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Article

Monitoring of biochemical indicators before and after quantitative load exercise for athletes based on computational intelligence

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Abstract: Biochemical monitoring of sports training is a major part of training monitoring. It uses biochemical methods and techniques to measure some biochemical indicators in athletes during training, so that athletes can maximize their sports ability. But for a long time, people's awareness of the importance of biochemical indicators monitoring of athletes is not enough, which is one of the main factors that restrict and affect the development of athletes themselves. In this paper, computational intelligence technology is used to research and analyze various indicators and strengths of athletes' load intensity. It takes the changes of creatine kinase, heart rate and hemoglobin before and after quantitative load exercise as the entry point. And through this intelligent technology, the changes in the index data can be objectively and accurately reflected, so that it is hoped that the subsequent practical training can be guided more scientifically and the blindness of training can be reduced. The results showed that the activity of serum CK (creatine kinase) enzyme increased, and the heart rate also reached a peak immediately after training, which indicates that after the optimization of the training model, these biochemical indicators can make more scientific analysis of training volume, training intensity and recovery status. Among them, the maximum difference between the values of CK and BU (blood urea) is 10. At the same time, it can also provide some reference and reference for formulating more reasonable training methods and plans in the later stage and adjusting exercise load in time.

Keywords: computational intelligence; quantitative load exercise; biochemical index monitoring; training intensity

1. Introduction

With the vigorous development of the Olympic Movement and the concept of "Sports for All", competitive sports competitions have intensified. Therefore, how to use algorithms and technologies to implement scientific and effective exercise plans for players, so as to further improve players' physical ability and sports performance, is a problem that researchers are thinking about and paying attention to.

Athletes' athletic ability is affected by many factors. At present, scientific and reasonable biochemical indicators are used to monitor the function of athletes, and some intelligent algorithms are used to optimize them, so there is little research on guiding sports practice. Therefore, this paper uses computational intelligence technology to measure the changes of a series of biochemical indicators before and after exercise, so as to verify the effectiveness and rationality of training model optimization, and has certain guiding significance for athletes' training arrangements. The innovation of this study lies in the application of computational intelligence technology to the monitoring and analysis of biochemical indicators of athletes, which is an area less covered in the existing literature. Through the combination of intelligent algorithm and sports science, the physiological changes of athletes before and after training can be reflected more accurately, which provides a basis for making a more scientific training plan.

The change of biochemical indexes directly reflects the motion state of organisms, which provides a new way for people to study the characteristics of biological motion. At the same time, more and more experts and scholars also began to pay attention to this point. Jones et al. investigated the use of physiological and biochemical indicators to monitor training load and fatigue in football players, and analyzed indicators such as heart rate, heart rate variability, and biochemical variables such as blood lactic acid and urea. The research results show that these indicators can effectively reflect the training status and fatigue level of athletes [1]. Marchewka discussed the effects of intermittent hypoxic training on selected biochemical indexes, hemorheological characteristics and red blood cell metabolic activities of rowers, and found that hypoxic training significantly improved athletes' performance, which was specifically manifested in the increase of red blood cell deformation ability and maximal oxygen uptake [2]. Ghoul et al. evaluated changes in selected biochemical markers in mixed martial arts athletes over a 14-week training cycle. Serum testosterone, cortisol, uric acid, myoglobin, total protein, creatine kinase, interleukin-6, and tumor necrosis factor were measured at different time points, and it was found that myoglobin and interleukin-6 increased significantly after the race, while other indicators such as cortisol and testosterone did not change significantly [3]. Tang et al. studied changes in hematology and biochemical markers in professional wrestlers, focusing on physical adaptation and load balance at different training stages. Studies have found that levels of interleukin-6 in wrestlers rise during training, while levels of interleukin-12 and interleukin-13 decrease, indicating changes in the immune response after strenuous exercise [4]. The above experts and scholars analyzed the role of biochemical indicators from different angles, but did not reveal the real reason for the change of these indicators from the point of view of data. Compared with these studies, the innovation of this paper lies in the real-time monitoring and dynamic analysis of athletes' biochemical indexes by computational intelligence technology, which makes the evaluation of training effects more accurate and detailed.

Computational intelligence can directly analyze data without relying on problems, so we refer to a series of related literatures. Utkarsh proposed a consensus-based distributed strategy and a consensus-based distributed CI (Computational Intelligence) technology for real-time optimal control of smart distribution networks with a large number of DGs (Distributed Generators) and CLs (Controlled Loads). The method he proposed treats each DG or CL as a separate private entity. Through simulations on a distributed test system of 149 nodes, he demonstrated the effectiveness of the method in terms of convergence, adaptability and optimality relative to centralized and benchmark algorithms [5]. Chen examined whether computational intelligence (CI)-inspired tools can effectively aggregate the rich information generated by the Web 2.0 economy to improve the quality of decision-making. More precisely, he focused on whether CI-driven sentiment analysis can generate signals such as prices, and whether CI can handle unstructured text data better than the market. He believed that the Web 2.0 economy may not be able to get rid of the information overload problem that has coexisted with the market for a long time [6]. Liu aimed to develop algorithms for music composition, and attempts to provide an overview of computational intelligence techniques used in music composition. First, he reviewed existing methods in terms of the main musical elements, wit, musical form, melody and accompaniment considered in the composition. Second, he also focused on the application of evolutionary algorithms and neural networks in music creation [7]. Aldhafferi developed a sensitivity-based linear learning method (SBLLM) to train a two-layer feedforward neural network to estimate the RCP (Relative Cooling Power) of manganese oxide-based materials with ionic radius and doping concentration as model inputs. He used the Gravitational Search Algorithm (GSA) to optimize the number of epochs and hidden neurons of the network. The results of his GSA-SBLLM model are in good agreement with experimental measurements [8]. The above-mentioned experts and scholars have applied computational intelligence to many fields, but they have not expanded the field of sports, and their research is still not comprehensive enough.

In this paper, through a series of experimental analysis, the following data results are obtained: After a training according to the optimized model, both the CK value and the BU value have been greatly improved immediately. Most importantly, the average accuracy of the monitoring model based on computational intelligence can reach 78.45%. In addition, the range of numerical increases was more pronounced after two weeks of training compared to before and after one week of training.

2. Computational intelligence and quantitative load exercise and biochemical index monitoring

2.1. Computational intelligence

With the development of artificial intelligence technology, computational intelligence also develops. Computational intelligence is a multidisciplinary interdisciplinary technology, which mainly includes computer science, neuroscience, physiology and so on. The basic standards of computational intelligence technology are some functions and characteristics in nature, as well as the mechanism of biology. This technology is mainly based on the characteristics and goals of the problem that the user needs to solve, and then extracts the corresponding calculation model, and then designs an intelligent algorithm according to the model. The above is also the basic working principle of this advanced technology. When it works, it will use connected modules to cooperate and perform some intelligent processing of information. These modules include the improvement of knowledge methods, the accumulation of information perception, the exchange of fixed-point information and the implementation of task scheduling, etc. [9]. With the development of time, computational intelligence has also played a relatively strong advantage, which also makes it widely used. Different degrees of positive impact have been produced in daily production and life, such as optimized design and computing power, information security, pattern recognition technology, data classification and mining, image processing functions, and so on. **Figure 1** shows the security computing module of the big data intelligent network.

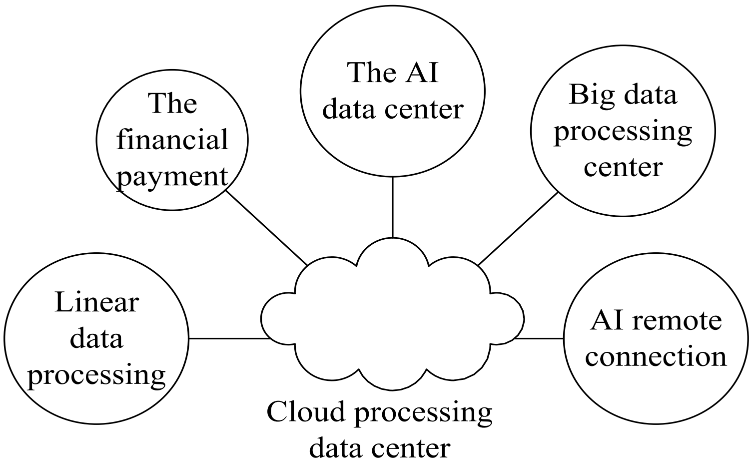

Figure 1. Secure computing module of big data intelligent network.

Next, the application of computational intelligence technology in the Internet of Things will be described in detail. This application mainly includes the following five functions, namely the collection and extraction of information and status, the extraction of services, the mining of data, and the classification of commands. First of all, the first function refers to the collection of sensors, display and processing. The human-machine interface agent plays an important role in this process. Its abbreviation is IA, that is, interface agent. The sensor will assign it a relatively random, and then use it to transmit information to the user in real time. The second function is to extract information. The main principle of this process is to collect the environmental information on the sensor nodes, and then transmit this information to the genetic neural network. Genetic fuzzy neural network is abbreviated as GFNN. The final status collector (CSC, complete status collector) will receive a series of data information and manage the information-aware agent, the information-aware agent is SA [10].

The third function has two branching functions, including generating commands and node management. The task to be performed by the former is to generate corresponding commands. These commands need to be able to play a controlling and leading role, and they perform a series of operations on the sensor. The management of the latter is mainly carried out through the nodes of information nodes and sensors. The fourth function is mainly responsible for the content of communication, and the communication revolves around the intelligent computing module and the database. The abbreviation of Intelligent Computing Module is ICM. GFNN will calculate the rules and operational capabilities in this process, and store the calculated data in the database for use. The specific operation process of the last function is: the user of the system inputs a series of commands in the terminal device, and uses some functions of the ICM to standardize and improve the commands. It should match it with the data retained in the database, and then repeat the operation of the previous function, that is, use GFNN to calculate the matching result [11]. After this function operation is completed, IA performs the next task, so that the user and the intelligent terminal interface can have interactive access. In order to show the process and function of the whole application more clearly, **Figure 2** lists the corresponding operation steps and measures.

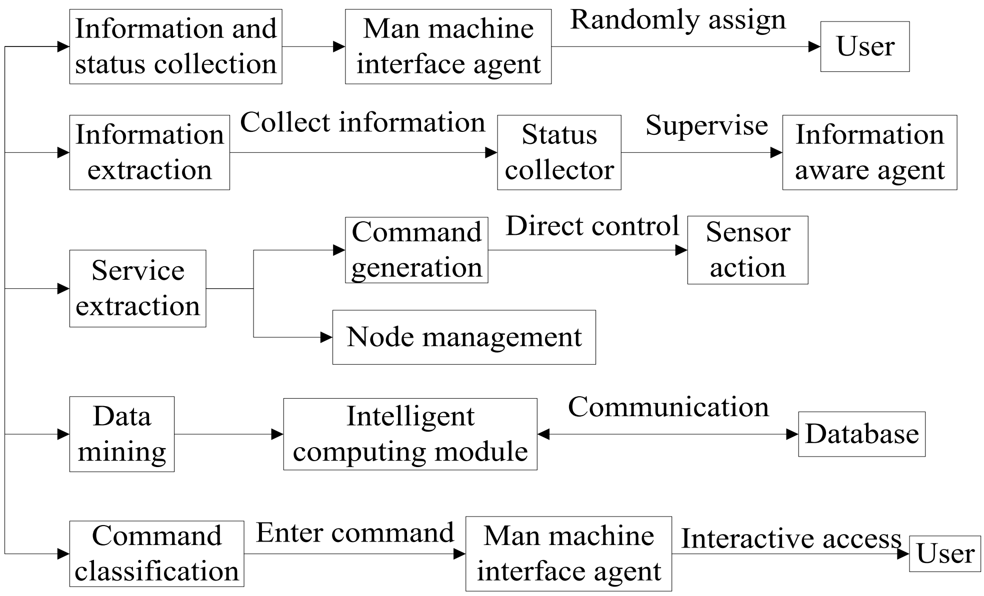

Figure 2. Application of computational intelligence technology in the Internet of Things.

Computational intelligence, also known as CI technology, is very cutting-edge. It is developed from artificial intelligence technology and represents the future development prospects of this field. Computational intelligence is a general method, which is designed by people inspired by the wisdom of nature, aiming to solve a series of complex problems, and has reached a new stage with the development of AI. It is one of the branches of intelligent technology. Generally, intelligence is divided into three central levels, namely artificial intelligence (AI), biological intelligence (BI) and computational intelligence (CI). The difference between the three is mainly reflected in the fact that the operating objects of CI are concentrated in data materials such as numbers and signals, and the dependence on knowledge is very weak. On the other hand, AI is just the opposite. It urgently needs the storage and absorption of knowledge to process various data information; biological intelligence is biased towards the intelligent behavior and operating habits of living things [12]. Nowadays, with the rapid development of intelligence and information technology, the distinction and boundary between the three are gradually blurred, and they have strong parallelism in the actual process in various fields of society. However, from the standpoint of applied technology alone, computational intelligence stands out among the three because of its intelligence and robustness. More importantly, it has extremely powerful adaptive and global search capabilities, of which the two most powerful are the computational intelligence methods of evolutionary computing. Problems of different nature correspond to different computational intelligence solutions. **Table 1** lists several different computational intelligence methods.

Table 1. Application comparison of various computational intelligence methods.

CI method	Method characteristics	Application mode
Evolutionary computation	Rich diversity of solution sets, strong global search ability and complex implementation	Solve optimization problems and improve global search ability
Swarm intelligence	Fast convergence speed, retained search information	Solve optimization problem and speed up the convergence speed
Artificial neural network	Strong online learning ability and adaptability	Accurate demand prediction and optimization of station site selection
Fuzzy system	Strong ability of fuzzy cluster analysis, and simple implementation	Simple and invisible evaluation indexes, and the correlation relationship

The development of computational intelligence began in the 1950s, which was marked by the extremely famous "Turing Test" at that time, which was a scientific research experiment initiated on artificial intelligence, as shown in **Figure 3**. The development of computational intelligence has attracted great attention from researchers in related fields. According to the development of this algorithm technology, its research can be roughly divided into three stages, namely 1950–1969, 1970–1989 and after 1990. The first stage is called the initial stage. In this stage, several basic algorithms of computational intelligence have been proposed, including genetic algorithm (GA), evolutionary strategy (ES), evolutionary programming (EP) and so on. The second stage is called the development stage, GA and ES have been greatly developed in this stage, and their theoretical foundations are continuously improved by practice, so the boundaries between them are becoming more and more blurred. Later, two algorithms, analog degradation and tabu search, were proposed, which enabled the overall optimization of computational intelligence. The third stage is called the continuous development stage. In this stage, various algorithms have been updated and upgraded, so the performance experience of computational intelligence itself has also been greatly improved, and its application scope has also expanded [13]. In some special cases, computational intelligence will appear in combination, including fuzzy systems, neural networks and evolutionary computing, the three parts are different from each other, but also complement each other. First, the fuzzy system can play a very strong role in the description of things and the absorption of experience, and the reasoning ability is relatively strong. The neural network then acquires experience and improves skills from the database. Finally, the optimal solution or the best solution is searched through evolutionary computation.

Computational intelligence is one of the most important branches of artificial intelligence technology, which, like artificial intelligence technology, is also based on big data. Connectionism and behaviorism are very instructive for the development of computational intelligence, and it also refers to the structural mechanisms of biological evolution and cellular networks. The technology establishes connections with each other through a series of behavioral manipulations and training. In addition to parallelism and adaptability, its main features are distributed, self-organized and autonomous learning, etc. Computational intelligence uses these characteristics to process some non-procedural and non-numerical information [14]. It can be combined with various mathematical methods, so it has also produced many branches, among which the more common ones include artificial neural network, genetic algorithm and ant colony algorithm, etc. The specific situation is shown in **Table 2**. However, this technology also faces many application problems in the process of development. As we all know, when using algorithms to perform certain calculations, the first thing to do is to select parameters, but at this stage, computational intelligence is in the selection of parameters. It mainly relies on past experiments or empirical principles derived by scholars, but has not been verified by calculation. In the traditional sense, artificial intelligence technology is largely based on the mechanism of processing symbols. It is worth noting that compared with traditional algorithms, computational intelligence still has certain advantages, and it is more suitable for solving some large-scale and extremely complex problems. Therefore, in the current era of big data, the application prospects of this technology will definitely develop more and more broad.

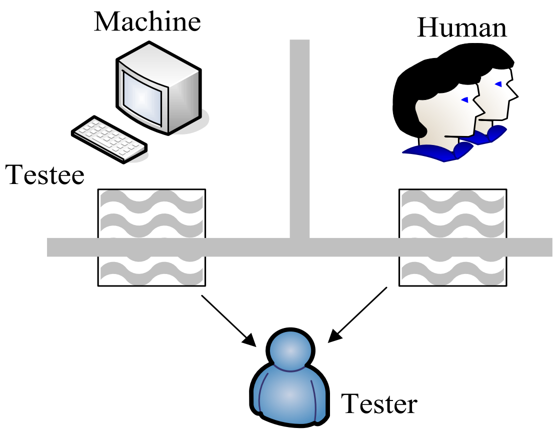

Figure 3. Schematic diagram of Turing test.

Table 2. Comparison of typical algorithms for computational intelligence and their applications.

Algorithms of CI	Composition unit	Structure		Application model	
Artificial neural network	Neuron	Recurrent networks	Forward network	Bidirectional associative memory	Boltzmann machine
Genetic algorithm	SGA	Selection, crossover	Variation and termination	Optimization problem	Production scheduling problem
Ant colony	TSP	Band clustering	Continuous orthogonal	Job shop scheduling problem	Vehicle routing problem

2.2. Quantitative load exercise

As the name suggests, quantitative load exercise refers to an exercise whose exercise intensity and exercise time are limited. In general, the intensity of quantitative load exercise will be lower than that of submaximal exercise. Under normal circumstances, exercisers can reduce the accumulation of blood lactic acid, accelerate the clearance rate, improve the body's acid resistance, and significantly reduce the level of blood and urine ammonia after performing quantitative load exercise [15]. The step test refers to the pulse test 1–3 minutes after the quantitative load exercise, which is one of the extremely important indicators that can well assess the functional level of the cardiovascular system. The following **Table 3** is a comparison of the heart rate data of a three-minute step test.

Table 3. Comparison of three-minute step test data.

Age	**18–25**		**26–35**		**36–45**		**46–55**	
Standard	**Male**	**Female**	**Male**	**Female**	**Male**	**Female**	**Male**	**Female**
Very good	< 79	< 85	< 81	< 88	< 83	< 90	< 87	< 94
Slightly good	90–99	99–108	90–99	100–111	97–103	103–110	98–105	105–115
Ordinary	100–105	107–117	100–107	112–119	104–112	111–118	106–116	116–120
Slightly poor	106–116	118–126	108–117	120–126	113–119	119–128	117–122	121–126
Very poor	> 128	> 140	> 128	> 138	> 130	> 140	> 132	> 135

In the monitoring report of quantitative load exercise, the indicator of load is often displayed. **Figure 4** shows the application process of load index in sports. Specifically, a quantitative external load acts on the body, and the body responds to external stimuli, thus creating an internal load. The load on the body can be measured in two ways, namely external load and internal load [16]. Among them, the external load is easily affected by a variety of factors, such as the daily training plan, difficult to quantify the environment and subjective emotions and so on. So this also leads to the effect of inaccurate quantification of exercise load by applying external load. In addition, individual differences in athletes and differences in training programs can also cause difficulties in quantifying exercise load.

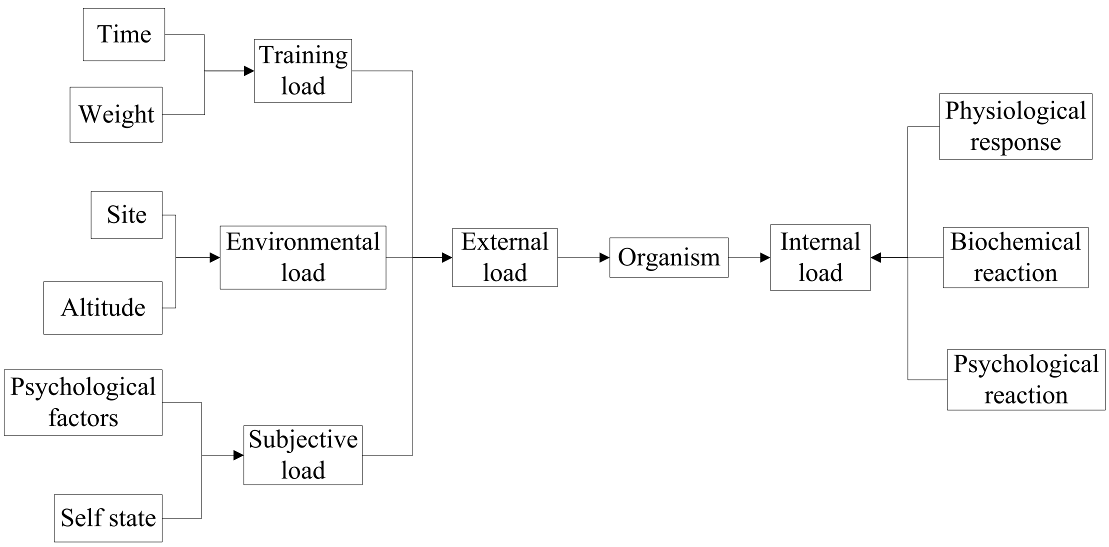

Figure 4. The specific process of quantitative load exercise.

2.3. Monitoring of biochemical indicators

In the process of training load monitoring, there are the following eight common physiological and biochemical indicators: HR (heart rate), BLa (blood lactate acid), CK (creatine kinase), Hb (hemoglobin), UPRO (urine protein), KET (urine ketone bodies), TESTO (serum testosterone) and BU (blood urea). Among them, the first five indicators are generally used to assess training intensity, while the last three indicators are used to assess training volume. Heart rate (HR) is an important indicator of heart load, and the more intense the training, the higher the heart rate. The increase of blood lactic acid (BLa) level indicates the enhancement of anaerobic metabolism and lactic acid accumulation. Creatine kinase (CK) is a marker of muscle injury, and its elevated level indicates that muscle fibers are damaged and that satellite cells are activated during repair. Changes in hemoglobin (Hb) levels reflect the oxygen-carrying capacity of the blood, which is usually temporarily reduced after training. Increased urinary protein (UPRO) and ketone bodies (KET) indicate impaired kidney function or abnormal energy metabolism. Serum testosterone (TESTO) is an important hormone index that reflects the total training load, and its decreased level indicates excessive training. Blood urea (BU) is a product of protein catabolism, and its increased level indicates higher training intensity or insufficient recovery. By monitoring the changes of these biochemical indicators, the training load and recovery state can be evaluated more scientifically, and the training plan of athletes can be guided. These indicators will be introduced one by one in the following.

1) Heart rate

HR refers to the heart rate, the full name is heart rate. If the heart rate during training or the immediate heart rate after a training session is tested, then the peak heart rate should be screened out. Before this, it is necessary to test the athlete's maximum heart rate and heart rate reserve as basic data for training intensity assessment. Heart rate is suitable for quantitative monitoring of low to moderate-intensity training and qualitative monitoring of high-intensity training. If the basal heart rate after training has increased by 5–10 beats/min from the usual heart rate, the athlete can be considered fatigued. Excessive fatigue is considered when there is an increased state for several consecutive days [17].

2) Blood lactate

BLa refers to blood lactic acid, the full name is blood lactic acid. The immediate value of an athlete after long-distance endurance training is the peak blood lactate. After short-distance training, it is most accurate to measure the value 1–5 minutes after stopping. Most importantly, the timing of blood sampling for athletes varies according to the duration and intensity of the exercise and the magnitude of the increase in blood lactate. Specifically, the longer the exercise time and the smaller the increase in blood lactate, the shorter the blood collection time. The opposite is also true, but the blood sampling time will not be longer than 5 minutes, so that the body's metabolism can be accurately estimated. This detection is suitable for quantitative analysis of various degrees of training intensity in addition to anaerobic training. In addition, blood lactate can also monitor the athlete's nervousness in a stable state.

3) Creatine kinase

CK refers to creatine kinase, the full name is creatine kinase. Under normal circumstances, the serum CK after a certain intensity of training is used for determination, especially after 20–30 minutes or the next morning after training. The higher the level of serum CK, the greater the intensity of exercise. When the organism adapts to the external environment, the increase in serum CK after training with the same load will decrease. It should be noted that the greater the decrease in the serum CK level the next morning, the better the recovery of the muscles of the athlete and the moderate training intensity [18]. If the effect after training is to be understood, blood samples can be taken within 2–6 hours after training and the peak value can be measured. If the serum CK level is significantly increased, it can be regarded as muscle damage. The conversion process of creatine kinase is shown in **Figure 5**.

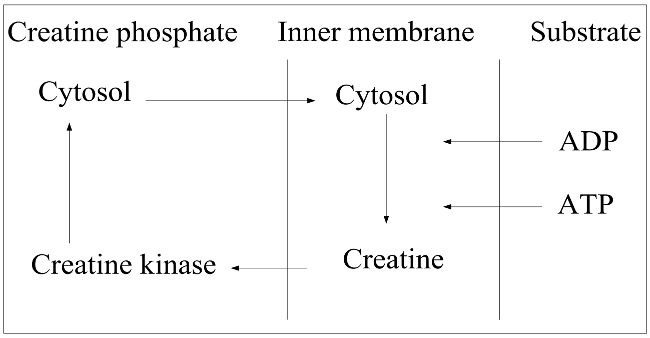

Figure 5. Creatine kinase conversion process.

4) Hemoglobin

Hb refers to hemoglobin, the full name is Hemoglobin or Haemoglobin. The main process of measuring hemoglobin is to measure the base value before exercise training, and then measure the recovery value the next morning after exercise training, and compare it with the base value before exercise. The greater the drop, the greater the intensity of the exercise and the greater the amount of exercise. Continuous testing of recovery values during periodic periods of exercise training allows monitoring of changes in training load intensity. Under normal circumstances, athletes can basically restore the hemoglobin level before training after 3 days of adjustment. At this time, the state is relatively good, and the training volume and training intensity are also relatively suitable. As the athlete gradually adapts to the external environment, the decline after training with the same load will decrease.

5) Urine protein

The full name of UPRO is urine protein, that is, urine protein. In general, the best results are obtained by testing about 15 minutes after endurance training. The higher the concentration of urine protein, the greater the intensity of exercise or the worse the physical function. This indicator is greatly affected by physical differences, so a more comprehensive and systematic observation of the subjects is required. However, as the athlete adjusts to the external environment, the increase in training with the same load will decrease. In general, this indicator will not be used alone to evaluate training load, but as an auxiliary indicator [19]. This indicator is also the best in the early morning of the next day of training. When the urine protein level drops significantly, it means that the athlete is recovering well and the training volume is appropriate. On the contrary, if there is no significant drop, it means that the training volume is too large.

6) Urinary ketone bodies

KET refers to urinary ketone body, the full name is Ketone. This auxiliary indicator generally takes value within 15 minutes after the end of the training session. The higher the concentration, the greater the training volume. Urinary ketone levels are elevated by a high-fat diet and lowered by sugar supplementation, so the test needs to rule out the interference of these factors. Under normal circumstances, this indicator will turn negative in the early morning of the next day of training, so the recovery of athletes has no practical guidance or reference for the evaluation of training volume.

7) Serum testosterone

TESTO refers to serum testosterone, the full name is testosterone. This index is mainly used to assess the total load of exercise training for more than one week, and the measurement cycle is once every two weeks, and the blood sampling is venous blood. If it is more than 20% lower than the normal sample value, it means that the training volume is too large, and the training intensity or training volume should be appropriately adjusted. It can be re-examined after 1 to 2 weeks. If the serum testosterone level does not rise, or even continues to decline, it indicates that the athlete is in a state of excessive fatigue. However, if its level has returned to a normal value, it means that the training volume has been adjusted appropriately and reasonably.

8) Blood urea

BU refers to blood urea, the full name is blood urea. This indicator is best measured within 20 minutes after the end of training, but if the measured value after exercise exceeds the measured value before exercise by more than 3 mmol/L, it indicates that the training volume is too large. When the increase value is around 2 mmol/L, the training volume is moderate, and when the increase value is around 1 mmol/L, the training volume is small. The next morning can be measured again, and the value of 8 mmol/L as the critical point, specifically: When the value drops to 8 mmol/L, it means that the recovery state is relatively good, and the training volume is relatively moderate; when the value does not drop significantly, or even remains higher than 8 mmol/L, it means that the training volume is too large. If you need to focus on the training effect, you need to measure the peak within 1 hour after training [20]. It should also be noted that high-protein diets tend to increase blood urea levels.

There are six general training methods: ATPCP (Anaerobic Threshold and Peak Cardio Performance) system training, maximum lactate training, lactate tolerance training, high-intensity interval endurance training, lactate threshold training, and maximum steady-state lactate training [21], as shown in **Table 4**.

Table 4. Quantitative load exercise training methods.

Training metabolic type	Maximum speed or strength exercise	Interval time(min)	HR (b/min)	BLa (mmol/L)	Metabolic functions
Anaerobic low lactic acid	> 95%	0.3–0.5	< 180	< 4	ATPCP energy supply system
Maximum lactate	About 1 min	3–5	> 180	> 15	Glycolysis (intensity) energy supply
Lactic acid resistant	85%–90%	4–5	180–190	10–12	Glycolysis (endurance) energy supply
Lactate threshold	About 1 min	> 30	140–180	4	Aerobic function (high intensity)
Maximal steady state lactate	10%–15%	> 30	160–170	< 4	Aerobic metabolism (long time)

For the convenience of distinction, these six training methods are represented by 1–6 respectively. The eight monitoring indicators mentioned above will change to varying degrees with the six different training methods, or increase or decrease, of course, in some special cases, they may remain unchanged, as shown in **Table 5**.

Table 5. Changes of monitoring indicators in different training methods

Training method	Development purpose	HR (b/min)	BLa (mmol/L)	CK	BU	Hb	UPRO	Ket
1	Maximum speed force	> 180	< 4	↑	→	→	↑/→	→
2	Maximum speed, strength and endurance	> 180	> 15	↑	↑/→	↓	↑	→
3	Sub maximum speed, strength and endurance	> 180	10–12	↑	↑/→	↓	↑	↑/→
4	Maximal aerobic metabolic capacity	> 160	About 9	↑	↑	↓	↑	↑/→
5	Maximal aerobic metabolic capacity	160–170	About 4	→	↑	↓/→	↑/→	↑/→
6	Aerobic endurance	< 160	< 4	→	↑	↓/→	↑/→	↑/→

2.4. Biochemical index coding and monitoring model

Many biochemical indicators of an athlete's body will change during exercise, which provides a data reference for us to study athlete's physical fitness and self-characteristics. In the practice process of index quantification, people gradually realize the necessity of establishing an index monitoring model.

Before modeling, we first need to encode the basic values of biochemical indicators as individual information in the search space of computational intelligence. In this process, it is necessary to consider the degree of applicability of encoding and decoding, so the most critical thing is to avoid extreme values in these individual information. Encodes a given set of basic values as follows:

$$\mathcal{X} = (Prior_1, Prior_2, \ldots, Prior_m) \tag{1}$$

$\mathrm{Prior_i}$ refers to the prior node of the i-th node. According to the basic algorithm of computational intelligence, the change process of the biochemical index data of athletes after training is as follows:

$$\mathcal{X}_i(r+1) = \mathcal{X}_i(r) + a * \left(\frac{\mathcal{X}_k(r) - \mathcal{X}_i(r)}{\|\mathcal{X}_k(r) - \mathcal{X}_i(r)\|} \right) \tag{2}$$

Among them, *i* refers to the index individuals that have changed, and *k* refers to the individuals with relatively high index values selected according to different training methods. *a* refers to the step size of the change, $\mathcal{X}_\mathrm{i}(\mathrm{t})$ refers to the value before individual *i* changes, and $\mathcal{X}_\mathrm{i}(\mathrm{t}+1)$ refers to the value after individual *i* changes.

After encoding the relevant values, the basic features of the values can be found from the encoding space, and this feature is the key to feature extraction for the encoding set.

$$T = m_i \sum_{i=1}^{n} |\Delta x_i| \tag{3}$$

$$\Delta x_i = \int_a^b (\sum \Delta x \sum_{i=1}^{n} n\%x)dx \tag{4}$$

Among them, T represents the feature index of the coding space, Δx represents the increment of the value, and m represents the error parameter in the feature extraction process. Under the constraints of various constraints, the eigenvalues of the data often change with the scale of the data, so the method of feature extraction needs to be adjusted.

$$x_i(t) = x_i(t-1) \xrightarrow{yields} x_j(t+1) \tag{5}$$

$$p_{ij}^{k} = \frac{\lim\limits_{k\to 0} \beta_{ij}^{\varepsilon}}{\sum_{i=1}^{n}\sum_{j=1}^{n} p\vartheta\mu^2} \tag{6}$$

$$\beta_{ij} = \sum_{ij\in A} \varphi_{ij}^{\alpha}\delta_{ij}^{\theta} \tag{7}$$

In the above formula, *t* represents the constraint of the data value, and β and p represent the position deflection and adjustment coefficient of the data value when the constraint condition is met. In this process, the constant change of the adjustment coefficient will directly affect the amount of information emitted by the data value. In addition, as the constraints continue to increase, so does the information and data required for modeling.

$$\tau_{ij}(t+n) = (1-\rho)\cdot\tau_{ij}(t) + \Delta\tau_{ij} \tag{8}$$

The calculation formula of the control parameters directly obtained by the improved intelligent control method through fuzzy calculation is as follows:

$$\mathcal{L}_i(\ell) = \mathcal{T}_{\mathcal{L}_i}^{\mathcal{D}}\big(w(\ell), wx(\ell)\big) \tag{9}$$

The result obtained by the fuzzification calculation is $\mathcal{T}_{\mathcal{L}_i}^{\mathcal{D}}$, and $wx(\ell)$ is the correction amount of the control parameter.

Neural networks have always been the first choice for establishing mathematical models, so we also introduced this method in the process of monitoring the changes of indicators, and realized its upgrade and adjustment.

$$y_i(m) = f(\sum_{i=1}^{n} w_{ij}\,x - \mu_j) \tag{10}$$

$$w_{ij} = \int [m(x_j)\delta\mu]dx \tag{11}$$

$$\mu_{ij}^{k} = \sigma\sqrt{x_{ij}\cos\rho} \tag{12}$$

Among them, w represents the threshold, μ represents the weight, and f represents the objective function. In this process, in order to monitor and feedback the changes of the indicators in real time, it is also added the μ-type function based on the original neural network, which can realize parallel distribution.

On this basis, the monitoring model has a preliminary scale, but the model is still unable to deal with a large amount of data and information. Therefore, it is very urgent to select and calculate the collected data.

$$S = \frac{\sqrt{\sin^{-1} xy}}{\lim\limits_{x\to 0}\cot xy} \tag{13}$$

$$P = \sum_{i=1}^{m} \beta\gamma_i \, \|x\| \tag{14}$$

$$\gamma_i = \vartheta_{ij}^{m} = {}^{S_x}/_{P_i} > \varepsilon \tag{15}$$

Among them, *S* represents the process of data calculation, which will split and reorganize all data that does not meet the expectations. *P* represents the fitness function, which is the standard for judging whether the data information meets the requirements, and γ represents the process of data selection.

$$A = \sqrt{x^2 + y^2} * [g(x)f(y)] \tag{16}$$

$$x = \iint sin\,x\,cos\,y\overline{x \oplus y} \tag{17}$$

In this process, x and y represent a coordinate point, which together constitute the dataset space. The arrival of big data provides new ideas for the establishment of models. Based on this, the modeling of the problem is completely abandoned, and the data is directly modeled and analyzed.

$$a = {}^{\sqrt{\alpha \cdot \pi}}/_{\rho} \tag{18}$$

$$\rho = tan\,x \times \sqrt{m(xy)^2} \tag{19}$$

Among them, a represents the parameters in the model, and ρ represents the scheduling parameters in the model. Among the many parameters, choosing different parameters will directly affect the final result of the model, so a simple evaluation of the model is required.

$$E(t) = \frac{1}{3}(t_{in}(n) - y_{int}(n))^2 \tag{20}$$

$$\varphi_{ij} = \sum_{\substack{0 \leq i \leq m \\ 0 < j < n}} g(i,j) \tag{21}$$

In the above formula, E represents the evaluation function, whose goal is to verify the model, and φ represents the error, whose goal is to minimize the objective function.

$$\mu = \sum\nolimits_{i,j} \tau(\sigma) \cdot (\Delta e) \cdot \mu_{ij} \tag{22}$$

Error amplification is more conducive to intuitively seeing the difference between the data in the process of the experiment. The relationship between the amplification factor σ and the data sequence σ in the above formula just illustrates this point.

3. Effect of load intensity training model

In this study, 20 male athletes, all members of local university teams, aged between 18 and 25, were selected to participate in the experiment during the recovery period of their training cycle. The study lasted 12 weeks and was conducted from March 2023 to April 2023. The experiment was conducted in the spring, with all physical activity and data collection taking place in local university gyms and sports fields. Each athlete underwent three major tests during the study period: primary, mid-stage and end-stage tests, which were conducted one week apart.

5ml of venous blood was used for analysis each time a blood sample was collected. The analysis of blood samples is carried out by the Sports Science Laboratory of the local university, which has complete biochemical analysis equipment and professional staff. All experiments are performed in accordance with the World Anti-Doping Agency (WADA) and local Ethics Committee Standard Operating procedures to ensure the accuracy and reliability of data. During blood collection and analysis, the following steps are strictly followed: athletes fast for 12 hours before blood collection, blood collection is performed in the athlete's resting state, samples are refrigerated immediately after blood collection, and sent to the laboratory for analysis within 24 hours. After the preparation activity, the first group of quantitative load exercise immediately, the second group of quantitative load exercise immediately and the next morning in a quiet and stable state, the electrocardiogram was recorded, and the blood lactate value of the two groups was measured at the same time. The model combines these values to evaluate the training intensity of athletes, and then uses an image analysis system to digitize the data. **Figure 6** shows the speed changes of the two groups of 7 athletes.

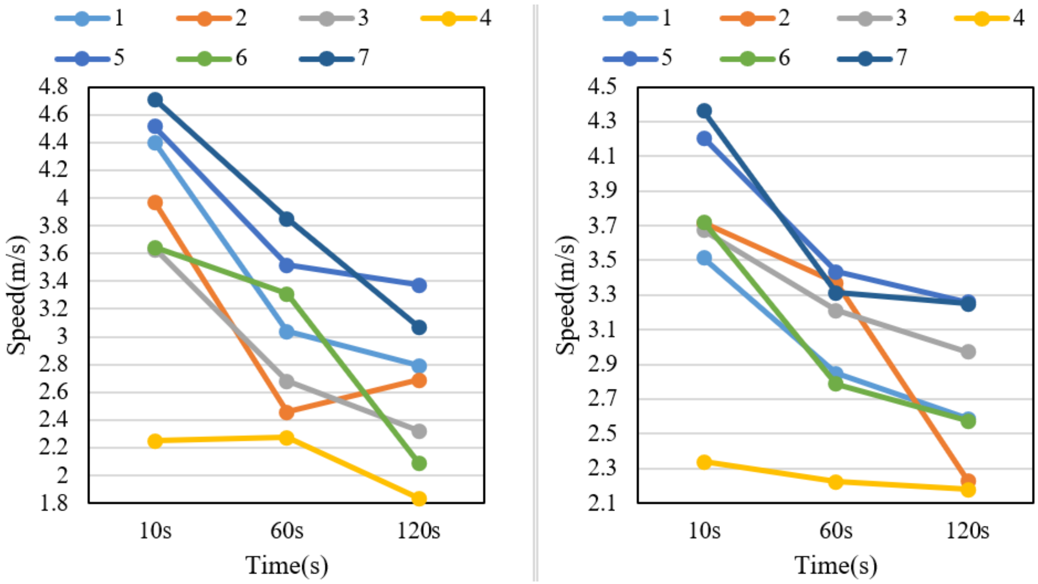

Figure 6. The trend of speed change in two groups of athletes with different loads.

According to the figure, we can see that the speed of the athlete will slow down with the extension of exercise time, which is the result of the gradual accumulation of lactic acid. In addition, the average speed of each athlete in the second load will be lower than the average speed of the first load, and the starting speed of the first load is generally greater than the starting speed of the first load, with a maximum difference of 0.46 in average between the two.

Next, use the algorithm to optimize and upgrade the athlete's training model to a certain extent, and compare it with that before the upgrade. The athletes' quiet state before training, immediately after training, and the next morning were measured. The measured indicators mainly include creatine kinase, blood urea, serum testosterone, etc. The results are shown in **Figure 7**.

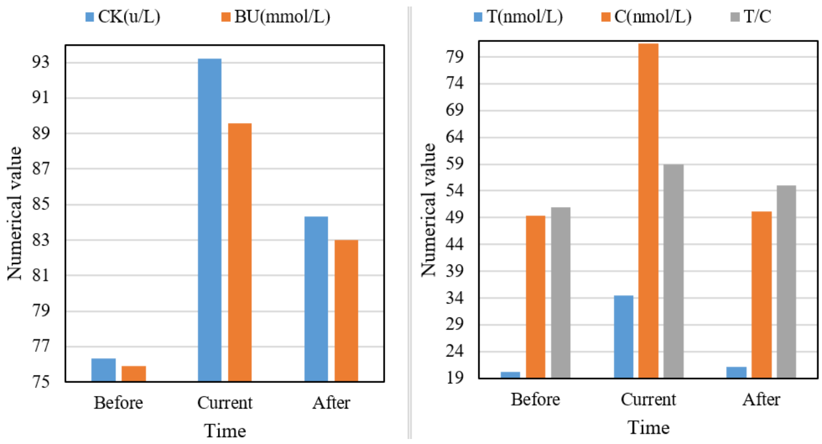

Figure 7. Influence of indicators on athletes before and after a training session.

It can be seen from the above figure that after one training according to the optimized model, both the CK value and the BU value have been greatly improved, with extremely significant difference ($P < 0.05$). The index values in the next morning are higher than those before training, and the BU value in the next morning is lower than the value just after training, showing a downward trend, and the maximum difference from the value before training is only 4. This shows that the optimized model has a certain degree of robustness, which can have a certain effect on the athletes' training day, and return to normal the next day.

The superiority of the monitoring model based on computational intelligence cannot be finally compared through conventional measurements and experiments, so the traditional monitoring model and the monitoring model based on neural network are selected to compare the model proposed in this paper, which as shown in **Figure 8**.

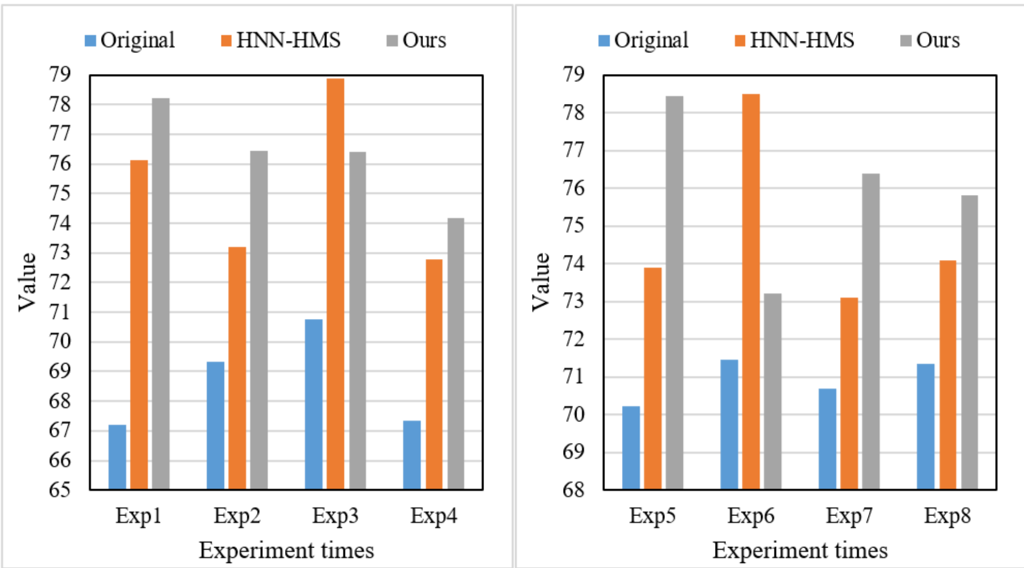

Figure 8. Indicator monitoring effects of different models.

As shown in the figure, the monitoring effects of the athlete indicators under different models are not the same. Among them, although the traditional monitoring model can adapt to the changing environment, its effect is not ideal. The highest monitoring accuracy of the indicators is only 71.45%, which cannot adapt to the increasingly stringent high-precision requirements. Although the monitoring model based on neural network can achieve the highest accuracy of 76.12%, its training time is relatively long, and its effect is not particularly stable. In contrast, the monitoring model based on computational intelligence can well overcome the above two shortcomings, and its average accuracy can reach 78.45%.

In addition, in order to verify the optimization effect of this model, the training time interval of athletes was compared and divided into one training and two weeks of uninterrupted training, and SPSS (Statistical Product and Service Solutions) statistical software was used to perform statistical processing on the tested data. The next step is to compare the index values after one week and two weeks with the index values before training and the next day. The results are shown in **Figure 9**.

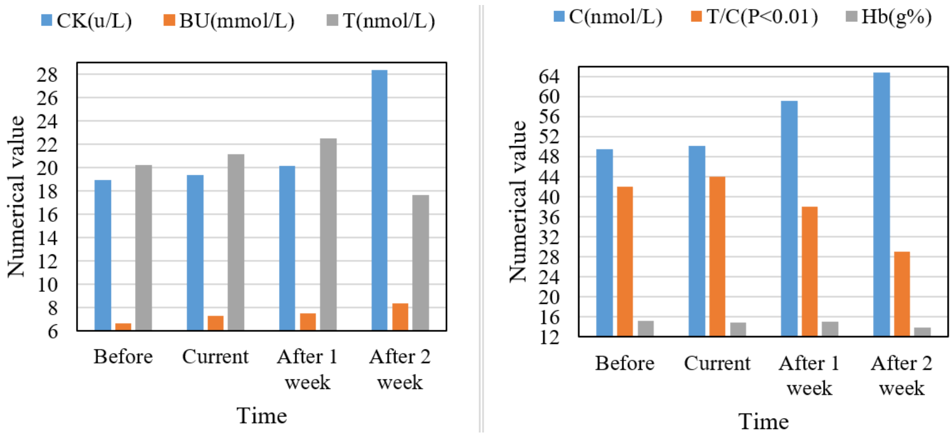

Figure 9. The effect of training at different time intervals on the indicators of athletes.

It can be seen from the figure that after one week of training, the CK value and the BU value both increased compared with those before the training, and the increased values differed by up to 10. After two weeks of training, compared with before training and after one week of training, the range of numerical increases is more obvious. Also, the T and C values after a week of training were slightly higher than the values before training. There are relatively large differences in the index values after two weeks of training, among which the T/C value and the C value are extremely significant compared to their pre-training trends.

These results are consistent with the existing theories of exercise physiology, exercise training and sports medicine. For example, changes in heart rate (HR) and blood lactic acid (BLa) support the anaerobic threshold theory, indicating that high-intensity training causes lactic acid buildup. Increased creatine kinase (CK) levels indicate muscle fiber damage and are consistent with the theory of muscle damage and repair. The change of hemoglobin (Hb) level is consistent with the theory of blood thinning effect and blood volume change. Increased urinary protein (UPRO) and ketone bodies (KET) indicate the effects of high intensity training on renal function and energy metabolism. The change of serum testosterone (TESTO) level reflects the effect of training load on the endocrine system. Increased blood urea (BU) levels indicate increased protein catabolism. Through the change of these indicators, the training load can be evaluated more scientifically and the training plan can be formulated.

In addition, the results of this paper are compared with other studies, and some similarities and differences are found. Changes in HR and BLa are consistent with the findings for long-distance runners, but differ from the findings for sprinters, which may be due to differences in training styles and sports. By exploring the reasons for these differences, new directions can be provided for future research. This monitoring can reflect the athlete's physical state in real time and provide scientific basis for training optimization. Future studies should further analyze the changes of specific biochemical indexes and their underlying movement characteristics.

4. Conclusion

Exercise is the main factor affecting the biochemical indicators of the body. Computational intelligence has been continuously integrated with other intelligent algorithms in the process of development, and it has become the trend of the times. On the one hand, the continuous maturity of big data technology provides new development ideas for computational intelligence; on the other hand, the use of various intelligent algorithms to complement each other's strengths has broadened the path for the development of computational intelligence. On this basis, the article first analyzes the concept and application of computational intelligence. Secondly, the article combines many intelligent algorithms to upgrade the computational intelligence method, and also extends it to the field of sports, which realizes the biochemical indicators of athletes before and after quantitative load exercise. In this process, the monitoring of athletes' biochemical indicators based on computational intelligence can display the physical state of athletes in real time, and provide a certain reference for their subsequent training and physical exercise. However, due to time reasons, the article did not explain and explain the specific biochemical index responses. In the future, the article will start with the actual data of biochemical indicator monitoring, focusing on analyzing the movement characteristics and current situation behind the indicators.

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