Combination of Multiple Global Descriptors for Image Retrieval

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Abstract

Recent studies in image retrieval task have shown that ensembling different models and combining multiple global descriptors lead to performance improvement. However, training different models for ensemble is not only difficult but also inefficient with respect to time or memory. In this paper, we propose a novel framework that exploits multiple global descriptors to get an ensemble-like effect while it can be trained in an end-to-end manner. The proposed framework is flexible and expandable by the global descriptor, CNN backbone, loss, and dataset. Moreover, we investigate the effectiveness of combining multiple global descriptors with quantitative and qualitative analysis. Our extensive experiments show that the combined descriptor outperforms a single global descriptor, as it can utilize different types of feature properties. In the benchmark evaluation, the proposed framework achieves the state-of-the-art performance on the CARS196, CUB200-2011, In-shop Clothes and Stanford Online Products on image retrieval tasks by a large margin compared to competing approaches.

1. Introduction

Since the ground-breaking in 2012 ImageNet competition [8, 25], image descriptors based on deep convolutional neural networks (CNNs) have surfaced as generic descriptors in computer vision tasks, including classification [25, 15, 49], object detection [10, 43, 42], and semantic segmentation [31, 5, 44]. They have been adopted to highly semantic tasks as well, such as image captioning [58, 57] and visual question answering [11, 33]. Moreover, recent works leveraging image descriptors based on deep CNNs have emerged for instant-level image retrieval task which used to apply conventional methods relying on local descriptor matching [32, 21] and re-ranking with spatial verification [35, 50, 27].

In the case of recent researches on image retrieval, fully connected (FC) layers after several convolutional layers are used as global descriptors followed by dimensionality reduction [3, 11]. Other works generate global descriptors from the activations of the convolutional layers. Representative global descriptors generated by global-pooling methods include sum pooling of convolutions (SPoC) [2], maximum activation of convolutions (MAC) [51], and generalized-mean pooling (GeM) [41]. The performance of each global descriptor varies by dataset as each descriptor has different properties. For example, SPoC activates larger regions on the image representation while MAC activates more focused regions [17, 4]. In order to boost their ability, variants of these representative global descriptors have been proposed such as weighted sum pooling [20], weighted GeM [55], regional MAC (R-MAC) [51], etc.

Recent researches have focused on ensemble techniques for image retrieval task. Conventional ensemble techniques which train multiple learners individually and use a combined model lead to increase in performance [29, 56, 40, 22]. Many high-ranked approaches in the recent Google landmark retrieval challenge [4] and Zehang et al. [29] boost retrieval performance by combining different global descriptors which are trained individually. However, explicitly training multiple learners for ensemble could lead to longer training time and greater memory consumption. In order to handle this problem, other ensemble approaches [22, 40] attempt to train a retrieval model in an end-to-end manner. These approaches can be tricky as they need specifically designed strategy or loss to control diversity among learners which also cause a harder training process.

In this paper, we focus on how to exploit multiple global descriptors to get an ensemble-like effect without explicitly training multiple learners and controlling diversity among learners. Our contribution is threefold. (1) We propose a novel framework, the combination of multiple global descriptors (CGD), that combines multiple global descriptors which can be trained in an end-to-end manner. It achieves an ensemble-like effect without any explicit ensemble model or diversity control over each global descriptor. Moreover, the proposed framework is flexible and expandable by the global descriptor, CNN backbone, loss, and...
Figure 1. The combination of multiple global descriptors (CGD) framework. The framework is described with ResNet-50 backbone where Stage 3 downsampling is removed. From the last feature map, each of \( n \) global descriptor branch outputs a \( k \)-dimensional embedding vector, which are concatenated into the combined descriptor for ranking loss. Exclusively the first global descriptor is used for auxiliary classification loss where \( M \) denotes the number of classes.

dataset. (2) We investigate the effectiveness of combining multiple global descriptors by quantitative and qualitative analysis. Our extensive experiments demonstrate that using combined descriptor outperforms a single global descriptor since it can use different types of feature properties. (3) The proposed framework achieves the state-of-the-art performance on CARS196 [24], CUB200-2011 [52] (CUB200), Standard Online Products [38] (SOP) and Inshop Clothes [30] (In-shop) by a large margin on image retrieval tasks. Our model implementation and pretrained models will be published on the online.

2. Related Works

In the recent works for image retrieval task, global descriptors based on deep CNNs have been used as off-the-shelf feature [45] over the conventional hand-crafted features such as SIFT [32]. SPoC [2] is sum pooling from the feature map which performs well especially due to the subsequent descriptor whitening. MAC [51] by max pooling is another powerful descriptor, while R-MAC [51] performs max pooling over regions, then sum over the regional MAC descriptors at the end. GeM [41] generalizes max and average pooling with a pooling parameter. Other global descriptor method includes weighted sum pooling [20], weighted GeM [55], multiscale RMAC [28], etc.

Some works [7, 13, 26] attempt using the additional strategy or the attention mechanism to maximize the activations of important features on the feature map. Dai et al. [7] present a strategy called batch feature erasing (BFE) to force the network to optimize the feature representation of different regions. Li et al. [26] propose a model that has soft pixel attention and hard regional attention along with simultaneous optimization of feature representations. The downsides of adopting the additional strategy or the attention mechanism are that it can not only lead to increase network size and training time, but also require additional parameters for training. However, our proposed framework does not need any additional strategy or attention mechanism when it requires only a few additional parameters for training.

The ensemble is a well-known technique that aims to boost performance by training multiple learners and obtains a combined result from the trained learners. In the last decades, it is widely used in image retrieval tasks [22, 40, 56, 29]. Xuan et al. [56] propose a method, where each embedding function is learned by randomly bagging and training labels into small subsets. Kim et al. [22] suggest an attention-based ensemble, where single feature embedding function is trained while each learner learns different attention modules. The downside of ensemble techniques is that it leads to an increase in computational cost as the model complexity increases [62], and requires additional control to yield diversity between learners [22, 39]. However, our proposed framework takes advantage of the idea of the ensemble technique when it can be trained in an end-to-end manner with no diversity control.

3. Proposed Framework

We propose a simple, yet effective framework which we refer to as a CGD framework for image retrieval tasks. It
learns a combined descriptor which is generated by concatenating multiple global descriptors in an end-to-end manner. Our proposed framework is depicted in Figure 1.

The proposed framework consists of a CNN backbone network and two modules. The first module is the main module that learns an image representation, which is a combination of multiple global descriptors for a ranking loss. Next, is an auxiliary module to fine-tune a CNN with a classification loss. The proposed framework is trained with a final loss, which is the sum of the ranking loss from the main module and the classification loss from the auxiliary module in an end-to-end manner.

### 3.1. Backbone Network

Our proposed framework can use any CNN backbones such as BN-Inception [19], ShuffleNet-v2 [34], ResNet [15] and its variants, etc, while we use ResNet-50 [15] as a baseline backbone described in Figure 1. To preserve more information in the last feature map, we modify the network by discarding the down-sampling operation between the Stage 3 and Stage 4 [7, 53]. This modification gives a $14 \times 14$ sized feature map for input size of $224 \times 224$, which improves the performance of individual global descriptor.

### 3.2. Main Module: Multiple Global Descriptors

The main module has multiple branches that output each image representation by using different global descriptors on the last convolutional layer. In this paper, we use three types of the most representative global descriptors on each branch including SPoC, MAC, and GeM.

Given an image $I$, the output of the last convolutional layer is a 3D tensor $X$ of $C \times H \times W$ dimension, where $C$ is the number of feature maps. Let $X_c$ be the set of $H \times W$ activations for feature maps $c \in \{1 \ldots C\}$. The network output consists of $C$ channels of such 2D feature maps. Global descriptor takes $X$ as an input and produces a vector $f$ as an output by pooling process. Such pooling methods can be generalized as follows:

$$f = [f_1 \ldots f_c \ldots f_C]^\top, \quad f_c = \left(\frac{1}{|X_c|} \sum_{x \in X_c} x^{p_c}\right)^{\frac{1}{p_c}}. \quad (1)$$

We define SPoC as $f^{(s)}$ when $p_c = 1$, MAC as $f^{(m)}$ when $p_c \to \infty$, and GeM as $f^{(m)}$ for the rest of the cases. For the case of GeM, the parameter $p_c$ can be manually set or trained because it is differentiable, while we use fixed $p_c$ parameter 3 throughout the experiments.

Output feature vector $\Phi^{(a_i)}$ from the $i$-th branch is generated by dimensionality reduction through the FC layer and normalization through the $l_2$-normalization layer:

$$\Phi^{(a_i)} = \frac{W^{(i)} f^{(a_i)}}{\|W^{(i)} f^{(a_i)}\|_2}, \quad a_i \in \{s, m, g\}, \quad (2)$$

for $i \in \{1 \ldots n\}$, where $n$ is the number of branches, $W^{(i)}$ is the weight of the FC layer and the global descriptor $f^{(a_i)}$ can be SPoC when $a_i = s$, MAC when $a_i = m$, or GeM for $a_i = g$.

The final feature vector referred to as combined descriptor $\psi_{CGD}$ of our framework combines output feature vectors of multiple branches and performs $l_2$-normalization sequentially:

$$\psi_{CGD} = \frac{\Phi^{(a_1)} \oplus \ldots \oplus \Phi^{(a_i)} \oplus \ldots \oplus \Phi^{(a_n)} }{\|\Phi^{(a_1)} \oplus \ldots \oplus \Phi^{(a_i)} \oplus \ldots \oplus \Phi^{(a_n)}\|_2}, \quad (3)$$

for $a_i \in \{s, m, g\}$, where $\oplus$ denotes concatenation. This combined descriptor can be trained with any type of ranking loss, while we use batch-hard triplet loss [16] as a representative.

In the proposed framework, there are two advantages in combining multiple global descriptors. First, it gives an ensemble-like effect with only a few additional parameters. To get the ensemble effect as aforementioned work [29] but make it trainable in an end-to-end manner, our framework extracts and combines multiple global descriptors from a single CNN backbone in an end-to-end manner. Second, it automatically provides different properties for each branch’s output without any diversity control. Recent works [22, 39] propose specially designed losses to encourage diversity among learners. However, our framework does not require any specially designed loss to control diversity among branches.

### 3.3. Auxiliary Module: Classification Loss

The auxiliary module fine-tunes the CNN backbone based on the first global descriptor of the main module by using the auxiliary classification loss. This follows the approach [12], which consists of two steps: fine-tuning a CNN backbone with a classification loss to improve convolutional filters, and then fine-tuning the network to improve the performance of a global descriptor. However, we modify their approach to have a single step for an end-to-end training, while [12] has to be trained with two steps. Training with auxiliary classification loss makes an image representation to have the inter-class separating property, and helps to train the network faster, and more stable than using only a ranking loss.

Temperature scaling [14, 61] in softmax cross-entropy loss (softmax loss), and label smoothing [49] are proven to be helpful for the training of classification loss. The softmax loss is defined as

$$L_{\text{Softmax}} = -\frac{1}{N} \sum_{i=1}^{N} \log \frac{\exp ((W^T_y f_i + b_y)/\tau)}{\sum_{j=1}^{M} \exp ((W^T_y f_j + b_j)/\tau)}, \quad (4)$$

where $N$, $M$, and $y_i$ are the batch size, the number of classes, and the corresponding identity label of $i$-th input, respectively. $W$, and $b$ are trainable weight, and bias, respectively, and $f$ is a global descriptor from the first branch,
where $\tau$ is a temperature parameter with default value 1. The temperature scaling with low-temperature parameter $\tau$ in the Equation 4 assigns a larger gradient to more difficult examples, and is helpful for intra-class compact, and inter-class spread-out embedding. The label smoothing enhances a model, thereby improves generalization by estimating the marginalized effect of a label-dropout during training. Therefore, to prevent over-fitting, and learn better embedding, we add label smoothing and temperature scaling in the auxiliary classification loss.

### 3.4. Configurations of Framework

Our proposed framework is expandable by the number of global descriptor branches and it allows different types of networks according to the configuration of global descriptors. As we use three global descriptors (SPoC, MAC, and GeM), and exclusively the first global descriptor is used for the auxiliary classification loss, we can make twelve possible configurations. To have simple notations for the configurations, we abbreviate SPoC as S, MAC as M, and GeM as G, and the first letter in the notation is the first global descriptor to be used for the auxiliary classification loss. For example with a configuration SMG, the first letter which is the first global descriptor S will be used for the auxiliary classification loss and the all S, M, and G are concatenated to be combined descriptor for ranking loss. Therefore, the twelve possible configurations are obtained as follows: S, M, G, SM, MS, SG, GS, MG, GM, SMG, MSG, GSM.

### 4. Experiments

#### 4.1. Datasets

We evaluate our proposed framework on image retrieval datasets including CUB200-2011 [52], CARS196 [24], Standard Online Products [38], and In-shop Clothes [50]. For the CUB200 and CARS196, cropped images with the bounding box information is used. We follow the same training and test split as [7] [22] [60] for fair comparisons with other works.

#### 4.2. Implementation

All experiments are implemented using MXNet [6] on a Tesla P40 GPU with 24 GB memory. We use BN-Inception [19], ShuffleNet-v2 [34], ResNet-50 [15], SE-ResNet-50 [18] with ImageNet ILSVRC-2012 [8] pre-trained weights from MXNet GluonCV. For every experiment, we use the input size of $224 \times 224$ and the 1536-dimensional embedding, unless otherwise noted in the experiment. In the training phase, the input image is resized to $252 \times 252$, cropped randomly to $224 \times 224$, and then flipped randomly to the horizontal. We use an Adam [23] optimizer with a learning rate of $1e-4$, and a step decay is used for scheduling the learning rate. A margin $m$ for triplet loss is 0.1, and a temperature $\tau$ for softmax loss is 0.5 for every experiment. For the batch size, 128 is used on every dataset, and for the number of instances per class, 64 is used on CARS196, and CUB200-2011, while 4 is used on In-shop Clothes, and Standard Online Products. In the inference phase, we only resize the image by the default input size of $224 \times 224$.

#### 4.3. Experiments for Architecture Design

##### 4.3.1 Training Ranking and Classification Loss Jointly

**Auxiliary Classification Loss** Our proposed framework is trained by the ranking loss with the auxiliary classification loss from the first global descriptor. We compare the performance between using the ranking loss exclusively, and the ranking loss with the auxiliary classification loss on CARS196 in the Table 1. In this experiment, we do not apply label smoothing, and temperature scaling on the auxiliary classification loss in every case. It proves that using both losses provides higher performance than using ranking loss exclusively. Classification loss focuses on clustering each class into a close embedding space in a categorical level. Ranking loss focuses on gathering samples in the same class and making a distance between samples from the different classes in the instance level. Therefore, training the ranking loss with the auxiliary classification loss jointly gives better optimization for categorical, and fine-grained feature embedding.

**Label Smoothing and Temperature Scaling** As mentioned in Section 3.3, label smoothing, and temperature scaling are proven to be helpful to learn better embedding
for the classification loss. We investigate if it can be applicable when a model is trained with both the ranking loss and the auxiliary classification loss jointly. We show the performance appraisal of the ‘no tricks’, the label smoothing, the temperature scaling with temperature term 0.5, and ‘both tricks’ on the auxiliary classification loss in Table 2. The experiment is performed on the ResNet-50 [15] backbone with the configuration SM. It shows that each label smoothing, and temperature scaling improves the performance compared to the ‘no tricks’. Moreover, applying ‘both tricks’ together stacks up each performance boost, and gives the best performance.

4.3.2 Combining Multiple Global Descriptors

Position of Combination As our proposed framework uses multiple global descriptors, we perform experiments with different positions of combination of multiple global descriptors to choose the best architecture. Architecture type A in the Figure 2A trains each global descriptor with individual ranking loss, and then combines them at the inference phase as in [22], while they use the same global descriptor for every branch and do not use classification loss. Architecture type B in the Figure 2B combines the raw output of global descriptors and train it with a single ranking loss, similar to studies of [46, 48], while they do not use multiple global descriptors. However, our proposed framework combines multiple global descriptors after the FC layers and l2-normalization as described in Figure 1. As shown in Table 3 the proposed position of the combination preserves the best performance over the architecture type A, and type B as it contains properties, and diversities of output feature vectors of multiple branches. In contrast, the final embedding of type A in the training phase is different from that of the inference phase, and the final embedding of type B loses each property of the global descriptor because of the FC layer after concatenation.

| Type     | Recall@K (%)                       |
|----------|------------------------------------|
|          | 1  | 2  | 4  | 8  |
| A        | 74.6 ± 0.4 | 83.5 ± 0.4 | 89.8 ± 0.3 | **94.0 ± 0.2** |
| B        | 73.7 ± 0.3 | 82.6 ± 0.3 | 89.2 ± 0.2 | 93.5 ± 0.2     |
| CGD      | **75.3 ± 0.5** | **83.9 ± 0.3** | **89.9 ± 0.3** | **94.0 ± 0.3** |

Table 3. Recall@K ± std. dev. among architecture type A, type B, and the proposed framework with the configuration SM on CUB200-2011. We report results over five runs.

| Comb. | Recall@K (%) |
|-------|--------------|
|       | 1  | 2  | 4  | 8  |
| Sum   | 73.8 ± 0.5  | 82.9 ± 0.4 | 89.4 ± 0.3 | 93.7 ± 0.1     |
| Concat | **75.3 ± 0.5** | **83.9 ± 0.3** | **89.9 ± 0.3** | **94.0 ± 0.3** |

Table 4. Recall@K ± std. dev. comparison by combination method with the configuration SM on CUB200-2011. We report results over five runs.

Method of Combination In terms of the combination method, concatenation, and summation of multiple descriptors are proven to enhance performance in [22, 46, 48, 51]. Therefore, we compare two combination methods to choose the best. As shown in Table 4, concatenation of multiple global descriptors gives better performance compared to their summation. This also indicates the importance of preserving each property, and diversity from multiple global descriptors, since the summation mix activations of each global descriptor up, while the concatenation maintains them.

4.4. Effectiveness of Combined Descriptor

4.4.1 Quantitative Analysis

The core of our proposed framework is exploiting multiple global descriptors. As we defined in Section 3.4, we conduct experiments with twelve possible configurations on each image retrieval dataset, where the framework uses the temperature scaling exclusively in the auxiliary classification loss. In the Figure 3 majorities of combined descriptors outperform over than a single global descriptor S, M, and G on the CARS196, SOP and In-shop. For the CUB200, the single global descriptors G and M show relatively high performance while the best performance configuration is still combined descriptor MG. The performance can be varied by the properties of datasets, the feature used for the classification loss, the size of input and the output dimension, etc. The main essence is that exploiting multiple global descriptors can give performance boosts compared to single global descriptor.

Table 5 shows the performance of individual global descriptors before combining operation and how much performance gain they can produce after the operation. Every combined descriptor have 1536-dimensional embedding vector, while each individual descriptor has
1536-dimensional embedding vector for S, M, G, 768-dimensional embedding vector for SM, MS, SG, MG, GM, and 512-dimensional embedding vector for SMG, MSG, GSM. Having a larger embedding dimension usually gives better performances. However, if the performance difference is not much between a large embedding dimension, and a small embedding dimension, it may be preferable to use multiple small embeddings from different global descriptors. For example, as individual descriptor GeM from SG with 768 embedding dimensions has similar performance with a single descriptor G with 1536 embedding dimensions, SG gets a big performance boost by combining different features of SPoC, and GeM.

### 4.4.2 Qualitative Analysis

A visualization tool proposed in [47] highlights the regions of images that contribute the most to pairwise similarity. We modify this work to be suitable for our framework in order to see how much each region of the image contributes to the similarity for each final embedding of different configurations. Figure 4 shows visualization of topmost (Recall@1) retrieved image of each configuration on the same query.

As mentioned in [47], the regions of similarity are large in the configuration S, while the configuration M has more focused regions of similarity. The configuration SM seems to have the similarity regions mixed with the configuration S, and M. SPoC tends to see the overall information when it lacks discriminability because they average the high activated outputs by non-active outputs [17]. MAC is preferable to retain the high activation when it is only powerful for

| Config. | Combined (1536-dim.) | Individual Descriptor |
|---------|----------------------|-----------------------|
| S       | 93.8                 | SPoC 93.8             |
| M       | 93.6                 | MAC 94.0              |
| G       | 93.9                 | GeM 93.9              |
| SM      | 94.3                 | 92.5 93.6             |
| MS      | 94.0                 | 93.2 93.5             |
| SG      | 94.5                 | 93.0 94.0             |
| GS      | 94.2                 | 93.5 93.9             |
| MG      | 93.9                 | 93.4 93.3             |
| GM      | 94.2                 | 93.9 93.3             |
| SMG     | 94.2                 | 92.2 93.0 93.0 93.8   |
| MSG     | 94.4                 | 92.7 93.0 93.8        |
| GSM     | 94.0                 | 92.7 93.2 93.0        |

Table 5. Recall@1 (%) of combined descriptor, and their individual descriptor on CARS196. Each individual descriptor is an output feature vector of each branch right before the concatenating operation. The combined descriptor is the final feature vector of the proposed framework. We report median values from ten runs.
### 4.5. Flexibility of CGD Framework

#### 4.5.1 Ranking Loss

Table 5 shows that CGD framework can use various ranking losses, such as the soft-margin or batch-hard triplet loss [16], the HAP2S loss [59], and the weighted sampling margin loss [54]. We compare the performance of the configuration S as the baseline for the single global descriptor and SM for multiple global descriptors using these losses. The coefficient $\alpha$ for HAP2S $P$ loss is set to 10, the coefficient $\sigma$ for HAP2S $E$ loss is set to 0.5, and the margin $\alpha$, and the boundary $\beta$ for margin loss are fixed at 0.1, and 1.2, respectively. In every case, the performance of the configuration SM is better than S, which shows that our framework is flexible to apply various losses.

#### 4.5.2 Backbone

Our framework can use different types of convolutional neural network backbone. We perform experiments on image retrieval datasets with various CNN backbone: BN-Inception [19], ShuffleNet-v2 [34], ResNet-50 [15], and SE-ResNet-50 [18]. In Table 7a and Table 7b each comparison case of the same color indicates the same CNN backbone and embedding dimension, which demonstrates that the CGD framework outperforms existing models. Additional experiments with ShuffleNet-v2 presents a reasonable performance even though it is a compact network. Another experiments with SE-ResNet-50 provide the best performance among all as the backbone is very powerful.

#### 4.5.3 Dataset: Comparison with State-of-the-Art

Finally, we compare our proposed framework with the state-of-the-art approaches on four image retrieval datasets in Ta-

| Config | Query | Reference |
|--------|-------|-----------|
| SM     | ![Tesla Model S Sedan 2012](image1) | ![Tesla Model S Sedan 2012](image2) |
| S      | ![Infiniti G Coupe IPL 2012](image3) | ![Infiniti G Coupe IPL 2012](image4) |
| M      | ![Jaguar XK XKR 2012](image5) | ![Jaguar XK XKR 2012](image6) |

Figure 4. Spatial similarity visualizations on CARS196. Heatmaps show the contribution of each region toward pairwise similarity computation. For each configuration SM, S, and M, we visualize top 1 retrieved image (a), (d), and (g), respectively, from the same query image. These images are denoted by SM, S, and M. They are used to visualize on different configurations (b, c, e, f, h, i), so that we can see the rank changes among the configurations. The green box indicates that the image is in the same class, while the red box indicates that the image is in a different class. “Cossim” denotes cosine similarity.
| Model       | Backbone     | Dim | CUB200 1 | CUB200 2 | CUB200 4 | CUB200 8 | CARS196 1 | CARS196 2 | CARS196 4 | CARS196 8 |
|-------------|--------------|-----|-----------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|
| Facility    | BN-Inception | 64  | 48.2      | 61.4      | 71.8      | 81.9      | 58.1      | 70.6      | 80.3      | 87.8      |
| Proxy-NCA   | BN-Inception | 64  | 49.2      | 61.9      | 67.9      | 72.4      | 73.2      | 82.4      | 86.4      | 88.7      |
| HTL         | BN-Inception | 512 | 57.1      | 68.8      | 78.7      | 86.5      | 81.4      | 88.0      | 92.7      | 95.7      |
| Margin      | ResNet-50    | 128 | 63.9      | 75.3      | 84.4      | 90.6      | 86.9      | 92.7      | 95.6      | 97.6      |
| ABE-8       | GoogleNet‡   | 512 | 70.6      | 79.8      | 86.9      | 92.2      | 93.0      | 95.9      | 97.5      | 98.5      |
| BFE*        | ResNet-50‡   | 1536| 74.1      | 83.6      | 93.6      | 94.3      | 96.8      | 98.3      | 98.9      |           |
| CGD (MG/S)  | BN-Inception | 64  | 61.8      | 73.2      | 82.5      | 93.2      | 95.7      | 97.4      |           |
| CGD (MG/S)  | ResNet-50    | 512 | 71.9      | 81.1      | 88.2      | 92.9      | 91.2      | 95.1      |           |
| CGD (MG/S)  | SE-ResNet-50‡| 1536| 84.2      | 93.9      | 97.4      | 99.2      | 98.0      | 99.1      |           |

(a) Recall@K (%) on CUB200-2011 (cropped) and CARS196 (cropped). CGD (MG/S) denotes that the configuration MG is used for CUB200-2011 and SG is used for CARS196 on the proposed CGD framework.

| Model       | Backbone     | Dim | SOP 1 | SOP 10 | SOP 100 | SOP 1000 | In-shop 1 | In-shop 10 | In-shop 100 | In-shop 1000 |
|-------------|--------------|-----|-------|--------|---------|----------|-----------|------------|-------------|-------------|
| Facility    | BN-Inception | 64  | 67.0  | 83.7   | 93.2    | -        | -         | -          | -           | -           |
| HTL         | BN-Inception | 512 | 74.8  | 88.3   | 94.8    | 98.4     | -         | -          | -           | -           |
| Margin      | ResNet-50    | 128 | -     | -      | 80.9    | 94.3     | 95.8      | 97.2       | 97.4        | 97.8        |
| ABE-8       | GoogleNet‡   | 512 | 76.3  | 88.4   | 94.8    | 98.2     | 96.7      | 97.9       | 98.2        | 98.5        |
| BFE*        | ResNet-50‡   | 1536| 83.0  | 93.3   | 97.3    | 99.2     | 96.3      | 97.6       | 98.5        | 99.1        |
| CGD (SG/GS) | BN-Inception | 64  | 75.6  | 89.0   | 95.5    | 98.6     | 96.6      | 97.4       | 97.9        | 98.2        |
| CGD (SG/-)  | BN-Inception | 512 | 80.5  | 92.1   | 96.7    | 98.9     | -         | -          | -           | -           |
| CGD (-/GS)  | BN-Inception | 128 | -     | -      | 88.5    | 97.1     | 98.0      | 98.5       | 98.8        | 98.9        |
| CGD (SG/GS) | ResNet-50    | 128 | 81.0  | 92.2   | 96.8    | 99.1     | 88.4      | 97.2       | 98.1        | 98.7        |
| CGD (SG/GS) | ResNet-50‡   | 1536| 83.9  | 93.8   | 97.5    | 99.2     | 90.9      | 98.0       | 98.7        | 99.0        |
| CGD (SG/GS) | ShuffleNet-v2| 1536| 78.7  | 90.9   | 96.1    | 98.8     | 86.1      | 96.9       | 97.8        | 98.4        |
| CGD (SG/GS) | SE-ResNet-50‡| 1536| 84.2  | 93.9   | 97.4    | 99.2     | 91.9      | 98.1       | 98.7        | 99.0        |

(b) Recall@K (%) on Stanford Online Products and In-shop Clothes. CGD (SG/GS) denotes that the configuration SG is used for Stanford Online Products and GS is used for In-shop Clothes on the proposed CGD framework.

Table 7. Performance comparisons with previous state-of-the-art approaches on image retrieval datasets. Values with same color (purple, blue, green, red) have the same backbone, and embedding dimension (Dim), while bold text indicates the best performance within the same color. † denotes 256 input size for inference phase, while the rest use 224 input size. ‡ refers to non-conventional usage.

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5. Conclusion

In this paper, we have introduced a simple but powerful framework called the CGD for image retrieval. The CGD framework exploits multiple global descriptors to get an ensemble-like effect when it can be trained in an end-to-end manner. Moreover, the proposed framework is flexible and expandable by the global descriptor, CNN backbone, loss and dataset. We analyze the effectiveness of combined descriptor quantitatively and qualitatively. Our extensive experiments show that exploiting multiple global descriptors lead to higher performance over the single global descriptor, since combined descriptor can manipulate different types of feature properties. Our framework performs the best on all the major image retrieval benchmarks considered.

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