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Analyzing UFC Mixed Martial Arts Data Based on a Multilayer Perceptron Algorithm to Provide Insight and Teach Performance Evaluation to College Fighters

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ABSTRACT
Teaching and correcting athletes' techniques by analyzing and referring to the performance of professional tournament players can improve the teaching level and quality of wushu movements. In this paper, the performance of college students in UFC tournaments is taken as the research data, and the multilayer perceptron algorithm is used to process the images and carry out the global modeling of wushu fighting action images. The network coding design is used to improve the data transmission rate of the algorithm, and the activation function is used as the nonlinear expression method of the algorithm. The Tanh_Softsign activation function is improved to counteract the noise interference of the dataset images, in order to construct the multilayer perceptual machine algorithm and develop the learning of martial arts fighting action scores. After optimizing the learning of UFC martial arts action scores by this algorithm, this algorithm shows a high correlation between the performance scores of students and the professional teachers' scores of an elective class of martial arts in a university with P>0.05, which indicates that the algorithm in this paper can accurately assess the students' action performance.

Keywords: multilayer perceptron, network coding, Tanh_Softsign activation function, martial arts fighting moves

1. Introduction

The purpose of building high-level sports teams in general colleges and universities is to cultivate comprehensively developed high-level sports talents for the country, with the goal of completing the participation in the World University Games and major international and Chinese sports competitions, and contributing to the national Olympic glory program and the sustainable development of competitive sports [1-3]. The main purpose of the construction of the evaluation index system of high-level sports teams in ordinary universities is to promote the quality of the

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construction of high-level sports teams in ordinary universities [4].

After more than 20 years of development, China's general high school high-level wushu sports teams have made achievements for all to see. The scale of development has been expanding and the athletic performance has been improving. However, there are some problems behind the achievements, which affect the construction and development of the team [5-6]. Evaluation index system is the concretization, behavioralization and operability of the evaluation goal, which is an important guarantee for the evaluated object to achieve towards the established goal. Therefore, there is an urgent need for a set of complete, scientific and operational evaluation programs to supervise and manage the construction of high-level wushu sports teams in general colleges and universities [7-9]. Compared with other sports, there have been few successful cases of using intelligent evaluation systems in wushu programs [10]. Since wushu originates from China, its cultural and social background is distinctly special, which leads to the fact that there are still very few international studies related to intelligent scoring systems for wushu sports [11-12].

The intelligent evaluation system is based on human action recognition, and effectively evaluates the recognition and analysis of martial arts movements. In the field of human action motion recognition and analysis, the acquisition and analysis technology of 3D motion data is relatively mature and has been widely used, which generally collects and analyzes data through multiple camera marker tracking technology, and due to the relatively complex composition of the equipment, the system is expensive and the use scenarios are limited, which is suitable for the installation and use of large-scale competition venues or large-scale professional sports venues [13-15]. Compared with the 3D action recognition and analysis system, the 2D action recognition and analysis system generally only needs a single camera sensor and is equipped with corresponding computing recognition and analysis equipment to realize the recognition and analysis of action, which significantly reduces the cost of the system, and is convenient to use, suitable for a wide range of scenarios, and has higher operation efficiency, but due to the singleness of the collected data, the accuracy of the action recognition results is relatively low [16-18].

In this paper, the UFC dataset is cleaned and outliers are processed as the data used for algorithmic research. Then it elaborates the principle of multilayer perceptual machine as a method to extract the contextual information of fighting action images. The network coding is designed to improve the transmission efficiency of the image data, and the activation function is used for the nonlinear expression of the algorithm, and the activation function is optimized to resist the noise interference of the data image, and the multilayer perceptron algorithm is built comprehensively. Finally, the algorithm of this paper is used to analyze and study the performance scores of martial arts movements, to test the correlation and significant difference between them and the scores of professional teachers, and to carry out the evaluation application and analysis of this paper's algorithm in practical teaching.

2. Data processing

2.1. Data sources

Started in 1993, the UFC is a global MMA competition and one of the most influential and largest fighting events in the world. The UFCSTATS website has data on every UFC fight since its inception in 1999, as well as personal data on every athlete who has ever competed in the UFC. The data used in this article was taken from the website and spans from January 2000 to December 2023.

2.2. Preprocessing of the UFC dataset

Data preprocessing, also known as data cleansing, is the process of fixing incorrect, incomplete, duplicate or otherwise erroneous data in a data set. It first identifies data errors and later changes, updates or deletes data to correct the errors. Data cleansing improves the quality of data sets and helps provide more accurate, consistent and reliable information. Data cleansing is a key part of the process and is one of the core aspects of data preprocessing. The main purpose of data cleaning is to create a unified and standardized dataset to support the subsequent research in this paper. After an in-depth analysis of the UFC big data, it is found that there are some outliers and missing values, so this chapter will focus on these outliers and missing values and take effective data cleaning measures to solve them.

2.3. Outlier Handling

In statistics, outliers are values that are significantly different from other observations, also known as outliers. Discovering and investigating outliers is the main task of outlier handling, and the common scenarios are listed below:

Outlier determination is a common method used when values are outside of a certain standard value to help check that the data is outside of the theoretical range and to ensure that the numbers are in line with reality. Through personal experience or specialized domain knowledge, it is possible to look at the maximum or minimum value in a numerical value.

Data greater than ± 3 standard deviation. When data are normally distributed, the 3σ principle is widely used to deal with singular values, i.e., data with deviated means greater than three standard deviations. Based on the properties of the normal distribution, data with more than three standard deviations may be recognized as erroneous and should therefore be excluded.

Odd values can be effectively identified using methods such as box-and-curve plots, descriptive analysis methods, and scatter plots. The boxplot can be used to calculate the minimum and maximum estimated values of the data, which can be considered as outliers if they are beyond this region and these outliers are marked on the dots in the boxplot for better identification. Therefore, in this paper, we use box-and-line plot to analyze the outlier data, and the boxplot() function of Pandas library is also used to draw the box-and-line plot. Considering that most of the original data table is standardized text-based data, this paper selected the most likely abnormal weight variable to draw the boxplot. From the graph, it can be seen that there are obvious outliers (outliers) in the weight of UFC athletes, so the outliers need to be processed. The processing of outliers is categorized into methods such as deletion, filling and no processing, but considering that this data does not contain useful information in the event win prediction task of this paper, this type of outliers are deleted in this paper.

This chapter begins by describing the data sources for the study of this paper, and the data cleansing and outlier treatment of these original data as a means of determining the data base for the study of this paper.

3. Multi-layer perception machine algorithms

As a top professional martial arts fighting event, the performance and winning characteristics of UFC fighters have certain reference significance in daily martial arts teaching and training. Since fighting is mainly based on body movements, which are presented in the form of images and videos, a multilayer perceptron algorithm is used in this chapter to develop the modeling of fighting action images. At the same time, the network coding design is introduced to improve the efficiency of data transmission, the activation function is used to realize the nonlinear expression of the model, and the Tanh_Softsign function is improved to fight against the noise interference in the network transmission, so as to realize the accurate modeling and analysis of the UFC dataset.

3.1. Multi-Layer Perception Machine

Thanks to the continuous development of computer technology, machine learning has developed rapidly as a way to realize artificial intelligence. As early as 1957, researchers first proposed the perceptual machine algorithm (PLA), which is the earliest model to appear in the field of machine learning. Perceptual machine has only one neuron, contains input layer and output layer, the algorithm is simple and easy to understand, its model structure is shown in Figure 1.

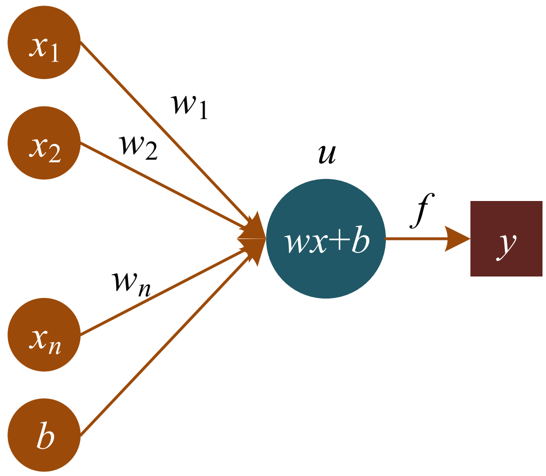

Fig. 1. The architecture of Perceptron Learning Algorithm

The single-layer perceptron, unlike the linear regression problem, is essentially a binary classifier, assuming that the activation function is a step function $\operatorname{sgn}(x)$ and outputs 1 when the input is greater than 0. When the input is less than or equal to 0, the output is 0. The single-layer perceptron can only be used to deal with the linear problem, and it can't fit a heteroscedastic function, which is computed as in Eq. (1):

$$y = f(u) = f\left(\sum_{i=1}^{n} w_i x_i + b\right) \tag{1}$$

Where, w_i is the input layer weights, b is the bias and y is the output.

Until the proposal of multilayer perceptron (MLP) can be used to solve nonlinear problems. One or more intermediate layers, called hidden layers, are added to the single layer perceptron. The multilayer perceptron contains an input layer, an output layer and a hidden layer, and its network model is schematically shown in Fig. 2.

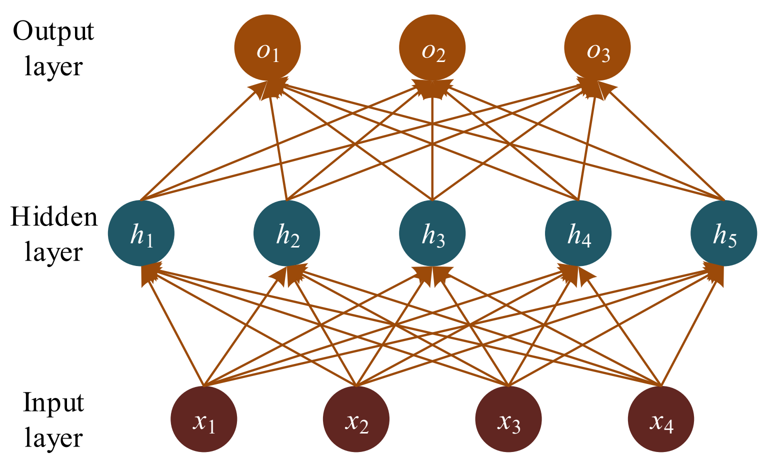

Fig. 2. Multi-Layer perceptron network architecture

The multilayer perceptron contains a hidden layer, an input layer and an output layer, where there are four inputs, three outputs, five neurons in the hidden layer, and the layers are fully connected to each other. The input layer does not have any computation, and the network output computation is only determined by the hidden layer and the output layer, however, the model still has a linear relationship between the input and the output, and a nonlinear element activation function needs to be introduced in order to realize the nonlinear fitting ability, and the multilayer perceptron is computed as in Eqs. (2) and (3):

$$H=\sigma\left(XW^{(1)}+b^{(1)}\right) \tag{2}$$

$$O=HW^{(2)}+b^{(2)} \tag{3}$$

where σ denotes the activation function, $W^{(1)}$ and $b^{(1)}$ denote the weights and biases of the hidden layer, and $W^{(2)}$ and $b^{(2)}$ denote the weights and biases of the output layer.

Adding nonlinear activation function in multilayer perceptual machine can effectively avoid the network model degradation into a single-layer linear network, so that the model can approximate any nonlinear function, common activation functions are Sigmod function, Tanh function, ReLU function, GELU function, etc., and the following sequential expansion of the specific introduction:

1) Sigmoid function. Sigmoid is a common nonlinear activation function, the output range of the function is $[0,1]$, applicable to the model whose output is the predicted probability, for each neuron output is normalized. However, the derivative range is small, and the training process is prone to saturation, and the network weights are difficult to update when backpropagation occurs, and it is easy for the gradient to disappear. In addition, the need for power operations, high computational complexity, the larger the inverse of the live function, the smaller the inverse, is still prone to gradient disappearance, and does not apply to the model whose outputs are all greater than 0. The Sigmoid function formula is defined in equation (4):

$$Sigmoid(x)=\frac{1}{1+e^{-x}} \tag{4}$$

2) tanh function. $\tanh$ function is a hyperbolic tangent function, whose output range is $[-1,1]$ and the function is an antisymmetric S type curve symmetric to the coordinate origin, which solves the problem that the Sigmoid function is not applicable to the model whose outputs are all greater than 0. However, there is still the problem of the gradient vanishing and the power operation with a large amount of computation. $\tanh$ The function formula is shown in equation (5):

$$\mathrm{Tanh}(x)=\frac{e^{x}-e^{-x}}{e^{x}+e^{-x}} \tag{5}$$

3) ReLU function. ReLU function is a linear function (x is a positive number), the advantage is that the convergence speed is faster than the Sigmoid and tanh function, ReLU function of the non-saturated nature of the effective solution to the problem of the gradient disappears, and the computational speed is fast there is no complex power operation, but can not be input for the negative number of the operation, ReLU function formula as in equation (6):

$$\sigma(x)=\begin{cases}\max(0,x), x\geq 0\\ 0, x<0\end{cases} \tag{6}$$

4) GELU function. The GELU function has non-zero gradient at the origin, which reduces the phenomenon of gradient vanishing and faster convergence in training.The RELU function has lower computational complexity and is suitable for convolutional neural networks, while the GELU function is generally used in the fully connected layer.The formula of the GELU function is shown in Eq. (7):

$$GELU(x)=x*P(X\leq x)=x*\Phi(x) \tag{7}$$

where $\Phi(x)$ is the cumulative distribution function of the normal distribution, which is simplified to give the GELU expression as in equation (8):

$$GELU(x) = 0.5x\left(1 + \tanh\left(\frac{x}{\sqrt{2}} * \left(x + 0.44715x^3\right)\right)\right) \tag{8}$$

3.2. Design principles of network coding based on multilayer perceptron machines

The idea of stochastic network coding is to encode a linear combination of all messages, the coefficients used are randomly selected, and the coefficients are selected without knowing any information about other nodes. The coding method based on multilayer perceptron is to co-design the channel input in the source martial arts fighting action node and the intermediate node, the topology of the physical system needs to be known in advance, and the input and output dimensions of the neural network are mapped to the network code of the node, in which each $l(l \neq 0)$ layer of the neural network can be selected to represent a node of the network, and the coding coefficients not only contain multiplicative coefficients but also additive coefficients, and the coefficients domains selected in this paper are real domain $\mathbb{R}^n$, instead of the finite domain in the classical network coding literature $GF(\cdot)$. The input signal is reconstructed as 4 by decoding the received noisy distorted network code using a neural network at each target node t. The input signal is then reconstructed as $\vec{X}^t$.

The network coding model based on multilayer perceptron is constructed by co-designing the channel inputs at the source and intermediate nodes. Also by choosing the activation function to incorporate a nonlinear factor, since each layer of the neural network is affine transformed followed by an element-by-element nonlinear function, so that the resulting network coding is nonlinear by design.

The network coding from node v_i to node v_j is designed by constructing a neural network with input dimension d_{in}^i and output dimension $k_{i,j}$.

When $v_i \notin S$, $d_{in}^i = \sum_{l \in c(i)} k_{i,j}$. when $v_i \in S$, d_{in}^i is the dimension of the signal generated at v_i, the generated signal is fed into the neural network. If $v_i \notin S$, during transmission, a cascade of the received fuzzy action image network code is input to the neural network at v_i. Again, the neural network layers are used to represent the noisy link. The output of the neural network is the network code $\vec{W}_{i,j}$ transmitted over the link (i, j).

In the fighting action model construction, the input signal is reconstructed as $\vec{X}^t$ by using a neural network at each target node t to decode the received fuzzy action image network code, and the target node t is used as the output layer of the decoder. In order to realize the reconstruction process and calculate the distortion measure between the original detail information and the reconstructed information at the action node t, this paper chooses the mean squared error loss function as in equation (9). Then, the network coding parameters are randomly initialized and trained to minimize this loss function to get the best network coding parameters.

$$Loss = \min_{\{\theta_i\}_i} \sum_{t=1}^{2} M_b\left(\vec{X}, \vec{X}^R\right) = \frac{1}{n}\sum_i \left(X_i^R - X_i\right)^2 \tag{9}$$

where M_b is the mean square deviation between the original action detail information and the reconstruction information at target node R.

3.3. Improved Tanh_Softsign activation function

Due to the large time span of the dataset studied in this paper, the collection of data information is limited by technical conditions, and the fighting action image information of earlier years is more or less characterized by high noise and low noise. The low-noise fighting action images are characterized by smooth and continuous gray scale changes, while the high-noise fighting action images are characterized by obvious random particles and speckles. Aiming at this characteristic, this subsection improves the model's ability to decode action image data under noise conditions by improving the Tanh_Softsign activation function.

3.3.1. Tanh_Softsign activation function principle. Based on the above analysis, it is found that the activation function with “ReLU-type” characteristics can provide better decoding effect under low noise conditions, but its resistance to interference under high noise conditions is relatively poor. On the other hand, the activation function with “S-type” characteristics has better anti-interference performance under high noise conditions, but its decoding effect is not as good as that of the “ReLU-type” activation function under low noise conditions. In order to further improve the anti-noise performance and robustness of the multilayer perceptron-based network coding, a new combined activation function Tanh_Softsign is proposed in this paper, and the expression of this activation function is shown in equation (10):

$$\mathrm{Tanh\_}\,Softsign = \begin{cases} \tanh(\alpha x) & x \geq 0, \alpha > 0 \\ softsign(\beta x) & x < 0, \beta > 0 \end{cases} \tag{10}$$

3.3.2. Performance analysis of Tanh_Softsign activation function. The Tanh_Softsign activation function image is shown in Fig. 3, where the Tanh_Softsign activation function behaves approximately linear around the positive semi-axis 0, and therefore retains a better performance at low noise. The image as a whole is of type S, so it has better immunity to interference in high noise situations.

On the positive half-axis, selecting the Tanh activation function, the parameter α can be adjusted so that it has some of the characteristics of the “ReLU-type” activation function in the 0-1 interval, and therefore maintains a good decoding performance in low noise conditions. Selecting the Softsign activation function in the negative half-axis and choosing the appropriate parameter β reduces the loss of information in the negative half-axis and avoids the phenomenon of losing all the information of the action output in the case of large noise disturbances; the Softsign activation function can keep the regular presentation of the information of the action output in the case of noise disturbances, and retains the anti-jamming properties of the “S-type” activation function. The Softsign activation function can maintain the regularity of the action output information under noise interference, retaining the anti-interference performance of the “Type 44” activation function. So no matter in low noise or high noise situation, can have better decoding effect.

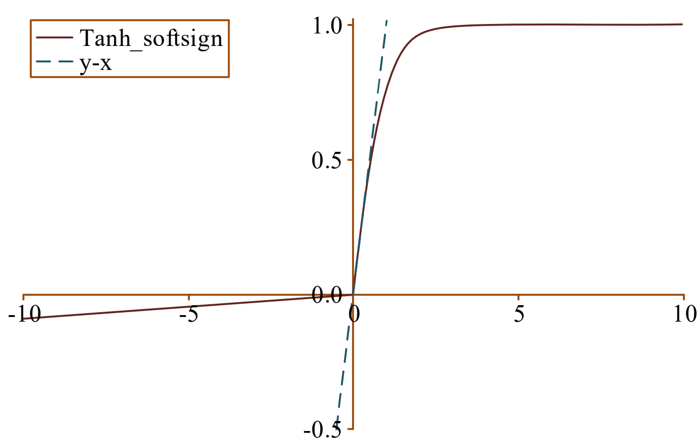

Fig. 3. Tanh Softsign activates the function

4. Wushu movement scoring based on multilayer perceptual machine algorithm

In order to analyze and evaluate the performance of wushu movements of students in colleges and universities from a professional point of view and to better correct them, this chapter uses the algorithm of this paper to learn and optimize the scoring of UFC wushu movements, and at the same time compares and examines the consistency between the system scoring and the teacher's scoring, which can be applied to the scoring of the wushu performance of students of wushu elective class in a university.

4.1. Wushu movement performance scoring based on the algorithm in this paper

In this paper, we conducted a two-way ANOVA with a 3 (groups) x 9 (intervals) two-way ANOVA with a mixed design for martial arts movements, where intervals are the number of repetitions, and the test was used to obtain objective scores for each body part (hand, torso, leg, and overall balance) as well as an estimate of the error. The three groups were the imitation expert group (A), the self-imitation group (B), and the no-imitation group (C). The retention test of the experiment was then analyzed by independent samples one-way ANOVA with rater scores as well as error estimates for each body part separately. The level of significance for this study was set at $P = 0.05$.

Figure 4 shows the delayed retention hand scores of the 3 groups at 9 intervals of practice and after 24 h. There was no interaction between the hand scores of the 3 groups in the continuous lunge kicking and punching maneuver, with no difference between the groups ($P > 0.05$), and the main effect of the intervals amounted to a significant difference of $P < 0.05$ (9 > 1-6, 7,8 > 1-4, 5,6 > 1-3, 4 > 1-2, 3,2 > 1).

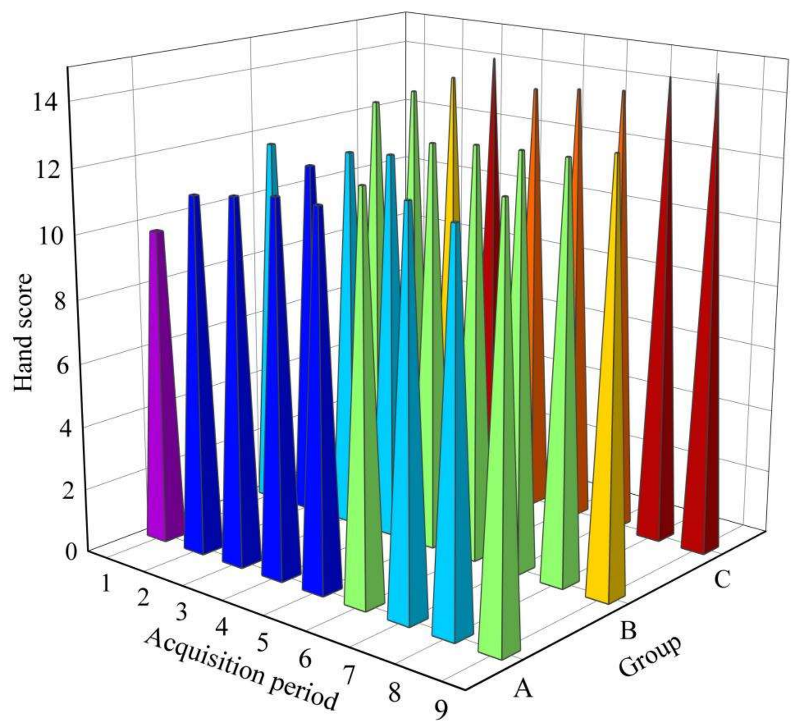

Fig. 4. Each group practiced and retained hand scores on the test in nine intervals

Figure 5 shows the delayed retention torso scores of the 3 groups at 9 intervals of practice and after 24 h. There was no interaction between the torso scores of the 3 groups in the continuous lunge kicking and punching maneuver, with no difference between the groups ($P > 0.05$), and the main effect of the intervals amounted to a significant difference of $P < 0.05$ (9 > 1-3,5,7,8 > 1-3,6 >

1-3,5,4,5 > 1-2, 3,2 > 1).

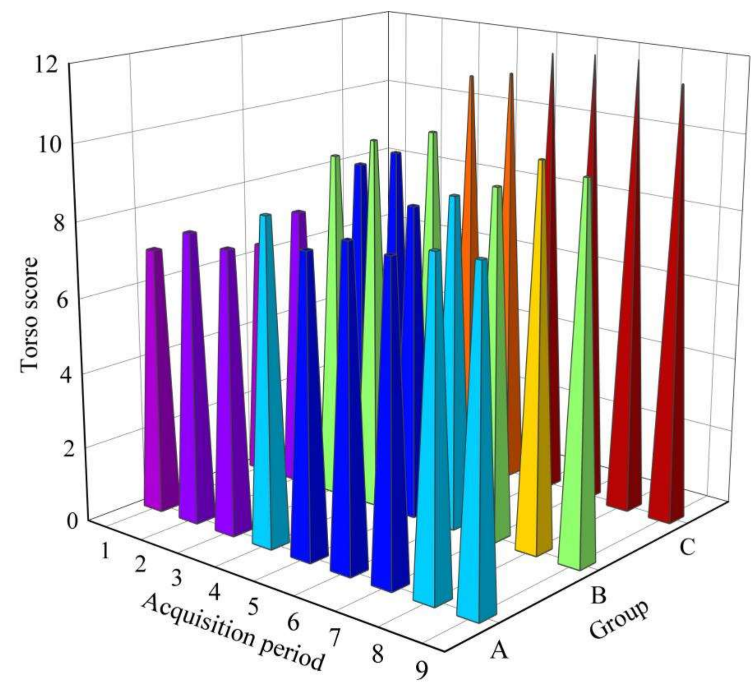

Fig. 5. Each group practiced and retained the torso scores of the test in 9 intervals

Figure 6 shows the delayed retention leg scores of the 3 groups at 9 intervals of practice and after 24 h. There was no interaction between the leg scores of the 3 groups in the continuous lunge kicking and punching maneuver, with no difference between groups (P > 0.05), and the main effect of the intervals amounted to a significant difference of P < 0.05 (9 > 1-6,8,8 > 1-3,7 > 1-6,6 > 1-3,3,4,5 > 1-2,2 > 1).

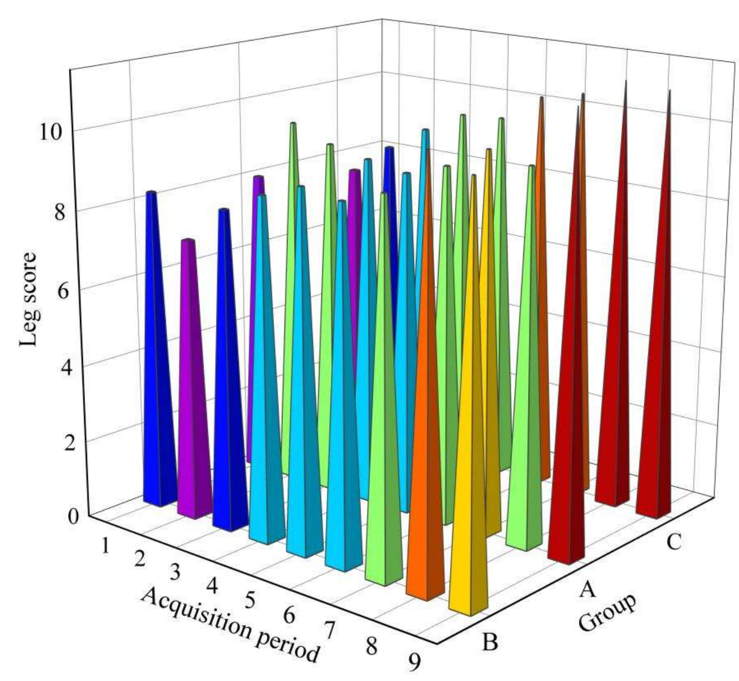

Fig. 6. Each group practiced and retained leg scores on the test in nine intervals

Figure 7 shows the delayed retention overall balance scores of the 3 groups at 9 intervals of practice and after 24 h. There was no interaction between the overall balance scores of the 3 groups in the continuous lunge kicking and punching maneuver, with no difference between groups ($P > 0.05$), and the main effect of the intervals amounted to a significant difference of $P < 0.05$ (9 > 1-7, 7,8 > 1-5, 6 > 1-4, 4,5 > 1-3, and 3 > 1).

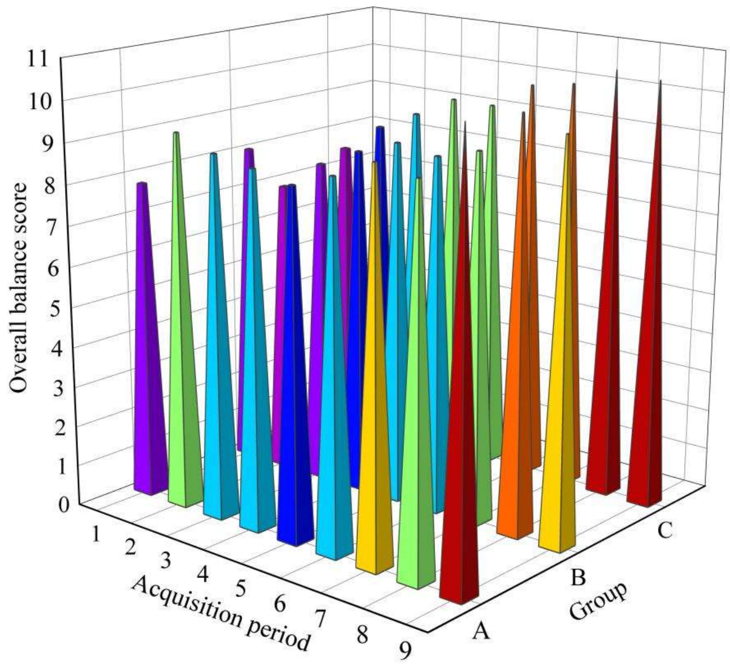

Fig. 7. Each group practiced and retained overall balance scores in 9 intervals

4.2. Optimized Action Scoring Results and Analysis

On the basis of this paper's algorithmic wushu movement performance scoring unfolded above, this section takes 2 wushu elective classes (E and F classes) of a university as the research object, in which there are 25 students in E class and 30 students in F class. Firstly, the optimization of the system scoring is carried out, followed by the correlation analysis between the system scoring at each stage and the scoring of the professional teachers of this university, and finally the scoring result analysis of the students' wushu fighting movements in the elective classes is carried out.

4.2.1. Correlation Analysis between Algorithm Scores and Teacher Scores. The initial stage of the algorithm to the optimization of the four stages are the initial algorithm (Initial), optimization of the first (Optimize 1), optimization of the second (Optimize 2), optimization of the third (Optimize 3), optimization of the fourth (Optimize 4).

The correlation analysis between the results of the professional teachers' ratings and the results of the algorithm's ratings at each stage is shown in Fig. 8. The correlation between the algorithm's initial stage ratings and the professional teachers' ratings was 0.816, with $P=0.000<0.001$ presenting a significant difference. The correlation between the algorithm optimization first stage scores and the professional teacher scores was 0.809, $P=0.009>0.001$ showing no significant difference. The correlation between the algorithm optimization second stage ratings and the professional teacher ratings was 0.854, $P=0.012>0.01$ no significant difference. The correlation between the algorithm optimization third stage ratings and the professional teacher ratings was 0.861, $P=0.029>0.001$ no significant difference. The correlation between the algorithm optimization fourth stage scores and the professional teacher scores was 0.868, $P=0.043>0.001$ no significant difference. This indicates that all optimization stages of algorithm scores showed high correlation with professional teacher scores and the results of the optimized algorithm scores were consistent with the teacher scores.

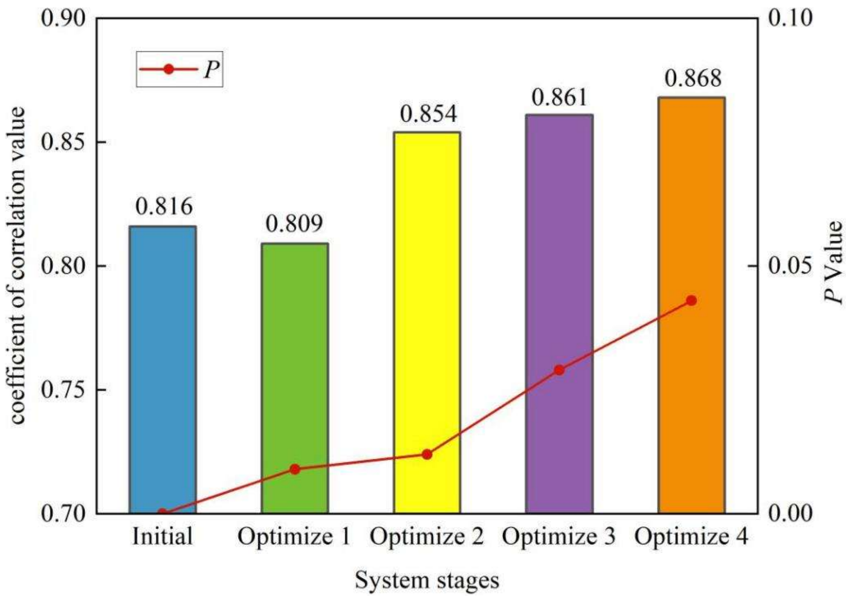

Fig. 8. Correlation analysis of scores

4.2.2. Comparison of scoring results for elective classes. The data of professional teacher ratings and algorithmic ratings of elective E class were analyzed by QQ plots to conform to normal distribution. A paired-sample t-test of the results of the Elective E class specialty teacher ratings and the algorithmic ratings is shown in Figure 9, with a p-value of 0.179 > 0.05, and there is no significant difference in the ratings of the two groups.

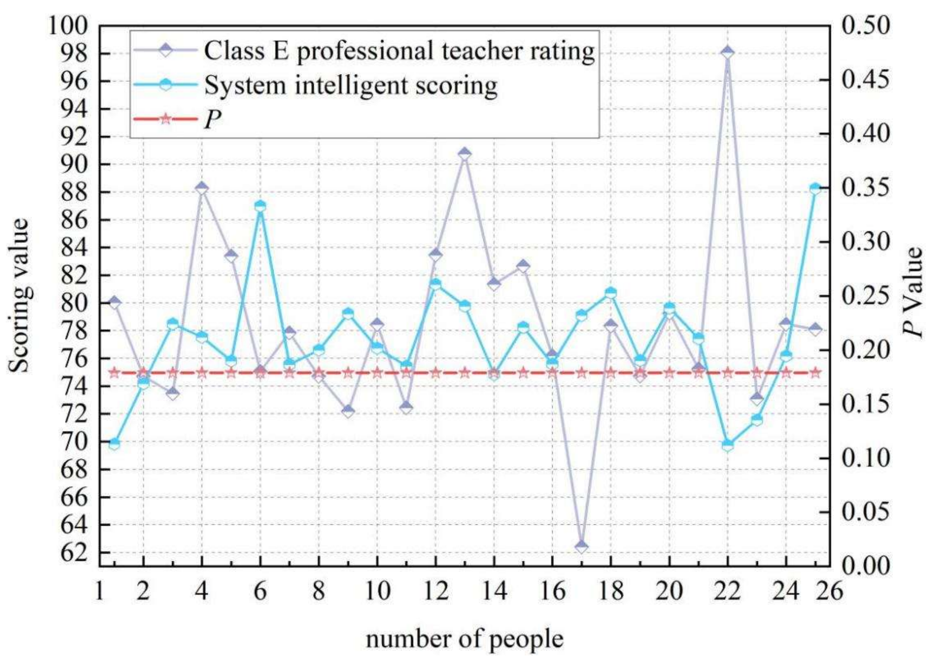

Fig. 9. Paired sample T test for class E scores(n=25)

The data of professional teacher ratings and algorithmic ratings of elective F class were analyzed by QQ plots to conform to normal distribution. A paired-sample t-test of the results of the elective F class specialty teacher ratings and the algorithmic ratings is shown in Figure 10, with a p-value of 0.556 > 0.05, and there is no significant difference in the ratings of the two groups.

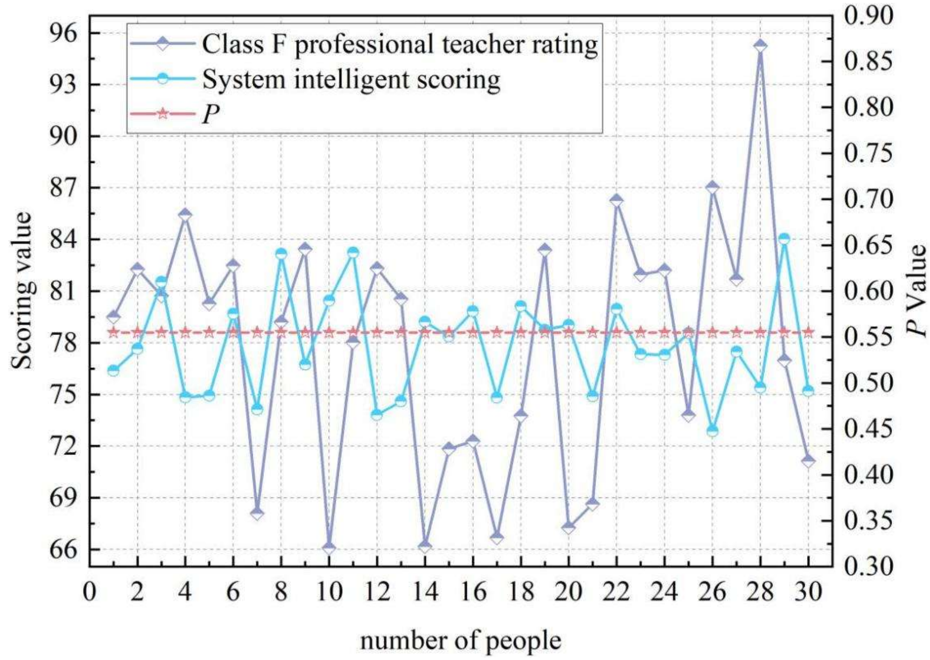

Fig. 10. Paired sample T test for class F scores(n=30)

Elective E and F class major teacher ratings and algorithmic ratings data were analyzed by QQ plots to conform to a normal distribution. A paired-sample t-test of the overall major teacher rating results and algorithmic rating results for Elective E and F classes is shown in Figure 11, with a p-value of 0.339 > 0.05, and there is no significant difference in the ratings of the two groups.

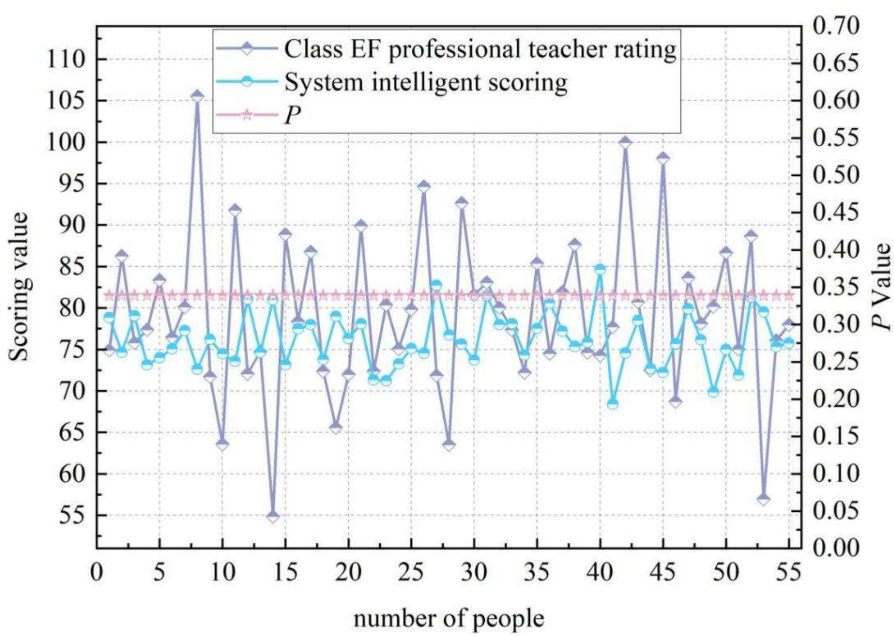

Fig. 11. Paired sample T test for class E and class F scores(n=55)

Comprehensive above can be seen, based on this paper's algorithm of wushu action scoring after optimization and professional teacher scoring is no difference, can more accurately reflect the student's action level, indicating that based on this paper's algorithm of wushu action assessment meets the evaluation needs of wushu action teaching.

5. Conclusion

In this paper, based on the UFC dataset, the multilayer perceptron algorithm is constructed by combining multilayer perceptron with network coding and improving Tanh_Softsigh activation function. Through training, optimization of this paper's algorithm martial arts fighting action scoring learning, so that its final and professional teacher ratings show high correlation and no significant difference. This paper's algorithm in a college martial arts elective class in the actual assessment of the application of its scoring results and professional teachers scoring results P>0.05, no significant difference, that is, this paper's algorithm on the assessment of students' performance of martial arts fighting movements and professional teachers to maintain consistency in the assessment results.

By designing a modeling and analysis method based on the performance data of professional tournament players, the algorithm in this paper realizes the accurate assessment and analysis of wushu fighting movements of college students, which provides an effective reference for the future innovation of wushu fighting teaching mode in colleges and universities.

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