Computer-Aided Design in Sports Nutrition and Health Data Analysis of College Students Using Artificial Intelligence Data Mining

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Abstract. This paper combines artificial intelligence and data mining to analyze college students' sports nutrition and health data to improve the analysis effect of sports nutrition and health data. It combines the policy gradient descent algorithm in reinforcement learning to provide a new data-driven controller for multi-rate sampling systems. Moreover, this paper conducts an extended dimension modeling for a general multi-rate sampling system, uses the expanded model to design a reinforcement learning controller, and then proposes a reinforcement learning controller design algorithm. The research verifies that artificial intelligence and data mining play a role in the analysis of nutrition and health data during college students' exercise and can provide good guidance for college students' physical health.

Keywords: artificial intelligence; data mining; college students; sports nutrition; health data; Computer-Aided Design.
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1 INTRODUCTION

Sports nutrition is a discipline that uses nutrition biochemistry and other related theories and technologies to evaluate and explore the characteristics of human metabolism and give targeted nutritional rehabilitation plans. Sports nutrition was born in the middle of the last century. So far, it has experienced decades of development history and formed an independent discipline system, which has contributed significantly to the development of modern sports. With the continuous development of social and economic levels, people's demand for sports and fitness is getting higher and higher, and sports nutrition is becoming more popular with the general public and shows a strong vitality. Human nutrition is an essential guarantee for sports. Whether competitive sports or social sports, it is necessary to study human nutrition comprehensively. We can achieve sound exercise effects and improve sports performance only with a healthy body.

How to scientifically handle the relationship between sports, learning, and physical development of college students so that they can achieve all-round development has become a topic of concern to many people, and it is also one of the critical areas of college physical education curriculum development at this stage. However, judging from the current development of physical education courses in colleges and universities, the development of sports, nutrition, and health courses for college students is basically at the theoretical level, and the practical content is less involved [14]. Judging from the current situation, most of the physical education courses in general colleges still have a certain lack of understanding; the understanding of sports nutrition is not comprehensive enough, and the physical nutrition of students is not fully considered in the process of arranging the amount of exercise, which leads to the application of recovery methodsIt is easy to imagine the development of the field of sports nutrition[11]. Due to various factors, most extracurricular sports activities in ordinary colleges and universities are not organized and managed uniformly and are in a "free mode." In this "free mode," most students stop exercising after playing with all their hearts and then eat and study with a high degree of fatigue, and it is difficult to get professional guidance. This exercise and learning mode suits students' physical and mental health. Very disadvantageous [6]. However, most students in ordinary colleges and universities need to learn more about sports recovery and nutrition. At the same time, because they have been away from sports nutrition for a long time, they are accustomed to uncontrolled exercise and nutritional requirements. Few people pay attention to this kind of disadvantage. The disadvantages of the state have long been farther and farther away from the development of modern society. The traditional college physical education curriculum mainly emphasizes cultivating students' motor skills and athletic ability and focuses on classroom teaching. Influenced by factors such as conventional educational concepts and educational utilitarianism, physical education in ordinary colleges and universities is more in the form of physical education and physical health education [12]. How to achieve a scientific balance between physical education courses and sports nutrition in ordinary colleges and universities so that the application of nutrition knowledge can be organically integrated into the physical education courses of common colleges and universities so that students can master more sports nutrition knowledge, cultivate students' awareness of scientific sports, and let students Achieving comprehensive development has become an issue that should be fully paid attention to in the process of sports development in ordinary colleges and universities under the background of the new era [16].

The so-called nutrition refers to the biological process of the body's intake, digestion, absorption, and utilization of nutrients in food to maintain life activities. Nutrition is the material basis of the body tissue; physical exercise can promote the body's digestion and absorption of nutrients and enhance its function [15]. The combination of reasonable nutrition and scientific exercise can effectively promote the healthy development of the body and significantly improve the health level and exercise ability. Therefore, to achieve good sports development, there must be appropriate nutritional guarantees [5]. With the development of sports science, people have in-depth research on sports and nutrients. In some developed countries, athlete nutrition and sports training have been organically combined to improve sports performance. The relationship between exercise and nutrients will be increasingly important in sports science [8]. In mass sports, the combination of sports and reasonable nutrition plays an increasingly prominent role in enhancing people's physique and health. Proper nutrition and moderate exercise effectively prevent and treat diseases that seriously endanger people's health, such as coronary arteriosclerosis, hypertension, coronary heart disease, diabetes, obesity, osteoporosis, etc. [2]. Only under reasonable nutrition can physical exercise enhance physical fitness and improve health. At the same time, nutritional means are also one of the most effective means of recovery after exercise. Reasonable nutrition can significantly improve the functional status of athletes; unreasonable nutrition will lead to physiological dysfunction, decreased exercise ability, and even disease and trauma [13].

The relationship between exercise and health is the relationship between means and ends. Whether training is beneficial to life and health has always been one of the issues that people are keen to discuss [10]. Nutrition is the foundation of physical health, and malnutrition will inevitably damage the body's health, significantly impacting life and learning. Universities must provide targeted guidance for college students who are malnourished. For example, special nutrition courses are set up so that students can understand the importance of nutrition and be more aware of the harm of nutritional imbalance. Let it actively change the quality and quantity of nutrient intake [9]. The so-called reasonable nutrition has the following requirements: First, all nutrients needed for the healthy development of the body should be ingested every day, including protein, fat, various vitamins, and trace elements [7]. Second, choose easily absorbed foods and increase appetite [3]. Third, the law should be enforced to include three meals a day, especially breakfast. Avoid eating foods that are harmful to the body [1]. Fourth, do not be a picky eater, do not partially eclipse, do not overeat, control your food intake, and stay away from the three high diseases of wealth [17]. A balanced intake of various nutrients has a positive effect on the body. It can provide all kinds of necessary nutrients for the body to maintain the body temperature at a constant level; it can also regulate and control the everyday life activities of the human body and can perform necessary actions on the human body when the human body is attacked and injured. 's repair. Only by reasonably and scientifically ingesting various nutrients needed for the body can the human body function better and ensure college students' healthy growth and development. Under balanced nutritional conditions, college students can have more abundant physical strength and flexible brains to improve study and work efficiency and interpersonal relationships [4].

This paper combines artificial intelligence data mining to analyze college students' sports nutrition and health data, improve the effective combination of their sports nutrition, and improve their physical and mental health.

2 DESIGN OF DATA-DRIVEN CONTROLLER FOR MULTI-RATE SAMPLING SYSTEM BASED ON POLICY GRADIENT DESCENT

Model-free reinforcement learning algorithms have two main branches: the reinforcement learning algorithm based on value function and the reinforcement learning algorithm based on policy gradient descent. However, the value function-based method and the policy gradient descent algorithm are developed on the classic reinforcement learning algorithm in the book. In the history of reinforcement learning algorithms, the Q-learning algorithm plays a pivotal role, and a commonly used Q-value function can be described as follows:

$$Q^{\pi_{new}}(s,a) = (1-\varrho)Q^{\pi}(s,a) + \varrho\left(r + \varepsilon \underset{a}{max} Q^{\pi}(s',a)\right) \tag{1}$$

Then, in the classical theory, the strategy π can be updated according to the following formula (2):

$$\pi^* = \underset{\pi}{argmax} Q^{\pi}(s,a) \tag{2}$$

The policy update brought by formula (2) has a big flaw when applied to the problem of continuous systems. In the literature, the author directly parameterizes the strategy π with the parameter θ and uses the cost function of the following formula to optimize:

$$J(\theta) = \mathbb{E}_{\rho\theta}[\sum_{t=0}^{\infty} \gamma^t r(s_t,a_t)] \tag{3}$$

Among them, $\rho_\theta = p(s_0)\pi(a_0|s_0)p(s_1|s_0,a_0)\cdots$. It can be seen from the literature that for this cost function, the descending gradient of the algorithm is

$$\nabla_\theta J = \mathbb{E}[\sum t \nabla_\theta \log \pi_\theta (a_t|s_t)(R_t - b_t)] \tag{4}$$

$R_t = \sum t' = t\gamma^{t'-t} r(s_{t'}, a_{t'})$ and $b_t$is a baseline value. Typically, $b_t = V_\theta(s_t) = \mathbb{E}_\theta[R_t|s_t]$ is chosen.

The Q function in (1) is called the action value function. Then, the advantage function $A = Q - V$ selects the action higher than the expected value in the current state. The advantage function is defined as follows:

$$A_\theta(s_t, a_t) = \mathbb{E}_\theta[R_t|s_t, a_t] - V_\theta(s_t) \tag{5}$$

A commonly used gradient descent estimation factor can be expressed as follows:

$$g = \mathbb{E}_t[\nabla_\theta \log \pi_\theta (a_t, s_t) A_\theta(t)] \tag{6}$$

Then, an optimizer is used to optimize the strategy replacement for such gradients. Generally, a stochastic gradient descent optimizer is used. This optimization composition is the most basic policy gradient descent algorithm.

In each iteration process, the trust region policy optimization algorithm will pass the current neural network parameter θ to the old neural network parameter θ_{old} and then optimize the policy with the following cost function:

$$J_{TRPO}(\theta_{new}) = \mathbb{E}_t\left[\frac{\pi_{\theta_{new}}(a_t, s_t)}{\pi_{\theta_{old}}(a_t, s_t)} A_{\theta_{old}}(t)\right] \tag{7}$$

The trust region policy algorithm adds a limit to prevent the step size from being too large. It uses KL (Kullback-Leibler) divergence to represent the difference between the two probability densities. This limit is:

$$KL[\pi_{\theta_{old}}|\pi_{\theta_{new}}] < \delta \tag{8}$$

First, an extended dimensional modeling of a general multi-rate sampling system will be carried out. Secondly, the reinforcement learning controller is designed by using the expanded model, and then the reinforcement learning controller design algorithm is proposed. The architecture of the overall reinforcement learning controller presented in this section is shown in Figure 1. Therefore, this section will start from these three parts.

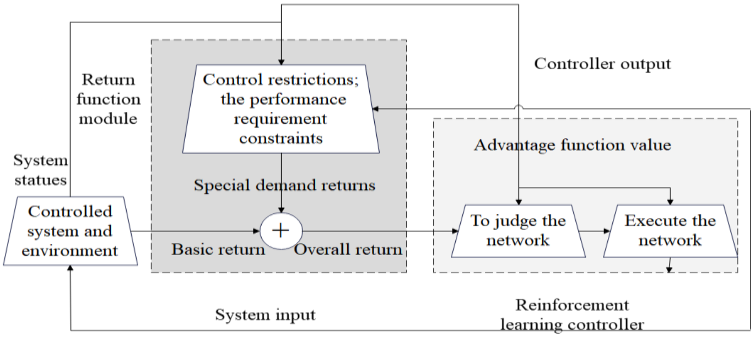

Figure 1: Data-driven controller model based on policy gradient descent algorithm.

An essential benefit of this dimension expansion method is that the controller utilizes the data collected by the system in the period $[(kN-N+1)h, kNh]$. Then, the controller outputs the system input with a span period $[kNh,(kN+N-p)h]$. This form of signal operation enables the implementation of neural networks. Therefore, a general multi-rate sampling system G is defined as follows:

$$\dot{x}(t)=A_c x(t)+B_c u(t) y(t)=C_c x(t) \tag{9}$$

By discretizing the matrix (9) with the period h, an equivalent linear discrete system G_d can be obtained as follows:

$$x(\tilde{k}+1)=Ax(\tilde{k})+Bu(\tilde{k})y(\tilde{k})=Cx(\tilde{k}) \tag{10}$$

Among them, $A=e^{A_c h}, B=\int_0^h e^{Ac\tau}\, d\tau B_c,\ C=C_c$.What is different here from Chapter 4 is that there are other periods between the input and the output, between the input and the output, and the sampling interval for measuring the q outputs is $n_1 h, n_2 h, \cdots and\, n_q h,$ respectively. Similarly, the period interval of p zero-order retainers is $m_1 h\ \ and\, m_2\, h \cdots m_p h$, respectively, and h is a positive integer. Then, we define the parameter N as the least common multiple of $m_1, m_2, \cdots m_p, n_1, n_2 \cdots n_q$. Then, according to the dimension expansion method provided by formula (4), the expanded system can be obtained.

$$\bar{x}(k+1)=\bar{A}\bar{x}(k)+\bar{B}\bar{u}(k)\bar{y}(k)=\bar{C}\bar{x}(k) \tag{11}$$

Despite the complexity of this model, it is ultimately linear and derivable. However, this chapter does not need a dynamic model of the system; it only needs to understand that the system depends on the actual model, and the algorithm in this chapter only needs input and output data. Therefore, the algorithm in this chapter needs more input and output data structures, and the input and output are not coupled. It is defined as follows:

$$\bar{x}(k)=\begin{bmatrix} x(kN-N+1) \\ x(kN-N+2) \\ \vdots \\ x(kN) \end{bmatrix} \bar{u}(k)=\begin{bmatrix} u_1 k \\ u_2 k \\ \vdots \\ u_p k \end{bmatrix}, \bar{u}_i(k)=\begin{bmatrix} u_i(kN) \\ u_i(kN+m_i) \\ \vdots \\ u_i(kN+N-m_i) \end{bmatrix} \bar{y}(k)=\begin{bmatrix} y_1 k \\ y_2 k \\ \vdots \\ y_q k \end{bmatrix}, \bar{y}_i(k)=\begin{bmatrix} y_i(kN-N+n_i) \\ y_i(kN-N+2n_i) \\ \vdots \\ y_i(kN) \end{bmatrix} \tag{12}$$

The following definitions are given.

$$r_t=r_a+r_s, r_s=\sum_{i=1}^{n} w_i r_{ci} \tag{13}$$

Among them, n is the number of constraints. Here, the particular demand return is determined to include two parts: the performance index demand return and the limit exceeding the penalty return. r_{ci} represents the reward of the i_{th}-th constraint, and w_i is the weight coefficient of the reward r_{ci}. However, this performance index may be different in different application situations. For this chapter's tracking problem to be solved, this indicator makes the tracking errors $(e(t))$ smaller and smaller. Therefore, we set r_a at time t to be:

$$r_a(t)=-|Qe(t)| \tag{14}$$

Among them, Q is the tracking performance parameter matrix, which the user needs to give before the algorithm training. Next, the weight matrix of the particular demand return r_s is defined as:

$$w_i=\begin{cases} 1, & r_{ci}<\underline{r_{ci}} \\ \sigma_i, & r_{ci}\geq \underline{r_{ci}} \end{cases} \tag{15}$$

r_{ci} is the reward value corresponding to condition c_i, $\underline{r_{ci}}$ is the reward trigger point of condition c_i, and σ is a sufficiently small rational number, which needs to be defined by the user, and $\sigma_i = 0.1, i = 1,2,\cdots,n$. When the reward is higher than the trigger point, the agent does not need it, reducing its impact on the agent and hoping that other conditional optimizations will affect the agent more.

t_{exp} is the rise time of the step response expected by the user; $e_s(t)$ is the error signal, e_m is the maximum tolerance value of the error signal $e_s(t)$ during the training process, and $\varphi = 0.5|e_m|$.

Condition c_1:If it is assumed that the tracked signal is $s_c(t)$ and the corresponding curve tracked has no or very little overshoot, then:

$$r_{ci}(t) = \begin{cases} -h\dot{e}_s(t), if\ \dot{e}_s(t) > \bar{c}_1 \\ 0. \qquad otherwise \end{cases}, \underline{r_{ci}} = 0 h = \xi_1 \frac{|e_m|}{\bar{c}_1}, \bar{c}_1 = 2\frac{\varphi}{t_{exp}} \tag{16}$$

Among them, ξ_1 is a hyperparameter, and $\xi_1 = 20$ is chosen in this section.

Condition c_2: If it is assumed that the interfering signal is $\omega(t)$ during training and the upper limit it can tolerate is $\bar{\epsilon}$, then for the tracking problem of the error signal $e_s(t)$, there are

$$r_{ci}(t) = -\left|\frac{\|e_s(t)\|_\infty}{\|\omega(t)\|_\infty}\right|, \underline{r_{ci}} = \bar{\epsilon} \tag{17}$$

Condition $assumes$ that the system has a strict signal limit. For a signal $s_u(t)$, its constraint is $\left[\underline{s_u}, \overline{s_u}\right]$. Then, for the tracking problem of this error signal $e_s(t)$, we set $\underline{r_{ci}} = 0$ and set:

$$r_{ci}(t) = \begin{cases} -|e_m| - \frac{\xi_2|e_m|}{|\overline{s_u}|+|\underline{s_u}|}(s_u(t) - \overline{s_u}), if \quad s_u(t) > \overline{s_u} \\ |e_m| - \frac{\xi_2|e_m|}{|\overline{s_u}|+|\underline{s_u}|}(\overline{s_u} - s_u(t)), if \quad s_u(t) < \overline{s_u} \\ 0. \qquad\qquad otherwise \end{cases} \tag{18}$$

Among them, ξ_2 is a hyperparameter, and $\xi_2 = 10$ is chosen in this section.

Based on the above introduction, $r_{ci}, i = 1,2,\cdots,n$ can be used to describe this multi-conditional controller design problem, and the weight w_i is used to reduce the impact of special requirements on the performance of the main target when the performance is roughly satisfied. Then, the total return r_t consisting of these two returns can be used to describe the control objective.

From formula (3) and the above description, it can be known that the goal of the algorithm is to collect all the rewards, so the expected cost function under the random strategy π is described as:

$$J_\pi = \mathbb{E}_{s0,a0,\cdots}[\sum_{t=0}^{\infty} \gamma^t r(s_t)] \tag{19}$$

γ is the decay factor constant, and $r(s_t)$ is the reward in state s_t. Then, according to formula (13), there are:

$$\mathbb{E}_{s0,a0,\cdots}[\sum_{t=0}^{\infty} \gamma^t r(s_t)] = \mathbb{E}_{s0,a0,\cdots}[\sum_{t=0}^{\infty} \gamma^t r_a(s_t)] + \sum_{t=0}^{n} \mathbb{E}_{s0,a0,\cdots}[\sum_{t=0}^{\infty} \gamma^t w_i r_{ci}(s_t)] \tag{20}$$

At the same time, according to formula (15), within the tolerance range, σ_i is sufficiently small that there is:

$$J_\pi = \mathbb{E}_{s0,a0,\cdots}[\sum_{t=0}^{\infty} \gamma^t r(s_t)] \approx \mathbb{E}_{s0,a0,\cdots}[\sum_{t=0}^{\infty} \gamma^t r_a(s_t)] \tag{21}$$

In the following derivation, we define $r(s_t) = r_t(s_t)$. At the same time, the definition of the value function V_π is given here, and the definition of the action-value function Q_π is as follows:

$$V_\pi(s_t) = \mathbb{E}_{a_t,s_{t+1}\cdots}[\sum{}_{t=0}^{\infty}\gamma^m r(s_{t+m})]Q_\pi(s_t,a_t) = \mathbb{E}_{s_{t+1},a_{t+1},\cdots}[\sum{}_{t=0}^{\infty}\gamma^m r(s_{t+m})] \quad (22)$$

Next, we define the advantage function A_π, and $A_\pi(s_t,a_t) = Q_\pi(s_t,a_t) - V_\pi(s_t)$ is mentioned in the previous subsection. Then, when the update strategy occurs, that is, the old strategy π_{old} is updated to the new strategy π_{new}, the following equation is handy, and the detailed proof can refer to the literature.

$$J_{\pi_{new}} = J_{\pi_{old}} + \sum_s \rho\pi_{new}(s)\sum_a \pi_{new}(a|s)A_{\pi_{old}}(s,a). \quad (23)$$

Among them, $a_t = \pi_{new}(a_t|s_t)$and $s_{t+1} = P(s_{t+1}|s_t,\ a_t)$.

ρ_π is defined as the decaying access frequency:

$$\rho_\pi(s) = P(s_0 = s) + \gamma P(s_1 = s) + \gamma^2 P(s_2 = s) + \cdots \quad (24)$$

Then equation (23) can be rearranged as:

$$J_{\pi_{new}} = J_{\pi_{old}} + \sum_s \rho\pi_{new}(s)\sum_a \pi_{new}(a|s)A_{\pi_{old}}(s,a). \quad (25)$$

This cost function reaches its lowest point when the expected advantage function equals 0. However, under some conditions, due to the estimation error of the value function $V_{\pi_{old}}(s)$ or the step size being too long, the expected advantage function of the state will be positive. From another angle, it is $\sum a\,\pi_{new}(a|s)A_{\pi_{old}}(s,a) > 0$. To solve this problem, this chapter applies a conservative strategy of iterative update. Formula (25) can be transformed into the following inequality.

$$J_{\pi_{new}} \leq L_{\pi_{old}}(\pi_{new}) + \varepsilon D_{KL}^{max(\pi_{old},\pi_{new})} \quad (26)$$

The variables can be represented as follows:

$$L_{\pi_{old}}(\pi_{new}) = J_{\pi_{old}} + \sum_s \rho\pi_{new}(s)\sum_a \pi_{new}(a|s)A_{\pi_{old}}(s,a)\ D_{KL}^{max(\pi_{old},\pi_{new})\underset{s}{max}_{KL}(\pi_{old}(\cdot|s)||\pi_{new}(\cdot|s))}\varepsilon = \frac{2K\gamma}{(1-\gamma)^2}, \mathrm{K} = \underset{s}{max}|\mathbb{E}[A_{\pi_{old(s,a)}}]| \quad (27)$$

D_{KL} is the KL divergence, which was mentioned before. The above inequality is replaced by the estimation form of the sampling form using resampling, and q is used as the sampling distribution for the state particular step; here are:

$$\sum_s \rho_{\pi_{old}}(s)[\cdots] = \frac{1}{1-\gamma}\mathbb{E}_{s\sim\rho_{\pi_{old}}}[\cdots]\sum_a \pi_{new}\,(a|s)A_{\pi_{old}}(s,a) = \mathbb{E}_{a\sim q}\left[\frac{\pi_{new}(a|s_k)}{q(a|s_k)}A_{\pi_{old}}(s_k,a())[]\right] \quad (28)$$

In practical application, the old strategy π_{old} is generally used to simulate and generate data, and this series of data is $s_0,\ a_o, s_1,\cdots$. In this way, $q(a|s) = \pi_{old}(a|s)$ can be obtained, and then by derivation, we have:

$$L_{\pi_{old}}(\pi_{new}) = J_{\pi_{old}} + \frac{E(s_k,a_k)}{1-\gamma}E(s_k,a_k) = \mathbb{E}_{a\sim q,s\sim p_{\pi_{old}}}\left[\frac{\pi_{new}(a_k|s_k)}{q(a_k|s_k)}A_{\pi_{old}}(s_k,a_k\ )\right] \quad (29)$$

From formula (26), the resulting penalty factor is a considerable g. Therefore, the authors assume that a constant $D_{KL}^{max(\pi_{old},\pi_{new})}$ is given in the literature. This paper finds that when the policy is updated, the cost function $J_{\pi_{old}}$ is independent of the new neural network parameter π_{new}. The objective can then be used to minimize $E(s_k,a_k)$, equivalent to reducing $L_{\pi_{old}}(\pi_{new})$.

In the controller research based on reinforcement learning, the return $r(s_k)$ is generally not greater than 0 and is usually harmful. The study uses the parameter θ to parameterize the policy $\pi(a|s)$. Then, rewrite the derivation process just now to get the following equation:

$$\underset{\theta}{max}\,\text{imize}^{\text{E}}\left[\frac{\pi_{\theta_{rgw}}(a_k|s_k)}{\pi_{\theta_{\partial di}}(a_k|s_k)}A_{\theta_{\partial di}}(s_k,\mathrm{a}_k)\right]$$
$$\text{subject to } D_{KL}^{max}(\pi_{\text{old}},\pi_{\text{new}}) < \text{ò}.. \tag{30}$$

Next, we further optimize formula (30) and define:

$$Tanh(x) = \mu \times \frac{e^{v(x-1)} - e^{-v(x-1)}}{e^{v(x-1)} + e^{-v(x-1)}} + 1, \Upsilon_t(\theta) = \frac{\pi_{\theta_{new}}(a_k|s_k)}{\pi_{\theta_{old}}(a_k|s_k)} \tag{31}$$

Among them, μ and v are both user-defined hyperparameters. Compared with formula (30), this chapter uses the following formula to optimize the strategy:

$$\underset{\theta}{max}\,\text{imize}^{\text{E}}\left[min\left(\Upsilon_t(\theta)A_{\theta_{\text{odd}}},\text{Tanh}\left(\Upsilon_t(\theta)\right)A_{\theta_{\text{did}}}\right)\right] \tag{32}$$

Based on formulas (30) and (32), the relationship between the objective optimization function and the neural network parameter ratio can be obtained, as shown in Figures 2 and 3. Here, we set the hyperparameters in formula (32) to be $\mu = 0.2$ and $v = 5$.In formula (30), the hyperparameter $\epsilon = 0.01$ is used. It is also assumed that under the old neural network parameter π_{old}, the neural network parameter ratio $\Upsilon_t(\theta)$ has an upper bound of 1.5 and a lower bound of 0.2.

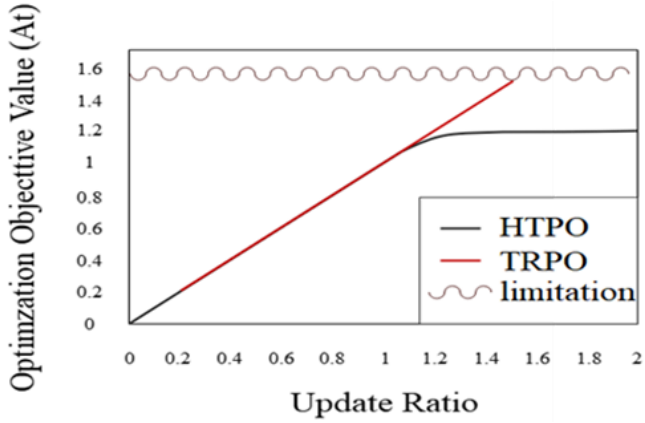

Figure 2: The relationship between the objective optimization function and the neural network parameter ratio (the Part Greater Than Zero).

From the definition of the neural network parameter ratio $\Upsilon_t(\theta)$, it can be seen that when $\Upsilon_t(\theta) = 1$ is, the new neural network parameters do not change compared to the old neural network parameters. In the TRPO algorithm, the strategy replacement is calculated using the conjugate gradient descent method. Before this calculation process, the TRPO algorithm still needs to derive the constraints twice, which is time-consuming. Formula (31) is defined as HTPO in this paper. In this paper, HTPO can not be used for derivation, so it is swift, saving convergence time and training time.

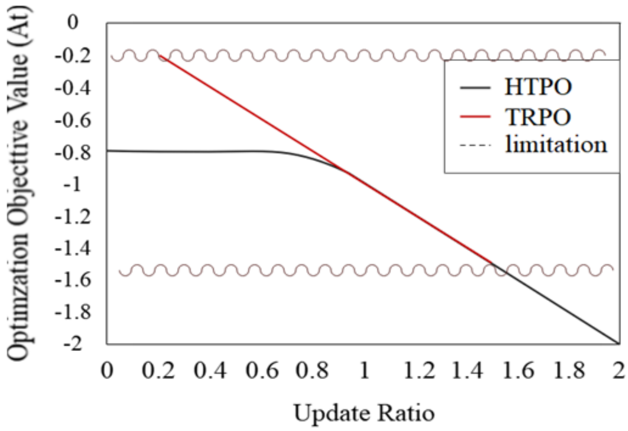

Figure 3: The relationship between the objective optimization function and the neural network parameter ratio (the part less than zero).

Next, we will introduce the controller implementation part in Figure 1. This implementation part is mainly based on the judgment-execution neural network architecture. The figure shows that the data-driven controller utilizes the collected reward function information and state information to return the output signal to the multi-rate sampling system as the system input. Then, the back-propagation neural network shown in Figure 4 is used to realize the controller's controller and the back-propagation neural network shown in Figure 4 is used.

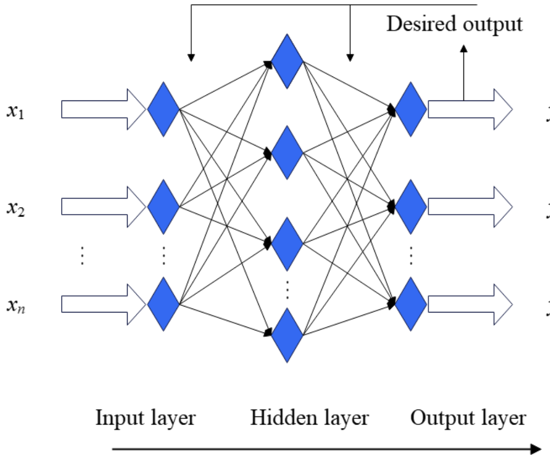

Figure 4: Artificial neural network.

For the judgment neural network part, this chapter adopts a three-layer neural network, which is defined as follows:

$$V_\phi(s) = W_1^T \varphi(W_2^T s + b_2) + b_1 \tag{33}$$

W_1 and W_2 are weight matrices, and b_1 *and* b_2 are offsets. The neural network uses the ReLu activation function $\varphi(\cdot)$ for this.

For a multi-rate system, the input is the data $\bar{y}(k)$ sampled over Nh. For sign unification, the measured output here is state s_t. The neural network's output is the value function based on the value judgment $V_\phi\big(s(t)\big)$ under the current state data.

For the judgment part, the purpose of the neural network controller is to minimize the advantage function $A_{\theta_{old}}(s_t)$, so there is:

$$A_{\theta_{old}}\big(s(t)\big) = \sum_{t^{\prime}>t} \gamma^{t^{\prime}-t} r(t^{\prime}) - V_\phi\big(s(t)\big) \tag{34}$$

Then, for a batch of time $T \times Nh$, the cost optimization function is defined as:

Therefore, the parameter ϕ of the judging neural network can be updated using the formula (35). The primary purpose of judging the neural network in this part is to make the surrounding reward environment (performance requirements, boundary conditions) described by the value function $V_\phi\big(s(t)\big)$ more and more accurate and meet the expected requirements.

The execution neural network is similar to the judgment neural network, but the output is $\bar{u}(k)$, with two output judgments for each parameter. The input is $\bar{y}(k)$, and the output is $\big(\bar{u}(k)\big)_{std}$ and $\big(\bar{u}(k)\big)_{mean}$. The reason for this is to investigate the neural network strategy. The final implementation is a probability density distribution. Because the probability density distribution can spread over the entire continuous space, not only but also because other values are tiny probabilities, which can stimulate exploration. Thus, the output is defined as $u_{\,mean}(t)$ and $u_d(t)$, corresponding to $\big(\bar{u}(k)\big)_{mean}$ and $\big(\bar{u}(k)\big)_{std}$, respectively, so there are:

$$u_{mean} = W_{1m}^T \varphi_2(W_2^T s + b_2) + b_{1m} u_d = \varphi_1\big(W_{1d}^T \varphi_2(W_2^T s + b_2) + b_{1d}\big) \tag{36}$$

W_{1m}, W_{1d} and W_2 are weight matrices, and b_{1m}, b_{1d} *and* b_2 are offsets. $\varphi_1(\cdot)$ and $\varphi_2(\cdot)$ are the soft plus and ReLU activation functions, respectively.

In the execution neural network part, the goal is to optimize an execution strategy as quickly as possible. According to formula (32), there is:

$$J_{actor}(\theta) = \sum_{t=1}^{T} min\Big(\Upsilon_t(\theta) A_{\theta_{old}}(t), Tanh\big(\Upsilon_t(\theta)\big) A_{\theta_{old}}(t)\Big) \tag{37}$$

The algorithm obtains $A_{\theta_{old}}(t)$ from the judging neural network part and then uses the optimization equation $J_{actor}(\theta)$ to optimize the execution neural network parameter θ.

3 SPORTS NUTRITION AND HEALTH DATA ANALYSIS OF COLLEGE STUDENTS BASED ON ARTIFICIAL INTELLIGENCE DATA MINING

This paper combines the artificial intelligence data mining algorithm proposed above to analyze college students' sports nutrition and health data. It conducts research through multiple data sets and obtains the results shown in Figure 5 and Figure 7.

The survey found that the current state of college students' physical health could be more optimistic, and the identification and conditioning of college students' constitutions should be carried out in depth. Physical fitness identification can guide the physical conditioning work so that the related work of physical fitness improvement of college students can be targeted. Moreover, the identification method is objective and easy to implement.

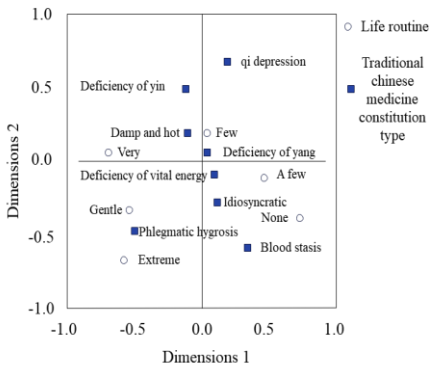

Figure 5: Correspondence analysis of daily routine and physical type.

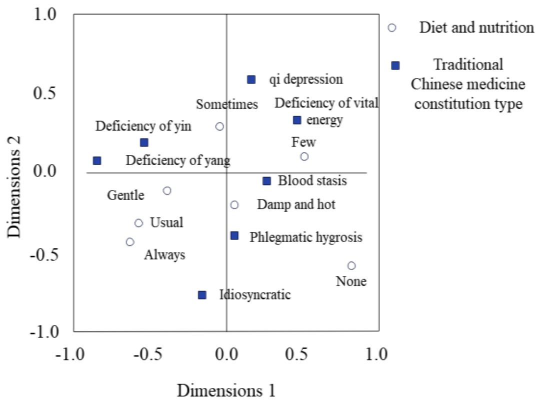

Figure 6: Correspondence analysis of dietary concepts and physical types.

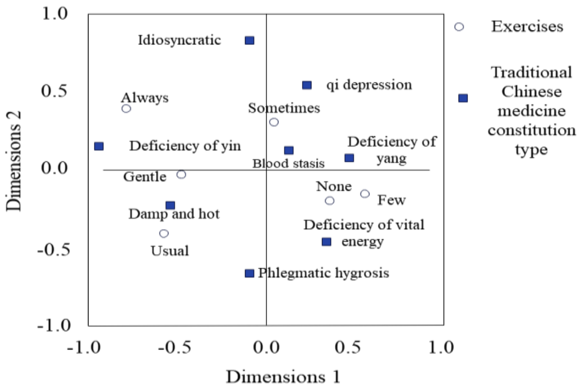

Figure 7: Correspondence analysis of exercise habits and physical types.

Therefore, the school hospital can introduce products such as physique identification software, instruments, and traditional Chinese medicine health management systems to identify the physique of new students entering the school. After identification, they can make personalized recommendations, conduct regular reviews, and dynamically monitor students' physical fitness. According to the results of physical fitness identification, the sports department can offer physical education courses suitable for various physical constitutions, guide students to choose courses according to their physical fitness and set up physical conditioning courses. Schools without a school hospital can cooperate with community hospitals to jointly carry out the work of physical conditioning of students. Correspondence analysis found that the three lifestyle factors of college students work and rest rules, dietary concepts, and exercise habits were strongly correlated with the physical type of college students. Therefore, we can start from these aspects to conduct the conditioning work of college students' physiques. In the current environment of changing social lifestyles, the lifestyle problems of college students are becoming more prominent. When college students leave their parents, most schools manage their lives loosely, and students with poor self-control stay up late at night to surf the Internet, etc., and their lives are irregular.

Moreover, they need to pay more attention to their diet and eat in some small restaurants or mobile vendors around the school, making it challenging to guarantee hygiene and nutrition. At the same time, due to the impact of the network, sports and physical activities are significantly reduced. The specific work of physical conditioning of college students can be jointly carried out by the Academic Affairs Office - School Hospital - Academic Affairs Office - Sports Department. First of all, it is necessary to carry out relevant popular science education in the form of micro-courses in the public elective courses of the university and set up a "preventive treatment" center in the school hospital. The Sports Department is responsible for constructing healthy lifestyles and sports patterns for college students, and the Academic Affairs Office cooperates with guidance and supervision. In addition, the school's Ministry of Education, Sports, hospitals, canteens, and other relevant departments can strengthen publicity and education, hold lectures, create an atmosphere, help college students establish a healthy lifestyle, and actively regulate their physique.

From the above research, it is verified that artificial intelligence and data mining play a specific role in analyzing college students' sports nutrition and health data and can provide good guidance for college students' physical health.

4 CONCLUSIONS

Suppose the nutrient supply of college students needs to be increased in physical training or competition. In that case, they will experience physical fatigue and a decline in sports performance, affecting the results of sports and competition. On the contrary, if college students have a very reasonable diet and can obtain timely nutritional supplements during exercise, their sports performance or training effect will also be ideal. Scientific sports training can show better training effects with the assistance of sports nutrition. It can provide the necessary nutrition for the exertion of various sports skills of college students, reduce sports injuries, and prolong sports life. This paper combines artificial intelligence data mining to analyze college students' sports nutrition and health data to improve the practical analysis of their sports nutrition. The research verifies that artificial intelligence and data mining play a specific role in studying college students' sports nutrition and health data and can provide good guidance for college students' physical health. Integrating CAD tools in sports nutrition planning and AI-driven data mining for health analysis among college students engaged in sports offers a promising avenue for personalized and optimized nutrition strategies. This approach could enhance athletic performance, recovery, and overall well-being. Still, careful attention to data ethics and accuracy is essential for its successful implementation and acceptance within the sports science community.

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