Fashion and Textiles

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Conceptual framework of hybrid style in fashion image datasets for machine learning

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Abstract

Fashion image datasets, in which each fashion image has a label indicating its design attributes and styles, have contributed to the achievement of various machine learning techniques in the fashion industry. Computer vision studies have investigated labeling categories (such as fashion items, colors, materials, details, and styles) to create fashion image datasets for supervised learning. Although a considerable number of fashion image datasets has been developed, different style classification criteria exist because of a lack of understanding concerning fashion style. Since fashion styles reflect various design attributes, multiple styles can often be included in a single outfit. Thus, this study aims to build a Hybrid Style Framework to develop a fashion image dataset that can be efficiently applied to supervised learning. We conducted focus group interviews with six fashion experts to determine fashion style categories with which to classify hybrid styles in fashion images. We developed 1,206,931K-fashion image datasets and analyzed the hybrid style convergence. Finally, we applied the datasets to the machine learning model and verified the accuracy of the computer's ability to recognize style. Overall, this study concludes that the Hybrid Style Framework and developed K-fashion image datasets are helpful, as they can be applied to data-driven fashion services to offer personalized fashion design solutions.

Keywords: Fashion image, Hybrid style, Machine learning, K-fashion, Supervised learning datasets

Introduction

Fashion image data plays an important role in the fashion industry. Over the past few years, fashion companies have applied machine learning techniques (where computers learn from their own accumulated data) in e-commerce services, particularly in product recommendations and searches to match consumer needs for specific designs (An et al., 2019; Seo & Shin, 2018). Fashion image datasets for supervised learning enable computer modeling of product classification and recognition (Gu et al., 2020). Supervised learning is a technique used to construct predictive models that applies machine learning to a large number of datasets, in which each image has a label indicating its ground-truth output (Zhou, 2018). Supervised learning datasets can estimate and classify such elements as fashion items and design attributes, and provide style recognition. Various studies have created fashion image datasets. However, previous studies have adopted the perspective of the computer vision discipline; the focus has been on performance measures for machine learning models (Nakajima et al., 2018; Simo-Serra & Ishikawa, 2016). Academic standards in style have not been considered sufficiently; hence, there has been a limited number of style categories (Jeon et al., 2021), thereby creating an issue in the field. Moreover, fashion styles are complex because they contain subjective images judged by various design attributes, and one fashion image often represents multiple styles (An et al., 2021). Consequently, style categories that cover academic criteria are necessary to develop fashion image datasets.

In 2020, the Government of Korea supported building supervised learning datasets for various fields to accelerate the development of AI techniques. Our team carried out a fashion project to develop Korean fashion (K-fashion) image datasets. The term K-fashion emerged globally with the spread of the Korean Wave in the 2000s. Unlike traditional Korean garments such as Hanbok, K-fashion has garnered attention as a contemporary fashion by combining various styles and design attributes with the rapidly changing fashion market trends (Kim et al., 2017). Accordingly, it has been recognized as a mixture of various young and contemporary styles that cannot be clearly defined (Kim, 2017). Thus, the study's primary research concern was the challenge of utilizing fashion style in dataset creation. Our team focused on developing a theoretical framework for a hybrid style and applying it to a K-fashion image dataset. Towards this end, the aims of the study were: (a) to suggest a Hybrid Style Framework that can serve as a theoretical basis for fashion image datasets, (b) to develop novel K-fashion image datasets labeled with a hybrid style, and (c) to verify the datasets by applying them to the machine learning model and accounting for their applications.

The following research steps were taken. First, we conducted a literature review of academic theories and previous studies of fashion image and style classification to build a Hybrid Style Framework. Second, focus group interviews (FGIs) were conducted with six fashion experts to determine K-fashion style categories. Third, fashion images were collected from 110 online shopping malls in Korea, and 386 fashion majors and non-fashion participants labeled 1,206,931 images with item, design attributes, and styles. Finally, we performed frequency analysis of hybrid styles in the K-fashion image dataset. We also applied the datasets to the machine learning model and evaluated the top- accuracy of the computer's ability to recognize style.

Literature Review

Machine learning and fashion datasets

Machine learning technologies can be categorized into two main groups—supervised and unsupervised machine learning. These two learning categories are associated with different machine learning algorithms that represent how the learning method works. Generally, with supervised learning, the outcome variable is present to guide the training process, whereas unsupervised learning develops a model from data without predefined examples (Omary & Mtenzi, 2010). The performance in supervised machine learning is heavily dependent on the amount and quality of datasets. Preparing datasets is a time-intensive process as datasets are made manually, requiring significant time and effort, with workers required to label each image directly (Cognilytica, 2019).

Table 1 Comparison of previously published datasets on fashion images

Dataset	Number of images	Style annotation	Number of styles	Hybrid style annotation	Data imbalance
HipsterWars (Kiapour et al., 2014)	1893	Yes	5	No	Weak
DeepFashion (Liu et al., 2016)	289,222	Weak	–	Yes	Yes
FashionStyle14 (Takagi et al., 2017)	13,126	Yes	14	No	No
DeepFashion 2 (Ge et al., 2019)	491,895	No	–	–	–
DeepFashion-MultiModal (Jiang et al., 2022)	44,096	No	–	–	–
K-Fashion	1,083,835	Yes	23	Yes	Yes

In the past decade, various computer vision studies have explored labeling categories for creating fashion image datasets. Initial approaches have focused on creating datasets that consist of item types and design attributes like color, material, and clothing details (Vittayakorn et al., 2015; Yamaguchi et al., 2013). To build higher-level datasets, Kiapour et al. (2014) created 1893 fashion image datasets with five style categories—bohemian, goth, hipster, pinup, and preppy. To increase the number of datasets, crowd-sourcing labeling methods have been applied and the Chinese University of Hong Kong established 800,000 image datasets with four design attributes—texture, fabric, shape and detail, and style (Liu et al., 2016). Takagi et al. (2017) created 13,126 fashion image datasets with 14 style categories—conservative, dressy, ethnic, fairy, feminine, gal, girlish, casual, Lolita, mode, natural, retro, rock, and street. Recently published datasets on fashion images (Ge et al., 2019; Jiang et al., 2022) focused on advanced machine vision problems such as position or pose prediction and image-to-text generation.

However, previous studies have certain limitations, as shown in Table 1. Unlike item and design attributes, fashion style recognition using fashion images is complicated because style is a higher-level concept that comprehensively combines low-level design attributes (An et al., 2021). As they attend to the perspective of the computer vision discipline, academic standards in style criteria have not been considered sufficiently; the focus has been more on performance measures for machine learning models. For example, previous studies have applied style categories with similar concepts (e.g., gal, girlish, lolita) but excluded some primary fashion styles (e.g., modern, classic) (Takagi et al., 2017). Moreover, the style categories were found to be incorrect, such as referring to t-shirts with Mickey Mouse on them as "Mickey" and raglan sleeve T-shirts as "baseball" style. In addition, some of the datasets failed to grasp reality, as data imbalances among styles were not captured (Takagi et al., 2017). Other studies ignored the possibility of having multiple styles per image (Kiapour et al., 2014; Takagi et al., 2017). These problems have led to an academic approach in the fashion sector that standardizes style criteria and categories to develop supervised learning datasets.

Hybrid style framework

Fashion style is defined as a durable and recognizable pattern of aesthetic choices (Godart, 2018). In many cases, styles are not exclusive, and often different styles have combined and emerged as new styles. Clothing styles create "mix and match" styles or "hybrids of older styles," as was the case with "seapunk," which evolved from a mix of beachwear and punk, or "athleisure," which is a portmanteau of "athletic" and "leisure," and refers to casual clothing designed to be worn for both outdoor exercise and general indoor use (Lipson et al., 2020; Petridis, 2014). Previous fashion studies have evaluated style using academic criteria. The most fundamental dimension of clothing style is gender. Davis (1985) and Forsythe (1988) describe the symbolism of clothing styles using gender-related criteria like masculine and feminine. Sweat and Zentner (1985) investigated the relationship between gender and the style categories of natural, classic, and romantic, and found significant effects and interactions. Their results indicated that the gender sector tended to select specific, but not necessarily the same styles under situations representing various behavioral constraints. Gurel et al. (1972) reported that personality dimensions correlate with adolescent clothing styles. Consequently, studies have pointed out that some styles are closer than others and this has led to measures of the closeness of or distance between styles. The approach of applying polarized terms with statistical methods, such as cluster analysis, multidimensional scale analysis, and factor analysis, has been suggested for evaluations of the distance between styles. Paek (1986) used conflicting personalities (conservative and casual) as significant criteria for fashion styles, creating two polarized terms (daring-conservative and dressy-casual) to explore personal ratings of garment styles. In later studies, the cultural environment is noted as a source of style. Kim and Lee (1997) have included regional dimensions, using terms such as ethnic-modern or urban-natural to evaluate style. Chung and Rhee (1993) applied masculine-feminine, mature-active, and urban-natural as the criteria in style classification and identified a hierarchy of clothing images.

Based on the literature review of style criteria provided above, several salient elements can guide fashion images' style classification. First, styles are prone to hybridization, and the characteristic of hybrid styles can influence the way they are perceived. Second, the way styles are implemented varies, and their implementation is more or less closely related to the dimensions of the gender, personality, and region that they refer to. Third, the criteria are necessary for classifying fashion styles, and polarized terms can be applied to define the range of styles. Based on this, we propose a conceptual framework of hybrid styles that can be used as a theoretical basis for fashion style classification. Figure 1 shows the circular conceptual model that integrates the hybrid style by ensuring the accessibility of the main style and substyles. We placed the main style at the circle's center and the substyles on its outer ring. This circle illustrates three dimensions of gender, personality, and region with relevant style criteria. Polarized terms from previous studies represent the style criteria (e.g., feminine-masculine, conservative-casual, ethnic-modern) placed opposite one another.

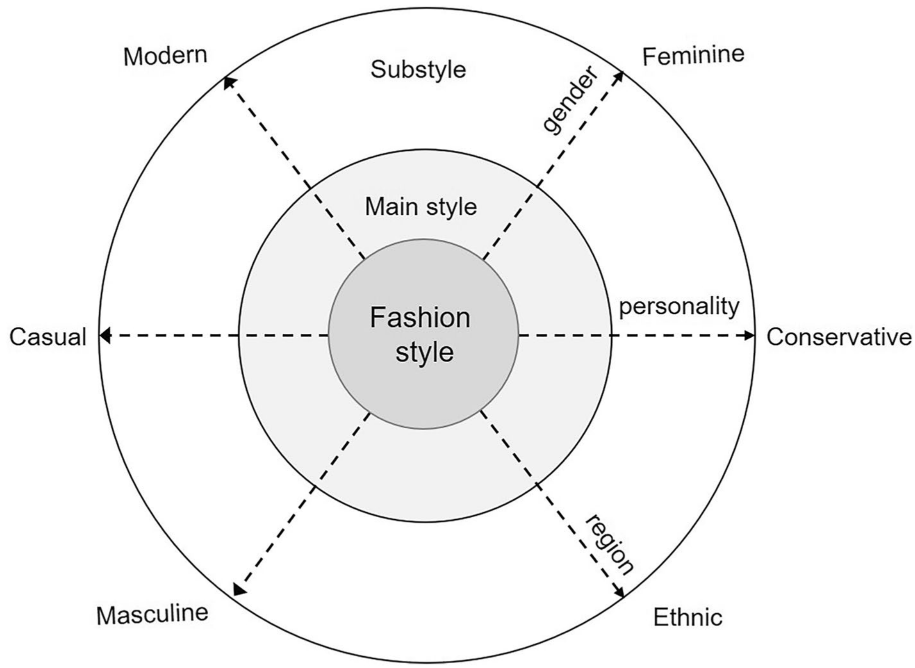

Fig. 1 Conceptual framework of the hybrid style

K-fashion style

K-fashion is a term that emerged in the process of forming the Korean Wave or Hallyu, which refers to the increase in international interest in South Korea and its popular culture, especially represented by the global success of South Korean music, film, television, fashion, and food (Oxford English Dictionary, 2022). Since the late 1990s, Hallyu has been evident in the east and southeast Asian regions; it has recently emerged as a transnational cultural phenomenon worldwide (Jin & Yoon, 2016). K-fashion is used in the same sense as Korean "Hallyu fashion." The term K-fashion is supposed to have emerged in 2005 with the first major export of Korean dramas (Ahn & Geum, 2016). Hallyu can be subdivided into the development stages of Hallyu 1.0, Hallyu 2.0, and Hallyu 3.0, based on content and how widespread the phenomena were (Elaskary, 2018). Hallyu 1.0 refers to the increased export of broadcast programs to East Asia, centering on Korean dramas. Hallyu 2.0 refers to increased interest in Korean products, centering on K-pop idol stars. Hallyu 3.0 refers to the expansion of cultural content ranging from music and drama to literature, art, and fashion to Europe and the Americas (Joint operation of related ministries, 2020). The Korea Creative Content Agency (2018) expanded the definition of the Korean Wave as "Korean fashion that is preferred by young people around the world and consumed with the image of the various social media contents." Global interest in the fashion and beauty styles of popular idols and celebrities is growing based on media content, such as YouTube, social media, online games, and mobile products (Choe, 2021). K-fashion is not limited to specific cultural styles but is recognized as a contemporary clothing style that reflects the latest lifestyle and market trends.

For example, K-fashion reflecting street style is an inspiration for global fashion brands. Clare Wait Keller, a designer of the French luxury brand Givic, announced

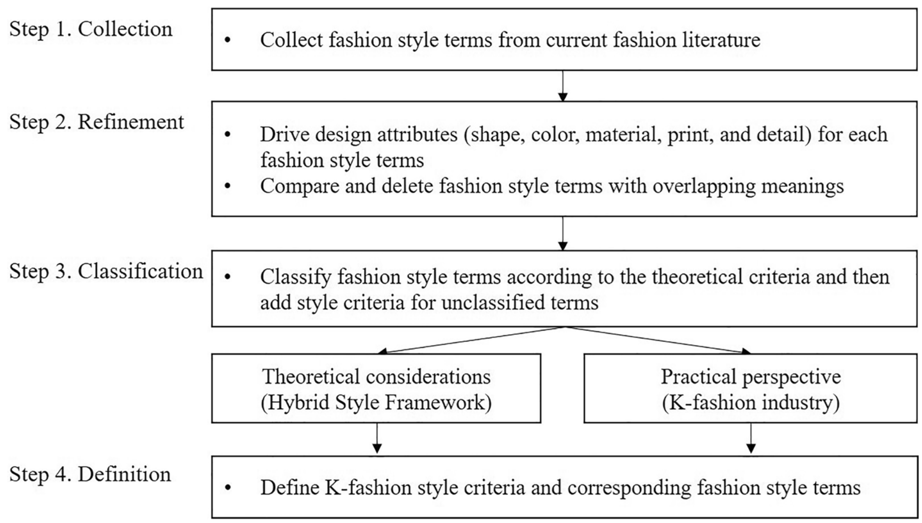

Fig. 2 Flow diagram for the FGI process

Givic's 2020 spring season collection inspired by Korean street fashion. In February 2019, Amazon surveyed Japanese Generation Z's preference for Korean fashion and opened a K-fashion brand exclusive page on Amazon Japan (Amazon.co.jp) by collecting products from Korean fashion brands that were well-recognized at home and abroad to increase online purchases. K-fashion is recognizable and distinct. It can be worn daily and is a modern, youthful, and contemporary taste accepted within the global fashion market (Kim, 2017).

Methods

We applied the Hybrid Style Framework as a theoretical basis to build a K-fashion image dataset that can be applied efficiently to supervised learning. This study comprised four stages: K-fashion style category determination, data collection, labeling, and analysis.

Focus group interview (FGI)

This study conducted FGIs with six fashion experts (two fashion designers, two fashion business managers, and two fashion trend researchers) to determine fashion style categories for classifying K-fashion images. Figure 2 shows the FGI process. First, the fashion experts collected fashion style terms from current fashion studies, magazines, and books. Second, they derived design attributes for shapes, colors, materials, prints, and details representing each fashion style term. Terms with overlapping meanings were deleted. Third, the experts classified terms according to the style dimension and the Hybrid Style Framework criteria. In addition, from a practical perspective, participants considered characteristics of the K-fashion industry and added new style criteria for unclassified terms. Finally, the fashion experts defined K-fashion style criteria and corresponding style terms. Each fashion style term was applied as a style category in data labeling.

Table 2 21 Items and 148 design attributes applied to the fashion image labeling

Type		Attributes
Item	Outer	Coat, jacket, jumper, padding, vest, cardigan, zip-up
	Top	Top, blouse, t-shirt, knitwear, shirt, bra top, hoodie
	Bottoms	Jeans, pants, skirt, leggings, jogger pants
	Dress	Dress, jumpsuit
Shape	Length	Crop, normal, half, long, maxi, mini, knee-length, midi, ankle, sleeveless, cap, short sleeve, three-quarter sleeve, long sleeve
	Neckline	Round, U, V, halter, off-shoulder, one-shoulder, square, no-collar, hood, turtle, boat, sweetheart
	Collar	Shirt, bow, sailor, shawl, polo, peter pan, china, tailored, band
	Fit	Tight, normal, loose, oversized, skinny, wide, bell-bottom
Color	–	Black, white, gray, red, pink, orange, beige, brown, yellow, green, khaki, mint, blue, navy, sky blue, purple, lavender, wine, neon, gold, silver
Material	–	Fur, suede, hair knitwear, corduroy, sequin, denim, jersey, knitwear, lace, linen, mesh, fleece, neoprene, silk, spandex, tweed, velvet, PVC, wool/cashmere, jacquard, leather, chiffon, woven, padding
Print	–	Floral, leopard, zebra, python, checkered, gingham, argyle, hound tooth, stripe, dot, heart, zigzag, lettering, skull, graphic, gradient, paisley, tie-dye, mix, camouflage, solid
Detail	–	Beads, spangles, studs, glitters, buttons, ribbons, bands, buckles, chains, zippers, X-straps, pockets, fringe, tassel, pom-pom, cable knit, stitch, embroidery, quilting, patchwork, frill, flare, shirring, pleats, ruffle, peplum, puff, fur-trimming, cut-off, cut-out, destroyed, slit, lace, lace-up, roll-up, asymmetric, single-breasted, double-breasted, drop-waist, drop-shoulder

Data collection

This study collected K-fashion images from 110 Korean online shopping malls. This study used full-length images of people mixing and matching 21 fashion items (i.e., coats, jackets, jumpers, padded jackets, vests, cardigans, zip-ups, tops, blouses, t-shirts, knitwear, shirts, bra tops, hoodie, jeans, pants, skirts, leggings, jogger pants, dresses, and jumpsuits). The collected images excluded photos of products hung on hangers, partial photos, and images in which the faces of the models were visible. The pre-processing resulted in the application of 1 206 931 images into labeling.

Data labeling

Eighty six fashion majors and university researchers and 300 crowdsourcing workers not involved in the fashion industry participated in the data labeling process. The data labeling process was carried out using a cloud server (www.kfashion.ai) developed by Opinion Live Co. Ltd.

First, non-fashion participants specified the section in the image data. They drew a polygon outline of items in the images and selected the product type (i.e., top, bottom, outer, and dress).

Second, the fashion major participants specified each polygon's item and design attributes. Table 2 shows the attributes of the item, shape, color, material, print, and detail. Item attributes were collected from previous studies (Liu et al., 2016; Takagi et al., 2017; Yamaguchi et al., 2013), and design attributes were derived from FGI. In particular, color attributes were obtained by considering the color theory's primary, secondary, and tertiary colors, as well as gray and neon colors, which are popular in contemporary fashion (Kwan, 2015; MacLaury et al., 2007; Mollica, 2013). During the labeling process, the attribute list was shown on the computer screen, and fashion majors selected the matching attributes in the order of item, design, and style. Particularly for style, the fashion majors chose the main style. If the fashion image was determined to be a hybrid style, they also chose one or more substyles (Fig. 3). Style labeling entailed a decision-making process that was undertaken by multiple participants. Accordingly, to maintain consistency and objectivity among participants, we validated the quality of the data with fashion experts after style labeling and corrected repeated errors. The first inspection was conducted among participants and the labeled data was cross-checked. The second inspection was performed by 16 researchers with master's degrees or higher; they reviewed 10,000 sample data, which were extracted from each style category; they confirmed that over 96% of the style labels were consistent.

Data analysis

We first performed frequency analysis of hybrid styles in the K-fashion image dataset. We analyzed the ratio of single and hybrid styles labeled in the dataset. To better understand the essential characteristics, we selected the three highest hybrid styles and compared their matching items and design attributes.

Furthermore, we verified our datasets by applying machine learning models. We adopted three deep learning models that have achieved state-of-the-art performance on several image classification benchmarks: Big Transfer ResNetV2 (Kolesnikov et al., 2020), EfficientNet (Tan & Le, 2019), and Vision Transformer (Dosovitskiy et al., 2021). Big Transfer ResNetV2 and EfficientNet are based on a convolutional neural network structure, which is a conventional deep learning structure for learning features from images. In contrast, Vision Transformer is based on transformer architecture, originally utilized for learning features from texts, and has an advantage in computing relationships between different parts of an image. Fine-tuning was performed with the style classification as a downstream task using the K-fashion dataset on the models with pretrained weights. The number of images utilized for training, validation, and testing were 867,073, 96,333, and 120,429, respectively. We evaluated the performance of our models using top-k accuracy, one of the most commonly used metrics for evaluating classification models. Here, k should be a whole number, such as 1 or 5, leading to top-1 or top-5 training objectives. Top-k accuracy measures the percentage of test images for which the correct class is among the k most probable predictions (Russakovsky et al., 2015).

Results

K-fashion style categories

K-fashion style criteria related to gender, region, and personality were developed as follows:

1. Criteria that reflect gender had the fundamental dimensions of feminine and masculine. Furthermore, we added gender-fluid criteria to reflect the growing genderless style trends in the k- fashion industry.
2. Criteria reflecting regional characteristics were region-oriented, ethnic and urban-oriented, contemporary. We added natural rural-oriented and subculture criteria to

Table 3 K-fashion style criteria and categories

Dimension	Criteria	Categories
Gender	Feminine	Romantic, feminine, sexy
	Gender fluid	Genderless
	Masculine	Masculine, tomboy
Region	Ethnic	Hippie, oriental, western
	Natural	Country, resort
	Contemporary	Modern, sophisticated, avant-garde
	Subculture	Punk, kitsch, retro, hip-hop
Personality	Conservative	Classic, preppy
	Casual	Street, military
	Sporty	Sporty

reflect the crossover tendency of various cultures combining in the K-fashion industry.

3. Criteria reflecting personality had the fundamental dimensions of conservative and casual. Additionally, as conservative criteria reflect static tendencies, we added sporty criteria to reflect active tendencies, considering the significant sporty style trends in the K-fashion industry.

Fashion style terms were classified according to K-fashion style criteria. Through the refinement process, the style terms with similar design attributes (e.g., romantic-girlish-lolita, feminine-elegance-glamorous, sporty-athleisure, street-normcore, etc.) were integrated into one, and the style terms were converged to 23. 15 terms were classified into style criteria in the Hybrid Style Framework (e.g., feminine, masculine, ethnic, contemporary, conservative, casual). Either unclassified terms were grouped into new style criteria (e.g., gender fluid, natural, subculture, and sporty). The terms were applied to the K-fashion image dataset as style categories. The K-fashion style criteria and categories derived from the FGIs are shown in Table 3.

Hybrid style frequency

A total of 1,206,931 fashion images were fully labeled with 21 items, 148 design attributes, and 23 style categories. Frequency analysis for style indicated that 677,883 (56.2%) images had a single style (labeled only as its main style) and that 529,048 (43.8%) images were labeled as hybrid (labeled as its main style and one or more substyles). In the case of single styles, street style had the highest frequency at 389,569 (32.2%), followed by resort style (4.4%) and feminine style (4.2%). Analysis confirms that punk styles (0.004%) are rare. Figure 4 is an example of K-fashion image data labeled as a single style.

Regarding hybrid style, we found that the style with the highest convergence was street style, at 172,817 (14.3%). Thus, we selected style convergence in the context of street style to reach a deeper understanding of its essential characteristics. Frequency analysis results for street style convergence with other styles indicated that all styles showed some convergence but that romantic (1.9%), modern (1.9%), and resort (1.7%) had the highest frequency (Fig. 5). We compared design attributes according to substyles and identified that, generally, convergences with street style consisted of matching tops

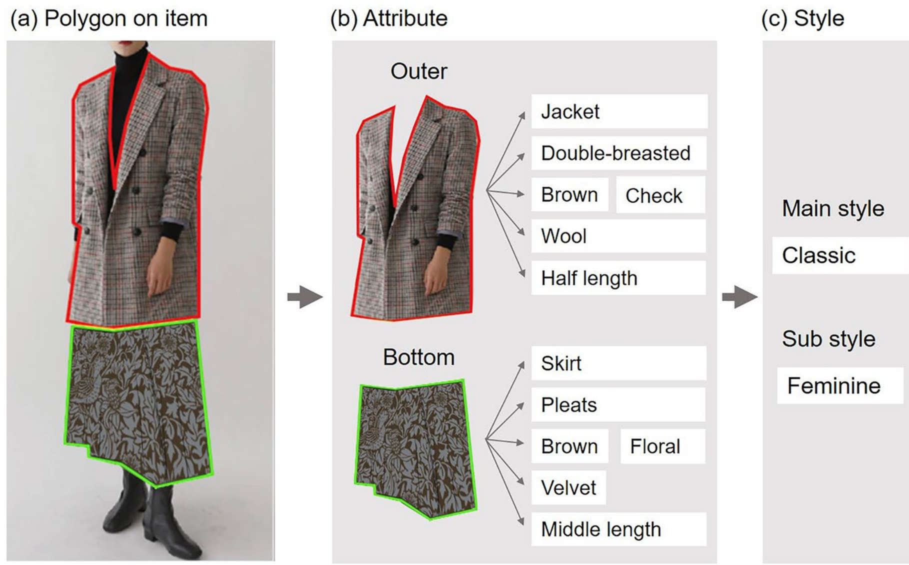

Fig. 3 Labeling Process of Fashion Images. **a** Non-fashion participants draw a polygon on the outline of each item in the fashion image, based on the top, bottom, outer, and dress. **b** Fashion majors chose attributes that corresponded to an item. **c** Fashion majors chose the main style, and if the fashion image is determined to be a hybrid style, they also chose one or more substyles

(t-shirts) and bottoms (jeans or pants). The design attributes of the items worn determined the hybrid style. We performed a quantitative analysis of what design attributes were critical for determining substyles. Street-romantic style was more frequent than other hybrid styles, and it made use of shirring, puff, and ruffle details; floral patterns; and mini-length design attributes. Street-modern style was relatively frequent and made use of drop shoulder details, black colors, and longer lengths, whereas street-resort style was relatively frequent and made use of slit details, jersey fabric, and wide fit design attributes (Table 4).

We created a visual representation of the hybrid style structure of the K-fashion image datasets. A total of 172,817 fashion image datasets indicated convergence with street style, the highest frequency of all styles. Therefore, "street" was placed at the center of the circle and applied to all 22 substyles. Conflicting substyle categories were placed opposite one another. On the outer ring of the circle, the criteria of substyle are proportional to the frequency of their combination with street style (Fig. 6). Regarding the dimension of gender, the broadest style category on the outer ring of the circle is feminine, which includes romantic, feminine, and sexy substyles. Masculine substyle is reflected in a small number of cases. Regarding proportions of the region dimension, the conflicting style categories, natural and contemporary show similar tendencies. In particular, modern and resort account for a large portion of substyles, reflecting the style trend of "normcore" during 2016–2020. Normcore is considered a street style, but it does not go as far as comfortable sleepwear like sweatpants. As it is a style trend that considers plainness and simplicity, street style harmonizes with resort and modern styles. These results show that the style of the K-fashion images accounts for a large proportion of street styles suitable for daily life, which notably tend to utilize the essential characteristics of feminine, modern, and resort design attributes.

Fig. 4 Example K-fashion image data with single styles

Model performance

The performance comparison results of the previously mentioned Big Transfer ResNetV2, EiffidentNet, and Vision Transformer are shown in Table 5. In terms of top-1 accuracy, a minimum 61.29% to a maximum 75.21% of instances were correctly

Table 4 Item and design attributes for Top3 hybrid style

	Rank	Street romantic (23,965, 1.9%)		Street modern (23,613, 1.9%)		Street resort (21,509, 1.7%)	
		DA	*f*	DA	*f*	DA	*f*
Item	1	Blouse	9550	Pants	9060	Pants	7280
	2	Jeans	6791	T-shirts	6778	T-shirts	6039
	3	T-shirts	4481	Dress	4054	Dress	4981
Length	1	Normal	9162	Ankle	10,859	Normal	12,854
	2	Ankle	7278	Normal	6766	Long	12,375
	3	Mini	4378	Long	5849	Ankle	3544
Neckline	1	Round	8614	Round	7915	Round	8614
	2	V	4161	V	2809	V	4161
	3	U	1142	Turtle	1751	U	1142
Collar	1	Shirts	1523	Shirts	3920	Shirts	1523
	2	Tailored	440	Tailored	1544	Tailored	440
	3	Band	372	Band	633	Band	372
Fit	1	Normal	19,693	Normal	15,999	Normal	19,693
	2	Loose	10 019	Loose	11,131	Loose	10,019
	3	Skinny	3499	Skinny	3298	Wide	3499
Color	1	White	12,462	White	11,593	White	12,462
	2	Pink	5278	Black	11,566	Pink	5278
	3	Sky-blue	4378	Beige	3750	Sky-blue	4378
Material	1	Woven	14,134	Woven	18,973	Woven	12,231
	2	Denim	7912	Knit	5406	Jersey	7564
	3	Knit	4230	Denim	5099	Knit	4182
Print	1	Solid	25,824	Solid	30,699	Solid	23,608
	2	Floral	3217	Stripe	2159	Stripe	2501
	3	Stripe	1455	Lettering	1061	Lettering	1507
Detail	1	Shirring	5349	Pocket	4838	Pocket	3446
	2	Puff	4112	Button	2448	Button	2157
	3	Ruffle	3170	Drop shoulder	2281	Slit	2099

Design attribute (DA), frequency (*f*)

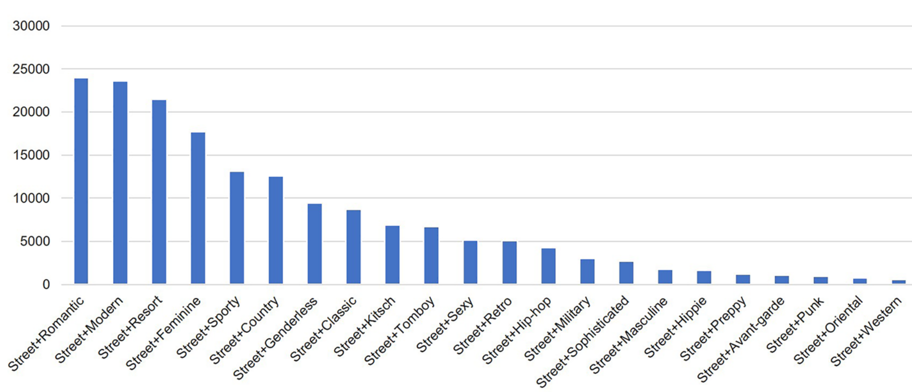

Fig. 5 Style convergence frequency with street style

Table 5 Style prediction performances of the compared models in terms of top-k accuracy and sublabel ratio

Model	Top-1 accuracy (%)	Top-3 accuracy (%)	Top-5 accuracy (%)	Top-3 sub label ratio (%)	Top-5 sub label ratio (%)
Big transfer ResNetV2	61.29	84.65	93.49	65.06	78.21
EifficientNet	61.19	85.44	93.37	63.96	78.20
Vision transformer	75.21	93.93	97.22	57.30	69.45

Table 6 Style classification performances of most infrequent 5 styles, punk, hip-hop, western, preppy, and military in terms of top-1 accuracy

Style	Number of instances	Big transfer ResNetV2 (%)	EfficientNet (%)	Vision transformer (%)
Punk	382	5.88	19.61	47.06
Hip-hop	1240	11.76	15.69	51.63
Western	1712	15.45	24.55	61.82
Preppy	2471	20.25	25.55	53.89
Military	3633	32.29	31.18	60.13

classified. In terms of top-3 accuracy, a minimum 93.49% to a maximum 97.22% of instances were correctly classified. In addition to top-k accuracy, we adopted the top-k sublabel ratio, which is the ratio of instances in which substyle is included in the k most probable style predictions when the main style prediction fails. According to the top-3 sub label ratio, 57.30% to 65.06% of instances were correctly classified into substyles. This implies that the style classification performances can be enhanced when a model addresses the concept of the hybrid style. For instance, adopting a loss function designed for a multi-label classification to a deep learning model enhanced classification performance (An et al., 2021).

Regarding the in-depth evaluation, the classification performances of the five most infrequent styles—punk, hip-hop, western, preppy, and military—are presented in Table 6. Overall, infrequent styles showed inferior performances compared to the average due to the data imbalance problem. Notably, Vision Transformer, which is a breakthrough model resulting in the recent rapid improvement in image generation, showed better performances for the minor styles.

Discussion

Our study offers a theoretical contribution in that it that presents the Hybrid Style Framework for fashion image datasets. First, the present study contributes to the literature by defining 23 style categories under the three dimensions of gender, region, and personality. The hybrid style framework serves as a valuable guide to a deeper understanding of fashion styles and can be effectively applied to develop supervised learning datasets in the fashion domain. Second, this study indicates that fashion image data preparation and labeling is a complicated process, which entails manual work and requires much discussion and effort. We divided the roles of fashion experts and non-fashion participants in the process of creating fashion image datasets. Verification and

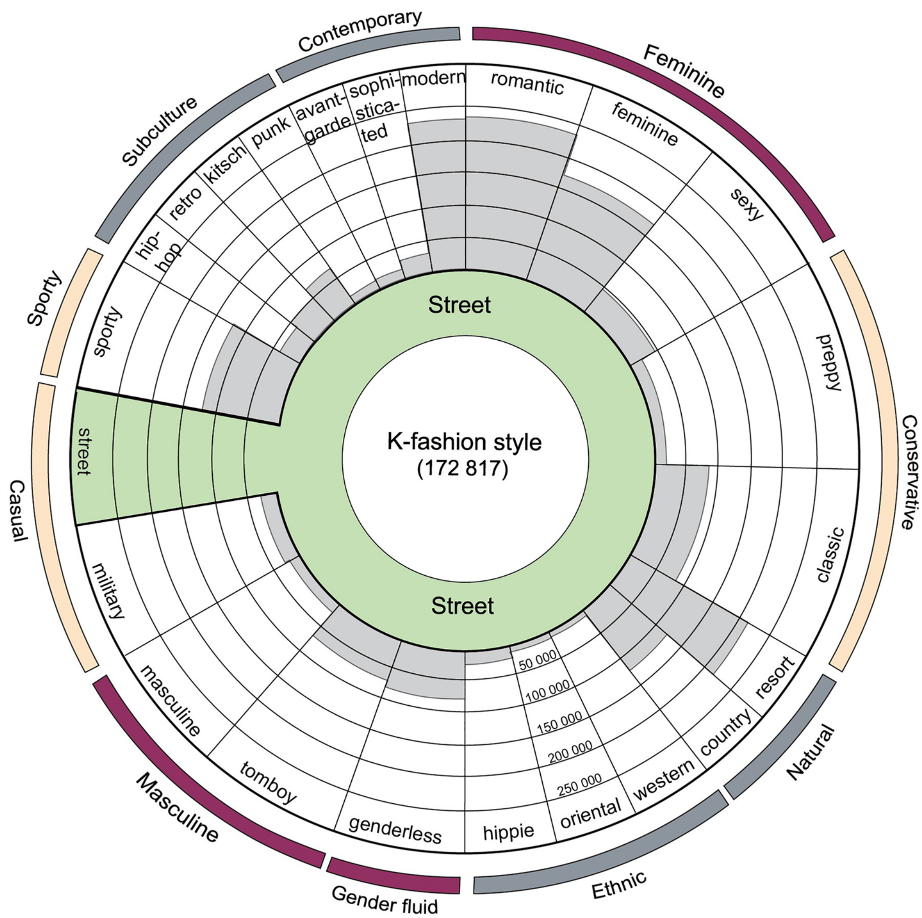

Fig. 6 Hybrid style structure of K-fashion image with 23 style categories

modification were necessary during the manual process, and cross-checking among participants was essential for data consistency. Third, the present study visually represented hybrid style structures by applying K-fashion image datasets. The hybrid style structure aids an immediate understanding of substyle convergence to ground style. In the field of fashion informatics, collecting and developing more clothing-matching data from various image sources is necessary to conduct machine learning research (Zhao et al., 2021). To the best of our knowledge, this is the first study to identify clothing-matching characteristics in hybrid style by applying more than 1.2 million fashion image datasets. Most K-fashion images with street styles contained t-shirts. However, we confirmed that there is a priority in design attributes depending on the substyle. The study presented item and design attributes of the three most prevalent hybrid styles and confirmed that each hybrid style has relatively matching colors, detail, and length of clothing.

The findings of this study can contribute to the fashion industry. First, our fashion image dataset can be effectively applied to style prediction models. The trained model can classify hybrid style in percentage values from various fashion images. We show some hybrid style classification examples in Fig. 7. We utilized the trained Big Transfer

Fig. 7 Quantitative hybrid style classification results from the fine-tuned big Transfer ResNetV2 model on the test image

ResNetV2 model, where overall style prediction performance was good, especially considering the style prediction results of the sublabel, for image testing. The lookbook photos of K-fashion brands LIE[1] WNDERKAMMER[2], [3] and EENK[4]., [5]., all participants in Seoul Fashion Week, were applied as test images. Below each image, we displayed the quantitative hybrid style ratios provided by the prediction results of the machine learning model. Each fashion image has a unique style index, and it can be seen that the style that occupies the highest ratio, along with various styles, becomes the main style. The hybrid style index could enhance fashion technology to improve product recommendations, counterfeit product analysis, and market trend analysis for fashion brands. Second, the fashion image dataset benefits clothing design automation. Clothing is considered a high-involvement product, and it has been suggested to be open to collecting data from several different sources to meet consumers' specific tastes (Solomon, 1986). In this paper, we established the relationship between fashion style and garment component elements by developing a large number of K-fashion image datasets labeled according to various fashion items, shapes, colors, materials, prints, details, and styles. The datasets results can provide a quantitative index of design information for a company targeting a specific market.

[1] F/W 2022, LIE. Seoul Fashion Week. https://www.seoulfashionweek.org/designers/view/63/2022FW/LIE/. Accessed 4 October 2022.

[2] S/S 2022, Wnderkammer. http://wnderkammer.com/collection/22ss.html. Accessed 4 October 2022.

[3] F/W 2022, Wnderkammer. Seoul Fashion Week. https://www.seoulfashionweek.org/designers/view/68/2022FW/WNDERKAMMER/. Accessed 4 October 2022.

[4] S/S 2022, Eenk. https://eenk.co.kr/shop_view/?idx=5378 Accessed 4 October 2022

[5] F/W 2022, Eenk. https://eenk.co.kr/shop_view/?idx=6134. Accessed 4 October 2022

Conclusions

Hybrid style analysis has become a significant aspect of fashion because various concepts and design attributes are fused, and new fashion styles are introduced each season rapidly. Existing studies in computer vision have not sufficiently discussed hybrid fashion styles as a comprehensive reflection of various design attributes to create fashion image datasets for machine learning.

This study presents a conceptual framework for hybrid style and creates fashion image datasets for machine learning. In particular, we quantitatively derived design attributes that are highly correlated with hybrid styles. The association index between hybrid style and design attributes is important for data-driven product recommendations, clothing design automation, and personalized fashion design solutions. However, this study encountered two technical limitations. First, it was conducted with limited data. We defined K-fashion style using images from Korean online women's shopping malls alone. Consequently, high-end brands were excluded from the analysis. We also used images taken during 2019–2020; trends from this period affected K-fashion's hybrid style structure. Second, despite notifying participants of the labeling criteria in advance, there was a difference in the perception of design attributes and styles during the labeling process. In particular, some colors and materials were difficult to recognize in the image. The distinction between natural and synthetic fibers was unclear, and the perception of color changed depending on the lighting in the image. There were also differences in perception among fashion professionals regarding fashion details (e.g., Is the small crease on the sleeves a puff detail?) and fit (e.g., Is the oversized princess line dress loose fitted?).

Despite these limitations, this study is significant because it presents a large amount of fashion image datasets based on the Hybrid Style Framework and verifies the datasets with Big Transfer ResNetV2, EiffidentNet, and Vision Transformer, which are the most widely used backbone models in machine learning. The study demonstrated that the Hybrid Style Framework was effectively applied in fashion image dataset creation. Our fashion image datasets provide various fashion business fields with better performance opportunities. In particular, fashion brands, designers, and consumers can apply supervised learning datasets to machine learning techniques on their e-commerce platforms, including automatic apparel classifications, recommendations, and styling. Moreover, the study's findings provide the global fashion industry with insights into the K-fashion market's segmented style trends in street style. In future studies, we would like to further implement fashion image datasets with supervised learning experiments and examine the mapping of design attributes. Such a project would be a collaborative effort with professional researchers in the field of computer vision. Collaborative research between fashion and computer vision is needed to accelerate data-driven machine learning technology in both research fields. Mainly the dataset provides challenges for the computer vision field as it reflects the real-world in terms of class imbalance and multi-label characteristics. Since the imbalance problem exists in real-world fashion images, it is important to develop a model that is robust to the problem. Further, it will be necessary to adopt actively researched learning approaches focused on addressing the data imbalance problem, such as few-shot learning, on enhancing style classification performance. This study should be a theoretical foundation for hybrid styles in machine learning in fashion.

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Authors' contributions
HA originated the research idea. HA carried out the research and drafted the first manuscript. KYL assisted with interpreting articles for the literature review and wrote the results section of the manuscript. YC carried out the data analysis and wrote the manuscript's results section. MP helped with interpretation and improvement of the manuscript. All authors read and approved the final manuscript.

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Availability of data and materials
This research (paper) used datasets from 'The Open AI Dataset Project (AI-Hub, S. Korea).' The datasets built in this research can be accessed through 'AI-Hub (www.aihub.or.kr).' The datasets generated and/or analyzed during the current study are available from the corresponding author on reasonable request.

Declarations

Competing interests
The authors declare that they have no competing interests.

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References
Ahn, B., & Geum, K. S. (2016). A study on the situation and perspective of K-fashion. *Journal of Basic Design & Art, 17*(1), 349–362.
An, H., Kim, S., & Choi, Y. (2021). Sportive fashion trend reports: A hybrid style analysis based on deep learning techniques. *Sustainability, 13*(17), 9530. https://doi.org/10.3390/su13179530
An, H., Kwon, S., & Park, M. (2019). A case study on the recommendation services for customized fashion styles based on artificial intelligence. *Journal of the Korean Society of Clothing and Textiles, 43*(3), 349–360. https://doi.org/10.5850/JKSCT.2019.43.3.349
Choe, S. (2021). From BYS to 'Squid Game': How South Korea became a cultural juggernaut. *The New York Times*. https://www.nytimes.com/2021/11/03/world/asia/squid-game-korea-bts.html. Accessed 4 May 2022.
Chung, I., & Rhee, E. (1993). A study on the hierarchy of clothing images. *Journal of the Korean Society of Clothing and Textiles, 17*(4), 529–538.
Cognilytica. (2019). *Data engineering, preparation, and labeling for AI 2019. Report No. CGR-DE100*. Washington DC: Cognilytica.
Davis, F. (1985). Clothing and fashion as communication. In M. R. Solomon (Ed.), *The Psychology of Fashion* (pp. 15–27). Heath.
Dosovitskiy, A., Beyer, L., Kolesnikov, A., Weissenborn, D., Zhai, X., Unterthiner, T., Dehghani, M., Minderer, M., Heigold, G., Gelly, S., & Houlsby, N. (2021). An image is worth 16x16 words: Transformers for image recognition at scale. In *Proceedings of the 9th International Conference on Learning Representations* (pp. 1–16).
Elaskary, M. (2018). The Korean wave in the middle east: Past and present. *Journal of Open Innovation: Technology, Market, and Complexity, 4*(4), 51. https://doi.org/10.3390/joitmc4040051
Forsythe, S. M. (1988). Effect of clothing masculinity on perceptions of managerial traits: Does gender of the perceiver make a difference? *Clothing and Textiles Research Journal, 6*(2), 10–16. https://doi.org/10.1177/0887302X8800600202
Ge, Y., Zhang, R., Wu, L., Wang, X., Tang, X., & Luo, P. (2019). Deepfashion2: A versatile benchmark for detection, pose estimation, segmentation and re-identification of clothing images. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition* (pp. 5337–5345).
Godart, F. C. (2018). Why is style not in fashion? Using the concept of "style" to understand the creative industries. In C. Jones & M. Maoret (Eds.), *Frontiers of creative industries: Exploring structural and categorical dynamics* (pp. 103–128). Emerald Publishing Limited. https://doi.org/10.1108/S0733-558X20180000055005

Gu, X., Gao, F., Tan, M., & Peng, P. (2020). Fashion analysis and understanding with artificial intelligence. *Information Processing & Management, 57*(5), 102276. https://doi.org/10.1016/j.ipm.2020.102276

Gurel, L. M., Wilbur, J. C., & Gurel, L. (1972). Personality correlates of adolescent clothing styles. *Journal of Home Economics, 64*(3), 42–47.

Jeon, Y., Jin, S., & Han, K. (2021). FANCY: Human-centered, deep learning-based framework for fashion style analysis. In *Proceedings of the Web Conference 2021* (pp. 2367–2378). *Association for Computing Machinery.* https://doi.org/10.1145/3442381.3449833

Jiang, Y., Yang, S., Qiu, H., Wu, W., Loy, C., & Liu, Z. (2022). Text2Human: Text-driven controllable human image generation. *ACM Transactions on Graphics, 41*(4), 1–11. https://doi.org/10.1145/3528223.3530104

Jin, D. Y., & Yoon, K. (2016). The social mediascape of transnational Korean pop culture: Hallyu 2.0 as spreadable media practice. *New Media & Society, 18*(7), 1277–1292. https://doi.org/10.1177/1461444814554895

Joint Operation of Related Ministries. (2020). K-culture promotion policy promotion plan. Retrieved from https://www.mcst.go.kr/kor/s_notice/press/pressView.jsp?pSeq=18151&pMenuCD=0302000000 Accessed on 5 May 2022.

Kiapour, M. H., Yamaguchi, K., Berg, A. C., & Berg, T. L. (2014). Hipster wars: Discovering elements of fashion styles. In *Proceedings of the IEEE International Conference on Computer Vision* (pp. 3519–3526).

Kim, H. S. (2017). An analysis of a strategy for the activation of Korean wave K-fashion. *Journal of the Korea Fashion and Costume Design Association, 19*(3), 175–192.

Kim, I. K., Cha, Y. M., & Lee, J. (2017). A comparative study of Korean fashion and K-fashion in 1980s–2010s. *The Eastern Art, 34*, 91–114.

Kim, Y. J., & Lee, K. H. (1997). A study on the visual evaluation about combination of contrary clothing image. *Journal of the Korean Society of Clothing and Textiles, 21*(8), 1297–1306.

Kolesnikov, A., Beyer, L., Zhai, X., Puigcerver, J., Yung, J., Gelly, S., & Houlsby, N. (2020). Big Transfer (Bit): General visual representation learning. In *Proceedings of European Conference on Computer Vision* (pp. 491–507).

Kwan, J. S. (2015). Characteristics of neon color in modern fashion. *Journal of the Korean Fashion and Costume Design Association, 17*(2), 207–222.

Lipson, S. M., Stewart, S., & Griffiths, S. (2020). Athleisure: A qualitative investigation of a multi-billion-dollar clothing trend. *Body Image, 32*, 5–13. https://doi.org/10.1016/j.bodyim.2019.10.009

Liu, Z., Luo, P., Qiu, S., Wang, X., & Tang, X. (2016). Deepfashion: Powering robust clothes recognition and retrieval with rich annotations. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition* (pp. 1096–1104).

MacLaury, R., Paramei, G., & Dedrick, D. (2007). *Anthropology of color: Interdisciplinary multilevel modeling*. John Benjamins Publishing Company.

Mollica, P. (2013). *Color theory: An essential guide to color-from basic principles to practical applications* (Vol. 53). Irvine, CA: Walter Foster.

Nakajima, T., Oki, T., & Miyamoto, R. (2018). Accuracy improvement of fashion style classification by appropriate training data and estimation of human regions. *IEICE Technical Report; IEICE Tech. Rep., 117*(516), 197–202. Retrieved from https://search.ieice.org/bin/index.php?category=D&lang=EN&curr=1&page=121&year=2018&vol=117&num=516

Omary, Z., & Mtenzi, F. (2010). Machine learning approach to identifying the dataset threshold for the performance estimators in supervised learning. *International Journal for Infonomics (IJI), 3*(3), 314–325.

OED Online. Hallyu, n. Oxford University Press, March 2022. www.oed.com/view/Entry/92458492. Accessed 5 May 2022.

Paek, S. L. (1986). Effect of garment style on the perception of personal traits. *Clothing and Textiles Research Journal, 5*(1), 10–16. https://doi.org/10.1177/0887302X8600500102

Petridis, A. (2014). Youth subcultures: What are they now. *The Guardian*. https://www.theguardian.com/culture/2014/mar/20/youth-subcultures-where-have-they-gone. Accessed May 4, 2022.

Russakovsky, O., Deng, J., Su, H., Krause, J., Satheesh, S., Ma, S., Huang, Z., Karpathy, A., Khosla, A., Bernstein, M., Berg, A. C., & Fei-Fei, L. (2015). Imagenet large scale visual recognition challenge. *International Journal of Computer Vision, 115*, 211–252. https://doi.org/10.1007/s11263-015-0816-y

Seo, Y., & Shin, K. (2018). Business application of convolutional neural networks for apparel classification using runway image. *Journal of Intelligence and Information Systems, 24*(3), 1–19. https://doi.org/10.13088/jiis.2018.24.3.001

Simo-Serra, E., & Ishikawa, H. (2016). Fashion style in 128 floats: Joint ranking and classification using weak data for feature extraction. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition* (pp. 298–307). https://doi.org/10.1109/CVPR.2016.37

Solomon, M. R. (1986). Deep-seated materialism: The case of Levi's 501 jeans. *Advances in Consumer Research, 13*, 619–622.

Sweat, S. J., & Zentner, M. A. (1985). Female appearance presentation: Gender differences in social attribution and situational choice. *Home Economics Research Journal, 14*(2), 175–186. https://doi.org/10.1177/1077727X8501400201

Takagi, M., Simo-Serra, E., Iizuka, S., & Ishikawa, H. (2017). What makes a style: Experimental analysis of fashion prediction. In *Proceedings of the IEEE International Conference on Computer Vision Workshops* (pp. 2247–2253). https://doi.org/10.1109/ICCVW.2017.265

Tan, M., & Le, Q. (2019). EfficientNet: Rethinking model scaling for convolutional neural networks. In *Proceedings of the 36th International Conference on Machine Learning* (pp. 6105–6114). PMLR 97.

Vittayakorn, S., Yamaguchi, K., Berg, A. C., & Berg, T. L. (2015). Runway to realway: Visual analysis of fashion. In *2015 IEEE Winter Conference on Applications of Computer Vision (WACV)* (pp. 951–958).

Yamaguchi, K., Kiapour, M. H., & Berg, T. L. (2013). Paper doll parsing: Retrieving similar styles to parse clothing items. In *Proceedings of the IEEE international conference on computer vision* (pp. 3519–3526).

Zhao, L., Li, M., & Sun, P. (2021). Neo-fashion: A data-driven fashion trend forecasting system using catwalk analysis. *Clothing and Textiles Research Journal,* 0887302X211004299. https://doi.org/10.1177/0887302X211004299

Zhou, Z. (2018). A brief introduction to weakly supervised learning. *National Science Review, 5*(1), 44–53. https://doi.org/10.1093/nsr/nwx106

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