

Systematic Review of AI-Based Approaches for Anthropometric and Fashion Landmark Detection in Body Measurement Estimation

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Abstract: This systematic review gives a detailed discussion of anthropometric landmark abstraction and dimension measurement techniques with a focus on their use in the Fashion and Apparel (F&A) industry. It starts with an overview of the leading object detection models and their application in the detection of garments and human body features. The review makes a clear distinction between fashion landmark detection, which aims at detecting key points on clothing, and anthropometric landmark detection, which isolates anatomical landmarks on the human body to obtain measurement estimates. Different measurement extraction techniques are addressed, which include 2D silhouette analysis, 3D body scanning, and mesh-based modeling to acquire standardized anthropometric parameters, which include lengths, breadths, depths, and circumferences. The originality of this review is that it is the first analytical framework that combines the two domains of anthropometric and fashion landmark detection that have been historically examined separately. The review fills the gap between the human body measurement estimation and clothing landmark abstraction by providing a cross-domain synthesis, which provides a unified view of algorithms, datasets, and evaluation metrics. Moreover, it compares new methods including classical machine learning methods and modern deep learning and ensemble methods, demonstrating the performance increase depending on the accuracy metrics like Mean Absolute Error (MAE) and Normalized Error (NE). The review identifies a clear research direction that is moving away the conventional computer vision pipelines to the data-driven deep learning solutions. In general, the review provides new knowledge that can be used to develop garment fit prediction, virtual try-on technologies, and intelligent apparel recommendation systems by incorporating anthropometric and fashion-based landmark detection strategies.

Keywords: Anthropometric Landmark Detection; Fashion Landmark Detection; Object Detection Models; Body Measurement Estimation; Deep Learning; Garment Fit Prediction; Virtual Try-On; Apparel Recommendation Systems

1. Introduction

Object detection has become one of the fundamental technologies in the fields of computer vision and image processing, especially in the context of human body detection. Object estimation is a task that requires the recognition of object instances in images or videos and classifying them as belonging to a particular class based on their location and size [1]. Object detection techniques are important in the fashion and apparel industry in the context of clothing recognition, garment detection, landmark localization, fashion recommendation, and visual search. Nevertheless, it is difficult to identify clothes in photographs because of the variety of textures,

materials, and styles of clothes. Thus, it is necessary to learn fast and accurate fashion object detection methods, and then proceed to the more challenging task of landmark detection.

The architectures that have been designed to detect objects can be broadly categorized into two: one-stage and two-stage detectors. One-stage detectors detect in a single network pass, which is optimal in speed, but two-stage detectors separate the process into sequential phases to enhance accuracy. Some of the most popular techniques used in landmark abstraction and measurement in object detection are discussed in this section.

- a. R-CNN: The Region-Based Convolutional Neural Network (R-CNN) is a two-stage detector, which starts with the selective search to generate candidate regions. These areas are resized and then subjected to a pre-trained CNN to extract features and then Support Vector Machine (SVM) classifiers to identify the presence of objects. Despite the fact that R-CNN is effective in detecting and classifying apparel in colorful fashion data with high reliability [2], it is characterized by high computational cost and reduced efficiency because of the large region processing.
- b. R-FCN: Region-Based Fully Convolutional Network (R-FCN) is more efficient because it uses fully shared convolutional layers and incorporates Region of Interest (RoI) pooling to generate class-independent bounding boxes. This is a balance architecture that is proposed by Dai et al. [3].
- c. YOLO: You Only Look Once (YOLO) framework by Redmon et al. [4] is a one-stage detector that processes the entire image at once. It breaks the image into a grid and estimates the bounding boxes and the probability of the classes at the same time. Subsequent iterations, such as YOLOv2, YOLOv3, and YOLOv4, improved detection accuracy and speed on a variety of apparel categories [4].
- d. SSD: The Single Shot Detector (SSD) proposed by W. Liu et al. [5] is another one-stage object detector that estimates the bounding boxes and class labels in a single step. It employs a set of filters of various aspect ratios to deal with objects of different sizes. Gabale et al. [6] have managed to use SSD in unsupervised fashion trend analysis of social media data, which shows its strength in applications related to apparel.
- e. Mask R-CNN: The Mask R-CNN (Matterport implementation) is a variation of Faster R-CNN that adds the object mask generation to the detection. It uses a RoI Align layer to match extracted features to input regions more accurately, which enhances the accuracy of segmentation. Yang et al. [7] used Mask R-CNN to identify functional areas of apparel, which increases the uniqueness of features obtained in various types of garments.

Object detection research in the context of the fashion and apparel industry can be characterized by two tasks that are closely related but distinct and are sometimes mixed up in the literature.

2. Fashion Landmark Detection and Anthropometric Landmark Detection

The former is concerned with determining the important points on clothes, whereas the latter is concerned with the identification of the anatomical points on the human body to estimate measurements. This work represents one of the earliest comprehensive efforts to review anthropometric measurement and fashion landmark detection in an integrated context. Generally, the perception of fashion can be divided into two major fields:

- Anthropometric Landmark Abstraction and Dimension Measurement, and
- Clothing Classification Fashion Landmark Abstraction.

Although a considerable amount of literature has focused on the apparel recognition and classification, the equally important field of human body landmark detection and dimensional measurement has been relatively under-researched. The author notes that this field is under-researched, even though it is applicable to accurate body modeling and estimation of garment fit. Despite some similarities in methodological basis, anthropometric and fashion landmark detection are fundamentally different in terms of focus, the former is concerned with the identification and measurement of anatomical landmarks on the human body, and the

latter is concerned with the identification and measurement of landmarks on clothing to classify and identify styles as shown in Table 1.

In order to have a complete and objective synthesis, the identification of relevant studies was done in a systematic search of major academic databases, such as Scopus, Web of Science, IEEE Xplore, and ScienceDirect. The search was conducted in 2015-2024, and the combinations of the keywords included 3D body scanning, anthropometric measurement, fashion landmark detection, pose estimation, and deep learning. Peer-reviewed journal articles and conference papers in English were only included. The studies were chosen according to their topicality in body measurement, landmark localization, or anthropometric applications in the field of apparel. Duplicates and papers that did not contain quantitative evaluation were eliminated. This process was done to make sure that the literature reviewed represents the technical development as well as the interdisciplinary nature of anthropometric and fashion landmark studies.

Table 1. An Overview of Prominent Inclusive Object Detection Architectures

Model	Learning Approach	Loss Function	Softmax Layer	End to end train	Platform	Language used
R-CNN [8] (Recurrent Convolutional Neural Network)	SGD and BP	Hinge loss, bounding box regression	Yes	No	Caffe	Matlab
SPP-net [9] (Spatial Pyramid Pooling)	SGD	Hinge loss, bounding box regression	Yes	No	Caffe	Matlab
Faster R-CNN [10] (Faster Recurrent Convolutional Neural Network)	SGD	Class Loss and Bounding Box regression	Yes	No	Caffe	Python
Faster RCNN [11]	SGD	Class Loss, Bounding Box regression and Semantic Sigmoid Loss	Yes	Yes	Caffe	Python/Matlab
Mask R-CNN [12]	SGD	Class log loss and Semantic Sigmoid Loss	Yes	Yes	TensorFlow/Keras	Python
YOLO [13] (You Look Only Once)	SGD	Object and background confidence, bounding box regression	Yes	Yes	Darknet	C
SSD [14]	SGD		No	Yes	Caffe	C++

(Single Shot	Class softmax
MultiBox	loss+bounding
Detector)	box regression

2.1. Anthropometric Landmark Abstraction and Dimension Measurement

The detection of landmarks has been a vibrant area of research because it is vital in prediction object tracking and detection. The fashion perception technology is extensive recognized, due to its importance in other fashion uses, including magic mirrors, 2D, 3D, and virtual try-ons [63]. Anthropometric landmark detection is a basic one step to estimate human features in image inputs preliminarily, aiding in the location of the region of clothing interest to be synthesized later. Therefore, perception in the fashion and apparel industry is the basis of higher research activities. This section primarily explores human body landmark detection as a measurement issue estimation. The discussion includes modern techniques, standard data sets, and performance differences in each field. Prior to the discussion of body landmark detection methodology, it is necessary to understand the input of the measurement extraction process, since outlined below as presented in Figure 1.

a. Measurement Extraction

Anthropometric measurements can be obtained from various sources, including 2D scans, 3D scans, and mesh models. Our focus revolves around two key anthropometric measurements distance, encompassing height, breadth, lengths, and depths, and circumference. A set of well-defined standardized anthropometric measures is outlined in Figure 1.

b. Measurement from 3D Mesh

When accessing the 3D mesh-fitted template, the number of vertices is known, each with semantic uniformity across all samples [14]. To compute distance measures, such as hip width, elbow-wrist, or bust width, the distances between these points are utilized. Circumference is calculated by determining the intersection between the 3D mesh and a plane, as illustrated in Figure (left part of the mesh).

c. Measurement from 3D Scan

Anthropometric measurements can also be directly obtained from a 3D scan. Focal points assist in acquiring distance measures along with circumferences. [13] Proposed computing circumferences from 3D point cloud data using convex hull.

d. Measurement from Image

If silhouettes are extracted from front and back views, measurements can be approximated by utilizing the distance between focal points on the silhouette (see figure). For instance, the waist breadth as the distance between T1 and T2, and the waist depth between U1 and U2 can be employed as major and minor axes to approximate the hip circumference as shown in Figure 2.

Human body measurements			
1 eye	12 forearm circum. L	23 weight	34 bicep circum. R
2 cervicale	13 forearm circum. R	24 height	35 shoulder breadth
3 shoulder-elbow L	14 neckbase breadth	25 BMI	36 elbow circum. L
4 shoulder-elbow R	15 thigh clearance	26 neck circum.	37 elbow circum. R
5 crotch height	16 wall-acromion distance	27 chest circum.	38 knee circum. L
6 tibial height	17 grip and forward reach	28 waist circum.	39 knee circum. R
7 chest depth	18 elbow-wrist L	29 thigh circum. L	40 neck base circum.
8 body depth	19 elbow-wrist R	30 thigh circum. R	41 neck circum.
9 thorax depth	20 hip circum.	31 calf circum. R	42 head circum.
10 chest breadth	21 buttock-popliteal	32 calf circum. R	43 trouser waist circum.
11 hip breadth	22 buttock-knee	33 bicep circum. L	44 iliac spine breadth

Figure 1. An example list of 44 standardized human body measurements. The measurements formed of distances (lengths, breadths, depths, and heights), circumferences, and soft biometrics (weight, height, Body Mass Index BMI) [23]

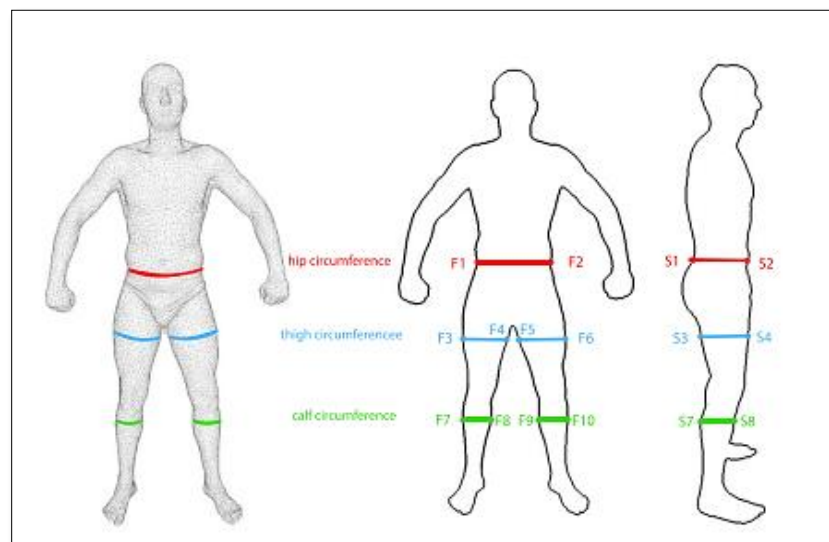


Figure 2. Body measurements on a 3D mesh (left) and correlating feature points on front- and side-view silhouettes (right). The feature points can be used to approximate the measurements. The mesh is generated using the SCAPE model [12]

2.2. Novel Methods for Body Landmark Detection

D. M. Anisuzzaman et al. [15] introduced the Kollman's distribution algorithm coupled with Canny Edge detection in 2019 to predict human body landmarks and shapes, aiming to optimize returns for online purchases. The proposed algorithm, incorporating pre-processing Canny Edge detection, derived dimensions such as neck, shoulder, waist, and length as 0.808, 1.478, 3.83, and 0.907, respectively, using a conventional camera to build a private dataset.

Tan Xiaohui et al. [16] put forth a system for personal body size recommendation and feature extraction using the Random Forest Regression (RFG) analysis approach. Analysis results indicated average errors of 1.33 cm for shoulder width and 0.76 cm for depth, with corresponding body shape categories as Slim (0.9354), Normal (1.3859), and Fat (0.6913).

Annalisa Baronetto et al. [17] proposed ResNet 18 and ResNet 34 architectures based on convolutional neural networks to estimate landmark detection for smart garments on 3D meshes. ResNet 34 demonstrated superior performance over ResNet 18, as measured by mean absolute error.

Xun Wang et al. [18] introduced an idea for dimension measurement on real images utilizing the Ellipse model referred to as ResNet. The ResNet model, entirely based on CNN, provided estimations for upper and lower body sides, achieving an accuracy of 98.60% for side images.

Iman Yi Liao et al. [19] suggested a human body detection algorithm with ImageNet dataset. Their model, the Attention-based Fashion-to-Body landmark Network (AFBN) had a highest classification accuracy of 0.38% and a mean landmark localization error of 0.225 where the classification accuracy is the percentage of correctly classified body parts and the mean error is the average distance between predicted and ground-truth landmark locations.

Eun Joo Ryu et al. [20] demonstrated focal points detection for the upper body on a Korean dataset, employing the Rhino and Grasshopper algorithm to classify landmark estimation based on human body physique.

Daud Ibrahim Dewan et al. [21] proposed 2-dimensional and 3-dimensional image measurements from simple depth cameras, incorporating edge detection and pose detection. Their reported accuracy stood at 81.47%. The results for all the methods, in terms of accuracy and Mean Absolute Error (MAE) related to human body landmark detection, are compiled in the provided Table 2.

Table 2. Review work on Body Landmark Detection Methods

Study (author year)	Problem Def. (What to do)	Dataset	Method/Technique	Accuracy	Error
D. M. Anisuzzaman et al., [15]	Landmark & Body shape prediction	Private data (name not mentioned)	Kollman's distribution algorithm with Canny Edge detection	-	RMSE: neck, shoulder, waist, length are obtained as 0.808, 1.478, 3.83 and 0.907
Tan Xiaohui et al., (2019) [16]	Auto feature extraction	3D Make Human Meshes	Random Forest Regression	-	Shoulder width (1.33), Depth (0.76), Slim: 0.9354 Normal: 1.3859 Fat: 0.6913
Annalisa Baronetto et al., (2021) [17]	Body landmark extraction for smart garments	3D meshes (MakeHuman software)	ResNet 18 and ResNet 34 based CNN	-	ResNet 34 outperforms over ResNet 18 Mean Error (ME) ResNet 34 (front): 3.38 ResNet 34 (back): 2.96

Xun Wang et al., (2020) [18]	Dimension measurement	Real images from laboratory staff	Ellipse Model, CNN, ResNet	Front image (head): 98.20% Side Image (front): 98.60%	-
Iman Yi Liao et al., (2022) [19]	Body Landmark detection	ImageNet	Deep NN, Attention-based Fashion-to-Body landmark Network (AFBN) model	Performance: 0.38	Mean Error: 0.225
Eun Joo Ryu et al., (2022) [20]	Estimation of upper body landmark	Size Korea data set	Rhino and Grasshopper algorithm	-	Standard Deviation values Obese: 2.0 Thin: 2.2 Normal: 2.7
Daud Ibrahim Dewan et al., (2022) [21]	2D image measurement	3D images from depth camera	Edge detection, pose detection	81.47%	-

2.3. Novel Methods for Body Measurement Estimation

Initially, Kaixuan Liu et al. [22] introduced a predictive model for computing body dimensions and creating patterns. They utilized a 3D body scanner on 120 young female participants from northeast China for input and learning anthropometric data. This paper presents a comparative analysis of machine learning techniques, specifically Back Propagation Artificial Neural Network (BP-ANN) and Linear Regression (LR). The results indicate that BP-ANN outperforms LR in predicting body silhouette and facilitating apparel making as presented in Figure 3.

Sahar Ashwami et al. [23] proposed a body estimation method using image processing and computer vision techniques. They estimated the size of online customers with Support Vector Machines and Haar cascade classifier, employing a simple smartphone camera for anthropometric measurements. The findings indicated that different body parts and genders had different accuracies. Joao W. M. de Souza et al. [24] suggested an ensemble model to predict body measurements with 2D images captured by a camera. They used classifiers like CNN with k-NN, SVM, Bayesian, decision trees, MLP, and EM on 38 subjects. The lowest mean squared error was obtained with Expectation Maximization, which shows better performance in the case of dense human pose estimation segmentation technique. Lining Wang et al. [25] proposed a data-driven method of measuring apparel with the help of Generalized Regression Neural Networks on the participants of the US Army. The comparison with other methods showed the R2 values, which showed the goodness of fit of various regression models. Stephven Kolose et al. [26] evaluated the precision of decision tree models in forecasting the size of shirts and trouser of the New Zealand army force. Both upper and lower body predictions were reported to have decision tree accuracy. The Skinned Multi Person Linear Body model (SMPL) was proposed by Nataniel Ruiz et al. [27] to estimate body measurements using silhouette images. BMnet using adversarial body simulator enhanced the performance of prediction on real bodies. Xuebo Liu et al. [28] proposed a hybrid method of 3D body measurement estimation with the help of Random Forest and XGBoost. Random Forest was found to be better than XGBoost in filling missing 3D body measurements following extensive comparative analysis as shown in Figure 4.

Abdul-Saboor Sheikh et al. [29] developed a deep learning system for size and fit estimation in the fashion and apparel industry, employing SFNet, Baseline, Bayesian models, and collaborative filtering technique. The study used ModCloth and RentTheRunWay datasets, with SFNet showing efficient results.

Nastaran Nourbakhsh Kaashki et al. [26] proposed a deep learning anthropometric measurement model from a single 3D scan using an encoder-decoder architecture. Multi-scale dynamic graph (DGCCN) with EdgeConv was introduced to learn local features, improving results on the ModelNet 40 dataset. Nastaran Nourbakhsh Kaashki et al. [31] utilized a photogrammetry-based scanner for automatic 3D anthropometric estimation. Their deep convolutional neural network with A-net complete and A-net partial models outperformed 3D-CODED-TM on synthesized datasets.

Song Yan and Joni-Kristian Kamarainen [3] proposed training on XXX-fit and CAESAR fit datasets using the SHAPE model and deep neural network. The obtained Mean Absolute Error (MAE) from CAESAR dataset was reported as minimum compared to XXX-fit as shown in Figure 5.

Dana Skorvankov et al. [3] focused on computer vision, deep learning, and neural network domains using 2D and 3D images. Their deep neural network approach on Conv BODIES and PC BODIES datasets for grayscale and binary images showed minimum error for convolution bodies on grayscale images.

Kristijan Bartol et al. [4] compared ground truth estimation methods on the CAESAR dataset for silhouette-based body measurement.

Further results were reported in a Table 4, Table 5, Table 6, Table 7, Table 8, Table 9 and Table 10 and the study investigated research questions related to purposes, issues, and motivations.

Table 3. Research Questions

RQ1.	Is there a comparative examination of machine learning and deep learning methods in the context of the fashion and apparel industry, and how does this industry influence the choice of one approach over the other?
RQ2.	What are the prospective considerations that should be addressed to advance and enhance the utilization of fashion input in the future?
RQ3.	In what tasks is Fashion & Apparel data employed for fitting prediction, and how has the utilization of this data evolved over time?

Table 4. Review Work on AI Approaches for Measurement Estimation

Authors	Problem Type (What to do)	Input Method	Dataset	Method/Technique	Model Performance
Kaixuan Liu et al., [22]	Body dimension calculation	3D body scanner	Participants from north east china	Back propagation ANN (BP-ANN), Linear Regression (LR)	Total Mean Squared Error (TMSE) BP-ANN: 2.06 LR: 3.60
Sahar Ashwa mi et al., [23]	Measurement estimation for upper, lower and full clothes (Computer vision and Machine Learning)	Simple Smart phone	Male: 34 Female: 26	Haar Cascade classifier, SVM	Upper clothes: 41% (male), 21% (female) Lower clothes: 72% (male), 28% (female) Full size

					Only female (28%)
Joao W. M. de Souza et al., [24]	Body measure prediction using 2D images	2D camera image (38 subjects)	Participants from health care	ML and CNN methods (Bayesian, k-NN, SVM, DT, Adaptive Boosting, RF, MLP, Expectation maximization classifiers)	Dense Human Pose estimation with EM: Mean Squared Error (MSE) 4.606 $\pm$ 3.412 cm
Stephven Kolose et al., [25]	Prognosis of military combat apparel sizing	Body Scanner Software	New Zealand Defence Force Anthropometry Survey (NZDFAS), n=154	Decision Trees	shirt size (58.1%), trouser size (61.7%)
Lining Wang et al., [26]	Anthropometric measurement prediction	-	US Army (ANSUR II)	Generalized Regression Neural Network (GRNN)	Average RMSE Without errors (5.1) With errors (6.2)
Xuebo Liu et al., [27]	Machine Learning enabled body measurement estimation		Participants from US Kansas-Missouri area	Random Forest, XG Boost	MAPE Random Forest (2.88%) XG Boost (3.85%)
Natanie I Ruiz et al., [28]	Measurement estimation (Computer vision and Machine Learning)	Real images	BodyM	Adversarial Augmentation by using BMnet model	MAE (29.13)
			Deep Learning		
Abdul-Saboor Sheikh et al., [29]	Deep learning for size estimation	3D scan images	ModCloth RentTheRunWay	SFNet, Naïve bayes, boosted tree, DL collaborative and content based modeling	Accuracy: Width (0.876 $\pm$ 0.003) (87%)
Nastaran Nourbakhsh Kaashki et [26]	Automatic measurement extraction from single 3D scan	photogrammetry-based scanner	ModelNet 40 (27 female, 25 males)	EdgeConv with Adam optimizer	Auc: 93.4% Model Size: 59 MB Time taken: 8.2 ms Average Absolute Error: 0.9

Song Yan et al., [31]	Benchmarking for silhouette body measurement	3D scan images	CAESAR scans, Body-rgb (86 male, 108 female)	Deep CNN	Large output, discussed in description table []
Nastaran Nourbakhsh Kaashki et al., [32]	Auto 3D measurement extraction	Photogrammetry based scanner	Anet Complete, Anet Partial	Deep CNN	Anet partial: (MAE is 6.7, Time 4.5 sec)
Song Yan and Joni-Kristian Kamarainen [33]	Anthropometry from rendered humans	3D scanned data set	CAESAR (Rendered RGB, Partial RGB)	Deep NN, Shape model	MAE: 6.9%
Dana Skorvankova et al., [34]	Automatic estimation (Computer vision and Deep Learning)	2D and 3D scanned data set	CAESAR	Deep NN for Conv-bodies, PC-Bodies	MAE: ConvBodies (Gray scale=4.64, Binary=7.60) PC-Bodies (4.95)
Kristijan Bartol et al., [35]	Self-estimation model (Computer vision and Deep Learning)	3D scanned data	BODY-fit, ANSUR	Linear regression model	MAE: 8.6

Table 5. Performance of State-of-The-Art Methods for Body Measurement Estimation using ANSUR Dataset [73]. The Best Performances are highlighted in Bold

Method	R ² value
Multi Linear Regression (MLR) [22]	0.764
Support Vector Regression (SVR) [24]	0.740
BP-ANN [27]	0.765
RBFN [27]	0.885
GRNN [3]	0.948
GRNN [28]	0.971

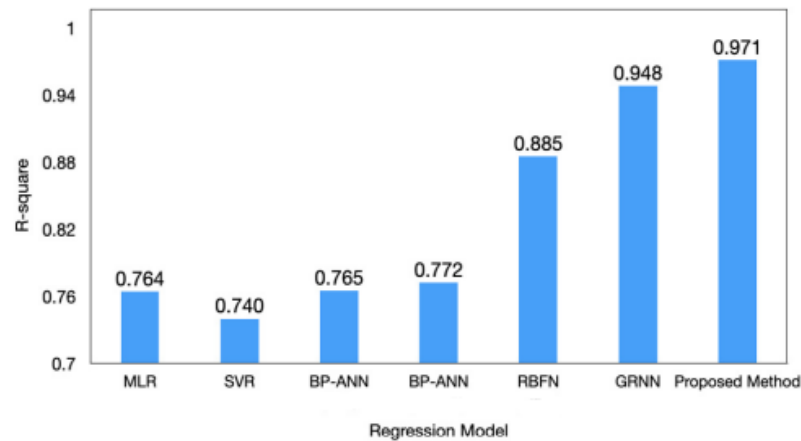


Figure 3. Evaluation of R^2 value for body measurement estimation using ANSUR dataset [22]

Table 6. MAE (mm) on different methods on BodyM dataset. The best performance are highlighted in bold

Measurements								
Study	Method	Ankle and arm	Bicep and calf	Chest and forearm	H2H and hip	Leg and thigh	Waist and wrist	Overall
Dibra et al. [18]	CNN	2 and 2.7	3.3 and 3.3	7.2 and 2.3	4 and 6	2.8 and 4.9	8.1 and 2	3.78
Smith et al. [16]	Multitask CNN	2.1 and 1.7	2.7 and 2.3	4.7 and 1.9	2.3 and 3	1.5 and 2.4	4.8 and 2.5	2.72
Nataniel Ruiz et al., [19]	Adversarial Augmentation SMPL	0.8 and 1.9	1.7 and 0.8	4.6 and 1.3	3.6 and 1.8	2.1 and 1.7	3.8 and 0.7	1.97

Table 7. MAE (mm) on different methods on Body-Fit dataset for male (top) and female (bottom) bodies. The best performance are highlighted in bold [18]

MAE					
Method		Chest	Hip	Leg Length	Waist
SPIN [11]	HMR (Many input)	75	65	35.81	77.39
STRAPS [12]	HMR (Many input)	82	64	48.71	108
Sengupta et al., [8]	HMR (Many input)	53	47.43	42.11	53.2
Nataniel Ruiz [17]	HMR (Single Input)	33.95	31.03	25.8	31.93

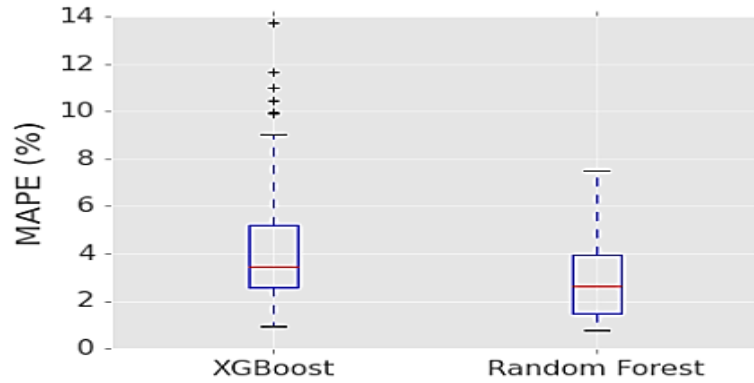


Figure 4. MAE (mm) on different methods on 3D Body Measure dataset. The best performance are highlighted in bold [14]

Table 8. Performance and Complexity of different models on ModelNet40 data set [25]

Model/Approach	Mean Class Accuracy (%)	Overall Accuracy (%)	Model Size (MB)	Time (ms)
PointNet [12]	86	89.2	40	3.9
PointNet++ [13]	-	90.7	12	10.6
PCNN [31]	88.1	92.3	94	380
DGCNN [22]	90.2	92.9	21	4.9
ModelNet40 [20]	90.8	93.4	59	8.2

Table 9. Mean Error on Synthesized data set [26]

Method	MARE (%)	MAE (mm)	Time (s)
3D-CODED-TM [31]	2.2	8.5	35
Anet-complete [32]	0.8	3.5	5.4
Anet-partial [33]	2	11	4.6
Anet-partial-clean [34]	1.3	6.7	4.5

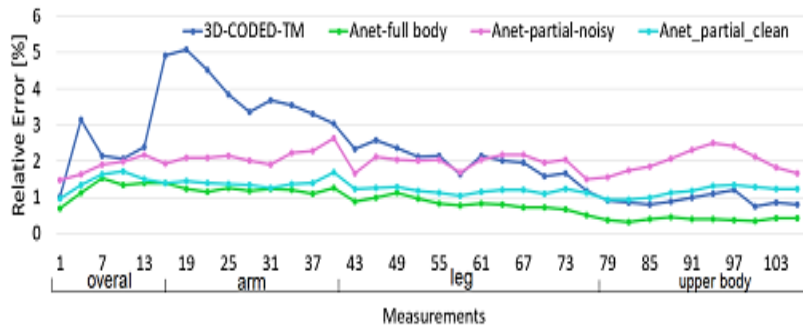


Figure 5. Mean Error on Synthesized data set [20]

Table 10. Mean Absolute Error (MAE) on CAESAR data set [27]

Method	Data set	Head and Neck	Shoulder and pelvis	Arm width and length	Torso Length	Bicep and wrist	Chest and waist	Leg length and calf	Inseam leg length	Thigh and knee	Mean
	Conv-BODIES	8.38 and 8.82	7.54 and 3.51	5.32 and 3.9	6.51	4.6 and 2.23	2.57 and 1.65	2.65 and 7.27	4.16	2.46 and 2.76	4.64
DNN [18]	PC BODIES	8.06 and 9.07	8.21 and 5.11	6.95 and 5.18	7.85	5.79 and 2.48	3.29 and 2.29	3.48 and 7.9	2.76	2.8 and 3.45	4.95

3. Evaluation Measures

While there are various performance evaluation metrics such as accuracy, sensitivity, specificity, precision, recall, time taken, and reliability, the absence of standardized measures complicates the comparison of diverse body measurement methods as shown in Table 11. Therefore, our emphasis is on accuracy, specifically measured through Mean Absolute Error (MAE), as it is predominantly reported in body estimation techniques. The Mean Absolute Error serves as an accuracy measure and is calculated between the body measurement estimation approach (Eest) and the ground truth (usually obtained from manual measures, Egt), as outlined in equation (1) below.

$$MAE = \frac{\sum_{i=1}^n |y_i - x_i|}{n}$$

Table 11. Performance Measures for Body Measurement Methods [28]

Author	Accuracy	MAE
Sahar Ashwami et al., [31]	28%	-
Stephven Kolose et al., [32]	61.7%	-
Lining Wang et al., [24]	-	6.2 %
Xuebo Liu et al., [22]	-	3.85%
Nataniel Ruiz et al., [21]	-	29.13%
Kaixuan Liu et a., [20]	-	2.06%
Nastaran et al., [78]	93.4%	0.9%
Abdul-Saboor Sheikh et al., [34]	87%	
Nastaran Nourbakhsh et al., [32]	-	6.7%
Song Yan et al., [32]	-	6.9%
Dana Skorv et al., [20]	-	4.64%
Kristijan Bartol et al., [19]	-	8.6%

3.1. Abstracting Fashion Landmarks for Apparel Categorization

Fashion landmark perception is an aspect of fashion and apparel industry that entails forecasting important points on clothes, which is essential in achieving a subtle depiction of various fashion images. This is a concept that marks important areas on contemporary fashion products such as edges or corners of cuffs, necklines,

shoulder lines, hemlines, waistlines, etc. These body landmarks do not just mark the areas of operation of apparels, but implicitly provide their bounding boxes, which are useful in differentiating the patterns of apparel designs with their corresponding categories in the best way possible. Essentially, the analysis of fashion images is highly supported by the extraction of body features in these landmarks. This process goes a long way to explain the differences between landmark prognosis and human pose analysis, which entails the identification of various joints of the human body as shown in Figure 6 (a). The estimation of landmarks is a more difficult task than human pose estimation, since garments are subject to non-rigid deformations, and body joints are subject to restricted and constrained deformations. Furthermore, the areas that are related to fashion landmarks have brighter and diversified looks compared to those related to body joints as shown in Figure 6 (b).

Figure 6. (a) The ocular difference between landmark prediction & pose estimation (b) The ocular difference between constrained and unconstrained landmark prediction [2]

3.2. Novel Methods for Fashion Landmarks Abstraction for Clothes Classification

The original idea of landmark detection was firstly presented by Z. Liu et al., [12] in 2016. This method is based on the premise that initial garment bounding box information is given and used during training and testing. Z. Liu et al. used FashionNet, a deep learning model that was trained to learn the features, attributes, and do landmark detection of apparel. They also suggested a three-stage Deep Fashion Alignment (DFA) model, comprising of a deep convolutional neural network (CNN), in the same year. The successive stages narrow down the previous prognoses. S. Yan et al., [11], proposed Deep Landmark Network (DLAN), a convolution and recurrent transformer hybrid. This model learns and trains landmarks and bounding boxes together, removing the limitation of garment bounding boxes, which is computationally costly and infeasible. In 2018, W. Wang et al., [23], introduced a study that uses heatmaps and positions of each landmark, which solves the non-linearity and complex optimization issues of regression models that are found in previous studies. Moreover, S. Lee et al., [21], illuminate contextual information of garments by suggesting a locally and globally embedded module to attain genuine landmark prognosis performance. Ge et al., [24], introduced a hybrid benchmark named Deepfashion2, which includes four tasks: garments detection, pose estimation, human body segmentation, and garments retrieval. To solve these tasks, they proposed an energetic model, Match R-CNN, which is built on the basis of Mask R-CNN. Alpana Dubey et al., [25], proposed two concepts in 2020 to help designers who are fine-grained landmark annotators in their design process. The former, Apparel Style Merge, creates new designs by adding high-level elements of garments, and the latter, Apparel Style Transfer, allows customizing garments by using various colors, styles, and patterns. They developed a new dataset called Deep Attribute Style based on deep neural network models like RCNN, faster RCNN and mask RCNN. Mask RCNN was found to be more efficient in accuracy compared to the other two models in silhouette, hemline, and sleeves with Union of Intersection (UOI) of 0.90, 0.81 and 0.78 respectively. To fine-tune the suggested design strategies, experiments were then re-trained with 500 garment images with an 80, 10 and 10 split between train, validation and test respectively. Wang et al., [26], came up with a mindful fashion grammar network to forecast landmark locations by tackling the issue of non-linearity in fashion landmark regression. They suggested a solution by forecasting a confidence map on each fashion focal point. Chen et al.,

[94], came up with the Dual Attention Feature Enhancement (DAFE) to improve landmark representation by feature map size.

Their fashion apparel landmark prediction is based on the Feature Pyramid Network (FPN). Li et al., [27], suggested Spatial Aware Non-Local (SANL), which leverages prior knowledge for spatial attention map consideration. Yu et al., [21], proposed a fashion Layout Graph (LGR) for fashion detection and classification to establish landmark relationships.

Kai et al., [22], worked on the FLD dataset and DeepFashion dataset with the MDDNet network, achieving the best score in terms of Normalized Error (NE) with values of 0.0267 and 0.0251 on FLD and Deepfashion datasets, respectively.

3.3. Performance Measures

The widely recognized evaluation metric for detecting fashion landmarks in an image is the Normalized Error (NE). NE is defined as the distance between the predicted key point and the ground truth, while PDL (Percentage of Detected Landmarks) is expressed as the percentage of detected landmarks. Typically, efficient results are indicated by a higher value of PDL and a minimal value of NE. The performance of all methods pertaining to fashion landmark detection in terms of NE, using the FLD and Deep Fashion C datasets, is presented in Table 12 and Table 13. The significant performances are emphasized in bold.

Table 12. Performance of FLD and Deep Fashion C Data Sets [27]

Data set	Approach	LC	RC	LS	RS	LW	RW	LH	RH	Avg.
Fashion Landmark Detection	FashionNet [98]	0.07 84	0.080 3	0.097 5	0.09 23	0.08 74	0.0822	0.0803	0.0894	0.086
	DFA [99]	0.04 8	0.049	0.091	0.08 9	-	-	0.072	0.073	0.068
	DLAN [100]	0.05 32	0.054 8	0.070 6	0.07 35	0.07 53	0.0749	0.0693	0.0676	0.0673
	AFGN [90]	0.04 64	0.047 2	0.067 2	0.06 15	0.06 35	0.0693	0.0636	0.0572	0.0584
	DAFE [101]	0.03 67	0.036 9	0.058 8	0.05 74	0.04 86	0.0486	0.0504	0.0498	0.049
	SANL [102]	0.02 97	0.029 9	0.048 9	0.04 81	0.04 02	0.0414	0.0546	0.059	0.0438
	LGR [103]	0.04 24	0.015 2	0.050 2	0.07 36	0.01 95	0.0513	0.0452	0.0394	0.042
	AGR [104]	0.02 57	0.026 4	0.043	0.04 32	0.03 47	0.0344	0.0458	0.0463	0.0374
	MDDNet [105]	0.01 94	0.019 6	0.037 2	0.03 57	0.02 55	0.0254	0.0259	0.0258	0.0267
	FashionNet [98]	0.08 54	0.090 2	0.097 3	0.09 35	0.08 54	0.0846	0.0814	0.0824	0.0874
	DFA [99]	0.06 3	0.063 7	0.065 9	0.06 22	0.07 26	0.0703	0.0658	0.0664	0.066
	DLAN [100]	0.05 71	0.061 1	0.067 3	0.06 47	0.07 03	0.0695	0.0625	0.0628	0.0643

Deep Fashion	AFGN [90]	0.04 16	0.040 4	0.039 7	0.05 03	0.05 23	0.0537	0.0576	0.0551	0.0484
	DAFE [101]	0.02 96	0.029 8	0.036 3	0.06 32	0.03 11	0.0313	0.0394	0.0402	0.0343
	SANL [102]	0.02 77	0.028 3	0.039 1	0.00. 0394	0.02 98	0.0299	0.0395	0.0401	0.0342
	LGR [103]	0.02 7	0.011 6	0.028 6	0.03 47	0.03 07	0.0435	0.016	0.0162	0.0336
	AGR [104]	0.02 56	0.025 1	0.031 8	0.03 24	0.02 71	0.0286	0.0328	0.0341	0.0297
	MDDNet [105]	0.01 82	0.018 6	0.031 1	0.03 07	0.02 27	0.0223	0.0273	0.0273	0.0251
	LC: Left Collar, RC: Right Collar, LS: Left Sleeve, RS: Right Sleeve, LW: Left Waist, RW: Right Waist, LH: Left Hem, RH: Right Hem, Avg: Average									

Table 13. Benchmark datasets associated with the detection of fashion landmarks [20]

Data Set Name	Publication Year	No. of images	No. of landmark annotation	Key Points	Source
DeepFashion-C [22]	2016	290,222	9	Annotated with apparel bounding boxes, pose estimation type, landmark detection, apparel type, category and attributes.	Google images and online shopping sites
Fashion Landmark Data set [12]	2016	123	8	Stimulating with body joints, apparel type, pose type, garment bounding box with landmark prediction.	Deep Fashion [2]
Unconstrained Landmark Detection Database [10]	2017	30,000	8	Images subjected to unconstrained data sets.	Deep Fashion [2], Fashion sites
Deep Fashion [16]	2019	49100	Not applicable	Apparel detection, pose estimation, image segmentation with retrieval	Deep fashion [2] and online sites

4. Discussion & Interrogation

We conclude this section by revisiting the initial inquiries, which largely remain open.

RQ1. Is there a comparative examination of machine learning and deep learning methods in the context of the fashion and apparel industry, and how does this industry influence the choice of one approach over the other?

Concerning the frequently employed approaches in the fashion industry, it is observed that deep learning methods outperform machine learning methods. As indicated in the tables discussed in previous sections, Convolutional Neural Networks (CNN) serve as a fundamental component in the majority of developed techniques. The diverse applications within the fashion and apparel industry significantly impact the choice between ML and DL approaches, creating a challenging and competitive landscape. Consequently, deep learning approaches are more prevalent and noteworthy in terms of performance.

RQ2. What are the prospective considerations that should be addressed to advance and enhance the utilization of fashion input in the future?

The customer searching strategy should be changed to allow the search of particular products. As an example, several techniques must be created to enable online buyers to add or post a picture, which will make the site or application send the precise product or at least a similar one. The second area of research should be on body landmark prognosis and measurement and apparel recommendation. Fashion companies should be able to predict the tastes of the consumers by collecting and analyzing customer behavior, profiles, and recognitions. There is also the need to venture into other fields such as online fit engines, object detection technology that forecasts style, and intelligent nodes that are built on artificial intelligence-driven search discovery platforms. This strategy, together with deep learning methods, will allow ecommerce and fashion retailers to offer online customers personalized suggestions of clothes. In this case, huge data annotation is necessary. With the abundance of information related to the fashion and apparel industry, there is a need to develop clear and specific annotations to minimize the costs, but the quality maintenance is a problematic issue. Therefore, one of the key efforts that are required to address this problem is the creation of a useful and affordable annotation strategy in terms of information in the fashion and apparel sector.

RQ3. In what tasks is Fashion & Apparel data employed for fitting prediction, and how has the utilization of this data evolved over time?

The initial research in the field of fashion was primarily concentrated on the classification of the images of individuals wearing some pieces of clothing with or without annotations. The focus was later on the identification of the key points or landmarks to assist in identifying apparel. With the emergence of such technologies as Generative Adversarial Network (GAN) and Attention-based Fashion to Body Landmark Network (AFBN), specific attention has been given to the creation of clothes and the possibility to predict measurements in arbitrary poses. Simultaneously, research in the fashion industry has also examined the potential of extracting information out of the images shared on the social network sites.

5. Challenges and Lesson Learnt

5.1. Insufficient Data Set Collection and Annotations

The fact that a deep learning model can be adapted to a particular task is a significant concern because there are no small-scale datasets available in the literature that can be used as benchmarks. It is a well-known fact that deep learning data-driven approaches are more efficient with the increase in the number of samples. In order to deal with this problem and emphasize it, scientists have turned to the development of artificial datasets. However, the predominant use of small datasets is evident, lacking in pose variations, diversity in apparel styles, fabric types, backgrounds, and resilience to heightened interpersonal variations in conventional landmark or focal point labeling. These challenges should be carefully considered and addressed in future data gathering procedures.

5.2. Domain-Specific Models

In the context of their respective fashion domains, it becomes imperative to choose AI-based models based on the specific task at hand, especially when there is no all-encompassing or unified solution for every task. As AI continues to evolve, the key challenge lies in understanding how to construct these models optimally and effectively, aligning them with the specific data for which they have been designed. By incorporating the expertise of domain specialists into AI models, the flexibility, reliability, and robustness of an algorithm can be maximized, enabling faster and more accurate decision-making. Furthermore, the knowledge gained from one task can be leveraged to address other related tasks, thanks to transfer learning strategies.

5.3. Hardware Limitations

Although the computational power of efficient CPUs is increasing and parallel and distributed high-performance computing is being developed, the computational cost of the tasks in this section is still high. We are not at the stage when the ratio between time/obtained and resources/consumed is equal, and the use of deep learning-based solutions is sometimes not feasible and efficient in comparison with more cost-effective manual solutions.

5.4. Image Augmentation, Data Set Collection & Annotations

Image augmentation is important in the deployment of deep learning methods that have a relatively small number of annotated images. Having considered different methods, it can be concluded that the baseline methods do not provide satisfactory results using small samples to detect landmarks. Augmentation should be used to increase the size of datasets to reduce the error rates in the baseline models. Many body landmark detection datasets do not have semantic and optimal sequence annotations, which present ambiguous signals to a model. The other important feature of deep learning solutions is that large datasets that are annotated strongly are required. Nonetheless, the findings of the current research point to several limitations and inherent problems of the body landmark datasets employed. The differences in images, errors in manual annotation, and high localization errors in body parts (e.g., left waist, right waist, left arm, right arm) indicate that alternative evaluation parameters are needed to evaluate these characteristics better. These are the issues that should be addressed by future researchers in the process of data collection.

5.5. Transfer Learning

Transfer learning is a typical method in the deep learning field that is important in defining the weight of the implemented network model. The difficulty is to determine what pre-trained model or network to apply to a specific domain or targeted task. We found in the recent study the relevance of fashion landmark detection (discussed above) as the source domain or task to the prognosis task of body landmarks/focal points. The above experimental results give a further insight that fashion landmark detection is useful knowledge that can be extrapolated to body landmark detection in a field that is related to the human body.

The review outlines some of the major challenges in the field. The heterogeneity of data and the lack of consistent standards of annotation are still significant challenges because the differences in body poses, shapes, and labeling can prevent a fair comparison and generalization of the models. Anthropometric and fashion integration remains a low-volume area, and few studies have succeeded in end-to-end personalization that is effective in integrating human geometry with garment fit parameters. The issue of computational efficiency is also a problem, with lightweight architectures that can perform real-time inference being under-researched. Moreover, privacy and ethical issues require consideration to provide safe processing and anonymity of sensitive 3D body data. Finally, the absence of standardized evaluation measures and benchmarking protocols limits reproducibility and cross-study validation. Taken together, these issues point to an evident research direction of multimodal, data-driven systems that bridge body-shape analysis and digital fashion applications to create scalable, ethical, and inclusive anthropometric technologies.

6. Conclusion

This review consolidates anthropometric and fashion landmark detection approaches into a single framework, highlighting the growing dominance of deep learning methods in the apparel and fashion industry. The integration of anthropometric body measurement techniques with fashion landmark abstraction provides a unique lens for understanding the evolution of fit prediction, size estimation, and apparel classification. Evidence from year-wise literature shows a shift from traditional ML methods toward deep neural networks, with significant improvements in accuracy and scalability. Despite these advancements, challenges remain, including limited annotated datasets, high computational costs, and the lack of unified evaluation standards across studies.

7. Future Work

Looking ahead, future research in anthropometric and fashion landmark detection should focus on building large-scale, standardized, and richly annotated datasets that capture diverse body shapes, poses, and garment variations. This will help overcome the current limitations of small and inconsistent benchmarks. Another promising direction lies in cross-domain transfer learning, where knowledge gained from fashion landmark detection can be leveraged to improve anthropometric body measurement models and vice versa, reducing the cost and complexity of training new systems. Hybrid approaches that integrate classical machine learning with advanced deep learning architectures may also provide a balance between computational efficiency and predictive accuracy, particularly for resource-constrained environments. Furthermore, there is a growing need to embed these detection techniques into real-time applications such as virtual try-on systems, intelligent apparel recommendation engines, and personalized fashion analytics platforms, which can transform the online retail experience. At the same time, privacy-preserving data collection methods, including federated learning and secure cryptographic techniques, will be essential to address concerns regarding the use of sensitive anthropometric data. Finally, optimizing models for deployment on lightweight hardware and edge devices will play a critical role in making these technologies scalable, accessible, and practical for widespread use in both commercial and consumer domains.

References

1. S. Yan, Z. Liu, P. Luo, S. Qiu, X. Wang, and X. Tang, "Unconstrained fashion landmark detection via hierarchical recurrent transformer networks," in Proc. 25th ACM Int. Conf. Multimedia, Oct. 2017, pp. 172–180.
2. C.-W. Hsieh, C.-Y. Chen, C.-L. Chou, H.-H. Shuai, J. Liu, and W.-H. Cheng. 2019. FashionOn: Semantic-guided imagebased virtual try-on with detailed human and clothing information. In Proceedings of the 27th ACM International Conference on Multimedia (MM'19). 275–283
3. Chang-Qin Huang , Member, IEEE, Ji-Kai Chen, Yan Pan , Han-Jiang Lai, Jian Yin, and Qiong-Hao Huang, (2019) Clothing Landmark Detection Using Deep Networks With Prior of Key Point Associations, IEEE TRANSACTIONS ON CYBERNETICS, VOL. 49, NO. 10, OCTOBER 2019
4. Z. Liu, P. Luo, S. Qiu, X. Wang, and X. Tang. 2016. DeepFashion: Powering robust clothes recognition and retrieval with rich annotations. In Proc. IEEE Conference on Computer Vision and Pattern Recognition (CVPR). 1096–1104.
5. Z. Liu, S. Yan, P. Luo, X. Wang, and X. Tang. 2016. Fashion landmark detection in the wild. In Proc. European Conference on Computer Vision (ECCV).
6. S. Yan, Z. Liu, P. Luo, S. Qiu, X. Wang, and X. Tang. 2017. Unconstrained fashion landmark detection via hierarchical recurrent transformer networks. In Proceedings of the 25th ACM International Conference on Multimedia (MM'17). 172–180
7. W. Wang, Y. Xu, J. Shen, and S. Zhu. 2018. Attentive fashion grammar network for fashion landmark detection and clothing category classification. In Proc. IEEE Conference on Computer Vision and Pattern Recognition (CVPR). 4271–4280
8. Zubair, M.; Hussain, M.; Albashrawi, M.A.; Bendeche, M.; Owais, M. A comprehensive review of techniques, algorithms, advancements, challenges, and clinical applications of multi-modal medical image fusion for improved diagnosis. Computer Methods and Programs in Biomedicine. 2025, 272, 109014. <https://doi.org/10.1016/j.cmpb.2025.109014>.
9. S. Lee, S. Oh, C. Jung, and C. Kim. 2019. A global-local embedding module for fashion landmark detection. In Proc. IEEE International Conference on Computer Vision Workshops (ICCVW). 3153–3156.
10. Kaiming He, Georgia Gkioxari, Piotr Dollár, and Ross B. Girshick. 2017. Mask R-CNN. In Proc. IEEE International Conference on Computer Vision (ICCV). 2961–2969
11. Y. Ge, R. Zhang, L. Wu, X. Wang, X. Tang, and P. Luo. 2019. A versatile benchmark for detection, pose estimation, segmentation and Re-Identification of clothing images. In Proc. IEEE Conference on Computer Vision and Pattern Recognition (CVPR). 5337–5345.
12. Cheng, W.-H., Song, S., Chen, C.-Y., Hidayati, S. C., & Liu, J. (2020). Fashion meets computer vision: A survey. arXiv. <https://arxiv.org/abs/2003.13988> arXiv+1
13. Lee, S., Oh, S., Jung, C., & Kim, C. (2019). A global-local embedding module for fashion landmark detection. arXiv. <https://arxiv.org/abs/1908.10548> arXiv
14. Hussain, M., Chen, C., Hussain, M. et al. Optimised knowledge distillation for efficient social media emotion recognition using DistilBERT and ALBERT. Sci Rep 15, 30104 (2025). <https://doi.org/10.1038/s41598-025-16001-9>
15. Wang, X., Liu, B., Dong, Y., Pang, S., & Tao, X. (2020). Anthropometric landmarks extraction and dimensions measurement based on ResNet. Symmetry, 12(12), 1997. <https://doi.org/10.3390/sym12121997>
16. Abu, A., Ngo, C. G., Abu-Hassan, N. I. A., et al. (2019). Automated craniofacial landmarks detection on 3D image using geometry characteristics information. BMC Bioinformatics, 19(Suppl 13), 548. <https://doi.org/10.1186/s12859-018-2548-9>
17. Meyer, P., Birregah, B., Beuseroy, P., Grall, E., & Lauxerrois, A. (2023). Missing body measurements prediction in fashion industry: A comparative approach. Fashion and Textiles, 10, Article 37. <https://doi.org/10.1186/s40691-023-00357-5> SpringerOpen

18. R. Alabdallat, M. Abualhaj, and A. Abu-Shareha, "Android Malware Detection Using a Modified Dwarf Mongoose Algorithm," *International Journal of Intelligent Engineering and Systems*, vol. 18, no. 8, 2025, Art. no. ijies2025.0930.21. DOI: 10.22266/ijies2025.0930.21.
19. Luo, S., Zhang, Q., & Feng, J. (2022). Automatic location and semantic labeling of landmarks on 3D human body models. *Computational Visual Media*, 8, 553–570. <https://doi.org/10.1007/s41095-021-0254-4>
20. Gadhiya, R. B., & Kalani, N. B. (2021). 2D Image Based Digital Anthropometry Using Deep Learning Approach. *International Journal of Intelligent Systems and Applications in Engineering (IJISAE)*.
21. Bojanić, D., Bartol, K., Petković, T., & Pribanić, T. (2024). Direct 3D body measurement estimation from sparse landmarks. In *Proceedings of (Insert Conference/Journal) SCITEPRESS*. [details approximate]. <https://doi.org/10.5220/0011238400003366>
22. Kim, S., Kim, H., Cho, Y., Lee, S., & Park, J. (2022). Automatic human body measurement for virtual fitting using deep learning: The Scan Avatar-Captured 2D Image Dataset. *International Textile and Apparel Association Annual Conference Proceedings*, 79(1). <https://doi.org/10.31274/itaa.16051>
23. Anisuzzaman, D. M., et al. (2019). Online trial room based on human body shape detection: Using Kollman's distribution algorithm and Canny edge detection for body and garment measurement [I.J. Image, Graphics and Signal Processing, 11(2), 21-29]. MECS. University of Helsinki+1
24. Tan, X., Xiaohui, T., & [other authors]. (2019). Personal body size recommendation and feature extraction using Random Forest Regression analysis.
25. Baronetto, A., Wassermann, D., & Amft, O. (2021). Deep 3D body landmarks estimation for smart garments design. In *2021 IEEE 17th International Conference on Wearable and Implantable Body Sensor Networks (BSN)*, 1-4. IEEE. mecspress.org
26. Z. Awais et al., "ISCC: Intelligent Semantic Caching and Control for NDN-Enabled Industrial IoT Networks," in *IEEE Access*, vol. 13, pp. 169881-169898, 2025, doi: 10.1109/ACCESS.2025.3614984. Liao, I. Y., Savero Hermawan, E., & Zaman, M. (2022). Body landmark detection with an extremely small dataset using transfer learning. *Pattern Analysis and Applications*. [details approximate] *ACM Digital Library*
27. Ryu, E. J., et al. (2022). Focal points detection for the upper body on a Korean dataset using Rhino and Grasshopper algorithm for landmark estimation.
28. Dewan, D. I., et al. (2022). Two-dimensional and three-dimensional image measurements from depth cameras: Edge detection and pose detection for body landmark measurement, . *International Textile and Apparel Association Annual Conference Proceedings*, 79(1). <https://doi.org/10.31274/itaa.16051>
29. Liu, K., Wang, J., Kamalha, E., & Zeng, X. (2017). Construction of a prediction model for body dimensions used in garment pattern-making based on anthropometric data learning, In *Proceedings of the 27th ACM International Conference on Multimedia (MM'19)*. 275–283.