STYLOSCAPE: An AI-Powered Undertone and Color Palette Analysis System for Personalized Fashion Recommendations.

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Abstract - Fashion advice is usually based on broad trends and not individual color analysis, resulting in style choices that do not fully cater to the individual. Styloscape is an AI-powered system that measures an individual's undertone and provides customized color palette suggestions for fashion. The system retrieves an image through computer vision principles, analyzes the skin undertone (cool, warm, or neutral), and recommends an optimal color palette. Also, the system uses Selenium-based web scraping to fetch real-time dress suggestions from Myntra, so users can directly explore and purchase outfits within their suggested color palette. Streamlit and Python are used to develop the system, which enables a seamless and dynamic user experience. This study explores the efficacy of AI-powered undertone detection in fashion technology, where it can play a pivotal role in enhancing more tailored shopping experiences. Challenges like lighting conditions, dataset diversity, and web scraping limits are also suggested, as well as viable improvements for real-time processing and more extensive e-commerce integrations.

Key Words: Gemini, Computer Vision, Machine Learning, Undertone, Color Palette, Python

1. INTRODUCTION

Fashion plays a vital role in personal expression, self-confidence, and social connections. Nevertheless, selecting the correct colors of the outfit that complement a person's skin undertone still poses a difficulty for most people. Traditional fashion advice is based on popular trends as opposed to personalized color analysis, hence leading to potential choices that are not good for a person's complexion. To address the gap, Styloscape presents an AI-based method of undertone identification and color-based fashion guidance.

limitations, anStyloscape identifies facial features from an input image using computer vision, determining the coolness, warmth, or neutrality of the person. The system then creates a customized color palette based on this categorization. In addition to providing a better experience, Styloscape combines Selenium-based web scraping to fetch up-to-date fashion suggestions from Myntra and enables users to browse and shop for fashion pieces based on their individualized color profile.

Utilizing Streamlit and Python, Styloscape offers a user-friendly and interactive framework for making fashion choices simpler. This study examines the ability of AI-based undertone recognition to enhance tailored fashion and emphasizes the system's technical features and likely future development. The study further explores the general implications of AI-driven fashion technology, such as its applications in virtual shopping assistants, e-commerce personalization, and digital wardrobe planning.

2. LITERATURE SURVEY

The use of artificial intelligence (AI), computer vision, and web scraping for the fashion industry has been a significant research interest in recent years. The study has centered on skin undertone detection, color analysis, customized fashion recommendations, and e-commerce automation. This part outlines pertinent studies and technologies that form the foundation of Styloscape.

While traditional undertone identification methods rely on expert opinion, manual color matching, or physical testing (e.g., vein color tests and jewelry comparisons). But with recent advances in computer vision, it is now possible to identify undertones using image processing and deep learning, allowing automatic identification. It explored the use of color space conversions (RGB to HSV, LAB) for upgrading skin tone classification[17]. It suggested deep learning models for skin tone identification, using convolutional neural networks (CNNs) to classify undertones precisely[11]. These studies highlight the potential of AI-based undertone analysis, which Styloscape offers for automated and scalable fashion personalization. It demonstrated how color harmony models can impact fashion choices and consumer preference[18]. Existing AI-based fashion recommendation systems, like IBM Watson's AI Stylist, use machine learning to predict suitable outfits based on color harmony and user preference. There's an AI model that analyzes color palettes based on facial features, clothing contrast, and lighting conditions to suggest fashion individually[22]. Styloscape improves these concepts by combining undertone analysis with real-time clothing recommendation, making it more convenient for online consumers.

The increasing prevalence of e-commerce platforms has made web scraping for up-to-the-minute fashion recommendations a crucial component of AI-powered styling solutions. In some papers, it is employed in research on automated web scraping by Selenium and BeautifulSoup to extract product information from e-commerce websites[20]. The research emphasized the significance of dynamic web scraping processes to refresh product recommendations. It was outlined how real-time product retrieval systems enhance online purchase[2]. Styloscape builds upon these processes by utilizing Selenium-based scraping to retrieve color-complementary clothes from Myntra, allowing users to discover and purchase clothes that complement their undertone.

AI-driven fashion retail solutions have demonstrated positive user engagement and personalization experiences. A few studies showcased AI-driven virtual fitting rooms where users

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can see how fashion products look on them[14]. In addition, an image-based clothing recommendation system using deep learning resonates with the application of computer vision in fashion retail automation[21]. Leveraging these developments, Styloscape utilizes computer vision for undertone detection and web scraping for fashion curation, adding to the field of AI-powered styling assistants.

3. METHODOLOGY AND IMPLEMENTATION

The Styloscape system is engineered to identify a user's skin undertone and offer personalized fashion suggestions based on computer vision, the Gemini API, and web scraping using Selenium.

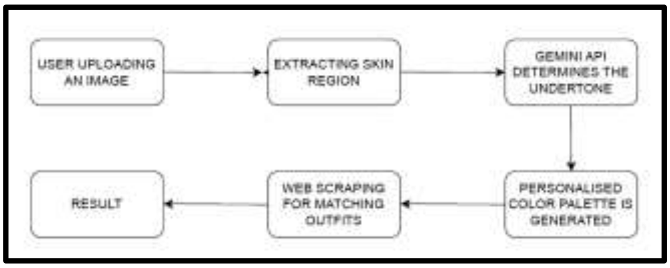

Fig 1: Flowchart

The approach includes the following modules:

3.1 Image Preprocessing: The image preprocessing module is in charge of separating relevant skin areas from the uploaded image. It includes the following steps:

3.1.1 Image Upload: The system allows users to upload images in JPG, PNG formats via Streamlit. Once uploaded, the image is imported as a NumPy array for further processing using OpenCV. To standardize the dimensions and reduce computational cost, the image is then resized accordingly.

3.1.2 Face Detection: Haar Cascades algorithm is used to identify the face area, thereby that only the skin area is being analyzed.

- Haar Cascades algorithm: Being both lightweight and efficient for face detection, Haar Cascades is ideal for real-time use such as in Styloscape, which demands fast and efficient extraction. Haar Cascades leverages an integral image and cascade classifier to identify faces at low computational cost, allowing for CPU-based execution without the need for a GPU. Haar Cascades is pre-trained and simple to implement with OpenCV, allowing easy deployment without extensive training on a dataset.

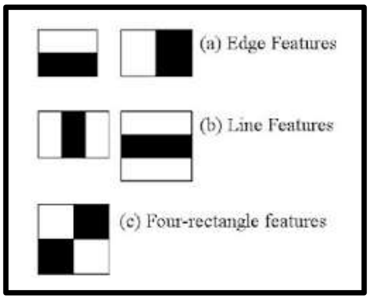

Fig 2: Face detection using Haar Cascade

3.1.3 Skin Region Extraction: Extract skin regions from **cheeks, jawline, and forehead** to determine the **user's undertone**.

- **Dlib:** Dlib is a robust facial detection library employed by Styloscape to enable accurate skin color analysis. By detecting facial landmarks based on HOG , SVM and CNN-based models, it fetch major areas of the skin such as the forehead and cheeks.
- **Convex Hull algorithm:** The convex hull algorithm aims to find the smallest convex shape that encompasses a given set of points. It does this by identifying the points that contribute to the outer perimeter or surface of this shape.

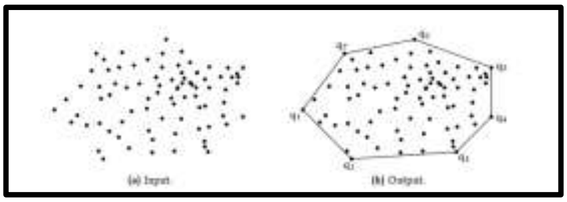

Fig 3: Convex Hull

3.1.4 Color Space Conversion: The extracted skin region is converted to LAB or HSV color space to enable more facilitated color analysis. More precisely, converting RGB to LAB helps by isolating the lightness (L) component from the color components (A and B). Since LAB is perceptually uniform, it proves ideal for accurate skin tone detection in Styloscape. This OpenCV-driven conversion enhances the precision of undertone classification, allowing for more customized and trustworthy fashion recommendations.

3.2 Skin Undertone Detection (Gemini API)

Based on the results of the skin analysis, the Gemini API is utilized to classify the user's undertone. The process is initiated by sending the processed image to the API for feature extraction. After these features are analyzed, the API classifies the skin into one of three undertone types: Cool (with bluish or pinkish hues), Warm (with yellowish or golden tones), or Neutral (an equal blend of warm and cool tones). To guarantee the reliability of the classification, the API also furnishes a confidence score, reflecting the accuracy of its assessment.

3.3 Color Palette Generation

Following the identification of undertone, a color palette is created based on predefined fashion color theory:

- **Cool undertones**: Ideal for shades of blue, purple, and silver shades.
- **Warm undertones**: Recommended color palette features red, orange, and gold.
- **Neutral undertones**: Balanced and earthy shades are most flattering

The selected color palette is then used to fetch matching fashion products from Myntra.

3.4 Fashion Product Retrieval

The fashion product retrieval module provides real-time recommendations tailored to the user's undertone and color palette. Using Selenium for web automation, the system constructs a search query based on LAB to HEX-converted colors and navigates Myntra's site through a headless Chrome browser. It scrapes key details like product name, brand, price, image, and purchase link. The results are then filtered and ranked by color relevance, user ratings, and price, with the option to enhance accuracy using a machine learning-based ranking system.

4. WORKING PRINCIPLE

The **working principle** of **Styloscape** involves a structured pipeline that integrates **image processing, color analysis, AI-based personalization, and web scraping** to generate fashion recommendations.

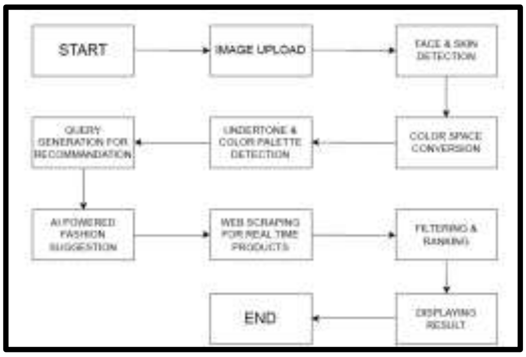

Fig 4: Workflow of the program

Below is a **detailed step-by-step breakdown** of how the system operates:

4.1 Image Acquisition & Preprocessing: The user uploads an image through the Streamlit interface. Face area is detected by Haar cascades (OpenCV). The algorithm separates prominent areas (forehead, jawline, cheeks) to detect the undertone of the user. The skin area delineated is translated from RGB to LAB/HSV for enhanced color analysis.

4.2 Undertone & Color Palette Detection: The average LAB values of the extracted skin region are computed. LAB values are compared to a predefined undertone mapping (Warm, Cool, Neutral). The predominant colors from the derived skin tone are determined through K-Means clustering. K-Means clustering is an unsupervised learning algorithm to split data into K clusters with similar features. It repeatedly puts a point in the closest centroid cluster, and it recalculates the centroids by taking the mean of points in the cluster. K-Means is efficient for big data but is sensitive to initial centroid position and the selection of K. The detected colors are converted into **HEX format** for display and web search compatibility.

4.3 AI-Powered Fashion Recommendation: A fashion query is generated based on the determined undertone and color scheme. The call is made to Google's Gemini API, which returns fashion suggestions and clothing categories that are matched with the user's personalized color palette. Users may tailor recommendations according to the desired intensity of color, style of clothing, or filtering according to the occasion.

4.4 Web Scraping for Product Fetching: Selenium WebDriver is utilized to browse Myntra to look for outfits by color palette extracted. Product name, brand, price, image, and direct purchase link are extracted using XPath/CSS Selector. The products that are fetched are ranked according to color similarity, customer reviews, and price category.

4.5 Output & User Interaction: The suggested fashion items are presented on the Streamlit dashboard with clickable buy links. Users can provide ratings for the recommendations such that the system can learn and improve through reinforcement learning.

5. RESULT ANALYSIS

Figure 5: Input Image

Figure 6: Output

CONCLUSION

Styloscape is a leading AI-powered fashion recommendation platform that surpasses traditional solutions with the integration of computer vision, machine learning, and real-time web scraping to deliver individualized fashion recommendations.

WHY STYLOSCAPE IS BETTER

Most traditional fashion recommendation systems would depend heavily on trend-based filtering or rule-based, pre-defined recommendations. Styloscape, however, applies principles of color science using LAB color space transformation to make the recommended outfits compatible with the natural color of the user's skin. This is more scientifically proven and accurate than traditional RGB-based methods. The second major strength of Styloscape is its intelligent AI integration. While other platforms are rule-based on static algorithms, Styloscape uses the Gemini API to generate context-based, AI-based insights for fashion choices.

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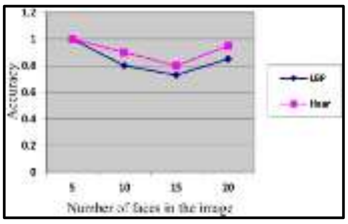

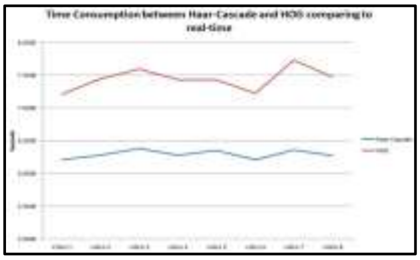

Figure 7:Comparison of Haar Cascade with other algorithms

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