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ORIGINAL

DECISION SUPPORT FOR BASKETBALL ATHLETE INJURY PROTECTION BASED ON PATTERN RECOGNITION

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ABSTRACT

Basketball is an intense competitive team sport, and sports injuries are a problem that athletes and coaches must face. Modern basketball sports body collision and confrontation is very powerful, so the risk of athletes in the training and competition process the chance of injury increased. To be able to find out the potential risk of injury early, to avoid serious injury law injury, this paper uses machine learning and pattern recognition technology, based on decision tree and random forest algorithm combined with wearable equipment to build basketball sports injury decision support model, to provide technical support for basketball player injury judgment. Through experimental verification, the decision support model proposed in this paper can effectively determine the injury situation of athletes and provide support for coaches to make further decisions.

KEYWORDS: Machine Learning; Pattern Recognition; Athlete Injury Protection

1. INTRODUCTION

Basketball, one of the three major sports in China, has been widely popularized because of its collective, confrontational and interesting features. In the basketball teaching classroom, the number of trainees is large, and they show a variety of techniques and tactics, fast speed of offense and defense, and strong competition, so the coach can only observe the trainee's body movements to judge the trainee's technical changes, and it is difficult to accurately and comprehensively understand the real-time mastery of each trainee's basketball skills. Therefore, through the introduction of artificial intelligence technology to estimate the movement posture of each student in real time, to help coaches grasp the learning progress of the students and adjust the training program in a timely manner, which will greatly promote the realization of personalized teaching (Huang et al., 2021; Lee et al., 2022).

Sports injuries are a prevalent issue for all athletes, and they are most likely to develop during training and competition. The incidence elements are related to the athlete's sport kind, technique and tactics, basic bodily movement ability, training and competition facility environment, and psychological factors. Basketball is another sport with a significant injury rate because to the high intensity of confrontation and high speed collisions, which misuse the joints, muscles, and ligaments. Because modern basketball collisions and confrontations are so powerful, the danger of injury during training and play grows (Choi, 2021).

The issue of injury throughout basketball's various intensity levels is a pressing one. According to studies and statistics, the most common acute injuries in basketball players are abrasions, contusions, fractures, joint sprains, and muscle strains. Sports injuries occur at a rate of up to 71.1%. Sports injuries occur at a rate of up to 71.1% (Åman et al., 2016). Sports injuries not only have a negative impact on the athlete's physical and mental health, but also on his or her competitive level and the development of the entire team, creating a vicious circle (Gibbs et al., 2006; Petralia et al., 2020).

Regarding the parts and causes of injuries in basketball players, Coleman believes that the main parts of injuries are: ankle, patella, meniscus, shoulder joint, wrist, finger joints, of which the knee is the most common part of injuries, and the main symptom is knee pain, which is aggravated by jumping, sliding, and stopping and turning, which is mainly caused by local trauma and repeated semi-squatting movements (Coleman, 2019).

Andreoli et al. population (Andreoli et al., 2018) believes that the types and incidence of injuries in basketball are related to the sports population. According to Andreoli, the type and incidence of injury in basketball is related to the sports population (Andreoli et al., 2018). For college students, the highest incidence of injury is in the finger, accounting for 26.42%, followed by the ankle 22.54%, knee 11.92%, low back 10.1% and wrist 8.81% (Callan et al., 2006), the causes of the injuries are mainly: (1) safety hazards of the field equipment. (2) Insufficient knowledge of prevention and poor awareness of self-protection. (3) Poor physical condition and unreasonable technique. Regarding the prevention of injuries to basketball players, Bolotin et al. believes that the following points should be done (Bolotin & Bakayev, 2016):

(1) Do sufficient preparatory activities. Preparatory activities can improve the excitability of the nervous system, accelerate blood circulation and reduce

muscle viscosity. In the preparatory activities should pay attention to the amount of activity, according to the individual situation is generally considered to the body to feel hot, the body slightly sweating is appropriate; Secondly, the content of the preparatory activities should be comprehensive and targeted, both a handful of preparatory activities and special preparatory activities, muscle stretching exercises should be combined with the formal sports content, the burden of the formal training in the larger, easy to injure parts of the body to do to strengthen the activities of the parts that have been injured to be extra careful.

(2) Strengthen the protection exercises for injury-prone parts. For example, in order to prevent skeletal strain, we can use the method of "standing pile" to improve the strength of quadriceps muscle; to prevent lumbar muscle strain and strengthen the strength of lumbar and abdominal muscles and so on.

(3) Strengthening the awareness of self-protection. It is discussing the role of physical training in the prevention of basketball injuries from the perspective of physical training in terms of strength, speed, endurance, coordination, sensitivity, flexibility, etc. He points out that good physical fitness is the guarantee for athletes to engage in training, competitions, and success, which not only improves the level of sports, but also reduces the rate of injuries caused by the sports. To prevent basketball injuries, firstly, it is necessary to strengthen the muscle strength of the injury-prone parts of the athletes; secondly, it is necessary to pay attention to reasonable and scientific arrangement of the amount of sports load, and the easy-to-injure movement exercises should be avoided as much as possible (Karaca & Durna, 2019).

For example, in order to effectively prevent patellar strain, through the knee half squatting power auxiliary exercises and special exercises cannot be arranged too concentrated and too much; Secondly, the preparatory activities of the injury-prone parts should be done sufficiently to avoid the occurrence of acute injury; Finally, the technical movements should be improved continuously during the practice so that the structure of the technical movements meets the requirements of human anatomy and biomechanics; meanwhile, it is necessary to strengthen the athletes' ability to fight against and cultivate self-protection ability (Johnson et al., 2012).

Machine learning and pattern recognition technologies have made a leap forward in the past decade, especially in image signal processing, which has made remarkable achievements. Exercise is the main way to improve cardiovascular health, muscle strength, and mental health, but sports injuries caused by incorrect force generation during exercise are very common. Most of the sports injuries are due to the presence of overload on the tissues, which in turn causes bone, joint and muscle wear and tear, and the accumulation of sports injuries can lead to obvious injury conditions. In this paper, DWT and random forest algorithms in machine learning will be used and combined with wearable monitoring devices to provide decision support for injury protection of basketball players (Ang et al., 2019).

2. Methodology

2.1 Automatic classification methods

The automatic classification method is an important means to realize the monitoring of the possibility of sports injury, after the athlete wears a wearable smart device, the daily activities and training process of the relevant sports data will be uploaded to the U disk or the cloud, once the athlete has a sports injury, the sports health investigators can quickly trace back the relevant activity data from the database, and then associated the relevant activities with the possibility of sports injuries, and ultimately, from a large number of athletes in the personal database, to extract and the content of the sports injury related to the construction of a large-scale monitoring of the database of sports injuries, and in the future sports injury prevention play a role.

2.2 Discrete wavelet transform

Discrete Wavelet Transformation (DWT) is to discretize the scale and displacement parameters of the fundamental wavelet (Kankanamge et al., 2020). During the construction of the current sports injury database, the data provided by the accelerometers in the athletes' smart wearable devices are all three-dimensional data containing X, $Y$and Z directions.

The computer is binary discrete way to process the data, so it is impossible to summarize the characteristics of three-dimensional data, in order to solve this problem, it is necessary to discretize the continuous wavelet and its wavelet transform.

The DWT method is to feature extract the acceleration data, decompose the three-dimensional acceleration of the athlete into three-axis vector wavelets of X, $Y$and Z , and then convert the three-dimensional acceleration into binary discrete wavelets through the translation and scaling of each wavelet. Assuming that the athlete realizes the total energy release of E_1 over a period of time, the total energy can be decomposed into i levels of wavelets, then there are.

$$E_T = A_i A_i^T + \sum_{j=1}^{i} D_j D_j^T \qquad (1)$$

where A_i represents the approximate coefficients of the level$i$wavelet, A_i^T is the transpose of A_i; D_i represents the actual coefficients of the level i wavelet. From this we can write the energy ratio of the approximate coefficients as EDR_A, and the energy ratio of the actual coefficients as EDR_{D_j}:

$$EDR_A = \frac{A_i A_i^T}{E_T} \tag{2}$$

$$EDR_{D_j} = \frac{D_i D_i^T}{ET}, j = 1,2,\cdots,i \tag{3}$$

2.3 Random Forest Algorithm

Based on the DWT method of converting athletes' three-dimensional acceleration data into discrete binary data, classifiers in machine learning need to be employed to automatically categorize athletes' activities (Liu & Wang, 2022), and finding more accurate and efficient classifiers can enhance the success of the injury likelihood monitoring system.

From the existing research, the closest neighbor algorithm ($k-NN$), radial basis function neural network (RBF Network), Naive Bayes and random forest algorithms are the four most commonly used types of classifiers (Nitze et al., 2012). Specifically, the core idea of $k-NN$ is that each sample can be represented by the closest k neighboring values, which is a relatively simple operation process but performs poorly when the samples are unbalanced; RBF Network realizes the prediction of the samples through feed-forward approximation, which is characterized by high planning efficiency but has a relatively simple structure; and Plain Bayesian classifier is based on the Bayesian theory for the a priori estimation, which has a low error rate among multiple classifiers, but its application scenario is relatively narrow due to the condition of independent homogeneous distribution.

Compared with the above three classifiers, the random forest algorithm is a relatively new fusion algorithm. Its basic idea originates from the bootstrap method in statistics, by self-sampling part of the original sample, and then constructing a decision tree, and then the average of the predictions obtained from all the decision trees individually as the final result, the Random Forest algorithm is essentially a strong predictor that integrates multiple weak decision makers.

Set θ as a random parameter vector and the corresponding decision tree as $T(\theta)$. Denote B as the domain of X, i.e., $X: \Omega \to B \subseteq R^P$, where $P \in N$ refers to the dimension of the independent variable. Each leaf node of the decision tree corresponds to a rectangular space in the B, denoted as $R_l \subseteq B(l = 1,2,\cdots,L)$. For the parameter $X \in B$, there is one and only one leaf node l that satisfies $X \in R_l$. Denote the leaf node of the decision tree $T(\theta)$ as $l(x,\theta)$. Based on the above setting, the basic steps of the random forest algorithm can be briefly summarized as follows.

(1) Bootstrap resampling of the data extracted from the original database to produce$k$training sets: $\theta_1, \theta_2, \cdots, \theta_k$Using the above training sets to form a

decision tree $\{T(x,\theta_1)\}$,$\{T(x,\theta_2)\}$,┈,$\{T(x,\theta_k)\}$.

(2) Assuming the existence of M feature dimensions, from which m features are extracted as the set of split features of the current node (the number of m remains unchanged during the growth of the forest); Assuming that each decision tree can be maximized and there is no pruning (i.e., the individual decision tree will be able to maximize the prediction).

(3) Assuming that there exist observations X_i in the decision tree $T(\theta)$ belonging to the leaf node $l(x,\theta)$ and not 0, the assignment weights can be defined as:

$$w_i(x,\theta) = \frac{\{X_i \in R_l(x,\theta)\}}{\{j{:}X_i \in R_l(x,\theta)\}}(i = 1,2,\cdots,n) \qquad (4)$$

The sum of the weights in Eq. (5) is 1.

(4) For a single decision tree, the predicted value is a weighted average of the observed values of each dependent variable, $Y_i(i = 1,2,\cdots,n)$, which is given by the following formula.

$$\hat{\mu}(x) = \sum_{i=1}^{n} \omega_i(x,\theta)Y_i \qquad (5)$$

(5) The weight of each observation Y_i can be obtained by combining the predicted values of each decision tree in Eq. (5) with the weights of Eq. (4) as follows:

$$w_i(x) = \frac{1}{k}\sum_{i=1}^{k} w_i(x,\theta_i)Y \qquad (6)$$

Then the predicted value of the Random Forest algorithm can be written as:

$$\hat{\mu}(x) = \sum_{i=1}^{n} \omega_i(x)Y_i \qquad (7)$$

3. Decision-making for sports injury protection

3.1 Overall Framework

Sports injury monitoring is a systematic and complex process, on the basis of the data processing program is basically clear, the research in this paper mainly examines the possibility of sports injuries in the lower body of basketball players (calves, thighs, hips), and puts forward suggestions for monitoring and preventing sports injuries in the knee and hip joints, so as to prove that the DWT and the Random Forest algorithms can be used for the design of the athletes' injury monitoring system. The system framework is shown in Figure 1.

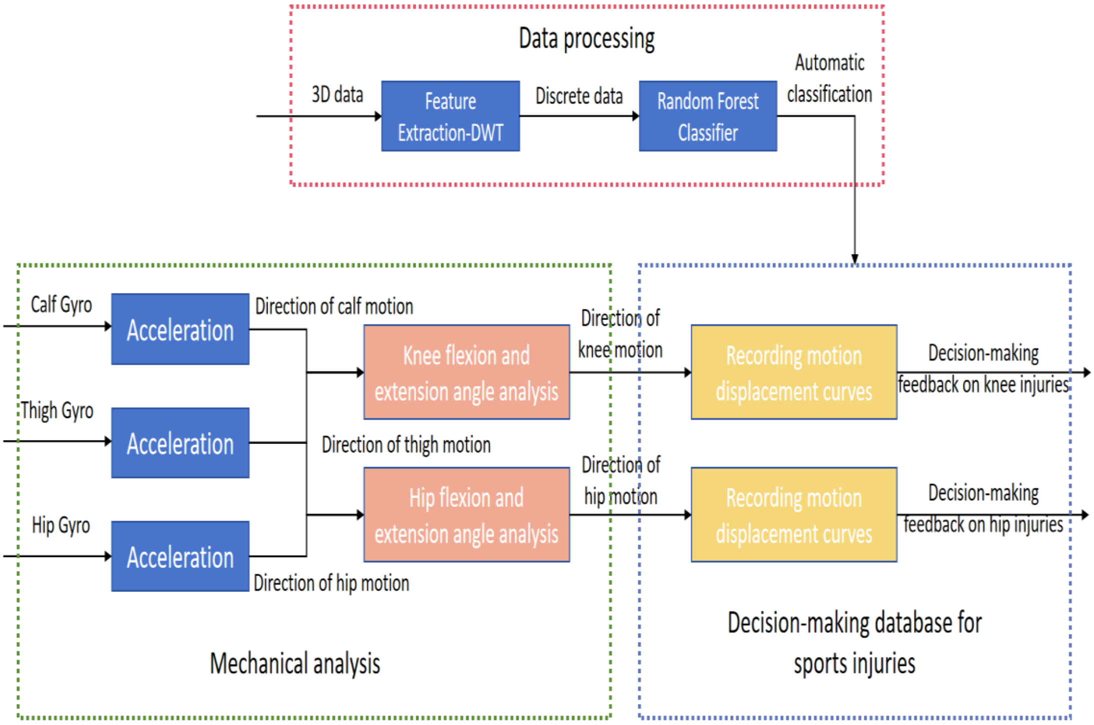

Figure 1: Decision support framework for sports injuries

As seen in Figure 1, the sports injury analysis framework consists of three core components. (1) Data processing process. Aiming at the three-dimensional data of motion acceleration feedback from wearable smart devices, the DWT method is used for feature extraction, and the relevant data are transformed into binary discrete data that can be processed by computers. And then through the random forest algorithm as a classifier, to realize the effective classification of the sports injury situation, the relevant data will be sent to the sports injury monitoring database, as the training obtained from the sports displacement curve that may cause sports injury.

(2) Mechanical analysis process. Because of the study of sports injuries in the three core parts of the lower body and the knee and hip joints of the main basketball players, it is necessary to install three-axis gyroscopes at the calf, thigh and hip respectively in the wearable smart device to record three-dimensional acceleration data.

Using the mechanical simulation of basketball posture and acceleration analysis, the flexion/extension angles of the knee and hip joints were obtained, and then the knee and hip joint directions were entered into the sports injury monitoring database, and compared with the possibility motion displacement curves automatically classified by the training set, and injury prevention suggestions were made for the similarity between the two.

(3) Sports injury monitoring database. The database consists of training sets and actual monitoring data, the database exists by the sports and health

experts for all kinds of possibilities of sports displacement curve to provide injury prevention recommendations, because machine learning is a long-term process, with the sports injury monitoring data continuously input into the database, the number of samples in the database will continue to improve, and then realize a more effective sports monitoring.

3.2 Wearable devices

Based on the sports injury analysis framework in Fig. 1, it is necessary to target the design of wearable monitoring devices for basketball players, respectively, in the left and right legs of the athlete to set up three gyroscopes (a total of six), gyroscopes are placed on the athlete's calves, thighs and hips.

Consistent with the experimental framework in Figure 1, the study mainly examines the possibility of sports injuries in the knee and hip joints, which is due to the fact that problems such as muscle strains and strains can be alleviated through recuperation, but joint injuries can cause a permanent decline in the athletic ability of basketball players.

In addition, in the process of sports injuries mainly from the foot and the ground contact with the formation of the impact, when the impulse along the calf upward movement, the muscle can be effectively dissolved through the contraction of the impact of the energy generated by the muscle, the deformation of the soft tissues not only leads to inaccurate measurement of the gyroscope, but also negatively affects the angle of the joints to estimate.

3.3 Mechanical analysis of sports injuries

The mechanical feedback of sports injury was further analyzed. The study mainly investigates the sports injury of basketball fast break movement. The reason for choosing the fast break movement is that it contains most of the basic movements of basketball and the kinetic impact generated by the basic movements.

The first is the kinetic impact generated by the contact between the foot and the ground; the second is the joint force phase, the muscle force will lead to two opposite forces reaching the upper and lower ends of the joints, and the incorrect way of force generation will lead to possible sports injuries; the third is the leg swing phase, the leg swing will lead to the friction between the soft tissues, which will result in the depletion of the joints, and generate potential sports injuries. Based on the above process, three actions can be classified and extracted by the Random Forest algorithm:

(1) Identify the foot-ground contact cycle (i.e., foot fully on the ground to the next foot fully on the ground) by the knee angle and tibial acceleration level, when the foot is fully on the ground, the leg as a whole will be out of the short-

lived retracted state, and the three gyroscope acceleration will be referred to as a sudden drop of the local cyclic acceleration when it reaches the maximum.

(2) Extracting knee and hip angles: Separate the current motion displacement curves and compare them to similar curve patterns in the training set. Due to the different movement rates of different athletes, the cycles (time characteristics) of the curves are not consistent, athletes in the start phase of the cycle is relatively long, while in the sprint phase of the cycle is relatively short, and at the same time the maximum and minimum values of the force of each cycle are not the same, in order to retain all the information of the displacement curves, it is necessary to take a normalized curve for data reading. The phase shift alignment method is used here.

$$x_i^*(t) = x_i(t + \delta_i) \tag{8}$$

$$SSE = \sum_{i=1}^{N} \int [x_i(t + \delta_i) - \mu(t)]^2 ds = \sum_{i=1}^{N} \int [x_i^*(t + \delta_i) - \mu(t)]^2 ds \tag{9}$$

As can be seen in Eq. (8) and Eq. (9), the periodicity property is used here and the minimum positive period is defined as δ_i, then examining the classification of movements in basketball, it is necessary to find the δ_i that minimizes the standard error of the mean (SSE), where the SSE is obtained based on the total mean $\mu(t)$ over the duration of the movement, i.e., the δ_i can be derived a priori from the data of the training set.

(3) Read in the above kinematic displacement curves according to the optimal iiii and after all the waveforms have been read in, repeat nnnn times using the self-sampling method until the waveforms do not change significantly, i.e.

$$SSE_{n-1} \leq SSE_n \approx SSE_{n+1} \tag{10}$$

At this point, the activity classification of the athlete is obtained, and the eigenvalues can be used to check whether the relevant motion displacement profile has a tendency to sports injury.

4. Experiment and result analysis

4.1 Experimental Objects

The test athletes consisted of 16 healthy male basketball players and 4 athletes with a history of knee injury. The subjects wore gyroscopes sensibly with the help of researchers and performed low-intensity exercise in a standard basketball court by training movements with different categories (healthy, injury-prone) of training content.

A basic training set was constructed by 8 healthy athletes and 2 athletes with a history of sports injuries, and another 10 athletes (8 healthy + 2 injured) served as a test set. The study examined the data related to six movements: standing dribble, speed dribble, jogging, sprint running, jumping rope, and vertical jump touch.

Each movement lasted for about 1 min, and the whole training process lasted for about 10 min. The data were efficiently recorded on a memory card, and peak alignment and curve entry were performed automatically by the software without any data interference by the researcher.

4.2 Categorical assessment

In Python software environment, DWT and Randomized Senlin algorithm were used to classify the above data efficiently, and the error matrix is shown in Table 1.

Table 1: Error matrix of the Random Forest algorithm

MOVEMENTS	STANDING DRIBBLE	SPEED DRIBBLE	JOGGING	SPRINT RUNNING	JUMPING ROPE	REACH JUMP
STANDING DRIBBLE	213	0	0	0	0	0
SPEED DRIBBLE	0	478	0	0	0	0
JOGGING	0	0	104	0	0	0
SPRINT RUNNING	0	0	0	341	0	0
JUMPING ROPE	0	0	0	0	89	0
REACH JUMP	6	8	3	9	2	172

Based on the error matrix in Table 1, the classifier precision, recall and F-value level of the random forest algorithm in the training set are further examined, and the results are shown in Table 2.

Table 2: Classifier precision, recall and F-value

MOVEMENTS	ACCURACY	RECALL	F-VALUE
STANDING DRIBBLE	0.994	0.987	0.992
SPEED DRIBBLE	0.981	0.992	0.987
JOGGING	0.957	0.954	0.986
SPRINT RUNNING	0.984	0.978	0.983
JUMPING ROPE	0.965	0.963	0.971
REACH JUMP	0.973	0.951	0.976

According to Table 2, using the random forest algorithm as a classifier, the F-value of the training set is greater than 0.90, and from the size order, the F-value of standing dribble, speed dribble and jogging is greater than 0.98, which indicates that the test accuracy of the three is the highest; sprinting running and jumping rope is greater than 0.97, and the test accuracy is a little bit lower, but it is still at a higher level.

The F-value of reach jump is 0.946, with the lowest precision, which may be due to the gyroscope in the process of large-scale change of direction, subject to the external influence of the larger, so the measurement accuracy has decreased. Based on the basic database of the above training set, the data of 10 athletes were entered again and the test results are shown in Table 3.

Table 3: Test Set Determination

ATHLETES	EXPECTED PROPENSITY TO INJURE (0, 1)	ACTUAL INJURY HISTORY (YES, NO)	OUTCOME OF THE DECISION
A	0	no	Correct
B	0	no	Correct
C	0	no	Correct
D	0	no	Correct
E	0	no	Correct
F	1	yes	Correct
G	0	no	Correct
H	0	no	Correct
I	1	yes	Correct
J	0	no	Correct
ACCURACY		100%	

As shown in Table 3, based on the classification criteria of the training set, all 10 athletes in the test set are correctly determined, which shows that the injury probability monitoring system based on DWT and Random Forest algorithm has a high accuracy.

5. Conclusion

In this paper, an athlete injury decision support model is constructed based on DWT and random forest algorithm, which can realize the discretization of three-dimensional acceleration vector data by using DWT algorithm, and then draw the moving displacement curve of basketball sports injury by random forest algorithm.

Secondly, the model measures the single-leg stress level through three gyroscopes of the smart wearable device, extracts the relevant acceleration data of the calf, thigh and hip, calculates the stress situation of the knee and hip joints, and then plots them into the mobile displacement curve, and then examines the injury potential of the athlete through the comparison of the classifier with the sports injury database.

The proposed modeling framework is of great significance in supporting athletes' injury decision-making: (1) it can effectively identify athletes' injury tendency; (2) it can provide targeted preventive suggestions through athletes' injury likelihood displacement curves.

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