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Pattern Recognition-based Intelligent Detection and Response System Design for Public Health Emergencies in Intelligent Communities

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Abstract Public health emergencies are characterized by fast spreading speed, wide range of influence, and great social harm, and the traditional response method has the problems of monitoring blind area and response lag. With the development of big data and artificial intelligence technology, the intelligent detection and response system based on pattern recognition can realize the integrated management of the whole process, improve the early identification and efficient disposal of community public health events, and provide information support for precise prevention and control. In this study, the BiLSTM+CNN hybrid neural network model was used to extract the deep semantic features of the text, and fused the multidimensional information such as basic user attributes, behavioral features, text features and communication features to realize the intelligent recognition and processing of the information on public health emergencies. The experiments use CHECKED extended dataset for model validation, which contains 813 rumor texts and 1894 non-rumor texts. The results show that the proposed BiLSTM+CNN multi-feature fusion model performs well in the rumor recognition task, with an F1 value of 0.985, and accuracy and precision of 0.978 and 0.974, respectively, which are better than the existing mainstream models. Further analysis of the response effect of community residents in Wuhan shows that the global Moran's I index of sentiment index and case index is -0.115, showing a significant negative correlation in the period of strict prevention and control. The results of the study proved that the pattern recognition method based on multi-feature fusion can effectively improve the intelligent detection and response ability of public health emergencies, and provide new ideas for community public health emergency management.

Index Terms public health emergencies, pattern recognition, intelligent detection, multi-feature fusion, BiLSTM+CNN, rumor recognition

I. Introduction

Public health emergencies refer to infectious disease outbreaks and mass unexplained diseases that occur suddenly and may cause serious social harm [1], [2]. Such events are characterized by unpredictability, fast spreading speed, wide range of influence, and have the potential to cause large-scale casualties, economic losses, and social instability in a short period of time [3]-[5]. Therefore, it is of great significance to design a scientific and effective intelligent detection and response system in the context of smart communities [6].The 2003 SARS epidemic exposed the weaknesses of China's public health system, and the 2020 New Crown Epidemic once again verified the importance of the measurement and response system [7], [8].

Smart community refers to a new community governance model that integrates community resources and establishes a comprehensive intelligent service system through a variety of new technologies such as the Internet, cloud computing, etc., which is an important part of the construction of smart cities [9]-[11]. Intelligent detection and response system for public health emergencies in smart communities is the first line of defense in epidemic prevention and control, and plays an important role in the development of public health events [12]-[14]. Intelligent detection and response system for public health emergencies is an intelligent system that detects and warns public health emergencies by detecting public health conditions and discovering public health problems, which can systematically collect, analyze, interpret, and release health-related information [15]-[18]. Intelligent community design public health emergencies detection and response system as an important content of public health system construction, to promote the reform of the disease prevention and control system, improve the construction of the community public health system, the establishment of a reasonable and effective early control mechanism of disease epidemics and emergency response mechanism of public health emergencies is of great significance, and it helps the community to improve the comprehensive ability to respond to the public health emergencies and dispose of the public health events [19]-[22].

Public health emergencies are major infectious disease outbreaks, mass unexplained diseases, major food and occupational poisoning, and other events that seriously affect public health, which occur suddenly and cause or are likely to cause serious damage to public health in the society. In recent years, public health emergencies have been occurring frequently around the world, posing a serious threat to people's lives and health, and bringing great challenges to socio-economic development. The traditional monitoring and response mechanism of public health events mainly relies on passive reporting by medical institutions, which has problems such as incomplete information collection, untimely monitoring and early warning, and imprecise emergency response. Especially in the community, which is the grassroots unit of epidemic prevention and control, how to discover potential risks in a timely manner, quickly identify rumor information, and realize accurate prevention and control and scientific response has become an important topic in the construction of the current public health emergency management system. With the rapid development of big data, Internet of Things, artificial intelligence and other emerging technologies, intelligent detection and response to public health emergencies provide new technical support and solution paths. In particular, the application of pattern recognition technology in the field of healthcare big data analysis and public health emergency response has created favorable conditions for the construction of intelligent detection and response system for public health emergencies in smart communities. Existing studies have shown that in public health emergencies, social media data contain rich user emotional and behavioral characteristics, which can be used as an important information source for early identification and risk assessment. However, social media information is of mixed quality, and the rapid spread of rumor information can intensify public panic and affect the effective response to public health emergencies. Therefore, how to construct an efficient rumor identification model to accurately identify false information in public health emergencies becomes a key aspect of the design of intelligent detection and response systems. Meanwhile, residents' response patterns to public health emergencies and their spatial distribution characteristics are important references for the development of accurate public health interventions.

Based on the above background, this study proposes a design scheme for intelligent detection and response system for public health emergencies in smart communities based on pattern recognition. The system adopts a layered architecture, including a data layer, a model layer and a functional layer, to realize the integrated management of the whole process of public health events. In terms of model construction, a multi-feature fusion rumor recognition model for public health emergencies is proposed, which comprehensively considers user features, text features, social media dissemination features, and temporal features, and adopts a BiLSTM+CNN hybrid neural network to extract deep semantic features of the text, and achieves high-precision rumor recognition through feature fusion and multi-layer DNN network. In terms of system validation, this study conducts experimental validation based on the CHECKED extended dataset, and analyzes the spatio-temporal pattern of residents' response using Wuhan as an example, and explores the spatial correlation between the community-scale sentiment index, perception index and case index, which provides a basis for the practical application of the system. The results of the study will provide theoretical guidance and technical support for the construction of a more intelligent and precise community public health emergency management system.

II. Intelligent Detection and Response System for Public Health Emergencies in Smart Communities

II. A. Intelligent public health emergency management platform construction

II. A. 1) General idea

According to the life cycle of public health emergencies, and oriented by the national public health emergency management needs, it builds an intelligent public health emergency management platform from 3 levels of risk management, emergency management and crisis management, in accordance with the process-oriented management of before-during-after, and is oriented to the emergency command departments, health administrative agencies, CDC, hospitals, emergency centers, community health service centers, the public, social groups, etc. to provide public health monitoring, risk assessment, early warning management, information reporting, comprehensive assessment, on-site investigation, emergency response, information dissemination, public opinion management and evaluation of the effect of the whole process of integrated public health emergency management as shown in Figure 1, in order to achieve multi-point monitoring of public health emergency management, comprehensive early warning, operational synergy, data sharing, etc. to provide informationization support.

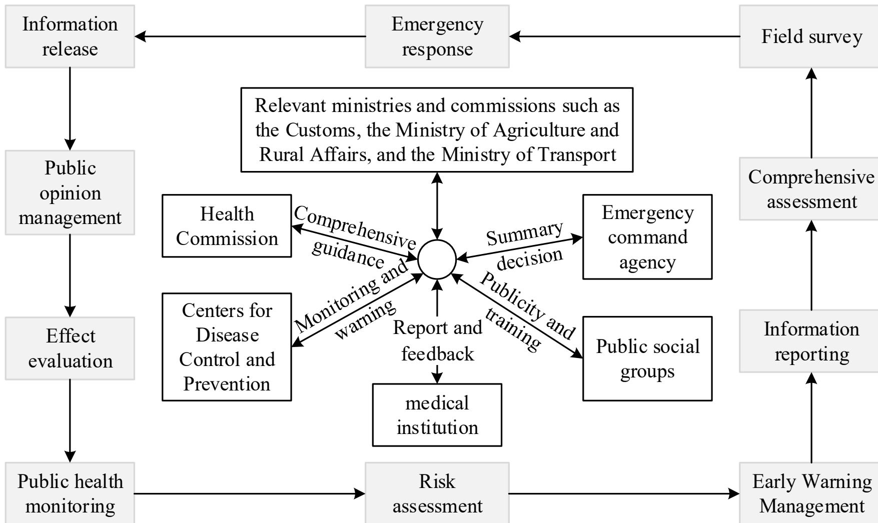


Figure 1: Intelligent public health emergency management platform builds the general idea

II. A. 2) Functional design

1. Data layer

Specific data sources can vary according to different public health emergencies and surveillance needs. The main data sources are: (1) Reporting by medical institutions. Suspected cases are detected by medical institutions in the course of disease diagnosis and treatment and reported to the disease prevention and control organization (referred to as “CDC organization”), which is a routine monitoring method. (2) Laboratory test data. Laboratory test results to understand the type, characteristics, mode of transmission and virulence of viruses or bacteria, to provide effective scientific evidence for the prevention and control of subsequent infectious diseases. (3) Transportation data. Based on aviation, railroad, highway and other transportation data, to understand the gathering of people and the flow trajectory, to assess the risk of disease transmission. (4) Social network data. Monitor social network data to identify and extract public opinion buzzwords based on data such as the frequency of different categories of inquiries and searches, and the mood of the population, so as to improve the sensitivity of early monitoring of symptoms. (5) Environmental monitoring data. Environmental factors are influential factors in the occurrence and development of infectious diseases, and monitoring abnormal environmental data such as water quality, air quality, climate, etc. can help in the early identification and early warning of infectious diseases.

2. Model Layer

It mainly includes early identification, risk assessment, early warning prediction, symptom identification model and emergency response knowledge base.

Early identification model: through the monitoring of abnormal situations, group behavior and risk factors, the potential danger of public health event outbreaks is identified at an early stage. Among them, abnormal situation monitoring is based on historical data or baseline models to detect abnormalities in current public health event data, such as abnormal infection rate, incidence rate or viral mutation, in order to detect potential disease risks and outbreaks; group behavior monitoring is a combination of social media data, search engine query data and so on.

Risk assessment model: used to determine the severity of the risk of potential public health emergencies. Facing the risk scenarios of different public health emergencies, hierarchical analysis and fuzzy comprehensive evaluation methods are used to assess the hazards of infectious diseases, the speed of transmission, the susceptibility of the population, and the accessibility of medical services.

Symptom identification model: Through the construction of a multi-factor comprehensive assessment framework for symptom identification, it recognizes specific symptoms and assists doctors in accurately identifying suspected patients, which involves data collection, feature extraction, deep learning, and symptom identification.

Emergency Response Knowledge Base: It is mainly used for the scientific and reasonable allocation of health resources in the process of public health emergency management, and sets up multi-level and multi-category emergency response programs within it.

3. Function Layer

Risk Management Module: This module aims at moving the gate forward and nipping the risk of epidemic in the bud with the help of early identification model, risk assessment model, and early warning and prediction model, which mainly involves dynamic monitoring, early identification, risk assessment, and early warning and prediction, among which, dynamic monitoring is the integration of traditional monitoring data, social media data, and environmental data and transportation data by using big data technology to provide data support for the follow-up intelligent data analysis and processing to provide data support.

Emergency decision-making management module: With the help of the emergency response knowledge base, the module assists decision-makers in judging the development trend in a timely manner when a public health emergency breaks out, and scientifically and reasonably carries out emergency response and resource allocation, mainly including analysis and judgment, hierarchical response, resource allocation and information release, among which, the analysis and judgment is mainly to use visualization technology to show the distribution of exposed populations, spatio-temporal distribution and development trends of public health emergencies, and generate intelligent emergency guidance programs to improve emergency response efficiency.

II. B. Characterization of public health emergencies

II. B. 1) User characteristics

(1) Basic user attributes. The basic attributes of users contain six dimensions: whether they are authenticated, members, location, user gender, user influence, and the total number of microblogs posted by users, which can be obtained by crawling the microblog fields; among them, members are categorized into whether they have opened a microblog membership or not, and their location is obtained through the geographic information in the microblog user profiles, and the final selected feature values include 34 provincial administrative regions in China, as well as The final selected feature values include 34 provincial administrative regions in China, as well as “Overseas” and “Others”, totaling 36 feature values. Since the number of fans and followers of a user may affect the popularity of a microblog, this paper uses the number of fans and followers to represent the user influence Uinfu, which is calculated as shown in Equation (1):

$$U_{infu} = \frac{n_{fans}}{n_{fans} + n_{followers} + 1} \tag{1}$$

where n_{fans} and $n_{follouers}$ are the number of fans and the number of followers of the user, respectively.

(2) User behavior characteristics. User behavioral characteristics include two secondary indicators, namely, recent creative enthusiasm and recent interaction, in which recent creative enthusiasm refers to the number of microblog entries related to the event posted or retweeted by the user 30 days prior to the occurrence of the event and 30 days after the data collection; recent interaction is defined here as the amount of interactions of all microblogs posted by the user 30 days prior to the occurrence of the event and 30 days after the data collection, including the amount of retweets, comments, retweets, and interactions of all microblogs. This includes the number of retweets, comments and likes. Generally speaking, in order to spread rumors, network water armies will retweet, comment, and reply to others in large quantities, so this paper restricts the time interval to 30 days before and after the rumor data collection mainly to determine the user's heat in the short term, and if the heat is too high, their tendency to publish rumors is higher.

II. B. 2) Text features

Text features include text structure features, semantic features and emotional tendency features: (1) emotional tendency features, this paper intends to use the emotional tendency analysis function of Baidu AI open platform to get the emotional tendency. (2) Topic category features, the topics of rumors in the new coronary epidemic event can be divided into medical, life, education, location, and social categories, and then according to the situation of topic categories of microblogging in the experimental data, this paper divides the topic categories into medical, health and epidemic prevention, governmental control, social, people, and other categories. (3) Text semantic features, most of the research only on the text content contained in the topic words or emotion words and other statistical data as a feature, did not dig deeper into the content contained in the semantic features, Bert can be extracted text semantic features.

II. B. 3) Social media communication characteristics

In this paper, we intend to consider the microblog comment content characteristics and microblog communication influence characteristics, microblog comment content characteristics including comment skepticism and comment sentiment, comment skepticism C_{doubts} formula is shown in formula (2).

$$C_{doubts} = \frac{\sum_{1}^{N} n_{i\_likes} * n_{i\_words}}{N_{comments}} \tag{2}$$

where n_{i_likes} is the number of likes for the i th comment in each original tweet, and n_{i_likes} is the number of skepticism words for the i th comment in each original tweet;

$N_{comments}$ the total number of comments on each original tweet, and N is the total number of comments on each original tweet. Comment Sentimentality S_{score} is then first calculated for each tweet comment and then summed up for all comments as shown in Equation (3). where $S_{i\_comments}$ is the sentiment propensity of the i th comment in each original tweet.

$$S_{score} = \frac{\sum_{1}^{N} n_{i\_likes} * S_{i\_comments}}{N_{comments}} \tag{3}$$

II. B. 4) Temporal characteristics

When the time is different, the number of users who can receive the information is also different, so this study will take the time period, week, holidays into account, where the time period of the user's work and rest pattern of the whole day will be divided into six stages: late at night (00:01-6:00), early in the morning (6:01-8:30), the morning (8:31-12:00), midday (12:01-14:00), afternoon (14:01-18:00), evening (18:01-24:00), and the daytime (18:01-24:00). -18:00), evening (18:01-24:00) six stages. Holidays include legal holidays and weekends.

II. C. Recognition model for multi-feature fusion

II. C. 1) Modeling framework

Public health emergencies have unique characteristics such as high public participation, strong negative tendency, increased panic among the people and extreme phrases, etc., and the user features and communication features are irrelevant to the domain to which the emergencies belong, and the user's historical behaviors have a certain auxiliary role in the recognition of the events [23]. As the bidirectional mechanism of BiLSTM [24] ensures that each word obtains semantics with full consideration of context, and realizes the deep extraction of text features.CNN can extract semantic representations and capture salient features in the planar structure, which has the advantage of capturing local context. Therefore, in this paper, BiLSTM is used to obtain the contextual semantics of the content, and CNN uses different convolutional kernels for the extracted features to capture multi-granularity local contextual semantic information, so as to obtain the inter-word contextual semantic structure of the textual content, and to extract the representative semantic features in the way of maximum pooling.

Introducing user history features on the basis of basic user features and content features and dissemination features, this paper proposes a multi-feature fusion rumor recognition model framework under unexpected public health events to achieve automatic and effective recognition of unexpected rumor events.

II. C. 2) Feature extraction

User basic features, communication features are extracted according to text data labels, statistical features are completed using statistical methods, python programming or EXCEL statistics of the number of symbols contained in the text, and the emotional feature values are directly used to calculate the content emotional score using Snow NLP library. Symbol statistics and Snow N-LP sentiment calculation is more mature, text semantic features reflect the user's viewpoints, opinions, emotions of the semantic expression, with uncertainty, is the key part of the recognition, this paper uses BiLSTM+CNN to extract semantic features.

II. C. 3) Feature Fusion

Feature fusion is to combine features from different perspectives to provide more basable information for classification. After normalizing the relevant data such as basic user features, user history features, propagation features, statistical features, and sentiment features, it is spliced with the 256-dimensional representative semantic feature vector T3 extracted by BiLSTM+CNN model to form a multivariate feature vector TU, which is used as the input of DNN network. The feature fusion process is shown in Eqs. (4)-(6):

$$T = T1 \oplus T2 \oplus T3 \tag{4}$$

$$H = H1 \oplus H2 \oplus H3 \tag{5}$$

$$TU = U \oplus T \oplus S \oplus H \tag{6}$$

where $\oplus$ stands for the cascade operation, i.e., splicing of the individual feature vectors.

II. C. 4) Rumor identification

Rumor recognition is trained using a multilayer DNN network for classification, and the input to the DNN is a multivariate feature vector TU. During the training of the classification model, the category labels are first encoded with One-Hot coding, and the tanh is used as the activation function in the hidden layer, and the categorical_crossentropy is used as the loss function of the model The model parameters are optimized. Finally, the classification is carried out by softmax layer to output the probability of microblog text as rumor and non-rumor, and the sum of the probability of the two is 1. The specific calculation process is shown in Eqs. (7) and (8).

$$\chi_k(x_i) = W_k^T \cdot x_i \tag{7}$$

$$P(y_i = k \mid x_i) = \frac{\exp(\chi_k(x_i))}{\sum_{i=1}^{K} \exp(\chi_k(x_i))} \tag{8}$$

where W_k is the weight coefficient matrix of the first k category, x_i is the multivariate feature vector of the first i text, y_i is the category of the first i text (rumor or non-rumor), $\chi_k(x_i)$ is the calculated value of the i text on the k category, and K is the total number of categories.

III. Experimental results and analysis

III. A. Experimental preparation

III. A. 1) Data sets

Considering the correlation between the rumor recognition task and the sentiment classification task, this paper uses the rumor and sentiment datasets in the scenario of public health emergencies. The rumor recognition dataset uses the rumor dataset of public health emergencies, CHECKED, which consists of rumor texts, non-rumor texts, and related information such as comment retweets. Among them, there are 352 rumor texts and 1714 non-rumor texts. Considering that there are few rumor texts and duplicates in CHECKED, which can easily lead to overfitting problems in the model, CHECKED is used to extend the dataset, in which 698 data from Tencent fact-checking platform are added, for a total of 2,751 pieces of data, including 813 rumor texts and 1,894 non-rumor texts. The sentiment dataset of public health emergencies was obtained from the Beijing Municipal Government Data Resource Network, with 2,497 data with positive sentiment tendency and 1,584 data with negative sentiment tendency.

III. A. 2) Experimental Environment and Parameter Settings

The configuration of the experimental environment in this paper is shown in Table 1.

Table 1: Experimental Environment

Experimental environment	Configuration details
CPU	NVIDIA GeForce RTX 3090
CPU	AMD EPYC 7601
Show off	24 GB
Memory	64GB
Development language	Python 3.8
Depth learning framework	PyTorch 1.10.0+CUDA 11.3

The rumor recognition task and sentiment classification task are learned simultaneously, and the parameter settings of the BiLSTM+CNN model are shown in Table 2. The training set, validation set and test set are divided hierarchically according to the ratio of 7:1:2.

Table 2: Parameter Settings of Deep Learning Algorithms

Training parameter setting	Model parameter	Parameter value
Training parameter setting	Batch_size	65
	Epoch	6
	Learning_rate	0.0002
BiLSTM+CNN	Word embedded dimension	771
	Hidden layer node number	771
	Layer number	3
	Dropout	0.1

Accuracy, precision, recall and F1 value are used as evaluation indexes in the experiments, which are calculated as shown in Equation (9)-Equation (12). Where TT denotes the number of public health emergency rumors correctly predicted as rumors, TF denotes the number of public health emergency rumors predicted as non-rumors, FT denotes the number of public health emergency non-rumors predicted as rumors, and FF denotes the number of public health emergency non-rumors correctly predicted as non-rumors.

$$Accuracy = \frac{TT + FF}{TT + TF + FT + FF} \quad (9)$$

$$Precision = \frac{TT}{TT + TF} \quad (10)$$

$$Recall = \frac{TT}{TT + FT} \quad (11)$$

$$F1 - score = \frac{2 \times Precision \times Recall}{Precision + Recall} \quad (12)$$

III. A. 3) Comparison experiments

(1) Data enhancement comparison experiment

In order to evaluate the effectiveness of the BiLSTM+CNN model proposed in this paper, eight data enhancement methods are selected to double the text data of rumors of public health emergencies in the training set, and compare them based on the MTL classification model.

(2) Multi-task learning comparison experiment

In order to evaluate the effectiveness of the hybrid neural network-based multi-feature fusion public emergency rumor recognition model proposed in this paper, TextCNN, DPCNN, BERT, BRET-Att-BiLSTM, DC-CNN, Single-Task, CEDA-Single-Task, MTL, CEDA-MTL, and nine models are selected are compared.

III. B. Experimental results and analysis

(1) Analysis of data enhancement results

Modify the text change rate of the four operations in CEDA to enhance the rumor text, and determine the best parameters by MTL model, the experimental results are shown in Fig. 2, the best text change rate of the four operations are 0.1, 0.4, 0.1, and 0.3, respectively.

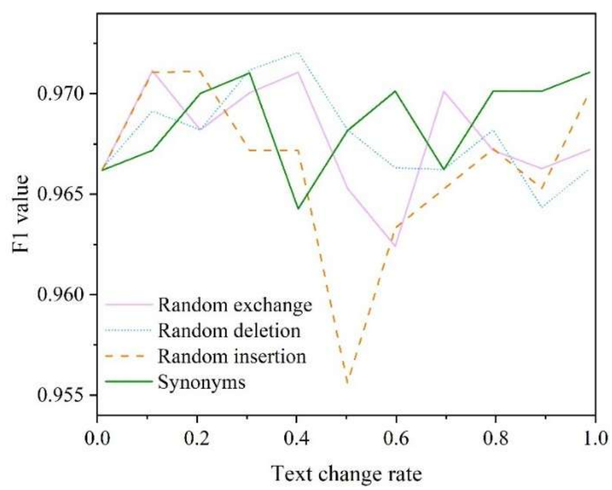


Figure 2: Effects of Different Text Change Rates on F1- score

Comparative data enhancement experiments based on the optimal text change rate are conducted and the results are shown in Table 3. Among the four methods of random exchange, random deletion, random insertion and synonym replacement, random deletion has the highest F1 value of 0.983. Experimental results 7 and 8 and experimental results 9 and 10 show that the synonym replacement method based on the extended synonym list can more effectively enhance the classification effect of rumor identification under the scenario of unexpected public health events. Comparing the experimental results 5 and 10, the F1 value is 0.983, probably because the gap between the number of positive and negative samples in the rumor dataset of this paper is small, and the EDA and CEDA methods use a ratio of 1:1:1:1 to augment the rumor text using four operations, which only doubles the rumor text, and fails to reflect the effectiveness of the integrated method.

Table 3: Results of Data Augmentation Comparative Experiment

Numbering	Data enhancement method	Accuracy	Precision	Recall	F1
1	-	0.969	0.963	0.981	0.977
2	Simple replication	0.97	0.956	0.992	0.977
3	SimBert	0.971	0.966	0.983	0.978
4	Random exchange(change_rate=0.1)	0.977	0.966	0.992	0.982
5	Random deletion(change_rate=0.4)	0.978	0.968	0.992	0.983
6	Random insertion(change_rate=0.1)	0.977	0.966	0.992	0.982
7	Synonyms(change_rate=0.3)	0.968	0.969	0.977	0.976
8	Extended synonyms(change_rate=0.3)	0.977	0.966	0.992	0.982
9	EDA	0.977	0.963	0.995	0.982
10	CEDA	0.978	0.973	0.987	0.983

(2) Analysis of multi-task learning results

The effects of different settings of hyperparameter K on the classification results are shown in Table 4. The classification model uses the MTL model, and the highest F1 value is 0.979 when the number of shared self-attention layers is 6, and the F1 value is 0.972 when the number of shared self-attention layers is 0, which is equivalent to the single-task learning of the model proposed in this paper. The classification results do not exactly increase with the number of shared layers, probably because the model has learned enough features when sharing three self-attention layers, however, how each self-attention model interacts with each other needs to be studied further.

Table 4: Results of Different Hyperparameters(MTL)

Shared layer number	Unshared layer number	Accuracy	Precision	Recall	F1
0	6	0.960	0.943	0.994	0.972
1	5	0.962	0.952	0.985	0.974
2	4	0.965	0.966	0.977	0.977
3	3	0.965	0.979	0.964	0.977
4	2	0.962	0.982	0.958	0.975
5	1	0.962	0.974	0.965	0.975
6	0	0.968	0.963	0.983	0.979

The results of the multi-task learning comparison experiments are shown in Table 5. Among the models 1-model 7 based on unbalanced dataset and single-task learning, the highest F1 value of the single-task learning model with shared 0-layer self-attention layer is 0.972, which indicates that the hybrid neural network-based multi-feature fusion public emergency rumor recognition model proposed in this paper has a strong semantic feature extraction capability, while the stronger text semantic comprehension of the BiLSTM model with attention mechanism is more favorable for global feature extraction. Comparing Models 7 and 8 and Models 9 and 10, it can be found that data enhancement of the unbalanced public health emergency rumor text dataset can improve the model performance.

Compared with each Baseline model, the BiLSTM+CNN model in this paper shows optimal results in three indicators: accuracy, precision and F1 value, in which the F1 value reaches 0.985, in addition, the BiLSTM+CNN structure is able to comprehensively extract the deep semantic features of the text. Therefore, BiLSTM+CNN model rumor recognition is optimal.

III. C. Analysis of the Effectiveness of Resident Response

III. C. 1) Resident Response Global Spatial and Temporal Patterns

Taking the 2020 Wuhan-era public emergency as an example, the changes in the daily sentiment index and perception index over time within Wuhan during the study period are shown in Fig. 3, which shows the general trend of city residents' feelings and concerns about the new coronary pneumonia on social media. The epidemic sentiment index was lower than the overall sentiment index throughout the time period of the study; during the period of normalized prevention and control and the period of strict prevention and control, the epidemic sentiment index was relatively stable, but after the liberalization of the prevention and control policy, the epidemic sentiment index had a large ups and downs fluctuation, showing a decreasing and then increasing trend. In the latter part of the period of normalized prevention and control, the sentiment index rose rapidly, and when analyzed with the epidemic data, it was found that it coincided with the time period of the rapid increase in confirmed cases; and then with the liberalization of the prevention and control policy, the sentiment index showed a tendency to rise and then fall.

Table 5: Results of Multi-Task Learning Comparative Experiment

Numbering	model	Accuracy	Precision	Recall	F1
1	TextCNN	0.913	0.905	0.906	0.906
2	DPCNN	0.92	0.881	0.781	0.829
3	BERT	0.866	0.865	0.927	0.894
4	BRET-Att-BiLSTM	0.906	0.853	0.998	0.921
5	BERT-RCNN	0.955	0.938	0.935	0.937
6	DC-CNN	0.968	0.959	0.962	0.961
7	Single-Task	0.967	0.944	0.996	0.972
8	CEDA-Single-Task	0.974	0.959	0.997	0.978
9	MTL	0.975	0.964	0.993	0.979
10	BiLSTM+CNN	0.978	0.974	0.997	0.985

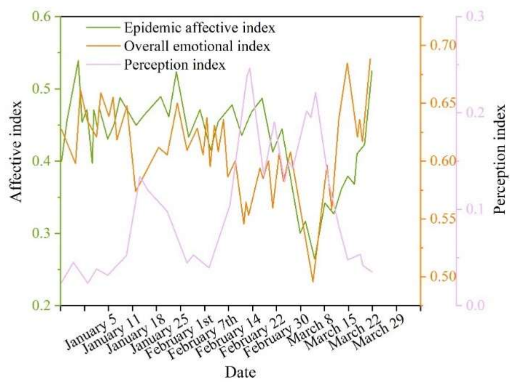
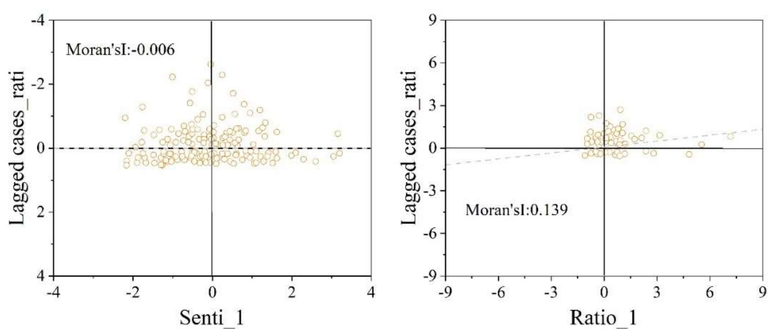
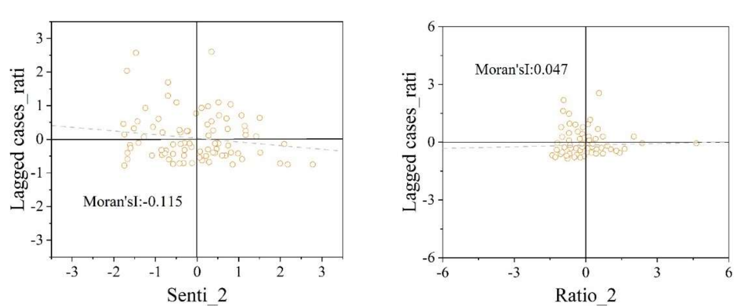


Figure 3: The temporal variation of sentiment index and perception index



(a) Index and case index (b) Perceived index and case index



(c) Index and case index (d) Perceived index and case index

Figure 4: Scatter plot of Moran's I of public response index and case index

III. C. 2) Spatial correlation analysis

Global bivariate spatial autocorrelation analyses of the community-scale sentiment index, perception index and case index at different stages in the study area were conducted separately, and the global Moran′s I index describing their global correlations can be obtained as shown in Figure 4. In the period of normalized prevention and control, the global Moran′s I index of the sentiment index and the case index was -0.006, which showed a weak negative correlation; in the period of strict prevention and control, the index decreased to -0.115, which showed a stronger negative correlation. And the global Moran′s I index of perception index and case index was 0.139 in the period of normalized prevention and control, and decreased to 0.049 in the period of strict prevention and control.The results showed that:(1) with the development of public health emergencies, the affective state of Wuhan residents continued to decrease, and the correlation with the severity of events in the community increased. (2) People's sensitivity to the discussion of topics related to public health emergencies and the exposure of cases in their community decreased, which may be related to the city's prevention and control policy of silent management during the period of strict prevention and control.

IV. Conclusion

This study constructed an intelligent detection and response system for intelligent community public health emergencies based on pattern recognition, realizing the integrated management of the whole process of public health events. The research results show that the proposed BiLSTM+CNN multi-feature fusion model performs excellently in the rumor recognition task of public health emergencies, with an accuracy of 0.978, a precision of 0.974, a recall as high as 0.997, and an F1 value of 0.985, which is superior to the existing mainstream models, such as TextCNN, DPCNN, BERT, and so on. The results of data enhancement experiments show that the CEDA method based on extended synonym table is effective in the rumor recognition task, and the model performs best when the text change rate is set to 0.3. The analysis of residents' response effect reveals the spatio-temporal change law of community residents' emotion and perception in public health emergencies, and the global Moran's I index of emotion index and case index decreases from -0.006 to -0.115 in the period of normalized prevention and control as compared with the period of strict prevention and control, presenting a stronger negative correlation, which reflects the dynamic change of residents' psychological state in the process of the development of public health events. The study proves that the intelligent recognition method of multi-feature fusion can effectively improve the monitoring and early warning of public health emergencies and emergency response capability, and the intelligent detection and response system of public health emergencies in smart communities provides new ideas and technical support for the realization of the public health emergency management goal of “multi-point monitoring, comprehensive early warning, business collaboration and data sharing”, which is of great practical significance for the construction of a resilient city and a healthy community. It has important practical significance for building resilient cities and healthy communities.

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