

Single-Item Fashion Recommender: Towards Cross-Domain Recommendations

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Nowadays, recommender systems and search engines play an integral role in fashion e-commerce. Still, many challenges lie ahead, and this study tries to tackle some. This article first suggests a content-based fashion recommender system that uses a parallel neural network to take a single fashion item shop image as input and make in-shop recommendations by listing similar items available in the store. Next, the same structure is enhanced to personalize the results based on user preferences. This work then introduces a background augmentation technique that makes the system more robust to out-of-domain queries, enabling it to make street-to-shop recommendations using only a training set of catalog shop images. Moreover, the last contribution of this paper is a new evaluation metric for recommendation tasks called objective-guided human score. This method is an entirely customizable framework that produces interpretable, comparable scores from subjective evaluations of human scorers.

Keywords: Fashion Recommendation, Cross-Domain, Augmentation, Evaluation.

1 INTRODUCTION

The ever-growing fashion e-commerce has led to a massive increase in the number of fashion items, including clothing, bags, shoes, and accessories, posted online. However, the bigger the market, the harder it will be for the customers to find items suited to their needs. Thus, online shops are beginning to implement visual search engines and recommender systems as these systems increase customer satisfaction by providing a pleasant shopping experience and facilitating the buying process.

Most of the conventional recommender systems are designed based on textual information and user similarities which means that they are incapable of using visual features, as a critical source of information and one of the most important aspects of fashion, to their advantage. Deep learning techniques can enable these systems to be capable of multi-level understanding of similarities, utilizing low-level details, namely shapes, edges, and colors, as much as higher-level abstractions and human-level notions of similarity. Unlike collaborative-filtering methods, deep learning is also promising in cold-start problems and high data sparsity cases.

This article takes three steps towards achieving a single-item fashion recommender system that can handle both in-shop and street-to-shop recommendations. The first step aims to design and develop a content-based recommender system using fashion items' "Shop" images. The proposed system uses deep convolutional neural networks to extract visual features of images and forms recommendations based on a similarity check. Then, we utilize this content-based

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structure to create a two-stage personalized recommender system and show that the proposed method improves previous works' results.

As most small e-commerce businesses utilize user-created fashion images and content, fashion recommenders must perform well on standard Shop images and handle Street/Wild images as well. Moreover, the primary connection of users to these systems is through uploading pictures that they have shot. Hence, the next stage of this research is dedicated to finding a solution that tackles the problem of cross-domain recommendation using a background augmentation technique.

Although fashion retrieval (finding an exact match) and fashion recommendation (finding similar items) might be very close and use similar methods, the main focus of this article is on recommendation tasks. While evaluation methods for retrieval tasks are numerous and well-developed, including precision/recall @ k and accuracy, it is challenging to define a precise objective evaluation metric for recommendation tasks. One can only use the same retrieval evaluation metrics for these tasks if similar items are labeled and ground truth is available, which is not most of the time. Thus, we also propose an evaluation framework to obtain quantitative information from subjective evaluations and be able to compare multiple recommendation systems with a specific goal in mind.

The main contributions of this article are as follows:

- It develops an in-shop content-based fashion recommender and shows its power in returning similar fashion items from single catalog image queries.
- It utilizes previous works to turn this system into a personalized fashion recommender that considers user preferences. An increase in performance is also illustrated.
- It presents a new background augmentation technique to narrow the gap between Shop and Street fashion image domains and develop a system much more robust to out-of-domain queries.
- Finally, it suggests a method of evaluating recommender systems with specific goals and discusses the evaluation results of several systems.

This work is organized into six sections. Sec. 2 provides a background of the matter. Sec. 3 further explains the methods, followed by the experiments presented in Sec. 4. Then, Sec. 5 discusses the results and different aspects of the system. Finally, Sec. 6 develops a conclusion and presents future research directions.

2 RELATED WORKS

Many studies used Bayesian Personalized Ranking (BPR) [1] for item recommendation tasks until [2] introduced VBPR, its visual form which takes into account the content of images as well. Reference [3] used a convolutional neural network, VGG, to be specific and cosine similarity for content-based recommendations. However, the network was trained using less than 50 thousand images, and it could only classify the items into seven single-label categories. On the other hand, [4] experimented with AlexNet and BN-Inception mixed with KNN as a similarity measurement, but the number of classes was still limited to nine categories and five texture types, which were classified using two separate networks. Like many other studies, this work did not provide a comparison for the recommendation task and only used classification accuracy as an implicit objective metric.

For personalization purposes, [5] proposed a structure using DenseNet, pre-trained on ImageNet, to capture user preferences and recommend a set of outfits for each user. Moreover, inspired by the structure of VisNet [6], [7] used ResNet101 paralleled with a shallow net to extract features and generated personalized recommendations using a second dense neural network. The importance of this study was twofold. First, it used ResNet101 and showed that the results

were superior compared to that of VGG16. Furthermore, unlike previous works, the proposed network used multi-label classification, and the number of classes was considerably high, which was closer to real-life conditions.

Another well-known challenge in fashion recommendation is the gap between professional catalog images used in online shops (called Shop images) and user-created images (called Street or Wild images). The problem of cross-domain recommendation has attracted lots of attention through the years as many researchers, including [8], [9], and [10], have tried to bridge the gap between two fashion domains. One of the most famous, because of its real-world application, examples of this is called street-to-shop. Reference [11] was one of the firsts to address this issue. Soon others gained interest as [12] used visual phrases and [13] used articulated pose estimation and image retrieval techniques. Deep learning-based approaches such as [14] and [15] led to far superior results. Zalando researchers proposed a model called Street2Fashion to segment the background of images in 2019, which highly improved their results [9]; unfortunately, they did not release their images. Furthermore, recent studies suggest that it is possible to further improve the results by using fashion landmarks [16], [17].

While most of the studies mentioned above use two sets of data (Shop and Street) to train their networks, these cross-domain fashion datasets are rarely available. It can be challenging to find a large-scale, publicly-available fashion dataset that meets the needs of training such systems as most of the existing datasets are either too small (in terms of size or number of tags) or not accessible to the public. Thus, we aim to put the idea, whether it is possible to achieve acceptable results using only one dataset of Shop images, to test. We propose a background augmentation technique to use a Shop dataset and simulate the conditions of Wild or Street fashion datasets.

3 SINGLE-ITEM CONTENT-BASED RECOMMENDER

The structure of the proposed content-based recommender is illustrated in Figure 1. The feature extractor part follows the work of [7], which is a multi-label classifier, with some modifications. We change the network from ResNet101 to ResNet50, which improves the system's efficiency without harming the final results. Intersection Over Union (IOU) can be calculated using predicted and ground truth tags from Equation 4 to evaluate this multi-label classification problem. Unlike accuracy, IOU can be a fantastic evaluation metric for multi-label classification tasks with large numbers of classes. The loss function for training the network is the same weighted cross-entropy used in [7] (Equation 1). It uses the frequency of each label i (f_i) in the set of all classes (C) to determine the weight of that label (ω_i) and uses these weights to calculate the loss between the target (t_i) and the output (o_i) of the system. We add a minor trick according to Equation 2 in which $F1$ (F-score) and IOU are not quantized values. This change helps further balance the results in terms of precision and recall and also gradually reduces the loss through the process as the system becomes stable and minute weight changes are required.

Equation 1

$$\text{loss}(o, t) = -\frac{1}{n} \sum_i \omega_i (t_i \cdot \log(o_i) + (1 - t_i) \cdot \log(1 - o_i)) \text{ where: } \omega_i = \left(\max_{j \in C} f_j + 0.01 \right) - f_i$$

Equation 2

$$\text{Loss} = \text{loss}(o, t) \times (1 - F1) \times (1 - IOU)$$

The final feature extractor is depicted in Figure 2. It takes a single fashion item catalog image as input and predicts labels for that image from a pool of 1102 labels. The features are extracted from the layer before the last (classification) layer.

Needless to say that this network can also be used directly in attribute and label prediction tasks in online shops. Now that visual features are obtained, a similarity check is needed to form the recommendation list. Cosine similarity is used here as it is fast and leads to great results.

The next phase is to personalize the recommendations. The same feature extractor network can be used for this purpose, as shown in Figure 3. For the second network, we use the structure proposed by [5]. The system can take a mix of previously purchased items' image features (called Cart or shopping cart items) as input and recommend a list of similar items tailored to a specific user's taste. This mix of items can be an average of all items' features weighted by user rating as in Equation 3. This way, there will not be a limit to the number of items before a prediction can be made, as this method supports carts with any number of items.

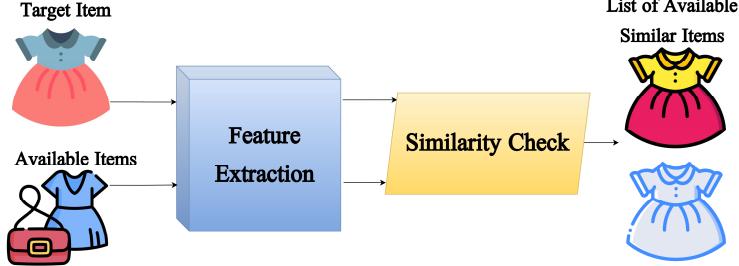


Figure 1: Structure of the content-based fashion recommender

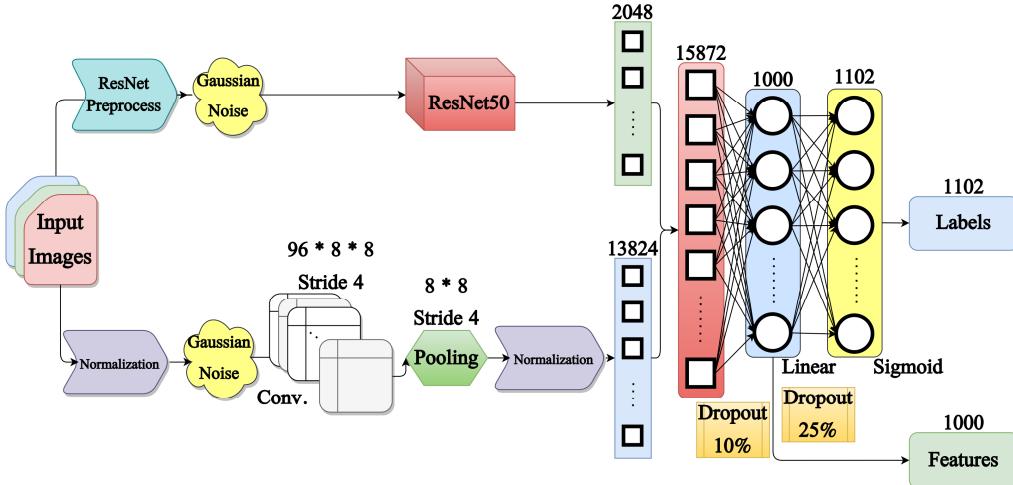


Figure 2: The feature extractor network (multi-label classification task)

Furthermore, this way, we explicitly use user preferences in the form of user ratings. The main downside to this is that carts should be uniform and from the same fashion categories. One way is to break a user's main cart into multiple smaller uniform carts and use the network to find recommendations for each group separately. For example, one can use K-Splits [18] to automatically identify different item categories formerly purchased by a user (namely shoes, shirts, jeans) and cluster similar items together. There are many ways to improve this system, but personalization is not the main focus of this article.

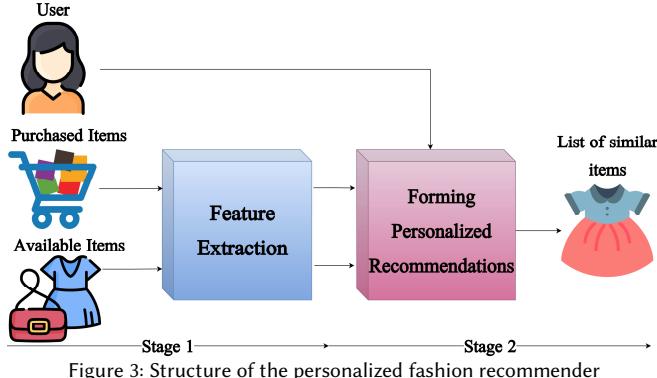


Figure 3: Structure of the personalized fashion recommender

Equation 3

$$Cart = \frac{\sum_{i \in Bought} (Rating_i \times Features_i)}{\sum_{i \in Bought} Rating_i}$$

3.1 Towards Street-To-Shop Recommendations

Previous works which used deep domain adaptation methods utilized images from two different domains. However, this research aims to train a network robust to street images by only using one fashion dataset made of Shop catalog images with neutral backgrounds and standard poses. Thus, it proposes a new augmentation technique to create street-like images that force the network to focus on fashion items present in the image and not the background.

The background augmentation technique puts fashion items in front of various backgrounds with different levels of complexity in the training phase of the network. For this purpose, we find the boundaries of the fashion item or model shown in the image by using contours. This task will generally be straightforward and error-free as shop images contain neutral and one-color backgrounds. After this, the main images are masked and cropped from the background. Next, we paste these masks onto random, more complex backgrounds. This method has several benefits. Firstly, the system sees the same fashion outfit in front of varying real-world backgrounds in each run, which helps focus attention only on the outfits and not the whole image. Secondly, we have complete control over the whole process. For instance, we can choose the settings that best suit the final goal of the system since both the complexity of background images and the ratio of images with backgrounds are controllable. Lastly, real-world scenes and images can be downloaded in bulk, and a good dataset of backgrounds can be gathered with minimum effort. Figure 4 shows images with standard augmentation techniques, including flip, rotation, shift, and shear, alongside images with background augmentation. This method can close the gap between fashion shop images and street images.

4 EXPERIMENTS

The experiments are conducted using Python 3.7.4 and Tensorflow and Keras libraries. Numerous significant publicly available fashion datasets exist. This work needs a large-scale dataset of “Shop” fashion images with user history and item descriptions. Thus, this research chooses the Amazon Fashion dataset [19] as it perfectly suits its needs.

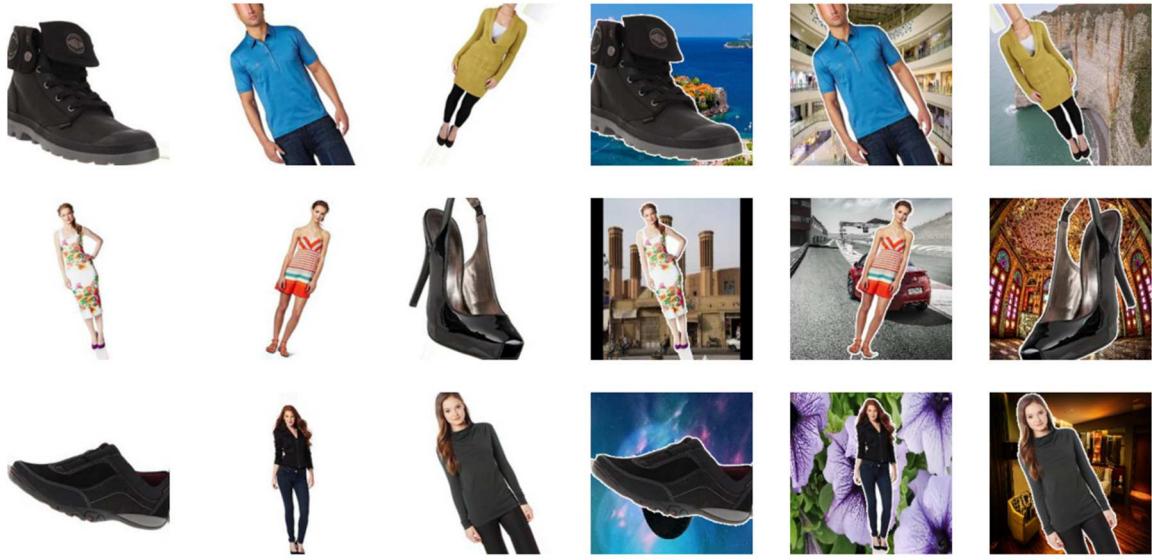


Figure 4: Images with regular augmentation (on the left) and with background augmentation (on the right)

4.1 Evaluation Methods

Metrics like accuracy are not applicable in evaluating multi-label multi-class classifications with huge numbers of classes. Thus, we use IOU to evaluate the label prediction task. Although IOU is more prevalent in evaluating object detectors, it provides excellent insight for multi-label classification tasks as well because it can measure the overlap of predicted and actual labels if formulated as Equation 4.

Equation 4

$$IOU = \frac{True\ Positive}{True\ Positive + False\ Positive + False\ Negative}$$

However, evaluating the recommendation results is not that straightforward as subjectivity plays an essential role in it, and there is no ground truth. Logically, better visual features lead to better recommendations. Thus, the IOU or feature extractor's classification accuracy can be used as implicit objective metrics for this purpose, but these are not one-to-one comparable. This article tackles this issue by proposing an objective-guided human score which turns a subjective evaluation of the results into comparable numerical values based on specific goals of the recommendation system.

Not all recommender systems are the same. In fact, the goal behind using such systems might be completely different from company to company. If the system is to be used as an image search engine, then the results are expected to be of the same category with similar shapes and colors. On the other hand, recommendation results for advertising need to be novel items with a wide variety. Hence, an objective-guided metric is proposed to evaluate different systems based on the goals they are meant to satisfy.

First, for an objective-guided human score, some fashion images are needed as queries. These images should be carefully chosen to indicate the goal of the system. For example, the ratio of Shop/Street images should be set based on the predicted ratio of Street image queries the systems need to handle in the future. It is good to mix a set of easy and more complex images to make sure the system works well under different circumstances. The number of images is also

optional; more images probably increase the accuracy of this evaluation, provided that they do not bore or tire the human scorers. In short, the number of chosen images, their domain, and their complexity are all controllable based on the system's goals.

Next, multiple criteria are defined to score the functionality of each system based on them. This step, again, is entirely flexible based on the needs of the evaluators. This article uses seven criteria: category, subtype, fabric/texture, color, variety, details, and shape difference. The order of showing the results, domain sensitivity, price range, and many more criteria can be added to this list optionally.

- **Category:** Defines the main category of an image, such as top, bottom, footwear, and jewelry.
- **Subtype:** Defines subtypes of the same category, such as boots, high heels, college, and slippers.
- **Fabric/Texture:** Shows the main fabric or garment's texture, such as denim, leather, smooth, and shiny.
- **Color:** Defines the dominant color of the item, such as red, green, blue, yellow.
- **Variety:** The number of novel items (different category, subtype, or color). Almost on the opposite side of the other criteria, because the higher the variety score is, the lower other scores will be.
- **Details:** The number of results that follow fine details, such as necklines, zipper, pockets, and design.
- **Shape Difference:** The number of items that do not follow the outline of the query item, such as images with different angles, different perspectives, rotations, flips.

Finally, we input the queries into all different recommender systems, save top-10 results for each, and create an evaluation sheet as shown in Figure 14. Every human scorer now scores each system separately based on individual criteria mentioned before. For each criterion, the scorer assigns a hit@10 score from 0 to 10. These scores can easily be turned into percentages later. All criteria scores are then processed using a weighted average, and the weight of each criterion is set based on its importance regarding the goal of the system. Additionally, all the scores for each system are averaged as well, and one final objective-guided human score for each system is obtained, which will be comparable to other scores provided that they have the same goals.

This method is called objective-guided as almost all of its parameters (queries, criteria, and weights) are flexible and can be set based on the needs of the evaluator. Nevertheless, once the parameters are set for a specific goal, the results of this evaluation will be directly comparable. Not only that, but evaluation results of each criterion are also comparable, which helps determine the effects of different methods on each criterion separately and increases interpretability. This article uses this evaluation method to compare different street-to-shop recommender systems in Sec. 4.5.

4.2 Preparing Data and Labels

Clean and well-labeled data plays a critical role in training networks. Hence, it is good to dedicate some time to make sure the data is properly cleaned. Amazon Fashion dataset contains information on 45,184 users and 166,270 items. However, some irrelevant images (Figure 5), duplicates, very small images, corrupted, and missing data in the dataset had to be taken care of. These summed up to 2,672 images which were deleted, and the final number of items turned to 163,589.



Figure 5: Samples of irrelevant images in the dataset

This article uses “Category” and “Title” information in the dataset to extract labels. First, all keywords are separated and extracted, duplicated and stop-words are removed, words are normalized and cleaned, and only labels with more than 50 repetitions are selected. Then, similar words and synonyms are merged, and finally, only words with 100 repetitions are extracted as labels. A word cloud of these 1102 final labels is presented in Figure 6. As shown in Figure 8, these labels are heavily imbalanced, but hopefully, the weighted loss function chosen for the task will mitigate this problem to some extent. Another potential problem is the imbalance of the number of labels per image. As a multi-label classification task, each image activates a tiny portion of neurons from the last layer. It can be seen from Figure 7 that images have 1-25 labels (one exception with 30 labels).



Figure 6: A word cloud of all 1102 extracted labels

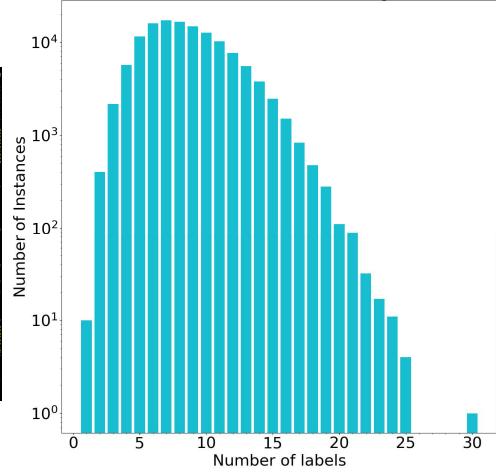


Figure 7: Distribution of the number of labels per image

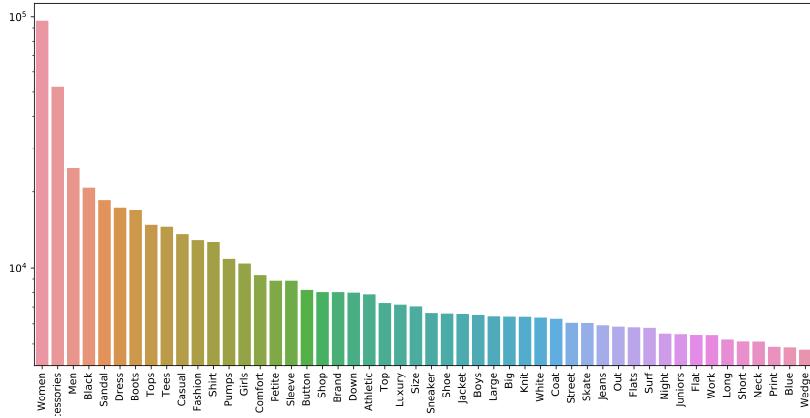


Figure 8: Total occurrence of Top-50 labels

4.3 In-Shop Content-Based Recommendations

For this purpose, the network shown in Figure 2 is used. The dataset is separated into 80% train, 10% test, and 10% validation. All images are resized to 224×224 with the aspect ratio unchanged. ResNet50 is loaded with ImageNet pre-trained weights, and the whole network is fine-tuned using the training data at hand. Dropout, regularizations, early stopping, and regular augmentation techniques are used to improve the results. The final test results of the trained system are 44.4% IOU, 73.1% precision, and 48.4% recall for the multi-label classification task.

Next, eight random images are chosen as queries, and after feeding them through the network, cosine similarity is used to form Top-8 recommendations. As shown in Figure 10, the results are fantastically similar in all aspects, including color, category, and design. Furthermore, random examples of label prediction results using the same network are illustrated in Figure 9.

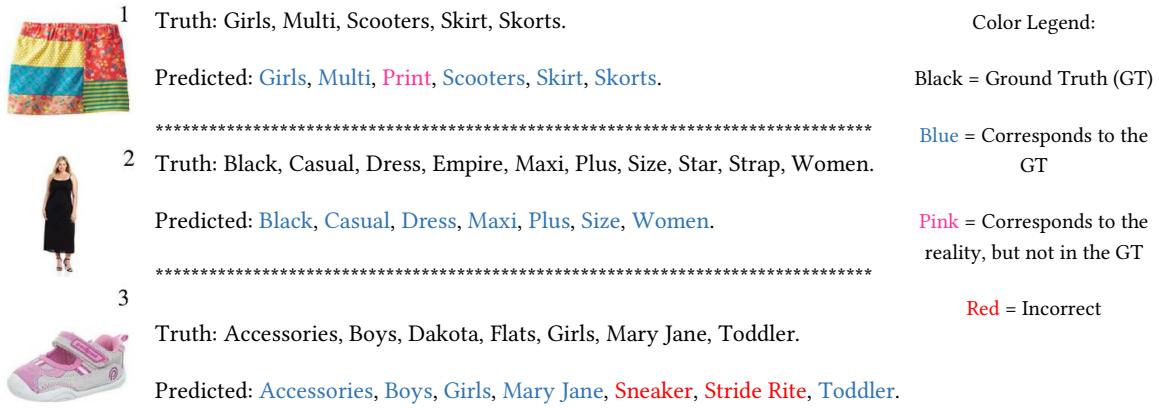


Figure 9: Label prediction results for three image queries



Figure 10: Top-8 recommendation results for eight random image queries

4.4 Personalized Recommendations

This section trains a second network on top of the feature extractor trained in the previous section to personalize the results using the structure illustrated in Figure 3. For personalization, the work of [5] is followed. 44,103 users are chosen, each with 5-7 reviews to balance the data. The total number of reviews is 269,104, so each user has approximately 6.1 reviews (bought items). Carts are calculated based on Equation 3 using these users, their bought items, and their ratings.

After training the network, it reaches 78.4% test accuracy. In Figure 11, the proposed method (fine-tuned ResNet50 paralleled with a shallow net and a personalizer network on top) is compared to collaborative filtering, VGG, ResNet101, fine-tuned ResNet101, and fine-tuned ResNet101 paralleled with a shallow net. The figure shows that the Recall@K result for the proposed method is almost always better than previous methods for all K values, except for Top-1 recommendation results.

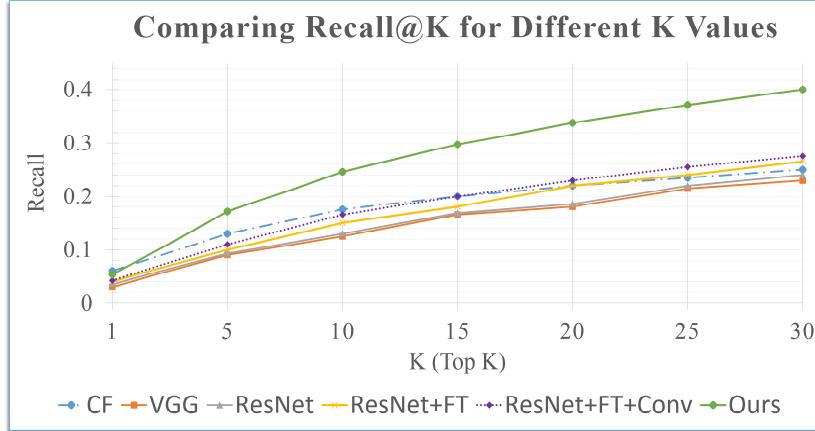


Figure 11: Recall@K comparison of different methods

Visual inspection also shows the power of this personalized recommender. The results are shown in Figure 12 for six random users. The network takes items bought by each user (their cart) and the ratings and outputs a list of similar items. Each row shows a user’s cart, followed by two rows of recommendations. ‘U’ stands for users, ‘B’ for the bought items, and ‘R’ for the recommendation results. User ratings for each bought item are also shown in the figure using stars. It can be seen that the results are of high quality and very similar.

4.5 Street-to-Shop Recommendations

Although the results in previous sections seem promising, if the image domain is changed to Street photos, the quality of results will decrease. The network is robust to some extent of change, but this robustness is not enough to enable the system to handle out-of-domain images efficiently. Thus, this section re-trains the network, this time using the background augmentation technique introduced in Sec. 3.1.

A dataset of several thousand backgrounds is collected, primarily natural or city scenes. The system randomly chooses a background for each image in each epoch. After completing the training process, the system will be able to handle both in-shop catalog images and more complex street-like queries. We collected a small dataset of out-of-domain images from online shops on Instagram to show that the proposed structure can find and recommend similar items to these queries from the items available in the shop. Examples are illustrated in Figure 13.

Next, the objective-guided human score is used to compare the results of multiple networks. Although the results presented here are the best of more than 80 versions and trials with different conditions, only five networks are compared in this section. These versions are as follows, and they all utilize the background augmentation and the same training techniques:

- **V1:** Only a ResNet50 network.
- **V2:** ResNet50 paralleled with a shallow network.
- **V3:** Similar to V2 but with heavier augmentations to check to what extent traditional augmentation techniques can improve street-to-shop recommendations.
- **V4:** Only an EfficientNet [20] with 300×300 input.
- **V5:** The same EfficientNet paralleled with a shallow network.

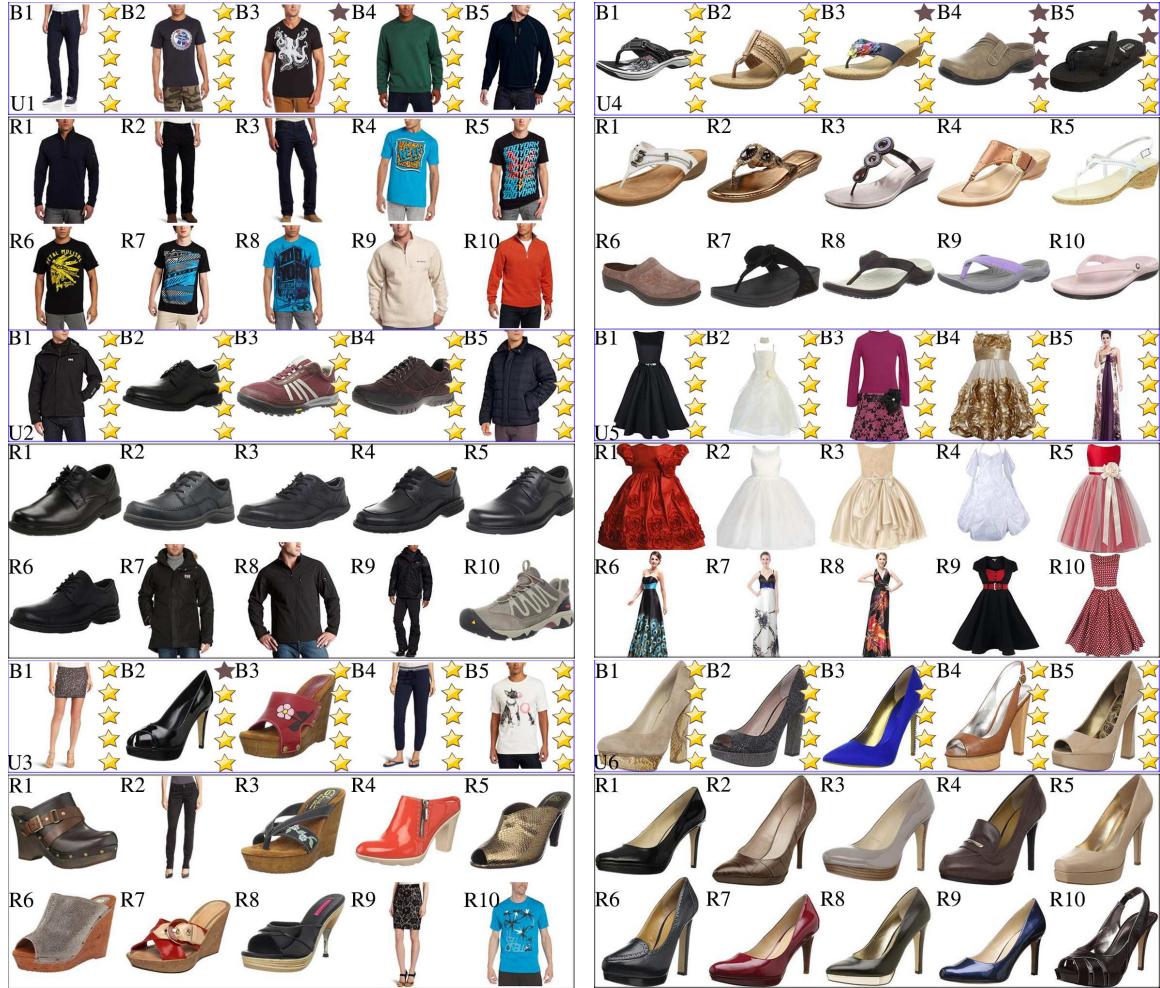


Figure 12: Top-10 personalized recommendation results for six random users

Top-10 street-to-shop recommendation results of different systems are gathered as an evaluation sheet depicted in Figure 14. It can be seen that it is challenging to subjectively rate and compare these recommendations as the results can sometimes be very close to, very different from, or even contradictory to other queries. The objective-guided human score is a framework that organizes these subjective evaluations into comparable percentage scores.

Seven criteria, explained in Sec. 4.1, are chosen to compare these systems. Fifty query images with mixed complexities and a Shop/Street ratio of 2/3 are prepared and fed to each system, resulting in 50 evaluation sheets like the one shown in Figure 14. Next, human evaluators rate (hit@10) the results of each system for each query based on each criterion separately. The scores are then processed using a weighted average based on the importance of each criterion for the specific goal of the network. The weights in this article are five for the category, four for subtype, one for color and variety and details, and 0.25 for the shape difference criterion. The scores for each criterion and the final objective-

guided human score (OHS) for each system are provided in Table 1 in percentages. The best and worst scores in each column are in green and red colors, respectively.

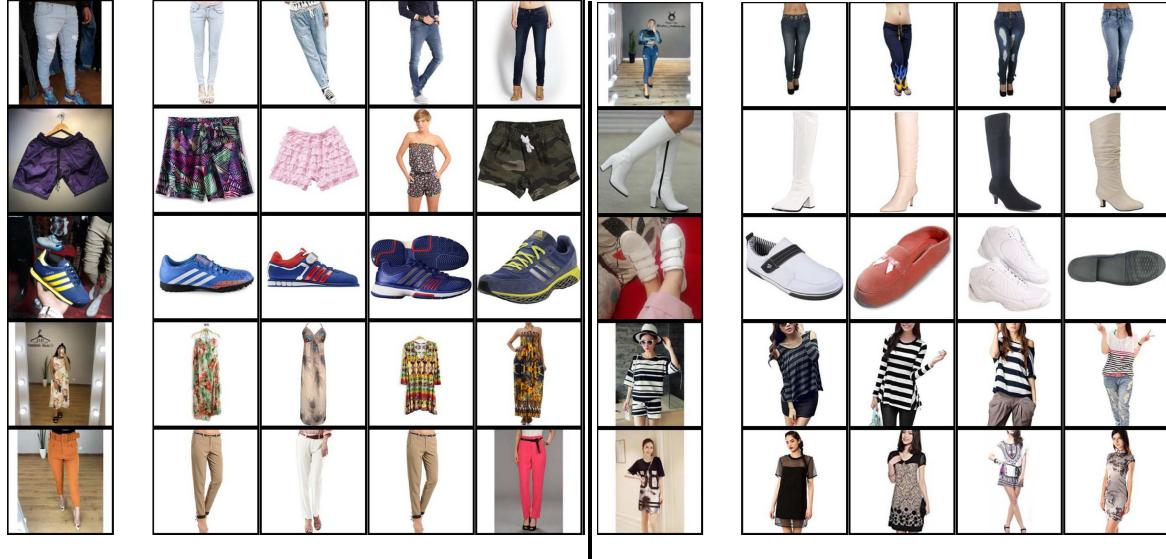


Figure 13: Top-4 street-to-shop recommendation results for ten random out-of-domain queries

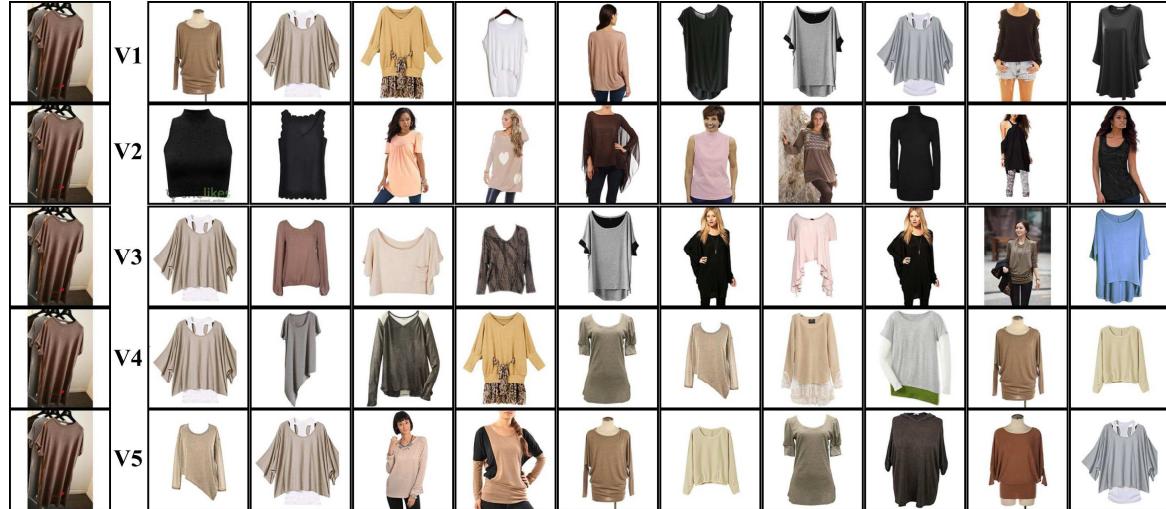


Figure 14: Sample evaluation sheet comparing the results of 5 different networks

Table 1 reveals fantastic information about the systems. First of all, it can be seen that although the IOU of the classification task of the feature extractor can be used as an implicit evaluation of the recommendation system, it is not directly comparable. IOU is also not interpretable either. On the other hand, OHS explicitly shows the effect of each parameter change on every single criterion.

Adding a shallow branch to deep networks marginally decreases the category score but improves color and variety scores. This finding agrees with [7] as they pointed out that a shallow net helps recover the color, which is usually lost in deeper network structures. Additionally, this technique leads to better results in terms of final OHS. The power of EfficientNet is also shown as both V4 and V5 output far more superior results. It seems that variety and shape difference are the only criteria in which the EfficientNets show weakness. Thus, it is preferable to use these networks in image search engines in which these two criteria are of less importance.

Table 1: Objective-guided Human Score (OHS) comparison of five networks

Version No.	Test IOU	Category	Subtype	Texture	Color	Variety	Details	Shape Difference	OHS
V1	44.6%	96.9%	71.5%	68.5%	67.2%	24.8%	36.3%	32.7%	73.6%
V2	43.9%	93.7%	70.4%	77.7%	68.3%	32.7%	43.5%	31.7%	74.0%
V3	44.5%	95.4%	71.7%	69.2%	64.8%	33.3%	33.3%	20.1%	73.2%
V4	45.2%	99.8%	77.3%	86.5%	70.2%	21.7%	43.4%	20.2%	78.1%
V5	44.1%	98.3%	86.3%	80.0%	73.5%	27.3%	37.9%	21.0%	80.0%

5 DISCUSSION

This section discusses several aspects of the experiments done on the recommender systems earlier. First, the amount of time and effort spent on preparing the dataset and labels, especially the label extraction phase, is of critical importance as it will be the base of other networks. This article used the old-fashioned label extraction method. However, newer natural language processing techniques and models, like BERT [21], might significantly improve the results as the relationship between the words are kept intact. Noisy and missing labels, for example, pink labels in Figure 9, also deteriorate the performance. A problem that can be solved by choosing a cleaner dataset with better labels.

Next is the overfitting problem. The training samples seem to be enough (more than 130 thousand images), and the network size is also logical. At first, it seems like that the heavy imbalance of labels leads to this problem. Even though it indeed has adverse effects on the results, it is not the only case. Further inspection of the labels reveals that most of them are repeated only 100 to 1000 times which makes them hard, if not impossible, to learn. In fact, apart from the imbalance, we are also facing a lack of data regarding each separate label. Statistically speaking, 775 labels (70% of total) have less than 500, and 456 labels (41% of total) have less than 200 repetitions. These 41% might be the reason why the recall evaluation metric is so low.

To further investigate this theory, we trained four networks using different sets of labels. In each trial, the least number of repetitions for tags is increased, and we delete more labels to see the effect these low repeated labels have on the network. The results are summarized in Table 2. It can be seen that precision is always high, and the system assigns the learned labels with high certainty; however, the recall is problematic due to the reasons mentioned earlier. This lack of data for some labels even causes numerous neurons in the last layer to die, and finding and pruning these might also improve the final results.

Table 2: Test results of training networks with different least number of label repetitions

Network No.	Least Number Of Label Repetitions	Number of Labels	Test IOU	Test Precision	Test Recall
1	100	1102	44.4%	73.1%	48.4%
2	500	327	49.1%	76.1%	53.4%
3	1,000	196	52.0%	77.6%	55.6%
4	10,000	14	78.8%	88.0%	83.1%

The true power of the background augmentation technique in bridging the gap between Street and Shop images can be seen in Figure 13. The system can successfully recommend similar items, although the inputs are more complex Street images that never existed in the training data. Almost none of the out-of-domain queries would lead to acceptable results without applying this technique.

Finally, the advantages of using the objective-guided human score for evaluating final recommendation results can be inferred from Table 1. Every aspect and detail of this method is customizable based on the user's goals, hence the name objective-guided. Furthermore, this scoring method is completely interpretable, and the effects on each criterion can be analyzed separately. Two things are essential to make sure this method provides reliable results. Firstly, the number of test queries and their complexity should be chosen carefully to show the whole dataset's qualities. Secondly, the more human scorers are, the more accurate the results will be.

6 CONCLUSION AND FUTURE WORK

Fashion e-commerce is growing at an unbelievably fast pace. However, as the number of fashion items in online shops increases exponentially, so does the difficulty of finding specific items in this vast market. Thus, online stores and companies are feeling the need for powerful content-based recommender systems and image search engines.

This article provided a single-item content-based fashion recommender for in-shop search and recommendation by training a convolutional neural network consisting of double branches, a deep ResNet50 network, and the other one a shallow net. Then, it used this network as a feature extractor in a two-stage structure to form personalized recommendations. Next, a background augmentation method was proposed to enable the system to make cross-domain suggestions. Finally, this work introduced objective-guided human score, an evaluation metric for recommendation tasks, a customizable framework that turns subjective evaluations into interpretable and comparable percentage values. The comparison results showed that EfficientNets could be superior to ResNets for the task at hand.

One future research direction is to utilize clustering methods like k-means and k-splits to guide the personalization system through the fashion feature space. Another promising direction is using advanced natural language processing methods and relation extraction techniques to obtain noise-free labels. Furthermore, a comparison of the method with a twin or triplet network would also be scientifically interesting.

REFERENCES

- [1] S. Rendle, C. Freudenthaler, Z. Gantner, and L. Schmidt-Thieme, "BPR: Bayesian Personalized Ranking from Implicit Feedback," *Proc. 25th Conf. Uncertain. Artif. Intell. UAI 2009*, pp. 452–461, May 2012, [Online]. Available: <http://arxiv.org/abs/1205.2618>.
- [2] R. He and J. McAuley, "VBPR: Visual Bayesian Personalized Ranking from Implicit Feedback," *30th AAAI Conf. Artif. Intell. AAAI 2016*, pp. 144–150, Oct. 2015, [Online]. Available: <http://arxiv.org/abs/1510.01784>.
- [3] S. Keerthi Gorripati and A. Angadi, "Visual Based Fashion Clothes Recommendation With Convolutional Neural Networks," *Int. J. Inf. Syst. Manag. Sci.*, vol. 1, no. 1, 2018.
- [4] H. Tuinhof, C. Pirker, and M. Haltmeier, "Image-Based Fashion Product Recommendation with Deep Learning," in *Lecture Notes in Computer*

Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), vol. 11331 LNCS, G. Nicosia, P. Pardalos, G. Giuffrida, R. Umeton, and V. Sciacca, Eds. Cham: Springer International Publishing, 2019, pp. 472–481.

- [5] Y. Lin, M. Moosaei, and H. Yang, “Learning Personal Tastes in Choosing Fashion Outfits,” in *2019 IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops (CVPRW)*, Jun. 2019, vol. 2019-June, pp. 313–315, doi: 10.1109/CVPRW.2019.00041.
- [6] D. Shankar, S. Narumanchi, H. A. Ananya, P. Kompalli, and K. Chaudhury, “Deep Learning based Large Scale Visual Recommendation and Search for E-Commerce,” *arXiv*, Mar. 2017, [Online]. Available: <http://arxiv.org/abs/1703.02344>.
- [7] E. Andreeva, D. I. Ignatov, A. Grachev, and A. V. Savchenko, “Extraction of Visual Features for Recommendation of Products via Deep Learning,” in *International Conference on Analysis of Images, Social Networks and Texts*, vol. 11179 LNCS, Cham: Springer International Publishing, 2018, pp. 201–210.
- [8] Y. Qian, P. Giaccone, M. Sasdelli, E. Vasquez, and B. Sengupta, “Algorithmic clothing: hybrid recommendation, from street-style-to-shop,” *arXiv*, May 2017, [Online]. Available: <http://arxiv.org/abs/1705.09451>.
- [9] J. Lasserre, C. Bracher, and R. Vollgraf, “Street2Fashion2Shop: Enabling Visual Search in Fashion e-Commerce Using Studio Images,” in *International Conference on Pattern Recognition Applications and Methods*, vol. 11351 LNCS, Cham: Springer International Publishing, 2019, pp. 3–26.
- [10] A. Ravi, S. Repakula, U. K. Dutta, and M. Parmar, “Buy Me That Look: An approach for recommending similar fashion products,” *arXiv*, 2020.
- [11] S. Liu, Z. Song, M. Wang, C. Xu, H. Lu, and S. Yan, “Street-to-shop: Cross-scenario clothing retrieval via parts alignment and auxiliary set,” in *MM 2012 - Proceedings of the 20th ACM International Conference on Multimedia*, 2012, pp. 1335–1336, doi: 10.1145/2393347.2396471.
- [12] J. Fu, J. Wang, Z. Li, M. Xu, and H. Lu, “Efficient Clothing Retrieval with Semantic-Preserving Visual Phrases,” in *Asian conference on computer vision*, vol. 7725 LNCS, no. PART 2, Berlin, Heidelberg: Springer, 2012, pp. 420–431.
- [13] Y. Kalantidis, L. Kennedy, and L. J. Li, “Getting the look: Clothing recognition and segmentation for automatic product suggestions in everyday photos,” in *ICMR 2013 - Proceedings of the 3rd ACM International Conference on Multimedia Retrieval*, May 2013, pp. 105–112, doi: 10.1145/2461466.2461485.
- [14] B. Gajic and R. Baldrich, “Cross-Domain Fashion Image Retrieval,” in *2018 IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops (CVPRW)*, Jun. 2018, vol. 2018–June, pp. 1950–19502, doi: 10.1109/CVPRW.2018.00243.
- [15] M. Kucer and N. Murray, “A Detect-Then-Retrieve Model for Multi-Domain Fashion Item Retrieval,” in *2019 IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops (CVPRW)*, Jun. 2019, vol. 2019–June, pp. 344–353, doi: 10.1109/CVPRW.2019.00047.
- [16] Z. Liu, P. Luo, S. Qiu, X. Wang, and X. Tang, “DeepFashion: Powering Robust Clothes Recognition and Retrieval with Rich Annotations,” in *2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, Jun. 2016, vol. 2016-Decem, no. 1, pp. 1096–1104, doi: 10.1109/CVPR.2016.124.
- [17] X. Liu, J. Li, J. Wang, and Z. Liu, “MMFashion: An Open-Source Toolbox for Visual Fashion Analysis,” *arXiv*, pp. 1–4, May 2020, [Online]. Available: <http://arxiv.org/abs/2005.08847>.
- [18] S. O. Mohammadi, A. Kalhor, and H. Bodaghi, “K-Splits: Improved K-Means Clustering Algorithm to Automatically Detect the Number of Clusters,” Oct. 2021, [Online]. Available: <http://arxiv.org/abs/2110.04660>.
- [19] W.-C. Kang, C. Fang, Z. Wang, and J. McAuley, “Visually-Aware Fashion Recommendation and Design with Generative Image Models,” in *2017 IEEE International Conference on Data Mining (ICDM)*, Nov. 2017, vol. 2017-Novem, pp. 207–216, doi: 10.1109/ICDM.2017.30.
- [20] M. Tan and Q. V. Le, “EfficientNet: Rethinking Model Scaling for Convolutional Neural Networks,” May 2019, [Online]. Available: <http://arxiv.org/abs/1905.11946>.
- [21] J. Devlin, M.-W. Chang, K. Lee, and K. Toutanova, “BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding,” Oct. 2018, [Online]. Available: <http://arxiv.org/abs/1810.04805>.