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# ORIGINAL

# A METHOD FOR PREDICTING SPORTS LOAD DATA IN COLLEGES AND UNIVERSITIES BASED ON DEEP LEARNING

**Yue Gu[1] , Xue Song Du[2 *], Guo Liang Yuan[2]**

[1] Department of police tactics and sports, Jiangxi Police Institute, Nanchang，330199，Jiangxi, China.
[2] College of Physical Education, Hengshui University, Hengshui 053000, Hebei, China.
**E-mail:** duxuesong7758521@163.com

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## ABSTRACT

In the face of the problem of low accuracy of university sports load data prediction method, a deep learning university sports load data prediction method is designed. Identify the style and rules of human movement, extract the characteristics of time domain to calculate in frequency domain, construct the target tracking model by deep learning, calculate the error of the output layer, extract the characteristics of college sports load, judge the rationality of the movement contact configuration between bones, and design the data prediction method. Experimental results: The average prediction accuracy of the college sports load data prediction method in this paper and the other two methods are 0.417, 0.342 and 0.333 respectively, indicating that the precision of the college sports load data prediction method designed after the full integration of deep learning technology has been improved.

**KEYWORDS:** Deep learning; College physical education; Exercise load; Data prediction; Athletic style; Upper limb motor chain

## 1. INTRODUCTION

Physical education in colleges and universities is the main way to achieve the goal of physical education in colleges and universities. It is a compulsory public course for college students to enhance their physique, improve their health and improve their physical literacy through reasonable physical education and scientific physical exercise. In order to classify exercise intensity more effectively, it is necessary to predict the data based on the characteristics of exercise load (Kang, Kim, Ko, Han, & Kwon, 2020; Miller, 2019).

In deep learning, human motion recognition technology has a high market value and has broad application prospects in intelligent monitoring, motion analysis, human-computer interaction, medical monitoring and other fields (Dhont, Wolfs, & Verhaegen, 2022; Fadil et al., 2021). Traditional video surveillance usually requires manual intervention to check and analyze suspicious people and events in the video by viewing real-time video on the spot or viewing playback video afterwards. But there are many problems with this traditional way of monitoring(Alexandre, Ricardo, Daniel, Dumitriu, & Salvador, 2018).

The division of the intensity of sports is an indispensable part of physical education management and an important means to check the quality of teaching. The rationality of physical load arrangement of P.E. class is an important index to evaluate the quality and scientificity of the class. How to evaluate the physical load intensity of a P.E. class and evaluate the long-term effects of P.E. teaching on students' physique are the key points in the evaluation of teaching quality of P.E. class.

Exercise load refers to the physical load (external load) imposed on the human body, which will inevitably lead to changes in the physiological function of the human body, namely physiological load (internal load)(Mersmann et al., 2021; Osman, Bentley, & Mak, 2021).

In the field of sports analysis, sports competitive events have been deeply loved by people. The application of human movement recognition in competitive sports can not only make a more fair and just judgment, but also help athletes to understand the movement mechanism of the human body, so as to further improve their competitive skills. Another major classification of exercise load data is action classification and recognition for depth maps or 3D skeleton sequences (Yang et al., 2020; Zhang & Wang, 2020).

Data research shows that even if the skeleton information of human body is estimated reliably, the motion classification based on 3D skeleton is not easy to achieve. The biggest problem is that semantically similar actions are not necessarily numerically similar. It is the physiological essence of physical exercise to induce responsive changes in body function and structure through appropriate external load stimulation.

The physical education load includes sports load and psychological load, among which the sports load refers to the physical and mental burden borne by students in the physical education, that is, the strength of a series of physiological and psychological reactions produced by the body (Freitas et al., 2020; Kaltsakas et al., 2021).

## 2. Prediction method of university sports load Data based on deep learning

### 2.1 Recognizing human movement style and rules

In the process of exercise, the number of steps is one of the characterization of exercise load (Hernández-Belmonte, Martínez-Cava, Morán-Navarro, Courel-Ibáñez, & Pallarés, 2021). Everyone has their own characteristics when walking, but all people have common characteristics in the process of walking, according to the common characteristics of human walking and then use software algorithm to achieve the monitoring of the number of movement steps. For sports style, it is difficult to measure it by specific standards without professional knowledge. In the absence of clear standards, clustering method is obviously a better choice for analysis. Therefore, this paper realizes the classification of motion data according to motion style through clustering algorithm.

According to the different distribution types of data prepared for clustering, clustering methods include k-means, DBSCAN, mean-shift and other methods. When we put the acceleration sensor on the waist or legs, we only need to consider the acceleration change of the body trunk or legs, but when the acceleration sensor is placed on the wrist, we need to consider the acceleration change of the arm movement as well as the acceleration change of the body trunk. As can be seen from the human walking process simulation diagram, the steps in the human walking process can be roughly divided into five stages.

The factor related to data distribution is the distance between cluster samples. However, each sample of the exercise load data in this project is the number of steps in a certain time dimension for a period of time, so the measurement of distance is also transformed into the measurement of the distance of the time series data curve. In this respect, in addition to directly calculating various defined distances from the original sample, Fourier transform and wavelet transform, which are widely used in the signal field, can also be used to extract the time-domain features to the frequency domain for calculation(Dmitriev, Bayazitov, Korznikova, Bachurin, & Zinovev, 2020).

The action in the first step can be used as the starting point of a step in a continuous walk. At this point, the body is leaning forward, the tip of the front foot is not completely landed, the root of the back foot is entrenched, and the left and right hands are respectively in the process of front and back swing. In the second step, the right foot touches the ground completely and acts as a supporting leg, while the left leg pedals the ground and prepares to move forward. At this moment, the left hand and right hand swing back and forth to the maximum range. The acceleration changes of the trunk during body movement are shown in Figure 1:

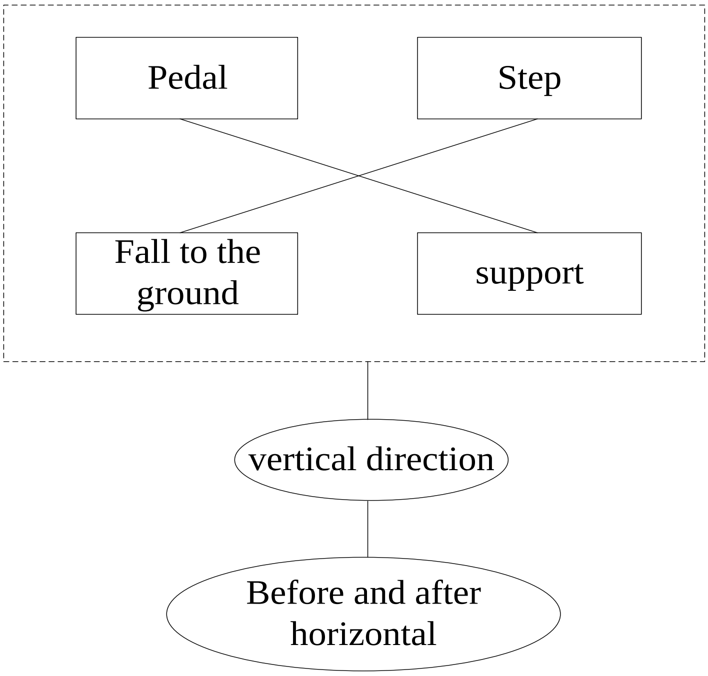


**Figure 1:** Change items of trunk acceleration during body movement

As can be seen from Figure 1, when people walk a step, the combined acceleration of body motion will produce a similar complete sinusoidal waveform in the process of acceleration increase and decrease. After separating the data of different movement styles, a simplified model is proposed, and a simplified multi-time dimension fusion prediction model is established to predict the future movement situation using the easily accessible historical movement data.

The third step in the right leg support, with the right leg as the axis, the left leg began to swing upward, the center of gravity of the body rises, and right now the left and right hands just swing perpendicular to the ground position. In the fourth step, the whole body is forward, the right leg is squatted, the left leg is forward for landing, the left hand and right hand are in the backward swing and forward swing respectively.

The acquisition of time motion characteristics is usually based on a variety of time dimensions. For example, for the step data of the athlete, the step data can be in the unit of month, day and hour. According to the different purposes of analysis and the different amount of data obtained, the step data of different time dimensions can be analyzed. In the fifth step, the right leg is ready to leave the ground, and the left leg touches the ground. After landing, the body gains a new balance because both feet touch the ground, and the hands continue to swing at this time, but the acceleration has not reached the maximum. It's the end of one step and the beginning of another. As can be seen from the gait diagram of human walking, the movement of human torso mainly consists of horizontal forward direction, backward direction and vertical direction. From the beginning to the end of the movement, the movement of the foot will go through the process of pushing, stepping, landing and then supporting. In this series of movements, the vertical acceleration of the body is caused by the combined force of the ground on the feet and gravity, while the forward and backward acceleration is caused by the friction between the feet and the ground. Based on the above description, complete the steps of identifying human movement style and law.

## 2.2 Deep learning building target tracking model

Both shallow learning and deep learning belong to the category of machine learning. Back propagation algorithm is mainly to find the optimal global parameter matrix and further apply the multi-layer neural network to classification or regression tasks (Jain, Zhang, & Huang, 2020; Parganlija et al., 2020). The artificial neural network algorithm is also called multilayer perceptron. In the framework of deep learning algorithm, there is no need to manually design features to carry out feature extraction operations, but only need to input data and output results through training. Deep learning can choose the layers of the network according to the needs of the task, and it can be mapped to any function in theory, so it can solve many complex problems (Park, Jang, & Ko, 2021; Ulrich, Goss, & Ebert, 2021).

Deep learning utilizes hierarchical learning of multi-layer neural network to achieve nonlinear mapping from input to output (Li, Ding, & O, 2020; Wang & Srikantha, 2021). Due to the slow development of early computer hardware, artificial neural network is trained by the CPU of the computer, but it is difficult to train multilayer network, so usually multilayer perceptron is a shallow model with only one hidden layer. During this period, some classical shallow machine learning models were also proposed, such as support vector machine and Random Forest. Based on the function principle of deep learning, the expression formula of activation function can be obtained as follows:

$$\gamma = \frac{1}{1+T^{-p_q}}$$

（1）

In formula (1), $T$ represents the value of neurons on a certain layer, $p$ represents the learning rate, and $q$ represents the bias coefficient. Although the motion energy map can reflect the spatial information of the movement, it cannot reflect the time information. Therefore, the historical image of motion arises on the basis of the energy image of motion. It presents the motion of the target in the form of image brightness by calculating the pixel changes of the same position in a certain period of time. This method belongs to the vision-based template method.

At present, the research on the application of deep learning in computer vision mainly focuses on three aspects: First, the output of the middle layer or multiple layers of the trained network acts as a feature extractor to replace the traditional feature extraction algorithm (Tan, Huang, Hsieh, & Lin, 2021; van de Worp et al., 2021). The second is to add new layers or reduce some layers in the existing network, fine tuning. Third, for specific tasks, build a new network structure, training from scratch. According to the propagation direction of error, the error calculation formula for the output layer is shown in Equation (2) :

$$L = \frac{1+T_p}{\left\|1-T_q\right\| \times \left\|\beta - T_q\right\|}$$

（2）

In formula (2), $\beta$ represents the predicted value of the output layer calculated by the activation function. The error calculation formula for the hidden layer is shown in Equation (3) :

$$L' = \sum \frac{H}{\beta\left(1-S\right)}$$

（3）

In formula (3), $H$ represents the value of the output layer, and $S$ represents the weight of the hidden layer. Deep learning, also known as deep neural network, uses machine learning algorithms to solve image and speech recognition problems on the constructed deep neural network. The core of deep learning is feature learning. Feature information of each layer is learned through hierarchical network, so as to solve the problem of manual feature design in the past. A large amount of training data is used and data features are learned independently to improve the accuracy of prediction. Deep learning layered feature extraction is similar to human vision mechanism, which is a process from edge to part and then to whole. The gray value of each pixel in the motion history image presents the motion status of position pixels in this group of video sequences. Based on formulas (1) ~ (3), the weight update formula is as follows:

$$D = \frac{1}{S} - \sum\left(\Delta V - 1\right)^2$$

（4）

In formula (4), $V$ represents the updated weight value. The closer the pixel's last motion is to the current frame, the higher its gray value will be. Compared to the motion energy image, it can not only show the sequence of actions, but also contain more details. Therefore, the motion history image can represent the movement of human body in an action process, which makes it widely used in the field of motion recognition research. Based on the above description, the steps of deep learning to build the target tracking model are completed.

### 2.3 Extracting the characteristics of college sports load

Kinematic chain is a mathematical model of mechanical system composed of a series of rigid bodies connected by links. It is a system formed by several components connected by kinematic pairs. Can be divided into closed chain and open chain two forms. Motion pair refers to two components (motion unit) contact directly and can produce relative motion of the movable connection. Exercise load refers to the workload that our airframe bears inside certain time in the course of exercise training.

According to the way in which the elements on the two components keep in contact with each other, the motion pair can be divided into force closed motion pair and form closed motion pair. Force sealing is to judge the rationality of the contact configuration by analyzing the force of the object and satisfying the condition of static equilibrium. Its size is measured by a series of exercise load indicators. For example, heart rate measurement has the characteristics of directness and convenience (Almutairi, 2022; Xu, Tian, & Fan, 2020).

Such as weight bearing or working power of the body in a certain exercise time. So it has become popular to use heart rate indicators to assess exercise load in different places and at different times, such as in the playground or the lab, before, during, or any time after a workout. Shape closure is to judge the rationality of the contact configuration by analyzing the kinematic freedom of the object according to whether the object satisfies the zero kinematic freedom (Choi, Kitchen, & Stewart, 2020). In the human body, intramuscular and intramuscular movements also meet the requirements of force closed form, and interskeletal movements are the motion pairs that meet the requirements of form closed form at the joints. The main principle of using heart rate to monitor exercise load is the linear relationship between heart rate and work power. Although heart rate and percentage of maximum heart rate can be used to describe the change of exercise load to a certain extent, the change of heart rate related indicators will be affected by many internal and external factors (Lee, 2020; Muhammad, Alqahtani, & Alelaiwi, 2021).

The joint is connected by articular cartilage on the surface of the joint head (face, socket) and ligaments growing on the bone. In the complete human movement, it needs two kinds of motion pair form in turn or at the same time to achieve a good movement. The classification of upper and lower limb chain movements is shown in Table 1:

**Table 1:** Classification of upper and lower limb chain movements

| CLASSIFICATION | NAME | DESCRIPTION |
|---|---|---|
| UPPER LIMB CHAIN | Double arm action | Alternating action, push, pull and push-pull synchronization |
| | Single arm action | Push and pull |
| LOWER LIMB CHAIN | Double leg action | Push, pull and push-pull synchronization |
| | Single leg action | Supporting leg, non supporting leg, whipping action |

It can be seen from table 1 that the upper limb movement chain subsystem is connected with the trunk through the upper limb belt composed of clavicle and scapula, with shoulder joint connected with the upper arm, limb joint connected with the forearm, and wrist joint connected with the hand bone. The muscles are grouped and arranged in layers according to the joint motion axis, and the motion chain subsystem is composed of blood vessels and brachial plexus nerves that dominate the movement and sensation of the arm. The main action forms can include push, pull, whip, torsion and other forms. It is the most abundant, active, flexible and largest human motion chain subsystem. The lower limb movement chain subsystem is connected with the trunk through the lower limb belt, the skeleton joint is connected with the thigh, the knee joint is connected with the lower leg, and the ankle joint is connected with the foot to form a movement chain subsystem with the bone as the central axis and the joint as the hub, and the muscles are grouped and arranged in layers according to the joint movement axis, which is composed of blood vessels and nerves controlling the movement and sensation of the lower limb. By extension, to complete the human body movement chain, each movement link needs to move in turn and stabilize each other.

The movement occurs alternately along the muscle chain towards the end of the movement (usually hand or foot), and the strength is maintained and increased in this process. By detecting the HRV index under quiet state and after exercise, we can analyze the load pressure borne by the central vascular system during exercise and the recovery state after exercise. This research is a very potential research method system to monitor the individual exercise adaptation state of athletes and the functional state of individual autonomic nervous system. When the various movement links of the human body generate excitement in a coordinated and orderly manner, the distal end of the limb can complete the action at the best position, at the best speed and at the best time. When the human body completes various competitive movements, the simple form of open chain movement or closed chain movement is very rare, and more is the form of mixed chain movement, that is, the alternating working form of open chain and closed chain. When the open chain and closed chain work alternately, the working state and nature of muscle will change, that is, the conversion between stability and power, that is, the redistribution of tension structure between muscle tension and muscle tension, which will affect the working state of sports chain. Both professional athletes and mass fitness people will face a problem that the state of the body is not always constant. External factors: environment, temperature, diet, sleep quality and personal physiology change periodically.

There are also training factors. An undeniable factor is that with the enhancement of training, athletes or fitness people will gradually adapt to the previous exercise load. From human actions, we can see that human actions often work with more than one muscle chain. Therefore, when working along the muscle chain, the rotation of the chain may cause movement deformation or "weak link" phenomenon, while the change of the working form of the movement chain may lead to compensation phenomenon and even sports injury. Based on the above description, complete the steps of extracting the characteristics of college sports load.

### 2.4 Designing data prediction method

According to the motion characteristics of human body and the experimental data, it is found that the acceleration change of human body presents periodic sinusoidal change, so we can detect the peak value of the signal waveform of acceleration change, and then judge the effective pace of movement according to the motion characteristics. First of all, the mass of crowd movement data can be preprocessed, such as filling in the vacancy value, deleting suspected abnormal data, etc., to prepare for the next step of analysis. Then, according to the movement data, sports people with different sports styles can be separated so as to establish different models for analysis of sports people with different styles. After the separation of motion data, the future motion situation can be predicted according to the historical motion data of different dimensions.

The first step is to detect the peak value of the motion acceleration. We need to detect the number of steps by calculating the sinusoidal wave of the curve from the acceleration data. Firstly, we need to find the peak value of the sinusoidal wave through certain methods. At present, the common method is to determine the slope of the point by subtracting the data of the previous point from the data of the next point of the sampling data, and then determine the slope of the point according to the value of the subtraction. After the data preprocessing of the above steps, the data can be input into the model for analysis. The fusion prediction model uses two different types of models to analyze the motion data of different time dimensions, and takes the output of one model as the input of the other model to predict. In this article, the hour-level user data to be predicted is also a sequence of steps with long intervals. For the movement data of a user, suppose that the data vector composed of its hour-level movement data is:

$$G = \begin{bmatrix} g_{00} & \cdots & g_{23} \\ \vdots & \ddots & \vdots \\ g_{Y0} & \cdots & g_{Y23} \end{bmatrix}$$

(5)

In formula (5), $g$ represents step number data, and $Y$ represents prediction time point. If the number of days prior to the forecast time point is $h$, then the dependent variable of the long-term forecast data on day $k$ is:

$$M = \sum (1-\delta)^2 - \frac{h}{k}$$

(6)

In formula (6), $\delta$ represents the independent variable. According to the calculation results, the correlation between environmental factors and movement can be analyzed. Finally, the analysis results are visualized, so as to provide feedback to users or further research, so as to put forward suggestions and guidance programs for sports. The source of motion data may have various acquisition channels, such as tables, binary files, databases and JSON files, etc. Different source formats need to be processed by different modules, but at last they need to be transformed into a unified format for the platform to process in the next step. The slope of this point is positive or negative to determine whether this point is the peak. By this method, all the peak values (including peak values and valley values) of a certain buffer are averaged, and the mean value is taken as the threshold of step judgment. In order to find the peak value correctly, this method needs the waveform of acceleration signal to be very smooth.

The miscellaneous peaks and burrs of the signal waveform will affect the judgment of step counting, and there will be a high probability of misjudgment when finding the peak value. The actual number of peak values found is far more than that in the ideal state, which will lead to inaccurate judgment of the following steps. The exercise data uploaded by users through pedometers or smart devices such as mobile phones may have data gaps for a certain period of time, and even the uploaded data may be forged exercise data. Before using the mathematical model to process the movement data of these steps, it is necessary to consider that the occurrence of these situations may lead to the failure of model processing due to the mismatch of data format, and the decrease of model accuracy and deviation of prediction results caused by abnormal data. Therefore, digital filtering is carried out on the original acceleration data before peak searching to remove some burrs. You can also compare the peak with the data in the adjacent area to determine whether the peak is really a peak. Once the peak is confirmed, it is necessary to judge the pace of movement by the peak. The slope of the solved sampling point is stored in the cache. If the slope turning point occurs, the data on both sides of the point is compared. When the error of positive points and negative points is within a certain range, it is regarded as an effective step counting.

Therefore, preprocessing is the prerequisite for inputting the obtained motion data into this platform for analysis and prediction. In this process, the basic statistical information of the obtained exercise data should also be fed back to the user so that the user can know whether the exercise data to be analyzed currently is expected by the user. This topic will first study the acquisition and unified processing of motion data, as well as the pre-processing methods such as filling, filtering and cleaning of the obtained motion data. This judgment method requires that both sides of the peak point of the sine wave have a good symmetry relationship, but in the actual movement of human body, the acceleration signal we get is not regular periodic signal, and the positive and negative slope points on both sides of the peak are not the same, so the application of this method has certain limitations. Based on the above description, complete the steps of designing the data prediction method.

## 3. Experimental analysis

### 3.1 Experimental preparation

The data in actigraph is transmitted through actilife. According to the different time questions of each exercise means, the experimental data are sampled, and SPSS statistical analysis software is used to test the normal distribution and difference of all index data, so as to further analyze the correlation between relevant indexes and exercise load. Firstly, the measured original data are converted into 1min data with sampling frequency. Before extracting the characteristic value of acceleration, the acceleration data must be preprocessed. For the data pretreatment, the median filter is used to process the noise of the original acceleration signal of human movement, and then the signal is separated by a low pass filter. Secondly, to eliminate the influence of body weight on energy consumption, the original data is converted into energy consumption (also known as relative energy consumption) per kilogram body weight per minute (kg-1×min-1) for analysis. Finally, the data results of the experiment were statistically analyzed by gender.

### 3.2 Experimental result

This experiment will analyze the use of different degrees of sports load conditions, through the form of comparative experiment, verify the effectiveness of the design of college sports load data prediction method. The prediction method of college sports load data based on data mining and association rules are selected to compare with the prediction method of college sports load data in this paper, and the prediction accuracy of sports load data prediction method is compared. The experimental results are shown in Figure 2-4:

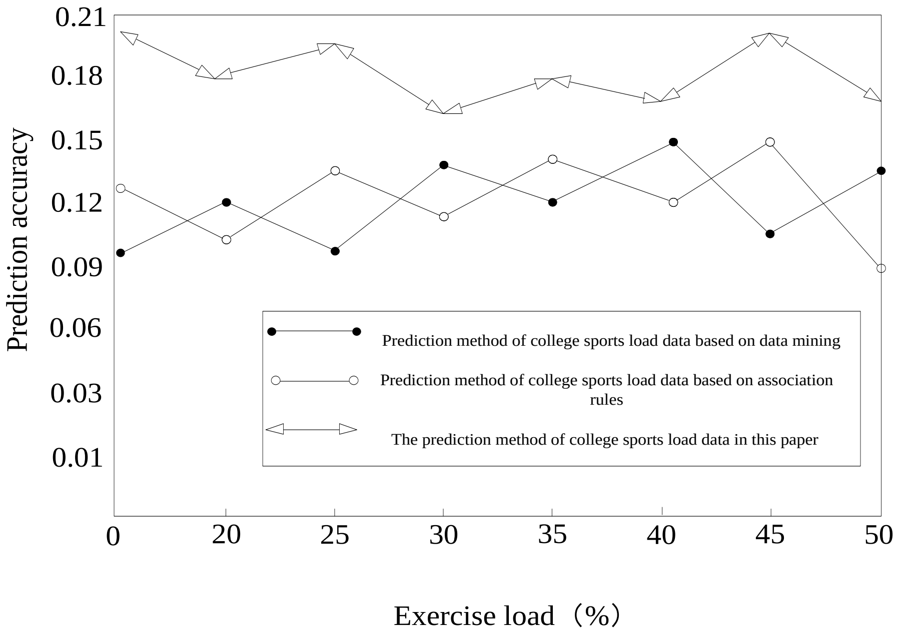


**Figure 2:** 50% Prediction accuracy of motion load

According to Figure 2, when the sports load intensity is 50%, the average prediction accuracy of the data prediction method of college sports load in this paper and the other two methods are 0.182, 0.101 and 0.098 respectively.

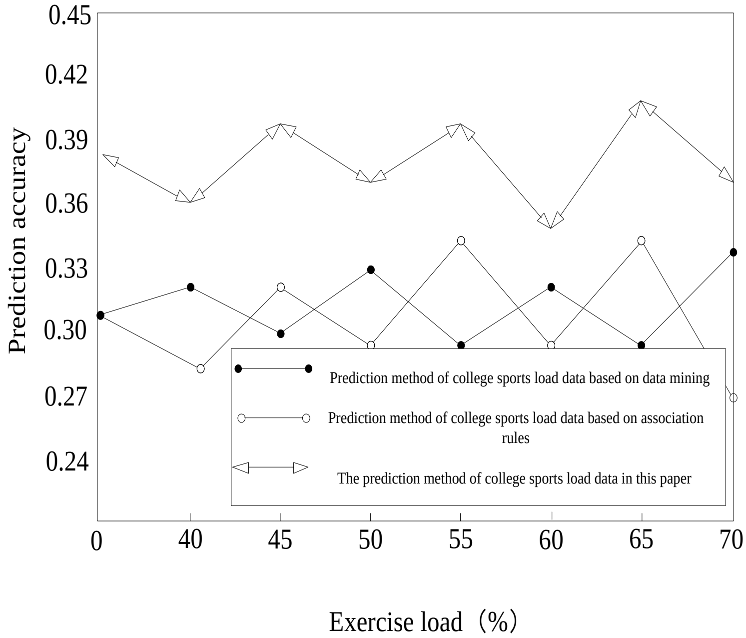


**Figure 3:** 70% prediction accuracy of motion load

According to Figure 3, when the sports load intensity is 70%, the average prediction accuracy of the data prediction method of college sports load in this paper and the other two methods are 0.406, 0.313 and 0.297 respectively.

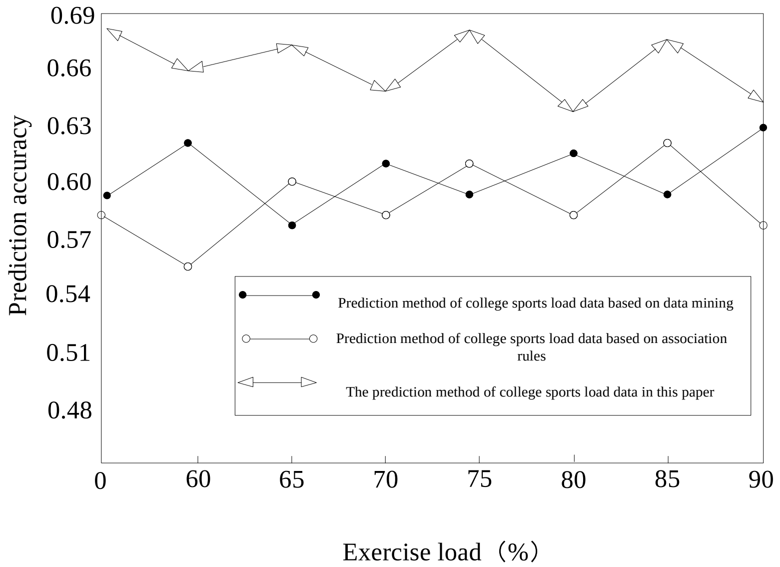


**Figure 4:** 90% prediction accuracy of motion load

According to Figure 4, when the sports load intensity is 50%, the average prediction accuracy of the data prediction method of college sports load in this paper and the other two methods are 0.662, 0.611 and 0.604 respectively. Although the intensity of sports load has a certain influence on the accuracy of data prediction, the prediction accuracy of the university sports load data prediction method and the other two methods can be maintained at a high level.

## 4. Conclusion

This article from the current data can collect to the colleges and universities sports load data, through the deep learning technology to the collected data and the depth of the relevant study data model is analyzed, and the design and implementation based on the movement load data of deep learning data forecasting method, provide the corresponding analysis and monitoring functions. Future research directions need to be improved in more dimensions of exercise data and personal health access and storage functions.

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