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A Survey on AI-Driven Personalized Fashion Recommendation System

MONISHA H M [1], PRABHJOT SINGH [2], PRERNA AGARWAL[3], SALADI KALYAN SOMANNA[4]
[1,2,3,4]*Department of Information Science and Engineering, BMS College of Engineering, Bengaluru, India*

Abstract - Artificial Intelligence (AI) has become a revolutionary force that has disrupted the fashion industry, bringing new-age solutions for design automation, personalized recommendation, and trend prediction.AI has transformed the fashion world by bringing innovation to design automation, personalized recommendation, and trend prediction. With the help of advanced machine learning techniques and extensive data analysis, ai is not only transforming the creative process but also revolutionizing the way consumers discover and interact with fashion. This research paper analyzes latest developments in AI-driven fashion systems, with an emphasis on customized styling agents, sketch-to-image generation, and real-time learning mechanisms. Based on eight leading research papers, it identifies key methodologies such as dataset generation (e.g., flora), generative models like gans and diffusion models, and adaptive components like kolmogorov-arnold networks (kan). The authors suggest a personalized AI fashion agent model, which integrates conversational interfaces, real-time trend analysis, and adaptive learning to offer users personalized fashion suggestions according to their preferences and the occasion. The work concludes by exploring the commercial feasibility of these systems, incorporating them into emerging technologies like augmented reality (AR) and virtual reality (VR), and directions for future research aimed at creating more ethical, inclusive, and user-focused fashion experiences.

Keywords: Artificial Intelligence, Fashion Recommendation, Personalized Styling, Deep Learning, FLORA Dataset, KAN.

I. INTRODUCTION

The fashion world, a continuously evolving and fast-paced industry, is increasingly being shaped by technological innovations. Artificial intelligence (AI), in particular, has impacted design innovation, retailing strategy, and consumer involvement. The global
The fashion sector, which is valued at approximately $2.4 trillion, is leveraging artificial intelligence (AI) to meet the growing demand for tailored experiences and rapid adjustment to fashion seasons. Conventional fashion cycles are being supplanted by data-driven, real-time processes where artificial intelligence (AI) facilitates quicker iterations in design, better consumer understandings, and more efficient supply chain functions.

This paper aims to explore the state of AI in fashion today, with a focus on those technologies that provide personalized and creative experiences. As generative models, adaptive learning systems, and large datasets become more readily available, the ability of fashion agents powered by AI is opening wide. These sophisticated systems not only recommend clothing but also generate fashion sketches, understand written descriptions, and converse in ways that resemble human communication.

Moreover, the evolution of AI has introduced fashion systems that are more inclusive, diverse, and socially conscious. AI tools have been a necessity in addressing global challenges, such as minimizing waste, reducing overproduction, and making fashion sustainable. Through learning from consumption patterns and predicting fashion cycles, AI has the potential to facilitate a more sustainable and eco-friendly fashion industry.

Moreover, the work here discusses the implications of AI in fashion business, cultural diversity, and user trust, which are required for broader societal uptake and commercial viability.

II. LITERATURE SURVEY

Deshmukh et al. [1] presented FLORA, a 4,330-text-sketch pair dataset optimized for fashion image synthesis. Under GPT-4o annotations and visual preprocessing, semantic richness was guaranteed to be high. KAN Adapters, an extension of LoRA, were introduced by the authors for improved adaptability for diffusion-based models, with remarkable improvement in CLIP-SIM and FID scores across various architectures. The study facilitates accurate text-to-fashion sketch generation and design automation.

Chakraborty et al. [2] studied 230+ papers to categorize fashion recommender systems into five categories, examining filtering techniques and algorithms such as CNNs, GANs, and Bayesian models. They focused on issues like data sparsity and suggested hybrid filtering and virtual try-on as future directions. The paper offers an in-depth roadmap for designing sophisticated, user-adaptive fashion recommendation systems.

Kotouza et al. [3] constructed a designer support system combining web crawling, NLP, and clustering for making tailored clothing suggestions. The system employed clustering algorithms (e.g., Pam, HAC) and reinforcement learning to improve proposals. Designers collaborate through a UI facilitating feedback, supporting dynamic data browsing and inspiration in the design process.

Anjan et al. [4] proposed a content-based recommendation system with ResNet-50 to feature extract from images of clothes uploaded by the users. The system recommends visually similar products from online e-commerce sites. The architecture consists of real-time scraping, user interaction using a Flask-Vue interface, and vector similarity matching, providing scalable and personalized fashion recommendations.

Thanuja et al. [5] developed a visual recommendation system based on ResNet-50 embeddings and cosine similarity with a big fashion dataset. The framework does effective image-based matching and recommends similar clothing. It utilized TensorFlow, NumPy, and OpenCV as the key tools. It shows the future of deep learning in scalable visual search in fashion retailing.

Zhang et al. [6] summarized AI methods in recommender systems with emphasis on deep learning, transfer learning, GNNs, and fuzzy logic. They explained how these approaches tackle cold-start, scalability, and preference modeling. Future directions presented in the paper include privacy-preserving systems and explainable recommendations in dynamic settings.
Sawalkar et al. [7] developed a mobile-fashion recommender based on CNNs and K-NN for visual similarity and personalization. User demographics (gender, height) add to the suggestion. Cold-start handling is achieved by the system and suggests new outfits through an Android interface with practical implementation for real-time clothing recommendation.

Deldjoo et al. [8] outlined a detailed overview of contemporary fashion recommender systems, dividing work into tasks (i.e., item, outfit, and size recommendation) and input data types (i.e., visual, textual, social). They also outlined critical challenges such as item compatibility, personalization, fit prediction, and explainability. The review also placed strong emphasis on multimodal data, such as CNN-derived image features, user social behavior, and contextual information such as weather and season. Evaluation criteria, the latest algorithms (such as VBPR, DeepStyle, OutfitNet), and rising directions like GAN-based generation and AR/VR incorporation were examined systematically.

Shirkhani et al. [9] presented an in-depth overview of AI-powered fashion recommender systems (FRS) with a special emphasis on image-based models based on deep learning. They stressed that visual compatibility, not just similarity, is at the core of useful recommendations within the fashion domain. The research classified FRS tasks into item retrieval, complementary item recommendation, and whole outfit generation, emphasizing the application of Content-Based Image Retrieval (CBIR) and Fashion Instance-level Retrieval (FIR). Deep learning methods such as Siamese networks, CNNs, and attention mechanisms played an important role in enhancing fashion compatibility estimation and personalization. Common evaluation processes that were discussed include Fill-In-The-Blank (FITB) and compatibility scoring, showing the efficacy of hybrid models integrating visual and contextual features.

Suvarna and Balakrishna [10] suggested a content-based fashion recommendation system based on a deep ensemble classifier with transfer learning. The system aggregates results from five pre-trained models, namely MobileNet, DenseNet, Xception, VGG16, and VGG19, and inputs their predicted probabilities to an ensemble classifier for making the final decision. Cosine similarity is then applied to retrieve visually similar products. It was tested on Fashion product and Shoe datasets with a classification accuracy of up to 96%, well above that of standard single-model systems. The method strengthens robustness and recommendation accuracy by exploiting the variety of model architectures.

Cassidy [11] discussed the shortcomings of conventional colour prediction in fashion and textiles, suggesting a model by colour preference of consumers rather than foreseen acceptance. The research contrasted three current personal colour analysis systems and noted discrepancies in the use of hue, saturation, and value dimensions (HSV). A new system built on HSV was created and tested with a survey sample of 49 participants. Findings suggested that the HSV model yielded a more uniform and ordered mechanism for incorporating personal colour preferences into forecasting, and hence its potential as a market research tool to enhance forecasting accuracy.

Rajput and Aneja [12] proposed IndoFashion, the initial large-scale dataset for Indian ethnic clothing classification, including 106,166 images spread over 15 classes. The dataset was sourced from diverse Indian e-commerce websites to represent all types of traditional outfits. With pretrained ResNet models, the authors reported state-of-the-art classification performance and obtained 88.43% accuracy using ResNet-50. Data augmentation (geometric transformations and color jitter) and dataset size were found to significantly affect performance. This research fills the ethnic fashion dataset gap and aids in the creation of domain-specific models for ethnic wear recognition.

Rathod et al. [13] created a fashion recommendation system that combined deep learning with a virtual trial room for personalized recommendation of outfits. The mechanism employs ResNet-50 for content extraction from images uploaded by users and employs k-Nearest Neighbors (k-NN) for suggesting similar products. Content-based filtering, collaborative filtering, and hybrid are all integrated with the system to make it more accurate. Streamlit-based easy-to-use interface and OpenCV-based try-on module virtualize the product in real-time, increasing user interaction and satisfaction. This model endeavors to fill the gap between online and offline experience with superior deep learning and computer vision technology.

Patil [14] introduced a content-based fashion recommendation system based on the ResNet-50 convolutional neural network for extracting visual features such as color, texture, and style from fashion images. The system handles more than 44,000 fashion images and employs k-Nearest Neighbors (k-NN) for visually similar item retrieval. The recommendation system is implemented within a Streamlit-based web application to upload images and get real-time recommendations. The model improves user experience by providing personal recommendations and shows real-world applicability in the e-commerce sector.

Aneesh et al. [15] proposed a wardrobe-based fashion recommendation system employing deep learning for clothing type and color classification. Their system detects four primary apparel types (shirt, t-shirt, pants, shoes) and 12 color classes with CNNs. Subsequently, a proprietary algorithm suggests the best outfit combinations for a given occasion from the user's clothing inventory. The system also includes a simple web interface and audio outputs for chosen outfits. This method focuses on occasion-driven suggestions, enhancing accessible fashion advice for users with poor fashion sense.

Dr. Edit Csanák [16] discussed the revolutionizing impact of Artificial Intelligence (AI) in fashion, where it is integrated in design, production, marketing, and consumer engagement. The research outlined how AI manages the vast and unstable world of fashion data with tools such as predictive sales forecasting, virtual fitting assistants, and smart trend analysis. AI-enabled applications like Nike Fit and the virtual dressing rooms developed by Gap are the epitomes of individualized consumer interactions, whereas algorithmic design systems created by Amazon and Zalando demonstrate the creative capabilities of AI. For all the technical advancements, the article also posed serious questions regarding the cultural and aesthetic consequences of automation in a historically human-centric creative industry. The book highlights both the potentials and philosophical conflicts brought about by AI in fashion design, manufacturing, and sustainability efforts.

Sarthak Vyavahare et al. [17] have introduced a hybrid fashion recommendation system called the Fashion Coordination Assistant combining deep learning with conventional recommendation approaches for better fashion personalization. The system results from the combination of content-based and collaborative filtering using Singular Value Decomposition (SVD) and Non-negative Matrix Factorization (NMF), supplemented with association rule mining using the Apriori algorithm. Based on transactional data from H&M and Myntra, it processes clothing attributes and user preferences to output personalized outfit recommendations. The hybrid approach allows the assistant to understand intricate interactions between user fashion and clothing items with a high accuracy rate of 97.32%. Future work involves further natural language understanding, context-based recommendation, and multimodal fusion of visual and text inputs for more interactive users.

Prof. S.R. Chunamari et al. [18] proposed LuxeVogue, an AI-based online fashion recommendation system that recommends clothes personalized to users' skin tone and body shape. The system utilizes computer vision by employing OpenCV and Detectron2 to identify skin tone through color segmentation and categorize body shape through keypoint landmark analysis. LuxeVogue predicts suitable clothes style, accessories, and color schemes based on seasonal color theory and shape-dependent heuristics. The Streamlit-built interface is augmented by IBM Watson chatbot and DuckDuckGo-powered visual outfit search to provide a seamless and interactive experience. The system proves useful AI-based fashion personalization and proposes possible integrations like e-commerce integration, mobile app deployment, augmented reality try-ons, and cultural customization. Venus L. Adhitya et al. [19] proposed a smartphone-based dress code suggesting system aimed to help users choose suitable attire according to event context, user preferences, and clothing usage history.

The system utilizes the K-Nearest Neighbor (KNN) algorithm for classification, achieving a peak accuracy of 83.67%, precision of 83.82%, and recall of 99.34% using optimized K-values. The Android application is built using CameraX for image capture, Jetpack Compose for interface design, and Cloud SQL for data storage. Users interact through intuitive pages including login, dashboard, camera, and suggestion interfaces. This smartphone solution provides a functional fashion companion that simplifies the selection of what to wear, increases consumer confidence, and alleviates decision fatigue with respect to every-day dressing choices.

References	Authors & Year	Methodology/Algorithm	Dataset Used	Key Features/Techniques	Evaluation Metrics	Performance Results	Main Contribution	Limitations
[1]	Deshmukh et al. (2024)	KAN Adapters with generative models for text-to-fashion sketch generation	FLORA Dataset (4,330 outfit-description pairs)	Kolmogorov-Arnold Networks (KAN), Stable Diffusion, FLUX, Diffusion models	FID (Fréchet Inception Distance), CLIP-SIM	FLUX with KAN: FID=6.05, CLIP-SIM=0.3412	Introduction of FLORA dataset and KAN adapters for fashion sketch generation	Limited to sketch generation, requires specialized dataset
[2]	Chakraborty et al. (2021)	Multi-approach survey covering CBF, CF, and hybrid methods	Various: DeepFashion, Polyvore, Amazon Fashion, social media data	CNN, RNN, LSTM, GAN, k-NN, Bayesian networks, autoencoders	Precision, Recall, F1-score, RMSE, AUC, Coverage	Performance varies by method: CNN-based approaches showing 80-90% accuracy	Comprehensive classification and analysis of FRS filtering techniques	Theoretical survey with limited novel algorithmic contributions
[5]	Thanuja et al. (2022)	Content-based filtering with ResNet-50	Fashion dataset with 47,000 rows and 5,000 images	ResNet-50 for feature extraction, cosine similarity for recommendation	Cosine similarity scores, recommendation accuracy	High similarity matching performance	Simple yet effective approach using proven CNN architecture	Limited dataset size, basic recommendation approach
[8]	Deldjoo et al. (2023)	Hybrid approach combining visual-aware CF, generative models (GAN), and content-based filtering	DeepFashion, Polyvore, Amazon Fashion	Visual feature extraction using CNN, collaborative filtering, matrix factorization, neural collaborative filtering	RMSE, Precision, Recall, F1-score, AUC	Various models showed AUC values ranging from 65-85% depending on approach	Comprehensive survey of modern fashion RS, taxonomy of filtering techniques	Limited evaluation on real-world deployment scenarios
[9]	Shirkhani et al. (2023)	Deep ensemble classifier with transfer learning using pre-trained models	Fashion Product Images Dataset, Shoe Dataset	MobileNet, DenseNet, Xception, VGG variants, cosine similarity for recommendation	Accuracy, Precision, Recall, F1-score	96% accuracy achieved with deep ensemble approach	Novel deep ensemble method combining multiple pre-trained models	High computational overhead, limited to specific product categories
[10]	Suvarna & Balakrishna (2024)	Deep ensemble classifier with transfer learning	Fashion Product Images Dataset, Shoe Dataset	Five pre-trained models (MobileNet, DenseNet, Xception, VGG16, VGG19), cosine similarity	Classification accuracy, similarity measures	96% classification accuracy	Enhanced accuracy through ensemble of pre-trained models with transfer learning	Computationally intensive, requires substantial processing power
[13]	Rathod et al. (2024)	Content-based filtering with CNN (ResNet-50) and k-NN	Fashion Product Images Dataset from Kaggle (15GB, ~47k images)	ResNet-50 for feature extraction, cosine similarity, virtual trial room with OpenCV	Similarity matching accuracy, user satisfaction	High similarity matching with virtual try-on capability	Integration of recommendation with virtual trial room functionality	Limited to upper body clothing, requires high computational resources
[17]	Vyavahare et al. (2024)	Hybrid system using SVD and NMF algorithms	H&M and Myntra datasets	Singular Value Decomposition (SVD), Non-negative Matrix Factorization (NMF), Apriori algorithm	RMSE, precision, recall	97.32% recommendation accuracy	Novel combination of SVD, NMF, and association rule mining	Limited scalability for real-time applications
[18]	Chunamari et al. (2025)	Computer vision-based personalization with skin tone and body shape detection	Custom dataset for skin tone and body shape analysis	OpenCV, Detectron2, YCrCb color space, Keypoint R-CNN, IBM Watson chatbot	Detection accuracy for skin tone and body shape	Effective skin tone detection and body shape classification	Novel approach combining physical attribute analysis with fashion recommendation	Limited to specific physical attributes, requires high-quality input images
[22]	Sridevi et al. (2020)	CNN with nearest neighbor recommender using transfer learning	DeepFashion dataset (289,222 images), Rent the Runway inventory	ResNet-50 with transfer learning, Spotify's Annoy library, cosine similarity	Training accuracy, validation loss, F-beta score	Training accuracy: 98.6%, Validation loss: 0.027, F-beta: 0.405	Effective combination of CNN feature extraction with nearest neighbor recommendation	Limited to visual features only, cold start problem for new users

Prof. Trupti Ghate et al. [20] proposed an ML-driven personalized clothing recommendation system to minimize fashion dissatisfaction and product return rates in e-commerce platforms. It is made up of two main modules: a body shape analysis model that uses computer vision to evaluate user-uploaded photos, and a deep learning-powered clothing feature extractor with a pretrained CNN (ResNet50). It utilizes k-Nearest Neighbors and collaborative filtering for personalized fashion recommendations. The web interface, developed on Flask and optimized using Intel OneDNN for deep learning acceleration, enables real-time fashion recommendations. With features such as human image classification, AR-based integration for virtual try-ons, and trend-sensitive updates, the system illustrates a scalable and user-oriented solution for smart style guidance in contemporary e-commerce.

Swapnil Thakur et al. [21] presented an innovative outfit recommendation system that makes personalization through the use of skin tone analysis, live weather information, and virtual wardrobe knowledge. The system utilizes a Convolutional Neural Network (CNN) to perform in-depth clothing feature extraction and applies machine learning techniques like K-Means clustering and Decision Trees to make refined user-based suggestions. Users may choose to select attire as a function of occasion, preference, and environmental circumstance through a web portal, with functionality such as occasion labeling, virtual try-on (AR), and feedback loops. By nudging optimal wardrobe utilization and minimizing impulse buying, the system promotes sustainable fashion habits while providing context-specific, style-adequate outfit recommendations.

M. Sridevi et al. [22] introduced a personalized fashion recommender system based on image-based neural networks to provide visually related clothing recommendations from a single query image. In contrast to history-based traditional systems, this system employs convolutional neural networks (CNNs) with transfer learning from ResNet50 to capture visual features from the DeepFashion dataset. The system combines these embeddings in a nearest neighbor search by utilizing Spotify's Annoy library and cosine similarity to return top-5 similar outfit suggestions from a curated inventory. With excellent training accuracy and minimal loss metrics on several epochs, the model is also shown to be robust when tested on varied real-world and web-sourced apparel images. This approach increases user interaction through visually resonating recommendations with personal taste styles, overcoming cold-start constraints in typical recommendation systems.

III. PROPOSED MODEL

Our envisioned AI Fashion Agent is a smart personal stylist that unites sophisticated machine learning with conversational interfaces to provide genuinely personalized fashion experiences. At its core, the system establishes a rich user profile by gathering data like the person's style inclinations, body shape, color preferences, and wardrobe requirements—be they casual clothes, formal, or party wear. This profile is dynamic in nature; it keeps changing as the user works with the system, enabling the AI to learn and align itself according to their shifting tastes and fashion aspirations over time.

The agent extends beyond mere outfit ideas by providing context-specific suggestions based on a particular occasion. Whether the user is getting ready for a corporate meeting, a weekend activity, or a celebration, the AI stylist knows the social context and suggests appropriate and trendy outfits. It has an adaptive learning algorithm that improves its recommendations over time based on explicit user feedback in the form of likes, dislikes, or skipped suggestions, making its recommendations more and more accurate and personal with each use.

To maintain synchronization with modern fashion trends, the system includes a trend scraping module that continuously gathers information from fashion websites, social media, and online shopping platforms. This makes the recommendations not just individual but also congruent with the latest global trends and styles. The user converses with the AI using a natural, interactive interface, making the process intuitive and fun. They can tell them what they are seeking, request recommendations, or even receive fashion tips, just as they would for a human stylist.

The whole process is made to be smooth across devices, so that users are able to interact with the AI Fashion Agent using smartphones, smart mirrors, or virtual fitting rooms with AR capabilities. This AI Fashion Agent, in effect, fills the space between automated design systems and personal styling know-how. Its modular design enables it to be scalable and adaptable for integration into different platforms like fashion apps, retail sites, or virtual shopping experiences, providing both business prospects and greater user satisfaction.

IV. CONCLUSION

This survey reviewed past AI-based personalized fashion recommendation system strategies and realized there were main challenges like lack of context understanding, limited adaptability, and generic user behavior in conventional recommender models. In light of this review, we introduced a hybrid approach that solves these deficits by integrating several state-of-the-art AI methods.

Our system architecture includes a Large Language Model (LLM) with Retrieval-Augmented Generation (RAG) to create personalized outfit recommendations from rich user profiles, encompassing parameters such as body type, skin tone, preferences, and occasion. It was chosen for its potential to make context-aware, conversational, and explainable recommendations, surpassing traditional collaborative or content-based filtering techniques.

We also incorporate a trend scraping module so that the recommendations are against the latest fashion trends, thus being topical and trendy. We also include a feedback loop within the system for adaptive learning over time so that the recommendations improve in accuracy and relevance with more user interaction.

The use of modular components as an architectural design—e.g., individual engines for user profiling, product matching through e-commerce APIs, and fashion trend analysis—facilitates scalability and extensibility in the future. The conversational interface also increases usability with its ability to enable users to communicate naturally with the system, ask for alternatives, and receive fashion recommendations based on moods or events.

Overall, the synergy between LLM-driven generation, adaptive feedback loops, and real-time trend incorporation gives our proposed method a more dynamic, user-focused alternative to conventional recommendation approaches. With fashion becoming increasingly personalized and data-driven, such systems hold the promise of changing how users are exposed to and interact with style in everyday and commercial settings.

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