

## Research Article

# Information Extraction and Spatial Pattern Analysis of Sports Events Based on Deep Learning

Quansheng Zheng 

*Physical Education Department, Guizhou University of Commerce, Guiyang 550014, China*

Correspondence should be addressed to Quansheng Zheng; zhengqsh@yeah.net

Received 10 March 2022; Revised 7 April 2022; Accepted 11 April 2022; Published 22 April 2022

Academic Editor: Sheng Bin

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The analysis of sports events information greatly promotes the formulation of scientific development strategy for sports events, the optimization of the spatial distribution of these events, and the popularization of sports culture. Most of the previous studies focused on the positive effects on sports events, but few quantified the effects. Besides, the broad environment of new media information communication was not considered. Therefore, this study carries out information extraction and spatial pattern analysis of sports events based on deep learning. Firstly, the texts of sports events information were classified by convolutional neural network (CNN), and the most valuable news or cases of sports events were screened. On this basis, a named entity recognition model was constructed to extract the most effective information from the data of sports events information. Next, a spatial pattern analysis approach was provided for the diffusion of sports event information flow. Finally, experiments were carried out to demonstrate the effectiveness of the proposed model and provide the spatial pattern analysis results on the diffusion of sports events information flow.

## 1. Introduction

Since the 2008 Beijing Olympiad, sports events have become an important part of social life in China. More and more people take part in sports, enjoy sports, and pay much attention to information of sports events [1–4]. All sorts of sports event information are delivered via information communication media, such as sports newspapers, sports television channels, sports websites, and sports new media [5–10]. The analysis of sports event information can disclose the public's concern over different types of sports events, reflect the spatial pattern of sports event information, and guide the organization of such events [11–16]. The information extraction and spatial pattern analysis of sports events greatly promote the formulation of scientific development strategies for sports events, the optimization of the spatial distribution of sports events, and the dissemination of sports culture.

With the dawn of the age of shallow reading and the proliferation of smartphones, data visualization has evolved into an ideal way to present news. As large sports

events become increasingly influential and eye-catching, visual communication wins the recognition of viewers thanks to its vivid display of data and news. Through a questionnaire survey, Xia [17] evaluated the influence of the propagation of large sports events against the backdrop of the big data. Facing the rapid growth of sports video data, it is critical to identify the information of interest. Chen and Du [18] analyzed the hidden Markov model, presented a semantic analysis method for sports videos, and clarified the analysis flow for the contents being played and not being played. Then, a few segments were selected for experiments. The experimental results show that the model achieved an accuracy of around 90%. Cannavò et al. [19] investigated the feasibility of the spatiotemporal position dataset collected from athletes and sports equipment during the games and utilized machine learning to automatically identify small sports events in datasets related to basketball. Choudhury and Breslin [20] adopted various approaches to test the named entities and important microevents in tweets published during the live broadcast of sports events, combined

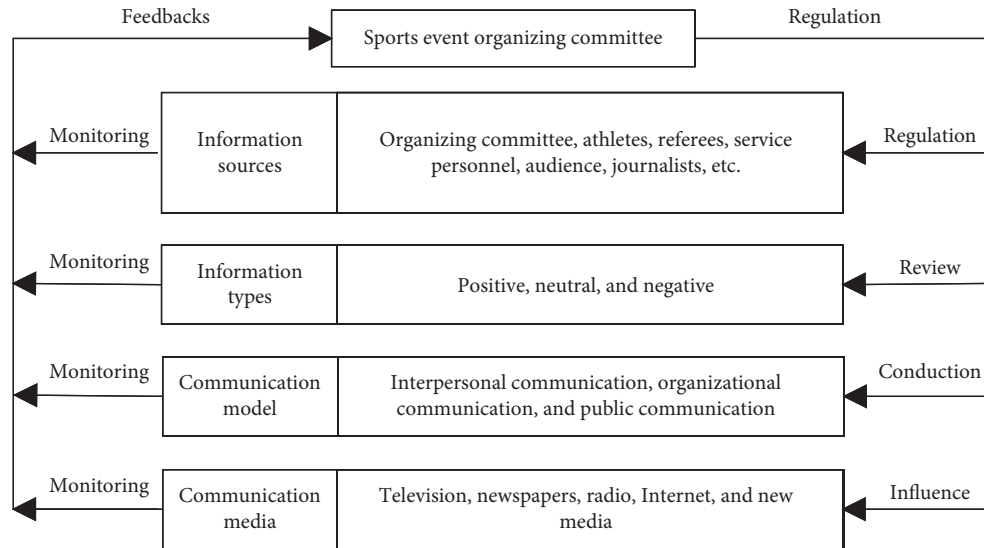


FIGURE 1: Communication channels of sports events information.

linguistic features with background knowledge, and achieved high-precision detection on different datasets.

Despite the fruitful research contents, most of the previous studies are too shallow and concentrated on the positive effects of sports events. However, very few scholars have quantified these effects. With the rapid development of information technology, the information communication method of the traditional method is gradually phased out by that of new media. In the context of new media, the Internet plays an important role in the acquisition of sports events information. This study targets the texts of sports events information on online media and mainly examines the information extraction and spatial pattern analysis of sports events. The main contents are as follows. Based on a convolutional neural network (CNN), Section 2 classifies the texts of sports events information and screens the most valuable news or cases of sports events. Next, a named entity recognition model was constructed to extract the most effective information from the data of sports events information. Section 3 provides a spatial pattern analysis approach for the diffusion of sports events information flow. Finally, experiments were carried out to demonstrate the effectiveness of the proposed model and provide the spatial pattern analysis results on the diffusion of sports events information flow.

## 2. Deep Learning-Based Information Extraction of Sports Events

The audience's attention to sports events is mainly manifested as the rating of live broadcasts on traditional media and the attendance in the venue. With the development of the times and information technology, more and more people prefer watching sports events online. To increase the visibility of a sports event, the organizer must communicate the event information in the most effective way. The common communication media for sports events can be divided

into three categories: interpersonal communication, organizational communication, and public communication. With the rapid development of information technology, the sports events communication can be achieved in the new media. This new communication model boasts low cost of loop playback, fast updates, large information volume, rich contents, strong interactivity, all-weather operation, and full coverage. Figure 1 shows the communication channels of sports events information.

This study focuses on the following communication features of sports events information, such as the diversity of communication subjects, the timeliness of communication, the fragmentation of information, the broadness of communication, and the fission propagation of information. As the most important transmission medium, new media has two basic functions, namely, receiving and publishing sports events information. The speed of information reception and publication directly bears on the visibility enhancement of sports events, which is sensitive to time. After logging onto new media software or apps on their mobile terminals, users can receive sports events information anywhere and anytime and post their reviews. This is the major advantage of the new media in the communication of sports events' information. With the aid of the new media, it is possible to carry out live broadcasts of sports events and deliver sports events information to more people in a shorter time.

In this study, the sports events information gathered by crawlers is preprocessed through format unification, duplicate removal, and word segmentation. After preprocessing, the texts of sports events information were classified by CNN, and the most valuable news or cases of sports events were selected from the original data. Next, a named entity recognition model was constructed to extract the most effective information from the data of sports event information. The principle and improvement of our methodology, as well as experimental design, are detailed in the following sections.

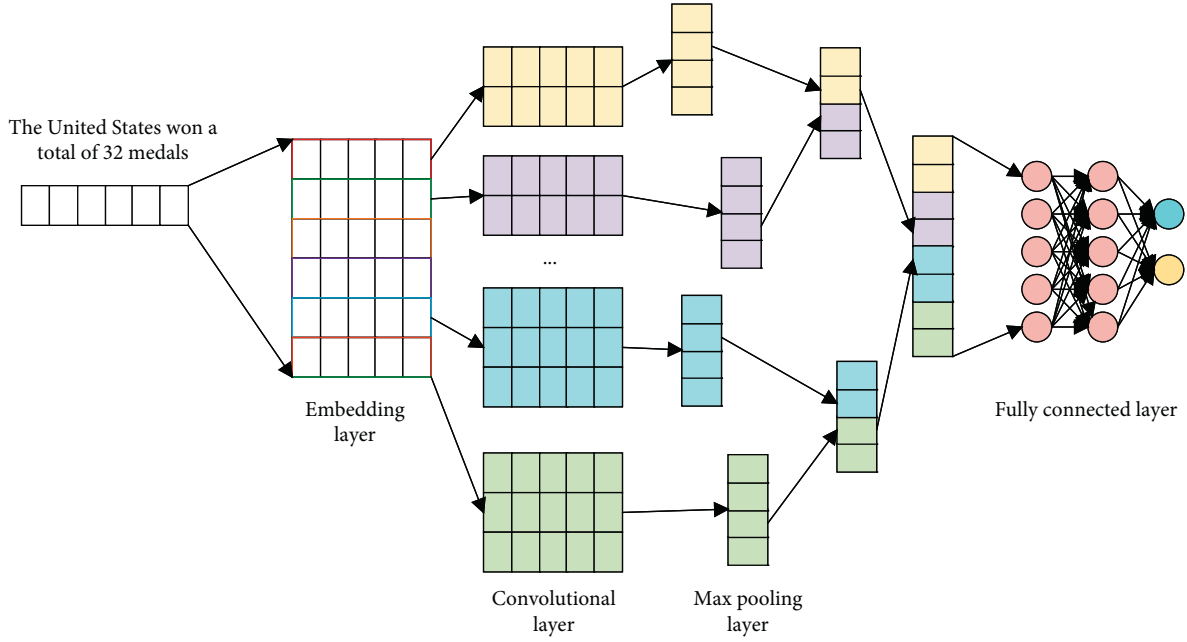


FIGURE 2: Structure of the CNN.

**2.1. Text Classification.** The CNN was introduced to classify the texts of sports events information. In the network, the input layer is responsible for formatting the information text series of sports events and converting the texts into word vectors. Figure 2 illustrates the structure of the CNN. Through convolution, the convolutional layer performs the continued multiplication and summation of the array elements in the matrix of the sentences in the texts of sports events information:

$$E = g(Q * C + \psi). \quad (1)$$

Let  $Q$  be the initial weight matrix,  $\psi$  be the offset vector, and  $E$  be the feature matrix of the convolutional layer output. Capable of sparse activation and preventing exploding gradients, the rectified linear unit (ReLU) function can be adopted to map the convolutional results nonlinearly. ReLU has two advantages as the activation function: (1) the gradient of the function is a constant in the positive quadrant, which prevents the diffusion of gradients; (2) the sparse activity ensures that the gradient of the function is zero in the negative quadrant, such that the nodes will not be trained. Thus, we have

$$\text{Relu}(a) = \begin{cases} a, & \text{if } a > 0, \\ 0, & \text{if } a \leq 0. \end{cases} \quad (2)$$

The pooling operations of the CNN include maximum pooling and average pooling:

$$\begin{aligned} \text{UQ} &= \text{MP}[E + \psi_J], \\ \text{UQ} &= \text{AP}[E + \psi_J]. \end{aligned} \quad (3)$$

The output layer adopts softmax logistic regression. Let  $A_i$  be the  $i$ th element in input  $A$ . Then, the softmax value of that element can be obtained by

$$\text{SOF}_i = \frac{e^{a_i}}{\sum_j e^{a_j}}. \quad (4)$$

Formula (4) shows that the softmax value is the proportion of the exponential value of the element in the sum of exponential values of all elements. If  $M$  texts of sports events information wait to be classified, an  $M$ -dimensional vector can be obtained through the softmax layer of the CNN. The  $i$ th value of the vector is the probability of a text of sports events information belonging to the  $i$ th class.

**2.2. Named Entity Recognition.** In the field of sports events, more than 80% of data are effective information extracted from the texts related to sports events news released on television, newspapers, radio, the Internet, and the new media. The information, including the time and location of each event, the athletes participating in the event, and the live broadcast of the game, greatly supports the judgment of the situation of major sports events, the promotion of sports culture, the feedbacks on event services, and the improvement of service quality. To recognize the entities in sports events, this study constructs a pretrained named entity recognition model embedded with a language representation module.

The model includes an embedded module, a feature extraction module, a conditional random field (CRF) module, and an adversarial training module. In the embedding module, the information text series of sports events, which is of the length  $m$ , supports three vector representations: token embedding  $R_{\text{TO}}(q_i)$ , segment embedding  $R_{\text{SE}}(q_i)$ , and position embedding  $R_{\text{PO}}(q_i)$ . The three representations share the same shape  $(1, m, 768)$ .  $R_{\text{TO}}(q_i)$ ,  $R_{\text{SE}}(q_i)$ , and  $R_{\text{PO}}(q_i)$  represent the character vector, the sentence vector, and the position of the input series, respectively.

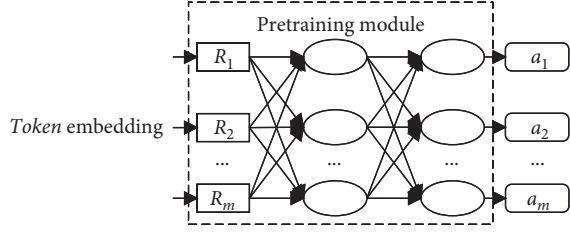


FIGURE 3: Structure of the transformer pretraining model.

The above embedding representations are summed up to generate the input to the encoder layer of the embedding module. The shape of the input is  $(1, m, 768)$ . That is, each character  $q_i$  is encoded into the following vector  $R_i$ :

$$R_i = R_{\text{TO}}(q_i) + R_{\text{SE}}(q_i) + R_{\text{PO}}(q_i). \quad (5)$$

Then, the character vector representation  $[a_1, a_2, \dots, a_m]$  of the input text series can be obtained through the transformer pretraining model in the embedding module. Figure 3 presents the structure of the transformer pretraining model. The character vectors are passed through the CNN to extract the features of the input series, providing a more complete vector representation for the subsequent adversarial training.

For information extraction of sports events, the effective information entities depend strongly on the context of the texts related to sports events information. Therefore, the current information is of equal importance as the information of the previous moment and that of the subsequent moment. To combine the information on both sides of the information text series of sports events, this study adopts the bidirectional long- and short-term memory (BiLSTM) network to extract features and thus comprehensively considers the context of the input text.

Based on the character vector series  $[a_1, a_2, a_3, \dots, a_m]$  obtained through traversal, the BiLSTM model with private tasks and that with shared tasks, respectively, output features  $F^{\phi} = [f_1^{\phi}, f_2^{\phi}, \dots, f_m^{\phi}]$  and  $F^c = [f_1^c, f_2^c, \dots, f_m^c]$ . Let  $f_p^{\rightarrow}$  and  $f_p^{\leftarrow}$  be the forward and backward hidden states of the  $p$ th character, respectively,  $f_p^{\phi} = f_p^{\rightarrow} \otimes f_p^{\leftarrow}$  be the private hidden state of the  $p$ th character, and  $\Omega$  be the execution process of the LSTM model. Then, we have

$$\begin{aligned} \vec{f}_p &= \vec{\Omega}(\vec{f}_{p-1}, a_p), \\ \overleftarrow{f}_p &= \overleftarrow{\Omega}(\overleftarrow{f}_{p-1}, a_p). \end{aligned} \quad (6)$$

The private BiLSTM model can only extract the features from the recognition task of a single named entity. Let  $\Omega^*$  be the execution of the LSTM model and  $\beta_c$  and  $\beta_{\phi}$  be the parameters of private BiLSTM and shared BiLSTM, respectively. Then, the hidden states of private BiLSTM and shared BiLSTM can be expressed as

$$\begin{aligned} f_p^c &= \Omega^*(f_p^c, a_p; \beta_c), \\ f_p^{\phi} &= \Omega^*(f_p^{\phi}, a_p; \beta_{\phi}). \end{aligned} \quad (7)$$

The outputs of the two BiLSTM models are spliced and introduced into a linear feedforward neural network layer:

$$f_p^{\text{CRF}} = Q(f_p^c \oplus f_p^{\phi}) + \psi, \quad (8)$$

where  $Q$  and  $\psi$  are the weight and bias of the linear feedforward neural network layer, respectively.

The BiLSTM fails to consider the sequential dependence of text series. To obtain the final labels of the series, this study adds a standard CRF layer atop the named entity recognition model. Let  $Q^{\text{CRF}}$  be the model parameter,  $U_{b_{p-1}, b_p}$  be the transfer probability matrix from label  $b_{p-1}$  to label  $b_p$ , and  $m$  be the length of the input sentence. Then, the definitions related to the score prediction can be given by

$$\begin{aligned} E(A, b) &= \sum_{p=1}^m \left( v_{p, b_p}^{\text{CRF}} + U_{b_{p-1}, b_p} \right), \\ v_p^{\text{CRF}} &= Q^{\text{CRF}} f_p^{\text{CRF}}. \end{aligned} \quad (9)$$

Let  $\hat{b}$  be the optimal text series label. For the character vector  $A = \{a_1, a_2, \dots, a_m\}$  of the input text series, the probability of outputting  $\hat{b}$  can be calculated by

$$\text{GR}(\hat{b}|A) = \frac{r^{a(A, \hat{b})}}{\sum_{\hat{b} \in B_A} r^{a(A, \hat{b})}}. \quad (10)$$

The CRF model is trained with the following loss function:

$$K_{\text{CRF}} = -\log \text{GR}(\hat{b}|A). \quad (11)$$

Inspired by the adversarial network, this study extracts the boundary information from the shared words in sports events information and generates the final features by the CNN for recognizing the effective information, aiming to optimize the named entity recognition task based on sports events' information sharing. The hidden state of private features for the Chinese word segmentation task can be expressed as

$$f_p^{\text{CWS}} = \Omega^*(f_{p-1}^{\text{CWS}}, a_p). \quad (12)$$

To segment Chinese words and recognize named entities, the feature series generated by the BiLSTM responsible for Chinese word segmentation can be spliced with  $f_p^c$ :

$$f_p^{\text{adv}} = f_p^{\text{CWS}} \oplus f_p^{\text{common}}. \quad (13)$$

Based on the CNN, the final features are shared by both tasks (Chinese word segmentation and named entity recognition); the discriminator of the adversarial training performs max pooling on the convoluted series using a convolutional operator:

$$\begin{aligned} \tilde{f}_p^{\text{adv}} &= \tanh(Q(f_{p-2}^{\text{adv}}, f_{p-1}^{\text{adv}}, f_p^{\text{adv}}, f_{p+1}^{\text{adv}}, f_{p+2}^{\text{adv}})), \\ f_p^{\text{adv}} &= \text{max pooling}(\tilde{f}_1^{\text{adv}}, \tilde{f}_2^{\text{adv}}, \tilde{f}_m^{\text{adv}}). \end{aligned} \quad (14)$$

Finally, the probability of an actual task  $l$  can be calculated by a fully connected layer:

$$\text{GR}(\hat{l}|A, \hat{b}) = \frac{\exp\left(\nu_l^{\text{adv}}\right)}{\sum_l \exp\left(\nu_l^{\text{adv}}\right)}, \quad (15)$$

where  $\nu^{\text{adv}} = Qf^{\text{adv}}$ . The total loss function contains the negative log-likelihoods of the two tasks:

$$K = -\log \text{GR}(\hat{b}|A) + \log \text{GR}(\hat{l}|A, \hat{b}). \quad (16)$$

### 3. Spatial Pattern Analysis on Diffusion of Sports Events' Information Flow

The diffusion strength index of information flow can characterize the spatial diffusion strength of sports events information flows based on the new media:

$$\alpha = \frac{P_{yi}}{P_y}. \quad (17)$$

The above index measures the regional spatial diffusion strength of sports events information. Let  $P_{yi}$  be the volume of information forwarded to the  $i$ th region based on the new media and  $P_y$  be the total volume of information forwarded based on the new media. The greater the  $\alpha_{yi}$ , the stronger the diffusion of sports events information flow towards the  $i$ th region.

The distribution law of regional size is often measured by primacy. There are three common indices of regional primacy: two-region index  $E_2$ , four-region index  $E_4$ , and 11-region index  $E_{11}$ . Among them,  $E_2$  refers to the ratio of the largest subregion in the region to the second largest subregion:

$$E_2 = \frac{T_1}{T_2}. \quad (18)$$

Let  $\varepsilon_1$  be a threshold. If  $E_2 > \varepsilon_1$ , then the largest subregion has a strong monopoly, and the subregions cluster moderately in the region.  $E_4$  refers to the ratio of the largest subregion to the sum of the second to fourth largest subregions:

$$E_4 = \frac{T_1}{(T_2 + T_3 + T_4)}. \quad (19)$$

$E_{11}$  refers to the ratio of the largest subregion to the sum of the second to 11th largest subregions:

$$E_{11} = \frac{2T_1}{(T_2 + T_3 + \dots + T_{11})}. \quad (20)$$

Both  $E_4$  and  $E_{11}$  use  $\varepsilon_2$  as the threshold. If  $E_4$  or  $E_{11}$  is greater than  $\varepsilon_2$ , then the subregions are over clustered in the region; if  $E_4$  or  $E_{11}$  is smaller than  $\varepsilon_2$ , then the subregions cluster moderately in the region.

The rank-size rule can be applied to explore the distribution features of subregion sizes, according to the correlations between subregion sizes and size ranking. Let CO be the ranking of subregion size and  $US_{CO}$  be the subregion size. Then, the rank size of subregions can be characterized by  $US_1 \geq US_2 \geq US_3 \geq US_{CO} \geq \dots \geq US_m$ . Let  $RS_i$  and  $CO_i$  be

the population and ranking of the  $i$ th subregion, respectively;  $\zeta$  be the constant. Then, we have

$$RS_i CO_i^w = \zeta \text{ or } RS_i = \zeta CO_i^{-w}. \quad (21)$$

Taking the logarithm of the two sides of the above formula,

$$\lg RS_i = \lg \zeta - w \lg CO_i. \quad (22)$$

### 4. Experiments and Results' Analysis

The data used in this section come from the Baidu Index Platform (<https://index.baidu.com>). The time range is from January 2018 to December 2020. The annual mean Baidu Index was solved for each marathon event.

Based on the relationship between the published volume of sports events information and time, this study divides the research period into three segments: Nov. 20–24, Nov. 25–29, and Nov. 30–Dec. 6. Then, the sports events information was split into four parts: those published in segment I, those published in segment II, those published in segment III, and those published through the research period IV. The spatial distribution features and spatial pattern of the information released in each period were analyzed (Figure 4).

Figure 5 shows the relationship between the information diffusion levels of different new media information on sports events and the number of regions. It can be observed that the relationship varied only slightly between segments I, II, and III and the overall period IV. However, the diffusion level of sports events information differed significantly between regions. From segment I to the overall period IV, more and more regions were covered by sports events information. The higher the diffusion level is, the greater the number of regions being covered. In general, the relationship between the information diffusion level and a number of regions obeyed a pyramid-shaped distribution.

The above experimental results show that sports events information diffuses differently from region to region. On a global scale, the sports events information is rather dispersed. On the local scale, information is strongly clustered. Overall, information diffuses widely across the space but clusters in local areas.

This study performs a log-log regression analysis on the diffusion of sports events information on different new media. The regression results (Table 1) show that the proposed regression equation passed the significance test, so did the regression coefficients. It can be seen that the diffusion of sports events information on different new media satisfied the rank-size distribution. Drawing on the fractal theory, the spatial distribution features were examined for the diffusion of sports events information. The primacy of sports events information on different new media was always smaller than 1, indicating that the diffusion of this information not only was uniformly distributed in space but also tended to be clustered; that is, most sports event information is published in a few regions.

The datasets used for our experiments are displayed in Table 2.

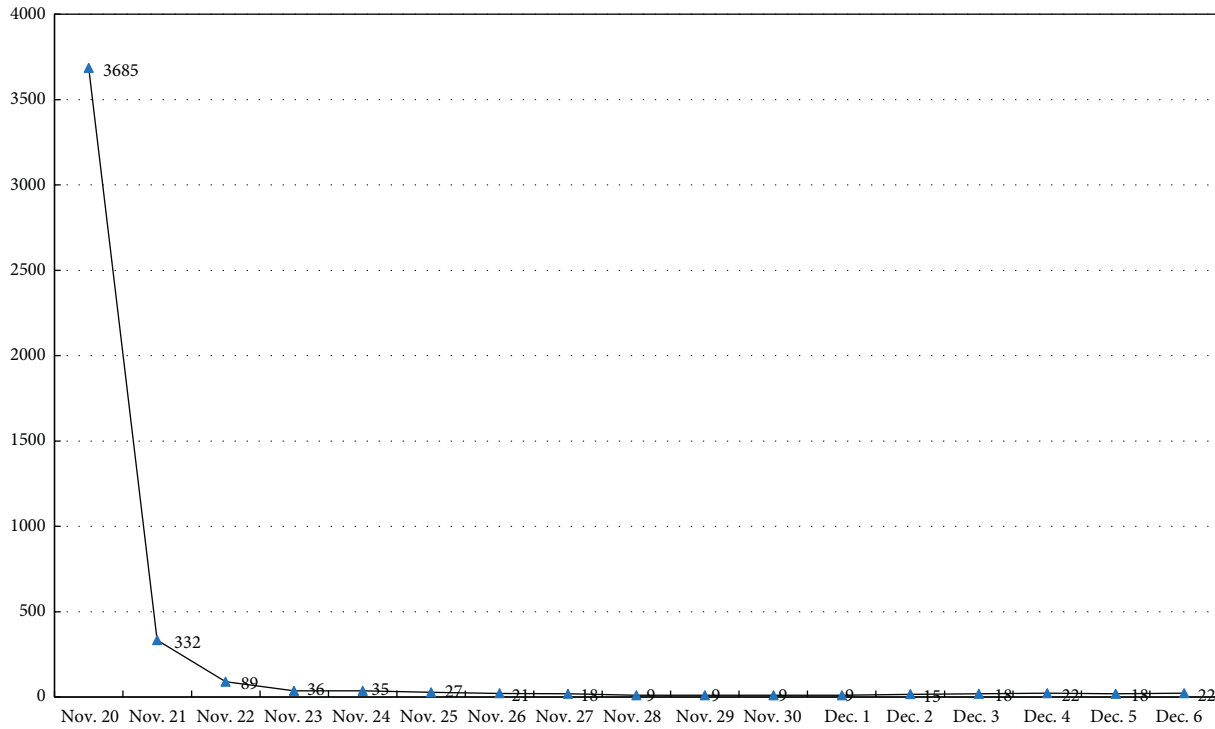


FIGURE 4: Relationship between the published volume of sports events information and time.

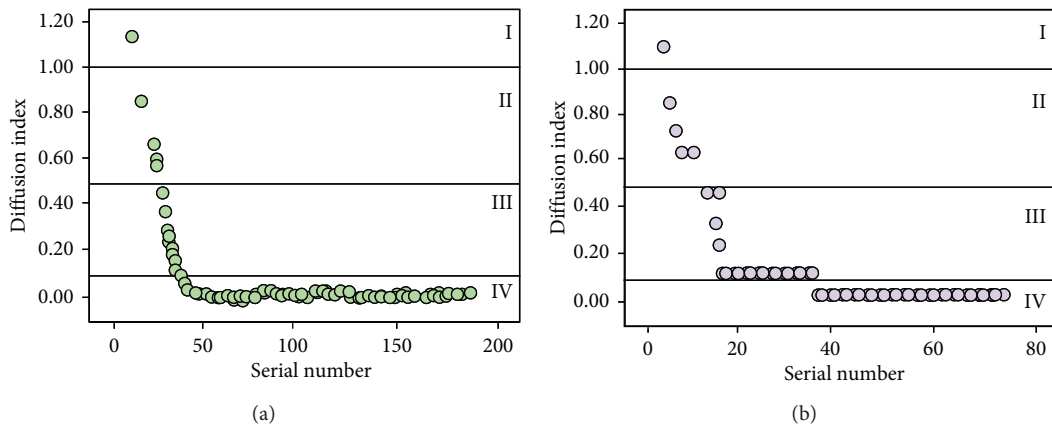


FIGURE 5: Relationship between the information diffusion level and number of regions.

TABLE 1: Rank-size regression on sports event information.

Time	I	II	III	IV
		New media 1		
Regression equation	$P_i = 353R_i^{1.374}$	$P_i = 125R_i^{1.250}$	$P_i = 18R_i^{1.718}$	$P_i = 502R_i^{1.258}$
$\alpha_{yi}$	1.285	1.086	1.174	1.326
$E$	0.728	0.925	0.718	0.682
$R^2$	0.958	0.926	0.847	0.926
		New media 2		
Regression equation	$P_i = 859R_i^{1.495}$	$P_i = 148R_i^{1.075}$	$P_i = 35R_i^{1.162}$	$P_i = 1057R_i^{1.274}$
$\alpha_{yi}$	1.485	1.062	1.148	1.317
$E$	0.924	0.846	0.851	0.715
$R^2$	0.915	0.947	0.936	0.918



TABLE 2: Datasets of the CNN.

Dataset	News on sports events	Other news
Training set	8557	7962
Validation set	2415	2607
Test set	1106	1808

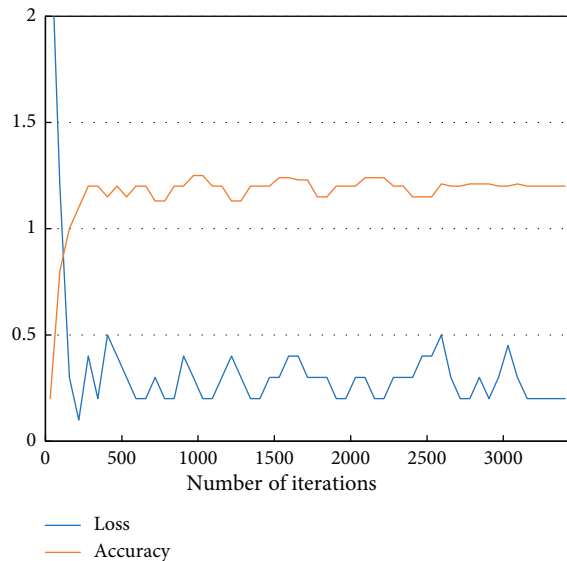


FIGURE 6: Training accuracy and training loss.

TABLE 3: Results of the classification experiment.

Dataset	Other news	Sports events' news
Precision	92.57	95.28
Recall	86.25	88.47
F1-score	90.18	92.75

The training accuracy and training loss of the CNN were observed (Figure 6). Initially, the loss curve dropped significantly, while the accuracy curve rose markedly. Later, both curves tended to be stable. Through the CNN training, the two indices changed in opposite directions. This meets the expectation of our model in training. Table 3 shows the text classification results of our model. It can be seen that the proposed text classifier performed well in classifying the texts related to sports events' information.

Furthermore, the embedding method our model was compared experimentally with another embedding model: word2vec. The experimental results are recorded in Table 4, where 1, 2, and 3 stand for three different training models: the conventional model, the conventional model coupled with the CRF layer, and our model. It is learned that our embedding method is superior to word2vec embedding in named entity recognition, especially after the introduction of the CRF layer and the adversarial training. The superiority of our model demonstrates that the word boundary information of the texts

TABLE 4: Experimental results of different embedding models.

Embedding method	Our model			Reference model		
	1	2	3	1	2	3
Training models	1	2	3	1	2	3
Precision	93.26	94.37	93.58	92.16	96.27	93.48
Recall	81.35	83.64	85.92	86.42	84.39	88.37
F1-score	86.19	86.53	87.48	88.69	91.48	93.58

obtained through adversarial training promotes the performance of named entity recognition and helps to solve the adaptation to different fields.

## 5. Conclusions

Based on deep learning, this study carries out information extraction and spatial pattern analysis of sports events based on deep learning. Initially, CNN was adopted to classify the texts of sports events information and to identify the most valuable news or cases of sports events. Next, the authors established a named entity recognition model to extract the effective information from the data of sports events information and provided a spatial pattern analysis approach for the diffusion of sports events information flow. Through experiments, the authors described the relationship between the information diffusion levels of different new media information on sports events and the number of regions and concluded that the relationship between information diffusion level and the number of regions obeyed a pyramid-shaped distribution. In addition, a log-log regression analysis was performed on the diffusion of sports events information on different new media. The analysis results show that the diffusion of sports events' information on different new media satisfied the rank-size distribution. Finally, the accuracy and loss of network training were compared, and different embedding models were tested, which confirms the effectiveness of our model.

Many users acquire sports events' information from new media, such as sports newspapers, sports television channels, sports websites, and sports news. Facing the huge amount of information about sports events, it is an arduous task to collect and analyze the basic data, and it is very difficult to study the information flow of sports events. Future research will further explore the information flow of sports events more comprehensively by expanding the size of the research dataset.

## Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

## Conflicts of Interest

The authors declare that they have no conflicts of interest.

## References

- [1] J. Chen, C. Zhang, and Z. Niu, "A two-step resume information extraction algorithm," *Mathematical Problems in Engineering*, vol. 2018, Article ID 5761287, 8 pages, 2018.

- [2] J. Gao, N. Liu, M. Lawley, and X. Hu, "An interpretable classification framework for information extraction from online healthcare forums," *Journal of Healthcare Engineering*, vol. 2017, Article ID 2460174, 12 pages, 2017.
- [3] S. S. Roy, P. Samui, R. Deo, and S. Ntalampiras, *Big Data in Engineering Applications*, Springer, Berlin/Heidelberg, Germany, 2018.
- [4] P. Samui, S. S. Roy, and V. E. Balas, *Handbook of Neural Computation*, Elsevier, Amsterdam, Netherland, 2017.
- [5] R. Niaz, X. Zhang, N. Iqbal, M. Almazah, T. Hussain, and I. Hussain, "Logistic regression analysis for spatial patterns of drought persistence," *Complexity*, vol. 2021, Article ID 3724919, 13 pages, 2021.
- [6] S. S. Roy, A. Ranjan, and S. Tomasiello, "Link prediction in social networks by variational graph autoencoder and similarity-based methods: a brief comparative analysis," in *Proceedings of the International Conference on Pattern Recognition*, pp. 422–429, Milan, Italy, January 2021.
- [7] H. Song, "Artificial intelligence-based design of a management information system for large-scale Chinese sports events," *Agro Food Industry Hi-Tech*, vol. 28, no. 1, pp. 2151–2155, 2017.
- [8] W. Yu and J. Xing, "Sports event level measurement indicator system using multisensor information fusion," *Journal of Sensors*, vol. 2021, Article ID 9330438, 9 pages, 2021.
- [9] M. Sindhvani and S. Bhattacharyya, "Using traffic information in operations and logistics management for major sporting events," in *Proceedings of the 19th Intelligent Transport Systems World Congress*, Article ID AP-00328, Vienna, Austria, October 2012.
- [10] H. Xu and T.-S. Chua, "Fusion of AV features and external information sources for event detection in team sports video," *ACM Transactions on Multimedia Computing, Communications, and Applications*, vol. 2, no. 1, pp. 44–67, 2006.
- [11] Z. Wang and D. Zhu, "Sports monitoring method of national sports events based on wireless sensor network," *Wireless Communications and Mobile Computing*, vol. 2021, Article ID 5739049, 19 pages, 2021.
- [12] S. J. Wu, "Image recognition of standard actions in sports videos based on feature fusion," *Traitement du Signal*, vol. 38, no. 6, pp. 1801–1807, 2021.
- [13] Y. X. Miao, "Paper research on the application of virtual reality panoramic news communication technology in sports events," in *Proceedings of the 2021 2nd International Conference on Education, Knowledge and Information Management (ICEKIM)*, pp. 670–673, Xiamen, China, January 2021.
- [14] Z. Li, H. Zhao, and Y. Li, "Research on coping strategies for network public opinion of sports events in the new media era," in *Proceedings of the 2021 4th International Conference on Information Systems and Computer Aided Education*, pp. 2704–2708, Dalian, China, September 2021.
- [15] F. Deng and A. Gudamu, "Research on Evaluation Method of Sports Events Based on Edge Algorithm," *Security and Communication Networks*, vol. 2021, Article ID 1903699, 2021.
- [16] H. Wang, "Recognition of wrong sports movements based on deep neural network," *Revue d'Intelligence Artificielle*, vol. 34, no. 5, pp. 663–671, 2020.
- [17] T. Xia, "Analysis of the influence of big data background on the spread of large-scale sports events," *Journal of Physics: Conference Series*, vol. 1744, no. 3, Article ID 032003, 2021.
- [18] Y. B. Chen and G. Du, "Sports events videos-based semantic content analysis and hidden Markov model application," *Bio-Technology: An Indian Journal*, vol. 10, no. 4, pp. 887–892, 2014.
- [19] A. Cannavò, D. Calandra, B. Basilicò, and F. Lamberti, "Automatic recognition of sport events from spatio-temporal data: an application for virtual reality-based training in basketball," in *Proceedings of the 14th International Joint Conference on Computer Vision, Imaging and Computer Graphics Theory and Applications (VISIGRAPP 2019)*, pp. 310–316, Prague, Czech Republic, February 2019.
- [20] S. Choudhury and J. G. Breslin, "Extracting semantic entities and events from sports tweets," in *Proceedings of the Making Sense of Microposts: Big Things Come in Small Packages: collocated with the 8th Extended Semantic Web Conference, ESWC2011*, pp. 22–32, Heraklion, Crete, May 2011.