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APPLICATION OF ARTIFICIAL INTELLIGENCE IN FASHION RECOMMENDATION SYSTEMS FOR SUSTAINABLE APPAREL DEVELOPMENT

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Abstract

This paper presents a conceptual architecture for an artificial intelligence-based fashion recommendation system oriented towards sustainable apparel development. The main functional components of the system are analysed, including data acquisition, garment detection and segmentation, visual and semantic feature extraction, user and context modelling, multi-criteria ranking, virtual try-on, and continuous feedback processing. The analysis shows that convolutional neural networks are effective for clothing recognition and classification, whereas hybrid and ensemble architectures provide broader opportunities for combining visual characteristics, user preferences, anthropometric information, and contextual factors. However, high classification accuracy on a simplified dataset should not be interpreted as evidence of effective real-world personalisation. The proposed approach treats fashion recommendation as a multi-objective task combining preference relevance, fit compatibility, contextual suitability, sustainability attributes, and predicted return risk. Such systems may support more informed product selection and demand-oriented apparel development, but their environmental contribution depends on reliable product data, responsible recommendation objectives, user privacy protection, and integration with production planning.

Keywords: Artificial intelligence, fashion recommendation system, deep learning, clothing detection, personalisation, sustainable apparel development, virtual try-on

Introduction

Fashion plays an important role in social identity, personal expression, and consumer behaviour. At the same time, short product life cycles, rapidly changing trends, inaccurate demand forecasts, unsold inventories, and frequent product returns create considerable economic and environmental pressures. The development of more sustainable apparel systems therefore requires not only improvements in materials and manufacturing but also better coordination between design decisions, consumer needs, and actual demand.

Artificial intelligence is increasingly used for fashion image recognition, garment classification, visual search, recommendation, trend analysis, virtual try-on, and product development. A broad review of smart-fashion research identified more than 580 studies covering 22 AI-related fashion tasks and documented 86 publicly available datasets [1]. Recent research also demonstrates that deep learning and generative models are being integrated into different stages of the apparel value chain, including design, production, marketing, retail, and recommendation [2].

Fashion recommendation differs from conventional product recommendation because an appropriate garment cannot be selected solely from a user's previous purchases. Colour, silhouette, material, pattern, garment category, body proportions, size, occasion, climate, cultural context, compatibility with other items, and individual style preferences may all influence the final choice. The problem therefore requires the integration of computer vision, user modelling, recommendation algorithms, and apparel-domain knowledge.

Traditional systems commonly use content-based filtering, collaborative filtering, or direct feature matching. These approaches can identify products with similar metadata or recommend items preferred by users with comparable behaviour. However, they may not adequately capture visual style, outfit compatibility, body-related requirements, or the contextual suitability of a garment. Machine-learning and deep-learning models extend these capabilities by learning more complex relationships between product images, attributes, user behaviour, and contextual information [3].

The sustainability contribution of an AI recommendation system should nevertheless be stated carefully. Recommendation itself does not automatically reduce material consumption or textile waste. Its contribution depends on whether the system improves product–user matching, lowers avoidable returns, supports longer product use, prioritises durable or circular alternatives, and supplies reliable demand information to apparel developers and manufacturers.

The purpose of this study is to analyse the functional architecture of an AI-driven fashion recommendation system and determine how its components may support sustainable apparel development. The study also examines the applicability and limitations of commonly used datasets and deep-learning models.

Functional Architecture of an AI-Driven Fashion Recommendation System

An effective fashion recommendation system requires the integration of several interconnected functional modules. Each module processes a particular type of information and transfers its output to the subsequent stage.

Data acquisition. The first stage involves collecting product, user, and contextual data. Product information may include garment images, category, colour, silhouette, material composition, size range, price, season, intended occasion, care requirements, durability indicators, and availability.

User information may be obtained from explicitly stated preferences, selected sizes, purchase and return history, saved items, ratings, browsing behaviour, and voluntary body measurements. Contextual information can include weather conditions, season, occasion, dress code, location, and garments already owned by the user.

Sensitive information, particularly body measurements and behavioural data, should only be processed with informed consent and appropriate privacy protection.

Image preprocessing and garment detection. Product and user-uploaded images may differ in resolution, illumination, background, pose, and orientation. Image preprocessing can include resizing, colour normalisation, contrast enhancement, background removal, and data augmentation.

Garment detection determines the location and category of clothing objects in an image, while segmentation separates individual garments from the body and background. Accurate segmentation is particularly important when an image contains several objects or when the system must analyse garment shape, colour, and texture independently.

Visual and semantic feature extraction. After detection, the system extracts visual features describing colour, texture, pattern, silhouette, garment type, and design details. Convolutional neural networks can learn hierarchical visual representations directly from images. Lower network layers generally capture edges and basic textures, whereas deeper layers represent more complex garment characteristics.

Visual features should be combined with semantic product information. Two garments may appear visually similar while differing considerably in material, thermal comfort, care requirements, durability, or suitability for a specific occasion. A multimodal representation combining images and structured metadata is therefore more appropriate for practical recommendation.

User and context modelling. The user profile represents individual preferences and behavioural patterns. It may include preferred styles, colours, garment categories, size information, price range, previous interactions, and feedback on earlier recommendations.

The profile should be dynamic rather than fixed. Preferences can change with season, occupation, age, lifestyle, or the purpose of purchase. Context-aware modelling allows the same user to receive different recommendations for professional work, travel, formal events, daily wear, or specific weather conditions.

Multi-criteria recommendation and ranking. Candidate garments are ranked according to their correspondence with the user profile and current context. For sustainable apparel development, the ranking objective should extend beyond predicted purchase probability.

A conceptual recommendation score may be expressed as:

$$S_i = w_p P_i + w_f F_i + w_c C_i + w_s E_i - w_r R_i$$

where:

- S_i is the total recommendation score of garment ii;
- P_i is the correspondence with user preferences;
- F_i is the predicted size and fit compatibility;

- C_i is the contextual suitability;
- E_i is the sustainability-related product score;
- R_i is the predicted risk of product return;
- w_p, w_f, w_c, w_s, and w_r are weighting coefficients.

This expression is a conceptual model rather than an experimentally validated equation. Its purpose is to show that recommendation quality and sustainability should be considered jointly. The sustainability component should only be used when traceable information on materials, durability, care, repairability, recycled content, or end-of-life options is available.

2.6. Recommendation presentation and feedback

The final recommendations may be displayed as individual garments, complete outfits, alternatives within a price range, or visually compatible items. Virtual try-on can help users evaluate garment appearance before purchase, although the reliability of the result depends on body representation, garment geometry, fabric behaviour, and image quality.

User actions such as acceptance, rejection, purchase, return, rating, or modification of a recommendation provide feedback for updating the profile and improving subsequent results.

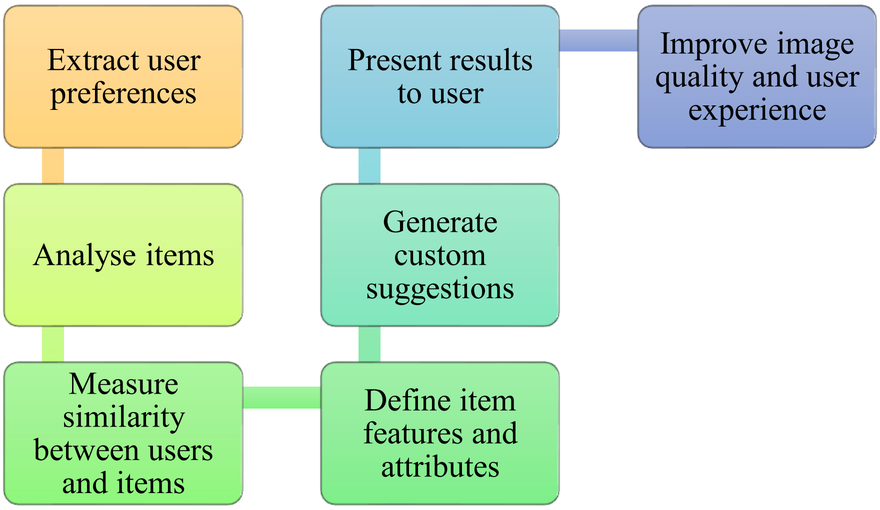

Fig.1. Pipeline of Cloting detection in personalized fashion design recommendation

Deep-Learning Models and Fashion Data Sources

Convolutional neural networks are widely used for clothing image classification, attribute recognition, detection, and visual similarity analysis. Their main advantage is the ability to learn relevant visual features without relying exclusively on manually defined descriptors.

Fashion-MNIST is frequently used as an initial benchmark for fashion image classification. It contains low-resolution grayscale images divided into ten general clothing categories. Vattikonda et al. compared CNN, feedforward neural network, and LSTM models using this dataset and reported that the CNN achieved 93.99% classification accuracy [4].

This result demonstrates the suitability of CNNs for basic fashion-item classification. However, Fashion-MNIST does not contain individual user preferences, body measurements, realistic textures, complete outfits, sustainability attributes, or purchase context. Consequently, classification accuracy obtained on Fashion-MNIST should not be presented as direct evidence of effective personalised fashion recommendation.

More comprehensive systems require realistic garment images and detailed annotations. YOLO-GARNet integrates garment analysis, clothing detection, recommendation, and virtual try-on within a unified architecture [5]. Such an end-to-end approach reduces the separation between individual computer-vision tasks and the final recommendation process.

Deep-learning-based personalisation can also support custom garment development. Lu proposed an intelligent clothing personalisation system that connects consumer information with apparel customisation processes [6]. This direction is relevant to sustainable production because products can be developed in closer accordance with actual user requirements. Nevertheless, the environmental benefit depends on how the system is connected to material selection, production quantities, and product longevity.

Ensemble approaches can be used when a single model cannot adequately represent all aspects of fashion style. Jaimunt and Chouvatut combined CNN, a conventional neural network, support vector machine, and Random Forest models for style classification in a clothing-assistant application. Their system also used garment segmentation and provided a similarity score between user-selected clothing and celebrity styles [7].

These examples demonstrate that the selection of an algorithm depends on the specific task. CNN-based models are suitable for image analysis; sequential models may process behavioural histories; graph-based models can represent relationships among users, garments, attributes, and outfits; and ensemble models can combine predictions obtained from different feature spaces.

Contribution to Sustainable Apparel Development

AI-based recommendation systems can contribute to sustainable apparel development through several mechanisms. First, improved correspondence between product characteristics and user requirements may reduce purchases caused by incomplete or misleading product information. Fit-aware recommendation and virtual try-on may also help prevent avoidable size- and appearance-related returns.

Second, recommendation systems can prioritise products according to durability, material composition, care requirements, repairability, recycled content, or recyclability. They can also recommend second-hand, rental, repair, alteration, or wardrobe-reuse options instead of limiting the user to newly manufactured garments.

Third, aggregated and anonymised recommendation data may provide designers and manufacturers with information about actual demand for particular colours, sizes, silhouettes, and product categories. When used responsibly, these data can support demand-oriented product development, smaller production batches, and improved assortment planning.

Fourth, AI systems may assist designers in identifying groups of consumers whose requirements are not adequately represented by standardised mass-market products. Personalised or configurable garment development may reduce the mismatch between available products and real anthropometric or functional needs.

These potential benefits remain conditional. A recommendation algorithm optimised only for clicks, engagement, or purchase frequency may stimulate unnecessary consumption. A sustainability-oriented system should therefore avoid treating increased sales volume as its only objective. Product longevity, expected use frequency, return probability, compatibility with the

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existing wardrobe, and verified environmental information should also be included in the recommendation criteria.

Technical and Methodological Challenges

The development of reliable fashion recommendation systems involves several unresolved problems.

Fashion datasets vary considerably in image quality, annotation structure, garment taxonomy, body representation, and cultural coverage. Models trained on limited populations or narrow fashion categories may provide less accurate recommendations for users who are underrepresented in the training data.

The cold-start problem arises when insufficient information is available about a new user or product. Hybrid recommendation methods can partly address this limitation by combining product content, user behaviour, and contextual data.

Anthropometric information and purchase histories are sensitive personal data. Their collection and processing require informed consent, secure storage, data minimisation, and clear explanation of how recommendations are generated.

Algorithmic interpretability is also important. Users should be able to understand whether an item was recommended because of its size, colour, compatibility, occasion, previous behaviour, or sustainability characteristics.

Real-time image processing and virtual try-on may require considerable computational resources. Lightweight models, model compression, and edge or mobile optimisation are therefore necessary for practical deployment.

Finally, evaluation based only on classification accuracy is insufficient. A fashion recommendation system should be evaluated using ranking metrics such as Precision@K, Recall@K, and NDCG, together with fit accuracy, user satisfaction, return rate, diversity of recommendations, response time, and clearly defined sustainability indicators.

The architecture discussed in this paper is conceptual. Its actual contribution to reducing returns, unsold inventory, or material waste must be verified through controlled implementation and lifecycle-oriented evaluation.

Conclusion

Artificial intelligence provides a technical basis for developing more personalised and context-aware fashion recommendation systems. Computer vision can detect and classify clothing items, deep-learning models can extract complex visual features, and hybrid recommendation methods can integrate product attributes with user preferences and behavioural information.

The most appropriate architecture consists of interconnected modules for data acquisition, garment detection and segmentation, feature extraction, user and context modelling, multi-criteria ranking, virtual try-on, and feedback processing. Treating these components as a unified system is more effective than applying isolated image-classification models.

The relationship between AI recommendation and sustainable apparel development is not automatic. Environmental benefits are more likely when the system improves product–user matching, accounts for fit and expected product use, supports durable and circular alternatives, and transfers aggregated demand information to apparel design and production planning.

Future research should validate the proposed architecture using realistic multimodal fashion datasets and compare recommendation quality with measurable indicators such as product returns, usage duration, recommendation diversity, inventory mismatch, and material efficiency. Particular attention should be paid to data reliability, privacy, algorithmic bias, explainability, and the risk that personalised recommendations may encourage excessive consumption.

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