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Machine Learning for Personalized Fashion Recommendation Systems: A Review

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Abstract: The rapid digital transformation of the fashion industry has amplified the need for intelligent tools that can navigate vast product catalogs and deliver personalized recommendations to consumers. Fashion recommender systems, leveraging machine learning and deep learning techniques, have emerged as a crucial solution to address challenges such as choice overload, style compatibility, and changing trends. This review examines the evolution of fashion recommender systems, from early content-based and collaborative filtering approaches to hybrid, context-aware, and deep learning-based models capable of processing multimodal data. The methodology involved a structured literature search across major academic databases, focusing on recent studies that directly address clothing and fashion recommendation. Key findings reveal that while significant progress has been made in personalization accuracy, diversity, and visual understanding, persistent limitations remain. These include reliance on small or proprietary datasets, lack of demographic and cultural diversity, inconsistent evaluation protocols, and domain shifts between curated catalog images and real-world contexts. Addressing these challenges will require the development of standardized, diverse benchmark datasets, transparent experimental reporting, and the integration of ethical considerations such as fairness, inclusivity, and privacy. This paper provides a comprehensive synthesis of existing research, identifies current gaps, and outlines future directions for building robust, contextually aware, and user-centered fashion recommender systems.

Keywords: *Content-Based Filtering, Collaborative Filtering, Hybrid Recommendation Models, Deep Learning, Machine Learning.*

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I. INTRODUCTION

The global fashion industry has witnessed a rapid digital transformation, with online shopping platforms increasingly replacing traditional brick-and-mortar stores (Zhu, 2023). As e-commerce continues to expand, consumers are exposed to an overwhelming number of clothing options, making it difficult to find products that align with their personal preferences, styles, and needs (Madanchian, 2024). To address this challenge, fashion recommender systems have emerged as critical tools for improving user experience by offering personalized product suggestions tailored to individual tastes (C.S. et al., 2024).

A recommender system is an intelligent algorithmic tool designed to predict and suggest items that a user may find interesting based on various forms of data, such as past interactions, demographic information, browsing behavior, or

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product attributes. In the context of fashion, these systems aim to simulate the personalized guidance a customer might receive from a sales associate, but in a digital environment (Fayyaz et al., 2020). Fashion recommendation goes beyond basic item suggestions it must account for complex factors such as style compatibility, color coordination, seasonality, cultural preferences, and current trends (Eldemerdash et al., 2023).

With the advancement of machine learning and deep learning techniques, modern fashion recommender systems can now process multimodal data like images, text, and user behavior to make accurate, visually-aware, and context-sensitive recommendations. Techniques such as collaborative filtering, content-based filtering, hybrid models, and more recently, convolutional neural networks and transformers, are increasingly being applied to understand fashion content and user intent (Deldjoo et al., 2024).

Moreover, the availability of large-scale fashion datasets such as DeepFashion, Fashion-MNIST, and Amazon Fashion has facilitated the training and evaluation of sophisticated models. These datasets include high-resolution images, textual descriptions, categories, and even user ratings, making them suitable for a wide range of recommendation tasks(Shushi & Adnan M. Abdulazeez, 2024).

Despite the progress, fashion recommender systems still face several challenges, including the cold-start problem (limited data for new users or items), the subjectivity of fashion taste, and the difficulty in capturing user intent in dynamic contexts such as changing seasons or evolving fashion trends. Additionally, issues of bias, data sparsity, and lack of diversity in recommendations remain areas of concern in existing systems(Joshi et al., 2022).

II. REVIEW METHODOLOGY

This literature review was conducted using a qualitative, narrative approach to explore and synthesize current knowledge on fashion recommender systems. The purpose of this methodology was to ensure a comprehensive understanding of existing research, technological developments, and practical implementations relevant to fashion recommendation. A wide range of academic databases and scholarly sources were consulted, including Google Scholar, IEEE Xplore, SpringerLink, ScienceDirect, the ACM Digital Library, and ResearchGate. These databases were selected based on their accessibility, relevance to computer science and engineering, and their inclusion of peer-reviewed content.

The search for literature was guided by specific keywords such as “fashion recommender system,” “clothing recommendation using machine learning,” “deep learning in fashion recommendation,” “image-based recommender system,” “hybrid recommender models for fashion,” and “personalized clothing recommendation.” These keywords were used individually and in various combinations with Boolean operators to refine the results and ensure a focus on fashion-related applications of recommender systems.

The review prioritized publications between the years 2015 and 2025 to capture recent innovations, especially those utilizing machine learning, deep learning, and advanced artificial intelligence techniques. Only English-language sources were considered to maintain consistency and readability, and only studies that directly addressed fashion recommendation, whether through theoretical models, algorithmic design, or practical applications, were included in the final review. Articles that lacked sufficient methodological detail or were not academically rigorous were excluded.

Relevant information from each selected study was carefully extracted and analyzed. This included the study’s objective, the type of recommender system used, the algorithms applied, the datasets employed, the evaluation metrics, and the main findings. Studies were then grouped according to the type of recommender approach they used, such as collaborative filtering, content-based filtering, hybrid models, or deep learning techniques. Additionally, attention was given to how these models were applied within the fashion domain, including how they handled challenges like visual similarity, user preferences, and seasonal trends.

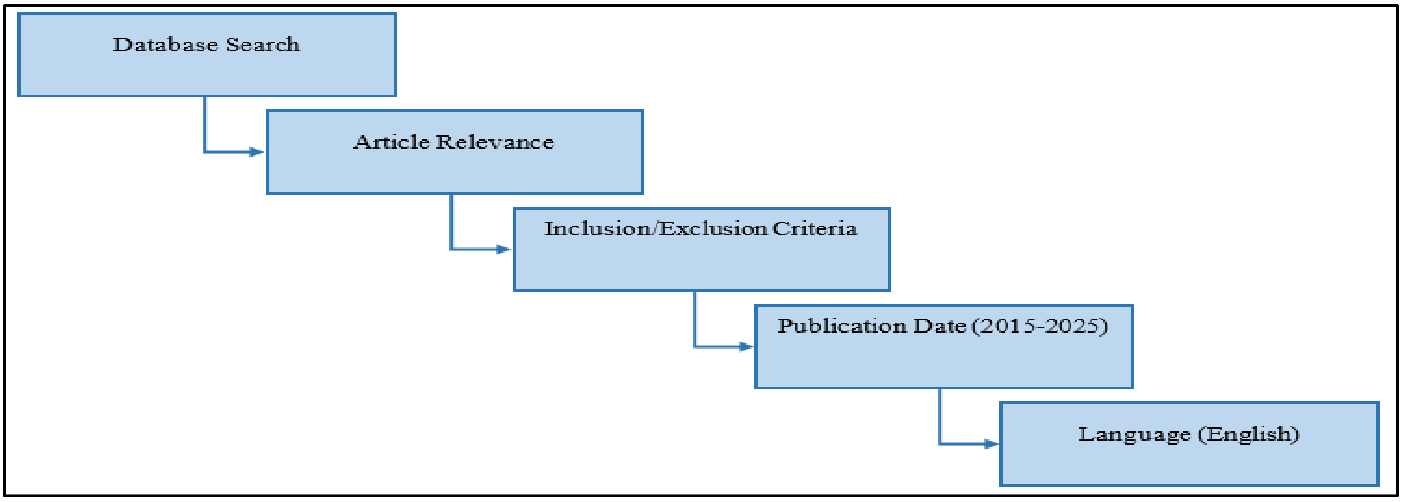

Fig 1 Article Selection Criteria

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III. RECOMMENDATION SYSTEM

Recommender systems are intelligent algorithms designed to analyze user data and suggest items that align with user interests and preferences. They have become an essential component of many online platforms, helping users discover relevant products, content, or services in a highly personalized manner (Kang & Wang, 2024). In the context of fashion, recommender systems assist users in finding clothing, accessories, and styles that suit their tastes, shopping behavior, and context-specific needs such as season, event, or cultural background (Deldjoo et al., 2024).

The primary goal of a recommender system is to reduce information overload by presenting users with curated selections from large product catalogs. These systems utilize various data sources, such as purchase history, product features, user demographics, browsing patterns, and even social interactions, to generate recommendations (Lu et al., 2015). With the rapid growth of fashion e-commerce and the increasing demand for personalization, fashion recommender systems have evolved to incorporate complex algorithms capable of understanding the visual, textual, and contextual characteristics of fashion items (Nguyen et al., 2024).

In fashion retail, the effectiveness of recommender systems directly impacts customer satisfaction, conversion rates, and brand loyalty. By learning from user interactions and identifying patterns, these systems enable a more engaging and efficient shopping experience (Eldemerdash et al., 2023).

➢ *Types of Recommender System*

Several types of recommender systems have been developed over the years, each with its strengths and limitations. The most commonly used types include content-based filtering, collaborative filtering, hybrid systems, and context-aware approaches.

- *Content-Based Filtering*

Content-based filtering is one of the foundational approaches in recommender system design. This method relies on analyzing the attributes or features of items that a user has previously interacted with such as viewed, liked, rated, or purchased to recommend similar items in the future. Rather than relying on the behavior of other users, content-based systems develop a personalized profile for each user by identifying patterns in the content they prefer (Sharad Phalle & Bhushan, 2024).

In the fashion domain, this approach involves extracting and analyzing specific product features, such as color, texture, fabric type, pattern, sleeve length, cut, style (e.g., casual, formal, vintage), brand, and category (e.g., dress, jacket, shoes). For instance, if a user frequently browses or purchases floral-patterned dresses made of chiffon, the system will recommend other dresses with similar floral prints or fabric characteristics (Shushi & Adnan M. Abdulazeez, 2024). The strength of content-based filtering lies in its ability to make highly personalized suggestions based on detailed item metadata (Chris et al., 2024).

Advanced content-based systems also incorporate image processing techniques, particularly using computer vision and convolutional neural networks, to extract visual features from clothing images. This enables the system to go beyond text-based attributes and understand visual aspects such as color palettes, garment shape, and style, which are particularly important in fashion (Shirkhani et al., 2023).

One of the main advantages of content-based filtering is that it does not require data from other users. This makes it effective in cold-start scenarios for users who are new to the system but have provided some initial preferences (Yuan & Hernandez, 2023). Also, content-based systems can continuously refine recommendations as the user interacts with more items.

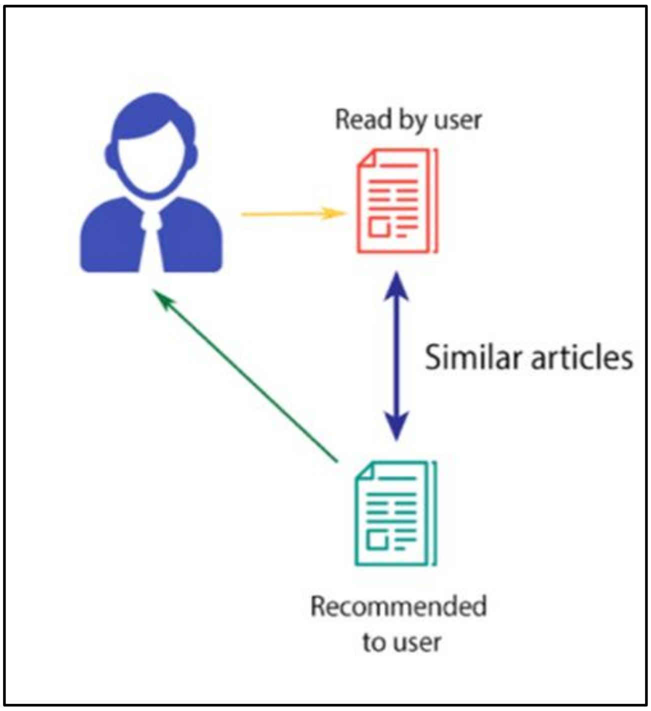

Fig 2 Content-Based Filtering, (Mohamed et al., 2019)

- *Collaborative Filtering*

Collaborative filtering models make recommendations based on user-item interaction data, such as ratings, clicks, and purchase history. These systems identify users with similar behavior and recommend items liked by those users (Kawasaki & Hasuike, 2017). Collaborative filtering can be either user-based or item-based, and is widely adopted due to its ability to provide unexpected or serendipitous recommendations. However, it struggles with the cold-start problem where recommendations cannot be made for new users or items without prior data (Wang et al., 2019).

Collaborative filtering is one of the most widely used techniques in recommender systems. Unlike content-based filtering, which relies on item attributes, collaborative filtering makes recommendations by analyzing patterns in user behavior and identifying relationships between users and items. This method operates under the assumption that users who exhibited similar preferences in the past are likely to

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share similar tastes in the future (Sharad Phalle & Bhushan, 2024).

In practice, collaborative filtering systems use user-item interaction data such as ratings, product clicks, purchase history, and browsing behavior to identify users with overlapping interests. The system then recommends items that similar users have liked or interacted with, even if the target user has not previously shown interest in those items. This enables the system to suggest novel or unexpected items, thus supporting serendipitous discovery and increasing the diversity of recommendations (Fareed et al., 2023).

There are two primary approaches to collaborative filtering: user-based and item-based.

In user-based collaborative filtering, the system identifies a group of users whose preferences are similar to the active user and recommends items favored by those peers.

In item-based collaborative filtering, the system identifies similarities between items based on the users who interacted with them and recommends items similar to those the user has already engaged with (Permana, 2024).

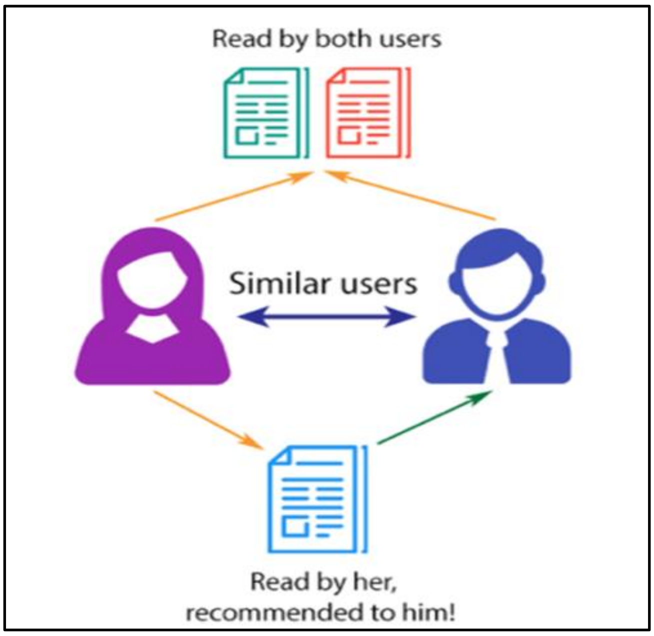

Fig 3 Collaborative Filtering, (Mohamed et al., 2019)

- *Hybrid Recommender Systems*

Hybrid recommender systems are designed to address the shortcomings of individual recommendation techniques by combining two or more algorithms most commonly, content-based filtering and collaborative filtering. This integration allows hybrid systems to leverage the strengths of each approach while mitigating their respective weaknesses, resulting in more accurate, diverse, and robust recommendations (Elahi et al., 2023).

In a typical hybrid framework, the system may simultaneously analyze user preferences (as in collaborative filtering) and item features (as in content-based filtering) to generate recommendations. This dual analysis enables the system to provide suggestions that are not only relevant to a user's past interactions but also aligned with the characteristics of products they are likely to find appealing (Sabiri et al., 2025). For instance, if collaborative filtering identifies that a user shares similar preferences with others who buy vintage-style clothing, and content-based analysis confirms the user's interest in floral patterns, the hybrid model can recommend vintage floral dresses with high confidence.

Hybrid models can be implemented using different architectural strategies. These include weighted hybridization, where outputs from multiple algorithms are combined using a weighted score; switching models, where the system selects a recommendation technique based on certain conditions; and model-based hybrids, where features from different models are used within a single unified learning framework (Çano & Morisio, 2017). More advanced implementations, particularly in fashion applications, often utilize deep learning architectures to blend collaborative and content-based signals, enhancing the system's ability to understand user intent and fashion aesthetics at a deeper level.

In the fashion domain, hybrid recommender systems are particularly useful due to the multi-dimensional nature of fashion preferences, which involve not only user-item interactions but also visual style, seasonality, social trends, and even emotional appeal (Deldjoo et al., 2024). For example, a hybrid model can combine visual similarity metrics from convolutional neural networks with purchase patterns from user-item interaction matrices to suggest stylish yet personalized clothing items.

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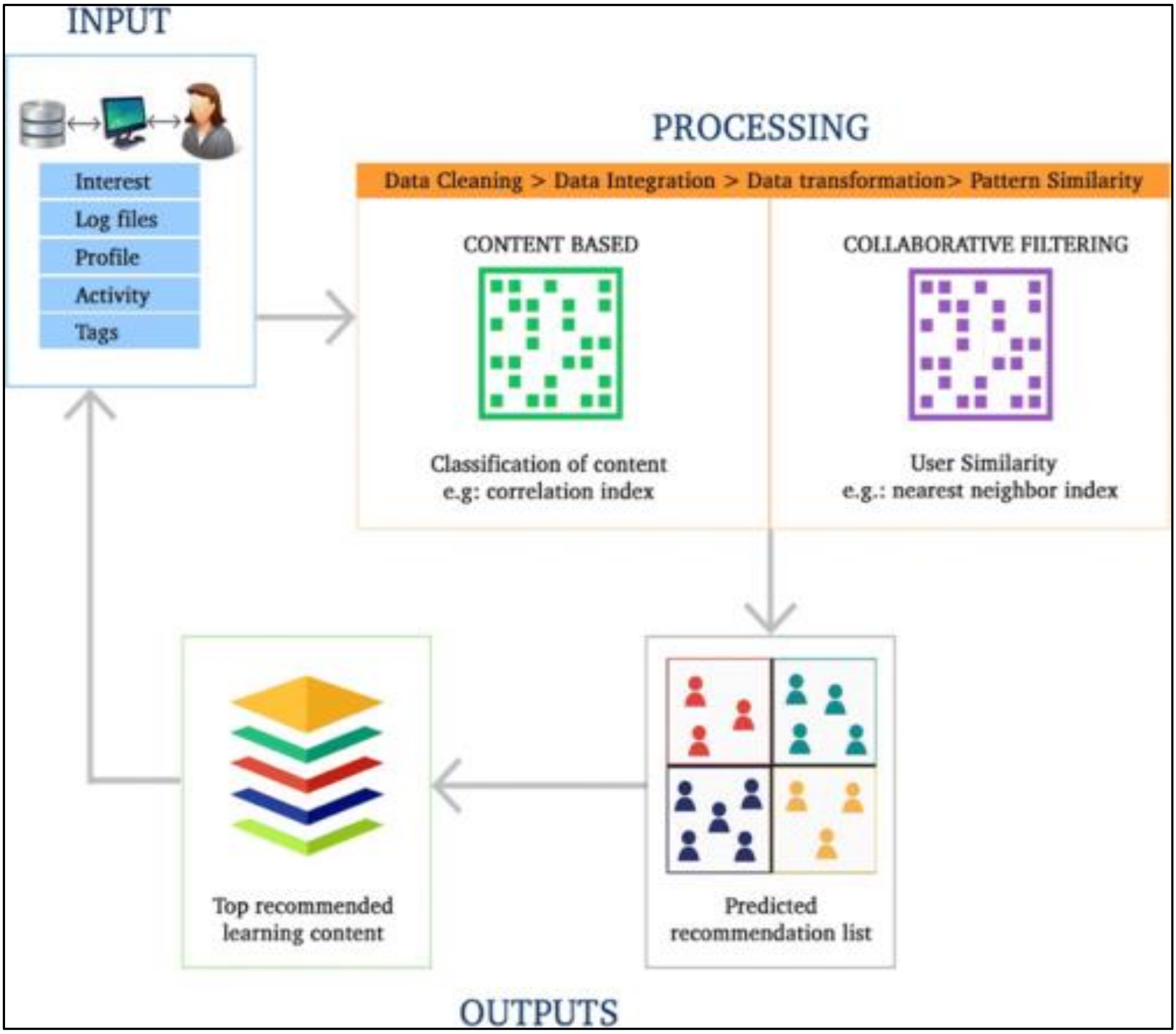

Fig 4 Hybrid Recommender System: (Khanal et al., 2020)

- *Context-Aware Recommender Systems*

Context-aware recommender systems represent a more advanced evolution of traditional recommendation approaches by incorporating situational or contextual factors into the recommendation process. These systems recognize that user preferences are not static but often influenced by external variables such as time of day, location, season, weather, device type, user mood, or social setting (Mateos & Bellogín, 2024).

In fashion applications, context plays a particularly crucial role. Clothing choices are highly dependent on factors such as climate conditions, occasions (e.g., weddings, job interviews, parties), cultural norms, and seasonal trends (Gazzola et al., 2020). A context-aware recommender system can, for instance, suggest lightweight, breathable clothing during summer, or recommend formal attire when a user indicates they are attending a professional event. This level of awareness allows for recommendations that are not only personalized but also practically relevant (Abugabah et al., 2020).

Technically, context-aware systems may use explicit context input, such as user-provided information, or implicit context extraction from sensor data like geolocation, calendar events, weather APIs (Ponce & Abdulrazak, 2022). The contextual data is then integrated into the recommendation algorithm either through pre-filtering (filtering the dataset based on context before generating recommendations), post-filtering (applying context rules after generating recommendations), or contextual modeling, where the context is incorporated directly into the learning model (Haruna et al., 2017).

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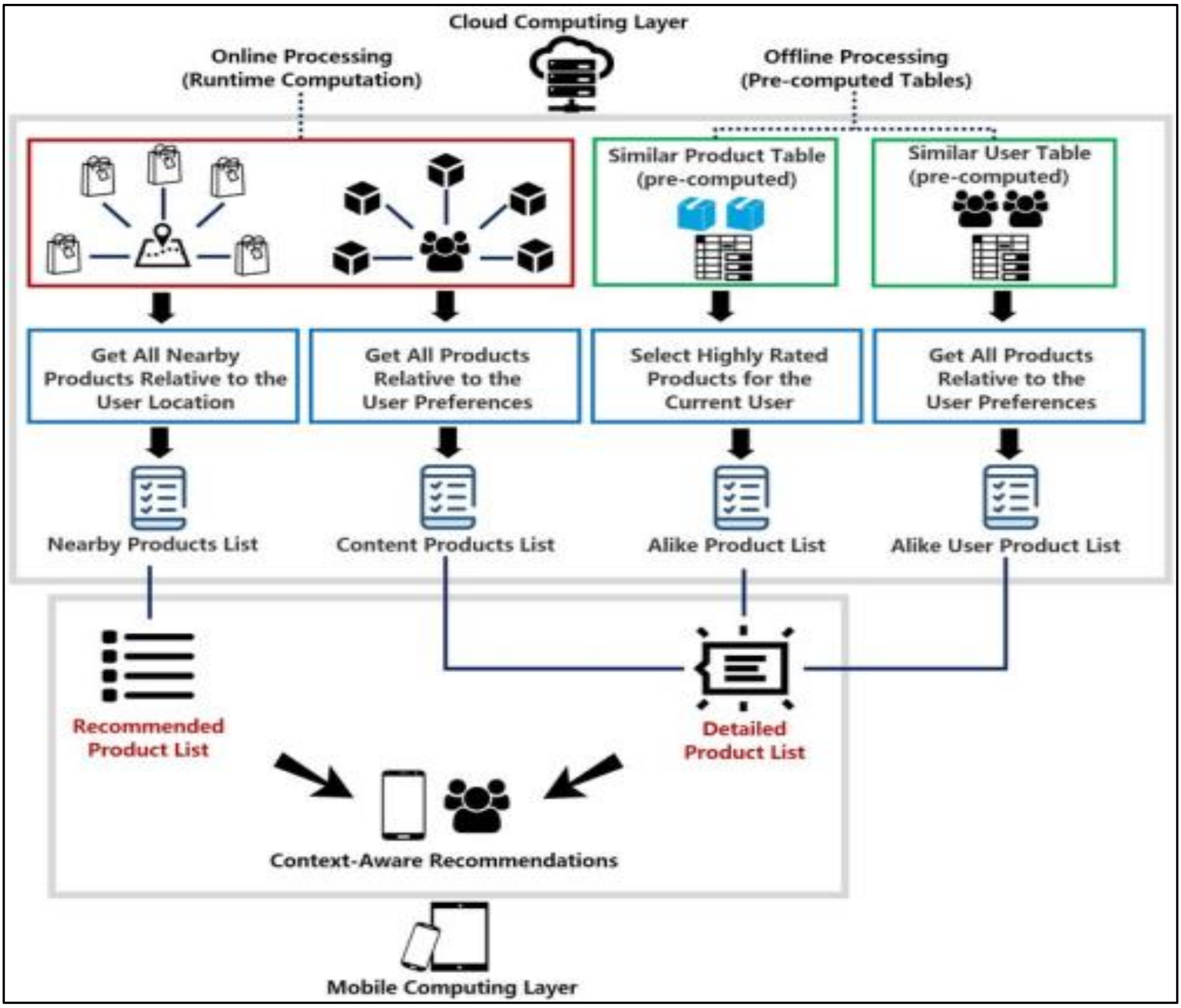

Fig 5 An Overview of Context-Aware Recommender System Algorithm, (Khan et al., 2020)

* *Deep Learning-Based Recommender Systems*

Deep learning-based recommender systems represent the most recent and innovative evolution in the field of recommendation technologies. These systems utilize deep neural networks to learn complex, non-linear relationships between users and items by processing large-scale, high-dimensional data. In the context of fashion, deep learning enables the extraction of intricate visual and textual features from fashion items, the modeling of sequential user behavior, and the generation of highly personalized, adaptive recommendations (Lee & Kim, 2022).

One of the primary advantages of deep learning in recommender systems is its capacity to handle multi-modal data, which is particularly relevant in fashion applications. Fashion items are rich in visual content, and their aesthetic appeal often depends on patterns, textures, shapes, and colors that traditional recommendation algorithms may fail to capture (Deldjoo et al., 2024). By using Convolutional Neural Networks, systems can extract high-level visual features from clothing images, allowing them to recommend products based on visual similarity or style alignment. This is especially useful for tasks such as visual similarity search, outfit generation, and style-based filtering (Hara et al., 2016).

Another common deep learning technique used in fashion recommendation is the Recurrent Neural Network (RNN), which excels in modeling sequential and temporal behavior. For instance, an RNN can capture a user's evolving fashion preferences over time, allowing the system to predict not just what the user likes now, but also what they might prefer in the future based on recent activity (Yoon & Jang, 2023). Similarly, Long Short-Term Memory (LSTM) networks and Transformer architectures have been employed to handle more complex sequences and contextual dependencies in user behavior (Mswahili & Jeong, 2024).

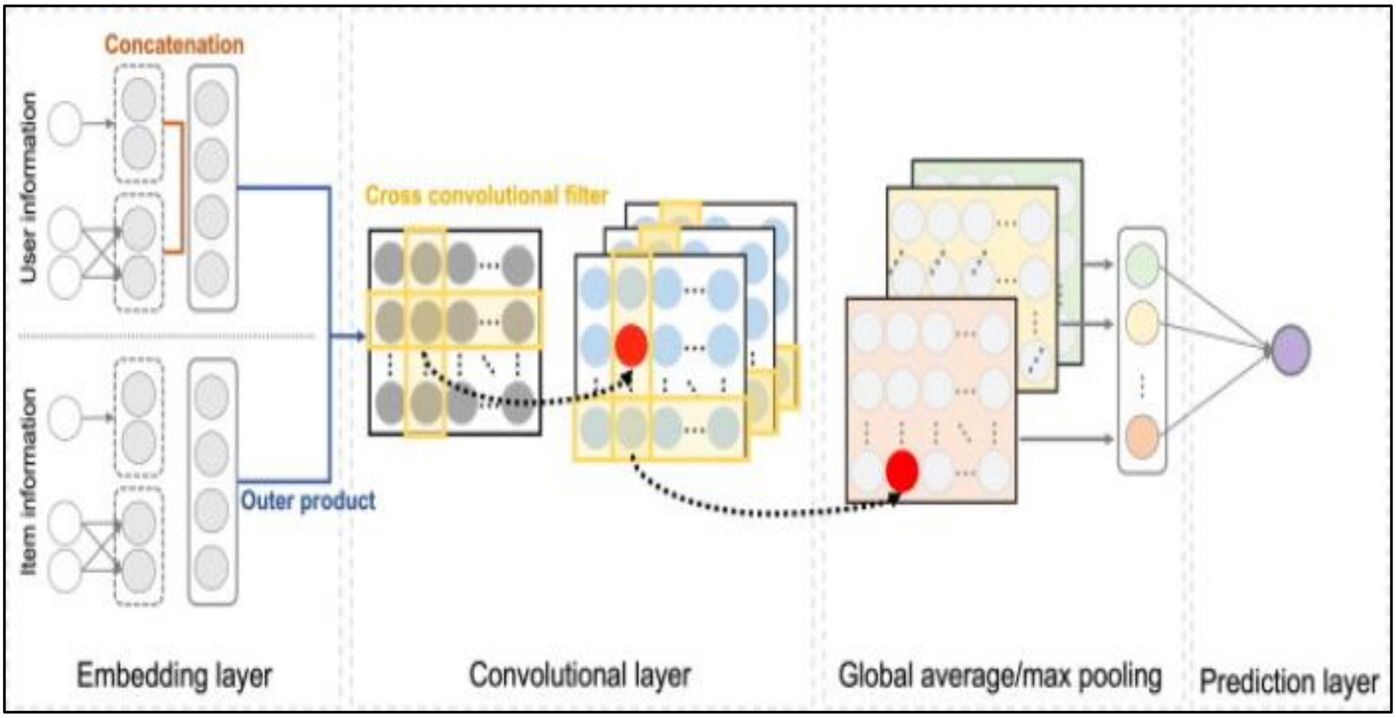

Fig 6 Deep Learning-Based Recommender System Using Cross Convolutional Filters, (Lee & Kim, 2022)

➢ *Application in Fashion*

The fashion industry, particularly within the e-commerce sector, has seen a transformative shift through the integration of recommender systems. These systems have become essential tools for enhancing user experience, improving product discovery, and driving sales through personalized engagement (Eldemerdash et al., 2023). Unlike traditional product catalogs, which treat all users equally, fashion recommender systems provide tailored suggestions based on individual preferences, behavior, context, and style inclinations. This level of personalization helps address key challenges in fashion retail, such as choice overload, changing trends, and subjective notions of style (Guan et al., 2016).

One of the most common applications of recommender systems in fashion is personalized product recommendation. These systems analyze users' browsing history, purchase behavior, and engagement patterns to suggest items that match their tastes (Shirkhani et al., 2023). For instance, a user who frequently views casual streetwear may receive recommendations aligned with that aesthetic, while another who shops for formal attire will be shown a different product mix.

Another key application is visual similarity search, where users can find products that are visually similar to an image they upload or select. This is particularly useful in fashion, where visual features such as color, cut, print, and texture are primary decision-making factors. Powered by convolutional neural networks, these systems can analyze and compare image features to return clothing items with similar visual characteristics. Visual search capabilities are increasingly being integrated into mobile fashion apps and web platforms, enabling users to search for products intuitively and efficiently (Jain & Wah, 2022).

Outfit recommendation is a more advanced application where the system suggests combinations of fashion items that go well together (Pralhad Magar & Kondvilkar, 2020). For example, it may recommend a pair of shoes and a handbag that match a selected dress. These systems are trained on curated outfit datasets or fashion lookbooks and rely on compatibility modeling, style recognition, and occasion-based reasoning. Outfit recommendation not only improves cross-selling opportunities but also enhances user satisfaction by simplifying the decision-making process.

IV. REVIEW OF RELATED LITERATURE

The study of fashion recommender systems has gained significant attention in recent years due to the growing demand for personalized online shopping experiences. Researchers have explored various techniques from classical filtering methods to cutting-edge deep learning approaches to address the complex nature of fashion recommendation, which often involves subjective, visual, and contextual elements.

(Suvarna & Balakrishna, 2024) proposed an enhanced content-based fashion recommendation system using deep learning and ensemble techniques. The study focused on improving recommendation accuracy by leveraging five pre-trained convolutional neural networks (CNNs): MobileNet, DenseNet, Xception, VGG16, and VGG19. These models were used to extract visual features from fashion product images, and their outputs were combined into a deep ensemble classifier. Recommendations were generated based on cosine similarity between the feature vectors of the input image and the items in the dataset. The system was tested using two publicly available fashion datasets from Kaggle, which included various apparel and shoe images. The proposed ensemble model achieved a classification accuracy

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of 96%, outperforming traditional single-model CNN approaches.

(ASIROGLU et al., 2019) introduced a "smart clothing recommendation system" that requires only a single photo of the user with no prior shopping history to suggest clothing items. The system begins by analyzing the image to detect the user's gender using a deep neural network. It then extracts additional visual features from the photo and searches a database of garments labeled by gender and other attributes. The model incorporates transfer learning via a ResNet-50 backbone, fine-tuned on a large inventory of fashion images (including data from DeepFashion), allowing it to capture complex visual representations despite limited user input. The study achieve 98% accuracy on color prediction, 86% accuracy on gender and cloth's pattern predictions and 75% accuracy on clothing recommendation.

(Yarahmadi Gharaei et al., 2021) developed a content-based clothing recommender system using a deep neural network that automatically classifies clothing by category and gender while extracting visual features from images. Trained on the Fashion Product Images dataset, the model outperformed the ResNet-50 baseline with lower loss and faster training time. It achieved a recommendation precision of 73.7% based on real user feedback and effectively addressed the cold-start problem by requiring only item images for new product recommendations. The system demonstrated high speed, accuracy, and the ability to generate novel and relevant suggestion.

(Lin et al., 2019) developed a content-based clothing recommendation system that integrates personal features (gender and body height) with clothing attributes (style, design, color, and texture) to suggest suitable apparel. Using deep learning models like InceptionV3, the system performs gender recognition, estimates body height from user photos, and identifies clothing attributes from images using the FashionAI dataset. These features are combined into a similarity score to match users with appropriate items in a large clothing gallery. A random generator is also applied to increase recommendation diversity. The system achieved high attribute recognition accuracy (up to 90.09% for collar design) and demonstrated strong recommendation performance. In user testing, the system achieved a precision of 71.8% for tops and 64.1% for bottoms when all features were used.

(Suvarna & Balakrishna, 2022) proposed a content-based fashion recommender that uses a custom deep convolutional neural network (CNN) to classify a query image and recommend visually similar products. They trained their model using a subset of nearly 15,000 fashion images from 12 different categories. The system achieved an image classification accuracy of 89.02%, enabling it to generate reliable and precise recommendations. The study demonstrates that a well-designed deep CNN can effectively serve as the foundation for a visually-driven, efficient, and scalable fashion recommendation engine.

A personalized fashion recommendation system that relies on visual similarity rather than user history was proposed by (Sridevi et al., 2020). The system uses a convolutional neural network, based on ResNet50 and fine-tuned using transfer learning, to extract visual features from clothing images. Recommendations are generated using cosine similarity and a nearest neighbor algorithm (Annoy library). The system was trained using the DeepFashion dataset and tested on a variety of real-world and internet-sourced images. It achieved a high classification accuracy of over 98% during training, demonstrating strong performance even with a limited dataset. The model effectively addressed the cold-start problem and produced visually similar recommendations based on a single input image, offering a fast, visually-driven, and scalable solution for fashion recommendation.

(Sawalkar et al., 2023) developed a content-based clothing recommender system using a deep neural network to automatically extract item features such as category and gender directly from images, eliminating manual feature engineering. The model incorporates demographic information, including gender, into the recommendation process. They compared performance with and without demographic features and found that including them led to lower training loss and improved relevance. The system was evaluated on an Android-based platform and effectively addressed the cold-start issue, producing novel and unexpected recommendations for new items. The results demonstrate that their deep learning approach enhances recommendation accuracy and diversity without requiring historical user data.

SAERS (Semantic Attribute Explainable Recommender System.) was proposed by (Hou et al., 2019) a fashion recommendation system that provides both accurate and explainable suggestions by focusing on fine-grained visual attributes of clothing, such as collar style or heel shape. Instead of relying solely on global image features, SAERS uses a Semantic Extraction Network to identify specific image regions linked to attributes and applies attention mechanisms to personalize recommendations based on individual user preferences. The system is trained with weak supervision and combines both global and attribute-level features. Experiments on the Amazon Fashion dataset show that SAERS outperforms existing methods in recommendation accuracy while also offering interpretable, attribute-based visual explanations.

(Sivaranjani et al., 2023) implemented a fashion recommender using a convolutional neural network (CNN) trained on images to suggest similar apparel and accessories. They divided their dataset into training and testing subsets and applied CNN for feature extraction, using K-nearest neighbors (KNN) to retrieve visually similar items. Compared to previous systems, their approach delivered results 80.6% faster. The system demonstrated effectiveness in personalized fashion retrieval, handling cold-start situations by recommending items based solely on image input.

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(Sarojadevi et al., 2023) developed a content-based fashion recommendation system that focuses on clothing style similarity. Using upper-body and lower-body garment images along with human model photos, the system extracts visual features through a CNN model based on ResNet-50. It compares these features to a large gallery of clothing images from a Kaggle fashion dataset using similarity matching. The model effectively handles the cold-start problem by providing outfit suggestions even for users or items with no prior interaction data.

(Syiam et al., 2023) developed an item-based collaborative filtering recommender for fashion products using purchase data from Rent the Runway. They preprocessed the data by cleaning, normalizing ratings, and splitting into training and testing sets. The system calculates item-to-item similarity using adjusted cosine similarity, then predicts user preferences via a weighted sum of neighbors. Evaluated using Mean Absolute Error (MAE) and Normalized Discounted Cumulative Gain (NDCG), the adjusted cosine method outperformed standard cosine similarity, achieving a lower MAE of 0.4424 (versus 0.4815) and higher NDCG around 0.9989. This confirms adjusted cosine as a more accurate metric for generating personalized fashion recommendations.

(Ye et al., 2023) a novel scene-aware fashion recommender system (SAFRS) that recommends outfits based on the context or environment (e.g., beach, office, gym). The system uses attention-based encoders to extract features from both scenes and outfits, then evaluates their compatibility through a joint scoring function. Trained on a newly curated dataset with scene-labeled outfits, SAFRS significantly outperformed existing models in recommending context-appropriate clothing. The study highlights the importance of environmental context in fashion recommendation to improve relevance and user satisfaction.

(Thakur, 2024) developed an outfit recommendation system that integrates user skin tone analysis, real-time weather data, and a digital wardrobe to suggest personalized ensembles. A Convolutional Neural Network (CNN) extracts visual features from clothing items stored in users' virtual wardrobes. Recommendations are then tailored using k-Nearest Neighbors (kNN), grouping users based on similar fashion preferences, and refined through decision tree algorithms. By considering contextual factors like skin tone and weather, the system provides both stylistically appropriate and comfortable outfit suggestions while promoting sustainable use of existing clothing.

(Ramesh & Moh, 2018) presented an outfit recommender system that designs complementary garment combinations using session-based user interaction data. The model analyzes user sessions series of item clicks and purchases to learn patterns and co-occurrence relationships between fashion items. It leverages a neural network to model these sequential interactions, identifying which clothing pieces are likely to be paired together. While the paper focuses primarily on modeling item compatibility rather than individual preferences, experimental results on real-world e-commerce datasets show that the system effectively suggests cohesive outfit combinations based on browsing behavior.

V. DATASET USED

The performance and generalizability of fashion recommender systems are highly influenced by the datasets used for their development and evaluation. Table 1 summarizes the datasets utilized in the selected studies

Table 1 Summary of Dataset Used

Author	Title	Dataset
(Suvarna & Balakrishna, 2024)	Enhanced Content-Based Fashion Recommendation System	Fashion Product Images dataset (Kaggle) + Shoe dataset (Kaggle)
(ASIROGLU et al., 2019)	Smart Clothing Recommendation System	DeepFashion dataset
(Yarahmadi Gharaei et al., 2021)	Content-Based Clothing Recommender System using Deep Neural Network	Fashion Product Images dataset (Kaggle)
(Lin et al., 2019)	Clothing Recommendation System Based on Visual Information Analytics	FashionAI dataset
(Suvarna & Balakrishna, 2022)	An Efficient Fashion Recommendation System using a Deep CNN Model	Fashion Product Images dataset (subset, ~15,000 images)
(Sridevi et al., 2020)	Personalized Fashion Recommender System with Image-Based Neural Networks	DeepFashion dataset
(Sawalkar et al., 2023)	Fashion Recommendation System	Custom wardrobe dataset
(Ye et al., 2023)	Show Me The Best Outfit for a Certain Scene: A Scene-Aware Fashion Recommender System	Scene-labeled outfit dataset (newly curated by authors)
(Sarojadevi et al., 2023)	Fashion Recommender System (FRS): Image Based Engine for Personalized Outfit	Kaggle fashion dataset
(Syiam et al., 2023)	Fashion Recommendation System Using Collaborative Filtering	Rent the Runway dataset
(Thakur, 2024)	Enhancing Outfit Recommendation with a CNN-kNN Hybrid Model and Digital Wardrobe Management	Custom-built digital wardrobe dataset
(Ramesh & Moh, 2018)	Outfit Recommendation	Fashion e-commerce dataset from STYL

VI. LIMITATIONS

Despite substantial recent progress, the body of work reviewed exhibits recurring limitations that constrain the generalizability, comparability and practical impact of current fashion recommender systems. A dominant limitation concerns the data. Many studies rely on small or narrowly curated datasets, or on proprietary databases and custom “digital wardrobe” collections that were collected for a single experiment. Such datasets frequently suffer from class imbalance, limited demographic and cultural diversity, and inconsistent or noisy annotations. The disparity between studio/catalog images and in the wild photos like street, user uploads, social media creates a domain shift that models trained on catalog data often cannot bridge. The common practice of using different, non-standard splits and undocumented preprocessing steps further prevents fair comparison between methods and hinders reproducibility.

These constraints underscore the need for larger, more diverse, and standardized datasets, along with transparent and reproducible experimental protocols, to ensure the advancement and real world applicability of fashion recommender systems.

VII. CONCLUSION

This review has examined the current state of fashion recommender systems, outlining their methodologies, datasets, and applications, while highlighting recurring limitations. The literature reveals a clear evolution from basic content-based and collaborative filtering techniques to more sophisticated hybrid and context-aware models that integrate visual, textual, and contextual signals. These advances have improved personalization, recommendation diversity, and adaptability to varying user needs and scenarios. However, persistent challenges remain. Issues such as limited and non-standardized datasets, lack of demographic diversity, inadequate modeling of contextual factors, and inconsistent evaluation protocols hinder both the reproducibility and the real-world applicability of these systems. Ethical considerations, including fairness, inclusivity, and user privacy, are still underexplored in most works, leaving gaps between academic research and commercial deployment. Going forward, the field would benefit from collaborative efforts to establish standardized, diverse benchmark datasets, transparent experimental reporting, and evaluation frameworks that incorporate both offline metrics and real-world user engagement. Furthermore, incorporating multimodal data, addressing cold-start problems, and embedding fairness and privacy mechanisms into system design will be crucial. By tackling these challenges, future fashion recommender systems can evolve into robust, inclusive, and contextually aware solutions that meaningfully enhance user experience and drive innovation in the fashion industry.

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