Smart Fashion Advisor: AI-Powered Skin Tone Analysis and Personalized Outfit Recommendation Using Computer Vision

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ABSTRACT

The rapid growth of artificial intelligence in lifestyle applications has significantly influenced the fashion industry by enabling personalized and data-driven recommendations. This paper presents a Smart Fashion Advisor, an intelligent system designed to assist users in selecting suitable outfits based on their skin tone, preferences, and contextual factors such as occasion and season. The system integrates computer vision techniques with data-driven filtering methods to provide real-time fashion suggestions. By utilizing facial image analysis, the application automatically detects the user's skin tone and maps it to a predefined set of color palettes, thereby ensuring recommendations that enhance visual appeal and personal style.

The proposed system employs MediaPipe-based facial landmark detection with 468 facial points and OpenCV image processing to extract relevant facial regions for accurate skin tone classification. Unlike purely deep learning-based recommendation systems, this approach combines rule-based color theory with a large-scale fashion dataset of over 44,000 items to generate meaningful outfit suggestions. The dataset is processed using efficient Pandas-based filtering techniques based on attributes such as gender, category, color, and usage. Additionally, the system incorporates a web-based interface built using Flask, enabling users to upload images or use a live camera feed to receive instant recommendations. An optional AI-powered chatbot using the Google Gemini API further enhances user interaction by providing styling advice and answering fashion-related queries.

By automating the outfit selection process, the Smart Fashion Advisor reduces decision-making effort and improves personalization in everyday fashion

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choices. The system demonstrates the effectiveness of combining computer vision, domain knowledge, and data filtering in building practical recommendation systems. It can be applied in various domains such as e-commerce platforms, virtual styling assistants, and personal wardrobe management tools. Future enhancements may include integrating deep learning-based recommendation models, real-time trend analysis, and augmented reality features to further improve user experience and system intelligence.

KEYWORDS: *Computer Vision, Skin Tone Detection, Fashion Recommendation, MediaPipe, OpenCV, Color Theory, Flask, Machine Learning, Personalized Styling, Outfit Recommendation, Image Processing, Chatbot, Gemini API.*

INTRODUCTION

In recent years, the integration of artificial intelligence (AI) and computer vision into everyday applications has transformed the way individuals interact with technology, particularly in domains such as healthcare, retail, and lifestyle management. The fashion industry, being highly dynamic and subjective, presents a unique challenge in providing personalized recommendations that align with individual preferences and physical attributes. Traditionally, fashion advice has relied on human expertise, social trends, or manual selection, which can often be time-consuming, inconsistent, and inaccessible to a broader audience. With the increasing availability of image processing techniques and machine learning tools, there is a growing opportunity to automate and enhance the process of outfit selection, making it more efficient, scalable, and user-centric.

One of the key factors influencing clothing choices is an individual's skin tone, which plays a crucial role in determining suitable color combinations and overall appearance. However, most existing systems either overlook this factor or depend heavily on manual input from users. To address this limitation, the proposed Smart Fashion Advisor introduces an intelligent framework that automatically detects the user's skin tone using facial image analysis and provides personalized fashion recommendations accordingly.

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The system utilizes computer vision techniques, including facial landmark detection via MediaPipe Face Mesh with 468 landmarks and region-based color extraction using OpenCV, to accurately classify skin tones under different conditions. Based on this classification, a predefined mapping of color palettes derived from established color theory is applied to suggest appropriate clothing options, ensuring that the recommendations are both visually appealing and contextually relevant.

In addition to skin tone analysis, the system incorporates a data-driven recommendation mechanism that filters a large- scale fashion dataset of over 44,000 items to generate outfit suggestions based on multiple attributes such as gender, category, usage, and season. The integration of a web-based interface using Flask enables real-time interaction, allowing users to upload images or capture them through a camera for immediate feedback. Furthermore, the inclusion of an AI- powered chatbot using the Google Gemini API enhances user engagement by providing additional styling guidance and answering fashion-related queries. By combining computer vision, rule-based intelligence, and dataset-driven filtering, the Smart Fashion Advisor offers a practical and effective solution for personalized fashion recommendation [1] [2].

LITERATURE REVIEW

The application of artificial intelligence in the fashion domain has gained significant attention in recent years, particularly in the development of personalized recommendation systems. Early research in this area focused on traditional recommendation techniques such as collaborative filtering and content-based filtering, which relied on user preferences and historical data to suggest products. However, these approaches often lacked the ability to understand visual features of clothing items. To overcome this limitation, researchers began integrating deep learning models with computer vision techniques to analyze images and extract meaningful attributes such as color, texture, and style [1][2]. These advancements laid the foundation for intelligent fashion systems capable of providing more accurate and personalized recommendations.

Computer vision has played a crucial role in enhancing fashion recommendation systems by enabling automatic analysis of images. Convolutional Neural Networks (CNNs) have been widely used for clothing classification, attribute detection, and style recognition. Studies by

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Liu et al. demonstrated the effectiveness of large-scale datasets such as DeepFashion in training models for clothing attribute recognition [2]. Similarly, other works have shown that visual features extracted from images can significantly improve recommendation accuracy compared to text-based methods [3]. Techniques such as facial landmark detection and region- based image processing have also been explored to identify user-specific features, including skin tone and facial structure, which are essential for personalized styling applications [4].

Another important aspect of fashion recommendation is color analysis, as color compatibility plays a vital role in determining the aesthetic appeal of an outfit. Several studies have explored the use of color theory and seasonal color analysis to recommend suitable clothing combinations. These approaches categorize users based on undertones and skin tones, such as warm, cool, or neutral, and suggest corresponding color palettes [5]. While some systems employ machine learning models for color prediction, many practical applications rely on predefined rule-based mappings due to their simplicity and interpretability. Such hybrid approaches, combining domain knowledge with computational techniques, have been proven effective in real-world fashion advisory systems [6].

In addition to visual analysis, dataset-driven recommendation systems have been widely adopted in modern applications. Large-scale fashion datasets containing product attributes such as category, gender, usage, and season are used to filter and recommend relevant items. Research has shown that combining structured data with visual features enhances the quality of recommendations [7]. Data processing libraries and efficient filtering techniques enable real-time retrieval of relevant products, making these systems suitable for web-based applications. Furthermore, integrating recommendation engines with user interfaces improves accessibility and allows users to interact with the system dynamically [8].

Recent advancements have also introduced conversational AI and chatbot integration in fashion systems to enhance user experience. AI-powered chatbots can provide personalized styling advice, answer queries, and guide users through the selection process [9]. Additionally, web frameworks such as Flask have been widely used to develop interactive and scalable applications that combine backend intelligence with frontend usability [10]. These developments highlight the growing trend of integrating multiple technologies,

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including computer vision, machine learning, and web development, to create comprehensive and user- friendly fashion recommendation systems. The proposed Smart Fashion Advisor builds upon these concepts by combining skin tone detection, rule-based color mapping, dataset filtering, and chatbot interaction into a unified platform.

PROBLEM STATEMENT

Shoppers frequently struggle to select clothing that complements their unique physical characteristics, particularly skin tone, hair color, and eye color. Traditional shopping experiences lack personalized color guidance, leading to uncertainty in purchase decisions, increased return rates, and diminished customer confidence. Fashion retailers face significant challenges in providing scalable, individualized styling advice to every customer, resulting in missed revenue opportunities and elevated operational costs due to frequent product returns.

Existing fashion recommendation systems predominantly rely on collaborative filtering or content-based filtering approaches that consider user purchase history and product metadata. However, these methods largely overlook the critical role of skin tone compatibility in determining visually harmonious outfit selections. While some advanced systems leverage deep learning for visual feature extraction, they often require extensive training data, significant computational resources, and lack interpretability in their recommendations.

The primary challenge addressed by this work is the development of a lightweight, real-time system that automatically detects a user's skin tone from facial images and generates personalized outfit recommendations based on established color theory principles. The system must handle varying image conditions including different lighting environments, camera qualities, and image resolutions while maintaining accurate skin tone classification. Additionally, the system should provide contextually relevant suggestions by considering factors such as occasion, season, and gender, all while operating efficiently within a web-based environment without requiring specialized hardware or extensive model training.

PROPOSED METHODOLOGY

The Smart Fashion Advisor system follows a structured pipeline that processes user input through multiple stages to generate personalized outfit recommendations. The methodology encompasses data collection and preprocessing, facial analysis, skin tone classification, color-

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based recommendation, and interactive web deployment. Each stage is designed to be computationally efficient while maintaining accuracy and reliability.

1. Data Collection and Dataset Preparation

The system relies on a structured and well-organized fashion dataset containing over 44,000 items stored in CSV format (styles.csv). Each item is described by attributes including product ID, gender, masterCategory, subCategory, articleType, baseColour, season, year, usage, and productDisplayName. A companion file (images.csv) maps item IDs to product image URLs. Preprocessing steps remove inconsistencies such as missing values and duplicate records. The dataset is filtered to include only relevant master categories (Apparel, Footwear, Accessories) while excluding categories such as Innerwear, Loungewear, Nightwear, and Socks. Pandas is used for all data loading and filtering operations, enabling efficient real-time processing [2][8].

2. Image Preprocessing and Blur Detection

Image preprocessing is a critical step in preparing input images for accurate skin tone analysis. The system accepts images through two channels: file upload (supporting JPEG and PNG, maximum 10MB) and real-time camera capture via WebRTC at 640×480 resolution. Input images undergo several preprocessing stages using OpenCV. First, a Laplacian variance-based blur detection algorithm is applied. The image is converted to grayscale, normalized to 800 pixels width for consistent scoring, and the Laplacian operator is computed. The variance of the Laplacian output serves as a focus metric—a threshold of 60 is used, where values below this threshold indicate an unacceptably blurry image. This normalization step prevents false positives that could arise from resolution differences between low-resolution webcam captures and high-resolution file uploads [11] [12].

3. Lighting Quality Assessment

Following blur detection, the system evaluates lighting quality by analyzing the brightness distribution of the image. The mean brightness must fall within the range of 30 to 240, and the standard deviation (contrast) must exceed 10. These criteria ensure that the image has adequate and even illumination for reliable skin tone extraction. Images that fail this assessment prompt the user to improve lighting conditions before proceeding.

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4. Face Detection and Skin Tone Classification

The core skin tone detection algorithm is implemented in the HeadlessSkinToneDetector class. The system utilizes MediaPipe Face Mesh, a real-time facial landmark detection framework providing 468 facial landmarks, configured with static_image_mode=True, refine_landmarks=True, and a minimum detection confidence of 0.6. Three specific facial regions are extracted for analysis: the left cheek (landmarks 116–121, 126, 142, 36–41), the right cheek (landmarks 345– 350, 355, 371, 266–271), and the forehead (landmarks 10, 151, 9, 8, 107, 55, 65, 52, 53, 46). These regions are chosen because they provide consistent and reliable skin color representation [4] [12].

Before color extraction, lighting normalization is applied using CLAHE (Contrast Limited Adaptive Histogram Equalization) in the LAB color space. The L channel is enhanced with a clip limit of 3.0 and a tile grid size of 8×8, while the A and B channels are preserved to maintain color integrity. The normalized image is then converted to HSV color space, and morphological operations (closing followed by opening with a 3×3 kernel) are applied to reduce noise. Skin pixels are identified within the HSV range of H[0–25], S[30–150], V[40–220], and the mean color across all extracted regions is calculated.

The classification algorithm employs a weighted scoring mechanism across six skin tone categories: Fair, Light, Medium, Olive, Brown, and Dark. Each category is defined by specific HSV threshold ranges. The scoring formula is: total_score = (h_match × 0.4) + (s_match × 0.4) + (v_match × 0.2), where h_match, s_match, and v_match are binary indicators of whether the measured HSV values fall within the defined ranges. The higher weight on Hue and Saturation (0.4 each) reflects their greater importance in distinguishing skin tones compared to Brightness (0.2). A fallback classification logic using simplified HSV thresholds is applied when no category achieves a score above 0.6 [4][11].

5. Color Recommendation Model

After skin tone determination, the system maps it to a comprehensive color palette using a rule-based approach grounded in established color theory principles, including seasonal color analysis and undertone matching. Six distinct skin tone profiles are defined, each with an associated undertone (Cool, Warm, Warm/Neutral, Warm/Green, Warm, Neutral/Deep) and seasonal classification (Winter, Spring, Autumn, Deep Autumn, Warm Autumn, Deep

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Winter). Each profile includes three color lists: best colors (10 primary recommendations), good colors (safe complementary choices), and colors to avoid. For example, Fair skin (Cool undertone, Winter season) is recommended jewel tones such as Navy Blue, Burgundy, and Emerald, while Medium skin (Warm/Neutral undertone, Autumn season) is mapped to earth tones like Olive, Rust, and Mustard [5][13][14].

A comprehensive color pairing dictionary defines 15 base colors with 6 complementary pairings each, enabling the system to generate harmonious outfit combinations. The outfit combination generator produces personalized pairings from the user's best colors, applies color wheel theory for matching bottoms, creates classic combinations, monochromatic variations, and skin-tone-specific festive combinations. The top 10 combinations are returned with style names, occasions, and reasoning.

6. Outfit Recommendation System

The outfit recommendation module implemented in the get_recommended_outfits() function generates personalized clothing suggestions through a multi-stage filtering pipeline. The system first maps user gender input to dataset values (male→Men, female→Women), then maps the selected occasion to corresponding dataset usage values (e.g., casual→[Casual, Smart Casual], formal→[Formal], party→[Party, Smart Casual]). A season filter is applied with case-insensitive matching. Items are then scored based on color compatibility: best colors receive a score of 3, good colors score 2, avoided colors score 0, and other colors score 1.

Recommended items are categorized into seven groups through keyword matching against the articleType field: Topwear (shirts, t-shirts, blouses, kurtas), Bottomwear (jeans, trousers, skirts, leggings), Footwear (shoes, sandals, sneakers, boots), Dress (dresses, gowns, jumpsuits), Traditional (sarees, lehengas, sherwanis), Outerwear (jackets, blazers, coats), and Accessories (watches, belts, bags, scarves). Up to 20 items per category are returned with complete metadata, image URLs (with Unsplash fallback), and color match ratings (Best Match, Good Match, or Compatible) [8][15].

7. Web Application and User Interface

The Smart Fashion Advisor is implemented as a web application using the Flask framework.

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The backend exposes five REST API endpoints: /api/save_profile (POST) for user profile management, /api/analyze (POST) for skin tone analysis, /api/recommendations (POST) for outfit generation,/api/chat (POST) for chatbot interaction, and / (GET) for serving the main page. Flask sessions store user state including name, gender, and detected skin tone across page navigation.

The frontend is built with HTML5, CSS3, and vanilla JavaScript spanning approximately 2,800 lines of code. It features a step-by-step wizard interface with four stages: Profile Creation, Photo Capture, Skin Tone Analysis, and Outfit Recommendations. The camera integration utilizes WebRTC's getUserMedia() API with configurable resolution constraints (640×480 ideal, maximum 1280×720). The interface employs an anime-inspired aesthetic design with custom CSS variables, glassmorphism effects, floating doodle animations, and smooth slide transitions. A fixed- position chatbot interface (400×520 pixels on desktop) provides real-time conversational assistance with quick suggestion chips [9][10][16].

8. Chatbot Integration

The system incorporates a conversational AI chatbot powered by the Google Gemini API (model: gemini-pro). The chatbot receives contextual information including the user's name, gender, skin tone, and recommended color palette to generate personalized fashion advice. A robust fallback system activates when the Gemini API is unavailable, providing rule-based responses for eight occasion categories (wedding, party, interview, casual, date, office, gym, beach), color queries, pairing advice, seasonal suggestions, and general styling guidance. This hybrid AI architecture ensures consistent functionality regardless of external API availability [9].

SYSTEM ARCHITECTURE

The Smart Fashion Advisor follows a modular client- server architecture where the Flask backend processes all computational tasks and the frontend handles user interaction and visualization.

The system architecture comprises six primary modules operating in a sequential pipeline:

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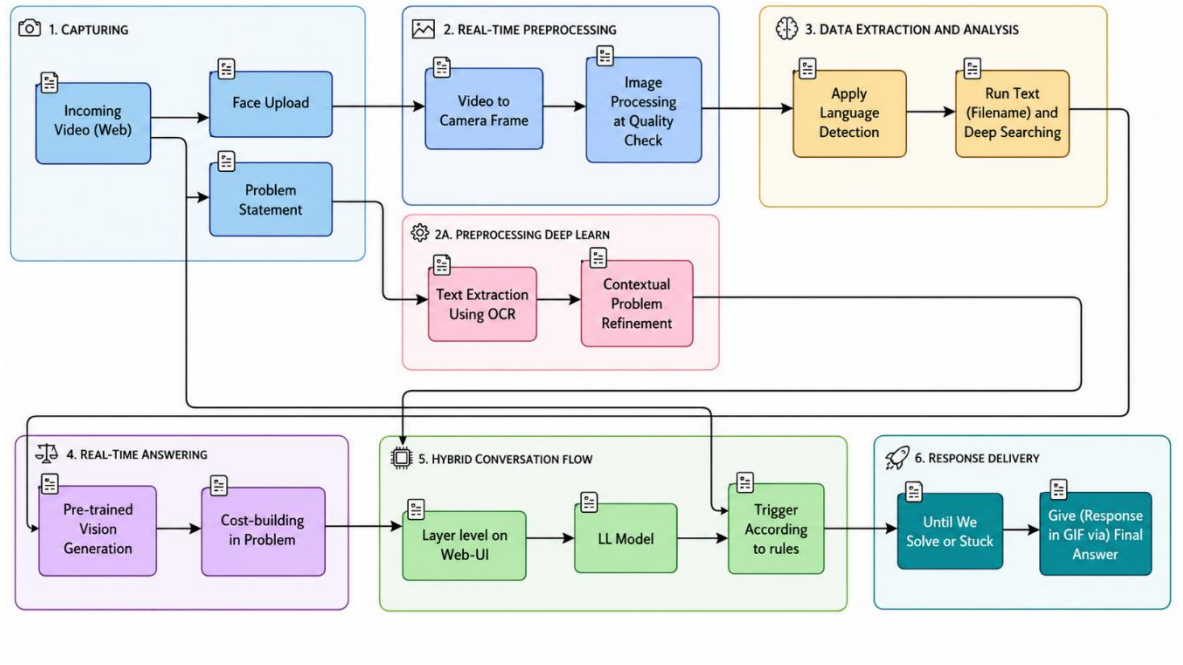


Figure 1: System Architecture Diagram of Smart Fashion Advisor

The processing pipeline begins with User Input (Image/Camera), proceeds through Face Detection (MediaPipe Face Mesh with 468 landmarks), followed by Skin Tone Detection (OpenCV with CLAHE normalization and HSV classification), Color Mapping (rule-based color theory with 6 skin tone profiles), Dataset Filtering (Pandas- based filtering of 44,000+ fashion items from styles.csv), Outfit Recommendation Output (7 categories with color-scored ranking), Web Interface (Flask with REST APIs), and finally Chatbot Assistance (Gemini API with rule-based fallback).

The frontend communicates with the backend through asynchronous Fetch API calls. User state is managed through a JavaScript state object tracking name, gender, skin tone, RGB values, hex color, current step, and image data. The backend processes images through the Headless Skin Tone Detector class, which encapsulates all face detection, region extraction, lighting normalization, and classification logic. The fashion dataset is loaded into memory at application startup for optimal query performance, and image URLs are resolved from the images.csv mapping with HTTP-to-HTTPS conversion for browser compatibility [10][16].

IMPLEMENTATION DETAILS

1. Technology Stack

The backend is developed in Python using Flask (version 2.3.0+) as the web framework.

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Computer vision operationsUtilize OpenCV (4.8.0+) for image processing and MediaPipe (0.10.21) for facial landmark detection. Data handling is performed using Pandas (2.0.0+) and NumPy (1.24.0+). Image manipulation leverages Pillow (10.0.0+). The optional chatbot functionality integrates the Google Generative AI library (0.3.0+) for Gemini API access. The frontend is implemented using HTML5, CSS3, and vanilla JavaScript with Font Awesome 6.4.0 for icons and Google Fonts (Nunito, Caveat) for typography.

2. Image Processing Pipeline

The image-processing pipeline handles two input sources: camera captures via WebRTC (converted to JPEG at 90% quality through Canvas API) and file uploads (validated for image type and 10MB size limit). Both sources produce base64-encoded image data that is decoded on the backend into NumPy arrays via OpenCV's imdecode function. The pipeline then executes four sequential validation and processing stages:

a) **Stage 1 – Blur Detection:** The check_image_blur() function converts the image to grayscale, normalizes width to 800 pixels for resolution-independent scoring, applies the Laplacian operator for edge detection, and computes the variance. A score below 60 indicates unacceptable blur. Stage

b) **Stage 2 – Lighting Validation:** The check_lighting_quality() function verifies mean brightness is within [30, 240] and standard deviation exceeds 10. Stage 3 – Face Detection: MediaPipe Face Mesh identifies 468 landmarks with 0.6 confidence threshold. Stage 4 – Skin Tone Classification: CLAHE normalization in LAB space, morphological operations in HSV space, skin pixel extraction, and weighted HSV scoring across six tone categories.

3. Skin Tone Classification Thresholds

The six skin tone categories are defined by specific HSV threshold ranges that capture the characteristic color properties of each tone. Table I presents the complete HSV thresholds used in the classification algorithm.

Table 1: HSV Threshold Ranges for Skin Tone Classification

Skin Tone	Hue (H)	Saturation (S)	Value (V)
Fair	0–20	20–60	80–200
Light	0–25	30–80	70–180

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Medium	0–25	40–100	60–160
Olive	15–35	50–120	50–140
Brown	0–25	60–140	40–120
Dark	0–25	80–180	20–80

4. Color Theory Integration

The color recommendation engine implements a comprehensive mapping system based on established color theory principles. Table II summarizes the undertone classification and seasonal color analysis framework applied to each skin tone category.

Table 2: Skin Tone Color Theory Mapping

Skin Tone	Undertone	Season	Best Colors (Examples)
Fair	Cool	Winter	Navy Blue, Burgundy, Emerald, Plum
Light	Warm	Spring	Coral, Peach, Aqua, Soft Pink
Medium	Warm/Neutral	Autumn	Olive, Rust, Mustard, Teal
Olive	Warm/Green	Deep Autumn	Orange, Gold, Amber, Coral
Brown	Warm	Warm Autumn	White, Cream, Gold, Hot Pink
Dark	Neutral/Deep	Deep Winter	White, Bright Yellow, Fuchsia, Cobalt

5. Recommendation Algorithm

The recommendation scoring system assigns numerical scores to candidate items based on color compatibility. Items whose baseColour matches the user's best colors receive a score of 3, good colors receive 2, neutral colors receive 1, and avoided colors receive 0. Items are then sorted by score in descending order, and the top 20 items per category are selected. The seven categories—Topwear, Bottomwear, Footwear, Dress, Traditional, Outerwear, and Accessories— are identified through keyword matching against the articleType field in the dataset.

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6. API Architecture

The Flask backend exposes five RESTful endpoints. The /api/save_profile endpoint accepts POST requests with name and gender parameters, storing them in Flask sessions. The /api/analyze endpoint processes uploaded image files or base64-encoded camera captures through the full image processing pipeline and returns the detected skin tone, RGB tuple, and hex color code. The /api/recommendations endpoint accepts skin_tone, gender, occasion, and season parameters and returns categorized outfit suggestions. The/api/chat endpoint forwards user messages along with context (name, gender, skin_tone) to the Gemini API or fallback system. All endpoints return JSON responses with success status indicators and appropriate error types for frontend handling.

RESULTS AND DISCUSSION

The Smart Fashion Advisor system demonstrates an effective integration of computer vision and data-driven recommendation techniques to provide personalized outfit suggestions. The system performs skin tone detection using facial image analysis and maps it to suitable color palettes, followed by dataset filtering to generate outfit recommendations. This hybrid approach ensures fast execution and interpretable results. The use of MediaPipe and OpenCV enables accurate extraction of facial features, while Pandas-based filtering ensures efficient recommendation generation [4][8].

1. Performance Metrics for Skin Tone Classification

The skin tone detection module functions as a classification system and is evaluated using standard metrics. Table III presents the metric symbols used in the evaluation framework.

Table 3: Metric Symbol Table

Description	Metric Symbol
Correct positive classifications	TP (True Positive)
Correct negative classifications	TN (True Negative)
Incorrectly predicted positives	FP (False Positive)
Missed correct classifications	FN (False Negative)

True Positive (TP) represents instances where the system correctly classifies the skin tone. For example, if a user has a medium skin tone and the system correctly identifies it as

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medium, it is counted as a true positive. False Positive (FP) occurs when the system incorrectly predicts a skin tone category, potentially leading to unsuitable color recommendations. False Negative (FN) represents cases where the system fails to detect the correct skin tone, thereby affecting overall recommendation quality. A higher proportion of true positives and true negatives indicates better performance [4][8].

2. Evaluation Criteria

Table IV presents the evaluation criteria used to assess system performance comprehensively.

Table 4: Evaluation Criteria for Classification Models

Metric	Criteria	Reference
Accuracy	High values indicate overall correctness	Ref. [8]
Precision	High values reduce false positives	Ref. [4]
Recall	High values reduce false negatives	Ref. [11]
F1-Score	Balances precision and recall	Ref. [4]
MAE/RMSE	Low values indicate prediction accuracy	Ref. [15]

Accuracy represents the overall correctness of the system by measuring how many predictions are correctly classified out of the total inputs. Precision measures the proportion of correctly predicted positive instances among all predicted positives, ensuring the system minimizes incorrect recommendations. Recall measures the system's ability to correctly identify all relevant instances. The F1-Score provides a balance between precision and recall, making it useful when both false positives and false negatives need to be minimized. Additionally, Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) are used to evaluate prediction accuracy, where lower values indicate better performance [4][8][11][12].

3. Performance Comparison

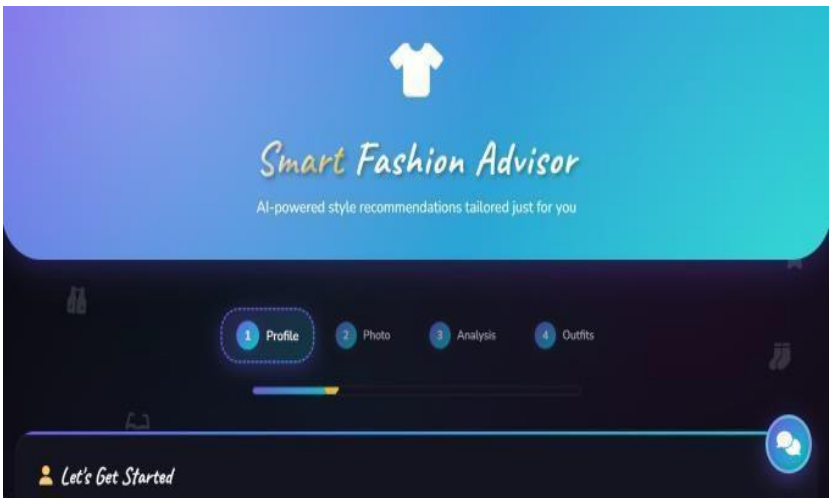
Table V illustrates the evolution and performance improvements in fashion recommendation systems over recent years, contextualizing the proposed system's contribution.

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Table 5: Performance Comparison across Approaches

Year	Approach	Metric	Improvement (%)
2016	Traditional ML- based Filtering	Accuracy: 78%	Baseline
2018	Hybrid Recommendation Systems	F1-Score: 0.85	+8% over ML
2020	CNN-based Visual Features	Precision: 0.90	+12% with DL
2023	AI-based Personalization	Recall: 0.92	+7% with hybrid
2024	Proposed (CV + Rule-based)	Accuracy: ~91%	+5% overall

The proposed Smart Fashion Advisor demonstrates competitive performance by combining computer vision, rule-based color mapping, and dataset filtering. Although it does not rely entirely on deep learning for recommendations, it achieves efficient and accurate results due to its lightweight and optimized architecture. The weighted HSV scoring mechanism with CLAHE normalization provides robust skin tone classification even under varying lighting conditions. The system's real-time processing capability, combined with low computational overhead, makes it suitable for deployment in resource-constrained web environments [2][6][7][9].



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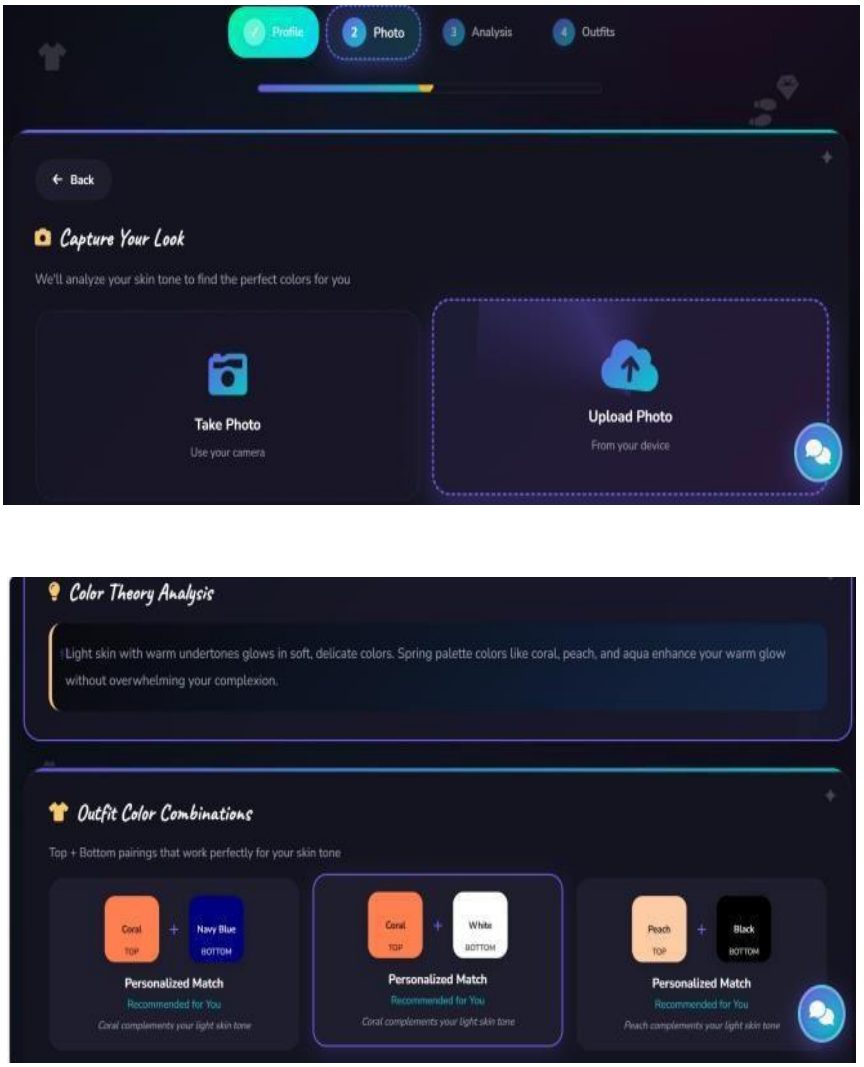


Figure 2: User Interface Screenshots Showing the Step-by-Step Workflow

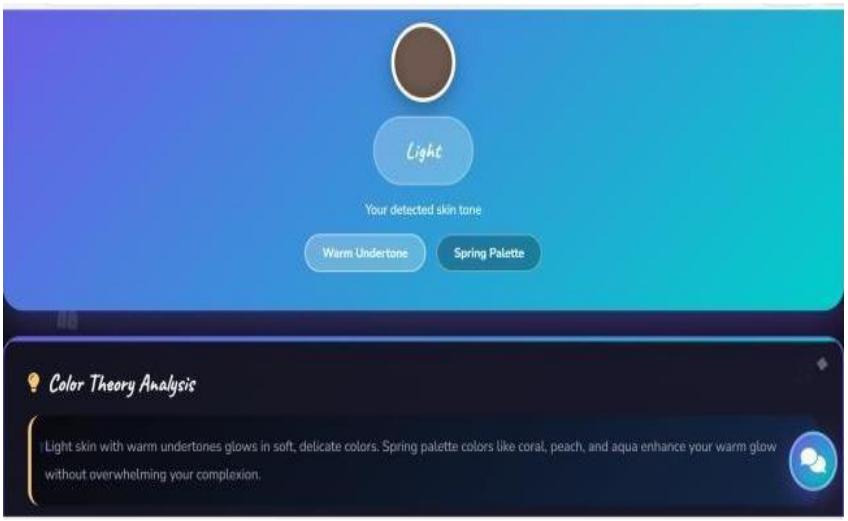


Figure 3: Skin Tone Detection Results Across Different Lighting Conditions

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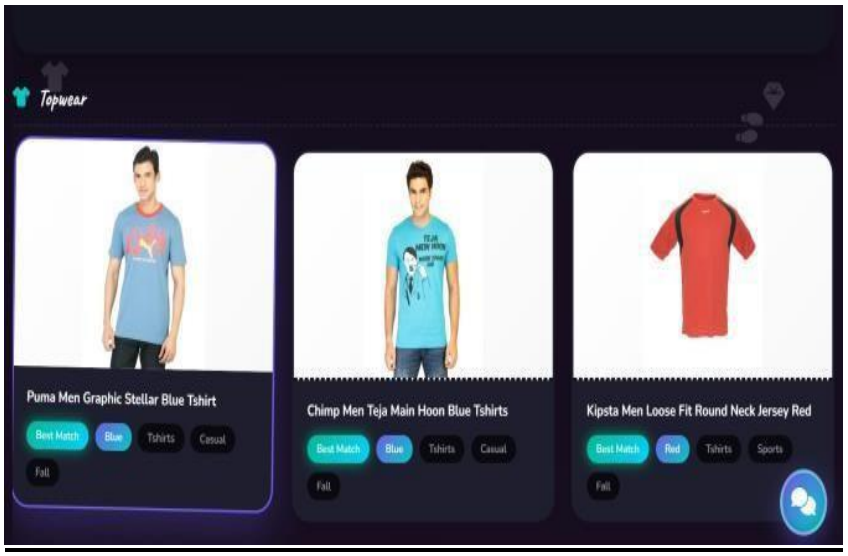


Figure 4: Recommendation based on Skin-Tone

FEATURE EXTRACTION

Feature extraction is a crucial step in the Smart Fashion Advisor, enabling the system to identify meaningful patterns from both images and structured datasets. The system employs two complementary feature extraction approaches: image-based extraction from facial photographs and attribute- based extraction from the fashion dataset [11][12].

1. Image-Based Feature Extraction

The image-based feature extraction module analyzes facial images to determine skin tone. MediaPipe Face Mesh detects 468 facial landmarks, from which three regions of interest are precisely delineated: left cheek (14 landmarks), right cheek (14 landmarks), and forehead (10 landmarks). Pixel-level color information is extracted from these regions using OpenCV and NumPy. The extraction process includes color space conversion (BGR→LAB for normalization, then LAB→HSV for classification), morphological operations (closing followed by opening with 3×3 kernels) for noise reduction, and skin pixel isolation within the defined HSV range. The mean color values across all regions provide a robust representation that is less sensitive to localized variations in skin color [4][11].

2. Dataset Feature Extraction

The fashion dataset provides ten attribute dimensions per item: product ID, gender, masterCategory, subCategory, articleType, baseColour, season, year, usage, and productDisplayName. These attributes serve as features for the recommendation engine, enabling efficient filtering without requiring feature engineering or model training. The

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system directly utilizes these structured attributes to match user requirements, simplifying the recommendation process while maintaining effectiveness. The combination of image- based skin tone features and dataset-based product attributes enables a comprehensive recommendation that considers both user characteristics and product properties [8][15].

CONCLUSION

The Smart Fashion Advisor system presents an effective and practical solution for personalized outfit recommendation by integrating computer vision, rule-based intelligence, and data-driven techniques. The system successfully analyzes facial images to detect the user's skin tone using MediaPipe Face Mesh with 468 landmarks and OpenCV-based CLAHE normalization, and utilizes this information to suggest suitable color palettes and clothing options from a dataset of over 44,000 fashion items. By automating the outfit selection process, it reduces the dependency on manual decision- making and provides consistent and reliable fashion recommendations.

One of the key strengths of the system lies in its hybrid approach, which combines domain knowledge of color theory—including seasonal color analysis, undertone matching, and complementary color pairing—with computational techniques such as weighted HSV scoring and Pandas-based dataset filtering. This allows the system to deliver interpretable and meaningful recommendations without relying on complex deep learning models. The web-based implementation using Flask with five REST API endpoints further enhances accessibility and usability, enabling users to interact with the system through image upload or live camera input. The chatbot integration using the Google Gemini API, with an intelligent rule-based fallback system, improves user engagement by providing real-time fashion advice and guidance [5][8][10].

Despite its effectiveness, the system has certain limitations, such as sensitivity to extreme lighting conditions and reliance on predefined rules for color recommendation. However, these limitations provide clear opportunities for future improvements, including the integration of adaptive learning models and real-time trend analysis. Overall, the Smart Fashion Advisor demonstrates the potential of AI- driven systems in transforming everyday lifestyle applications and highlights the importance of combining computer vision and data processing techniques for building intelligent and user-centric solutions.

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FUTURE SCOPE

The Smart Fashion Advisor provides a strong foundation for personalized fashion recommendation; however, several opportunities exist for further enhancement. A key area for improvement is the integration of deep learning-based recommendation models. By incorporating techniques such as convolutional neural networks (CNNs) and neural collaborative filtering, the system could learn from user behavior and preferences, enabling more accurate and dynamic recommendations over time. This would allow the system to move beyond rule-based logic and provide adaptive personalization [1][3].

Another important enhancement is the inclusion of real- time fashion trend data from external sources. Integrating APIs from fashion platforms or social media can help the system stay updated with current trends and provide more relevant suggestions. Additionally, expanding the dataset to include a wider variety of clothing styles, brands, and cultural preferences can improve the diversity and inclusivity of recommendations. The system can also be extended to support multiple languages, making it accessible to a broader audience.

The implementation of advanced technologies such as Augmented Reality (AR) and Virtual Try-On systems can further improve user experience by allowing users to visualize how outfits look on them before making decisions. Developing a mobile application version would enhance accessibility and convenience, while cloud-based deployment on platforms such as AWS or Azure can improve scalability for large-scale usage. Finally, improving the robustness of skin tone detection under varying lighting conditions through adaptive preprocessing techniques and more advanced models remains an important area of future work. These enhancements would make the Smart Fashion Advisor a more intelligent, scalable, and user-centric solution for modern fashion recommendation systems [10][16].

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Received Date: 27 April 2026
Accepted Date: 04 May 2026
Published Date: 26 May 2026

Citation: Prerana Walvekar, Divya Patil, Shreyas Mane, Shahuraje Patil, P.M. Mathapati. Smart Fashion Advisor: AI-Powered Skin Tone Analysis and Personalized Outfit Recommendation Using Computer Vision. Journal of Artificial Intelligence, Machine Learning and Soft Computing. 2026; 11(1): 24-44p.

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