

## Original Research

# Artificial Neural Network-Based Model for Evaluating Maximum Oxygen Uptake from the Incremental Squatting Test in Young People

Xiangyu Wang<sup>1</sup>, Yongzhao Fan<sup>1</sup>, Meng Ding<sup>2,\*</sup>, Hao Wu<sup>1,\*</sup><sup>1</sup>Graduate Student Department, Capital University of physical Education and Sports, 100191 Beijing, China<sup>2</sup>School of Physical Education, Shandong Normal University, 250014 Jinan, Shandong, China\*Correspondence: [dingmeng@sdsu.edu.cn](mailto:dingmeng@sdsu.edu.cn) (Meng Ding); [wuhao@cupes.edu.cn](mailto:wuhao@cupes.edu.cn) (Hao Wu)

Submitted: 20 December 2021 Revised: 20 January 2022 Accepted: 9 February 2022 Published: 22 August 2022

## Abstract

**Background:** Currently, there are two methods for testing maximal oxygen uptake: the direct and indirect methods, but both have certain requirements for testing equipment, site, and personnel. There is a lack of a convenient and effective method for testing maximum oxygen uptake ( $\text{VO}_2\text{max}$ ). With the development of artificial neural network (ANN), a solution to this gap is provided. **Objective:** The goal of this study was to design a method to evaluate the cardiopulmonary function of young people and verify its feasibility and reliability. **Methods:** The incremental squat test (IST) and Young Men's Christian Association (YMCA) test were designed with 196 subjects (97 males and 99 females). The back propagation (BP) neural network was used to construct the model of  $\text{VO}_2\text{max}$  by recording and analyzing squatting times, height, weight, gender, age, leg length, Manou Riers Skelic index (MRSI), and  $\text{VO}_2\text{max}$ . **Results:** Three hidden layers and 65 nodes were employed in the BP neural network. Each hidden layer contained 19 nodes. Other parameters of this network were 0.01, 0.9, and 2000 for the learning rate, momentum, and iterations, respectively. The difference between the measurements and predictions was not significant ( $p > 0.05$ ), and the correlation between them was extremely strong ( $r = 0.98, p < 0.01$ ). **Conclusions:** We conclude that the model constructed using the BP neural network is accurate, and the IST is feasible for predicting  $\text{VO}_2\text{max}$ . This method can be used as a substitute for other cardiopulmonary fitness test protocols in cases of insufficient venues and equipment. thereby preventing health complications. In subsequent studies, the sample size should be expanded, and separate prediction models should be developed for different genders.

**Keywords:** cardiorespiratory endurance assessment; indirect; maximum oxygen uptake; incremental squatting test; BP neural network

## 1. Introduction

The recent increase in the incidence of cardiovascular diseases due to physical inactivity has led to close attention to physical activity and cardiorespiratory endurance and the critical role of cardiorespiratory endurance in human health status, which has become one of the most active research areas in public health and exercise science [1,2]. Accurate cardiorespiratory endurance assessment has an important role and significance in assessing the general public's fitness level and the prevention and rehabilitation of related chronic diseases.

Maximal oxygen uptake ( $\text{VO}_2\text{max}$ ) is an important index to evaluate cardiopulmonary endurance [3]. It reflects cardiovascular function skeletal muscle oxidative function, and pulmonary ventilation diffusion capacity and indicates the combined ability to transport oxygen from the atmosphere to the mitochondria for work. Currently, studies of cardiopulmonary endurance in physical fitness, public health and epidemiology, and clinical practice mostly use  $\text{VO}_2\text{max}$  as a measurable physiological index [4–6].

$\text{VO}_2\text{max}$  is measured both directly and indirectly. The direct measurement of  $\text{VO}_2\text{max}$  is an extreme exercise test using a running table or a power bike [7–9]. The test starts with a warm-up with a small load, i.e., the subject performs a slow exercise on a power bike or running platform, fol-

lowed by increasing exercise load in levels, each level being approximately 3 min. The subject must wear a respiratory detection device during the exercise to perform gas analysis; this allows for detecting the subject's oxygen uptake plateau at the end of the test, which is the subject's  $\text{VO}_2\text{max}$ . Because this test requires the subject to perform an extreme amount of exercise, it requires a certain level of physical fitness and, if necessary, medical supervision.

Since the direct measurement of  $\text{VO}_2\text{max}$  requires individuals to undergo extreme exercise loads, it is inappropriate for certain populations suffering from cardiovascular and pulmonary diseases. In addition, due to physical and site conditions, the direct measurement cannot be guaranteed to be performed successfully, so the indirect measurement of  $\text{VO}_2\text{max}$  is used. Commonly used indirect measurement methods consist of 6-minute walk, 6-minute stairs, 12-minute run, step test, 20-m shuttle run, etc [10–14].

Existing indirect measurement of  $\text{VO}_2\text{max}$  avoid extreme amounts of motion, and special motion equipment, but also have the following problems: (1) requires the cooperation of a test team [10,11]; (2) requires physiological testing apparatus or laboratory equipment [13,14]; (3) requires a certain size test site [13]. Therefore, there is a need for a more straightforward method of cardiorespiratory en-



duration testing that can be performed anywhere and any-time by individuals without the need for other professionals and various physiological index testing instruments.

With regard to modeling methods, most field tests use a linear regression model to predict  $\text{VO}_2\text{max}$  [15–19] whereas this method can be affected by the number of the sample size and fail to find the non-linear relationship of data, it also requires assumptions about the data in advance and is susceptible to interference from the observation window and the number of samples collected.

Artificial neural network (ANN) is a new modeling concept [20–23], which does not require advanced assumptions about the relationship between data. This concept is borrowed from bionic ideas, using computers and mathematical models to mimic the human brain. In contrast to linear models, he can find nonlinear relationships between input and output variables. Back propagation neural network (BPNN), also known as multilayer feedforward networks, are an important class of neural networks. This network has three components: an input layer (perceptual unit), a computational layer (hidden layer), and an output layer. The input signal is propagated forward through the network on a layer-by-layer recursive basis. The BPNN uses a supervised learning approach, called the error back-propagation algorithm, which has been successfully applied to different complex and challenging problems [24–27].

Compared to the linear regression model, BPNN can be much more reliable. In previous studies, artificial neural networks have been used to perform studies on the estimation of  $\text{VO}_2\text{max}$ , with a significant improvement in accuracy compared to linear regression models [28–31].

In this study, we designed a method to evaluate  $\text{VO}_2\text{max}$  in young people using an incremental squat test (IST). Our study broadens the method of evaluating cardiopulmonary endurance in young people and validates the feasibility of this method. The addition of BPNN makes the relationship between the subjects' parameters and their  $\text{VO}_2\text{max}$  more specific, laying a methodological foundation for further studies.

## 2. Basic Principles of BPNN

Multilayer feedforward networks are an important type of neural networks. As shown in Fig. 1, the network consists of three parts: the input, hidden, and output layers. The input signals propagate forward through the network on a progressive basis. This type of network is essentially input-to-output mapping. It can learn a large number of mapping relationships between the input and output without any precise mathematical expressions between the input and output.

The network used in this study is known as the BP algorithm. When an input mode is provided, the transmission of the input signal from the input layer to the output layer is a forward propagation process. If the output signal is different from the expected signal, that is, there is an error, then

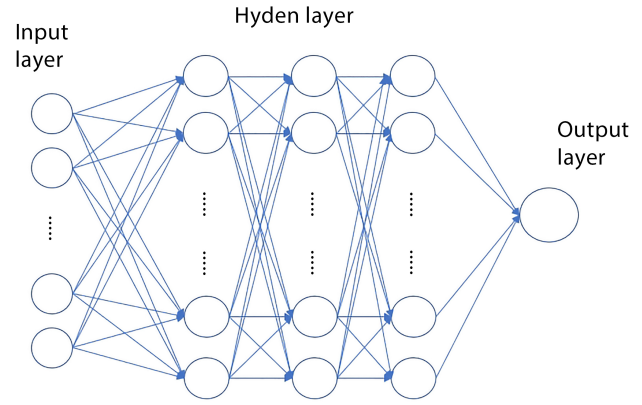


Fig. 1. BP neural network.

it turns into the process of error back propagation, and the weight value of each layer is adjusted according to the error of each layer.

Each node of the hidden layer in the network has a nonlinear function. The nonlinear function used in this test is a sigmoid function, as follows:

$$S(x) = \frac{1}{1 + e^{-n_p^k}} \quad (1)$$

where  $n_p^k$  denotes the input of  $p$  node in the layer  $k$ .

The specific steps of BP algorithm are as follows:

Step 1: Perform random assignment on each weight term  $W_{p,q}^k$  and intercept term  $b_{p,q}^k$ ;

where  $W_{p,q}^k$  denotes the weight from the  $p$  node in layer  $k-1$  to the  $q$  node in layer  $k$ .

Step 2: Normalization;

To remove the unit limit of the data, the data are normalized, and the input and output data are uniformly mapped between  $[0, 1]$ . The conversion formula is as follows:

$$Y = \frac{(X - X_{\min})}{(X_{\max} - X_{\min})} \quad (2)$$

where  $X$  represents the original value,  $X_{\min}$  the minimum value in the original data, and  $X_{\max}$  the maximal value in the original data.

Step 3: Input the input and output indexes into the model;

Step 4: Calculate each node in the training set;

Calculate the input and output of each node in the first layer as follows:

$$n_q^1 = \sum_6 W_{p,q}^1 X_P + b_q^1 \quad (3)$$

$$O_q^1 = \text{sigmoid}(n_q^1) = \frac{1}{1 + e^{-(\sum_6 W_{p,q}^1 X_P + b_q^1)}} \quad (4)$$

Calculate the input and output of each node in the second layer as follows:

$$n_q^2 = \sum_l W_{p,q}^2 O_p^1 + b_q^2 \quad (5)$$

$$O_q^2 = \text{sigmoid}(n_q^2) = \frac{1}{1 + e^{-(\sum_l W_{p,q}^2 o_p^1 + b_q^2)}} \quad (6)$$

Calculate the input and output of each node in the third layer as follows:

$$n_q^3 = \sum_i W_{p,q}^3 O_p^2 + b_q^3 \quad (7)$$

$$O_q^3 = \text{sigmoid}(n_q^3) = \frac{1}{1 + e^{-(\sum_i W_{p,q}^3 o_p^2 + b_q^3)}} \quad (8)$$

Calculate input and output of the output layer as follows:

$$n_1^4 = V = \sum_m W_{p,1}^4 O_p^3 + b_1^4 \quad (9)$$

From the presented equations, p and q denote the orders of nodes, whereas  $O$  denotes the output of nodes. For instance,  $O_p^k$  denotes the output of the p node in layer k.

Step 5: Calculate the error between expected output and network output;

For the output layer of the network, the error between the output  $O_p^k$  of its p node and expected output  $d_p^k$  is expressed as follows:

$$E_p = \frac{1}{2} (O_p^k - d_p^k)^2 \quad (10)$$

Then, the total error of the network is obtained as follows:

$$E = \sum_j E_p = \frac{1}{2} \sum_j (O_p^k - d_p^k)^2 \quad (11)$$

where j denotes the number of nodes in the output layer.

Because there is one node in the output layer of this network, the total error of the network is obtained as follows:

$$E = \frac{1}{2} (V - d)^2 \quad (12)$$

Step 6: Reverse calculate and correct the network weight value;

The purpose of learning and training the BP network is

to minimize  $E$  by adjusting the model parameters. The gradient descent method was used to reduce the weight value along the negative gradient of the error when adjusting the weight value. The adjustment formula is as follows:

$$\Delta W_{p,q}^k = -\eta \delta O_p^{k-1} \quad (13)$$

where  $\eta$  denotes the learning coefficient, and  $W_{p,q}^k$  the weight value from the p node in layer k-1 to the q node in layer k. Term  $\Delta W_{p,q}^k$  denotes the adjustment quantity of the weight value.

When k is the output layer,

$$\delta = (V - d) \cdot \text{sigmoid}'(n_1^4) \quad (14)$$

When k is not the output layer,

$$\delta = \left( \sum_t \frac{\partial E}{\partial n_t^{k+1}} \cdot W_{q,t}^{k+1} \right) \cdot \text{sigmoid}'(n_q^k) \quad (15)$$

where t denotes the order of the node in layer k+1.

When the learning coefficient  $\eta$  is larger, the learning speed is higher, but the convergence is poor, and oscillation may occur. However, if the learning coefficient  $\eta$  is excessively small, the learning speed will be affected. Therefore, the value of  $\eta$  is typically determined experimentally. In addition, in practical use, the momentum term  $\alpha$  is usually added to the equation as follows:

$$\Delta W(t+1) = -\eta \delta O_p^{k-1} + \alpha \Delta W(t) \quad (16)$$

where  $\Delta W(t)$  denotes the adjustment quantity of the weight value during the last learning. This is conducive to accelerating the learning process, such that the training efficiency of the model has a significant relationship with the learning coefficient and momentum term.

Step 7: Transfer to step 4 and repeat.

The convergence of the back-propagation algorithm cannot be generally proved. Moreover, there is no clearly defined stopping criterion. Evidently, the weight value must be made the error surface for the weight gradient vector, which is zero. Therefore, we propose the following stopping criterion:

Stop criterion 1: When the norm of the gradient vector reaches a sufficiently small value, the back-propagation algorithm is considered to have converged.

Stop criterion 2: When the change rate of the mean square error reaches a sufficiently small value, the back-propagation algorithm is considered to have converged, and the desired error goal of the network is 0.0001.

**Table 1. Subjects' characteristics.**

	Males (97)	Females (99)	Total (196)
Age (years)	20.14 ± 0.68*	19.89 ± 0.5	20.02 ± 0.61
Height (cm)	174.63 ± 5.79**	164.05 ± 5.24	169.76 ± 7.65
Weight (kg)	69.01 ± 11.98**	56.46 ± 7.56	63.23 ± 11.94
Leg length (cm)	80.44 ± 3.73**	74.16 ± 3.85	77.55 ± 4.91
MRSI	85.43 ± 3.57**	82.54 ± 4.35	84.1 ± 4.19

\*Significant differences exist between males and females ( $p < 0.05$ ).

\*\*Significant differences exist between males and females ( $p < 0.01$ ).

### 3. Methods

#### 3.1 Participants

A total of 196 undergraduates (97 men and 99 women) were classified as “low risk” according to American College of Sports Medicine risk stratification. Before exercise testing, all participants received a detailed explanation of the goal and clinical implications of this experiment. All participants read and signed an informed consent form approved by the Shandong Normal University Institutional Review Board. The physical characteristics of the subjects are summarized in Table 1, where MRSI denotes the Manou Riers Skelic index.

#### 3.2 Experiment

The experiment process is shown in Fig. 2.

The interval between the two tests is 7 days. The order in which the subjects took part in the two tests was random.

##### 3.2.1 IST

- (1) Measurement index: time for movement.
- (2) Standard of movement.

Start position: keep upright (Fig. 3)

As shown in Fig. 4, when people squat, their arm should rise in front and stop when the thigh is parallel to the ground. Thereafter, they should stand back up (Fig. 3).

Breathe in when squatting, and breathe out when standing back up.

- (3) Control of movement range.

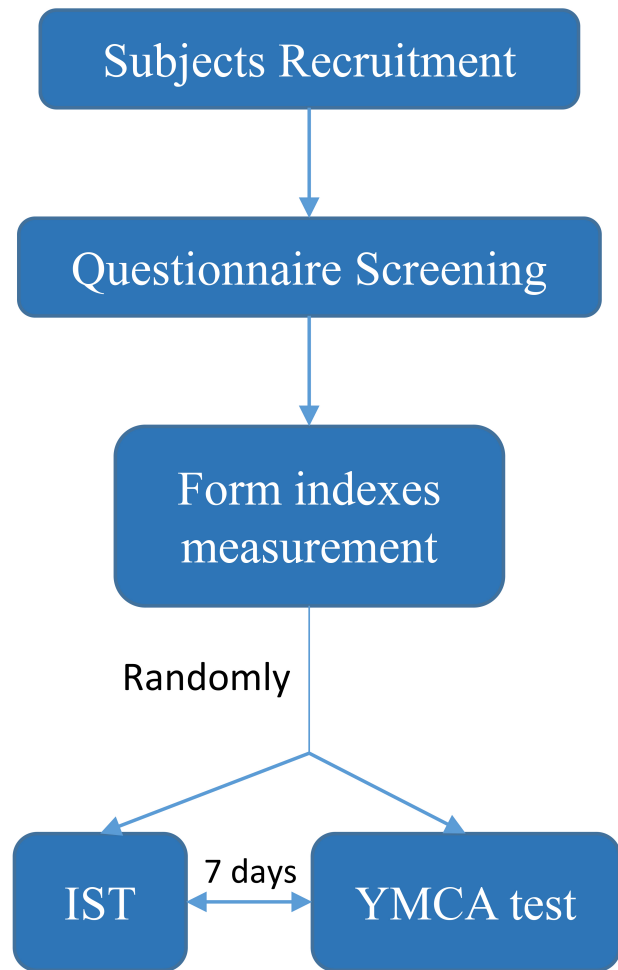
To control the range of movement, two marking lines were set. As shown in Fig. 5, the following marking line should be the height of the tibial trochanter of the subjects, and the upper marking line should be maintained at the same height as the upper edge of the patella of the subjects.

As shown in Fig. 6, if the participant's buttocks intersect with the marking area between the two marking lines when they squat down, the movement is effective.

As shown in Figs. 7,8, if the participant's buttocks were above or below the marking area, the movement is ineffective.

- (4) Method of squatting test execution.

We used signal sound software to play the signal sound. The squatting movement was synchronized with the signal sound, that is, the signal sound is played once, and



**Fig. 2. All subjects need to take part in two tests (IST and YMCA test).**

the subjects perform the movement once. The number of signal sounds increased by grade. The squatting times that participants should perform in each grade of this test are listed in Table 2.

- (5) Criteria for stopping.

- Appearance of angina pectoris symptoms;
- Dyspnea, lower limb spasm;
- Mild headache, unconsciousness, ataxia, paleness, cyanosis, nausea, or moist cold skin;
- The subjects ask to stop;





**Fig. 3. Start position.**



**Fig. 4. Action standard of squatting down.**

**Table 2. Squatting times of each grade.**

Grade	Time (s)	Squatting times
1	30	10
2	30	15
3	30	20
4	30	25
...	...	...
...	...	...
n	30	$10 + 5(n - 1)$



**Fig. 5. Marking lines.**



**Fig. 6. Effective movement.**

- The subjects exhibit extreme fatigue orally or physically;
- Failure in the test equipment;
- More than three consecutive movements fail to keep up with the rhythm of the signal sound;
- More than 3 consecutive movements fail to achieve the standard.

### 3.2.2 Cardiopulmonary Exercise Test

Measurement index:  $VO_2\text{max}$ .

YMCA test is used to indirectly measure the  $VO_2\text{max}$  of the subjects.

### 3.2.3 Measurement of Form Indexes

Measurement indexes: height, sitting height, leg length, and MRSI.

The leg length is calculated using the method of “height-sitting height”. The calculation formula of MRSI is  $[(\text{height} - \text{sitting height}) / \text{sitting height}] \times 100$ , which can reflect the leg-to-body ratio of the subjects.



Fig. 7. Above the marking area.



Fig. 8. Below the marking area.

### 3.3 Mathematical Method

#### 3.3.1 Squatting Time Calculation

The time was calculated based on the time of the signal tone, as described by the following formula:

$$\text{INT}(X) = \text{INT} \left( \frac{t}{3} + \frac{t(t-30)}{360} \right) \quad (17)$$

As observed from the formula, “INT” denotes integer-valued function, and “t” the time of the squat test (s).

#### 3.3.2 BP Neural Network Model

The model used to estimate  $\text{VO}_2\text{max}$  from the IST is a BP neural network. The inputs of this network were gender, age, height, leg length, MRSI, squatting times, and body weight. The output was  $\text{VO}_2\text{max}$ .

In the process of machine learning modeling, the usual method is to divide the data into training and test sets. The test set was independent of the training data and did not participate in the training. This was used to evaluate the model. To improve the accuracy of the evaluation results and avoid the problem of overfitting in the training process, we used the 10-fold cross-validation method to model, that is, to separate a part of the training data as a validation set.

#### 3.3.3 Correlation Analysis between Predicted and Measured $\text{VO}_2\text{max}$

To observe the effectiveness of this model, 30 samples were used as the test sets in this model. After training, we performed a paired-samples *t*-test for  $\text{VO}_2\text{max}$  and predicted  $\text{VO}_2\text{max}$ . Thereafter, we analyzed the correlation between them.

## 4. Result

#### 4.1 BP Neural Network Model

Fig. 9 shows the model of this study.

As shown in Fig. 9, three hidden layers and 65 nodes are proposed in the network used in this study. Each hidden layer contained 19 nodes. The other parameters of this model are 0.01, 0.9, and 2000 for the learning rate, momentum, and iterations, respectively.

#### 4.2 Training Results

When the network was iterated 200 times, the loss decreased to 0.9. The change in the loss with the number of iterations is shown in Fig. 10.

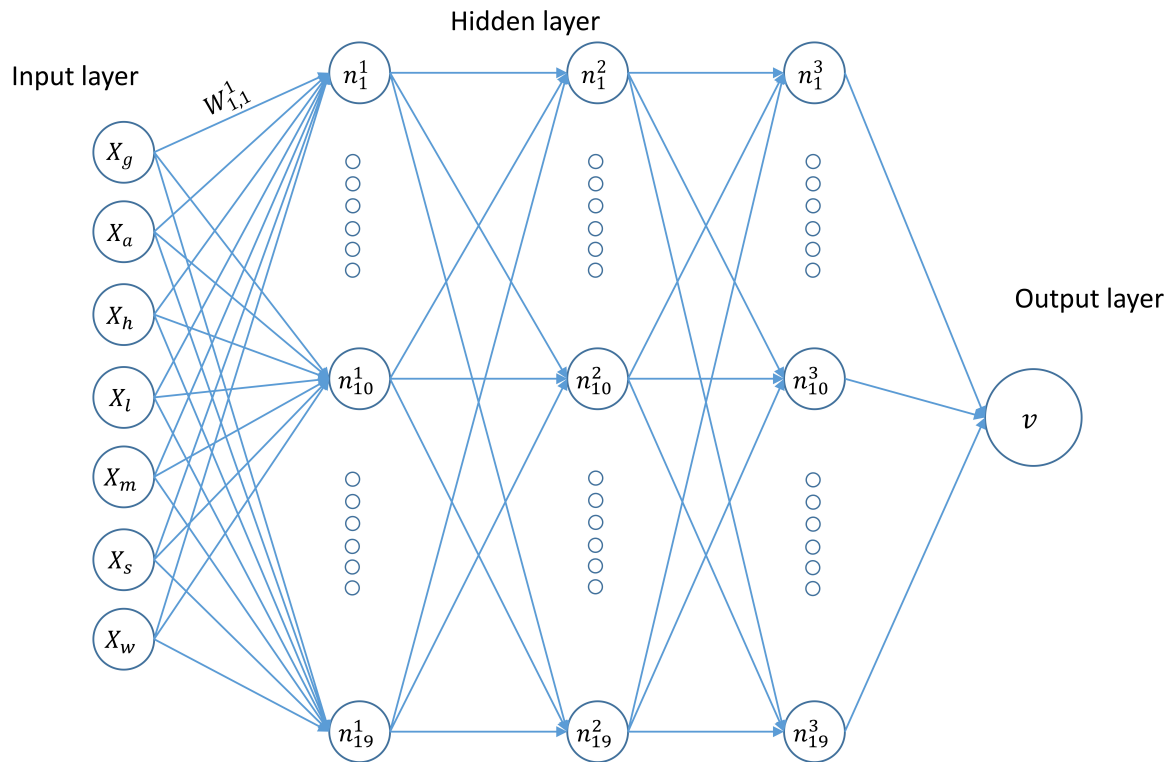
When the network iterated 2000 times, the loss decreased to  $1 \times 10^{-10}$ , the network training curve was stable, and there was no significant turbulence. The change in the loss with the number of iterations is shown in Fig. 11.

At this moment, the model had achieved the aforementioned “Stop criterion 2”, and the back-propagation algorithm had converged.

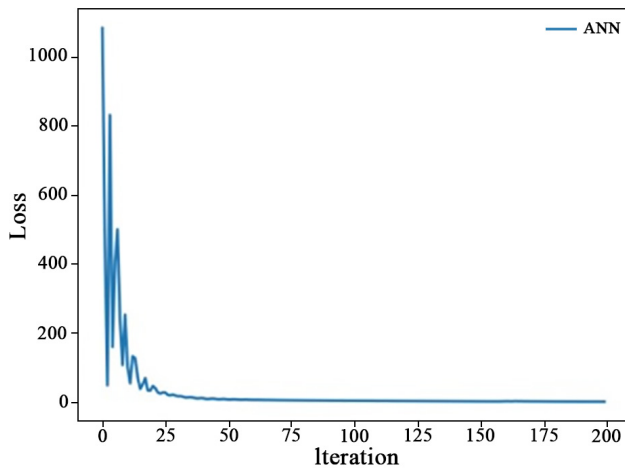
#### 4.3 Performance Testing

We used a test set to analyze the performance of the model. The measured and predicted  $\text{VO}_2\text{max}$  of  $\text{VO}_2\text{max}$  in the test set are as follows (Table 3). There was no statistical difference between the predicted and measured  $\text{VO}_2\text{max}$  ( $p > 0.05$ ).

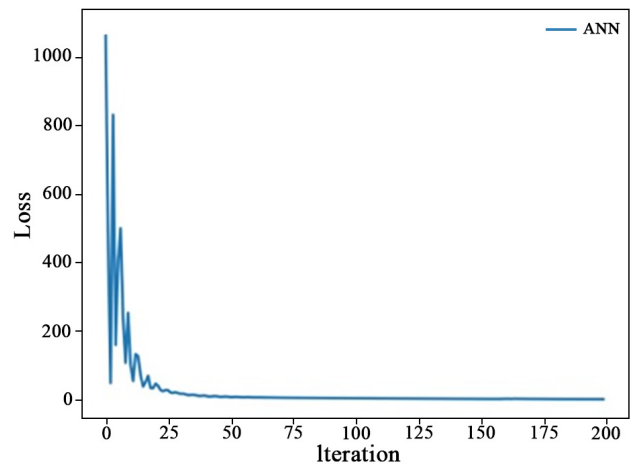
The correlation analysis was performed between the measured and predicted  $\text{VO}_2\text{max}$ . From Fig. 12 and Table 4, there was an extremely strong correlation between the measurements and predictions ( $r = 0.98$  and  $p < 0.01$ ).



**Fig. 9. Structure of the network,  $X_g, X_a, X_h, X_l, X_m, X_s$ , and  $X_w$  denote the input variables, which are gender, age, height, leg length, MRSI, squatting times, and body weight, respectively. The output variable  $V$  is  $VO_{2max}$ . Terms  $n_1^1, n_1^2$ , and  $n_1^3$  are respectively the first node in the first, second, and third layer,  $W_{1,1}^1$  denotes the weight value from the first node in layer 0 to the first node in layer 2.**



**Fig. 10. When the network iterates 200 times.**



**Fig. 11. When the network iterates 2000 times.**

**Table 3. Measured and predicted values.**

$VO_{2max}$	Mean	SD	Maximum	Minimum
Predicted value	32.979	5.44215	40.999	23.394
Measured value	32.765	6.09471	44.09	23.15

There was no significant difference between measurements and predictions, and the correlation between them

was extremely strong. Therefore, it is feasible to use IST to evaluate cardiopulmonary endurance in cases of insufficient venues and equipment.

## 5. Discussion

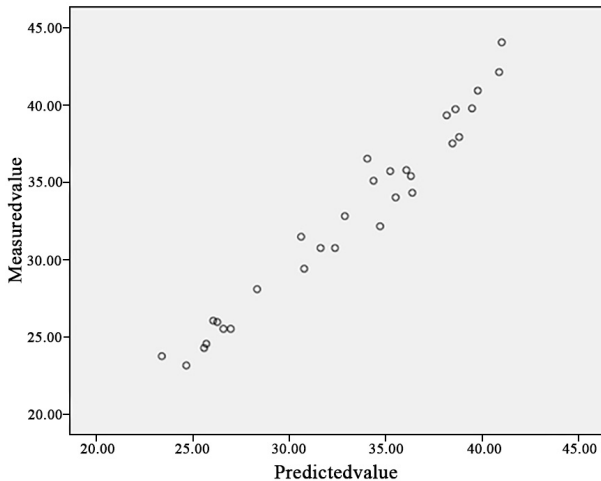
In this study, an IST was performed. This study used the data of 196 subjects (including 97 men and 99 women) to establish a predicted model of  $VO_{2max}$  based on the BP



**Table 4. Correlation analysis.**

		Predictions
Measurements	Pearson Correlation	0.980**
	Sig. (2-tailed)	0
	N	30

\*\*, Correlation is significant at the 0.01 level (2-tailed).

**Fig. 12. Relationship between measurements and predictions.**

neural network. All variables in this test can be easily measured without any special instruments. To obtain a high-quality prediction model, all the technical and environmental factors were strictly controlled during the experiment. After 200 training cycles, the loss of the network decreased to 0.9, and the network did not converge.

In previous squat tests, no uniform squat range was achieved and no uniform control method for the squatting range was formed [32–34]. In this case, even if the standard for evaluating individual cardiopulmonary function by IST was established, the results would be meaningless owing to different squat ranges. In addition, previous studies have mostly used quantitative load squatting (QST). In comparison with QST, the initial intensity of the incremental load is small and gradually increases with time, which meets the requirement of overcoming the physiological inertia of the human body. To address the aforementioned problems, an IST was adopted in this study.

There are similar field tests such as the 20-m multi-stage shuttle run fitness test [35–37] and increasing load shuttle walk test (ISWT) [38–41]. In terms of implementation, these three sports do not require expensive equipment, but the area required for squatting is small and the implementation conditions are more convenient than those of the other two field tests.

After analysis, we found that age, height, weight, leg length, and MRSI were significantly different between males and females ( $p < 0.05$ ). However, there was no sig-

nificant difference in squatting and  $VO_{2max}$  between the two genders ( $p > 0.05$ ). This is different from the results of previous studies [42–44]. We concluded the following two possible reasons: first, the number of subjects in this test was small and covered a smaller range of oxygen uptake; second, the heart rate was not observed during squatting exercise, so it could not be determined whether the subjects reached exhaustion. The sample size should be expanded in subsequent studies, and heart rate bands should be worn during squatting exercises to maximize the likelihood that subjects will reach a state of exhaustion.

Due to hardware limitations, we were unable to assess the  $VO_{2max}$  of the subjects using direct assays at the time of this study and therefore used the YMCA assessment protocol. This is the limitation of our study. However, even with the YMCA method, we obtained good results, which provided a sound basis for our later study and demonstrated the feasibility of using IST in combination with BPNN to assess individual maximal oxygen uptake. In our later study, we will use the direct assay method to detect the  $VO_{2max}$  and update the BPNN formula to improve the model's performance.

## 6. Conclusions

We used the BP neural network to establish a model to predict  $VO_{2max}$ . The input indexes of the model were gender, age, height, leg length, MRSI, squatting times, and body weight, whereas the output index was  $VO_{2max}$ . Other parameters of this network were 0.01, 0.9, and 2000 for the learning rate, momentum, and iterations, respectively. The results demonstrated that the difference between the predicted and measured  $VO_{2max}$  was not significant ( $p > 0.05$ ), and the correlation between them was extremely strong ( $r = 0.98$ ,  $p < 0.01$ ). Thus, the IST is a feasible method for estimating  $VO_{2max}$ . This method can be used as a substitute for other cardiopulmonary fitness test protocols in cases of insufficient venues and equipment.

In this study, the age, height, weight, leg length, and MRSI were significantly different between males and females ( $p < 0.05$ ). However, there was no significant difference in squatting and  $VO_{2max}$  between the two genders ( $p > 0.05$ ). We believe this is the reason for the small sample size. In subsequent studies, the sample size should be expanded, and separate prediction models should be developed for different genders.

## Author Contributions

All authors contributed to the study conception and design. Material preparation, data collection, analysis. First draft of the manuscript was performed by XW. MD and HW commented on previous versions of the manuscript and critically revised the manuscript. And YF gave guidance to data analysis and checked the mistake of the English writing. All gave final approval and agree to be accountable for all aspects of work ensuring integrity and accuracy.

## Ethics Approval and Consent to Participate

All participants read and signed an informed consent form approved by the Shandong Normal University Institutional Review Board (ethical approval number 2018A33).

## Acknowledgment

Thanks to all the peer reviewers for their opinions and suggestions.

## Funding

This work was supported by State Key R&D Program (No. 2018YFF0300603) Characteristics of Winter Sports Athletes' Special Ability and Key Techniques for Scientific Selection, Key Technology Research of Special International Training Platform for Winter Skill Sports Research and Applications (No.2018YFF0300902).

## Conflict of Interest

The authors declare no conflict of interest.

## References

- [1] Furian M, Flueck D, Latshang TD, Scheiwiller PM, Segitz SD, Mueller-Mottet S, *et al.* Exercise performance and symptoms in lowlanders with COPD ascending to moderate altitude: randomized trial. *International Journal of Chronic Obstructive Pulmonary Disease*. 2018; 13: 3529–3538.
- [2] Kunutsor SK, Laukkanen T, Laukkanen JA. Cardiorespiratory Fitness is Associated with Reduced Risk of Respiratory Diseases in Middle-Aged Caucasian Men: a Long-Term Prospective Cohort Study. *Lung*. 2017; 195: 607–611.
- [3] León-Ariza HH, Botero-Rosas DA, Zea-Robles AC. Heart Rate Variability and Body Composition as Vo2max Determinants. *Revista Brasileira De Medicina do Esporte*. 2017; 23: 317–321.
- [4] Toulouse L, Baquet G, Heyman E, Pezé T, Berthoin S, Schill A, *et al.* Respiratory responses and rating of perceived exertion of severely obese adolescents during continuous and intermittent graded walking protocols: Application to cardiorespiratory field tests. *Journal of Sports Sciences*. 2020; 38: 1009–1017.
- [5] Kokkinos P, Kaminsky LA, Arena R, Zhang J, Franklin B, Kraus W, *et al.* New Equations for Predicting Maximum Oxygen Uptake in Patients with Heart Failure. *The American Journal of Cardiology*. 2020; 128: 7–11.
- [6] Policarpo Barbosa F, Silva PE, Guimarães AC, Pernambuco CS, Dantas EH. Prediction of maximum oxygen uptake through incremental exercise testing using ventilometry: a cross-sectional study. *Brazilian Journal of Physical Therapy*. 2020; 24: 365–372.
- [7] Cooper DM. Rethinking Vo2max: right problem, wrong solution (Letter to the Editor regarding Poole and Jones' "Measurement of the maximum oxygen uptake Vo2max: Vo2peak is no longer acceptable"). *Journal of Applied Physiology*. 2017; 123: 498.
- [8] Rusdiana A. Analysis Differences of Vo2max between Direct and Indirect Measurement in Badminton, Bicycle Racing and Rowing. *International Journal of Applied Exercise Physiology*. 2020; 9: 162–170.
- [9] Sun ZW, Zhang B, Ma YP. 'Comparative and Validation Study on Foreign Classic Estimation Equations about VO2max in 1-mile Jog', *Proceedings of the International Symposium on Common Development of Sports and Modern Society*. Suzhou, China, F Dec 27–28, 2014. Science & Research Central Ltd: Newark. 2014.
- [10] Guo H, Wang Z, Zhang Y. Predicting Vo2max from a 6-minute Stairs Climbing and Descending Test (6MSCDT). *Medicine & Science in Sports & Exercise*. 2016; 48: 93.
- [11] Hansen D, Jacobs N, Thijs H, Dendale P, Claes N. Validation of a single-stage fixed-rate step test for the prediction of maximal oxygen uptake in healthy adults. *Clinical Physiology and Functional Imaging*. 2016; 36: 401–406.
- [12] Jalili M, Nazem F, Sazvar A, Ranjbar K. Prediction of Maximal Oxygen Uptake by Six-Minute Walk Test and Body Mass Index in Healthy Boys. *The Journal of Pediatrics*. 2018; 200: 155–159.
- [13] Magee MK, White JB, Merrigan JJ, Jones MT. Does the Multistage 20-m Shuttle Run Test Accurately Predict VO2max in NCAA Division I Women Collegiate Field Hockey Athletes? *Sports*. 2021; 9: 75.
- [14] Plasqui G, Westerterp KR. Accelerometry and heart rate as a measure of physical fitness: cross-validation. *Medicine and Science in Sports and Exercise*. 2006; 38: 1510–1514.
- [15] Aandstad A, Holme I, Berntsen S, Anderssen SA. Validity and Reliability of the 20 Meter Shuttle Run Test in Military Personnel. *Military Medicine*. 2011; 176: 513–518.
- [16] Higino WP, Sorroche ADS, de Mattos Falqueiro PG, Suzuki Lima YC, Higa CL. Determination of Aerobic Performance in Youth Soccer Players: Effect of Direct and Indirect Methods. *Journal of Human Kinetics*. 2017; 56: 109–118.
- [17] Santos-Silva PR, Fonseca AJ, Castro AW, Greve JM, Hernandez AJ. Reproducibility of maximum aerobic power (VO2max) among soccer players using a modified Heck protocol. *Clinics*. 2007; 62: 391–396.
- [18] Takao K, Ueno H, Hamaguchi K, Isaka T. Comparison of aerobic profiles between the field-based 20 m-shuttle run test and the laboratory-based bike ergometer test in runners. *Gazzetta Medica Italiana Archivio per Le Scienze Mediche*. 2021; 180: 59–64.
- [19] Canino M C, Cohen B S, Redmond J E, *et al.* The Relationship Between Soldier Performance on the Two-Mile Run and the 20-m Shuttle Run Test[J]. *Military Medicine*(5-6):5-6.
- [20] Chen H, Liu C. Research on Knee Injuries in College Football Training Based on Artificial Neural Network. 2020 IEEE Conference on Telecommunications, Optics and Computer Science (TOCS). 2020; 35–37.
- [21] Drywień M, Górnicki K, Górnicka M. Application of Artificial Neural Network to Somatotype Determination. *Applied Sciences*. 2021; 11: 1365.
- [22] Hayakawa Y, Oonuma T, Kobayashi H, Takahashi A, Chiba S, Fujiki NM. Feature Extraction of Video Using Artificial Neural Network. *International Journal of Cognitive Informatics and Natural Intelligence*. 2017; 11: 16.
- [23] Liankun J, Yangyong. Hybrid Neural Network Based Risk Assessment Method for Large Scale Sports Events. 2014 Fifth International Conference on Intelligent Systems Design and Engineering Applications. 2014; 524–527.
- [24] Tümer AE, Koçer S. Prediction of team league's rankings in volleyball by artificial neural network method. *International Journal of Performance Analysis in Sport*. 2017; 17: 202–211.
- [25] Saikia H, Bhattacharjee D, Lemmer HH. Predicting the Performance of Bowlers in IPL: an Application of Artificial Neural Network. *International Journal of Performance Analysis in Sport*. 2012; 12: 75–89.
- [26] Hagenbuchner M, Cliff DP, Trost SG, Van Tuc N, Peoples GE. Prediction of activity type in preschool children using machine learning techniques. *Journal of Science and Medicine in Sport*. 2015; 18: 426–431.
- [27] Akay MF, Inan C, Bradshaw DI, George JD. Support vector regression and multilayer feed forward neural networks for non-exercise prediction of VO. *Expert Systems with Applications*. 2009; 36: 10112–10119.
- [28] Lee SH, Ju HS, Lee SH, Kim SW, Park HY, Kang SW, *et al.*



- Estimation of Health-Related Physical Fitness (HRPF) Levels of the General Public Using Artificial Neural Network with the National Fitness Award (NFA) Datasets. *International journal of environmental research and public health*. 2021; 18: 10391.
- [29] Park HY, Jung H, Lee S, Kim JW, Cho HL, Nam SS. Estimated Artificial Neural Network Modeling of Maximal Oxygen Uptake Based on Multistage 10-m Shuttle Run Test in Healthy Adults. *International Journal of Environmental Research and Public Health*. 2021; 18: 8510.
- [30] Ramírez-Lechuga J, Ruiz JR, Ortega FB, Benitez JM, Arauzo-Azofra A, Sanchez-Muñoz C, *et al.* Use of Artificial Neural Network-based Equation for estimating VO<sub>2</sub>max in adolescents. *Medicine & Science in Sports & Exercise*. 2008; 40: S197.
- [31] Ruiz JR, Ramirez-Lechuga J, Ortega FB, Castro-Piñero J, Benitez JM, Arauzo-Azofra A, *et al.* Artificial neural network-based equation for estimating VO<sub>2</sub>max from the 20 m shuttle run test in adolescents. *Artificial Intelligence in Medicine*. 2008; 44: 233–245.
- [32] Inoue Y, Nakao M. Prediction of maximal oxygen uptake by squat test in men and women. *The Kobe Journal of Medical Sciences*. 1996; 42: 119–129.
- [33] Papini G, Bonomi AG, Stut W, Kraal JJ, Kemps HMC, Sartor F. Proof of concept of a 45-second cardiorespiratory fitness self-test for coronary artery disease patients based on accelerometry. *PLoS ONE*. 2017; 12: e0183740.
- [34] Haramura M, Takai Y, Yoshimoto T, Yamamoto M, Kanehisa H. Cardiorespiratory and metabolic responses to body mass-based squat exercise in young men. *Journal of Physiological Anthropology*. 2017; 36: 14.
- [35] Mayorga-Vega D, Aguilar-Soto P, Viciano J. Criterion-Related Validity of the 20-M Shuttle Run Test for Estimating Cardiorespiratory Fitness: A Meta-Analysis. *Journal of Sports Science & Medicine*. 2015; 14: 536–547.
- [36] Lamonedá J, Huertas-Delgado FJ, Cadenas-Sanchez C. Feasibility and concurrent validity of a cardiorespiratory fitness test based on the adaptation of the original 20 m shuttle run: the 20 m shuttle run with music. *Journal of Sports Sciences*. 2021; 39: 57–63.
- [37] Zou Z, Chen P, Yang Y, Xiao M, Wang Z. Assessment of physical fitness and its correlates in Chinese children and adolescents in Shanghai using the multistage 20-M shuttle-run test. *American Journal of Human Biology*. 2019; 31: e23148.
- [38] Ekren PK. A comparison of maximal oxygen uptake obtained from different tests in chronic obstructive pulmonary disease patients. *Turkish Journal of Thoracic and Cardiovascular Surgery*. 2014; 22: 88–94.
- [39] Alves R, Lima MM, Fonseca C, Dos Reis R, Figueiredo PH, Costa H, *et al.* Peak oxygen uptake during the incremental shuttle walk test in a predominantly female population with Chagas heart disease. *European Journal of Physical & Rehabilitation Medicine*. 2016; 52: 20–27.
- [40] Ozalp O, Inal-Ince D, Cakmak A, Calik-Kutukcu E, Saglam M, Savci S, *et al.* High-intensity inspiratory muscle training in bronchiectasis: a randomized controlled trial. *Respirology*. 2019; 24: 246–253.
- [41] Barlow R, Jones B, Rogerson M, Bannister H, Stuart R, Iqbal J, *et al.* An Evaluation of Service Provision and Novel Strength Assessment on Patient Outcomes in a UK-Based Pulmonary Rehabilitation Setting. *Journal of Chronic Obstructive Pulmonary Disease*. 2020; 17: 280–288.
- [42] Malek MH, Berger DE, Housh TJ, Coburn JW, Beck TW. Validity of VO<sub>2</sub>max equations for aerobically trained males and females. *Medicine and Science in Sports and Exercise*. 2004; 36: 1427–1432.
- [43] Sawyer BJ, McMahon N, Thornhill KL, Baughman BR, Mahoney JM, Pattison KL, *et al.* Supra-Versus Submaximal Cycle Ergometer Verification of VO<sub>2</sub>max in Males and Females. *Sports*. 2020; 8: 163.
- [44] Maldonado-Martin S, Mujika I, Padilla S. Physiological variables to use in the gender comparison in highly trained runners. *The Journal of Sports Medicine and Physical Fitness*. 2004; 44: 8–14.