Application of Back-propagation Neural Network to Categorization of Physical Fitness Levels of Taiwanese Females

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Abstract

The purpose of this study is to establish the feasibility of adopting the back-propagation neural network (BPNN) to predict fitness category. In this study, 2218 healthy Taiwanese females aged 20 to 65 participated. Data collected included five parameters required for the physical fitness (PF) passport: subject's age, body mass index (BMI), performance in the sit-and-reach test, 1-min bent-leg curl-ups, and cardiorespiratory endurance. The network structure of BPNN adopted here consisted of three layers: input layer (5 neurons), hidden layer (5 neurons), and output layer (4 neurons). To prove the ability of BPNN in categorizing PF accurately and speedily, its learning effect must be confirmed. To achieve this purpose, the samples were divided randomly into two parts: training samples (n = 1218) and testing samples (n = 1000). Thereafter, learning algorithms of the BPNN were executed. The learning rate was assumed to be 0.75, and 1000 learning cycles were run. The results demonstrated that the root mean square (RMS) for the training samples was 0.059, while the RMS for the testing samples was 0.065. Such small RMS is evidence that the BPNN converged well and had a good learning effect. On the other hand, the mean degree of accuracy of the BPNN was 96.83% in identifying body composition, 98.41% for muscular flexibility, 94.39% for muscular strength and endurance, and 97.25% for cardiorespiratory capacity. The mean degree of accuracy for these four items was as high as 96.72%. Overall, the mean relative error for categorizing PF was 3.28%, which was within the acceptable range. Therefore, the results confirmed the reliability of the BPNN for categorizing PF. BPNN can be converted into software to assess the subject's PF in a precise and speedy manner, thus eliminating the need to refer to a chart of the modular standard to decide the fitness category.

Keywords: Category, Neural network, Physical fitness (PF)

1. Introduction

Artificial neural network (ANN) is a computing system comprising hardware and software. Its design is based on the biocomputation and information processing technique of biological neural networks simulated by plentiful supply of simple artificial neurons. The concept of an ANN was proposed and soon took off [1]. However, interest in this concept dwindled in the mid-1960s. The contributing factors for this dwindling included the fact that there was no major breakthrough in the theory of the ANN, as well as the nonavailability of high-speed computing technology at that time [1]. Researchers started studying ANN again in the 1980s, and it soon gained popularity. This was attributed to the establishment of ANN theory and the development of ANN models. Because of advances in our understanding of human physiology and psychology, a deeper understanding of biological neural network ensued, thus hastening the development of ANN models. This combination of ANN theory and ANN models contributed to the solving of problems in computer science and artificial intelligence [2].

Back-propagation neural networks (BPNN), a branch of ANN, are neural networks capable of learning and recall. Thus far, the learning and recall algorithms of BPNN have been successfully applied in many areas, such as the analysis of biomechanics [3], analysis of computing muscular signals [4], and study of human gait patterns by adopting BPNN to distinguish leg length [5,6]. BPNN have also been applied to the analysis of biomedical signals such as electrocardiography [7], electromyography [8], and electroencephalograms [9]. BPNN have also been adopted in sports research. For example, Aslan and Inceoglu (2007) used one to conduct a study on predicting the results of soccer games [10]. Using a BPNN, Yoon et al. (1994) analyzed the signals from the shift in the weight of the legs during a golf swing, and the results demonstrated that the BPNN was capable of analyzing and identifying signals [11]. Wong applied artificial intelligence to table tennis [12,13], involving the processing technology of identifying images to formulate a judgment system to assist

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umpires in making judgments. Although BPNN have been widely adopted in many areas as listed above, there is little evidence for similar research in any field of PF, let alone categorization aspects.

Taiwan's Ministry of Education has established modular standards for categorization of PF of males and females. It has also been promoting the practice of "physical fitness (PF) passports" for students' and citizens, which has resulted in increased prevalence of the PF test. However, current PF passports fail to offer an exercise prescription, which is essential for improving one's PF. According to the American College of Sports Medicine [14], an exercise prescription should include three components: duration of exercise, frequency of exercise, and intensity of exercise. These three components should be determined by one's body composition, muscular flexibility, muscular strength and endurance, and cardiorespiratory endurance [15].

Without accurate categorization of one's PF and the prescribed duration of exercise, frequency of exercise, and intensity of exercise, one would be unable to benefit from the intended effect of training. At present, in Taiwan, PF is categorized on the basis of the modular standard, and examiners have to refer to the chart manually to make the categorization, which is a time-consuming and less efficient process.

The drawback of manual categorization has lead researchers to put their efforts into finding an alternative to the traditional way. It is then hypothesized that BPNN is capable of categorizing PF accurately and speedily. The purpose of this study was to establish the feasibility of adopting the BPNN method to predict the fitness category subjects belong to. It was expected that BPNN could promote the efficacy of judging PF level. The data for this study were derived from the five sources listed in the PF passport: age, body mass index (BMI), performance in sit-and-reach test, 1-min bent-leg curl-ups, and cardiorespiratory endurance index (CEI). Thereafter, experiments were conducted to obtain evidence for and establish the capability of the BPNN in judging subjects' PF.

2. Methods

In the study, 2218 Taiwanese females were the subjects. To prove that the BPNN had a learning effect, the samples of the subjects were divided randomly into two groups: training sample (n = 1218) and testing sample (n = 1000). The data on their age, BMI, performance in sit-and-reach test, 1-min bent-leg curl-ups, and CEI acted as input vectors for the BPNN. Thereafter, the learning algorithm of BPNN was executed on these samples, the aim being to prove the convergence of the BPNN. Next, the recall algorithm was executed on them to confirm the BPNN's ability to categorize PF.

2.1 Subjects

The participants were from 21 cities and counties – 100 to 140 subjects from each city/county. Out of them, 1218 were treated as training sample, while the remaining 1000 acted as testing sample. Their ages ranged from 20 to 65 (weight: 57.2 ± 9.8 kg, height: 158.5 ± 8.4 cm). The Aerobic Fitness & Health Association in R.O.C. was in charge of testing their PF. Each subject was interviewed and asked to respond to a questionnaire to ascertain she could undergo the PF test without risking her health.

2.2 BPNN structure

The network of this study was composed of three layers: input layer, hidden layer, and output layer (Fig. 1). There were 5 neurons in the input layer $(x_j, j=1,2,..,5)$, 5 neurons in the hidden layer $(q_q, q=1,2,..,5)$, and 4 neurons in the output layer $(y_r, r=1,2,..,4)$. Input vector x_j, output vector y_r, and target vector d_r were needed to execute the learning algorithm of the BPNN. To maintain the learning quality, the BPNN has to be convergent, and the mean square error function E is the criterion to judge whether the network converges. In this study, E was defined as follows [1,16,17]:

$$E = (1/2)[\ \sum (d_r - y_r)^2\ ] \tag{1}$$

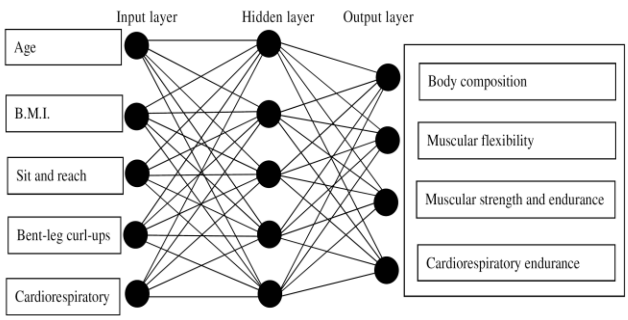

Figure 1. BPNN structure.

The BPNN will have better categorization capability if the training samples are sufficient and representative. The strength of the BPNN lies in its ability to generalize the training sample; namely, the network learning would focus on the female training sample, taking no male or children's sample into account. Therefore, researchers should avoid switching from one type of training sample to another lest the network forgets what it has learned before [1].

Fewer neurons in the hidden layer will cause a larger error. Although more neurons will reduce the error value, the convergence speed will decrease, thus increasing the computing time [18]. To ensure that the error is small and convergence speed is high, it was assumed in this study that the hidden layer had 4 neurons. Further, this study adopted one hidden layer, since Cybenko proved that one hidden layer was enough to approximate any continuous function [19]. Too many hidden layers would make the network too complicated to converge.

When the learning rate of the BPNN is either too large or too small, the convergence of the network is adversely affected. At a high learning rate, the synaptic weight of the network would approach the minimal function faster. However, it would also result in oscillation of synaptic weight and the failure of network convergence. After numerous computations were made with computer programs, it was found that better convergence is possible at a learning rate of 0.75.

2.3 Training samples

The data on subjects' age, BMI, performance in sit-and-reach test, 1-min bent-leg curl-ups, and CEI (Eq. (3)) acted as the input vector x_j of the BPNN. Subjects' performances in body composition, muscular flexibility, muscular strength and endurance, and cardiorespiratory endurance were converted into the output vectors y_r of the BPNN.

$$\text{BMI} = \text{Weight (Kg)} / \text{Height}^2\ (\text{m}^2) \quad (2)$$

$$\text{CEI} = \frac{\text{Duration of exercise (sec)} \times 100}{\text{Total pulses obtained after repeating measurement thrice} \times 2} \quad (3)$$

To make the network converge within the acceptable range, this study, on the basis of previous research experience, assumed the input values as follows: x_1 = age/100, x_2 = BMI/100, x_3 = number of sit-and-reach instances/100, x_4 = number of 1-min bent-leg curl-ups/100, x_5 = CEI/100. There are two main reasons to use 100 to normalize each input parameter. For one thing, using 100 to normalize each input parameter can make the value of each parameter range from 0 to 1 [20]. For another, the researchers had conducted a preliminary study in which the BPNN's learning capability was examined. It was found that using 100 to normalize the parameters could render far more accurate results than using no normalization.

The target vectors were from four fitness elements, which were defined as follows: d_1 = body composition, d_2 = muscular flexibility, d_3 = muscular strength and endurance, and d_4 = cardiorespiratory endurance. Each of the four fitness elements comprised five levels, with qualitative variables. The numerical number of each fitness element level, namely the output, also ranges from 0 to 1, with the first level being 0.2; the second level 0.4; the third level 0.6; the fourth level 0.8, and 1.0 for the fifth level. The level value of each fitness element composed the target vector d_r.

2.4 Data collection procedure

When conducting the experiment, the author followed the same procedure for the PF test as that for the PF passport. The subjects first answered the exercise safety questionnaire before being tested on fitness. Each subject's height and weight were measured. Then they had to take the sit-and-reach test, do 1-min bent-leg curl-ups, and take the 3-min step test (Fig. 2). The entire process was completed in an appropriate sequence to prevent one test from influencing the performance in subsequent tests. Subjects' cardiorespiratory endurance (3-min step test) was tested last, since this test would have had a greater impact on the results of the other tests.

2.5 Data analysis

In this study, the author developed software edited in C++ programming language to execute learning algorithms and recall algorithms of the BPNN. The root mean square (RMS) was the indicator of the convergence of the BPNN, while the mean relative error was used to prove the feasibility of the BPNN in categorizing fitness. After pre-testing the computer program many times, the author found that BPNN would converge well and have effective learning when it had run 1000 learning cycles at the learning rate of 0.75.

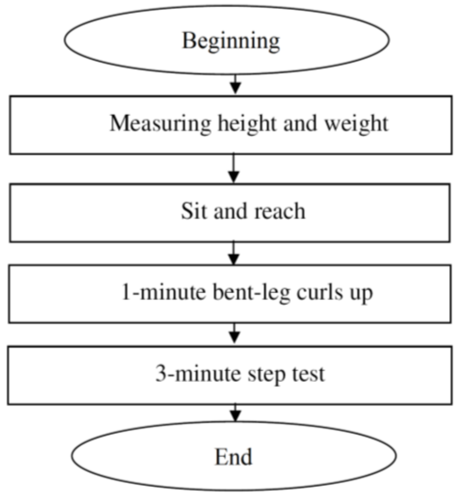

Figure 2. Procedure of testing PF.

3. Results

The data from 1218 subjects' fitness tests served as the training samples of the BPNN. After running 1000 learning cycles, the author obtained an RMS of 0.059 (Table 1). Thereafter, the learning algorithm was executed on the 1000 testing samples. The RMS for the testing samples was 0.065 (Fig. 3).

Table 1. RMS for training samples and testing samples.

	Number	RMS
Training samples	1218	0.059
Testing samples	1000	0.065

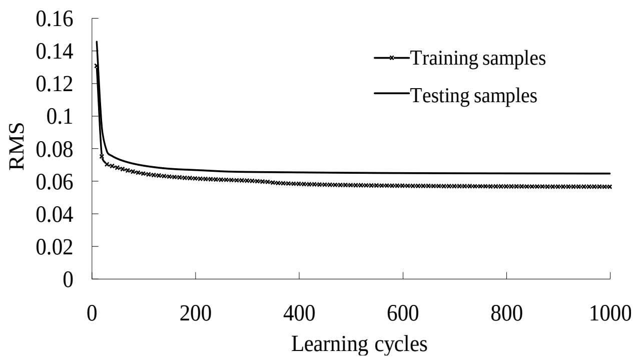

Figure 3. RMS for training samples and testing samples.

On the other hand, to comprehend the fitness categorization ability of BPNN, ten testing samples were randomly selected and processed with BPNN. It was found that the mean relative error for BPNN prediction was 2.89% (Table 2). Furthermore, BPNN was applied in 1218 training samples to categorize their fitness. The result showed that the mean degree of accuracy was 97.64%. Meanwhile, the recall algorithm of BPNN was executed on 1000 testing samples to estimate the categories, respectively, for body composition (Fig. 4), muscular flexibility (Fig. 5), muscular strength and endurance (Fig. 6), and cardiorespiratory endurance (Fig. 7). The result indicated that the mean degrees of accuracy were 96.83%, 98.41%, 94.39%, 97.25% , respectively.

Table 2. The relative error for input values and output values of 10 testing samples.

Input values					Relative error			
x_1	x_2	x_3	x_4	x_5	R1(%)	R2(%)	R3(%)	R4(%)
0.62	0.27	0.20	0.00	0.69	3.1	3.6	2.9	5.3
0.39	0.21	0.34	0.22	0.70	4.9	1.4	4.6	7.2
0.33	0.18	0.42	0.18	0.69	1.5	3.7	4.1	6.3
0.40	0.23	0.37	0.10	0.45	3.0	0.5	3.2	4.3
0.30	0.20	0.23	0.00	0.66	3.6	1.5	1.1	2.1
0.48	0.24	0.29	0.10	0.49	2.4	1.1	3.5	1.2
0.48	0.20	0.37	0.10	0.47	0.5	1.7	3.5	1.4
0.20	0.24	0.33	0.27	0.60	5.3	3.5	1.3	0.9
0.45	0.22	0.29	0.17	0.83	2.0	1.5	2.7	4.7
0.38	0.23	0.38	0.17	0.50	1.2	5.3	0.3	4.0

Note: The mean relative error for testing samples (n = 10) was 2.89%; *R1, R2, R3, R4* were the relative errors between output vector y_1, y_2, y_3, y_4 and target vector d_1, d_2, d_3, d_4, respectively.

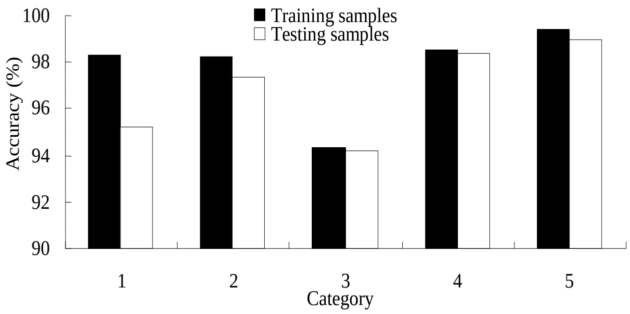

Figure 4. Accuracy of categorizing body composition with BPNN.

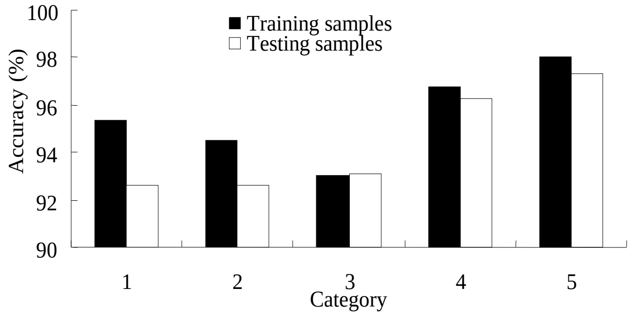

Figure 5. Accuracy of categorizing muscular flexibility.

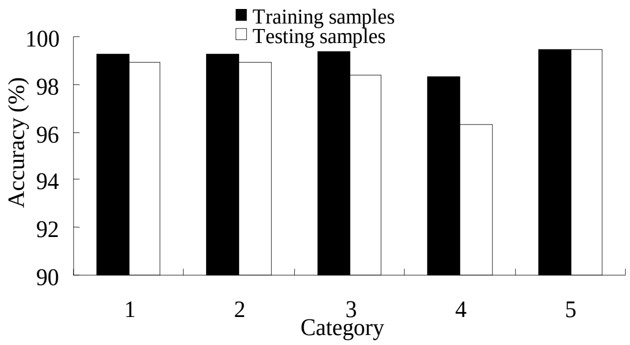

Figure 6. Accuracy of categorizing muscular strength and endurance.

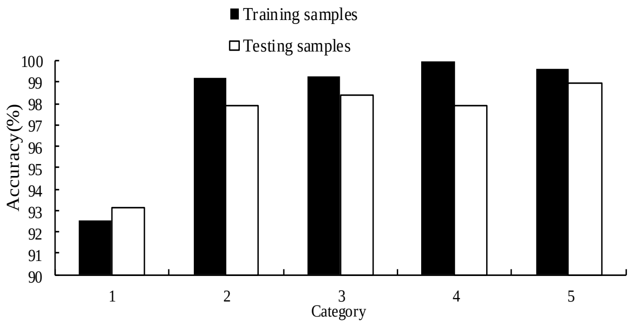

Figure 7. Accuracy of categorizing cardiorespiratory endurance.

4. Discussion

RMS is the criterion to decide if BPNN converges well. The RMS values in this study, 0.059 and 0.065, were considerably smaller than 0.08748 and 0.16169 [21]. Therefore, the result supported that the BPNN model in this study had successfully converged (Fig. 3). The following requirements had to be met to reach such a satisfactory level of convergence: (1) sufficient and generalized samples, (2) even distribution of sample' ages to make them representative, and (3) precision and consistency of keyed-in subjects' data [1]. By meeting these three requirements, this study developed a well-convergent BPNN that was competent in categorizing PF.

A pre-test was conducted on 10 randomly selected testing samples (Table 2). The result showed that the network was capable of categorizing PF, since the categorization result predicted from output vectors corresponded to target outputs, with the relative error being 2.89%. This small mean relative error indicated that the BPNN was stable and reliable in predicting the fitness category.

This study adopted the BPNN to draw inferences on the fitness category. The mean relative error for the recall algorithm of the BPNN executed on the 1218 training samples was 2.36%; in other words, the experiment reached a mean degree of accuracy of 97.64% (Table 3). Thereafter, the recall algorithm was also executed on 1000 testing samples. It was found that the mean degree of accuracy was 96.83% for inferring fitness category, 98.41% for inferring the muscular flexibility, 94.39% for inferring the category of muscular strength and endurance, and 97.25% for inferring cardiorespiratory endurance (Figs. 4-7). The average for the four mean degrees of accuracy was 96.72%; namely, the mean relative error was 3.28%, which closely approximated the degree of accuracy obtained in a previous study by Chiu [15], who had predicted the exercise intensity and exercise duration of Taiwanese college students by means of the BPNN.

Table 3. Accuracy of categorizing PF with BPNN.

Factors	Training samples (%)	Testing samples (%)
Body composition	97.75	96.83
Muscular flexibility	99.14	98.41
Muscular strength and endurance	95.53	94.39
Cardiorespiratory endurance	98.12	97.25

Note: The average accuracy for training samples (n = 1218) and testing samples (n = 1000) were 97.64% and 96.72%, respectively (mean relative errors were 2.36% and 3.28%, respectively).

BPNN was also adopted in the study by Yeh [21], who experimented with 1000 training samples and 1000 testing samples. Its resulting mean relative errors were 37.0% and 42.0% respectively. In contrast, the mean relative errors concurring in this study were 2.36% and 3.28%. Obviously, this study produced much smaller mean relative errors, thus proving that it was feasible to apply the BPNN to categorize fitness. The speed and accuracy yielded by the BPNN categorization gives it an edge over the traditional way of manually categorizing PF.

Although a small error was likely to occur in categorizing PF with the BPNN, it can be further reduced. There are two ways to attain this goal. It is recommended that in future studies, the number of samples should be increased, and the distribution of ages in the samples should be even to make the data more generic. The other way of reducing the error is to increase the number of neurons in the hidden layer [18]. However, researchers should exercise caution since too many neurons will slow down the convergence speed of the network and prolong the computing time.

5. Conclusion

Educating citizens on the need for PF has been a major concern of many countries, and Taiwan is no exception. At present, the categorization of PF in Taiwan is done manually by referring to the chart of the modular standard. The process is both time-consuming and less efficient, and is prone to human errors. To improve this situation, this study was undertaken to determine the fitness category by using a BPNN. The results showed that the RMS for the learning algorithm of the BPNN executed on training samples were 0.059 and 0.065 for testing samples. These figures proved that the BPNN had converged in the experiment and had learning effect. Furthermore, the results evidenced that it is feasible to determine the fitness category through application of the BPNN since the mean relative error produced from inferring PF category was only 3.28%, which was within the acceptable range. In addition, it is practical to develop the BPNN into application software for the purpose of classifying the PF. Firstly, it can reduce the time the examiners spend on referring to the chart of the modular standard to decide on the fitness category; secondly, it can eliminate frequent human errors. Finally, coaches will find it easy and convenient to make exercise prescriptions with this software.

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Application of Back-propagation Neural Network to Categorization of Physical Fitness Levels of Taiwanese Females. Ching-Hua Chiu. * Graduate Institute of Sports and Health Management, National Chung Hsing University, Taichung 402, Taiwan, ROC Received 4 Nov 2009; Accepted 20 Mar 2010; doi: 10.5405/jmbe.695. Abstract. The purpose of this study is to establish the feasibility of adopting the back-propagation neural network (BPNN) to predict fitness category. In this study, 2218 healthy Taiwanese females aged 20 to 65 participated. Data collected included five parameters required for the physical ... In neural network, any layer can forward its results to many other layers, in this case, in order to do back-propagation, we sum the deltas coming from all the target layers. Thus our linear calculation stack can become a complex calculation graph. This figure shows the process of back-propagating errors following this schemas: Input -> Forward calls -> Loss function -> derivative -> back-propagation of errors. At each stage we get the deltas on the weights of this stage. Diagram of Forward and Backward paths.