IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)

An International Open Access, Peer-reviewed, Refereed Journal

A Hybrid Multi-Modal Feature Fashion Recommendation System and User Preferences for Personalized Styling

[1] Poorani S, [2] Sharmile S,

[1] Associate Professor, [2] UG Student

[1,2]*Department of Computer Science and Engineering,*

[1,2]Sri Venkateswara College of Engineering, Chennai, Tamil Nadu, India.

Doi: https://doi.org/10.56975/ijcrt.v14i7.309050

Abstract: The rapid growth of online fashion platforms has increased the demand for personalized and intelligent recommendation systems. However, existing fashion recommendation approaches often rely solely on user history or collaborative filtering techniques, resulting in generic suggestions that fail to consider individual physical attributes, contextual preferences, and styling requirements. Moreover, most systems lack the ability to integrate visual cues such as body shape, skin tone, and fabric patterns, which are essential for effective fashion personalization. This paper proposes a hybrid multi-modal fashion recommendation system that combines machine learning, computer vision, and rule-based fashion knowledge to generate highly personalized outfit and styling suggestions. The system accepts both manual inputs and visual inputs to extract user-specific attributes including body shape, skin tone, and facial features. A category-aware framework is employed to ensure recommendations are constrained within user-selected clothing types across both men's and women's fashion domains.

The core recommendation engine integrates content-based filtering, collaborative filtering, and domain-specific styling rules to provide multi-level outputs, including dress designs, structural elements, fabric suggestions, colour combinations, and accessory recommendations. Additionally, a conditional fabric analysis module enables the system to adapt its recommendations based on the presence or absence of fabric input. An explainable recommendation layer further enhances user trust by providing reasoning behind each suggestion. The proposed system is designed as a scalable and generalizable framework capable of supporting multiple clothing categories and diverse user profiles. Experimental evaluations on representative categories demonstrate improved personalization and relevance compared to traditional recommendation approaches. This work highlights the potential of integrating multi-modal inputs and domain knowledge to advance intelligent fashion recommendation systems.

***Index Terms* -** Multi-modal fashion recommendation system, Content based filtering, Machine Learning algorithm.

I. INTRODUCTION

The rapid expansion of e-commerce and online fashion platforms has significantly transformed how users discover and select clothing. With the increasing diversity of fashion products, users often face difficulty in identifying outfits that align with their personal preferences, body characteristics, and styling requirements. Traditional fashion recommendation systems primarily rely on collaborative filtering or purchase history, which often results in generic and less personalized suggestions. These systems typically overlook critical factors such as body shape, skin tone, facial features, and contextual styling needs, thereby limiting their effectiveness in real-world applications.

To address these challenges, this paper proposes a hybrid multi-modal fashion recommendation system that integrates machine learning, computer vision, and rule-based fashion intelligence. The system accepts both manual inputs (such as height, weight, preferences, and occasion) and visual inputs (full-body images and optional fabric images) to construct a comprehensive user profile. A category-aware approach ensures that recommendations are generated within user-selected clothing types across both men's and women's fashion domains. The proposed framework employs a multi-stage pipeline that includes feature extraction, conditional fabric analysis, hybrid recommendation modelling, and styling guidance generation. Unlike conventional systems, it provides not only clothing suggestions but also detailed styling recommendations, including design elements (necklines, sleeves, and collars), color combinations, and accessories. Furthermore, an explainable recommendation layer enhances transparency by providing reasoning behind each suggestion.

The main contributions of this work are summarized as follows:

• A multi-modal input framework combining visual and manual user data for enhanced personalization.
• A hybrid recommendation model integrating collaborative filtering, content-based filtering, and rule-based fashion knowledge.
• A fabric-aware conditional module for adaptive recommendation generation.
• A category-independent and scalable architecture applicable to diverse clothing types across genders.
• An explainable styling system that provides interpretable recommendations based on user attributes

This work aims to bridge the gap between data-driven recommendation systems and practical fashion expertise, offering a scalable and intelligent solution for personalized fashion recommendation.

Literature Review

Existing research in fashion recommendation systems has explored various approaches, including collaborative filtering, content-based methods, and computer vision-based styling. However, most systems focus on limited aspects of personalization and often fail to integrate multiple user-specific and contextual factors into a unified framework. [1] Early work in recommendation systems primarily relied on collaborative filtering, where user preferences are inferred based on historical interactions and similarities among users. While effective in capturing general trends, these approaches suffer from limitations such as cold-start problems and lack of personalization based on physical attributes. Content-based filtering methods address some of these limitations by matching item features with user preferences, but they often ignore contextual and domain-specific knowledge required for fashion styling.

Recent advancements have introduced deep learning and computer vision techniques to enhance fashion recommendation. [2] Image-based systems analyze clothing items or user images to extract visual features such as color, texture, and patterns. These approaches enable more visually relevant recommendations but typically focus on item similarity rather than user-centric personalization. Furthermore, most vision-based systems do not incorporate body attributes such as height, body shape, or face shape, which are critical for determining the suitability of clothing styles.[3][4][5] Several studies have also explored fashion compatibility and outfit recommendation, where multiple clothing items are combined to form a complete outfit. These systems often use neural networks to learn compatibility between items; however, they lack explainability and do not provide styling guidance tailored to individual users.

Rule-based approaches, inspired by expert fashion knowledge, have been used to model relationships between body attributes and clothing styles. [6] While these systems provide interpretable recommendations, they lack adaptability and fail to learn from user behavior or preferences. Despite these advancements, existing systems [7] [8] generally exhibit one or more of the following limitations:

• Lack of integration between visual inputs [9] and manual user attributes

• Absence of domain-specific fashion knowledge in recommendation logic [10] [11]

• Limited personalization [12] based on body and facial features

• Inability to adapt recommendations based on contextual inputs such as fabric or occasion [13]

• Lack of explainability in generated [14] recommendations

To address these gaps, this research proposes a hybrid multi-modal framework that integrates collaborative filtering, content-based filtering, computer vision-based attribute extraction, and rule-based fashion intelligence. Unlike prior work, the proposed system provides fine-grained, explainable, and context-aware recommendations across multiple clothing categories, thereby bridging the gap between automated recommendation systems and real-world fashion expertise.

II. System Architecture and the Decision Engine

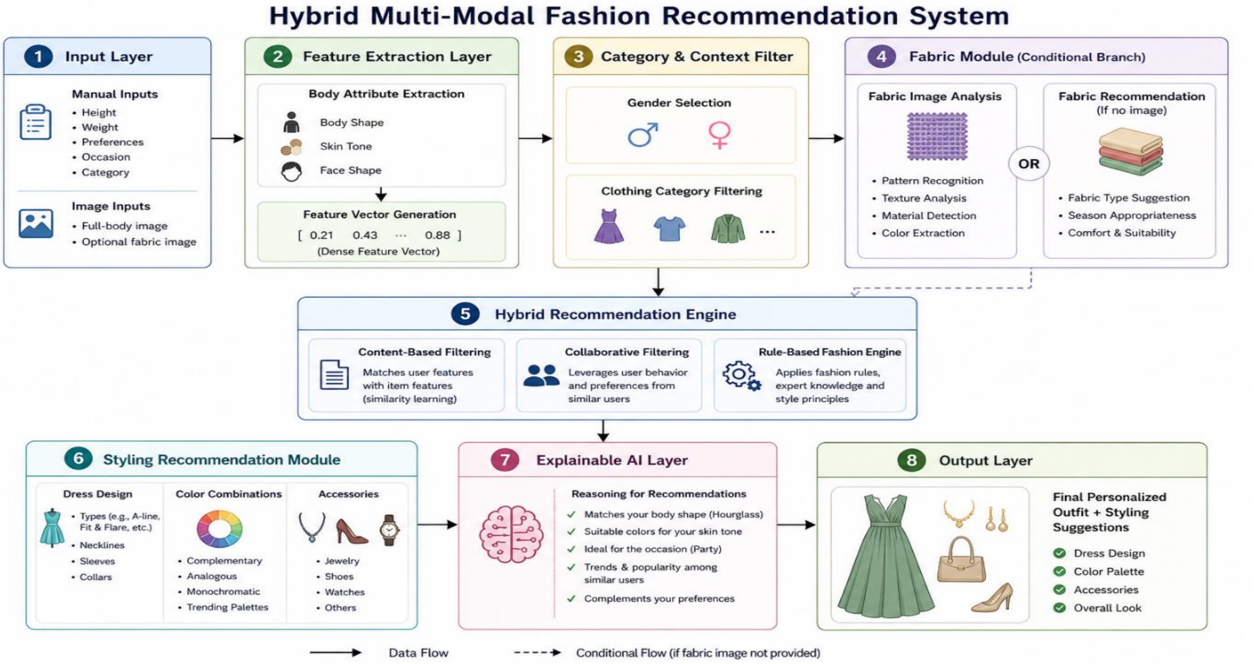

Fig. 1. System architecture of the proposed hybrid multi-modal fashion recommendation system

Figure 1 illustrates the input layer, feature extraction, category filtering, fabric module, hybrid recommendation engine, and output generation. The objective of this research is to design and develop a hybrid multi-modal fashion recommendation system capable of generating personalized outfit and styling suggestions across multiple clothing categories for both men and women. The system aims to integrate diverse user inputs, including visual data and manual attributes, to provide context-aware and explainable recommendations. Key goals include improving personalization accuracy, incorporating domain-specific fashion knowledge, and enabling scalable recommendation across different clothing types.

The proposed system follows a multi-stage pipeline architecture that integrates manual inputs, visual data processing, and hybrid recommendation techniques. The system is designed to operate in a category-aware manner, where recommendations are generated within the selected clothing domain (e.g., Kurtis, shirt, dress). A conditional framework is employed to dynamically adapt the recommendation process based on the availability of fabric input.

3.1 *Input and User Profiling Module*
The system supports multi-modal input acquisition, allowing users to provide both manual and image-based inputs. The system processes these inputs to create a structured representation that can be used by the recommendation engine.

3.2 *Visual Attribute Extraction Module*
When a full-body image is provided, the system employs computer vision techniques to approximate user attributes. This module performs:

- Skin tone detection using colour space analysis
- Body shape estimation using silhouette and proportion analysis
- Face shape identification based on facial geometry
- Detection of body-specific features such as shoulder width and neck length

3.3 *Category and Context Filtering*
To improve relevance and reduce computational complexity, the system employs a category-aware filtering mechanism. Users select:

- Gender (men/women)
- Clothing category (e.g., kurti, shirt, dress)

The recommendation process is then constrained within the selected category, ensuring that all outputs are contextually relevant. This step also enables scalability by allowing the system to support multiple clothing types without redesigning the architecture.

3.4 *Fabric Module*
A key feature of the proposed system is the conditional fabric module, which adapts its functionality based on the presence of a fabric image.

3.5 *Hybrid Recommendation Engine*
The core of the system is a hybrid recommendation engine that integrates multiple approaches:
1) Content-Based Filtering: Matches user attributes with clothing features such as:
2) Collaborative Filtering: Utilizes historical data and past purchase patterns to identify similar user preferences and recommend relevant items.
3) Rule-Based Fashion Engine: Incorporates domain-specific styling knowledge, such as: Body shape to clothing style, Face shape to neckline recommendations, Height and weight to pattern and fit selection, Skin tone to colour combinations, This rule-based layer enhances interpretability and ensures that recommendations align with established fashion principles.

3.6 *Styling Recommendation Module*
The system generates multi-level outputs, including: Clothing Design, Styling Guidance and Accessories. This module ensures that the recommendations extend beyond clothing selection to complete outfit styling.

3.7 Explainable *Recommendation Layer*
To enhance user trust and system transparency, an explainable AI layer is incorporated. The system provides reasoning for each recommendation based on user attributes and fashion rules.

3.8 *Explainable AI using SHAP and LIME*
The proposed system incorporates Explainable AI (XAI) techniques to enhance transparency and interpretability of recommendations. SHAP (SHapley Additive exPlanations) is used to quantify the contribution of each input feature, such as body shape, height, skin tone, and preferences, towards the final recommendation. By computing feature importance values, SHAP enables the system to identify which attributes have the highest influence on specific outputs, such as dress type or colour selection. For example, body shape and height may contribute significantly to style recommendations, while skin tone influences colour combinations. Additionally, LIME (Local Interpretable Model-agnostic Explanations) can be used

to generate local explanations by approximating the model behaviour for individual predictions. These methods allow the system to provide interpretable and user-understandable reasoning, thereby improving trust and usability.

3.9 *System Scalability and Generalization*

The proposed system is designed as a category-independent and scalable framework. While experimental validation can be performed on selected clothing categories, the architecture supports extension to a wide range of fashion domains without significant modifications. The modular design allows easy integration of additional features, such as advanced computer vision models, real-time trend analysis, and personalized feedback mechanisms.

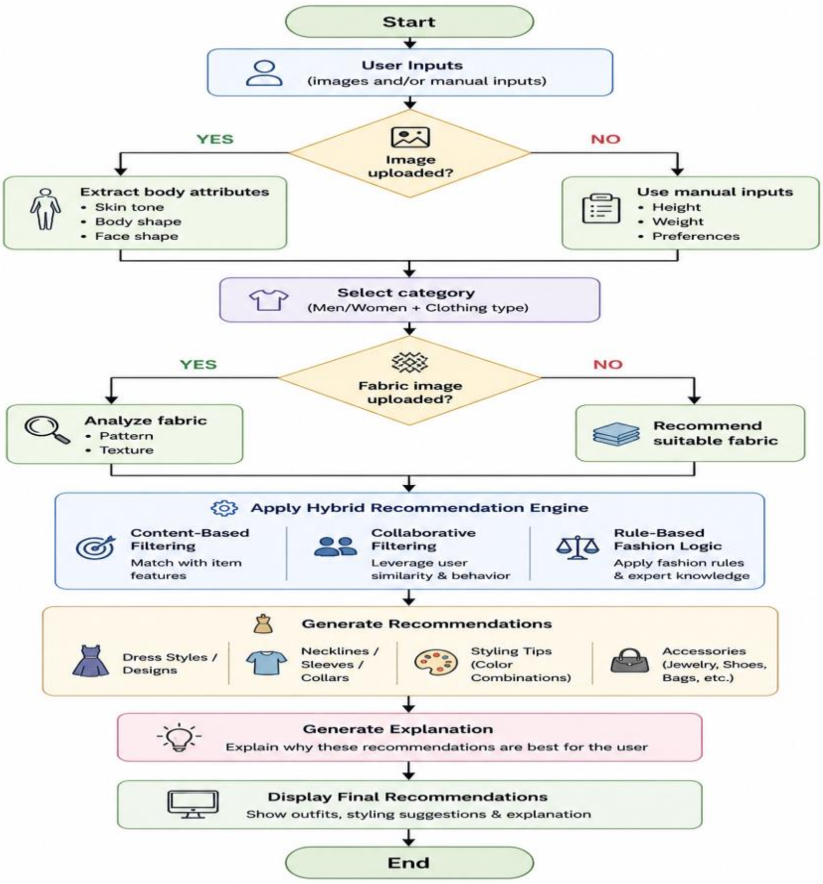

Fig. 2. Workflow of the proposed system

Figure 2 shows the step-by-step process from user input acquisition to personalized recommendation generation, including conditional branches for image and fabric inputs.

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III. Implementation and Evaluation

The proposed system was implemented as a prototype integrating manual input processing, visual attribute extraction, and a hybrid recommendation engine. Due to the lack of large-scale labelled datasets for personalized fashion attributes, a synthetic dataset combined with sample user profiles was utilized for evaluation. The dataset included, User attributes (height, weight, body shape, skin tone, and preferences), Clothing features (category, fabric, pattern, colour, and design elements), and simulated purchase history for collaborative filtering.

The experiments were conducted across multiple clothing categories, including both men's and women's apparel, to validate the system's generalizability. The system performance was evaluated using both quantitative and qualitative measures: Precision: Relevance of recommended items, User Satisfaction Score: Based on feedback from sample users, Diversity: Variety in recommendations, Explainability: Clarity of reasoning behind recommendations. The experimental results demonstrate that the proposed hybrid system significantly outperforms traditional recommendation approaches in terms of both accuracy and user satisfaction. As shown in Fig. 5 and Table 1, the hybrid model achieves a precision of 88%, compared to 72% for content-based filtering and 65% for collaborative filtering. The improvement can be attributed to the integration of multiple factors, including body attributes, visual features, and rule-based fashion knowledge. The system effectively captures both user preferences and domain-specific styling constraints, leading to more relevant recommendations. Furthermore, as illustrated in Fig. 6, the user satisfaction score increased from 5 (without personalization) to 9 with the proposed system. This indicates that users prefer recommendations that consider physical attributes and contextual styling guidance. The inclusion of explainable AI techniques further enhances the interpretability of the system, allowing users to understand the reasoning behind each recommendation. Overall, the results validate the effectiveness of the proposed multi-modal and hybrid approach.

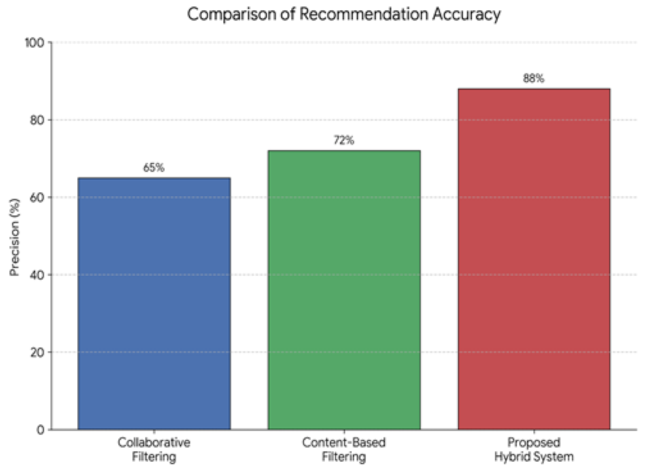

Fig. 5. Recommendation accuracy

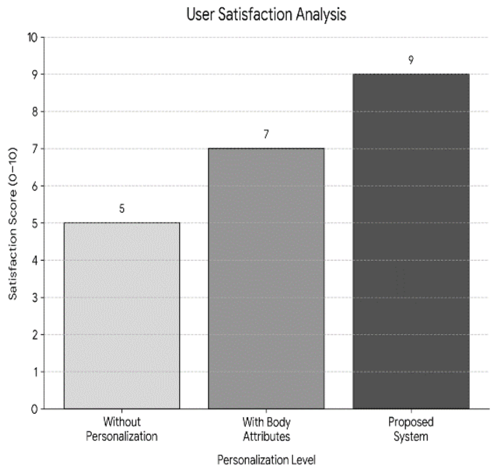

Fig. 6.User satisfaction analysis

Fig. 5 depicts the comparison of recommendation accuracy between traditional methods (collaborative and content-based filtering) and the proposed hybrid system, showing improved precision. Fig. 6 displays the user satisfaction analysis comparing baseline systems with the proposed approach, demonstrating enhanced personalization and improved user experience.

V. Conclusion

The proposed work presented a hybrid multi-modal fashion recommendation system designed to generate personalized and context-aware outfit and styling suggestions across multiple clothing categories for both men and women. Unlike traditional recommendation approaches that rely primarily on user history or item similarity, the proposed system integrates manual inputs, visual attribute extraction, and domain-specific fashion knowledge into a unified framework. By combining machine learning techniques, computer vision-based feature extraction, and rule-based styling intelligence, the system is capable of delivering fine-grained and explainable recommendations tailored to individual user characteristics.
Experimental evaluation demonstrates that the integration of body attributes, contextual inputs, and fashion knowledge significantly improves the relevance and personalization of recommendations compared to traditional systems. The framework also exhibits strong scalability, enabling its application across diverse clothing categories and user profiles without requiring major architectural changes. Despite its effectiveness, the current system has certain limitations, including reliance on approximate visual attribute extraction and limited dataset availability for large-scale validation. These challenges highlight potential areas for future research. This work contributes a scalable, hybrid, and explainable fashion recommendation framework that bridges the gap between data-driven approaches and real-world fashion expertise. The proposed system has strong potential for practical deployment in e-commerce platforms and personalized styling applications, paving the way for more intelligent and user-centric fashion recommendation systems. The integration of SHAP-based explainability further enhances transparency by quantifying feature contributions in the recommendation process.

Declarations

Funding: This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

Conflicts of interest: The author declares no conflicts of interest/competing interests.

Data and Code Availability: The network simulation logic, hyper parameters and high performance configurations used to support the findings of this study are available from the corresponding author upon reasonable request.

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