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Predicting fashion trend using runway images: application of logistic regression in trend forecasting

Samit Chakraborty, S M Azizul Hoque and S M Fijul Kabir

Wilson College of Textiles, North Carolina State University, Raleigh, NC, USA

ABSTRACT
Trend forecasting is a challenging job and needs precise prediction based on colour, pattern, and style. Nowadays, researchers are applying machine learning and predictive models to predict the trend. Fashion runways are considered important events by high-street and fast fashion retailers. These events inspire them to design and develop different styles for the mass people. This research presented an approach to predict pattern and outfit based on the images collected from New York Fashion Week Fall/Winter 2019 (NYFW-19). Instagram posts, using logistic regression. The results predicted the patterns that could be used by retailers in the coming season for mass-market consumers. However, it could not predict outfit as a function of colour as there was no relationship between these two variables.

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KEYWORDS
Trend forecasting; fashion; runway images; logistic regression; machine learning

1. Introduction

Fashion stylists and designers express their ideas and thoughts through their textile and fashion design (Thomassey, 2014). Fashion has become an integral part of our daily lives. There has been a continuous worldwide expansion of fashionable clothing since last decade. The global fashion market is now worth of USD $3 trillion (Al-Halah, Stiefelhagen, & Grauman, 2017). Fast fashion trend has forced fashion designers and retailers to bring variation in each season (Caro & Martínez-de-Albéniz, 2015). Runway events (organised in London, Paris, New York, and Milan), trend forecasting companies and most recently social media images (particularly Instagram) play a crucial role in predicting fashion trends (Park, Ciampaglia, & Ferrara, 2016; Rousso & Ostroff, 2018). Therefore, the recent inrush of internet users has motivated the whole fashion industry to apply machine learning techniques to extract all forms of important information from the online mediums to forecast fashion trends, customise their customer service based on the mostly weighted contents and hence meet consumers' demands (Lord, Macdonald, Lyon, & Giaretta, 2004; Mona, 2017; Park et al., 2016). Nevertheless, it is costly and also difficult to correctly analyse the colour, pattern, and outfit (Park et al., 2016; Rousso & Ostroff, 2018). Using computational predictive analysis of runway images collected from popular social networking sites (such as Instagram) would facilitate small brands to forecast these crucial factors and survive in the age of fast fashion. In spite of this huge influx of social media users and various contents available, most of the big data or metadata analysis conducted till now is based on textual data such as comments, reviews, blogs etc. However, an immense collection of visual data is available in an unstructured way in the form of billions of images or photos uploaded every day in the photo-sharing sites. The use of machine learning for pattern recognition and trend analysis has been very popular in recent times. These analyses helped researchers to predict the contents and thus eliminate uncertainty related to product or process development (Doersch, Singh, Gupta, Sivic, & Efros, 2012; Gebru et al., 2017; Wang, Korayem, & Crandall, 2013; Zhu, Lee, & Efros, 2014).

This research considered runway images shared on Instagram by New York Fashion Week for Fall/Winter 2019 season (NYFW, 2019). This approach will add value to the product development and marketing strategies (Matzen, Bala, & Snavely, 2017). Today, it is not enough to entirely depend on sales record to predict the future demand or trend. Therefore, the application of machine learning in the fashion retailing area has become a crucial aspect (Al-Halah et al., 2017). The objective of this research is to predict (whether a particular colour or colour combination could tell us the most probable pattern and outfit based on the images analysed) the next season fabric pattern and outfit based on the colour extracted from runway images

CONTACT S M Azizul Hoque shoque@ncsu.edu Wilson College of Textiles, North Carolina State University, Raleigh, NC 27695, USA

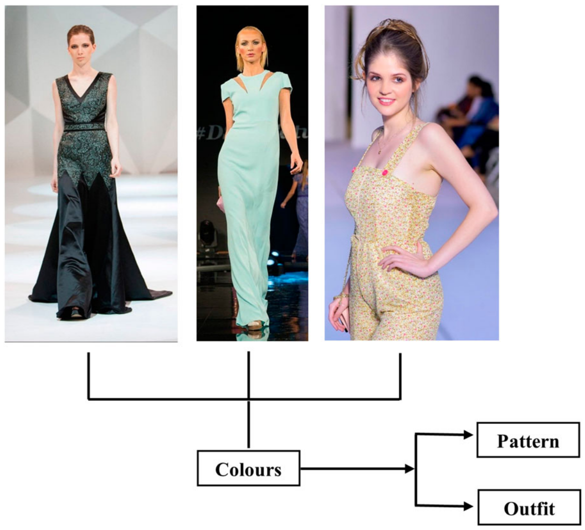

Figure 1. Examples of pattern and outfit for a given colour extracted from the runway images (Pixabay, 2020).

(Figure 1) using the logistic regression; both fabric pattern and outfit are categorical variables with six levels (monochrome or solid, check, stripe, multicolour all over print (AOP), multicolour placement print (PP) and multicolour jacquard design (JD)) and five levels (top part clothing, dress, bottom part clothing, jumpsuit, and outerwear), respectively.

2. Literature review on fashion trend forecasting

2.1. Procedures of forecasting fashion trends

Generally, trend is originated from colours two years ahead of its availability in the retail stores (Brannon, 2010). Organisation, such as Pantone LLC, exhibits possible colour trend long before the start of a new season. Fashion trend forecasting agencies like WGSN (Worth Global Style Network) and Trend Union announce the potential colour and outfit or style trends two years before their availability in the market. The fashion design departments of the respective companies then start analysing the combination of materials and colours for the upcoming seasons. Meantime, the creative fashion designers also begin presenting their designed products in the fashion week or runway events arranged in London, Paris, New York, and Milan. The luxury fashionable clothing presented in these events is presented in the latter half of the year. However, the information of these new clothing items already gets spread through different online and offline mass media, which play a pivotal role in the formation process of fashion trends. Recently, online bloggers and social media users influence the marketing strategy of fashion retailers and consumers' fashion consumption to a great extent. As a result, fashion retailers and designers now consider and evaluate the mostly discussed content liked and shared on virtual mediums, because these contents may contain different messages relevant to trend as well as sales forecasting (Furukawa, Miura, Mori, Uchida, & Hasegawa, 2019; Wang et al., 2013; Zhu, Lee, & Efros, 2014).

2.2. Forecasting based on outfit type and shape

Prior to technological developments in the clothing industry and mass market garment production measurements of dress such as length of the skirt and neckline width were used to study future fashion trends (Furukawa et al., 2019). For instance, the chronological changes in evening dress silhouettes were shown in the research article published by Kroeber (1919). Richardson and Kroeber (1940)'s study on women's formal dresses showed both short-term and long-term cycles in the measurements of dress silhouette brought by designers from 1605 to 1936. Lowe and Lowe (1982) adopted time series analysis to determine the dimensions, which exhibited the stylistic and silhouette changes in women's formal outfits. This method was also utilised to analyse other forms of outfits (Furukawa et al., 2019). Belleau (1987) showed a repeated change in the waist and length of women's day dresses for the period 1860–1980. Researchers also showed a repeated change in the dimensions of outfits based on the fashion catalogues printed between 1954 and 1990 (Curran, 1999). Moreover, Balkwell and Ho (1992) also conducted an analysis to explore the relationship between economic factors and dimensions of outfit such as length of the skirt and neckline width from 1966 to 1986. However, the earlier research mostly concentrated on change of clothing shapes to predict the short-term and long-term fashion trends (Furukawa et al., 2019), that hardly develop a relationship between colour combination and type of outfit, which might be a significant criterion for assessing the consumers' perception for clothing. Therefore, this paper explored the possibility of predicting the types of outfit or style utilising the colour adopted by designers during NYFW-19, so that designers and retailers could apply a similar strategy for the upcoming fashion season.

2.3. Forecasting based on colour and pattern

Clothing colour can generate a strong impression and hence is considered an influential factor in forecasting fashion trends (Furukawa et al., 2019). Researchers developed various methods to forecast colour trends such as colour image scale consisting of three axes, namely clear–greyish, soft–hard, and warm–cool (Kobayashi, 1981). The researcher applied factor analysis to determine the axes based on the values derived from the semantic differential method. Cassidy and Cassidy (2012) showed in their research that colour largely influenced fashion trends and also discussed how clothing design, production, sales, marketing strategies, and consumers' buying intention could be used to improve the colour trend forecasting process. The research also proposed an efficient procedure to upgrade the forecasting method by applying soft systems methodology. Koh and Lee (2013) analysed colour extracted from various digital photos and images of Ready-to-Wear clothing collections displayed in 2010 Autumn/Winter (A/W) fashion weeks held in London, Paris, New York, and Milan. The colour data used for this research were composed of 16 colour palettes including pink, silver, and gold. The results from this analysis showed that purple was the most frequently used colour in the London fashion week, but it was infrequent in the Milan 2010 A/W fashion collection. Xiong, Junk, Kitaguchi, and Sato (2016) analysed the colour appearance of outerwear available in the form of the digital images posted in different online stores. These online stores sell clothes of popular fast fashion retailers. They explained the colour trends of each respective brands based on their online sales of previous year. They also discussed how colour pallets and distribution of colour spectrum differ between men and women outerwear. Xiong, Kitaguchi, and Sato (2017) also applied this method to compare the outfits of five luxury fashion companies (Hermès, Louis Vuitton, Gucci, Chanel, and Prada) based on their ready-to-wear collections displayed from 2006 to 2015. The results of this research showed that Chanel exhibited a high proportion of black and white clothing. On the other hand, brown was the most frequently used colour for over a decade in the clothing designed by Hermès. Al-Halah et al. (2017) conducted a similar analysis on the images of clothing items sold on Amazon for a specific period to discover the future fashion trends. Researchers have considered colour of textile materials as one of the most influential factors in trend forecasting. The optical properties of textile materials are another important factor considered by designers while predicting fashion trends. However, no one can simply depend on colour or its hue, saturation, and brightness to bring changes in or predict the upcoming fashion products. Not all colours or colour combinations can be used to test the consumers' choice (Furukawa et al., 2019). The colour selection as well as the colour combination should reflect an appeal similar to the clothing displayed by designer brands. Therefore, this paper explored the relationship between colour and different types of pattern to minimise the uncertainty in fashion forecasting.

2.4. Forecasting based on machine learning

The extensive use of internet, blogs, and social media has enabled people to easily access to a large number of photos, annotations, opinions, and comments related to fashion products and fashion-concerned people (Furukawa et al., 2019). Gaimster (2012) mentioned that the impact of technology on fashion industry cannot be overlooked. The technological advancement developed a new research area of image processing and analysis of fashion products and outfits (Liu, Liu, & Yan, 2014; Yamaguchi, Kiapour, Ortiz, & Berg, 2012). Vittayakorn, Yamaguchi, Berg, and Berg (2015) proposed an image retrieval model that segments images posted in the popular photo-sharing website named Chictopia used by fashion followers. The pictures used for that research were selected from major runway events held between 2000 and 2014. They developed a system using the machine learning algorithms that could count all similar images.

Researchers also analysed fashion trends and assessed fashion designs by using geographic distribution of people across different countries, cities, and societies based on the data derived from Chictopia (Simo-Serra, Simo-Serra, Fidler, Moreno-Noguer, & Urtasun, 2015). Their research framework was based on the conceptual model proposed by Yamaguchi et al. (2012). He and McAuley (2016) developed a machine learning technique to show sequential changes in fashion trends based on the fashion products sold by the online retailers of Amazon.com. The continuous advancements in machine learning techniques since last few years have motivated fashion retailers to adopt these methods in their fashion supply chain (Furukawa et al., 2019). Huge number of training datasets are now available in the internet because of the availability of e-crowd sourcing services (Liu et al., 2012; Yamaguchi et al., 2012). However, the quality of these datasets has not been discussed in previous works.

Computer vision researchers have shown a growing interest in fashion trend forecasting in recent years. They focused to detect type, colour, shape, style, annotations, and transaction of clothing based on the images collected from different web sources (Berg, Berg, & Shih, 2010; Bossard et al., 2012; Bourdev, Maji, & Malik, 2011; Chen, Gallagher, & Girod, 2012; Parikh & Grauman, 2011). Although visual colour extraction from pictures has been performed visually in these research works, there are also some other related works in which image parsing has been carried out to segment clothing attributes (Vittayakorn et al., 2015; Yamaguchi, Hadi Kiapour, & Berg, 2013; Yamaguchi et al., 2012). However, it is difficult to predict trends based on clothing style as it changes from time to time (Furukawa et al., 2019). There are also various works related to recognising features and concepts that predict demographic variables such as occupation (Shao, Li, & Fu, 2013; Song, Wang, Hua, & Yan, 2011) and social identity (Kwak, Murillo, Belhumeur, Kriegman, & Belongie, 2013). However, this research paper used the images collected from fashion week or runway events similar to the research done by Furukawa et al. (2019) and Vittayakorn et al. (2015). Vittayakorn et al. (2015) also evaluated human judgements to find out the outfit similarity and also looked into the changes in fashion trends over a specified period. Their study also found the variations in the fashion style, which were not considered in earlier research works (Berg & Belhumeur, 2013; Gavves, Fernando, Snoek, Smeulders, & Tuytelaars, 2013). In spite of the availability of such research articles, the relationship among colour, colour patterns, and outfits has been often overlooked in the literature; hence, the present research is designed to ease the forecasting process.

3. Research method

3.1. Analytical method: logistic regression

Logistic regression can be stated as a predictive analysis used to discover the chances of an event to have occurred in near future (Grayson, Gardner, & Stephens, 2015). This is an appropriate method to predict the dichotomous or binary dependent variable(s) based on its relationship with predictors or independent dummy variables. The Logistic regression analysis is a form of machine learning technique that describes a dataset containing single or multilevel independent and dependent variable(s). The independent and dependent variables can be of different types such as ordinal, interval, nominal, or ratio-level (Allison, 2012; Statistics Solutions, n.d.). The following formula shown in Equation (1) represents the logistic regression model, where X is the value of the predictor, β_0 and β_1 are the regression coefficients, and p is the probabilistic value to be determined. Each unit increase of X changes the log odd value by β_1 (Grayson et al., 2015).

$$\begin{aligned} &\mathrm{Log}(p/(1-p)) = (\beta_0 + \beta_1 X_1 + \ldots + \beta_k X_k) \\ &=> p/(1-p) = e^{-(\beta_0+\beta_1 X_1+\ldots+\beta_k X_k)} \\ &=> p = 1/(1+e^{-(\beta_0+\beta_1 X_1+\ldots+\beta_k X_k)}) \\ &=> p = 1/(1+e^{(-\mathrm{lin}(x))}) \end{aligned} \tag{1}$$

Here, $p/(1–p)$ can be stated as odd ratio from which the probability of dependent variable can be found. The logarithm of the odds ratio is termed as logit from which we can explore the probability of an event to occur (Allison, 2012; Statistics Solutions, n.d.). The probability formula was applied to execute the logistic regression analysis in this research to predict the pattern and outfit from Equations (2) and (3), respectively.

$$\text{Prob (Pattern)} = 1/(1+e^{-\mathrm{lin(colors)}}) \tag{2}$$

$$\text{Prob (Outfit)} = 1/(1+e^{-\mathrm{lin(colors)}}) \tag{3}$$

3.2. Data collection

For data collection, it is essential to identify the image source which truly reflects the trend for upcoming seasons. Previous researchers have suggested runway events organised in London, Paris, New York, and Milan as a source of fashion images (Park et al., 2016; Rousso & Ostroff, 2018). Hence, a source that contains images from single or multiple runways should be selected for data collection. Setting some criteria, such as the number of likes, image frequency, and image quality, helps screen more useful images for trend forecasting. After the selection, image analysis is performed based on colour, pattern, and output. The process flow of the present research is summarised in Figure 2.

The total no of images analysed in the research was 140 that were collected from the NYFW-19 Instagram posts that received more than 1000 likes (NYFW, 2019). The images were visually analysed to identify the clothing colour (Black (Bl), White (W), Grey (G), Red (R), Pink (P), Magenta (M), Green (Gr), Brown (Br), Yellow (Y), Orange (O) and Blue (B)), pattern (Monochrome or Solid, Check, Stripe, Multicolour All Over Print (AOP), Multicolour Jacquard (JD), Multicolour Placement Print (PP)), and outfit or style (top part clothing, bottom part clothing, jumpsuit, and outerwear). Colour was a binary variable (0, 1), where 0 represented the presence of colour(s) and 1 represented the absence of colour(s) for a given pattern and outfit. For instance, if an outfit was made of black, red, and green colours, then these colours were assigned to 1 and the

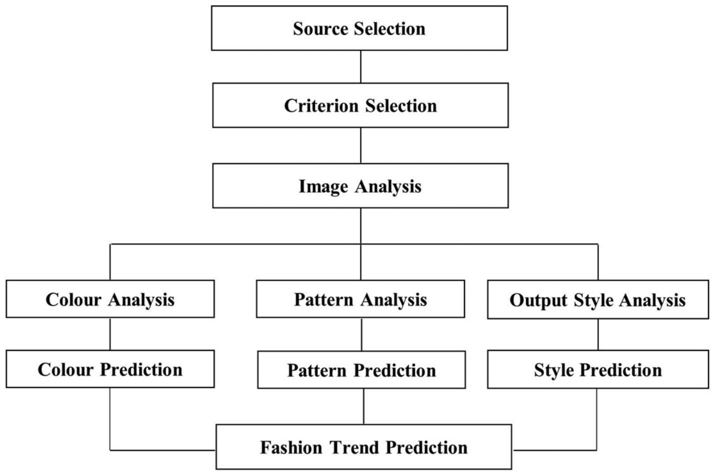

Figure 2. The process flow of the present research.

rest of the colours were assigned to 0 for that respective image. The outfit present in each image was analysed separately, which generated a dataset of 210 (the total no of outfits) records. Two logistic regression models were fitted for this dataset to predict pattern and outfit using JMP software.

4. Results and discussion

4.1. Distribution of images and colours

The distribution analysis of the pictures (posted by New York Fashion Week in its Instagram homepage) showed that black colour (found in the 40% of total images used for this research) has been most frequently used in the NYFW-19 followed by white (24%), yellow (17%), brown (17%), red (16%), green (14%), blue (13%), grey (13%), pink (9%), and orange (4%). The distribution graph of image percentages for each colour has been presented in Figure 3.

4.2. Pattern prediction

4.2.1. Distribution of colours for each pattern

The graph shown in Figure 4 demonstrates distribution of images containing black and orange colours for different patterns. For instance, Figure 4(a) shows that black colour was most frequently used to design monochrome or solid colour outfits (found in 41% of the total images) followed by multicolour AOP (24.2%), multicolour JD (12.3%), check (12.3%), multicolour PP (5.5%), and stripe (4.8%). A similar analysis could be conducted for the rest of the colours to display their frequencies. For example, Figure 4(b) shows that orange colour was most frequently used to design multicolour AOP pattern (found in 40% of total images) followed by monochrome or solid colour (28.6%), multicolour JD (14.3%), check (14.3%), and stripe (2.9%), although it has not been used in designing any outfit having multicolour PP.

Similarly, the distribution percentage of pattern has been presented in Figure 5, which shows that the most commonly used pattern for this season was monochrome or sold colour (63%) followed by multicolour all over print (16%), multicolour jacquard design (8%), check (7%), multicolour placement print (3%), and stripe (3%).

4.2.2. Nominal logistic fit for pattern

Figure 6(a,b) present the summary of the effects of colour to show the impact of the individual colours on predicting the pattern. Figure 6(a) shows the probability value (p-value) for all of the colours is less than 0.05 (at 5% significance level). Therefore, it appears that the colours possess significant impact on the pattern prediction. Moreover, Figure 6(b) demonstrates χ^2-test with a p-value of less than 0.001, which states that the

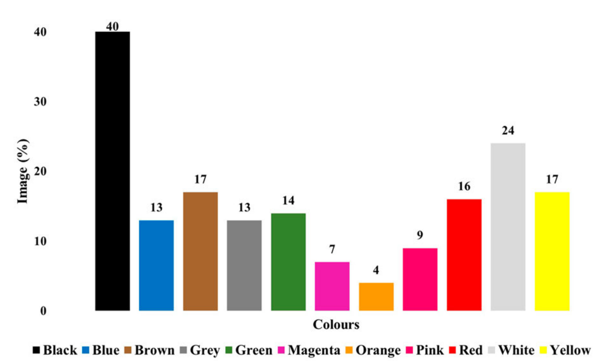

Figure 3. Distribution of colour (%) based on image dataset collected from the Instagram posts of NYFW-19.

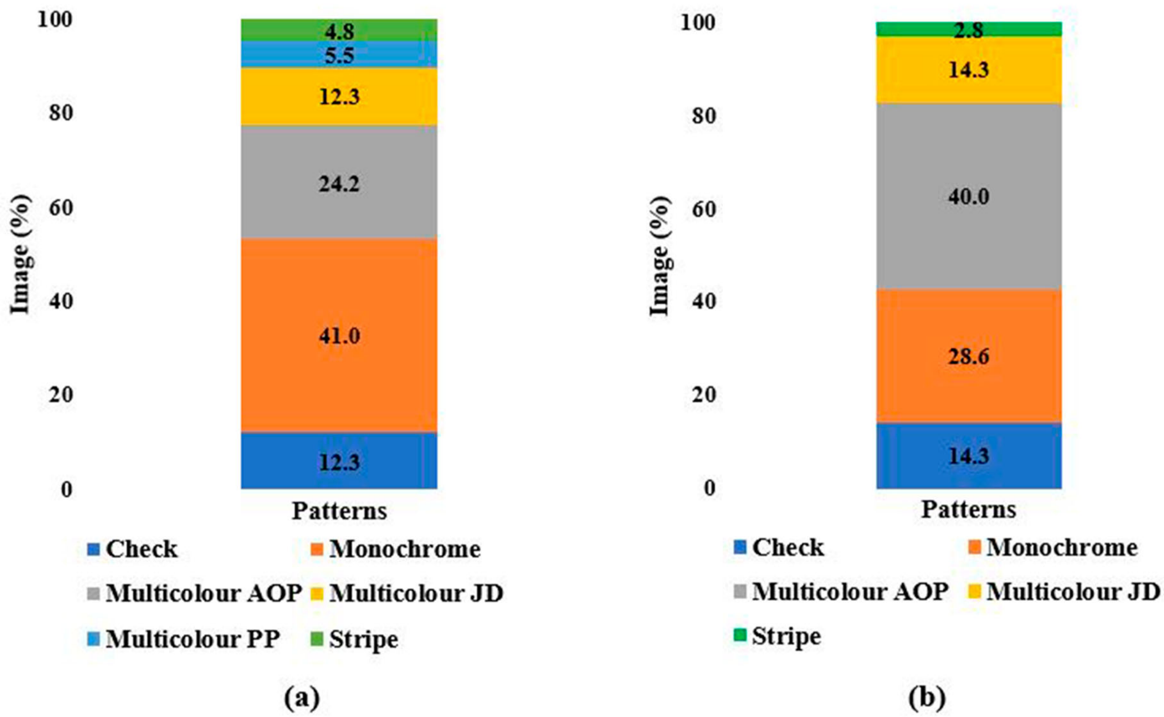

Figure 4. Images (%) containing black (a) and orange (b) in different patterns.

model is highly significant, and the pattern can be mathematically predicted based on colours.

4.2.3. Prediction model for pattern

Prediction model is used to have a clear understanding of the model and determine the predicted probabilities. Any change in the independent variable leads to a new probability value for dependent variable. Thus, it helps to understand the individual as well as combined impact of the independent components on the outcome variable (Grayson et al., 2015). Logistic regression models for different patterns were fitted, and probabilities of the respective patterns were calculated from the fitted models based on colour/s. For instance, Equation (4) presents the logistic regression model for multicolour AOP that can be developed for other patterns too (such as for Stripe, Check, Multicolour PP, Monochrome, and Multicolour JD).

$$\begin{aligned}\text{Lin(Multicolour AOP)} = {} & 0.101 + 0.366{*}Bl + 0.074{*}W \\ & + 0.246{*}G + 2.728{*}R + 1.888{*}P \\ & + 0.176{*}M + 1.142{*}Gr + 0.333{*}Br \\ & + 0.546{*}Y + 0.965{*}O + 0.166{*}B\end{aligned} \tag{4}$$

Using the fitted models of the patterns, the probability of Multicolour AOP can be derived using Equation (5). For example, if black, white, red, and green colours are present (1) and other colours are absent (0), then the most probable pattern would be a Multicolour AOP (54%), as shown in Table 1. Likewise, for the given colours, the probability of Check, Multicolour JD, and

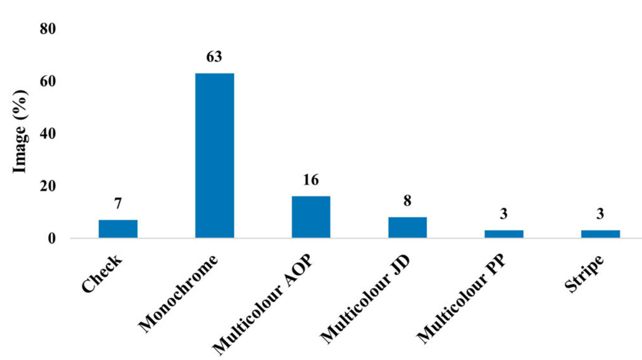

Figure 5. Pattern-wise image (%) used in NYFW-19.

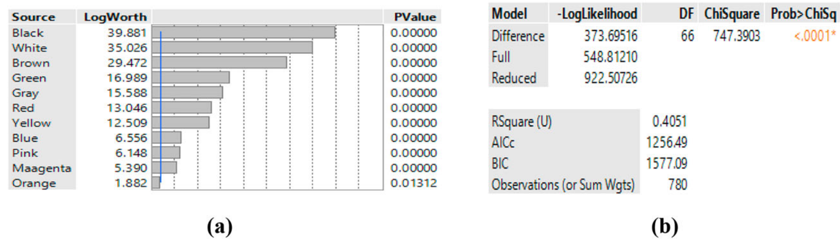

Figure 6. Effect summary of colours and whole model test.

others are 26%, 14%, and 6%, respectively.

$$\begin{aligned}\text{Prob (Multicolour AOP)} = 1/(1 + \text{Exp (Lin[Check]} \\ -\text{Lin[Multicolour AOP])} \\ +\text{Exp (Lin[Monochrome]} - \text{Lin[Multicolour AOP])} \\ +\text{Exp (Lin[Stripe]} - \text{Lin[Multicolour AOP])} \\ +\text{Exp (} - \text{Lin[Multicolour AOP])} \\ +\text{Exp (Lin[Multicolour JD]} - \text{Lin[Multicolour AOP])} \\ +\text{Exp (Lin[Multicolour PP]} - \text{Lin[Multicolour AOP]))}\end{aligned} \tag{5}$$

However, if the colours are changed to Black, Grey, and Green (for example), the most probable pattern becomes Multicolour JD (40%), followed by Multicolour AOP (33%), check (16%), and others (11%), as presented in Table 2. Consequently, it can be concluded that the pattern prediction changes with the change of the colour or colour combination.

4.3. Outfit prediction

4.3.1. Distribution of colours for each outfit

The graph in Figure 7 demonstrates distribution of images containing black colour for different outfits. For instance, black colour was most frequently used to design dress (found in 30.6% of total images) followed by bottom part clothing (23.9%), top part clothing (21.9%), outerwear (18.7%), and jumpsuit (4.8%) (Figure 7(a)).

A similar analysis could be conducted for the rest of the colours to show their frequency. For instance, orange colour was most frequently used to design dress (found in 37.1% of total images) followed by top part clothing (25.7%), outerwear (20%), bottom part clothing (14.3%), and jumpsuit (2.9%) (Figure 7(b)).

The distribution percentage for outfit has been presented in Figure 8. The figure shows the mostly designed outfit for this season was dress (30%) followed by top part clothing (23%), bottom part clothing (22%), outerwear (19%), and jumpsuit (6%).

4.3.2. Nominal logistic fit for outfit

Figure 9(a,b) present the summary of the effects of colour to show the impact of the individual colours on predicting the outfit. Figure 9(a) shows the probability value (p-value) for all of the colours was above than 0.05 (at 5% significance level). Consequently, it indicates that the colours do not possess a significant impact on the outfit prediction. Figure 9(b) demonstrates χ^2-test with a p-value of more than 0.05, which states that the model is not significant in predicting the outfit.

Figure 10 illustrates the distribution of most likely outfits for different patterns. The analysis of image dataset shows how the distribution of a particular outfit could be presented in terms of different pattern. For instance, according to this figure, most of bottom part clothing (64.9%) was designed using monochrome or solid colour pattern followed by multicolour AOP (15.5%), check (10.9%), stripe (4.6%), multicolour jacquard design (3.4%), and multicolour placement print only 0.6%. Similarly, according to this figure, most of the top part clothing (63%) was designed using monochrome or solid colour pattern followed by multicolour all over print (16%), multicolour jacquard design (7.7%), check (6.1%), multicolour placement print (3.9%), and stripe (3.3%). A similar analysis can be applied for the rest of the individual outfit. This distribution graph can be used as a framework while creating the designs of different outfits using different patterns.

Table 1. Prediction of the patterns for the presence (1) of Black, White, Red, and Green colours.

Pattern	Bl	W	G	R	P	M	Gr	Br	Y	O	B
Multicolour AOP (0.54) Check (0.26) Multicolour JD (0.14) Others (0.06)	1	1	0	1	0	0	1	0	0	0	0

Table 2. Prediction of the patterns for the presence (1) of Black, Grey, and Green colours.

Pattern	Bl	W	G	R	P	M	Gr	Br	Y	O	B
Multicolour JD (0.40) Multicolour AOP (0.33) Check (0.16) Others (0.11)	1	0	1	0	0	0	1	0	0	0	0

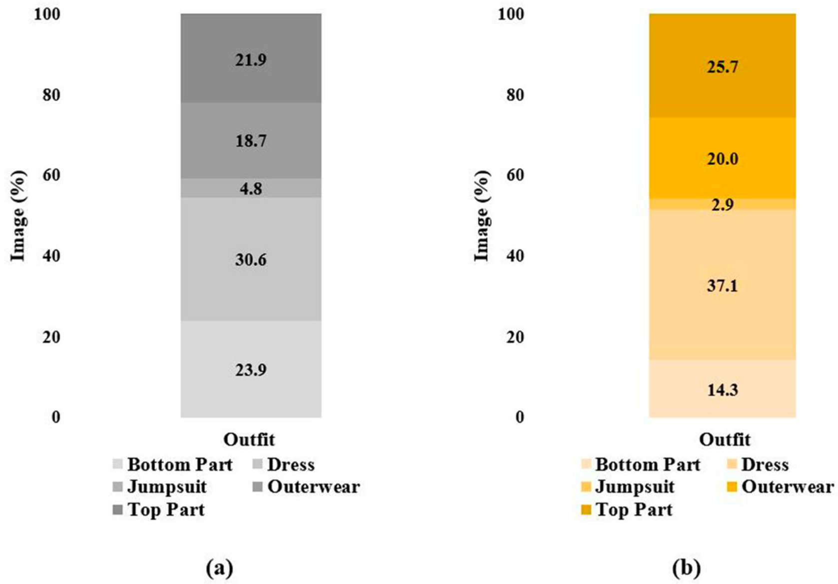

Figure 7. Images (%) containing black (a) and orange (b) in different outfits.

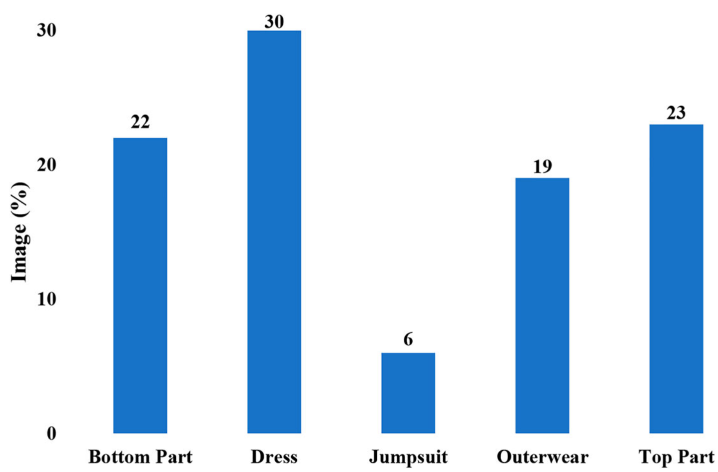

Figure 8. Outfit-wise image (%) designed for NYFW-19.

5. Managerial implications

Different researchers have adopted different approaches to present their prediction results of fashion trend forecasting. Image processing and social media analysis have become popular foundations for these research studies. Due to the absence of an established relationship among colour, pattern, and outfits, the present research addressing this gap presents a solution to

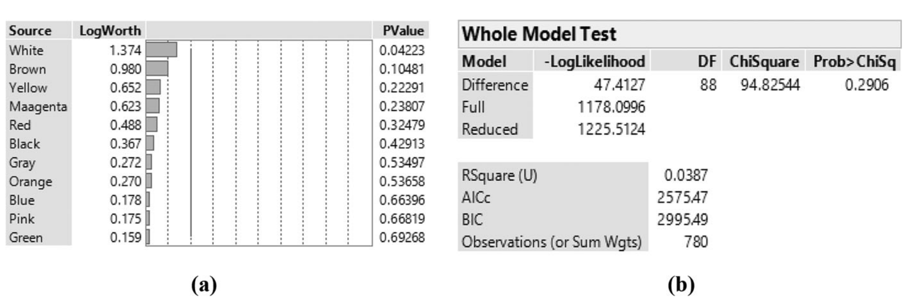

Figure 9. Effect summary of colours (a) and whole model test (b).

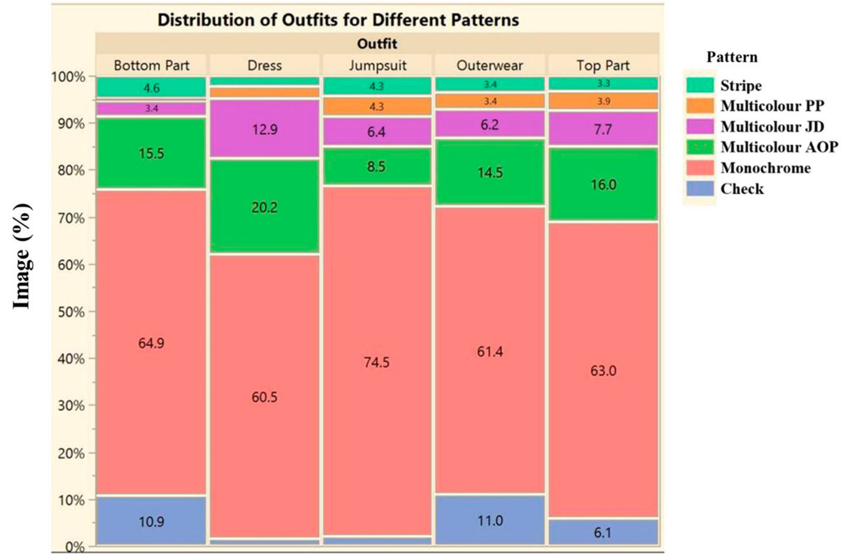

Figure 10. Distribution of most likely outfits for NYFW-19.

make the forecasting process much easier compared to the existing conventional methods. It also used the popular social media platform, such as Instagram, for collecting the runway photos that received maximum likes from the users. Hence, this research would be beneficial for both retailers and designers considering its contemporary significance in fashion retailing. This research has provided a detailed overview of the distribution of colours, patterns, and outfits used in NYFW-19 season. According to the colour, pattern, and outfits analysis, monochromic or solid coloured dress would have the potentiality to be a popular trend in the upcoming seasons. Multicolour all over print might be the second most prominent pattern for the outfits to be designed for the mass market. The use of black colour in designing dresses would be a wise selection by the designers and mass-market fashion retailers for the upcoming Fall/Winter 2019 season. The prediction model would be an effective tool to find out instantly what colour or colour combination could be used to design a specific pattern. The selection of colour for an outfit's pattern could also be retrieved from the distribution analysis of most likely outfit for most likely pattern. However, the research could not predict outfit because insignificant correlation between colour and outfit categories.

This research would facilitate a more prompt and economic approach towards fashion trend forecasting compared to an expensive collaboration with trend forecasting agency. The holistic approach of collecting image or visual data of runway events from social media and then analysing it with machine learning technique would facilitate brands to quickly respond to the probable mass market demand and present outfits that influenced from the designs created by high-end fashion designers. It would also enable fashion retailers to stand out their designs from the rest of the companies that produce outfits of almost similar pattern every season.

6. Limitations and future research directions

This research has few limitations too. The main limitation of this research is the small sample size. Further research that could explore other social media can also be extracted to enlarge the dataset. Similar research can be conducted applying other machine learning techniques and the results can be compared to them to determine the most efficient method. The shape of the outfit was not considered in this research. Future researchers can include this variable as it also contributes to change the fashion trend. There might be further research on the predicting outfit based on colour or colour combination. The addition or subtraction of categories in independent or dependent variable can lead to exploring the relationship between outfit and colour. Future researchers can utilise convolutional neural network using large dataset (Milan, Paris, London fashion, and Street style images) for more accurate prediction. Further research can be conducted on analysing Instagram hashtag images and comments of brands accounts to predict the fashion trend. Another interesting research project would be the comparison of output results with the sales history of online fashion retailers to understand the practical implications of this analysis.

7. Conclusion

Fashion trend forecasting is a both challenging and interesting topic to the researchers, designers, technologists, and marketing persons. This research would enable designers and retailers to explore different patterns and outfits using various combinations of colours. Therefore, the use of computational predictive analysis of runway images collected from popular social networking sites (such as Instagram) would facilitate small brands to compete with other brands in the current age of fast fashion. The application of logistic regression in trend forecasting will help designers and retailers to understand the product type, style, and pattern that would be popular in the coming season. It would minimise the uncertainty in sales forecasting as well. This research can be used as a basis for the further research studies related to fashion trend forecasting.

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ORCID

Samit Chakraborty http://orcid.org/0000-0002-4315-1779
S M Azizul Hoque http://orcid.org/0000-0001-7192-7485
S M Fijul Kabir http://orcid.org/0000-0002-9354-2022

References

Al-Halah, Z., Stiefelhagen, R., & Grauman, K. (2017). *Fashion forward: Forecasting visual style in fashion*. Proceedings of the IEEE International Conference on Computer Vision (pp. 388–397).

Allison, P. D. (2012). *Logistic regression using SAS: Theory and application*. Cary, NC: SAS Institute.

Balkwell, C., & Ho, S. H. (1992). A quantitative analysis of dress dimensions: Comparison of models for Taiwan and the United States from 1966 to 1986. *Clothing and Textiles Research Journal*, *10*(4), 47–53.

Belleau, B. D. (1987). Cyclical fashion movement: Women's day dresses: 1860–1980. *Clothing and Textiles Research Journal*, *5*(2), 15–20.

Berg, T., & Belhumeur, P. (2013). *Poof: Part-based one-vs.-one features for fine- grained categorization, face verification, and attribute estimation*. Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (pp. 955–962).

Berg, T. L., Berg, A. C., & Shih, J. (2010). Automatic attribute discovery and characterization from noisy web data. In K. Daniilidis, P. Maragos, & N. Paragios (Eds.), *European Conference on Computer Vision* (pp. 663–676). Berlin: Springer.

Bossard, L., Dantone, M., Leistner, C., Wengert, C., Quack, T., & Van Gool, L. (2012). Apparel classification with style. In K. M. Lee, Y. Matsushita, J. M. Rehg, & Z. Hu. (Eds.), *Asian Conference on Computer Vision* (pp. 321–335). Berlin: Springer.

Bourdev, L., Maji, S., & Malik, J. (2011). *Describing people: A poselet-based approach to attribute classification*. 2011 International Conference on Computer Vision (pp. 1543–1550). IEEE.

Brannon, E. L. (2010). *Fashion forecasting*. New York, NY: Fairchild Books.

Caro, F., & Martínez-de-Albéniz, V. (2015). Fast fashion: Business model overview and research opportunities. In N. Agrawal & S. A. Smith (Eds.), *Retail supply chain management* (pp. 237–264). Boston, MA: Springer.

Cassidy, T. D., & Cassidy, T. (2012). Using soft systems methodology to improve the colour forecasting process. *JAIC-Journal of the International Colour Association*, *7*, 27–50.

Chen, H., Gallagher, A., & Girod, B. (2012). Describing clothing by semantic attributes. In A. Fitzgibbon, S. Lazebnik, P. Perona, Y. Sato, & C. Schmid (Eds.), *European Conference on Computer Vision* (pp. 609–623). Berlin: Springer.

Curran, L. (1999). An analysis of cycles in skirt lengths and widths in the UK and Germany, 1954–1990. *Clothing and Textiles Research Journal*, *17*(2), 65–72.

Doersch, C., Singh, S., Gupta, A., Sivic, J., & Efros, A. (2012). What makes Paris look like Paris? *ACM Transactions on Graphics*, *31*, 1–9.

Furukawa, T., Miura, C., Mori, K., Uchida, S., & Hasegawa, M. (2019). Visualisation for analysing evolutionary dynamics of fashion trends. *International Journal of Fashion Design. Technology and Education*, *12*(2), 247–259.

Gaimster, J. (2012). The changing landscape of fashion forecasting. *International Journal of Fashion Design, Technology and Education*, *5*(3), 169–178.

Gavves, E., Fernando, B., Snoek, C. G., Smeulders, A. W., & Tuytelaars, T. (2013). *Fine-grained categorization by alignments*. Proceedings of the IEEE International Conference on Computer Vision (pp. 1713–1720).

Gebru, T., Krause, J., Wang, Y., Chen, D., Deng, J., Aiden, E. L., & Fei-Fei, L. (2017). Using deep learning and google street view to estimate the demographic makeup of the us. *arXiv preprint arXiv:1702.06683*.

Grayson, J., Gardner, S., & Stephens, M. (2015). *Building better models with JMP Pro*. Cary, NC: SAS Institute.

He, R., & McAuley, J. (2016). *Ups and downs: Modeling the visual evolution of fashion trends with one-class collaborative filtering*. Proceedings of the 25th International Conference on World Wide Web (pp. 507–517). International World Wide Web Conferences Steering Committee.

Kobayashi, S. (1981). The aim and method of the color image scale. *Color Research & Application*, *6*(2), 93–107.

Koh, Y., & Lee, J. (2013). A study of color differences in women's ready-to-wear collections from world fashion cities: Intensive study of the Fall/Winter. 2010 collections from New York, London, Milan, and Paris. *Color Research & Application*, *38*(6), 463–468.

Kroeber, A. L. (1919). On the principle of order in civilization as exemplified by changes of fashion. *American Anthropologist*, *21*(3), 235–263.

Kwak, I. S., Murillo, A. C., Belhumeur, P. N., Kriegman, D. J., & Belongie, S. J. (2013). From bikers to surfers: Visual recognition of urban tribes. *BMVC*, *1*, 2.

Liu, S., Feng, J., Song, Z., Zhang, T., Lu, H., Xu, C., & Yan, S. (2012). *Hi, magic closet, tell me what to wear!*. Proceedings of the 20th ACM International Conference on Multimedia (pp. 619–628). ACM.

Liu, S., Liu, L., & Yan, S. (2014). Fashion analysis: Current techniques and future directions. *IEEE MultiMedia*, *21*(2), 72–79.

Lord, P., Macdonald, A., Lyon, L., & Giaretta, D. (2004). *From data deluge to data curation*. Proceedings of the UK e-science All Hands meeting (pp. 371–375). National e-Science Centre.

Lowe, J. W., & Lowe, E. D. (1982). Cultural pattern and process: A study of stylistic change in women's dress. *American Anthropologist*, *84*(3), 521–544.

Matzen, K., Bala, K., & Snavely, N. (2017). Streetstyle: Exploring world-wide clothing styles from millions of photos. *arXiv preprint arXiv:1706.01869*.

Mona, D. (2017). *Predicting fashion using machine learning techniques* [Master's dissertation]. KTH Royal Institute of Technology Stockholm.

NYFW. (2019). *The official Instagram account for NYFW: The shows*. Retrieved from https://www.instagram.com/nyfw/

Parikh, D., & Grauman, K. (2011). *Relative attributes*. 2011 International Conference on Computer Vision (pp. 503–510). IEEE.

Park, J., Ciampaglia, G. L., & Ferrara, E. (2016). *Style in the age of Instagram: Predicting success within the fashion industry using social media*. Proceedings of the 19th ACM Conference on Computer-Supported Cooperative Work & Social Computing (pp. 64–73).

Pixabay. (2020). Free image on - Fashion show, fashion, catwalk. Retrieved from www.pixabay.com/

Richardson, J., & Kroeber, A. L. (1940). Three centuries of women's dress fashions, a quantitative analysis. *Anthropological Records*, *5*(2), 111–153.

Rousso, C., & Ostroff, N. K. (2018). *Fashion forward: A guide to fashion forecasting*. New York, NY: Bloomsbury Publishing.

Shao, M., Li, L., & Fu, Y. (2013). *What do you do? Occupation recognition in a photo via social context*. Proceedings of the IEEE International Conference on Computer Vision (pp. 3631–3638).

Simo-Serra, E., Simo-Serra, E., Fidler, S., Moreno-Noguer, F., & Urtasun, R. (2015). *Neuroaesthetics in fashion: Modeling the perception of fissionability*. Proceedings of the IEEE Conference on Computer vision and pattern recognition (pp. 869–877). IEEE.

Song, Z., Wang, M., Hua, X. S., & Yan, S. (2011). *Predicting occupation via human clothing and contexts*. 2011 International Conference on Computer Vision (pp. 1084–1091). IEEE.

Statistics Solutions. (n.d.). Logistic regression – statistics solutions. Retrieved from https://www.statisticssolutions.com/regression-analysis-logistic-regression/

Thomassey, S. (2014). Sales forecasting in apparel and fashion industry: A review. In T.-M. Choi, C.-L. Hui, & Y. Yu (Eds.), *Intelligent fashion forecasting systems: Models and applications* (pp. 9–27). Berlin: Springer.

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

Wang, J., Korayem, M., & Crandall, D. (2013). *Observing the natural world with Flickr*. Proceedings of the IEEE International Conference on Computer Vision Workshops (pp. 452–459). IEEE.

Xiong, Q., Junk, H., Kitaguchi, S., & Sato, T. (2016). Color feature of fast fashion brand outerwear on official online store. *International Journal of Affective Engineering*, *15*(1), 1–9.

Xiong, Q., Kitaguchi, S., & Sato, T. (2017). Color feature of luxury brand clothing, and its change in recent 10 years. *International Journal of Affective Engineering*, *16*(3), 203–211.

Yamaguchi, K., Hadi Kiapour, M., & Berg, T. L. (2013). *Paper doll parsing: Retrieving similar styles to parse clothing items*. Proceedings of the IEEE International Conference on Computer Vision (pp. 3519–3526). IEEE.

Yamaguchi, K., Kiapour, M. H., Ortiz, L. E., & Berg, T. L. (2012). *Parsing clothing in fashion photographs*. 2012 IEEE Conference on Computer vision and pattern recognition (pp. 3570–3577). IEEE.

Zhu, J. Y., Lee, Y. J., & Efros, A. A. (2014). Averageexplorer: Interactive exploration and alignment of visual data collections. *ACM Transactions on Graphics (TOG)*, *33*(4), 160.