Abstract—Logo retrieval is a challenging problem since the definition of similarity is more subjective than image retrieval, and the set of known similarities is very scarce. In this paper, to tackle this challenge, we propose a simple but effective segment-based augmentation strategy to introduce artificially similar logos for training deep networks for logo retrieval. In this novel augmentation strategy, we first find segments in a logo and apply transformations such as rotation, scaling, and color change, on the segments, unlike the conventional strategies that perform augmentation at the image level. Moreover, we evaluate suitability of using ranking-based losses (namely Smooth-AP) for learning similarity for logo retrieval. On the METU and the LLD datasets, we show that (i) our segment-based augmentation strategy improves retrieval performance compared to the baseline model or image-level augmentation strategies, and (ii) Smooth-AP indeed performs better than conventional losses for logo retrieval.

I. INTRODUCTION

Segment Augmentation and Differentiable Ranking for Logo Retrieval

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For a query logo, identifying the similar ones in a database of logos is a content-based image retrieval problem. With the rise in deep learning, there have been many studies that have used deep learning for logo retrieval problem [1]–[5]. Existing approaches generally rely on extracting features of logos and ranking them according to a suitable distance metric [1], [5], [6].

Logo retrieval is a challenging problem specifically for two main reasons: (i) Similarity between logos is highly subjective, and similarity can occur at different levels, e.g., texture, color, segments and their combination etc. (ii) The amount of known similar logos is limited. We hypothesize that this has limited the use of more modern deep learning solutions, e.g. metric learning, contrastive learning, differentiable ranking, as they require tremendous amount of positive pairs (similar logos) as well as negative pairs (dissimilar logos) for training deep networks.

In this paper, we address these challenges by (i) proposing a segment-level augmentation to produce artificially similar logos and (ii) using metric learning (Triplet Loss [7]) and differentiable ranking (Smooth Average Precision (AP) Loss [8]) as a proof of concept that, with our novel segment-augmentation method, such data hungry techniques can be trained better.

Main Contributions. Our contributions are as follows:

- We propose a segment-level augmentation for producing artificial similarities between logos. To the best of our knowledge, ours is the first to introduce segment-level augmentation into deep learning. Unlike image-level augmentation methods that transform the overall image, we identify segments in a logo and make transformations at the segment level. Our results suggest that this is more suitable than image-level augmentation for logo retrieval.
- To showcase the use of such a tool to generate artificially similar logos, we use data-hungry deep learning methods, namely, Triplet Loss [7] and Smooth-AP Loss [8], to show that our novel segment-augmentation method can indeed yield better retrieval performance. To the best of our knowledge, ours is the first to use such methods for logo retrieval.
II. RELATED WORK
A. Logo Retrieval
Earlier studies in trademark retrieval [6] used hand-crafted features and deep features extracted using pre-trained networks and revealed that deep features obtained considerably better results. Perez et al. [5] improved the results by combining two CNNs trained on two different datasets. Later, Tursun et al. [1] achieved impressive results by introducing different attention methods to reduce the effect of text regions, and in their most recent work [4], they introduced different modifications and achieved state-of-the-art results.

B. Data Augmentation
Data augmentation [9], [10] is an essential and well-known technique in deep learning to make networks more robust to variations in data. Conventional augmentation methods perform geometric transformations such as zooming, flipping or cropping the entire image. Alternatively, adding noise, random erasing or synthesizing training data [11] are key approaches to improve overall model performance. Random Erasing [12] is a recently introduced method that obtains significant improvement on various recognition tasks. Although augmentation methods that focus on cutting and mixing windows [13]–[15] rather than the whole image are not widely used, they have shown significant gains in performance.

In logo retrieval, studies generally use conventional augmentation methods. For example, Tursun et al. [16] applied a reinforcement learning approach to learn an ensemble of test-time data augmentations for trademark retrieval. An exception to such an approach is the study by Tursun et al. [1], who proposed a method to remove text regions from logos while evaluating similarity.

C. Differentiable Ranking
Image or logo retrieval are by definition ranking problems, though ranking is not differentiable. To address this limitation, many solutions have been proposed recently [8], [17], [18]. These approaches mainly optimize Average Precision (AP) with different approximations: For example, Cakir et al. [17] quantize distances between pairs of instances and use differentiable relaxations for these quantized distances. Rolinek et al. [18] consider non-differentiable ranking as a black box and use smoothing to estimate suitable gradients for training a network to rank. Finally, Brown et al. [8] propose smoothing AP itself to use differentiable operations to train a deep network to rank. These approximations have been mainly applied to standard retrieval benchmarks. In this paper, we show that differentiable ranking-based loss functions can lead to a performance improvement for logo retrieval as well.

D. Summary
Looking at the studies in the literature, we observe that (1) No study has performed segment-level augmentation either for logo retrieval or for general recognition or retrieval problems. The closest study for this research direction is the study by Tursun et al. [1], which just removed text regions in logos while evaluating similarity. (2) Promising deep learning approaches such as metric learning using e.g. Triplet Loss and differentiable ranking have not been employed for logo retrieval.

III. METHOD
In this section, after providing a definition for logo retrieval, we present our novel segment-based augmentation method and how we use it with deep metric learning and differentiable ranking approaches.

A. Problem Definition
Given an input query logo \( I_q \), logo retrieval aims to rank all logos in a retrieval set \( \Omega = I_i, i = \{0, 1, ..., N\} \), based on their similarity to the query \( I_q \). To be able to evaluate retrieval performance and to train a deep network that relies on known similarities, we require for each \( I_q \) to have a set of positive (similar) logos, \( \Omega^+(I_q) \), and a set of negative (dissimilar) logos, \( \Omega^-(I_q) \). Note that logo retrieval defined as such does not have the notion of classes of a classification setting.

B. Segment-level Augmentation for Logo Retrieval
We perform segment-level augmentation by following these steps: (i) Logo segmentation, (ii) segment selection, and (iii) segment transformation. See Figure 2 for some samples.

1) Logo Segmentation:
There are many sophisticated segmentation approaches available in the literature. Since logo images have relatively simpler regions compared to images, we observed that a simple and computationally-cheap approach using standard connected-component labeling is sufficient for extracting logo segments. See Figure 3 for some samples, and Supp. Mat. Section S4 for more samples and a discussion on the effect of segmentation quality.

2) Segment Selection:
The next step is to select \( n \) random segments to apply transformations on them. Segment selection is a process that should be evaluated carefully since the number of segments or the area for each segment is not the same.
for each logo. Simplicity of logo instances also affects the number of available components and many logo instances have less than five components. Therefore, the choice of \( n \) can have drastic effects especially when the number of components in a logo is small, especially for the ‘segment removal’ transformation. For this reason, ‘segment removal’ is not applied to a segment with the largest area, and \( n \) is chosen to be small values. We present an ablation study to evaluate the effect of \( n \) on model performance for the introduced augmentation strategies. For the same reason, the background component is removed from available segments for augmentation.

3) Segment Transformation: For each selected segment \( S \), the following are performed with probability \( p \):
- ‘(Segment) Color change’: Every pixel in \( S \) is assigned to a randomly selected color.
- ‘Segment removal’: Pixel values in \( S \) are set to the same value of the background component.
- ‘Segment rotation’: We first select a segment and create a mask for the segment. The mask image and the corresponding segment pixels are rotated with a random angle in \([-90, 90]\). Then, the rotated segment is combined with the other segments. See also Figure 4 for an example.

Fig. 4. The steps of rotating a segment.

See Figure 2 for some sample augmentations.

C. Adapting Ranking Losses for Logo Retrieval

1) Mini-batch Sampling for Training: For training the deep networks, we construct the batches as follows, similar to but different from [8] as we do not have classes: Each mini-batch \( B \) with size \(|B|\) is constructed with two sub-sets: the similar set \( B^+ \) and the dissimilar set \( B^- \). The similar logo set \( B^+ \) consists of logos that are known to be similar to each other (this information is available in the dataset [19]; logos with known similarities are provided as the “query set”), and \( B^- \) contains logos that are dissimilar to the logos in \( B^+ \) (to be specific, logos other than the query set of the dataset are randomly sampled for \( B^- \)). The size of \( B^+ \) is set to 4, and that of \( B^- \) is \(|B| - 4\). For training the network, every \( I \in B^+ \) has label as “1” and \( I \in B^- \) has label “0”.

2) Smooth-AP Adaptation: Smooth-AP [8] is a ranking-based differentiable loss function, approximating AP. The main aspect of this approximation is to replace discrete counting operation (the indicator function) in the non-differentiable AP with a Sigmoid function. Brown et al. [8] applied their study to standard retrieval benchmarks such as Stanford Online Products [20], VGGFace2 [21] and VehicleID [22]. However, the logo retrieval problem requires a dataset with a different structure as there is no notion of classes as in the Stanford Online Products [20], VGGFace2 [21] and VehicleID [22] datasets. Hence, Smooth-AP cannot be applied directly to our problem.

The first adaptation is about the structure of the mini-batch sampling. In Smooth-AP, Brown et al. explain their sampling as they have “formed each mini-batch by randomly sampling classes such that each represented class has \( P \) samples per class” [8]. Standard retrieval benchmarks have a notion of classes and are assumed to have sufficient instances per class to distribute among the mini-batches; however, there are not enough instances for known similarity “classes” in logo retrieval. This difference requires an adaption in both sampling and calculation of the loss. Smooth-AP Loss is calculated as follows [8]:

\[
\mathcal{L}_{AP} = \frac{1}{C} \sum_{k=1}^{C} (1 - \tilde{AP}_k),
\]

where \( C \) is the number of classes and \( \tilde{AP}_k \) is the smoothed AP calculated for each class in the mini-batch with their Sigmoid-based smoothing method.

Our mini-batch sampling (Section III-C1) causes a natural contradiction because our batches only contain two classes: “similar” and “dissimilar”; therewith the “dissimilar” class should not be included in the calculation of the loss. Dissimilar class instances have the same label (“0”), but that does not mean they have the same class; they are just not similar to the similar logo set \( B^+ \) in the mini-batch. Hence, the ranking among \( B^- \) does not matter in our case. This difference in the batch construction and the notion of classes lead to our second adaptation. In this adaptation, the only calculated AP approximation belongs to the known “similar” class (logos in \( B^+ \)). Therefore, the loss calculation becomes:

\[
\mathcal{L}_{AP} = 1 - \tilde{AP}_+,
\]

where \( \tilde{AP} \) is calculated (approximated) in the same way as in the original paper [8].

3) Triplet Loss Adaptation: Triplet Loss [7] is a well-known loss function used in many computer vision problems. Triplet Loss is differentiable, but, unlike Smooth-AP Loss [8], rather than optimizing ranking, it optimizes the distances between positive pairs and negative pairs of instances. In this paper, for each mini-batch, triplets consist of one “anchor” instance, one positive instance, and one negative instance. For the same reasons discussed in Smooth-AP Loss [8], only the instances of known similarity classes can be used as the anchor instance. Optimizing the distances between dissimilar logo instances is not sensible because, as discussed in the previous...
section, instances of the dissimilar logos do not have any known similarity between them. Thus, triplet loss calculation is limited to the triplets that contain known similar instances as the “anchor” instance.

IV. EXPERIMENTS AND RESULTS
We now evaluate the performance of the proposed segment-augmentation strategy and its use with Triplet Loss and Smooth-AP Loss.

A. Experimental and Implementation Details
1) Dataset: We use the METU Dataset [19], which is one of the largest publicly available logo retrieval datasets. The dataset is composed of more than 900K authentic logos belonging to actual companies worldwide. Moreover, it includes query sets, i.e. similar logos, of varying difficulties, allowing logo retrieval researchers to benchmark their methods against other methods. We have used 411K training images, 413K test images, and 418 query images.

2) Training and Implementation Details: For every experiment that will be discussed, we use ImageNet [11] pre-trained ResNet50 [23] as our backbone architecture which has a linear layer with 512 dimensions, rather than a final Softmax layer. We use the Adam optimizer with the hyper-parameters tuned as $10^{-7}$ for the learning rate and 256 for the batch size.

3) Evaluation Measures: Following the earlier studies [1], [19], we use Normalized Average Rank (NAR) and Recall@K for quantifying the performance of the methods. NAR is calculated as:

$$NAR = \frac{1}{N \times N_{rel}} \left( \sum_{i=1}^{N_{rel}} R_i - \frac{N_{rel}(N_{rel} + 1)}{2} \right), \quad (3)$$

where $N_{rel}$ is the number of similar images for a particular query image; $N$ is the size of the image set; and $R_i$ is the rank of the $i$th similar image. NAR lies in the range $[0, 1]$, where 0 denotes the perfect score, and 1 the worst. Recall@K (R@K) is recall for top-K similar logos.

**TABLE I**
THE EFFECT OF USING TRIPLET LOSS AND SMOOTH-AP LOSS FOR LOGO RETRIEVAL. NEITHER IMAGE-LEVEL NOR SEGMENT-LEVEL AUGMENTATION IS USED FOR ANY METHOD IN THIS TABLE.

| Method               | NAR ↓ | Recall@1 ↑ | Recall@8 ↑ |
|----------------------|-------|------------|------------|
| Baseline             | 0.102 | 0.310      | 0.536      |
| Triplet Loss (No augmentation) | 0.053 | 0.344      | 0.586      |
| Smooth-AP Loss (No augmentation) | 0.046 | 0.339      | 0.581      |

B. Experiment 1: Effect of Ranking Losses
Before analyzing the effect of segment-level augmentation, in this section, we first provide a stand-alone analysis to illustrate the effect of the ranking losses. We compare Triplet Loss and Smooth-AP Loss with a baseline that compares features extracted with the pre-trained Resnet50 backbone using Cosine Similarity. For this analysis, no image-level or segment-level augmentations are used, except for the Random Resized Crop to fit the images to the expected resolution of the network, i.e. $224 \times 224$.

The results in Table I suggest that both loss adaptations provide a significant performance improvement in both NAR and Recall measures and Smooth-AP adaptation achieves the best performance. Applying Cosine Similarity on off-the-shelf ResNet50 features shows adequate results in no-text logo instances, however, it performs worse on logos with text (see Supp. Mat. Section S5).

It is evident that the improvement in Recall is not as visible as NAR. This difference states that the adapted loss functions highly affect the overall rankings of the similar known instances. However, these effects are not completely reflected by the Recall because of the selected $K=8$ value.

**TABLE II**
THE EFFECT OF IMAGE-LEVEL (H. FLIP, V. FLIP) AND SEGMENT-LEVEL AUGMENTATION. ONLY THE BEST AUGMENTATION STRATEGIES ARE REPORTED. SEE SECTION IV-E FOR AN ABLATION ANALYSIS.

| Method               | NAR ↓ | Recall@1 ↑ | Recall@8 ↑ |
|----------------------|-------|------------|------------|
| Baseline             | 0.102 | 0.310      | 0.536      |
| Triplet Loss (No augmentation) | 0.053 | 0.344      | 0.586      |
| Smooth-AP Loss (No augmentation) | 0.046 | 0.339      | 0.581      |
| Smooth-AP Loss (S. Color) | 0.040 | 0.354      | 0.610      |

C. Experiment 2: Effect of Segment Augmentation
We now compare our segment-based augmentation methods with the conventional image-level augmentation techniques on the METU dataset [19]. In every experiment, we resize the images with Random Resized Crop to fit them to the expected resolution of the network, i.e. $224 \times 224$. For both segment-based and image-level augmentation, the same number of images are augmented and the probability $p = 0.5$ is used for selecting a certain transformation.

We have provided a comparison between the best resulting methods for both image-level and segment-level augmentation methods in Table II. We see that image-level augmentation can improve ranking performance. However, the results suggest that segment-level augmentation provides a significantly better gain both in terms of NAR and R@K measures. Detailed comparison between image-level and segment-level methods is provided in ablation study.
D. Experiment 3: Comparison with State of the Art

We compare our method and the state-of-the-art methods on the METU dataset [19]. It is important to note that a fair comparison between the methods is not possible because they differ in their backbones, training datasets, or training regime. For some methods, these details are not even reported. See the text for details.

| Method | NAR ↓ |
|--------|-------|
| Hand-crafted Features (Feng et al. [2]) | 0.083 |
| Hand-crafted Features (Tursun et al. [19]) | 0.062 |
| Off-the-shelf Deep Features (Tursun et al. [6]) | 0.086 |
| Transfer Learning (Perez et al. [5]) | 0.047 |
| Component-based attention (SPoC [24], [1]) | 0.120 |
| Component-based attention (CRow [25], [1]) | 0.140 |
| Component-based attention (R-MAC [26], [1]) | 0.072 |
| Component-based attention (MAC [26] [1]) | 0.120 |
| Component-based attention (Jimenez [27], [1]) | 0.093 |
| Component-based attention (CAM MAC [1]) | 0.064 |
| Component-based attention (ATR MAC [1]) | 0.056 |
| Component-based attention (ATR R-MAC [1]) | 0.063 |
| Component-based attention (ATR CAM MAC [1]) | 0.040 |
| MR-R-MAC w/UAR (Tursun et al. [4]) | 0.028 |
| Segment-Augm. (Color Change) w Smooth-AP (Ours) | 0.040 |

E. Experiment 4: Ablation Study

1) Choice of Hyper-Parameters: Our segment-level augmentation has two hyper-parameters: The number of segments, \( n \), selected for augmentation, and the probability, \( p \), of applying a selected augmentation. Table IV shows that the best performance is obtained with \( p \) as 0.5. A similar analysis for \( n \) (with values 1, 2, \( L/3 \) and \( L/2 \) where \( L \) is the number of segments in a logo) provided the best performance for \( n \) as \( L/3 \).

2) Effects of Individual Augmentation Methods: Tables V (Smooth-AP Loss) and VI (Triplet Loss) list the effects of both image-level and segment-level augmentation. The tables show that, among the segment-level augmentation methods, (Segment) ‘Color Change’ outperforms the others for both loss functions. With Triplet Loss adaptation, (Segment) ‘Removal’ and ‘Rotation’ provide slightly better NAR values than the baseline. Another point worth mentioning is that combining (Segment) ‘Rotation’ or ‘Removal’ degrades the NAR performance measure whereas the combination of (Segment) ‘Removal’ and ‘Color Change’ yields the best result at Recall@8.

3) Experiments with a Different Backbone: Section S1 in the Supp. Mat. provides an analysis using ConvNeXt [28], a recent, fast and strong backbone competing with transformer-based architectures. Our results without any hyper-parameter tuning are comparable to the baseline or better than the baseline with the R@8 measure.

4) Experiments with a Different Dataset: Section S2 in the Supp. Mat. reports results on the LLD dataset [29] that confirm our analysis on the METU dataset: We observe that segment-level augmentation provides significant gains for all measures.

F. Experiment 5: Visual Results

Section S6 in the Supp. Mat. provides sample retrieval results for several query logos for the baseline as well the adaptations of Triplet Loss and Smooth-AP Loss with our segment-level augmentation methods. The visual results also confirm that segment augmentation with our Smooth-AP adaptation performs best.

G. Supplementary Material

The supplementary material provides more experiments and discussion on the performance of the methods.

V. CONCLUSION

We introduced a novel data augmentation method based on image segments for training neural networks for logo retrieval. We performed segment-level augmentation by identifying segments in a logo and do transformations on selected segments. Experiments were conducted on the METU [19] and LLD [29] datasets with ResNet [23] and ConvNeXt [28] backbones and suggest significant improvements on two evaluation measures of ranking performance. Moreover, we use metric learning and differentiable ranking with the proposed segment-augmentation method to demonstrate that our method can lead to a further boost in ranking performance.
We note that our segment-level augmentation strategy generates similarities between logos that are rather simplistic: It is based on the assumption that two similar logos differ from each other in terms of certain segments having differences in color, orientation and presence. An important research direction is exploring more sophisticated augmentation strategies for introducing artificial similarities. However, our results suggest that even such a simplistic strategy can improve the retrieval performance significantly and therefore, our study can be considered as a first step towards developing better segment/part-level augmentation strategies.

### TABLE V
Normalized Average Rank (NAR) and Recall@K values for data augmentation experiments with Smooth-AP Loss.

| Image Level | Segment Level | NAR ↓ | R@1 ↑ | R@8 ↑ |
|-------------|---------------|-------|--------|--------|
| Resized Crop | Hor. Flip | Vert. Flip | Rotation | Color Jitter | S. Color Change | S. Rotation | S. Removal |
| Baseline | | | | | | | |
| ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | |
| Baseline | | | | | | | | |

### TABLE VI
Normalized Average Rank (NAR) and Recall@K values for data augmentation experiments with Triplet Loss.

| Image-Level | Segment-Level | NAR ↓ | R@1 ↑ | R@8 ↑ |
|-------------|---------------|-------|--------|--------|
| Resized Crop | Hor. Flip | Vert. Flip | Rotation | Color Jitter | S. Color Change | S. Rotation | S. Removal |
| Baseline | | | | | | | | |
| ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | |
| Baseline | | | | | | | | |

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