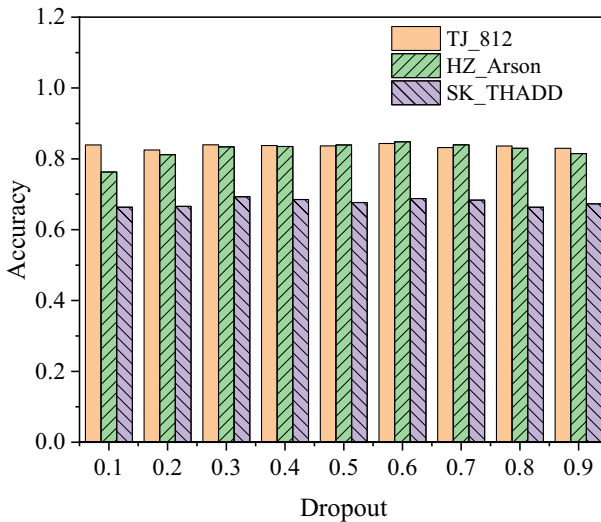


Fig. 6 The impact of Dropout on the proposed NPO-oriented ERM

overfitting. Meanwhile, when the Dropout value is 0.1 and 0.2, it will lead to fewer neuron features because of few inputs. Thus, when Dropout=0.3–0.7, the accuracy of the proposed NPO-oriented ERM is better.

The L2 norm can also prevent over-fitting. The influence of the L2 norm on the proposed NPO-oriented ERM is portrayed in Fig. 7.

Figure 7 shows that the influence of the L2 norm on the proposed NPO-oriented ERM is not obvious, and there is no obvious rule. This may be caused by the simple model or the data structure. After careful consideration, when the L2 norm is 0 or 1, the model's recognition accuracy is the highest.

Then, the mini-batch sizes are selected as 32, 64, 96, and 128, respectively, to reveal the influence of the mini-batch size on the proposed NPO-oriented ERM, as detailed in Fig. 8.

Figure 8 presents that the larger the mini-batch is, the better the recognition effect of the model is. However, a larger mini-batch demands more iterations, larger memory space, and more training time.

Based on the above analysis, the dimension of the word vector set is 200. The number of convolution kernels is 300. The convolution kernel size is 1, 2, and 3. The mini-batch is 128; the Dropout is 0.6; the L2 norm is 1. These three public emergencies are trained through the optimal hyperparameters set, and the specific training effects are illustrated in Fig. 9.

As Fig. 9 indicates, the model's emotion recognition accuracy has increased from 84.68% to 85.33% for the "Tianjin Explosion Incident," from 68.84% to 74.66% for the "Hangzhou Nanny Arson Incident," and from 84.93% to 86.88% for the "THAAD entering South Korea" events. With great improvement, the CNN classifier using the adjusted optimal hyperparameters is more effective in classifying public emotions than the original one.

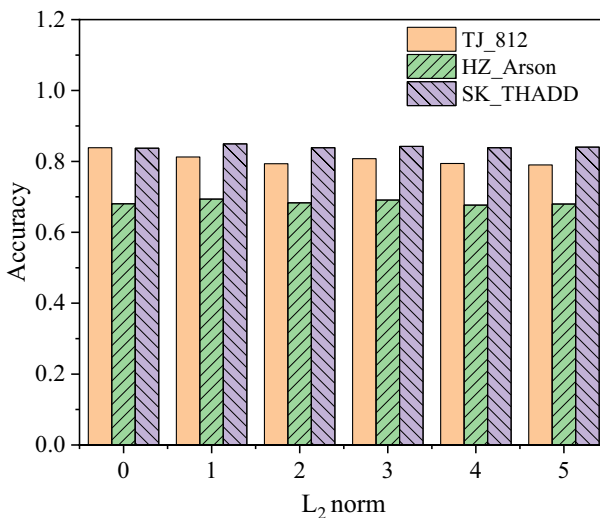


Fig. 7 The influence of the L2 norm on the proposed NPO-oriented ERM

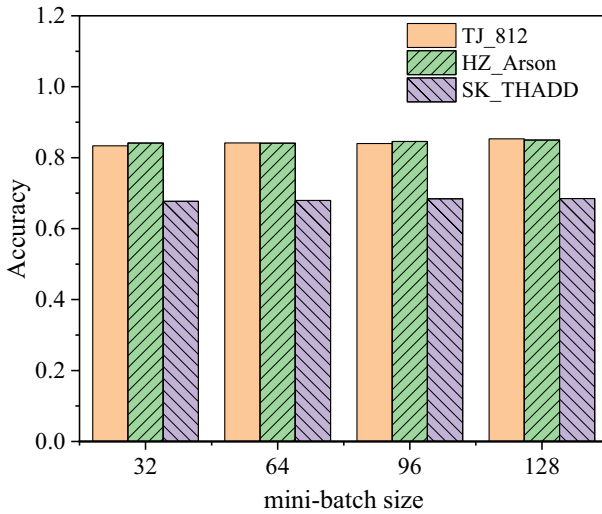


Fig. 8 The influence of mini-batch size on the proposed NPO-oriented ERM

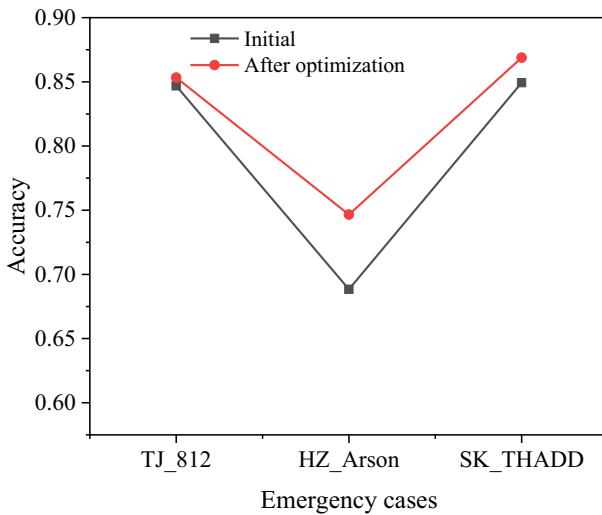


Fig. 9 The impact of optimized hyperparameters on the classification performance of proposed NPO-oriented ERM based on CNN

This section verifies the impact of the standard data set of the OCC emotion rule on the proposed NPO-oriented ERM. The comparison data set adopts the natural standard data set and is then inputted into the proposed NPO-oriented ERM. The specific result is compared in Fig. 10.

Figure 10 shows that using the OCC emotional rule as the emotional standard has greatly improved the model's emotion recognition accuracy for the "Tianjin

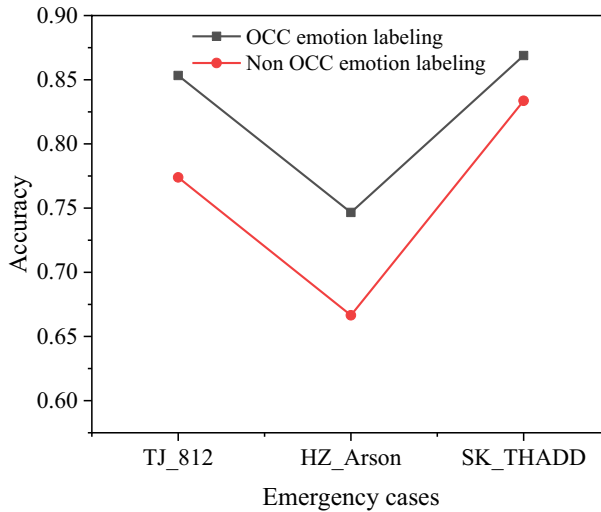


Fig. 10 The impact of OCC emotion labeling on the proposed NPO-oriented ERM

bombing incident," "Hangzhou nanny arson incident," and "THAAD entering South Korea incident." The OCC emotion rule provides a reasonable and standardized annotation system and a path for standardizing difficult-to-judge texts. Thus, the recognition performance of the model can be improved.

The word vector is trained through TensorFlow's vocabulary index and the "tf.nn.embedding_lookup" method. This method randomly initializes the word vector and then becomes the optimized parameter in the training process, which is recorded as "cnn_rand" and is compared with "cnn_word2vec". The result is denoted in Fig. 11.

Figure 11 displays that Word2Vec's method has a better recognition accuracy on the "Tianjin bombing incident" and "Hangzhou nanny arson incident" than the "cnn_rand" method. The difference between these methods for the "THAAD entering Korea incident" is not very obvious. Hence, the proposed NPO-oriented ERM presents better performance under the Word2Vec method.

The same feature representation method is used in CNN and Support Vector Machines (SVM) to compare their emotion recognition performance, as listed in Fig. 12.

Figure 12 shows that compared with SVM, CNN proposed herein has an excellent emotion recognition effect for NPO. This is because CNN adopts forward propagation prediction and error backpropagation methods and has fewer connections and parameters. Thus, it is better than other neural networks and can be more easily trained.

4.5 Discussion

To sum up, the appropriate word vector representation dimension is determined according to the actual emotion of the text information about public emergencies. Without changing other hyperparameters and variables, when word

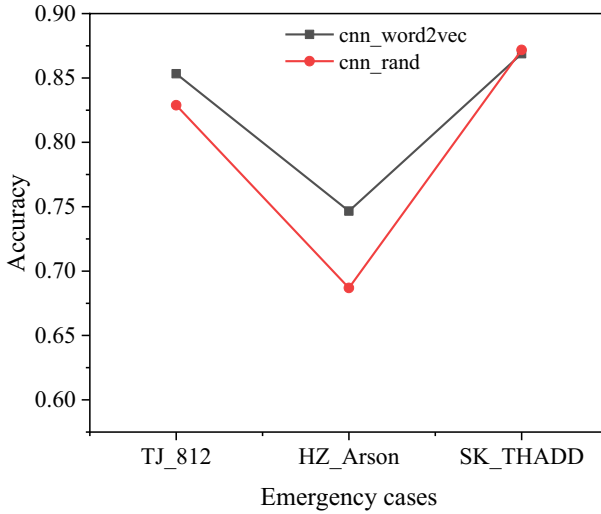


Fig. 11 The influence of the text representation method on the proposed NPO-oriented ERM

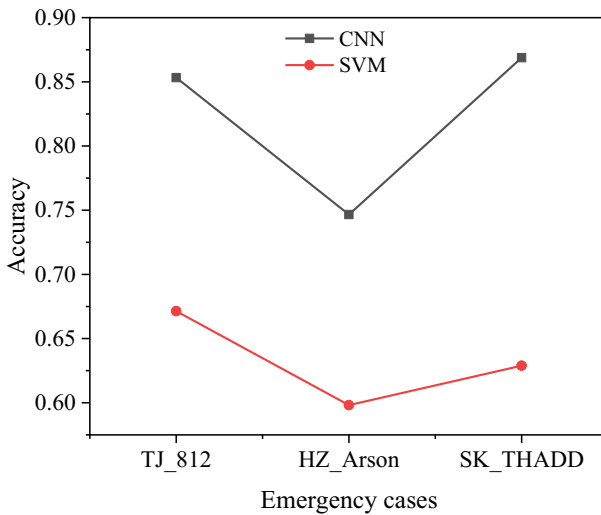


Fig. 12 The influence of emotion classifier on the proposed NPO-oriented ERM

vector dimension=200, the proposed NPO-oriented ERM's recognition accuracy for "THAAD Korean incident" and "Hangzhou Nanny arson incident" is the highest. When the convolution kernel size is 1, 2, and 3, the model's accuracy for "THAAD Korean incident," "Hangzhou nanny arson incident," and "Tianjin explosion incident" is the highest. When Dropout=0.6, the model's recognition accuracy or "Tianjin explosion event" and "THAAD entering South Korea event" is the highest.

Meanwhile, when Dropout=0.3, the model's recognition accuracy for "Hangzhou nanny arson event" is the best. Additionally, after the model hyperparameters are optimized, the model's recognition accuracy is improved from 68.84% to 74.66% for the "Hangzhou nanny arson incident" and from 84.93% to 86.88% for "THAAD entering South Korea." The results show that the proposed NPO-oriented ERM based on CNN can improve the recognition performance of the basic CNN and has practical application value for emotion recognition and NPO classification.

5 Conclusion

5.1 Research contribution

The research on NPO has been widely concerned, especially NPO-oriented emotion classification, which is the major task in NLP. This work selects three public emergencies to study NPO. Based on the OCC model, an emotional rule system is established as emotional standards. Additionally, CNN is used as a classifier to implement the NPO-oriented ERM and verify its performance through comparative experiments. The research results demonstrate that the proposed NPO-oriented ERM's emotion recognition effect is the best when the convolution kernel size is 1, 2, and 3, and the kernel number is 300. Meanwhile, the dimension of the word vector of 200 is more suitable, fully expressing the features of NPO text information and preventing overfitting. In terms of regularization constraints, when Dropout=0.3–0.7 and L2 norm=0 or 1, the performance of the proposed NPO-oriented ERM is better.

5.2 Future works and research limitations

Overall, after the optimal hyperparameter adjustment, the proposed NPO-oriented ERM recognition effect based on the CNN classifier on NPO has been greatly improved. Compared with SVM, the improved CNN performs significantly better in recognizing NPO. The finding provides a basis for relevant government agencies to handle NPO in public emergencies scientifically. The disadvantage is that only three emergencies are selected for empirical research. Future research will add more parameters, and the proposed model should be applied to more types of public emergencies to improve its universality further.

6 Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors without undue reservation.

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Declarations

Conflict of interest All Authors declare that they have no conflict of interest.

Ethical approval This article does not contain any studies with human participants or animals performed by any of the authors.

Informed consent Informed consent was obtained from all individual participants included in the study.

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