Computer-Aided Design AND APPLICATIONS www.cadanda.com

Applications of Data Mining in Intelligent Computer-aided Athletic Training

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Abstract. The mining and application of data in sports training through intelligent computer-aided research, this paper proposes a system development and design method to improve the development and design efficiency of the data visualization system and reduce the development cost by using the Python language to handle the high efficiency of system programming and the convenience of charts. Thus, it further improves the efficiency and interactivity of the information management of training data and the convenience and stability of managing training data. This system is a preliminary exploration of Python language and Echarte technology in the management of training data of sports training programs. Because of the integration of training programs with computer application technology and data visualization technology, the system still needs to be strengthened in terms of data processing methods and the diversity of chart styles generated. In the future, the use of artificial intelligence, big data analysis, and other technologies in sports training data management and analysis has more room for development. The model only needs to measure 14 indicators of bipedal closed-eye standing and single-leg closed-eye standing movements to achieve the ability to predict the balance of motor training, and its accuracy meets the clinical requirements. This method has a shorter measurement time and fewer metrics than traditional methods.

Keywords: smart computers; assisted athletic training; data mining applications.
DOI: https://doi.org/10.14733/cadaps.2021.S4.1-12

1 INTRODUCTION

As "data-driven sports training and sports decision-making" has been applied in-depth in developed countries, it has become a hot field in the development of modern competitive sports

[1]. The application of artificial intelligence technology in competitive sports through big data and intelligent algorithms can accurately monitor the physical state of each athlete before, during, and after the game, help coaches adjust tactics in real-time, and at the same time develop more personalized training modes and efficient game strategies for athletes, to enhance the athletes' competitive level [2]. The good combination of AI and sports is an important grasp and feasible way to win the first opportunity of sustainable development for the cause of fitness for all. On the one hand, some sports equipment based on AI technology can realize the visualization and automatic analysis of people's health results through screening and matching in intelligent mode; on the other hand, through the collection and integration analysis of sports and health data, the objective assessment of the current state of national physical fitness can be carried out, and the results of the assessment are of great significance to the formulation of relevant sports policies [3]. With the support of the development strategy of combining artificial intelligence and sports and the application of relevant intelligent sports products, as a sunrise sports industry with both economic and ecological benefits, it can help the capital market tap market opportunities, generate changes in business models, improve customer service experience, innovate the management system and improve decision-making ability, thus realizing the high-quality development of the sports industry [4]. The main teaching objects of school sports are primary and secondary school students, who are the future power of AI development. Through the teaching of intelligent knowledge and the use of intelligent products in daily physical education, the information literacy of primary and secondary school students is subliminally improved, and the purpose of improving the AI science education system and providing talent reserve for the development of AI is achieved [5]. Sharma said that sports training is an extreme sport that uses the waves as a driving force and challenges the waves with its balance [6]. Fouad mentions in the article that sports training is a water sport that uses waves as a driving force and the sports training board as a tool to ride the waves in the sea [7]. Giger et al. suggest that a good level of aerobic fitness may be an important overall indicator of fitness development in sports trainers [8]. During offshore training, the athletic trainer performs paddling on land, replacing the athletic training board with a kayak bench, which is mounted on a railing and secured. The athlete performs a simulated paddling exercise by changing the paddling posture to achieve the training effect. Schuh et al. argue that in athletic training sports, due to the constantly changing environment, athletic trainers need to develop agility, balance, flexibility, and muscular strength to gain Better athletic training experience [9]. Dhull et al. consider an athletic training program to be an intermittent exercise program [10]. Lower body strength exercises, such as quadrupedal and augmented jumps, allow athletic training athletes to gain greater strength and control during athletic training. Burns et al. mention that paddling technique is an important part of athletic training programs, and for athletic trainers to catch the waves, it takes strong strength to create the momentum to hit the shore, allowing the Athletic training boards and athletic trainers catch the waves [11]. The text also develops courses for athletic training exercises that may include paddling (indoor or outdoor in the water), open water swimming, paddle towing on an athletic training board, or bicycling (indoor or outdoor).

Interviews with coaches were conducted to understand the needs of the system for visualizing training data from athletic training programs, including functionality, performance, and interface. The framework structure and functional modules of the system were designed, with features for data management, data presentation, and batch uploading. Then the design work of the database was completed by using the database conceptual model and table structure model, and the implementation of each functional module was completed by using Python language and Charts. The object of this research is the application of artificial intelligence such as big data and basketball robotics in the field of basketball and its implementation approach and feasibility. Specifically, it analyzes how the introduction of big data and basketball training robots affects players, teams, and the game of basketball, and whether they can be effectively implemented. Finally, conclusions are drawn and recommendations are given. When dealing with larger amounts of athlete data, the collected data needs to be imported into the system in bulk; when dealing with smaller amounts of data, the training data and personal information of the athletes needs to be added gradually. At the same time, in the later process of graphical data, if any data loss, omission, or error is found, the system needs to add, delete, modify, and query the data at any time. The indicators obtained from the athletic training coaches are divided into two main categories, namely, physical fitness and athletic training specific technical movements. The system needs to classify these two parts of the indicators to ensure that coaches can quickly find the corresponding data through classification when using the system, to display graphically and improve the efficiency of data management.

2 INTELLIGENT COMPUTER-AIDED ATHLETIC TRAINING DATA-MINING APPLICATION DESIGN

2.1 Intelligent Computer-Aided Athletic Training Data System Design

The prerequisite for multi-sensor information fusion is the calibration between sensors, and since the coordinate systems between different sensors are independent of each other and have different acquisition frequencies, the sensor data must be time-aligned and converted from their respective coordinate systems to the same coordinate system to achieve information fusion. The measurement principle of LiDAR is introduced. For LiDAR and image sensor, since the image sensor acts in front of the driverless car, and the field of view of LiDAR greatly exceeds the field of view of the image sensor, so the coordinate transformation of laser point cloud data becomes the key to solve the calibration of point cloud and image data. In this paper, the YMAnet network framework and composition structure are shown in Figure 1.

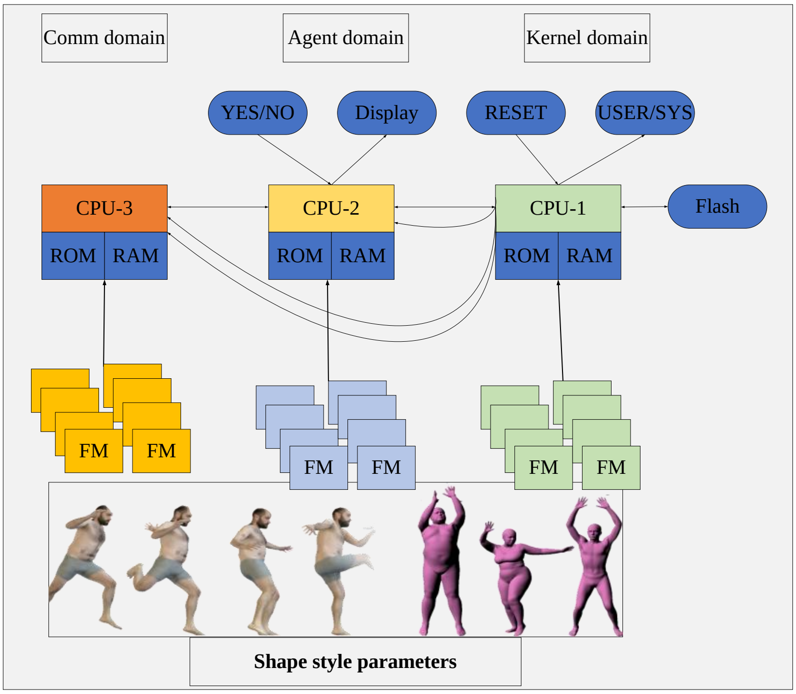

Figure 1: Schematic diagram of the intelligent computer-aided sports training system network.

Monet is designed according to a one-stage target detection network model structure, which can be trained end-to-end [12]. This structure reduces the complexity of the network design and allows the initialization of the network with existing model weights to speed up the network training. The feature fusion of this network is embodied in two aspects: the introduction of an attention mechanism to fuse the extracted point cloud features and image features at three different scales; and the design of a lightweight fusion module to cascade and fuse the features at different scales of the context. This design greatly enhances the effectiveness of feature-level fusion. The fused multiscale features are input into the prediction module for target classification and localization. The whole network consists of three parts, namely, the feature extraction module, the multi-feature fusion module, and the multi-scale prediction module.

To understand expert systems, we need to look at their most basic components. It usually consists of five components: the human-computer interface, the knowledge base, the inference engine, the integrated database, and knowledge acquisition. Of all these five components, the most basic structures are mainly the knowledge base and the reasoning engine. The knowledge base corresponds to the knowledge storage function of our human brain, which contains all the knowledge needed to solve problems, and it is all expert knowledge. The reasoning engine is equivalent to the problem-solving function of the human brain, which uses a large amount of knowledge stored in the knowledge base to solve the actual problems encountered in the field. But the construction of a knowledge base requires not only knowledge engineers, but also a large number of domain experts to work together to better organize the knowledge in the minds of experts in the relevant domain and store it in the knowledge base using a systematic approach to knowledge. To get expert conclusions from the system when people are solving problems, the users just need to provide some known data to the system.

Currently, the reconstruction of human models can be done by laser, vision, etc., and the capture of human motion information can be done by inertia, optics, and vision. Although these two research areas have been developed for a long time, because they integrate a wide variety of different techniques, they form highly integrated systems for automatic evaluation of functional movement patterns, which in this way satisfies the user's ease of use while also ensuring the robustness of the system. However, there are still many technical challenges to be solved in terms of data measurement accuracy and environmental applicability. Therefore, if we want to accelerate the widespread adoption of functional action pattern evaluation systems, the focus is on establishing a good system of action metrics and resolving key technical issues. Using sensor devices, the system obtains basic basketball movement pattern data from the players, then automatically calculates the movement metrics and evaluates the results using an expert pool system. Also, the system provides individualized, data-based improvement solutions to help test participants improve their basketball skills through targeted training.

$$f_0(x) = \arg\max_c \sum_{i=1}^{M} L\left(x_i, c\right) \tag{1}$$

$$R_{im} = -\left[\frac{\partial L\left(x_i, f_i(x_i)\right)}{\partial f_i(\mathrm{y}_i)}\right]_{f(x)=f_{m-1}(x)} \tag{2}$$

With the above events, we can see that intelligent data analytics systems offer another novel way of understanding the game, which challenges traditional methods of analyzing team data and can even replace them to some extent.

$$R_{jm} = \arg\max \sum_{x_i \in R_{jm}} L(x_i, f_{m-1}(\mathrm{y}_i) + \delta) \tag{3}$$

$$f_m(\mathrm{y}) = f_{m-1}(\mathrm{y}_i) + \sum_{i=1}^{J} R_{jm} I(R_{jm}) \tag{4}$$

$$f(\mathrm{y}) = f_M(\mathrm{y}) = F_0(y) + \sum_{i=1}^{J}\sum_{i=1}^{J} R_{jm} I(R_{jm}) R_{jm} I(R_{jm}) \sum_{i=1}^{J} R_{jm} I(R_{jm}) \quad (5)$$

The system can track each player's movements on the pitch, knowing that this is something that traditional data analysis would have been difficult to do anyway. With improved access to information comes a lot of data processing.

$$f_T = \chi(W_f \cdot [H_0 X_1] + b_m) \quad (6)$$

2.2 Athletic Training Data Mining Application Design

In this model, the browser acts as a special client. The two modes are not only different from each other, but also interrelated, each has its advantages and disadvantages. This system should provide more comprehensive data management functions, which can support the basic needs of various operations on training data in the later stage of the system. As shown in Figure 2, the management function is divided into three parts: personnel list, test management, and performance management. The personnel list module displays the basic information of athletes and can perform corresponding operations; the test management module manages the training data indicators; the performance management module manages the original training data.

The display module is the core part of the whole system, through the visualization chart generated by the display module, it can reflect the changes in athletes' training data intuitively. The whole display module is divided into five parts, respectively, line graph, histogram, scatter chart, and pie chart. The system functions provide the choice of different indicators, and the charts of different indicators data are obtained according to the needs.

The algorithm proposed in this chapter is an exploratory experiment based on the full consideration of the importance of human proprioception through the analysis, mining, and pathological study of a large amount of dynamic balance examination data. Through literature research and conversations with several sports balance rehabilitation practitioners, our assessment model uses the balance index as the predictive outcome (or fit, label, etc.). To verify the accuracy and feasibility of the proposed method, this chapter adopts the Goodness of Fit and categorical error assessment models, and the whole experimental training process and validation process are shown in Figure 2. To test whether there is redundant information between the data, the experiment uses a linear correlation analysis to analyze whether there is a linear correlation between the 48-dimensional attributes of the data. The Pearson correlation coefficient was used to calculate the correlation between attributes. After analysis, it is found that there is a linear correlation between the data, but the linear correlation between the 48-dimensional indicators and the equilibrium index does not directly guide the model construction. Instead, we can only extract artificial features from the data from a theoretical point of view. Through reviewing many literatures, we found that human proprioception has a significant influence on dynamic balance and is important for the assessment of human dynamic balance. For the above reasons, we attempted to start with the measurement of two movements in the closed-eye condition in middle-aged and elderly people, from which we hope to construct a model for the assessment of motor training. After extensive research, the hypothesis of this paper was found to be correct and is presented subsequently. Therefore, the 48 indexes from four movements were further streamlined, and the movements were reduced from the original four movements to two movements: standing with eyes closed on both feet and standing with eyes closed on one foot, and the data indexes were also reduced from the original 48 to 24 dimensions.

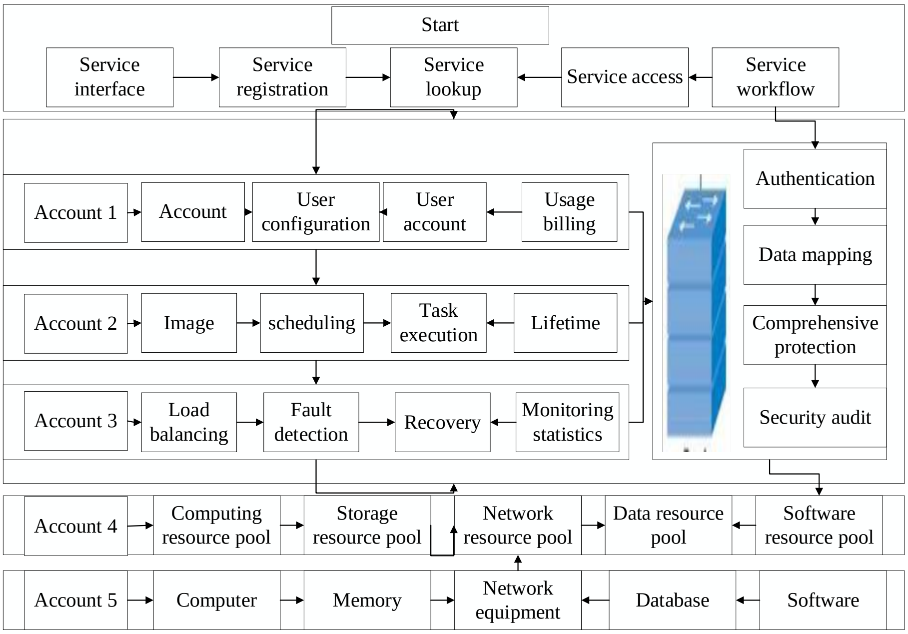

Figure 2: Functional module design.

To facilitate model training, the above data need to be standardized. Standardization is an essential process of the data mining process, through the standardization of the original data is only a certain degree of scaling, but does not change the distribution of data. Especially in the machine learning model training process, due to the inconsistency of the various dimensions of the data outline, may lead to additional training process in the training process, increase the training difficulty of the machine learning model, or even not converge, but through the data standardization process, can be normalized to a certain range of characteristics of the different dimensions of the data, and thus reduce the training process of the model, reduce the training time. After the data processing operations in section 2.1, the data in the data set currently still maintains the data composition, that is, the data sample space is still 24 dimensions, and the label is the equilibrium index. Of course, these 24-dimensional input features are not the input features of the final model training process, because there are still redundant and interfering information in these 24-bit sample features. To further extract the valid features from the input data and reduce the interference of other irrelevant features, we need to perform further feature extraction operations on the remaining 24-dimensional features. The feature extraction algorithm used here is the RFR-RFE feature extraction algorithm mentioned in Section 2.1. This algorithm uses the regression algorithm of random forest (RFR) as a learning model to continuously extract important features from the data through continuous iterations of RFE, and then achieve feature extraction based on the feature importance index of RFR.

3 ANALYSIS OF RESULTS

3.1 Intelligent Computer-Aided Athletic Training System Performance Results Analysis

The amplitude-frequency characteristic of the Hamming window is the large attenuation of the side-valve, and the attenuation from the peak of the main valance to the peak of the first valance can be up to 40dB. Each time the Hamming window is moved, the attenuated information of the sEMG data in the previous one is enhanced again, thus improving the stability of the sliding Hamming window and controlling the frequency leakage of the SPM features to a certain extent. To balance the time and frequency information of the SPM features, the window size of the Hamming window is set to 15 samples and the sliding step is set to 12 samples. To reduce the data volume of SPM features, the SPM features of each channel are first flattened into one-dimensional features with a feature size of 64×1 and then merged in the channel direction to obtain SPM features of eight channels with a feature size of 64×8. The contribution of variance and the contribution of the cumulative variance of the SPM features are shown in Figure 3. According to Figure 3, the contribution of the cumulative variance of the four principal components of the SPM characteristics is 99.2%, so the four principal components of the SPM characteristics are retained using PCA. The improved SPM characteristics contain sufficient valid information from the original eight principal components, and the data size is optimized to 64×4.

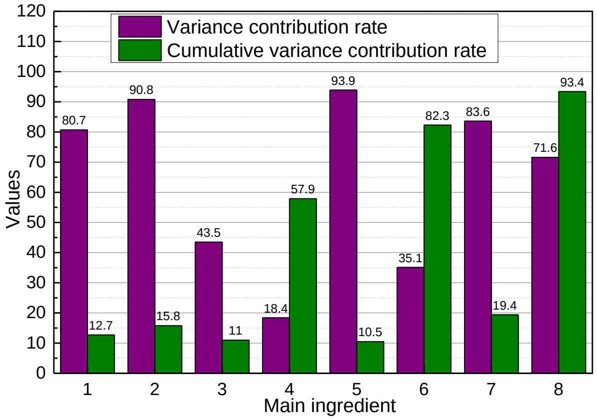

Figure 3: Contribution of variance and cumulative contribution of variance.

Take the first grip as an example, take any segment of the sEMG data obtained by segmentation, and the improved SPM characteristics are obtained as shown in Figure 4.

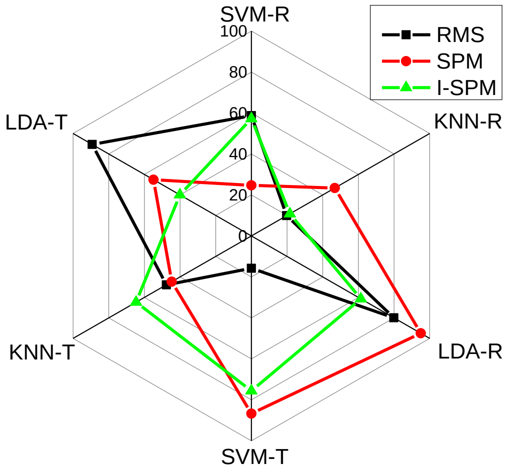

Figure 4: Performance Comparison of the Three Features.

The improved SPM features were entered into the three classifiers and compared with the original SPM features and the better performing RMS features, and the accuracy and running time of the classifiers were used as the evaluation metrics of the features. Under the three classifiers, it can be seen in Figure 4 that the improved SPM features retain the valid information in the original SPM features, and the accuracy still reaches the original level under different classifiers, which ensures the stability of the features. And because the improved SPM features are processed by PCA, the amount of data is greatly reduced compared with the original SPM features, and the running time of the classifier is reduced, which is close to the running time of other features with the same level of accuracy. Combining the stability, accuracy, and runtime of the features, the improved SPM feature performs best. However, for ten hand movements, an accuracy of more than 80% is not sufficient for intelligent prosthetics. The different features are input into three classifiers, namely, SVM, KNN, and LDA, respectively, and the performance differences are analyzed according to the accuracy and running time of the classifiers. An improved SPM feature based on PCA is then proposed, where the amount of data for the features is optimized while retaining sufficient valid information. Finally, the experimental results are analyzed to select the best features, and the improved SPM feature is selected for hand motion recognition to complete the acquisition of valid information for sEMG, as shown in Figure 5.

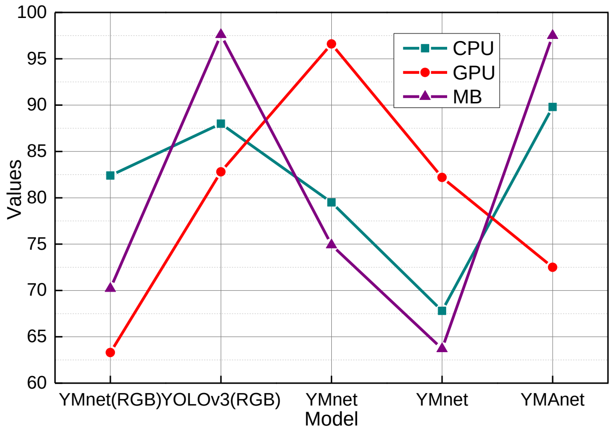

Figure 5: Real-time comparison of the fusion model.

Figure 5 shows that for the same model, the GPU can significantly speed up the forward reasoning task relative to the CPU by a factor of 1 to 5, demonstrating the computational power of GPU parallel computing. When compared to YOLOv3, YMAnet is faster on both the CPU and GPU platforms, and more than doubles the inference time on the CPU platform, and the inference speed is sufficient for real-time processing on both platforms. Also, on the GPU platform, YMAnet requires 517MB of video memory for inference, much less than the 6533MB required by YOLOv3, making YMAnet more suitable for performance on mobile platforms such as autopilot.

3.2 Analysis of Results from Data Mining Applications

A comprehensive analysis of the final performance and detection results of the model is performed. Figure 6 shows the training curve plot of YMAnet using fused GIoU Loss as the bounding box loss, which shows that the convergent fit of the three losses in the training process is good and no overfitting occurs. After the training is completed, the model is loaded into YMAnet and the training set is used to analyze the detection performance of the rider, vehicle, and pedestrian targets.

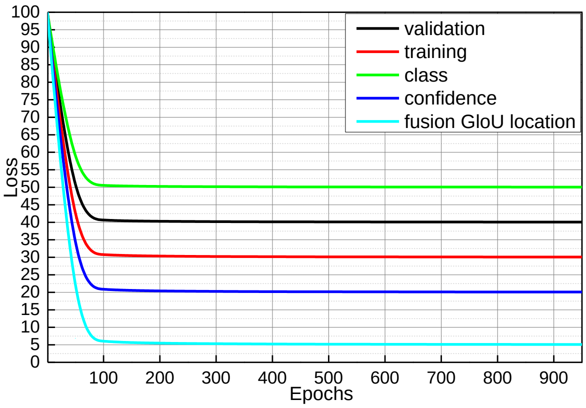

Figure 6: Training Curve.

From Figure 6, the model has a high recall rate for all three types of targets: rider, car, and pedestrian, and the curve is in the upper right of the figure. This means that even if we change the target score threshold at the time of detection, the model can still perform target detection with high accuracy and recall, indicating that the model is robust to the detection of different targets. Since the model in this chapter is built based on the four measurement action correlation assumptions, only a deep learning algorithm based on time series can be chosen for the algorithm comparison, two sets of control experiments will be set up in this chapter to verify the superiority of our method. The overall neural network structure of the comparison experiment is shown in Figure 7, except that the middle three layers of LSTM neural networks are replaced by three layers of RNN and three layers of GRU neural networks, respectively, to ensure the reliability of the comparison experiment, except for the different settings of the middle three layers of neural networks based on time series, all other experimental conditions are kept consistent. Similarly, to quantify the results of the comparison experiments, the quantification metrics still use macro accuracy, macro recall, and macro values to evaluate the performance of the model. The specific experimental results are shown in Figure 7.

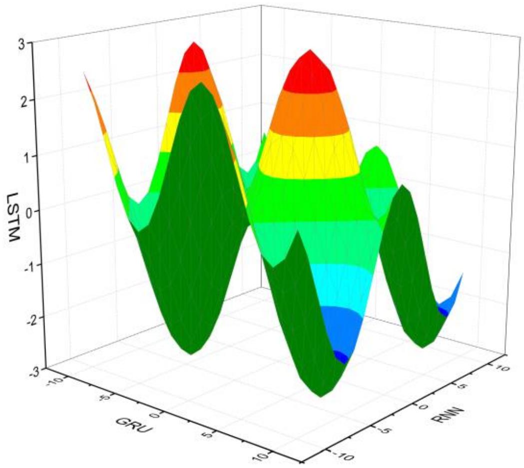

Figure 7: Experimental and control group experimental results.

It can be found that the overall difference between the three algorithms is not very great, with RNN being the worst, but its Macro-Precision also reaches 0.8425, while GRU is more capable of learning RNN, with its Macro-Precision, Macro-Recall, and Macro-F1. Theoretically, this can be explained by the fact that GRU's network mechanism is more complex and its generalization ability is better than RNN's. Therefore, it is only natural that GRU will perform better than RNN in the test set. However, compared with the above two algorithms, our LSTM-based multilayer neural network model has the best performance, with Macro-Precision, Macro-Recall, and Macro-F1 all reaching over 0.86. The analysis shows that our method is more efficient than the RNN-based one. The reason why our method is superior to the GRU method is that the LSTM network mechanism is more complex and has better learning ability than the GRU method. Of course, during the experiment, we also tried to add the number of GRU layers to four, but the results showed that the trained model had a serious overfitting phenomenon, so we conclude that the LSTM-based multilayer neural network structural model is more suitable for the current sports training data, and its classification model and classification effect are better than RNN and GRU.

A scatter plot is used to visualize the data, which is used to observe whether there is a correlation between the training data and if there are data points that deviate from the majority of the points, then the scatter plot can be visualized. The scatter plot can provide coaches with the function of the overall change trend of athlete training data, which is an important means for coaches to judge the effect of training methods. The scatter plot designed by this system also satisfies the function of visible selection of items, training phases, and athletes. Figure 8 shows the scatter plot of the plate support data of 8 athletes from June to October 2019. From Figure 8, it is evident that among the 8 athletes, the data coordinate points of the obvious athlete 2 is in the upper level of the coordinate system, and the data points are spaced at a larger interval, with each month's coordinate points being higher than the previous month's, indicating that their level of plate support is improving, which shows that athlete 2 is more adapted to the current training method. This shows that athlete 2 is more adaptable to the current training method. As athlete 2 is younger, coaches should pay more attention to maintain her training condition. Figure 8 shows that there is no significant change in the data points of athlete 4, indicating that athlete 4's ability of plate support has not changed significantly after the training period, and coaches should find out the reason and make corresponding training adjustments according to the athletes' competitive status. Coaches can also make targeted adjustments to the training methods of other athletes based on the changes in their coordinates.

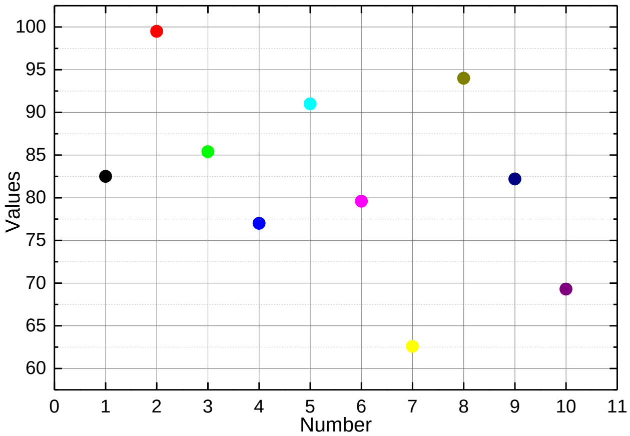

Figure 8: Scatter plot of athletic training data.

The analysis of the data in this paper was done with the help of a visualization system made in Python, and the initial exploration of the sports training program is the further integration of computer technology and sports science, but there are still many shortcomings in this system, in the way the data is processed and the variety of graphs and charts generated need to be strengthened, and it is hoped that in the future, artificial intelligence will be added to the functions of expert decision-making. The supervision process of the exercise training provides real-time diagnosis as well as monitoring functions. The purpose of this paper is to analyze and mine the data of middle-aged and elderly people's body balance utilizing machine learning, and then build a mathematical model. The purpose of this paper is to analyze and mine the motion balance data of middle-aged and elderly people through machine learning means or methods, and then build a mathematical model. By investigating the relevant research on exercise training at home and abroad in recent years, it is found that the foreign research on human dynamic balance is mainly focused on the research of equipment and methods, and there are articles involving machine learning related contents, but basically, they are based on experimental data collection, the amount of data is relatively small, and the measured data are used for simple model construction, and the core algorithm is simple and single.

4 CONCLUSION

In this paper, two machine learning algorithms are proposed to construct different athletic training assessment models by mining over 17,000 athletic training data. The first model is based on GBDT, which is a regression analysis-based exercise training evaluation model based on RFR-RFE and GBDTR, and the model shows good performance through a large amount of data training: the model can fit the data samples well, with a goodness of fit of 0.888, classification error with the help of the original data, and classification error with the help of the original data. Although the overall model performance is good, there is still great room for improvement. In the model validation stage, the validity and flexibility of the experimental hypothesis were effectively verified through the comprehensive evaluation of two aspects: action combination and machine learning training algorithm, and the reliability and superiority of the measurement method were also verified through the comparison of the experimental methods. Based on the assumption that there is a correlation between measurement actions, i.e., there is a correlation between the four measurement actions, the correlation is used for motor training classification. Compared to the first model, this model is a classification model and has a different model focus.

5 ACKNOWLEDGMENT

the special project of "Epidemic Situation and Education" planned by Education Science in Shandong Province in 2020, "Research on Evaluation and Optimization Strategy of Online Teaching Effect of Physical Education in Schools During Epidemic Prevention and Control in Shandong Province" (subject No. 2020YZB013.

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