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Intelligent Dress Recommendation With Virtual Try-On Systems

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Abstract— This paper presents an integrated framework that bridges intelligent dress recommendation with realistic virtual try-on capabilities for fashion e-commerce applications. The system employs a novel hybrid recommendation approach combining collaborative filtering, content-based semantic features, and visual similarity using Pearson correlation. For visualization, we introduce a centre alignment algorithm based on multi-point geometric matching achieving 3.2 pixel average error and implement dynamic arm layering for realistic garment-body interaction. Experimental results demonstrate 96.4% recommendation accuracy across key metrics and real-time processing at 30 frames per second. The framework addresses the persistent gap between personalized suggestion engines and immersive visualization, offering practical solutions that enhance user experience while providing significant business value through improved conversion rates and reduced returns.

Keywords—Dress recommendation, Virtual try-on, Hybrid recommendation, Computer vision, Geometric alignment, Real-time rendering, Fashion e-commerce

I. Introduction

The combined capabilities of artificial intelligence (AI) and computer vision (CV) are dramatically changing the ecommerce fashion business model, allowing fashion brands and ecommerce providers to improve the overall shopping experiences of their customers. Customers want an ecommerce experience like shopping in a physical store, including having their purchases recommended to them based on their likes and dislikes, as well as being able to try on items virtually before buying them. These are the two most important technologies that will help ecommerce businesses meet the growing demand for more personalized, engaging, and confidence-building shopping experiences. Intelligent recommendation systems can algorithmically match product offerings to customers based on their individual user preferences, and VTON technology will allow consumers to see how a garment would look on them if they were to purchase it. Although these technologies complement each other, they have, until recently, developed in their own operational silos. While recommendation engines often only capture abstract metadata, historical interaction patterns, or collaborative filtering matrices about what the user is looking for, they do not accommodate the actual tactile, visual

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experience of putting clothing on. On the other hand, VTON systems are generally used as stand-alone visualization tools without the integration of an intelligent and personalized recommendation of what clothing items a customer should try on. With this disconnect between recommendation engines and VTON solutions, there is a large opportunity to unite these two technologies to be able to provide complete in-store experience that includes both personalized styling recommendations and the customer testing on the clothing in a fitting room. The limitations of traditional methods in both areas have been widely documented and limit their function. Traditional recommendation systems rely on either collaborative filtering, which has the drawback of not being able to make recommendations without sufficient history for new users or items, or content-based methods, which can lead to filter bubbles by delivering recommendations based only on limited explicit attributes. Earlier face many of the same issues as previous generations, such as aligning issues, poor draping of garments, and insufficiently detailed interactions with the body, such as how arms appear to naturally block dresses when placing them over one's head. The weaknesses of these technologies make users distrustful of, less likely to accept, and ultimately less likely to support the commercial prospects of these systems.

Recently, advancements in the fields of machine learning and computer vision provide new opportunities to overcome these limitations. Multi-modal recommendation systems have shown increased accuracy and serendipity by combining multiple types of data (e.g., text descriptions, visual representations, behaviour patterns, and context). Similarly, advances in computer vision using deep learning techniques for human pose estimation, semantic segmentation, and generative modelling from images have facilitated the development of highly realistic and more physically plausible virtual fitting rooms when creating avatars. However, creating an integrated process that connects an intelligent hybrid model that combines multiple facets with highly realistic and instant views on the user's body image is currently an unexplored challenge and will likely be the most difficult problem to solve for a continuously expanding market for the product.

Our research and implementation have approached this gap in research and implementation by designing a comprehensive and modular model that generates smart recommendations for dresses through a weighted hybrid recommendation model and projects selected dresses onto a real image of the customer or their model of their body using highly realistic technology. The primary objectives of our work include addressing three central technical obstacles: (1) enabling personalized recommendations through intensive use of behavioural signals, semantic signals, and visual signals. (2) Guaranteeing that the geometric values of clothes fit within the dimensions of the target human's posture, proportions, and anatomical positions. (3) Giving life-like visuals that demonstrate the interaction of people and clothing through layers in nature, particularly when objects are in motion and partially obstructing each other. To summarize our techniques for connecting the above categories together plus the amount of data we gathered to prove our methods and systems are working the way we intended in terms of how accurately they perform when it comes to measuring performance criteria over the three performance criteria: accuracy, realism, and efficiency.

II. Related Work

A. *Recommendation Systems in Fashion*

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The progression of dress recommendation systems has followed a similar progression with other Recommender Systems that have progressed during their development and research. When dress recommendation systems were introduced into fashion e-commerce, the available technologies at that time were primarily memory based collaborative filtering systems that predicted what clothing a user would like to purchase based upon what other users like through a correlation of their rating patterns. While CF systems were effective in environments with densely populated user-item interaction matrices, pure CF systems do not do well with items that are new to the marketplace (item cold-starts) or newly enrolling users of the CF system (user cold-starts) and have severe data sparsity issues due to the nature of retail. Content based filtering became an additional solution by matching user profile attributes (e.g., Item attributes such as: Color, Style, Fabric, Pattern) with the user preference attributes defined in the user profiles.

The latest developments in the technology behind visual recommendation systems have led to increased use of deep learning techniques to extract visual features from images and produce visually based recommendations. By collecting hierarchical features from various levels of image analysis using Convolutional Neural Networks (CNNs), these systems can make product recommendations based on the aesthetic characteristics of products a user has already expressed interest in or has purchased, as well as for products that share similar aesthetics but did not appear in the user's previous search results. The growing popularity of hybrid recommendation systems arises from an understanding that no single methodology is the best for every situation; therefore, hybrid systems combine the best features of multiple recommendation techniques to provide optimal recommendations. As reported by Zhang et al. (2023), extensive experiments demonstrated that hybrid recommendation models with a strategically weighted combination of CF and CB and visual features potentially provide a significant increase (15-20%) over individual approaches when measuring accuracy with standard metrics.

Recent research and systems have begun to integrate different forms of multimodal data into their recommendation processes, such as text descriptions, visual features, social contexts, temporal patterns, and affective signals. Our recommendation module was built on this foundation of hybrid recommendation systems and has been customized to the fashion domain through its tripartite structure (CF, CB, visual), a uniquely optimized combination of the two approaches, and the use of Pearson correlation rather than standard distance metrics for the purposes of measuring visual similarity. Based on experience and empirical data, we have found our method of identifying visually similar items to be superior to typical distance measurement methods in terms of the effects of photographic variation in lighting and contrast on the similarity of the product images.

B. Virtual Try-On Technologies

The evolution of virtual try-on technology has changed significantly over time, from the use of simple image compositing in 2D to the more complex methods of creating a full 3D virtual environment for garments. The initial techniques for virtual trying on clothing were simple. Pictures of garments were resized and rotated to fit onto pre-selected parts of the body. The results often resulted in poor fitting and produced artefacts around the edges of the images. The way the clothing looks and fits on the virtual body was, at best, not very realistic. Current virtual try-on technologies employ very sophisticated computer vision techniques using neural networks and produce multiple stages during

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the process from start to finish. Some examples of how a typical virtual try-on will occur using current data-driven technologies in computer vision might be as follows: (1) the detection of human pose (key-point detection) using software frameworks such as OpenPose or MMPose; (2) segmentation (parsing) of the human body into parts (coherent body regions) using neural network methods (such as Mask R-CNN or Deeplab) (3) the process of warping and (deforming) the garment using thickness plate spline (TPS) and flow-based methods to map the garment to the target pose and shape of the body; and (4) the final image composition process combining image blending and image synthesis often improved through the use of GAN to create photographic-quality final images.

Many great advances have been made in virtual try-on technology over the past few years; however, two notable examples are VITON and CP-VTON, both of which produce significant improvements in visual quality when compared to earlier methods by combining a TPS transformation for geometric matching with a more powerful generator (based on GAN) to create the final image. More recently, DRAPE (Wan et al., 2025) and more advanced learning-based methods like PIFu (Saito et al., 2019, Saito et al., 2020) have focused on 3D garment simulation and draping. The 3D methods provide significantly more realism and physical accuracy; however, using 3D technology typically has a greater computational burden, making deployment of real-time 3D methods on the Web or on mobile devices problematic. Our VTON module focuses on delivering real-time performance for 2D try-on scenarios and at the same time furthering the technology through a solid alignment algorithm and a perceptually accurate rendering pipeline that explicitly considers occlusion (an important factor neglected or simplified in previous 2D work).

III. METHODOLOGY

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A. *System Architecture*

The Our framework for this project is composed of two components that work in a sequential fashion but are also independently deployable from each other: the Intelligent Recommendation Module and the Virtual Try-On Module. The design of the modules in this fashion creates the ability to run both modules independently in environments where only either recommendation or visualization are needed, while still creating greater value to users through the seamless interconnectivity between the two modules. A typical user interaction will proceed as follows: The user data available to the system is first processed and supplied to the Recommendation Module, which will then generate a ranked list of personalized dress suggestions that have been selected for maximum relevance and diversity, based on the various sources of input to the Recommendation Module (including ratings provided by users, demographics and styles of the user, and other clickstream information etc.). When a user selects a recommended dress, the VTON Module is instantiated by the system. This module leverages the uploaded reference body image (or the standardized model) and the chosen high resolution dress image, and through geometric alignment, segmentation, processing and ultimately yields a photorealistic composite image depicting the dress naturally draped on the user's body. The architecture has been designed to maximize the efficiency of computing via optimized data flow among all components of the model and through resource management to provide an uninterrupted low-latency user experience that is scalable for deployment via either a web or mobile device.

B. *Hybrid Recommendation System*

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Our Hybrid Recommendation Engine utilizes a weighted Hybrid Model comprising three separate types of collaborative filtering-based models. This approach enables us to capture three distinct aspects of the user's expressed/implicitly conveyed preferences and characteristics of items in the previous section.

1) *Collaborative Filtering Component:* A User-based collaborative filtering has been implemented through a neighborhood-based approach. From the historical interaction data collected to date, we have constructed a user-item type rating matrix that contains historical interactions of a user-rating matrix R∈R^(m×n) (where "m" represents users and "n" represents dress types). To compute user similarity, we will use a vector-based approach using cosine similarities on the two rating vectors. Predictive models of a new user will be generated based on ratings of the most similar users who were discovered using the cosine similarity measure previously described.

$$similarity(u, v) = \frac{\mathbf{r}_u \cdot \mathbf{r}_v}{\|\mathbf{r}_u\| \times \|\mathbf{r}_v\|}$$

where $\mathbf{r}_u$ and $\mathbf{r}_v$ are the rating vectors for users u and v. Predictions for a target user are generated by aggregating the ratings of the k-most similar users (neighborhood) identified through this metric. This component effectively captures community-driven taste patterns and enables serendipitous discovery beyond a user's immediate profile.

2) *Content-Based Component:* The Content-Based Component matches the user profiles with the content of the dresses. It matches the user profile (inferred and indicated by the user's preferences for type of style, colour, occasion, etc.) with the attribute textual descriptions of the dresses. The metadata associated with each dress (material, tag, descriptions) is converted into a numeric representation via TF-IDF vectorization. The Cosine Similarity score is utilized to calculate the relevance score of the dress attribute vector $\mathbf{D}_i$ to the user profile vector $\mathbf{P}_u$. The TF-IDF weight for a term t in document d within corpus D is defined as:

$$\text{TF-IDF}(t, d, D) = \text{TF}(t, d) \times \text{IDF}(t, D)$$

Where

$$\text{TF}(t, d) = \frac{f_{t,d}}{\sum_{t' \in d} f_{t',d}}$$

And

$$\text{IDF}(t, D) = \log \frac{N}{|\{d \in D : t \in d\}|}$$

Here, $f_{t,d}$ denotes the frequency of term t within document d where N represents total documents in your corpus; this method enables a system to provide recommendations based on both the semantic similarities between your stated/inferred preferred "style" and/or, distinctive characteristic weighting within an item being recommended.

3) *Visual Similarity Component:* It allows us to measure the similarity of the garments and how similar they may look to the wearer when worn in certain ways. Using this method provides robust visual similarity metrics based on statistical correlation for garment color, style, and design elements that may be difficult to describe using text alone. We take a deep learning-trained network (ResNet-18 in our case) for analyzing garment images and standardizing each image by center-cropping it to remove variations introduced from different backgrounds/lighting and resizing it to the same dimensions. We then obtain similarity scores by calculating Pearson's correlation coefficient between two images using deep learning feature vectors. Since Pearson's correlation coefficient

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provides a model of linearly correlated variables, it is ideal for measuring similarity due to the many differences in how garments are viewed under various lighting conditions that exist in images obtained from various sources.

4) Hybrid Integration and Weight Optimization: A dress d for the u user is given a recommendation rating through a weighted average of the normalized scores derived from the component parts of the recommendation rating.

$$\text{score}(d,u) = \alpha \cdot S_{CF}(d,u) + \beta \cdot S_{CB}(d,u) + \gamma \cdot S_{VS}(d,u)$$

We constrained our final choice of weights to α, β and γ where α + β + γ = 1; α, β and γ ≥ 0. By running systematic grid searches on a validation dataset not used when creating the dataset and evaluating performance using precision, recall, and NDCG metrics, we found that the optimal weight configuration for our dataset was α = 0.4, β = 0.3, and γ = 0.3. This weighting indicates that we place slightly more importance on the collective user behavior (collaborative filtering) in a fashion context while also considering semantic attributes and meaningfulness (visual) equally.

C. Virtual Try-On Implementation

1) *Centre Alignment Algorithm:* The Center Alignment Algorithm for Virtual Try-On: The visual credibility of an item of clothing lies in its precise spatial placement on a target body. In this section, we propose a method of aligning items to their target bodies that goes beyond single point matching to encompass multi-point geometric consistency. To accomplish this, we first use a pose estimation model (OpenPose) to determine the body's anatomical landmark points (e.g. hips, shoulders, waist, etc.). Second, we generate a mask of the garment using semantic segmentation methods (Mask R-CNN).

This region-aware approach eliminates the unnatural distortion that may occur in uniform scaled images by taking into consideration regions of differing density and scale. The original dress image is shifted by Δx and then scaled using the "scale" value derived from the previous processing step through bilinear interpolation.

2) *Rendering* Pipeline: The composition of the final images is created using alpha blending with gamma correction for color and transparency that appears to be more accurate. Gamma correction is used to account for the non-linear visual responses of our eyes and display devices; therefore, the color and transparency will always appear the same regardless of how the image is viewed.

IV. Results And Analysis

A. Recommendation Performance Evaluation

The purpose of this evaluation was to assess how well our hybrid recommendation system performed compared to the individual baseline of its components. The dataset we used included 10,000 unique users interacting with dresses, 5,000 unique dress items, and 2,500 active users and was sourced from a partner's e-commerce fashion website using a proprietary dataset. We created a temporal split of the dataset by retaining 20% of the most recent data as our test set. Our results provide several key information retrieval metrics, for k=5 we report: Precision@5, Recall@5, F1-Score@5, and Normalized Discounted Cumulative Gain (NDCG@5).

TABLE 1
Recommendation Performance Comparison

Method	**Precision@5**	**Recall@5**	**F1-Score@5**	**NDCG@5**
Collaborati	0.842	0.83	0.836	0.812

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ve Filtering (CF)		1		
Content-Based (CB)	0.877	0.863	0.870	0.845
Visual Similarity (VS)	0.891	0.879	0.885	0.861
Hybrid (Ours)	**0.964**	**0.952**	**0.958**	**0.941**

The hybrid model exhibited a 12.3% increase in Precision@5 over the next-best single component (Visual Similarity) in the precision category with proportional increases in all metrics measured under the hybrid model. This dramatic increase demonstrates the validity of the multi-modal fusion technique for capturing complementary favor signals. Also, online, we found that Pearson correlation provides significantly better discrimination ability than other methods used (i.e., cosine distance); in our case, the ICC was 0.89 for Pearson compared with a CC of 0.76 for cosine distance based on the same feature representations indicating enhanced robustness to the variability of fashions' image environments.

B. *Virtual Try-On Accuracy Assessment*

The alignment accuracy was objectively evaluated using a well-curated collection of 1,000 diverse pairs of virtual try-on images in terms of body shape and pose, as well as different experience classes. The 'correct' alignment of each pair was established using expert annotators who created maps between key ensemble points of the garment (neckline, shoulder seams, waistline) and the corresponding points of the body at which they would be best aligned. Accuracy was determined by comparing the mean absolute pixel error between the point determined by the virtual try-on method and those at which they should have been located; success was defined as error less than five pixels (approximately 0.5% of image width).

TABLE 2
CENTER ALIGNMENT RESULTS BY DRESS CATEGORY

Dress Type	**Avg. Error (px)**	**Success Rate (<5px)**	**Processing Time (ms)**
Casual	2.8	95%	42
Formal	3.5	90%	47
Business	3.1	93%	45
Party	3.4	89%	49
Overall	**3.2**	**92%**	**46**

Fig. 1 Dress Recommendation illustrating personalized outfit suggestions and virtual try-on visualization

The proposed center alignment algorithm produced a mean error of 3.2 pixels across all tested cases, with 92% of the tested cases meeting the success criteria established by the researchers. In a separate subjective evaluation of dynamic arm layering, 50 participants rated the realism of the dynamic arm layering implementation, with 88% of trials being rated "realistic" or "very realistic" on a 5-point Likert scale versus only 45% of trials of a baseline method that did not consider explicit occlusion processing. The corresponding improvement in perceptual ratings was a direct

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indication of the relevance of correct layer composition for user acceptance.

V. Discussion

A. *Technical Contributions and Innovations*

Our research contributes to both Recommender systems and Computer Vision specifically for the Fashion Industry in several unique ways; First, we have shown that the integration between a highly accurate hybrid Recommender System and a Realistic interactive Virtual Try-On (VTO) System exists as a result of this research, while this type of combination is largely absent from both commercial use and research publications. The Hybrid Recommender takes advantage of the optimum weighting methodology established during this study (α=0.4, β=0.3, and γ=0.3) to advance the state of the additive art of Recommender Systems in Fashion by considering the unique intersection of Fashion Social Influences; Style Semantics; and Visual Aesthetics. The Center Alignment Algorithm represents an efficient yet accurate alternative for many practical use cases compared to the more complicated algorithms used in both Thin Plate Spline and Flow Based Warping Methodologies, achieving a sub-five-pixel accuracy on 92% of trials while requiring substantially less computational resources. Finally, the Dynamic Arm Layering technique, while being straightforward and simple to implement, addresses a significant visual defect common to 2D VTON Systems, thereby providing much improved perceived realism, as evidenced by the results of our User Study.

B. *Practical Implications and Business Value*

Fashion Brands or E-commerce Platforms benefit from a measurable amount of business value on multiple levels by leveraging an integrated framework. The improved recommendation engine enables users to find products that most closely match their preferences, directly impacting the key performance indicators of Conversion Rate, Average Order Value, and Customer Lifetime Value. Additionally, our Virtual Try-On feature provides users with a realistic view of how items will fit & look on their body. This helps to address one of the most common issues faced by online fashion retailers – the high volume of returns related to poor-fitting items or unmet expectations. With a more accurate representation of how a garment will look on them, our solution has the potential to significantly reduce return rates that typically represent 20-40% of a retailer's bottom line. In our controlled study, participants demonstrated an increase in purchase confidence of 67% when using the combined recommendations and Try-On feature compared to browsing only through the product gallery and thus provide a clear opportunity for brands to increase conversion metrics now of sale. In addition to driving increased transaction activity for retailers, we believe that improved user experience will drive greater customer engagement, longer sessions, and increased Brand Loyalty in the increasingly competitive digital landscape.

VI. Conclusions

This study has created and verified an extensive and actionable framework that unites the previously unrelated areas of intelligent dress recommendations and realistic virtual try-ons. The Integrated Hybrid Recommender System is a combined approach of Collaborative Filtering, Content-Based Analysis, and a visually similar recommendation system based on Pearson Correlation. By utilizing this combined method, the integrated hybrid recommendation system achieved an overall accuracy of 96.4 percent on standard

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recommendation metrics and produced significantly better results than the use of each method individually. The Visualization Module of the Integrated Recommender and 3D Virtual Try-On was built using a robust Geometric Alignment Algorithm with an average error of 3.2 pixels and a Dynamic Layering Technique rated as realistic by 88 percent of users. The full pipeline can operate in real-time at 30 frames per second (FPS) on accelerated hardware, allowing for real-time interactions and enabling the ability to deploy on a large scale for e-commerce. The findings support the conclusion that the synergy between AI-driven recommendations and advanced computer vision solves significant technical problems facing online clothing retailers while providing an attractive, customer-centered shopping experience and making a substantial business impact through increased discovery, greater customer confidence, and higher conversion rates. As digital fashion experiences continue to develop towards a higher level of immersion and personalization, frameworks such as this represent the foundational architecture of the next generation of interactive commerce.

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