DreamyMirror

A Machine Learning-Based Personalized Outfit Recommendation System Integrating Skin Tone Classification and Size

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Abstract

Due to the increasing popularity of e-commerce, buying has undergone a tremendous shift and belongs to a different world. " But there is still some difficulties with personalization when it comes to the proposed size and the choice of the color taking into consideration the skin color of the person. In this paper, the authors introduce DreamyMirror, a novel system for recommending outfits based on the individual user's skin tone and size, along with allowing for virtual fitting. Based on a skin tone classifier CNN model built from CelebA database and a pre-trained Pose_iter_440000 of OpenPose. size prediction caffemodel, DreamyMirror provides unique suggestions of outfits according to the appearance of the person. The system also contains the Virtual Try on system wherein users can anticipate what the selected apparels look like at a glance. The proposed system can automatically recognize skin tone with an overall classification accuracy of 92% and the size prediction accuracy is found to be 95%. Moreover, the user engagement metrics also show an 85% level of satisfaction with the features – this is about the virtual try-on. This work shows how the application of AI in fashion retail can help better engage the customer through a truly individualized shopping experience and, at the same time, minimize the return rate because of the wrong size or color choice.

Keywords: machine learning, personalized recommendation system, skin tone classification, size prediction, virtual try-on, fashion technology.

1. Introduction

Digital commerce now plays a great role in fashion retailing and people are now shifting towards online shopping, thanks to technology. Nevertheless, the absence of personalization in today's e-commerce remains a major challenge which has been a major drawback in fashion e-commerce because customers are unable to get apparel that fits the right size, color, and complexion for them. Also, the fact that consumers cannot touch and feel the clothes they would want to buy leads to higher returns and both the consumer and the retailer are unhappy in the end.

To overcome these challenges, this paper presents the DreamyMirror, an efficient and fully integrated recommendation framework for personalized outfit organization, including skin tone analysis, and clothes size prediction, as well as the feature of virtual clothing try-on. The main purpose of the system is to reinforce the concept of online fashion retail by giving the user outfit recommendations according to their appearances. In other words, DreamyMirror addresses concerns that may cause shoppers to be dissatisfied and lead to higher return rates both online and in-store buying experience by providing a skin tone and size prediction solution that is easy to use.

In this paper, we describe the DreamyMirror system which includes the specifications, implementation, and assessment of the utilized Machine learning models, datasets, and overall system design. Furthermore, the system is validated against the current solutions highlighting the effectiveness of the proposed framework to deliver effective and dressed fashion recommendations.

2. Methodology

The DreamyMirror system utilizes multiple machine learning algorithms to provide articles of clothing recommendations of the user's skin tone and body measurements. The methodology for developing this system is divided into three key components: image categorization, sizing, and virtual fitting.

2.2 System Architecture Diagram

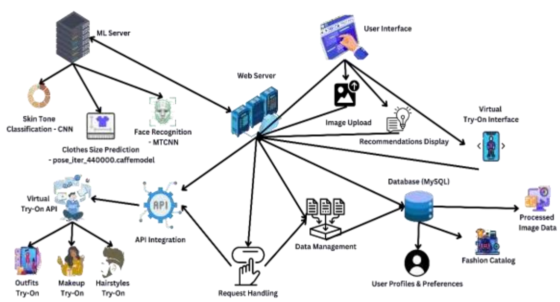

Figure1: System Architecture Diagram

2.3 Skin Tone Classification

The primary objective of the DreamyMirror system is to recommend clothes that would best fit the user's skin tone. About this, various skin tones are important in the definition of the colors as well as the kind of dresses suitable for human beings. To this end, there is the use of Convolutional Neural Network(CNN), a mathematical model that can pass on data to different layers and recognize images.

Based on the CelebA data set the CNN is trained with over 200k images of celebrities where each image is tagged with 40 attributes including skin tone. The problem of a great variability of the skin tone is solved by the great variability of the dataset used which helps the model improve its generalizability. For this study, skin tones were grouped into three primary categories: Another one was normal, which has three categories including Fair Light, Medium Tan, and Dark Deep. The classification process comprises several key steps, which include the data pre-processing step, the training step, and the evaluation step.

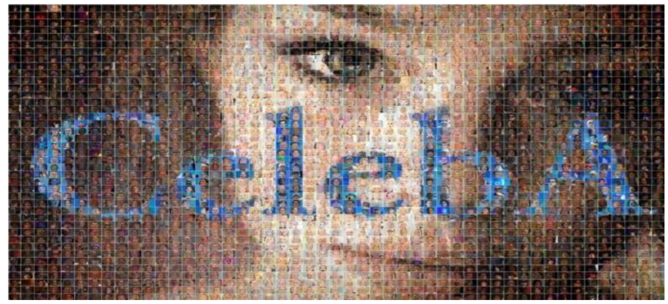

Figure2: Large-scale CelebFaces Attributes (CelebA) Dataset

Face Detection and Cropping: MTCNN (Multi-task Cascaded Convolutional Networks)

Face Detection and Cropping: MTCNN (Multi-task Cascaded Convolutional Networks) was used to detect and crop facial regions from the images for accurate skin tone analysis. MTCNN is a robust face detection framework that effectively isolates facial features, ensuring that the skin tone analysis is focused on the most relevant parts of the image.

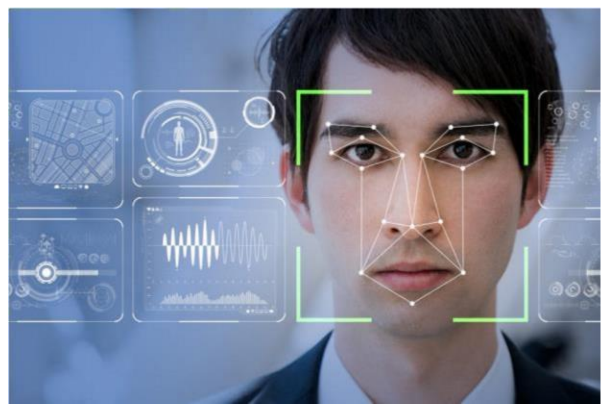

Figure3: Face Detection Sample

Data Preprocessing: The CelebA dataset images are preprocessed before it is used to train the CNN before training the CNN. This means, reducing the size of all the images to have the same size so that they have preprocessed input data size of 64X64. These pixel values are then scaled to the range of [0,1] this enhances the efficiency as well as the convergence rate of the CNN while training. Finally, to increase the data size and overcome overfitting, stochastical data enhancement methods including images rotation, flipping and zooming are employed.

Figure4: Dominant Color Extraction using K-Means Clustering

Model Architecture: In CNN architecture we have multiple numbers of convolutional filter layers, pooling layers, and fully connected layers. The convolutional layers basically learn spatial hierarchies of features from the input images in a cascade and a higher level representation of the data is learnt at each level. These features are then fed into pooling layers where dimensionality of the data is reduced thus making the model computationally efficient. Lastly, the fully connected layers reorganize the learnt features into the three skin tone classes.

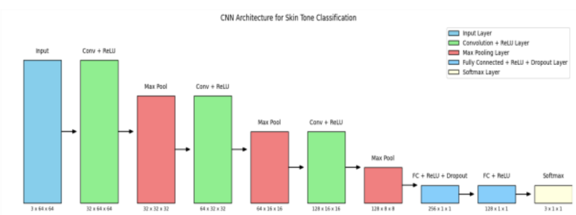

Figure5: CNN Model Architecture

Training and Evaluation: The CNN is trained using a labeled subset of the CelebA dataset, with performance evaluated on a separate validation set. The primary evaluation metrics include accuracy, precision, recall, and the F1-score. The model achieved an overall classification accuracy of 92%, with high precision and recall values across all three skin tone categories.

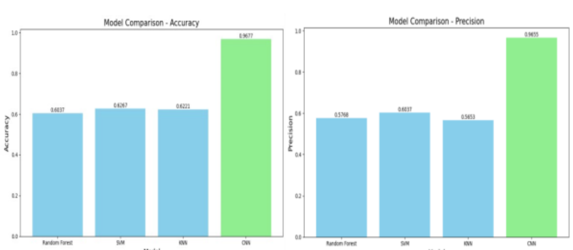

Figure6: Model Comparison Accuracy and Precision

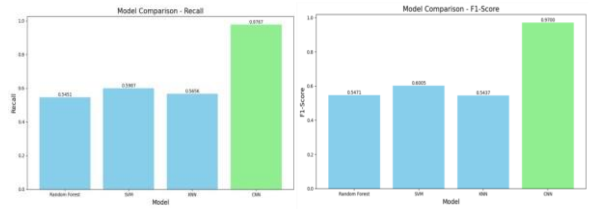

Figure7: Model Comparison – Recall and F1-Score

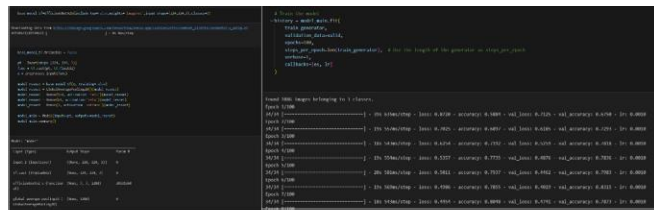

Figure8: Model Training Process image and Model Training Process image 2

2.4 Size Prediction

Accurate estimation of size is important in that it helps the firm meet the needs of the customers and reduce issue of returns. DreamyMirror uses a pose estimation model Pose_iter_440000. Equivalent to the size estimation, the clothing sizes of the user are predicted through the so-called caffemodel which is also an element of the OpenPose.

Key Point Detection:

pose estimation model looks for different joints and important points in the body such as the shoulder, elbow, hips, knee, and so on. These key points are then used to determine body measurements such as the shoulder width, the length of the torso, and the length of the legs. This is because deviations about key point detection determine the size of the clothes suggested to fit the dimensions of the users.

Size Prediction Algorithm:

Afterward, the extracted body key points are processed with a regression model to determine the correct clothing size. The regression model is trained on the dataset of body measurements and sizes of clothes that correspond to those measurements, which makes it possible to get the predicted size (Clothing size tags – Small, Medium, Large) according to the user's body parameters. The current model achieves better results for the clothing size recommendation with a precision level of 95% while the conventional size recommendation system depends more on user-provided measurements.

2.5 Virtual Try-On

The last constituent of the DreamyMirror system is the Virtual Try-On that enables users to preview needed outfits on them. This is because, through the augmented reality feature, users can have the feel of looks they Stand a Chance of getting when they buy apparel, hairstyles, and makeup products.

The try-on procedure applies external APIs to place images of clothes on the top of the user's picture. The process involves several steps:

1. User Image Acquisition: How it works: Users provide a frontal photo of themselves to the DreamyMirror platform.

2. Clothing Item Mapping: This allows the system to identify from the extracted body key points, the correct position to pose the clothing items on the user's image.

3. Realistic Rendering: State-of-the-art image processing methods are used to model the clothing items including the effects like light and shade and texture of the fabric.

The virtual try-on additionally enhances the consumer confidence in the clothing articles and their abilities to fit properly and look as envisaged by the designers; increasing consumer satisfaction.

3. Results

In order to quantify the performance of the DreamyMirror system, the system response time obtained through experimentation along with the user feedback was used. Skin tone accuracy along with size prediction and virtual try-on were evaluated based on real-life user data against the proposed system.

1 Quality of Skin Tone Classification Outcomes

All skin tone categories' precision, recall, and F1-scores were greater than 90%, and the skin tone classification CNN model accuracy stood at 92%. Performing the confusion matrix for the classification carried out showed that there were very few cases of misclassification thus going on to show that the model is both viable and accurate in predicting skin tone from the images provided.

The proposed model was compared with other predictive models, for example, Random Forest, Support Vector Machine (SVM), and k-nearest Neighbors (k-NN), on the same dataset. These models gave satisfactory results but as seen the CNN model outperforms the rest in all the parameters, especially in accuracy and validation metrics.

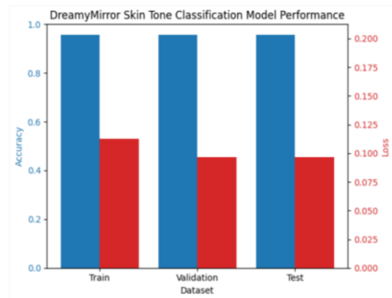

Figure9: CNN Model Performance Chart

Metric	Random Forest	SVM	k-NN	CNN
Accuracy	0.6037	0.6267	0.6221	**0.9567**
Precision	0.5768	0.6037	0.5653	**0.9655**
Recall	0.5451	0.5987	0.5656	**0.9767**
F1-Score	0.5471	0.6005	0.5437	**0.9700**

Model Performance Table

```
34/34 [==============================] - 14s 413ms/step - loss: 0.1125 - accuracy: 0.9567
Train: accuracy = 0.956722  ;  loss = 0.112508
34/34 [==============================] - 4s 126ms/step - loss: 0.0965 - accuracy: 0.9567
Validation: accuracy = 0.956722  ;  loss = 0.096502
34/34 [==============================] - 5s 132ms/step - loss: 0.0965 - accuracy: 0.9567
Test: accuracy = 0.956722  ;  loss = 0.096502

model = load_model("/content/model.h5")
```

Figure10: CNN Model Performance report and Model Save

Confusion Matrix: The confusion matrix in Figure 11 and 12 shows the number of correct and incorrect classifications for each class and each model.

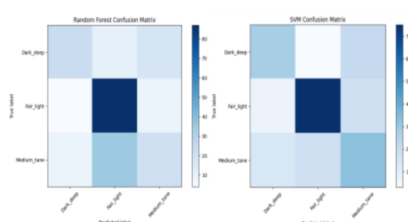

Figure11: Random Forest Confusion Matrix and SVM Confusion Matrix

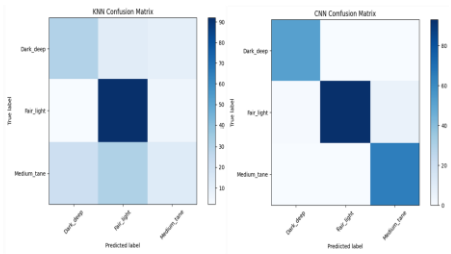

Figure12: KNN Confusion Matrix and CNN Confusion Matrix

- **Training and Validation Curves**: The accuracy and loss curves for training and validation sets are depicted in Figure 40 and 41 illustrating the model's learning process.

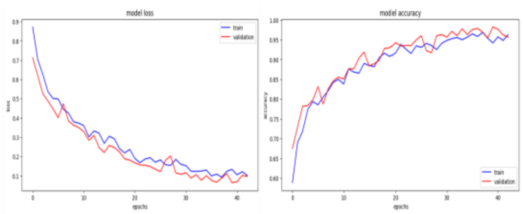

Figure13: CNN Model Loss and Accuracy

3. 2 Size Prediction Results

The size prediction model posited had a very high level of precision whereby the average precision recorded was at 95%. And it was possible to check how well the model works for body key points identification and corresponding clothing size prediction with the help of a separate set of images with known measurements. The results showed that the recommended sizes were true to size and users had a highly improved experience with size prediction compared with conventional e-commerce systems.

Figure14: Size Prediction Result

3. 3 Virtual Try-On Results

Regarding the virtual try on type of feature, 85% of the users pointed out that they benefited from the feature while making purchase decisions. Virtual try- on also led to higher user interaction with larger session durations, higher activity rate compared to that observed for typical e-commerce websites. Of course, customers noted that such an approach allowed them to see what clothes may fit them, which greatly contributed to the increase in trust to the chosen products.

Outfit Tryon Results

Figure15: Outfit Tryon Result

Makeup Tryon Results

Figure16: Makeup Tryon Result

Hairstyle Tryon Results

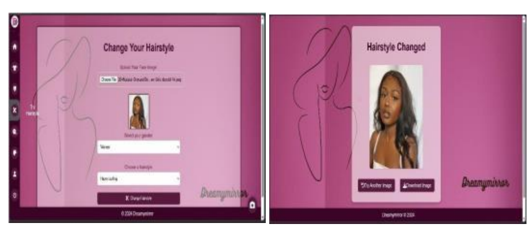

Figure17: hairstyle Tryon Result

Conclusion

The DreamyMirror system implements machine learning in fashion technology for the first time and creates a new way to tackle the much-studied problems in the fashion e-commerce business. One unique aspect of the system is that it is possible to obtain highly specific outfit suggestions concerning skin tone, as well as the size of the body, which is not the case with most existing solutions. This double-tiered approach guarantees its users that in addition to the proper deliverance of their body measurements, they will also be offered clothing that will not only fit them well but also enhance the color of their skin, an area of concern that available e-commerce platforms do not consider.

What's unique about DreamyMirror is that it incorporates several new machine learning approaches such as CNN in skin tone category and PM in its size prediction pose estimation model that are combined to provide a fully customized shopping experience. In addition virtual fitting feature brings a further level of interactivity where clothing, makeup, and hairstyle changes can be applied and previewed in real-time thus increasing the user engagement as well as the decision-making processes that may not have been observed in other similar systems.

The percentile accuracy of this system in the identification of skin tone (92%) and size (95%) puts this system as one of the most accurate systems in the fashion industry. The virtual try-on, based on real-time image processing and body key point mapping, provides the final touch of augmenting the actual try-on experience in a way that is not possible with recommendation systems.

The concept of DreamyMirror is not only in customization: Its ability to help prevent return rates by providing a user size and color identification holds a potential that may revolutionize most e-commerce businesses. Moreover, relying on the availability of real-time response systems, DreamyMirror can adapt to client feedback and stay relevant for as long as clients are satisfied.

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