Ann. For. Res. 65(1): 6506-6519, 2022
ISSN: 18448135, 20652445

ANNALS OF FOREST RESEARCH
https://www.e-afr.org/

SPORTS INJURY PREDICTION MODEL BASED ON DYNAMIC SAMPLING AND TRANSFER LEARNING

Zebin Xiao[1], Yingman Ye[2,*]
1.Qiongtai Normal University, Haikou,571127,China
2.Hainan University,Danzhou, 571737,China
995581045@qq.com

Abstract: Accurate prediction of vulnerable parts can effectively avoid the injury caused by intense exercise. In order to accurately predict the degree of sports injury, it is necessary to analyze sports injury accurately. Therefore, the design of sports injury prediction model based on dynamic sampling and transfer learning is proposed. The sports injury prediction model based on dynamic sampling and transfer learning describes the influencing factors of vulnerable parts of athletes in high-intensity sports. By calculating the regression function of vulnerable parts and human parts, the functional relationship between the exercise intensity of human body parts and exercise intensity is obtained. Combined with the theory of dynamic sampling and transfer learning, the prediction model of human vulnerable point is established, and the reliability of the prediction model is obtained, and the prediction model of vulnerable point of human body in optimal motion state is given. The simulation results show that the model can accurately predict the situation of sports injury.

Keywords: Dynamic sampling; Transfer learning; Sports injury; Injury prediction;

0 Introduction

Traditional sports injury prediction method is based on the fuzziness of various variables of human body injury degree, and establishes fuzzy judgment and prediction standards to complete the prediction of human injury degree[1]. It can not accurately describe the relationship between sports injury and human injury degree, and the prediction error is large. Therefore, a sports injury prediction model based on dynamic sampling and transfer learning is proposed. Combining dynamic acquisition with transfer learning, a sports injury prediction model was established. Using transfer learning method to automatically extract the semantic information of outpatient records can better describe the characteristics of outpatient records[2]. The sports injury record is transformed into vector representation, and the dynamic sampling method is used to collect and extract the sample features of different sports injury data, and the semantic information of different length sports injury is improved[3]. Then, a new method combining the number of sports injury samples and the number of negative samples is proposed to ensure the accuracy of sports injury prediction and improve the credibility of the model prediction results by dynamic collection method.

1 Design of sports injury prediction model based on dynamic sampling and transfer learning

1.1 Dynamic sampling of characteristic information of sports injury

On the basis of dynamic collection method, the characteristic data of sports injury is processed by multi label, and the training set of sports injury is transformed into the multi classification

training set of binary classification. Different types of sports injury diagnosis models are established, and the multi label transfer learning prediction model is trained for sports injury, and the parameters obtained from training are retained[4]. In the training process, the same small sample sports injury prediction model as the small sample is selected, and most of the parameters of the model are transferred to multiple sports injury models, and most of the parameters are taken as the initial values of the small sample sports injury model[5]. The unified data set is trained by dynamic acquisition training method. On this basis, multiple single category sports injury prediction models are combined into multiple classification models, and the whole sports injury prediction model is explained.

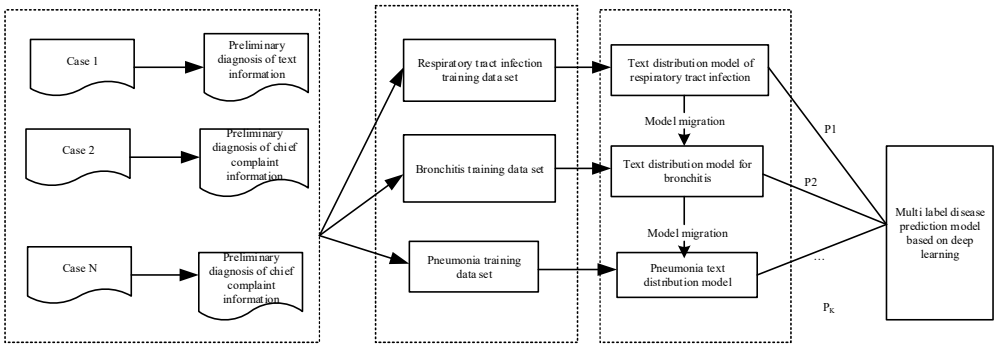

Fig. 1 Motion injury data acquisition framework based on dynamic sampling

When dynamic sampling is used to predict sports injury, firstly, the characteristic information of sports injury is input, and then the sports injury is divided into two categories. The medical record text was segmented and transformed into a group of words Skipgram model is used to train the text of sports injury medical record[6]. The semantic vector of low dimensional continuous space is used to represent the discrete word symbol, and the word vector is used to represent the information text of sports injury medical record. Finally, two dynamic data vectors representing the medical record of sports injury are obtained. Finally, through dynamic sampling and pool operation, the word vector matrix in sports injury medical record text is extracted The injuries were classified and analyzed[7]. The following figure shows the sports injury prediction model and the data processing model of sports injury characteristics.

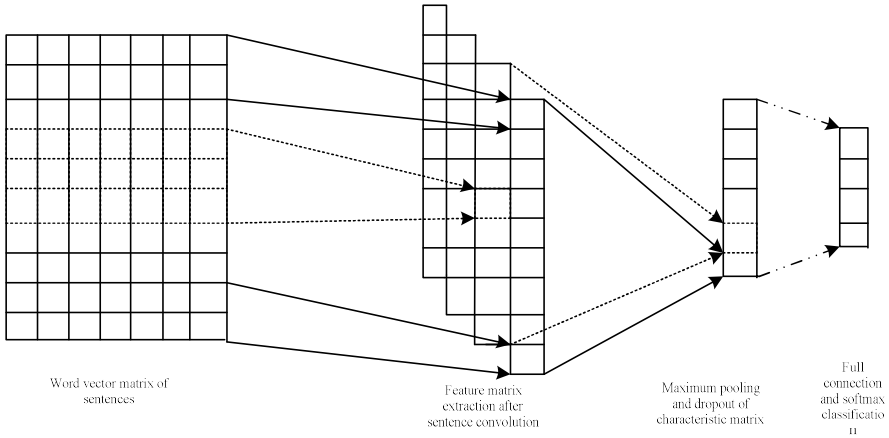

Fig. 2 Data processing model of sports injury characteristics

Further, W_t is used for feature prediction. The dynamic data of motion damage in p window is characterized by $W_t = (W_t - n, W_t - n + 1)$. The model is trained by the maximum logarithmic likelihood function to obtain the vector representation of each word:

$$L = \sum_{r \in \text{Coatexet}(W_i)} \lg\left(p\left(c \mid W_t\right)\right) \quad (1)$$

Further, the prediction principle of sports injury characteristic data is demonstrated, as shown in the figure

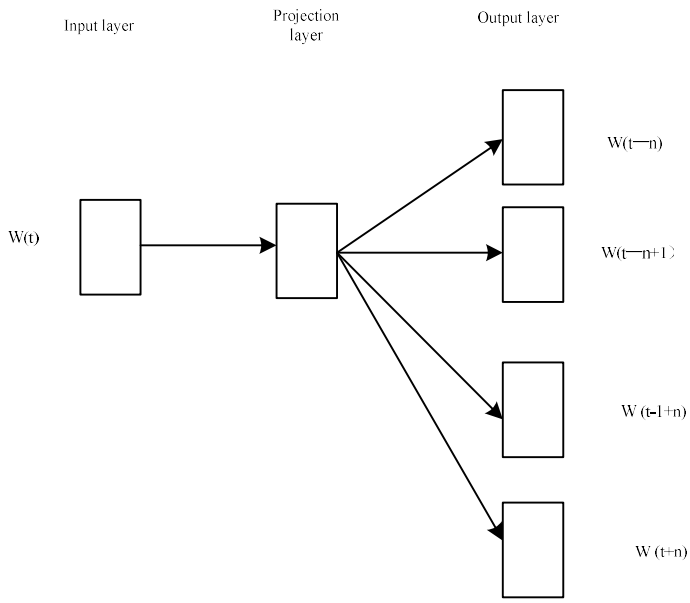

Fig. 3 Prediction principle of sports injury

Suppose that the dynamic data vector of sports injury is n-dimension, and $x_n = k$ represents the ith injury vector. Then the calculation results are as follows:

$$X_{1_{:}n} = x_1 \oplus x_2 \oplus \cdots \oplus x_n \quad (2)$$

The 2-d matrix representation of the sports injury data is carried out, the results are input into the convolutional layer, and the dynamic feature extraction of the sports injury data is carried out by using the convolution checking the training data[8]. Assuming that the word order is X_n : $n+m-1$, and there is a window vector matrix between $n+m-1$ and $i+m-1$, the matrix of W is given, so that W acts on b continuous word vector, and the output is obtained. Generate SPORTS injury data:

$$c_i = f\left(w \cdot X_{1_{:}n} + \text{Xi}b\right) \quad (3)$$

Where f is a nonlinear function. More semantic information of sports injury can be obtained through different Windows, so as to extract richer representation of text data. According to the change of dynamic data of sports injury, the characteristic chart of dimension change is generated. Because of the large dimension of classification, it is difficult to train the appropriate classification

model directly. The feature map is used as input to the pool layer to obtain the most important information in a dimensionless way.

1.2 Sports injury prediction index based on Transfer Learning

In order to reduce the influence of unbalanced training data on prediction performance and improve the accuracy and convergence speed of sports injury prediction, a transfer learning algorithm is adopted. When the other types of data in the training data are unbalanced, the comparative analysis is made according to the class II training data of various sports injuries, because the sample distribution is uneven in various sports injuries[9]. There are several common sports injuries are more common, there are several rare sports injuries are relatively rare. There are also different types of sports injuries[10]. Due to the large difference of different types of training data, especially in the case of balanced injury, small samples and large samples are easier to select in training, which leads to insufficient learning of small samples and poor prediction performance, which can not meet the needs of research[11]. In order to ensure the accuracy of the prediction results, this paper analyzes the common sports injury parts and causes, and puts forward prevention strategies, hoping to help.

Table 1 List of common sports injuries（n=50）

Injury site	Number of injured persons / person	Percentage /%
joint	38	76
skin	8	16
head	2	4
bones	1	2
other	1	2

Through the selection of training samples, error calculation and parameter updating, the motion data is divided into several small pieces, each block has a fixed size sample, and then these sample data are selected for model training[12]. As can be seen from the figure, the training data set is divided into n small blocks, and then the block data is selected for model training. Based on this, the data processing steps of sports injury based on transfer learning are optimized, as shown in the figure 4:

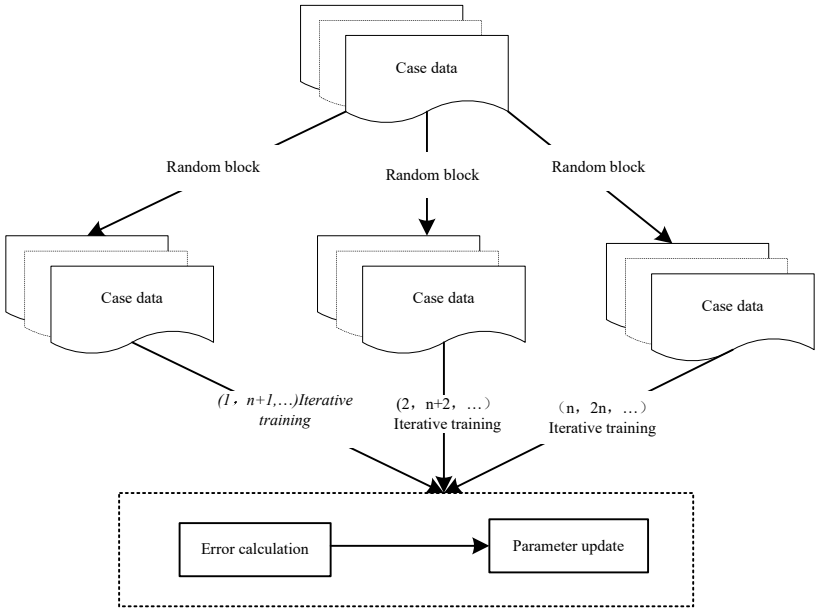

Fig. 4 Steps of sports injury data processing based on Transfer Learning

In order to establish an effective sports injury data model, transfer learning technology and dynamic probability sampling technology are used in the prediction model. The large sample sports injury model with high symbiosis rate and sufficient data was selected[13]. The small sample prediction model was used to predict the training process. The training samples were selected by dynamic collection method, and the positive samples and negative samples were separated[14]. Finally, the sampling rate is merged into the training data of the next round to process the sports injury data based on transfer learning. The specific method is shown in the figure 5.

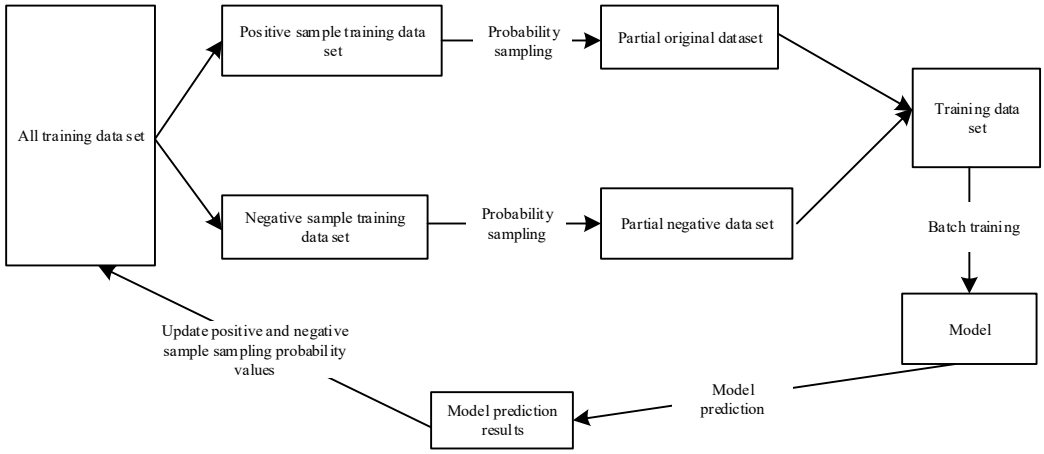

Figure 5 Sports injury data processing based on Transfer Learning

Furthermore, the training algorithm of small sample sports injury prediction transfer learning model combining transfer learning and dynamic sampling is used to collect multi label sports injury data and calculate.

$$D=\{(x_1,y_1),(x_2,y_2),\cdots,(x_N,y_N)\},x_i\in X\subseteq R^n,y_i\in\{c_1,c_2,\cdots,c_K\} \quad (4)$$

R^n represents the total number of sports injury markers; Sports injury marker y_i to be trained; Number of iterations N; The size of each iteration of the training data block. For any c_j label, calculate the frequency of sports damage label c_i and c_j, then calculate:

$$P\left(c_i, c_j\right) = \sum_{\omega_n} \sum_{\substack{i=y_n \\ n \in D}} I\left(\left\{c_i, c_j\right\} \subseteq y_n\right) \quad (5)$$

$$I\left(\left\{c_i, c_j\right\} \subseteq y_n\right) = \begin{cases} 1, & c_i \in y_n \text{ and } c_j \in y_\pi \\ 0, & c_i \notin y_n \text{ or } c_i \notin y_n \end{cases} \quad (6)$$

I is divided into some binary data sets of sports injury D_k, where D_{i} is the training set of sports injury label C_i. C_K is selected in the sports injury label C_i, which has the highest frequency of occurrence. Based on C_K training data set D_k, the sports injury prediction model $F_i(x)$ was established, and the parameters of T were retained. Its algorithm was:

$$F_i(x) = \mathrm{T}(\mathrm{C_i}\text{-}\mathrm{C_K})\,\mathrm{rain}\left(D_{\mathrm{i}} + D_k\right) \quad (7)$$

On the basis of this model, a non-parametric multi-correlation sample consistency detection method is proposed to check the consistency of indexes. If the value range of transport coordination coefficient is 0-1, it is used to describe the overall consistency of each indicator. When T>0.05, the reliability of expert assessment and prediction is poor, and the results of assessment and prediction are not ideal[15]. When T<0.05, the reliability of expert assessment and prediction was good and the results were reliable. Based on this, the consistency of damage prevention indicators is standardized, as shown in the table 2:

Table 2 Consistent parameters of damage prevention indexes

Grade index	Number of experts (n)	Chi square	Degree of freedom (DF)	Concordance coefficient (Kendall's w)	Progressive significance (P value)
Primary indicators	14	30.577	4	.510	.000
Secondary indicators	14	105.519	21	.335	.000
Third level index	14	84.151	21	.267	.000

As shown in the table 2, the first-level coordination coefficient of the prevention system is 0.510, with a P value of 0.000<0.05; the second level is 0.335, with a P value of 0.000<0.05; the third level is 0.267, with a P value of 0.000<0.05. It shows that the experts have highly consistent opinions on the evaluation of the indicators of the expert group and the evaluation results are credible.

1.3 The realization of sports injury prediction

It is difficult to accurately extract some fuzzy parameters when analyzing the moving vulnerable parts. Put forward a predictable model of human body injury, to calculate the various factors affecting the credibility of the wearing parts, and gives a prediction model of dynamic movement human body damage, concrete steps as follows: in the process of human body damage prediction model is established, the evaluation of the first face-to-face, the body parts of reverse damage properties and its range of inner link, through the combination of methods, to express and describe and record, specific can be written as:

$$U = \{u_1, u_2, \cdots, u_e\} \quad (8)$$

The collection of all possible site sites of body parts injury is denoted as:

$$V = |v_1, v_2, \cdots, v_n| \quad (9)$$

For the fuzzy influencing factors of different motion types, the influencing factors of different categories can be divided into different subclasses, and the number of different subclasses of the influencing factors of different categories can be equated, so that:

$$u_i = \{u_{i1}, u_a, \cdots, u_{ij}\} \quad (10)$$

The confidence degree $r = Vu_{ij}$ of the influencing factors of class I movement that cause the damage point of type J body indicates the membership degree of u_{i1} to u, that is, the degree to which the influencing factors of movement at the damage point of type j body may reach:

$$0,, r_{ij} < 1 (i = 1, 2, \cdots, n; j = 1, 2, \cdots, m) \quad (11)$$

According to the fuzzy set matrix on R, the possibility of body injury point is obtained

$$R = \begin{pmatrix} R_1 \\ R_2 \\ \vdots \\ R_4 \end{pmatrix} = \begin{pmatrix} r_{11} & r_{12} & \cdots & r_{1m} \\ r_{21} & r_{22} & \cdots & r_{2m} \\ & \vdots & \vdots & \vdots \\ r_{n1} & r_{n2} & \cdots & r_{nm} \end{pmatrix} \quad (12)$$

Further build a sports injury comprehensive evaluation prediction model:

$$B = A^\circ R = (b_1, b_2, \cdots, b_n) = (a_1, a_2, \cdots, a_n) \quad (13)$$

$$\begin{pmatrix} R_1 \\ R_2 \\ \vdots \\ R_n \end{pmatrix} = \begin{pmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ a_{m1} & a_{m2} & \cdots & a_{mn} \end{pmatrix} \begin{pmatrix} r_{11} & r_{12} & \cdots & r_{1m} \\ r_{21} & r_{22} & \cdots & r_{2m} \\ \vdots & \vdots & \vdots & \vdots \\ r_{m1} & r_{m2} & \cdots & r_{ma} \end{pmatrix} \quad (14)$$

In the prediction of sports injury, the predicted value should be determined according to dynamic sampling and migration learning variables, and the evaluation model of dynamic sampling should reflect the degree of injury. As an index parameter, the model has a large modeling error when analyzing the moving vulnerable parts[16]. Therefore, it is necessary to generate eigenvectors of fixed length after pooling. The classification of feature vectors in the

input fully connected classification layer and the formation of the relationship between dynamic acquisition and transfer learning is an important index to describe the sports injury assessment model. To facilitate the analysis, the relationship between dynamic sampling and transfer learning is proposed and combined with input-output delay estimation[17]. If the input motion damage data contains a specific sequence, the output is estimated to be 1; otherwise, the output is 0, and there is a finite delay length, but the estimates and estimates between the two are uncertain. Therefore, the relationship between dynamic acquisition and transfer learning still belongs to the uncertainty in the unconscious sequence[18]. To solve the above problems, it is necessary to first analyze the manifestation of the relationship between dynamic sampling and transfer learning, specifically as figure 6:

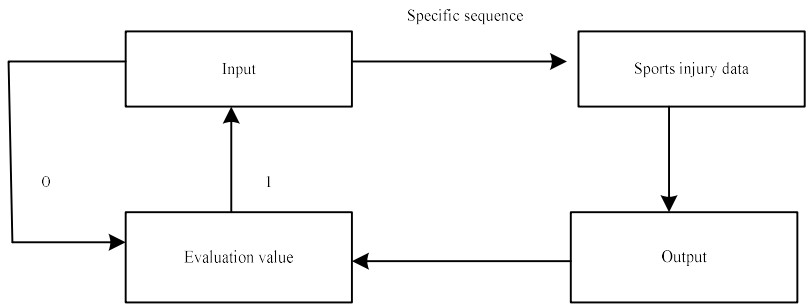

Fig. 6 Representation diagram of the relationship between dynamic sampling and transfer learning

Sources and Identification methods of sports injury risk Factors In order to effectively avoid the uncertainty problem in the unconscious sequence, before the evaluation of sports injury, it is necessary to determine the risk source of injury[19]. The risk sources of sports mainly include rule guidance, equipment demand, sports mode, sports crowd, sports difficulty and so on. Through the identification of sports injury risk factors, according to the identified hazard sources, using a specific algorithm to determine the risk level of sports injury, so as to achieve the purpose of judging the severity of injury[20]. If the hazard form is adopted, the hazard identification of sports injury risk factors can be in the following form:

$$\eta(s) = \frac{1}{2}\sum_{n=0}^{n}[\xi s(l)^n] \qquad (15)$$

In the above formula, n represents an uncertain variable, which can vary with the value of s. The specific algorithm is used to complete the risk identification of sports injury. And l is used to represent the specific parameters generated by sports injury risk factor in the risk source. The comprehensive evaluation is carried out based on the pre-evaluation results of sports injury. See the chart for the specific procedure of evaluation.

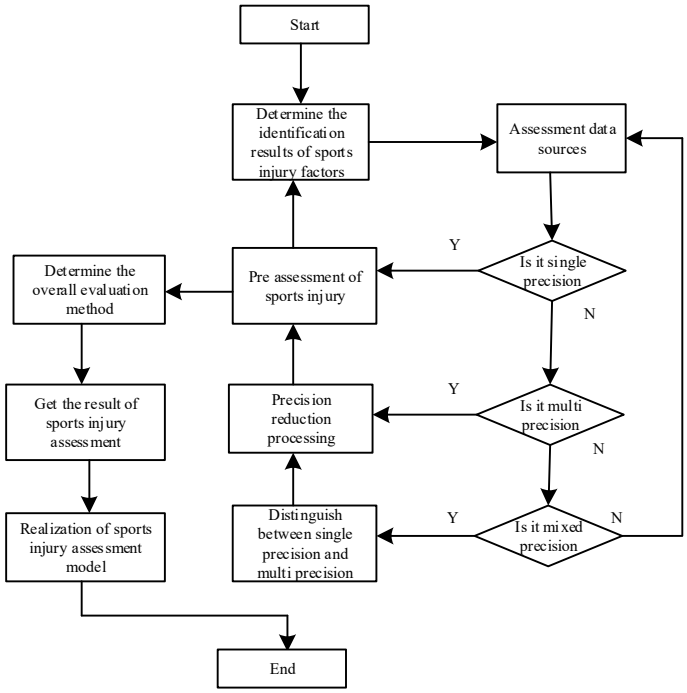

Fig. 7 Flow chart of sports injury assessment based on injury risk factors

The prediction of sports injuries based on the above methods can further improve the accuracy of sports injuries prediction and ensure the validity of the prediction results, so as to better guarantee the health of athletes and make reasonable sports arrangements.

2 Analysis of experimental results

In order to verify the practical application effect of the sports injury prediction model based on dynamic sampling and transfer learning, the experimental data were obtained from six groups of 102 people. Using the method of questionnaire survey, statistical analysis of injury and injury of athletes in each team. The experimental group and experimental group were randomly selected. Track the investigator's half year training and analyze the most vulnerable part of the body in speed training.

Table 3 Basic information of experimental data set

	Number of positive cases	Negative cases	IR
Public datasets	500	1500	3
	500	1500	3
	500	1500	3
Private dataset (most classes)	1210	750	1.61
	631	1359	2.15
	433	1527	3.53
Private datasets (minority classes)	131	1829	13.96
	113	1847	16.35
	66	1894	28.70

Record athletes' movements with professional cameras. The motion video is segmented by professional software, and the segmentation results are analyzed. Select the relevant indicators, combined with the situation of athletes' joint injury to carry out correlation analysis. The details are as table 4:

Table 4 Detection indexes of knee joint injury of athletes

Biomechanical study on knee joint injury of athletes	Special physical fitness of athletes
Speed of body center of gravity	Speed endurance (half marathon time)
Speed of knee joint	Strength and endurance
Knee angular velocity	
Knee bending angle	Speed sensitivity

SPSS software was used for statistical analysis of athletes' performance and difference analysis. Video analysis showed that of the 180 athletes, 126 had knee injuries, 54 had no injuries, 70 percent had knee injuries, and 30 percent had no injuries. Meniscus injury was 60 cases, accounting for 48% of knee joint. Patella strain was found in 34 cases, accounting for 27%. Injury of collateral ligament in 28 athletes, accounting for 22%; Patella softening, accounting for 3% of the total athletes; The statistical analysis results of the questionnaire are as table 5 and table 6:

Table 5 Questionnaire results of the degree of knee joint injury of athletes

The severity of knee injury in athletes	
Mild injury	30（24%）
moderate lesions	90（71%）
Severe injury	6（5%）

Table 6 Questionnaire results of the degree of knee joint injury of athletes

Degree of injury	Exercise time
Mild injury (30 cases)	1 ~ 2 times / week, 3 ~ 6h / time (8 persons, 27%)
	7 ~ 9 times / week, 3 ~ 6h / time (22 persons, 73%)
Moderate injury (90 cases)	1 ~ 2 times / week, 3 ~ 6h / time (14 persons, 16%)
	7 ~ 9 times / week, 3 ~ 6h / time (38 persons, 84%)
Severe injury (6 cases)	7 ~ 9 times / week, 3 ~ 6h / time (6 persons, 100%)

The results showed that the injury of knee joint was mainly moderate. Long-term and frequent sports make the knee joint bear a lot of pressure, easy to cause injury. It also made the injury more serious. Combined with the present situation and characteristics of knee joint injury, this paper analyzes the cause of knee joint injury. The statistical analysis of 126 athletes' knee injuries showed that 71.4% of the 90 athletes' knee injuries were mainly caused by lack of exercise. Fourteen athletes (11.1%) were overtired as a result of overtraining. The main causes of knee joint injury were body collision, weak consciousness of self-protection and poor physique, accounting for 8%. Other factors, such as lack of targeted rehabilitation training, injuries during training or competition, and poor weather conditions, will be ruled out.

Table 7 Analysis results of inducing factors of knee joint injury

Inducing factors	Number of people	proportion
The preparations are unreasonable	90	71.4%
Insufficient cooling	10	7.9%
Physical fatigue of athletes	14	11.1%
Body collision between athletes	4	3.2%
Athletes have poor self-protection consciousness	4	3.2%
Poor physical fitness of athletes	2	1.6%
Treadmill equipment and location	2	1.6%
Lack of targeted rehabilitation training	0	0%
Practice or play with injuries	0	0%
Adverse climatic factors	0	0%

By training the data samples, the high-dimensional continuous dense word vectors are obtained and converted into word order matrix to obtain the semantic feature expressions of the input text. Then, the vulnerable parts of athletes are predicted by convolution, aggregation and full connectivity respectively, and the vulnerable parts of athletes are predicted by three models. This paper compares and analyzes the vulnerable parts of athletes' speed training and the actual injured parts, and measures the advantages and disadvantages of different models by comparing the results. The details are shown in the table 8.

Table 8 Comparison of the advantages of different models in predicting the vulnerable parts of the body during strenuous exercise

	T	No.	Injured part
Ai	180	20	Foot, hip joint, tendon injury, lower limb muscle, leg ligament strain
Im_1	180	20	Foot, hip joint, tendon injury, lower limb muscle, leg ligament strain
Im_2	180	20	Waist, lower limb muscle, foot, bare joint
Im_3	180	20	Waist, foot and hip joint

Among them, T is the training time, no is the training times, Ai is the injured site, IM_1 is the prediction result of the conventional model, IM_2 is the prediction result of the conventional model, and IM_3 is the prediction result of the conventional model. It can be seen from the table that when the damage degree of the moving vulnerable parts is predicted by the model, the deviation between the predicted result and the actual damage position is large. However, the injury risk predicted by the model is basically consistent with that in the training of board shoes. The main reason for this phenomenon is that in the process of modeling, it is necessary to determine the relationship between the position of sports injury and the amount of exercise, so as to ensure the accuracy of the prediction model, and then establish the corresponding model. Through the comparative experiment of the three models, the feature of the predicted damage location is extracted. The chart shows the contrast effect.

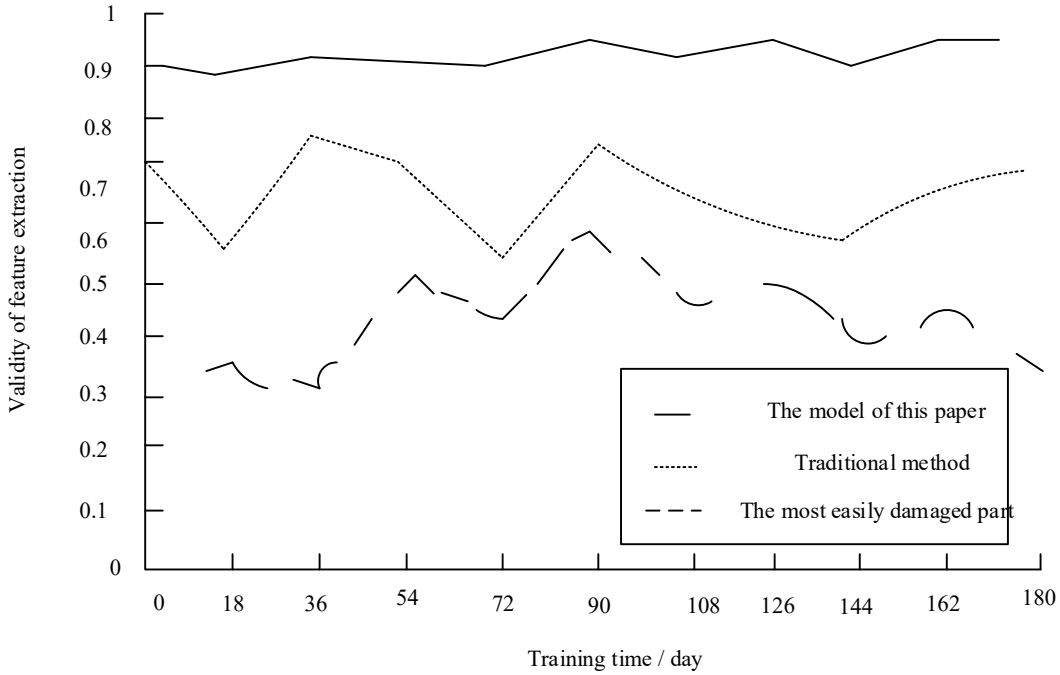

Fig. 8 Comparison of damage prediction characteristic data processing effect

The simulation results show that the prediction effect of the model is better than that of the conventional model. Based on this, this paper gives a sample regression function of sports vulnerable groups, establishes the prediction model of sports vulnerable groups with the sample regression function, and verifies it with, and obtains the best prediction model of sports vulnerable groups. The results show that this method can effectively extract the features of sports injury prediction. Through the prediction experiment of three different models of sports injury location, the prediction error of sports injury location is compared, and the following results are obtained.

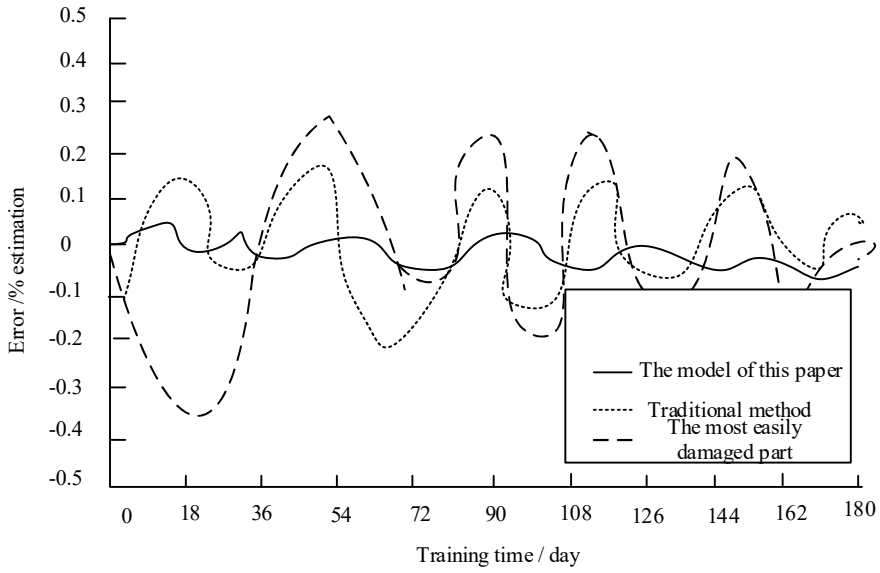

Fig.9 Comparison of prediction errors

Compared with the traditional model, it shows that the prediction error of the model is small, and the prediction result is quite different from the traditional model. By establishing the internal relationship between the injury attribute and the motion amplitude of each part of the human body, the change rule between the injury attribute and the easily damaged attribute of each part of the human body is calculated. According to the risk probability of sports injury site and the relationship between injury site and sports environment, the sample regression function is calculated, and the prediction model with lower prediction error is established. The experiment shows that the sports injury prediction model proposed in this paper has high prediction accuracy and fully meets the research requirements.

3 Conclusion

The occurrence of sports injury is usually related to the characteristics of sports, technology and tactics, training level, sports environment and sports conditions. In order to ensure the health of athletes, a design method of sports injury prediction model based on dynamic acquisition and transfer learning is proposed. One of the effective measures to prevent sports injury is to strengthen the training of sensitive and relative sensitive parts and improve their motor function. For example, we should strengthen the training of big muscles, strengthen the strength, improve the coordination ability, and prevent trauma.

Reference

[1] Henderson K , Liu X , Folden J , et al. Design and Calibration of a Fast Flying-Dot Projector for Dynamic Light Transport Acquisition[J]. IEEE Transactions on Computational Imaging, 2020, PP(99):1-1.

[2] Kocman V , Mauro G M D , Veglia G , et al. Use of paramagnetic systems to speed-up NMR data acquisition and for structural and dynamic studies[J]. Solid State Nuclear Magnetic Resonance, 2019, 102(5):36-46.

[3] A T A W , B V A N . A linear-quadratic Gaussian approach to dynamic information acquisition[J]. European Journal of Operational Research, 2018, 270(1):260-281.

[4] Khatami A , Babaie M , Tizhoosh H R , et al. A Sequential Search-Space Shrinking Using CNN Transfer Learning and a Radon Projection Pool for Medical Image Retrieval[J]. Expert Systems with Applications, 2018, 100(JUN.):224-233.

[5] Di F , Mohsen K , Gordon C . Active Prior Tactile Knowledge Transfer for Learning Tactual Properties of New Objects[J]. Sensors, 2018, 18(2):1-19.

[6] Alencastre-Miranda M , Johnson R R , Krebs H I . Convolutional Neural Networks and Transfer Learning for Quality Inspection of Different Sugarcane Varieties[J]. IEEE Transactions on Industrial Informatics, 2020, PP(99):1-1.

[7] Bulla P , Anantha L , Peram S . Deep Neural Networks with Transfer Learning Model for Brain Tumors Classification[J]. Traitement du Signal, 2020, 37(4):593-601.

[8] Sajja T , Retz M , Kalluri H K . Lung Cancer Detection Based on CT Scan Images by Using Deep Transfer Learning[J]. Traitement du Signal, 2019, 36(4):339-344.

[9] Colino E , Felipe J L , Hooren B V , et al. Mechanical Properties of Treadmill Surfaces Compared to Other Overground Sport Surfaces[J]. Sensors, 2020, 20(14):3822.

[10] Wilk M P , Walsh M , O'Flynn B . Multimodal Sensor Fusion for Low-Power Wearable Human Motion Tracking Systems in Sports Applications[J]. IEEE Sensors Journal, 2020, PP(99):1-1.
[11] Jayaratne M , Nallaperuma D , Silva D D , et al. A data integration platform for patient-centered e-healthcare and clinical decision support[J]. Future generation computer systems, 2019, 92(MAR.):996-1008.
[12] Gugouch F , Sandabad S , Mouhib N , et al. Damage Prediction of CPVC Based on Energy Method at Different Temperatures[J]. Key Engineering Materials, 2019, 820(5):179-187.
[13] Sugimoto S , Hattori Y , Itoh H . A Damage Prediction System for Electric Power Distribution Equipment against Typhoon and Utilization of Meteorological Simulation Techniques[J]. Journal of the Institute of Electrical Engineers of Japan, 2018, 138(3):141-144.
[14] Okuno Y , Ishikawa N , Akiyoshi M , et al. Degradation prediction using displacement damage dose method for AlInGaP solar cells by changing displacement threshold energy under irradiation with low-energy electrons[J]. Japanese Journal of Applied Physics, 2020, 59(7):074001 (7pp).
[15] Abouzar J , Roberto D . Estimation of Load-Induced Damage and Repair Cost in Post-Tensioned Concrete Rocking Walls[J]. Journal of Shanghai Jiaotong University, 2018, 23(001):122-131.
[16] Tang B , Wu F , Wang Q , et al. Damage prediction of hot stamped boron steel 22MnB5 with a microscopic motivated ductile fracture criterion: Experiment and simulation[J]. International Journal of Mechanical Sciences, 2019, 169(10):105302.
[17] Chen H , Wang F S , Ma X T , et al. The coupling mechanism and damage prediction of carbon fiber/epoxy composites exposed to lightning current[J]. Composite Structures, 2018, 203(NOV.):436-445.
[18] Diasse A , Li Z . Multi-view deep unsupervised transfer leaning via joint auto-encoder coupled with dictionary learning[J]. Intelligent data analysis, 2019, 23(3):555-571.
[19] Zhao X , Liang Y , Guo A J X , et al. Classification of small-scale hyperspectral images with multi-source deep transfer learning[J]. Remote Sensing Letters, 2020, 11(4):303-312.
[20] Jiang M , Huang Z , Qiu L , et al. Transfer Learning based Dynamic Multiobjective Optimization Algorithms[J]. IEEE Transactions on Evolutionary Computation, 2017, 22(4):501-514.