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A COMPREHENSIVE REVIEW ON IMAGE BASED STYLE PREDICTION AND ONLINE FASHION RECOMMENDATION

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Abstract. Image analysis, processing, classification, and segmentation have become pivotal in style prediction and fashion recommendation. Fashion retailers have shown an increasingly growing interest in adopting this branch of artificial intelligence in their supply chains. Computer scientists and engineers have published several scholarly works on this topic since the last decade. Based on the previous studies, this is the first academic paper that has presented comprehensive review on this topic. These scholarly articles are related to image-based style prediction and online fashion recommendation. This is a form of method paper that illustrates research designs of the selected articles and research methods used by the researchers. Both style prediction and online fashion recommendation have been reviewed together in this paper, because study on recommendation system can facilitate an easy understanding of fashion style prediction and vice versa. Finally, the study will be helpful for fashion retailers and future researchers to understand the nature of style prediction and online fashion recommendation using image processing technique. The scientific contribution of this paper is that it has proposed a novel approach of reviewing research methods used in style prediction and fashion recommendation systems. Additionally, the article has also proposed a personalized recommendation model for the image-based fashion recommendation system.

Keywords: Image analysis, style prediction, fashion, online recommendation, methods, machine learning algorithm, recommendation model.

AMS Subject Classification: 68T00, 68W00.

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1 Introduction

Clothing is a kind of symbol, presents wearer internal perception through the outer appearance (Smith, 2014). It can convey the information of wearers' choice, faith, personality, profession, social level and attitude towards life. Therefore, clothing as a major part of outer appearance of people is believed to be a nonverbal way of communication (Barnard, 2013). With the development of internet and technology, clothing image posted by wearer especially in social media is largely available. Each day people upload billions of pictures to photo-sharing platforms and social networking sites. These images contain information about people around the world. These posted portraits and selfies are a good source of clothing image which is followed by billions of users (Clement, 2019) in social media (Bagadiya, 2017). The literature review from previous studies has found two types of social networking sites for fashion consumers, which are

(a) image-based social networking (e.g., Snapchat, and Instagram), and (b) text-based social networking (e.g., Twitter, and Yik Yak). The study found that image-based social networking sites are more popular among the fashion consumers than the text-based social networking sites. However, the text-image combined social sites (like Facebook) have overthrown both of the techniques (Pittman & Reich, 2016). There are already a vast number of social networking sites with Facebook being regarded as the most popular on the world (Spiller & Tuten, 2015). Most participants however reported that Instagram is the primary site of preference in fashion. This was backed by AbdelFattah et al. (2017), who noted that Instagram triggered strong reactions and emotions, creating participants however reported that Instagram is the primary site of preference in fashion to produce images of greater 'social value.' In addition, a number of fashion-based communities such as Chictopia and Loo-book, which are also known for sharing personal fashion styles. The features and attributes of these clothing images posted in social media can express more information about wearers' personality (Wei et al., 2017). Although, researchers have studied textual content of social media such as post and comment prediction (Zarei & Jabbarzadeh, 2019), emotion and information diffusion (Stieglitz & Dang-Xuan, 2013), research with the image analysis of social media is still limited in analyzing fashion styles or trends (Shin et al., 2019). However, online clothing image from social media and other sources can be a good source for analyzing and constructing online fashion recommendation (Jagadeesh et al., 2014; Ma et al., 2019; McAuley et al., 2015; Yamaguchi et al., 2014). Fashion choice of consumer often depends on many factors, such as demographic, geographic, individual preference, interpersonal-influence, age, gender, season, and culture (Rocha e al., 2005; Zhang et al., 2017; Zhang & Kim, 2013). Moreover, the image analysis researches (Matzen et al., 2017) showed that fashion preference varied not only from country to country but also from city to city as well. The combination of clothing style consistency (found in user images) and the above-mentioned factors associated with clothing choice could transmit the image features to fashion style understanding (Sun et al., 2018). Therefore, the analyses of consumers' choice and predictions of fashion trends are valuable for fashion designers and retailers (Matzen et al., 2017) (Hu et al., 2014). With the rapid expansion of social networks and fashion websites, clothing recommendation has attracted more attention of modern-day researchers, as it can facilitate an effective prediction of future fashion. Apparel and fashion recommendation for personal dressing is continuing from the oldest times. With the change of fashion period, the change in clothing style leads to the change in the fashion recommendation (Guan et al., 2016). The online clothing recommendation provides specific recommendation to the consumer. This recommendation system considers user social circle, image parsing, and fashion style consistency as important factors since they possess critical impacts on users' purchasing decisions. This type of analysis can be considered as a strong foundation for the online fashion recommendation system (Liu et al., 2018; Sun et al., 2018). In this modern era effective recommendation system (Dick & Basu, 1994; Srinivasan et al., 2002) is a crucial tool for successfully conducting e-commerce business. In the case of fashion recommendation, application of convolutional neural network or deep learning for image analysis, statistical analysis for recommendation systems comparison, use of appropriate methodology (quantitative or mixed-method based on research design) and formulating experimental models for the implementation of machine learning can be a crucial combination for designing an effective fashion recommendation system (Chen et al., 2015; Kang et al., 2017; Liang et al., 2015; Liu et al., 2018; Luce, 2018; Reece & Danforth, 2017; Stan & Mocanu, 2019; Sun et al., 2018; Tuinhof et al., 2018). Therefore, this paper aimed to find out how images could be used in the predictive analysis of fashion trends and online fashion recommendations. In order to fulfill this aim, this research paper reviewed the researches relevant to the topic. Also, it has analyzed the research designs of these scholarly articles to sum up them, which will work as a research methodology guideline for the future researchers willing to conduct research in this field. This method paper is the first of its kind that has been ever worked in this field.

2 Channels of Scholarly Dissemination

For the review purpose, the scholarly article searched in Google Scholar, Scopus and Web of Science group by using the keyword fashion recommendation, clothing image, deep learning, image analysis, machine learning, social media image and apparel recommendation. The most recent articles published from 2011 to 2020 have been considered for the review purpose of this article. These articles have been used to review the state-of-the-art recommendation and style prediction techniques. The following presents the distribution of these articles along with the key highlights derived from the articles.

No	Reference	Key Features
1	Tangseng & Okatani, 2020	Proposed reliability analysis for rating clothing attributes
2	Sachdeva & Pandey, 2020	Proposed a powerful online shopping system that use the feedback of a picture of clothing and automatically retrieve photos from a vast image collection.
3	Wu; Zhao; & Cui	Developed a two-stage integrated treatment analysis model to identify the obvious and unseen attitudes of the user against the target product and offer textual clarifications by highlighting those terms.
4	Jo, Lee, Lee, Lee, & Lim, 2020	Explicitly illustrated positive performance by using vector-based preference fashion recommendation model.
5	Grauman, 2020	Investigated ways to uncover Internet image trends, understand how people bring their outfits together and the hidden patterns that they share.
6	Lasserre et al., 2020	Explored that back propagation could exploit additional data substantially more effectively and improve its performance at very low cost.
7	Liang, Lee, & Workman, 2020	Result indicated perceived utility, perceived user-friendliness and performance risk were important in customer attitudes to AI.
8	Ma et al., 2020	The KERN model proposed can capture the complex functions of objective fashion elements effectively and can thus predict the trend in fashion.
9	Shi & Lewis, 2020	The suggested machine-learning model can discover specifics of clothing the human eyes cannot easily see with 24/7 tirelessness.
10	Küçükbay & Turha, 2019	For majority voting, the average accuracy of the 4 separate algorithms is 67 per cent, which is similar to the Dataset 1 performance of the Neural Network algorithm.
11	Zhou et al., 2019	Algorithm is developed to render mix-and-match suggestions by combining categories derived from the image and information attributes are with attributes dependent on text.
12	Kang et al., 2019	Crafted a crop-based approach to create STL (Shop the Look) data CTL data sets. CTL approach produces qualitatively consistent suggestions for a dynamic 'style' notion.

No	Reference	Key Features
13	Chelliah, Biswas, & Dhakad, 2019	Covered many other facets of fashion suggestion using visual cues (e.g. cross-scenario extraction, attribute classification) and also incorporate text information (e.g., interpretable embedding).
14	Hsieh & Li, 2019	Developed a system of recommendation that would infer fashion patterns derived from the social trade forum and suggest clothing for the users with great high precision.
15	Li, Feng, Ahmad, & Wang, 2019	To know the representation, they are following a multi-task deep learning system. And for learning variance they suggested multi-weight profound neural networks.
16	Yin, Li, Lu, & Zhang, 2019	This method is superior to several AUC baselines and diversity indicators, the test results show.
17	Chen et al., 2019	In order to improve the fashion recommendations, they suggested jointly leveraging image area level functionality and user experience details.
18	Yan, Chen, & Zhou, 2019	The test results showed that the factorization machine model produces better recommendations have been achieved through a segregated recommendation approach for both active and inactive users.
19	Yan et al., 2019	Showed that StyleNet can achieve better classification accuracy by applying the multi-task representative learning framework.
20	Aşiroğlu et al., 2019	Created two initial convolutional neural networks as a sample component in order to propose a material, and one feeds the neural network as a suggestive.
21	Hou et al., 2019	The study findings of a large-scale real-world data collection clearly showed the effectiveness and explanatory ability of SAERS.
22	Sonie, Chelliah, & Sural, 2019	Introduced case-by-case fashion and used these techniques for modeling image, text and sequence data to define user profiles, provide customized suggestions tailored to evolving user preference and interest.
23	Nash, 2019	The results have shown that consumers use a range of internal and external motives that affect their actions and expectations of high-street fashion stores.
24	Zou et al., 2019	A large-scale information dataset with a manual annotation is given in high quality.
25	Jing, Ye, Nie, Liu, & Su, 2019	Created a supervised training system by using two forms of supervision knowledge from classified data to improve the representation capability.

No	Reference	Key Features
26	Stefani et al., 2019	Proposed a recommendation system proposing score ratings for providing fashion experts' advice to registered users.
27	Chen et al., 2019	Their platform outperformed other potential solutions in terms of suit usability, outfit creation and suggestion with substantial margins.
28	Zhan et al., 2019	The data collection tests demonstrated the benefits of the new system over state-of-the-art approaches to both street photos and product images.
29	Guan, Qin, & Long, 2019	Revealed three-staged reliable model to predict attributes of apparel using the clothing photos, and the second is to forecast clothing definitions based on predicted attributes more specifically.
30	Zhang & Caverlee, 2019	Helped customers easily select apparel from internet through fuzzy technique.
31	Alamsyah et al., 2019	The validation test showed that object identification models have an accuracy value of 0.9897 by retraining the CNN models. The level of precision depended on the design, data size and testing dataset used.
32	Ngai et al., 2018	Introduced an IDSS4FA program that can be used for informative analysis of social media texts and images, online fashion magazines, e-commerce and fashion pages.
33	Liu et al., 2018	Experiments with the H2WB dataset demonstrated this approach to the area identification of clothes; clothes pair recommendation and distance fusion performance.
34	Sun et al., 2018	In order to thoroughly test the concept, detailed studies have been performed on two real-world datasets obtained from the popular social fashion website, which illustrate the feasibility of the proposed customized clothing suggestion process.
35	Hanke et al., 2018	This assessment revealed that the ability to distinguish garments and consumers in intelligent fitted cabins makes the product recommendation system more relevant.
36	Agarwal, Vempati, & Borar, 2018	Experimental findings on a popular ecommerce site (MYNDRA) demonstrated that by personalizing specific product suggestions that can boost key metrics.
37	Wibowo et al., 2018	Results demonstrated that modeling constraints are an essential phase in the clothes domain, either by manual curing from outside tools or by automatic acquisition from within the dataset.
38	O'Halloran et al., 2018	Demonstrated how a digital world provides different possibilities to turn qualitative data into quantitative data in order to use multi process analysis data mining and information visualization.

No	Reference	Key Features
39	Checco et al., 2017	Demonstrated how to overcome these challenges by introducing an interconnected data ecosystem focused on simple in-memory databases primitivities, deep text processing and crowd sourcing.
40	Wang et al., 2017	Specific state-of-the-art POI Recommending Programs have been presented in the system suggested.
41	Al-Halah et al., 2017	Demonstrated that fashion forecasts are far more valuable than textual or meta data information about goods from visual analyzes.
42	Heinz, Bracher, & Vollgraf, 2017	Successfully combined long-term evolution of design and short-term consumer intent commitment to dramatically boost consistency and validity of recommendations.
43	Zhang et al., 2017	The application of hierarchy viewpoint by using by fuzzy technique improves accuracy and potency of the weak-looking function test.
44	Barros Costa et al., 2017	Advice methodology tested and the preliminary findings revealed that consumers with appropriate clothing options are significantly assisted.
45	Goel, Chaudhury, & Ghosh, 2017	Approach to clothing like various models on a selection of clothing from different websites has been checked, verified and given an appropriate user experience for the suggestion of clothing.
46	Tangseng et al., 2017	Proposed a system that achieved accuracy and precision, which indicated that the algorithm can calculate the consistency of the equipment consistently.
47	Chen & Liu, 2017	Showed that the proposed system can make substantial improvements to three style classification public clothing datasets.
48	Rawat & Wang, 2017	Proposed model showed considerable improvement in image classification activities and setting state of the art on a variety of difficult classification requirements related to image classification.
49	Li, Cao, Zhu, & Luo, 2017	Although it is very difficult to quantify mode equipment and composition, this model achieved high accuracy using small mixing and matching function.
50	Park, Ciampaglia, & Ferrara, 2016	This system predicted most of the latest common models that were efficient published in 2015.
51	Guan et al., 2016	In this report high-tech integrated clothing systems were categorized into 3D CAD systems, custom design systems and suggestion systems.
52	Zhang, Zeng, Koehl, & Dong, 2016	Combined data on the body and user desires with visual and keyword variations and shapes it into two bases of information.

No	Reference	Key Features
53	Dang et al., 2016	The experimental result revealed that the suggested method helped to select the appropriate clothes based on a particular client's preference.
54	Perkinian & Vikkraman, 2015	The image suggestion tests demonstrated that our approach to object learning greatly outperformed other state-of-the-art approaches.
55	Geng, Zhang, Bian, & Chua, 2015	This proposed a method of functional tensor factorization to model the relationships between the user-item and item-item.
56	Yang Hu, Yi, & Davis, 2015	Presented a new deep domain adaptation network for the problem of representing individuals based on the characteristics of fine grain garments.
57	Nogueira et al., 2015	A new collaborative filtering strategy has been implemented which uses visual aspects to identify images and to mitigate the current cold-start problem.
58	Zempo & Sumita, 2015	The CCPV (Color Class Vector Profile) that reflected the overall perception of a product-containing digital image was introduced categorize several different colors, resulting in 14 color groups, as each object has its color in the database.
59	Limaksornkul et al., 2014	The innovative aspect of the Smart closet program was that it preserved information on commonly used clothes and accessories and recommended the style for current conditions and special occasions.
60	Wang, Zeng, Koehl, & Chen, 2014	Consumers using fuzzy cognitive maps modeled the dynamic relationship between simple, sensory and trendy descriptors.
61	Peng & Al-Sayegh, 2014	Provided a big breakthrough for reviews of low-cost sizes made from a single e-commerce image that enhanced only new apparel shopping by combining tailored body dimensions with customized garments.
62	Liu, Liu, & Yan, 2013	The two key aspects of the system are both automated and intelligent, and this work would display two conceptual sub-systems relating to the entire Magic Mirror system.
63	Yamaguchi et al., 2012	Recent interesting findings on clothing estimates to enhance the recognition of poses and the framework for prototype of pose-independent visual apparel retrieval are presented.
64	Sekozawa et al., 2011	Developed a system, which, using the Fuzzy Logic technology that arrange clothes that are ideal for a single customer's taste.

3 Method Analysis

3.1 Review of the Research Purposes

The research focuses have been categorized into the following subcategories through the integral review of researchers' main objectives.

To Propose a Clothing Recommendation System. The main purpose of these types of research (Ngai et al., 2018; Checco et al., 2017; Chen et al., 2015; Geng et al., 2015; Liu et al., 2018; Sun et al., 2018; Wei et al., 2017; Yan, 2011) were to develop a recommendation system for online shoppers and social media users (mostly Instagram and facebook) to benefit both consumers and retailers. Among these various researchers (Geng et al., 2015; Liu et al., 2018; Ngai et al., 2018; Sun et al., 2018) used image (of product and user) and text (in image and comment) content analysis approach to understand fashion analytics across different demographics and then applied it a new recommendation framework. (Checco et al., 2017; Chen et al., 2015) intended to explore how product recommendation could be made more accurate in e-commerce sites based on the product attribute analyzing and clothing style matching. (Wei et al., 2017) intended to find out how consumers' clothing style and personality could be correlated to facilitate a novel recommender system. Toward explainable fashion recommendation (Tangseng & Okatani, 2020) suggested a method that does not only include a successful score for an outfit but also include a justification to justify the result. To this end, they suggest a method for quantifying how influential each attribute of each object is to the score. (Zhang & Caverlee, 2019) offered a consumer-oriented method of advice through fuzzy strategies and AHP that can be used as a virtual sales adviser inside a clothing online shopping system. The proposed program would help customers pick clothing from the Internet.

To Explore Different Fashion Styles and Trends. (Sachdeva & Pandey, 2020) focused on the analysis of patterns for different consumer groups with finely-grained fashion elements. Within the first time, a large-scale fashion trend dataset (FIT) compiled from Instagram reports and usage details was provided and proposed Knowledge Enhanced Recurrent Network model (KERN), which took advantage of the capacity of deep recurrent neural networks to model time series details. Moreover, to model the time series of fashions elements of very complex patterns effectively. It leveraged both domestic and outside fashion awareness that affected the dynamics of developments in fashion elements throughout the time sequence. The integration of domain information strengthened the deep learning paradigm in the detection of variations in some design components and the analysis in potential developments. Another thesis (Shi & Lewis, 2020) suggested a data-driven computational abstraction method utilizing an artificial intelligence (A.I.) algorithm to increase the reliability of the data processing of these image-based data and to bring down the cost of the processing of fashion images. In various contexts, for example in online shop and street snapshots, an A.I. model, in specific, had been focused on fashion photographs from a broad data collection. This model had been used to distinguish garments and attributes of clothes such as textures, clothing design and picture and video description. This research also stated that the A.I. model can establish rich explanations of the area detected and link the clothes in images with accuracy. (Gu et al., 2017; Matzen et al., 2017) conducted deep learning approaches to explore fashion styles fashion trends across different demographics based on the street fashion images retrieved from different sources of Internet. (Al-Halah et al., 2017) also adopted a similar approach to predict the future popularity of styles based on the images of product sold in Amazon. (Park et al., 2016) proposed a novel research to predict the possibility of fashion models for being selected in the next fashion season based on their previous photos uploaded into Instagram. Image parsing can also be crucial to understand product attributes and human postures, which could be applied to understand fashion products preferences. Hence, it can help researchers to develop new model of fashion recommendation system. (Liang et al., 2015; Yamaguchi et al., 2012) adopted image-parsing technique to define constituent fashion products and their combination, and predict the posing based on the images retrieved from photo sharing sites. To Describe People's Personality Traits and Activities Based on Images. Reece & Danforth (2017) used Instagram images and Pittman & Reich (2016) applied Facebook images and texts to explore whether these contents could reveal the markers of depressions and predict people's loneliness respectively (Li et al., 2015; Wang et al., 2017) conducted similar research approach to explore the point-of-interest of users for different activities (such as travelling, shopping and visiting restaurants) to provide related business owners and retailers with an effective recommender system. (You, Bhatia, Sun & Luo, 2014) adopted a novel approach of using social media images to predict the gender. A close similarity was found in (Turner & Hunt, 2014) research, where they wanted to study how observers perceive unknown people's characteristics based on profile pictures or photo contents. (Hu et al., 2014) proposed research study to predict Instagram users' categories (including fashion items) based on their uploaded image and number of audience or followers. (Nash, 2019) adopted an interpretative, exploratory approach to explore the degrees to which social media platforms influence the process of consumer decision-making for Generation X and Y retail-fashion consumers.

3.2 Review of Research Methodology

This research paper has included fifteen quantitative and six mixed-method methodology-based researches, as listed in table 1.

3.2.1 Use of Quantitative Method in Researches

Quantitative research method involves a modern way (Tangseng & Okatani, 2020) of describing outfits from item-feature-wise. The method is capable of quantifying the effect of interpretable characteristics of each object on an outfit's goodness with the suggested Item Feature Influence Value (IFIV). Using IFIV in an outfit, can detect the wrong item in an outfit and lower its score by choosing the item pair with the highest negative IFIV. The next area to discover is a new interactive system (Sachdeva & Pandey, 2020) allowing the use of fashion clothes. It aims to achieve productive shopping systems online, which take the image of the clothes as an input and automatically retrieve photos from a vast array of picture clothing details. Quantitative research is also assessing of objective theories and investigating the interrelationship of variables (Creswell & Creswell, 2017). Quantitative approaches included detection of fashion attributes from images by using A.I. model (Shi & Lewis, 2020), developing a Sketch-Product fashion retrieval model and vector-based fashion model chosen for consumers (Jo et al., 2020), extraction of clothing product features (Liu et al., 2018), analyzing showing the relationship among social circles, assigning likert scale to user-clothing records (Sun et al., 2018) assigning different style of clothing, clothing areas from the images and personality-related features as input data for training the experimental model (Wei et al., 2017; Chen et al., 2015; Geng et al., 2015; Gu et al., 2017; Matzen et al., 2017; Tangseng et al., 2017; Yan, 2011). Statistical analysis of image contents (Park et al., 2016), survey method (Reece & Danforth, 2017), image mapping of point-of-interests (Li et al., 2015), combining the global semantic information and the local fine details of images (Liang et al., 2015; Yamaguchi et al., 2012) and image mining based on product features (Checco et al., 2017; Wang et al., 2017) facilitated quantitative image retrieval and evaluation approaches.

3.2.2 Use of Mixed Method Design in Researches

Mixed method study involves the integration of research data to design the analysis through affiliating the data, describing them, developing of one database from another, or inserting the data within a bigger structure (Creswell & Creswell, 2017). Researchers used mixed method design while analyzing images embedded with text contents (such as comments, likes and tweets around photos uploaded into social media or blogs) or reviews (product reviews by online shoppers and retailers). Some of the researchers used observation method as a qualitative approach to explore the product features and personality traits. (O'Halloran et al., 2018) illustrates how a digital world provides new possibilities of turning qualitative data into quantitative data for mixed-method analysis using data mining and visualization. This modern approach towards the study of mixed methods is evidenced by a paradigm that incorporates qualitative methods of multimodal discourse analysis with quantitative methods for data mining and data visualization in a multilevel, contextual model, resulting in an integrated, theoretical and methodological platform for the analysis of broad multimodal text datasets. Observers' ratings on open ended questionnaire and comments on the text contents and profile pictures were then used as the variables of quantitative analysis (Turner & Hunt, 2014). (Pittman & Reich, 2016) adopted qualitative method to support the tested and probable quantitative variables to explain the findings. Researchers used qualitative categorization of images extracted from social media and photo sharing sites before the quantitative assessment of users' features in relation to their photos, profile information, captions and tags (Hu et al., 2014; Ngai et al., 2018; Yamaguchi et al., 2012; You et al., 2014) also applied this approach to categorize fashion products for image parsing.

3.3 Review of Sampling Methods

Researchers used simple random sampling; stratified sampling, cluster sampling and deep feature based strategic sampling methods for the researches listed in table 1. Some researchers used combination of two different sampling techniques based on the nature of the samples.

3.3.1 Simple Random Sampling

Researchers (Creswell & Creswell, 2017) use this sampling method to ensure that each individual sample has equal chance of being selected. As a result, a wide range of product or image features can be included for developing the data set. (Fricker, 2016) stated that Simple random sample (SRS) is one approach that is equally likely to be chosen from all classes of equal size in the population. Mathematically, a simple random sample selects n units from a population in size N, which gives every sample in size n equal opportunities to be drawn. Yan (2011) applied simple random sampling for selecting user profile-based recommendation pages from Syskill and Webert. Photo sharing sites (such as Pinterest, Chictopia.com), street style photos collected from online image database (such as ImageNet), fashion blogs (such as Jiepai Gunshu) and e-commerce sites (such as Amazon) were the best sources for collecting a large number of random samples (for instance, from thousands to millions of photos). Such sampling facilitates big data analytics and a robust machine learning model randomly selected fashion models from random fashion model agencies (Al-Halah et al., 2017; Geng et al., 2015; Gu et al., 2017; Liu et al., 2018; Ngai et al., 2018; Park et al., 2016; Wei et al., 2017; Yamaguchi et al., 2012).

3.3.2 Stratified Sampling

(Fricker, 2016) defined stratified random sampling as dividing up the population into non-overlapping strata that are then sampled separately. This is helpful if a variety of homogeneous groups are present within the population. In such cases, the stratification of the population into homogenous groups may be feasible or statistically effective (or both) first and then use SRS to take samples of each group. As a result, it reduces the error percentages in the research results (Creswell & Creswell, 2017). Researchers applied this method to select the samples from various categories of personality traits (Turner & Hunt, 2014; Wei et al., 2017) clothing styles (Matzen et al., 2017), geographical areas like cities or countries (Li et al., 2015; Wang et al., 2017), demographics such as gender and education (Pittman & Reich, 2016; You et al., 2014). Yamaguchi et al. (2012) divided randomly collected samples into further strata based on the clothing category, which enabled them to label or codify clothes and poses to configure initial pose relevant to their research their purpose.

3.3.3 Cluster Sampling

This sampling technique can be effective in clustering mutually homogeneous but internally heterogeneous groups. It can be utilized to reduce the possibility of including extreme values by chance (Hurford & Schneider, 2007). Checco et al., (2017) applied taxonomy building followed by cluster sampling using crowdsourcing to analyze the fashion trends based on the history of items sales. Hu et al. (2014) applied cluster sampling using the application program (API) interface of Instagram having homogeneous image characteristics yet unique user category. Reece & Danforth (2017) collected data from Amazon's Mechanical Turk crowdsourcing platform as well as Instagram based 71 different clusters yet showing history of depression. Liang et al. (2015) applied similar approach to collect real-world human pictures from chictopia.com based on different categories of poses, occlusion and clothes. Yan (2011) clustered similar user profiles for different image and text analysis while proposing a new online recommendation framework.

3.3.4 Deep Feature Based Strategic Sampling

Sun et al. (2018) applied this novel sampling approach to collect samples from two datasets having positive (clothing items of similar categories and similar visual similarity) and negative samples (clothing items of different categories with visual dissimilarity). One dataset contained clothing items shared by fashion icons and the other dataset was collected from personalized clothing recommendation system. It resulted in least error percentage compared to random sampling method.

3.4 Review of Data Analysis Methods

Experimental models for developing convolutional neural network, survey method for descriptive analysis of variables, exploratory statistics of image contents, probabilistic semantic analysis and matrix factorization (MF) for developing recommendation system, semantic segmentation for image parsing, support vector machine (SVM) and binary logistic regression to predict the relationship among variables, sentiment analysis to analyze the texts embedded with uploaded photos, and semantic segmentation for pixel analysis and image parsing. Researchers (Liu et al., 2018; Matzen et al., 2017; Sun et al., 2018; Wei et al., 2017) adopted a combination of these methods to analyze image contents in predictive analysis. Data mining or image mining is the primary foundation of these researches. Precision-Recall metric was used to measure the quality of output data. Here precision is an estimate of output result relevancy and recall is an estimate to calculate the relevant results that have returned (Geng et al., 2015; Gu et al., 2017; Liu et al., 2018; Ngai et al., 2018; Reece & Danforth, 2017).

3.4.1 Machine Learning Algorithm

Convolutional Neural Network (CNN). It is a set of machine learning algorithms of deep neural networks, mostly used by researchers to find abstract features from vast information of visual images (Alamsyah et al., 2019; Gu et al., 2017; Liu et al., 2018; Sun et al., 2018). The statistical information of images of fashion products, social media users and randomly selected people from photo sharing sites were tested through different convolutional neural network (CNN) models such as to analyze and visualize fashion trends based on street style photos (Gu et al., 2017; Matzen et al., 2017) visual geometry group (VGG16) to predict point-of-interest (Wang et al., 2017), contextualized-CNN to integrate the image layers to facilitate image parsing (Liang et al., 2015), Siamese CNN (conventional neural network) to learn the dataset and differentiate the product categories deep convolutional model for attribute prediction, using the images labeled with semantic attributes (Al-Halah et al., 2017; Liu et al., 2018; Sun et al., 2018). Alamsyah et al., (2019) extracted insights from Instagram postal data by using the CNN model to recognize the popular leading fashion accessories in a certain area. This result offered a foundation for decision-making awareness of businesses such as assessing consumer patterns in different regions, product penetration and identifying common products. (Ngai et al., 2018) used Image Recognition and Segmentation (IRS) Engine to create the neural network. It analyzed the contents of clothing attributes and different other factors, such as gender, age and location. Geng et al. (2015) applied AlexNet CNN architecture for image classification and extracting image features to develop deep user based efficient recommendation system through comparing homogeneity of user vector with image vector. He applied an advanced CNN algorithm, which employs an asynchronous parallel stochastic gradient descent technique to reduce the time required for training various user-image pairs. The data are used as input variables or functions to train the model. Algorithms used in the experiments predict the outcome. Chen & Liu (2017) used deep net theory to decide the style of clothing and suggested three improvements to the deep architectural systems in the distribution of the computational world driven by deep learning's robust classification capacity and its ability to process a huge data volume during the big data age. The following other machine learning algorithms were used in the selected researches to develop recommendations and predictive analysis models.

Network-in-Network (NIN). Chen et al., (2015) applied an extension of CNN named as Network-in-Network (NIN) model to extract features for each candidate region to describe a person based on his/her clothing attributes. Support vector regression associated learning algorithms was used for the classification and regression analysis of clothing features. The Network-in-Network (NIN) approach proposed by Rawat & Wang (2017) showed that these multilayered perception (MLP) convolutional layers model local image patches rather than standard convolutional layers.

Matrix Factorization (MF). (Sun et al., 2018) adopted this method for fusing three social factors- personal interest, interpersonal interest similarity and interpersonal influence and fashion style consistency to develop a unified personalized recommendation. They also applied Root Mean Square Error (RMSE) and the Mean Absolute Error (MAE) to compare different models of PMF. Wang et al. (2017) adopted a similar approach to recommend a new point-of-interest model, where Posterior probability was used to form the algorithm. Li et al., (2015) applied PMF to explore the behaviors of Instagram users and predict POI recommendation based on Stochastic Gradient Descent (SGD) machine learning algorithm. You et al. (2014) employed Probabilistic Latent Semantic analysis to analyze the visual words and prepare the algorithms to carry out the statistical analysis. Al-Halah et al., (2017) applied non-negative matrix factorization to discover the clothing features or latent styles. Checco et al., (2017) integrated matrix factorization with on-the-fly clustering techniques and used incremental version of the algorithm to provide a hierarchical prediction of fashion trends.

Support Vector Machine (SVM) and Logistic regression . Wei et al., (2017) adopted support vector machine, a machine learning algorithm for predicting the inherent relationship between a person's personality and clothing expressions. They also applied Binary Logistic regression to test the significance level of correlation between clothing attributes and personality types. Reece & Danforth, (2017) applied Bayesian logistic regression to assess the strength of depression predictors measured computationally from the Instagram photos and related metadata. Dang et al., (2016) suggested processing and classifying raw text data on the basic of the Vector Space Model and Support Vector Machine. This research demonstrated the utility and precision of the framework in extracting Twitter and Facebook fashion related contents. Guan et al. (2016) mentioned the SVM method in a case study that demonstrated its usefulness in examining complicated interactions between users and apparel functions as well as occasions. Zhang, Begole, Chu, Liu, & Yee (2008) used the method for extraction features of sleeve lengths, collar, placket, style color, skin color, style and prints from the camera sensor were used to support linear vector machines and decisions stump method.

Auto Regression (AR) and Linear Regression Model. (Ngai et al., 2018) used autoregressive (AR) model (or ARMAX) for predicting style or trends using the images retrieved from social media, online fashion magazine, popular e-commerce, fashion site blogs, and discussion forums. It facilitates accurate prediction of trends as the data patterns are retrieved over a certain period (Fung, Wong, Ho, & Mignolet, 2003). Two distinct studies by Liu et al., (2013) and Nenni, Giustiniano, & Pirolo (2013) showed that the theoretical contents of these forecasting models in depth and discussed the various forms of general approaches. Statistical methods like auto-regression, exponential smoothing, ARIMA and SARIMA were commonly used to evaluate fashion sales because they were simple, fast, well-informed and easy to comprehend. Demiriz (2018) suggested a system in which retail goods can be forecast weekly by linear regression models in multi-processing groups that contain both positive and negative goods. Dynamic pricing models have been then used to validate markdown decisions on the basis of multi-item groups forecasts. Grouping objects in predictive models may be viewed as a method of variable selection to avoid overfitting. Besides the findings from the single-item regression model, they then displayed regression results from multiple-item groupings on the real-world dataset given by a clothes retailer. In addition, they then reported markdown optimization outcomes for single items and groupings of multi-items on which multi-item forecasting models are based. In contrast to the one-item model, the findings suggested that the regression models offer better estimates in multiple groupings.

Decision Tree and Random Forest Algorithms. Park et al. (2016) applied decision tree, random Forest, and AdaBoost machine learning algorithms to predict the success of fashion models based on body measurements, physical features, binary information about their belonging to agencies. In another study by Nugroho & Santosa (2016), a user model for e-commerce personalization based on the customer community was developed. There were 100 participants in this survey, including 25 children, 25 adult women, 25 boys, and 25 adult men. In order to include a decision tree as a user interface divided by age and class, data processing was performed using the RapidMiner Studio 5. This research showed that both men and women in different age groups had differing preferences for process identification. In age group recognition female users have a shorter cycle than male users. Reece & Danforth (2017) adopted 100-tree Random Forests classifier algorithm to measure the capacity of prediction model.

User Modeling Algorithm. Yan (2011) used user-modeling algorithm to predict users' new and recent browsing activities, which detect the changes in their interests and consequently updates the user profile. The researcher also combined this algorithm with collaborative filtering to update user profile based on their user feedback rating and browsing behavior. Kompan, Kassak & Bielikova (2019) introduced a new user model that focuses on the analysis of user behavior changes on the level of individual actions. A contrast of the current User Session Data with previous sessions strengthens this model concept. He assessed our model in the e-learning and news domains by predicting session-end intentions.

Semantic Segmentation. Yamaguchi et al. (2012) used semantic segmentation for analyzing image super pixels, predict clothes and re-estimation of pose configuration. Liang et al. (2015) applied similar approach using human detection algorithm to detect the human body and understand different body postures relevant to clothing category. Analyzing image pixels, global image descriptors (for image retrieval, object detection and classification), local descriptors (for object recognition/identification) and determining the connected layers of images were used in semantic segmentation (Liang et al., 2015; Yamaguchi et al., 2012).

Exponential Smoothing Model (EXP) and Fourier transform algorithms (FFT). Al-Halah et al. (2017) applied exponential smoothing model (EXP) to capture the current observed trends and popularity of fashion styles that have higher influence on the forecasted trends than earlier observations. In a study by Fumi, Pepe, Scarabotti & Schiraldi (2013), a comparison was made of a historical sales data from four years of a medium to large Italian fashion company with medium turnover sales of 60+ million, operating in the clothes & textile industries, based on the fast Fourier transform algorithm and two additional techniques based on average moving and exponential smoothing. The study was carried out in detail on a common spreadsheet to prove that precise results can be obtained without necessarily using costly software whereas using sophisticated numerical calculation techniques. Sentiment Analysis. Researchers Zhang, Wang & Liu (2018) studied sentiment analyzes mainly at three granularity levels: document level, sentence level and aspect level. The classification of sentiment at document levels categorized an opinion paper (e.g. a product review) as having a positive or negative overall view. The document as a whole regarded as the basic information and suggested that the document was understood to be opinion based on a particular individual (e.g. a particular phone). The sentiment classification at sentence level classified every sentence in a document. The aspect level sentiment analysis or aspect-based sentiment analysis was more fine-grained compared with the text level and sentence level sentiment analysis. The goal was to collect and sum up opinions shared by people about individuals and their aspects / personality traits. Park et al. (2016) applied sentiment analysis of likes and comments received in Instagram pictures using Naive Bayes classifier. The mean sentiment score was calculated of each model using Vader algorithm. It outperformed other algorithms and even human rating system.

Survey Method. Reece & Danforth (2017) used clinical depression survey in their research. The (Center for Epidemiologic Studies Depression Scale) questionnaire was used to assess pre- and post-survey photos of healthy and depressed sample persons. The picture was rated on a scale of 0 to 5 for the statistical analysis of the relationship between human impressions and depression indicators.

3.4.2 Statistical Analysis

Descriptive Analysis, T-test, ANOVA and MANOVA. Hu et al. (2014) applied descriptive analysis and normal distribution for analyzing image categories, and used two-tailed t-tests for analyzing the difference in the number of audiences. These experiments could categorize and differentiate Instagram users based on their uploaded images. For understanding observers' perception about unknown people's characteristics based on profile pictures or photo content, applying ANOVA and MANOVA tested observers' judgements. Profile owners and observers' responses were compared by applying intraclass correlation (ICC) (Turner & Hunt, 2014). Pittman & Reich (2016) applied descriptive analysis, t-test, ANOVA and MANCOVA in their research using 7-point Likert scale to predict and compare loneliness of social media users based on their uploaded images. Park et al. (2016) used descriptive analysis of body and fashion product measurements to estimate the normal distribution of fashion models before forecasting their success in next fashion season.

3.5 Research Findings and Discussion

Many researchers (Chen et al., 2015; Geng et al., 2015; Li et al., 2015; Liu et al., 2018; Park et al., 2016; Pittman & Reich, 2016; Sun et al., 2018; Wang et al., 2017) have not considered time series analysis to include images of different times, while extracting photos from users' social media except in the researches of (Hu et al., 2014; Ngai et al., 2018; Reece & Danforth, 2017). Some of the researches excluded describing product category (Gu et al., 2017), geographical locations (Matzen et al., 2017), demographic factors (You et al., 2014), and difference in semantic segmentation between mobile captured photos and photographed images with edited color and background (Al-Halah et al., 2017; Checco et al., 2017; Chen et al., 2015). Some of the researches (Park et al., 2016; Wei et al., 2017; Yamaguchi et al., 2012; Yan, 2011) lacked large dataset, suitable for machine learning algorithm. Many of the studies (Hu et al., 2014; Li et al., 2015; Tangseng et al., 2017) currently underway, especially those which employ Convolutional Neural Networks (CNNs), focus on black-box models which can work well with respective tasks but can't clarify the reasons for their opinions. Researches that used mixed method could have applied sentiment analysis for text content analysis and computational content analysis instead of observation method (Hu et al., 2014).

4 Proposed Method

Hyper-Personalization is an innovative methodology focused on the idea of personalization that has to be looked at first to fully understand it (Warshaw et al., 2015). Personalization is a process that uses consumer profiling to make specific claims about consumers. These assumptions are based on certain specialized factors that are associated derived from profiling. For instance, it is a very common strategy we all see these days to suggest ads to buyers based on the fact that they have ordered or searched a similar product online. According to their sales reports, this personalization technique brought a huge boom in sales for the companies (Hsieh & Li, 2019). Hyper-personalization incorporates and operates based on the same technique. It not only looks at the object or commodity that was purchased in this methodology, but looks more comprehensive, for example the purchasing place, the mode of buying, the purchasing rate, keywords used during the transaction, demographic details about the individual who bought and several more. To conclude, it can be said that Hyper-Personalization delves into complex information and therefore creates much smoother and more successful personalization, which makes it a big explanation that everybody is seeking to do it (Zeng et al., 2013).

4.1 Benefits of Hyper-Personalization

- It aims to deliver better results in terms of satisfaction and customer requirements: Hyper-personalized e-commerce leads to greater income, reduced product returns that increase the reputation of brands. This approach contributes to higher sales because it maximizes the amount of consumer touch points for data collection.

- Since hyper-personalization provides improved search results from comprehensive customer profiling, which in turn represents higher consumer loyalty and better user feedback from customer analysis to buy.

- Studies show that customers are more frustrated if a particular website is not personalized, which shows how well the concept of personalization is in the marketing context as well.

- One of the main things social media marketing has in common is reliable data. Using the relevant data hyper-personalization systems for users can play a big part (Aïmeur & Tremblay, 2018).

In the proposed fashion recommending hyper-personalized framework, the data will be retrieved from the previous quest about the types of clothing that the individual is likely to wear. From that, we'd also pick the colors and labels they want. For size details, a better choice would be to take manual feedback and we would take the person's picture as an example. Once we get the measurements of the individual and the photo, we send the picture to the R-CNN for localized recognition of the body parts and using SwapNet, we can develop an image of the person with the option of clothing that will help the person to realize how it will look when they wear it, allowing a better decision and a better user experience. The typical issue with online shopping is that people can only visualize how a piece of apparel would look at them, so with this hyper-personalized recommendation system, we would be able to help a person consider how they would look at them with a small margin of error. The flowchart of this process is provided below:

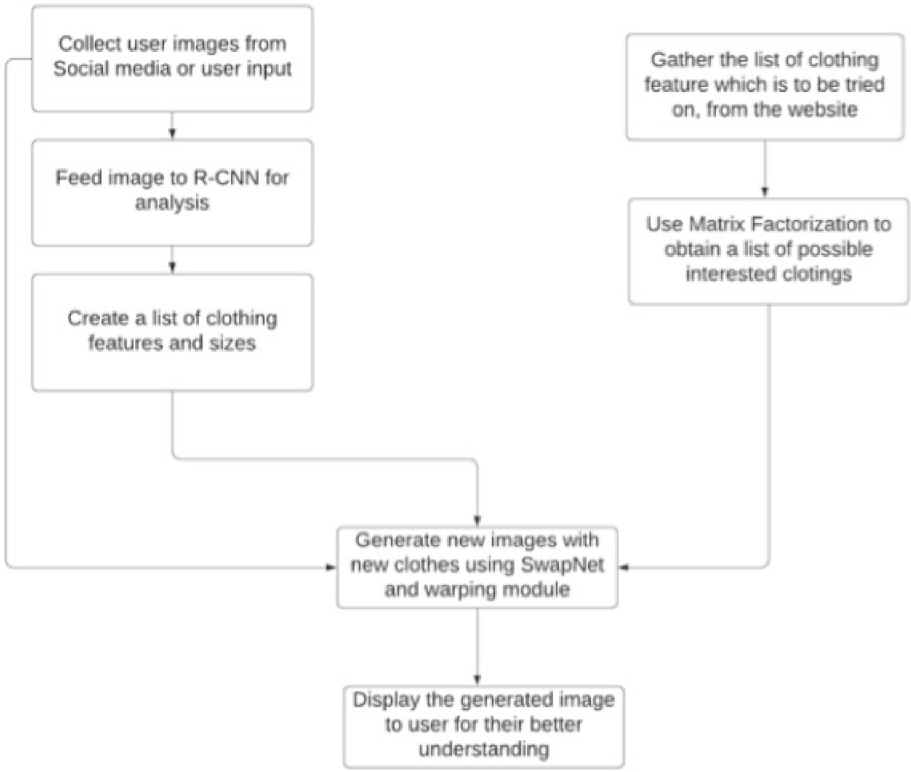

Figure 1: Proposed Recommendation Model

5 Conclusion

Use of social media is increasingly rapidly around the world. Nevertheless, retailers and researchers have not widely explored the potentiality of using social media images for clothing recommendation. There are insufficient researches on using image analysis for online fashion recommendation. Researchers mostly incorporated clothing parsing, style consistency, purchasing frequency, text reviews etc. to conduct researches on fashion items recommendation. Most of image analysis researches are mostly based on quantitative approaches and involve developing an experimental model based on convolutional neural network (CNN). However, researches that considered both image and text contents used mixed method research design, where researchers conducted qualitative researches for text content analysis and quantitative researches for image content analysis. Therefore, further researches on users' social media should include images containing both texts and facial expressions to make the recommendation system more effective. Future researches should concentrate on including time series analysis and accurate categorization of products and images based on variety of color, trend and style, which would be beneficial to develop an effective recommendation system. More researches should be conducted on social media photos, as these photos vary in resolution and technical features compared to celebrity photos with high pixel and brightened background.

6 Future Scope

Future researchers will be able to design their work based on the research methods and findings provided in this review paper. The author will use the proposed hyper-personalization technique to develop a robust recommendation system.

7 Conflict of Interest

There is no conflict of interest in this work.

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