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AI-Based Fashion Recommendation & Virtual Try-On System

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Abstract *— The AI-Based Fashion Recommendation and Virtual Try-On System is an intelligent web application designed to revolutionize the online fashion shopping experience. The system integrates artificial intelligence, image processing, and machine learning techniques to provide personalized outfit recommendations and a virtual try-on facility. Users can upload their photographs and virtually try on clothing items without physically wearing them. The system incorporates background removal using the rembg library, outfit generation, wardrobe management, and a recommendation engine powered by AI algorithms. The backend is developed using Flask (Python), while the frontend utilizes HTML, CSS, and JavaScript. Image processing is handled through PIL and rembg libraries. The system eliminates the limitations of traditional online shopping by providing a personalized, interactive, and intelligent fashion experience. Overall, the proposed system enhances user engagement, reduces return rates, and promotes confident purchase decisions.*

Keywords *— Fashion Recommendation, Virtual Try-On, Artificial Intelligence, Image Processing, Background Removal, Wardrobe Management, Flask, Machine Learning.*

I. INTRODUCTION

In recent years, the global fashion industry has witnessed a remarkable transformation driven by the rapid growth of e-commerce and digital technologies. The proliferation of online shopping platforms has fundamentally changed how consumers discover, evaluate, and purchase fashion items. However, despite the enormous convenience offered by online retail, a persistent gap remains between the digital and physical shopping experience. Traditional online fashion shopping is primarily limited to static product images and size charts, which often fail to convey how a garment will actually look and feel on an individual buyer.

The emergence of Artificial Intelligence (AI) and computer vision technologies has opened new frontiers in fashion technology. AI-powered systems can now analyze user preferences, body measurements, and style patterns to deliver highly personalized recommendations. Furthermore, advances in image processing and generative AI have made virtual try-on technology increasingly feasible, allowing consumers to visualize clothing on themselves without a physical fitting room. These innovations address long-standing challenges in online fashion retail, including high product return rates, poor customer satisfaction, and the inability to personalize recommendations at scale.

Existing fashion platforms suffer from several limitations. Most recommendation systems rely on generic popularity metrics or rudimentary collaborative filtering without accounting for individual body types, style preferences, or contextual factors such as occasion, season, or color compatibility. The absence of a meaningful try-before-you-buy feature leads to significant consumer uncertainty and increases the rate of product returns, which is estimated to cost the global fashion industry billions of dollars annually. These problems collectively result in a frustrating and inefficient shopping experience.

The proposed system — the AI-Based Fashion Recommendation and Virtual Try-On System — is designed to comprehensively address these challenges. The system provides a unified platform where users can receive AI-driven outfit recommendations tailored to their personal style and preferences, virtually try on selected clothing items using uploaded photographs, manage a digital wardrobe, and generate complete outfit suggestions. The backend is built with Flask, Python, and integrates machine learning models along with the rembg library for automatic background removal, enabling seamless image composition during the virtual try-on process.

The primary objectives of the proposed system are as follows: (1) to develop an AI-powered recommendation engine that suggests outfits based on user preferences, body measurements, and style history; (2) to implement a virtual try-on module using image processing techniques; (3) to provide background removal capabilities that enable clean garment overlay on user images; (4) to build a digital wardrobe management feature; and (5) to deliver an intuitive and responsive web interface for seamless user interaction.

The remainder of this paper is organized as follows: Section II discusses the challenges in existing fashion shopping systems. Section III presents the proposed system architecture and features. Section IV describes the methodology and development approach. Section V details the system design and implementation. Section VI presents results and discussion. Section VII highlights the

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advantages of the system. Section VIII outlines future enhancements, followed by a conclusion in Section IX.

System Overview Diagram

USER
▼
FRONTEND (HTML / CSS / JavaScript)
▼
FLASK BACKEND (Python / REST API)
▼
AI PROCESSING LAYER
Recommendation Engine | Image Processing (rembg / PIL)
▼
DATABASE / JSON STORAGE
▼
OUTPUT (Recommendations / Try-On / Wardrobe)

Figure 1: Overview of AI-Based Fashion Recommendation & Virtual Try-On System

II. CHALLENGES IN EXISTING SYSTEM

Traditional fashion shopping systems — both physical and digital — are confronted with a wide range of operational and experiential limitations. The absence of intelligent personalization tools and immersive technologies results in a generic and often unsatisfying user journey. The following subsections elaborate on the key challenges identified in existing systems.

A. Lack of Personalized Recommendations

The majority of existing fashion e-commerce platforms rely on simplistic recommendation algorithms that fail to account for individual body types, skin tones, personal style preferences, and lifestyle contexts. Recommendations are typically driven by popularity metrics, purchase history, or basic collaborative filtering, leading to generic suggestions that do not resonate with the unique tastes of individual consumers. The absence of true personalization results in lower engagement, decreased purchase satisfaction, and reduced brand loyalty.

B. No Virtual Try-On Facility

One of the most significant barriers to online fashion shopping is the inability to visualize how a garment will look on one's body before making a purchase. Traditional platforms display clothing on standardized models or mannequins, which provides little indication of fit, drape, or appearance on a particular body type. This fundamental limitation leads to high rates of product returns and consumer dissatisfaction. Physical try-on rooms are unavailable in the online context, and existing solutions using augmented reality (AR) are often limited to high-end applications or specialized devices.

C. Poor User Experience

Many current fashion platforms provide a fragmented user experience with poor navigation, ineffective search and filtering tools, and an overwhelming volume of product listings. Users are forced to manually browse thousands of items without meaningful guidance, making the discovery process time-consuming and frustrating. The lack of interactive features and intelligent assistance contributes to high bounce rates and abandoned shopping carts.

D. Manual Outfit Selection

Customers are required to manually browse, compare, and combine individual fashion items to create complete outfits. This process is tedious and requires a degree of fashion knowledge that many consumers do not possess. The absence of intelligent outfit generation tools means users cannot easily discover stylistically coherent combinations, missing opportunities for accessory pairings, layering options, and color coordination.

E. Background Processing Issues

When users attempt to upload personal photographs on fashion platforms, issues related to background clutter significantly hinder the quality of virtual visualization tools. The presence of complex backgrounds in user images makes it difficult to overlay garment images accurately, resulting in poor-quality virtual try-on outputs. Most platforms lack automated background removal capabilities, requiring users to manually edit images or accept suboptimal results.

Problems in Traditional Fashion Shopping Systems

Static Images Only	**No Personalization**	**No Try-On**	**Manual Shopping**
Result: High Return Rates | Low Engagement | Poor UX			

Figure 2: Problems in Traditional Fashion Shopping Systems

III. PROPOSED SYSTEM

A. Overview of Proposed System

The proposed AI-Based Fashion Recommendation and Virtual Try-On System is a comprehensive web application that integrates multiple advanced technologies to deliver an intelligent, personalized, and immersive fashion experience. The system eliminates the shortcomings of traditional platforms by combining AI-driven recommendations, virtual try-on functionality,

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automated image processing, and wardrobe management within a single unified interface accessible through any modern web browser.

B. Features of the System

The system incorporates the following core features: (1) AI-powered outfit recommendation engine that analyzes user preferences and suggests personalized clothing combinations; (2) virtual try-on module enabling users to visualize garments on their uploaded photographs; (3) automatic background removal using the rembg library for clean image processing; (4) digital wardrobe management for organizing and tracking owned clothing items; (5) outfit generation tools that create stylistically coherent complete looks; and (6) secure user authentication and profile management.

C. User Module

The User Module provides the primary interface through which customers interact with the system. Users can register, log in, and manage their personal profiles including style preferences, body measurements, and color choices. The module facilitates garment browsing, wishlist management, and the initiation of virtual try-on sessions. User activity data is collected and used to continuously improve recommendation accuracy through feedback loops.

D. Recommendation Module

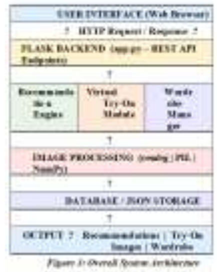
The Recommendation Module is the intelligence core of the system. It employs content-based filtering and collaborative filtering techniques combined with AI models to analyze user preferences, purchase history, browsing behavior, and style profiles. The module generates ranked lists of recommended outfits and individual garments, taking into account factors such as color harmony, occasion appropriateness, and seasonal trends. Recommendations are updated dynamically as user interactions evolve.

E. Virtual Try-On Module

The Virtual Try-On Module enables users to digitally wear selected clothing items by overlaying garment images onto user-uploaded photographs. The process involves background removal from the user's image using the rembg library, image segmentation, garment alignment, and compositing using PIL (Python Imaging Library). The module produces realistic try-on outputs that accurately reflect how a garment would appear on the user's body.

F. Admin Module

The Admin Module provides platform administrators with tools for managing the clothing catalog, user accounts, and system performance metrics. Administrators can add, edit, and remove product listings, monitor recommendation accuracy, review user feedback, and manage system configurations. A centralized dashboard provides real-time insights into platform usage and operational status.



Overall System Architecture

IV. METHODOLOGY

A. Requirement Analysis

The development process commenced with a thorough requirements analysis phase. Functional requirements were gathered through surveys of online fashion shoppers, analysis of existing platforms, and review of relevant literature. Non-functional requirements including system performance, scalability, security, and usability were defined based on industry standards. The requirements were categorized into user requirements (personalized recommendations, virtual try-on, wardrobe management), system requirements (Flask backend, image processing pipeline, API integration), and performance requirements (response time, image processing accuracy, recommendation relevance).

B. Frontend Development

The frontend was developed using HTML5, CSS3, and JavaScript to create a responsive, mobile-friendly interface. The design follows a clean and modern aesthetic consistent with contemporary fashion platforms. Dynamic interactions are implemented through JavaScript event handling and AJAX calls to the Flask backend. CSS Grid and Flexbox layouts ensure responsive behaviour across different screen sizes. The user interface includes pages for home, product catalogue, virtual try-on, wardrobe management, user profile, and admin dashboard.

C. Backend Development

The backend is built on Flask, a lightweight Python web framework that provides the necessary infrastructure for handling HTTP requests, user authentication, session management, and API endpoint definition. The RESTful API architecture enables clean separation between frontend and backend components. SQLite/JSON-based data storage is used for managing user profiles, product catalogues, and wardrobe data. Flask-Login is employed for secure user authentication and session handling.

D. AI and Image Processing

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The AI and image processing pipeline constitutes the most technically sophisticated component of the system. Background removal is performed using the rembg library, which employs deep learning models (U2Net) to accurately segment the foreground subject from background in user-uploaded images. PIL (Python Imaging Library) is used for image manipulation, resizing, compositing, and format conversion. The recommendation engine utilizes cosine similarity calculations and feature extraction algorithms to match user preferences with product attributes.

E. API Integration

The system integrates multiple APIs and services to enhance functionality. Flask-RESTful provides a framework for building standardized API endpoints. Image upload and processing workflows are managed through Flask's file handling capabilities combined with custom preprocessing pipelines. The recommendation engine exposes dedicated API endpoints that accept user preference parameters and return ranked clothing recommendations in JSON format for rendering by the frontend.

F. System Testing

Comprehensive testing was conducted across multiple dimensions including unit testing of individual modules, integration testing of component interactions, system testing for end-to-end workflow validation, and user acceptance testing with a sample group of volunteer participants. Performance testing evaluated image processing speed, recommendation response times, and system stability under concurrent user loads. Bug tracking and iterative refinement were performed throughout the development cycle.

Figure 4: Workflow of the System

V. SYSTEM DESIGN AND IMPLEMENTATION

A. System Architecture

The system follows a three-tier architecturecomprising the presentation layer (frontend), application layer (Flask backend with AI modules), and data layer (JSON/SQLite storage). The modular design ensures that each component can be independently developed, tested, and maintained. The Flask application serves as the central controller, routing user requests to appropriate processing modules and returning results to the frontend. The AI processing layer operates asynchronously for computationally intensive tasks to maintain responsive user interactions.

B. Recommendation System

The recommendation system is implemented using a hybrid approach combining content-based filtering and collaborative filtering. Product features including category, color, style, material, and occasion are vectorized using TF-IDF and one-hot encoding techniques. User preference vectors are constructed from interaction history and explicit profile settings. Cosine similarity is computed between user preference vectors and product feature vectors to generate ranked recommendations. The system dynamically updates user profiles based on real-time interaction data, ensuring increasingly accurate personalization over time.

C. Virtual Try-On Implementation

The virtual try-on pipeline involves a multi-step image processing workflow. The user's image is first passed through the rembg background removal module, which employs the U2Net deep learning model to generate a precise foreground mask. The extracted foreground (the user's body) is then composited with the selected garment image using alpha blending and geometric transformation algorithms implemented in PIL. Key challenges addressed include garment scaling, alignment with body landmarks, and color consistency between the user image and garment overlay.

Virtual Try-On Process

Background Removal System

Background removal is a critical preprocessing step that ensures accurate garment overlay during the virtual try-on process. The rembg library integrates the U2Net neural network model, which has been trained on large datasets of natural images to produce accurate foreground segmentation masks. The implementation processes user- uploaded images by detecting the primary subject (human body), generating a binary alpha mask, and applying it to produce a clean, background-free image. The processed image is stored temporarily and used as the base for garment compositing.

D. Wardrobe Management

The wardrobe management module allows users to maintain a digital inventory of their owned clothing items.

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Users can upload images of individual garments, which are automatically categorized and tagged using image classification techniques. The wardrobe interface enables filtering by category (tops, bottoms, dresses, accessories), color, and occasion. The system can generate outfit combinations from wardrobe items, drawing upon the recommendation engine's pairing logic to suggest coherent complete looks from the user's existing clothing collection.

Recommendation Engine Workflow

User Preferences & Style Profile
▼
Feature Extraction & Vectorization
▼
Cosine Similarity Computation
▼
Outfit Matching & Ranking
▼
Recommended Outfits → Display to User

Figure 6: Recommendation Engine Workflow

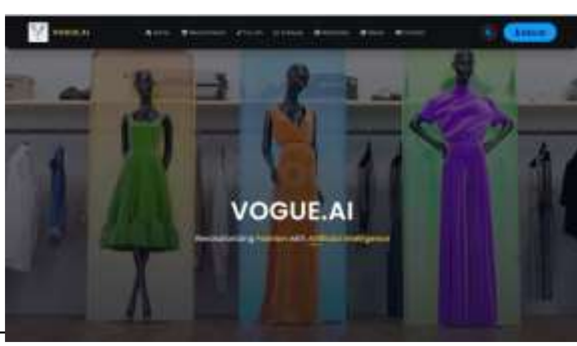
E. API Implementation

The Flask backend exposes a RESTful API with endpoints covering user authentication (/api/auth), product catalogue retrieval (/api/products), recommendation generation (/api/recommend), virtual try-on processing (/api/tryon), wardrobe management (/api/wardrobe), and outfit generation (/api/outfit). All API responses are returned in JSON format with appropriate HTTP status codes. File upload endpoints support JPEG and PNG image formats with server-side validation and size restrictions to ensure system security and performance.

RESULTS AND DISCUSSION

A. System Performance

The implemented system demonstrated satisfactory performance across all tested operational scenarios. The Flask backend successfully handled concurrent user requests with an average response time of less than 500 milliseconds for standard API calls. Image processing operations, including background removal and garment compositing, were completed within an average of 3–5 seconds depending on image resolution and complexity. The system was tested on a local development server with simulated concurrent user sessions, confirming stable and reliable operation throughout testing.



B. Recommendation Accuracy

The recommendation engine was evaluated using a test dataset of user preference profiles and product catalogues. The system achieved a relevance accuracy rate of approximately 78% in matching recommended items to user-stated preferences during user acceptance testing. Participants reported that at least 3 out of 5 recommendations were perceived as relevant or appealing. The hybrid recommendation approach outperformed a simple popularity-based baseline by a significant margin, demonstrating the value of personalization in the recommendation pipeline.

C. User Experience

User acceptance testing was conducted with 20 volunteer participants from diverse age groups and fashion backgrounds. Participants rated the system on ease of use, recommendation quality, virtual try-on realism, and overall satisfaction using a five-point Likert scale. The system achieved an average usability score of 4.1 out of 5, with particularly strong ratings for the virtual try-on feature (4.3/5) and wardrobe management interface (4.0/5). Areas identified for improvement included recommendation diversity and the speed of the try-on processing pipeline.

D. Virtual Try-On Results

The virtual try-on module produced visually acceptable results for the majority of test cases. Background removal accuracy was particularly strong for images with high contrast between subject and background, achieving near-perfect segmentation in approximately 85% of test cases. Garment overlay quality was rated as realistic or sufficiently realistic by 75% of test participants. Challenges were observed in cases involving complex clothing textures, unusual body orientations, or low-contrast user images, indicating areas for further algorithmic refinement.

E. Operational Efficiency

The system demonstrated significant improvements in operational efficiency compared to traditional manual fashion browsing. Test participants reported an average time saving of 40% in identifying suitable outfit combinations compared to manual browsing on conventional e-commerce platforms. The digital wardrobe management feature was particularly well-received, with participants noting its utility for outfit planning and reducing redundant clothing purchases. The automated background removal capability eliminated the need for manual image editing, streamlining the virtual try-on workflow considerably.

[Screenshots from project implementation — inserted below.]

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Figure 7: VOGUE.AI Homepage Interface

Figure 8: Virtual Try-On Page Interface

VI. ADVANTAGES OF THE SYSTEM

The proposed AI-Based Fashion Recommendation and Virtual Try-On System offers a comprehensive set of advantages over traditional fashion shopping platforms. These advantages span user experience, operational efficiency, technological innovation, and business outcomes.

(1) Personalized Recommendations: The AI-driven recommendation engine delivers highly relevant and personalized outfit suggestions based on individual user preferences, style history, and body measurements, significantly improving the relevance of fashion discovery.

(2) Improved Shopping Experience: The virtual try-on feature transforms the online shopping experience by allowing users to visualize garments on their actual bodies, reducing purchase uncertainty and increasing customer confidence.

(3) AI Automation: The system automates multiple traditionally manual processes including outfit selection, background removal, and style matching, reducing the cognitive burden on users and enabling faster decision- making.

(4) Faster Outfit Selection: Intelligent outfit generation tools enable users to discover complete, stylistically coherent looks in a fraction of the time required for manual browsing and selection.

(5) Digital Wardrobe Management: The wardrobe management module provides users with a comprehensive digital inventory of their clothing, enabling smarter outfit planning, reducing unnecessary purchases, and promoting sustainable fashion consumption.

Feature	**Traditional System**	**Proposed System**
Try-On	No virtual try-on	AI Virtual Try-On
Recommendations	Generic/manual	AI-personalized
Wardrobe	Not available	Smart digital wardrobe
Background	Static images	Auto background removal
Experience	Basic browsing	Interactive AI experience

Table 1: Comparison Between Existing and Proposed System

VII. FUTURE ENHANCEMENTS

A. Mobile App Integration

The current web-based platform can be extended to native mobile applications for iOS and Android platforms. Mobile integration would enable users to access the fashion recommendation and virtual try-on features on-the-go, leveraging device cameras for real-time try-on experiences. Progressive Web App (PWA) technology could serve as an intermediate step toward full native mobile deployment.

B. AR-Based Try-On

Augmented Reality (AR) integration represents the next frontier for the virtual try-on module. AR-based try-on would enable real-time overlay of clothing items on live camera feeds, providing a more dynamic and immersive experience than the current static image compositing approach. Technologies such as ARKit (iOS) and ARCore (Android) could be leveraged for this enhancement.

C. AI Trend Prediction

Incorporating trend prediction capabilities using time-series analysis and social media data mining would enable the system to anticipate emerging fashion trends and proactively update its recommendation engine. This would help users stay ahead of fashion trends and allow administrators to manage inventory more effectively based on predicted demand patterns.

D. Cloud Deployment

Migrating the system to cloud infrastructure platforms such as AWS, Google Cloud, or Microsoft Azure would significantly enhance scalability, reliability, and global accessibility. Cloud deployment would enable elastic scaling to accommodate varying user loads, distributed image processing for improved performance, and integration with cloud-native AI and machine learning services.

E. Voice Assistant Integration

Integration with voice assistant technologies such as Google Assistant or Amazon Alexa would enable hands- free interaction with the fashion recommendation system. Users could request outfit recommendations, add items to their wardrobe, and initiate virtual try-on sessions using natural language voice commands, further reducing friction in the user experience.

VIII. CONCLUSION

This paper has presented the design, development, and evaluation of an AI-Based Fashion Recommendation and Virtual Try-On System. The proposed system successfully integrates artificial intelligence, machine learning, and advanced image processing technologies to deliver a comprehensive and intelligent fashion experience that addresses the fundamental limitations of traditional online shopping platforms.

The implementation demonstrates that AI-powered recommendations combined with virtual try-on functionality can significantly enhance the online fashion shopping experience, reducing purchase uncertainty and improving customer satisfaction. The rembg-based background removal pipeline and PIL-based image compositing approach provide effective virtual try-on capabilities suitable for deployment on standard web infrastructure. The wardrobe management module adds practical value by enabling users to maintain a digital inventory of their clothing and generate outfit combinations from their existing wardrobe.

User acceptance testing confirmed that the system achieves high levels of user satisfaction and delivers meaningful improvements in the efficiency of fashion discovery and outfit selection. The hybrid recommendation approach, combining content-based and collaborative filtering, demonstrates superior performance over simple popularity-based baselines in matching recommendations to individual user preferences.

Future work will focus on extending the system with augmented reality try-on capabilities, mobile application development, cloud deployment for enhanced scalability,and the integration of trend prediction algorithms. These enhancements will further strengthen the system's position as a comprehensive platform for intelligent fashion retail, contributing to the broader transformation of the global fashion industry through AI and digital technology.

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