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Retraction

Retracted: Sports Injury Risk Assessment Based on Blockchain and Internet of Things

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1].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

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

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

In addition, our investigation has also shown that one or more of the following human-subject reporting requirements has not been met in this article: ethical approval by an Institutional Review Board (IRB) committee or equivalent, patient/participant consent to participate, and/or agreement to publish patient/participant details (where relevant).

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

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

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

References

[1] J. Liu, "Sports Injury Risk Assessment Based on Blockchain and Internet of Things," *Journal of Sensors*, vol. 2021, Article ID 6820728, 13 pages, 2021.

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Research Article

Sports Injury Risk Assessment Based on Blockchain and Internet of Things

Jihua Liu

Department of Physical Education, Beijing Union University, Beijing 100101, China

Correspondence should be addressed to Jihua Liu; jihua.liu@buu.edu.cn

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With the increase of people's exercise in today's society, how to exercise scientifically and healthily has attracted much attention. Therefore, sports injury risk assessment and monitoring system has attracted more and more attention in real-time, flexibility, intelligence, and other aspects. To solve the above problems, this paper proposes a sports injury risk assessment based on blockchain and Internet of Things. By introducing computational power weight, a computational power balance D-H algorithm based on Internet of Things blockchain network architecture is proposed. It can provide a secure and trusted interactive environment for the Internet of Things. On the basis of blockchain and Internet of Things, a multisensor data fusion algorithm is proposed to be applied to the analysis and evaluation of sports injury. A variety of physiological parameters of human motion state are collected through multisensor, the collected physiological parameters are processed by data fusion, and finally, sports injury risk assessment is carried out. The built system takes the embedded esp8266wifi module as the hardware processing core and uses body temperature sensor, blood pressure sensor, EMG sensor, and pulse sensor to form wearable devices. By wearing wearable devices, four human physiological parameters such as body temperature, blood pressure, electromyography, and pulse can be collected. In the process of decision level fusion, different weights are set for the focal elements causing information conflict, and the optimized D-S evidence theory algorithm is used. Thus, according to the data detected by multisensor, the injury risk of user motion state is evaluated.

1. Introduction

Maintaining a healthy body requires not only a reasonable diet but also scientific exercise habits. A large number of studies have proved that regular aerobic exercise is beneficial to human health and can improve human exercise ability and physical fitness. In terms of health results and effectiveness of intervention programs, accurate quantification of physical exercise and physical health is very important [1]. If we can collect and analyze the health information and sports information of human body, we can give effective guidance and intervention to athletes in sports and health [2]. For ordinary athletes, real-time monitoring of their health and exercise status can help people adjust their exercise intensity or amount in time according to their daily exercise situation, so as to avoid physical discomfort caused by excessive or too little exercise and remind themselves to improve their exercise status in time and maintain a healthy body and healthy life. Research shows that sports enthusiasts and professional athletes in the process of sports, and sports risks are not only caused by a single reason but is also usually caused by the superposition of multiple factors. Traditional sports injury risk assessment methods focus on sports mode, and the risk calculation scope is limited. At the same time, there are some problems such as low efficiency and poor accuracy of evaluation, which are not suitable for large-scale evaluation [3]. According to the above problems, this paper proposes sports injury risk assessment based on blockchain and Internet of Things. Reanalysis of risk factors, introducing fuzzy D-S evidence theory algorithm [4], analyzing risk factors, adjusting calculation methods, and obtaining basic risk correlation data, thus, realizing the evaluation of sports risks. Through simulation experiments, three experiments are carried out: evaluation efficiency, evaluation accuracy, and evaluation ability. The experimental results show that the sports injury risk assessment method designed in this paper is suitable for sports risk assessment of large, medium, and small scales and has high accuracy and high assessment efficiency.

Physical training in colleges and universities is an increasingly important part of college curriculum, and how to evaluate and determine the degree of sports risk should also be paid attention to. We propose a video summarization algorithm based on block sparse representation, combined with a certain heavy rainfall as the experimental background to study the factors affecting the risk of college sports, mainly establishing a fuzzy comprehensive evaluation model to determine the risk degree, weight, and prevention system. The purpose is to put forward reasonable suggestions, improve the safety awareness of teachers and students, strengthen the school safety management mechanism and improve various safety guarantees, and strengthen the management of school sports facilities [5]. As a professional athlete, injuries in daily training and competition are very common. Traditional three-dimensional knee joint moment (KJM) can provide early warning for athletes' knee injury risk. It mainly solves the portability problem by building a linear statistical extrapolation model, which relies too much on force plate and downstream biomechanical model. A pretrained CaffeNet convolution neural network (CNN) model has the strongest overall average correlation of 0.8895 with the source model, which is more accurate and belongs to a multidisciplinary research method, which can significantly promote the physical model and provide an effective application for athletes' training [6].

With the rapid development of Internet of Things technology, it is becoming more and more popular in our lives. It is applied to our traditional dragon boat training to solve our knowledge and understanding of the causes of injuries of athletes in this competition. The training intensity of dragon boat race is great, mainly based on strength and technology. The greater the training intensity, the higher the possibility of injury. We propose data fusion algorithm and clustering maintenance optimization algorithm to study the cause of injury and then use cluster maintenance optimization algorithm to improve the start-up time. Through analysis, the accuracy of the etiology detection system is almost perfect, which shows that it is consistent with the actual sports injury detection results [7]. Experiments show that the research on the causes of dragon boat sports injuries based on Internet of Things technology is effective, better detection of injury rules, so that athletes can effectively prevent injuries and a comprehensive understanding. Big data analysis of sports injury data realized by neural network is a new evaluation model of sports injury based on big data analysis and RBF neural network. In the constructed big data network, the evaluation of sports injury is realized by identifying hazard sources and various factors. After testing, the model is not restrained by various conditions, and its operation effect is good [8]. Badminton involves many injured parts, including legs, back, hands, and shoulders. We usually reduce injuries by increasing physical fitness plans and preventing training injuries [9]. Now we need to propose a more effective badminton evaluation system to make up for the lack of objective knowledge and method evaluation system.

2. Topology Model of Internet of Things Based on Blockchain Technology

Blockchain is a tamper-proof distributed network ledger technology that only contains real information. In addition, the peer-to-peer technology (P2P) of blockchain ensures that it does not need to rely on any central entity [10]. Therefore, blockchain technology can provide direct communication between IoT devices without centralized organization and can effectively solve the problems of computing node failure, transaction serial timeline error, privacy, trust, and reliability of new nodes in IoT [11]. In order to effectively apply blockchain technology to the Internet of Things network and realize the reliable identity authentication function of devices with certain computing power in the Internet of Things, this chapter proposes an Internet of Things network model based on blockchain technology under the Internet of Things network. At the same time, according to the characteristics of IoT equipment for sports injury risk assessment, the data structure of block body is improved, and a set of data interactive authentication method under this model is designed with cryptography algorithm. Ensure the stable transmission and safety of sports injury risk assessment data.

2.1. Design of New Block Structure. Blockchain is essentially different from traditional trading network and has many special characteristics. Their key features include encryption (asymmetric encryption), hashing, chaining blocks, and smart contracts. Blockchain transactions represent the interaction between two parties. For cryptocurrency, transactions represent the transmission of cryptocurrency between blockchain users. These transactions can also refer to message transmission or recording activities. Each block in the blockchain can contain one or more transactions, and the block structure is designed according to the things of the block.

Figure 1 illustrates the data structure of a general block body, which is a scattered, distributed, and common number composed of blocks. Typically, each block is connected to a timestamped transaction set. As you can see, this technique allows nodes to exchange data by creating transactions, each of which depends on another transaction, where the output of one transaction is referenced as an input in the other transaction, thereby creating a chain structure in it.

Blocks in blockchain are divided into block headers and block bodies. The block headers are like indexes in databases. The block header structure of Ethereum is too complex for the Internet of Things environment. In view of this situation, this paper cancels the data structures like GasLimit and Coinbase and simplifies the block headers data, as shown in Table 1, making the lightweight block headers more suitable for the Internet of Things environment.

Table 2 shows the main data structure of the new block body. According to the actual existence and uniqueness of Internet of Things devices, the device ID and company ID are used to locate the devices. The type field mainly stores the transaction type, which is used to locate and negotiate transactions between gateway nodes.

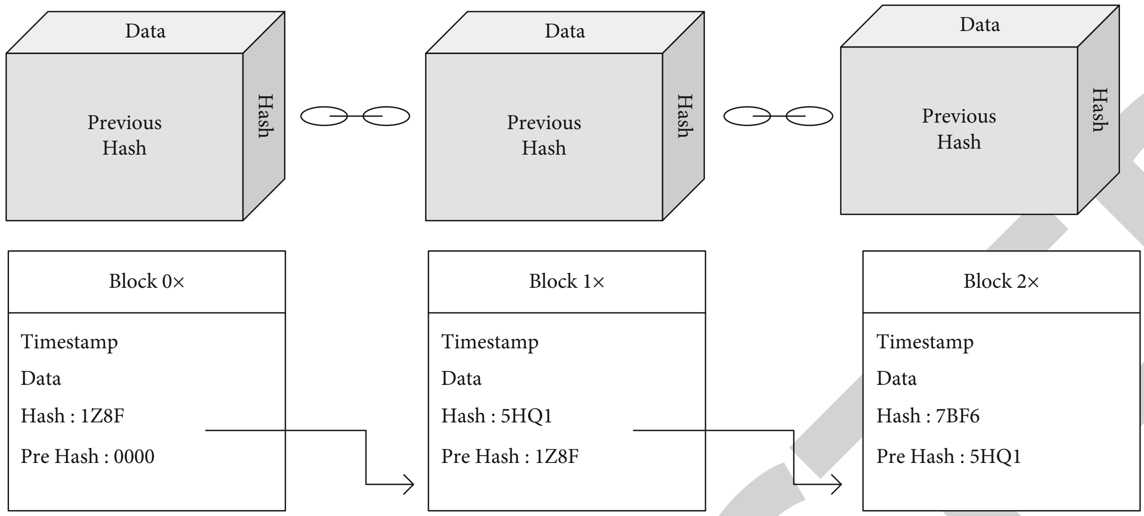

Figure 1: Logical structure of block body.

Table 1: Block structure of new area.

Attribute	Individual meaning
father_hash	Point to parent block (parentB1ock). Except for GenesisB1ock, each block has only one parent block.
Number	Serial number of the block. The number of a block is equal to its parent block number +1.
Merkel_root	The root of Merkel tree. Merkel tree is a kind of hash tree. Leaf node contains stored data or its hash value, middle node is the hash value of its two child nodes, and the top root node is composed of the hash value of its two child nodes.
Timestamp	The time when the block "should" be created. Determined by consensus algorithm, generally, it is either equal to parentB1ock. Time +10 s or equal to the current system time.

Table 2: Structure of new block body.

Attribute	Individual meaning
Type	0x00 stores type of things
Company	The number of the company is convenient for identity verification and ensures the global uniqueness of ID.
device_code	The number of the device is convenient for identity verification and ensures the global uniqueness of the ID.
dh_value	Field required for Diffie-Helman authentication, which is a struct, including a prime number and its source root.
ffs_value	The gateway node proves the set of global parameters through the zero recognition generated by its own random number R.
new_ffs_value	The updated set of zero recognition proof global parameters, which is empty when new devices are registered.
envelope_pk	Public key for envelope encryption.
Calculate	Node computing power weight is used to balance the computing power between nodes and improve efficiency.

2.2. D-H Algorithm of Computing Power Balance Based on Internet of Things-Blockchain Network Architecture. After completing the identity authentication of the blockchain gateway node, all the nodes in the network recognize the legitimacy of the node. One of the characteristics of the Internet of Things is that the computing power of devices is uneven, which will lead to a large time gap in the calculation of large numbers. In the process of establishing information interaction things such as instant messaging, it is inevitable that the party with strong computing power needs to wait for the party with weak computing power, which greatly wastes time and resources. In order to solve this inevitable problem in the Internet of Things environment, this section refers to Diffie-Hellman key exchange method [12] and proposes a key exchange method based on the Internet of Things-blockchain network architecture that can balance the computing power gap by introducing computing power weight.

Assuming that node A needs data interaction with node B, as shown in Figure 2, the node has calculated the intermediate shared value Y of random number S in advance and kept it confidential. The party with low computing power

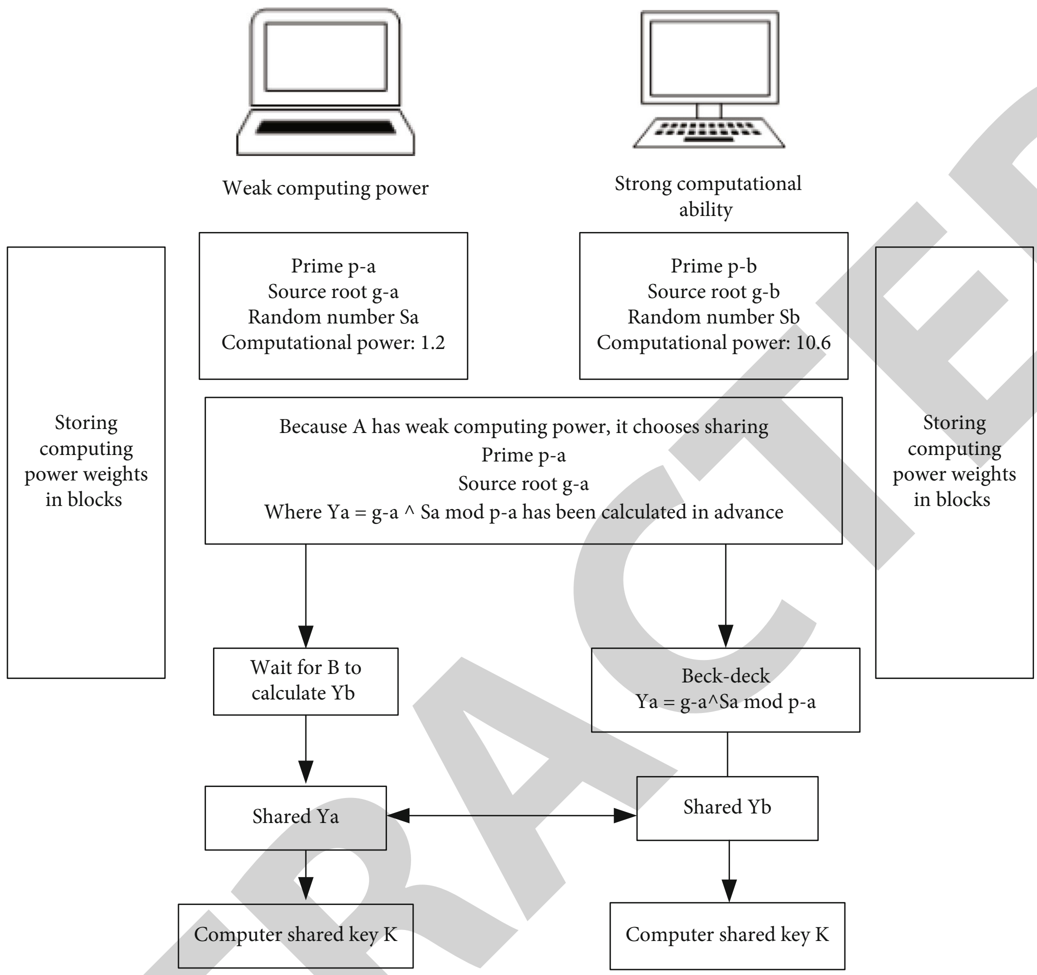

Figure 2: Balanced computing power key exchange process under blockchain-Internet of Things structure.

selects the calculated data as shared data. Suppose that node A needs time t_{ya} to calculate Ya, and node B needs time t_{ya} to calculate Ya, where $t_{ya} > t_{yb}$. The time for node A to calculate the shared key is t_{ka}, the time for node B to calculate the shared key is t_{kb}, and the communication network delay totals t_{network}. If the traditional D-H key sharing algorithm is adopted, the time for communicating and sharing keys between nodes is as follows:

$$T_{\text{total}} = t_{\text{network}} + \max\left(t_{ya}, t_{yb}\right) + \max\left(t_{ka}, t_{kb}\right). \quad (1)$$

If the sharing algorithm based on blockchain-Internet of Things computing power balance is adopted, the time for nodes to communicate and share keys is

$$T_{\text{total-new}} = t_{\text{network}} + \min\left(t_{ya}, t_{yb}\right) + \max\left(t_{ka}, t_{kb}\right). \quad (2)$$

The time savings of the whole process are

$$T_{\text{save}} = abs\left|\left(t_{ya} - t_{yb}\right)\right|. \quad (3)$$

In the Internet of Things environment, where the computing power of individual devices is quite different, this key exchange algorithm using cache and exchanging space for time saves considerable time.

Figure 3 shows the connection between a node A in the same node group and other devices by using ordinary D-H algorithm and computing force balance D-H algorithm, respectively. It is obvious that the new algorithm has shorter connection time.

3. Evaluation of Human Motion Data Based on Fuzzy D-S Evidence Theory Algorithm

The health monitoring system based on blockchain and Internet of Things proposed earlier brings convenience for users to detect their health status during exercise. The design of this system is mainly through the user's body temperature, blood pressure, EMG, and pulse four basic physiological parameters of human body data to judge the user's health status [13]. Through the optimized fuzzy set and D-S evidence theory, the discrimination algorithm proposed in this paper is introduced. In feature level fusion, fuzzy set theory algorithm is used. In the process of decision level fusion, a fuzzy D-S evidence theory discriminant algorithm is obtained by using the D-S evidence theory algorithm. This algorithm is applied in the sports injury risk assessment

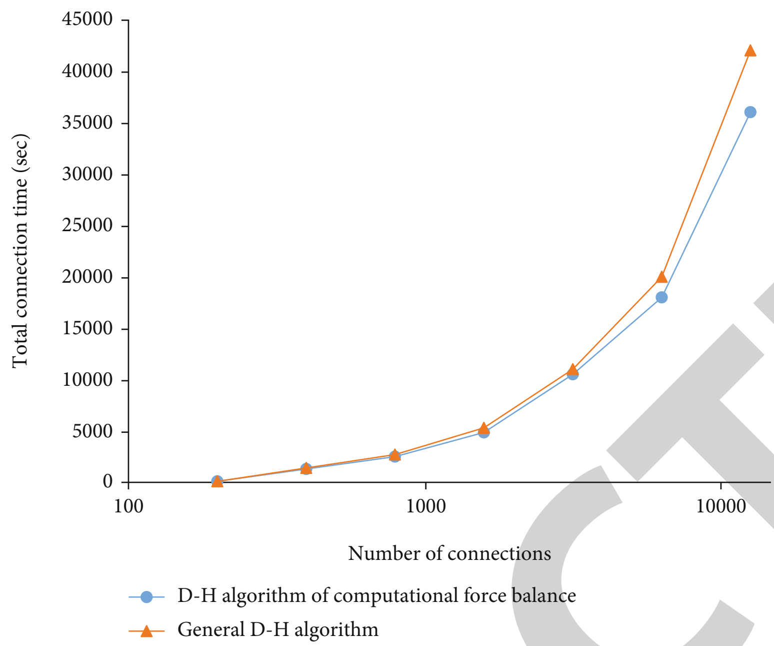

Figure 3: Comparison of the time required for devices to connect using different algorithms.

system and can be used to judge whether the user's sports behavior is healthy or not according to the data results detected by multiple sensors.

3.1. Intelligent Data Processing Algorithm. The information collected by each sensor and its observation information are combined according to certain optimization criteria, and these information are further processed. Considering the floating error of human health indicators and the difference of health representation weights of different health indicators, this study adopts the sports injury risk assessment algorithm based on fuzzy D-S evidence theory and realizes the evaluation of human health status to be detected based on the collected human health indicators data.

3.1.1. Fuzzy Sets. Fuzzy sets and fuzzy subsets are used to represent the whole thing with fuzzy definition characteristics.

Representation of fuzzy sets:

(1) Zadeh notation

$$A = \frac{A(u1)}{u1} + \frac{A(u2)}{u2} + \frac{A(u3)}{u3} + \cdots. \tag{4}$$

(2) When the number of elements in the fuzzy set is infinite, it is expressed by Zadeh method:

$$A = \int \frac{A(u)}{u}. \tag{5}$$

It is very important to test and analyze the accuracy, validity, and precision of information observation data in sensors, which is of great significance and helps to extract effective information observation data, ensure the reliability of data, and control the accuracy of final fusion results.

If the obtained absolute information amount of positioning is $Si(t)\ (i = l, 2, \cdots n)$ in positioning data, the absolute data information amount obtained at time t is used for positioning measurement, and the positioning value is placed on the number axis:

$$dis(t) = |si(t) - sj(t)|, \tag{6}$$

where $si(t)$ is the information data at time t, $d_i(t)$ is the distance between all the information data values, and $\bar{d}i(t)$ is the average distance.

$$di(t) = \sum_{j=1}^{n} disij(t), \tag{7}$$

$$\bar{d}i(t) = \sum_{i=1}^{n} di(t). \tag{8}$$

If dit satisfies the following conditions and regards all the data in the neighborhood of a set of valid information data as φ, then, this set is called the optimized fuzzy set.

$$di(t) < \bar{d}i(t) + M, \tag{9}$$

$$di(t) \geq \bar{d}i(t) - M. \tag{10}$$

The observation data set of n sensors of t-time fuzzy set is obtained by the definition of t-time optimal fuzzy set. For the optimized T-time fuzzy set of observation data, the smaller $Si(t)$ and $Sj(t)$ are, the more complex the fusion between T-time and observation data of two sensors is,

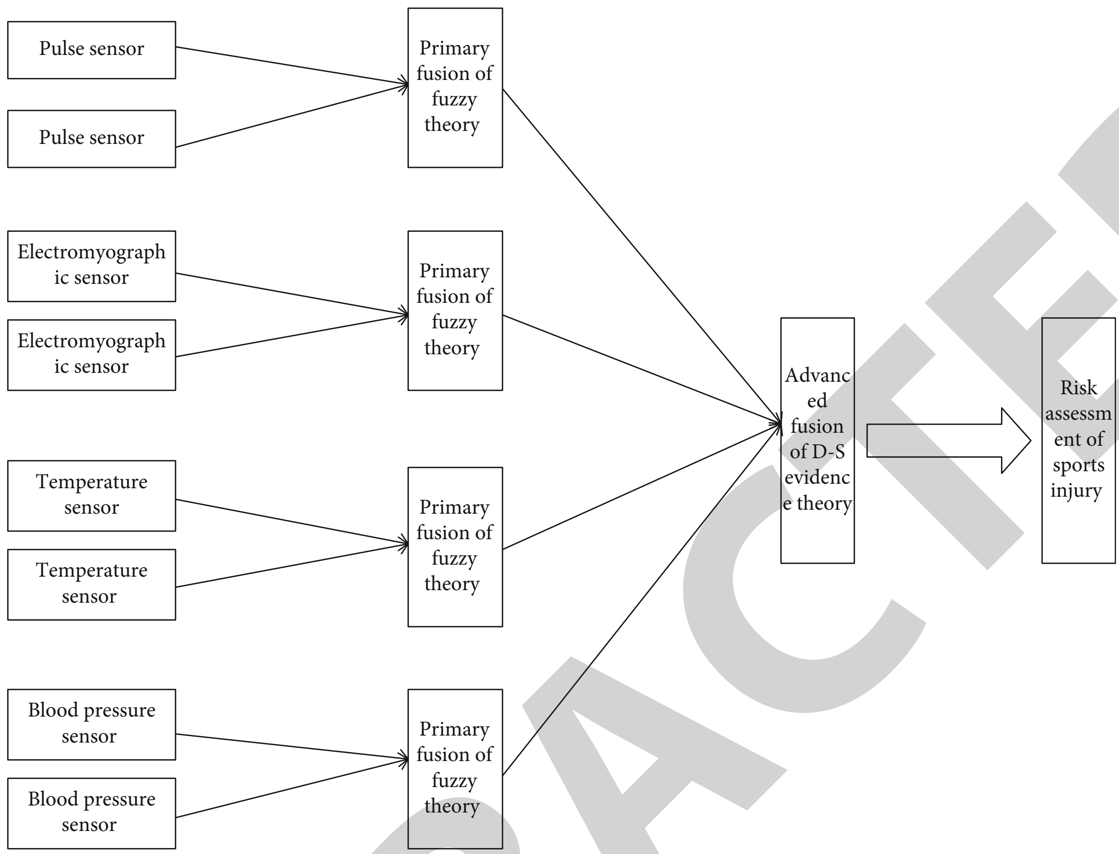

Figure 4: Flowchart of algorithm fusion.

and the higher the fusion complexity between data is. On the contrary, it shows that the lower the complexity of data fusion, the deviation of the fusion degree of observed data values between sensors. In order to facilitate the analysis and processing of the fusion complexity and values between the observed data of fuzzy sets, the concept that the fusion degree of fuzzy sets belongs to a function in mathematical theory is put forward. $Si(t)$ and $Sj(t)$ are mapped to each other to obtain a fusion degree membership function matrix $Cij(t)$, and the value range of $Cij(t)$ is [0, 1]. The membership function of the matrix $Cij(T)$ directly reflects the degree of fusion between the sensor and the observation data of the two sensors at T time. The expression defined by the fusion function is as follows:

$$Cij(t) = \exp\left\{-\frac{1}{2}|si(t) - sj(t)|\right\}. \tag{11}$$

It can be seen from the formula that the closer the $cij(t)$ value is to 1, the better the fusion of the two sensors and the higher the fusion degree of observation data. On the other hand, the $Cij(t)$ value is infinitely close to 0, and the fusion degree of the two sensors is worse. According to the definition of fusion degree, the data fusion degree matrix C is

$$C = \begin{bmatrix} 1 & C_{12}(t) & \cdots & C_{1m}(t) \\ C_{21}(t) & 1 & \cdots & C_{2m}(t) \\ \vdots & \vdots & \ddots & \ddots \\ C_{m1}(t) & C_{m2}(t) & \cdots & 1 \end{bmatrix}. \tag{12}$$

A larger sum of the elements of any row of matrix C indicates that $Si(T)$ is closer to the average. On the contrary, if the sum of the elements in this row is smaller, the greater the deviation of the observed data of sensor Si.

T is time, and the consistency fusion degree of sensor Si can be expressed as

$$\mu i(t) = \frac{\sum_{j=1}^{m} cij(t)}{m}. \tag{13}$$

However, the average consistency fusion degree cannot prove the stability of Si sensor. If the monitoring data transmission of sensor Si is very stable, the deviation between its fusion degree and sensors of other information sources will become very small. The deviation affects the distribution balance of fusion degree. Therefore, the definition of distribution balance is used.

Table 3: Mass values of body temperature, pulse, EMG, and blood pressure.

	S1	S2	S3	S4	S5	…
Electromyography	0.889	0.782	0.696	0.432	0.802	…
Pulse	0.754	0.723	0.512	0.231	0.772	…
Body temperature	0.709	0.689	0.594	0.302	0.632	…
Blood pressure	0.723	0.705	0.612	0.172	0.805	…

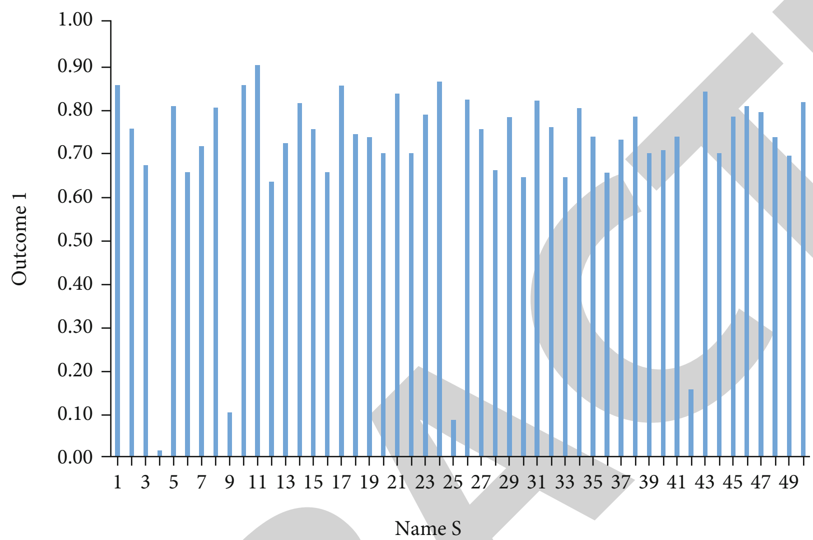

Figure 5: EMG and pulse fusion results 1.

The distribution balance of sensor Si at time t is

$$\tau i(t) = 1/\sum_{j=1}^{m}\left(ui(t) - cij(t)^2\right)/m. \quad (14)$$

In the actual process of sensor fusion, we should try to use sensors with consistent fusion degree and relatively balanced fusion degree distribution. The higher the uniformity and fusion coefficient of sensors, the more balanced the distribution of fusion degree and the greater the fusion degree weight of sensors. Therefore, the uniform fusion coefficient of a sensor can be multiplied by the distributed balance coefficient of the sensor as the fusion weight balance coefficient of the sensor.

The weight coefficient of sensor Si at time t is

$$\omega i(t) = ui(t) \times \tau i(t). \quad (15)$$

The above formula is normalized to obtain:

$$Wi(t) = \frac{\varpi(t)}{\sum_{i=1}^{m}\varpi i(t)}. \quad (16)$$

The fusion result is

$$\widehat{x} = \sum_{i=1}^{m} wi(t)si(t) = \sum_{i=1}^{m}\frac{\omega i(t)si(t)}{\sum_{i=1}^{m}\omega i(t)}. \quad (17)$$

Fuzzy sets are more valuable in multisensor data fusion. When used in multisensor information fusion, the first step is to observe the data monitored by each sensor, then use the concept of fuzzy set to complete the process of information synthesis according to relevant fusion rules, then use fuzzy set to complete multi-sensor information fusion or reasoning, and make the final information fusion decision.

3.1.2. D-S Evidence Theory. Evidence theory is a reasoning method using uncertainty. It can also be simply regarded as an improvement of subjective Bayesian estimation method. But it also has many advantages that Bayesian estimation reasoning method cannot match [14]. Bayesian estimation reasoning method usually needs to synthesize hypothetical prior probability and corresponding conditional probability, while the new generation D-S evidence analysis theory can calculate the probability of overcoming prior probability and corresponding condition according to its comprehensive basic reasoning rules. At present, it has been widely used in multisensor information fusion data processing system.

3.2. Data Fusion of Fuzzy Sets and D-S Evidence Theory. In order to minimize the decisive influence of low credibility evidence on conflict decision-making results, based on the research results of scholars at home and abroad, this paper proposes a new consistency algorithm of conflict evidence credibility synthesis. The algorithm basically combines the advantages of original reliability evidence consistency

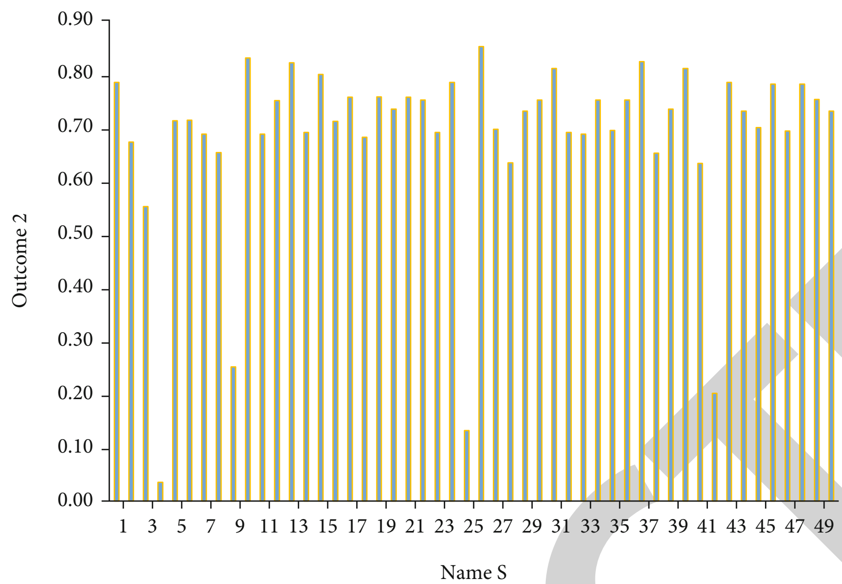

FIGURE 6: Results obtained by fusion of body temperature and blood pressure 2.

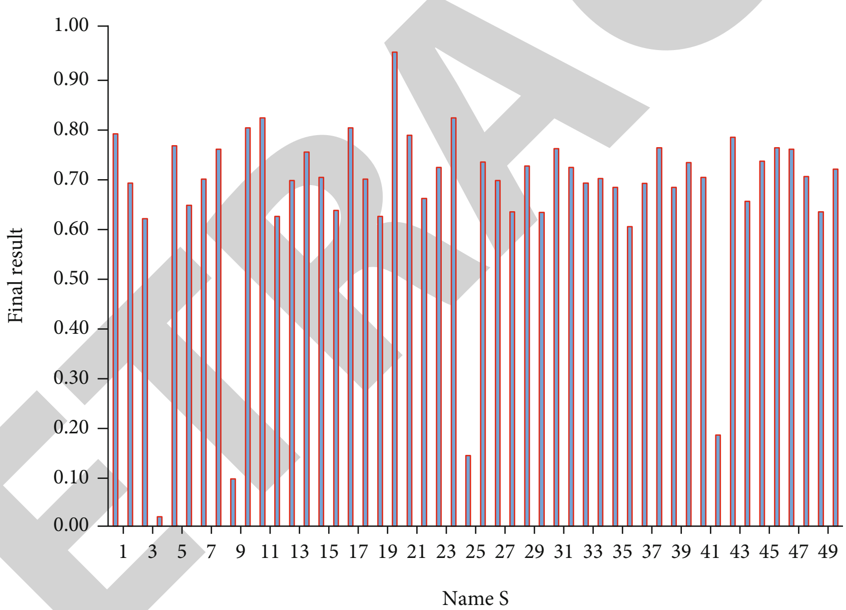

FIGURE 7: Final result.

modification and sensor combination rule consistency modification. In addition, the conflict evidence is not completely removed, and the conflict information and the consistency information between the conflict evidence are properly reserved. This new consistency algorithm not only improves the reliability of sensor evidence but also improves the accuracy of evidence fusion processing and reduces the risk that the weighted credibility evidence will affect the decision results.

Basic probability distribution function of combination:

$$\begin{aligned} m(A) &= 0 && \mathrm{A} = \varnothing, \\ m(A) &= \frac{\sum_{AiBj=A} m_1(Ai) m_2(Bj)}{1 - \sum_{AiBj=\phi} m_1(Ai) m_2(Bj)} && \mathrm{A} = \varnothing. \end{aligned} \tag{18}$$

m_1 and m_2 represent their basic confidence distribution functions. Ai and Bi are the focus elements. The global reliability of each evidence in the fusion system can be calculated by equation (19). The evidence with the highest reliability after calculation is called the weight evidence of the fusion system, which can be expressed by u_k:

$$\mu_k(E_k) = \max_{1 \le i \le m} (\mu i(Ei)). \tag{19}$$

Taking the weighted evidence as a reference and the overall credibility of the evidence as the basis for measuring the weight coefficient of the evidence, the weight coefficients of other evidence can be expressed as follows:

$$\tau i = \frac{\mu i(Ei)}{\mu k(EK)} = \frac{\mu i(Ei)}{\max\limits_{1\le i\le m} \mu i(Ei)}. \tag{20}$$

Through normalization method, the basic confidence function $W\_i\,(t)$ can be obtained:

$$Wi(t) = \frac{\varpi i(t)}{\sum_{i=1}^{m} \varpi i(t)}. \tag{21}$$

The weight coefficient of each evidence is redistributed to obtain a new basic probability distribution function:

$$mi(A_k) = \begin{cases} \tau i \cdot mi(A_k), \\ 1 - \sum \tau i \cdot mi(B_k). \end{cases} \tag{22}$$

The improved combination rule is used to fuse the new basic probability distribution function, and the improved combination rule is shown in the following equation.

$$\begin{cases} m(\varphi) = 0 \\ m(A) = \sum\limits_{\substack{A_k \cap B_k = A \\ A_k \cdot B_k \subseteq \theta}} \tilde{m}i(A_k) \cdot mj(B_k) + \sum\limits_{\substack{A \cap B_k = A \\ B_k \subseteq \theta}} \lambda(A, B_k), \end{cases} \tag{23}$$

$$\lambda(A, B_k) = \frac{\tilde{m}i(A)^3}{\tilde{m}i(A)^2 + \tilde{m}j(B_k)^2} + \frac{\tilde{m}i(B_k)^3 \tilde{m}j(A)}{\tilde{m}i(B_k)^2 + \tilde{m}j(A)^2}. \tag{24}$$

From the consistency description of equation (21), it can be clearly seen that the new method fully excavates the information consistency between high-reliability evidences and the conflict consistency information between information and evidence and fully considers the security and reliability of relevant evidence information sources on the basis of assigning information weights to information conflict evidences.

4. Experiment

4.1. Application of 4.1 Fusion Algorithm in Sports Injury Risk Assessment System. Because the data transmitted based on the Internet of Things is human motion data transmitted at the same time, data-level fusion cannot be provided. According to the characteristics and functions of human physiology and data information, the two-level feature information data fusion technology is used to realize the information processing in the human sports injury risk assessment system and the judgment of human sports health results in Figure 4.

First, it is a feature level information analysis and fusion, which belongs to an intermediate level feature data fusion in the whole feature information processing process. Based on the analysis and fusion of feature data and the fusion of data processing information extraction, it is a fusion of global and local feature information. Second, information analysis and

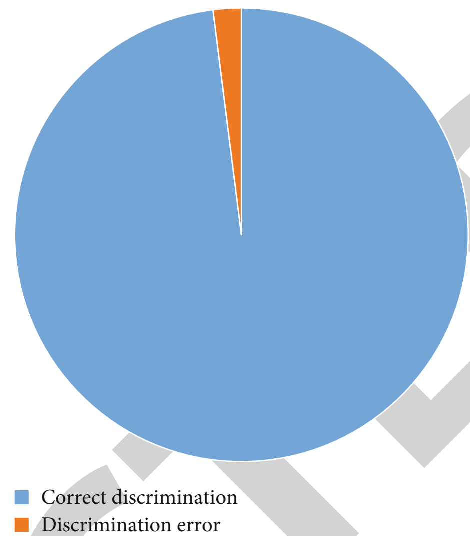

Figure 8: Correct rate of fuzzy D-S evidence theory algorithm.

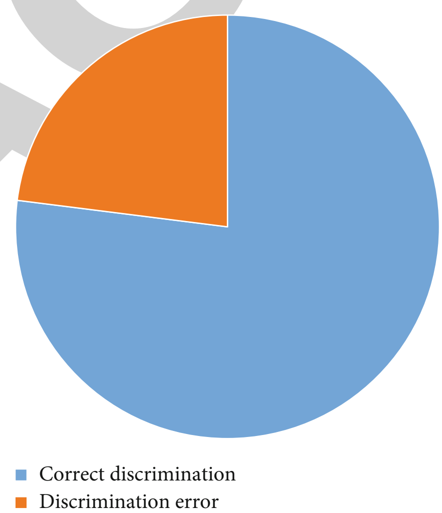

Figure 9: Correction rate of weighted average data fusion algorithm.

fusion at decision level are high-level technology of local feature information analysis and fusion [15]. It makes final decision analysis on the whole local feature information processing process formed by the fusion of local feature data and information of different feature types, that is, it makes the analysis and fusion of feature data and local information for each independent decision, so that the decision maker can obtain consistent whole feature information decision and judgment. The flow chart of algorithm fusion is shown in Figure 4.

The physiological data parameters of body temperature, pulse, EMG, and blood pressure were fused preliminarily. Then, the global credibility of each evidence is calculated, and the weight evidence of the fusion system is determined, defined as:

$$\mu_k(E_k) = \max_{1\le i\le m} (\mu i(Ei)). \tag{25}$$

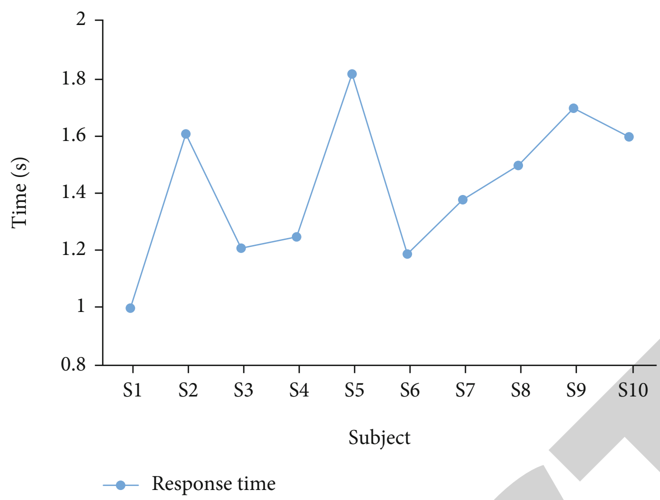

Figure 10: Response time of device in indoor environment.

Taking the weighted evidence as a reference and the overall credibility of the evidence as the basis for measuring the weight coefficient of the evidence, the weight coefficients of other evidence can be expressed as follows:

$$\tau i = \frac{\mu i(Ei)}{\mu k(Ek)} = \frac{\mu i(Ei)}{\max\limits_{1\le i\le m} \mu i(Ei)}. \tag{26}$$

Normalized to obtain the basic confidence function:

$$Wi(t) = \frac{\varpi i(t)}{\sum_{i=1}^{m} \varpi i(t)}. \tag{27}$$

From the above formula, it can be concluded that the primary fusion results of the three groups of sensors have the most normal pulse rate of 80, EMG of 210 mV, blood pressure of 86 mmHg, and body temperature of 36.7 degrees Celsius. Before the beginning of this experiment, the body temperature, pulse, EMG, and blood pressure of 50 subjects were tested with professional medical instruments. The subjects S4 and S9 showed hyperthermia, S25 showed high pulse rate, and S33 and S42 showed high blood pressure. Therefore, the physical movement state of subjects S4, S9, S25, S33, and S42 is "unhealthy."

In this experiment, we do not do any specific research on the basic probability distribution function, but get the assignment of the basic probability distribution function of the above sensors through the expert knowledge system, as shown in Table 3.

Fuse the body temperature and pulse of two sets of evidence related to human physiological parameters, and the fusion process is as follows.

First, the weight coefficients of the evidence are redistributed according to formula (28) to obtain a new distribution function.

$$\tilde{m}i(A_k) = \begin{cases} \tau i \cdot mi(A_k), \\ 1 - \sum \tau i \cdot mi(B_k). \end{cases} \tag{28}$$

Taking the value of τi as 1, we get a new mass function, as follows:

$$\tilde{m}i(A_k) = \begin{cases} mi(A_k), \\ 1 - \sum mi(B_k). \end{cases} \tag{29}$$

Then, S1-S50 is substituted into equation (29) to obtain a new expression for the basic probability distribution function, as follows:

$$\tilde{m}(X) \begin{cases} m(\delta 1) \cdots X = \delta 1, \\ m(\delta 2) \cdots X = \delta 2, \\ m(\delta 3) \cdots X = \delta 3, \\ m(\delta 4) \cdots X = \delta 4, \\ m(\delta 5) \cdots X = \delta 5, \\ 1 - m(\delta 1) - m(\delta 2) - m(\delta 3) - m(\delta 4) - m(\delta 5) \cdots X = \theta. \end{cases} \tag{30}$$

Using the basic probability distribution function calculated by Android platform of intelligent mobile terminal, EMG and pulse evidence are fused first. The result of ECG and pulse fusion is obtained, as shown in Figure 5.

Then, through the new principle of evidence combination, the blood pressure and body temperature are fused. The fusion of blood pressure and body temperature is obtained, as shown in Figure 6.

Finally, through the new evidence combination principle, the two groups of fusion results are fused. The final fusion result of the four items of data is obtained, as shown in Figure 7.

It can be seen from the final result diagram that the physical movement state detected by subjects S4, S9, S25, and S42 is "unhealthy," while other subjects are "healthy." Before the beginning of this experiment, the physical movement states of subjects S4, S9, S25, S33, and S42 were all "unhealthy" measured by professional medical instruments.

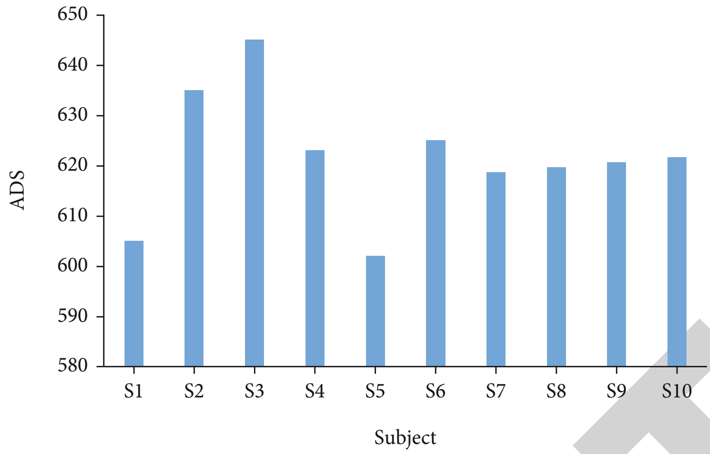

Figure 11: Change of AD value of EMG signal in indoor environment.

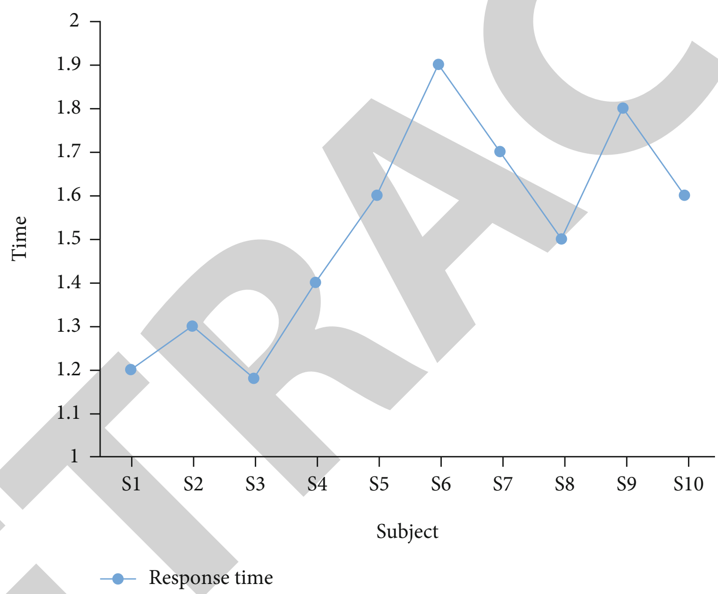

Figure 12: Response time of device in outdoor environment.

By comparison, it can be seen that the experimental results of S33 are inconsistent with those measured by professional medical devices. Therefore, this discriminant algorithm has a high accuracy in judging the status of human sports injuries, with a correct rate of 98% and an error of 2%. It conforms to the application standard in normal sports environment and has certain practical significance.

4.2. Comparison of Fuzzy D-S Evidence Theory Algorithm and Weighted Average Data Fusion Algorithm. In this section, the fuzzy D-S evidence theory algorithm and weighted average data fusion algorithm are compared, and the experimental results can be used to prove the effectiveness of the algorithm selected in this paper. First, the fuzzy D-S evidence theory algorithm is applied to 50 groups of experiments, and the experimental results are shown in Figure 7. The correct rate of human sports injury risk assessment is 98%, and the error is 2%. The accuracy of the experimental results of fuzzy D-S evidence theory algorithm is shown in Figure 8.

Using the same basic experimental data and applying weighted average data fusion algorithm, the sports injury risk detected by subjects S4, S9, S10, S12, S14, S16, S19, S20, S27, S33, S42, S45, S48, and S49 is assessed as "unhealthy," while other subjects are "healthy." Compared with the experimental results measured by professional medical devices, the correct rate is 77% and the error is 23%. The accuracy of experimental results of weighted average data fusion algorithm is shown in Figure 9.

From the comparison results of Figures 8 and 9, it can be seen that the correct rate of weighted average data fusion algorithm for human motion injury risk assessment is 77%. Although the correct rate is high, the correct rate of fuzzy D-S evidence theory algorithm for human motion injury risk assessment is 98%. In the application of human motion injury risk assessment, fuzzy D-S evidence theory algorithm

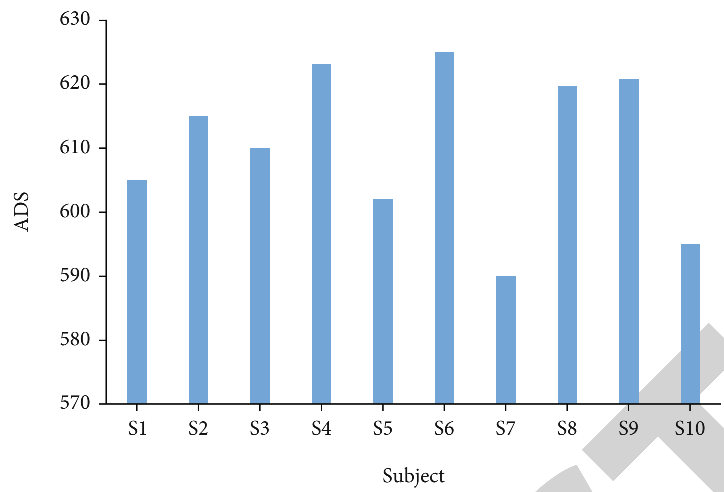

Figure 13: Change of AD value of EMG signal in outdoor environment.

has higher accuracy than weighted average data fusion algorithm and performs better and more stable in the overall performance. Therefore, fuzzy D-S evidence theory algorithm is more suitable for human sports injury risk assessment.

4.3. Human Muscle Fatigue Detection. If you exercise improperly or excessively, it may directly lead to severe muscle stiffness. Severe muscle stiffness is a natural physiological reaction of "self-defense signal," which indicates that your local muscles are completely tired. On the basis of realizing the risk assessment of human sports injury based on the system proposed in this paper, a muscle fatigue detection based on blockchain and Internet of Things is also designed in the experiment. This system judges the muscle fatigue state of users by detecting EMG signals on the surface of human skin. The following is the realization of human muscle fatigue detection and performance index evaluation.

Before the test, all the participants used the massager of the same specification to relax their muscles for 2 minutes. All the participants adopted standing posture, with their arms drooping naturally, holding 1.5 kg dumbbells of the same specification, repeating wrist flexion and extension for 10 times, and taking the average value of the final experimental data for 10 times. The test environment is indoor. Indoor environment: the temperature is 26 degrees, and the wind is weak, so it is regarded as calm in Figures 10 and 11.

Sometimes outdoor activities are also carried out. In order to facilitate the detection of anti-interference index and the evaluation of anti-interference performance of the adaptive system, a group of interference tests are also carried out in outdoor environment in Figures 12 and 13. Outdoor environment: temperature is 6 degrees, and wind level is 3.

Experiments show that environmental factors have little influence on the response time and accuracy of the system. With the help of the proposed system, the fatigue state of human muscles can be monitored in real time. The sports injury risk assessment is helpful to the healthy management of muscle fatigue and has high popularization and use value.

5. Conclusion

Blockchain and Internet of Things technology are developing rapidly and vigorously and have become a new development normal in the process of realizing information management of daily life for modern people. Internet data fusion applied to wireless sports health detection is also increasing day by day. To solve the above problems, a sports injury risk assessment based on blockchain and Internet of Things is proposed. In this chapter, through the application of fuzzy D-S evidence theory algorithm in human motion monitoring system, we can judge whether the user's motion state is healthy or not according to the results of multisensor detection data based on blockchain and Internet of Things. Experiments on 50 subjects show that the algorithm has high accuracy in judging human sports health status, which accords with the application standards in normal environment and has certain practical significance. It is compared with the risk assessment algorithm of human motion injury based on weighted average data fusion. Fuzzy D-S evidence theory algorithm is more accurate than weighted average data fusion algorithm, and it is better and more stable in the overall performance. Finally, the detection of human muscle fatigue is studied, and two groups of experiments are carried out under indoor and outdoor conditions. Experiments show that environmental factors have little influence on the response time and accuracy of the system, and it can monitor the state of human muscle fatigue in real time.

In this paper, D-S evidence theory algorithm is used to fuse the data of different sensors, and the benefits are ideal in this paper. However, the correlation between collected data has not been demonstrated, and the memory relationship of data sets has not been further analyzed. It is necessary to use other methods to analyze the correlation of data first and further analyze the independent data, so as to determine which are the main factors.

Data Availability

The experimental data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declared that they have no conflicts of interest regarding this work.

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References

[1] T. Nakano, T. Sakai, and K. Kasuga, "Influence of noncognitive ability scores on physical fitness improvement: an examination using longitudinal data," *Medicine & Science in Sports & Exercise*, vol. 51, no. 6S, p. 831, 2019.

[2] Y. Zhang, Y. Zhang, X. Zhao, Z. Zhang, and H. Chen, "Design and data analysis of sports information acquisition system based on internet of medical things," *IEEE Access*, vol. 8, pp. 84792–84805, 2020.

[3] H. Wang, R. Yumei, and H. Wang, "Research on sports risk assessment method based on big data analysis," *Modern Electronic Technology*, vol. 10, pp. 140–142, 2018.

[4] H. Jing and T. Yungang, "Multi-sensor data fusion algorithm based on D-S evidence theory and fuzzy mathematics," *Acta Instrumentation*, vol. 6, pp. 644–647, 2017.

[5] L. Wu and H. Li, "Risk assessment of extreme rainfall climate change and sports stadium sports based on video summarization algorithm," *Arabian Journal of Geosciences*, vol. 14, no. 16, p. 1661, 2021.

[6] W. R. Johnson, A. Mian, D. G. Lloyd, and J. A. Alderson, "On-field player workload exposure and knee injury risk monitoring via deep learning," *Journal of Biomechanics*, vol. 93, pp. 185–193, 2019.

[7] S. Wang and X. Zhao, "Application research of internet of things technology in the causes of dragon boat sports injury," *Mathematical Problems in Engineering*, vol. 2021, 10 pages, 2021.

[8] F. He, "Early warning model of sports injury based on RBF neural network algorithm," *Complexity*, vol. 2021, 10 pages, 2021.

[9] J. Yang, H. Xia, Y. Wang, and H. Tian, "Simulation of badminton sports injury prediction based on the internet of things and wireless sensors," *Microprocessors and Microsystems*, vol. 81, no. 1, p. 103676, 2021.

[10] Z. Sheping, D. Hongyu, and L. Zhaozhao, "Blockchain technology: application and problems," *Journal of Xi'an University of Posts and Telecommunications*, vol. 23, 2018.

[11] S. Li, K.-K. R. Choo, Z. Tan, X. He, J. Hu, and T. Qin, "IEEE access special section editorial: security and trusted computing for industrial internet of things: research challenges and opportunities," *IEEE Access*, vol. 8, pp. 145033–145036, 2020.

[12] F. Chao, Z. Quan, and T. Chaojing, "Automatic proof of computationally reliable Diffie-Hellman key exchange protocol," *Acta Communications Sinica*, vol. 10, pp. 118–126, 2011.

[13] Z. Yi, "Simulation design of remote monitoring system for human physiological parameters based on single chip microcomputer system," *Journal of Changchun Normal University (Natural Science Edition)*, vol. 39, no. 4, pp. 28–31, 2020.

[14] J. Zhang and T. U. Guoping, "A new method to deal with conflicting evidence in D-S evidence theory," *Statistics and Decision Making*, vol. 13, no. 13, pp. 21-22, 2007.

[15] W. A. N. G. Gang, W. E. I. Shouzhi, and Z. H. A. O. Hai, "Research on decision-level information fusion algorithm based on fuzzy evaluation," *Computer Engineering and Application*, vol. 15, pp. 18-19, 2002.