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*Research Article*

# Application and Evaluation of Sports Event Management Method Based on Recurrent Neural Network

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The methods of sports event management are the life cycle management method, which can be divided into four stages: start-up planning, plan preparation, real-time control, and followup evaluation. The administrative measures management law includes administrative orders, instructions, regulations, and systems of administrative organizations at all levels. The system management law has four characteristics: mandatory, authoritative, stable, and preventive. The current management mode of sports events is mainly that the government is deeply involved in the operation of the entire event, and relevant personnel are selected from various government departments to form an organizing committee, and the resources related to the event are controlled and regulated by the government. However, in our country, there is currently no unified sports event management standard. Therefore, this paper proposes the application and evaluation of sports event management method based on recurrent neural network (RNN). The comments of sports events are extracted from the network, classified with an RNN, and finally, an improvement plan is obtained through evaluation. The main work of this paper is as follows: (1) the development status of sports event management at home and abroad and the application of RNN are introduced, and RNN is used in the evaluation and classification of sports event management. (2) We propose a sentiment classification model GCNN-GRU that fuses local feature extraction. Aiming at the defect that the basic model is easy to lose key phrase information, a CNN with a gating mechanism is used to extract and filter local features. The classification experiment results show that the proposed GCNN-GRU has the best classification effect on the Chinese sentiment dataset.

## 1. Introduction

Sports is an important symbol of social development and human progress and an important manifestation of comprehensive national strength and social civilization. People of all ethnic groups play an irreplaceable and important role in promoting the spirit of pursuing excellence and breaking through themselves [1–4]. Sports has become an important part of human life today. All activities of competitive sports are guided by competition. The selection and training of athletes must determine the direction and standards according to the needs of the competition for the athletes' competitive ability, and through competition, the level of competitive sports of a sports team, a region, or a country can be evaluated; sports competition has played a very important role in the entire competitive sports [5–7]. In recent years, more and more large-scale international sports events have been held in my country, and the degree of market-oriented operation has become higher and higher. However, generally speaking, the level of industrialization and professionalization of our sports events is not high, and the organization and management are not standardized enough. In 2012, according to the requirements of the Sports Bureau, the competition management of the annual provincial competitions of the projects managed by each unit was separated from the training work. These series of measures conform to the requirements of sports reform, improve the ability of sports authorities to control events, and standardize the process of provincial sports event management. However, these measures have not fundamentally solved various problems in the management of sports events, such as the low degree of marketization, unreasonable distribution of event resources, and inadequate supervision and inspection. However, it is obviously unrealistic to solve these problems manually in the short term [8]. The rapid advancement of neural networks has ushered in a new era for nonlinear issues. Deep learning algorithms have had a lot of success in image identification, natural language processing, speech recognition, video processing, and other domains in recent years, therefore its use in sports event management has gotten a lot of attention. Among them, the RNN algorithm has a good effect on the prediction of time series data and has been widely used in natural language processing, event time series analysis, and other data analysis with time characteristics and has achieved great success [9].

These successful applications are mainly attributed to the RNN algorithm of the LSTM structure. This algorithm has a very good prediction effect for long-term sequences, but its structure is relatively complex. For the deep LSTM algorithm, the calculation required for learning and training amount is huge. Therefore, under the premise of ensuring the prediction effect, the more efficient training of the RNN has become the focus and difficulty in the application of the RNN. Compared with the RNN of LSTM structure, the RNN of GRU structure has fewer threshold units, relatively low computational complexity, and requires shorter training time, which is more suitable for the timeliness requirements in sports event management applications. The structural RNN can also effectively solve the gradient disappearance problem of the traditional RNN and has a good processing effect on time series data [10]. As a result, in this research, the RNN algorithm of the GRU structure is introduced into the management of sports events, and the GRU model is used to extract all of the comments on the network of sports events and perform sentiment category analysis using the GRU model. Then, the scores of different emotion categories are summed up and then graded according to the scores, and finally, the corresponding plan is given according to the score results.

The following is a summary of the research: Section 2 discusses the related work and background. Section 3 discusses the methods of the proposed work; Section 4 discusses the experimental analysis. Finally, the conclusion brings the paper to a finish in Section 5.

## 2. Related Work

Reference [11] elaborates on sports competition management from three aspects. The first aspect is the sports competition management system; the second aspect is the operation of management functions in sports competition management; the third aspect is the evaluation of sports competition management effect. The author expounds on the content of the evaluation of sports competition management. From the perspective of management, it is divided into three aspects: competition organization work, social benefit, and economic benefit. Reference [12] elaborated in detail from the two aspects of sports event management and operation. In sports event management, the essence and characteristics of sports events are described, and the whole process of sports event management is divided into five aspects: event initiation, event planning, event organization, event control, and event closing management. In sports management, the concept and specific characteristics of management are described and the concept of sports event marketing, the specific content of sports event tickets, and event intangible asset marketing are described in detail. Reference [13] from the perspective of sports event organizers, from the level of sports event organization, describes the event preparation time and the main special work content of the event, focusing on the grasp of the concept of time, in the order of time, and follow the rules and characteristics of the preparation and organization of the event, and the overall work process of the comprehensive sports meeting. Reference [14] expounds on the concept of sports events and points out that the core of sports events is competition performance, so from the essence and basic characteristics of the marketization of sports events, the economic characteristics of the events, the main body of event management and the basic process of management, the products and marketing of events, and the management of event management skills and performance are expounded in detail. Reference [15] states that in the operation of the event, it is necessary to emphasize the standardization of the working methods, and it must be completed efficiently in order to have a good effect. It also emphasizes the need to improve the legal and risk awareness of the event and to exercise the correct legal behavior. Combining the concept of event operation management concept with the actual situation of event operation, the definition of sports event operation is put forward, which means that the sports event organizer can only plan, organize, organize and manage the human, material, financial, and information technology invested in the event through the exercise of management. The process of implementing and controlling and rationally using and distributing, efficiently and effectively creating competition products and related services, so as to achieve the purpose and objectives of the competition. Foreign scholars have conducted more and more in-depth research on the administrative system of sports events in Victoria, Australia [16]. The Victorian government has not introduced a system on the management responsibilities of sports events but has incorporated sports events into the management scope of large-scale events, which are organized and managed by specialized large-scale event companies. The responsibilities of the Victorian government in the management of sports events are clearly stipulated, including sports event planning, prematch identification and evaluation, in-game fund management, and postmatch event evaluation, and each part has a clear corresponding government agency or designated department [17]. The sports events held in New York City mainly rely on the New York Sports Commission for organization and management. Although the New York City Sports Commission is a government-level sports administrative agency, its responsibilities are very limited compared with the sports administrative department in our country. The main work is to attract various sports competitions and sports activities to New York City and encourage and assist various sports organizations or businesses and enterprises to carry out sports competitions and activities in New York City [18]. American volleyball competition management has the characteristics of both improvement and popularization, and it is the object of many foreign scholars' research. The US adult volleyball competition system includes the university competition system and the Volleyball Association adult competition system. The youth volleyball competition system mainly includes the middle school competition system and the volleyball association youth competition system. There are high school sports associations in every state in the United States, and the main responsibility is to implement comprehensive organization and management of interschool competitions in various middle school projects in the state [19]. The RNN has unique advantages in processing time series sequences in structure. Information is transmitted between its hidden layers through connections, so that the time series information of the samples is linked, so that the network needs to accept the input data at the current moment during the training process and also influenced by the state [20]. For example, reference [21] proposed an RNN-based health factor extraction method and used it for relevant AI prediction. Many scholars have done exploratory research on RNN-based fault diagnosis and prediction methods, due to their unique structure, high stability, and high accuracy. Therefore, compared with other methods, it is more suitable for trend forecasting [22–24]. RNN-based forecasting methods can play a huge role in the intelligent advancement of sports event management.

## 3. Method

*3.1. Principle of Traditional RNN Algorithm.* RNNs (recurrent neural networks) are a type of neural network that can be used to model genomic information. Expanding the RNN in time, you can see the structural characteristics of the RNN more clearly. The forward propagation algorithm is to calculate in chronological order, and the back-propagation algorithm is also to pass the accumulated value of residuals backward in time order and adjust the update weights. This back-propagation algorithm across time steps is an improvement of the traditional back-propagation algorithm and is called back-propagation through time (BPTT). The schematic diagram of the structure of the RNN after time expansion is shown in Figure 1.

In Figure 1, $I_t$ is the input of the RNN at time $t$, $h_t$ is the hidden state of the RNN at time $t$, $O_t$ is the output of the RNN at time $t$, and $a$, $b$, and $c$ are the parameter matrices shared by the RNN.

*3.1.1. RNN Forward Propagation Algorithm.* For any time $t$, the hidden state $h_t$ at this time is measured from the input $I_t$ at the present time and the hidden state $h_t$ at the previous time. The following is the calculating formula:

$$h_t = \alpha(Q_t) = \alpha(aI_t + ch_{t-1} + p), \tag{1}$$

where $\alpha$ the activation is a function of the RNN, and $p$ is the bias of the linear relationship.

The computation formula for the anticipated output value $O_t$ of the RNN at the present instant, knowing the hidden state $h_t$, is

$$O_t = \alpha(bh_t + q), \tag{2}$$

where $q$ is the linear relationship's distortion and $a$ is the RNN's perceptron. Different activation functions might be chosen depending on the application's difficulty. In the classification problem, for example, the softmax function is commonly used.

*3.1.2. RNN Back-Propagation Algorithm.* RNN uses the BPTT algorithm to modify the weights by using the gradient descent method along the time step. For the convenience of description, the loss function of RNN is selected as the logarithmic loss function, the activation function of the output layer is selected as the softmax activation function, and the activation function of the hidden layer is selected as the tanh activation function. Since the loss value of RNN needs to calculate the cumulative value over all time steps, the final loss function $l$ is

$$l = \sum_{t=1}^{T} l_t. \tag{3}$$

Here, the gradient calculation of $b$ and $q$ is relatively simple, and the calculation formula is as follows:

$$\frac{\partial l}{\partial q} = \sum_{t=1}^{T} \frac{\partial l_t}{\partial q} = \sum_{t=1}^{T} P_t - O_t, \tag{4}$$

$$\frac{\partial l}{\partial b} = \sum_{t=1}^{T} \frac{\partial l_t}{\partial b} = \sum (P_t - O_t)(h_t)^{\tau}, \tag{5}$$

The gradient calculation of $c$, $a$, and $q$ is relatively complicated. When RNN is backpropagating, the gradient loss at time $t$ is determined by the gradient loss corresponding to the output at the current time and the gradient loss at time $t+1$. The hidden state gradient at time $t$ is defined as $\varphi_t$, and $\varphi_t$ is recursively derived from $\varphi_{t+1}$. The calculation formula is as follows:

$$\varphi_t = \frac{\partial l}{\partial h_t} = b^{\tau}(P_t - O_t) + c^{\tau}\varphi_{t+1}\mathrm{diag}\left(1 - h_{t+1}^2\right). \tag{6}$$

In the calculation formula of the above-given RNN back-propagation algorithm, $P_t$ is the real value, $O_t$ is the predicted value, $a$, $b$, and $c$ are the parameter matrix shared by the RNN, $p$ and $q$ are the bias terms, and $T$ is the last moment index. After the gradient value of the parameter is calculated according to (6), the update method of the parameter weight is similar to that of the BP neural network.

*3.2. GRU RNN Algorithm and Its Improved Algorithm.* The structure of the GRU RNN is similar to the overall structure of the traditional RNN, and it is also composed of

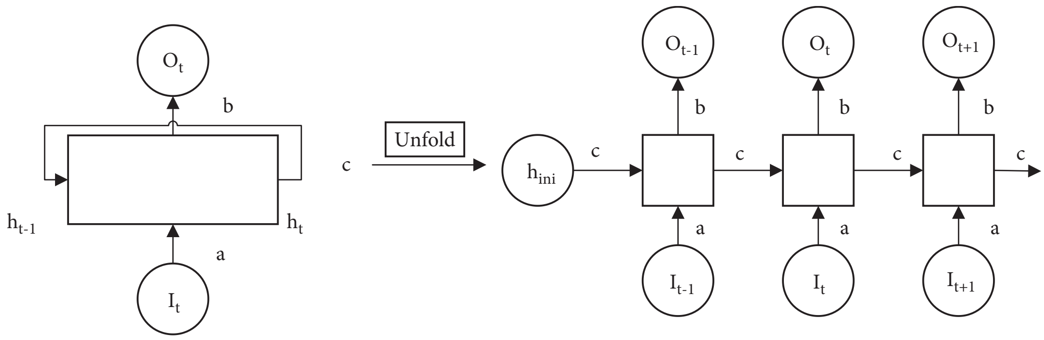


Figure 1: Schematic diagram of the structure of RNN expanded by time.

multiple repeated neural unit modules, but the neural unit module of the GRU is a more complex threshold structure, and the traditional RNN unit module is only the most-simple tanh function or relu function. Although the GRU RNN effectively solves the gradient disappearance problem of the traditional RNN, its training method is still based on the gradient descent algorithm, which cannot guarantee the global optimal solution, and it is still necessary to use a varying learning rate to ensure as much as possible that the algorithm ends up with a globally optimal solution. However, the changing learning rate may cause the parameter update to be unstable, which reduces the reliability of the foreign exchange rate prediction method. When the market fluctuates violently, the prediction method may fail, which may cause significant economic losses to users. In order to improve the stability of the GRU RNN algorithm, this paper adds a sliding average method to the GRU RNN parameter update and controls the decay rate to control the gap before and after the parameter update, reducing the amount of parameter change. The calculation formula is as follows:

$$W_b = \lambda \cdot W_b + (1 - \mu) \cdot W, \tag{7}$$

where $W_b$ is the value before parameter update, $W$ is the value of the parameter to be updated, $\lambda$ is the decay rate.

And, the update speed of the algorithm is controlled by controlling the decay rate. For example, the value before the parameter update is 10, and the value of the parameter to be updated is 5, then after using the moving average method, the actual update value of the parameter is a value between 10 and 5. The larger the decay rate is, the more stable the algorithm update is. Generally, the decay rate is set to a number very close to 1. In order to make the algorithm update faster in the early stage of training, this paper will dynamically control the value of the decay rate through the number of training iterations. While improving the stability of the algorithm, the training speed of the algorithm should be improved as much as possible. The calculation method of step control decay rate is as follows:

$$\min\left\{\lambda, \frac{1+s}{10+s}\right\}. \tag{8}$$

Here, at the beginning of the training iteration, the decay rate is small, and the algorithm training update is faster. As the number of iterations step increases, the decay rate becomes larger and larger until the set maximum decay rate $\lambda$ is reached.

### *3.3. Network Word Sentiment Analysis Model*

*3.3.1. Sentiment Classification Incorporating Parts of Speech.* When dealing with sentimental texts, RNNs tend to ignore key phrase information. In order to solve this problem, this paper integrates the local feature extraction ability into the RNN classification model and proposes an RNN classification model (GCNN-GRU) that integrates local feature extraction. In this paper, two variant structures are used to complete the feature extraction of the classification model, namely, GCNN and GRU. The main method is to use the CNN GCNN with a gating mechanism to extract and filter local features. The neural network variant structure GRU obtains higher-level semantic features. Compared with traditional CNN, this model mainly includes two improvements: one is to optimize the word vector in consideration of the relevant characteristics of online comment information, and the processing of part-of-speech tagging is introduced into the word vector. To the deeper semantic correlation representation in the text, the word embedding part in the model tries to use the BERT pretraining model to mine the text semantic relationship and its feature representation.

*(1) Part-of-Speech Tagging.* Part-of-speech is considered as a grammatical category specific to words when understanding text corpus, and part-of-speech tagging refers to the process of marking a word according to its part of speech in a sentence. At the same time, the difference of parts of speech does not have the same effect on understanding the polarity of text emotions. Usually, adjectives and negative words usually hide strong emotional tendencies, while adverbs contain less emotional tendencies. Therefore, adding part-of-speech tagging to the text sentiment analysis task can provide effective help for text semantic understanding and sentiment feature extraction, in order to lay a better foundation in subsequent experiments. Two commonly used part-of-speech tagging methods are described below. The first is the rule-based part-of-speech tagging method: its basic idea is to disambiguate words containing multiple possible parts of speech through preset rules according to the

collocation relationship and context and retain its unique part-of-speech. The rule-making was initially performed by humans, but the increase in the size of the data set made manual operations difficult, and now in more cases, automatic rule extraction methods based on machine learning are usually used. The second is the statistical-based part-of-speech tagging method: the basic idea is to complete the manual tagging process for some of the content in advance and then use the statistical method to complete the automatic tagging process for the new data; that is, through a series of word sequences that already have part-of-speech tags, it is determined which part of speech the next word is most likely to be.

*3.3.2. BERT Model.* BERT model, that is, bidirectional encoder representation from transformers. Specifically, BERT is a network training model proposed by Google in 2018. It is worth noting that it performs well in many technologies in the NLP field, including 11 tasks such as classification, question answering, and translation. The BERT model can be regarded as an improved scheme of NNLM to capture more contextual information by sharing the structure. Then, compared with NNLM and other language models, the specific characteristics of the BERT model in research tasks are as follows: internally, BERT can be viewed as a bidirectional encoder representation composed of transformer models. In contrast to the classic sequence model, the transformer can perform corresponding operations in parallel on all words or symbolic expressions in the text sequence, and each word in the text sequence can also be executed in many phases. Focusing on other arbitrary words in the sentence, using self-attention can combine the context with relatively distant words, which greatly improves the training speed and training effect. Therefore, the BERT model with an internal integrated transformer can fully learn the feature relationship between word-level and sentence-level in the text and deeply mine the grammatical and syntactic features.

*3.4. Classification Evaluation Index System.* In order to better manage sports events, it is necessary to collect online evaluation information for the sports events held and then classify the collected information in this paper, which is mainly divided into positive evaluation, negative evaluation, and neutral evaluation. The model classifies a large amount of evaluation information collected on the network to get a score and then gives a specific improvement plan for sports event management according to the score. This paper sets up five improvement plans for sports events, which correspond to the five evaluations grade output by the neural network. Table 1 is the evaluation index system.

In terms of the evaluation criteria of the classification model, this paper adopts the evaluation criteria used by the evaluation official to evaluate the performance of the classification model, which are the macro average precision rate (Macro-Per), the recall rate (Macro-Rec), and the $F1$ value (Macro-$F1$). The calculation of the macro average index needs to obtain the precision rate, recall rate, and $F1$ value of each category. The accuracy rate can show how many of the samples predicted as positive by the classification model are positive samples; the recall rate is used to show how many positive samples are predicted correctly; the $F1$ value is used to judge the overall performance of a classification model.

$$\mathrm{Per} = \frac{\mathrm{TP}}{\mathrm{FP} + \mathrm{TP}}, \tag{9}$$

$$\mathrm{Rec} = \frac{\mathrm{TP}}{\mathrm{FN} + \mathrm{TP}}, \tag{10}$$

$$F1 = \frac{2 \cdot \mathrm{TP}}{2 \cdot \mathrm{TP} \cdot \mathrm{FP} \cdot \mathrm{FN}}, \tag{11}$$

where TP means that the sentence sentiment category is a positive example, and the classification model prediction result is a positive example; TN means that the sentence sentiment type is a negative example, and the classification model prediction result is a negative example; FP means that the sentence sentiment category is a negative example, and the classification model prediction result is a positive example; FN means that the sentence sentiment category is a positive example, and the classification model predicts a negative example.

In sentiment classification research, positive examples represent the original sentiment category, and negative examples represent other sentiment categories other than this category. The macro average indicator is the average of the three categories of indicators, and only the calculation method of the macro average accuracy rate is shown. The calculation of other indicators is similar, and the calculation formula is as follows:

$$\mathrm{Macro} - \mathrm{Per} = \frac{\left(\mathrm{Per}_0 + \mathrm{Per}_1 + \mathrm{r}_2\right)}{3}. \tag{12}$$

## 4. Experiment and Analysis

*4.1. Data Set.* This paper adopts the Chinese implicit sentiment analysis evaluation dataset of the 2018 National Social Media Processing Conference. Official evaluation tasks provide training, validation, and test sets. Since the annotation information of the test set cannot be obtained, this paper only uses the training set and verification set officially provided by the evaluation task and divides the training set according to the ratio of 4 : 1 for the training process of the model; the officially provided verification set is used as a test set to evaluate the performance of each classification model. There are three kinds of sentiment labels: positive, negative, and neutral. The details of the extracted text data are shown in Table 2.

*4.2. Comparative Experiment.* In order to facilitate the intuitive comparison of the feature extraction characteristics of the classification model, when using the word vector, this paper uses the same latitude 0 to fill the words that do not appear in the word vector set. The internal parameters of the word embedding layer structure do not participate in the

Table 1: Text classification evaluation index system.

| Primary indicator | Secondary indicator | Num. | Label | Score |
|---|---|---|---|---|
| | Excellent, great, et al. | 1 | A1 | 0.9–1.00 |
| Positive evaluation | Good, interesting, et al. | 2 | A2 | 0.8–0.89 |
| | Not bad, pass, et al. | 3 | A3 | 0.7–0.79 |
| Neutral evaluation | Common, not so bad, et al. | 4 | A4 | 0.6–0.69 |
| | A bit bad, not good, et al. | 5 | A5 | 0.5–0.59 |
| Negative evaluation | Poor, terrible, et al. | 6 | A6 | 0.4–0.49 |
| | Very bad, trash, et al. | 7 | A7 | 0.0–0.39 |

training process of the classification model. Before the output layer, this paper uses the Dropout mechanism with a value of 0.5 to reduce the overfitting phenomenon of each classification model. In the comparative experiment part, this chapter selects the models used in implicit sentiment classification and explicit sentiment classification research. The details are as follows:

(1) *LSTM Sentiment Classification Model*. As the basic model studied in this paper, LSTM has shown good performance in multiple sentiment classification tasks and implicit sentiment classification tasks. After obtaining the text feature representation, this paper uses the LSTM network structure to obtain the temporal relationship of words and the dependencies between words and establishes the LSTM implicit sentiment classification model on this basis.

(2) *GRU Sentiment Classification Model*. As the basic model studied in this paper, GRU simplifies the design of the LSTM network structure on the basis of retaining the LSTM model to obtain the time series features. After obtaining the text feature representation, this paper uses the GRU network structure to obtain the temporal relationship of words and the dependencies between words and on this basis, establishes the GRU implicit sentiment classification model. The GRU classification model is also used to verify the effectiveness of GCNN-GRU in local feature extraction.

(3) *DRNN Sentiment Classification Model*. Interrupted RNN DRNN on the basis of limiting the fluidity of the RNN, the RNN is used instead of the convolution structure for feature extraction. In multiple sentiment classification tasks, DRNN achieves better sentiment classification results than CNN, LSTM, and GRU.

(4) *A Sentiment Classification Model*. That fuses gated CNN and gated recurrent units proposed in this paper. In this paper, the single-layer GCNN structure is used to extract local features, and on this basis, the GRU structure is used to enhance the distance-dependent characteristics and obtain higher-level semantic feature information.

*4.2.1. Hyperparameter Settings*. The value of hyperparameters has a great influence on the classification results. There are two kinds of hyperparameters in total, one is the hyperparameters common to all classification models, mainly including the word embedding dimension and the hyperparameters used for batch training; the other is the hyperparameters specific to different classification models, such hyperparameters are passed through choosing a suitable value for the experiment. The classification model mainly includes two categories, one is the classification model related to the RNN, in which the number of hidden neurons has a great influence on the classification results; the other is the classification model related to the CNN, the convolution kernel number and window size have a greater impact on the model classification results. When determining the optimal value of the hidden layer neurons, the values are set to 8, 16, 32, 64, 128, and 256, respectively. When determining the hidden layer neurons of GCNN-GRU and DRNN, this paper refers to the sensitivity research of CNN in text classification tasks and sets the number of convolution kernels to 100, the window size to 1, and the DRNN window size to 10. This section uses the macro-average F1 value as the evaluation index, conducts an experiment on the test set, and records the experimental results of each classification model. The experimental results are shown in Figure 2.

By analyzing the experimental results, when the number of neurons in the hidden layer is 64, the classification models related to the RNN can achieve good classification results. When studying the hyperparameters of classification models related to CNN, the window sizes were set to 1, 3, 5, 7, 10, and 15, respectively. The experimental results are shown in Figure 3.

Analysis of the experimental results shows that the DRNN classification model can achieve good classification results when the value is 15. Based on the experimental results of other large data sets, the DRNN window size is set to 15. The macroaverage $F1$ value of the GCNN-GRU classification model decreases as the window increases, and it is optimal when the value is 1.

*4.2.2. Experimental Results and Analysis*. This paper carried out 5 repeated experiments to obtain the macro average precision, recall, and $F1$ value of each classification model. The standard deviation of each evaluation index is in brackets. The experimental results and detailed information are shown in Figures 4–6.

Compared with LSTM, DRNN, and GRU classification models, GCNN-GRU has more local feature extraction and information screening capabilities, which verifies the effectiveness of GCNN-GRU proposed in this paper in fused local feature extraction.

Table 2: Experimental dataset.

| Data set | Annotated datasets | Positive | Negative | Neutral |
|---|---|---|---|---|
| Training set | 18000 | 5000 | 5000 | 8000 |
| Test set | 4500 | 1000 | 1000 | 2500 |

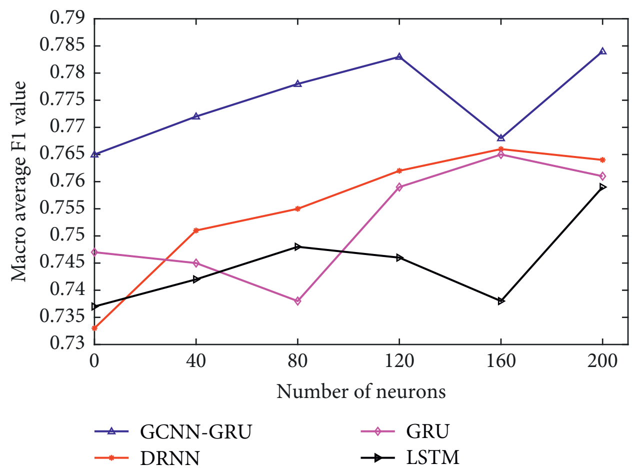


Figure 2: The relationship between the number of neurons and the macro-average $F1$ value.

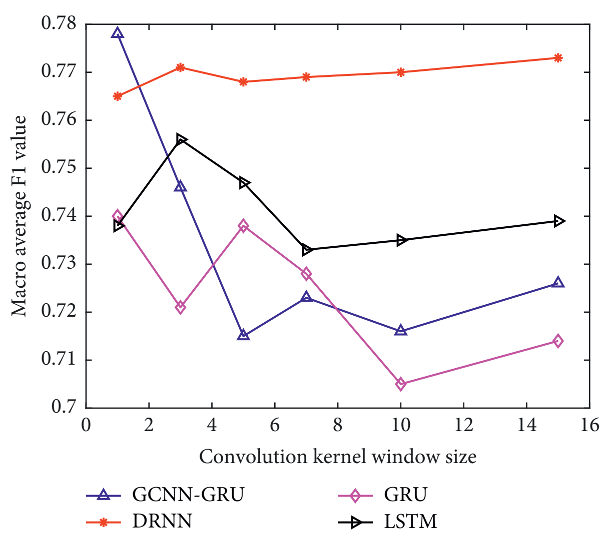


Figure 3: The relationship between the CKWS and the macro-average $F1$ value.

*4.3. Comparative Experiment of Sports Event Management Scheme.* In order to verify the effectiveness of the model proposed in this paper, this paper sets up five corresponding improvement plans for sports event management in the corresponding scoring interval and lets two experts in sports event management evaluate, and set up in advance, and it is divided into five programs: A, B, C, D, and E. The final experimental results are shown in Table 3.

The experimental results show that the accuracy of the model set in this paper reaches 95.8%, which proves the effectiveness and feasibility of the model proposed in this paper.

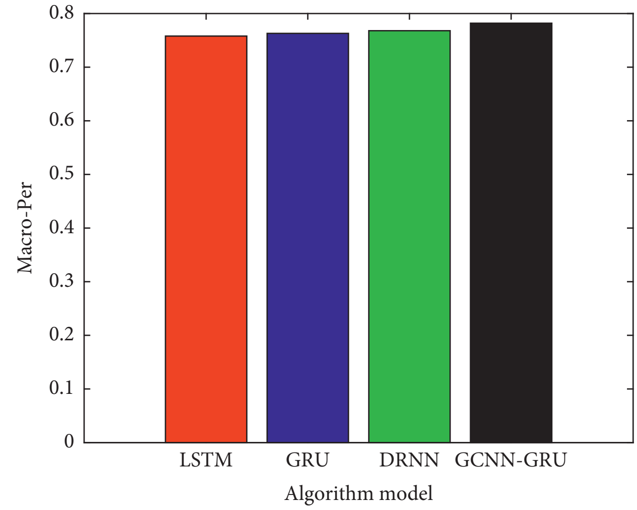


Figure 4: Macro-average precision of different models.

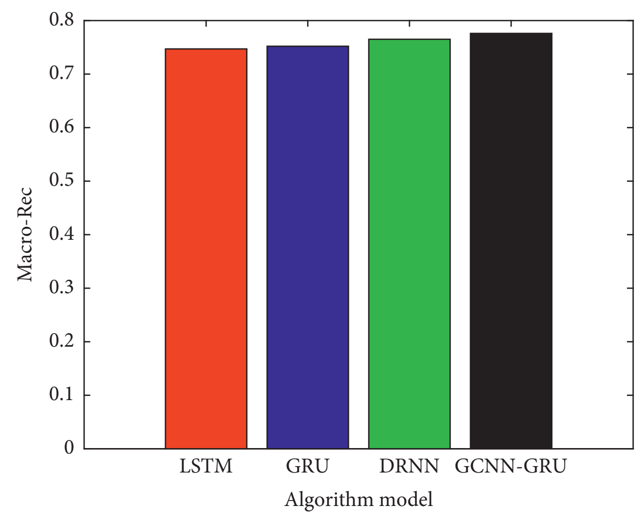


Figure 5: Macro-average recall of different models.

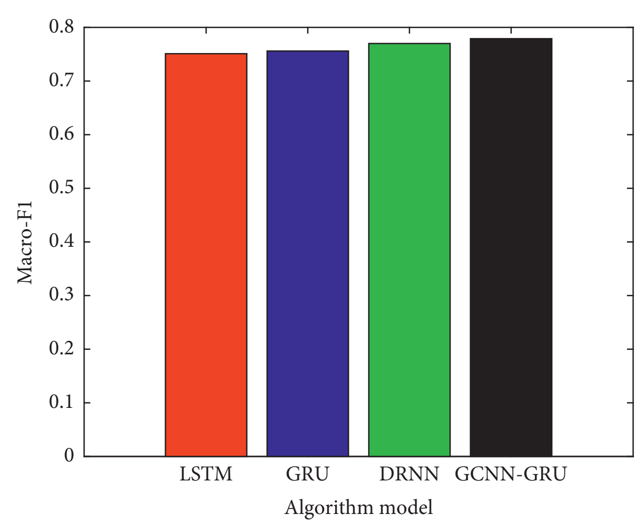


Figure 6: Macro-average $F1$ value of different models.

Table 3: Comparison of the evaluation scheme of the model and the expert scheme.

| Output solution | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|---|---|---|---|---|---|---|---|---|---|---|
| Expert solution | A | C | B | B | C | D | E | D | A | C |
| Model solution | A | C | B | D | C | D | E | D | A | C |

## 5. Conclusion

Sports competitions in our country are composed of competitions at all levels and types, including national competitions as well as competitions at the provincial and municipal levels and even the district and county levels. From the standpoint of the management system, our country manages sports tournaments in a hierarchical and categorized manner. As a result, it can be separated into national comprehensive sports competitions, national individual sports competitions, local comprehensive sports competitions, and local single sports competitions based on the many management subjects. The content of sports event organization and management mainly includes firstly, at the level of social and economic relations, economic form, and economic system, it is concentrated in the transformation from a planned economic system to a socialist market economic system. Secondly, it is concentrated expressed for the transformation of the government administrative management system to an integrated management system at the superstructure level. Under this background, this paper proposes the application and evaluation of sports event management methods based on RNN and completes the following work:

(1) The development status of sports event management at home and abroad and the application of RNN are introduced, and the RNN is used in the evaluation and classification of sports event management.

(2) We propose a sentiment classification model GCNN-GRU that fuses local feature extraction. Aiming at the defect that the basic model is easy to lose key phrase information, a CNN with a gating mechanism is used to extract and filter local features. The suggested GCNN-GRU provides the best classification impact on the Chinese sentiment dataset, according to the classification experiment results.

(3) In the sports event management scheme acquired from network sentiment analysis, the model described in this study has an accuracy rate of more than 95%, demonstrating that the model is feasible.

## Data Availability

The datasets used during the current study are available from the corresponding author upon reasonable request.

## Conflicts of Interest

The authors declare that there are no conflicts of interest.

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## References

[1] L. Jiang, Z. Q. Liu, and J. H. Chen, "Research on construction and development of competitive sports administration system in colleges and universities," *Journal of Beijing University of Physical Education*, vol. 55, no. 2, pp. 201–215, 2001.

[2] N. Fejgin, "Participation in high school competitive sports: a subversion of school mission or contribution to academic goals?" *Sociology of Sport Journal*, vol. 11, no. 3, pp. 211–230, 1994.

[3] C. J. Liu, "Research on application and development of competitive sports simulation based on virtual reality technology," *Advanced Materials Research*, vol. 179-180, pp. 1063–1068, 2011.

[4] S. Pan and H. Chen, "Strategic Study on the State and Development of Competitive Sports in High School After-Olympics Times-Take PE of High School in Zhejiang Province as an example," *Ningxia Engineering Technology*, 2009.

[5] Y. C. Vanlandewijck and R. J. Chappel, "Integration and classification issues in competitive sports for athletes with disabilities," *Sport Science Review*, pp. 65–88, 1996.

[6] S. Motegi and N. Masuda, "A network-based dynamical ranking system for competitive sports," *Scientific Reports*, vol. 2, no. 1, p. 904, 2012.

[7] J. Heo, B. Culp, N. Yamada, and Y. Won, "Promoting successful aging through competitive sports participation," *Qualitative Health Research*, vol. 23, no. 1, pp. 105–113, 2012.

[8] H. Lawrence, M. Wells, and J. Williams, "Event management blueprint: creating and managing successful sports events," *Smej*, vol. 4, no. 1, pp. 106-107, 2010.

[9] K. Greff, R. K. Srivastava, J. Koutnik, B. R. Steunebrink, and J. Schmidhuber, "LSTM: A Search Space Odyssey," *Transactions on Neural Networks and Learning Systems*, vol. 28, no. 10, pp. 2222–2232, 2016.

[10] N. Srivastava, G. Hinton, A. Krizhevsky et al., "Dropout: a simple way to prevent neural networks from overfitting[J]," *Journal of Machine Learning Research*, vol. 15, no. 1, pp. 1929–1958, 2014.

[11] O. Budzinski, "The institutional framework for doing sports business: principles of EU competition policy in sports markets," *Ilmenau Economics Discussion Papers*, vol. 11, no. 1, pp. 44–72, 2011.

[12] S. Lei, C. Ghosh, and H. Srinivasan, "Should they play? Market value of corporate partnerships with professional sport leagues," *Journal of Sport Management*, vol. 24, no. 6, pp. 702–743, 2010.

[13] L. Huang and X. C. A. Fu, "Theoretical analysis on the notion of the organization of Chinese sports events under the perspective of confucians viewpoint of harmony," *Journal of Capital University of Physical Education and Sports*, vol. 18, no. 02, pp. 11–13, 2006.

[14] Q. Yao and J. J. Luo, "Analysis of administrative system of sports events in foreign countries," *Journal of Shanghai University of Sport*, vol. 35, no. 1, p. 4, 2011.

[15] L. P. Wang, W. B. Xue, and X. Yang, "Characteristics of American volleyball match administration and its enlightenment to China," *Journal of Wuhan Institute of Physical Education*, vol. 44, no. 3, p. 5, 2010.

[16] W. He and L. Z. Li, “An analysis of the concept and characteristics of business sports match,” *Journal of China University of Labor Relations*, vol. 22, no. 1, p. 3, 2008.
[17] Z. M. Xing and Z. Song, “Study on model of government role in melbourne’s sporting events organization,” *Journal of Tianjin University of Sport*, vol. 26, no. 3, p. 5, 2011.
[18] J. H. Zheng and S. H. Zhang, “A comparative study on the training modes of Chinese and American competitive athletes,” *Journal of Xingtai University*, vol. 22, no. 2, pp. 64–66, 2007.
[19] Y. Li, “Discussion on the Concept of Sports Event Operation and Management,” *Journal of Liaoning Academy of Governance*, vol. 9, no. 1, p. 2, 2007.
[20] B. C. Yin, W. T. Wang, and L. C. Wang, “A survey of deep learning research,” *Journal of Beijing University of Technology*, vol. 41, no. 01, pp. 48–59, 2015.
[21] G. Saon and M. Picheny, “Recent advances in conversational speech recognition using convolutional and recurrent neural networks,” *IBM Journal of Research and Development*, vol. 61, no. 4/5, pp. 1–10, 2017.
[22] J. A. Pérez-Ortiz, F. A. Gers, D. Eck, and J. Schmidhuber, “Kalman filters improve LSTM network performance in problems unsolvable by traditional recurrent nets,” *Neural Networks*, vol. 16, no. 2, pp. 241–250, 2003.
[23] B. Ji, Y. Li, D. Cao, C. Li, S. Mumtaz, and D. Wang, “Secrecy performance analysis of UAV assisted relay transmission for cognitive network with energy harvesting,” *IEEE Transactions on Vehicular Technology*, vol. 69, no. 7, pp. 7404–7415, 2020.
[24] X. Lin, J. Wu, S. Mumtaz, S. Garg, J. Li, and M. Guizani, “Blockchain-based on-demand computing resource trading in IoV-assisted smart city,” *IEEE Transactions on Emerging Topics in Computing*, vol. 9, no. 3, pp. 1373–1385, 2021.