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Review Article

A Review on the Influence of Deep Learning and Generative AI in the Fashion Industry

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Abstract: Incorporating deep learning models has marked a significant advancement in integrating trends and technology within the fashion industry. These models are extensively applied in the realm of image recognition, product recommendation, and trend prediction, employing deep learning techniques such as Convolutional Neural Networks (CNNs), Generative Adversarial Networks (GANs), Recurrent Neural Networks (RNNs), and Autoencoders. This paper aims to cover various aspects of the textile industry's supply chain processes, highlighting these deep learning techniques' present influence and potential future directions. It includes a comprehensive analysis of some of the most recent and well-recognized studies in the industry that focus on different parts of a product's lifecycle in the industry, such as Design and Trend Forecasting, Production and Quality Control, Marketing and Sales, and Distribution and Retail. While deep learning has significantly improved the efficiency of processes across the supply chain, our review highlights some of the existing challenges, such as dependency on large datasets, manual annotation needs, and limitations in creative design generation, encouraging future research to focus on more sophisticated models incorporating multimodal data and personalized factors like body types and aesthetic preferences. Additionally, areas like sewing pattern generation, body-aware designs, and ethical sourcing are critical areas of the fashion industry that require further exploration.

Keywords: Autoencoders; Convolutional Neural Network; Deep Learning; Fashion; Generative AI; Generative Adversarial Network.

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1. Introduction

In recent years, deep learning models have emerged as useful tools for resolving complex problems in various industries, including fashion. With e-commerce and social media usage rising, fashion and textile businesses are under tremendous pressure to immediately adapt to the newest trends and provide customized advice to their clients [1]. Deep learning models have proven incredibly effective at analyzing huge amounts of data, identifying patterns, and making predictions, making them the ideal solution to these issues.

This literature review provides a fundamental understanding of popular deep learning techniques and explores the application of these techniques in multiple areas of the textile and fashion industry supply chain. The main categories chosen for review are design and trend forecasting, production and quality control, marketing and sales, and distribution and retail. These categories were further divided into modules such as fashion design generation and trend prediction, fabric defect detection, product recommendation systems, inventory management, and virtual try-on, respectively.

Initially, papers that primarily focus on any deep learning techniques that demonstrate applications in any of the above areas within the fashion industry were chosen. In order to narrow down the scope, those published in the most recent years (2019 onwards) were chosen. Further, to maintain the focus on some of the most recognized work, the selected papers were filtered based on the number of times they had been cited by other published papers, ensuring that only those with significant academic impact were included. As Google Scholar is known for being a comprehensive data source for academic writing[2], it was used as the primary source of literature for this review.

While there exists several deep learning models introduced throughout the years, this review primarily focuses on the popular deep learning techniques such as Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), Autoencoders, and Generative Adversarial Networks (GANs). Applying these techniques in fashion design generation enables innovative and personalized designs. In trend prediction, these techniques enhance the ability to forecast fashion trends accurately[3]. In quality control, deep learning models significantly improve production standards and efficiency through fabric defect detection[4]. The review also covers the application of deep learning in distribution and retail, particularly in inventory management [5] and virtual try-on technologies [6], which enhance customer experience and operational efficiency. By consolidating insights from various application areas, the study underscores the transformative impact of deep learning on the future of fashion.

The structure of this review is organized as follows. Section 2 explores the architecture, development, and technical details of the deep learning techniques previously mentioned, emphasizing their current applications and future potential. Section 3 organizes these techniques into essential processes, such as design generation, trend prediction, production quality management, marketing approaches, and retail innovations, while also identifying limitations and gaps in their use. Section 4 provides a critical analysis of the work, comparing and assessing different studies, highlighting research gaps and under-explored areas in each process. Lastly, Section 5 summarizes the overall influence of deep learning on the fashion industry, presenting potential avenues for future research to overcome current challenges and optimize the potential of these models. This structured review offers a comprehensive understanding of the relationship between deep learning and the fashion industry, highlighting both present progress and future opportunities.

2. Deep Learning in The Fashion Domain

Deep learning, a subset of ML algorithms that have gained popularity in recent years due to their ability to perform exceptionally well on a variety of tasks, has transformed the fashion industry in a revolutionary manner by providing progressive solutions for a variety of activities, including image recognition, recommendation systems, and fashion design. It involves using neural networks with several layers (therefore the term "deep") to learn complicated information about data representations, similar to the function of the human brain. Each layer in the network transforms the given input towards producing the desired output. According to [7], the effectiveness of Deep Learning Models is commonly accepted to depend upon 2 key elements.

1. Massive datasets that contain millions of samples,
2. The significant computational power provided by the clusters of Graphics Processing Units(GPUs).

Some of the popular Deep Learning Models in the fashion industry are CNNs, RNNs, Autoencoders, and GANs.

2.1. Convolutional Neural Networks (CNNs)

Computer processing systems called Artificial Neural Networks (ANNs) are modeled after biological nervous systems like the human brain. Neurons, the interconnected computing units that make ANNs, collaborate to learn from incoming data and maximize the output. ANNs are used to process a range of data sources, including image data, and can be learned using supervised or unsupervised learning methods.

CNNs, which are a type of ANN, are employed largely for image processing and recognition applications. They comprise layered, interconnected neurons that can recognize and extract image characteristics [8]. CNNs are geared toward the complex and high-dimensional data commonly present in images, as opposed to regular ANNs, which operate with structured data. Convolutional layers, which apply filters to the input image to extract features at various scales and orientations, are the primary invention of CNNs. Following the passage of these features via completely linked layers (Figure 1), the image is classified using extracted features. CNNs are frequently employed in the fashion industry for several key tasks, such as image recognition, object detection, and segmentation. CNNs have shown promising results in various studies on fashion categorization tasks, such as identifying clothing categories and fashion styles and predicting fashion traits.

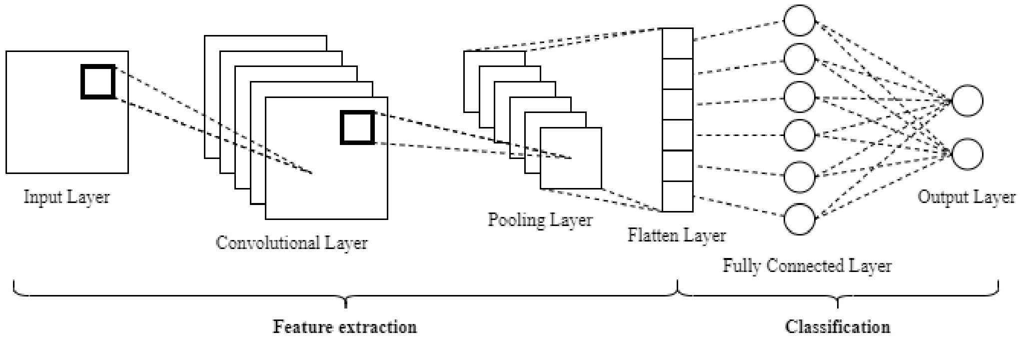

Figure 1. Layers of a CNN [8]

2.2. Recurrent Neural Networks (RNNs)

RNNs are a type of artificial neural network that recognizes patterns in data sequences such as text, genomes, or time series. They are distinguished by their internal memory, which stores information about what has been processed and assists in predicting what will happen next. An RNN comprises nodes that create a directed graph along a temporal sequence, allowing it to behave dynamically across time (Figure 2). Unlike ANNs, RNNs can interpret input sequences using their internal state (memory), making them particularly valuable for sequential decision-making[9].

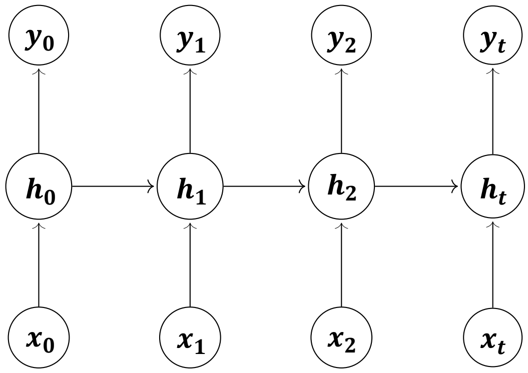

Figure 2. A simple illustration of a Recurrent Neural Network (RNN). The network processes the input sequence $x_0, x_1, x_2, \ldots, x_t$ through its hidden states $h_0, h_1, h_2, \ldots, h_t$, and generates outputs $y_0, y_1, y_2, \ldots, y_t$. The arrows indicate the flow of information [9].

RNNs have made important contributions to the fashion and textile industries by forecasting demand, analyzing trends, and modeling customer preferences. RNNs have also been used in automated design and creative pattern generation[10], where they process historical design sequences to develop new clothing patterns and designs, assisting designers in producing fashion that is consistent with emerging trends.

2.3. Autoencoders

Autoencoders are neural network models comprising two main components: an encoder and a decoder. The encoder reduces the dimensionality of input data to a lower-dimensional representation, while the decoder reconstructs the original data from this compressed form (Figure 3), aiming to minimize the reconstruction error, i.e., the discrepancy between the original and reconstructed data. Autoencoders facilitate data compression, new data generation, and feature extraction, and can be expanded into deeper architectures to learn more complex data features and cater to various needs within the fashion industry.

Among the various autoencoder types, Variational Autoencoders (VAEs) are particularly significant in the fashion industry. Introduced by Kingma and Welling [11], VAEs employ a probabilistic approach that integrates the encoder and decoder into a unified model. Here, the encoder maps input data to a probability distribution in a latent space, and the decoder uses this distribution to generate data that closely resembles the original input. VAEs not only aim to minimize reconstruction errors but also ensure the learned distributions closely match a predefined prior distribution. This model is advantageous over traditional autoencoders due to its ability to generate new, realistic samples, learn organized and continuous data representations, and handle incomplete data effectively.

Figure 3. Basic Autoencoder Architecture[9].

2.4. Generative Adversarial Networks (GANs)

GANs are becoming increasingly prevalent in the fashion industry, where they serve various applications, including image generation, style transfer, and outfit recommendation. Introduced by [12], a GAN consists of two competing models: a generative model, which aims to mimic the data distribution, and a discriminative model, which attempts to distinguish between the generated samples and the actual training data (Figure 4). This adversarial process enables the generation of high-quality, realistic images. Several variations of GANs have been developed to address specific needs within the fashion sector. Conditional GANs, for instance, allow for the generation of images conditioned on certain attributes, such as the type or color of clothing. Progressive growth of GANs (ProGAN) enables the generation of increasingly high-resolution images through a gradual training process, starting from lower resolutions[13]. These advanced GAN models have significantly enhanced the capacity to create detailed and varied fashion-related imagery, catering to various design and marketing applications.

In addition to CNNs, RNNs, Autoencoders, and GANs, other deep-learning techniques have significantly impacted the fashion industry. Deep Neural Networks (DNNs) have provided foundational models capable of handling various complex tasks by stacking multiple layers to learn hierarchical representations of data[14]. Transformers, which utilize self-attention mechanisms, have revolutionized natural language processing and are now being applied to image and video understanding in the fashion domain [15]. Siamese Networks, known for their ability to compare pairs of inputs, are particularly useful for tasks such as fashion item similarity and verification[16]. Residual Networks (ResNets) employ skip connections to enable the training of very deep networks, thus enhancing performance on image recognition tasks crucial for fashion categorization[17]. These advanced deep learning models continue to drive innovation in the fashion industry, enabling more accurate predictions, enhanced image analysis, and improved design automation.

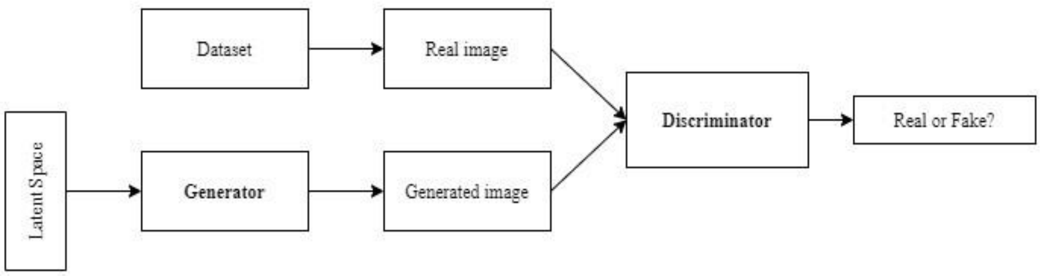

Figure 4. Architecture of a GAN[18].

3. Applications of Deep Learning in Fashion/Apparel

This section provides an in-depth review of the selected studies that present different deep-learning-based solutions for key processes within the textile industry's supply chain. A summary of the reviewed papers under each category is provided in Table 1.

Table 1. Domain areas and papers reviewed

Domain	Sub Domain	Description of the Study	Year	Deep Learning Techniques Applied
Design and trend forecasting	Fashion design generation	[19] Given an unconstrained human image, the algorithm accurately recovers the underlying garment sewing pattern accommodating cost-effective 3D garment design.	2023	Transformer Network
		[20] A text-to-image synthesis model for designing intricate Indian clothing designs that capture details given in the text.	2022	GAN
		[21] Creates unique product designs for the target category, providing designers with inspiration for work.	2021	CNN, DCGAN, and Cond-GAN
		[22] compares the ability of StyleGAN and VQ-VAE-2 in generating sewing patterns, where, although not usable, patterns generated by VQ-VAE-2 were truly new.	2021	StyleGAN vs VQ-VAE-2
		[23] A generative model for African-style clothing design.	2021	GAN
		[24] A framework for generating product designs, retrieving similar images, and recommending matching products, demonstrating the use of one DL architecture for multiple areas.	2020	VAE
		[25] Automated generation of fashion product images with the desired visual attributes while preserving other factors using supervised learning.	2020	GAN
		[26] generation of new clothing patterns while using a style transfer neural network to add Dunhuang elements.	2020	GAN
		[27] demonstrates a method to disentangle the effects of multiple inputs by customizing conditional GANs using a consistency loss function.	2018	Cond-GAN
		[28] proposes a model that successfully designs new fashion products that compose features of trending fashion products with high demand.	2018	CNN, VAE
		[29] proposes a two-stage GAN framework that generates a human segmentation map and a garment for dressing the wearer, given the image of a person. Achieved the best results when compared with four other baseline approaches.	2017	GAN
	Trend Prediction	[30] Forecast the popularity of new fashion products by extracting visual features and textual descriptions instead of historical data.	2022	QAR neural network
		[3] Short-term sales prediction of new fashion products by feature extraction, clustering, and classification.	2022	CNN, Vanilla NN
		[31] Trend prediction of a given product considering relations among fashion elements and user groups. Uses a sliding temporal attention mechanism to capture temporal patterns for long-range forecasts.	2021	RNN, LSTM
		[32]predicts dominant colors and styles for each season and popular outfit combinations. The quality of prediction depends on the quality of training data.	2021	RCNN
		[33] forecasts fashion trends of people in various groups using an LSTM encoder-decoder framework to model time series fashion data.	2020	RNN, LSTM

Domain	Sub Domain	Description of the Study	Year	Deep Learning Techniques Applied
Quality Control	Fabric defect detection	[34] uses an advanced CNN-based model to detect small-scale fabric defects.	2022	YOLOv4
		[35] Optimizes a CNN model using False-Negative reduction methods as undetected defects have a higher impact than non-defective fabrics detected as defective, attaining an accuracy level of 95%.	2021	CNN
		[4] Addresses the manual annotation cost of datasets with a segmentation network and decision network achieving real-time defect detection.	2021	CNN
		[36] improves a Faster R-CNN model using a deep residual network for feature extraction and multi-scale fusion to achieve small object defect detection.	2020	Faster R-CNN
		[37] Synthesizes defects into new fabrics using a GAN model trained on individual defect types. Demonstrates the potential of these synthetic datasets by training fabric defect detection models.	2020	GAN
		[38] extends the standard DCGAN by adding an encoder to reconstruct query images without defects, then subtracts the reconstruction from the original image to highlight possible defect areas.	2019	DCGAN
		[39] addresses limitations in the training dataset by a model trained to synthesize and incorporate realistic defects in new defect-free samples with varying texture backgrounds.	2019	Multistage GAN
Marketing and Sales	Product recommendation systems	[40]A sequence-to-sequence generative model is trained on Semantic IDs from a user session to predict the next item the user will interact with.	2023	Transformer Network
		[41] extracts required features from the given product image and recommends novel and related product items, addressing the cold start problem.	2021	DNN
		[42] Given a clothing collocation, it produces a score that indicates the degree to which the clothes match.	2021	DNN
		[43] A style recommendation model trained on expert-recommended clothing styles for each body type.	2021	GoogleNet, Inceptionv3, BiDNN
		[44] A similar image based on the features and texture is recommended for a given fashion image using the Cosine Similarity Measure.	2020	CNN
		[45] A Sketch-to-Product fashion retrieval model and a vector-based fashion recommendation model that uses implicit user profiling.	2020	GAN, CNN, DNN
		[46] recommends patterns by considering the color compatibility of the textile products.	2020	CNN
		[47] Outfit complementary item retrieval using a category-based subspace attention network (CSA-Net). A CNN extracts visual features, CSA-Net captures item similarity through embeddings, and KNN retrieves compatible items.	2020	CNN, CSA-Net
		[48] Given an image of a person, identifies the best garments for their body shape, showing its effectiveness over body-agnostic recommendations through automated metrics and human feedback.	2020	CNN
		[49] proposes a model that takes multiple modes of input (product images, descriptions, review texts) and provides a list of fashion recommendations.	2019	Stacked Convolutional Auto-encoders

Domain	Sub Domain	Description of the Study	Year	Deep Learning Techniques Applied
Distribution and Retail	Inventory	[50] A multi-class outfit image classification model that improves training time and fine-grained accuracy over traditional branching CNNs.	2021	CNN
		[51] provides 5 different architectures of CNN models for classification, comparing their accuracy over 2 datasets.	2020	CNN
	Virtual Try-On	[52] A refined image-based VTON system that addresses issues in earlier models, such as errors in human representation, dataset, network design, and cost function. However, it is limited to simple clothing and standard human poses.	2020	CNN
		[53] An AR-based fashion design system, where a sketch and theme image are fed into a Controllable GAN to generate dresses, and the virtual apparel is visualized in real-time.	2022	GAN
		[54] Garments are automatically placed on human models in any pose, with alignment, stitching, and result refinement all handled by a single network.	2020	GAN
		[55] A video virtual try-on system that transfers clothes onto a person and creates realistic videos in any pose using flow-guided fusion for smooth synthesis, a warping net for clothes and texture refinement, and parsing constraint loss to fix segmentation misalignment.	2019	GAN
		[56] seamlessly transfers clothing onto a person in an image using a coarse-to-fine approach, showing that 2D image-based synthesis can be a cost-effective alternative to 3D methods.	2018	GAN

3.1. Design and Trend Forecasting

3.1.1. Fashion Design Generation

Deep learning can be used to enhance fashion design by automating the creation of innovative and aesthetically pleasing designs, exploiting neural networks to learn and replicate intricate patterns and styles from vast datasets of existing fashion items. This technology enables designers to rapidly prototype and experiment with new ideas, reducing time and costs associated with manual design processes while maintaining high levels of creativity and uniqueness.

Study [24] emphasizes how consumers can create fashion products that suit their tastes by using VAEs' capacity to generate latent codes for generative modeling and feature extraction. Additionally, the paper offers encouraging outcomes for image retrieval and clustering using VAEs, with mAP for the top-10, top-25, and top-50 most similar image retrieval reaching 0.95. The application can also take advantage of image extraction algorithms and user-generated latent codes for various cross-product recommendations. As demonstrated in the paper, this is a helpful tool for the fashion industry. Further aiding the production of new fashion items with popular styles learned from historical data [28] introduced a model fusing CNN with VAE. Incorporating both product features and popularity information derived from transaction data, products are automatically designed based on discovered popular styles. Regardless of the model's flexibility in replacing transactional data with consumer preference data (votes) for more relevant results, the proposed approach is highly dependent on the dataset used and may not be practical in a dynamic industry like fashion and textile.

As we observed, a rather unexplored application of deep learning in fashion is the generation of sewing patterns to aid garment production. Research [22] compared the performance of StyleGAN and VQVAE-2 in generating sewing patterns for garments. However, as demonstrated in the experiments, both models failed to produce sensible results due to the limited training data, according to the author. However, the study provides an idea to build upon and introduce more accurate techniques to generate sewing patterns for garments that precisely fit the defined silhouette. Meanwhile, [19] proposed Sewformer, a two-level Transformer network for sewing pattern prediction given an RGB image of an outfit. Although the model's ability is limited to generalized clothing designs, it paves the way for further exploration of similar models that help customize patterns to fit individual silhouettes, apply different styles to basic patterns, and consider the effect of different fabrics and textures on sewing patterns.

Also aiding in garment design tasks, FashionGAN was proposed [29], where a fresh garment design is created using a combination of a wearer's photograph and a textual description of the desired outfit. This technique helps create new designs efficiently, cutting the time and expense needed for conventional design techniques. Additionally, it may be utilized to produce personalized designs for each user based on their personal preferences and needs. Yet, it's essential to point out that FashionGAN does not necessarily help produce any unique or creative designs but simply paints the picture based on the artist's description.

Focussing on image reconstruction, [25] created images of fashion products with appropriate visual characteristics using a DA-GAN (Design Attribute GAN) model. Experiments on a sizable fashion dataset demonstrate the promise of GAN for attribute-aware generative design. This helps designers solve challenges faced in their devotion to specific ideals and the expanding demands of consumers. To regulate the color, texture, and shape of a generated garment image, [27] provided a way to decouple the impacts of various input factors in GANs. The technology is based on customized conditional GANs with consistency loss functions. The generator offers the chance to create and modify fashion images quickly. Adding more color inputs can enhance the approach to allow texture input directly from a picture or another piece of content and more sophisticated control over the production process, improving fashion product design and adjustment.

Aiding in fashion image generation, [21] proposed an "emotionally intelligent" model for designing and recommending fashion products to solve the cognitive differences between designers and consumers in emotional product design. The approach consists of two models; a product image recognition model based on CNN and a design generation model comprised of a DCGAN and Conditional GAN. While the image recognition model was used for image labeling, the generation model generated unique product designs, in this case, male and female footwear. Experiments conducted depict the model's capability to generate intricate details of each style of footwear and distinctly identify and learn the differences between each category (formal, casual, male, female).

GANs have also been used to create fashion datasets that resemble unique traditions and cultures, which can potentially help provide personalized recommendations, as seen in [20] which introduces a GAN-based text-to-image synthesis model Vastr-GAN for creating complicated Indian clothing designs. Numerous trained GAN models have been integrated into the research. The model successfully captured the details provided in the text descriptions through thorough testing on the dataset. Similarly, [23] and [26] also propose models for generating designs with different traditional elements. These studies could inspire the design of more fashionable items incorporating traditional elements as well as other environmental factors.

3.1.2. Trend prediction

Trend prediction systems enable designers and retailers to anticipate and respond to emerging consumer preferences and market demands. By identifying patterns and predicting future trends, businesses can make informed decisions about design, production, and inventory management, reducing the risk of overproduction and stockouts.

Knowledge Enhanced Recurrent Network Model (KERN) is a forecasting model proposed by [33] for forecasting fashion trends of people in various user groups (defined by geographical region, age, and gender), leveraging both internal and external knowledge. Inspired by Deep Recurrent Neural Networks, the model uses an LSTM encoder-decoder framework to model time series fashion data. LSTM encoder decoder architecture is a type of RNN, specifically designed to remember information for long periods of time. Extending this work, the researchers also propose a Relation Enhanced Attention Recurrent (REAR) network [31], which considers relationships among fashion elements as well as those among user groups for improved accuracy.

Neo-fashion [32] used a different approach to predict dominant colors in each season, seasonal styles, and popular outfit combinations by combining computer vision and machine learning. The system uses a Region Convolutional Neural Network (RCNN) to detect clothes on the model in the images from the prepared catwalk images dataset and uses the K-means algorithm for trend analysis and forecasting. To forecast demand for an end product, [3] uses historical sales data for short-term sales prediction (weekly) of new fashion items. This intelligent forecasting system extracts the product image features using CNN, identifies the clusters for product historical sales data using the K-means algorithm, and classifies accordingly using a vanilla neural network which outperformed Support Vector Machines (SVM), Random Forest (RF), and Na¨ıve Bayes (NB). Addressing the limitation of needing historical product data for trend forecasting, [30] forecasts the popularity of new products that lack historical data using a multimodal multilayer perceptron (FusionMLP) and a Quasi-Auto-Regressive (QAR) neural network.

While various trend forecasting systems exist that consider different data sources, studies can be conducted to analyze and identify which yields the best results for a given context.

3.2. Quality Control

3.2.1. Fabric defect detection

Fabric defect detection is critical for quality control and efficiency in the fashion and textile industry. Most studies in this domain employ CNN-based models with high accuracy to automatically identify and classify defects, such as holes, tears, stains, and weaving inconsistencies. However, a concern raised in many studies within this domain is the lack of data representing all fabric defects.

A study [36] introduced an improved Faster R-CNN for fabric defect detection. Its improvements include using a deep residual network for feature extraction instead of the conventional method (VGG-16), multiscale fusion to detect small object defects, and softmax regularization to improve network convergence ability and classification accuracy. Likewise, [35] optimized a CNN-based model developed for fast and automatic defect detection using False-Negative reduction methods, as undetected defects have a higher impact on businesses than non-defective fabrics detected as defective. To reduce manual annotation effort for labeling training data of such models, [4] developed a CNN for fabric defect segmentation and detection, where with only 50 defect samples, the model achieved real-time defect detection capability. Following these studies, [34] presented a YOLOv4 (an advanced CNN-based model) improved for detecting small-scale fabric defects close to the background shape. The paper also suggested an improved SPP (Spatial Pyramid Pooling) structure that can be adapted to other YOLO models to improve detection accuracy.

In contrast to the above-discussed studies, some studies utilized generative models for synthesizing and detecting fabric defects. Research [38] automatically detects defects in fabrics extending the standard DCGAN by introducing a new encoder component. This extension helps reconstruct a given query image such that no defects but only normal textures will be preserved in the reconstruction. Then, subtracting the reconstruction from the original image creates a residual map to highlight potential defective regions. Addressing limitations in the training dataset mentioned earlier, [39] combined a deep semantic segmentation network with a multistage GAN trained to synthesize and incorporate realistic defects in new defect-free samples with varying texture backgrounds. By continuously updating the fabric defect dataset, the multistage GAN contributes to fine-tuning the deep semantic segmentation network. Similarly, [37] trained a GAN model on individual defect types in an image-to-image translation framework requiring a limited annotated training dataset and synthesized defects into new fabrics at the locations specified by a segmentation mask of arbitrary shape. The authors also successfully demonstrated the potential of these synthetic datasets for developing versatile fabric defect detection models.

While studies like those by [36] and [34] have improved detection accuracy and addressed small-scale defect detection, the reliance on extensive manual annotation still remains a challenge, as highlighted by [4]. In addition, although generative models like those proposed by [38] and [39] offer innovative approaches to augment datasets with synthetic defects, the effectiveness of these synthetic datasets in real-world applications requires further validation. More research on integrating various deep learning models to create a robust, end-to-end defect detection system that can handle diverse fabric textures and defect types with minimal manual intervention can also be explored within this problem domain.

3.3. Marketing and Sales

3.3.1. Product recommendation systems

Regardless of the application domain, recommender systems have been employed in several areas including e-commerce, entertainment as well as education platforms. The fashion industry is one such area where recommender systems are heavily used. These systems use various deep-learning techniques to provide personalized shopping experiences and improve customer satisfaction. While there are various reviews [57]–[60] conducted solely on recommender systems that employ neural networks, this section briefly outlines a few.

While most early recommender systems consider only single input sources, Deep-MINE [49], a recommendation model employing stacked convolutional auto-encoders, takes multiple content sources such as product images, textual descriptions, and reviews to provide a suitable recommendation list. As this system only considers consumer purchase behavior, it could be further extended to consider other influential factors that affect consumer purchase decisions.

Although not "personalized" as claimed in its title, [44] proposed a recommender system that recommends outfits similar to the given fashion image based on the features and textures identified. This was implemented using a CNN and Cosine similarity measure. Providing a similar capability, [41] introduced a recommendation model built on a DNN. In addition to the query image, this model also recognizes the gender of the given outfit to recommend suitable items. Also addressing the fashion product retrieval task, [45] proposed a Sketch-Product fashion retrieval model and a vector-based user-preferred recommendation model using an implicit user profiling method. The model employs a GAN to up-sample sketches, a CNN to convert to image features, and a DNN to learn fashion profile.

Aiding in complimentary product recommendation tasks, [46] introduces a model that considers the color compatibility of textile products and recommends matching patterns. Similarly, [47] suggests a complementary item retrieval model using a Category-based Subspace Attention network (CSANet). Incorporating a CNN for visual feature vector extraction and a KNN for compatible item retrieval, this system's capability was well demonstrated on fashion outfits. These models are ideal candidates to be used along with design generation or styling systems for fashion products. Further enhancing these use cases, [42] introduces a model that produces a score that indicates the degree to which given clothing pairs match. Unlike other similar systems, this model considers both clothing design as well as clothing color collocation. In contrast to the above discussed, [40] trains a generative model, specifically a Transformerbased sequence-to-sequence model, to predict the Semantic ID of the next item that the user will interact with, given Semantic IDs for items in a user session.

A rather less explored gap within the domain, as we observed, is the inclusion of different body types in these recommendation models, to provide consumers the opportunity to make more informed fashion choices. Studies [43] and [48] are among the few such body-aware garment recommendation systems. Study [48] proposed ViBE, a VIsual Body-aware Embedding system, that identifies the most complementary garments to the body shape identified from the given image of the person. This employs a CNN to mine attributes for dresses. Research [43] used GoogleNet Inception-v3, a CNN-based model, and a Bidirectional symmetrical DNN (BiDNN), VAE-based, to recommend clothing styles for each body type as recommended by fashion experts.

3.4. Distribution and Retail

3..4.1. Inventory management

Deep learning techniques are useful in improving inventory classification and management in the fashion and textile industry by enabling precise categorization and efficient handling of stock. While trend forecasting systems discussed previously are highly important for efficient inventory management, product classification systems help automate various manual tasks. The Condition-CNN model proposed by [50], solves the drawbacks of other existing models by reliably and efficiently predicting many levels of classes. In comparison to baseline CNN models, Condition-CNN provides higher prediction accuracy while using fewer trainable parameters using the "Teacher Forcing" training technique with conditional probabilities. This method can be used in the fashion sector to precisely classify photographs based on their class hierarchy aiding in product recommendation, visual search, and image retrieval. The work of [51] also recommends CNNs for image classification demonstrated on handwritten digits and clothing items. The study demonstrates the model's effectiveness by achieving high accuracy rates for MNIST and Fashion-MNIST datasets.

3.4.2. Virtual try-on

Virtual try-on technology provides realistic and interactive experiences for customers by allowing them to visualize clothes and accessories without wearing them physically. Utilizing deep learning techniques in the process ensures that garments fit naturally and look realistic to customers, thereby increasing purchase confidence and decreasing return rates.

The virtual try-on network used in VITON by [56] uses a GAN that uses a multi-task encoder-decoder and a refinement network to realistically transfer apparel from product photos to a human while using RGB images. The proposed technique could be used in online shopping and virtual fitting rooms to let customers virtually try on clothing before purchasing. Personal styling advice, virtual wardrobe organizing, and even virtual fashion shows can be potential future uses for this technology. The FW-GAN is a revolutionary framework that creates visually realistic videos for a "video virtual try-on system" [55]. It employs a warping net to enhance clothing textures, a flow-guided fusion module to warp previous frames and a parsing constraint loss to fix misalignment problems. It outperforms previous techniques in terms of producing realistic and coherent movies with excellent outcomes for virtual try-ons. Other than fashion, the FW-GAN can also be used in entertainment and gaming industries where video-based virtual try-on is desirable. Poly-GAN is a conditional GAN that enables fashion synthesis by autonomously placing a reference cloth on human models in various positions and dressing them in various outfits [54]. In contrast to earlier efforts that required numerous networks, it uses a single architecture to carry out many functions, such as matching the fabric item with the human position, stitching the cloth, and improving the output. Fashion items unique to each customer depending on his/her body form, size, and style preferences could be created using this approach. Additionally, Poly-GAN is also a potential plugin for both online and offline clothing retail stores.

Research [53] utilizes a conditional GAN-based model to generate synthetic fashion images capturing the colors and textures of a given theme image according to a base sketch of a design. The model then uses OpenCV for computer vision-based AR and integrates with the GAN component to map the generated image to human body coordinates. This research mainly focuses on bridging the gap between virtual try-ons and theme-based fashion design.

Employing a CNN, CP-VTON+ [52], an enhanced image-based virtual try-on system, addresses shortcomings in earlier methods, such as inaccuracies in human representation and the dataset, network architecture, and loose cost functions. Both quantitatively and qualitatively, the system greatly outperforms modern contemporary techniques. However, it is also noted that a 2D image-based technique has drawbacks when dealing with various human stances and attire. Therefore, we believe 3D reconstruction may be more appropriate for related business use cases.

4. Critical Analysis of Work

Studies reviewed on design and trend forecasting demonstrate the promising application of deep learning techniques in generating clothing designs and predicting fashion trends. Research [24] and [28] showcase the potential of VAEs and CNN-VAE hybrids to generate designs and recommend products based on learned styles. However, the dependency on the quality and diversity of training datasets remains a critical limitation, which may affect the practical applicability of these models in the dynamic fashion industry. While [19] and [22] explored the generation of sewing patterns using deep learning, the limited training data significantly hampered the effectiveness of their models, indicating a need for larger, more diverse datasets and further model refinement. Additionally, during this review, a limited number of studies were observed that focused on sewing pattern generation despite it being a complex process where designers actually need significant help. More research is needed to address this gap and assist designers in automating this intricate task. Moreover, although FashionGAN [29] and subsequent studies like [21] and [25] highlight the innovative use of GANs in design generation, they primarily focussed on generating designs from predefined descriptions or styles rather than encouraging true creativity. This shows that while these models can aid designers in their work, they may not fully replace the creative process inherent in fashion design.

The studies on trend prediction systems highlight diverse methodologies for enhancing fashion trend forecasting. KERN [33] and its extension REAR [31] leverage LSTM and attention mechanisms to capture trends across user demographics. Research [32] adopts a computer vision-centric approach using RCNN and Kmeans clustering, emphasizing image-focused trend prediction. Study [3] combines CNNs and traditional ML algorithms for short-term sales predictions, while [30] addresses data scarcity using multimodal MLPs and QAR neural networks. These studies collectively underscore the complex nature of trend forecasting, each contributing unique insights and methods. However, a critical comparative analysis of these approaches in their application contexts is necessary to discover their relative efficacy and applicability, which could guide businesses in selecting the most appropriate forecasting system tailored to their needs.

Fabric defect detection is a critical area where deep learning has shown substantial progress, yet significant challenges remain. Studies like [34] and [36] have improved defect detection accuracy using enhanced CNN-based models, addressing issues such as small object detection and convergence ability. However, the need for extensive manual annotation of training data, as pointed out by [4], poses a significant bottleneck, limiting scalability and real-world applicability. Generative models proposed by [38] and [39] offered innovative solutions to augment datasets with synthetic defects, which can diminish some of the data scarcity issues. Nevertheless, the real-world effectiveness of these synthetic datasets needs further validation, as discrepancies between synthetic and actual fabric defects might still exist. Using deep learning to create a robust, end-to-end defect detection system that can handle diverse fabric textures and defect types with minimal manual intervention is a promising direction for future research, addressing the current gaps in the literature.

The studies cited on product recommendation systems reveal significant advancements and diverse approaches that utilize deep learning to enhance personalization and customer satisfaction. Early systems like Deep-MINE [49] innovatively integrated multiple content sources to generate recommendations, yet they remain limited by focusing predominantly on consumer purchase behavior, neglecting other influential factors such as social trends and contextual data. Similarly, [41] and [44] propose models based on CNN and DNN, respectively, for image-based outfit recommendations, but their personalization abilities are limited by their relatively narrow focus. More advanced models, such as the Sketch-Product fashion retrieval system by [45] and complementary item recommendation models by [46] and [47], demonstrated the potential of GANs and CSA-Nets in enhancing fashion product retrieval and matching tasks. These studies, however, often overlook the complexity of integrating design aesthetics and user preferences. Although [42] and [40] provided novel methods for evaluating clothing pair compatibility and predicting user interactions using generative models, they do not fully address the personalized needs of diverse body types. The inclusion of body-aware recommendation systems by [43] and [48] marks an essential step towards more inclusive fashion recommendations, highlighting the need for further research in incorporating diverse body types and personalized fitting into recommendation algorithms to ensure broader applicability and consumer satisfaction.

Additionally, inventory management in the fashion industry can be greatly improved through deep learning-based classification systems. The Condition-CNN model [50] and other similar models like those proposed by [51] show high accuracy in classifying fashion items, which is crucial for efficient inventory management. However, these models also rely heavily on extensive and well-annotated training datasets, highlighting a common challenge across deep learning applications in fashion. Enhanced methods for dataset augmentation and annotation efficiency, possibly through semi-supervised or unsupervised learning techniques, could address this limitation and enhance the applicability of these models in realworld scenarios.

In virtual try-on technology, deep learning techniques have significantly enhanced the realism and interactivity of virtual fitting experiences. Models such as VITON [56] and FW-GAN [55] demonstrate the ability of GANs to transfer apparel onto human models with high visual fidelity, which can transform online shopping by reducing return rates and increasing customer satisfaction. However, these models often struggle with varying human poses and attire complexities, suggesting that future developments might benefit from incorporating 3D reconstruction techniques for more accurate representations.

5. Conclusions and Future Work

In conclusion, deep learning has revolutionized the fashion industry by improving the efficiency of tasks throughout the fashion industry's supply chain. CNNs, RNNs, Autoencoders, GANs, Transformers, and other deep learning models have proven to be effective tools for various tasks, from image recognition and defect detection to product recommendation and virtual try-on systems. These technologies have enabled more accurate and efficient processes, contributing to better customer experiences and streamlined operations within the fashion sector. However, challenges such as the dependency on large, high-quality datasets, the need for extensive manual annotation, and the limitations of current models in generating truly creative designs or accurately representing the influential factors that affect clothing choices, such as different body types remain significant.

Future research should focus on developing more sophisticated deep-learning models that can handle the fashion industry's dynamic nature and consumers' diverse needs. This includes creating larger and more diverse training datasets, enhancing model architectures to improve accuracy and reduce the need for manual annotation, and integrating multimodal data sources to capture a wider range of influential factors in trend forecasting and product recommendation. Additionally, exploring the use of 3D reconstruction for virtual try-on systems and incorporating diverse body types into recommendation models will ensure more personalized and inclusive fashion experiences. The aspect of assessing personal preferences, i.e. aesthetic and emotional connotations associated with a fashion design, may be further approached by combining the aforementioned AI methods with neuroscience technologies. For instance, electroencephalography (EEG) is emphasized in creating wearables for fashion design due to its capability to detect cognitive processes and aesthetic appraisal[61].

While the performance of the existing models can be improved, there have been a limited number of studies on sewing pattern generation, body-aware clothing design generation, prediction of near future fashion trends, and complimentary clothing item recommendations. Moreover, as this review only focused on selected areas within the fashion industry, future studies could focus on the applications of deep learning in other areas of the fashion industry, such as apparel production optimization, customer behavior analysis, ethical sourcing, and Circular Fashion. By addressing these areas, AI has the potential to innovate and transform the fashion industry, driving it towards a more efficient, creative, and sustainable journey.

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References

[1] A. Singha Roy, E. D'Amico, A. Lawlor, and N. Hurley, "Addressing Fast Changing Fashion Trends in Multi-Stage Recommender Systems," *Int. FLAIRS Conf. Proc.*, vol. 36, May 2023, doi: 10.32473/flairs.36.133307.

[2] A. Martín-Martín, M. Thelwall, E. Orduna-Malea, and E. Delgado López-Cózar, "Google Scholar, Microsoft Academic, Scopus, Dimensions, Web of Science, and OpenCitations' COCI: a multidisciplinary comparison of coverage via citations," *Scientometrics*, vol. 126, no. 1, pp. 871–906, Jan. 2021, doi: 10.1007/s11192-020-03690-4.

[3] C. Giri and Y. Chen, "Deep Learning for Demand Forecasting in the Fashion and Apparel Retail Industry," *Forecasting*, vol. 4, no. 2, pp. 565–581, Jun. 2022, doi: 10.3390/forecast4020031.

[4] Y. Huang, J. Jing, and Z. Wang, "Fabric Defect Segmentation Method Based on Deep Learning," *IEEE Trans. Instrum. Meas.*, vol. 70, pp. 1–15, 2021, doi: 10.1109/TIM.2020.3047190.

[5] J. W. Chong, W. Kim, and J. Hong, "Optimization of Apparel Supply Chain Using Deep Reinforcement Learning," *IEEE Access*, vol. 10, pp. 100367–100375, 2022, doi: 10.1109/ACCESS.2022.3205720.

[6] T. Islam, A. Miron, X. Liu, and Y. Li, "Deep Learning in Virtual Try-On: A Comprehensive Survey," *IEEE Access*, vol. 12, pp. 29475–29502, 2024, doi: 10.1109/ACCESS.2024.3368612.

[7] J. Fan, C. Ma, and Y. Zhong, "A Selective Overview of Deep Learning," *Stat. Sci.*, vol. 36, no. 2, May 2021, doi: 10.1214/20-STS783.

[8] K. O'Shea and R. Nash, "An Introduction to Convolutional Neural Networks." Nov. 26, 2015. [Online]. Available: http://arxiv.org/abs/1511.08458

[9] A. Zhang, Z. C. Lipton, M. Li, and A. J. Smola, *Dive into Deep Learning*. Cambridge University Press, 2023. [Online]. Available: https://d2l.ai/d2l-en.pdf

[10] M. Yanning, Q. Na, and Z. Qing, "Motion-Variational Recurrent Neural Network for Character Garment Simulation," in *2021 6th International Conference on Intelligent Computing and Signal Processing (ICSP)*, Apr. 2021, pp. 1359–1363. doi: 10.1109/ICSP51882.2021.9408913.

[11] D. P. Kingma and M. Welling, "Auto-Encoding Variational Bayes," Dec. 2013, [Online]. Available: http://arxiv.org/abs/1312.6114

[12] I. Goodfellow *et al.*, "Generative adversarial networks," *Commun. ACM*, vol. 63, no. 11, pp. 139–144, Oct. 2020, doi: 10.1145/3422622.

[13] T. Karras, T. Aila, S. Laine, and J. Lehtinen, "Progressive Growing of GANs for Improved Quality, Stability, and Variation," *ArXiv*. Oct. 27, 2017. [Online]. Available: http://arxiv.org/abs/1710.10196

[14] Y. LeCun, Y. Bengio, and G. Hinton, "Deep learning," *Nature*, vol. 521, no. 7553, pp. 436–444, May 2015, doi: 10.1038/nature14539.

[15] A. Vaswani *et al.*, "Attention Is All You Need," in *Advances in Neural Information Processing Systems 30 (NIPS 2017)*, Jun. 2017. [Online]. Available: http://arxiv.org/abs/1706.03762

[16] G. Koch, R. Zemel, and R. Salakhutdinov, "Siamese Neural Networks for One-Shot Image Recognition," vol. 2015. [Online]. Available: https://www.cs.cmu.edu/~rsalakhu/papers/oneshot1.pdf

[17] K. He, X. Zhang, S. Ren, and J. Sun, "Deep Residual Learning for Image Recognition," in *2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, Jun. 2016, vol. 2016-Decem, pp. 770–778. doi: 10.1109/CVPR.2016.90.

[18] A. Dash, J. Ye, and G. Wang, "A review of Generative Adversarial Networks (GANs) and its applications in a wide variety of disciplines: From Medical to Remote Sensing," *IEEE Access*, pp. 1–1, 2023, doi: 10.1109/ACCESS.2023.3346273.

[19] L. Liu, X. Xu, Z. Lin, J. Liang, and S. Yan, "Towards Garment Sewing Pattern Reconstruction from a Single Image," *ACM Trans. Graph.*, vol. 42, no. 6, pp. 1–15, Dec. 2023, doi: 10.1145/3618319.

[20] H. Shastri, D. Lodhavia, P. Purohit, R. Kaoshik, and N. Batra, "Vastr-GAN: Versatile Apparel Synthesised from Text using a Robust Generative Adversarial Network," in *Proceedings of the 5th Joint International Conference on Data Science & Management of Data (9th ACM IKDD CODS and 27th COMAD)*, Jan. 2022, pp. 222–226. doi: 10.1145/3493700.3493721.

[21] C. Yang, Y. Zhou, B. Zhu, C. Yu, and L. Wu, "Emotionally Intelligent Fashion Design Using CNN and GAN," *Comput. Aided. Des. Appl.*, vol. 18, no. 5, pp. 900–913, Jan. 2021, doi: 10.14733/cadaps.2021.900-913.

[22] S. Lehtiniemi, "Generative Models in Sewing Pattern Creation," Aalto University. [Online]. Available: https://aaltodoc.aalto.fi/server/api/core/bitstreams/92e87fab-815e-4726-afa7-68a306c98b48/content

[23] M. Salami, W. Oyewusi, and O. Adekanmbi, "AFRIGAN: African Fashion Style Generator using Generative Adversarial Networks(GANs)," in *Black in AI Workshop, Thirty-fifth Conference on Neural Information Processing Systems (NeurIPS)*, 2021.

[24] J.-A. Sarmiento, "Exploiting Latent Codes: Interactive Fashion Product Generation, Similar Image Retrieval, and Cross-Category Recommendation using Variational Autoencoders," *arXiv*. Sep. 02, 2020. [Online]. Available: http://arxiv.org/abs/2009.01053

[25] C. Yuan and M. Moghaddam, "Attribute-Aware Generative Design With Generative Adversarial Networks," *IEEE Access*, vol. 8, pp. 190710–190721, 2020, doi: 10.1109/ACCESS.2020.3032280.

[26] Q. Wu *et al.*, "ClothGAN: generation of fashionable Dunhuang clothes using generative adversarial networks," *Conn. Sci.*, vol. 33, no. 2, pp. 341–358, Apr. 2021, doi: 10.1080/09540091.2020.1822780.

[27] G. Yildirim, C. Seward, and U. Bergmann, "Disentangling Multiple Conditional Inputs in GANs," in *AI for Fashion in KDD Conference*, Jun. 2018. [Online]. Available: http://arxiv.org/abs/1806.07819

[28] J. Zhu, Y. Yang, J. Cao, and E. C. F. Mei, "New Product Design with Popular Fashion Style Discovery Using Machine Learning," in *Artificial Intelligence on Fashion and Textiles*, 2019, pp. 121–128. doi: 10.1007/978-3-319-99695-0_15.

[29] S. Zhu, S. Fidler, R. Urtasun, D. Lin, and C. C. Loy, "Be Your Own Prada: Fashion Synthesis with Structural Coherence," in *2017 IEEE International Conference on Computer Vision (ICCV)*, Oct. 2017, pp. 1689–1697. doi: 10.1109/ICCV.2017.186.

[30] S.-I. Papadopoulos, C. Koutlis, S. Papadopoulos, and I. Kompatsiaris, "Multimodal Quasi-AutoRegression: forecasting the visual popularity of new fashion products," *Int. J. Multimed. Inf. Retr.*, vol. 11, no. 4, pp. 717–729, Dec. 2022, doi: 10.1007/s13735-022-00262-5.

[31] Y. Ding, Y. Ma, L. Liao, W. K. Wong, and T.-S. Chua, "Leveraging Multiple Relations for Fashion Trend Forecasting Based on Social Media," *IEEE Trans. Multimed.*, vol. 24, pp. 2287–2299, 2022, doi: 10.1109/TMM.2021.3078907.

[32] L. Zhao, M. Li, and P. Sun, "Neo-Fashion: A Data-Driven Fashion Trend Forecasting System Using Catwalk Analysis," *Cloth. Text. Res. J.*, vol. 42, no. 1, pp. 19–34, Jan. 2024, doi: 10.1177/0887302X211004299.

[33] Y. Ma, Y. Ding, X. Yang, L. Liao, W. K. Wong, and T.-S. Chua, "Knowledge Enhanced Neural Fashion Trend Forecasting," in *Proceedings of the 2020 International Conference on Multimedia Retrieval*, Jun. 2020, pp. 82–90. doi: 10.1145/3372278.3390677.
[34] Q. Liu, C. Wang, Y. Li, M. Gao, and J. Li, "A Fabric Defect Detection Method Based on Deep Learning," *IEEE Access*, vol. 10, pp. 4284–4296, 2022, doi: 10.1109/ACCESS.2021.3140118.
[35] T. Almeida, F. Moutinho, and J. P. Matos-Carvalho, "Fabric Defect Detection With Deep Learning and False Negative Reduction," *IEEE Access*, vol. 9, pp. 81936–81945, 2021, doi: 10.1109/ACCESS.2021.3086028.
[36] M. An, S. Wang, L. Zheng, and X. Liu, "Fabric defect detection using deep learning: An Improved Faster R-approach," in *2020 International Conference on Computer Vision, Image and Deep Learning (CVIDL)*, Jul. 2020, pp. 319–324. doi: 10.1109/CVIDL51233.2020.00-78.
[37] O. Rippel, M. Muller, and D. Merhof, "GAN-based Defect Synthesis for Anomaly Detection in Fabrics," in *2020 25th IEEE International Conference on Emerging Technologies and Factory Automation (ETFA)*, Sep. 2020, pp. 534–540. doi: 10.1109/ETFA46521.2020.9212099.
[38] G. Hu, J. Huang, Q. Wang, J. Li, Z. Xu, and X. Huang, "Unsupervised fabric defect detection based on a deep convolutional generative adversarial network," *Text. Res. J.*, vol. 90, no. 3–4, pp. 247–270, Feb. 2020, doi: 10.1177/0040517519862880.
[39] J. Liu, C. Wang, H. Su, B. Du, and D. Tao, "Multistage GAN for Fabric Defect Detection," *IEEE Trans. Image Process.*, vol. 29, pp. 3388–3400, 2020, doi: 10.1109/TIP.2019.2959741.
[40] S. Rajput *et al.*, "Recommender Systems with Generative Retrieval," in *The 37th Conference on Neural Information Processing Systems (NeurIPS 2023)*, May 2023, pp. 10299–10315. [Online]. Available: http://arxiv.org/abs/2305.05065
[41] N. Yarahmadi Gharaei, C. Dadkhah, and L. Daryoush, "Content-based Clothing Recommender System using Deep Neural Network," in *2021 26th International Computer Conference, Computer Society of Iran (CSICC)*, Mar. 2021, pp. 1–6. doi: 10.1109/CSICC52343.2021.9420544.
[42] C. Zhang, X. Yue, C. Yu, and Z. Wang, "Clothing Color Collocation with Deep Neural Networks," *AATCC J. Res.*, vol. 8, no. 1_suppl, pp. 173–180, Sep. 2021, doi: 10.14504/ajr.8.S1.21.
[43] S. C. Hidayati *et al.*, "Dress With Style: Learning Style From Joint Deep Embedding of Clothing Styles and Body Shapes," *IEEE Trans. Multimed.*, vol. 23, pp. 365–377, 2021, doi: 10.1109/TMM.2020.2980195.
[44] M. Sridevi, N. ManikyaArun, M. Sheshikala, and E. Sudarshan, "Personalized fashion recommender system with image based neural networks," *IOP Conf. Ser. Mater. Sci. Eng.*, vol. 981, p. 022073, Dec. 2020, doi: 10.1088/1757-899X/981/2/022073.
[45] J. Jo, S. Lee, C. Lee, D. Lee, and H. Lim, "Development of Fashion Product Retrieval and Recommendations Model Based on Deep Learning," *Electronics*, vol. 9, no. 3, p. 508, Mar. 2020, doi: 10.3390/electronics9030508.
[46] U. Turkut, A. Tuncer, H. Savran, and S. Yilmaz, "An Online Recommendation System Using Deep Learning for Textile Products," in *2020 International Congress on Human-Computer Interaction, Optimization and Robotic Applications (HORA)*, Jun. 2020, pp. 1–4. doi: 10.1109/HORA49412.2020.9152875.
[47] Y.-L. Lin, S. Tran, and L. S. Davis, "Fashion Outfit Complementary Item Retrieval," in *2020 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, Jun. 2020, pp. 3308–3316. doi: 10.1109/CVPR42600.2020.00337.
[48] W.-L. Hsiao and K. Grauman, "ViBE: Dressing for Diverse Body Shapes," in *2020 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, Jun. 2020, pp. 11056–11066. doi: 10.1109/CVPR42600.2020.01107.
[49] Y. Guan, Q. Wei, and G. Chen, "Deep learning based personalized recommendation with multi-view information integration," *Decis. Support Syst.*, vol. 118, pp. 58–69, Mar. 2019, doi: 10.1016/j.dss.2019.01.003.
[50] B. Kolisnik, I. Hogan, and F. Zulkernine, "Condition-CNN: A hierarchical multi-label fashion image classification model," *Expert Syst. Appl.*, vol. 182, p. 115195, Nov. 2021, doi: 10.1016/j.eswa.2021.115195.
[51] S. S. Kadam, A. C. Adamuthe, and A. B. Patil, "CNN Model for Image Classification on MNIST and Fashion-MNIST Dataset," *J. Sci. Res.*, vol. 64, no. 02, pp. 374–384, 2020, doi: 10.37398/JSR.2020.640251.
[52] M. R. Minar, T. T. Tuan, H. Ahn, P. L. Rosin, and Y. Lai, "CP-VTON+: Clothing Shape and Texture Preserving Image-Based Virtual Try-On," *Paper with Code*. 2020. [Online]. Available: https://paperswithcode.com/paper/cp-vton-clothing-shape-and-texture-preserving
[53] A. Sandamini, C. Jayathilaka, T. Pannala, K. Karunanayaka, P. Kumarasinghe, and D. Perera, "An Augmented Reality-based Fashion Design Interface with Artistic Contents Generated Using Deep Generative Models," in *2022 22nd International Conference on Advances in ICT for Emerging Regions (ICTer)*, Nov. 2022, pp. 104–109. doi: 10.1109/ICTer58063.2022.10024084.
[54] J. He, C. Zhang, X. He, and R. Dong, "Visual Recognition of traffic police gestures with convolutional pose machine and handcrafted features," *Neurocomputing*, vol. 390, pp. 248–259, May 2020, doi: 10.1016/j.neucom.2019.07.103.
[55] H. Dong, X. Liang, X. Shen, B. Wu, B.-C. Chen, and J. Yin, "FW-GAN: Flow-Navigated Warping GAN for Video Virtual Try-On," in *2019 IEEE/CVF International Conference on Computer Vision (ICCV)*, Oct. 2019, pp. 1161–1170. doi: 10.1109/ICCV.2019.00125.
[56] X. Han, Z. Wu, Z. Wu, R. Yu, and L. S. Davis, "VITON: An Image-Based Virtual Try-on Network," in *2018 IEEE/CVF Conference on Computer Vision and Pattern Recognition*, Jun. 2018, pp. 7543–7552. doi: 10.1109/CVPR.2018.00787.
[57] Y. Deldjoo, T. Di Noia, D. Malitesta, and F. A. Merra, "A Study on the Relative Importance of Convolutional Neural Networks in Visually-Aware Recommender Systems," in *2021 IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops (CVPRW)*, Jun. 2021, pp. 3956–3962. doi: 10.1109/CVPRW53098.2021.00445.
[58] S. Chakraborty, M. S. Hoque, N. Rahman Jeem, M. C. Biswas, D. Bardhan, and E. Lobaton, "Fashion Recommendation Systems, Models and Methods: A Review," *Informatics*, vol. 8, no. 3, p. 49, Jul. 2021, doi: 10.3390/informatics8030049.
[59] S. Shirkhani, H. Mokayed, R. Saini, and H. Y. Chai, "Study of AI-Driven Fashion Recommender Systems," *SN Comput. Sci.*, vol. 4, no. 5, p. 514, Jul. 2023, doi: 10.1007/s42979-023-01932-9.
[60] Y. Deldjoo *et al.*, "A Review of Modern Fashion Recommender Systems," *ACM Comput. Surv.*, vol. 56, no. 4, pp. 1–37, Apr. 2024, doi: 10.1145/3624733.

[61] R. Ashford, "ThinkerBelle EEG amplifying dress," in Proceedings of the 2015 ACM International Joint Conference on Pervasive and Ubiquitous Computing and Proceedings of the 2015 ACM International Symposium on Wearable Computers - UbiComp '15, 2015, pp. 607–612. doi: 10.1145/2800835.2801673.