

## *Retraction*

# **Retracted: Early Warning Model of Sports Injury Based on RBF Neural Network Algorithm**

### **Complexity**

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

- (1) Discrepancies in scope
- (2) Discrepancies in the description of the research reported
- (3) Discrepancies between the availability of data and the research described
- (4) Inappropriate citations
- (5) Incoherent, meaningless and/or irrelevant content included in the article
- (6) Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

### **References**

- [1] F. He, "Early Warning Model of Sports Injury Based on RBF Neural Network Algorithm," *Complexity*, vol. 2021, Article ID 6622367, 10 pages, 2021.

## Research Article

# Early Warning Model of Sports Injury Based on RBF Neural Network Algorithm

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Sports injury is a common problem in athletes' training. The sports injury assessment model is a physical method to determine the sports injury attributes of specific parts by predicting and evaluating the risk of sports injury. In this paper, we use a neural network to realize big data analysis of sports injury data. Big data network is a method of capturing Internet information by means of cloud computing, which is usually used in the construction of Wan and LAN. This paper analyzes the source of sports risk and the main injury factors, designs the sports injury estimation model based on big data analysis, establishes a new assessment model based on RBF neural network, and builds the big data network environment required for the model operation by improving the topological structure, combining big data and deep neural network. In the built environment, the risk assessment of sports injury can be completed by determining the risk source and identifying the risk factors. The realization of the model can be constrained by the uncertainty conditions so that it can achieve a good operation state.

## 1. Introduction

As the “mother of sports”, track and field plays an important role in competitive sports. In fact, its strength is an important symbol of a country's competitive sports level. It is the event with the most gold medals in the Olympic Games, and it is also one of the most concerned hot spots. How to make athletes avoid and delay the occurrence of injuries to the greatest extent, so that the best competitive state can be extended for the longest time is an urgent problem to be solved in the process of track and field training and competition [1]. Sports injury assessment model is a kind of physical method which can predict and evaluate the risk of sports injury, and then complete the determination of sports injury attributes of specific parts. Traditionally, risk identification theory is used to complete the communication risk management. On this basis, through a large number of numerical operations, the risk factors of specific parts are recognized, and then the severity of injury caused by sports is grasped [2, 3]. However, with the continuous progress of science and technology, people have higher and higher requirements for the accuracy of sports injury assessment. In

order to better adapt to this development situation, the emergence of a new evaluation model has become an inevitable trend [4, 5]. Neural network is a method of capturing Internet information by means of cloud computing. It is usually used in the construction of Wan and LAN.

Artificial neural network has good robustness, self-organization, adaptability, parallel processing ability, distributed storage, and other characteristics, as well as excellent fault tolerance and nonlinear approximation ability. At present, artificial neural network algorithm is widely used in complex system hardware fault detection, medical diagnosis, medical image processing and other complex tasks, classification, and prediction and achieved good results [6–9]. In terms of risk prevention of sports injury, dfmurphy and rbohrr, on the basis of previous studies, divided the risk factors of sports injury into two categories: internal factors and external factors. Chen et al. [10] established a dynamic chain model to explain the interaction between risk factors and their contribution to the occurrence of damage. To sum up, in the research of sports injury risk early warning, predecessors have done a lot of research on sports injury causing factors and

established qualitative models, but there is no quantitative evaluation research. The artificial neural network algorithm has good performance in the classification and prediction of complex systems, so it is a very meaningful work to apply the artificial neural network algorithm to the research of sports injury risk early warning [11]. The concept of big data network is introduced to establish a new sports injury assessment model based on the big data network. The big data network environment required for the operation of the model is built by improving the topological structure and combining big data with the deep neural network.

The occurrence of sports injury is not caused by a simple reason but is often the result of multiple factors. In order to make a more accurate early warning of sports injury, it is necessary to study what factors will directly or indirectly lead to the occurrence of sports injury. The analysis of related factors of sports injury risk early warning is the basis of the whole intelligent early warning of sports injury. The artificial neural network algorithm can solve this kind of problem better, but when using the neural network algorithm, we need to use the sample library to train it [12–14]. The quality of the sample library directly affects the accuracy of the neural network algorithm. The demand data of the sample database includes all the related factors information of sports injury risk early warning and the corresponding warning level. The required factor information can be obtained by questionnaire survey in the initial stage, and the factor information related to physiological and biochemical indicators can be obtained from the weekly measurement data of sports teams [15, 16]. However, it is a difficult task to determine the early warning level accurately through these indicators. Only through the perceptual judgment of coaches and experts, it is obviously not accurate enough. Therefore, this project first establishes a linear dynamic chain model, using the collected information of sports injury-related factors to determine the early warning level quantitatively. By combining the early warning evaluation results of coaches, experts, and linear model, the final early warning level is obtained and provided to the sample database for use. This paper analyzes the sources of sports risk and main injury factors, designs a sports injury estimation model based on big data analysis, and establishes a new sports injury assessment model based on RBF neural network. By improving the topological structure, combining big data and deep neural networks, the big data network environment required for model operation is built.

## 2. Construction of Big Data Sports Injury Assessment Model

*2.1. Analysis of Sports Injury Factors.* A large number of studies have shown that the sports injury of athletes in the process of sports is not a simple cause, but is usually caused by a number of factors. The risk factors of sports injury are usually divided into internal factors and external factors. However, it is not enough to analyze the injury factors only from the perspective of internal factors and external factors. It is necessary to build a complete sports injury estimation model [17]. At the same time, it is also necessary to analyze

the interaction between different factors and the role of causing injury events.

Based on the analysis of domestic and foreign scholars' research on sports injury causing factors, the causes of sports injury are divided into three types: A internal injury factors, B external injury factors, C stimulation inducing factors. According to the relevant information and the actual situation of sports injury, the risk assessment of different injury factors is carried out to provide an important basis for the prevention of sports injury. In the sports injury estimation model, when a factor appears, athletes are regarded as "people with injury tendency"; at present, if there are different class B factors, athletes can be regarded as "injury-prone population." At present, the risk of certain specific injuries of athletes in different events is gradually increasing. If the athlete is already an "injury-prone population," the occurrence of class C factor will greatly increase the probability of sports injury. The following is a detailed analysis of three different types of injury factors. Tables 1 and 2 describe the risk assessment table of internal injury and external factors.

The risk source of sports injury is the basis to determine the risk factors of injury. It may be too one-sided to analyze the risk of sports injury from a single perspective. In order to effectively avoid this kind of phenomenon, it is necessary to determine the source of injury risk before evaluating sports injury. Taking gymnastics as an example, its risk sources include rule guidance, equipment requirements, action types, action groups, and movement difficulty. The project can be divided into 10 subcategories according to male and female groups. The relationship between each subitem and the risk source of the injury wind path can be shown in Figure 1.

The identification of sports injury risk factors completes the identification of sports injury risk sources. The identification of risk factors of sports injury is to calculate the risk level of sports injury with a specific algorithm according to the identified risk sources and then to judge the severity of the injury. If the determined risk source is expressed as  $s$ , then, under this risk source, the identification of sports injury risk factors can be expressed by the following formula:

$$\varphi(t) = \frac{1}{2} \sum_{k=0}^N [\xi s(\text{loss})^n + \omega\varphi], \quad (1)$$

where  $n$  represents the uncertain variable, which can change with the change of  $s$  value;  $\xi$  represents the specific algorithm to complete the identification of sports injury risk;  $\text{loss}$  represents the specific parameter generated by identifying the risk factors of sports injury under  $s$  risk source.

Through the calculation of formula (1), a certain result of sports injury factor identification can be obtained. In order to facilitate the subsequent injury assessment, the result of sports injury factor identification is defined as the data source of injury assessment. Generally, data sources can be divided into single precision, multiprecision, and mixed precision. The single-precision data source does not need any processing and can be directly used to preevaluate the sports injury according to the specific numerical results. For

TABLE 1: Risk assessment of internal injury factors.

Index	Low risk of injury	At risk of injury	High risk of injury
Age	Under 25 years old	* *	Over 26 years old
Gender	Male	* *	Female
BMI	[20, 30]	* *	<20 or >30
Joint stability	Good	Normal	Poor
Body balance	Preferably	Commonly	Poor
Muscle strength	The difference is small	* *	The difference is large

TABLE 2: Risk assessment of external injury factors.

Index	Low risk of injury	At risk of injury	High risk of injury
Technical level	High	Commonly	Lower
Gym shoes	Replacement within one-quarter	First-quarter to half a year	More than half a year
More than half a year	Plastic cement	Cement floor	Out-of-flatness
Weather factors	Sunny	High temperature	Rain and snow

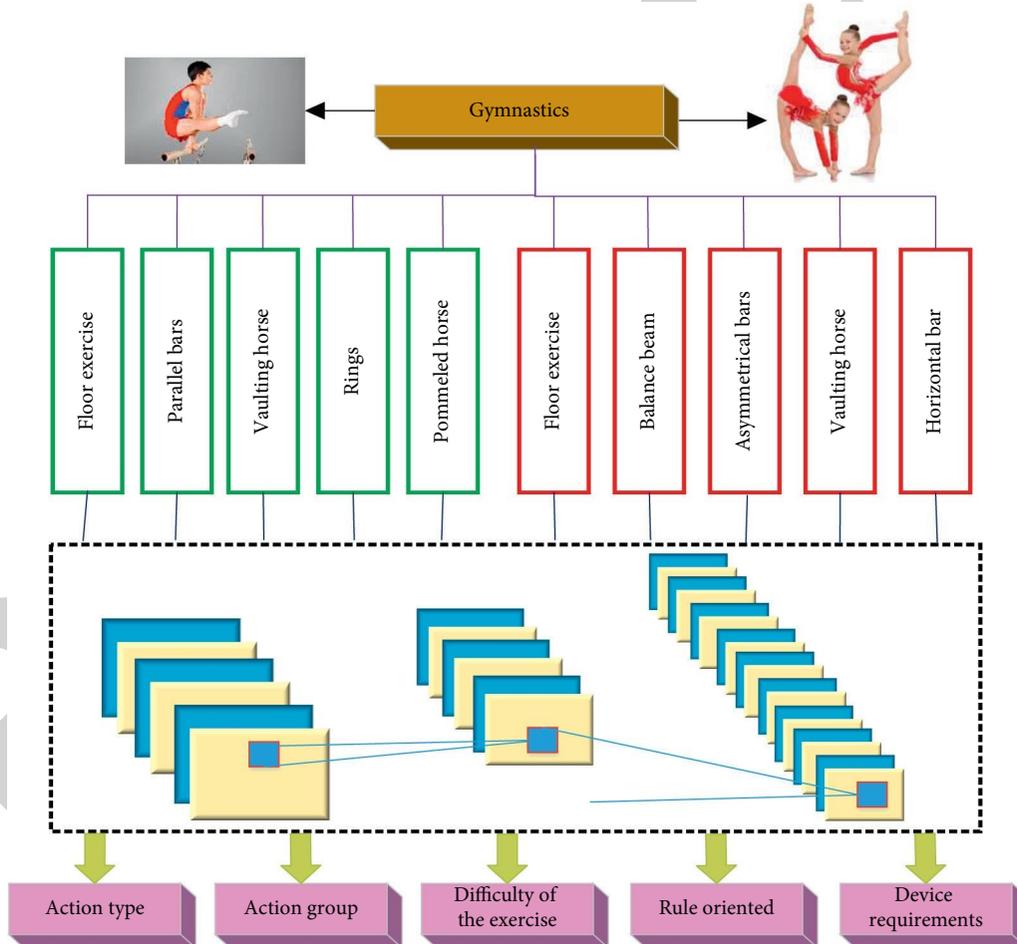


FIGURE 1: Schematic diagram of risk source determination of sports injury.

multiprecision data sources, the accuracy reduction processing should be completed first, and all the data should be simplified into single-precision data before the sports injury preassessment can be carried out. The data sources of mixed precision should be classified into two categories: single-

precision data sources and multiprecision data sources, and then the above operations should be carried out for the two data sources, respectively. According to the results of preassessment of sports injury, the method to complete the overall assessment can be determined.

*2.2. Design of Sports Injury Estimation Model.* In track and field training, there are many factors related to sports injury. How to find out the relationship between them and the risk of sports injury and give quantitative indicators is a very difficult work. The early warning system of track and field sports injury risk provides a method of early warning of track and field sports injury risk by establishing the early warning model of track and field sports injury [18].

On the basis of in-depth analysis of the domestic and foreign research on the injury of track and field middle and long-distance running, this paper obtains 28 injury factors including injury history, injury recovery status, wrong technical movements, poor joint stability, improper arrangement of training and competition load, poor psychological state in training and competition, and muscle strength. The injury risk factors are divided into three categories: internal injury factors, external injury factors, and stimulation inducing factors, and a dynamic chain model of injury causing factors in middle- and long-distance running is proposed [19]. The weight of each factor in the dynamic chain model of early warning injury factors in track and field sports was analyzed by AHP. The weight proportions of internal injury factors, external injury factors, and stimulation inducing factors were 53.9%, 16.4%, and 29.7%, respectively. Based on this, the dynamic chain quantitative model of early warning injury factors in track and field sports was established.

According to the grading of injury factors, the total score of injury risk was calculated. Sports injury early warning includes model initialization, attribute discretization, attribute reduction, sample extraction, and RBF learning. The specific process is shown in Figure 2.

- (1) Using the factors in the dynamic chain quantitative model of injury early warning factors in track and field, this paper establishes the early warning sample bank and test sample bank of track and field injury risk. It includes athlete's basic information: name, event, athlete's grade, and BMI; early warning information of sports injury risk: training load, technical error, joint protection measures, subjective fatigue condition, psychological state in training competition, joint stability, body balance ability, arch shape, technical level, frequency of sports shoes replacement, injury history, recovery training status after injury, and so forth; training monitoring information: red blood cell count, serum creatine kinase, blood urea, serum testosterone, serum cortisol, serum testosterone/serum cortisol, white blood cell count, and so forth.
- (2) Judge the discreteness of the data corresponding to the factors in the sample library. If not, call the SOM neural network discretization method to discretize the factor data. The decision table is composed of the factor data after SOM neural network discretization and the initial discrete value data.
- (3) According to the reduction process of RS theory, attribute reduction and rule extraction of decision

table are carried out, and RBF neural network is constructed based on the simplified decision table.

- (4) According to the reduced decision table, select the corresponding data of track and field sports injury risk early warning sample database, train RBF neural network until convergence, and meet the accuracy requirements.
- (5) Use the test sample data to judge whether the trained RBF network has got the correct diagnosis results. If not, select other reduction results in (3) and turn to (4) until the trained neural network sample database is obtained.
- (6) The trained RBF neural network is used to evaluate the relevant information submitted by athletes and output the correct risk warning results.

### 3. Motion Injury Estimation based on RBF Neural Network

In the big data network environment, deep neural network data can solve the problem of identification and evaluation of sports injury data. When motion injury data is labeled, corresponding depth neural network data will be generated automatically, and the data is unique. When multiple motion injury data are labeled, multiple depth neural network data are automatically generated, and every depth neural network data is automatically connected with its corresponding sports injury data [20]. Therefore, no matter how much deep neural network data are generated at the same time, the corresponding chaos will not occur. The relationship between big data and deep neural network is an important index to describe the sports injury evaluation model in the big data network environment. In order to facilitate the analysis, it can be considered that the relationship between big data and deep neural network is a connection mode from input end to output end as an evaluation delay line. Radial basis function (RBF) network has a topology structure of only one hidden layer [21]. The hidden layer is the radial base layer, and the output layer is the linear layer. It is a kind of network form with excellent approximation ability, classification ability, and learning rate.

*3.1. Radial Basis Function Network Structure.* RBF is a special kind of three-layer feedforward neural network. The radial basis function neural model and RBF network structure are shown in Figure 3. The input layer transmits information to the hidden layer. Only when the input falls within a specified small range, the hidden layer cell will make a nonzero response, while the output layer is a linear combination of the outputs of the hidden layer elements. When the network is used for classification, the sigmoidal function is used for the output node, and the linear function is used for function approximation. On the basis of big data analysis technology, a sports injury estimation model is constructed by the RBF neural network. The following is a detailed analysis. RBF

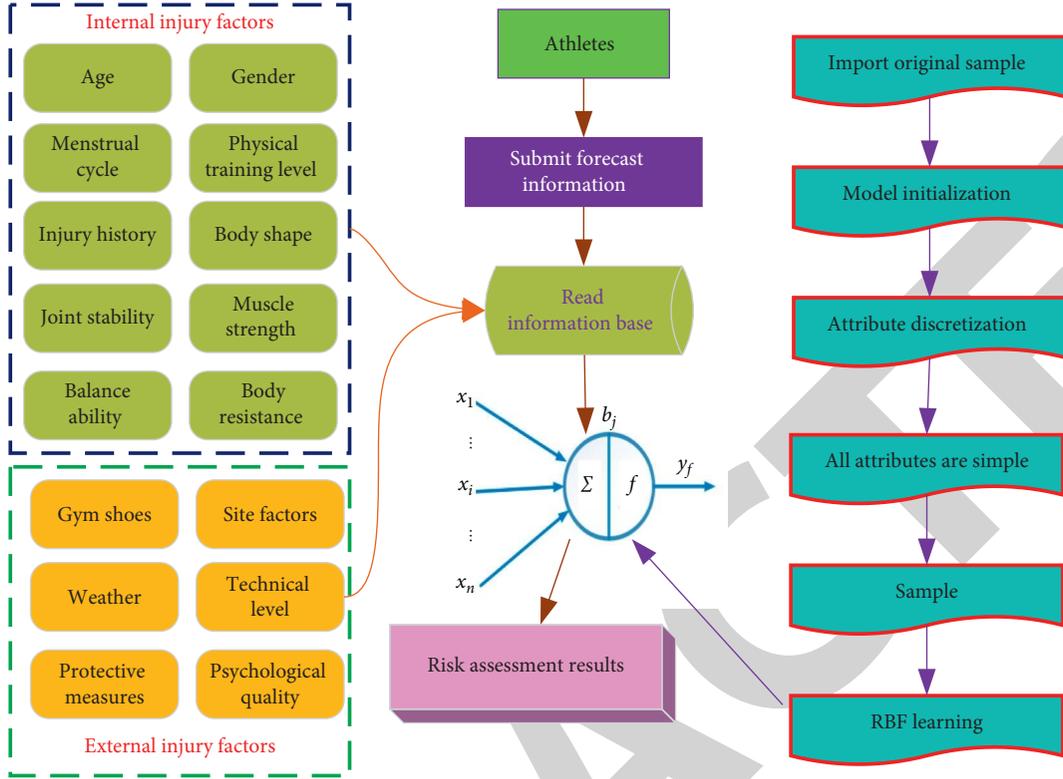


FIGURE 2: Flow chart of track and field injury warning.

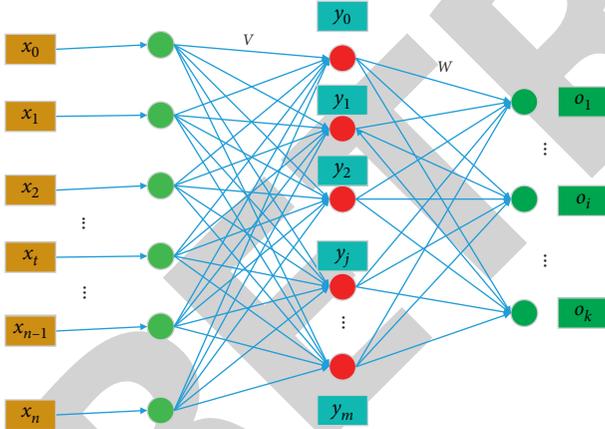


FIGURE 3: Structure diagram of RBF neural network.

neural network mainly includes input layer, hidden layer, and output layer.

The output of the RBF neural network can be described as follows:

$$g(x) = \sum_{i=1}^N \chi_i \Psi(x) + \beta, \quad (2)$$

where  $K$  describes the number of neurons in the hidden layer;  $X = (x_1, x_2, \dots, x_m)$  describes the input vector;  $\alpha$   $K$  describes the connection weight between the  $k$ th hidden layer neuron and the output layer neuron; and  $\phi$   $K$  describes the output of the  $k$ th hidden layer neuron, that is,

$$\Psi(x) = e^{-\frac{\|x - \mu_i\|}{\sigma_i^2}} \quad (3)$$

, where  $\mu$   $K$  describes the center vector and  $\sigma$   $K$  describes the variance.

Through the RBF neural network, according to the input information to assess the injury risk level of athletes, the details are shown in Table 3. In other words, RBF neural network is used to establish an estimation model, which mainly includes the selection of the basis function; the design of the hidden layer; and the change of the center, weight, and width of radial basis function.

Radial basis function (RBF) network has a topology structure of only one hidden layer. The hidden layer is the radial base layer, and the output layer is a linear layer. It is a kind of network form with excellent approximation ability, classification ability, and learning rate. Its neuron transfer function can take various forms, and the most commonly used one is the Gaussian function. The input of  $F(n)$  is the distance between the input vector  $p$  and the weight vector  $w$ , then multiplied by the threshold value  $B$ . The transfer function can be expressed as follows:

$$F(n) = e^{-(n+\varepsilon)^2} \quad (4)$$

RBF is a typical local approximation network. It can be seen that when the distance between the input vector and the weight is 0, that is,  $n = 0$ , the maximum value of the function output is 1; when the distance between the input vector and

TABLE 3: Comparison table of RBF output and risk level assessment.

Output value of RBF neural network	Risk level of sports injury
1	Low
2	Middle
3	High

the weight is 0.833, that is,  $n = 0.833$ , the output is 0.5; that is, the smaller the distance between the weight vector  $w$  and the input vector  $p$ , the larger the output. Given the input vector of radial basis function neuron, if the distance between the input vector and the weight vector is large, the output value tends to 0, and the influence on the output of the linear neuron can be ignored; if the distance between the input vector and weight vector is very small, the output value tends to 1, which will activate the output weight of the second-layer linear neural cell. Therefore, the response is a local response, which indicates that the RBF network has good local approximation ability.

**3.2. Establishment and Training of RBF Network.** In the neural network toolbox of MATLAB, the design functions of the RBF network are `Newrbf` and `newrbf`. When they are used to create the network, the network weights and thresholds are modified in different ways, so there is no special training and learning function for the RBF network.

If the number of radial basis function neurons is equal to the number of input samples, its weight is the transposition of the input vector:

$$[WB] = P^T \ln F(n). \quad (5)$$

The threshold values of all neurons in the radial base were as follows:

$$b = -\frac{1}{2} \log e^{-\ln(\sigma+\mu)}. \quad (6)$$

In the above formula, spread is the expansion coefficient of radial basis function, and the default value is 1.0 without input. The selection of spread is very important, and its value should be large enough to make some radial basis function neurons respond to the interval covered by the input vector, but it does not need to be large enough to be like this for all radial basis function neurons. The larger the spread, the smoother the output, but it will bring difficulties to the numerical calculation. If the "rank default" warning appears when designing the network, it indicates that the value is too large, and the spread value should be appropriately reduced to redesign.

Taking the output of radial basis function (RBF) neurons as the input of linear network layer neurons, the weights and thresholds of linear layer neurons are determined to meet the following requirements:

$$[\text{one}; A\{1\}] = \frac{T}{W\{1,2\}b\{2\}}. \quad (7)$$

The above process only needs one time to get a radial basis function with zero error, so it is very fast to use the

`Newrbf` function to create the FRB network. However, because the number of radial basis function neurons is equal to the number of input samples, when the number of input samples is large, the scale of the network is also large. A more effective method is to create a radial basis function through the `newrbf` function.

Using the `newrbf` function to create the RBF network can automatically increase the number of hidden layer neurons of the network. Only one radial basis function is added in each cycle, and each additional neuron can reduce the error as much as possible until the mean square deviation meets the accuracy requirements or the number of neurons reaches the set upper limit:

$$N = \text{net}(T, G, S, P), \quad (8)$$

where  $P$ ,  $T$  are input and output samples;  $S$  is expansion coefficient of radial basis function; and  $G$  is training accuracy.

The value of spread has a great impact on the accuracy of the network. If the value of spread is too small, more neurons will be generated in the process of network approximation, and the function fitting phenomenon will be too suitable, as shown in Figure 4; if the value of spread is too large, the function fitting will not be suitable, as shown in Figure 5.

In this paper, we use the `newrbf` function to create the RBF network. When using different expansion constants, the network training accuracy and generalization ability are not the same. Therefore, in the network design, we try to choose the appropriate spread value and finally get the ideal approximation accuracy.

The RBF neural network is trained according to the sports injury risk sample database, and the training process is shown in Figure 6. After the training of the RBF neural network, the sports injury data is input into the RBF neural network. When the transmission data corresponds to a certain sports injury risk level, the RBF neural network will output the corresponding value to realize the sports injury estimation.

## 4. Experiment and Analysis

In the above process, the establishment of an early warning model of sports injury based on the RBF neural network algorithm is completed. In order to verify the practical value of the model, two computers with the same configuration were used as the experimental objects, one of which was equipped with a new damage assessment model and the other as a control group, carrying the traditional damage assessment model. The data are collected from the real experiment, not the database, so there is no download address.

**4.1. Experimental Parameter Setting.** The parameters in Table 4 represent injury parameters, evaluation accuracy, network safety factor, sports injury grade, transverse injury judgment accuracy, and longitudinal injury judgment accuracy. Among them, the network safety coefficient is grade III, which represents the big data network environment used

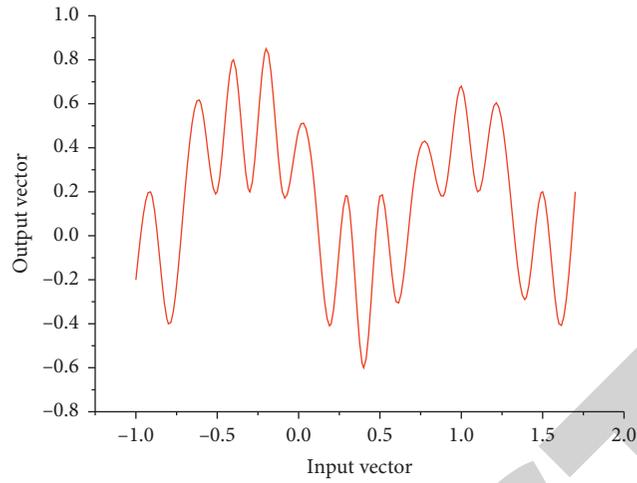


FIGURE 4: Network over adaptation.

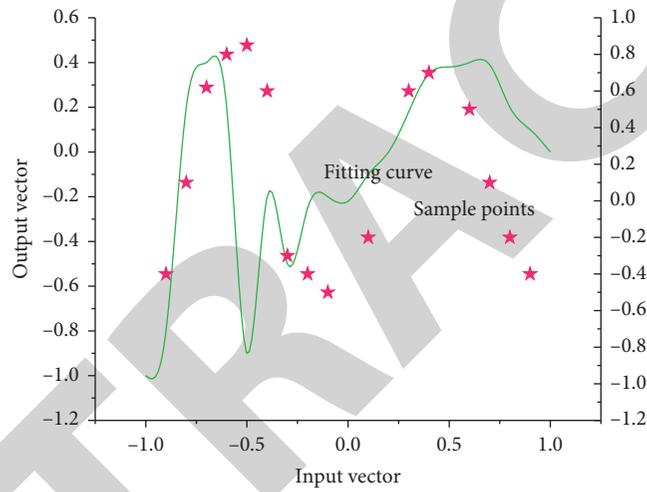


FIGURE 5: Network discomfort.

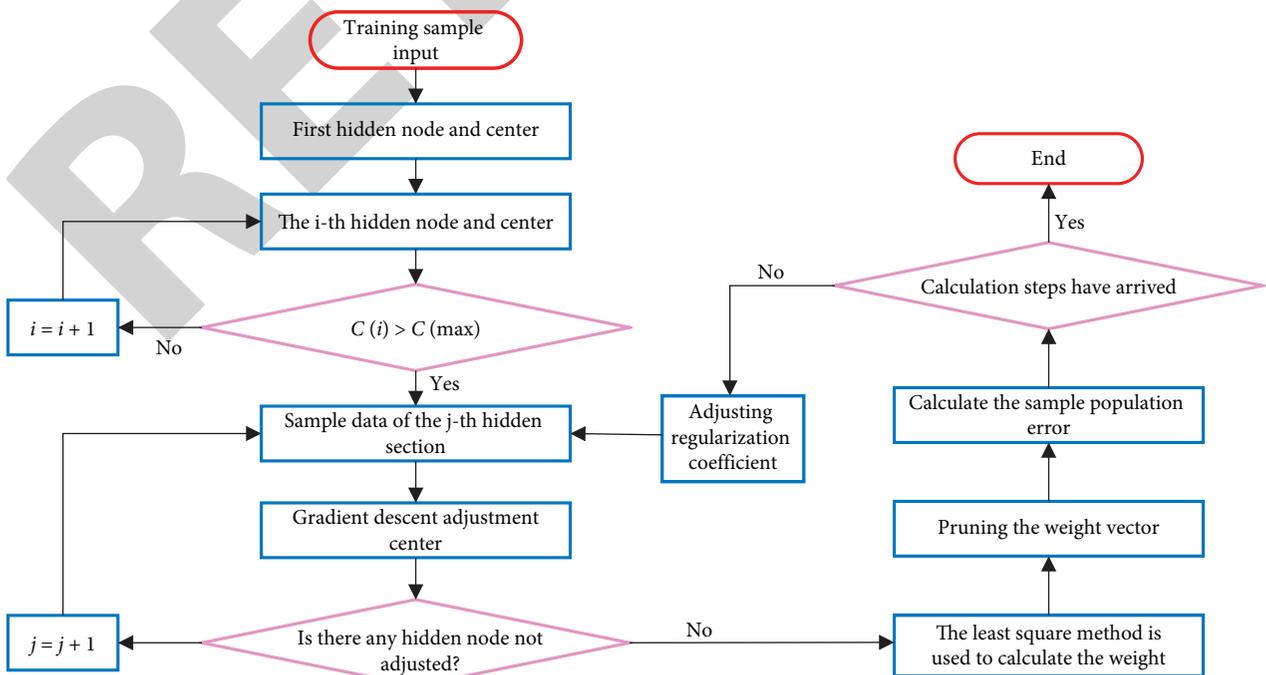


FIGURE 6: Training flow of RBF neural network.

TABLE 4: Experimental parameter setting table.

Parameter name	Experience group	Control group
Damage parameters	$8.83 \times 10^{-7}$	$8.83 \times 10^{-7}$
Assessment accuracy	93.59	93.59
Network security factor	0.67	0.67
Sports injury level	II	II
Accuracy of transverse damage judgment	95.78	95.78
Accuracy of longitudinal damage judgment	94.62	94.62

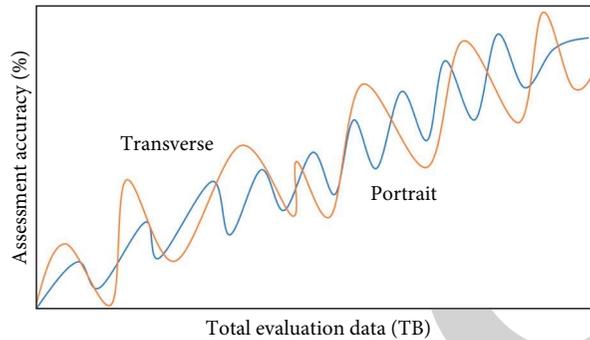


FIGURE 7: Accuracy of risk assessment of transverse and longitudinal sports injury.

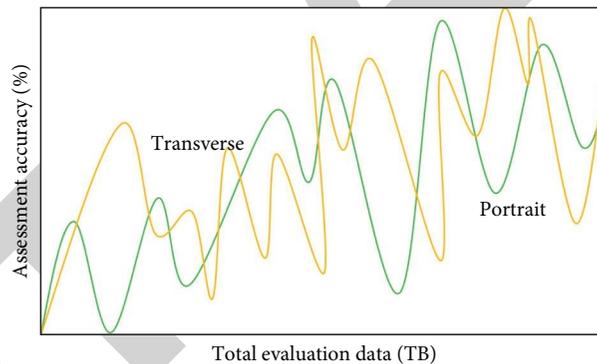


FIGURE 8: Accuracy of risk assessment of transverse and longitudinal sports injury.

by the sports injury assessment model, and always maintains a safe state. In order to ensure the fairness of the experiment, the experimental parameters of the experimental group and the control group were always consistent.

**4.2. Comparison of Transverse and Longitudinal Damage Risk Assessment.** If the risk assessment of transverse and longitudinal sports injury can be carried out at the same time, the accuracy difference between transverse and longitudinal sports injury assessment is small, and the same upward or downward trend is always maintained. If the transverse and longitudinal sports injury risk assessment cannot be carried out at the same time, the accuracy of transverse and longitudinal sports injury assessment is quite different and always keeps the opposite upward or downward trend. Using a special detection method, the experimental group and the control group were recorded, respectively. The accuracy of transverse and longitudinal sports injury risk assessment is

as follows: compared with Figures 7 and 8, the maximum accuracy of transverse damage risk assessment in the experimental group was 94.67%, and the maximum value of longitudinal damage risk assessment accuracy was 93.51%. The two always kept the same trend, and the difference was small. In the control group, the maximum accuracy of transverse injury risk assessment was 96.22%, and the maximum value of longitudinal injury risk assessment accuracy was 85.38%. The change trend of the two was not always consistent, and the difference was also large. Therefore, it can be proved that the application of the big data network sports injury assessment model can indeed carry out transverse and longitudinal damage risk assessment at the same time, while the traditional model cannot.

**4.3. Comparison of Sports Injury Attribute Judgment.** The longer the vertical line is, the more serious the damage is; if the composite damage occurs in the damaged part, the

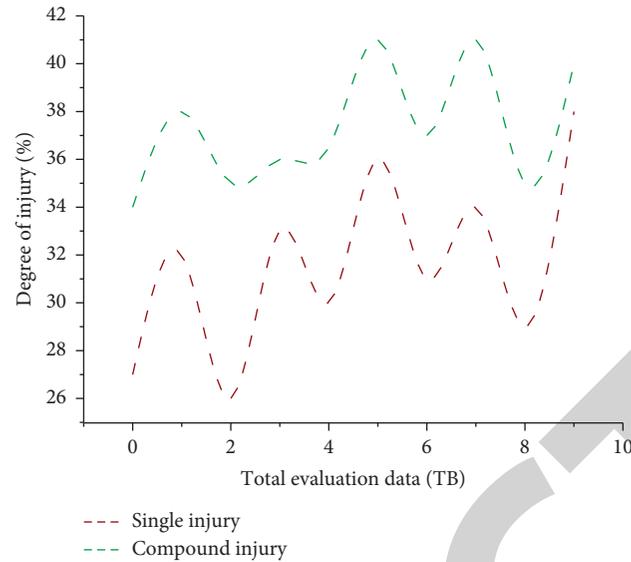


FIGURE 9: Comparison chart of damage degree.

horizontal line is the result, and the longer the horizontal line is, the more serious the damage is. The risk assessment of transverse and longitudinal injury was carried out, and the sports injury attributes of specific parts were judged.

It can be seen from Figure 9 that, according to the judgment results, the experimental group can clearly analyze whether the damage occurring in specific parts is single or compound, the maximum value of single damage degree is 38.75%, and the maximum value of composite damage degree is 40.02%. In the control group, all the analysis results had a certain angle, which could not clearly analyze whether the damage occurring in specific parts was single or compound, and the results were not convincing. Therefore, it can be proved that the application of the big data network sports injury assessment model can really judge the sports injury attributes of specific parts, but the traditional model cannot. In this paper, a sports injury estimation model based on big data analysis, on the basis of big data analysis technology, constructs a sports injury estimation model through RBF neural network, and the accuracy and efficiency of the designed model are verified by experiments.

## 5. Conclusion

The sports injury assessment model based on the big data network, with the big data network environment as the application background, can improve the stability of operation; at the same time, it can carry out the risk assessment of transverse and longitudinal injuries, and judge the sports injury attributes of specific parts. In order to improve the accuracy of sports injury estimation, this paper proposes a sports injury estimation model based on big data analysis. On the basis of big data analysis technology, the model is constructed by RBF neural network. The experimental results show that the designed model has high accuracy and efficiency. In the built environment, the risk assessment of sports injury can be completed by determining the risk

source and identifying the risk factors. The realization of the model can be constrained by the uncertainty conditions so that it can achieve a good operation state. The new model of sports injury assessment has more practical value in the aspects of real-time assessment of transverse and longitudinal injury risk and the accuracy of judging specific sports injury attributes.

## 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 known conflicts of interest or personal relationships that could have appeared to influence the work reported in this paper.

## References

- [1] J. F. Zheng, J. D. Jiao, and L. P. Sun, "A modeling approach for early-warning of water bloom risk in urban lake based on neural network," *Zhongguo Huanjing Kexue/china Environmental Science*, vol. 37, no. 5, pp. 1872–1878, 2017.
- [2] P. Zhaodong, T. Ping, L. Liangkun et al., "Hierarchical decentralized control of building structure based on adaptive RBF neural network algorithm," *China Civil Engineering Journal*, vol. 51, no. 1, pp. 51–57, 2018.
- [3] H. Meng, F. Yuan, T. Yan, and M. Zeng, "Indoor positioning of RBF neural network based on improved fast clustering algorithm combined with LM algorithm," *IEEE Access*, vol. 7, pp. 5932–5945, 2019.
- [4] T. Muling, T. Muqin, Y. Jieming, and J. Li, "Optimization of RBFneural network used in state recognition of coal flotation," *Journal of Intelligent & Fuzzy Systems*, vol. 34, no. 2, pp. 1193–1204, 2018.
- [5] Y. Chen, H.-W. Ma, and M. Dong, "Automatic classification of welding defects from ultrasonic signals using an SVM-based RBF

- neural network approach,” *Insight - Non-destructive Testing and Condition Monitoring*, vol. 60, no. 4, pp. 194–199, 2018.
- [6] J. d. D. Beas-Jiménez, A. León Garrigosa, P. Doñoro Cuevas et al., “Translation into Spanish and proposal to modify the orchard sports injury classification system (OSICS) version 12,” *Apunts Sports Medicine*, vol. 55, no. 207, pp. 105–109, 2020.
  - [7] M. E. Karar and M. A. El-Brawany, “Fully tuned RBF neural network controller for ultrasound hyperthermia cancer tumour therapy,” *Network*, vol. 29, no. 1–4, pp. 20–36, 2018.
  - [8] H. K. Ghritlahre and R. K. Prasad, “Exergetic performance prediction of solar air heater using MLP, GRNN and RBF models of artificial neural network technique,” *Journal of Environmental Management*, vol. 223, no. OCT.1, pp. 566–575, 2018.
  - [9] M.-c. Chen, S.-q. Lu, and Q.-l. Liu, “Global regularity for a 2D model of electro-kinetic fluid in a bounded domain,” *Acta Mathematicae Applicatae Sinica, English Series*, vol. 34, no. 2, pp. 398–403, 2018.
  - [10] M. Chen, S. Lu, and Q. Liu, “Uniform regularity for a Keller-Segel-Navier-Stokes system,” *Applied Mathematics Letters*, vol. 107, Article ID 106476, 2020.
  - [11] P. Lin, C. Wang, and T. Chen, “A stall warning scheme for aircraft engines with inlet distortion via deterministic learning,” *IEEE Transactions on Control Systems Technology*, vol. 26, no. 4, pp. 1468–1474, 2018.
  - [12] A. Angeline and B. Prabhu, “Sports-injury encephalopathy,” *Southern Medical Journal*, vol. 112, no. 10, pp. 547–550, 2019.
  - [13] L. Shi and F. Luo, “Research on risk early-warning model in airport flight area based on information entropy attribute reduction and BP neural network,” *International Journal of Security & its Applications*, vol. 9, no. 10, pp. 313–322, 2015.
  - [14] M.-Y. Chen, Y.-L. Kuo, and C.-Y. Chou, “Lateral abdominal muscle symmetry and risk of sports injury in baseball players,” *Medicine & Science in Sports & Exercise*, vol. 52, no. 7S, p. 83, 2020.
  - [15] M. Xiang, J. Min, Z. Wang et al., “A novel fault early warning model based on fault gene table for smart distribution grids,” *Energies*, vol. 10, no. 12, pp. 1963–1979, 2017.
  - [16] K. Deng, X. Zhang, Y. Cheng et al., “A remaining useful life prediction method with long-short term feature processing for aircraft engines,” *Applied Soft Computing*, vol. 93, Article ID 106344, 2020.
  - [17] Z. Liao, X. Xiong, X. Li et al., “An early warning method of transmission line galloping based on BP neural network,” *Dianli Xitong Baohu Yu Kongzhi/Power System Protection and Control*, vol. 45, no. 19, pp. 154–161, 2017.
  - [18] Y. Sun and R. Chai, “An early-warning model for online learners based on user portrait,” *Ingénierie des systèmes d information*, vol. 25, no. 4, pp. 535–541, 2020.
  - [19] Z. Chen, F. Huang, W. Sun, J. Gu, and B. Yao, “RBF-Neural-Network-Based adaptive robust control for nonlinear bilateral teleoperation manipulators with uncertainty and time delay,” *IEEE/ASME Transactions on Mechatronics*, vol. 25, no. 2, pp. 906–918, 2020.
  - [20] H. Han, X. Wu, L. Zhang et al., “Self-organizing RBF neural network using an adaptive gradient multiobjective particle swarm optimization,” *IEEE Transactions on Cybernetics*, vol. 49, no. 1, pp. 69–82, 2018.
  - [21] J. S. Everhart, K. Harris, A. Chafitz et al., “Psychological assessment tools utilized in sports injury treatment outcomes research: a review,” *Journal of Sports Science & Medicine*, vol. 19, no. 2, pp. 408–419, 2020.