Predicting Human Body Measurements Using MediaPipe Pose Auto-Capture

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Abstract

Anthropometry plays a crucial role in understanding the human body and its variations, contributing to advancements in various fields such as health, sports, and design. However, the current practices for identifying human body shapes for apparel production and design are limited. This study aims to address this gap by utilizing MediaPipe Pose to recognize human body measurements based on front and side poses, laying the foundation for a novel clothing sizing system. We used MediaPipe's framework for auto-capturing poses and visual recognition to identify human body outlines. The width, depth, and height of the shoulders, chest, waist, and hip were calculated based on user input height. The body scan comparison from the pilot test data suggested that the captured outline tended to underestimate widths more than depths, particularly for the female subject. Future studies may collect and manually verify a large amount of picture data and corresponding body data to develop an AI model for human body shape categorization.

Keywords: Keywords: body measurement prediction, MediaPipe, image auto-capture

1. Introduction

Clothing fit is a critical factor in consumer satisfaction when shopping for clothing. The convenience of online shopping has led to a significant increase in the number of consumers purchasing clothing online. However, the inability to try on clothing before purchase can result in dissatisfaction with the fit and lead to high return rates [1]. Consumers who shop online tend to have a higher rate of returns due to clothing fit issues as compared to those who shop in-store [2]. Consumers with lower confidence in their ability to evaluate their own body size and shape were found to be more likely to experience fit issues when shopping for clothing online [3].

To mitigate the issue of fit in online shopping, several solutions have been suggested and explored. One approach is the use of virtual fitting technology, such as Google's virtual try-on feature [4],, which allows consumers to virtually try on clothing with their body measurements or a 3D scan. Another solution is to use augmented reality (AR) technology, which allows consumers to superimpose virtual clothing onto a live image of themselves. Recent studies found that AR technology can improve consumer satisfaction with online shopping by providing a better visualization of the clothing fit [5], [6]. However, there is a need to explore the effectiveness of these approaches in reducing return rates and improving consumer satisfaction with online clothing purchases.

Therefore, this study aims to explore human body measurements based on the front width and side depth by utilizing MediaPipe pose to auto-capture the front and side standing poses. The existing practices primarily focus on kinesiology and online shopping experiences to match size rather than identifying human body shapes for apparel production and design [7]. This study aimed to address this gap by using MediaPipe Pose to recognize human body outlines based on front and side poses, laying the foundation for a novel clothing sizing system.

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2. Literature Review

2.1. Anthropometric measurements

Anthropometry provides valuable insights into the human body and its variations, contributing to advancements in various fields such as health, sports, and design [8]-[10]. Previous research in kinesiology aimed to establish reference values for body composition and athletes' anthropometric measurements, which are used to assess physical performance and evaluate athletic performance, identify talent, and develop training programs [11]-[13]. In medicine, anthropometry has been used to assess growth and development in children, diagnose malnutrition, and evaluate obesity risk in adults [14], [15]. Waist circumference was used to assess abdominal obesity to indicate the increasing risk of metabolic disorders [16]. In ergonomics, anthropometry has been used to design products, equipment, and workspaces that fit the human body to minimize the risk of injury and improve efficiency [17]. In the context of clothing making, anthropometric measurements are essential for creating well-fitting garments that are comfortable and flattering for the wearer [9]. Typically, the traditional method of measuring the upper torso is based on the circumferences taken at the bust, waist, and hips. However, two people who have the same circumference may have different shapes or mixed body shapes [18].

2.2. Body scan technology

Body measurement scan technology is a non-intrusive solution that is widely used across multiple fields. Three-dimensional (3D) body scan measurement solutions were initially developed for custom apparel applications in industry or the military [19]. In the fitness industry, body scan technology is used to create personalized fitness programs based on an individual's body composition and fitness goals. Or, this technology can be used to measure body circumferences and volumes of athletes, suggesting that body scanners may be a practical tool for evaluating body size and shape [20].. In the fashion industry, body scan technology is used to create custom clothing and improve the online shopping experience for consumers. A study conducted by Ashdown et al. [7] found that using 3D scans in the fit analysis process has potential benefits such as recording one instance of fit, creating databases of multiple fit models, and evaluating garment/body relationships during movements. The use of 3D body-scanning technology for more accurate measurements has the potential to significantly reduce the rate of returned products for online retailers. This may consequently lead to increased profit margins [21]. Nevertheless, 3D body scanning may require extra effort and maybe not only time-consuming to perform but also impossible to access.

2.3. Mobile body scanning applications for commercial use

Online/mobile body scanning applications are becoming increasingly popular as people prioritize purchasing the right sizes and prefer to shop online due to their convenience. Size inconsistency was found in different fashion brands [22]. According to CB insights, the size recommendation tools and plug-ins, such as TrueFit, Fit Analytics, and Easysize, were all valued at over 100 million [23]. Other emerging products with 3D technology, such as ZozoSuit, is a full-body suit with landmarks, which requires the use of a smartphone to capture wearing photos and measure the wearer's body dimensions [24]. Fitmatch is a machine learning-based system that provides personalized outfit recommendations to users based on their preferences, body type, and occasion [25]. Mobile applications, such as 3DLOOK, leverage computer vision technology to generate 3D models of a user's body from 2D photos [26]. Although all of these products aim to offer sizing recommendations and fit solutions, they all require extra effort from both the shoppers and retailers. In this research, MediaPipe was adopted to enable the detection of body posture and analysis of body dimensions using only photos or videos, eliminating the need for supplementary equipment or manual measurements. Ultimately, the choice of solution depends on the individual needs and preferences.

3. Methods

This study developed a website application based on MediaPipe to auto-capture human body outlines and measurements of the front and side body width. MediaPipe is a cross-platform framework used for building machine learning pipelines that process time-series data like video and audio. The framework allowed developers to configure pre-built processing pipelines to apply machine learning solutions to their apps, which provided faster and more engaging results. To obtain the body measurements from the images after identifying the landmarks on the outline, an algorithm of neural networks for the chest, waist, and hips was trained based on 1968 female body measurements from the Anthropometric Survey of US Army Personnel (ANSUR II) from Open Lab in Pennsylvania State University [27].

The users were required to follow the instructions to submit five photos by utilizing MediaPipe's framework to set for auto-capture in three seconds and used visual reorganization on the captured image to identify the human body outline. Then the width and depth of the shoulder, bust, waist, and hip were recognized within the outline. The related measurements were calculated based on the height, which was provided by the user. Two scanning experiments were conducted with one female and one male participants, who were also measured manually on the width and depths of the same body parts. A comparison between the app captured and manually measured was analyzed to validate the accuracy and identify areas to improve. The technical steps included setting the environment, posture recognition and automatic photo capturing, contouring the outline of the human body edge, calculating the measurements of the key body parts, and comparing the manually measured data to the MediaPipe data.

3.1. Environment settings

Because the collected images were used as the foundation of the visual reading data, consistent environment settings could reduce computational complexity, reduce data noise, and improve the recognition accuracy of original data. To capture the entire body, the camera should be positioned at the center of the body (waistline) perpendicular to the ground with enough space in front. The camera must stay in the same position during the automatic shooting process. The background color was recommended to be clean with minimal interference and had a higher contrast with skin and outfit colors to aid outline reading distraction. Reflective ground surfaces were avoided to facilitate recognition of the feet contour line. Tight-fitting clothes were required to minimize the effect of extra space on the body outline. Lastly, the height and weight were collected to use as the proportional calculating foundation.

3.2. Posture recognition and auto-capturing

The system required a total of five pictures to acquire all necessary body data, including a pure background shot and four posture-guided shots. The auto-capture utilized the MediaPipe - Pose API to obtain data for 32 key points of the human body. The automatic photo-taking required the connection between the live capturing camera and MediaPipe Library to detect the main joints of the human body, such as hands, elbows, shoulders, hips, knees, and ankles. By analyzing the position relationship between these key points, the system was able to determine the user's posture and orientation in the camera. In cases where the posture did not meet the requirements, the website provided instructions on how to correct it. Once the posture met the requirement, the system prompted the user to stay in the posture and initiated a three-second countdown. Upon completion of the countdown, the system automatically captured the image and progressed to the next posture until all required photos were taken.

The auto-captured images were collected from one male and one female participant. Both were Asian and 35 years old. As seen in Figure 1, five photos were instructed to be taken.

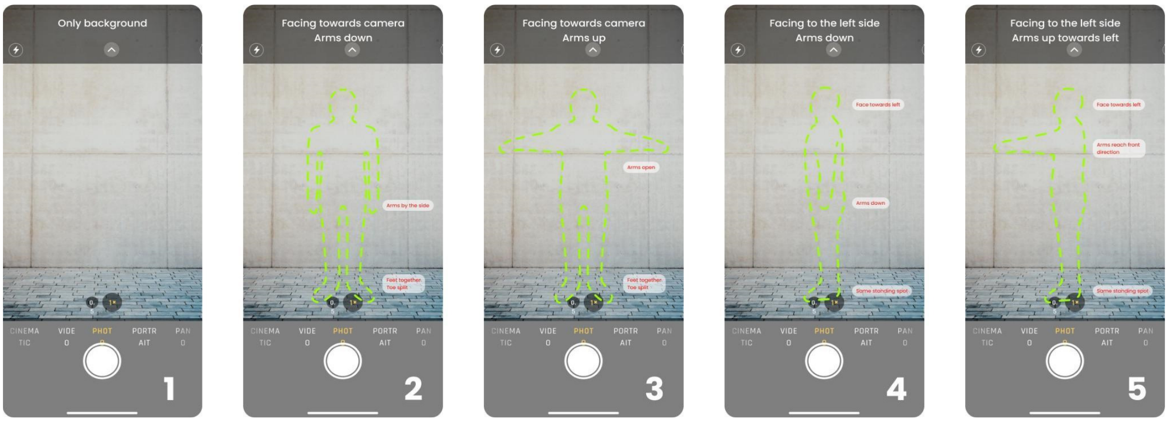
3.3. Contouring the outline of the human body edge

MediaPipe's Pose API provided several techniques to enhance the accuracy of human body recognition, yet it was not developed to obtain accurate human body data. During the testing, the outlined images contained significant gaps and errors on the contoured outline (See Figure 2). Therefore, an additional body outline correction was added to the code. Based on previous studies, image convolution calculation with specific kernels could effectively recognize object edges in images [28]. In this project, the same method was used to correct human body outlines.

The process used the three RGB color channels to determine the maximum difference point as the new edge point, with this process repeated until all contour points were recalculated. Computer vision adjustments with RGB color reading and pixel indent were implemented to detect the body area. The height was determined by taking the highest and lowest points of the contour line for the top of the head and bottom of the feet, respectively, while using MediaPipe's identification points for the shoulders and hips. The development process is explained as follows:

1. The human body areas generated by MediaPipe API were processed to obtain a list of each point on the edge, ensuring the adjacent points' coordinates were also adjacent in the list.

2. By recognizing the relationship between each point and several neighboring points around it, the direction toward which this point should be retracted from the edge was obtained.
3. Based on the direction, the convolution kernel was created. For example, if the direction was top to bottom, the convolution kernel was [[0,-2,0], [0,0,0], [0,2,0]]. If the direction was left, the convolution kernel was [[0,0,0], [-2,0,2], [0,0,0]].
4. 5 points before and after the direction of edge indentation together with the target point for a total of 11 points were taken. Convolution calculation on the human body image and background image was performed.
5. The convolution value at the corresponding point in the background image from the convolution value at each point in the human body image was subtracted; the point with the maximum value among 11 points as the new edge point was taken.
6. All points in the list to form a new human body edge line were traversed.



(a) Plain background (with no person present) to establish an environmental baseline.

(b) Stand straight with hands by the thigh and toe separated by 30-60 degrees with heels touching.

(c) Keep the lower limb still and extend both arms horizontally to form a T-shape.

(d) Rotate 90 degrees around one foot as an axis, keeping heels and toes together and arms at the sides.

(e) Keep the lower limbs stationary and extend both hands forward horizontally without leaning back to form a 7-shape

Figure 1. Five-step instructions for auto-capture

3.4. Calculating the measurements of the key body parts

The MediaPipe Pose API provided the landmarks of joints, which set the determination of the height of the waist and chest in the images. During prototype development, the waist was determined using the most concave point of the back in the side photo, while the chest was calculated by identifying the widest position from the shoulder to the crotch in the side view. The contour line of each picture and the height of each position were used to find the pixel distance of the width and depth of each position. However, if the widest position height was closer to the crotch height, a line segment was created connecting the outermost point of this height and the outermost point of the shoulder height to calculate the chest height. Under this method, error results were identified during testing due to the unpredictable curve outline of the human body.

During the improving development, the upper truck proportion values were incorporated. According to Scott's research on the body regions defined by stable landmarks [29], the alternative proportional length between the shoulders and high hips was 100%, with the chest at 37.5% and the waistline at 62.5%, resulting in the determination of the height of the chest and waistline in the image [29]. Given the outline of the human body, the height of each key point, and the height, width, and depth of each position could be obtained by using the proportional relationship between height and the width and depth of each position in relation to the shoulder, chest, waistline, and hips.

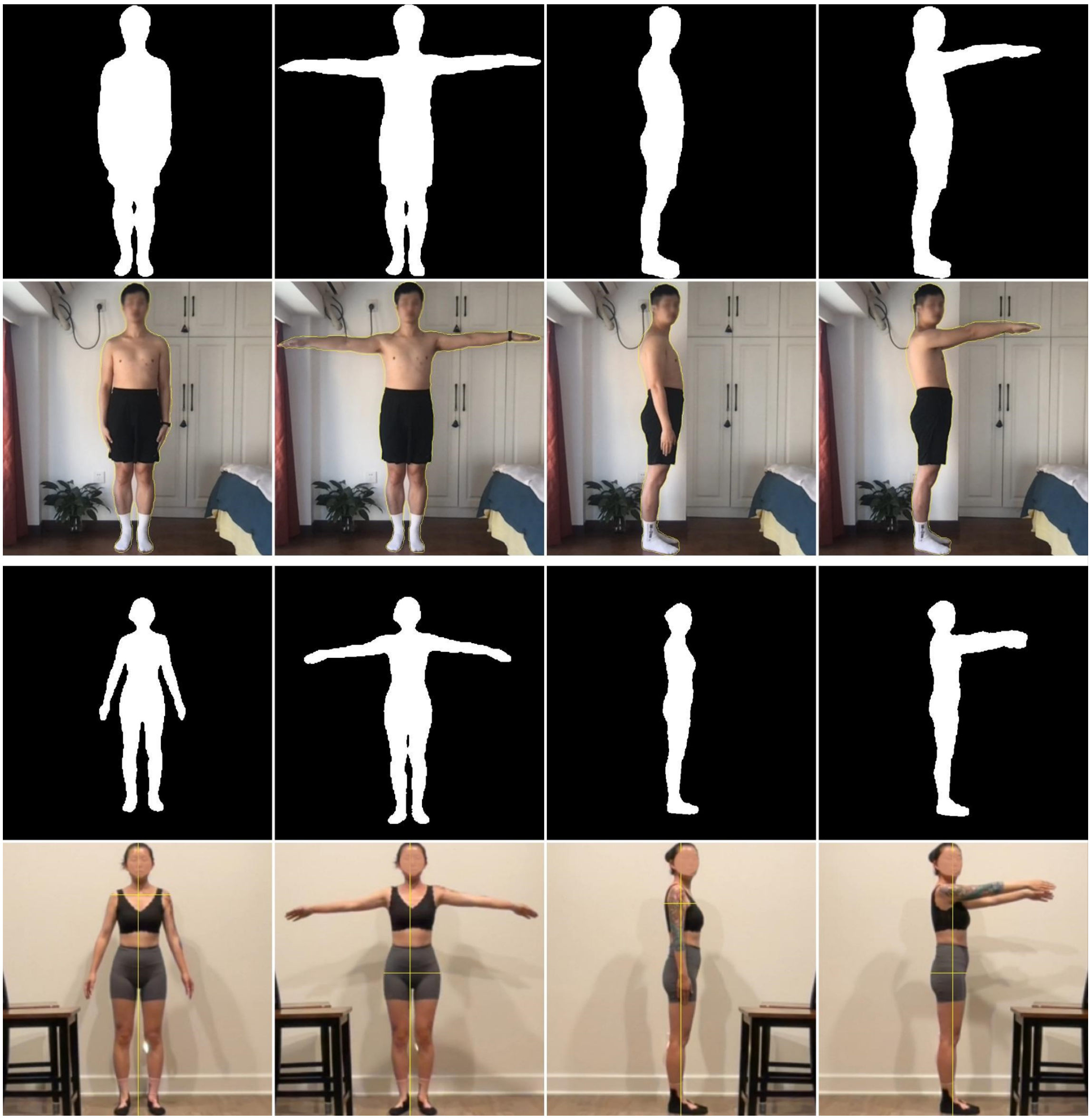
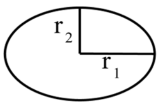


Figure 2. MediaPipe subtracted body outlines and height definition for male and female

The images obtained the width and depth of each position, and the circumferences were calculated as seen in Equation (1). Based on the formula for calculating the circumference of a circle using radius and the formula for calculating the circumference of an ellipse using width and height, a double-hidden-layer fully connected neural network was created for each position. By knowing the height, weight, width, and depth of each position, the circumference of each position could be obtained.



$$A = 2\pi\sqrt{\frac{r_1^{\,2} + r_2^{\,2}}{2}} \qquad (1)$$

3.5. Comparing the MediaPipe and manually measured data

Both male and female participants underwent the auto-capture process twice, noted as Test 1 and Test 2, in the same background and outfit. The results were recorded and averaged to minimize the deviation of the condition. The same participants were manually measured for widths, depths, and circumferences of the shoulders, bust/chest, waist, and hips based on ISO 7250: Basic human body measurements for technological design [30]. The manually measured data were noted and used to compare the accuracy of the captured image data.

4. Results

The collected data was compared based on gender and body parts to analyze the accuracy. The data compares measurements from a male and a female subject, including shoulder, chest, waist, and hip width and depth measurements, as well as girth measurements for the shoulders, chest, waist, and hips. Each measurement was taken twice digitally and averaged. Percent errors were calculated between the averaged test readings and the manual measurements. The digital scans seem to underestimate widths more than depths for the female subject and overestimate depth more for the male subject. The largest differences between manual and image-captured measurements were seen in shoulder and hip depth for males (See Figure 3).

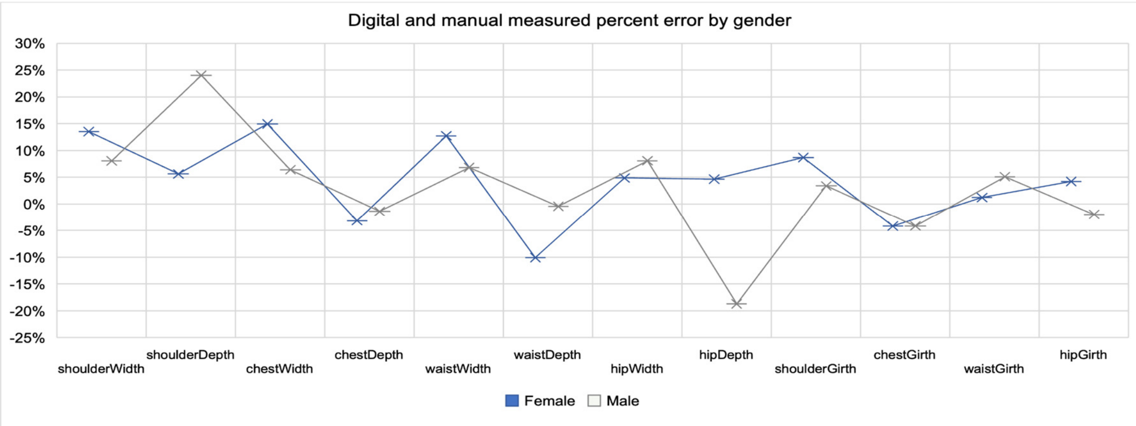


Figure 3. Percent error of body parts comparison by gender

As seen in Table 1, for the male subject, the digital readings underestimated width measurements by 3-8% on average compared to the reference. Depth measurements had more variance, with -1% to -19% differences. Similarly, for the female subject, the digital readings underestimated width measurements by 5-15% on average.

Table 1. Manual vs image-captured measurements by gender

	Male subject's measurements			**Female subject's measurements**		
	Manual	**MediaPipe Mean (SD)***	**% difference**	**Manual**	**MediaPipe Mean (SD)***	**% difference**
Shoulder Width (mm)	440.00	404.50	8%	420.00	370.00	**14%**
Shoulder Depth (mm)	250.00	190.00	**24%**	160.00	151.50	6%
Chest Width (mm)	320.00	299.50	6%	300.00	261.00	**15%**
Chest Depth (mm)	250.00	253.50	-1%	215.00	222.00	-3%
Waist Width (mm)	330.00	307.50	7%	270.00	239.50	**13%**
Waist Depth (mm)	230.00	231.00	0%	165.00	183.50	**-10%**
Hip Width (mm)	390.00	358.50	8%	355.00	338.50	5%
Hip Depth (mm)	230.00	273.00	**-19%**	225.00	215.00	5%
Shoulder Girth (mm)	1050.00	1014.50	3%	915.00	842.00	9%
Chest Girth (mm)	940.00	979.00	-4%	835.00	871.50	-4%
Waist Girth (mm)	940.00	892.00	5%	670.00	662.00	1%
Hip Girth (mm)	1040.00	1060.50	-2%	915.00	878.00	4%

Note: * Mean was calculated by taking the averages MediaPipe tests 1 and 2.

Depth measurements were closer, with -3% to 10% differences. Girth measurements for both subjects were generally within 5% of the reference, with a mix of slightly under and overestimations. The correlation between the manually measured and averaged test readings was analyzed using the Pearson correlation test. The results showed a significant positive correlation between the two methods for both male ($r = 0.99$, $p < 0.001$) and female subjects ($r = 0.98$, $p < 0.001$). This indicated that the MediaPipe auto-captured image measurements might potentially measure body dimensions accurately.

5. Conclusions

The use of 3D human body modeling has become increasingly popular in the fashion industry, where virtual try-on experiences are employed to enhance the online shopping experience [31]. By enhancing the accuracy of auto-captured data using sophisticated 3D technology, a foundation for various consumer products can be established. As noted by Kang et al. [32], collecting more detailed anthropometric data could provide more comprehensive information about the human body.

Overall, the MediaPipe-captured measurements have the potential for improving the understanding of the human body and developing consumer applications in various industries. The developed image captured body measurements represented the step towards improving the understanding of the human body and developing new applications in various industries. Although the current version of the auto-captured solution only collected the measurements of shoulders, bust, waist, and hips, it has the potential to collect more data on other body parts. These findings highlighted the importance of considering digital scan accuracy when assessing body measurements and suggest that further research is needed to improve the accuracy of these methods.

The neural networks developed for calculating the circumferences of the chest, waist, and hips were trained with limited amounts of female data in ANSUR II, which only presented limited types of body shapes and ages. Thus, deviations between manually measured and MediaPipe-captured data were expected. The significant errors for shoulder depth were caused by the lack of training data. The neural network for shoulder circumference was predicted by algorithmizing the correlated data of chest, waist, and hip measurements. With sufficient consistent anthropometric data, the accuracy of prediction in neural networks is projected to increase. Moreover, inconsistencies were observed in analyzing and calculating the output measurements due to variations in standards across the anthropometric datasets. For instance, in ANSUR II, bust circumferences varied for different height positions, which might be caused by different preferences of bras or outerwear while taking measurements. Other measurement variables were also recognized, such as shoulder, waist, and hip depth.

To improve accuracy, several enhancements can be investigated. The limited diversity of tested subjects suggests that recruiting diverse participants and taking multiple readings may reduce variability. While auto-captured data is based on five images, the complexity of anthropometric data could be analyzed through videos. Additionally, MediaPipe is used for posture recognition and initial contour recognition, and not developed to capture body measurements. Further exploration with open-source human mesh recovery (HMR) technology may be conducted to compare the accuracy of different motions. HMR technology could generate a 3D model of the human body for broader usage. Such continuous research may provide accuracy and reliability to digital scanning technology in measuring body dimensions. For future development, a sufficient number of auto-captured images and corresponding body data should be collected and verified for landmark points to minimize errors in identifying measured body parts. An artificial intelligence (AI) model could then be built and trained with the data, replacing the system when the correct rate is acceptable.

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