AI-Driven Personalized Outfit Recommendation with NLP and GAN Enhanced Chatbot

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Abstract. A new AI-powered fashion assistant which employs machine learning strategies operates as our core presentation to elevate the online shopping operations. The system uses fashion item recommendations since it integrates both user preferences alongside body measurements and visual search functions. Natural language processing (NLP) performs with image generation models like Stable Diffusion to generate individual fashion designs through the assistant. Through our method we generate specific fashion product recommendations that know about user demographics along with personal style characteristics and their actual dimensions. The recommender system delivers recommendations through a content-based filtering method that focuses on precision and satisfaction among users when matching them with clothing products. The combination of features like deep learning along with computer vision permits us to establish an advanced responsive fashion recommendation platform. The obtained results show how AI-motorized instruments have the capability to revolutionize the fashion sector by developing shopping encounters which better understand individual preferences.

Keywords: AI Fashion Assistant, Personalized Recommendations, Machine Learning, Natural Language Processing, Fashion Recommender System, Body Measurements, Stable Diffusion, Custom Design Generation, Computer Vision, User Preferences.

1 Introduction

The fashion industry advances through permanent transition because customers demand individually tailored purchase journeys with enhanced shopping effectiveness. The increasing growth of e-commerce has caused an exponential rise in demanding sophisticated recommendation systems since customers seek personalized shopping experiences with efficiency. Traditional e-commerce systems receive poor treatment from shopping mothers who seek customized recommendations that would fit their physical and preference requirements. As a proposed AI-based fashion assistant uses computer vision and machine learning technology it generates personalized clothing recommendations through a user-provided body size and visual search capability along with their preferred fashion styles.

The system operates with content-based filtering to generate recommendations following user criteria that include gender identification specifications together with dimensional characteristics and color preferences at specific events. Through the user interface Stable Diffusion functions as one of the available advanced AI tools that users can use to develop customized clothing designs. Users who provide style code and description terms enable the system to create exclusive personalized custom fashion products. Online shopping visuality

ICITSM-Part I 2025, April 28-29, Tiruchengode, India

DOI 10.4108/eai.28-4-2025.2357796

stands to gain major transformation through the combination of personalized suggestions together with made-to-order tools in an interactive system which supports better user satisfaction and interaction.

The document presents its content through two distinct sections including Section II that focuses on fashion recommendation system approaches and existing methodologies. The present document presents Section III as its development methodology for the AI Fashion Assistant followed by Section IV which contains results. The paper presents its discussion of findings and future perspectives in Section V as its concluding segment.

2 Literature Review

The formerly used content-based and collaborative filtering recommendation systems failed to provide adequate solutions for complicated user preference patterns. Wang and Qiu [1] created a deep neural network system that applies e-commerce side information to fashion collocation provides precise outfit suggestions. Users can interact and benefit from the NLP-driven responses of DigAI chatbot-based fashion recommender system designed by Landim [2]. Research reveals how AI Shapes fashion recommendations but lacks approaches for creating novel outfit imagery based on user criteria.

Researchers now dedicate efforts to apply GANs in developing personalized fashion designs for the industry.

Painguzhali et al. [3] explored artificial intelligence effects along with generative models on fashion through AI-driven design generation systems which optimize personalization in their research. The article written by Shanti [4] examined how AI-generated models improve customer shopping experiences through advanced customized solutions. Singapore explained in his research that the fashion and apparel industry benefits from machine learning algorithms which generate dynamic recommendations based on user preferences [5]. The research on GANs mainly explores theoretical advancements while failing to show actual implementations of these models operating within interactive applications utilizing recommendation-based chatbots.

The Text2FashionGAN defines a system that merges conditional GANs and Word2Vec embeddings to deliver custom fashion recommendations per Madhan et al. [6]. By employing this method the system delivers better user-customer communication that enables them to describe particular outfits using ordinary speech. Gichuhi et al. [7] created a Fashion Artificial Intelligent Robot that implements GANs for developing personalized style suggestions through their system. Although the study implements generative models it fails to incorporate reinforcement learning for system enhancement based on user feedback.

Bansal et al. [8] studied large language models (LLMs) for helping web personalization system development and analyzing contemporary AI recommendations and prospective future trends. NLP stands established as a crucial technology for enhancing chatbot recommendations. Huang et al. [9] produced a multi-modal clothing recommendation method by uniting VAEs with large models for enhancing fashion recommendation precision. Research has enhanced computerized fashion recommendations yet new scientific work needs to develop one efficient multicomponent system by connecting NLP with GANs and reinforcement learning. Our project addresses the usability challenge through a recommendation algorithm that pairs chatbots and artificial intelligence for designing outwear.

3 System Architecture and Methodology

3. 1 Methodology

The proposed fashion recommendation system follows a hybrid approach that integrates traditional recommendation techniques with advanced machine learning models to enhance personalization and user experience. The system combines Content-based Filtering, Collaborative Filtering, Convolutional Neural Networks (CNNs), and Generative Adversarial Networks (GANs), all while continuously learning from user interactions through Reinforcement Learning. The methodology is divided into the following key steps:

3.1.1 Data Collection

The dataset contains fashion images with fine-grained product information, which include signals from image (category, color, type of clothing etc.) and corresponding attribute words in text (usage, season as formal description for those latent attributes). We use these details to train the recommendation models and derive important features for personalized recommendations as well.

3.1.2 Feature Extraction using CNNs

For advanced image processing, Convolutional Neural Networks (CNNs) are used. The visual attributes such as color, texture, and style of the fashion items are analysed using CNNs and hence it is empowered to recommend products similar in terms of their visual features. This step improves over filtering approaches by now considering both item attributes, and images.

3.1.3 User Interaction with Chatbot

At its core is an NLP-driven chatbot, which Sippola says walks the user through their preferences and taste by conversing with them. Receives its predictable direction from GPT and BERT models in order to understand user intent creating an easier flowing interaction. When users define their personalized attributes (e.g., style, color, size or occasion), the system adapts its forecasting.

3.1.4 Recommendation Generation

A hybrid recommendation engine uses both Collaborative Filtering (based on user-item interactions) and Content-based Filtering (based on item features) to generate recommendations. The system calculates similarities between users and items to suggest relevant products.

3.1.5 GAN-based Outfit Generation

Once a user expresses a desire for a unique outfit or combination, Generative Adversarial Networks (GANs) are employed to generate entirely new outfit images based on user inputs. Conditional GANs (cGANs) are specifically used to ensure that the generated outfits match user preferences related to style, body type, gender, color, and occasion.

3.1.6 Reinforcement Learning

As users interact with the system, reinforcement learning techniques continuously improve the recommendation model. The system learns from user feedback (e.g., positive or negative reactions to suggestions) and adjusts its future recommendations based on this real-time feedback loop.

3.2 System Architecture

The architecture of the fashion recommendation system is composed of several interconnected modules, each serving a distinct function in the recommendation pipeline:

3.2.1 Data Input Layer:

The system ingests fashion product data, including product descriptions, images, and user feedback. This data is preprocessed to handle missing values, clean text data, and normalize the images.

3.2.2 Feature Extraction Layer (CNN):

The images of fashion products are processed using Convolutional Neural Networks (CNNs). This layer extracts high-level features from the product images, such as texture, color, and design, which are essential for content-based recommendations.

3.2.3 Recommendation Engine Layer:

- **Collaborative Filtering**: The collaborative filtering module calculates the similarity between users based on their past interactions with products and recommends items that similar users have liked.
- **Content-based Filtering**: The content-based module matches users with products based on the extracted features (such as category, style, and color).

3.2.4 User Interaction Layer (NLP Chatbot):

Providing a kind of natural language refinement for users to qualify their preferences all in the context of an NLP-driven chatbot. By using GPT and BERT models, the chatbot also infer user intent and catch relevant attributes that it can suggest to them (same as what colors they like, what is their size, preferred styles) so in turn we able to do some kind of products recommendation with personalized experience.

3.2.5 Outfit Generation Layer (GAN):

In particular, conditional-GANs (cGANs) can also generate novel combinations based on user specifications for outfit recommendation; creating personalized recommendations when the desired exact item may not exist in the dataset.

3.2.6 Reinforcement Learning Layer

The reinforcement learning module then adjusts in the system according to feedback from the users. Rather, it learns from its users: The system refashions the recommendations on the fly, refining itself over time to better anticipate what users will accept or reject.

3.2.7 Output Layer:

This yields final personalized outfit recommendations, which are either those from the recommendation engine, or GAN outputs depending on the state and confidence score (0–100%) that determines how likely we think these recommended outfits would be to match to events with our user.

3.3 System Flow

3.3.1 User Input:

The user interacts with the system through the chatbot, providing their preferences regarding fashion styles, sizes, colors, and occasions.

3.3.2 Feature Extraction & Recommendation:

The system processes the input to recommend matching products using both collaborative and content-based filtering. It then uses CNNs to analyze product images and match them with user preferences.

3.3.3 GAN-based Customization:

If the user is unsatisfied with the recommendations, the system uses GANs to generate new, customized outfits based on the user's input.

3.3.4 User Feedback and Learning:

The system learns from user feedback, improving its future recommendations via reinforcement learning. By integrating these methodologies and components, the system not only offers personalized fashion recommendations but also continuously adapts to user preferences, making it an intelligent and dynamic solution for fashion e-commerce

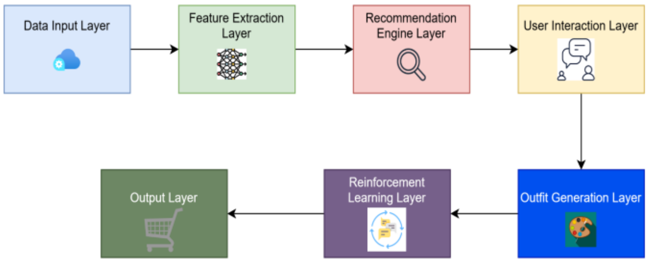

Fig. 1. System Architecture.

4 Experimental Setup and Results

4. 1 Data Distribution Analysis

We analyzed the distribution of fashion items in various categories, including usage, color, gender, and master category. The following observations were made:

4.1.1 Usage Distribution

The Casual category dominates the product landscape since it comprises more than 35,000 items yet Sports Ethnic and Formal categories contain reduced numbers of items. The skewed distribution shows that casual fashion items outnumber other categories thus affecting recommendation precision for customers who favor different styles. (Fig 2 Usage Distribution Graph).

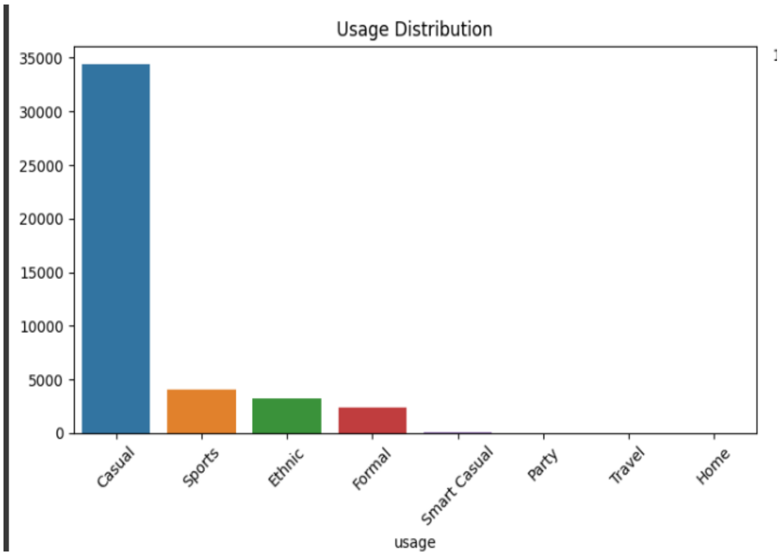

Fig. 2. Usage Distribution Graph.

4.1.2 Top 10 Colors

Black stands out as the dominant color followed by White and Blue according to the color distribution graph that contains thousands of attired items. The dominant colors within the dataset show the most commonly selected fashion choices because they allow the system to support customers who prefer basic yet versatile clothing options. Fig 3 shows Top 10 Colors Graph.

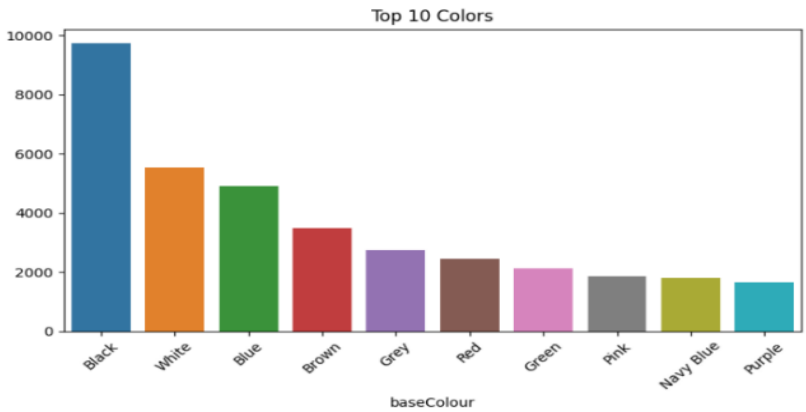

Fig. 3. Top 10 Colors Graph.

4.1.3 Gender Distribution

The gender distribution graph shows Men and Women categories include the most availability of products while Boys and Girls and Unisex categories display less product existence. Traditional gender-based categories absorb most of the items available in the fashion sector. Fig 4 shows Gender Distribution Graph

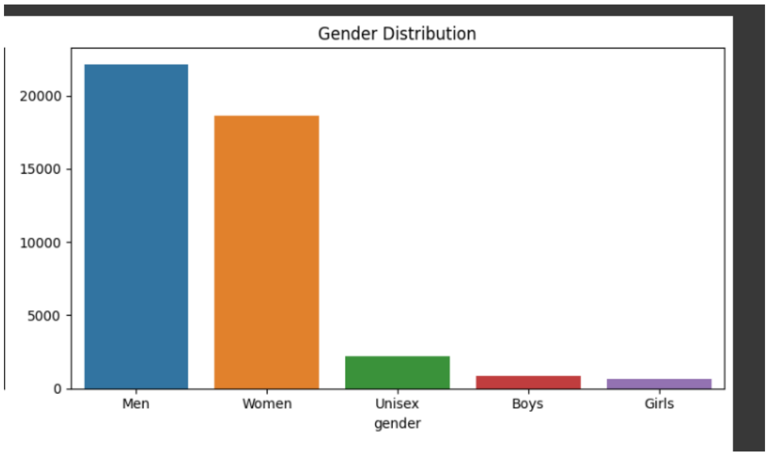

Fig. 4. Gender Distribution Graph.

4.1.4 Master Category Distribution

The substantial portion of data belongs to Apparel items while Accessories and Footwear items form the secondary portions in the dataset. The system's major emphasis rests on clothing and fashion accessories which explains why Personal Care and Sporting Goods contain only a small number of items. The Fig 5. Master Category Distribution Graph.

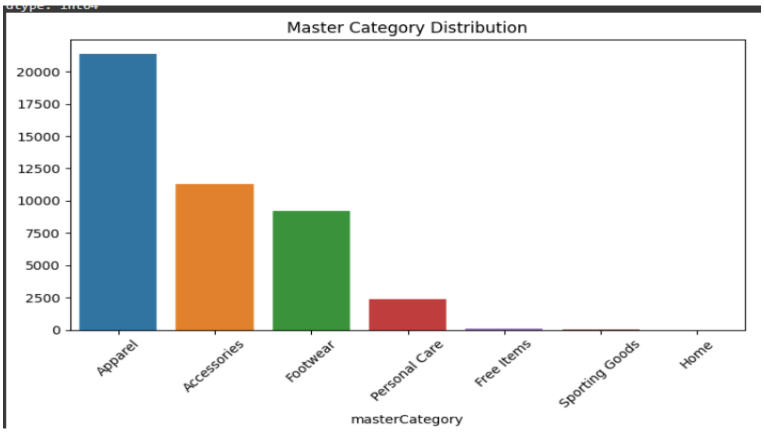

Fig. 5. Master Category Distribution Graph.

4.1.5 Recommendation Accuracy

A recommendation system evaluation method involved matching system outputs to user preferences while calculating similarity measuring between suggested products. Based on user preferences regarding style color along with category the system produced effective recommendations for each individual user. The casual style product request from users received recommendations that matched to the 0.80 - 1.00 similarity scale. Table 1 shows Product Recommendation Breakdown.

The system provided detailed breakdowns of recommendations, including:

- Product names
- Color, style, and category
- Similarity scores between the user’s preferences and the recommended items.

Table 1. Product Recommendation Breakdown

Rank	Product Name	Similarity Score	Color	Style	Category	Fit Type	Pattern
1	ADIDAS Men Black Bag	0.80	Black	Casual	Accessories > Bags > Laptop Bag	Regular	Solid
2	Fastrack Men Black Backpack	0.80	Black	Casual	Accessories > Bags > Backpacks	Regular	Solid

3	Fastrack Men Black & Orange Backpack	0.80	Black	Casual	Accessories > Bags > Backpacks	Regular	Solid
4	United Colors of Benetton Men Olive Duffel Bag	0.80	Olive	Casual	Accessories > Bags > Duffel Bag	Regular	Solid
5	Wrangler Men Auston Navy Blue Shirt	1.00	Navy Blue	Casual	Apparel > Shirts	Regular	Solid
6	Scullers Men Grey Waistcoat	0.80	Grey	Casual	Apparel > Waistcoats	Regular	Solid

4.1.6 Generated Outfit Images

The system generates unique fashion products by using GAN-based image generation technology that follows user specifications. Users who provide a request for a summer season red dress receive a generated image output which Fig 1 presents as an example. The system accurately produces the requested outfit based on the user-provided descriptions including colors and fabric selection. GANs produce customized real-looking product images according to text descriptions which makes the user experience better by offering personalized clothing choices outside of current product options.

The feature depends on the Stable Diffusion Pipeline model for pre-training purposes to produce images that meet user-defined style requirements together with specified color and seasonal demands. Shoppers receive personalized products thanks to description-based image generation which represents a modern shopping solution over traditional recommendation systems.

4.1.7 Output Screenshots

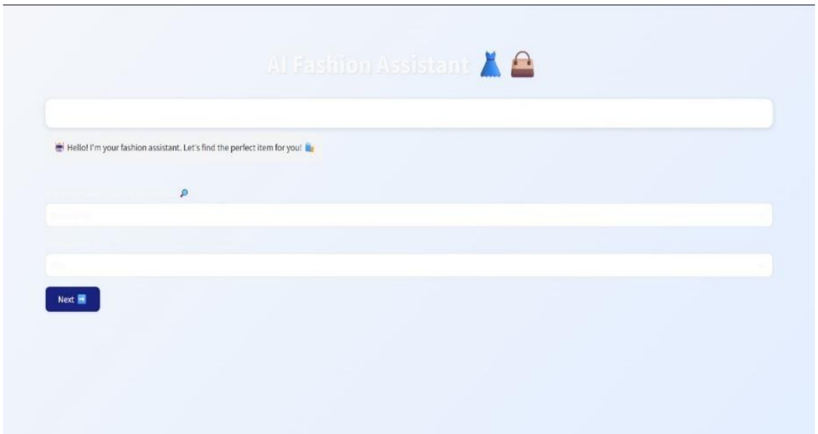

Fig. 6. Home Page.

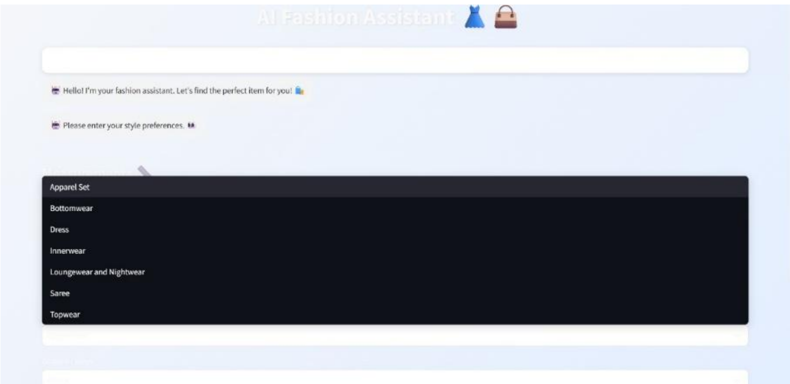

Fig. 7. Item Preferences Selection Page.

Fig 6 shows Home page and Fig 7 shows Item Preferences Selection Page.

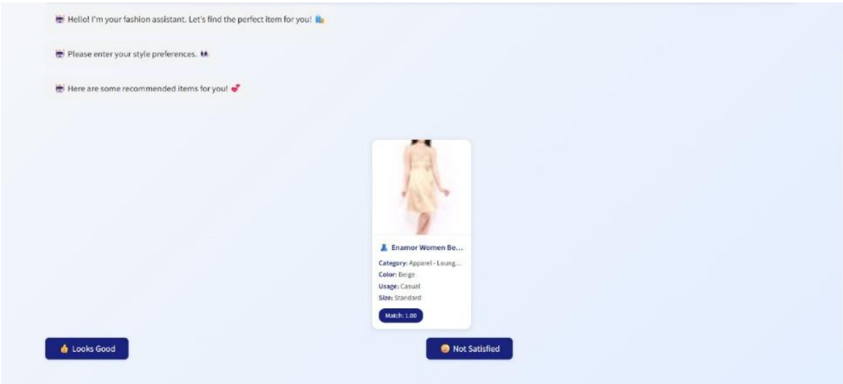

Fig. 8. Suggesting the Outfits.

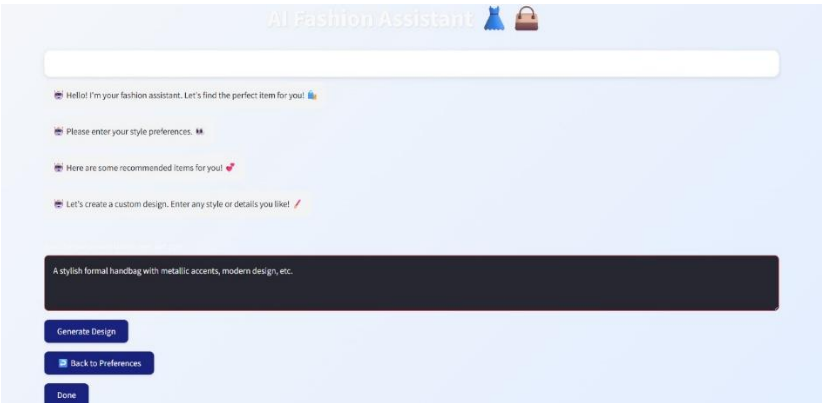

Fig. 9. Interaction with Chatbot.

Fig 8 shows Suggesting the Outfits, Fig 9 Interaction with Chatbot and Fig 10 Chatbot Showing Recommendations.

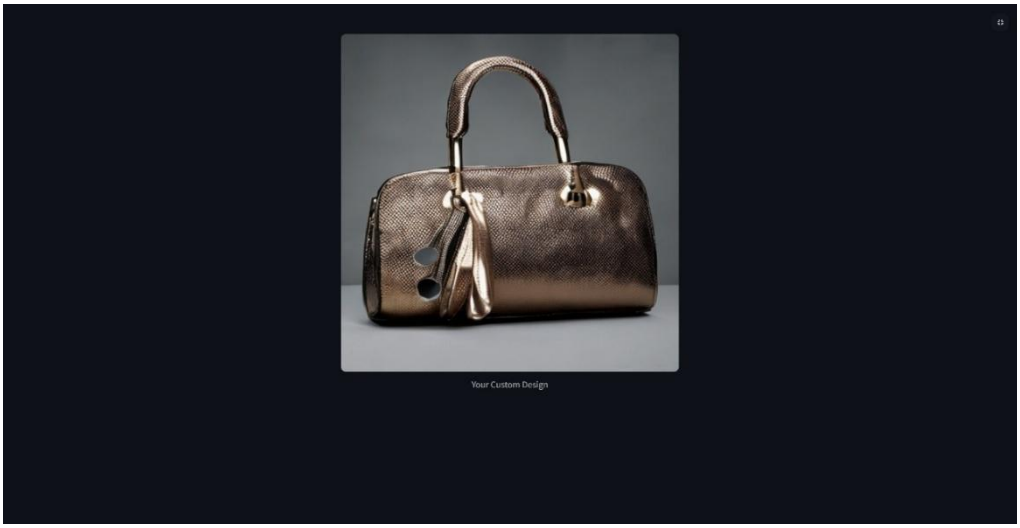

Fig. 10. Chatbot Showing Recommendations.

5 Conclusion

The fashion recommendation system created in this research implements combination of content-based filtering plus collaborative filtering together with CNNs and GANs for delivering precise personalized outfit recommendations. User preferences change more effectively because the system generates precise product recommendations through continuous feedback integration from the product characteristics of style and color and category type. The system faces two main obstacles which include data imbalance problems affecting particular categories and the need to improve GAN image generation algorithms. The system's capability to deliver an extreme personalized shopping experience will improve for broader users when these aspects receive additional improvements.

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