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Article

Prediction and treatment of joint injuries in basketball training based on improved regression algorithm from the perspective of sports biomechanics

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Abstract: With the increasing popularity of basketball, especially in collegiate competitions like the University Basketball Super League, the sport has become a significant part of student life. The intensity of basketball training and competition has risen, necessitating athletes to have enhanced physical capabilities to meet modern demands. This heightened physical confrontation often leads to various injuries, with joint injuries being particularly common and impactful. This study integrates sports biomechanics with machine learning to address the prediction and treatment of joint injuries in basketball training. By employing an improved regression algorithm and leveraging high-performance computing, we have experimentally analyzed the prediction of joint injuries and proposed effective solutions. Our results indicate that the difference between the highest and lowest predicted residual values for the Back Propagation (BP) model was 0.92, and for the Extreme Learning Machine (ELM) regression model was 0.87. Notably, the improved ELM regression model demonstrated a reduced residual difference of 0.43. This improvement suggests that the enhanced ELM regression model offers superior prediction accuracy for joint injuries in basketball training and provides more comprehensive monitoring of athletes' physical health, thereby supporting the advancement of basketball training programs.

Keywords: joint injury prediction; regression algorithm; ELM regression algorithm; BP model

1. Introduction

With the continuous development of basketball, the corresponding skills of basketball players are also constantly improving. Meanwhile, the physical fitness of players should also keep up with this progress. In the basketball industry, various competitions are often held, and with the rapid development of basketball, the number of competitions has been continuously increasing. Therefore, the possibility of athletes' injuries in competitions has increased year by year, which seriously affects the internationalization of basketball. However, because basketball is full of competitiveness and antagonism, it has quickly become the most popular sport for more and more people with its unique charm. Currently, in daily training, athletes need to predict various situations that may occur in the competition and find ways to solve them. As a result, the workload of athletes has increased, and higher requirements have been put forward for their physical ability and confrontation ability. Compared with other professional basketball players, those who have been engaged in high-intensity sports for a long time suffer particularly serious joint injuries. In cases of severe injury, athletes may face retirement, which can have a significant impact on their physical and mental well-being. In view of the above situation, it is particularly important to use sports biomechanics combined with machine learning and high-performance computing in medical applications to predict joint injuries in basketball training and propose treatment plans. Therefore, this study improves the regression algorithm and takes effective preventive measures, which can effectively reduce the incidence of joint sports injuries and prolong the sports life of athletes.

In recent years, due to the continuous strengthening of training intensity, the probability of athletes' body injury in basketball training is growing, so the importance of the prediction and treatment of athletes' injuries is growing. Li and Xu [1] proposed that the current research of artificial intelligence (AI) in basketball training mainly focuses on the prediction of match results, the analysis and prediction of shooting, and the prevention of sports injuries. His research showed that AI technology can improve the training level of basketball players, help coaches formulate appropriate competition strategies, prevent sports injuries, and improve the fun of the game [1]. Shimozaki et al. [2] proposed that higher body mass index (BMI) and hip abductor strength are independent risk factors for non-contact anterior cruciate ligament injury of Japanese female high school basketball players. He pointed out that it may be difficult to complete a complete screen, but attention should be paid to the injury of the anterior cruciate ligament, especially for highly competitive players with strong muscles [2]. Owoeye et al. [3] examined the effectiveness of neuromuscular training (NMT) warm-up program in reducing the risk of ankle sprain injury (ASI) of basketball players. Wu and Wang [4], based on medical big data, explored the high-risk injury factors of basketball players' lower limb patellar tendon nesting, and accurately identified athletes' lower limb injuries. His research results processed the data through deep learning algorithm and parallel computing to find the most appropriate joint angle, so as to maximize the muscle's concentration ability in the movement process, thereby minimizing the body damages and injuries [4]. Various researchers have done some research on various injuries of players in basketball training, but in basketball training, the most common injury accident is joint injury. Therefore, this paper uses improved regression algorithm to predict the joint injury in basketball training and propose a treatment plan.

At present, athletes are vulnerable to various injuries due to the enhancement of training intensity in sports training, so many scholars have proposed relevant prediction methods. Van Eetvelde et al. [5] proposed that injuries are very common in sports, which can cause significant consequences to the body and psychology. Machine learning (ML) methods can be used to improve damage prediction and allow correct damage prevention methods. The existing ML method can be used to identify athletes with high injury risk and help to find the most important injury risk factors [5]. Bond et al. [6] proposed a functional sports screen and a new basketball exercise ability test as a tool to evaluate the injury prediction of college basketball players. The results showed that identifying injury risks and implementing preventive measures can help reduce the occurrence of injuries, and ultimately may improve sports performance [6]. Zadeh et al. [7] collected quantifiable data to generate insights that enable it to predict and prevent injuries related to the wearer's physical exertion in sports activities. His research results showed that wearable technology can identify players with increased risk of injury and carry out targeted intervention. The above studies are various methods proposed by many scholars to reduce injuries in sports, but the most likely joint injuries in sports have not been analyzed and predicted. Therefore, this paper predicts the joint injuries in basketball training based on the improved regression algorithm, so that basketball training can be further developed.

From the perspective of sports biomechanics, joint injuries in basketball players are not only related to their training intensity and frequency but also closely linked to their biomechanical characteristics. Sports biomechanics research analyzes the mechanical properties of athletes during movement to reveal the forces on joints in various athletic states and the mechanisms of injury [8,9]. Utilizing high-frame-rate cameras and manual annotation techniques, combined with data augmentation methods, allows for more accurate capture of athletes' movement details, thereby providing more precise data support for injury prediction [10,11]. Detailed biomechanical analysis of athletes' movements can identify specific movement patterns and mechanical loads that lead to joint injuries, offering a scientific basis for improving training methods and developing preventive measures [12,13]. This study, from the perspective of sports biomechanics and integrating an improved regression algorithm, aims to predict and provide treatment plans for joint injuries in basketball training. By enhancing the accuracy of injury prediction, it also offers guidance for athletes' rehabilitation and training.

Based on the improved regression algorithm, this paper forecasts the joint injuries in basketball training, and selects 82 consecutive observation joint injuries data of a special basketball training team in an urban area in the recent 8 years as experimental data for experimental analysis. In order to check whether the prediction model of the improved ELM regression algorithm meets the joint damage prediction of basketball training, this paper also uses BP algorithm and ELM regression algorithm to compare and analyze with them. It can be seen from the final experimental data that the highest prediction residual value in the prediction residual curve of BP algorithm reached 0.47, and the lowest was −0.45; in the prediction residual curve of ELM regression algorithm, the highest prediction residual value reached 0.47, and the lowest was −0.4; in the prediction residual curve of improved ELM regression algorithm, the highest prediction residual value was 0.26, and the lowest was −0.17. By comparison, it can be seen that the prediction residuals obtained by the improved ELM regression algorithm were closer to the training data. Therefore, the algorithm used in this paper can be more accurately applied to the prediction of joint injuries in basketball training.

2. Prediction model based on improved regression algorithm

2.1. Causes of joint injuries in basketball training

In order to better and more comprehensively understand the joint injury status of professional basketball athletes in special training, this paper adopted the method of random sampling to conduct an individual survey of 56 basketball athletes [8]. **Table 1** shows the statistics of joint injuries of 56 athletes during training:

Table 1. Number of joint injuries in students.

Number of injuries	Number	Percentage
0	0	0
1	30	53.6%
2	12	21.4%
More than 3 times	14	25%
Total	56	100%

The data in **Table 1** shows that 56 athletes have experienced joint injuries, which indicates that joints are easy to be injured in the process of athletes' training. The specific causes of joint injuries are as follows:

(1) Athletes are not fully prepared before basketball training. If one is not prepared for warm-up, his body and mind cannot adapt to the high-intensity training, which may lead to physical and psychological discomfort and injury.

(2) There is a problem with the use of the basketball training ground. When playing basketball on the court, special attention needs to be paid because the ground is smooth or uneven. The uneven course and slippery ground may easily lead to the collision and fall of athletes, which can damage each joint.

(3) In sports of basketball, athletes exercise excessively. The most common cause of sports injury is excessive exercise load. Moderate exercise can make people strong, but if excessive exercise, the physical function of athletes may be unbearable. The longer the training time, not only the lower the physiological function and sports ability of the body, but also the slower the reaction may be, with poor coordination ability and inflexible actions.

(4) Athletes lack safety awareness. They have a weak awareness of injury prevention, can't take preventive measures actively, or blindly train or act too quickly. They don't follow the principle of step by step and acting according to their ability either, resulting in injuries.

(5) The athletes' skill movements are not standard. In sports training, movement techniques conflict with the structural characteristics and movement rules of the human body, which can lead to sports injuries.

(6) The training plans are unreasonable. If the content of the training plan breaks the rules which are from simple to complex, from skilled fields to unknown fields, and from incomprehensible to understandable, and in terms of training methods, it lacks the requirements for continuity and effectiveness of actions, or does not change the teaching steps in time according to the characteristics of basketball, then the probability of athletes' joint injuries is large.

Given the aforementioned causes of joint injuries in basketball training, even a slight lapse in care can lead to joint injuries for athletes. To prevent such occurrences, this study integrates sports biomechanics with machine learning to predict joint injuries using an improved regression algorithm. It also proposes corresponding solutions to effectively prevent these injuries.

2.2. Overview of regression algorithm

Regression algorithm is a machine learning method, which is widely used in various fields [9]. It is usually used to express the special relationship between the independent variable X and the dependent variable Y. To put it another way, it is to establish a corresponding algorithm model to realize the mapping of X and Y, and learning the algorithm is to find a function to optimize the relationship between the parameters. **Figure 1** is the function diagram of the basic regression algorithm.

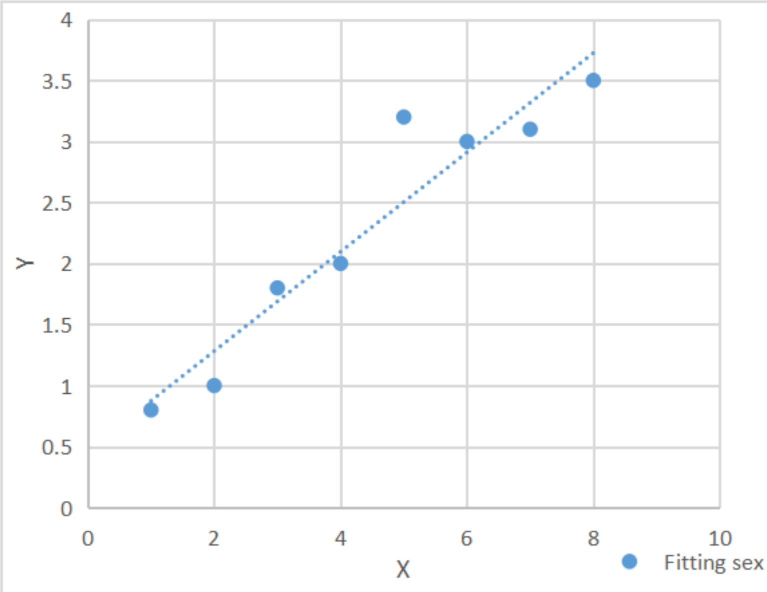

Figure 1. Function diagram of regression algorithm.

In order to better predict and analyze various joint injuries that may occur in basketball, this paper combines the principles of experience risk minimization and structural risk minimization, and applies them to traditional ELM regression methods, thus establishing a new ELM regression model [10]. The following is a detailed introduction to several algorithms.

(1) Extreme learning machine (ELM) regression algorithm

ELM is a feedforward neural network (FNN) algorithm based on a single hidden layer. It is the same as the running process of the artificial neural network, and each layer is connected by the feature mapping function. After inputting data, the information of the input layer shall be processed by the hidden layer, and then the processed information shall be input to the output layer. Finally, the corresponding calculation results are obtained in the output layer according to the corresponding relationship, thus completing the entire calculation process of the algorithm. The algorithm has good generalization performance and extremely fast learning ability [11].

The improved ELM algorithm effectively alleviates the overfitting problem and enhances the model's generalization ability for unknown data by introducing regularization terms. The algorithm maintains the fast-training characteristics of ELM, and further improves the training efficiency by optimizing parameter selection. Combining the principles of empirical risk and structural risk minimization, the improved ELM algorithm achieves a balance between training error and generalization error while controlling the complexity of the model. The experimental results verify the significant improvement of the improved ELM in prediction accuracy, especially in the specific field of basketball training, where its prediction residual is significantly lower than that of the traditional model, showing higher accuracy. The stability and adaptability of the improved ELM algorithm also enable it to cope with the diversity and complexity of data, providing an innovative and effective solution for the prediction of joint injuries in basketball players.

The network training mode of the extreme learning machine is generally based on the simplest single hidden layer. It is assumed that the number of nodes in the input layer is m; that in the hidden layer is N; that in the output layer is 1. When the number of nodes is set, the network structure of the network is shown in **Figure 2**:

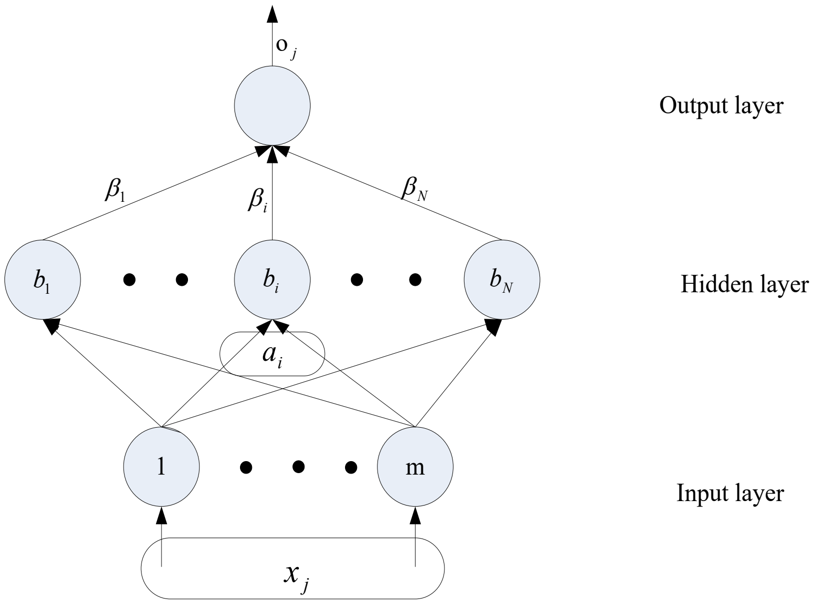

Figure 2. Extreme learning machine network structure diagram.

Given a dataset $T = \{(x_1, y_1), L, (x_i, y_i)\}$, in this dataset, there are $x_1, y_1 \in R^m, y_i, x_i \in R$, and $i = 1, L, \dots N$. Then the corresponding ELM training model is given:

$$f(x) = \sum_{i=1}^{N} \beta_i \beta G(a_i, b_i, x_i) = \beta \times h(x) \tag{1}$$

In Equation (1), β_i means the weight of output layer neurons; a_i is the connection weight between the input layer neuron and the i-th node of the hidden layer; b_i represents offset (the i-th hidden layer node); $h(x) = [G(a_i, b_i, x_i), L, G(a_N, b_N, x_N)]$, which means the corresponding output matrix of the hidden layer; G is the excitation function. The expression of G is specifically expressed as Equation (2):

$$G(a, b, x) = 1/(1 + \exp(-(a \times x) + b)) \tag{2}$$

Before the training, the input weight a_i and offset b_i are random and not determined. As long as the training starts, the value of a_i cannot be changed, only the value entered. On this basis, the following linear equation set, as shown in Equation (3), is given, and its output weight β_i is calculated by calculating this equation set.

$$\min \sum_{i=1}^{N} \|\beta \times h(x_i) - y_i\| \tag{3}$$

In Equation (3), it is solved by the least square method and expressed by the Moore Penrose generalized inverse H^+ of the output matrix *H*. Finally, its output weight parameter $\beta = H^+ \cdot Y$ is determined.

(2) Improved ELM regression algorithm

ELM regression algorithm is an empirical risk minimization principle with the minimum training error as the measurement criterion. This algorithm has many advantages, but it may lead to over fitting in the training process, thus reducing the generalization performance of the model [12,13]. In order to solve this problem, this paper combines the two principles of empirical risk minimization and structural risk minimization to construct a new ELM regression method.

In the improved ELM regression algorithm, the linear Equation (3) can be converted into:

$$\min \frac{1}{2}\|\beta\|^2 + \frac{1}{2}\zeta \sum_{i=1}^{N} {\delta_i}^2 \tag{4}$$

In Equation (4), there are $\delta_i = y_i - h(x_i)$ and $\delta_i \geq 0$, $i = 1, L, N$. $\sum_{i=1}^{N} {\delta_i}^2$ represents empirical risk; $\|\beta\|^2$ represents structural risk; ζ is the penalty coefficient. According to these, Equation (4) is transformed into the corresponding Lagrange equation [14]:

$$L = \frac{1}{2}\|\beta\|^2 + \frac{1}{2}\zeta \sum_{i=1}^{N} {\delta_i}^2 - \sum_{i=1}^{N} \alpha_i [y_i - h(x_i) - \delta_i] \tag{5}$$

In Equation (5), α_i is the Lagrangian factor. According to the calculation principle of optimization, assuming that the partial derivatives of L to β, α_i and δ_i all are 0, then a set of linear equation can be obtained:

$$\begin{bmatrix} 0 & {I_\tau}^T \\ I_V & \Omega + I/\zeta \end{bmatrix} \begin{bmatrix} 0 \\ \alpha \end{bmatrix} = \begin{bmatrix} 0 \\ y \end{bmatrix} \tag{6}$$

In Equation (6), there are $y = (y_1, y_2, \cdots, y_N)^T$, $I_V(1,1,\cdots,1)^T$ and $\alpha = (\alpha_1, \alpha_2 \cdots, \alpha_N)^T$. Ω is a square matrix, which can be specifically analyzed as:

$$\Omega_{ij} = [G(a_i, b_i, x_i), \cdots, G(a_N, b_N, x_N)] \times [G(a_i, b_i, x_j)] \tag{7}$$

It can be known from Equations (5) and (6) that the improved ELM regression model does not need to calculate b_i in the hidden layer, thus improving the training speed of the model. Meanwhile, the improved ELM regression model also applies $\sum_{i=1}^{N} {\delta_i}^2$ and $\|\beta\|^2$ together, thus making up for the shortcomings of the ELM regression algorithm and reducing the risk of over fitting.

(3) Back propagation algorithm (BP algorithm)

In this paper, BP algorithm is used to compare with ELM and improved ELM algorithm [15].

BP neural network is the main technology in machine learning modeling at present [16]. The most basic BP neural network used in this paper includes input layer, hidden layer and output layer. In its network structure, the neurons of each adjacent layer can be connected with each other, but if they are neurons of the same layer, they are not connected with each other. The specific structure is shown in

Figure 3:

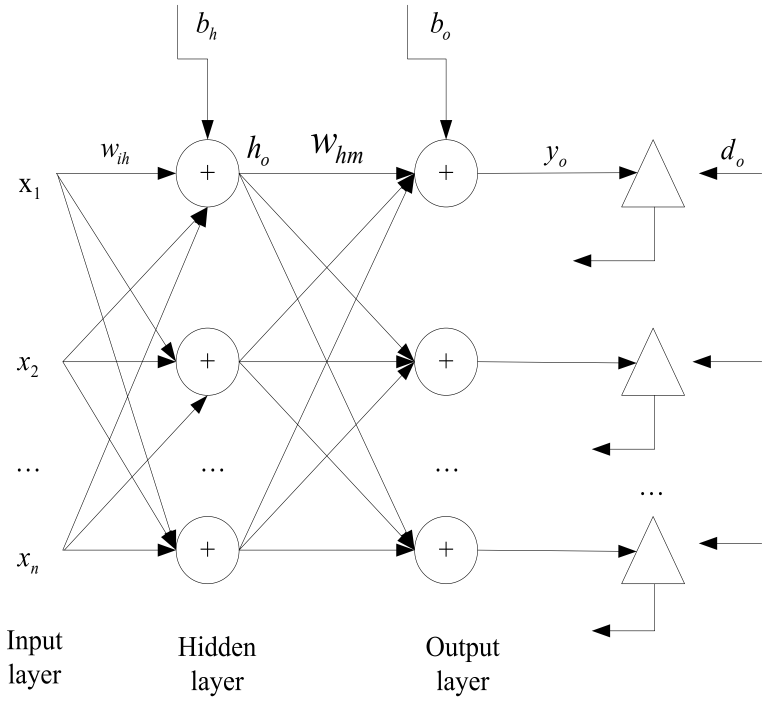

Figure 3. Typical three-layer BP neural network structure.

BP algorithm is divided into two stages:

(1) (Forward transmission processing) The output value of each unit is calculated step by step from the input layer to the hidden layer. This paper sets the excitation function as f(net), and then:

The output of the h-th hidden layer neuron is:

$$h_{oh}(k) = f(\sum_{i=1}^{n} W_{ih} X_i(k) - b_h) \tag{8}$$

The output of the m-th output layer neuron is:

$$y_{om}(k) = f(\sum_{h=1}^{p} W_{hm} h_{oh}(k) - b_o) \tag{9}$$

(2) (Reverse transmission) The error of the output layer is calculated layer by layer forward, and then the corresponding error of each unit in the hidden layer is calculated. The previous weight is corrected using this error. In this paper, the error function $e = \frac{1}{2}\sum_{o=1}^{q}(d_o(k) - y_{om}(k))^2$ is set, and the learning rate is η. Then the followings can be obtained:

The weight between the output layer and the hidden layer is adjusted to:

$$\Delta W_{hm} = -\eta \frac{\partial e}{\partial W_{hm}} \tag{10}$$

The weight between the hidden layer and the input layer is adjusted to:

$$\Delta W_{ih} = -\eta \frac{\partial e}{\partial W_{ih}} \tag{11}$$

The specific flow chart of BP algorithm is shown in **Figure 4**:

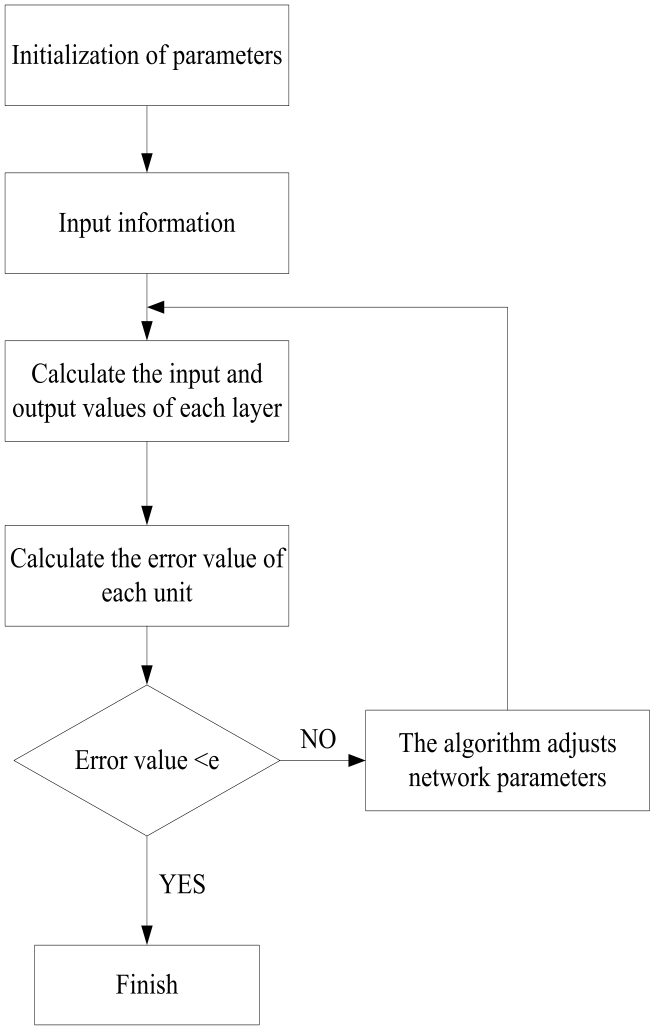

Figure 4. Flow chart of BP algorithm.

2.3. Prediction model based on improved elm regression algorithm

Previous studies have shown that traditional regression models, including the basic ELM and BP algorithms, may not achieve the expected prediction accuracy in specific application scenarios. The ELM algorithm may encounter overfitting problems when dealing with complex nonlinear relationships, while the BP algorithm may fall into a local optimal solution during training due to its gradient descent characteristics. To overcome these limitations, this paper uses an improved ELM regression algorithm to predict joint injuries in basketball training. The algorithm effectively balances the complexity of the model and the prediction accuracy by introducing regularization terms and an optimized weight adjustment strategy.

When conducting the test, the specific method flow is as follows:

1) Standardization: Before network training, standardized pre-processing must be carried out, that is, the data is linearly mapped to a specific interval according to a certain proportion, usually using the maximum minimum method [17].

$$x_k = (x_k - x_{\min})/x_{\max} - x_{\min} \tag{12}$$

In Equation (12), $x_{\max}$ is the maximum value and $x_{\min}$ is the minimum value in the data series.

2) Determination of the number of delay steps: During the experiment, in order to obtain the network input structure most conducive to the experiment, it is necessary to determine the number of delay steps[18,19]. In the time series (x), the autocorrelation coefficient of the delay k step is expressed as $r(k)$. The specific calculation equation of $r(k)$ is shown in Equation (13):

$$r(k) = \sum_{i=k+1}^{i} (x_i - \bar{x})(x_{i-k} - \bar{x}) / \sum_{i=1}^{i} (x_i - \bar{x}) \tag{13}$$

If $r(k)$ complies with Equation (14):

$$r(k) \notin [\frac{(-1 - u_{\alpha/2})\sqrt{(N-k-1)}}{N-k}, \frac{(-1 + u_{\alpha/2})\sqrt{(N-k-1)}}{N-k}] \tag{14}$$

then it is said that the delay k-step correlation of the time series is significant; otherwise, it is not significant, and the k value that maximizes $r(k)$ is taken as the final delay steps.

3) Determination of network structure: The delay steps have been calculated in 2), so the corresponding network structure is determined by using the calculated delay steps. During the experiment, the number of nodes in the input layer is set as m, the number of nodes in the output layer as 1, and the number of nodes in the hidden layer as $N = 2\mathrm{m} + 1$.

4) Model testing: In the process of running the model, the experimental data needs to be used to verify the model. First, the residual value $\varepsilon(i) = x_p(i) - x_i(i)$ is calculated, where x_p and x_i represent the predicted value and the test value respectively. Then, the variance of the test sequence and residual is calculated respectively to obtain:

$$\begin{cases} {S_1}^2 = \frac{1}{n}\sum_{i=1}^{n}[x_t(i) - \bar{x_t}]^2 \\ {S_2}^2 = \frac{1}{n}\sum_{i=1}^{n}[\varepsilon_t(i) - \bar{\varepsilon}]^2 \end{cases} \tag{15}$$

In Equation (15), $\bar{x_t}$ and $\bar{\varepsilon}$ represent the mean values, which are the mean values of the predicted data and the residual respectively. C is used to express the ratio between two variances, that is, $C = S_1/S_2$. The smaller the ratio, the better the prediction effect of the model. $C < 0.5$ indicates that the test results are consistent; on the contrary, if it is unqualified, the network is trained again by adjusting the number of hidden layer nodes, and finally it is qualified.

5) Model prediction and final analysis: The data required by the experiment for final prediction is input, and then root mean square error (RMSE), mean relative error (me_error) and maximum relative error (max (me_error)) are used to evaluate the results obtained[20,21]:

$$\mathrm{RMSE} = \sqrt{\sum_{i=1}^{n}[y_i - {y'}_i]^2/n} \tag{16}$$

$$\mathrm{me\_error} = \frac{1}{n}(\sum_{i=1}^{n}\left|\frac{y_i - {y'}_i}{y_i}\right| \times 100\%) \tag{17}$$

$$\max(\text{me\_error}) = \max\left(\sum_{i=1}^{n}\left|\frac{y_i - y'_i}{y_i}\right| \times 100\%\right) \tag{18}$$

3. Model validation based on improved ELM regression algorithm

In order to verify the specific application of the improved ELM regression algorithm based on medical applications of machine learning and high-performance computing in joint injuries in basketball training, this paper uses 82 consecutive joint injuries observed in a basketball special training team in a certain city over 8 years as the data of this experiment, covering athletes of different ages, genders, and skill levels. In the experiment, the 82 data of the first 50 periods were used as training samples, and the conclusions drawn from these training samples were used to predict the joint injury data of the last 32 periods, and finally the results were compared with the actual data. In order to ensure the accuracy and reliability of the improved extreme learning machine (ELM) regression model in predicting joint injuries in basketball training, strict data validation measures were taken[22]. The generalization ability of the model was evaluated by implementing cross-validation, and the performance of the model prediction was comprehensively measured using statistical indicators such as root mean square error, mean absolute error, and coefficient of determination[23]. In addition, in-depth analysis of the residual distribution further verified the unbiasedness and consistency of the model prediction. The ideas used in the experiment were drawn into a thought map, as shown in **Figure 5**:

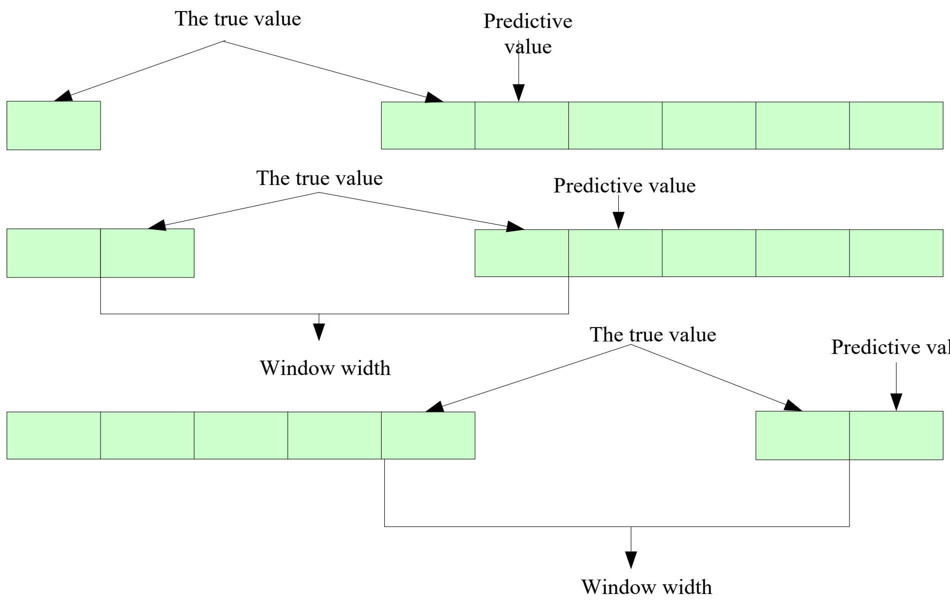

Figure 5. Schematic diagram of the basic idea of joint injury prediction.

After standardizing the original data, first the delay step *k* was calculated (the value range of *k* is 3 to 10). The autocorrelation coefficient was *r*(*k*), and the optimal *k* was 5 after calculation. Therefore, it was determined that the window width in **Figure 5** was 5, that is, the joint damage data of the first five phases were used to predict the joint damage data of the sixth phase. After many times of training and model verification (the penalty function was set to 46.03), the optimal number of hidden layer nodes was determined to be 16, thus determining the improved ELM model network structure, specifically 5 × 16 × 1.

In this paper, BP algorithm and ELM algorithm were also used for training and prediction, and the results were compared with the algorithm in this paper. All the excitation functions in this paper were sigmoid functions. After many times of training, the three models have obtained the optimal network structure, which was 5 × 25 × 1, 5 × 14 × 1, 5 × 16 × 1. The final predicted residual sequence diagram is shown in **Figures 6–8**.

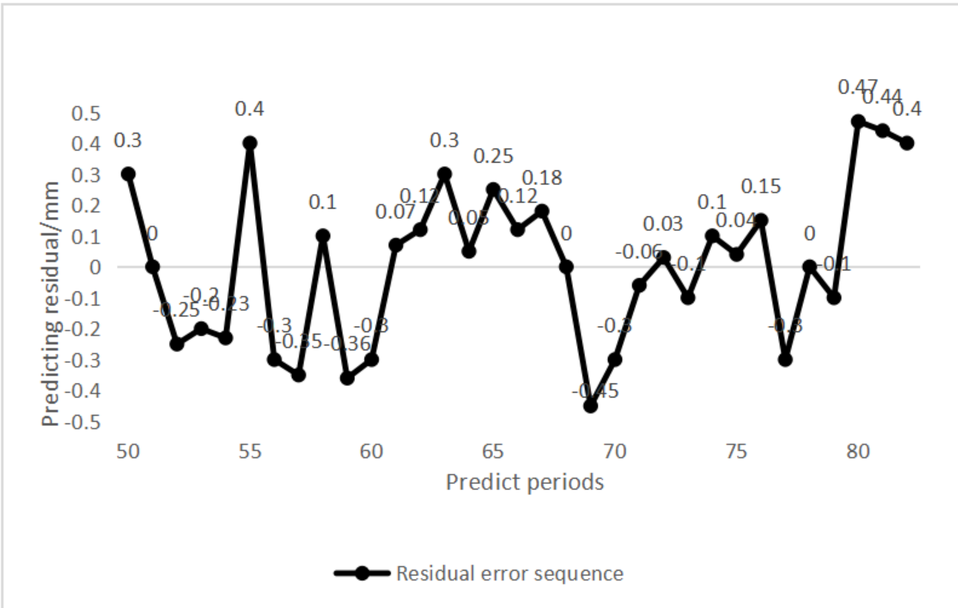

Figure 6. Residual sequence of BP prediction.

Figure 6 shows the prediction residual curve of BP algorithm. It can be seen from **Figure 6** that the fluctuation of the prediction residual value was still large. The highest prediction residual value reached 0.47, and the lowest was −0.45, with a difference of 0.92. These data showed that there was a large difference between the prediction error value and the training error value in the BP model, and the over fitting phenomenon occurred in the training process, which led to the result that was not close to the experimental value. Therefore, the model based on BP algorithm is not suitable for the prediction of joint injury in basketball training.

Figure 7 shows the prediction residual curve of the model built under the ELM regression algorithm. It can be seen from the data in **Figure 7** that the fluctuation of the prediction residual curve was still large, with the highest prediction residual value reaching 0.47, and the lowest prediction residual value as low as −0.4, with the gap reaching 0.87. Compared with BP model, ELM regression model was still closer to training error. Therefore, ELM regression model is more conducive to the prediction of joint injury in basketball training. However, the prediction error is still large when using the ELM regression model only. Therefore, this paper improved the ELM regression algorithm. The specific prediction residual curve is shown in **Figure 8**.

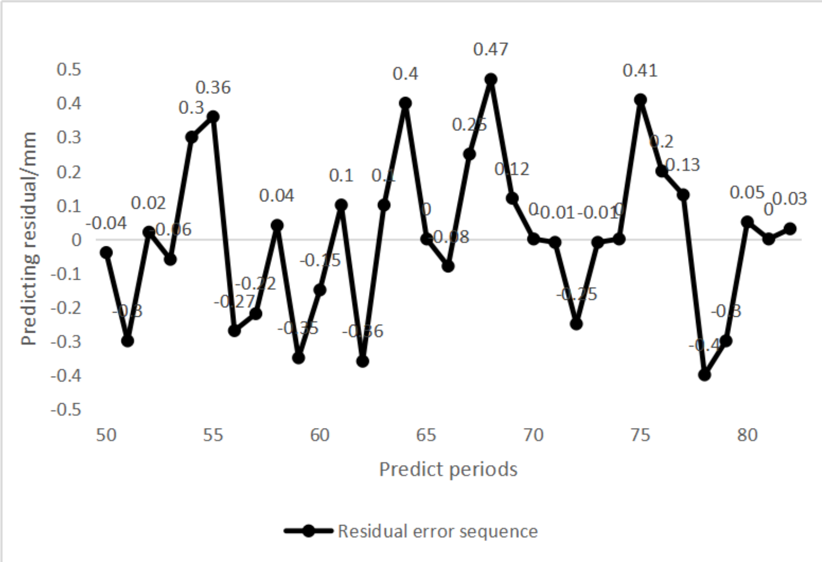

Figure 7. Residual sequence of ELM prediction.

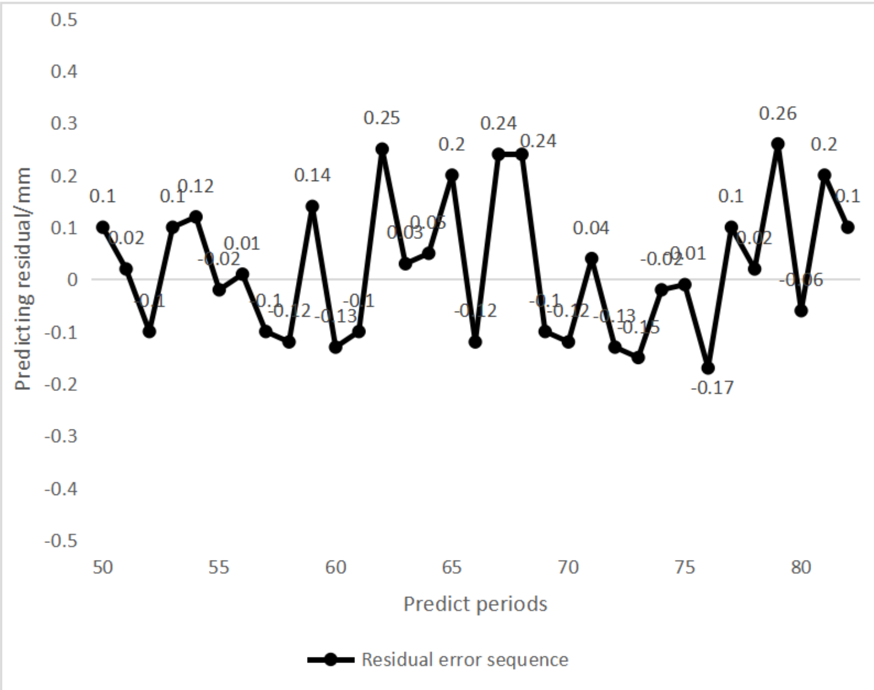

Figure 8. Residual sequence of improved ELM prediction.

Figure 8 shows the prediction residual curve of the improved ELM regression algorithm. It can be seen from the data in **Figure 8** that the values in the prediction model built under the improved ELM regression algorithm were closer to the training error than those in BP model and ELM regression model. Its highest prediction residual value was 0.26, while that of BP model and ELM regression model was 0.47. The lowest prediction residual value of the improved ELM regression algorithm was −0.17, while that of BP model and ELM regression model was −0.45 and −0.4 respectively. The difference between the highest predicted residual value and the lowest predicted residual value under the improved ELM regression algorithm was 0.43, while the difference between BP model and ELM regression model was 0.92 and 0.87. The prediction residual curve of the improved ELM regression algorithm changed less, and the prediction results were closer to the real data during training. Therefore, the improved ELM regression algorithm in this paper is more suitable for application, and can better predict the joint injuries of athletes in basketball training, so as to put forward corresponding protective measures, reduce the probability of joint injuries of athletes, contribute more healthy athletes to the basketball cause, and promote the further development of the basketball project.

It can be seen from the curves in **Figures 6–8** that the prediction residuals obtained by the prediction model based on the improved ELM regression algorithm proposed in this paper were basically distributed between −0.17 mm and 0.26 mm. Compared with the other two models, the prediction results using the improved ELM regression algorithm were the closest to the original data. The specific data were summarized and compared, as shown in **Table 2**:

Table 2. The prediction results of three models.

Prediction model	BP	ELM	Improved ELM
The training error RMSE/mm	0.19	0.21	0.15
The prediction error RMSE/mm	0.27	0.33	0.16
Mean relative error/%	3.68	3.73	3.15
Maximum relative error/%	9.62	12.31	7.91

From the data in **Table 2**, after comparing the training error and prediction error of each model, the prediction error obtained by the prediction model based on the improved ELM regression algorithm was the closest to the training error, so a series of conclusions can be drawn. The specific conclusions are as follows:

1) The prediction error and training error of BP and ELM models are extremely unequal, which indicates that the two methods have the situation of over fitting in the training process. The improved ELM regression method is similar to the training results in the prediction accuracy, which can solve the problem of over fitting well.

2) According to the prediction error in the table, namely root mean square error (RMSE), the prediction accuracy of this method has been significantly improved compared with the other two methods.

3) From the two aspects of me_error and max(me_error), it can be seen that the improved ELM algorithm is closer to the data of conventional training.

Therefore, the algorithm in this paper has a high practical value in the field of joint injury prediction in basketball training. In this paper, the prediction model built under the improved ELM regression algorithm can be used to predict and propose corresponding preventive measures and treatment plans, as follows:

1) The rehabilitation plan shall be formulated according to the injured part and degree of the patient. Active rehabilitation exercises can promote the functional recovery of joints.

2) According to the degree of joint injury, physical therapy such as ultrasonic, infrared, ultrashort wave and massage is used to relieve inflammation around the joint in the early stage of rehabilitation, so as to relieve pain.

3) The injured part is stimulated with medium frequency electric stimulation to improve the function of neuromuscular system and promote tissue regeneration and repair.

4) Athletes' joints may have been injured, and the joints that have been injured before should be allowed to move actively without bearing weight, so as to effectively prevent or reduce the adhesion within the joints.

This study successfully verified the accuracy of the model in predicting joint injuries in basketball training through an improved extreme learning machine (ELM) regression model. In order to deeply understand the scientific principles behind the prediction results, the key factors affecting joint injuries and their interactions with the biomechanical characteristics of basketball were further analyzed. Through careful data analysis and biomechanical evaluation, it was found that the athlete's body mass index, muscle strength, and the correctness of the sports technique are key factors in predicting joint injuries. A higher BMI may increase the burden on the lower limb joints, leading to a higher risk of injury. An imbalance in muscle strength may cause instability during exercise and increase the possibility of joint sprains. The accuracy of technical movements directly affects the distribution of joint forces, and irregular movements may cause abnormal stress on the joints, thereby increasing the risk of injury. These factors are closely linked to the biomechanical characteristics of movements such as jumping, sprinting, and turning in basketball, and together determine the possibility of athletes being injured.

Although the model has shown high accuracy in predicting joint injuries in basketball training, it still has certain limitations and assumptions that affect the model's predictive ability and practical application. The model's predictions are based on historical data sets and cannot fully capture all variability in future data. The model assumes that there is a stable correlation between injury data and factors such as the athlete's training intensity and technical movements, but in reality, these relationships may be affected by unconsidered factors. In addition, the generalization ability of the model is limited by the representativeness of the training data. If the data set has deviations in certain features, it will reduce the applicability of the model in different populations or situations.

4. Conclusions

This study effectively improved the prediction accuracy of joint injuries in basketball training by combining sports biomechanics with an improved extreme learning machine (ELM) regression model, which has important implications and broad application prospects in the field of sports medicine. By adopting an improved ELM regression algorithm, combined with the principles of empirical risk minimization and structural risk minimization, the accuracy of joint injury prediction was improved. Experimental results show that the improved ELM regression model has higher prediction accuracy than the traditional method, and the residual is reduced to 0.43. The research results not only provide a scientific basis for injury prevention and the formulation of personalized training plans for basketball players, but also provide a feasible methodology for injury risk assessment and management in other sports. In the future, by further expanding and diversifying the data set and considering more dimensional factors such as the athletes' psychology, nutrition and lifestyle, the generalization and accuracy of the model can be optimized. The methodology of this study can also be applied to the field of sports rehabilitation to assist the athletes' rehabilitation process. Although this study has achieved remarkable results in the field of basketball, its potential is far more than that, and it is expected to have a profound impact on the development of sports medicine. With the continuous advancement of technology, it is expected that this study will inspire more interdisciplinary innovative research and make greater contributions to improving the overall health and sports performance of athletes.

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