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AI-Powered Virtual Fashion Try-On and Product Finder

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***Abstract*—A persistent challenge in digital fashion retail is the inability of shoppers to accurately assess how garments will look and fit prior to making a purchase. This limitation contributes to diminished buyer confidence, elevated return rates, and inefficient product discovery processes. To address these issues, this paper introduces an AI-driven virtual fitting room platform that integrates computer vision, machine learning, and augmented reality to facilitate realistic virtual garment try-on and deliver context-aware fashion recommendations. The system architecture incorporates Convolutional Neural Networks (CNNs), Generative Adversarial Networks (GANs), and semantic segmentation models to achieve high-fidelity visualization and personalized outfit suggestions tailored to individual body morphology, aesthetic preferences, and prevailing style trends. Experimental validation yields an SSIM score of 0.924, an IoU score of 0.943, and a user satisfaction rating of 4.31 out of 5, reflecting marked improvements over comparable state-of-the-art solutions. Deployment outcomes further indicate a prospective 30% reduction in merchandise return rates and a potential 200% uplift in customer conversion rates.**

***Index Terms*—Virtual Try-On, Computer Vision, Deep Learning, Fashion Technology, Augmented Reality, Recommendation Systems**

I. INTRODUCTION

The worldwide fashion e-commerce sector has witnessed remarkable expansion, with digital clothing transactions now constituting approximately 42% of total global fashion revenue. Nonetheless, this shift toward online retail has introduced considerable difficulties for consumers and merchants alike. One of the most significant drawbacks is the lack of physical interaction with products prior to purchase, which has pushed return rates for online fashion platforms well beyond 80%, inflicting financial losses on the industry estimated at around $550 billion each year [1][2].

Conventional online shopping interfaces fail to replicate the tactile and visual assurance that brick-and-mortar stores naturally provide, leaving buyers uncertain about garment fit, appearance compatibility, and overall styling. This fundamental shortcoming has driven the demand for technologically advanced solutions capable of narrowing the experiential gap between virtual and physical retail environments.

The convergence of artificial intelligence, computer vision, and augmented reality has created unprecedented avenues for delivering immersive digital shopping journeys. Virtual fitting room solutions represent a foundational shift in how consumers engage with clothing products in an online context, carrying the potential to reshape the entire fashion e-commerce landscape [3].

This research presents a comprehensive response to the growing necessity for sophisticated virtual try-on capabilities. The proposed system allows users to digitally try on clothing through uploaded photographs or generated avatars, while a smart product discovery engine offers outfit suggestions grounded in the user's body proportions, style inclinations, and trending fashion data. By harnessing computer vision techniques, machine learning models, and intelligent recommendation algorithms, the platform delivers a tailored, interactive experience designed to improve fit accuracy, strengthen shopper confidence, and substantially lower merchandise return rates [4][5][6].

II. LITERATURE REVIEW

2.1 Evolution of Virtual Try-On Technology

The earliest generation of virtual try-on frameworks relied predominantly on 2D image overlay strategies, wherein clothing items were superimposed onto user photographs without accounting for body contours, postural differences, or fabric deformation characteristics. Though these approaches offered computational simplicity, their outputs lacked realism and delivered minimal interactivity for users.

Subsequent architectures, notably VITON and CP-VTON, introduced data-driven methodologies that combined pose estimation with image warping to better conform garments to body structure. These frameworks substantially enhanced visual realism by coordinating garment positioning with the subject's posture. Despite these improvements, challenges remained around handling non-standard poses, accommodating diverse garment categories, and faithfully reproducing fine texture detail.

TABLE 1. LITERATURE REVIEW OF VIRTUAL TRY-ON APPROACHES

Author	Method	Performance	Limitation
VITON	2D Image-based	Alignment accuracy: 92.3%	Restricted pose handling
CP-VTON	Character-Preserving	Dice coefficient: 0.89	Imprecise lower garment handling
Deep Fashion2	Landmark Detection	800K+ annotated images	High annotation dependency
FashionNet	Recommendation System	Accuracy: 94.2%	Restricted to upper body garments
StyleGAN Virtual Try-On	Generative Modeling	Realism rating: 4.2/5	High computational demand

B. Computer Vision in Fashion

Computer vision constitutes the foundational layer of contemporary virtual try-on systems, enabling essential operations including human pose estimation, body part segmentation, and clothing region identification. Libraries such as MediaPipe and OpenCV are routinely employed for landmark detection and image preprocessing, while deep learning frameworks like U-Net provide fine-grained segmentation of anatomical regions and garment boundaries.

These capabilities collectively underpin accurate garment-to-body alignment and produce visually coherent outputs, particularly under challenging conditions involving varied poses or inconsistent background environments.

Pose Detection and Segmentation Module: This component leverages MediaPipe to extract skeletal body landmarks and employs an improved U-Net variant for partitioning the human body and clothing zones, enabling precise correspondence between user anatomy and target garments.

Virtual Try-On Engine: The try-on engine adopts a composite strategy that merges Thin Plate Spline (TPS) transformation for spatial geometry warping with Generative Adversarial Networks (GANs) for photorealistic synthesis, resulting in natural-looking garment overlays that faithfully retain original texture characteristics.

Feature Extraction Module: A hybrid framework combining Convolutional Neural Networks (CNNs) with Vision Transformers (ViTs) is used to derive both local detail features and global structural representations from clothing imagery, significantly improving the system's capacity to interpret complex patterns and fabric textures.

The similarity matching sub-module identifies visually comparable products across multiple platforms using extracted feature descriptors, supplemented by web scraping and API-based integration. It additionally furnishes users with comparative data including pricing and stock availability.

C. Deep Learning Architectures

Contemporary developments in deep learning have meaningfully elevated the capabilities of virtual try-on systems. CNNs serve as the workhorse for hierarchical feature extraction, while GANs facilitate the synthesis of photorealistic imagery and complex textures. Vision Transformers (ViTs) have further emerged as a powerful complement, capturing long-range contextual dependencies across image regions and enhancing interpretation of intricate garment structure. The synergistic integration of these architectural paradigms allows modern systems to generate try-on outputs that are more detailed, spatially consistent, and perceptually convincing than earlier single-model approaches.

III. MATERIALS AND METHOD

System Architecture

The proposed framework adopts a component-based modular design wherein multiple specialized subsystems operate in coordination to deliver an end-to-end virtual try-on and product discovery experience.

1. Image Processing Module: Responsible for the initial preparation of input imagery, this module handles operations such as resolution normalization, pixel value scaling, and noise suppression, ensuring all inputs conform to a standardized format suitable for downstream processing.
2. Pose Detection and Segmentation Module: MediaPipe-driven landmark extraction is paired with an enhanced U-Net segmentation pipeline to delineate and distinguish between body regions and clothing areas, establishing the spatial correspondence required for garment alignment.
3. Virtual Try-On Engine: A hybrid warping and synthesis approach is employed, combining TPS-based geometric deformation to reshape garments according to the user's body structure with GAN-based rendering to produce texturally faithful and visually natural outputs.
4. Feature Extraction Module: CNN and ViT components collaborate to extract multi-scale clothing features, capturing both granular texture information and high-level structural patterns to enable more accurate cross-platform product matching.

Technical Implementation

1. Deep Learning Architecture: The system pipeline incorporates the following specialized networks:

- Human Parsing Network: A U-Net variant with adaptive mixed pooling layers for high-resolution body part delineation
- Clothing Warping Module: Spatial Transformer Networks (STN) integrated with TPS for geometrically accurate garment registration
- Texture Synthesis Network: A StyleGAN-inspired architecture for producing detailed and realistic garment texture renderings
- Recommendation Network: ResNet50 serving as a feature backbone with task-specific classification heads for fashion attribute analysis

2. Training Strategy: Model training leverages transfer learning from pre-trained feature extractors, progressive training schedules, and adversarial optimization. Robustness is further enhanced through augmentation strategies encompassing pose perturbation, illumination variation, and garment texture manipulation.

Improved U-Net Segmentation Method

The segmentation pipeline employs an enhanced U-Net architecture that incorporates a mixed pooling mechanism. The mixed pooling operation is expressed as:

Mixed pooling = η · max(a,b)∈Ai,j IPkba + (1-η) · (1/|Ai,j|) Σ(a,b)

Here, IPi,j denotes the pixel intensity value at row i and column j of the input image IP; η is a learnable blending coefficient drawn from [0,1]; |Ai,j| specifies the spatial extent of the pooling region; and m, n indicate the image dimensions in width and height respectively.

The encoder comprises four sequential blocks, each containing a pair of convolutional layers with 3×3 receptive fields activated by Leaky ReLU nonlinearities. A mixed pooling operation with a 2×2 kernel is applied between blocks to reduce feature map resolution while preserving spatially discriminative information. The decoder branch reconstructs spatial detail via transposed convolution layers with 3×3 kernels, with skip connections bridging corresponding encoder layers to retain multi-scale contextual information throughout the network.

IV. EXPERIMENTATION AND RESULT

A. Dataset Composition

System evaluation drew upon a curated combination of publicly available benchmarks and custom-collected data to ensure broad coverage across body types and garment categories:

- DeepFashion2: A comprehensive benchmark comprising over 800,000 annotated fashion images with detailed clothing attributes and skeletal keypoints.
- VITON Dataset: A standard evaluation corpus of 16,253 paired person-garment images specifically designed for virtual try-on assessment.

- Custom Dataset: An internally compiled collection of over 5,000 samples representing diverse body morphologies and clothing styles, used primarily for recommendation system validation.

B. Implementation Details

The experimental configuration allocated 20 samples to the test partition and 99 to the training partition. Input imagery was uniformly resized to 256×256 pixels with aspect ratio preservation and zero-padding applied to fill remaining regions. Each model was trained across 250 epochs using mini-batches of size six. The AdamW optimizer was employed with an initial learning rate of 0.0002. Experiments were conducted on a workstation equipped with dual Intel Xeon processors, 32 GB of RAM, dedicated GPUs, and 384 GB of total memory. The PyTorch 1.5.1 framework was used throughout, with all code authored in Python 3.6.8.

C. Performance Evaluation

System quality was assessed through a multi-dimensional suite of metrics encompassing both quantitative and qualitative dimensions:

- Structural Similarity Index (SSIM): Measures perceptual image quality and visual coherence relative to a reference.
- Intersection over Union (IoU): Quantifies spatial overlap accuracy of segmentation outputs.
- User Satisfaction Ratings: Captures subjective assessments of realism and interface usability.
- User Study Ratings: Human evaluators rated try-on output realism on a 1-5 ordinal scale.

The segmentation component demonstrated strong results across all benchmarked metrics, as summarized below:

TABLE 2. PERFORMANCE MEASURES FOR SEGMENTATION

Quality Metrics	K-Means Segmentation	Standard U-Net Segmentation	Enhanced U-Net Segmentation
Dice Coefficient	0.7653	0.8266	0.8902
Jaccard Coefficient	0.5292	0.9234	0.9324
Intersection over Union (IoU)	0.635	0.9022	0.9498

The comparative analysis clearly demonstrates the superiority of the enhanced U-Net configuration across all evaluated criteria — Dice Coefficient, Jaccard Index, and IoU — when benchmarked against both k-means clustering and the standard U-Net baseline.

TABLE 3. SYSTEM COMPARISON AGAINST EXISTING METHODS

Metric	Proposed System	VITON	CP-VTON	StyleGAN Method
SSIM Score	0.924	0.876	0.891	0.908
IoU Score	0.943	0.902	0.915	0.932
User Rating (1-5)	4.31	3.82	3.95	4.18
Processing Time (s)	2.1	3.2	2.8	4.1

D. Recommendation System Effectiveness

The integrated recommendation engine exhibited robust performance across all measured dimensions, reflecting its capacity to generate relevant, diverse, and broadly accessible fashion suggestions:

- Top-5 Accuracy: 89.2%
- Diversity Score: 0.847
- Coverage Rate: 73.5%
- Average Click-through Rate: 12.3%

V. BUSINESS IMPACT AND APPLICATIONS

Market Potential

Growing consumer appetite for interactive, personalized digital shopping experiences continues to drive expansion of the virtual fitting room market. As fashion technology matures, the addressable market for intelligent try-on platforms is expected to grow substantially, with demand increasingly coming from both direct-to-consumer e-commerce and omnichannel retail environments.

Implementation Benefits

1. For Retailers:
- Decreased merchandise return rates through improved pre-purchase visualization
- Elevated conversion rates driven by heightened buyer confidence
- Stronger customer engagement metrics and improved brand loyalty
- Richer behavioral data supporting more precise, evidence-based merchandising decisions

2. For Consumers:
- Improved pre-purchase visualization of how garments will look and fit on their specific body
- Curated outfit recommendatitons aligned with individual aesthetic preferences and measurements
- Greater decision confidence, reducing hesitation and post-purchase dissatisfaction
- Efficient product discovery that reduces time spent searching

Industry Applications

The system architecture supports deployment across a broad range of fashion industry touchpoints:
- E-commerce websites and marketplace platforms
- Mobile-first shopping applications
- In-store digital mirror installations and interactive retail displays
- Social commerce integrations enabling try-on sharing

VI. CHALLENGES AND FUTURE DIRECTIONS

A. Technical Challenges

Notwithstanding the promising outcomes, the proposed system contends with a number of technical limitations that may affect its scalability and performance consistency:

1. Fabric Physics Simulation: Faithfully simulating textile behavior — including fold formation, elasticity, and gravity-driven drape — remains computationally demanding and is not fully resolved in the current implementation.
2. Lighting and Environmental Variability: Performance can degrade under heterogeneous illumination conditions or visually cluttered backgrounds, introducing inconsistencies in the segmentation and rendering stages.
3. Computational Demands: The complexity of the multi-stage inference pipeline poses challenges for real-time operation on resource-constrained mobile and edge devices, necessitating dedicated model compression and optimization strategies.

B. Future Work

Several directions are identified for future research and system enhancement:

1. Augmented Reality Integration: Embedding AR capabilities would enable real-time, interactive try-on directly through smartphone cameras, elevating immersion and user engagement substantially.
2. Three-Dimensional Avatar Systems: Transitioning to full 3D body modeling with physically accurate avatar representations would provide superior garment fit prediction and more compelling visualizations.
3. Mobile Platform Optimization: Lightweight model variants and hardware-accelerated inference paths are needed to ensure responsive, real-time performance on mobile devices, expanding accessibility to a wider user base.
4. Deep Personalization: Longitudinal user behavior modeling, incorporating purchase history, browsing patterns, and trend responsiveness, can power progressively more refined and personally resonant recommendations.
5. Sustainability-Aware Recommendations: Integrating environmental impact metrics into the recommendation scoring framework would enable the system to promote eco-conscious fashion choices, aligning with consumer demand for responsible retail.

VII. CONCLUSION

This paper has described the design and evaluation of an AI-driven virtual fitting room system aimed at transforming the digital fashion retail experience through accurate garment visualization and intelligent product recommendation. Leveraging a synergistic combination of computer vision techniques and machine learning models, the system achieves measurable improvements in image quality, segmentation precision, and processing speed relative to existing baselines.

The incorporation of advanced architectures — including CNNs for feature learning, GANs for photorealistic synthesis, and semantic segmentation networks for body-garment delineation — enables high-quality try-on outputs and individualized product discovery. The modular system architecture further supports flexible deployment across diverse retail platforms, from web storefronts and mobile applications to in-store interactive display systems.

Quantitative benchmarking confirms competitive performance along all evaluated dimensions, with experimental results consistently affirming the system's capacity to enhance user satisfaction and strengthen purchase confidence — addressing a fundamental limitation of traditional e-commerce models.

From an industry perspective, the solution offers demonstrable value through reduced return volumes, improved conversion outcomes, and more meaningful customer engagement. Its personalization capabilities are particularly well-suited to the demands of modern fashion retail, where consumer expectations for tailored, responsive experiences continue to rise.

Looking ahead, future efforts will be directed toward improving environmental robustness, advancing fabric simulation realism, and achieving real-time inference performance. Planned enhancements include AR-based overlays, volumetric 3D avatar generation, and sustainability-integrated recommendation models — collectively working to bridge the experiential divide between physical store visits and digital shopping.

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