Automated Extraction of Body Measurements Using Computer Vision

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Abstract

Extracting body measurements manually is a time-consuming and challenging process that can be impractical without the appropriate tools. This paper proposes a method to obtain body measurements, which can then be used in applications such as finding the perfect clothing fit. By leveraging computer vision, the developed system calculates body measurements from a photo submitted by the user, along with their height. Utilizing essential libraries and detailed digital image processing techniques, we successfully performed the calculations to return the user's body measurements. Test results demonstrate that the model achieves high accuracy, underscoring the efficiency of this approach and offering a swift alternative for obtaining body measurements. The developed method can be employed in numerous other applications that require precise body measurements.

Keywords

Computer Vision, Digital Image Processing, Body Measurement

1 Introduction

When individuals are aware of their body measurements, they gain valuable and essential information for various purposes, including health and fitness monitoring, sports performance analysis and tracking, and selecting the appropriate clothing. However, obtaining these measurements manually can be complex and, in some cases, impractical, especially without access to a tape measure or other essential equipment. In the context of health and fitness, body measurements are frequently used to assess an individual's progress toward specific goals. Parameters such as weight, height, waist circumference, body fat percentage, and Body Mass Index (BMI) are commonly monitored to determine the effectiveness of exercise programs and dietary plans. These measurements offer a comprehensive view of body fitness and help identify areas needing improvement, thus contributing to the prevention of lifestyle-related diseases [1].

Also, in the field of sports, body measurements play a crucial role in performance analysis and tracking. Athletes and coaches use data such as weight, height, muscle mass ratio, and body composition to evaluate performance, identify areas of weakness, and develop personalised training strategies. These measurements not only help maximise athletic potential but also aid in injury prevention, efficient recovery, and assessing whether an athlete has the ideal body measurements for their sport, as described in [2].

Additionally, clothing selection is influenced by body measurements. The fashion industry recognises the importance of properly fitting clothes, not just for aesthetics but also for comfort and performance. Accurate measurements ensure that garments fit properly, promoting freedom of movement. For athletes and fitness enthusiasts, appropriate sportswear can enhance performance by facilitating body temperature regulation and reducing friction during physical activity. Some studies, such as [3], objectively describe how clothing impacts physical activity performance.

In this context, the advantage of easy access to one's body measurements becomes evident. This work proposes a technological and accessible solution for extracting body measurements through computer vision techniques. The developed system can extract human body measurements from a single photo and the user's provided height, offering an efficient and convenient alternative to manual measurement. To demonstrate the broad applicability of the proposed approach, we have also developed a server-based service. Additionally, we built an application for clothing selection that queries this service, extracts the body measurements, and suggests the best clothing size according to the brand's size references and the user's preferences.

2 Computer Vision

It is important to differentiate between vision and image. The concept of vision generally refers to the perception or ability to observe something directly, while an image is a static visual representation, such as a photograph, painting, graphic, or any other form of visual depiction. Computer vision, an interdisciplinary field that combines computational techniques and image processing, finds its roots in this fundamental distinction between vision and image. While human vision involves the interpretation of visual information to understand the world around us, computer vision aims to enable computational systems to perform similar tasks. This is achieved through the analysis and interpretation of digital images, allowing computers to comprehend visual content and make decisions based on that understanding, for example, identifying objects, recognising patterns, and understanding depth and motion in a scene [4, 5].

Today, computer vision has achieved a high level of development, with a wide variety of libraries, algorithms, and frameworks dedicated to its use. This reflects the remarkable growth and sophistication of the field, providing professionals and researchers with the tools to explore and apply computer vision concepts in various domains, including medical diagnostic systems [6, 7], augmented reality [8], agriculture [9], sports [10], body measurement detection [11], and more.

2.1 Computer Vision Applied to Body Measurement

Computer vision offers a wide range of applications, one of which is the extraction of body measurements from 2D or 3D images. The process of extracting body measurements through computer vision involves utilizing 2D cameras (such as a smartphone camera), 3D cameras (such as LIDAR), or depth sensors (such as Kinect). These devices, combined with image processing algorithms, enable the identification and quantification of human body characteristics such as height, hip width, limb length, and other parameters. The quantity and accuracy of the extracted parameters often depend on the quality and method of image capture, as well as the algorithm used or developed.

These measurements can be utilised in a variety of applications, ranging from assessing a patient's health status (analysing body mass) [1] to personalising clothing or sports equipment (estimating body measurements and comparing them with those indicated by clothing and sports equipment manufacturers). This demonstrates the extensive potential of this technology. Also, computer vision in the context of physical training [12] stands out as a crucial ally, playing a significant role in enhancing the quality of training. From precise movement analysis and tracking to personalised performance evaluations, injury prevention, and integration with augmented reality, computer vision emerges as a catalyst driving the physical training landscape. It allows individuals to train autonomously without the need for professional support and serves as a powerful tool for those with existing knowledge to achieve new milestones and overcome challenges.

2.2 Digital Image Processing

Firstly, it is essential to understand the role of pixels in the context of image processing. Pixels, short for "picture elements", are the fundamental building blocks of a digital image. Each pixel represents a tiny point in a grid, and the meticulous combination of millions of these points results in the image we view on our electronic devices [13]. These individual points carry information about color and light intensity, serving as the essential components of any digital image. Image processing encompasses a set of techniques and algorithms used to manipulate these pixels. This can include enhancing image quality, extracting useful information, and performing specific tasks such as pattern recognition or object detection [14]. Understanding the fundamentals of pixels and image processing techniques leads us to explore a vast array of applications, from refining photographs to designing advanced systems like those in computer vision. This also opens up various application possibilities, such as in facial recognition algorithms [15].

In this context, it is crucial to highlight the importance of image processing for the development of computer vision algorithms. Numerous libraries assist with various image processing tasks. In the context of this work, we will discuss some widely used and relevant libraries for computer vision, highlighting their key characteristics and functionalities. The libraries used include the Open Source Computer Vision Library (OpenCV) for image processing and edge detection algorithms, MediaPipe for image segmentation and pose estimation algorithms, and NumPy for body measurement calculations.

The **OpenCV** library[1] is a widely recognised and respected tool in the field of image processing and computer vision, offering a comprehensive set of tools for various computer vision tasks. Its open-source nature allows developers to modify and customise the code according to project-specific needs, while its multi-platform compatibility ensures scalability and accessibility across different devices and operating systems. Additionally, OpenCV's integration with other popular libraries and frameworks, coupled with abundant documentation and learning resources, makes it a solid choice for developers seeking a robust and flexible solution for image processing and computer vision applications. A prime example is its widely used Canny edge detection algorithm.

The **MediaPipe** library[2], an open-source library developed by Google, provides pre-built components for various image and video processing tasks, enabling developers to create applications for object detection, facial recognition, hand tracking, pose estimation, and other computer vision and machine learning functionalities. One of its key features is MediaPipe Pose Detection, which uses Convolutional Neural Networks (CNNs) to extract specific landmarks from the human body and trace its skeleton, offering 33 landmarks for various applications. Figure 1 shows an illustration of the 33 landmarks extracted using MediaPipe. The library's efficiency in estimating human poses and the abundance of landmarks were primary factors in its selection for this project. Additionally, MediaPipe offers image segmentation capabilities, allowing for the division of images into regions, such as isolating the human body from the rest of the photograph.

The **NumPy** library[3] is an essential library for numerical processing in Python, especially for mathematical operations on images. It provides a wide range of powerful features for handling multidimensional arrays, including matrix operations and advanced indexing. One of NumPy's main advantages is its extensive collection of array manipulation functions, which include basic arithmetic operations, advanced mathematical functions, shape adjustment, and size manipulation, among others. Its simple and efficient syntax enables the concise execution of complex operations. In the specific context of image processing, NumPy is often utilised for tasks such as filtering, geometric transformations, histogram manipulation, and gradient calculation. Its capability to handle multidimensional arrays facilitates the representation and manipulation of images as matrices, which is crucial for the efficient implementation of image processing algorithms.

3 Body Measurements Extraction using Computer Vision

This work proposes an approach for extracting body measurements using computer vision, which can be utilised in a variety of applications. The benefits of easily accessible body measurement extraction

[1]https://opencv.org
[2]https://developers.google.com/mediapipe
[3]https://numpy.org/

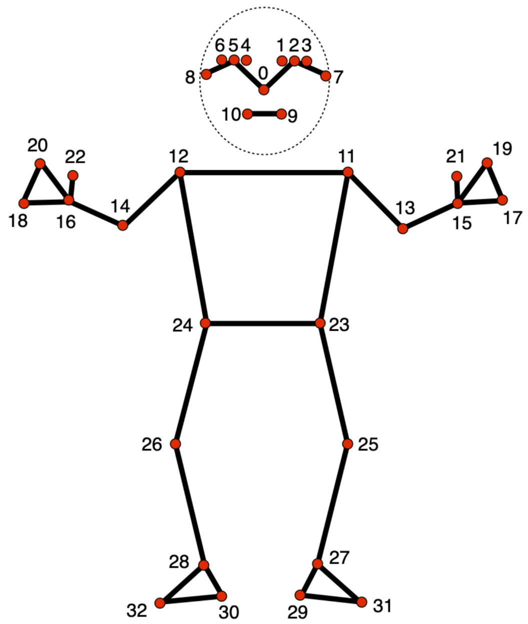

Figure 1: Landmarks extracted by MediaPipe Pose Detection.

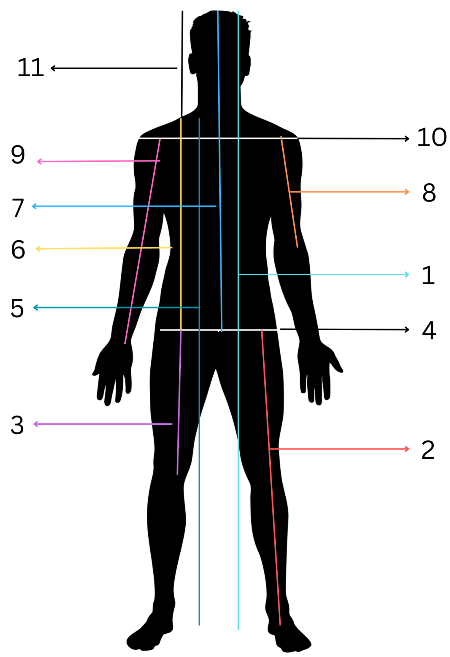

Figure 2: Extracted Body Measurements.

algorithms are evident. Such techniques can enable pragmatic solutions for obtaining precise and convenient anthropometric data, spanning a variety of application areas from health to fashion.

In this work, an approach is proposed where measurements are extracted from a simple photograph of the user, along with their height measurement. Upon receiving this photograph, the proposed approach performs image segmentation, removing the background and leaving only the person's body visible. Next, the modified image is sent to the body measurement extraction algorithm, where the image is processed using edge detection and pose detection techniques, subsequently extracting a set of predefined measurements. The proposed approach was developed to process 2D photographs with a front-facing body position, correct proportions, and good lighting. These image characteristics ensure that the extracted body measurements are as accurate as possible. The measurements extracted by the approach proposed in this work are illustrated in Figure 2, and their descriptions are listed in Table 1.

As stipulated, along with the photograph, it is essential to provide the user's height. This information is crucial in establishing the correlation between pixels and centimeters within the image. We utilise the user's height, denoted by the line 1 in Figure 2. The decision to utilise height as a reference is justified by the widespread familiarity individuals have with their own height, as well as the fact that minor variations in this measurement have a diminished impact on the final results due to its broader scale compared to other measurements.

In the developed methodology, following the segmentation of the user's photograph, it undergoes processing using OpenCV. The image is read and converted to grayscale to enhance performance, as this reduces the volume of data to be processed, thereby accelerating algorithms that do not rely on colour information, such as edge detection (Canny) and pose detection (MediaPipe). Afterward, edge detection is executed using OpenCV via the cv2.Canny function. Subsequently, the MediaPipe library is utilized to detect the pose, providing the requisite information to extract the body measurements intended for this study.

To derive body measurements, it is imperative to pinpoint the specific body part to be measured, thereby directing the appropriate technique for application. For instance, let us consider extracting measurement 7 from Table 1, necessitating the extraction of both pose points and edges, as delineated in the subsequent steps:

(1) Obtain the landmarks for the left hip, right hip, and nose. The landmarks are reference points obtained through pose detection, as depicted in Figure 1, corresponding to landmarks 23, 24, and 0, respectively.
(2) Calculate the midpoint of the hips (the average of the x and y coordinates of the left and right hip landmarks). Essentially, identify the coordinates of the right and left hips, divide by 2 to find the center of the hips. This allows extracting a straight line from the hips to the nose (the first segment of the measurement to be extracted).
(3) Convert the coordinates of the hip midpoint and the nose from normalized coordinates to pixels. The landmarks are represented as normalized coordinates, meaning values between 0 and 1, where (0,0) represents the top left corner of the image and (1,1) represents the bottom right corner.

Table 1: Extracted Body Measurements.

No.	Measurement (Length)	Description
1	Height	Distance from the top of the head to the bottom of the feet
2	Leg Length	Distance from the hip to the foot
3	Knee Length	Distance from the hip to the knee
4	Hip Width	Distance from one hip to the other
5	Leg + Trunk	Distance from the foot to the shoulder
6	Trunk	Distance from the hip to the shoulder
7	Trunk + Head	Distance from the hip to the top of the head
8	Sleeve Length	Distance from the shoulder to the elbow
9	Arm Length	Distance from the shoulder to the wrist
10	Shoulder Width	Distance between the shoulders
11	Neck to Head	Distance from the base of the neck (end of the trunk) to the top of the head

Therefore, before converting to pixels, the normalized coordinates are multiplied by the dimensions of the image (width and height) to convert to pixel coordinates in the original image.

(4) Calculate the vertical distance between the hip midpoint and the nose in pixels. This measurement corresponds to the first segment of measurement 7.
(5) Calculate the vertical distance from the nose to the farthest edge above the landmark (representing the top edge of the head) is calculated, thus obtaining the final segment for measurement extraction. Note that there is no landmark at the top of the head, hence the need to combine measurements between landmarks (or lines established by them) and edges. Edges can be easily verified in the processed image through the Numpy library using the `np.zeros` function, where the matrix formed by edge detection is used as a parameter, and the implementation finds the edge element farthest from the nose landmark, indicated by the top of the head.
(6) With this distance obtained, it provides the pixel length from the hips to the nose and from the nose to the top of the head. The distance in centimeters is then calculated using the `foundPixels` function, which calculates the number of pixels per centimeter the image has based on the user's provided height and the pixel height extracted from the proposed approach, i.e., measurement 1 from Figure 2. The calculation of pixels per centimeter is performed according equation (1). With the pixel-to-cm ratio, the obtained pixel distances can be calculated.

$$Pixels/cm = \frac{Height\ in\ cm}{Height\ in\ pixels} \tag{1}$$

(7) With the distances obtained, it provides the pixel length from the hips to the nose and from the nose to the top of the head. To convert this distance to centimeters, multiply the pixel distance result by the value returned by the `foundPixels` function.
(8) Finally, return the sum of the two previously calculated distances, which represents the total distance between the hips and the head in centimeters. This is the final result of the extracted measurement.

A distinct methodology is employed for each extracted measurement, with measurement 7 encompassing all essential techniques. For example, in computing hip width, denoted as measurement 4 in Table 1, landmarks corresponding to the left and right hips are utilised, and the nearest horizontal edges to these landmarks are identified accordingly. Certain measurements are contingent upon previously derived values. For instance, measurement 11 from Table 1 is determined by the difference between the measurement from hip to head and the measurement from hip to trunk yields the measurement from neck to head. Furthermore, for height validation, the combined results of the measurements from hip to head and leg length are scrutinised. This cumulative measurement must precisely match the height input by the user.

At the conclusion of the extraction process, the body measurements outlined in Table 1 are obtained. The proposed methodology distinguishes itself through its simplicity of inputs, requiring solely a photograph and a reference measurement (height). It can seamlessly integrate into numerous applications without necessitating substantial computational resources. Furthermore, it can potentially evolve into measurement extraction services, a concept elaborated upon later in this document. In all these scenarios, the methodology demonstrates promise in efficiently collecting anthropometric data in a practical and precise manner. Its efficiency and accessibility are particularly noteworthy characteristics, as will be further evidenced in the subsequent results.

3.1 Implementation

The body measurement extraction algorithm was implemented using three main libraries: OpenCV, MediaPipe, and NumPy. OpenCV plays a fundamental role in image processing. It loads the image in a compatible format for processing with NumPy, provides the Canny edge detection algorithm, and allows manipulation of the image as numerical matrices, thereby facilitating processing operations. OpenCV is also utilised for image standardisation to apply the pose model from MediaPipe and for edge detection via the cv2.Canny method, which is crucial for the precise identification of body features. NumPy is utilised for mathematical operations, particularly for calculating distances between points and edges. MediaPipe provides landmarks representing the skeleton of the person in the image, with 33 indexed points for normalised coordinates. NumPy enables mathematical operations between these landmarks, allowing for distance calculations and estimation of missing measurements. For instance, when calculating hip width, where landmarks do not cover the entire region, NumPy assists in finding the nearest horizontal edges for accurate measurements. Additionally, MediaPipe offers image segmentation, which segments the body from the background, resulting in an image with a white background. This step is essential before applying the measurement extraction algorithm.

3.2 Service Abstraction

To enhance the versatility and evaluate the developed approach comprehensively from both a general and application-specific standpoint, the proposed approach was transformed into a service, underscoring its broad applicability. By configuring the developed body measurement extraction approach as an API on the application side, its utilisation becomes straightforward. This service abstraction allows seamless integration of the approach into various platforms, such as web applications.

The extracted measurements find utility in diverse contexts. For instance, they can be leveraged to develop applications in the clothing sector, focusing on suggesting ideal clothing based on user measurements provided on the application side. Detailed presentation of such applications will be provided in the subsequent section. Notably, the developed service exhibits potential utility beyond clothing applications. It could also find use in applications analysing changes in body measurements, such as weight loss or muscle gain tracking, or even in monitoring a child's growth trajectory over time.

3.3 Clothing Application

The fashion industry plays a pivotal role globally, particularly with the rise of online shopping platforms. Consumers prefer online shopping over physical stores and online purchases are increasing significantly. Given this shift in consumer behavior, understanding body measurements has become imperative, especially in the realm of shopping for clothing and sports apparel online. This necessity arises from the inability to physically try on items before purchase. For instance, diverse legislation grants consumers the right to withdraw from a contract within few days of signing or receiving the product or service, particularly for purchases made outside physical establishments.

Thus, having knowledge of one's body measurements while shopping online offers benefits to both consumers and businesses. For consumers, it ensures greater precision in selecting the correct size, leading to fewer frustrations and returns. For retailers, it can significantly reduce return rates, lower logistical costs, and enhance customer satisfaction. Given the relevance of the developed body measurement extraction service in the clothing context, a clothing application was created utilising the proposed approach. In this clothing application, users submit their photograph and height. The application then computes their body measurements, compares them with the clothing size charts provided by the corresponding online store, and suggests the most suitable clothing size.

Figure 3 illustrates the application flow. Initially, as described, the user submits their photograph and height, serving as input data for the application. Using this information, the application queries the body measurement extraction service, which returns the extracted measurements, as previously presented in Table 1. Subsequently, the application filters the returned measurements, retaining only those relevant to the context of the application. The pertinent measurements are then fed into a fuzzy system that infers the best clothing size for the user based on the reference measurements provided by the brand/company during the application setup. Figure 4 exemplifies the fuzzy set modelling process for t-shirt size.

At the end of this process, the application suggests the ideal clothing size, with an option for customisation based on fit preference. Users can indicate whether they prefer tighter or looser clothing, enabling the system to adjust the suggestion accordingly, especially when inferring similar relevance for closely related sizes. For instance, if the system infers similar relevance for sizes S and M, with relevance scores of 0.7 and 0.65 respectively, and the user prefers looser clothes, suggesting a size M would be appropriate due to the marginal difference in relevance calculated by the inference system.

This technology can seamlessly integrate into virtual store applications, offering a more personalised and convenient shopping experience. Consumers can specify their preferred clothing fit and receive a personalised recommendation from the application. By implementing the body measurement extraction approach in a clothing application, accurate clothing size suggestions considering individual fit preferences have been achieved. This enhancement is expected to provide a more satisfying and personalised shopping experience for users.

4 Results and Discussion

To assess our body measurement extraction approach performance, we manually extracted 15 body measurements, as described in Table 1, from 15 voluntary participants. The photographs and participants' heights were provided as inputs to the algorithm, enabling a comparison between the measurements extracted by the algorithm and the participants' actual measurements. The results of this analysis, indicating the error range between the extracted and actual measurements for each considered dimension, are presented in Table 2.

Table 2: Error Relationship between Extracted and Actual Measurements.

Measurement	Error interval (cm)
Height	0
Leg Length	1-3
Knee Length	1-3
Hip Width	1-3
Leg + Trunk	1-3
Trunk	1-3
Trunk + Head	1-3
Sleeve	1-3
Arm Length	1-2
Shoulder Width	1-3
Neck to Head	1-3

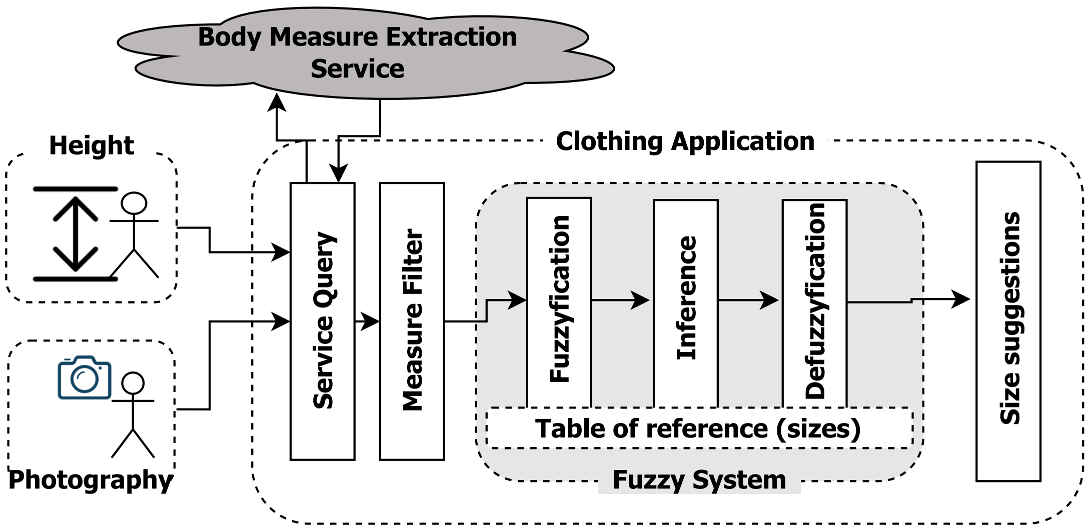

Figure 3: Clothing Application Diagram.

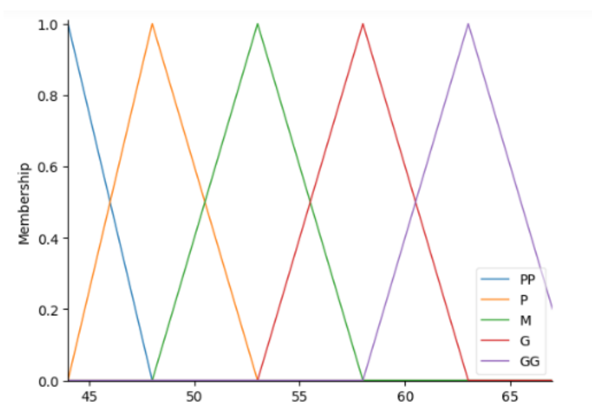

Figure 4: Fuzzy Sets for T-shirt Size.

Table 3: Average Results of Measurements Obtained in Centimeters.

Measurement	Real Average	Extracted Average
Height	173.12	173.12
Leg Length	87.93	86.05
Knee Length	37.26	37.71
Hip Width	36.00	36.19
Leg + Trunk	143.60	141.49
Trunk	55.87	55.49
Trunk + Head	85.23	87.23
Sleeve Length	24.47	22.74
Arm Length	49.40	49.09
Shoulder Width	42.20	43.22
Neck to Head	29.67	31.72

From this analysis, the following observations stand out: (i) The slight discrepancy observed in leg length extraction can be attributed to variations in hip position, as the algorithm occasionally identifies the hip slightly above or below the real position. This issue also influenced the extraction of measures that require this identification, such as trunk, trunk + head, leg + trunk, etc. However, this variation resulted in an insignificant difference, indicating the algorithm's good precision in calculating these measures; (ii) The variation between 1 and 3 centimeters in knee length extraction can be attributed, in part, to variations in hip position, similar to what occurs for leg length, as well as the identification of the knee's starting point. The algorithm occasionally locates the knee slightly below the real position, especially for participants wearing pants; (iii) The variation of 1 to 3 centimeters in sleeve length extraction is related to the identification of the elbow position; occasionally, the algorithm recognises the elbow position before the real position, resulting in a shorter length than the actual one; and (iv) Measures like neck to head length in the algorithm are derived from other measurements. The accuracy of this measure depends on the accuracy of the previous ones.

For a more comprehensive analysis, we calculated the averages of the actual measurements and the extracted measurements based on the data from the 15 participants in the evaluation. This analysis aimed to ascertain the average size of the participants' measurements and compare the error with these measurements. If the error is only a few centimeters and the measurement being analysed is large, it indicates a small error. The average values were obtained by separately calculating the average of the actual measurements and the average of the extracted measurements. Table 3 displays the average results of the measurements. Comparing the values reveals that, overall, they are quite similar, with minimal differences between them.

Also, we calculated the Mean Error (ME), which is a simple measure indicating the average of errors in relation to correct values. It was one of the metrics used to assess whether the model evaluated body measurements above or below expected values for each measurement. A negative result indicates that the detected body

Table 4: Comparison Table of Body Measurements by Height.

	Height <= 170		Height > 170	
Measurement	**Actual Average**	**Extracted Average**	**Actual Average**	**Extracted Average**
Height	166.00	166.00	178.00	178.00
Leg Length	84.50	82.65	90.22	88.32
Knee Length	36.50	36.25	37.78	38.68
Hip Width	35.50	35.60	36.33	36.59
Leg + Trunk	136.17	134.71	148.56	146.01
Trunk	52.00	52.39	58.44	57.57
Trunk + Head	81.33	83.36	87.67	89.81
Sleeve	23.67	21.36	25.00	23.66
Arm Length	48.17	47.87	50.22	49.91
Shoulder Width	40.17	40.74	43.56	44.88
Neck to Head	29.33	30.97	29.89	32.23

measurement is larger than the expected value, while a positive result indicates it is smaller. Equation (2) represents the calculation of the Mean Error (ME), where y_i is the observed value and $\hat{y}_i$ is the predicted value.

$$ME = \left(\frac{1}{n}\sum_{i=1}^{n} y_i\right) - \left(\frac{1}{n}\sum_{i=1}^{n} \hat{y}_i\right) \tag{2}$$

As observed in Table 5, there is a variation between -2.10 and 2.10. Overall, the mean errors are relatively small. This analysis suggests that for both positive and negative values, discrepancies are generally minimal. Another point to note is that leg length tends to be underestimated, while hip width and head length present values higher than expected. This difference may be related to the hip position, where the error in one measurement can compensate for the error in another.

Table 5: Mean Error Between Extracted and Real Measurements.

Measurement	Error (cm)
Height	0
Leg Length	1.88
Knee Length	-0.44
Hip Width	-0.19
Leg + Trunk	2.10
Trunk	0.37
Trunk + Head	-2.10
Sleeve	1.72
Arm Length	0.30
Shoulder Width	-1.02
Neck to Head	-2.06

For a more detailed analysis of the algorithm's accuracy, the data were divided into two height groups: height less than or equal to 170 cm and height greater than 170 cm. The shorter height group consisted of 6 individuals, while the taller group included 9 individuals. The average values of the actual and extracted body measurements for each group were calculated. Table 4 presents the relationship between the extracted averages and the actual averages for the measurements considered.

The results reveal a strong correlation between the measurements extracted by the algorithm and the participants' actual measurements, underscoring the effectiveness of the algorithm in body measurement extraction. The close proximity of the algorithm-calculated measurements to the actual measurements highlights the precision and reliability of the proposed method. However, certain aspects merit discussion. Throughout this work, we delved into the process of body measurement extraction, particularly understanding the relationship between pixels and centimeters derived from image height. It's crucial to emphasize that this relationship significantly influences the accuracy of the results. Notably, a substantial error in the person's height, whose measurements are being extracted, can lead to inaccurate measurements. Conversely, providing an accurate height tends to yield more precise results.

5 Related Work

In [16], the authors describe an approach to automated measurement of body dimensions using 3D body scanners and present neural network models to predict body sizes, which are then used for clothing customisation. In summary, the study explores the use of neural networks and 3D body scanners to improve size prediction and clothing customisation.

In [17], the authors focused on estimating body measurements through photographic analysis using CNNs. Using 2D photographic images, the proposed work estimates BMI through CNNs. Anthropometric data and photographs of 161 participants from Cameroon and Senegal were collected. The images were preprocessed to generate simplified silhouettes (image segmentation, turning the background white and the entire body of the person black) to facilitate the training of the machine learning model. The study concludes that using CNNs on photographic images may be a viable and efficient approach for estimating BMI in large populations.

In [18], the authors utilise a CNN called Body Measurement network (BMnet), specifically developed to estimate three-dimensional anthropometric measurements of the human body from 2D silhouette images. BMnet is trained with data from real individuals and enhanced with the use of an Adversarial Body Simulator (ABS), allowing it to handle a variety of body shapes. BMnet takes as input two silhouette images of a person (one front-facing and the other side-facing), which are combined to form a single input image. Additionally, height and weight information of the individual are included as metadata. Following this data input step, feature extraction, measurement regression, and enhanced training are carried out, respectively, resulting in promising outcomes in estimating body measurements in real-world scenarios.

In [19], the authors address the measurement of swine body dimensions. Using sophisticated cameras, they obtained high resolutions images, enabling the calculation of pixels per cm. Subsequently, they processed the images to remove the background and reduce noise, converting them to grayscale and applying filters to enhance processing. They then processed the data to highlight the contours of the swine, removing the head and tail. In this process, they developed a method to identify key points, enabling precise extraction of body measurements. To validate the algorithm's accuracy, experiments were conducted using swine images and manual measurements. The results showed that the algorithm had high accuracy in extracting body measurements, with a low relative error compared to manual measurements.

6 Conclusion and Future Work

In this paper, we presented an approach for extracting body measurements from a 2D photograph of a person, using their height as a reference measure. To demonstrate its application in various scenarios, it was transformed into a service, emphasising its feasibility in practical applications, such as an application to find the ideal clothing size. The evaluation revealed that the technique employed in this study is both effective and accessible, allowing for the swift and precise acquisition of anthropometric data. As demonstrated in Section 4, the approach exhibits a good accuracy in predicting body measurements, with minimal variation between predicted and actual measurements.

The developed approach shows great potential for use in various applications, such as determining the ideal clothing size, tracking physical measurements for sports [12], and analysing measurements for disease purposes [1], among others. The algorithm's application in online clothing shopping enhances the customer experience by providing more accurate size recommendations based on the user's body dimensions. In the realm of physical fitness, leveraging the extracted body measurements enables tracking a user's physical progress over time, offering insights into muscle gain or fat loss. Such applications could be versatile, allowing users to track their progress effortlessly with just a photo, showcasing the technology's adaptability and convenience.

In our future work, we also intend to integrate machine learning techniques, which would enhancing the precision of the results. Machine learning models can address challenges such as camera angle distortion and improve the accuracy of body measurements estimation. For instance, using Convolutional Neural Networks (CNNs) can detect camera tilt and apply geometric corrections to normalise the image perspective. Supervised learning with labelled data can further refine the accuracy by training models to recognise distorted images and apply corrections automatically. Additionally, incorporating machine learning into measurement calculations can improve result accuracy, especially with regression algorithms trained on real measurement data. Predictive capabilities can also be explored, enabling the model to estimate a person's measurements based on provided data or even an image, showcasing the potential for advanced technological advancements in this field. Also, we intend to explore the proposed approach in embedded devices, such as those described in [20].

In conclusion, this work stands out for the simplicity of required inputs, accuracy of results, and speed in obtaining measurements. It also represents a promising tool for applications requiring reliable and fast body measurements, such as in the fashion, health, and sports industries.

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