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Designing a Contactless, AI System to Measure the Human Body using a Single Camera for the Clothing and Fashion Industry

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Abstract

We present a system that estimates upper human body measurements using a set of computer vision and machine learning techniques. In a nutshell, the main steps involve: (1) using a portable camera (such as from a smartphone); (2) improving the image quality; (3) isolating the human body from the surrounding environment; (4) performing a calibration step; (5) extracting features of the body from the image; (6) indicating markers on the image; (7) producing refined final results. Using a single RGB camera to obtain accurate body dimensions rather than measuring these manually or via more complex multi-camera or more expensive laser-based sensors, has a high application potential for the apparel (fashion) industry. We also present in this paper, ellipse-like approximations with the aim of minimizing the difference between the results of direct (hand) and software measurements. The human body circumferences can be well approximately represented by varying elliptic cross sections, and these can be adapted to each individual. We show that better results than the current state-of-the-art are obtained based on a simple criterion. In our study, we selected a set of two equations, out of many other possible choices, to best estimate upper human body horizontal cross sections. We experimented with the system on a diverse sample of participants. The results for the upper human body measurements in comparison to the traditional manual method of tape measurements, when used as a reference, show ±1cm average differences, which is sufficient for a number of applications.

Keywords: Human Body Measurement, Machine Learning, Computer Vision, Fashion Technology, Ellipse equations

1 Introduction

Online shopping platforms have been attracting a continuously growing number of customers over the years since their introduction at the turn of the century. A well-known problem for online cloth retailers is the high return rate due to a poor fit [1–3]; e.g. at the start of 2022, returns for U.S.A. retailers accounted for over $761 billion in lost sales [4].[1] Customers will often end-up ordering the same piece in different sizes to choose the right fit and then send back the others. This causes significant costs for the retailer and also has a significant negative impact on the environment.

Due to a lack of accuracy, robustness, and ease of use, existing body measurement systems based on affordable consumer hardware (such as smartphones or tablets) are unable to satisfy both consumers and retailers. These technologies rely heavily on user input. This implies that the user must follow specific instructions in order to obtain accurate measurements, such as performing specific movements in front of the camera or holding various poses for a specified amount of time.

The return rate could be dramatically reduced if customers had an easy way of obtaining anthropometric measurements. Of course, there should be better understanding and communication between retailer and customers to have a consistent definition of the anthropometric measurements relevant for selecting the size of the correct garment. Current approaches for analysing the accurate 3D shape of the human body often require expensive hardware, such as 3D scanners based on lasers or multiple fixed camera domes. Such hardware is typically not widely available, not portable, and expensive.

As Gen Z, which makes up 35% of the global population, begins to enter the workforce, companies in various industries must be ready to accommodate changing customer needs as stated by Leej and Wei [5]. According to IBM and the National Retail Federation [6], almost 50% of Gen Z shoppers want products specifically tailored to their preferences. Furthermore, according to a study by Imran *et al.* at McKinsey [7], more than 90% of that generation believes companies are responsible for addressing social and environmental issues.

Through the help of AI-powered technology, businesses should offer items based on accurate measurements to better suit the Gen Z population. If successful, consumers will be satisfied not only with the garments they receive, but also with the positive changes firms are making to the environment and the industry.

However, significant challenges need to be addressed, including: (1) the complexity of the human body, especially with the non-rigid parts of the body, (2) the variability of the human physique across individuals and across time, (3) the complexity of human skeletal structure, (4) the impact of breathing, as the body expands and contracts, (5) variable lighting conditions that produce shadows, (6) depth, i.e. the loss of 3D data

[1] https://nrf.com/research/customer-returns-retail-industry-2021

that results from observing the pose from 2D planar image projections, and (7) the difficulty of capturing human body parts covered by loose clothing or long hair.

In this article, we present the results of our study which demonstrate the feasibility to design a simple, yet accurate and cheap system, based on the use of a single camera-phone to retrieve useful body metrics with the potential to address current problems of the industry.

1.1 Our solution in a nutshell

In order to achieve accurate and efficient measurements of the human upper body, we conducted a thorough investigation into various methods for evaluating elliptic fitting. Our primary focus was to identify the most precise approach, leading us to compare six distinct ellipse equations at the outset of our study. These equations were subsequently narrowed down to two as shown below, based on their ability to provide better accuracy levels tailored to different body shapes. The detailed comparison and evaluation of these equations can be found in the appendix.

$$P \approx 2 \times \pi \times \sqrt{\frac{(dist1_f \times dist1_s) + (dist2_f \times dist2_s)}{2}} \tag{1}$$

$$P \approx \pi \Big[3(dist_f + dist_s) - \sqrt{(3dist_f + dist_s)(dist_f + 3dist_s)} \Big] \tag{2}$$

By scrutinizing the performance of these equations, we aimed to determine the optimal approach for our specific measurement objectives. Our analysis considered the varying characteristics and shape variations found among individuals. As a result, we selected two ellipse formulas that demonstrated superior accuracy levels and were well-suited for capturing different body shapes effectively. This research underscores the significance of accuracy in human upper body measurements and emphasizes the importance of tailoring the approach to accommodate diverse body shapes.

The following statistics in (Figure 1) represent the average error in centimeters of different horizontal sections of the human body for five different applications. These applications were chosen based on various factors such as accuracy, reliability, popularity, availability, and relevance to the research topic. During the capturing process, each user was instructed to stand in front of the camera approximately 10 times to ensure accuracy. Multiple measurements were taken using the mentioned five applications to obtain a range of data points. Subsequently, the measurements obtained from each session were compared, and the most accurate measurement was selected for further analysis and inclusion in the statistics. Please note that users were divided by gender to account for the anatomical differences between males and females. Participants were advised to wear appropriate or tight-fitting clothing during the capturing process to obtain more precise information otherwise the looseness of the clothes might be observed as part of the human body.

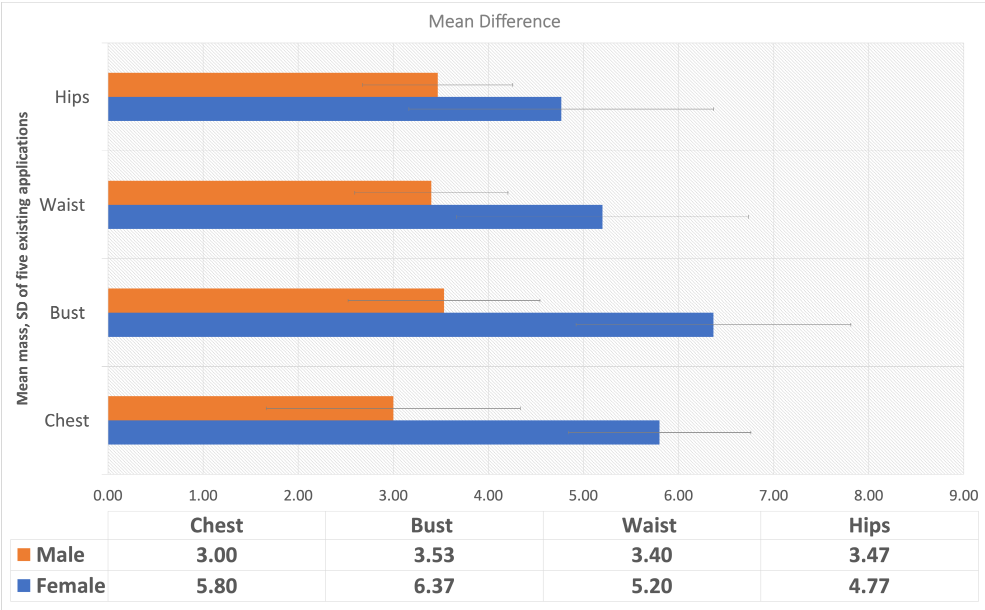

Fig. 1 We report the average difference (in cm) and standard deviation for the selected five existing apps on the market. This information was collected from a total of 30 (who self-identified) as female or male participants in *uniform conditions* across five different applications available off the shelf (see text). For more information please refer to Appendix A

"Uniform conditions" refers to ensuring consistent and standardized conditions for measurements across the five different applications that were used in the study. It means that the same parameters, settings, and guidelines were followed while using each application to capture the measurements. By maintaining uniform conditions, the aim is to minimize any potential variations that could arise due to differences in how the applications function or in their default settings.

Motivated by this current situation, we propose a simple, yet effective, technique providing a state-of-the-art lightweight measurement system (e.g. based on a smartphone to capture data) that is capable of extracting sufficiently accurate anthropometric measurements to capture the relevant data of the upper human body with applications in the apparel/fashion sector. The result is a fully trained system that can choose the best ellipse equation according to the human body shape.

Based on our research, we aim for an average error of 1cm or less in the measurements retrieved from our system. This target relates to industry standards and previous studies that have shown that an error of up to 1cm is acceptable for garment sizing [8–10]. Manual methods for measuring the body, such as tape measurements and manual anthropometry, have been shown to have errors ranging from 1cm to 3cm [11–14]. Therefore, our target accuracy of 1cm or less would represent a significant improvement over manual methods and would be suitable for practical use in the fashion industry.

Additionally, there can be significant differences between the direct (tape) measurement results and those based on software, especially for upper human body circumferences such as for the chest and waist. The problem emerges because there has not been a careful study of which mathematical models to use to better represent upper human body circumference anthropometric variables.

Given these challenges and the potential for improvement, we decided to focus on the upper body — from the hips and up. While capturing measurements for the lower body is achievable, concentrating on the upper body allowed us to address the greater variations in body contour specific to this region and explore more accurate and reliable solutions for body measurements, particularly for fashion-related applications. The upper half of the body presents more variations in shape and size, both between individuals and for an individual over time. In contrast, the lower body, particularly below the hips, exhibits less deformations and can be very well approximated using ellipses for cross-sections.

2 Background

2.1 Traditional measurements

Traditional anthropometric measurement extraction methods can be divided into two groups: landmark-based methods and template-based methods. Landmark-based methods involve taking multiple measurements of the body at selected points called landmarks, which are usually located at or near the joints or other identifiable body features. Based on these landmarks, various body measurement standards, including by the ISO, permit to characterise the human body. While these methods can accurately measure the body's proportions and size, they are time-consuming, requiring manual measurements. In addition, most brands have their own measuring standards, leading to incompatibilities between outputs.

Template-based methods, on the other hand, involve measuring specific body proportions using a template, which is a scaled 2D/3D representation of the body based on specific dimensions. The template is placed over a person, and the distance between the template's points is measured to obtain the measurements. This method evaluates the body's size, shape, and proportions to determine the correct clothing size. Template-based approaches are quick and reliable. They are also a cost-effective way of measuring the body, saving both time and money. However, the templates represent averages over population groups and do not account for a large variety of body types. Complicated body shapes cannot be well approximated using only templates. Therefore, their use is unsuitable for custom-made clothing, which requires more precise measurements. In addition, it does not allow for the individual's preferences and does not permit design flexibility.

While both types of methods are still used in the industry, there are other techniques available to overcome the growing problem of wrong fit for online shopping. These recent techniques are not landmark-based or template-based and include technologies like 3D body scanning, virtual try-on systems, and artificial intelligence (AI). These technologies, which we briefly survey next, can provide more accurate and precise measurements, allowing for a better fit and more personalized clothing options.

2.2 Computerised recent methods

To overcome the problem of wrong fit for online shopping [15], many research projects have been conducted and one of the most promising solutions is by directly estimating the human body measurements from 2D images. This typically requires users to only wear very tight clothes or just underwear. Another group of studies use more complex depth-sensing systems to obtain 3D images which are then used to estimate body measurements. Below, we present a brief summary of recent research efforts that focus on estimating the human body from outer surface measurements.

Xiaohuia *et al.* [16] developed a technique to automatically extract feature points and measure clothing on 3D human bodies. The method requires a depth-sensing platform, which is currently unavailable to the majority of online customers. Additionally, numerous poses must be captured. Chang *et al.* [17] presented a dynamic fitting room that allows users to view a real-time image of themselves while trying on various digital garments. The method employs the Microsoft Kinect©sensing platform and augmented reality technologies. The system calculates the user's body height based on head to foot loci and depth data collected by two Kinect cameras, for front and side views. The system produces results that are sufficiently accurate (less than a centimeter error on average).

Chandra *et al.* [18] developed an approach that aims to determine human body measurements by using portable cameras such as with smartphones. When the system recognizes a human body in its viewing field, it tracks the body's outline. To achieve this, the system searches for the face, neck, and shoulders, which are taken as markers for the upper body. However, there are some constraints as users must set up certain environmental parameters (including light, background, and the type and contrast of clothes) and must perform the measurement capture at least five times. Francesca *et al.* [19, 20] created a cloud API utilizing Amazon Web Services (AWS) that can be easily integrated into other platforms to extract up to 24 body measurements from two images (front and side views). Existing open-source algorithms are utilized. According to their findings, the median difference is less than 2.6 cm (or one inch), which is insufficient for commercial applications.

Nourbakhsh Kaashki *et al.* [21] developed Anet, a deep neural network for automating 3D anthropometric measurements from 3D human body scans. Anet consists of two components: a feature extraction network and an anthropometric measurement extraction network. Features are recovered from a 3D scan, including posture, shape, and proportions. The anthropometric measurement extraction network then uses these features to automatically estimate 3D anthropometric measurements. Compared to existing methods, Anet had a mean absolute error of less than one centimeter. This suggests Anet could reduce the cost and time associated with obtaining anthropometric measurements and generate digital human models for virtual reality and computer animation. Such software, however, may be overly complex for practical deployment, due to estimating anthropometric measurements from dense accurate 3D data.

Closer to our own work, Sahar *et al.* [22] presented an approach to estimate human body measurements with smartphone cameras. They use Haar-based detectors that provide markers focused on the upper, lower and full body areas. Difference between markers are then used to estimate body measurements. Their method can only provide very coarse ranges — such as the commonly used in retail classification in ”small, medium, large, XL, XXL”. The accuracy achieved is not sufficient for our goals.

2.3 Deep Learning Methods: State-of-the-art

As a leading representative of recent progress made in applying deep learning methods to the problem of recovering the 3D body shape of humans, we summarise here a leading project, the SHAPY framework, created by Michael Black *et al.* [23], which provides a novel method for accurate 3D body shape estimation without explicit 3D shape supervision. The framework uses linguistic shape attributes and anthropometric measurements as proxy annotations for training a regressor, enabling accurate body shape predictions. The framework is evaluated on various datasets, including the “Human Bodies in the Wild” (HBW) dataset, which provides natural and varied body shapes and clothing in real-world settings. The HBW dataset is comprised of photographs of individuals in lab settings as well as in the field, accompanied by 3D shape data derived from body scans.

SHAPY’s efficiency is evaluated using various metrics. The framework obtains impressive results on the HBW dataset, outperforming existing methods. It exhibits superior performance in estimating body measurements such as height, chest, waist, and hip circumference, with mean absolute errors ranging between 5.8 and 6.2 mm for various gender and attribute combinations. The accuracy of estimating anthropometric measurements is also evaluated, and the mean absolute errors between measured and estimated values are reported.

SHAPY’s advantages include its superior performance compared to existing methods, its ability to accommodate diverse body shapes and apparel variations, and its potential to reduce the cost and time required to obtain anthropometric measurements. The framework’s use of linguistic attributes and anthropometric measurements as auxiliary annotations increases precision and enables novel applications in virtual reality, computer animation, and the apparel industry.

However, limitations exist. SHAPY’s model-agency training dataset may not be representative of the entire human population, which can impact the accuracy of body shape predictions for individuals whose shape is not well represented in the training set. Due to the computational intricacy of estimating anthropometric measurements from dense and accurate 3D data, the framework’s implementation in practice may also prove challenging.

In conclusion, the SHAPY framework represents a major enhancement in the field of 3D body shape estimation. As a consequence of its use of linguistic attributes and anthropometric measurements as proxy annotations, its accuracy and precision are enhanced. SHAPY’s performance on challenging datasets and its potential for practical applications make it a promising instrument for a variety of applications.

In comparison to the more sophisticated recent deep learning methods, our method aims at simplicity, yet with sufficient accuracy for our application domain. Also, it does not rely on any re-training or access to large datasets, as we only use deep learning on a pre-trained network for the single purpose of an initial 2D image segmentation of the body’s contour or profile.

3 Method

In our approach, (i) once a body is detected (using a smartphone camera and a deep learning model), we then (ii) improve the image quality, (iii) use a region of interest (ROI) to discard irrelevant or unwanted part of an image, (iv) use calibration to determine the depth of field — as the distance from the camera focal point to the human body, (v) extract body features from the image, (vi) semi-automatically set a small number of markers, and (vii) by computing the differences between markers, we estimate a human upper body measurements.

The overall pipeline is illustrated in Figure 2. As part of the data capture process users can wear casual clothing, but with a few constraints, including that they should wear clothing which is tight enough around the waistline, shoulder line and neck, so as to not mask these areas. Note that this is much less restrictive than many other proposed approaches which require to be either naked or wearing only very tight clothes over the entire body. In terms of poses, our system requires a so-called "A-pose" for the frontal view capture, while there are no restrictions for the side views (examples to follow). The A-pose is only needed for situating markers for the shoulders. Again, this is more flexible than what can be found currently in available applications or published work using only a smartphone camera to provide image data.

3.1 Body detection

Our goal is not to only extract the human body (its contour) from the image, as we also need to differentiate between the upper and lower human body parts, as well as extract categories such as head, chest, bust, waist, hips, shoulder, and height. This aspect of segmenting the human body into specific sections, we refer to as Regions Of Interest (ROI), and it will be discussed further in § 3.3. The purpose of this classification is to enable us to speed up the process of measuring each body area more precisely.

In our method, we start by isolating the body contours in captured images based on machine learning (ML). This is a natural first step, which has been used by others, such as Sahar et al. [24]. For our ML module, we selected the MobileNet SSD, pre-trained on a dataset to detect the human body [25]. MobileNet uses depth-wise separable convolutions to build a lightweight deep neural network, which was selected in preference to other object detection methods as it well suited to mobile devices and other embedded applications.

In terms of advantages over classic methods, for comparison, when using other methods such as those based on Haar Cascade detectors [24], we observed difficulties when applying the technique to side views (profiles). Furthermore, such methods give poorer results than MobileNet when dealing with difficult lighting conditions or cluttered backgrounds. Thus, the MobileNet SSD architecture is preferred due to its effectiveness in handling side views, difficult lighting conditions, and textured backgrounds. It provides better segmentation results in such scenarios.

After conducting a thorough evaluation of various methods, including YOLO, OpenPose, and EfficientNet, we concluded that while models like EfficientNet may provide more accurate results in certain scenarios, MobileNet SSD offered a combination of performance, efficiency, and compatibility that made it the preferred

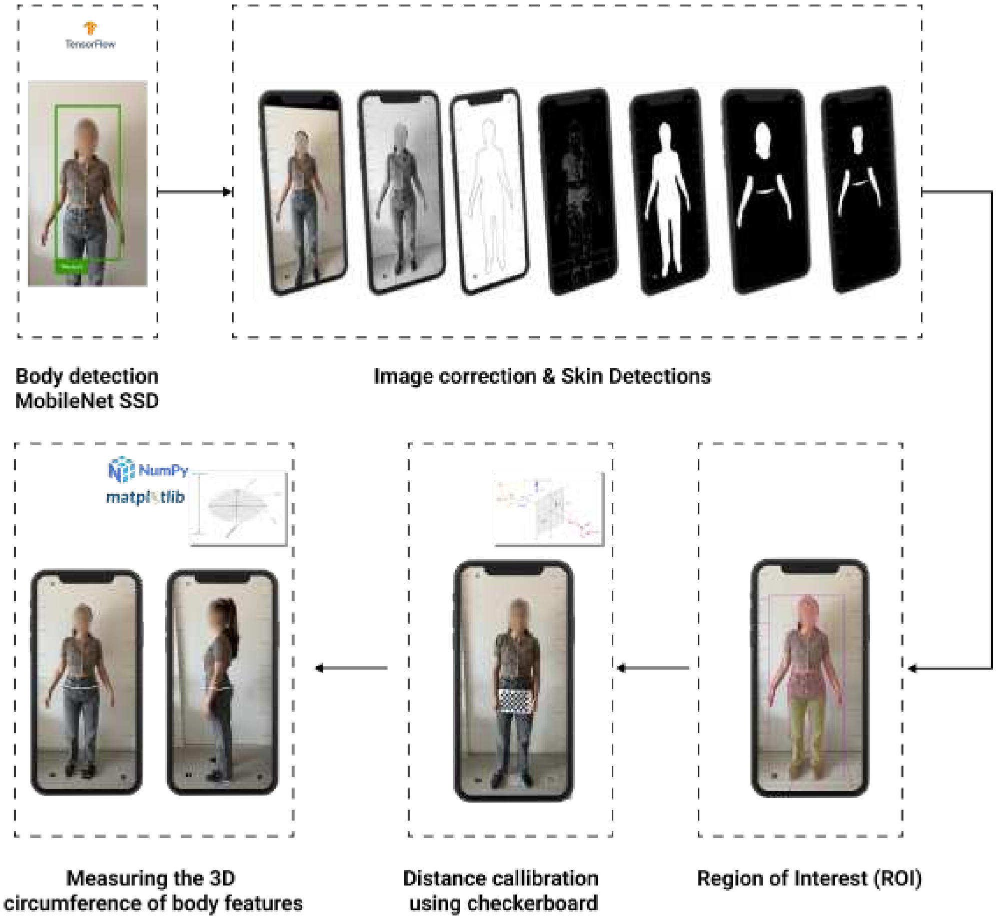

Fig. 2 Pipeline - The following flowchart displays every stage to calculate the human upper body measurements.

choice for our software. When compared to YOLO, MobileNet SSD demonstrated better accuracy and robustness in segmenting human body contours from complex backgrounds, particularly under challenging lighting conditions and textured backgrounds. Additionally, MobileNet SSD outperformed OpenPose by providing more accurate segmentation results, especially in side views and scenarios with difficult lighting conditions. Compared to EfficientNet, MobileNet SSD's lightweight architecture and efficient inference made it particularly suitable for resource-constrained devices, such as smartphones, without compromising real-time performance. Furthermore, our experiments consistently showed that MobileNet SSD provided better segmentation results and improved the efficiency of subsequent image corrections and human body area measurements.

Once the human body has been segmented from the background using the ML module, additional processing is performed using image corrections (§ 3.2). This is required as the resulting segmentation may still include some small amount of the background information near the image contour of the body. Difficult backgrounds (especially when textured) may create larger bleeding effects at the obtained body edges. Also, potential localisation errors could result from causes such as reflections, shadows, and low contrast. We next describe ways to improve the MobileNet segmentation outcomes.

3.2 Image corrections

In our current pipeline, we proceed as follows: (i) metric correction of an affine camera model, (ii) grey level mapping of an RGB input, together with removal of small image regions and image smoothing [26, 27], (iii) detecting edges [26], (iv) mask opera-tions on matrices and thresholding [28] (v) skin detections. Figure 3 illustrates some of these steps of image improvement in the proposed system.

We consider two general categories of problems in this section: image distortions and low-level feature enhancement.

In the first phase of our pipeline, we focus on addressing image distortions, which primarily involve geometric corrections and improving the image's spatial accuracy and clarity. To achieve this, we perform metric correction using an affine camera model. This step helps rectify distortions caused by factors such as camera angles or lens imperfections. By applying these corrections, we aim to optimize the overall geometric quality of the image.

Simultaneously, we also move into the low-level feature enhancement. This category encompasses various techniques aimed at improving the quality and characteristics of the image's low-level features. We begin by transforming the image from RGB to grayscale through grey level mapping. This simplification step aids in highlighting essential features and reducing the complexity of data processing.

The next phase involves further refining the image by removing small image regions and applying image smoothing techniques. For image smoothing, we employ Gaussian smoothing, a widely used method known for its effectiveness in reducing noise and enhancing the overall quality of the image. Additionally, we perform edge detection using the Canny edge detection algorithm, a fundamental technique for accurately identifying and highlighting edges within the image. By employing these techniques, we enhance the contrast between various regions and features, leading to improved visual clarity.

It is worth noting that Gaussian smoothing serves a dual purpose in our pipeline. Apart from its role in image smoothing, it is also commonly utilized in edge detection algorithms. This technique helps to suppress noise and refine the edges, ultimately enhancing the accuracy and quality of the detected edges.

During the final phase of our pipeline, we present a technique for accurately identifying and isolating human skin in images, known as skin detection. Our method consists of a comprehensive procedure involving color space transformation, region of interest (ROI) selection (refer to § 3.3 for more information), parameter estimation, and skin segmentation. By utilizing the HSV (Hue, Saturation, and Value) and YCbCr (Luminance, Chrominance Blue, and Chrominance Red) color spaces, which are known for their effectiveness in skin color representation, we can improve the skin detection process.

To elaborate on the methodology, after transforming the image into the HSV and YCbCr color spaces, we identify and isolate image areas that resemble human skin. This is accomplished using a combination of methods. Initially, we use a region of interest (ROI) approach to classify and differentiate various body parts. By focusing initially on the upper body, we ensure that the software's attention remains on the most important areas.

Next, specific color space operations are performed on each body section. This phase is essential for enhancing the distinctive qualities of each region. By carefully analyzing the color distribution and patterns within the HSV and YCbCr channels, we are able to create effective segmentation thresholds for skin. These thresholds enable us to distinguish between skin and non-skin areas, such as clothing and the surroundings.

Our method is distinguished by its comprehensive nature and incorporation of color space transformation, ROI-based labeling, and intelligent thresholding techniques. By analyzing the specific characteristics of human skin in different color spaces, it is possible to effectively identify and isolate skin areas in images. The significance of skin detection in numerous applications, particularly those involving human subjects, highlights the importance of our innovative method. Through these sequential stages, our pipeline ensures that the image is optimized for further analysis.

Fig. 3 displays the complete process of image corrections in our software, starting from metric correction and grayscale conversion, followed by edge detection, thresholding and finally, skin detection

3.3 Regions of Interest (ROI)

Regions of Interest (ROI) are defined by selecting rectangular regions in an image to isolate certain areas for further processing. Since the image correction itself does not totally separate the human body from the background, we decided to use ROI to more completely process the human body present in an image.

After image edges have been identified, the contour of a human body is extracted.[2] We then calculate and generate a ROI of the human body based on such a contour, which results in a rectangle surrounding the entire human body.

[2] We have used the findContours() function of OpenCV for this purpose.

We then proceed to further segment the intial ROI into six smaller more specific regions: (i) head, (ii) neck, (iii) hands (shoulder width for two side views), (iv) bust/chest, (v) waist, and (vi) hips and (vii) height.An example of the automatic extraction of such ROIs is inllutrated in Figure 4.

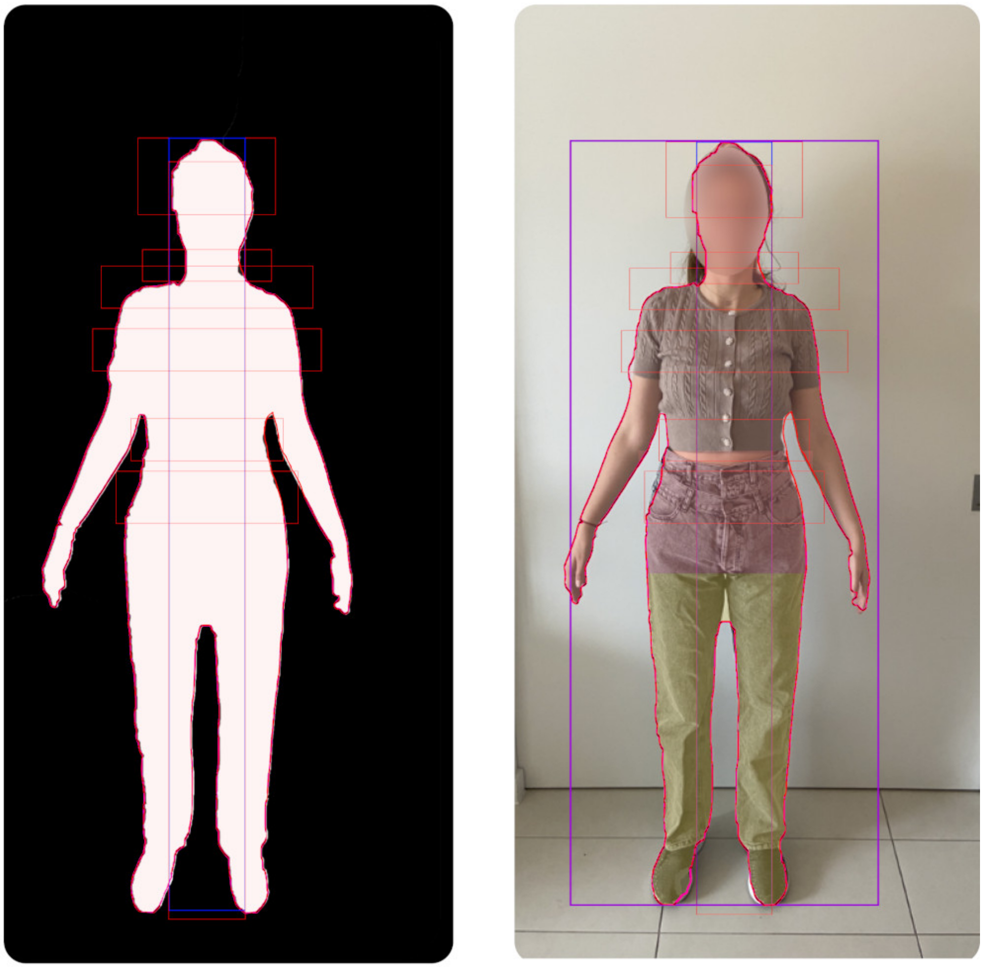

Fig. 4 Image obtained by adding masks from a set of training images

3.4 Camera calibration

Calibration is used to determine camera parameters, including the classic: 3x3 matrix intrinsic matrix K, 3x3 rotation matrix R, and 3x1 translation vector t using a set of known 3D points (Xw, Yw, Zw) and their corresponding image co-ordinates (u, v). The camera is said to be calibrated when both intrinsic and extrinsic parameters have been accurately estimated.

The intrinsic parameters are evaluated by measuring the size of the image in pixels and the size of the object in the image. Next, the extrinsic parameters are determined using a calibration pattern or calibration object, which allows us to measure the camera's position in 3D space relative to the object.

We use a classic computer vision technique for such a calibration step. Currently, it is based on using a checkerboard pattern that the user positioned in the scene, such that is approximately facing the camera. This can be repeated from multiple viewpoints for greater accuracy. Corners in the image of the checkerboard pattern are then automatically extracted to estimate the camera matrix, distortion coefficients, rotation vectors, and translation vectors.[3] The camera matrix contains the intrinsic parameters of the camera, including the focal length, principal point, and skew. The rotation and translation vectors describe the camera's position and orientation in the 3D world.

The classic Levenberg-Marquardt algorithm, a nonlinear least-squares algorithm, is employed to estimate these parameters from multiple viewpoints. Additionally, the number of inliers or points within a certain threshold of the reprojection error, is determined using the well-known RANSAC algorithm. A lower reprojection error and a higher number of inliers indicate a more accurate calibration. Note that other objects (of known dimensions and shape or pattern characteristics) could be used in place of a checkerboard, such as business or bank cards (which follow a standard sizing).

3.5 Measuring the elliptic circumferences of horizontal body contours

The primary objective of our feature extraction phase is to identify specific points of interest — we call **markers** — from the detected body. The measurements of various horizontal body regions, including the waist, chest, hips, and shoulders, are then estimated based on these markers. We identify markers by pairs, along horizontal body "slices". To accomplish this, we first find the best vertical body line to utilize as an approximate mirror-like splitting axis. Then, we search for the right and left pairs of body extremities, i.e., pixel locations at the body's edge.

We first identify a top central head point — head tip — which we use to center our vertical splitting line. From there we walk along the body contour on one side (left or right) and monitor the slope of a line segment between the head tip and the current body edge point. When this slope goes through a large change in value, we determine a potential marker location. In our experiments, this works well for markers in the neck and shoulder areas. Note that we use the A-pose to identify shoulder markers, as the shoulder line (between the shoulder markers) corresponds to the ISO (the International Organization for Standardization) suggested method for measuring such segments.

A collection of measurements from the ISO 8559 standard, which prescribes the location of anthropometric measurements used in the production of physical and digital anthropometric databases, has been selected in order to compare the suggested method with other state-of-the-art approaches. The selected anthropometric measurements are shown in Table 1.

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[3]Our current calibration process uses OpenCV's Camera Calibration Algorithm, using the cv2.findChessboardCorners() and cv2.calibrateCamera() functions.

Table 1 Anthropometric measurements chosen from ISO 8559 standard.

Title	Measurement Type	Title	Measurement Type
opx	Chest/Bust Girth	opn	Neck Girth
opp	Under Chest/Bust Girth	oph	Wrist Girth
ot	Waist Girth	SvRv	Shoulder Length
ob	Hips Girth	SyTy	Back Length

Currently, in our system, other markers for the chest and waist measurements require a semi-automatic method where a user moves a horizontal virtual line along the medial vertical axis to identify the useful additional pairs of markers. We note that this step can be calculated automatically, e.g. based on machine learning, however requiring additional training data, which we have yet to produce. On the other hand, we can provide our targeted users, such as tailors and consumers, the option of selecting these specified landmarks manually.

After obtaining our set of marker pairs, we can approximate the circumferences of the upper human body for each horizontal slice by fitting an ellipse to the data points, using both the frontal and side views. The idea of using an ellipse as an approximate geometric model of human horizontal body contours has been previously validated [29].

Then, by evaluating the semi-axes of the ellipse from the two images (front and side), the circumference of a human body "slice" with respect to the selected marker pair may be estimated (e.g., waist, circumference). Figure 5 shows a semi-automatic marker along the shoulder-bust-waist-hips line.

Note that for our domain of application in the fashion sector, using an ellipse-like form tightly fit to a body horizontal contour (slice) is what is needed in most cases: i.e. we do not want a piece of clothing to follow too closely all the body contour details and deformations when considering or designing a pattern for cutting the fabric to be assembled into a wearable piece. For a different application domain, such as the medical realm, recovering detailed contour measurements might be desirable and the ellipse fitting process may only provide an initial approximation.

Fig. 5 Indicating markers (semi-auto): Our advanced computer vision algorithms detect the dressed human body on 2D images taken with any smartphone against any background, and depending on the detected body, will indicate semi-auto markers. Additionally, users can indicate their own marks.

3.5.1 Elliptical mathematical models

To conduct linear regression, we consider the following variables: 'x1/2', representing the semi-major axis, and 'x2/2', representing the semi-minor axis derived from the human body circumference. Figure 6 illustrates these variables in relation to waist circumferences.

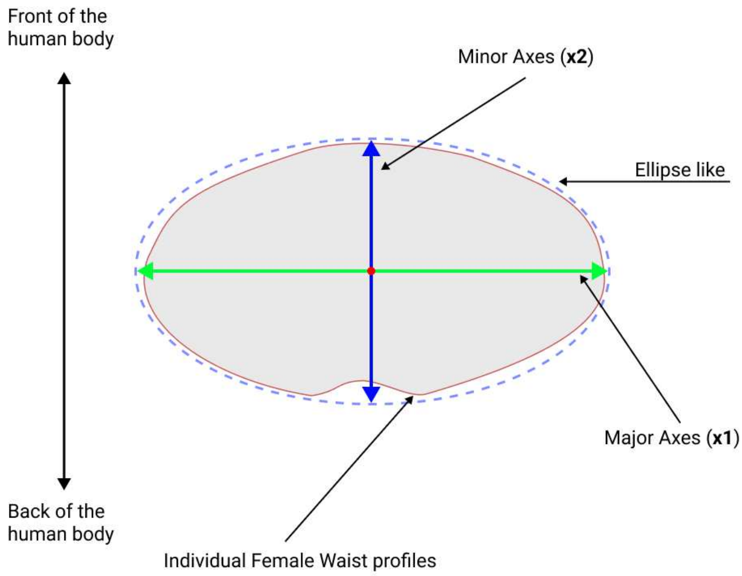

Fig. 6 presents a participant's waist circumferences, showcasing the variability in measurements.

The real circumferences of human subjects are only approximately elliptical (Figures 7 and 8). The challenge is to discover the best fit. Unlike for a circle, there is no explicit or closed form formula for calculating the precise ellipse's circumference. According to our data, the differences between each shape can impact the final estimation. This motivated us to study and better understand how to tackle this issue based on the data acquired (see § 4.1). We decided to use multiple elliptical equations to estimate the human body circumference based on body shape in order to reduce the difference with actual measurements. As can be seen in Figure 7, the body slices can become rounder, almost rectangular (top row) or, at another extreme, become squashed alike a pressed oval shape (bottom row).

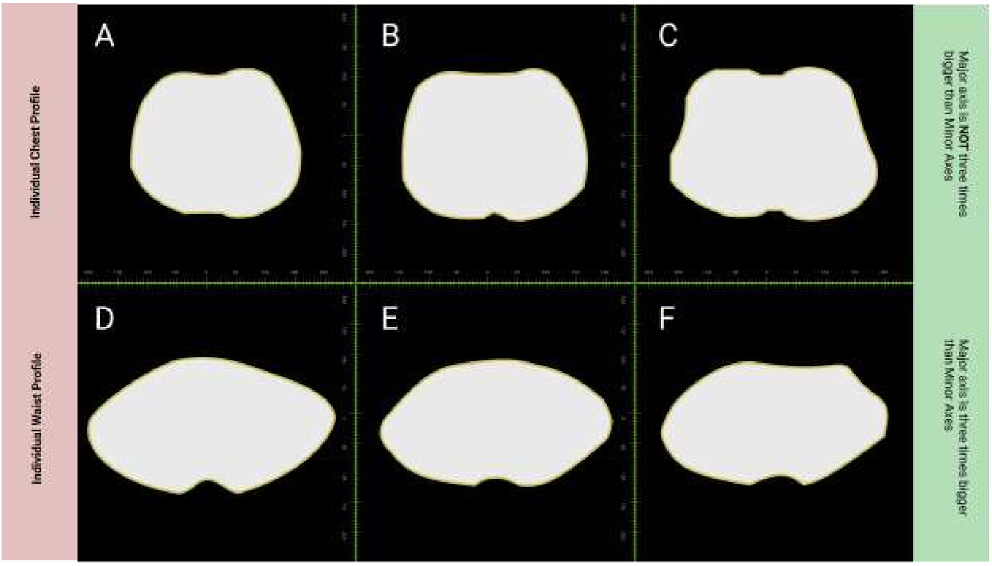

Fig. 7 Variations in circumferences measurement and curvature.

Note: Figure 7 displays the shapes of participants for whom data was collected during the capture procedure. The initial step involved using PifuHD [30] to transform the photos into 3D models (.fbx files). Subsequently, Autodesk Maya was utilized to separate the specific body parts from these 3D models.

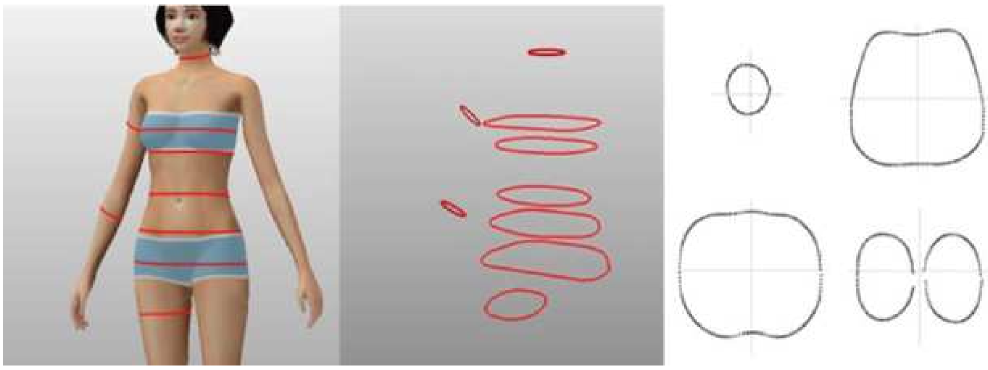

Fig. 8 Female template chosen from ISO. Examples of virtual body cross sections [31]

3.5.2 Final measurement step

For each pair of markers, we need to find the actual distance between these points, by converting pixel units to centimeters. We can then fit our measured distances for front (f) and side (s) views in Equation 1, Equation 2 according to different human body shapes.

As previously mentioned, the majority of horizontal circumferences (slices) of the human body are approximately elliptical in shape. To acquire an accurate measurement of the human body torso in particular, we evaluate it as the perimeter of the best-fitted ellipse.

Experimentally, we have established that numerous formulas are required to yield more accurate results when measuring human body circumferences in apps driven by AI-powered technology. Equation 1 produces more accurate answers for ellipses with semi-major axes that are no more than three times longer than their semi-minor axes; otherwise, Equation 2 provides more accurate results when the ellipse is more squashed.

4 Result and Discussion

To effectively design a combined machine learning model with additional computer vision techniques, we require a well-trained dataset of sufficient size that has precise annotations (in our case, pairs of specific markers). Our study necessitates a compilation of human body images and their associated measurements for chest, bust, waist, and hip circumference. As there was, at the start of our research, an absence of pre-existing appropriate datasets, we created our own.

Participants in the dataset are volunteers who self-identified as female and are over 18 years old. According to several surveys, women purchase clothing on-line more than men, and thus we decided to focus our study first on women. In addition, based on our study and experiments, the average inaccuracy of various applications is greater for women than for men (Figure 1). Being more challenging, we decided to continue our research focusing on women. Thus far, we have collected for training purposes, a relatively small dataset, of 78 female body, representing a variety of body shapes and heights. Nevertheless, our results are promising.

Using tape measurements, "ground truth" references are obtained from each individual.[4] The participants were then photographed in various environments with different lighting, backgrounds, body posture, distance from the camera, and clothing types.

The photographs were taken with an iPhone 10 (or later) and a Galaxy S21, as these smartphones are representative of the most commonly used ones. In an effort to reduce human error, we have obtained our tape measurements in accordance with the procedures outlined in ISO 8559-1 [32], ISO 8559-2 [33], and ISO 8559-3 [34]. In addition, we received assistance from an experienced couture designer of fashion for women in London, Nevena Nikolova, who assisted us in obtaining our tape measures.

To improve the state-of-the-art in terms of accuracy, we first examined and compared different ellipse equations according to different human body shapes to verify and select the most accurate formulas, and then we used these for our light-weight

[4]Here "ground truth" corresponds to what fashion designers have traditionally be happy to use for centuries.

Algorithm 1 Human Upper Body Measurements

Require: Calibration failure flag

Ensure: Set of Measurements $\mathbf{M}$, where t^{th} row is the measurement around joint j_t

```
while Calibration = failure do
    Call findChessboardsCorners
    if User Detected then
        Affine correct (convert image to grayscale, smooth it, detect edges, thresholding)
        Skin Detection (HSV & YCbCr Color space)
        Isolate Human body from Surrounding Environments (ROI) using findContours(), boundingRect()
        Compute principal axes (u, v, w)
        Request users to Draw Circles
        Get head point
        Call analyzeChessboard
        if User calibrated then
            Save calibrated pose
            Call Calibration
            while Calibration = Success do
                Call getDistance
                for Joint label t = 1 to T do
                    if J_t is available then
                        Set automated point around body
                        Request semi-auto marker from user
                        Convert pixel unit to cm
                        Compute intersection points
                        Ellipse fitting to obtain m_t
                        if Semi-Major axes is not 3 times longer than Semi-Minor axes then
                            Use Equation 1
                            if m_t is available for all T joints then
                                Save M
                                Break
                            end if
                        end if
                        if Semi-Major axes is 3 times longer than Semi-Minor axes then
                            Use Equation 2
                            if m_t is available for all T joints then
                                Save M
                                Break
                            end if
                        end if
                    end if
                end for
            end while
        end if
    end if
end while
Print Perimeter
```

systems to calculate the human body measurements with the help of AI-Powered technologies. Later in this section, we will present the results of our studies.

The quantitative data for the 78 female participants were analyzed by using descriptive statistics and a t-test with two samples assuming unequal variances. Data description has been used throughout all phases of our data collection. The dependability of measured data is compared between Equations 1 and 2 using an t-test with two samples assuming unequal variances (Welch's t-test). Lastly, we also used a t-test to compare our software results to actual tape measures to ensure that we were able to improve the accuracy of the state-of-the-art. At each stage, the quantitative data were analyzed and compared in terms of the accuracy and reliability of each method and technique.

4.1 Ellipsoid Model Results

In this section, we present the results of a t-test analysis conducted to compare the accuracy of two ellipse-based formulas (Equations 1 and 2) for estimating upper human body circumferences. The t-test was chosen to determine if there is a statistically significant difference between the means of the two formulas, which represent the average difference to the tape measurements. Lower mean values indicate higher accuracy.

The sample mean for Equation 1 was 0.7578cm, and for Equation 2, it was 0.6647cm. The respective variances for these formulas were 0.2149 and 0.1981. The two-sample t-test yielded a t-statistic of 2.5585 and a degrees of freedom (df) of 621. The one-tailed p-value was found to be 0.0054, and the corresponding t-critical value for a one-tailed test was 1.6473. The two-tailed p-value was calculated as 0.0107, with a t-critical value of 1.9638 for a two-tailed test.

The t-test results indicate that there is a statistically significant difference between the means of the two ellipse-based formulas for estimating upper human body circumferences. The t Statistic (2.5585) is greater than the t Critical two-tail value (1.9638), and the two-tailed p-value (0.0107) is less than the significance level (0.05). These results support the conclusion that the two formulas are significantly different in their performance for estimating upper human body measurements. Since the mean value for Equation 2 (0.6647) is lower than that for Equation 1 (0.7578), it can be inferred that Equation 2 has a higher accuracy level in estimating upper human body circumferences.

Although Equation 2 offers better accuracy than Equation 1 on average, the descriptive statistics revealed that out of the 312 data points collected for human body circumferences (chest, bust, waist, and hips), Equation 1 provided more accurate measurements for approximately 35.9% of the instances, while Equation 2 was more accurate for the remaining 64.1% of the instances. This observation suggests that the accuracy of these equations varies depending on the specific body shape (horizontal slices), with one equation being more accurate than the other in minimizing the discrepancy between direct measurements and software-based estimations.

Based on our collected data from the participants, and by best fitting the human body shape (horizontal slices) by ellipses, we observed that for elliptic profiles such that their major axis were not more than 3 times longer than their minor axis, the stress level of Equation 2 ($M= 0.857$, $SD = 0.232$, $n = 112$) was hypothesized to be greater than the stress level of Equation 1 (M = 0.456, SD = 0.101, n = 112). This difference proved extremely significant: t(192) = -7.361, p = 5.19981E-12 (2 tail). Statistically, the differences between the groups are significant, as the p-value is significantly less than 0.05, and we can reject the null hypothesis (Figure 9).

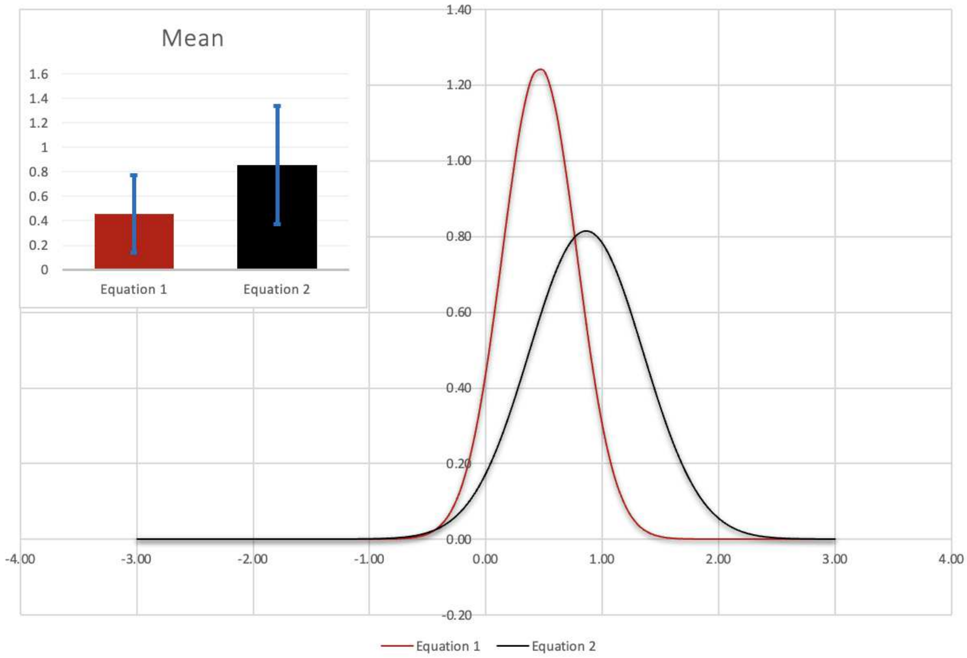

Fig. 9 Illustration of stress levels of each formula on a bell curve. It also presents the average variance and standard deviation for each formula when comparing the measurements of chest, bust, waist, and hip circumference obtained through direct (tape) measurements and our software. This comparison specifically focuses on elliptic profiles where the major axis is *at most* three times longer than the minor axis.

On the other hand, it was hypothesized that when the major axis of the body shape is three (or more) times longer than the minor one, the stress level of Equation 1 (M = 0.927, SD = 0.200, n = 200) would be higher than the stress levels of Equation 2 (M = 0.556, SD = 0.147, n = 200). This difference was highly significant: t(389) = 8.917, p = 1.89062E-17 (2 tail). Please refer to the bell curve below to see the data in more detail (Figure 10).

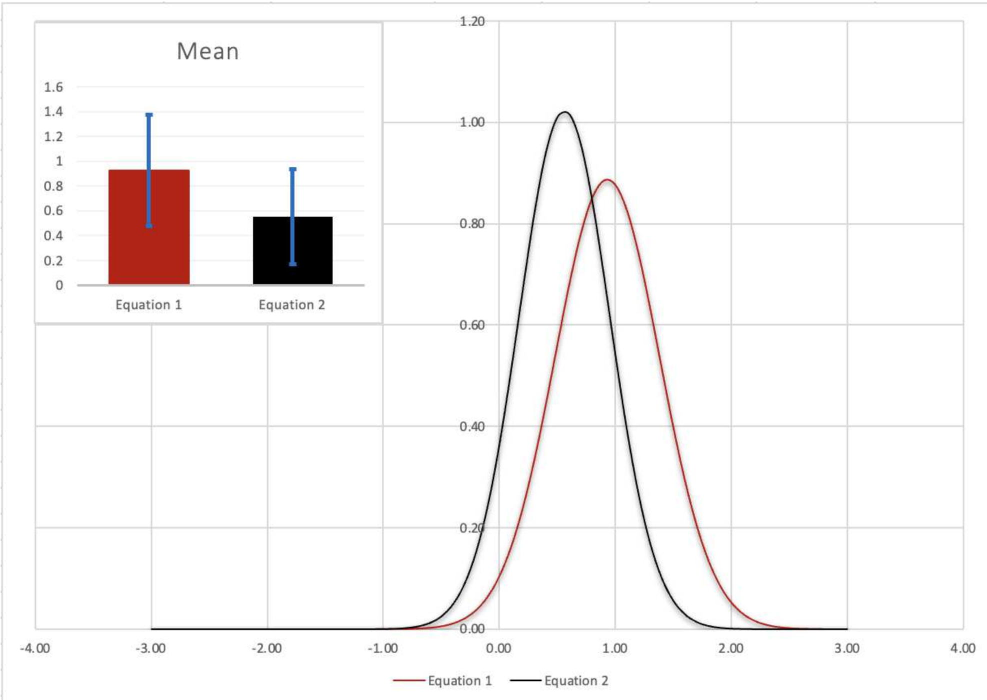

Fig. 10 Illustration of stress levels of each formula on a bell curve. It also presents the average variance and standard deviation for each formula when comparing the measurements of chest, bust, waist, and hip circumference obtained through direct (tape) measurements and our software. This comparison specifically focuses on elliptic profiles where the major axis is *more* than three times longer than the minor axis.

The following tables report on the mean, median, minimum and maximum differences as well as the standard deviation, for each equation according to different body shape.

Table 2 Summary of the average difference in measurement errors between our software and tape measurements for 78 female participants. The table presents the mean, median, minimum, maximum, and standard deviation of four body sections: chest, bust, waist, and hips. It highlights the statistical characteristics of the measurement variances between the two methods. The data in this table was collected using Equation 1.

Body Type	**Chest**	**Bust**	**Waist**	**Hips**
Mean Differences (cm)	0.73	0.7	0.85	0.75
Median Differences (cm)	0.77	0.71	0.77	0.76
Max Differences (cm)	2.39	2.48	3.01	3.02
Min Differences (cm)	0.01	0.01	0.02	0.02
Standard Deviation (cm)	0.46	0.4	0.47	0.51

Table 3 Summary of the average difference in measurement errors between our software and tape measurements for 78 female participants. The table presents the mean, median, minimum, maximum, and standard deviation of four body sections: chest, bust, waist, and hips. It highlights the statistical characteristics of the measurement variances between the two methods. The data in this table was collected using Equation 2.

Body Type	Chest	Bust	Waist	Hips
Mean Differences (cm)	0.62	0.71	0.61	0.71
Median Differences (cm)	0.62	0.7	0.57	0.65
Max Differences (cm)	1.73	2.21	1.75	3.4
Min Differences (cm)	0.04	0.02	0.04	0.03
Standard Deviation (cm)	0.35	0.43	0.36	0.59

These results indicate that, as a function of variations in body shape (horizontal slices), one formula is more accurate than others in minimizing the difference between direct measurement and software solutions. For body shapes with semi-major axes that are not more than three times longer than their semi-minor axes, or in other words, ellipses that are not overly elongated, Equation 1 provides more accurate results, whereas Equation 2 provides more accurate results for body shapes with semi-major axes that are more than three times longer than their semi-minor axes (alike squashed ellipses).

Furthermore, the t-test is used to compare direct measurements with our developed software. By utilizing two ellipse equations based on different body shapes, we were able to reduce the mean (average) inaccuracy to ±1cm, which is sufficient for a number of real-life applications.

4.2 Final Results

The quantitative data for the 78 female participants were analyzed by using descriptive statistics. We captured 2D images of each participant based on the following five scenarios:

1. with a plain background;
2. with a cluttered or textured background;
3. using a pair of different body postures (A-Pose and Relax Pose)
4. using different distances from the camera
5. Clothing that has creases

With 78 participants, this has resulted in an initial dataset with 312 data points.

Table 4 displays the average differences between measurements produced by our technique and those taken using a measuring tape for all 78 participants. Our upper human body measurements show an average variance of less than ±1 cm. Figure 11 also displays the error correlation for each individual participant.

Table 4 A summary of the differences between our software and tape-measured data for the 78 participants (312 total cases).

Body Type	**Chest**	**Bust**	**Waist**	**Hips**
Mean Differences (cm)	0.78	0.78	0.96	0.78
Median Differences (cm)	0.76	0.76	0.82	0.76
Max Differences (cm)	3.14	2.66	3.19	3.82
Min Differences (cm)	0.01	0.01	0.02	0.02
Standard Deviation (cm)	0.55	0.50	0.62	0.56

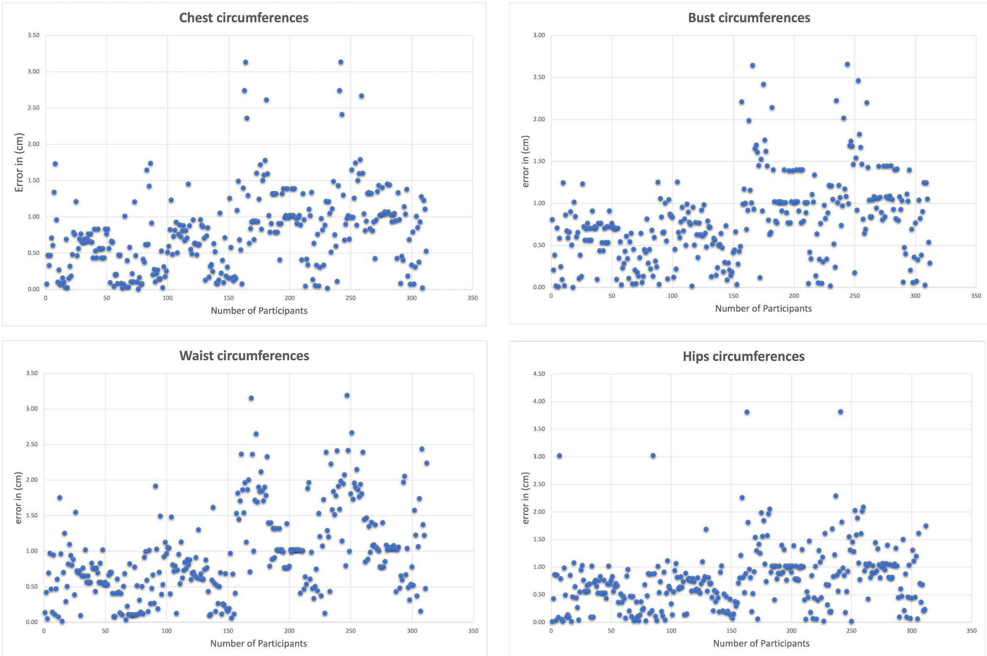

Fig. 11 The four plots correspond to the error difference for the circumferences of: chest, bust, waist and hips. Horiztonal axis is the participant number (ID) while the vertical is the error in cm.

From our detailed experiments, we noted that the maximum measured differences from ground truth occurred when a participant wore creased clothing, or when the camera's focal distance was rather close or rather far from the participant (i.e. either less than 0.5m or more than 3m). However, when the background was highly cluttered or when the lighting was not well diffused, our software's inaccuracy rose by an average of only 0.1cm demonstrating that our method is able to improve the image quality and reduce to adverse effects of noise.

The tests conducted in this research have demonstrated the significance of high-quality images being uploaded by the users. In general, current RGB cameras generate a high resolution for this type of application. Having clear directions and examples in a tutorial can alleviate challenging circumstances. Our experience has shown that this can lower the mean difference of our software by up to ± 0.5cm. From a designer's perspective, the ability to measure human body circumferences with an average difference of at most 1cm from the customer's body shape enables more efficient processing from raw materials to completed products and can significantly reduce returns and wastes.

Comparing our results with existing software and technologies in the market reveals several advantages of our system. Existing applications typically suffer from limitations such as the need for external devices like 3D scanners, which may not be easily accessible to all users. In contrast, our system utilizes a portable camera, such as a smartphone, making it more convenient and widely available. Additionally, some software solutions provide only coarse ranges of measurements, such as small, medium, large, XL, or XXL classifications used in retail. In contrast, our system aims for simplicity while maintaining sufficient accuracy. It does not require re-training or access to large datasets, relying on a pre-trained network solely for initial 2D image segmentation.

It is important to note that existing applications and software in the market have certain limitations and requirements. For instance, many of these applications require users to stand still for a few seconds without any movement, and some even necessitate a plain background for accurate measurements. Additionally, maintaining an optimal distance between the user and the camera is crucial, as standing too close or too far can affect the system's ability to scan and measure the human body accurately. In some cases, users are also required to provide their height information for calibration purposes. However, it has been observed that a significant number of users do not possess precise height information, which can impact the calibration process and subsequent measurements.

In contrast, our system aims to overcome these limitations by offering a more user-friendly and convenient solution. Our system does not require users to stand still for extended periods or against a specific background. It is designed to handle varying distances between the user and the camera, providing flexibility without compromising measurement accuracy. Furthermore, our system minimizes the dependency on user-provided height information, reducing the impact of inaccurate or unknown height measurements.

By addressing these limitations present in existing applications and software, our system offers significant advantages. Utilizing a portable camera, it simplifies the measurement process while maintaining accuracy. It eliminates the need for complex external devices like Kinect or 3D scanners, making it more accessible to a broader user base. Additionally, our system provides detailed measurements beyond coarse size classifications, enabling more precise fitting and customization.

Addressing the challenges faced by users, our system is capable of capturing the human body accurately regardless of the background, whether plain or cluttered. It accommodates various body postures, shapes, and distances between the camera and participants. Furthermore, our system can predict personal details like clothing to provide accurate measurements. However, it should be noted that our system is not designed for measuring garments like jackets and works best with certain types of clothing, such as shirts, t-shirts, and dresses.

In conclusion, our system for estimating upper human body measurements using computer vision and machine learning techniques demonstrates promising results. The study involving 78 female participants shows an average difference of ±1 cm compared to tape-measured data, with minimal deviations across different body circumferences. Our system's robustness against cluttered backgrounds and lighting conditions, coupled with its simplicity and accuracy, makes it a valuable tool for the apparel industry. Further improvements, such as providing clear directions and tutorials to users, have the potential to reduce the mean difference in software measurements up to ±0.5cm. Overall, our system offers a convenient and cost-effective solution for accurately capturing human body dimensions, contributing to more efficient processes in the apparel industry and reducing waste and returns.

5 Conclusion

In this research, the proposed technique aims to improve and facilitate the experience of the E-Commerce apparel/fashion sector by providing a simple method for everyday people to estimate their characteristic human body measures from a pair of 2D smartphone images.

We provide our findings regarding the human upper body. While Junfeng et al. [29] previously stated that the ellipse is suitable for estimating human body cross sections including the torso and limbs, our results indicate that this method can be utilized to measure additional regions of the human body accurately enough for practical uses. It is hypothesized that a better approach to anthropometric measurements based on 2D images will provide sufficient accuracy for real-world applications, with an average error of less than one centimeter. To estimate human body circumferences, two different elliptical formulae are utilized based on variations in body shape (horizontal slices).

On 78 participants (who self-identified as female), these strategies allowed us to improve the state-of-the-art in terms of accuracy by a maximum of ±1cm (compared to tape measurement methods). In the future, we intend to remove entirely the dependency from a calibrating checkerboard and entirely automate the marker identification step. We shall also develop a larger database and test our system on a more diverse human body population, which will allow us to add more images and postures to the training set in order to improve the stability and accuracy of body shape extractions.

Supplementary information. If your article has accompanying supplementary file/s please state so here.

Authors reporting data from electrophoretic gels and blots should supply the full unprocessed scans for key as part of their Supplementary information. This may be requested by the editorial team/s if it is missing.

Please refer to Journal-level guidance for any specific requirements.

Acknowledgments. Acknowledgments are not compulsory. Where included they should be brief. Grant or contribution numbers may be acknowledged.

Please refer to Journal-level guidance for any specific requirements.

Declarations

- Funding: The authors did not receive support from any organization for the submitted work
- Conflict of interest/Competing interests: The authors declare that there are no conflicts of interest or competing interests associated with the research presented in this manuscript.
- Ethics approval: The ethical form for this study was approved by Goldsmiths University of London, allowing data collection from participants on 13/10/2021
- Consent to participate: Ethical approval for this study involving human participants was obtained from Goldsmith University of London, and informed consent was obtained from all participants prior to their involvement in the research.
- Consent for publication: All co-authors have provided their consent for the submission and publication of this manuscript.
- Availability of data and materials: The datasets generated or analyzed during the current study are available upon reasonable request. Researchers interested in accessing the data may contact [M.Montazerian@gold.ac.uk or F.Leymarie@gold.ac.uk]. for inquiries and collaboration opportunities. The datasets will be provided in Excel sheets to facilitate data sharing and reproducibility.
- Code availability: The custom code and software applications used in this study are not publicly available. The code has been developed for internal use within our organization and cannot be released for public distribution. However, we are committed to ensuring transparency and reproducibility of our research. For inquiries or further details regarding the methodology and implementation, interested researchers may contact [M.Montazerian@gold.ac.uk or F.Leymarie@gold.ac.uk].
- Authors' contributions: All authors contributed equally to the conception, design, and execution of the study, as well as the writing and revision of the manuscript.

Appendix A Error Correlation for the Five existing apps in details

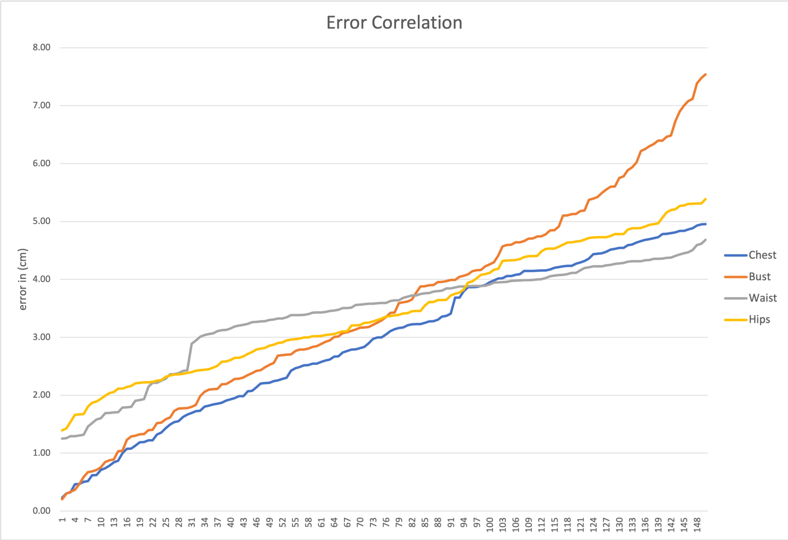

Fig. A1 Male Error Correlations

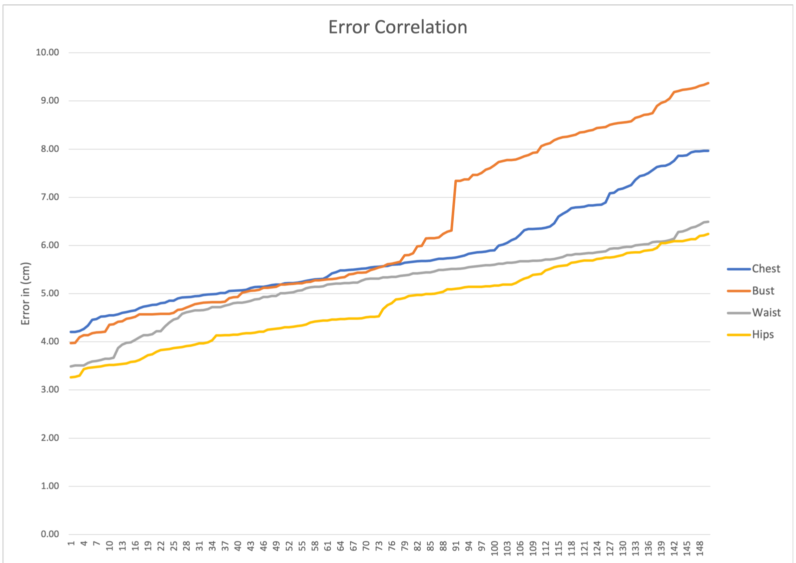

Fig. A2 Female Error Correlations

Appendix B Calculation of an Ellipse Perimeter

According to Yao *et al.* [29], the human body can be well approximated by a series of ellipses stacked vertically along a main body axis, seen as a number of horizontal slices. For any such slice, the circumference of the human body can be approximated using the equation for an ellipse. To determine the perimeter of the ellipse accurately, for which there are no closed-form solutions, we need to calculate the semi-major and semi-minor axes. In our study, we evaluated six different approximations from the literature, for evaluating the perimeter of an ellipse, with the aim of identifying a compromise between accuracy versus complexity [35–38]. In the main paper, we have discussed in detail two of these approximations Equation 1 and Equation 2. The remaining four approximations are provided below:

$$P = \Pi(dist_a + dist_b) \tag{B1}$$

$$P = \Pi\sqrt{2dist_a^2 + dist_b^2} \tag{B2}$$

$$P \approx \Pi((dist_a) + (dist_b))(1 + \frac{3h}{10 + \sqrt{(4 - 3h)}}) \tag{B3}$$

Where h is:

$$h = \frac{(dist_a - dist_b)^2}{(dist_a + dist_b)^2} \tag{B4}$$

$$P = 4\int_0^{\pi/2} \sqrt{dist_a^2 cos^2\theta + dist_b^2 sin^2\theta d\theta} \tag{B5}$$

It is evident from Figure B3 that the variations in the shapes of ellipses can have a significant effect on the accuracy of the final estimation. As a result, we have undertaken further investigations to determine the most suitable equations for our software, which will be specifically tailored to human body shapes.

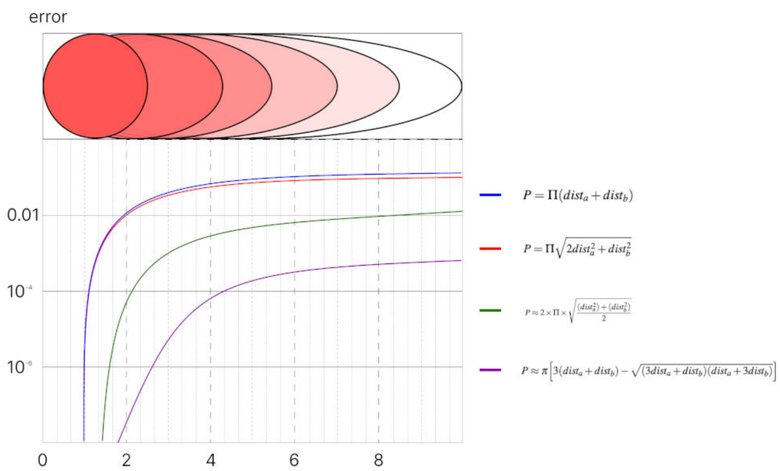

Fig. B3 A comparison of various formulae for the perimeter of an ellipse

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