Decoding the fashion trend of sports shoes with empowered computer vision

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ABSTRACT – REZUMAT

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To adapt to the rapidly changing market and capricious trends, fashion brands need to understand trends and market conditions precisely and fast to produce marketable products. The traditional fashion trend analysis has relied heavily on the subjective judgement of experts, inevitably leading to biased decisions and is time-consuming. The development of computer vision and machine learning provides an objective and systematic approach to processing images and analysis of fashion products. However, most studies focus on clothing trends analysis, few are on shoe trends analysis. Hence, this study aimed to decode and analyse the fashion trend of sports shoes with empowered computer vision technology. In this paper, a dataset containing e-commerce images of sports shoes with precise annotations was established; then Mask-RCNN was utilized to classify and extract the shoe from the background image; a modified version of the K-means clustering algorithm was employed to detect the shoe colour. The results indicated that fashionable sports shoes and casual sports shoes were the most prevalent two styles. Besides neutral tones, yellow, red ochre and reddish orange were popular in casual sports shoes, fashion sports shoes and basketball shoes respectively and Atlantic Blue in board shoes and trainers. This study demonstrated the promising potential of computer vision and machine learning as a new method to analyse footwear fashion trends efficiently and economically.

Keywords: *fashion trend analysis, sports shoes, fashion attribute recognition, computer vision, machine learning, K means clustering*

Decodificarea tendinței în modă pentru pantofii sport cu tehnologie de viziune computerizată

Pentru a se adapta pieței în schimbare rapidă și tendințelor capricioase, brandurile de modă trebuie să înțeleagă tendințele și condițiile pieței cu precizie și rapiditate, pentru a produce produse comercializabile. Analiza tradițională a tendințelor modei s-a bazat în mare măsură pe judecata subiectivă a experților, ceea ce duce inevitabil la decizii părtinitoare și consumatoare de timp. Dezvoltarea viziunii computerizate și a învățării automate oferă o abordare obiectivă și sistematică a procesării imaginilor și analizei produselor de modă. Cu toate acestea, cele mai multe studii se concentrează pe analiza tendințelor de îmbrăcăminte, puține fiind efectuate pe baza analizei tendințelor de încălțăminte. Prin urmare, acest studiu și-a propus să decodifice și să analizeze tendința modei pentru pantofii sport cu tehnologie de viziune computerizată. În această lucrare, a fost stabilit un set de date care conține imagini de comerț electronic cu pantofi sport cu adnotări precise; apoi Mask-RCNN a fost utilizat pentru a clasifica și extrage pantoful din imaginea de fundal; a fost folosită o versiune modificată a algoritmului de grupare K-means pentru a detecta culoarea pantofului. Rezultatele au indicat că pantofii sport la modă și pantofii sport casual au fost cele mai răspândite două stiluri. Pe lângă tonurile neutre, ocru roșu și portocaliu roșiatic au fost populare în cazul pantofilor sport casual, pantofilor sport la modă și, respectiv, pantofilor de baschet, iar albastrul Atlantic s-a dovedit a fi popular la tenişi și adidaşi. Acest studiu a demonstrat potențialul promițător al viziunii computerizate și al învățării automate ca nouă metodă de a analiza tendințele modei încălțămintei în mod eficient și economic.

Cuvinte-cheie*: analiza tendințelor modei, pantofi sport, recunoașterea atributelor modei, viziune computerizată, învățare automată, grupare K-means*

INTRODUCTION

Fashion trend represents the latest fashion elements such as styles, ornaments, shapes, and silhouettes, which is greatly influenced by political, economic, cultural and technological macro contexts of a certain time and determined fundamentally by consumers. With socio-economic and technological developments, fashion cycles are getting shorter fashion trends become more volatile and it is harder to predict than before. Additionally, consumers seek new styles more incessantly when stimulated by the short life cycle product models of fast fashion [1]. As consumers become more fashion-sensitive and demand becomes more diverse to showcase themselves to the fullest, fashion companies have to manufacture a large variety of products, which would not meet the consumer demand, thereby leading to problems such as heavy inventory and business loss [2]. Therefore, investigating fashion trends and changes in consumer behaviour precisely become a compulsory course in the fashion industry. Forecasting the fashion trend as precisely as possible was a challenge. Traditional short-term fashion forecasts heavily rely on the intuition of experts, which inevitably leads to biased decisions and is time-consuming [3].

Recently, fashion studies on fashion attribute detection and trend analysis have seen an increasing interest in the adoption of computer vision and machine learning [4], which provides an objective and systematic approach to processing images and analysis of fashion products and outfits efficiently. Earlier works [5] utilized SIFT, texture descriptors, colour in LAB, and skin probabilities to conduct feature extraction. Furthermore, Support Vector Machines(SVM) classifiers were trained to detect a wider range of 40 attributes. Bossard et al. [6] applied a Random Forest to classify the type of clothing and used several SVMs to train 78 attributes for recognizing the style of the clothing. With the development of deep learning, Liang et al. [7] developed two Convolutional Neural Networks (CNNs) and directly predicted the label masks to fully capture the complex correlations between structure and human appearance. Some state-of-the-art object detection algorithms like Faster R-CNN and Mask R-CNN were deployed for generating item proposals and classifying. Jia et al. [8] modified the Faster R-CNN model with ResNet 101 and ROI-align, additionally trained on a large-scale localization dataset with 594 fine-grained attributes to recognize fashion attributes. Shi et al. [9] modified Faster R-CNN and Mask R-CNN for recognizing attributes from images and videos respectively, thus recognising attributes such as textures, style, and design details and ultimately summarizing the fashion trend. Zhao et al. [10] applied Mask R-CNN to segment and classify clothing and used k-means clustering to extract colours, finally analysed fashion trends in colours, styles, other attributes and clothing combinations. All those deep learning algorithms showed better performance than the traditional method.

Several studies have explored how fashion trends changed from temporal and spatial perspectives by exacting cross-media fashion data [4, 11]. Chen et al. [12] investigated whether fashion trends at fashion shows influence streetwear. Getman et al. [13] visualized the patterns of baseball caps and tracked their frequency and emergence it from 2000 to 2018. Vittayakorn et al. [14] earned similarity functions on the features over the semantic parse of clothing to mimic the outfit similarity and compared fashion trends from the runway to the real world. Song et al. [15] predicted human occupation by modelling the appearances of human clothing and surrounding context based on semantic-level descriptions. Yamaguchi et al. [16] quantified the influence of fashion visual, textual, and social factors on the popularity of fashion images.

Datasets with rich data sources, specific targets and diverse attributes are the key to fashion analysis. There exists a wide variety of benchmark datasets that contributed to a comprehensive understanding and analysis of fashion, mainly coming from e-commerce like Amazon, eBay, and ModShop [17,18] and social media [19]. Among these datasets, the largest dataset is Deepfashion which comprises 800k annotated clothing images of shopping websites and Google Images, containing 50 categories and 1,000 attributes and landmarks [20]. Yamaguchi et al. [21] collected 158k photographs from a social networking website for fashion bloggers called Chictopia, which covers 56 clothing label annotations, comments, links and 685 masks estimating complete and precise regions of outfits. The database can be used for clothing recognition and retrieval. Matzen et al. [22] built a worldwide annotation dataset named STREETSTYLE-27K which retrieved more than 100 million photos with geolocation and timestamp from Instagram and 48 million geotags from Flickr 100M. However, all of these datasets mainly include clothing and there is no clean exclusive dataset for shoe images.

Although the footwear trend is generally in line with the clothing trend, it has specific characteristics due to its relatively small size and complicated colour combination. Meanwhile, consumer demands in the footwear industry are diversified, such as the prevalent demand for comfort and athleisure in line with style and performance in activewear [23].

Nevertheless, most studies have focused on the fashion trends of clothing and there has been little discussion about the trend of footwear.

Among the many image recognition algorithms such as R-CNN, Fast R-CNN, Faster R-CNN and Mask R-CNN, Mask R-CNN has the best accuracy and speed performance. It adds a branch for predicting an object mask in parallel with the existing branch for classification and bounding box regression based on Faster R-CNN, fulfilling pixel-to-pixel alignment between network inputs and outputs. Moreover, a RoIAlign layer is proposed to remove the harsh quantization of RoIPool, which properly aligns the extracted features with the input and greatly improves mask accuracy. Hence, Mask R-CNN is chosen to recognize and extract the shoes from complex backgrounds.

This study aims to decode and analyse the colour trend of sports shoes with empowered computer vision technology. To begin with, images of sports shoes from representative websites and brands in 2021 were collected to create a dataset; then Mask R-CNN was utilized to recognize the shoe style and separate them from the background; the K-means clustering algorithm was employed to detect the shoe main colour; ultimately all those attributes were summarized for fashion trend analysis. According to our study, we would like to further approve the potential application of computer vision and machine learning as a new method to decode footwear fashion trends in an efficient and time-saving way. Meanwhile, accurate trend analysis would ensure the company achieves efficient and accurate design and decision-making.

METHODOLOGY

To analyse shoe trends, this study proposed a novel fashion trend analysis system based on computer vision technology. There were two parts of models used in this study: Mask-RCNN for segmenting the shoe from the background and recognizing basic attributes; K-means clustering for colour extraction. Algorithms were taught the attributes of the image with labelling annotation, which is called training. The Mask-RCNN was trained with 4744 images of shoes, of which there are 2846 fashion sports shoes, 806 casual sports shoes, 759 board shoes, 142 training shoes, and 190 basketball shoes. Then 100 images of each category collected were used as the validation of accuracy and robustness for the classification test.

Dataset building and labelling

11,267 sneaker images from representative online shopping websites and classic footwear brands were selected as the main trend sources in this paper, covering SSENSE, FARFETCH, SHOPBOP, NIKE, UNDER ARMOUR, ADIDAS, CONVERSE and so on for the whole year 2021. A team of design-related students were recruited and guided for manual annotation using LabelMe and Excel. LabelMe [24] is an open-access image annotation software for labelling. For each given image, students were required to label the outline of each shoe mode.

Category classification and segment

This study utilized Mask R-CNN [25] for category classification and segmentation from the background, which is a deep convolutional neural network for solving the instance segmentation problem. As the most widely used instance segmentation network in recent years, it can simultaneously perform the tasks of object detection, classification, and semantic segmentation. The Mask RCNN is a two-stage framework, where the first stage scans the image and generates proposals about the regions that are likely to contain a target; and the second stage predicts the class of objects, refines the bounding box and generates a mask of objects at the pixel level. The main network framework of the Mask RCNN consists of 6 main components: the backbone network, the Feature Pyramid network (FPN), the region proposal network (RPN), the proposal regions of interest (ROI), the rolling and the multitasking module. ResNet101-FPN was chosen as the backbone of the Mask R-CNN, which uses a top-down structure and lateral connections to extract the RoI according to the scale of the different levels of the feature pyramid and has the most balanced performance compared to other backbone networks [26].

Extract shoe colours

This study utilised the most commonly used modified version of the K-means clustering algorithm (mean-ranked K-means) clustering algorithm [27] to identify the main colours of the shoe, which avoided a large number of distance calculations when finding the nearest cluster centre for each point. K-means clustering is a specific theoretical partitioning method that randomly selects initial cluster centres and classifies pixels by performing clustering operations on the initial cluster centres [28].

EXPERIMENTS AND RESULTS

Experiments

After extracting shoes from the background, CIELAB was used to indicate the colour of a shoe instead of using RGB. Since CIELAB is considered to be perceptually uniform in terms of human colour vision, which means that the same amount of numerical alteration in these values equates to the approximately same amount of visually perceived adjustment [29]. In this study, the obtained RGB image pixels were mapped to Lab colour space and then classified into 25 clusters using the K-means clustering algorithm (figure 1).

The results of shoe categories

Table 1 demonstrates the frequency and distribution of all categories of sports shoes for various seasons and top types. In general, the numbers of fashionable sports shoes and casual sports shoes were the second highest among all types, with 4520 (40.12%) and 2705 (24%) respectively, whereas the figure for basketball shoes was the fewest at 537 (4.77%). In all categories, spring and autumn styles appeared most frequently with 10228, followed by summer style with 567, and winter style with 472, indicating that consumers mainly consider spring and autumn styles when buying fashion sports shoes or fashion sports shoes are mostly produced.

Of all the shoe categories, low-top styles had the largest proportion among all tops except basketball shoes which the high-top styles took the vast majority. The high-top styles of fashion sneakers and trainers represented the smallest among all tops, while casual sneakers and board shoes had the smallest proportion of medium tops. The vast majority of fashion sneakers were low-top types accounting for 81.42% (3680). In spring and autumn, all styles were predominantly low-top, except for basketball shoes (predominantly mid-top). Trainers and fashion sneakers constituted the least of high-top types, and casual sneakers and board shoes represented the least of mid-top types in spring and autumn. In winter, all shoe styles were dominated by high-top styles to keep warm. In contrast, there were primarily low-tops in summer, when the high-tops were the fewest type except for board shoes.

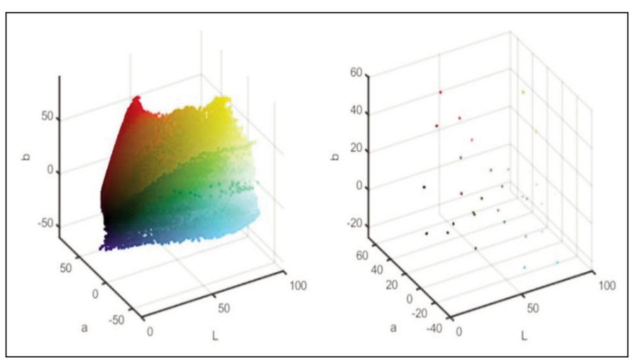

Fig. 1. Clustering process in lab colour space

Table 1

THE FREQUENCY OF ALL TYPES OF SPORTS SHOES FOR VARIOUS SEASONS AND TOP TYPE					
Style	**Top**	**Season**			
		Spring/autumn	**Winter**	**Summer**	**Total**
Fashion sports shoes	**Total**	**4386**	**78**	**56**	**4520(40.12%)**
	low top	3601	29	50	3680(81.42%)
	mid top	447	15	4	466(10.31%)
	high top	338	34	2	374(8.27%)
Casual sports shoes	**Total**	**2461**	**178**	**66**	**2705(24%)**
	low top	1761	37	57	1855(68.58%)
	mid top	313	30	7	350(12.94%)
	high top	387	111	2	500(18.48%)
Board shoes	**Total**	**2209**	**93**	**394**	**2696(23.93%)**
	low top	1779	14	338	2131(79.04%)
	mid top	112	3	2	117(4.34%)
	high top	318	76	16	410(19.24%)
Training shoes	**Total**	**713**	**58**	**38**	**809(7.18%)**
	low top	471	5	35	511(63.16%)
	mid top	164	8	3	175(21.63%)
	high top	78	45		123(15.20%)
Basketball shoes	**Total**	**459**	**65**	**13**	**537(4.77%)**
	low top	82	2	6	90(16.76%)
	mid top	204	3	4	211(39.29%)
	high top	173	60	3	236(43.95%)
Total	-	10228	472	567	11267

The results of colour detection

Figure 2 demonstrates the percentage of 10 colours of all sports shoes according to different seasons and categories. In general, the main colour palette was black, white and grey in different shades of light. Light grey accounted for the largest colour proportion (60% in fashion sports shoes and 52% in all categories) except trainers and board shoes where black took up the largest percentage (approximately 30%). On the contrary, fashion sports shoes and basketball shoes represented small proportions of black (only 5%). The colour that constituted the second largest proportion was medium grey among casual sports shoes, board shoes, fashion sports shoes and basketball shoes, ranging from 10% to 20%. The overall colour scheme of casual sports shoes was a simple warm grey and the smallest percentage of all colours was rufous. The distribution of different grey colours in casual sports shoes was also in keeping with the colour style of casual wearing. It can be seen that several vibrant colours such as blue, fruit green, orange and red are in board shoes, trainers and basketball shoes. And it was not uncommon to apply these sporty, energetic and fashionable bright colours to those types of sneakers. On the other hand, one of the few bright and vibrant colours in fashion sports shoes was red, only occupying 0.5%, while the major colour was light grey. This was mainly because most people considered the matching of shoes and clothes when choosing fashionable sports shoes.

The lightness of the colours of sneakers varied from season to season. In winter, there were around half of the sneakers with dark colour, comprising 28% dark grey and 18% black. The general hue was warm in winter shoes while the hue was fresh and cool in spring, autumn and summer. The shoe colours conformed to the laws of the seasons just like clothes. Among the three seasons, black ranked the smallest percentage in summer and was more taken place by cool light grey compared to winter.

Figure 3 depicts the ten primary bright and spritely colour distributions of different seasons and categories. In addition to blue dominating board shoes and trainers, warm colours such as red and brown occupied the most position and cold colours such as green accounted for the least colour among casual sports shoes, fashion sports shoes and basketball shoes generally.

Concerning casual sports shoes, orange and red ranked as the largest two positions, while green and modena ranked the smallest relatively. Red ochre and reddish orange became the colour trend of fashion in sports shoes and basketball shoes respectively. It makes sense to see a vibrant colour like reddish-orange in basketball shoes and casual yellow in casual sports shoes. In terms of seasonal trendy colours, cold colours like blue and modena were the

Fig. 2. 10 main colour distribution of different: *a* – categories; *b* – seasons

trend in summer while dark colours like red ochre for winter and warm colours such as reddish orange were the trend in spring and autumn in 2021.

DISCUSSION

The proposed AI method based on computer vision can accurately recognize the fashion attributes of sports shoes, including category and colour. In this study, the backbone network ResNet101-FPN has been used to recognize board shoes, sneakers and boots with intersection over union (IOU) of 79.12, 74.59, and 71.19 respectively. The reason for the difference may be that there is not enough training and the number of each category is not evenly distributed. Moreover, there exist some exaggerated and unconventional design appearances that might affect this. The average similarity of recognition of Mask-RCNN was above 85.5% and the inference time was 0.1s for each image, which exceeded the precision in the previous research and enabled the algorithm to analyse images more effectively and accurately compared to the traditional manual trend analysis method [9, 30]. In addition, 25 types of lab colours were extracted and analysed in this research, including the most used, compatible and basic colours and some trendy colours.

The datasets established in this research contain 11,269 collected e-commerce images with 4754 clean mask annotation, which is inclusively focused on sports shoes. Nevertheless, most of the fashion datasets are primarily clothing-relevant and some researchers train the models with a weakly supervised

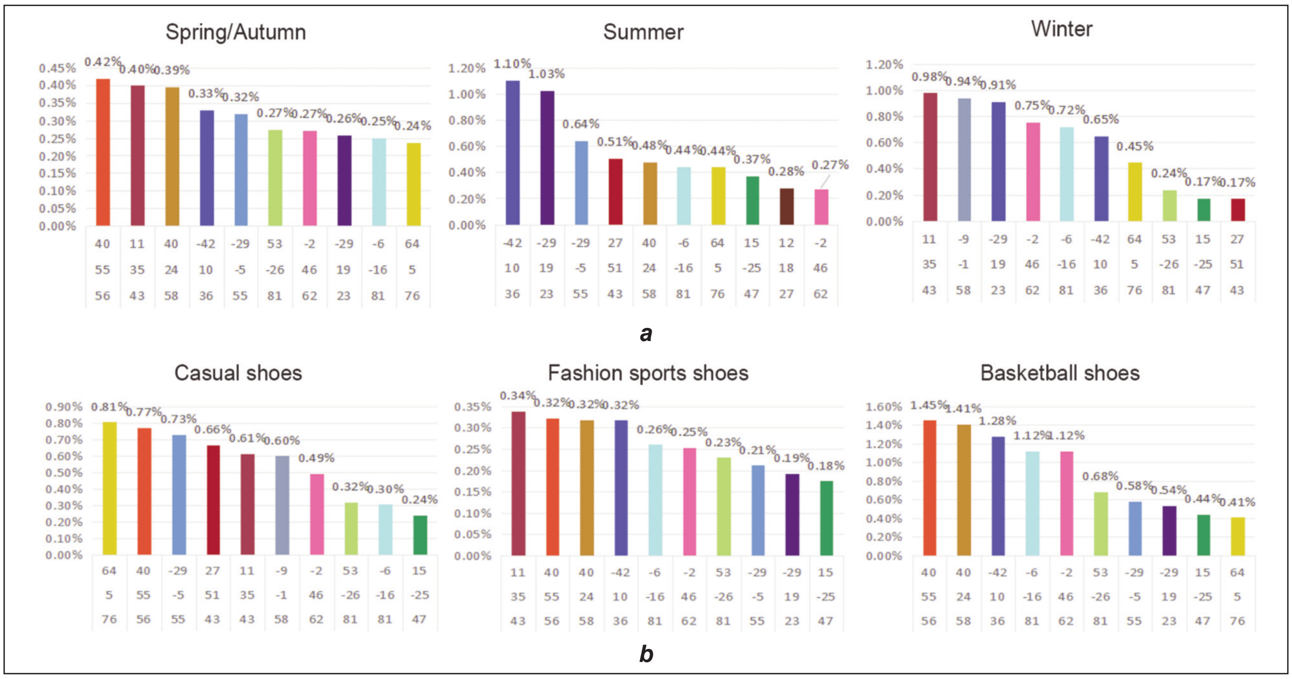

Fig. 3. 10 primary bright colours distribution over different: *a* – seasons; *b* – categories

approach that learns through noisy text labels, which may lead to inferior performance [31, 32]. With the development of online media, social media has become an important medium for fashion trend dissemination and fashion trend analysis combined with social media images from the temporal-space dynamics perspective can be the next direction. Future enlarged datasets sourcing from street photographs, runways and social media from different places and times are therefore recommended.

The exaction results indicated that the numbers of fashionable sports shoes and casual sports shoes are the highest two types, which was consistent with the current consumer attitude of focusing more on both comfort and fashion in consumption and life. It is also likely that the dataset mainly comes from fashion e-commerce, therefore fashion sneakers take up the most percentage. As for top styles, low-top styles represented the largest proportion among all tops except basketball shoes which the high-top styles took the vast majority. Although the design of the low-top is convenient for taking on and off movement, the high-top of the basketball shoe is designed to offer protection to the ankle and Achilles tendon when playing basketball.

The most frequent colours were neutral tones and were seen in the trend analysis by WGSN. About bright colours, blue dominated board shoes and trainers, which was also in line with Atlantic Blue in the sneakers trend report in 2021 by WGSN [31]. Warm colours occupied the most position and cold colours accounted for the least colour among the other 3 types of shoes generally. In summary, the primary sneakers' colours were grey, white and black, which are clean and simple. The trendy colours varied from season to season, predominantly cool colours in summer, and warm colours in spring, autumn and winter. As for trendy colours in different categories, yellow, red ochre and reddish orange represented the most popular colours in casual sports shoes, fashion sports shoes and basketball shoes respectively and Atlantic Blue represented the most popular in board shoes and trainers.

The interpretation of methods proposed in this study would be as follows: (1) by combining the Mask-RCNN with k-means, we could quantify the fashion element of shoes to automatically classify and extract; (2) subsequently, we could explore their correlations within various fashion elements, and then further establish the mathematical forecast model of the fashion trend; (3) this whole process would be independent to the viewpoints of the traditional experts. It sources from the massive data existing in the public and reflects the real-world acceptance of fashion trends. Therefore, this approach will have a wide range of applications in reality.

CONCLUSION

This study explored the potential of computer vision and deep learning as a new method to analyse footwear fashion trends efficiently and accurately compared to quantitatively conventional manual methods, according to the analysis of a dataset containing 11,269 images of sports shoes established from representative websites and brands. This study has identified yellow, red ochre and reddish orange as the most popular colours in casual sports shoes, fashion sports shoes and basketball shoes respectively and Atlantic Blue represented the most popular in board shoes and trainers in addition to neutral tones. It appears to be a pioneering study to build a dataset within the domain of sports shoes and with fine-grained attribute annotations, which will facilitate subsequent research into shoe fashion trends analysis. This time-saving and economical method of trend analysis enables fashion companies to the fast respond quickly to trends and market information quickly, thus introducing products that meet the trend efficiently and economically.

Considering the relatively limited amounts of data, training time and technical support for the training of the project, students were asked to label only the category of the shoes. In the future, more shoe images covering wider categories can be labelled and fed into the dataset to refine the instance segmentation algorithm and fashion attributes such as patterns and materials can be considered for recognition. The fashion dataset should be expanded, containing not only online shopping images but also images from runway, street and social media and other text information like brand, year, location comments, etc. A further study focused on the multi-dimensional analysis of fashion trends such as fashion propagation and the influence factors is therefore suggested.

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