Journal of Fiber Bioengineering and Informatics 16:1 (2023) 69–87
Cite as: R. Pan et al.
doi:10.3993/jfbim02172

Classification and Identification Model of Young Women's Torso Shape Based on Human Surface Curve Features

Rou-Xi Pan, Chen Yu, Rui-Liang Guo*

Beijing Institute of Fashion Technology, Heping Street, Chaoyang District, Beijing, 100029, China

Abstract

Human body shape analysis is an important reference basis for garment sizing and modification. The study of human body shape is to better master the relationship between the size and shape of different body parts and the overall shape of the garment. In this paper, 245 young women aged between 18 and 24 years in school in northern China were selected as the study subjects by applying the 3D human body measurement technology. Using the statistical software SPSS, principal component analysis, correlation analysis and R-type clustering were performed to evaluate 16 variables, including height, girth, and body surface angles. Five body angles were extracted as classification indexes: chest angle, back inclination, dorsal angle, body lateral angle, and buttocks angle. These indexes were critical in explaining the characteristics of the torso surface curve. Consequently, the body types were divided into three categories using K-means clustering. More detailed characteristics of the eight body types Y_{II} to B_{III} were classified by combining the chest-waist drop of the Chinese National Standard classification indication. Then according to the classification results, a recognition template that can automatically classify body shape was created through the Baidu AI EasyDL development platform. Experimental results showed that the average precision of the body type recognition model reached 91.7%, among which the recognition accuracy for Type III S body shape was over 95%, providing a meaningful reference for body type classification research.

Keywords: Torso Shape; Body Angles; Body Shape Classification; Deep Learning

1 Introduction

In recent years, consumers have had increasingly high aesthetic requirements for clothing, personalized, intelligent customization, and well-fitting clothing are becoming more popular among consumers. Therefore, body shape analysis is crucial for identifying garment sizes and making patterns. Many scholars explore different perspectives to classify and identify body types. The main methods found in the literature are as follows: research on specific body parts, especially for persons with unique body shapes like shoulders and backs [1-4]; by calculating the body model index to reflect the proportion of different human body parts [5, 6]; intercepting the cross-sectional

*Corresponding author.
Email address: fzygrl@bift.edu.cn (Rui-Liang Guo).

Mar. 2023

curve of the human body by 3D scan and extracting the value of body characteristic parts to refine the classification index [7-10]. The most popular way to classify body size is using circumference size and circumference difference as classification indicators, mostly used for size customization in various countries. Peng Li [11] defined waist girth as the most important dimensional variable of the female torso, and chest-waist drop and waist-hip drop as the most important shape variables. However, Zouhour [12] mentioned that information such as circumference cannot fully describe the shape of the human body. Considering only dimensional information such as body circumference and body proportions in the design of garment structure and ignoring the body surface curve form can cause reduced fitness of garments. In addition, the angle variable also contains a certain amount of information about the thickness of the human body The body silhouette curve mainly records the human body shape, and the body angle variable can represent its morphological changes. Wang Xiaoxia [42], by studying the relationship between young women's upper body and paper samples, proposed that the human body surface angle corresponds to the dart angle of the prototype of the garments, and that the body surface angle parameter can be used to predict the angle value on the prototype to improve the fit of the garments. Hence, the importance of human body surface angles for improving the fit of garments can be seen. However, only a few studies have been published concerning investigations into body angles as important indicators of body shape characteristics.

The human body can be considered as a multifaceted geometry, and there are many indicators to describe the geometry [13,14]. In this paper, we extract the longitudinal curves to obtain the body surface angle values that best explain the body shape characteristics. As a result, our method is more intuitive and clearer to reflect the three-dimensional human morphology with two-dimensional data. Our data analysis and screening extract a few angular variables that reflect the human body's local and overall morphological characteristics. A more detailed classification is determined according to the chest-waist drop of the Chinese National Standard classification index. The detailed classification uses the size index and shape indices to jointly define women's body shape, effectively distinguishes individual body surface morphological differences and provides the basis for developing basic paper patterns for clothing.

In addition, as technology advances, access to information related to clothing and body type gradually moves from text to images, with increasingly more retrieval recognition moving to more convenient visual image data [15]. This technological advancement in the field of research is based on deep learning, where physical images are trained and analyzed to form a discriminatory mechanism similar to the neural network of human brain perception, classifying new objects based on existing experience. Several researchers have used deep learning approaches such as BP neural networks, radial basis networks (RBF) [4], support vector machines (SVM) [16], and extreme learning machines (ELM) [10] to train body shape recognition models [17]. Traditional BP neural networks were widely used in body type recognition and have been developed relatively maturely given the early age of research. However, traditional BP neural networks are constrained by the training sample base and the complexity of the training samples, which can easily reduce the learning rate due to the prolonged training time. Neural networks require large-scale training samples to achieve a more desirable recognition accuracy, which needs to be improved. Sun [18] uses the Adaboost algorithm based on BP neural network to recognize the body size of young women, combining multiple weak neural networks into one BP neural network. It yields better generalization ability and high robustness. Li [19] uses the automatic classification method of convolutional neural networks, and experiments prove that convolutional neural network can effectively extract the features with good representation in the original image. Yao [9] uses R language to construct LVQ neural network body type recognition model to recognize the body type classification of young women based on longitudinal curves, and trains and tests the network with an overall recognition rate of 97.4%.

Since most people do not have the required coding expertise to build recognition models, generalization and use of classification recognition models for body types by society are limited. In this paper, based on the results of body type classification, an AI model for recognizing body types is created using the Baidu AI EasyDL deep learning development platform. The model can be assessed based on the testing outcomes and is made available as an H5 mode APP and a shared cloud API interface. Baidu has launched EasyDL Classic for zero AI-based developers and EasyDL Professional for professional AI developers with codable features. The framework provided for the public is easy to learn, more user-friendly and convenient for non-professional developers to maintain data and model tuning later. It is also worth noting that the EasyDL platform requires only a small amount of data to train a high-precision model. AI models developed on third-party platforms have a shorter completion period than other neural network models. Many preliminary tasks such as network selection and algorithms can be done by the AutoDL Transfer built into the EasyDL platform.

2 Experiment and Data Processing

2.1 Experiment

This measurement was conducted on young women aged 18 to 24 who were in school in northern China. Normally, females have reached full physical maturity after the age of 18. As students, young women are basically unmarried and childless, and their body shape is less affected by external factors. It is important to ensure that the measurement groups are at approximately the same level regarding living environment and physical development to study individual differences in depth.

2.2 Sample size of the Experiment

In industrial production and scientific research, to maximize the coverage of various types of human body, a 95% confidence interval is usually used. China's national clothing size standards specify the standard deviation and maximum permissible error of the size of each part of the adult human body, usually the waist circumference were calculated the minimum sample size, according to the formula (1) to calculate the sample size N = 173. where N is sample size, μ_α is probability of α level (when $\alpha = 0.05$, $\mu_\alpha = 1.96$), σ is standard deviation of waist circumference, and Δ is maximum permissible error. Considering that singular values and invalid samples will be eliminated, a certain sample size should be appropriately increased, so the sample size of young women measured is 245.

$$\mathrm{N} = \mu_\alpha^2 \cdot \left(\frac{\sigma}{\Delta}\right)^2 \tag{1}$$

2.3 Measuring Instruments and Experimental Environment

The Scenario SYMCAD 3D body measurement system was used as the equipment for this experiment. According to GB/T 23698-2009 General Requirements for Three-Dimensional Scanning

Body Measurement Methods, the temperature of the experimental environment was 27±3 °C, and the relative humidity was 60%±10%. The subjects were asked to be tight underwear, tie the hair up, stand on a body position board, look straight ahead, and breathe naturally to ensure the accuracy of the extracted data. Each participant was measured three times using the same sample at the designated measurement site. Two experienced experimenters who were familiar with the tools and protocols made all measurements. Determination of anthropometric items concerning GB/T 16160-2017, anthropometric measurements and 3D human point cloud files related to the torso shape were collected.

2.4 Data Processing

Using Geomagic Studio, the 3D human point cloud file was used to fill in holes and remove redundant interfering points, and finally exported as a 3D pdf file. The sagittal and coronal cross-sectional curves over the human shoulder tips and chest height points were intercepted with AdobeReader. CorelDRAW X7 rounded the original longitudinal curve, and the smooth curve was processed as shown in Fig. 1. The exported jpg image file served as the final processing format. It was used as input to the body shape identification model.

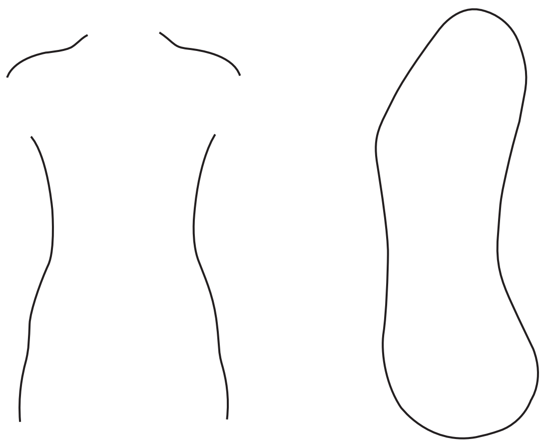

Fig. 1: Sagittal and coronal cross-sectional curves

3 Methods

3.1 Extraction of Important Variables

Based on previous literature, the female torso shape can be divided into four parts: bust shape, shoulder and back shape, hip shape, and waist shape [20]. This study selected representative measurements from these four body parts. Therefore, 16 measurements were extracted, including 7 angular measurements, 5 girth measurements, 2 height measurements, and 2 length measurements [21, 22]. The angular measurements provided a great picture of the human torso's curves, including chest angle, abdomen angle, dorsal angle, body lateral angle, back inclination, buttocks angle, and shoulder slope. Detailed measurement items are shown in Table 1, and Fig. 2 presents diagrams of the anthropometric angles. After removing outliers from the data, 230 human body data points conforming to normal distribution were obtained. Table 2 shows the results of the descriptive analysis of the 230 human body data points, with mean and standard deviation. Fig. 3 shows the error bars.

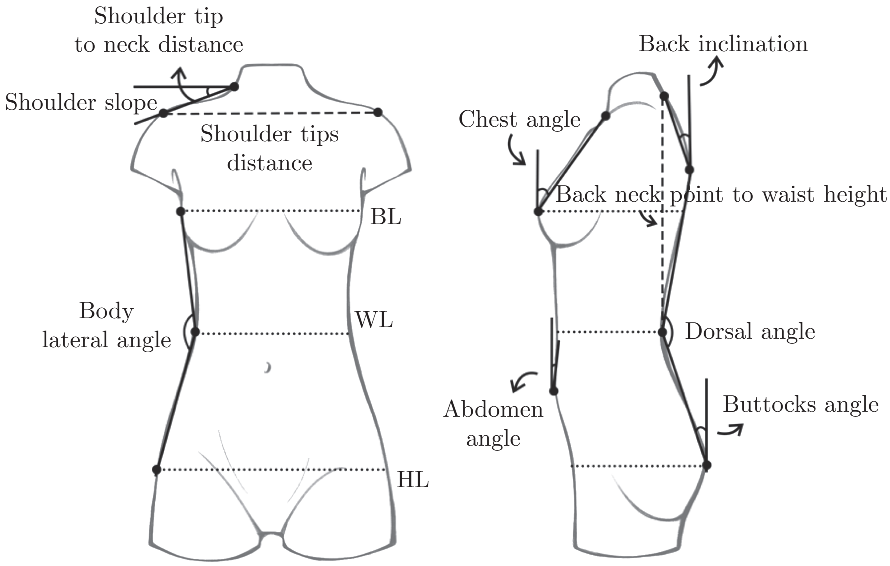

Fig. 2: Diagrams showing anthropometric angles

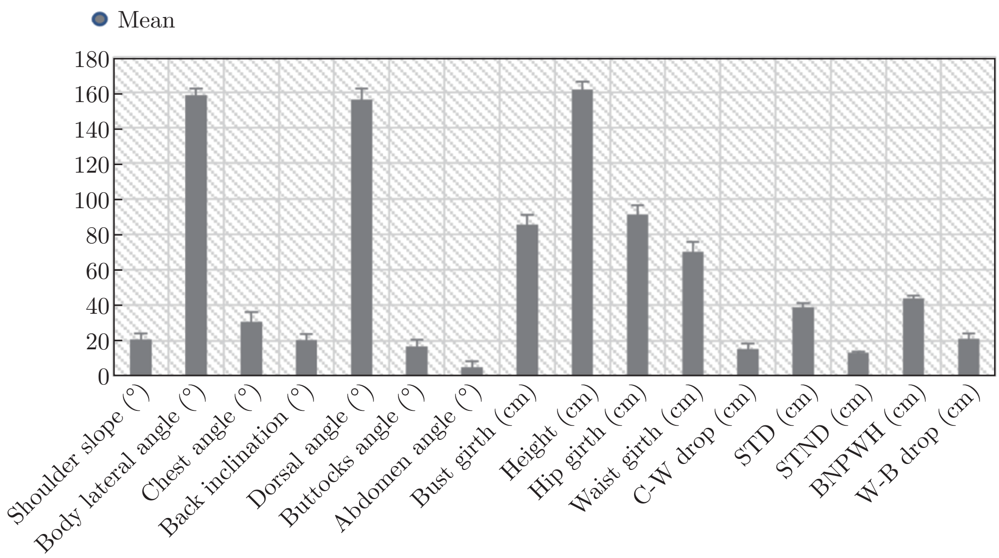

Fig. 3: Error bar

3.2 Factor Analysis

To verify whether the selected angle measurements can objectively provide a comprehensive explanation of human body shape characteristics, the 16 variables mentioned above were imported into the SPSS software for factor analysis. Factor analysis was used to reduce the dimensionality by extracting common factors with as little loss of original information as possible. It acts as a good filter when dealing with numerous parametric variables and helps clarify the focal part of our subjects. The factor analysis results screened 12 significant variables for this study, including angle, height, and girth.

Table 1: Definition of the 16 anthropometric measurements

No.	Measurement name	Definitions
1	Shoulder slope	Angle between the line joining the point of the lateral neck and the tip of the shoulder and the horizontal line passing the point of the lateral neck
2	Body lateral angle	Angle between lateral lumbar point and tangent of axillary point and tangent of the lateral hip point
3	Chest angle	Angle between the upper tangent of the thoracic eminence and the vertical line
4	Back inclination	Angle between the line joining the back prominence and the back neck point and the vertical line of the back prominence
5	Dorsal angle	Angle between the posterior lumbar point and the tangents of the buttock and dorsal prominence points
6	Buttocks angle	Angle between the upper tangent of the back protrusion point of the hip and the vertical.
7	Abdomen angle	Angle between the upper tangent of the anterior abdominal eminence and the vertical line
8	Bust girth	Horizontal girth of the point through the thoracic process, axillary point, and scapula
9	Height	Distance from the top of the head to the ground
10	Hip girth	Horizontal girth at the fullest part of the hip
11	Waist girth	Horizontal girth at the thinnest part of the waist
12	Chest-waist drop (C-W drop)	Difference between chest girth and waist girth
13	Shoulder tips distance (STD)	Distance between shoulder peaks
14	Shoulder tip to neck distance (STND)	Distance from shoulder peak to lateral neck point
15	Back neck point to waist height (BNPWH)	Vertical height from the back neck point to the waistline
16	Waist-buttock drop (W-B drop)	Difference between waist girth and hip girth

Table 2: Statistical analysis of the body measurements of 230 subjects

	Shoulder slope (°)	Body lateral angle (°)	Chest angle (°)	Back inclination (°)	Dorsal angle (°)	Buttocks angle (°)	Abdomen angle (°)	Bust girth (cm)
Average	20.65	158.20	30.81	20.46	155.69	16.68	5.19	85.29
SD	3.45	3.79	5.33	3.44	6.26	4.01	3.19	5.78
	Height (cm)	Hip girth (cm)	Waist girth (cm)	C-W drop (cm)	STD (cm)	STND (cm)	BNPWH (cm)	W-B drop (cm)
Average	161.56	91.23	69.98	15.52	38.71	13.09	43.77	21.25
SD	4.47	5.13	5.71	2.92	2.65	0.80	1.84	2.73

3.3 Correlation Analysis

In the objective world, things are often not independent of each other but are objectively connected. This is also true of the human body. For example, taller people tend to have wider shoulders, with an increase in waist and hip circumference values. Therefore, Pearson bivariate correlation analysis was carried out on the 12 variables to explore the correlation between angle variables and the correlation between angle and other important variables. Through correlation analysis, we intuitively observed how body surface angles affect each body size to prove whether the selected body surface angle is representative and can be used to reflect the body's shape characteristics.

3.4 Extraction of angular classification variables

In the subsequent classification of body types, the more classification indicators there are, the more complicated the analysis will be and the less practical it will be to apply. Although all selected body angle measurements are the leading variables for the five principal components, it is unclear whether they are the most streamlined indicators of classifications. Factor analysis in Section 3.2 combined all the dimensions to screen out the significant variables that represent the variation in young women's torso. To further screen out angle variables with significant features, R-type clustering of variables related to body surface angles helps to visualise the correlation between angles more intuitively. There is a strong correlation between variables of the same category and a low correlation between variables of different categories. R-type clustering is also a form of dimensionality reduction, and analysing variables with the same dimensions can increase the credibility of the results of dimensionality reduction.

Frequency analyses provide an observation of the changes in the angle variable. Body surface angle averages reflect the average of the group being measured. The standard deviation describes a degree of dispersion in the same angular value, and there is a positive correlation between the size of the standard deviation and the degree of dispersion; as the standard deviation increases, so does the degree of dispersion.

3.5 K-means Clustering

The fundamental principle of k-means clustering is to randomly select K initial clustering centers in the data set, determine the Euclidean distance between the remaining data objects and the clustering center, find the closest clustering center to the target data object, and assign the remaining data objects to the clusters corresponding to the clustering center. Determining the number of clusters often depends on experience and practical requirements. It is also noted that there is no optimal method to accurately identify the number of clusters. To serve the purpose of personalized mass production of clothing, four categories of Y, A, B, and C in Chinese national standards are utilized as a reference for our study. Therefore, the number of body type categories is initially defined as three or four clusters.

3.6 EasyDL Recognition Model for Body Type Classification

Artificial intelligence (AI) is quietly subverting our daily lives with the arrival of the fourth industrial revolution. Internet technology giants such as Google, Microsoft, Facebook, and Baidu have strategically deployed into this new wave of AI to develop their own AI industry and development platforms. One of the important directions of this is deep learning. Since its inception in 2006, deep learning has been an important branch of machine learning within AI. Unlike traditional neural networks, which require the annotation of features on data, deep learning can learn directly from itself and automatically adjust and optimize throughout the task. Although there are still many technologies in the field of AI that are in a conceptual state, technologies like speech recognition, lexical analysis, text recognition, and image recognition are already considered very mature, and through open third-party AI platforms, people can choose the framework they need to create AI models.

Although companies in all industries would like to create their own AI models, AI development requires significant investment, including a lot of talent for deep learning, large-scale data acquisition and tuning, and high requirements for data annotation. It takes a lot of time to train the model and debugging it. Many companies feel inhibited with such a high upfront investment and still no way to predict the final result. However, Baidu AI EasyDL does not require a foundation in algorithms to create highly accurate deep learning models, the platform will provide users with different algorithms to help train the models. Most importantly, with only a small amount of data under better conditions, the model can be 90% or more accurate and efficient to train. The fastest only need 15 minutes to complete the training. It can be flexibly applied to a variety of scenarios and operating environments, which supporting publishing as an API or offline SDK. EasyDL not only improves productivity and decreases expenses, it also assists enterprises in generating new revenue. Moreover, secondary development can also be done for persons with algorithmic ability using the local Tensorflow or PaddlePaddle frameworks. In this paper, we apply the EasyDL custom training platform for deep learning of body type classification, which now supports deep learning of image classification, object detection, sound classification, and text classification [23].

The operation steps are very simple, for those with no algorithmic foundation for EasydDL model development only requires four steps; (1) Data processing: including data uploading, creating datasets and manual labeling. It is worth noting that EasyDL provides intelligent human-computer interaction annotation, where the machine first filters out the high-quality data, and only 10% manual annotation is required to enable EasyDL to complete the rest of the full annotation. (2) Model training: users must determine the deployment method and algorithm before training the model. Different deployment programs have different algorithms to choose from. (3) Model Calibration and Verification: After the model training is completed, the model can be calibrated and verified online. (4) Model Deployment: The completed model can be converted into determined deployment that meets the usage scenario.

After learning how EasyDL works, we created a body type classification recognition model. To begin with, we need to create a model and data set in the development platform, label the body surface curve images by body type and then package and upload them. The images used to train our model were the coronal cross-section curve images and the sagittal cross-section curve images of the human upper body extracted and fitted by AdobeReader and CorelDRAW X7 as shown in Fig. 1. The processed image has a sharp edge, well defined line and background, and a resolution of 300 dpi. A total of 230 images were collected, combined with the results of the previous body type analysis, and were manually tagged and divided into three categories.

Next, AutoDL Transfer was used to train the model and test the results. The AutoDL Transfer algorithm is more fine-grained. For female upper bodies with similar body curves, the fine-grained algorithm can better differentiate between different body types. After the model was deployed, it was be prepared for training. Depending on the quantity of photos, 70% of the training set was chosen at random, and the remaining 30% made up the test set. The model can be trained using AutoDL Transfer in around an hour, and the results may be observed in the data center.

4 Results and Discussion

4.1 Factor Analysis Result

As shown in Table 3, were subjected to KMO and Bartlett tests. When the KMO of sampling adequacy was greater than 0.5, and Bartlett's test was less than 0.05, the correlation between the variables is considered strong and suitable for factor analysis. Then after 25 iterations, five factors, with eigenvalues above 1 and accounted for 76.486% of total variance, were obtained, and 12 variables were included. All seven of these angle variables were kept, and their respective coefficients were greater than 0.4. Table 4 shows the Principal Component Analysis (PCA) loading matrix of these five components. The result demonstrates that the angle measurements selected in 2.3 can be used to make a relatively comprehensive interpretation of the human body shape.

Table 3: Results of Kaiser-Meyer-Olkin (KMO) and Bartlett's Tests

KMO Measure of Sampling Adequacy		0.686
Bartlett's test of Sphericity	Approx. Chi-Square	1 354.408
	df	66
	Sig	0.000

Table 4: Result of Factor Analysis

Dimension	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5
Waist girth	0.869	0.546	–	–	–
Hip girth	0.825	–	–	–	–
Bust girth	0.777	–	–	–	–
Dorsal angle	0.706	–	–	–	–
Buttocks angle	–0.671	–	–	–	–
BNPWH	0.540	–	–	–	–
Chest angle	–	0.787	–	–	–
Height	–	–	0.708	–	–
Back inclination	–	–	–	0.630	–
Shoulder slope	–	–	–	0.505	–
Abdomen angle	–	–	–	–	0.493
Body lateral angle	–	–	–	–	0.465
Variance explained	32.451%	14.523%	11.717%	9.446%	8.349%

4.2 Correlation Analysis Result

Table 5 lists only variables for which there is a correlation with confidence levels between 0.95 and 0.99.

Table 5: Results of Pearson Correlation Analysis with Confidence Levels Above 95%

	Shoulder slope	Dorsal angle	Buttocks angle	Abdomen angle	Back inclination	Body lateral angle	Chest angle
Shoulder slope	1	–	–	–	–	–	–
Dorsal angle	–0.326**	1	–	–	–	–	–
Buttocks angle	0.205**	–0.820**	1	–	–	–	–
Abdomen angle	−0.269 ∗∗	0.328**	–0.299**	1	–	–	–
Back inclination	–	–	–	0.171*	1	–	–
Body lateral angle	–	0.306**	–0.252**	–	–	1	–
Chest angle	–	–	–	–	–0.141*	-0.191*	1
Bust girth	−0.132∗	0.311**	−0.325 ∗∗	–	0.139*	–	0.513**
Hip girth	–	0.353**	-0.298**	0.283**	–	–	0.171*
Waist girth	−0.158∗	0.442**	−0.393**	0.303**	0.146*	0.318**	0.248**
STD	–	–	-0.285**	–	–	0.209*	–
C-W drop	–	–	–	–	–	-0.225*	0.512**
W-B drop	–	–	–	–	–	-0.224*	–
BNPWH	-0.133*	0.333**	-0.291**	0.229*	–	–	-0.167*

(1) The shoulder slope does not correlate with the body's circumference or height, suggesting that it is relatively independent of the body's two-dimensional dimensions and serves as a separate basis for judgment. However, in the relationship with other angles, it has a negative correlation with the dorsal angle and a positive correlation with the buttocks angle. It can be inferred that if the human body's back waist is tightened and the hips are lifted, that is when the dorsal angle decreases. When the buttocks angle increases, the shoulder tips will often extend backwards and downward, resulting in larger shoulder slope angles when measuring the shoulder slope angle from the front of the human body.

(2) The dorsal angle, abdomen angle, and shoulder slope are all related. To exclude the effect of the third variable on the other two variables, the third variable can be used as a control variable before conducting a bivariate analysis called a partial correlation analysis. In this case, shoulder slope was used as a control variable in a partial correlation analysis between the dorsal angle and abdomen angle, and the results are presented in Table 6. The correlation coefficient between the dorsal angle and abdomen angle declines to 0.264, suggesting the size of the abdomen angle only has a low correlation with the dorsal angle. Table 5 also demonstrates the dorsal angle is correlated with several variables such as body lateral angle, buttocks angle, hip circumference, waist circumference, chest circumference, shoulder tips distance, shoulder-neck distance, and neck-waist height. It is worth noting that the dorsal angle is significantly negatively correlated with the buttocks angle, with a correlation coefficient as high as 0.820. The body lateral angle, however, is related to both, so it was also employed as a control variable for the partial correlation analysis

Table 6: Results of Partial Correlation Analysis of Dorsal and Abdomen Angle with Shoulder Slope as the Control Variable

Control variable			Dorsal angle	Abdomen angle
Shoulder slope	Dorsal angle	Correlation	1.000	0.264
		Significance (2-tailed)	·	0.000
		df	0	227
	Abdomen angle	Correlation	0.264	1.000
		Significance (2-tailed)	0.000	·
		df	227	0

of the buttocks and dorsal angle. The results show that the correlation between the dorsal angle and buttocks angle is still significantly negative, as seen in Table 7. A preliminary conclusion can be drawn that the dorsal angle mainly affects the body shape of backside.

Table 7: Results of Partial Correlation Analysis of the Dorsal and Buttocks Angle with the Body Lateral Angle as the Control Variable

Control variable			Dorsal angle	Buttocks angle
Body lateral angle	Dorsal angle	Correlation	1.000	−0.807
		Significance (2-tailed)	·	0.000
		df	0	227
	Buttocks angle	Correlation	−0.807	1.000
		Significance (2-tailed)	0.000	·
		df	227	0

To further examine the relationship between the dorsal angle and the body lateral angle, and between the body lateral angle and the buttocks angle, the buttocks and dorsal angle were used as control variables, respectively, for the partial correlation analysis with the body lateral angle. Table 8 indicates there is also a low correlation between the body lateral angle and the dorsal angle, with a correlation coefficient of 0.18. Table 9 shows the correlation between the buttocks angle and the body lateral angle is very low, with a correlation coefficient of 0.01. In conclusion, the human body shape's sagittal and coronal planes are relatively independent, and the waist circumference is the only body size that affects the body's lateral angle.

(3) As shown in Table 5, back inclination does not correlate with other angles, and the correlation with other height and circumference variables is also very low. It is the most morphologically independent variable among the seven body angles and can better characterise the back shape. Therefore, the back inclination can be selected as the angle of significant features.

4.3 R-type clustering and frequency

The icicle and tree plots of the clusters are shown in Fig. 4 and Fig. 5. When four, five, or six clusters were categorized, the data were relatively evenly divided into each cluster. Given the

Table 8: Results of Partial Correlation Analysis of the Dorsal Angle and Body Lateral with Buttocks Angle as the Control Variable

Control variable			Dorsal angle	Body lateral angle
Buttocks angle	Dorsal angle	Correlation	1.000	0.180
		Significance (2-tailed)	·	0.006
		df	0	227
	Body lateral angle	Correlation	0.180	1.000
		Significance (2-tailed)	0.006	·
		df	227	0

Table 9: Results of Partial Correlation Analysis of the Buttocks and Body Lateral Angle with Dorsal Angle as the Control Variable

Control variable			Buttocks angle	Body lateral angle
Dorsal angle	Buttocks angle	Correlation	1.000	−0.001
		Significance (2-tailed)	·	0.982
		df	0	227
	Body lateral angle	Correlation	−0.001	1.000
		Significance (2-tailed)	0.982	·
		df	227	0

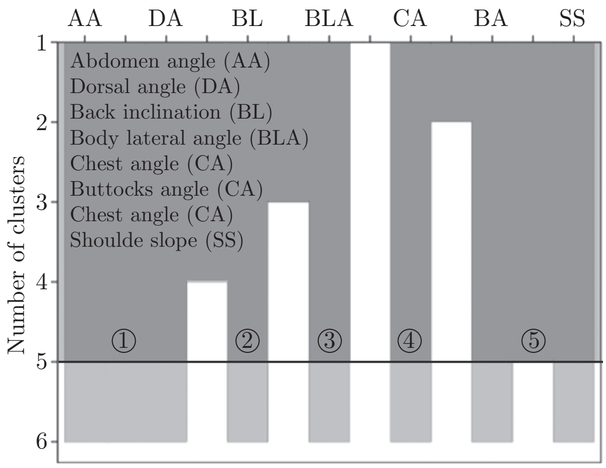

Fig. 4: Clustered icicle chart results

four clusters, the cluster distance was 10, while cluster 1 had three variables: back inclination, abdomen angle, and dorsal angle. More angles were included in that cluster, which couldn't be used as a good reference, so we concluded that four clusters were not clear enough. When there were five clusters, the chest angle, body lateral angle and back inclination each make up one cluster; with the buttocks angle and shoulder slope clustered together, as were the abdomen angle and dorsal angle. The five clusters distributed the seven angles more evenly. Therefore, we concluded that five clusters are more appropriate than the four clusters. When there are six

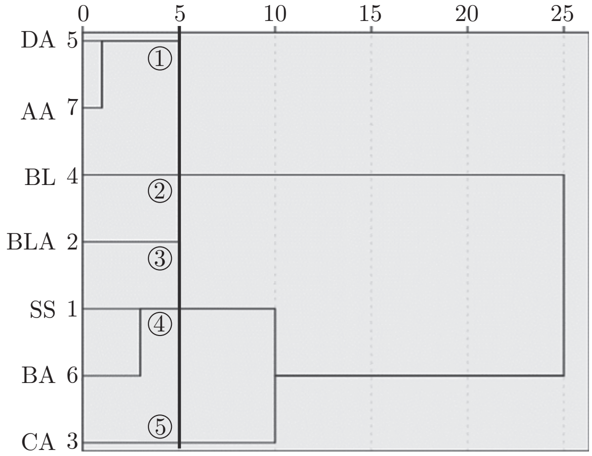

Fig. 5: Clustering dendrogram results

clusters, the abdomen and dorsal angles fell into the same category, while the remaining angles were each in a separate category. Only one angle variable was classified, which was not very helpful for subsequent classification. In summary, five clusters produced the best clustering result and were consistent with results from previous correlation analysis of body angles: dorsal angle was correlated and clustered into one category with abdomen angle, and shoulder slope was clustered into another category with buttocks angle.

Table 10 displays the results of a frequency analysis to determine the overall degree of variation in the five angles. The range of values for the shoulder slope and abdomen angle was small compared to the other angles. The standard deviation was also smaller, indicating that the dispersion of the shoulder slope and abdomen angle were more concentrated and had little impact on the body shape of young women. Additionally, based on the results of R-type clustering, the dorsal angle and the buttocks angle might be employed as independent variables to create regression equations for the shoulder slope and abdomen angle, respectively. Therefore, the dorsal angle and the buttocks angle were kept as the angles of distinguishing body characteristics, and the shoulder slope and the abdomen angle were removed. Five body surface angles of back inclination, body lateral angle, chest angle, dorsal angle, and buttocks angle were finally determined as the classification indexes.

Table 10: Results of Frequency Analysis of Seven Angles

Dimension	N		Mean	SD	Mode	Minimum	Maximum
	Valid	Missing					
Abdomen angle	230	0	5.19	3.19	1.18	0.12	14.76
Back inclination	230	0	20.46	3.44	18.43	11.8	30.10
Shoulder slope	230	0	20.65	3.45	18.79	11.37	29.78
Buttocks angle	230	0	16.68	4.01	15.95	7.13	30.28
Chest angle	230	0	30.81	5.33	26.57	14.51	43.82
Dorsal angle	230	0	155.69	6.26	152.40	132.85	169.89
Body lateral angle	230	0	158.20	3.79	158.88	147.57	168.48

4.4 K-means Clustering Analysis

The k-means cluster analysis was performed to categorize the 230 young women into three and four clusters. The classification results are displayed in Table 11. In the three-cluster model, cluster I had a straight front silhouette, slightly flat chest, thick back, and moderate hips, which tend to be "H-shaped". Cluster II had a plump bust, thin back, flat waist and abdomen curve on the front view, and flat buttocks, and cluster III had a curve front silhouette, plump chest, thin back, and prominent buttocks.

Table 11: Cluster Centers with Three and Four Clusters of Body Types

	Three-cluster model			Four-cluster model			
	I (n=66)	II (n=101)	III (n=63)	I (n=29)	II (n=74)	III (n=69)	IV (n=58)
Variables for cluster analysis	Flat chest and straight shape	Plump chest and straight shape	Plump chest and curve shape	Significantly curve shape	Curve shape	Round chest and straight shape	Flat chest and straight shape
Body lateral angle	159.30	158.76	156.15	154.95	157.63	159.50	159.01
Chest angle	25.55	32.90	33.16	32.82	34.56	30.88	24.93
Dorsal angle	154.90	160.46	148.88	145.19	154.79	162.37	154.14
Buttocks angle	18.06	13.68	20.05	22.15	16.89	12.65	18.50
Back inclination	22.16	20.18	19.13	19.63	19.07	21.06	21.95

In the four-cluster model, cluster I had a significantly curve front silhouette, relatively full bust, thin back, and full and upturned buttocks. Cluster II had a curve front silhouette, plump bust, thin back, and prominent buttocks. Although cluster I had the curviest front silhouette compared to cluster II, they had a shape similar to each other. Cluster III had a straight front silhouette, round chest, thick back, and undulating waist and hip curve on the side. Cluster IV had a slight curve front silhouette, flat chest, thick back, and moderate hips. When compared to cluster I and II of the three-cluster model, cluster IV and III of the four-cluster model were largely consistent. However, the four-cluster model did not have much merit when compared to the three-cluster model. In conclusion, the three-cluster model was more reasonable, which can be termed as flat chest and straight shape (Cluster I), plump chest, and straight shape (Cluster II), plump chest and curve shape (Cluster III).

4.5 Comparative Analysis of Body Type Characteristics

To analyze the difference in body shape between a young female in this sample and most females in China, 230 young women were classified based on chest-waist difference according to the Chinese national standard GB/T I335-2008. As shown in Table 12, the proportion of body types of young women in this sample was mainly concentrated in body type A (average) with 63%, followed by B (slightly fat) with 25.7%, while Y (thin) and C (fat) body types were significantly less represented. This conclusion was basically consistent with the national standard that body type A accounts for the largest proportion of the average body size of Chinese women. However, body type A

Table 12: Comparison of the Results of Body Shape Classification and Distribution Based on a Chest-Waist Drop with Chinese National Size Series

Chinese national body type	Y(thin)	A(average)	B(slightly fat)	C(fat)
Chest-waist drop(cm)	24∼19	18∼14	13∼9	8∼4
N	21	415	59	5
Percentage of samples	9.1%	63%	25.7%	2.2%
Percentage of Chinese national standards	14.82%	44.13%	33.72%	6.45

only accounts for 44.13% of the average body size of Chinese women in the national standard, while body type B accounts for 33.72%. So, we can conclude that, in this paper, most young women between the ages of 18 and 24 have a visible difference in chest and waist circumference, mainly between 18∼14 centimeters, relatively little fat accumulation in the abdomen, thin build, and very plump chest. And there are relatively few Y body types with very pronounced waist and chest curve.

Using chest-waist drop as a classification index is convenient for the measurement of the waist and chest circumference and for apparel making. It can describe the fullness of the waist and hips in terms of circumference, but it cannot depict the curved features of the human chest, back, hips, and shoulders. On the other hand, the body angle can better represent the changes in concavity and silhouette of the human body. Therefore, by utilizing the body angle and waist-chest drop together as classification indexes, the size and shape of human body parts can be more specifically depicted. Along with the chest-waist drop, three body type groups were further subdivided, and Table 13 displays the percentage of each body type following the subclass classification.

In body type A, Group A_{II} (plump chest, medium build, and straight shape) had the largest proportion of young women with a bust-waist difference between 18 and 14 centimeters, characterized by full breasts, a visible difference in chest and waist circumference, slightly flat hips and less visible curves on the sides. The second largest group was A_{III} (plump chest, medium build, and curve shape), which tended to have fuller buttocks than A_{II}, with more pronounced curves in both the front and side. Among the Y body types, Group Y_{II} (plump chest, thin build, and straight shape) and Y_{III} (plump chest, thin build, and curve shape) accounted for the majority of these body types. The combination of Y_{II} and Y_{III} body types revealed that people with Y body types were slimmer overall but have very full breasts, small waist circumference, and flat buttocks. Group B_{I} (flat chest, slightly fat build, and straight shape) and Group B_{II} (plump chest, slightly fat build, and straight shape) made up 83.1% of all B body types, indicating that this group had a lower hip-waist difference, flatter buttocks, bigger back inclination and thicker back than Y and A types. In addition, due to the low number of people in Group C, the breakdown of type C body shape was insufficient to infer a clear conclusion. Additionally, the classification results of Y body type also showed that there were insufficient individuals in Group Y_{I} (flat chest, thin build, and straight shape). Therefore, Group Y_{I} and type C were excluded, and the eight types of Y_{II} to B_{III} were finally obtained.

4.6 Accuracy of EasyDL Recognition Model

The model evaluation report presents both the overall evaluation results and the evaluation results for each type of body, enabling the model to be modified more precisely in response to the findings.

Table 13: Somatotype Classification and Distribution Based on Combination of Chest-Waist Drop and Body Angles

Body type	Y			A		
	Y_I (6.5%)	Y_{II} (64.5%)	Y_{III} (29%)	A_I (24.8%)	A_{II}(45.4%)	A_{III} (29.7%)
	–	plump chest, thin build, and straight shape	plump chest, thin build, and curve shape	flat chest, medium build, and straight shape	plump chest, medium build, and straight shape	plump chest, medium build, and curve shape
N	2	20	9	36	66	43
Total percentage	0.8%	8.3%	3.7%	15%	27.5%	17.9%
Body type	B			C		
	B_I (42.4%)	B_{II} (40.7%)	B_{III} (16.9%)	C_I (60%)	C_{II} (20%)	C_{III} (20%)
	flat chest, slightly fat build, and straight shape	plump chest, slightly fat build, and straight shape	plump chest, slightly fat build, and curve shape	–	–	–
N	25	24	10	3	1	1
Total percentage	10.4%	10%	4.1%	1.2%	0.4%	0.4%

Table 14 displays the evaluation findings for the recognition model.

Top1 was the precision at the first recognition time with the highest confidence level. mAP (mean average precision) refers to the number of samples correctly classified as a percentage of the total number of samples. Accuracy is the ratio of the number of samples correctly predicted to be of a particular body type to the number of samples predicted to be of that body type. Recall rates is the ratio of number of samples correctly predicted to be of that body type to total number of samples of that body type. F1-score is the summed average of accuracy and recall rates for a given body type, i.e., the inverse of the arithmetic means of the inverse of accuracy and recall rates. As shown in Table 14, the model can retrieve an average of 93 correct samples out of 100. The overall recognition mPA of the trained model was 91.7%.

According to Table 15, the mPA for Class I, Class II, and Class III was 87%, 91%, and 95%, respectively. This finding suggests that the more obvious the feature points, or curve characteristics, of the input training data, the higher the accuracy of the model. The debugged model can then be made available once the results have stabilized to a manageable level. The model published on the Common Cloud API can be published as an H5 model after customizing the interface address. A QR code can be created and later scanned with the mobile phone to create an app for the body shape classification model. When the body shape classification model is used

Table 14: Overall Assessment of Results of the Model

	mAP	F1-score	Accuracy	Recall rates
Top1	91.7%	91.6%	90.9%	93.2%
Top2	100%	100%	100%	100%
Top3	100%	100%	100%	100%
Top4	100%	100%	100%	100%
Top5	100%	100%	100%	100%

Table 15: Model Assessment Results for the Three Body Types

	Class I	Class II	Class III
mAP	87%	91%	95%

to assess the longitudinal curves of the human body, images can then be uploaded directly. The application interface of the H5 model is shown in Fig. 6.

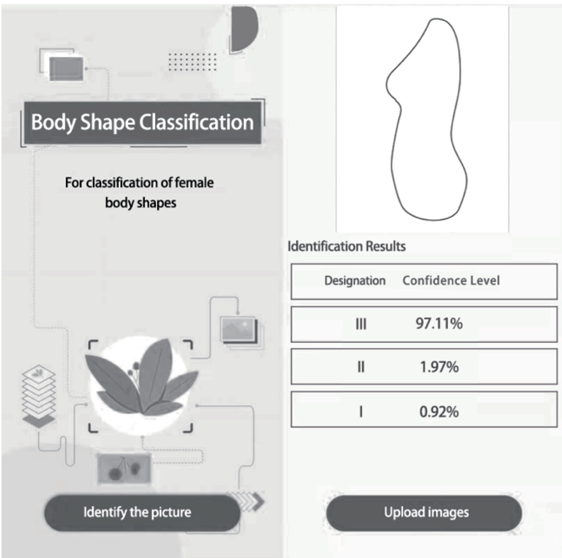

Fig. 6: Body Type Classification Model H5 Test Interface

5 Conclusion

(1) In this paper, we used correlation analysis and R-type clustering to determine five body angles as the classification indexes that best reflect the characteristics of body curves. Body types of 230 young women in northern China were categorized by k-means clustering analysis into S-type with a curve shape on the front and side, H-type with a straight shape, and plump chest and straight shape with a more pronounced curve on the chest than on the hips. This finding could enrich the body type classification of young women in northern China and provide a theoretical basis for personalized apparel.

(2) Combined with the Chinese national standards, most female in this paper have a plump chest, medium build, and straight shape, followed by a plump chest, medium build and curve shape. According to the female body type division in GB/T 1335-2008, women in this study with Ythinbody type have very full breasts, small waist circumference, and flat buttocks. Those with A (average) body type tend to be more curve in the front and side, and those with B (slightly fat) have less obvious body curves and thicker shoulders and back than the previous two body types.

(3) Using the Baidu EasyDL development platform to create a body type recognition model, the total recognition mAP reached 91.7%, with Type III body types achieving the highest recognition accuracy at 95%. The shared cloud API interface was released after creating the H5 model, which can be developed twice.

Our results also demonstrated that the more obvious the feature points of the input training data, i.e., curve features, the higher the model accuracy. Using the body type recognition model built with Baidu's EasyDL development platform for type recognition of unknown body types is relatively easy to operate. Not only does it have a better generalization ability, but it also has a higher recognition accuracy. However, according to the prediction results of the AI model, the accuracy of identifying the other two body types with less obvious curve features among these three categories requires further improvement. For body types with relatively insignificant body surface curves, fatness and thinness can also be used as discriminatory indicators. For example, the results of angle-based body type classification studies can be combined with the BMI index, which reflects the degree of body fullness. In a follow-up study, the body characteristics of young women can be further analyzed to develop more accurate and significant body shape classification rules, further optimizing the generalization ability of the model.

Acknowledgement

The authors wish to acknowledge the Beijing Institute of Fashion Technology for providing the laboratory equipment, and sincerely thank all the subjects for participating as volunteers in this study. The authors are also grateful to Professor Gou Ruiliang for his help in conducting this study. The authors would also like to extend their gratitude to Rouxi Pan and Chen Yu for writing this article.

References

[1] Zhang J, Xu KY, Zhao SL, Gu BF. Classification and identification of neck and shoulder morphology in young men based on two-dimensional photographs. Journal of Textiles: 2022; 5: 143-149.

[2] Xing XY, Shang XM. Analytical methods and trends in serving human control part data. Modern Silk Science and Technology: 2014; 29: 197-199.

[3] Qian XN, Yin B. Research on the recognition of human body shape segmentation based on 3D anthropometry. Journal of Textile: 2011; 32: 107-111.

[4] He LW. A model for body segmentation and identification of bow-backed young men based on shoulder cross-sectional curves. Journal of Suzhou University: 2018.

[5] Song Q, Zhang YX. Discussion on the method of classifying body types of Chinese women. China Fiber Inspection: 2008; 7: 71-73.

[6] Kuang CY, Li R, Wu YJ, Yu YB. A study on the classification index of female body shape. Textile Herald: 2010; 9: 117-118.

[7] Ni SM, Yao Y, Ye XL, Xin YY, Zhou FY. Extraction and fitting of sagittal contour curves in young women. Journal of Zhejiang University of Technology: 2015; 33: 41-45.

[8] Xia FQ. A study on the classification of body size based on the longitudinal profile of human body. Journal of Donghua University: 2017.

[9] Yao Y. Wavelet coefficient-based body size classification and prototype generation for young women. Journal of Zhejiang University of Technology: 2018.

[10] Pang CY. A study on body type segmentation and identification of young men based on cross-sectional morphology. Journal of Zhejiang University of Technology: 2015.

[11] Peng L. Applied A shape classification scheme for female torso. Applied Ergonomics: 2023.

[12] Zouhour BA. Characterizing human shape variation using 3D anthropometric data. The Visual Computer: 2006; 5: 302-314.

[13] Li XZ, Li XJ, Liu H. Calculation of circumference dimensions based on point clouds of body sections. Journal of Textile: 2019; 40: 128-132.

[14] Luan T, Yuan HF, Wang DS, Meng XD, Xia W. Classification of the upper body shape of young men using three-dimensional anthropometry. Journal of Henan College of Engineering (Natural Science): 2020; 32 (03).

[15] Zhou D, Xiao NF. Part Recognition Method Based on Visual Selective Attention Mechanism and Deep Learning. Journal of Fiber Bioengineering and Informatics: 2015; 4: 791-800.

[16] Zhang SY, Zhou FY, Ding XY, Chi JM. SVM-based body type classification of young women. Journal of Zhejiang University of Technology: 2008; 25 (1): 41-45.

[17] Liu TT, Xu H, Mei XY, Liu YX, Xiao AM. Hip body shape discrimination and prototype correction for Xinjiang women based on XGBoost algorithm. Journal of Textile: 2020; 41 (07): 147-153.

[18] Sun J. Research on human body shape analysis and number archiving based on neural network integration. Journal of Zhejiang University of Technology: 2013.

[19] Li QQ, Zhong YQ, Wang X. Classification of Female Apparel using Convolutional Neural Network. Journal of Fiber Bioengineering and Informatics: 2016; 4: 209-216.

[20] Xing YM, Wang ZJ, Kan Y, Zhang N, Shi XM. Identification of adult female body size characteristics based on factor analysis and hierarchical clustering. Journal of Henan College of Engineering (Natural Sciences): 2019; 31 (02): 8-12.

[21] Xu JY. A classification study based on the body morphology of young men. Light Industry Science and Technology: 2012; 28: 103-104.

[22] Zhou FY, Ding XJ, Pan LF. A study on the characteristic indicators and ridge regression prediction of body size in young women. Journal of Textile: 2006; 4: 56-59.

[23] Xie YK. Deep Learning Development Platforms and Applications. Artificial Intelligence: 2020; 3: 43-53.