

Breast morphology classification method based on generalized neural network

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ABSTRACT

In order to establish a breast shape classification method with general indicators, this paper selects six measurement indicators that can characterize the three-dimensional shape of the breast, such as circumference, length, width, and height. The relevant data of the measurement indicators are used to establish a generalized neural network model, and the generalized neural network is applied to the evaluation of breast shape classification recognition. The MATLAB software toolbox is used, based on training sample data, We have established a generalized neural network (GRNN) model, which involves establishing corresponding functional relationships through training to approximate the training data. After obtaining the function relationship through training, the predicted values were obtained, and the prediction results reflected that the established generalized neural network GRNN model is quite reliable for predicting the category of breast shape. By establishing a mapping relationship between the input quantity of breast feature parameters and the output quantity of categories, training samples can be established. When encountering new test data, these data can also be used as test samples. Based on the established model, appropriate spreads can be adjusted to predict the output quantity, providing relevant personnel with basic and simple basis for judgment and evaluation. It can also provide convenience for customers in various consumption channels. Accurate bra size recommendations can help consumers purchase bras that fit well and are comfortable.

KEYWORDS

Breast morphology classification; Classification method; Prediction of morphological changes; Generalized neural network.

1. INTRODUCTION

The fit of clothing is closely related to the characteristic dimensions of the human body, and bra products that are close to the skin require measurement data as support. However, research shows that more than 85% of women find it difficult to choose suitable bra products. The reason is that female breasts have diverse appearances, and each woman has its own unique breast shape. In addition, it is a three-dimensional soft tissue structure fixed on the framework of bones and muscles, which will not remain unchanged over time [2]. The shape of the breast is affected by physiological changes related to puberty, ovulation, pregnancy, breastfeeding, and aging, making accurate measurement of breast tissue very difficult [3].

At present, there are two methods for measuring chest shape in the clothing industry: manual measurement and 3D scanning measurement. Manual measurement is mainly carried out using a soft ruler. During the measurement process, first place the tape measure around the fullest part of the breast (mostly the nipple), then place the tape measure close to the lower edge of the breast and wrap

it around the body, usually around the base of the breast, to obtain the size of the lower chest circumference [4]. The study by Zheng et al. [5] pointed out that the current bra size method, which estimates bra cup size based on the difference between chest circumference and lower chest circumference measurements, is unreliable because bra size should be related to the three-dimensional breast shape, not just linear dimensions around the body. Only measuring chest circumference and lower chest circumference data for settlement cannot reflect the full shape of the breast, resulting in low accuracy of measurement results.

Compared with manual measurement, the 3D scanning method for breast measurement has many advantages and can extract human measurement data in a short time, greatly improving measurement efficiency [6]. However, due to the complex shape of the breasts, three-dimensional scanning measurement methods still face difficulties. For example, handheld scanners require measurement personnel to have good scanning operation skills, and to move around the subject, causing a lot of inconvenience and effort, and requiring measurement of several dozen breast details. The operation process is lengthy and the data conversion is complex [7]. Therefore, manual measurement technology has not been completely replaced to this day.

In order to obtain size data that can express chest shape features, scholars have conducted various methods of research and exploration. Liang Suzhen [8] used breast spacing and BP point height as indicators to evaluate chest shape, and found that the standard ratio of chest circumference height to height for young women in southern China is 0.710, with an ideal breast spacing of half the chest width; Chen Huirong et al. [9] believe that the difference in upper and lower chest circumference and breast depth is the most significant difference in female breast morphology indicators; Li Yan [10] pointed out that the main parameters affecting breast morphology are breast spacing, breast root circumference spacing, breast depth, and lower cup length. These parameters respectively characterize the degree of cup aggregation, width, fullness, and height of the cup; Duan Xiaojuan [11] pointed out that women wearing the same size bra have significant differences in dimensions such as breast width and arc length, breast root circumference, and BP point spacing. However, existing research focuses on the extraction of breast surface data, such as linearity, angle, and curvature. These measurement parameters are numerous and complex, lacking the establishment of general indicators, making it difficult to operate the measurement process, record measurement data, and classify measurement results.

In terms of breast morphology classification, Chang Lixia [12] selected 270 young women from western China as experimental subjects and measured 35 items such as height, breast spacing, and breast height. After clustering analysis of the obtained data, the breast morphology was divided into 9 categories: chubby erect type, chubby medium type, chubby flat type, moderately erect type, moderately flat type, thin erect type, thin medium type, and thin flat type. Liang Suzhen [13] used breast spacing and chest height as indicators to characterize breast morphology, dividing breast morphology into 9 categories based on the degree of external expansion and erection. Zhang Longlin [14] classified breast morphology into 6 types based on breast lateral morphology, and further studied the compatibility between breast morphology and bra cups. Catanauto G et al. [15] proposed a method for dividing different parts of the breast surface based on six measurement contents, including breast spacing, angle parameters, curvature parameters, breast surface area, symmetry, and breast fundus curve, and classified the chest shape using a BSA breast morphology analyzer. He Yanjun [16] used Imageware reverse engineering software to extract the curves of the breast fundus, and measured parameters such as height, length, arc length, and angle. The breasts were divided into four types: inward oblique, symmetrical A, symmetrical B, and outward oblique. However, currently, the feature parameters used in chest classification research have less consideration for chest height data, and therefore cannot fully characterize the three-dimensional shape of the chest.

Therefore, in the current classification methods for breast morphology, the complex and chaotic measurement items in the existing chest shape feature measurement are urgent problems that need to be solved, and there is a lack of acquisition of three-dimensional breast shape measurement data,

making it difficult to predict changes in breast shape. This study selects measurement indicators that can characterize the three-dimensional shape of the breast, and establishes a generalized neural network model based on the relevant data of the measurement indicators. Applying generalized neural networks to the evaluation of breast shape classification recognition can provide accurate classification methods while predicting changes in breast shape, providing convenient and accurate bra size recommendations for customers across various consumption channels, helping consumers purchase fitted and comfortable bras.

2. RELATED WORK

Artificial neural networks (ANNs) have developed rapidly in the past decade. They simulate the neural processing of the human brain, perform parallel information processing and nonlinear mapping processes, and have the ability to perform large-scale computing [17]. Researchers of artificial neural networks have conducted mathematical research on neural networks and established many artificial neural network models. Among them, the BP neural network is mainly used in function approximation, pattern recognition, classification, and the establishment of input-output models due to its powerful function, simple algorithm, and strong feasibility. Along with the application of BP neural network, some drawbacks of BP neural network have also been exposed. Specifically, it includes:

1) The number of hidden layers is difficult to determine, and the number of neurons set up in each hidden layer is also difficult to determine, often requiring the designer's experience and multiple trainings to determine [18]. Although many empirical formulas have emerged, there is no ideal analytical formula, and the construction of its network structure is the key to the success or failure of BP neural network engineering applications. Increasing the network structure can reduce system errors, but the training efficiency is not high; 2) For some complex problems with long training time, it is necessary to choose a finite moment size to converge in the actual process, which also needs to be judged and determined based on the actual situation; 3) The convergence value cannot guarantee the global minimum of the error plane, and using gradient descent method may generate multiple local minimum values; 4) Learning and memory have uncertainty, and there are many parameters to adjust [19].

Broomhead and Lowe were the first to use radial basis functions in 1988 and proposed a new approach to neural network learning [20]. A generalized regression neural network (GRNN) is a combination of radial basis neurons and linear neurons. It consists of two layers, with the middle layer being the radial base layer and the output layer being the linear layer. The generalized regression neural network GRNN shown in Figure 1 has Q sets of input vectors, with R elements in each set, i.e. P (p1, p2,..., pR) in Figure 1. The first layer of the network is the radial basis hidden layer, and the number of neurons is equal to the number of training samples. The weight function of this layer is the Euclidean distance function, which is:

$$\|IW-P\| = \sqrt{\sum_{i=1}^R (IW_i - p_i)^2} \quad (1)$$

Equation (2) is represented by $\|dist\|$, which calculates the distance between the network input and the weight IW of the first layer. b is the threshold of the hidden layer; The symbol “ \cdot ” represents the relationship between the input of "dist" and the threshold b, where $n1 = \|dist\| \cdot b$.

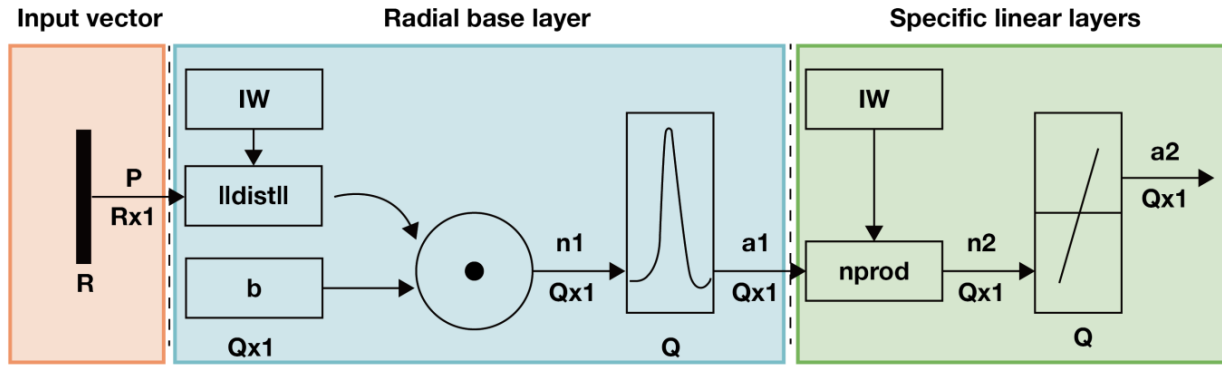


Fig. 1 Generalized regression neural network structure

The transfer function of the hidden layer is the radial basis function, usually using Gaussian function as the network transfer function:

$$a1 = \text{radbas}(n1) \quad (2)$$

In the formula, $\text{radbas}(n1) = \exp(-n1^2)$. As the action function (basis function) in the hidden layer nodes of the network adopts a Gaussian function, it is a non negative nonlinear function that locally distributes and attenuates the center radial symmetry. It will respond locally to the input signal, that is, when the input signal is close to the central range of the basis function, the hidden layer nodes will produce a larger output and have good local approximation ability, This is also the reason why the network has a faster learning speed.

In the Matlab neural network toolbox, $b = [-\ln(0.5)]0.5/\sigma_i = 0.8326/\sigma_i$, Thus obtaining:

$$a_1 = \exp\left(-0.8326^2 \times \frac{\|\text{dist}\|^2}{\sigma_i^2}\right) \quad (3)$$

In Eq. σ_i determines the shape of the basis function in the i th hidden layer position, so it is also called the smooth factor spread value. Layer 2 of the network is a linear output layer with a normalized dot product weight function (denoted by $nprod$ in Fig. 1), which implements the normalization operation of LW with $a1$ and computes the result $n2$. Each of its elements is the dot product of the elements of each row of the vector $a1$ and the weights matrix LW and then divides the result by the sum of the elements of the vector $a1$. Finally, the result $n2$ is provided to the linear transfer function, $a2 = \text{purelin}(n2)$, with the number of neurons equal to the number of input samples and a threshold-free vector input, which is calculated to obtain the output data of the network.

During network training, training starts with 0 neurons and the grid is made to automatically add neurons by checking the output error. Each time it is recycled, the input vector corresponding to the maximum error generated by the grid is used as the weight IW to generate a new hidden layer neuron, and then the error of the new grid is checked and the process is repeated so as to reach the error requirement or the maximum number of hidden layer neurons specified until the grid has the characteristics of strong self-adaptation and the output is independent of the initial value, etc., and the generalized neural network has a better advantage compared with the BP neural network in dealing with these problems has a better advantage, corrects the shortcomings of BP neural network, and solves the problem of BP lattice to determine the number of hidden layers is difficult.

Currently, generalized neural networks have been widely applied in various fields due to their excellent classification and recognition performance. Liu Wei et al. [21] established a remote sensing image classification model based on generalized algorithms; Tang Qihua et al. [22] combined genetic algorithm with generalized neural network to achieve recognition of seabed substrate types such as bedrock, gravel, sand, fine sand, and mud; Luo Zhizeng et al. [23] proposed a generalized neural network classifier that combines wavelet packet transform and algorithm, which can recognize

hand movements of surface electromyography signals; Ma Tianxiao et al. [24] used generalized neural networks to classify forest site types; Hu Yaomin et al. [25] proposed an improved GLVQ algorithm based on attribute data range to classify vehicle models; Cuevas Erik et al. [26] utilized generalized neural networks to achieve face recognition and tracking; Melin Patricia et al. [27] used generalized neural networks to classify electrocardiogram features; Biswal et al. used a classifier to classify time series data of unstable signals.

In the field of textile and clothing, generalized neural networks are commonly used in research on fabric detection and recognition based on image recognition technology. Kuo C.F.J et al. used a generalized neural network to automatically identify fabric texture types by analyzing fabric texture images. The results showed that it can accurately identify the basic structure of woven fabrics, knitted fabrics, and non-woven fabrics. Liu Jianli et al. identified fabric defects through wavelet analysis and generalized neural networks. Hua Yong used a generalized neural network to classify and recognize the organizational structure of weft knitted single-sided fabrics.

Therefore, when the chest shape measurement data of the sample is known, the generalized neural network is applied to the evaluation of breast shape classification recognition, and a model of the generalized neural network is established based on relevant data to verify the advantages and adaptability of this method and its feasibility in handling similar problems.

3. ESTABLISHMENT OF TRAINING MODELS

3.1. A. Selection of breast morphology characteristic parameters

Underwear structural design is the basic technology for the design and production of underwear products. Chest size measurement is the data source and reference for determining the structural size in underwear structural design, as well as the basis for determining model size and size division in underwear industrial production. Size is a professional term used to describe the size of clothing, which is a description of the corresponding relationship between the human body and clothing size based on specific body circumference. The formulation of clothing size is a way of categorizing people with consistent body types based on the classification of the human body, and developing corresponding sizes according to the controlled parts and gear differences. The “size” and “shape” of a bra correspond to the chest circumference size and breast shape characteristic size, respectively.

The chest circumference size describes the degree of obesity and thinness of the human body, including parameters such as chest circumference, width, and thickness. Due to the diverse shapes of women's breasts, changes in breast shape are equally important for chest shape analysis, rather than just absolute breast volume data. In this study, the defined size of breast morphological features mainly evaluates chest features, including shape parameters such as length, width, height, position, and position parameters.

Combined with the demand for female breast shape measurement characteristics and measurement size range definition, with reference to the Chinese standards GB/T16160-1996 anthropometric basic items used for technical design", the Beijing Institute of Clothing - Amore Institute of Ergonomics measurement parts and bra production-related anthropometric measurements, etc., the selection of breast morphology Characteristic parameters for the circumference category (lower chest circumference), length category (upper breast cup plumb line distance, lower breast cup arc distance), width category (front breast cup arc distance, side breast cup arc distance) and height category (breast height) a total of four major categories and six sub-items, as shown in Figure 2.


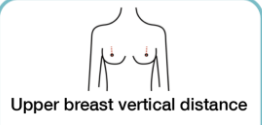
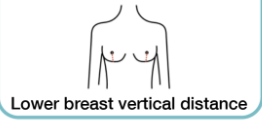

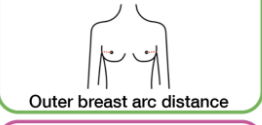

Category	Measurement Parameters	Parameter Description
A. Circumference	 lower chest circumference	The maximum horizontal circumference measured by the lower edge of the breast
B. length	 Upper breast vertical distance	The vertical distance from the nipple to the upper edge of the breast
	 Lower breast vertical distance	The vertical distance from the nipple to the lower edge of the breast
C. Width	 Inner breast arc distance	The horizontal arc length from the nipple to the inner edge of the breast
	 Outer breast arc distance	The horizontal arc length from the nipple to the outer edge of the breast
D. Height	 Breast height	The straight-line distance of the vertical mapping from the nipple to the chest wall

Fig. 2 Selected parameters for chest shape measurement

3.2. Extraction of training sample data

By measuring the bilateral breast parameters of 30 women, the chest shape measurement experiment was conducted at different times of the day and under random lighting conditions. Participants are required to complete the experiment naked. To ensure comfort, the experiment is conducted in a laboratory with a room temperature of $(25 \pm 2) ^\circ\text{C}$, a relative humidity of $(65 \pm 5)\%$, and a wind speed of less than 0.1m/s. All breast measurement parameters obtained as samples were obtained by a recognized, 5-year experienced first level anthropometrist, in accordance with the standard International Society for the Advancement of Kinesiology (ISAK) program. The measurement data are shown in Table 2 as training sample data. Among them, SA1-A2 is the lower chest circumference, A2-A2` is the left breast height, A1-A1` is the right breast height, A2-B2 is the left inner breast arc distance, A1-B1 is the right inner breast arc distance, A2-C2 is the left outer breast arc distance, A1-C1 is the right outer breast arc distance, A2-D2 is the left vertical distance from the nipple to the lower edge of the breast, A1-D1 is the right vertical distance from the nipple to the lower edge of the breast, A2-E2 is the left svertical distance from the nipple to the upper edge of the breast, A1-E1 is the right vertical distance from the nipple to the upper edge of the breast.

TABLE I. Training sample input parameters and actual values

No.	SA1-A2	A2-A2'	A1-A1'	A2-B2	A2-C2	A1-B1	A1-C1	A1-A2	A2-D2	A1-D1	A2-E2	A1-E1
1	68.3	1.8	1.3	7.5	7.1	7.5	7.2	18.0	4.5	5.3	8.0	7.5
2	67.0	2.0	1.0	7.6	7.4	7.9	7.4	17.5	4.7	4.6	7.8	7.7
3	68.0	2.0	1.5	8.5	8.5	8.3	8.3	17.2	6.2	6.0	8.5	8.5
4	66.2	1.8	2.5	8.2	7.8	8.0	8.0	17.2	5.2	5.4	7.8	7.8
5	67.5	1.5	1.0	7.3	7.2	8.5	7.5	18.0	5.0	6.0	8.8	8.0
6	67.4	1.5	1.0	7.2	7.3	8.0	7.8	18.0	5.5	5.5	9.6	9.0
7	73.0	0.5	0.2	7.4	7.1	7.3	7.2	18.3	4.4	4.7	9.0	9.0
8	68.1	3.2	2.8	8.2	8.0	8.5	8.2	17.7	5.4	5.3	9.5	9.0
9	67.2	2.3	1.2	8.6	7.4	8.8	7.7	19.6	5.5	5.9	8.0	8.0
10	67.5	1.7	1.4	7.7	7.6	8.0	8.0	17.5	5.5	5.5	8.3	8.2
11	76.5	1.3	1.1	8.4	8.1	8.4	8.2	17.6	6.0	5.8	10.0	10.0
12	72.1	3.4	2.7	9.0	8.5	9.2	9.0	19.4	6.7	6.0	12.3	11.7
13	73.3	2.1	1.0	8.2	8.0	8.2	7.8	18.6	5.3	5.3	13.5	13.0
14	72.1	1.9	1.2	8.7	8.0	8.8	8.0	19.5	6.0	6.0	11.2	11.2
15	79.0	4.9	4.3	8.1	8.1	8.5	8.4	18.6	4.6	4.2	13.8	13.0
16	72.1	1.2	1.1	7.8	7.8	8.5	8.0	18.7	5.9	5.7	12.0	12.0
17	77.9	2.9	2.3	8.5	7.7	8.7	7.6	19.4	7.3	7.0	10.2	10.0
18	72.0	2.2	2.3	8.0	8.0	8.0	8.0	17.0	5.5	5.8	8.5	9.0
19	75.9	2.2	2.0	8.0	8.0	9.0	8.5	18.0	5.3	5.0	8.5	8.5
20	79.9	2.5	2.4	9.2	9.1	9.0	9.0	19.8	6.1	6.3	11.7	11.2
21	81.0	6.2	6.1	8.3	8.2	9.0	8.5	20.3	6.0	6.7	12.0	12.0
22	83.2	6.0	6.0	8.5	8.5	8.0	8.0	19.5	4.2	4.0	14.9	14.5
23	84.0	5.0	4.7	9.5	8.5	11.0	8.9	22.7	6.5	6.0	13.0	13.0
24	85.3	5.5	5.0	10.0	8.0	10.0	9.0	21.2	7.2	7.0	12.0	11.0
25	85.8	2.0	2.0	8.7	8.7	9.5	9.3	19.2	2.2	2.5	16.5	16.5
26	79.6	3.8	3.0	10.0	9.2	11.6	9.7	23.8	6.8	6.7	10.0	8.0
27	84.2	5.0	4.2	10.3	9.5	10.5	9.5	22.4	3.0	2.8	15.0	11.5
28	80.1	4.5	4.0	8.3	8.3	8.3	8.2	17.8	4.0	4.4	12.6	13.0
29	82.0	3.0	2.8	9.8	9.2	10.0	8.0	22.4	6.9	7.0	9.0	10.0
30	78.4	4.5	4.0	8.3	8.0	8.5	8.0	18.4	5.5	5.5	8.5	7.0

3.3. Training model establishment

Using the above indicators as input variables, set the number of input neurons to 12, use categories as output variables, and output variables to 3, namely category 1, category 2, and category 3. Based on the data in Table I, the indicator variables are used as training input data, and the corresponding categories are used as training output data. The training sample data is shown in Table 2, and 6 are selected as test samples. The test sample data is shown in Table II.

Setting the smoothing factor spread, which refers to the impact of the basis function on the performance of the GRNN network, requires an attempt to determine its value. In theory, the smaller the spread value, the more accurate the approximation of the function, but the longer the training time required; The larger the spread value, the greater the approximation error. When programming with Matlab, in order to test and compare, and to demonstrate the convenience of using GRNN neural networks, the spread values are set to 0.01, 0.1, 1.0, 5.0, and 10.0 based on the cyclic relationship during programming, in order to compare the error with the actual value and determine the spread value used.

TABLE II. Test sample input parameters and actual values

No.	SA1- A2	A2- A2'	A1- A1'	A2- B2	A2- C2	A1- B1	A1- C1	A1- A2	A2- D2	A1- D1	A2- E2	A1- E1
1	68.3	1.8	1.3	7.5	7.1	7.5	7.2	18.0	4.5	5.3	8.0	7.5
2	67.0	2.0	1.0	7.6	7.4	7.9	7.4	17.5	4.7	4.6	7.8	7.7
3	73.3	2.1	1.0	8.2	8.0	8.2	7.8	18.6	5.3	5.3	13.5	13.0
4	72.1	1.9	1.2	8.7	8.0	8.8	8.0	19.5	6.0	6.0	11.2	11.2
5	81.0	6.2	6.1	8.3	8.2	9.0	8.5	20.3	6.0	6.7	12.0	12.0
6	83.2	6.0	6.0	8.5	8.5	8.0	8.0	19.5	4.2	4.0	14.9	14.5

Using the MATLAB software toolbox and based on the training sample data (see Table 2), a generalized neural network GRNN model was established, which approximates the training data by establishing corresponding functional relationships through training. Data1 is the input training sample, data2 is the actual result of the training sample, data3 is the input test sample, and data4 is the actual result of the test sample. Given the training and test samples, the training results of the training samples obtained based on the functional relationship established during training are assigned a temp variable, while the training results of the test samples are assigned a y variable_ Test variables, where spread values are set to 0.01, 0.1, 1.0, 5.0, 10.0.

After testing and training, it was found that the setting of the spread value has a significant impact on the results. When the spread values are 1.0, 5.0, and 10, the accuracy is far lower than when the spread values are 0.1 and 0.01. When the spread is 5.0 or 10.0, there is a significant error between the training and testing samples and the actual results. Only when the spread is ≤ 1 , can the influence of the spread value on the results be ignored. When using the test results for testing, the results are satisfactory.

The prediction results in Tables III and IV reflect that the established generalized neural network GRNN model is quite reliable in predicting the category of breast shape. By establishing a mapping relationship between the input of breast feature parameters and the output of categories, training samples are established. When encountering new test data, these data can also be used as test samples. Based on the established model, appropriate spreads can be adjusted to predict the output volume, providing relevant personnel with a relatively basic and simple basis for judgment and evaluation.

The neural network model based on GRNN can effectively control local errors, without the need to change the number of hidden layers and the number of neurons in the hidden layers based on experience, training, and testing results like BP neural network. The GRNN network has a faster computational speed. In addition, selecting the appropriate smoothing factor spread can have a good effect in network operations, as the adjusted parameters only have spread values, so a suitable network can be quickly found. Compared with BP neural networks, it has significant computational advantages.

By classifying and predicting breast shapes, it was found that the generalized neural network method has higher prediction accuracy. After selecting appropriate spread values, the prediction accuracy of the network model reached 100%. Therefore, the generalized neural network model in this article can serve as a practical prediction tool for breast morphology classification.

4. CONCLUSION

This study defined six items for breast shape measurement based on bra size specifications, including breast dimension item sizes that characterize human obesity and thinness, as well as length, width, and height item sizes that describe three-dimensional breast data. A generalized neural network algorithm model was constructed to quickly classify breast shape and serve as a practical tool for predicting breast shape changes. The research results of this project have good application prospects,

providing new ideas for existing chest research, and laying the foundation for personalized customization and virtual fitting of bra products. However, there are still shortcomings that need to be further improved. Specifically, there are the following points: (1) Expanding experimental samples: Under limited time and conditions, the distribution of the 30 samples selected in this study is relatively small in certain sizes. In future research, the number of samples for corresponding sizes can be appropriately increased to reduce experimental errors and limitations. (2) Change of research subjects: The subjects in this study were all young women who were not pregnant, with certain limitations in age and geography. In future studies, sample types and sizes can be expanded for female participants of different age groups and regions. (3) The relationship between quantitative chest shape and bra structure design: This study classifies chest shapes based on the three-dimensional shape of the breast, and further quantifies the relationship between various chest shapes and bra structure design.

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