NecklaceFIR: A Large Volume Benchmarked Necklace Dataset for Fashion Image Retrieval

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Abstract. In this paper, we present a new necklace dataset related to the fashion domain, namely, NecklaceFIR. In recent years, the retrieval of clothing items has attracted a lot of attention. However, fashion products that are complex in nature, such as jewellery, have not received much attention due to the absence of a proper dataset. To address this problem, we have collected the dataset. The dataset contains over ∼4.8K high-definition necklace images collected from various online retailers. The dataset is structurally labeled in 49 categories. To benchmark the dataset, we have used various classical methods and state-of-art deep models. The dataset will be publicly available at: https://github.com/skarifahmed/NecklaceFIR.

Keywords: Fashion image retrieval · Ornament dataset · Image retrieval dataset

1 Introduction

Online shopping is a fast growing market. In recent years, research in the fashion domain is gaining a significant momentum for its substantial possibilities in the fashion industry. Recently, lots of research has been carried out for fashion retrieval [1–3], fashion matching and recommendation [4–6], fashion parsing [6–8], attribute detection [9–11], and many more due to the growing demand of fashion industry. Fashion image retrieval can be performed by using any of the two popular retrieval techniques, TBIR or CBIR. Many fashion sites use TBIR, where fashion images are annotated by text and images are retrieved using a keyword-based search as per user interest. Fashion items have many visual characteristics that cannot be represented by words. Thus, recently, CBIR has got much more attention by the researchers, where similar or identical items are retrieved from the gallery by using the visual contents like color, texture, or shape of a given query image. Applications of CBIR system manifolds such as face detection, fingerprint identification, medical applications, Digital Libraries,

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crime prevention, fashion recognition, fashion recommendation, and remote sensing, etc. In fashion image retrieval, similar fashion items are retrieved from the fashion image gallery based on users' queries. Figure 1 shows the fashion image retrieval process where FIR uses various similarity measurement methods like shape, color, design, and texture similarity to retrieve similar images for a given query. Recently, fashion image retrieval (FIR) has become more popular due to the growing demand for online shopping. Still, FIR has some limitations like the presence of multiple objects in a fashion image, the query image has different viewpoints or captured in low light, and the complex shape, design or texture of fashion image [12].

In the past few years, most of the fashion-related research are on garments. However, the research on ornament retrieval has got less attention due to its complexity in design and lack of proper ornament datasets. It has been noticed that there is a wider variety of jewellery design compared to fashion products such as clothing or footwear.

According to our observations, there is no dataset other than the Ring-FIR dataset [13] that works exclusively with ornament images. This observation inspires us to create a dataset of ornament images.

To address the above challenges, this work has two main contributions. (1) we build a novel fashion image dataset containing ∼4.8K high quality nacklace images, namely, NacklaceFIR. (2) State-of-art image retrieval methods are used to benchmark the dataset.

The rest of the paper is structured as follows: the related work in FIR is summarized in Sect. 2; the details of the proposed dataset are explained in Sect. 3; the state-of-the-art benchmarking methods and results are detailed in Sect. 4; finally, Sect. 5 summarizes the conclusion.

2 Related Works

Image retrieval is a challenging issue in computer vision. Various classical methods and deep neural networks are used to solve this problem. Here, we have explained various image retrieval datasets and fashion image retrieval methods.

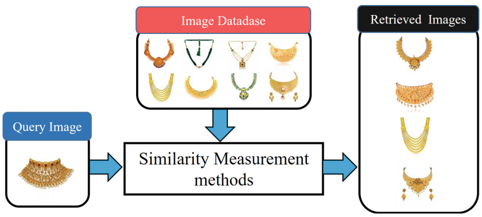


Fig. 1. Fashion image retrieval (FIR) process.

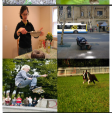
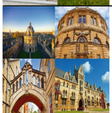
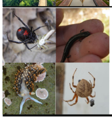
Fashion Image Retrieval Datasets: Huang et al. [14] presents a garment dataset, containing 206,235 cloth images with descriptions. To address the problem of cross-domain image retrieval, Huang et al. [15] proposed a clothing image dataset, containing 453,983 online upper-clothing images from online shopping websites and about 90,000 offline counterpart images of those online images. For exact matching real world clothing images with online shop images, Kiapour et al. [16] introduced a novel dataset, namely, Exact Street2Shop, containing 404,683 online clothing images from different online shops and 20,357 real world street images. Liu et al. [17] constructed a clothing dataset, namely, Multi-view Clothing dataset (MVC), to address view-invariant clothing retrieval problem. Liu et al. [18] introduced a large-scale clothing dataset, DeepFashion, containing over 800,000 fashion images that are annotated with large numbers of attributes, landmarks, and cross-pose/cross-domain image pairs. To retrieve exactly same garments from online shops that appeared in the videos, Cheng et al. [19] proposed a cross-domain dataset Video2Shop, containing 26,352 clothing trajectories from videos and 85,677 online clothing images. Ge et al. [20] introduced a versatile benchmark dataset DeepFashion2 for detection of cloth, estimation of pose, segmentation, and clothing retrieval. For cross-domain clothing image retrieval, Kuang et al. [21] build a benchmarked dataset FindFashion, by revisiting the existing datasets Street2Shop [16], and DeepFashion [18] and contains 565,041 clothing images. For attribute-specific fashion retrieval, Ma et al. [22] created a fashion dataset by rebuilding three fashion datasets, namely, DARN [15], FashionAI [23] and DeepFashion [18] with attribute annotations.

Other Image Retrieval Datasets: In addition to fashion image datasets, image datasets include various types of medical diagnosis, fingerprint detection, landmark detection, crime prevention, face detection, and more.

Deng et al. [24] introduced a database called ImageNet, which contains over ∼1.2M annotated images according to the WordNet hierarchy. For sentence-based image description Plummer et al. [25] created a dataset namely, Flickr30k, which contains ∼3K images that focus primarily on humans and animals, and ∼1.5K English captions. Oh et al. [26] collected a dataset of online products for metric learning, namely, Stanford Online Products (SOP) by crawling eBay.com, and contains 120k images of 23k classes. Weyand et al. [27] introduced a new dataset, Google Landmarks Dataset v2, that includes about 5M images of natural and man-made landmarks all over the world. Van et al. [28] created a unique dataset, iNaturalist, consisting of over 8M images of various species of plants and trees captured around the world.

Some of the image datasets that are used for various image retrieval problems are shown in the Table 1.

Table 1. Some well-known image datasets are used for image retrieval, recognition, and classification problems.

Samples	Dataset	Description	Application	Annotation
	Fashion10000 [29]	A large scale fashion dataset	Fashion recommendation	32,398 fashion outfits
	Multi-view Clothing dataset [17]	View-invariant clothing dataset	Clothing retrieval	161,638 clothing images
	Exact Street2Shop [16]	Clothing items are matched between street and shop images	Image retrieval	∼404k online shop and ∼20k street images
	DeepFashion [18]	A large scale clothing dataset with annotation	Image retrieval and recognition	800k fashion products
	CIFAR-10 [30]	Gray-scale fashion product images	Classification	70k fashion items
	ImageNet [24]	A large-scale dataset of objects	Object recognition	∼100k objects
	Flickr30k [25]	Sentence-based image description dataset	Classification	∼3K images with ∼ 1.5K captions
	Oxford5k [31]	Benchmarked Oxford landmarks images	Image retrieval	∼5K landmark images
	Paris6k [32]	Benchmarked Paris landmarks images	Image retrieval	∼6K landmark images
	CUB-200-2011 [33]	A large-scale dataset of bird images	Image retrieval and Classification	∼11K bird images of 200 bird species
	Google Landmarks Dataset v2 [27]	Natural and man-made landmarks	Image retrieval and classification	∼5M landmark images around the world
	iNaturalist [28]	Images of species of plants and trees	Image retrieval and classification	∼8M benchmarked images

According to our observations, there are no datasets available that are exclusively related to ornamental images. This inspires us to build a dataset of ornament images.

State-of-the-Art Fashion Image Retrieval Methods: As fashion e-commerce has grown year after year, there is a high demand for an innovation solution to help customers easily find the fashion item of choice. For Exact Street-to-Shop image retrieval, Hadi et al. [16] introduced three different methods, including two in-depth learning methods and a method to compare the similarity between street and shop fashion images. For in-shop clothing retrieval, Kinli et al. [34] proposed a triplet-based design of capsule network architecture to calculate the similarity between triplets. To train a network that matches fashion item images captured by users with the same item images taken in controlled condition by a professional photographer, Gajic et al. [1] use triplet loss. To retrieve the same or attribute similar clothing images from online shopping, for a user-captured clothing image, Huang et al. [15] developed a Dual Attribute aware Ranking Network (DARN) that integrates feature and visual similarity limitations into retrieval feature learning. For interactive fashion item search, Zhao et al. [35] proposed a memory augmented attribute manipulation network, where the memory block consists of a memory to store a prototype representation of various attributes, and a neural controller, for interactive attribute manipulation. To learn the features of garments with joint predictions of clothing features and landmarks, Liu et al. [18] has developed a novel deep model, namely, FashionNet. A new Match R-CNN framework was proposed by Ge et al. [20] to resolve clothes detection, pose estimation, segmentation, and retrieval problems in an end-to-end manner. Ma et al. [22] proposed a novel Attribute-Specific Embedding Network (ASEN) with two attention networks Attribute-aware Spatial Attention (ASA) and Attribute-aware Channel Attention (ACA), to learn multiple attribute-specific embeddings and to measure fine-grained fashion similarity prediction in the same space. Zheng et al. [36] proposed a weakly supervised contrastive learning framework (WCL) to tackle the class collision problem of contrastive learning. To retrieve weakly-supervised multi-modal instance-level products, Zhan et al. [37] has collected a dataset called Product1M and proposed a hybrid-stream transformer called CAPTURE. To perform weakly supervised classification of unlabeled data, Presotto et al. [38] proposed a rank-based model.

3 Proposed Dataset and Benchmark

There are no datasets available that exclusively deal with ornament images. Ornament images are more complex in nature and a large number of designs are available rather than other fashion image datasets. An earring dataset and its benchmarking have described in [13]. In this paper, we have created an ornament dataset, namely, NecklaceFIR, a collection of high resolution golden necklaces. The datset contains 4,803 images from 49 different classes that are collected from various online shopping sites. Figure 2(A) shows the sample images from our dataset and Fig. 2(B) shows the distribution of images over different classes.

Data Collection: We have collected the dataset by visiting various jewellery chains like Tanishq, Malabar Gold and Diamonds, Kalyan Jewellers, Anjali Jewellers, Senco Jewellers, and PC Chandra Jewellers and from some popular shopping websites such as, voylla, myntra, amazon, and flip-kart. To form the datset, we have marged the images collected from various jewellery chains and online shopping sites. We refine the dataset by deleting the duplicate entry images and low resolution images.

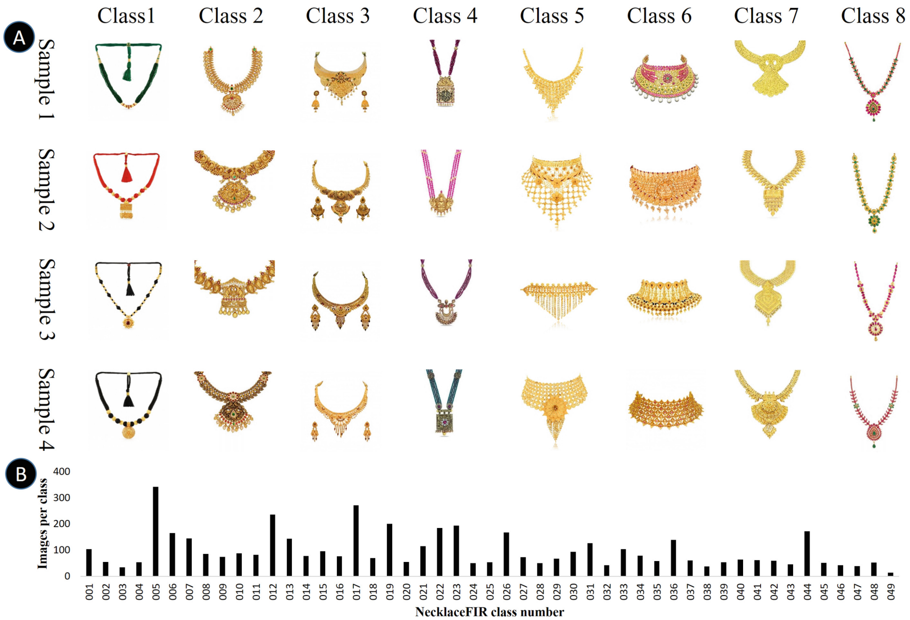


Fig. 2. (A) Samples from the dataset of varied designs are selected randomly to be shown as examples. (B) The images of different classes are also distributed evenly in tabular from.

Image Annotation: Annotation of the dataset is the most crucial part of our work. Here, grouping earrings by visual similarity has been mentioned as an annotation. For this purpose, we have involved 5 female volunteers who have expertise in jewellery and 25 end-user female volunteers. We have also designed a small application for this purpose. The application will show some random query images on the screen and the volunteers will select similar images from the image gallery. The process was repeated for ∼1000 times and ∼50K arbitrary annotations are collected. Then, based on the maximum vote, the necklace images are grouped into various classes. Finally, we have got 49 different classes of necklace images.

4 Benchmarking Methods and Discussion

To benchmark the NecklaceFIR dataset, we have used various existing classical methods and state-of-art deep models where Histogram similarity using Bhattacharyya distance, Pearson Correlation Coefficient, Chi-Square, and intersection are the classical methods and ResNet50, ResNet101, ResNet152, VGG16, NASNetMobile, MobileNet, DenseNet121, DenseNet169, and DenseNet201 are the deep networking models used for benchmarking.

To extract the features of an image and image retrieval, we have used various deep models. To extract the features of the query and gallery image pair, we have used Imagenet as the baseline image classifier. Then, the feature distance of the query and gallery image pair is calculated using Euclidean distance. The similarity score is calculated using feature distance and based on the similarity score, the ranking of the gallery images are assigned.

We have divided the dataset into train and test sets where 70% of the dataset is the train set used to train the deep network models and remaining 30% is test set used for validation. For validation, 10 images from each class have been separated. Based on the similarity score, the gallery images are sorted images in descending order for a given query image. To record the performance of retrieval, we have used top-k retrieval accuracy. To achieve any true result from the specific test performed by considering any single query image, one item is required to match with the existing gallery. This has to be achieved only within the first k results. At first, the deep models are trained with Imagenet and fine-tuned with our novel dataset NecklaceFIR. Then the features of the query and gallery images

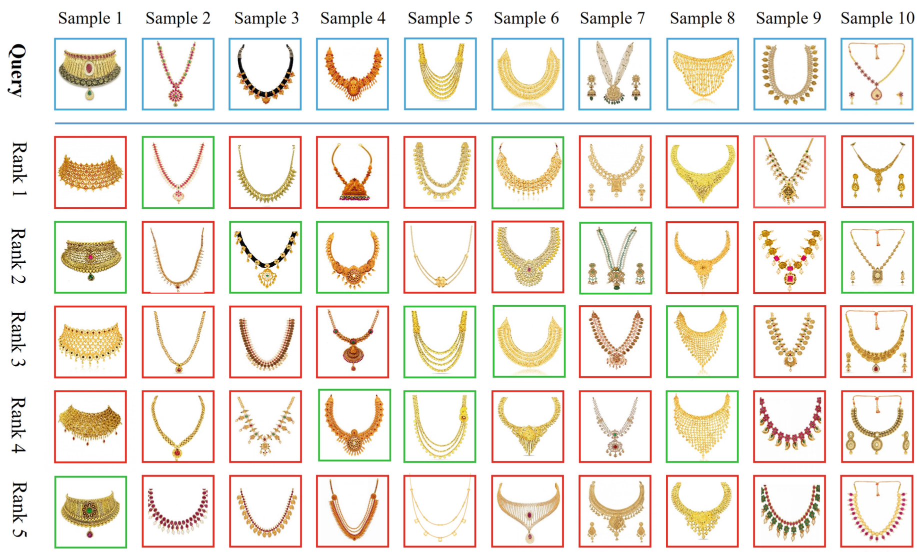


Fig. 3. Some arbitrary retrieval examples using NASNetMobile, where green boundary indicates successfully retrieved images and red boundary indicates failed images.

are extracted using the trained deep model. Finally, feature differences are used as similarities; the less the difference, the greater the similarity. The top-1, top-5, top-10, and top-20 retrieval accuracy's on NecklaceFIR using various methods are summarized in Table 2. The Fig. 3 shows the results of random retrieval using NASNetMobile and Fig. 4 shows the graphical representation of Top-k retrieval accuracy using various methods.

It can be observed that the retrieval accuracy using classical image retrieval methods is not good and state-of-art deep models also perform poorly. And the top-1 accuracy is very low for all methods. It can be also noticed that classical image retrieval methods like Bhattacharyya distance and Chi-Square compete with state-of-art deep models.

From the results, we can conclude that due to less variation in design, color and texture details are the main cause of less retrieval accuracy by the state-of-art deep models and classical methods. We need a custom designed neural network for ornament dataset to achieve better retrieval accuracy.

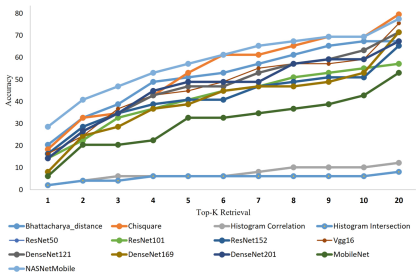


Fig. 4. Top-k retieval accuracy on NecklaceFIR dataset using various state-of-art methods.

Table 2. Accuracy using various state-of-art classical, deep learning methods

Method	Accuracy (%)			
	Top-1	Top-5	Top-10	Top-20
Bhattacharyya [39]	20.41	51.02	67.35	67.34
Correlation [39]	2.04	6.12	10.20	12.24
Chi-Square [39]	18.37	53.06	69.39	79.59
Hist. Intersection [40]	2.04	6.12	6.12	8.16
VGG16 [41]	16.33	44.90	59.18	75.51
ResNet50 [42]	14.29	40.82	55.10	57.14
ResNet101 [42]	14.29	40.82	55.10	57.14
ResNet152 [42]	16.33	40.82	51.02	65.31
DenseNet121 [43]	14.29	46.94	63.27	71.43
DenseNet169 [43]	8.16	38.78	53.06	71.43
DenseNet201 [43]	14.29	48.98	59.18	67.35
NASNetMobile [44]	28.57	57.14	69.39	77.55
MobileNet [45]	6.12	32.65	42.86	53.06

5 Conclusion

In this paper, we have introduced a novel fashion image retrieval dataset featuring large sized gold necklaces, namely, NecklaceFIR containing ∼4.8K high-resolution images and labelled in 49 categories. The dataset is also benchmarked using various well-known classical methods and state-of-art deep neural models. As per our observation, the dataset is challenging and the retrieval accuracy using various state-of-art methods is very low. The main challenges of the dataset are: (1) Unlike many other fashion datasets such as shoes and clothing, the idea of matching necklace is abstract because similarity may be based on structure or it may be based on structure and appearance of other material like stone, 2) large interclass variations. We hope that the dataset will make a valuable contribution to the computer vision community and it will attract the researchers. In the future, we will expand the dataset by including other ornaments and will also add textual tags to the ornaments to improve retrieval accuracy.

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