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Fit Moi: Online Virtual Fitting Room With Texture Identification And Recommendation System

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ABSTRACT

Virtual fitting rooms have attracted the sights of the market need in the past two years; The world faced a colossal pandemic that led everything to be online.
This proposed framework aims to solve the online shopping problem using deep learning algorithms and techniques.
Users face significant issues, whether finding the perfect fit, recognizing the fabric, or styling their outfits. As a result, merchants' profit is impacted, resulting in a high percentage of returns.
This proposed model aims to generate a 3D human model. Based on the measurements extracted from the user's images and the user's weight and height for more accurate results. The user can see how simulated 3D clothes will look on his 3D body model, and Then he will know the exact size that fits him and can view the texture. Finally, the user will have styling tips recommended according to his chosen outfit.

1. Introduction

Since the beginning of the pandemic, most people have opted to shop online rather than in traditional stores. As a result, online shopping has unquestionably become the dominant form of retail commerce. According to [1] and [2], the income generated online increased by 44% in 2020 and by 39% annually during the first three months of 2021. Unfortunately, e-commerce is plagued by a major problem that significantly threatens its profitability. This problem consists of providing customers with incorrect sizing information, preventing them from trying on and identifying the garments they purchase.
This leads to a high return rate, which impacts the retailer's business. This paper proposes the development of a mobile application for a virtual fitting room.

Users can upload images of themselves to have their body sizes extracted and generate a 3D human model that will be equivalent to their measurements. Additionally, users can try on clothes, get recommendations for outfits or styling tips, and identify the fabric texture. They want to view an extremely detailed 3D model of the article of clothing that they intend to buy.

This paper provides a comprehensive description of each stage. The main contribution of this paper is broken down into the following sections: section [2] provides background on virtual fitting rooms, and section[3] provides an overview of several other relevant studies. In this Section, the research study presents several articles that use algorithms and methods comparable to the proposed model. Section [4] presents the proposed model methdology, and Section [5] presents the tests that have been conducted and the results of those tests. In conclusion, a succinct overview can be found in section [6].

2. Background

The concepts in our proposed framework are briefly introduced in this Section.

2.1. Virtual Fitting Rooms

Shoppers have traditionally hesitated to shop for clothing online because they worry it might not fit. Many businesses have been attempting to create a solution to address customer issues while also delivering a more engaging shopping experience since the early 2010s. Innovative sizing solutions have emerged due to the past decade's rapid technical improvements. Virtual fitting tools, which simulate the experience of a dressing room using augmented reality and artificial intelligence, are among the advancements. Virtual fitting rooms are quickly becoming a necessity for fashion stores as they answer customers' sizing problems and assist brands in achieving their inclusivity and sustainability goals while boosting business success.

3. Related Work

This study provides other research publications with ideas comparable to the proposed model; furthermore, this study will continue to examine and display the important points, explaining the methodologies and algorithms utilized in each paper.

In [1] and [2], the main problem of the researchers was that they wanted to get the most accurate measurements of a human body out of 2D images to make it easier for the nutritions to know their patient's body measurements. They made the image go into several steps, first of all, acquisition. Furthermore, in [3], This is the step to get the input images from the patients; they specified a pose for the patients to get better results and asked them for four photos in 4 directions. After that, the images went through segmentation using DensePose, and they passed those images to the classifiers like CNN, Bayesian, KNN, and SVM to acquire a prediction of the body part and calculate the outline of the body. The dataset used is 38 skinfold measures that a professional calculated. And I think that the dataset used is not large enough to test the system's accuracy. They concluded that the Bayesian approach displayed the least error percentage in the Thigh and Pectoral measures. Moreover, KNN was the highest percentage for Fist's measure.

Hao Zhu et al. in [4] and [5] stated that the main problem they faced was reaching the best 3D detailed model with any pose possible of the human. They constructed a primary parametric mesh model along with the existing SMPL model. It is possible to anticipate the 3D mesh vertex movement, and they developed a coarse-to-fine refining strategy. they fed the network window-cropped images, which resulted in a more reliable and precise prediction of deformation., They also incorporated a photo-metric term to enable the recovery of high-frequency features.

In [6], These methods were integrated to create a process that considerably enhances the reconstructed human shape from only one image aesthetically and numerically. Their framework was divided into four phases: The input photo is first used to estimate an initial SMPL mesh. The following three stages are refinement phases that forecast the mesh's deformation to generate a precise human shape. The first human mesh model was predicted using the HMR approach.

Furthermore, in [7], They created a deep neural network at each level, and they trained these networks using the Adam Optimizer, with a learning rate of around 0.0001. The experiment used three datasets:

WILD Dataset, which contains many pictures with 2D joints, and two other minor datasets used to evaluate 3D metrics. The 3D meshes that sided images with depth were inaccurate and had high error percentages.

Aymen Mir et al. in [8] and [9] implicit pointed out that There was a problem in transferring the texture of clothes to a 3D model to detect the texture. as they wanted to identify the texture of clothes from a 2D image as fitting is costly and error-prone. Their main idea was not to write the type of texture but to be detected by the customer. First, they developed an effective neural mapping technique (Pix2Surf) to map the mesh's texture to an image based on the skeleton shape. As the image was taken with a background that has to be deleted, as in[10] and [11], they used an Image segmentation technique which was (GrapCut), and then they collected a foreground mask using thresholding. Finally, they filled the holes in the mask by closing operations.

In [12], They created their dataset, which consists of 2267 front and 2267 back images of T-shirts, 2277 for shorts, and 3410 for pants. This dataset works effectively and covers the absence of a back view photo; in conclusion, they successfully detected clothes' texture from a 2D image to 3D clothing used by virtual humans. Also, in [13] and [14], they minimized the conversion time by making it run in real time, which will help many applications. They considered that the measurements of the clothes are known, which is incorrect as they have to detect the measurements from the image.

Sahib Majithia et al. in [15] and[12] stated that the main issue they faced was the requirement to present a trustworthy 3D garment digitization technology that can function well with real-world fashion; they performed high-quality texture mapping from an input catalogue photo to UV map panels. In [16] and [17], They began by anticipating a small group of 2D landmarks along the edge of the garment, then used these landmarks to transfer texture using a thin-plate spline on UV map panels. They altered the JPPNet architecture, first proposed for clothing milestone prediction on the human body.

The dataset comprises 1300 items, 1000 of which are for testing and 300 of which are for training. This network applies the proper texture to each panel in the UV using information from the image's non-occluded regions. Two hundred images from the data were chosen for this project, and five different annotators annotated the image.

In [18], they trained the network over 20 epochs using 3000 pictures and 7300 masks for the T-shirts and 12000 photos and 12000 for the pants. However, they used substantially fewer (almost 50\% fewer) real-world training photos. In [19], They also found that a network built utilizing synthetic and real-world data performs nearly double the JFNet in NMSE. The only drawback is that the dataset was too small, leading to inaccurate results.

Xin Yang, BO Wu and Yueqi Zhong introduced in [20] that deep network-based recommendation systems are equally crucial for users and sellers. Many current recommendation systems depend on the user's previous shopping behaviours or feedback to produce the ideal recommendation. However, they created a recommendation for clothing using the selected photos from the user by combining machine learning and embedding techniques, such as CNN, to compare the features at different layers. For the recommendation portion, they used the ResNet-50 model as their backbone model Dataset for the recommendation part. Also, other related work in [21-36] has been proposed in recent years to address machine learning and its application in different fields.

4. Proposed Approach

This Section demonstrates the proposed method for generating a 3D human body, identifying clothing texture, and generating compatible outfits by the recommendation system.

4.1. The Proposed Model Overview

Our proposed model only requires a mobile device with a camera and a reliable internet connection, making it more affordable and convenient for users than other systems requiring expensive devices.

Our workflow is divided into four phases as shown in Figure 1. The first phase is where the admin of the integrated brand uploads the 2D photos of the products, and then these photos go through image segmentation techniques which is a part of texture identification.

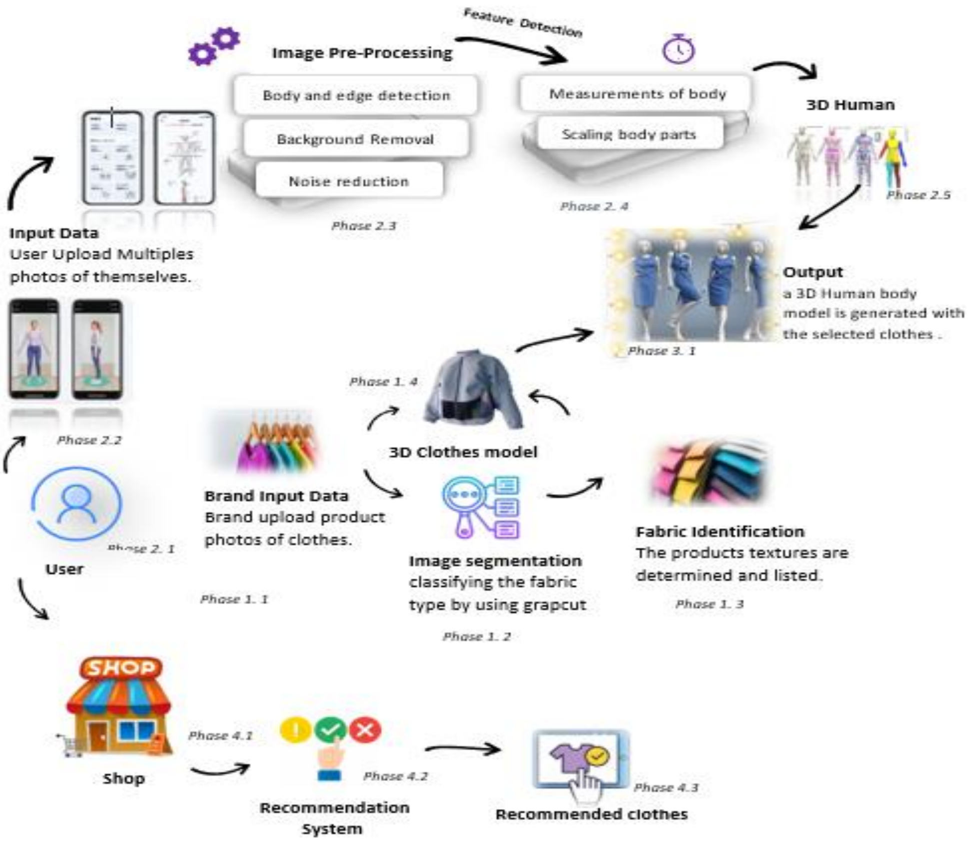

Figure 1 The proposed Virtual fitting room framework

Moving to the second phase, where the user uploads multiple photos of themselves to increase the accuracy of body measurements and edge detection, the uploaded photos will go through a preprocessing stage in which the photo converts from RGB to a grey-scale image.

Furthermore, the normalization stage will enhance it using the noise reduction feature.
However, the edge detection phase is then achieved in many ways: dilation, background removal, and body contours; as for the feature extraction, it will convert the 2D model to 3D
and identify the suitable size for the user. And our third phase is the output, where a 3D human model with 3D clothes is shown.

Finally, in the fourth phase, when the user browses the shop and selects a product, the recommendation system will suggest suitable products that match the selected product.

4.2. Generating A 3D human model

Our proposed workflow automatically extracts body measurements from provided images and calculates them using the following formula:

$$X(\text{ meter }) = \frac{\text{height (meter)} \times x(\text{ pixels })}{height\text{ (pixels)}} \quad (1)$$

A new value of "x" is computed and converted into meters for each extracted measurement. The measurements are obtained using detectron2, an open-source framework known for its fast and accurate object detection model. Each measurement's width and depth are calculated using the RCNN algorithm, which was trained using the CoCo key points recognition.
To calculate certain anthropometric measurements with an elliptical shape, such as waist, hip, and thigh, the perimeter of an ellipse formula is applied by the Grith(G) equation.

$$\text{Girth } \pi(A+B) \times \frac{t+3-(A-B)^3}{(A+B)^2 \times \left(10+\sqrt{4-3\times(A-B)^2+(A+B)^2}\right)} \quad (2)$$

Three pieces of a modelling system are used to process the collected measurements. The first stage, called Imputation, involves predicting missing values for body measures using the SPRING dataset. This dataset contains the body measurements of around 1500 men and women. There are other imputation methods available, such as k-nearest-neighbour and MICE. However, the majority advise MICE to achieve the greatest results. The MICE imputation technique is used in this work to fill in the missing values for the characteristics listed in Table I.

TABLE 1: The MICE imputation techniques

Numbers	**Measurements calculated**
I	Height
II	Weight
III	Chest
IV	Neck
V	Waist
VI	Hip
VII	Shoulders

However, in this study, just the five primary body measurements: height, weight, waist, hip, arm, and chest are taken into consideration; the following part includes the selector, which takes as input a dataset made 0up of meshes and the characteristics that go with them. The selector generates relevance masks and mapping matrices using the local mapping technique. In the experiments section, we compared local mapping to global mapping and discovered that local mapping produced superior results. The changes in the shape of each triangle aspect are first found as a 3x3 matrix. Which can be expressed as foll

$$\boldsymbol{D} = [\boldsymbol{Q}_{\boldsymbol{i},\boldsymbol{1}} \quad \boldsymbol{Q}_{\boldsymbol{i},\boldsymbol{2}} \quad \cdots \quad \boldsymbol{Q}_{\boldsymbol{i},\boldsymbol{m}}] \tag{3}$$

The mapper uses the selector's relevance masks and the measurements that underwent Imputation for each aspect to create a k-dimensional vector P.

The following formula is used to obtain the transformation matrix:

$$T = MF' = \begin{bmatrix} m_{1,1} & m_{12} & \cdots & m_{1,1} \\ m_{2,1} & m_{23} & \cdots & m_{2,1} \\ \vdots & \vdots & \vdots & \vdots \\ m_{0,1} & m_{92} & \cdots & m_{s,1} \end{bmatrix} \begin{bmatrix} p_1 \\ p_2 \\ \vdots \\ p_1 \end{bmatrix} = \begin{bmatrix} w_1 \\ \omega_1 \\ \vdots \\ m_2 \end{bmatrix} \tag{4}$$

4.3. Texture Identification

Regarding the approach for identifying textures, a powerful neural mapping method called Pix2Surf was applied to map the texture of the mesh to an image only based on the form of the skeleton. Because the picture was captured with a backdrop that has to be removed, as described in [10] and [11], we made use of an image segmentation approach called (GrapCut), and after that, they gathered a foreground mask by thresholding. In the final step, we performed closure operations to close the gaps in the mask. The accompanying Figure 6 provides a very good illustration of these procedures' closing operations. These steps are illustrated clearly in the following Figure 6.

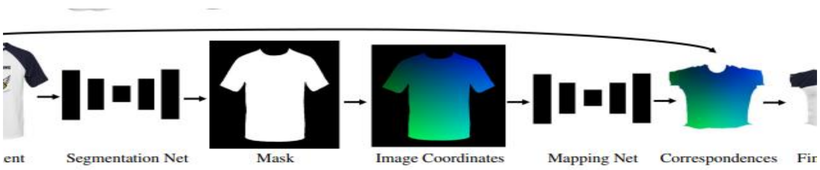

Figure 2 Image segmentation by using GrapCut

A neural model called Pix2Surf direct maps to pixels. Pix2Surf runs in real-time, which is essential for many applications, such as virtual try-on, while the optimization approach takes 10 minutes to converge. Our main concept is to learn a relationship map based solely on silhouette shapes from picture pixels to a 2D UV parameterization of the surface.

We demonstrate that Pix2Surf outperforms traditional methods like direct image-to-image translation techniques and 2D TPS warping (while being orders of magnitude faster)

. GrabCut is used in an automatic mode. Because clothing is often taken against plain backgrounds, we use thresholding to create an approximate foreground mask. We then execute a closure operation on this mask to close the holes and erode it to acquire a prior for "absolute foreground." The differential region between the mask and its counterpart.

The deteriorated version is labelled "probable foreground". Similarly, dilation yields "absolute background" and "probable background." We obtain realistic silhouettes without manual annotation by using these past maps to initialize GrabCut.
The garment surface was fitted to silhouettes in two steps. In the first stage, we minimize the following objectives: clothing position, shape, and camera translation.

$$E_1(\boldsymbol{\beta}, \boldsymbol{\theta}, t) = w_{,}E_s + w_\beta E_j + w_\theta E_\theta \tag{5}$$

The goal in this equation is composed of a silhouette Es, a shape regularisation term E, and a pose prior term E, as explained below. Weights w are used to balance the various words.

To offer greater supervision to the network, we utilize a differentiable sampling kernel to directly infer a texture map from the correlation map.
We want to minimize a dense photometric loss between predicted and target texture maps. Projective texturing yielded Y.

$$L_{\text{rewe}} = \sum_{i}^{N} \sum_{k,1}^{KL} \left\| \mathbf{I}\left[f_{i\lambda}^{1}\left(\mathbf{X}^i; \mathbf{w}\right)', f_{i\lambda}^{2}\left(\mathbf{X}^i; \mathbf{w}\right) \right] - \mathbf{Y}_{k,1}^{i} \right\|_1 \tag{6}$$

Both networks are trained using the Adam optimizer. To increase performance, we utilize a UNet with instance normalization and colour jittering in the input data for the segmentation network. We utilize a six-block ResNet for Pix2Surf. The option of normalization.
Custom UV Map: Because the SMPL UV map produced by the artist cuts the clothing into different islands (which is poor for learning continuous mapping), we utilize a custom UV map for each garment category. Using Blender, we cut the garment surface into front and rear and computed the UV map. This creates two islands (front and back), making the image to UV mapping continuous and hence easy to understand.

As for the dataset, according to [8], they created datasets consisting of 2267 front images of T-shirts. The networks about the back are trained using a dataset of 2267 images, of which 964 are back view images, and the rest are front images. The front shorts dataset has 2277 items. We use the same dataset to train the networks about the back views. For pants, they collect a dataset of 3410 front views. We create a dataset for back views by horizontally flipping the front view images and their corresponding silhouettes. The back dataset has 3211 items. The optimization-based registration method's failure explains the discrepancy between the number of items in the front and back views. Exploiting these front-back symmetries works well in practice and allows us to compensate for the unavailability of back-view images.

4.4. Recommendation System

Furthermore, our proposed model recommendation system provides fashion suggestions compatible with the products or photos uploaded. Designing the compatibility between fashion items is the core of style guidance. In computer vision, the harmonious and aesthetically pleasing combination of many clothing categories into a single outfit is called outfit compatibility. To achieve optimal compatibility, it is necessary to have a thorough awareness of both the aesthetics behind each fashion category and the compatibility between various categories. Furthermore, we provided a multilayer non-local feature fusion network, which fuses low-level features with high-level features to represent the image visually and employs non-local operations to capture global information. We have used it to predict pairwise fashion outfit compatibility, crucial for outfit match diagnosis and fashion advice.

Using the user's selected photos, we combined machine learning and embedding techniques, such as CNN, to compare the features at different layers. We used the ResNet-50 model as the backbone model and Polyvore-T as our dataset for the recommendation portion.

MCN is divided into four sections, beginning with the multi-layered feature extractor, which extracts features in many aspects. The comparison modules then compare the enumerated pairwise similarities across features and various layers, and the MLP predictor computes a score from all of them. Multimodal information is handled using visual semantic embedding. MCN's approach begins by forecasting outfit compatibility and backpropagating a gradient from the output score to the input similarities. Similar studies have been published that visualize the response of each pixel to different classes to explain the CNN classification. Still, our goal is to visualize the response of each similarity to the compatibility score.

After evaluating each item with others in various characteristics, such as colour, texture, and style, outfit compatibility can be taken as a summary. A simple linear model with high interpretability can be used to understand the link between holistic compatibility and pairwise similarities. The weights of each input dimension reflect the importance of the output. The linear model's limitation is its limited capacity. The multilayer perceptron (MLP) model has a higher capacity, but the hidden unit is difficult to explain. To use MLP while retaining diagnostic interpretability, we use backpropagation gradients to approximate the importance of each similarity considering the incompatibility.

Given an outfit of N pieces, its characteristics in a given aspect, such as colour, can be denoted as a set X = x1, x2,..., xN, where xi is the vector for the i-th item. The features' enumerated pairwise similarities can be expressed as a matrix.

5. Experimental Results

This Section aims to evaluate our system's effectiveness by testing it with alternative approaches. Two approaches, local mapping and global mapping, were used to reconstruct 3D models. Then, we estimated the measures of the output human models and compared them with the actual data. The local mapping outperformed other approaches, as seen by Table [II] findings, since it resulted in a smaller mean error for every body measurement.

TABLE 2: Mean Error of the local and global mapping

Parameters	**Global Mapping**	**Local Mapping**
Chest	29.22	11.42
Waist	94.08	11.70
Arm	11.56	5.91
Hip	22.80	3.44
Neck	9.54	4.36

These were the male and female-generated measurements, compared with the real measurements mentioned in the following tables:

TABLE 3: Male Measurements

Parameters	Real Measurements	Detected Measurements
Height	168	
Weight	63	
Chest	93	93.011
Hip	100	108.29
Back	48	49.6

TABLE 4: Female Measurements

Parameters	Real Measurements	Detected Measurements
Height	171	
Weight	64	
Chest	92	98.52
Hip	102.43	113.11
Back	40	41

Moreover, after running several tests, our system's input and output score from the application is the recommendation system's result.

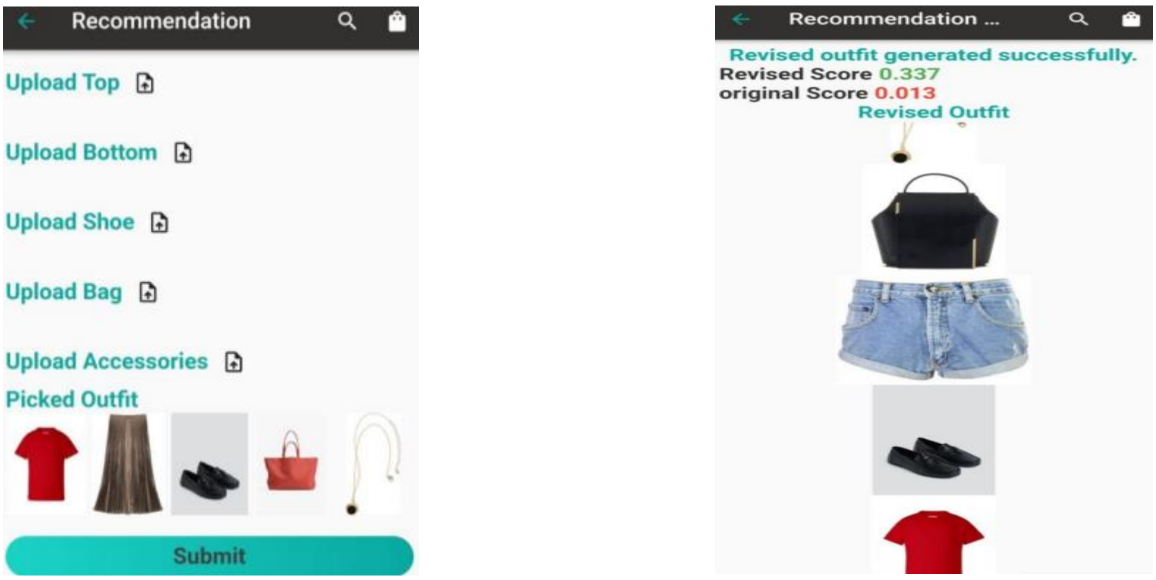

Figure 3 Recommendation System Input and output

Furthermore, while testing the fabric identifcation part after the image is transformed into a mesh, it will be wrapped as a tshirt in the final output as the following figure.

Figure 4 Texture Identifcation Output

6. Conclusion

This proposed framework offers an appropriate strategy for e-commerce shops hoping to boost their profit margins and reduce the percentage of returns brought on by incorrect sizes, a garment's style that does not match the customer's style, or failure to identify the texture.

Furthermore, not all clients can recognize their measurements precisely; therefore, we uploaded their body images to extract them, making it simpler and quicker for the user.

This was the first challenge we faced while developing our system. Another difficulty was that we could not obtain all of the parameters from the body photos as our system needed to generate the 3D model. We applied an imputation approach to forecasting the additional factors that cannot be determined from the photos. To improve customers' e-commerce purchasing experiences, a deep learning approach was combined with an accurate 3D human body system remodelling utilizing some characteristics. The selector then builds the proposed local mapping' relevance masks and mapping matrices.

Furthermore, the selector used the MICE approach to anticipate the majority of these parameters for Imputation. It converts the parameters' dimensional vectors into a 3D body model (mesh-based) that can be shown in the application.

Moreover, we also managed to identify the texture of the clothes using the image segmentation tool (grap-cut) and the recommendation system, which produces styling tips based on multi-layered networks CNN and Resnet-50.

In our future work, we plan to enhance texture identification, generate 3D body models for children, and add a face recognition feature, which will increase the accuracy in visualizing the user' selected outfit.

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