International Journal of Electrical and Computer Engineering (IJECE)
Vol. 14, No. 4, August 2024, pp. 4616~4626
ISSN: 2088-8708, DOI: 10.11591/ijece.v14i4.pp4616-4626

Machine learning-based clothing recommendation system for women: case study of Lady's confecciones

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Article Info

Article history:

Received Feb 9, 2024
Revised Apr 2, 2024
Accepted May 18, 2024

Keywords:

Body type predicting system
Clothing recommendation
Fashion recommender system
Machine learning
Recommendation system

ABSTRACT

This paper presents a clothing recommendation system for women based on their body type, aiming to facilitate the purchasing process on the online sales channel of the company Lady's Confecciones located in the city of Santa Marta, Colombia. For this process, a user interface was designed to function in two ways: using a prediction model that takes as inputs a photograph of the user and their height, and a manual mode that receives the measurements of bust, hip and waist. The prediction model implemented the OpenCV library and the skinned multi-person linear (SMPL) model to process images and predict body shape and pose. Five body types were considered: triangle, apple, rectangle, hourglass and inverted triangle, differentiated by bust, waist and hip measurements, according to the conditions provided by the company. The system was able to predict the body measurements of the female participants with a maximum Pearson correlation coefficient of 0.97. For predicting body type, the best results were obtained for the rectangle body shape, with an accuracy of 92.31%.

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1. INTRODUCTION

The online fashion industry faces significant challenges regarding garment returns due to issues associated with size changes [1]. One of the main problems lies in the logistical and environmental costs this process incurs, as shipping items to and from consumers for size exchanges generates high operational expenses and increases the environmental footprint [2]. These returns impact the customer experience, potentially leading to dissatisfaction if the received size does not meet expectations, subsequently affecting brand perception and customer loyalty [3]. Such situations also create inefficiencies in inventory management, complicating the forecast of demand for certain sizes and causing overstock or understock issues in specific sizes, affecting profitability and the ability to meet consumer needs [4], [5].

In this context, Lady's Confecciones, a company specializing in the manufacture of garments, primarily uniforms for companies, schools, universities, clinics, among others, recently launched its new e-commerce line named "Ziruma". This line offers garments for both national and international markets, made from recyclable fabrics, in response to shifting consumer demands focused on minimizing their carbon footprint. To market these garments, the fashion industry typically employs an online store, where customers select sizes using a measurement chart provided by the company for the bust, waist and hips. Size guides encounter effectiveness issues due to the lack of standardization, complexity in interpretation, lack of personalization and visual limitations, leading customers to be uncertain about the size to purchase. This results in returns and garment exchanges due to size errors, fit problems or design issues [6], [7]. These limitations have been identified by different authors in previous studies and translate to up to a 60% return rate on purchases made [8].

The female audience, in particular, has been affected by the variability in clothing sizes and styles, making it even more challenging to select garments that fit different body shapes and preferences precisely. These challenges have led to a growing demand for innovative solutions that help consumers find the most suitable sizes with greater ease and accuracy. The garment sector has recently been exploring the use of some technological tools, such as virtual fitting rooms within online stores, with examples including retailers like Falabella and El Corte Inglés, and brands like Zara, Land's End, Uniqlo, Rebecca Minkoff and Timberland [9], [10]. This presents an opportunity for a garment company in a growth phase with plans for internationalization to leverage Industry 4.0 to sophisticate its size verification process for online sales.

The literature contains various studies that explore aspects concerning size selection in e-commerce [11], [12]. Chrimes *et al.* [13] examined how body shape affects garment fit for 30 women in the United Kingdom, concluding that small businesses should support this consumer segment by aiding their clothing decisions based on body shape. Wang *et al.* [14] developed a 3D parametric model of the lower body, successfully classifying body types into three categories based on height and weight. These findings were relevant for virtual 3D visualization applications of clothing. Yao *et al.* [15] implemented a method for classifying female body shapes using 2D images based on computer vision technology. The researchers reported a recognition rate of 94.8%, demonstrating the effectiveness of computer vision technology and the selection of proposed classification indices in the study. Lin *et al.* [16] created a fashion recommendation system based on gender and body height, which was tested with 23 individuals of both genders, showing its effectiveness in suggesting various clothing types.

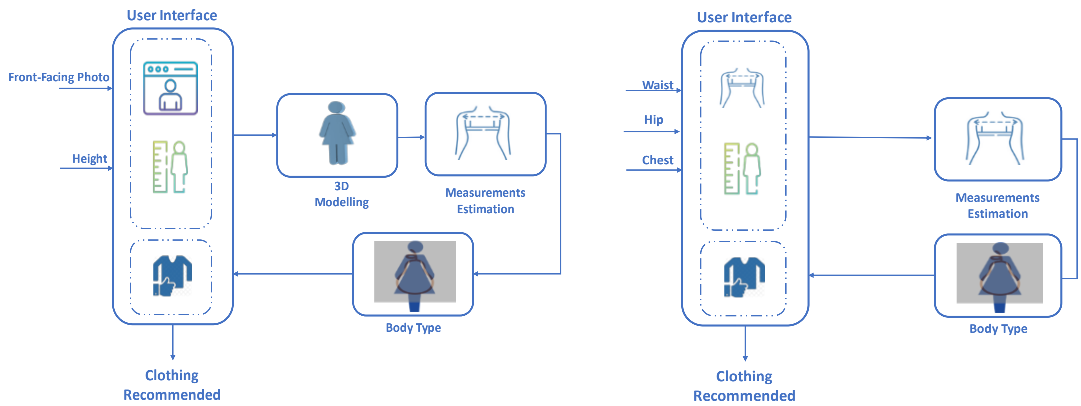
Despite the advances reported in the literature, there are still areas in the processes of size selection in e-commerce that require further research. It is necessary to continue exploring machine learning techniques to enhance the accuracy of recommendation systems, considering different variables [17], [18]. In this context, Lady's Confecciones, with the aim of improving the shopping experience for its customers, has proposed implementing a sizing recommendation system based on machine learning techniques for 3D body modeling. This system aims primarily to offer personalized recommendations for women's garments, tailored to the body types of the customers, thus minimizing uncertainty at the time of purchase and significantly reducing returns. In this regard, the main contribution of this work is the implementation of an innovative clothing size recommendation system based on machine learning techniques and 3D modeling specifically tailored for Lady's Confecciones company in Colombia.

2. METHOD

The processes described in the following sections are systematically used in a web application programming interface (API) consumed by the ladysstore.co website, developed as one of the outcomes of this research. The API was created using the FastAPI framework in Python, known for its development speed, execution speed and readability [19], [20]. The API consists of two endpoints that perform the logic behind the clothing recommendation process on the ladysstore.co website. The main difference between the two endpoints lies in the fact that the user will have different input parameters to access the clothing recommendation system. The first endpoint utilizes 3D prediction models of body shape and pose, and also implements cross-sectional calculations to estimate body measurements. This endpoint receives as input parameters a frontal image of the user and their height in meters as shown in Figure 1(a). These measurements are evaluated against a series of conditions to determine the body type. The second endpoint receives bust, waist and hip measurements in centimeters as input parameters and uses the conditions to determine the body type. It then processes this information to estimate the body type based on the given measurements as shown in Figure 1(b).

2.1. 3D modeling

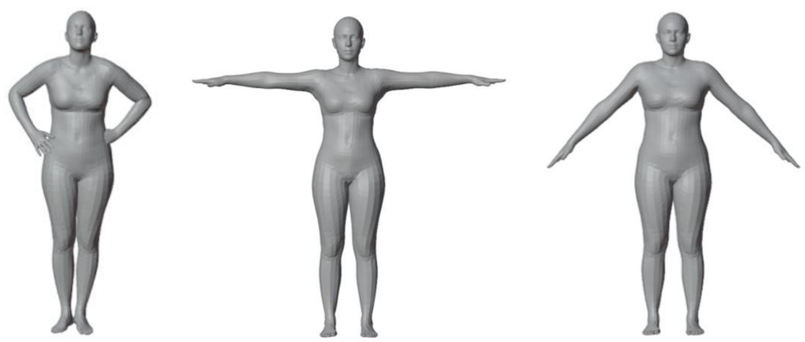
Each uploaded image is processed to be used by the model, which supports *.jpeg*, *.jpg*, *.webp*, and *.png* files. The image is validated and converted to the *.png* format, primarily using the OpenCV library for image handling. The processed image is then delivered to the model in the form of a NumPy array. The estimation of body shape and pose is performed using the code from the "HierarchicalProbabilistic3DHuman" repository [21], which was modified according to the requirements of this research. The code from the repository was utilized to make inferences on the images, for which it was necessary to design a function that allows loading each configuration parameter for the specific case of female bodies. These modifications were made in the *predict_poseMF_shapeGaussian_net* function of the *predict_poseMF_shapeGaussian_net.py* file, responsible for detecting human bounding boxes in the input image using Marks-RCNN. Subsequently, the following steps were implemented:



(a) (b)

Figure 1. Endpoints implemented in the API (a) endpoint with prediction model and (b) endpoint with body measurements

a. The skinned multi-person linear (SMPL) model was utilized to estimate the shape and pose of the subject in the image, which was initially estimated as shown in Figure 2(a). This file was modified to perform the estimation of the body shape distribution, thereby obtaining the neutral pose as shown in Figure 2(b). Then, the values of the vertex tensor at positions 47 and 50 were modified to 5.5 and -5.5, respectively, to obtain the pose corresponding to the desired figure (final pose, as shown in Figure 2(c)). Once the model achieved the adjusted pose, the prediction was recalculated using this pose and the beta shape values obtained from the *pose_shape_model* function. This process yielded the vertex tensor of the 3D model in the desired pose.



(a) (b) (c)

Figure 2. Implementation of the SMPL model (a) initial shape and pose, (b) neutral shape and pose, and (c) final shape and pose

b. Once the model vertices were obtained, the maximum and minimum values of the coordinates $[:,:,1]$ on the vertical axis of the 3D model were calculated. This provides the upper and lower bounds of the model's height, which are then subtracted to obtain the model's height in three-dimensional space. Subsequently, the scale factor was calculated by dividing the actual height by the model's height. It is important to note that the actual height is obtained through the API. Finally, the scale factor is applied to the model vertices, adjusting the model values to be scaled to the actual height.
c. Another file that underwent significant changes was *run_predict.py*, specifically in its *run_predict* function, where the SMPL model class is instantiated and the *predict_poseMF_shapeGaussian_net* function is invoked. This *run_predict* function is responsible for executing all the necessary steps for model prediction and returns the vertices obtained from the execution of the *predict_poseMF_shapeGaussian_net* function, as well as the faces of the 3D model obtained from the SMPL model. These values, both vertices and faces, are used for the reconstruction and visualization of the 3D models. It is important to note that these values are returned as a NumPy array.

2.2. Prediction of body measurements

After obtaining the adjusted data from the 3D model, the code from the "3d-body-measurements" repository was used [22], which measures body parts given a 3D model. For this purpose, a function called *body_measurement* was developed, which receives as parameters the faces and vertices of the 3D model used to instantiate the Body3D class from the repository. Once the class is instantiated, the respective methods are used to obtain measurements of the bust, waist and hip. The 3D model is positioned in the pose of the desired image as shown in Figure 2(c) because this pose is one of the requirements of the code from the repository. For the recommendation system implemented in this research, the body types shown in Figure 3 were considered: triangle as shown in Figure 3(a), apple as shown in Figure 3(b), rectangle as shown in Figure 3(c), hourglass as shown in Figure 3(d) and inverted triangle as shown in Figure 3(e) [23], [24]. In (1)–(5), the implemented conditions for classifying body types are observed, based on bust, waist and hip measurements in centimeters. These values were provided by the staff of Lady's Confecciones company, and they are adjusted to the types of garments marketed by the company.

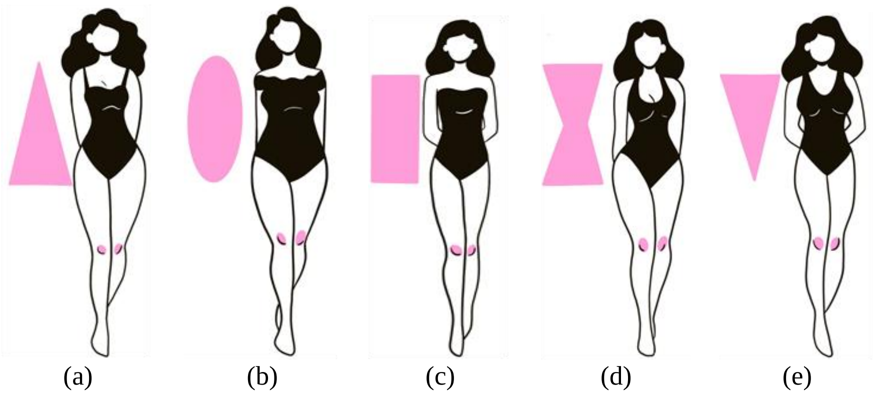


Figure 3. Body types considered in the recommendation system (a) triangle, (b) apple, (c) rectangle, (d) hourglass, and (e) inverted triangle

$$Triangle: (Hip - Bust \geq 9.14)\ and\ (Hip - Waist < 22.86) \tag{1}$$

$$Apple: (Hip - Bust > 5.08)\ and\ (Hip - Waist \geq 17.78)\ and\ \left(\frac{Hip}{Waist}\right) \geq 5.08 \tag{2}$$

$$Rectangle: (Bust - Hip \geq 9.144)\ and\ (Bust - Waist < 22.86)$$

$$Hourglass: (Hip - Bust \leq 2.54)\ and\ (Hip - Bust < 9.14)\ and\ (Bust - Waist > 22.86) \tag{3}$$

$$or\ (Hip - Waist \geq 25.4)$$
$$or\ (2.54 < (Bust - Hip) < 10)\ and\ (Bust - Waist \geq 22.86) \tag{4}$$
$$or\ (9.144 \leq (Hip - Bust) < 25.4)\ and\ (Hip - Waist \geq 22.86)\ and\ \left(\frac{Hip}{Waist}\right) < 4.90$$

$$Inverted\ triangle: (Bust - Hip \geq 9.144) and\ (Bust - Waist < 22.86) \tag{5}$$

2.3. User interface

During the user interface design process, various factors were considered, including the previous design of the ladysstore.co website implemented on WordPress, color palettes and typography. This was done with the aim of preserving visual coherence and ensuring a harmonious experience for the user. Initially, an overview of the available options is displayed to the end user to infer clothing recommendations within the virtual store. These options include the possibility to "upload an image" or "enter your measurements" as shown in Figure 4. Under the "upload an image" option, there is the alternative to upload a preferably frontal image along with the user's height in meters as shown in Figure 5(a). In the "enter your measurements" option, the possibility to enter bust, waist and hip measurements in centimeters is provided as shown in Figure 5(b).

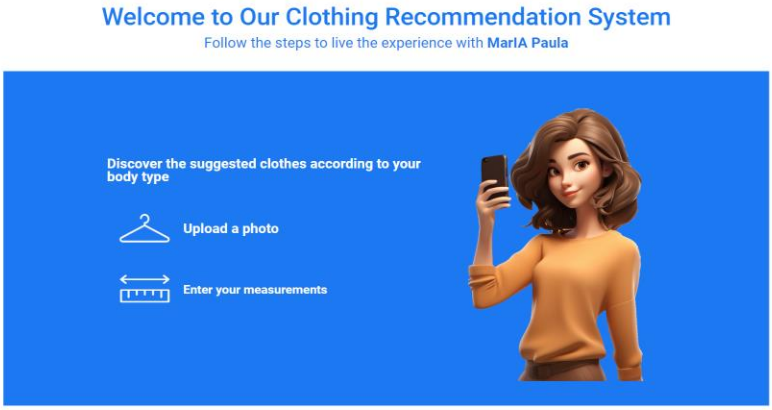
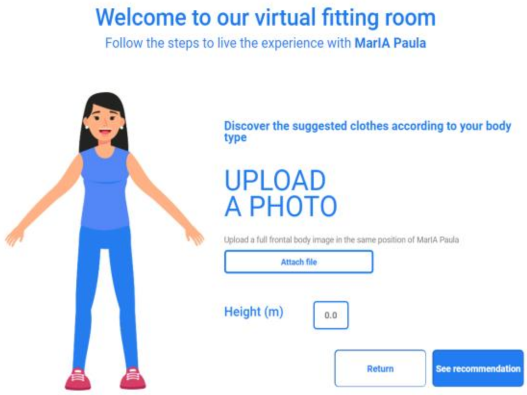
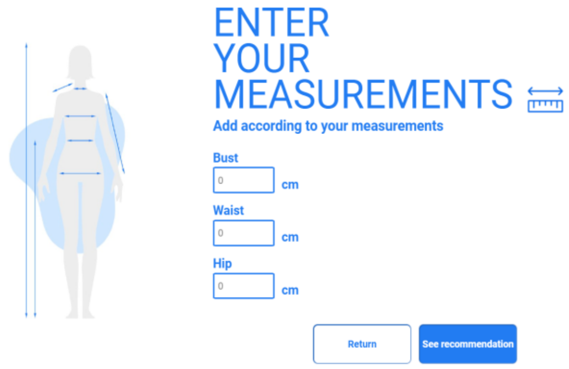


Figure 4. User interface of the recommendation system



(a)



(b)

Figure 5. Alternatives to use the recommendation system (a) prediction model from a photo and (b) recommendation based on body measurements

For coding the designs, HyperText markup language (HTML) and cascading style sheets (CSS) were used. These codes were integrated directly into the custom HTML code block of the native WordPress editor. Once the interface was implemented, the connection with the API was established using JavaScript code, primarily utilizing the fetch API. Figures 6(a) and 6(b) demonstrate how the API is consumed for the prediction route with the 3D model and the manual route with the measurements provided by the users.

```
const data = new FormData();
data.append('file',inputFile.files[0])
data.append('height',inputHeight.value)
loader.style.opacity = 1;
loader.style.display = "flex";

await fetch(URL_file, {
    method: 'POST',
    mode: 'cors',
    body: data
})
.then(response => response.json())
.then(data => {
    location.replace(`https://ladysstore.co/product-tag/${data}/`)
})
.catch(error => {console.log(error);alert(error)});
```

(a)

```
const data = new FormData();
data.append('busto',busto.value);
data.append('cintura',cintura.value)
data.append('cadera',cadera.value)
loader.style.opacity = 1;
loader.style.display = "flex";

setTimeout(async function(){
    await fetch(URL_manual, {
        method: 'POST',
        mode: 'cors',
        body: data
    })
    .then(response => response.json())
    .then(data => {
        location.replace(`https://ladysstore.co/product-tag/${data}/`)
    })
    .catch(error => {console.log(error);alert(error)});
},2500)
```

(b)

Figure 6. API consumption (a) 3D prediction model and (b) manual route with the user's body measurements

The main differences in consuming the two endpoints of the API lie in the parameters they receive for their operation; however, in both cases, a standard value between 1 and 5 is returned, which is employed in constructing a web address in the format: *https://ladysstore.co/product-tag/03/*. The first section corresponds to the ladysstore.co domain, followed by the path of the tagged products, and finally, the number representing the filter tag, in this case, the recommendation provided by the API. It is worth noting that all products were previously tagged with a code number associated with one or more recommendations, according to the criteria established by the clothing lines of ladysstore.co and the five body types considered in this work. Figure 7 shows what the user interface displays when filtered by tag 2, corresponding to the apple body type.

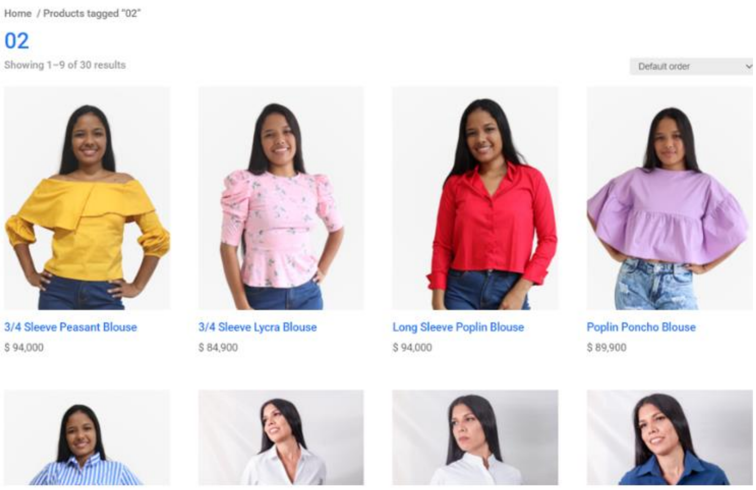


Figure 7. Example of tagged garments for the apple body type

2.4. Participating users

As test subjects, we worked with 15 female volunteers who participated in the research with the purpose of evaluating and understanding the effectiveness of the model in predicting female body types. Photographs of each participant were taken in different poses, and the height of all participants was documented, all due to the nature of the model's operation. Additionally, measurements of bust, waist and hip were manually taken in advance to establish a clear reference for the program's performance by comparing the resulting data with real values. It is important to highlight that all participants are of legal age and signed an informed consent agreeing to their participation in the project and the use of images for research purposes. Each volunteer was requested to wear tight-fitting clothing to minimize errors in predicting body measurements with the 3D model.

3. RESULTS AND DISCUSSION

In order to predict the body type, the first task performed with the recommendation system was to predict the sizes of the bust, waist and hip measurements of each participant, using 3D modeling and artificial intelligence. In this case, a 5% acceptance value was established for the percentage error, according to the company's recommendation. Additionally, the tests were conducted using photographs of the volunteers, whose recommended pose was established after various trials as shown in Figure 2.

3.1. Prediction of body measurements

In the evaluation of the bust measurement estimation, the model exhibited good performance in most tests, according to the recommended acceptance threshold as shown in Table 1. Additionally, some results fell within a range of significant values, especially those that did not exceed the 8% limit in error. However, there were also results with errors close to 9%, which always corresponded to participants wearing clothing with some pleats or looseness, affecting the accuracy of the 3D model. Overall, an acceptable average error of 6.4% was achieved in the bust measurement. In the results of the waist measurement predictions, there were few variations in the percentage errors of some participants, with good results below 5% as shown Table 1. There are some data that are around 9%, but do not exceed the 10% error. In this case, an average error of 6.31% was obtained. The best results were obtained for hip measurement predictions, with an average error of 4.56%, with only one participant with an error of 9.05% as shown Table 1. As a final point to consider, the relative standard deviation in the percentage error of bust, waist and hip measurements estimates correspond to 4%, 5%, and 3%, respectively. This highlights the variability in the data relative to their averages. Furthermore, it emphasizes that hip measurement predictions were more accurate compared to those of other body measurements.

With the purpose of measuring the accuracy of the model in comparison to the observed data as shown in Table 1, the calculation of the Pearson correlation coefficient was performed. This indicator allows quantifying the strength and direction of the linear relationship between the variables under study, enabling the determination of the model's reliability for future tests. For each prediction of body measurements, a scatter plot was used to calculate the linear regression in each instance and, thus, obtain the Pearson correlation coefficient. In the case of the bust measurement, in the scatter plot as shown in Figure 8(a), the resulting trend line yields a Pearson coefficient of 0.96. The same procedure was implemented for the estimates of the waist measurement as shown in Figure 8(b) and the hip measurement as shown in Figure 8(c), where Pearson coefficients of 0.97 and 0.84 were obtained, respectively. These results indicate a strong positive correlation between the actual and predicted values by the model, demonstrating the good performance of the algorithms implemented in predicting body measurements. Temitayo *et al.* [25] also succeeded in predicting body measurements for applications in anthropometry, sizing, and clothing fitting; however, it was necessary to use hardware such as the Kinect sensor and perform two iterations to achieve good performance.

Table 1. Results of the prediction model for body measurements

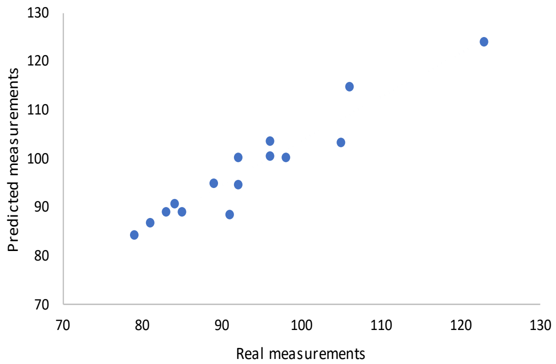
Subject	Bust (cm)		Error (%)	Waist (cm)		Error (%)	Hip (cm)		Error (%)
	Real	3D model		Real	3D model		Real	3D model	
1	98	100.41	2.46	79	84.10	6.46	105	106.71	1.63
2	96	100.52	4.71	81	86.25	6.48	103	99.28	3.61
3	92	94.77	3.01	78	80.11	2.71	105	105.47	0.45
4	105	103.47	1.46	86	90.96	5.77	108	108.47	0.44
5	91	88.57	2.67	77	75.19	2.35	102	100.79	1.19
6	79	84.36	6.78	69	72.86	5.59	99	94.63	4.41
7	84	90.81	8.11	71	75.82	6.79	100	102.66	2.66
8	89	95.01	6.75	73	79.97	9.55	100	104.96	4.96
9	83	89.22	7.49	67	73.24	9.31	90	95.53	6.14
10	85	89.21	4.95	68	74.62	9.74	94	101.54	8.02
11	81	86.99	7.40	73	75.26	3.10	91	95.28	4.70
12	123	124.26	1.02	110	110.15	0.14	116	125.11	7.85
13	106	114.85	8.35	93	100.51	8.08	108	116.69	8.05
14	92	100.25	8.97	75	82.11	9.48	100	105.19	5.19
15	96	103.83	8.20	81	88.33	9.05	98	106.87	9.05
	Average error		5.49%	Average error		6.31%	Average error		4.56%

3.2. Prediction of body type

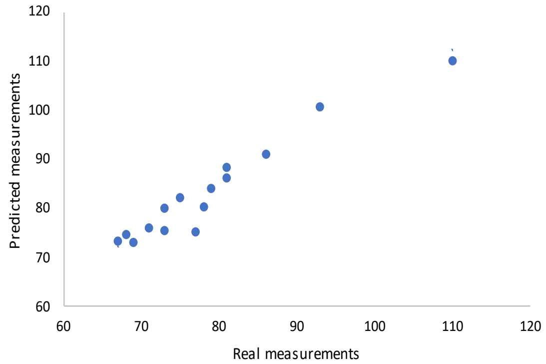
To assess the model's performance in predicting body types, 45 photographs and manually taken measurements of bust, waist and hip were utilized. These measurements allowed for the identification that the participants' bodies fell into 3 of the 5 body types addressed in this research. In the results of the prediction model presented in Table 2, the accuracy in predicting rectangle body types is highlighted, reaching 92.31% accuracy. This means that only one out of the 13 tests conducted with rectangle body type women was incorrectly anticipated. However, in relation to the other body types, the results were not as outstanding, with a 44.4% accuracy in triangle body types and 0% precision in predicting hourglass body types.

An important aspect is the model's confusion in anticipating the hourglass body type. As evidenced in the results, the model tends to confuse them with rectangle body types, whose proportions are primarily distinguished by the waist measurement when performing calculations. Considering the analysis of the waist measurement prediction as shown in Table 1, it can be inferred that the deviation in the predicted data may be the main reason for the limited effectiveness of the model in anticipating hourglass body types. However, it is important to highlight that the clothing in Lady's Confecciones catalog may be associated with more than one body type, and therefore the results obtained in this phase of the research are applicable to the company.

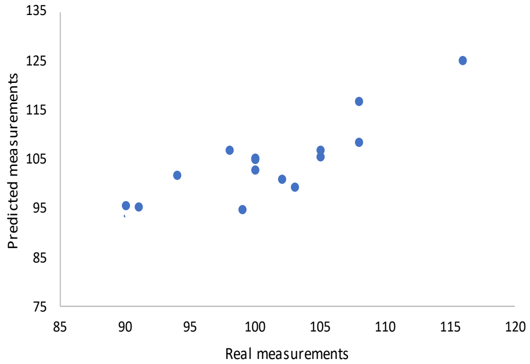
One significant aspect we identified, which affected the prediction model, is related to the type of clothing worn by the participants for photograph registration. Overall, all women in the study were asked to wear tight-fitting clothing, but the implemented prediction model tends to increase body measurements. We were able to establish that when clothing worn by participants has pleats or is slightly loose, the prediction results are affected. Prediction model results with two participating women is shown in Figure 9(a)-(d). In Figure 9(b), it can be observed that the 3D model obtained with machine learning maintains a correct relationship with the body type in Figure 9(a). In this case, it can be seen that the user wore tight-fitting clothing that favors the identification model. On the contrary, in Figure 9(d), it can be observed that this result predicts a body type with larger measurements compared to the original photo in Figure 9(c). In this case, the type of clothing worn by the user resulted in a 3D model that increased her body structure, and therefore the prediction of bust, waist and hip measurements is affected.



(a)



(b)



(c)

Figure 8. Linear regression between prediction model and the real measurements (a) bust, (b) waist, and (c) hip

Table 2. Model performance in body type prediction

	Model classification					
Observed	Triangle	Apple	Rectangle	Hourglass	Inverted Triangle	Accuracy (%)
Triangle	8	0	10	0	0	44.4
Apple	0	0	0	0	0	0.00
Rectangle	1	0	12	0	0	92.31
Hourglass	2	0	4	0	0	0.00
Inverted Triangle	0	0	0	0	0	0.00

Our findings have significant implications for the fashion industry and e-commerce. By implementing a clothing recommendation system based on machine learning and 3D modeling techniques, we are enhancing the user shopping experience and increasing customer satisfaction. This innovative approach not only benefits Lady's Confecciones by boosting sales and customer loyalty but also sets a precedent for other fashion companies looking to enhance their online product offerings. As part of future efforts, we propose the incorporation of additional data, such as style preferences and usage occasions to further personalize recommendations. Additionally, we suggest exploring the integration of emerging technologies, such as augmented reality, to enable users to visualize how recommended clothing would look on them before making a purchase. It is also important to continue researching and developing machine learning algorithms to improve the accuracy and efficiency of the recommendation system, especially regarding body type identification and the selection of properly fitting garments, for which increasing the number of participants is crucial. Finally, we propose a detailed study of the results presented in [26], where good outcomes were achieved in the application of deep learning for fashion product classification, in order to apply them to the enhancements of the proposed clothing recommendation system.

(a) (b) (c) (d)

Figure 9. Prediction model results with two participating women (a) user with rectangle body type, (b) 3D model, (c) user with hourglass body type, and (d) 3D model

4. CONCLUSION

After completing this research, the viability and potential of a clothing recommendation system based on machine learning techniques and 3D modeling to enhance the shopping experience in Lady's Confecciones e-commerce have been demonstrated. Our results indicate that the system shows promise in accurately identifying body types and suggesting garments that fit appropriately. The system allows predicting bust, waist and hip measurements with a total average error of 6%, and a relative standard deviation between 3% and 5%, indicating that the data provided by the prediction model are closely clustered around the mean. Regarding the prediction of body type, the best results were obtained for the rectangle body type with 92.31% accuracy, while problems were encountered during the prediction for hourglass and triangle body types in some participants. However, the results obtained are fully functional for the company since, in general, the garments they produce are designed for more than one body type at a time.

ACKNOWLEDGEMENTS

We appreciate the funding of the research by *Fondo Nacional de Financiamiento para la Ciencia, la Tecnología y la Innovación*, Fondo Francisco José de Caldas, grant number 112721-118-2023. The APC was funded by Vicerrectoría de Investigación of the Universidad del Magdalena.

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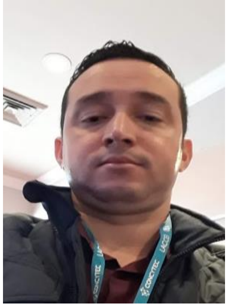

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