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Research Article

Machine Learning-Based Aerobic Exercise Recognition and Its Effect on Health Status of College Students

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It was to explore the role of motion recognition technology based on the convolutional neural network (CNN) model in guiding the aerobic exercise of college students and its impact on their physical and mental health, providing a scientific and effective method for students to have a healthy body and mood. 256 college students were randomly divided into control group (appropriate aerobic exercise was selected by self-evaluation, and exercise was performed spontaneously) and observation group (aerobic exercise under the guidance of machine learning model-based motion recognition technology), 128 cases in each group. The changes in the physical and psychological status of the two groups of college students were evaluated after one year. The recognition rate of CNN algorithm test results (92.98%) and the recognition accuracy of stationary, walking, running, squatting, hand raising, seated position, lunge, and other movement states were higher than those of recurrent neural network (RNN) (52.22%) and deep neural network (DNN) (40.21%) algorithms ($P < 0.05$); after 1 year of exercise, the 800/1,000 m running performance, standing long jump performance, 1 min sit-up performance, vital capacity, maximal ventilator volume per minute (MVV) and vital capacity/body mass index, stroke volume (SV), cardiac output (CO), ejection fraction (EF), heart rate (HR), ejection time (ET), mean systolic ejection rate (MSER), mean velocity of circumferential fibre shortening (MVCF) of the observation group were superior to those of the control group, and tension, anger, depression, fatigue, panic, energy, self-related emotions, and the improvement of total mood disturbance (TMD) score were also superior to those before exercise. The improvement effect of physical fitness, cardiopulmonary function, and mentality of college students in the observation group was better than that in the control group ($P < 0.05$). Aerobic exercise can effectively improve the physical fitness, cardiopulmonary function, and adverse mentality of college students, and through the assistance of machine learning, exercise recognition technology can further improve the effect of aerobic exercise, which is worthy of application and promotion.

1. Introduction

In recent years, due to the fierce competition of learning and society, the physical and psychological state of many college students is affected to varying degrees, which brings a great impact on their subsequent study, life, and work. After research statistics, the common physical effects of college students include poor physical fitness caused by exercise deficiency, rejuvenation of cardiovascular disease, and increased incidence of sudden cardiac death [1]. Psychological effects include psychological anxiety caused by various stresses (learning, body shape, etc.), which indirectly leads to behavioral disorders such as substance abuse and dependence, eating disorders, and Internet addiction in college students [2]. With the continuous reform of the educational system, the state attaches more and more importance to the physical and mental health of college students and proposes that the assessment system of schools should be included in the detection of physical health levels [3]. In order to make students have a healthy body and mood, most colleges and universities are advocating the strengthening of aerobic exercise. Aerobic exercise is defined as a physical exercise by an exerciser in a state of adequate oxygen supply [4]. Aerobic exercise is performed by rhythmic adjustment of respiratory status, and it can enable exercisers to control the intensity of exercise according to

their own physical condition and physical fitness, which can greatly improve cardiopulmonary function [5]. Guadagni et al. [6] have proposed that reasonable aerobic exercise can improve people's physical fitness, reduce the possibility of cardiovascular disease [7], enhance people's self-confidence and well-being, and reduce the occurrence of psychological diseases [8]. At present, the more common and easily popularized aerobic exercises mainly include jogging, swimming, Tai Chi, and others combine various exercise methods [9]. However, the movement mode and movement state will have a certain impact on the effect of movement.

Motion state recognition refers to the establishment of a motion model by using corresponding technical means through a large number of data acquisition and data analysis of the motion state of the exerciser [10]. The key link of motion state recognition technology is the establishment of model, and the basis of model establishment is technical means. The previous motion model is based on the traditional classification algorithm, but the data information obtained by this algorithm is relatively single, and the self-learning ability is poor, resulting in that there are often certain errors in the obtained data, and the application range is more limited due to the inconvenience of carrying measurement tools [11]. With the rapid development of the Internet and deep learning technology, in order to make the application of data measurement tools unlimited, it can be widely used in many fields (such as medical and health care, military training, virtual reality) [12]. Yu et al. [13] have proposed a motion state recognition method based on a multilayer neural network, which can use smartphones to collect data and accurately identify the motion state. The multilayer neural network model includes convolutional neural network (CNN)—image recognition and speech recognition [14], recurrent neural network (RNN)—natural language processing and speech audio recognition [15], deep neural network (DNN)—improving overfitting phenomenon [16]. Several studies have shown that the self-extraction and feature retention characteristics of CNN can effectively improve the accuracy and stability of motion recognition technology [17, 18].

It was to further explore the guiding role of exercise recognition technology based on the CNN network model for the aerobic exercise of college students and its impact on the physical and mental health of college students. College students were selected as the study subjects. By analyzing the physical and mental health of college students before and after exercise, the motion recognition technology based on the CNN network model was applied to evaluate the physical function of college students, evaluate the application value of this technology, and provide multiple scientific and effective methods for students to have healthy bodies and emotions.

2. Research Methods

2.1. Study Subjects. 256 college students enrolled in 2017, 2018, 2019, and 2020 in XXX school were randomly selected as the study subjects. There were 173 male college students and 83 female college students, aged between 23 and 27 years old, with an average age of (25.23 ± 1.34) years old, weighing between 50 kg and 80 kg, with an average weight of (67.10 ± 17.01) kg. All the subjects were divided into the control group and the observation group by the random number table, 128 cases in each group. The college students in the control group selected the appropriate aerobic exercise through self-evaluation and performed the exercise on their own. The college students in the observation group performed the exercise of aerobic exercises under the guidance of the motion recognition technology based on the CNN network model. The changes in the physical and psychological status of the two groups of college students were evaluated after one year. This experiment was approved by the relevant ethics committee.

Inclusion criteria were as follows: college students; students who voluntarily participate in this experiment; students who signed informed consent; students without previous systematic aerobic exercise and other exercises.

Exclusion criteria were as follows: patients with severe psychological diseases and no autonomous consciousness; patients with severe viscera diseases, immune system diseases, and other diseases; people who failed to complete this experiment; nonschool sports students.

2.2. Motion State Recognition Model Based on CNN Network. It is supposed the number of data attribute values collected by the smartphone is N. Then, the input data set can be expressed as $Q_{(0,i)} = \{q_1, q_2, \ldots, q_N\}$, and the output result of the convolution layer of the CNN network can be expressed as follows:

$$C_{(l,j,i)} = \alpha\left(b_j + \int_{w=1}^{W} e_{(j,w)} * q_{(0,j,i+w-1)}\right), \tag{1}$$

where α represents the excitation function, l represents the data of convolution layer, j represents the number of feature groups, b represents the bias, w means the size of convolution kernel, e means the number of neurons, and i means the number of data. The output result of convolution layer passes through the pooling layer, and the maximum pooling is used for data processing.

$$P_{(l,j,i)} = \max_{r\in R}\left(C_{(l,j,i\times T+r)}\right), \tag{2}$$

where R represents the size of the pool layer, and T indicates the step size. The hidden features in the data are obtained by multiple processing of the data according to the above equation. Then, the Softmax classifier is used to classify the data in order to distinguish different motion states. The Softmax classifier is located at the top of the CNN network. The feature vector set obtained from the pooling layer can be expressed as $P_s = \{p_1, p_2, \ldots, p_S\}s$, s means the number of units in the final pooling layer, and the expression of the Softmax classifier is as follows:

$$F_{(D,P)} = \arg\max_{d\in D}\left\{\frac{\exp\left(p_{(l-1)} * e_l + b_l\right)}{\int_{K=1}^{H_D} \exp\left(p_{(l-1)} e_k\right)}\right\}, \tag{3}$$

where D represents the category, l represents the latest level of data, and $H_D$denotes the category quantity value. The final motion state category can be obtained through the

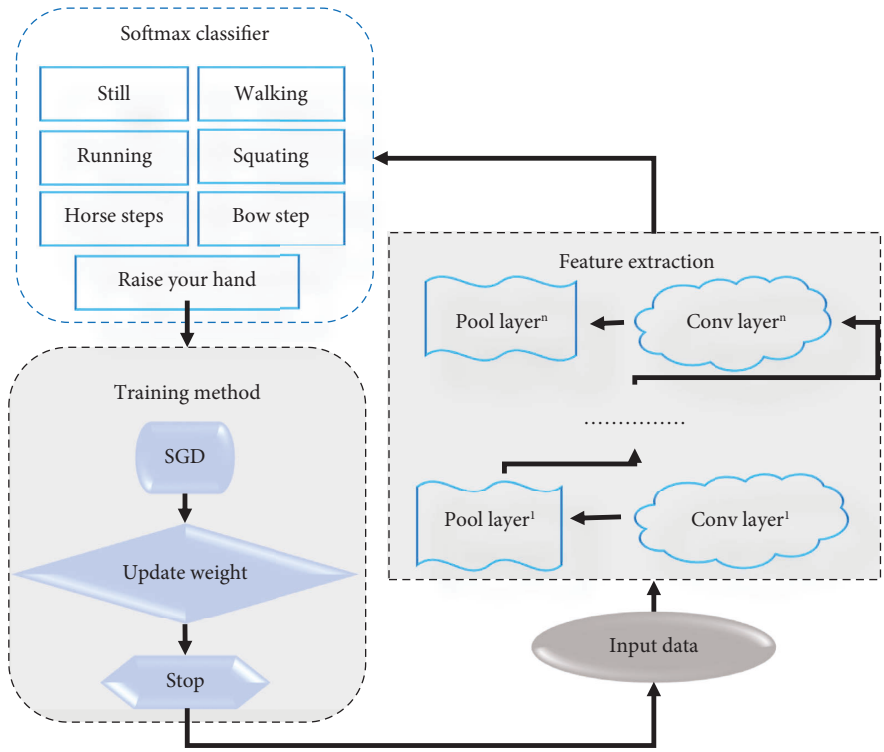


Figure 1: Structure of CNN.

classification of the classifier. The CNN network representation for motion state recognition is shown in Figure 1.

Figure 1 shows an operation process of motion state recognition and a feed-forward operation part of the CNN network, in which the weight values of the CNN network are shared. The error rate of classification can be obtained by this running network, and then, the new weight can be obtained by using the stochastic gradient descent method (SGD). The specific expression of SGD is as follows:

$$\beta Z/\beta V_{ab} = \int_{i=0}^{H-W-1} \frac{\beta Z}{\beta Y_{(l,i,j)} \bullet x_{(l-1)|(i+\varepsilon)}}, \tag{4}$$

where Z represents the loss function and $x_{(l-1)|(i+\varepsilon)}$ means the nonlinear mapping function. When the accuracy of front feedback reaches the estimated value or other conditions are met, the calculation can be stopped.

Because the data of the CNN network are in matrix format, and the data format in the smart phone is inconsistent with it, it is necessary to learn from the red green blue (RGB) data format in the field of image processing, which is mainly processed by sliding window folding method. It is assumed that the data set is M, the length is L, the length of the sliding window is l, and the step size is s, and the processing expression of the sliding window folding is as follows:

$$M = \{x_1, x_2, \ldots, x_{L-1}, x_L\}. \tag{5}$$

After conversion, $\overline{\overline{M}}$ can be obtained.

$$\overline{\overline{M}} = \left\{ \begin{matrix} x_1, x_2, \ldots, x_l \\ \vdots \\ x_{L-l+1}, x_{L-l+2}, \ldots, x_L \end{matrix} \right\}. \tag{6}$$

The calculation of the corresponding convolution layer and pooling layer can be expressed as follows.

The calculation of the corresponding convolution layer is as follows:

$$\begin{aligned} C_{(i,l)} &= K * A, \\ K &= \left\{ \begin{matrix} m_1 * n_1, m_2 * n_2, \ldots, m_l * n_l \\ \vdots \\ m_{L-l+1} * n_{L-l+1}, m_{L-l+2} * n_{L-l+2}, \ldots, m_L * n_L \end{matrix} \right\}, \\ A &= \{(i-m+1), (j-n+1)\}, \end{aligned} \tag{7}$$

where A represents the matrix to be convoluted, $C_{(i,l)}$ is the convolution output matrix, K is the convolution kernel, and $m * n$ means the size of the matrix.

The pooling layer is mainly used to reduce the dimension of the data in the convolution layer. The length and width of the pooling kernel are expressed as p_x and p_y, respectively. Then, the operation of maximum pooling is expressed as follows:

$$F_{ij} = \left\{ \begin{matrix} z_{(i,j)\cdot l}, z_{(i,j+1/l)\cdot l}, \ldots, z_{(i,j+p_x/l)\cdot l} \\ \vdots \\ z_{(i+p_y/l,j)\cdot l}, z_{(i+p_y/l,j+1/l)\cdot l}, \ldots, z_{(i+p_y/l,j+p_x/l)\cdot l} \end{matrix} \right\}. \tag{8}$$

The motion state recognition is carried out according to the model, and its application performance is evaluated by calculating its recognition rate (S) of the total motion state and the recognition accuracy (A) of different motion states.

The specific calculation method is as follows.

$$S = \frac{\Delta S}{S_m} * 100\%,$$
$$A = \frac{A_{mn} - A_{en}}{A_{mn}} \times 100\%, \quad (9)$$

where S_m represents the actual motion state category, and ΔS means the recognized motion state category. A_m represents the total number of cases of a certain type of motion, A_e is the number of cases of recognition errors of a certain type of motion, and n is the number of types of motion states.

2.3. Exercise Methods. According to the common aerobic exercise methods, the exercise conveniently implemented by college students is the main exercise, including Tai Chi, jogging, and combined exercise methods. The college students in the control group selected the appropriate exercise method according to their own conditions, did not receive the guidance of any person or technique during this period, and could be adjusted according to their physical fitness; the college students in the observation group selected the aerobic exercise method and performed more accurate exercise under the guidance of the CNN network-based motion state recognition technique; that is, the exerciser's limbs and muscles were adjusted through the identification of the motion state to maximize the exercise effect. The training cycle and time are 3 times/week and 90 min/time, and the control group was consistent with the observation group.

2.4. Outcome Measures. The changes in physical fitness, cardiopulmonary function, and mentality in the two groups before and after one year of exercise were compared.

Determination method of physical change: according to relevant content and expert opinions, the main physical fitness indicators measured included running performance, standing long jump performance, and 1 min sit-up performance.

Cardiopulmonary function assessment methods, the vital capacity, maximal ventilator volume per minute (MVV) and vital capacity/body mass index, stroke volume (SV), cardiac output (CO), ejection fraction (EF), heart rate (HR), ejection time (ET), mean systolic ejection rate (MSER), mean velocity of circumferential fibre shortening (MVCF), were measured to evaluate the changes of cardiopulmonary function.

The mentality assessment method, mentality assessment, uses the profile of mood states (POMS) [19]. The test indicators mainly included tension, anger, depression, fatigue, panic, energy, and self-related emotions. The five-level scale was used, which was almost no—0 point, a little—1 point, moderate—2 points, quite a lot—3 points, and very—4 points. The highest scores of the above seven aspects were 24, 28, 24, 20, 20, 24, and 20, respectively, and the lowest scores were 0. Afterwards, a total mood disturbance (TMD) score was calculated to assess mood state. The specific calculation was as follows:

$$TMD = (\text{Score}_A + \text{Score}_B + \text{Score}_C + \text{Score}_D + \text{Score}_E) - (\text{Score}_F + \text{Score}_G) + 100. \quad (10)$$

Score_A to Score_G indicate the score results of tension, anger, depression, fatigue, panic, energy, and self-related emotions. The lower TMD indicates the better mood state.

2.5. Statistical Methods. SPSS 22.00 statistical software was adopted for data entry, sorting, and statistical analysis. χ^2 test was used to compare the counting data; the measurement data were expressed by (mean ± standard deviation), and t-test was used. $P > 0.05$ indicated that there was no significant difference; $P < 0.05$ indicated that there was significant difference; $P < 0.01$ indicated a very significant difference.

3. Results

3.1. Comparison of Recognition Rate of Motion State. Data were acquired by 140 students holding a smartphone with a sampling frequency of 50 HZ. The CNN algorithm recognition rate was compared with RNN and DNN algorithms. The results showed that the training results and test results of the CNN algorithm were 96.67% and 92.98%, respectively. There was no significant difference between the two groups ($P > 0.05$). The training results and test results of the RNN algorithm were 65.11% and 52.22%, respectively, and there was a significant difference between the two groups ($P < 0.05$). The training results and test results of the DNN algorithm were 90.65% and 40.21%, respectively, and there was a very significant difference between the two groups ($P < 0.05$) (Table 1). The recognition rate of the CNN algorithm was higher than that of RNN and DNN algorithms ($P < 0.05$).

3.2. Comparison of Accuracy Rate in Different Movement States. It mainly identified movement states such as stationary, walking, running, squatting, hand raising, seated position, and lunge. The recognition accuracy of CNN, RNN, and DNN algorithms for different motion states was calculated (Figure 2). Through observation, the recognition accuracy of various motion states was the highest in the CNN algorithm model, of which the recognition accuracy of stationary, walking, seated position, and lunge was 100%, 98.87%, 99.67%, and 97.99%.

3.3. Comparison of General Conditions. Table 2 shows the general condition of college students in the two groups. In the control group, the male college students accounted for 69.53%, and the female college students accounted for 30.47%. The proportion of male college students in the observation group was 65.63%, and the proportion of female college students was 34.38%. In the control group, the proportion of college students with normal blood pressure

Table 1: Comparison of recognition rate of different algorithms.

Motion state	CNN		RNN		DNN	
	Training result	Test result (%)	Training result	Test result (%)	Training result	Test result (%)
Recognition rate	96.67%	92.98	65.11%	52.22	90.65%	40.21
t	1.221		2.511		3.812	
P	0.191		0.041		0.001	

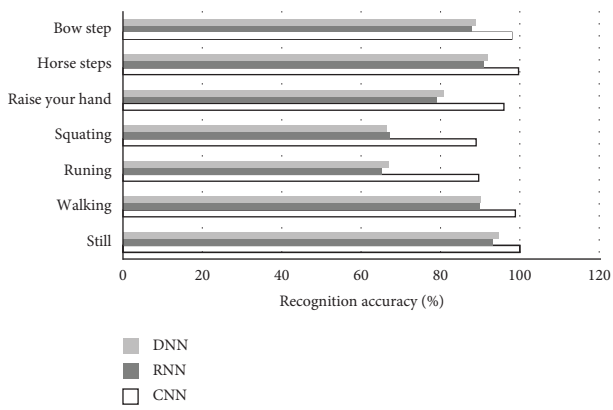


Figure 2: Comparison of recognition accuracy of different motion states.

was 48.44%, and the proportion of abnormal blood pressure was 51.56%. The proportion of normal blood pressure in the observation group was 53.91%, and the proportion of abnormal blood pressure was 46.09%. The average age and average weight of college students in the control group were (24.23 ± 1.76) years old and (68.73 ± 16.12) kg, respectively. The average age and average weight of college students in the observation group were (25.66 ± 1.06) years old and (67.12 ± 16.87) kg, respectively. After comparison, there was no significant difference in gender distribution, average age, average weight, and blood pressure distribution between the two groups ($P > 0.05$). It suggested that the two groups had certain comparability.

3.4. Comparison of Physical Changes. Figure 3 shows the comparison of the 800/1,000 m running scores of the two groups of college students before and after one year of exercise. Before exercise, the average running score of the control group was (3.61 ± 0.08) min/s, and that of the observation group was (3.64 ± 0.07) min/s. There was no significant difference between the two groups ($P > 0.05$). After one year of exercise, the average running score of the control group was (3.40 ± 0.04) min/s, and that of the observation group was (3.04 ± 0.03) min/s. The 800/1,000 m running scores of the control group and the observation group after 1 year of exercise were better than those before exercise, and the running score of the observation group after 1 year of exercise was better than that of the control group ($P < 0.05$).

Figure 4 suggests the comparison of the standing long jump scores of the two groups of college students before and after one year of exercise. Before exercise, the average standing long jump score of the control group was (1.71 ± 0.03) m, and that of the observation group was (1.72 ± 0.04) m, with no significant difference ($P > 0.05$). After one year of exercise, the average standing long jump score of the control group was (1.76 ± 0.06) m, and that of the observation group was (1.82 ± 0.07) m. After comparison, the standing long jump scores of the control group and the observation group after one year of exercise were better than those before exercise. The standing long jump score of the observation group was better than that of the control group after 1 year of exercise ($P < 0.05$).

Figure 5 shows the comparison of 1 min sit-up performance before and after one year of exercise between the two groups. Before exercise, the mean 1 min sit-up performance was (34 ± 4) in the control group and (35 ± 3) in the observation group, with no significant difference ($P > 0.05$). After 1 year of exercise, the mean 1 min sit-up performance was (42 ± 7) in the control group and (56 ± 4) in the observation group. After comparison, the 1 min sit-up performance after 1 year of exercise in the control group and the observation group was superior to that before exercise, and the 1 min sit-up performance in the observation group was superior to that in the control group after 1 year of exercise ($P < 0.05$).

3.5. Comparison of Changes in Cardiopulmonary Function. Figure 6 shows the results statistics of vital capacity, MVV, and vital capacity/body mass index of college students in the two groups before and after 1 year of exercise for the assessment of pulmonary ventilation function. Before exercise, the vital capacity, MVV, and vital capacity/body mass index of college students in the control group were (2,810.12 ± 121.65) mL, (102.01 ± 3.98) l/S, and 48.22 ± 4.02, respectively, while those in the observation group were (2,798.89 ± 126.02) mL, (103.35 ± 3.87) l/S, and 47.67 ± 4.23, respectively, and there was no significant difference ($P > 0.05$). After one year of exercise, the vital capacity, MVV, and vital capacity/body mass index of college students in the control group and the observation group were improved, (2,910.67 ± 131.77) mL, (116.34 ± 4.99) l/S, and 50.02 ± 4.92 in the control group, and (3,102.42 ± 125.09) mL, (120.33 ± 4.87) l/S, and 52.12 ± 4.65 in the observation group, respectively. After comparison, the improvement effect of vital capacity, MVV, and vital capacity/body mass index in the observation group was superior to that in the control group ($P < 0.05$).

Figure 7 shows the statistics of the changes in cardiac pumping function before and after one year of exercise in the two groups of college students. Figure 7(a) indicates the detection results of SV, CO, EF, HR, ET, MSER, and MVCF in the control group and the observation group before the exercise. It can be observed that there was no significant

Table 2: Statistics of general conditions of college students in the two groups.

Index		Control group ($n = 128$)	Observation group ($n = 128$)	t	P
Gender	Male (cases)	89	84	1.211	0.122
	Female (cases)	39	44	1.071	0.201
Age (years old)	Range	23~26	23~27	—	—
	Average	24.23 ± 1.76	25.66 ± 1.06	1.221	0.129
Weight (kg)	Range	51 kg~80 kg	50 kg~80 kg	—	—
	Average	68.73 ± 16.12	67.12 ± 16.87	1.021	0.220
Blood pressure	Normal (cases)	62	69	1.982	0.089
	Abnormal (cases)	66	59	1.991	0.071

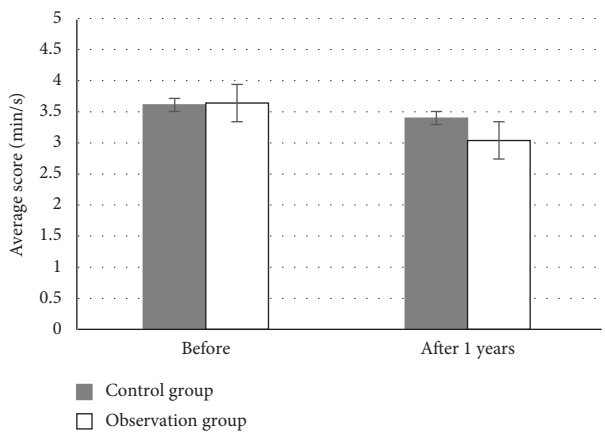


Figure 3: Comparison of 800/1,000 m running performance.

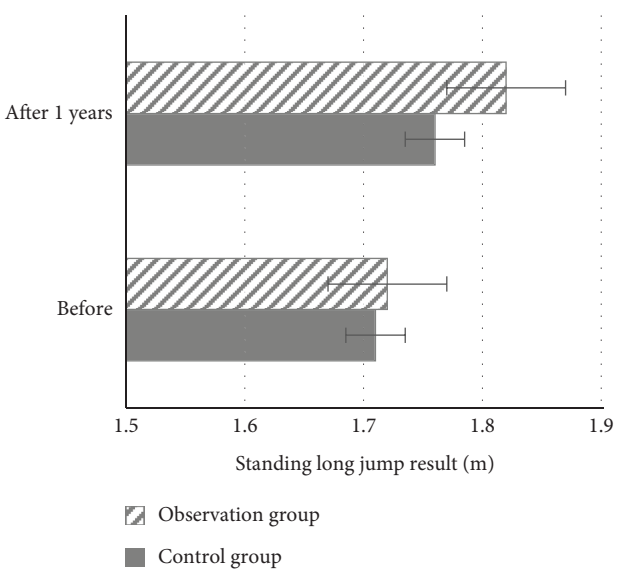


Figure 4: Comparison of standing long jump performance.

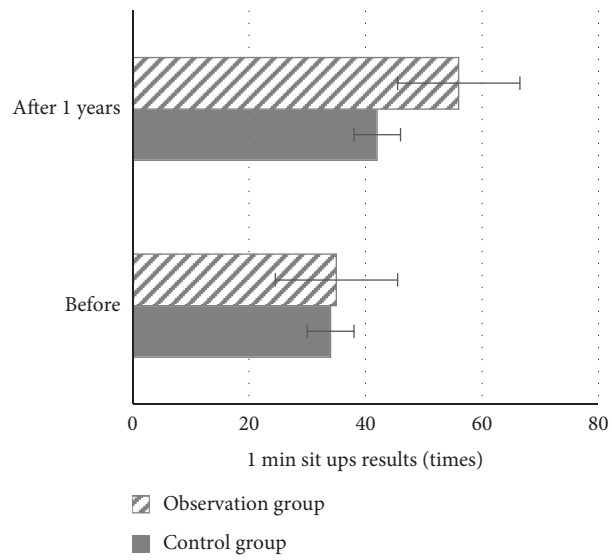


Figure 5: Comparison of 1 min sit-up performance.

difference in the detection of the above indicators between the two groups of college students ($P > 0.05$). Figure 7(b) reveals the detection results of SV, CO, EF, HR, ET, MSER, and MVCF in the two groups of college students after exercise. The detection results of SV, CO, EF, MSER, and MVCF in the observation group were higher than those in the control group, and the detection results of HR and ET were lower than those in the control group. There was significant statistical difference between the two groups ($P < 0.05$).

3.6. Comparison of Mentality Changes. POMS was used to evaluate the changes in mentality before and after exercise in the two groups. Table 3 shows the results of POMS scores of college students in the two groups before exercise, and there was no significant statistical difference in tension, anger, depression, fatigue, panic, energy, self-related emotions, and TMD scores between the two groups ($P > 0.05$). Figure 8 shows the comparison of tension, anger, depression, fatigue, panic, energy, self-related emotions, and TMD score results between the two groups after one year of exercise. The scores of tension, anger, depression, fatigue, panic, and TMD of college students in the two groups decreased, and the evaluation of energy and self-related emotions increased, and the improvement effect of the observation group was significantly better than that of the control group ($P < 0.05$).

4. Discussion

With the gradual attention to physical health, physical exercise has attracted widespread attention. Today's health contains not only physical aspects but also psychological health. As the hope of the country, the physical and mental health of students has become a hot spot of attention. At present, aerobic exercise has been generally recognized and practiced by people, and many studies have shown that aerobic exercise can effectively regulate and improve the

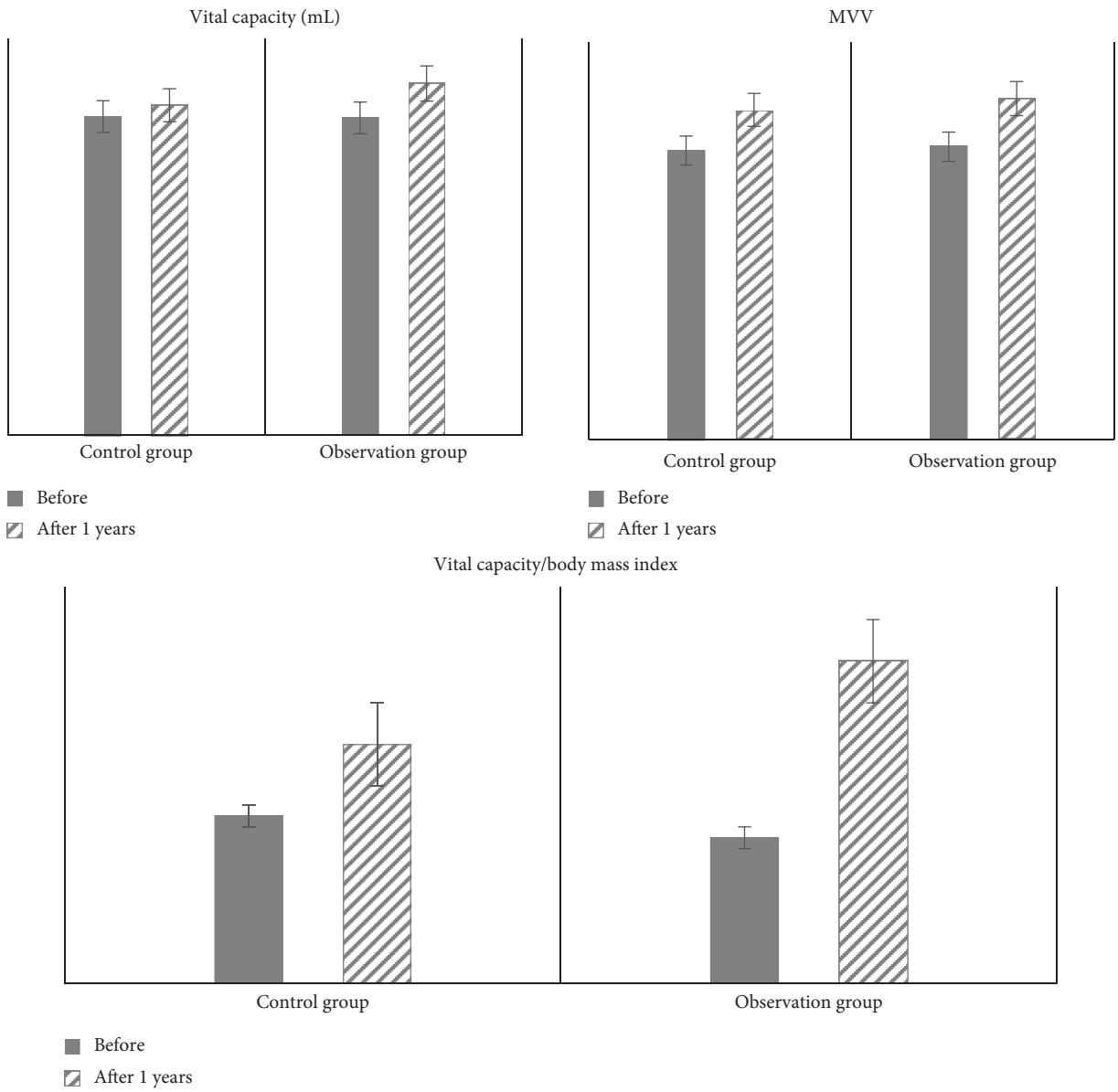
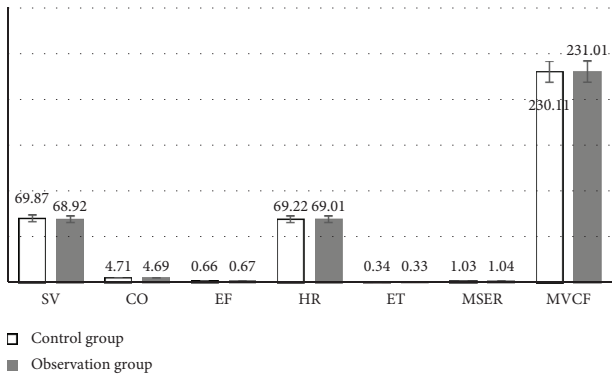


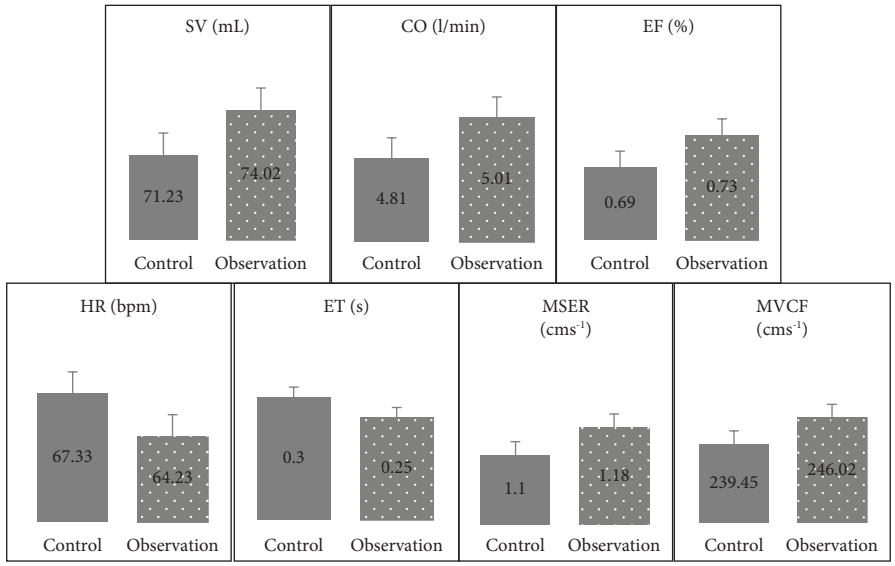
Figure 6: Test results of pulmonary ventilation function.

function of the human body [20, 21]. In order to improve the accuracy of exercise and maximize the exercise effect, aerobic exercise was combined with motion state recognition technology based on the CNN algorithm, which was applied to the healthy exercise of college students.

The accuracy and intensity of the motion can be accurately adjusted by identifying the motion state of the exerciser. The recognition rate of CNN algorithm test results (92.98%) was higher than that of RNN (52.22%) and DNN (40.21%) algorithms ($P < 0.05$). The recognition accuracy of the CNN algorithm was higher than that of the RNN algorithm and DNN algorithm for stationary, walking, running, squatting, hand raising, seated position, and lunge. The recognition accuracy of the CNN algorithm for stationary, walking, seated position, and lunge was 100%, 98.87%, 99.67%, and 97.99%. Some related studies have also concluded that the performance of the CNN-based motion state recognition model was significantly better than other algorithms, and the accuracy was the highest [22]. Moreover, by comparing the training results and test results of the CNN algorithm, RNN algorithm, and DNN algorithm, it was found that there was no significant difference between the training results and test results of the CNN algorithm ($P > 0.05$), while there was significant difference between the two results of DNN algorithm and RNN algorithm ($P < 0.05$), suggesting that the stability of CNN performance was higher than that of RNN and DNN algorithms. Chen et al. [23] mentioned that the CNN algorithm had good stability in application testing. Xu et al. [24] also proposed that the recognition accuracy and stability of the CNN algorithm were better than those of recognition methods based on time domain and frequency domain characteristics. Through the above analysis, it was found that the adopted motion state recognition technology based on the



(a)



(b)

Figure 7: Changes in cardiac pumping function. ((a)before exercise, (b)after one year of exercise).

Table 3: POMS score results of college students in the two groups before exercise.

Score result (point)	Factor	Control group ($n = 128$)	Observation group ($n = 128$)	t	P
	Tension	12.67 ± 3.05	12.89 ± 2.89	1.341	0.198
	Anger	12.14 ± 2.67	12.45 ± 2.19	1.098	0.200
	Depression	11.19 ± 2.45	11.37 ± 2.51	0.987	0.321-
	Fatigue	12.00 ± 2.23	12.04 ± 2.18	1.021	0.199
	Panic	10.05 ± 3.54	10.21 ± 3.23	1.980	0.987
	Energy	9.67 ± 2.99	9.83 ± 2.67	1.020	0.221
	Self-related emotions	7.98 ± 3.87	8.07 ± 3.35	2.082	0.069
	TMD	137.44 ± 9.85	138.07 ± 9.62	2.008	0.061

CNN algorithm had good feasibility. In order to further explore the auxiliary effect of the above motion state recognition technique on aerobic exercise in college students, 256 college students were divided into the control group and the observation group for application effect evaluation.

Through the study, it was found that the physical fitness of the two groups of college students was improved after one year of exercise, and the 800/1,000 m running score, standing long jump score, and 1 min sit-up score of the control group and the observation group after one year of exercise were superior to those before exercise ($P < 0.05$), suggesting that aerobic exercise can effectively improve people's physical fitness. Farenia et al. [25] proposed that aerobic exercise had a better effect in improving the structure of myofibers compared with anaerobic exercise and can better promote people's exercise level. In addition, the results of cardiopulmonary function indexes (vital capacity, MVV, vital capacity/body mass index, SV, CO, EF, HR, ET, MSER, and MVCF) and POMS (tension, anger, depression, fatigue, panic, energy, self-related emotions, and TMD) were improved after one year of exercise in both groups ($P < 0.05$), suggesting that aerobic exercise can

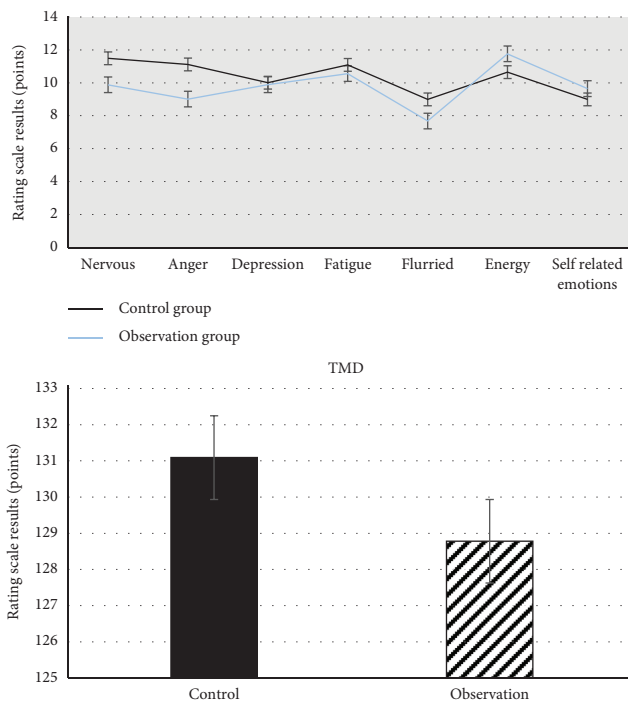


Figure 8: Results of POMS scores of college students in the two groups after one year of exercise. (a: scoring results of tension, anger, depression, fatigue, panic, energy, and self-related emotion).

effectively improve people's cardiopulmonary function and improve people's mood state. Aburub et al. [26] mentioned the positive effects of aerobic exercise on cardiac health. Messaggi-Sartor et al. [27] proposed that aerobic exercise can assist in high-intensity respiratory muscle training to effectively improve the exercise capacity and respiratory muscle strength of patients after lung cancer resection. Santoso et al. [28] proposed that aerobic exercise had the effects of improving NT-pro BNP, ventilatory efficiency, aerobic capacity, maximum load, and left ventricular function in patients with heart failure. Moreover, the acute effects of aerobic exercise on improving mood and reducing anxiety have also been demonstrated in clinical and non-clinical populations [29]. These studies have shown that aerobic exercise can enhance people's cardiopulmonary function, which is basically consistent with the trend of the results of this exploration. Brand et al. [30] proposed that aerobic exercise was more likely to play a role in improving all dimensions of psychological function when people's motion coordination needs were met. The motion state recognition technology can accurately detect people's motion coordination. Moreover, Mohamed et al. [31] found that exercise recognition can effectively improve the effect of rehabilitation training, indicating that motion state recognition technology has a good application prospect in clinical medical treatment.

5. Conclusion

The motion recognition technology based on the CNN network model was used to guide the aerobic exercise of college students, and its application value in the physical and mental health of college students was studied. The results show that aerobic exercise can effectively improve the physical fitness, cardiopulmonary function, and adverse mentality of college students, and the motion recognition technology based on the CNN network model can further improve the effect of aerobic exercise, which is worthy of application and promotion. However, due to the relatively limited selection range of study subjects and the lack of some extensiveness of the results, further studies are needed to confirm the general applicability of aerobic exercise as well as motion recognition techniques based on deep learning in the application of physical and mental health improvement in college students.

Data Availability

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Conflicts of Interest

All authors declare that they have no conflicts of interest.

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References

[1] T. M. Barnett, A. McFarland, J. W. Miller, V. Lowe, and S. S. Hatcher, "Physical and mental health experiences among african American college students," *Social Work in Public Health*, vol. 34, no. 2, pp. 145–157, 2019.

[2] A. M. Al-Khani, M. I. Sarhandi, M. S. Zaghloul, M. Ewid, and N. Saquib, "A cross-sectional survey on sleep quality, mental health, and academic performance among medical students in Saudi Arabia," *BMC Research Notes*, vol. 12, no. 1, p. 665, 2019 Oct 21.

[3] M. Grasdalsmoen, H. R. Eriksen, K. J. Lønning, and B. Sivertsen, "Physical exercise, mental health problems, and suicide attempts in university students," *BMC Psychiatry*, vol. 20, no. 1, p. 175, 2020.

[4] A. Ströhle, "Sports psychiatry: mental health and mental disorders in athletes and exercise treatment of mental disorders," *European Archives of Psychiatry and Clinical Neuroscience*, vol. 269, no. 5, pp. 485–498, 2019.

[5] F. Yu, D. M. Vock, L. Zhang et al., "Cognitive effects of aerobic exercise in alzheimer's disease: a pilot randomized controlled trial," *J Alzheimers Dis*, vol. 80, no. 1, pp. 233–244, 2021.

[6] V. Guadagni, L. L. Drogos, A. V. Tyndall et al., "Aerobic exercise improves cognition and cerebrovascular regulation in older adults," *Neurology*, vol. 94, no. 21, pp. e2245–e2257, 2020.

[7] H. Gezer, O. Z. Karaahmet, E. Gurcay, D. Dulgeroglu, and A. Cakci, "The effect of aerobic exercise on stroke rehabilitation," *Irish Journal of Medical Science*, vol. 188, no. 2, pp. 469–473, 2019.

[8] E. Grazioli, E. Tranchita, G. Borriello, C. Cerulli, C. Minganti, and A. Parisi, "The effects of concurrent resistance and aerobic exercise training on functional status in patients with multiple sclerosis," *Current Sports Medicine Reports*, vol. 18, no. 12, pp. 452–457, 2019.

[9] D. M. LeBouthillier and G. J. G. Asmundson, "The efficacy of aerobic exercise and resistance training as transdiagnostic interventions for anxiety-related disorders and constructs: a randomized controlled trial," *Journal of Anxiety Disorders*, vol. 52, pp. 43–52, 2017.

[10] Z. Yu, S. U. Amin, M. Alhussein, and Z. Lv, "Research on disease prediction based on improved DeepFM and IoMT," *IEEE Access*, vol. 9, pp. 39043–39054, 2021.

[11] Y. Li, J. Zhao, Z. Lv, and J. Li, "Medical image fusion method by deep learning," *International Journal of Cognitive Computing in Engineering*, vol. 2, pp. 21–29, 2021.

[12] S. Zhao, "Optimization of human motion recognition information processing system based on GA-BP neural network algorithm," *Computational Intelligence and Neuroscience*, vol. 2021, Article ID 1110503, 10 pages, 2021.

[13] Q. Yu, P. Zhang, and Y. Chen, "Human motion state recognition based on flexible, wearable capacitive pressure sensors," *Micromachines*, vol. 12, no. 10, p. 1219, 2021.

[14] D. Roy, P. Panda, and K. Roy, "Tree-CNN: a hierarchical deep convolutional neural network for incremental learning," *Neural Networks*, vol. 121, pp. 148–160, 2020.

[15] X. Liu, C. Liu, R. Huang et al., "Long short-term memory recurrent neural network for pharmacokinetic-pharmacodynamic modeling," *International Journal of Clinical Pharmacology & Therapeutics*, vol. 59, no. 2, pp. 138–146, 2021.

[16] X. Qin, L. Zhang, M. Liu, Z. Xu, and G. Liu, "ASFold-DNN: protein fold recognition based on evolutionary features with variable parameters using full connected neural network," *IEEE/ACM Transactions on Computational Biology and Bioinformatics*, vol. 15, p. 1, 2021.

[17] A. M. Saleh and T. Hamoud, "Analysis and best parameters selection for person recognition based on gait model using CNN algorithm and image augmentation," *J Big Data*, vol. 8, no. 1, p. 1, 2021.

[18] H. Wu, Q. Huang, D. Wang, and L. Gao, "A CNN-SVM combined model for pattern recognition of knee motion using mechanomyography signals," *Journal of Electromyography and Kinesiology*, vol. 42, pp. 136–142, 2018.

[19] A. Malinenko, A. Jonchère, L. Girard, S. Parrès-Maynadié, O. Diat, and P. Bauduin, "Are keggin's POMs charged nanocolloids or multicharged anions?" *Langmuir*, vol. 34, no. 5, pp. 2026–2038, 2018.

[20] C. Nery, S. R. A. Moraes, K. A. Novaes, M. A. Bezerra, P. V. C. Silveira, and A. Lemos, "Effectiveness of resistance exercise compared to aerobic exercise without insulin therapy in patients with type 2 diabetes mellitus: a meta-analysis," *Brazilian Journal of Physical Therapy*, vol. 21, no. 6, pp. 400–415, 2017 Nov-Dec.

[21] Y. Wang and D. Xu, "Effects of aerobic exercise on lipids and lipoproteins," *Lipids in Health and Disease*, vol. 16, no. 1, p. 132, 2017 Jul 5.

[22] S. Xie, Z. Yu, and Z. Lv, "Multi-disease prediction based on deep learning: a survey," *Computer Modeling in Engineering and Sciences*, vol. 128, no. 2, pp. 489–522, 2021.

[23] R. Chen, S. Zhao, W. Wu et al., "A convolutional neural network algorithm for breast tumor detection with magnetic detection electrical impedance tomography," *Review of Scientific Instruments*, vol. 92, no. 6, Article ID 064701, 2021.

[24] L. Xu, K. Zhang, Z. Xu, and G. Yang, "[Convolutional neural network human gesture recognition algorithm based on phase portrait of surface electromyography energy kernel]," *Sheng Wu Yi Xue Gong Cheng Xue Za Zhi*, vol. 38, no. 4, pp. 621–629, 2021.

[25] R. Farenia, R. Lesmana, K. Uchida, T. Iwasaki, N. Koibuchi, and N. Shimokawa, "Changes in biomarker levels and myofiber constitution in rat soleus muscle at different exercise intensities," *Molecular and Cellular Biochemistry*, vol. 458, no. 1-2, pp. 79–87, 2019.

[26] A. Aburub, S. J. Ledger, J. Sim, and S. M. Hunter, "Cardiopulmonary function and aerobic exercise in Parkinson's: a systematic review of the literature," *Mov Disord Clin Pract*, vol. 7, no. 6, pp. 599–606, 2020.

[27] M. Messaggi-Sartor, E. Marco, E. Martínez-Téllez et al., "Combined aerobic exercise and high-intensity respiratory muscle training in patients surgically treated for non-small cell lung cancer: a pilot randomized clinical trial," *European Journal of Physical and Rehabilitation Medicine*, vol. 55, no. 1, pp. 113–122, 2019.

[28] A. Santoso, R. Maulana, F. Alzahra et al., "The effects of aerobic exercise on N-terminal pro-B-type natriuretic peptide and cardiopulmonary function in patients with heart failure: a meta-analysis of randomised clinical trials," *Heart Lung & Circulation*, vol. 29, no. 12, pp. 1790–1798, 2020.

[29] A. M. Abrantes, S. G. Farris, R. A. Brown et al., "Acute effects of aerobic exercise on negative affect and obsessions and compulsions in individuals with obsessive-compulsive disorder," *Journal of Affective Disorders*, vol. 245, pp. 991–997, 2019.

[30] S. Brand, M. Gerber, F. Colledge, E. Holsboer-Trachsler, U. Pühse, and S. Ludyga, "Acute exercise and emotion recognition in young adolescents," *Journal of Sport & Exercise Psychology*, vol. 41, no. 3, pp. 129–136, 2019.

[31] A. A. Mohamed, Y. K. Jan, W. H. El Sayed, M. E. A. Wanis, and A. A. Yamany, "Dynamic scapular recognition exercise improves scapular upward rotation and shoulder pain and disability in patients with adhesive capsulitis: a randomized controlled trial," *Journal of Manual & Manipulative Therapy*, vol. 28, no. 3, pp. 146–158, 2020.