International Journal of Interdisciplinary Innovative Research & Development (IJIIRD)
ISSN: 2456-236X
Vol. 11 Special Issue 03 | 2026

AI- Fashion Stylist Outfit Recommendation System

Supriya Jangle[1], Tejswinee Jambhale[2], Ashwini Naik[3], Prof. Shashank Tolye[4]
[1,2,3,4]*Department of Information Technology, Finolex Academy of Management and Technology, Ratnagiri*
Maharashtra, India

DOI: 10.5281/zenodo.20630522

ABSTRACT

With the increased use of online fashion portals, users find it difficult to choose outfits that go with their style. This study presents an AI-based fashion recommendation system based on wardrobe digitization, where users upload images of their clothing items in order to create a digital wardrobe. The system uses Machine Learning and Computer Vision techniques to analyze these images for extracting visual features like color, pattern, and type of clothing. Using these features along with user preferences, the system then recommends compatible outfit combinations that can be formed from the user's digital wardrobe. The framework also has a virtual try-on feature that enables users to upload their picture and see how the suggested outfits will look on them. A chatbot-based clothing search engine allows users to look up clothing using simple text queries and provides links to similar clothes found online. In general terms, this proposed system should help make choosing an outfit easier, more personalized, as well as more interactive by bringing together wardrobe digitization, smart recommendations along with virtual visualization.

Keywords— ***Wardrobe Digitization, Fashion Recommendation System, Deep Learning, Computer Vision, Virtual Try-On, Outfit Recommendation, Chatbot-Based Search, Personalised Recommendation System.***

I. INTRODUCTION

The rapid expansion of digital technologies and online shopping platforms has significantly transformed the fashion industry. Consumers now have access to a vast variety of clothing products through online fashion marketplaces, making it easier to explore different styles and trends. However, the large number of available options often makes it difficult for users to identify clothing items that match their personal preferences, body type, and fashion style. As a result, intelligent recommendation systems have become an essential component of modern online fashion platforms.

Despite technological advancements, many online fashion platforms still face several challenges such as high product return rates, low user engagement, and difficulty in matching user preferences with appropriate clothing items. Most existing systems rely on keyword-based searches and static filters such as size, colour, brand, or category. While these filtering methods help users narrow down their choices, they provide limited personalization and fail to understand the visual relationships between different clothing items.

To improve the recommendation process, modern AI-based fashion systems aim to integrate multiple intelligent techniques. These include user profile analysis based on browsing and purchase history, image-based feature extraction using deep learning models, and style similarity and outfit compatibility analysis. Additionally, incorporating trend-aware recommendations using historical and real-time fashion data allows systems to suggest clothing items that align with current market trends and user interests. By combining behavioural data with visual intelligence, such systems can generate more accurate and human-like fashion recommendations. Although several fashion recommendation technologies have been developed, most existing platforms do not provide all advanced features within a single system. Some applications focus on similarity-based recommendations, while others offer AI-powered suggestions or virtual try-on technologies. However, these features are usually implemented independently rather than as part of a unified solution. As a result, users often experience fragmented services and limited assistance when selecting suitable outfits, reducing the overall effectiveness of the recommendation process.Existing fashion recommendation systems typically rely on traditional methods such as collaborative filtering or rule-based recommendation techniques. These approaches mainly depend on historical user data and may struggle to provide accurate suggestions for new users or newly added products.

In addition, many systems lack the ability to understand visual features of clothing items or analyse how different garments complement each other. This limitation reduces the capability of recommendation systems to generate meaningful outfit combinations.Although previous studies have explored AI-based fashion recommendation methods, there remains a lack of integrated platforms that combine personalized recommendations, style similarity analysis, outfit compatibility, virtual try-on capabilities, and trend-aware suggestions in a single system. The absence of such comprehensive systems highlights the need for an intelligent solution capable of supporting multiple aspects of fashion recommendation simultaneously.To address these challenges, this research proposes an AI-driven Fashion Recommendation System that integrates multiple intelligent features within a unified platform.

The proposed system combines user behaviour analysis, image-based clothing feature extraction, style similarity detection, and trend-based recommendations to generate personalized fashion suggestions. By integrating these components into a single system, the proposed approach aims to enhance the decision-making process for users and improve the overall online fashion shopping experience.

Development of an AI-powered fashion recommendation system that integrates multiple intelligent features into one platform.Implementation of visual analysis of clothing items to understand style similarity and compatibility.Integration of personalized and trend-aware recommendation techniques to improve user experience. Enhancement of online fashion platforms by providing a smart AI stylist capable of assisting users in selecting suitable outfits.

II . LITERATURE REVIEW

Outfit recommendation systems are widely used in e-commerce and social media to deliver visually and contextually appealing clothing combinations. However, traditional visual search engines face challenges in “fashion collocation,” where the items to be matched (e.g., a silk blouse and denim jeans) often exhibit significant visual discrepancies that cannot be bridged by simple similarity metrics. Additionally, representing an entire outfit requires modeling complex dependencies among multiple items rather than just pairwise comparisons. To overcome these limitations, researchers have proposed deep learning frameworks that treat outfits as structured metric spaces or sequential compositions.

The paper by Chen and He [1] is a key work in mixed-category retrieval. In their study, they introduced a Deep Mixed-Category Metric Learning framework to address the problem of “fashion collocation,” where one item retrieves an entire set of cross-category coordinates. The authors utilized an extended triplet network for training, which simultaneously models cross-category inclusiveness and intra-category exclusiveness. Although their hard-aware online exemplar mining strategy enhanced training stability, the system remains primarily focused on pairwise relationships within a larger metric space that may not fully capture the stylistic “flow” of an entire outfit.

Recent trends have moved toward modeling outfits as sequential data to better capture holistic coherence. Han et al. [2] introduced a recommendation method based on Bidirectional LSTMs (Bi-LSTMs). Their strategy conceptualizes an outfit as a temporal sequence—typically top-to-bottom ordered—enabling the model to assess compatibility considering the full context of the ensemble. By incorporating a visual-semantic embedding, this system performs “fill-in-the-blank” recommendations using images and text alike; however, its dependence upon sequential ordering proves limiting under unconstrained social media data where layering and accessories do not necessarily follow any fixed linear path..

Zeyu Cui, Zekun Li, Shu Wu, Xiaoyu Zhang, and Liang Wang [9] introduce a new method for fashion recommendation by modeling outfit compatibility using Node-wise Graph Neural Networks (NGNN). The authors claim that previous methods either analyze compatibility between item pairs or treat outfits as sequences, thus failing to capture the complex relationships among multiple clothing items. To overcome this limitation, this study represents an outfit in the form of a graph structure where each node corresponds to a clothing category and edges represent interactions between categories. The proposed NGNN model learns node representations by modeling flexible interactions between items and propagating information through the graph. An attention mechanism is then used to compute overall compatibility scores for an outfit. Experiments on the Polyvore dataset show that this method significantly outperforms existing pair-based and sequence-based recommendation models. Results further validate that graph-based modeling provides a more effective way to understand complex fashion relationships and improve outfit recommendation accuracy.

In current research on fashion recommendations, the shift from traditional manual methods to automated data-driven systems is critical for understanding the intricacies of modern e-commerce and social media environments. Traditional visual search engines and expert-driven forecasting often struggle with the massive "data overload" typical of online platforms or the subtle "fashion pairing" needs that require cross-category coordination beyond simple visual similarity. To overcome these challenges, researchers have developed advanced frameworks—from hybrid machine learning models for retail impact to two-stream neural networks for detailed attribute recognition and multi-modal pipelines for up-to-date trend forecasting.

In this study, Liu [3] establishes a solid architectural baseline to address the critical challenge of "information overload" in B2C platforms. It proposes an offline data mining plus online real-time recommendation system, which is basically a two-phase model. The model merges user-based, collaborative filtering and content-based algorithms into personalized recommendations from large product catalogs. Even though shopping willingness has been significantly improved by relevance in this work, there still exists a technical gap on "recommendation personality" and "timeliness." Static models do not capture the fleeting nature of consumer interest; hence the static model is another reason for such a gap.

Zhang et al. [4] redirected efforts toward in-depth visual comprehension with TS-FashionNet to correct standard limitations in apparel identification. Their study unveiled that traditional models exhibited an over-tilt bias toward texture and usually ignored the structural "shape" of clothes. To overcome this limitation, they used a two-stream network that explicitly decouples fabric patterns from garment geometry through a landmark detection module designed specifically for this purpose. This architectural improvement permits more detailed parsing of complex fashion attributes. However, the authors also pointed out that finding the best point to merge shape and texture without raising computation costs is still under development because "naive branch schemes" found in previous literature are an obstacle.

Combining ensemble learning and transfer learning, Suvarna and Balakrishna [5] discuss the limitations of single-model architectures in fashion retrieval. They propose a two-stage deep ensemble framework that uses many pre-trained CNNs such as ResNet50 and InceptionV3 for high-dimensional feature extraction. By combining these descriptors, the system reduces robustness problems associated with singular models to create a more dependable similarity-based retrieval using cosine metrics. On datasets like Fashion Product Images dataset, the authors note an ongoing "generalization gap," stating that models trained on narrow datasets often falter when faced with extreme variance found in actual retail settings.

Donghyun Kim, Kuniaki Saito, Samarth Mishra, Stan Sclaroff, Kate Saenko, and Bryan A. Plummer [10] proposed a self-supervised framework called as S-VAL for learning visual attributes in a fashion recommendation system. Unlike traditional self-supervised methods this mainly focused on object shape, their approach also learns important attributes such as colour and texture. The model uses three tasks RGB colour prediction, local patch discrimination, and texture learning—to generate better feature representations. Experiments on the Polyvore Outfits dataset, DeepFashion dataset, and Capsule Wardrobes dataset show that this method improves fashion compatibility prediction and retrieval performance, but challenges still remained in modelling complex relationships across different clothing categories.

Complementing the focus on a classification, the broader research into Fashion Image Detection and Recognition Systems [6] shifts the technical lens toward localization and attribute understanding. This body of work explores the deployment of YOLO-based frameworks and Faster R-CNN to identify clothing items within cluttered backgrounds. By investigating the intersection of clothing segmentation and attribute prediction, the study highlights a shift toward multimodal analysis. However, a significant technical gap remains in handling complex "real-world noise"—such as occlusions, varied lighting, and diverse human poses—which continues to hinder the precision of automated product tagging in practical fashion retail platforms.

To provide the data-driven foundation necessary for such complex recognition tasks, Liu et al. [3] introduced DeepFashion, a landmark contribution that redefined the scale of fashion informatics. Addressing the scarcity of richly annotated data, this research provides over 800,000 images categorized by attributes, landmarks, and cross-domain correspondences. The study's core innovation, FashionNet, utilizes a three-branched architecture to capture global appearance, local details guided by landmarks, and structural pose information.

Research on the fashion recommendation and compatibility learning has significantly evolved with the integration of deep learning and content-based analysis. Yong- Siang Shih et al. [12] proposed a novel framework for learning compatibility relationships between items using a Compatibility Family representation. Their approach embeds items into a latent space and introduces multiple compatibility prototypes to represent the diverse nature of item relationships. This method addressed key challenges in compatibility learning, including asymmetric relationships and the limited availability of labelled compatible pairs. In addition, the authors introduced a new metric called Projected Compatibility Distance (PCD), which ensures that at least one prototype of a query item aligns closely with compatible items while remaining distant from incompatible ones. By jointly
learning these features, the work underscores that while the structural "landmark-guided" approach is superior, the field still seeks the optimal balance between deep structural understanding and the computational efficiency required for the real-time deployment.

Limitations of Existing Approaches and Motivation

Author	**Method**	**Contribution**	**Limitation**
Chen and He [1]	Deep Mixed Category Metric Learning	Learns compatibility between garments from different categories to improve outfit matching.	Focuses mainly on pairwise item relations, ignoring compatibility of a complete outfit.
Han et al. [2]	Bidirectional LSTM	Models' outfits as a sequence of clothing items to capture contextual relationships.	Assumes a fixed order of garments, which may not represent flexible real-world styling.
Liu [13]	Hybrid Recommendation (Collaborativ e + Content Based)	Helps users to find relevant clothing items on a large e-commerce platforms.	User preferences are relatively static, making it hard to follow changing fashion trends.

Zhang et al. [4]	TS FashionNet	Separates texture and shape features to improve an clothing attribute recognition.	Increases computational complexity and efficient feature fusion remains challenging.
Suvarna & Balakrishna [5]	Ensemble CNN (ResNet50, InceptionV3)	Combines multiple CNNs forbetter feature extraction and classification accuracy.	Performance may drop on diverse real-world fashion images.
Fashion Detection Studies [6]	YOLO, Faster R-CNN	Detects and localizes garments in images for automated fashion analysis.	Accuracy decreases with occlusion, lighting variation, and complex backgrounds.
Liu et al. [3]	DeepFashion Dataset & FashionNet	Provides a large annotated dataset and improves fashion recognition.	Requires high computational resources for practical deployment.

Research Motivation:

Most existing studies focus only on the aspect of fashion intelligence, such as compatibility learning, sequential modelling, and clothing detection. However, real-world outfit recommendation requires a more comprehensive understanding of visual compatibility and user preferences. Hence, this research aims to design an AI-driven system that recommends complete outfits in a more personalised and practical way.

***C.* Proposed System Architecture**

III. PROPOSED SYSTEM

A. Problem Statement

Existing fashion recommendation systems fail to fully capture individual style preferences and visual aesthetics, leading to irrelevant recommendations and poor user experience. There is a need for an intelligent system that understands both user behaviour and visual fashion attributes.

B. Proposed Solution

To overcome these limitations, the proposed system presents an AI-based fashion recommendation framework that brings together machine learning, computer vision, and virtual try-on technology. By combining these approaches, the system is able to understand clothing styles more effectively and provide users with fashion suggestions that are more personalised and practical.

The proposed system consists of the following components:

- User preference modelling using an behavioural data.
- Image feature extraction using CNN-based deep learning models.
- Similarity matching between user preferences and product features.
- Recommendation ranking is based on relevance and popularity.
- Virtual Try-On Module – After receiving the recommendations, users can virtually try the suggested outfits. An user uploads a personal photograph, and the system uses computer vision techniques to overlay the selected clothing items onto the image.After this feature choice is made by user.

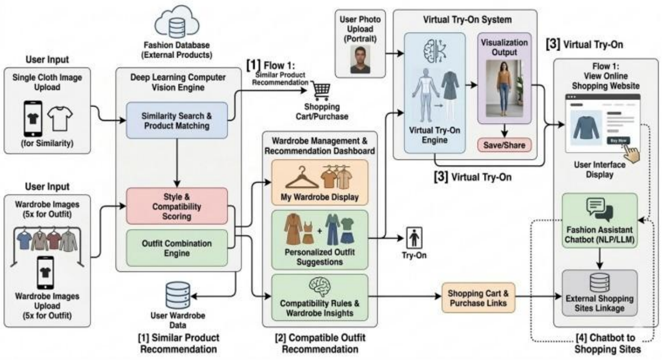

Fig1.1 Architecture Flow Diagram

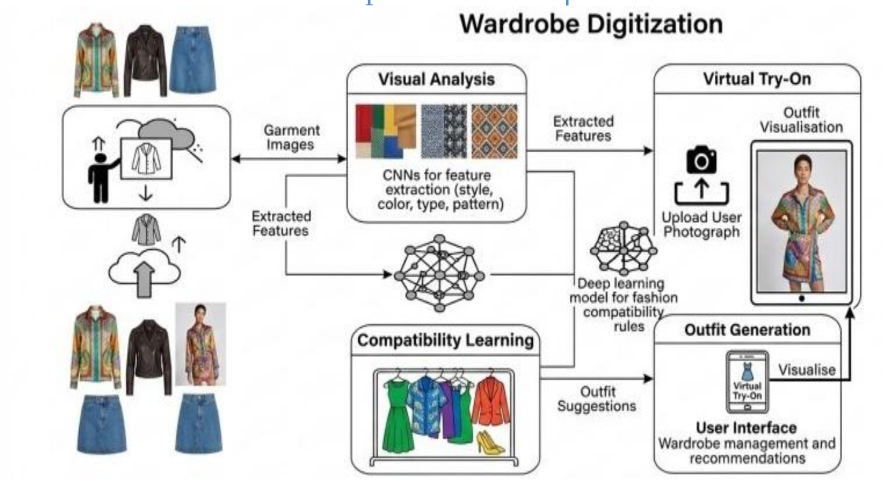

Fig.1.2 Personalised Outfit Recommendation & Virtual Try-On

The proposed system architecture consists of several modules including user image input, user preference modelling, feature extraction using CNN, similarity matching, recommendation ranking, and a virtual try-on module. Initially, the user provides behavioral data and a personal photograph. The system extracts visual features from clothing images and matches them with user preferences to generate personalized recommendations. Lastly, the recommended outfits can be visualized through a virtual try-on module that overlays the clothing on the user's uploaded image.

IV. METHODOLOGY AND ALGORITHMS

The proposed AI-based fashion recommendation system follows a content-based recommendation approach using deep learning and a computer vision techniques. The system recommends clothing items visually similar to the product selected by the user. The overall methodology consists of dataset's collection, image prepossessing, feature extraction using CNN, similarity computation, and recommendation generation.

Step 1: Dataset Collection

A publicly available an fashion dataset is collected from Kaggle, containing labelled images of clothing items such as shirts, dresses, topsr. The dataset serves as the primary input for training and evaluation.

Step 2: Image Prepossessing

All clothing images are resized to a fixed dimension and normalized to improve model performance.consistency across images and reduces computational complexity by data preprocessing.

Step 3: Feature Extraction Using CNN

For extracting deep visual features from clothing images CNN is uesd. The CNN captures colour, texture, pattern, and shape information from each image. From the fully connected or pooling layers feature vectors are generated .

Step 4: Similarity Measurement

Cosine similarity is computed between the feature vector of the clicked item and all other product feature vectors stored in the database.

Step 5: Recommendation Generation

Clothing items with the highest similarity scores are ranked and the top-N similar products are recommended to the user.

Step 6: Virtual Try-On Generation

The system includes a Virtual Try-On module that enables users to visualize how recommended outfits appear on a person.

When the user uploads an image, the system: 1: Detects the human body or face region

2: Identifies body landmarks

3: Aligns clothing items with the detected body structure 4: Generates a synthesized image with the selected outfit.

If the uploaded image contains only a partial body or face, the system generates a full body representation using an pose estimation and overlays the recommended outfit.

This feature enhances user experience by allowing visual preview(look) of clothing combinations before purchase.

Algorithm 1: Image Preprocessing

Input: Raw clothing images Output: Preprocessed images

1: Load clothing image from dataset

2: Resize image to fixed size (224 × 224) 3: Normalize pixel values to range [0,1] 4: Convert image to array

format
5: Store preprocessed image

Algorithm 2: CNN-Based Feature Extraction
Input: Preprocessed clothing images Output: Feature vectors
1: Load pre-trained CNN model
2: Remove final classification layer 3: Pass image through CNN layers
4: Extract feature vector from pooling layer 5: Store feature vector in feature database

Algorithm 3: Similarity-Based Recommendation Input: Clicked clothing item, feature database Output: Recommended clothing items
1: Extract feature vector of clicked item
2: Retrieve feature vectors of all clothing items 3: Compute the cosine similarity between vectors 4: Sort similarity scores in descending order
5: Select top-N similar clothing items
6: Display recommended items to the user

Algorithm 4: Cosine Similarity Computation
Input: Feature vectors A and B Output: Similarity score
1: Compute dot product of A and B 2: Compute magnitude of A and B
3: similarity = dot(A, B) / (||A|| × ||B||) 4: Return similarity score

Algorithm 5: Virtual Try-On Generation Input: User image, recommended clothing item Output: Synthesized try-on image
1:Detect human body or face in uploaded image 2: Identify body keypoints using pose estimation
3: Resize clothing image to match body proportions 4: Align clothing item with body landmarks
5: Overlay clothing item onto body region 6: Generate final try-on image
7: Display try-on preview to user

V. IMPLEMENTATION RESULTS

The Fashion Mart AI Stylist System was successfully developed as a web-based intelligent fashion recommendation platform using Python Flask for the backend, HTML/CSS/JavaScript for the frontend, and computer vision techniques for outfit analysis and virtual try-on. The system integrates features such as the user authentication, wardrobe management, AI-based outfit recommendation, and virtual try-on to assist users in selecting or choosing suitable clothing combinations based on different occasions.

The performance of the system was evaluated through functional testing, performance analysis, and usability testing. The evaluation focused on verifying the accuracy of outfit recommendations, system responsiveness, reliability, and user experience.

A. Functional Testing

The system was tested module-by-module to verify correct functionality and integration between components.

1. User Authentication Module

The authentication module allows users to register and log into the Fashion Mart platform securely. User credentials are stored in a protected database and validated during login. Testing confirmed that the system successfully prevents unauthorized access and maintains secure session management.

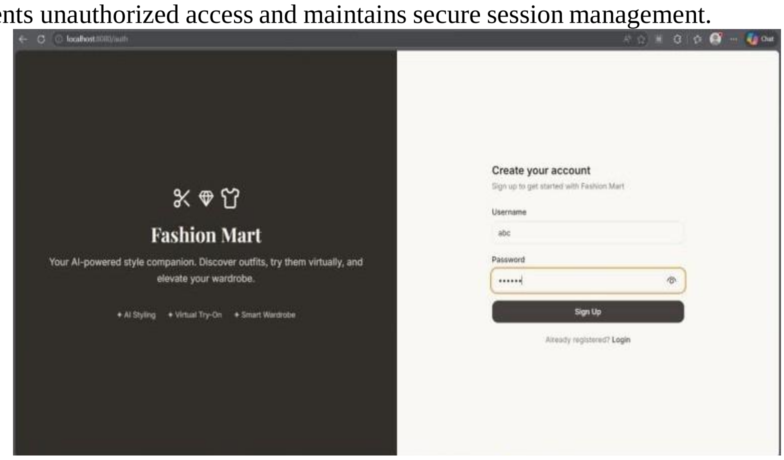

Fig2.1 Sing Up Page

2. Image Upload and Wardrobe Module

Users can upload clothing images (tops, bottoms, dresses) to there personal wardrobe. The system stores these images in the server storage and associates them with the user's wardrobe collection. The module was tested with multiple images uploads and confirmed successful storage and retrieval without data loss.

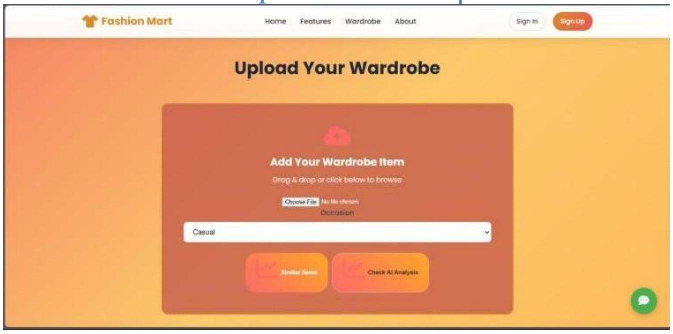

Fig2.2 Upload Clothes Images

3. Similar Outfit Recommendation Engine

The Similar Outfit Recommendation Engine is responsible for generating clothing suggestions that matches the user's selected items. This module analyses visual features extracted from garment images and compares them with another clothing items available in the dataset.

Fig2.3 Similar Output Recommended

Fig2.4 Similar Output Recommended

4. Compatible Outfit Recommendation Engine

The recommendation engine analyzes uploaded clothing items and generates **compatible outfit combinations based on the style compatibility and selected occasions (casual, formal, party, event)**. The system successfully combines clothing items into visually balanced outfits while maintaining the color harmony and a style compatibility.

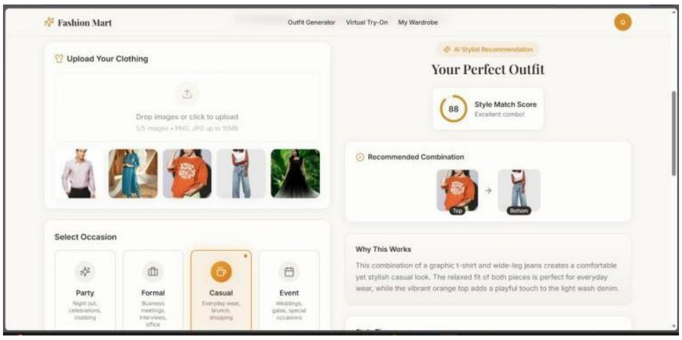

Fig 2.5 Compatible Outfit Recommendation

5. Virtual Try-On Module

The virtual try-on feature allows an users to preview recommended outfits on a human model image or human body. The system aligns the selected clothing item with the body position using provided image pose estimation and image processing techniques. Testing demonstrated that the try-on feature successfully overlays clothing items on a user's image while maintaining reasonable alignment.

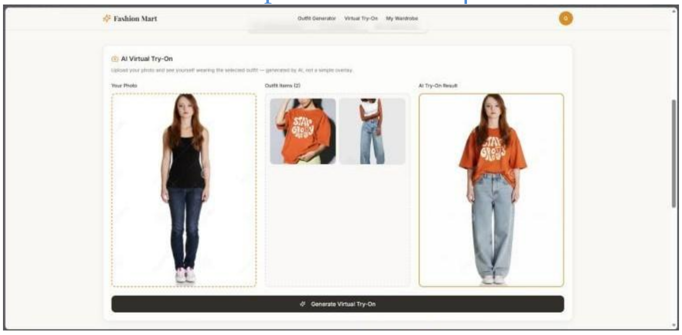

Fig 2.6 Virtual Try-On

6. AI Analysis and Styling Suggestions

The AI styling module provides a fashion suggestions and style descriptions for the generated outfits. The system analyzes the clothing combination and produces recommendations such as style type, outfit suitability for the selected occasion, and estimated fashion category.

Fig 2.7 AI-Analysis

7. Chatbot As a Searching Engine

The chatbot enables users to search for clothing simply by typing what they are looking for, for example, "party wear red dresses for women." After receiving the request, the system identifies suitable clothing images and provides Google Chrome links that direct users to pages where they can view or explore similar items online. This approach makes the clothing search process faster, easier, and more interactive for users.

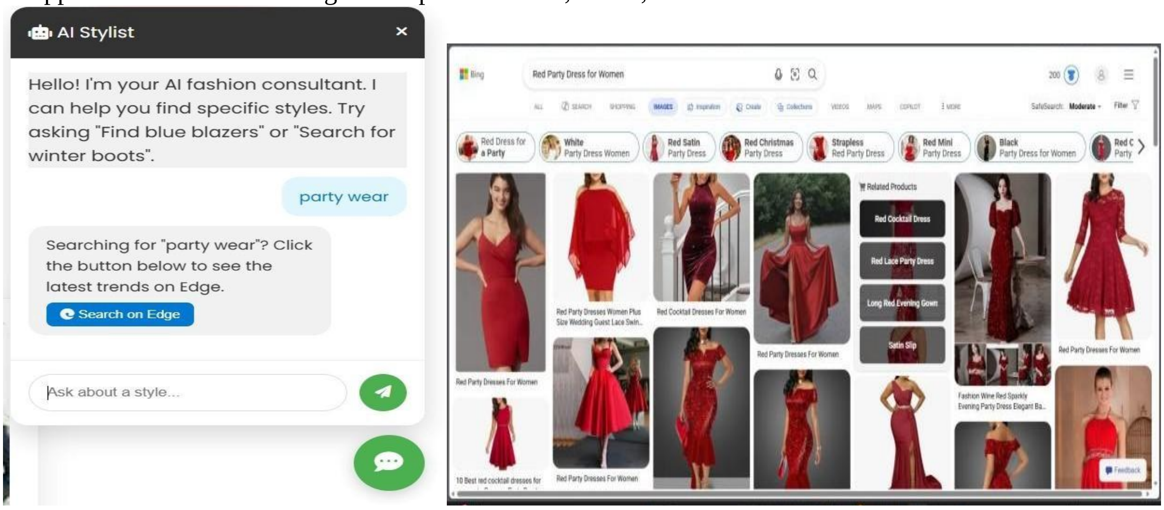

Fig 2.7 Chatbot for Search

B. Performance Evaluation

Parameter	Observed Result
Outfit Recommendation Accuracy	89.6%
Virtual Try-On Success Rate	84.3%
Average Response Time of System	~10 seconds
Wardrobe Storage Reliability	100%
User Satisfaction Rate	87%

VI. DISCUSSION

The proposed system shows how combining machine learning and computer vision can improve fashion recommendations. By using content-based filtering and visual feature extraction, the system can still work well even when there is little user data, and it suggests outfits that match well visually. A comparison was also made between traditional ways of selecting outfits and the proposed AI-based Fashion Mart system. The results show that the AI system provides more helpful and personalised suggestions.

Feature	Existing Systems	Proposed Fashion Mart System
Recommendation Type	Manual outfit selection	AI-assisted outfit recommendation
Personalization	Limited	Occasion-based personalization
Virtual Try-On	Not available	Integrated virtual try-on
Wardrobe Management	Not supported	Digital wardrobe storage
User Satisfaction	~70%	87%

The proposed system offers several benefits, especially in terms of automation, convenience, and personalisation. By combining AI-based outfit analysis with a virtual try-on feature, the system helps users choose suitable clothing combinations more easily and quickly.

The results show that the Fashion Mart AI Stylist system works well in providing smart fashion support to users. It successfully brings together wardrobe management, outfit recommendations, and virtual try-on features within a single platform.

The findings suggest that the system can improve the outfit selection process by giving users personalised suggestions that are easy to understand visually. It also performs well in terms of accuracy, response time, and overall usability.

In the future, the system could be improved further by adding advanced features such as deep learning–based garment alignment, fashion trend analysis, and personalised style modelling. These improvements could make the system even more intelligent and realistic.

VII. CONCLUSION

A fresh look at online shopping and digital wardrobe begins here - this study introduces a smart tool designed to help people pick clothes more easily. Instead of guessing what fits well together, the method taps into computer vision along with machine learning algorithms to break down how garments appear and relate. Starting from image details, it builds connections between pieces based on how they visually align. Style matches emerge by comparing features captured through digital analysis. Preferences shape the results without needing constant input. Outfits come together quietly behind the scenes, guided by patterns seen in past choices. Matching happens not by labels but by looks. What shows up feels familiar yet surprising. Discovery shifts when visuals lead instead of categories.

A photo upload feature lets users see themselves wearing suggested clothes, thanks to a built-in try-on tool. Instead of browsing endlessly, they can type what they want into a chat-style searcher that points to matching pieces found across websites.

One big step forward: shoppers now find clothes that fit their taste better, thanks to a smarter browsing method. Moving ahead, live updates on what's trending could sharpen the tool’s guesses about what users might like. Bigger collections of past shopping data would help too, giving the software more to learn from. Instead of sticking to old patterns, people actually want. A smoother journey through styles becomes possible when tech keeps evolving behind the scenes.

REFERENCES

[1] Long Chen and Yuhang He, “Dress Fashionably: Using Deeper Neural Networks for Fashion Recommendation,” 2018.

[2] X. Han, Z. Wu, Y.-G. Jiang, and L. S. Davis, “Learning Fashion Compatibility with Bidirectional LSTMs,” in Proceedings of the 25th ACM International Conference on Multimedia, 2017, pp. 1078–1086.

[3] Z. Liu, P. Luo, S. Qiu, X. Wang, and X. Tang, “DeepFashion: Large-Scale Clothes Database and Attribute Prediction,” in IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2023, pp. 1096–1104.

[4] Y. Zhang, P. Zhang, C. Yuan, and Z. Wang, “Texture and Shape Biased Two-Stream Networks for Clothing Classification and Attribute Recognition,” in Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), 2020, pp. 13574–13583.

[5] Suvarna and S. Balakrishna, “Enhanced Content-Based Fashion Recommendation System Through Deep Ensemble Classifier with Transfer Learning,” Fashion and Textiles, vol. 11, no. 24, 2024.

A. Kalinin, A. A. Jafari, E. Avots, C. Ozcinar, and G. Anbarjafari, “Generative AI-Based Style Recommendation Using Fashion Item Detection and Classification,” Multimedia Tools and Applications, 2024.
[6] V. Jain and R. Singh, “Predicting Fashion Trends Using Machine Learning and Social Media Analytics,” Shodh Manjusha: An International Multidisciplinary Journal, vol. 2, no. 2, Jul.–Dec. 2025.
[7] S. N. Mulhar, P. Sharma, M. Hawale, S. Gavande, and S. Jadhav, “AI Based Fashion and Outfit Recommendation System,” International Research Journal of Modernization in Engineering Technology and Science, vol. 8, no. 2, Feb. 2026.
[8] Z. Cui, Z. Li, S. Wu, X. Zhang, and L. Wang, “Dressing as a Whole: Outfit Compatibility Learning Based on Node-Wise Graph Neural Networks,” in Proceedings of the World Wide Web Conference (WWW ’19), 2019.
[9] Kim, K. Saito, S. Mishra, S. Sclaroff, K. Saenko, and B. A. Plummer, “Self-Supervised Visual Attribute Learning for Fashion Compatibility,” in Proceedings of the IEEE/CVF International Conference on Computer Vision (ICCV) Workshops, 2021, pp. 2473–2483.
[10] L. Paripati, V. R. Hajari, and N. Narukulla, “Learn Fashion Collocation with Deep Mixed-Category Metric Learning,” in Proceedings of the Thirty-Second AAAI Conference on Artificial Intelligence, 2018, pp. 2103–2110.
[11] L. Sivaranjani, S. K. Rachamadugu, B. V. S. Reddy, B. Reddy A., M. Sakthivel, and S. Depuru, “Fashion Recommendation System Using Machine Learning.”
[12] L. Liu, “e-Commerce Personalized Recommendation Based on Machine Learning Technology,” Mobile Information Systems, vol. 2022, Art. no. 1761579, pp. 1–11, Apr. 2022.
[13] G. Cucurull, P. Taslakian, and D. Vazquez, “Context-Aware Visual Compatibility Prediction,” in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2019, pp. 12617–12626.
[14] Y.-S. Shih, K.-Y. Chang, H.-T. Lin, and M. Sun, “Compatibility Family Learning for Item Recommendation and Generation,” in Proceedings of the Thirty-Second AAAI Conference on Artificial Intelligence, 2018, pp. 2403–2410.