Small, Accurate, and Fast Vehicle Re-ID on the Edge: the SAFR Approach

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Abstract

We propose a Small, Accurate, and Fast Re-ID (SAFR) design for flexible vehicle re-id under a variety of compute environments such as cloud, mobile, edge, or embedded devices by only changing the re-id model backbone. Through best-fit design choices, feature extraction, training tricks, global attention, and local attention, we create a re-id model design that optimizes multi-dimensionally along model size, speed, & accuracy for deployment under various memory and compute constraints. We present several variations of our flexible SAFR model: SAFR-Large for cloud-type environments with large compute resources, SAFR-Small for mobile devices with some compute constraints, and SAFR-Micro for edge devices with severe memory & compute constraints. SAFR-Large delivers state-of-the-art results with mAP 81.34 on the VeRi-776 vehicle re-id dataset (15% better than related work). SAFR-Small trades a 5.2% drop in performance (mAP 77.14 on VeRi-776) for over 60% model compression and 150% speedup. SAFR-Micro, at only 6MB and 130MFLOPS, trades 6.8% drop in accuracy (mAP 75.80 on VeRi-776) for 95% compression and 33x speedup compared to SAFR-Large.

1 Introduction

Increasing numbers of traffic camera networks in the wild have coincided with growing attention towards the traffic management problem, where the goal is to improve vehicle detection and recognition for better traffic safety and emergency response. Several works in the past decade have focused on this problem [Ananthanarayanan et al., 2017; Wan et al., 2014]. An important consideration is small and fast models for edge and mobile deployment on cameras to reduce bandwidth costs and distribute processing from cloud to edge [Ananthanarayanan et al., 2017]. The primary challenge remains vehicle re-id where the same vehicle must be identified across multiple cameras [Chang et al., 2018].

Vehicle Re-ID. There have been several recent works towards accurate vehicle re-id [Liu et al., 2018; Wang et al., 2019; Zhou and Shao, 2019; Lou et al., 2019; Bai et al., 2018]. Vehicle re-id has two primary challenges: (i) inter-class similarity, where two different vehicles appear similar due to assembly-line manufacturing, and (ii) intra-class variability, where the same vehicle looks different due to different camera orientations. Re-id relies on representational learning, where a model learns to track vehicles by learning fine-grained attributes such as decals or emblem. End-to-end re-id models using automatic feature extraction for re-id are common; these approaches are designed for offline re-id since due to their complexity, size, and compute cost, they are suitable only for cloud environments with more compute resources.

Multi-dimensional Models. For vehicle re-id in video data from traffic monitoring cameras, there is an opportunity for flexible and scalable models running on the cloud, edge, or mobile devices, depending on varied performance (e.g., real-time) or resource requirements [Jiang et al., 2018]: edge re-id can be used for local tracking, mobile re-id can be used for validating edge re-id results, and cloud re-id can be used for sophisticated and complex vehicle re-id models. Theoretically, different models could be used in different system tiers, but it would be expensive to develop and maintain those disparate models, and their non-trivial interactions may degrade system performance. In this paper, we propose the Small, Accurate, and Fast Re-id (SAFR) approach, capable of generating classification models with significantly different sizes and speeds (from 0.18GFLOPS to 4GFLOPS), while preserving model accuracy (with less than 10% loss from the largest to smallest of models). The SAFR approach to vehicle re-id enables flexible and effective resource management from cloud to edge, without requiring major changes or integration of different models, simplifying deployability and improving monitoring efficiency [Chen et al., 2015].

The SAFR Approach. In this paper, we propose SAFR - a small, accurate, and fast re-id design that achieves state-of-the-art performance on vehicle re-id across a variety of datasets. Since vehicle re-id requires identifying fine-grained local attributes of vehicles across camera orientations, we develop an unsupervised parts-based local features extractor to detect vehicle parts across orientations. By learning fine-grained variances between vehicles, e.g. headlights, decals, emblem, SAFR’s local attention modules for local feature extraction addresses the intra-class variability problem. Simultaneously, SAFR uses a global attention module to ensure that
models do not overfit on fine-grained features, thereby retaining important contextual information. SAFR performs rich feature extraction on a single backbone compared to multi-branch networks with expensive fully connected layers covered in §3, allowing re-id models based on SAFR’s design to be both smaller and faster.

Contributions. First, we present SAFR, a small, accurate, and fast multi-dimensional model design approach for vehicle re-id that integrates global attention, local attention, ground-up backbone design, and training tricks to deliver state-of-the-art accuracy at significantly reduced model size and orders of magnitude faster speed. Second, we develop several variations on SAFR to illustrate the flexibility of the approach and the robustness of SAFR models across the spectrum of model sizes. Illustrating large-size models, SAFR-Large has best accuracy for traditional offline re-id with mAP 81.34 on VeRi-776; in the middle range, SAFR-Medium and SAFR-Small achieve accuracy within 2-5% of SAFR-Large, and are between 30-60% smaller; at the small-size end of spectrum (6MB, 5% of SAFR-Large), SAFR-Micro achieves accuracy within 6.8% of SAFR-Large, running at about 34 times faster (130 MFLOPS).

2 Re-Id for the Edge

Video analytics is resource heavy yet often requires real-time analysis, necessitating research into flexible models that can be deployed on cloud and edge [Jiang et al., 2018; Ananthanarayanan et al., 2017]. Such flexible models can be deployed in edge cameras with commodity or low-power processors and memory capacity; more importantly, they should be scalable classifiers that follow effective re-id design principles for accurate re-id (see §3.2). Such scalable classifiers for ML on the edge can be built with multi-dimensional optimization strategies to reduce model speed and size with small tradeoffs in accuracy. Such classifiers are compressed and accelerated for mobile and edge deployment. This is “the only approach that can meet the strict real-time requirements of large-scale video analytics, which must address latency, bandwidth, and provisioning challenges” [Ananthanarayanan et al., 2017]. Different from model compression techniques that perform compression and acceleration on large models after training, SAFR models are naturally small and fast re-id models that achieve high accuracy; SAFR-Micro achieves better than state-of-the-art results despite being over 100x smaller and faster than related work (Table 2).

Edge and Mobile Models. Since edge models are a recent development, consensus on what constitutes an edge model is difficult. Recent advances have focused on model compression and acceleration while maintaining accuracy. Since edge models trade accuracy for small model size, more powerful re-id models are still useful for richer feature extraction. So, we develop models for cloud (SAFR-Large), mobile (SAFR-Small), and edge (SAFR-Micro).

While there are several small and fast object detection models [Ma et al., 2018; Howard et al., 2017], progress towards such edge models in vehicle re-id has been limited; approaches in §3 perform offline vehicle re-id without edge device memory and compute constraints. We show in Figure 1 some recent approaches for vehicle re-id and their approximate parameter count and speed. The approaches essentially use several branches of feature extractors to get supervised features. These features are then combined with compute-expensive fully-connected layers to get re-id features. Such approaches hold limited benefit for edge or mobile devices that have low memory and compute requirements [Ananthanarayanan et al., 2017]. We also show SAFR models; since we use a single backbone instead of multi-branch networks, SAFR models are smaller. Our baseline, described in §4.3, uses only convolutional layers, improving speed.

We also show trends in accuracy for re-id models in Figure 2. Our baseline performs better than related approaches due to training tricks we describe in §4. Our SAFR-Large model achieves state-of-the-art results while being 3x smaller (Table 2) due to global and local attention. Since SAFR-Small and SAFR-Micro use smaller backbones, they have slightly lower accuracy compared to SAFR-Large; global and local attention allows both to still outperform larger and slower multi-branch re-id models.
3 Related Work

3.1 Efficient Models for the Edge

Effective model designs have been instrumental in improving the state-of-the-art in several areas [He et al., 2016; Redmon et al., 2016]. Model acceleration has also been applied to create compressed models, including quantization, pruning, and factorization [Cheng et al., 2017]. Moreover, the focus has widened to include efficient model design to allow high quality networks on mobile and edge devices, such as SqueezeNet, ResNet, or GoogLeNet.

3.2 Models for Vehicle Re-ID

We now describe several recent effective model designs for vehicle re-id. Most approaches use supervised multi-branch networks to improve feature extraction. The orientation-invariant approach in [Wang et al., 2016] uses 20 key points on vehicles to extract part-based features. Vehicles are clustered on orientation to improve feature generation. Twin Siamese networks are proposed in [Shen et al., 2017], along with contrastive loss, the approach also uses path proposals to improve vehicle track retrieval. Similar to [Wang et al., 2016], the region aware network in [Liu et al., 2018] uses 3 submodels, each focusing on a different region of a vehicle. A viewpoint network that focuses on different vehicle views is proposed in [Zhou and Shao, 2018]. The approach in [Kanaci et al., 2018] combines four subnetworks: color image, black-and-white image, orientation, and global features. The approach in [Zhu et al., 2019] proposes subnetworks for directional features in images.

There are also models that exploit re-id training to improve accuracy. Re-id training uses the triplet loss, where each iteration uses three images: the anchor, the positive, and the negative, where the anchor and positive are from the same identity, and the negative is a separate identity. The approach in [Bai et al., 2018] proposes a modification to the triplet loss to improve intra-class compactness. Similarly, [Luo et al., 2019] proposes simple training tricks to improve inter-class separability and intra-class compactness. Synthetic negatives are used in [Lou et al., 2019] to improve fine-grained features.

Suitability for Edge. Since these approaches use multiple large subnetworks (usually ResNet50/152), they are not suitable for edge devices. Edge devices require small model footprints (5M or less parameters) and may support up to 1-2 GFLOPS on models for real-time (20-50FPS) performance (see footnote in Figure 1) Models described above range from 5-20GFLOPS with 50-500M parameters (see Figure 1).

3.3 Vehicle Re-ID Datasets

VehicleID [Liu et al., 2016] provides front and rear-view images of 13K unique vehicle identities. With 250 vehicle models, the VehicleID dataset has high inter-class similarity. VeRi-776 [Liu et al., 2017] contains images of vehicles from multiple orientations; it has 576 identities for training and 200 identities for testing. Compared to VehicleID, VeRi-776 contains more intra-class variability. VeRi-Wild [Lou et al., 2018] is a larger version of VeRi-776 with 3000 identities in the test set. YRIC [Kanaci et al., 2019] contains additional adversarial conditions such as multi-scale, multi-resolution images with occlusion and blur; it has 2811 identities in the test set.

4 The SAFR Approach

We now describe our SAFR design for small, accurate, and fast re-id. Building models for cloud, mobile, and edge requires effective model design (§3). We build SAFR from ground up to be flexible for different compute settings.

The Re-ID Task. In the vehicle re-id problem, any image from the gallery set is ranked based on its distance to the provided query. Distance is calculated on features extracted from CNN backbones under a metric learning loss such as the triplet loss, with the following constraints: features of vehicles with the same identity should be close together regardless of orientation, and features of vehicles with different identities should be further apart even under inter-class similarity conditions (e.g. image of two different white sedans from the front view). These tasks can be classified as (i) feature extraction to identify the important global and local image features, and (ii) feature interpretation to project the global and local features to the output dimensionality for metric learning with triplet loss. Effective model design addresses both tasks in re-id to deliver accurate results. In our case, our goal is also to create efficient models for mobile and edge devices.

4.1 Feature Extraction

We improve feature extraction with global and local attention modules. Global attention allows richer feature extraction from the entire query image; the local attention identifies parts-based local features for fine-grained features.

Global Features. It is well known that the first conv layer in a CNN is critical for feature extraction since it is closer to the root of the CNN tree. We found when testing the re-id backbone that many kernels in the input conv layer jave sparse activations. Also, many first-layer kernels are activated by mostly irrelevant features such as shadow. Recent work in [Gale et al., 2019; Narang et al., 2019] suggests sparsity should be low initially and increase with network depth. So, we reduce sparsity of the re-id model with a global attention module.

Our global attention module increases the number of activated features. We use two conv layers with kernel size 3 and leaky ReLU activation. The small kernel sizes increase computation efficiency. Since they reduce expressiveness and filter field of view, we use two layers of $3 	imes 3$ kernels. The leaky ReLU activation allows negative activations, reducing loss of features. We then use sigmoid activation to generate the attention weights. Since pooling causes loss of features, we use elementwise multiplication instead of channel and spatial attention with pooling that is used in [Woo et al., 2019].

Figure 3: Impact of Global Attention Global attention increases feature activation density. After the global attention module, more features are available to the remaining network for fine-grained feature extraction.

\(^2\text{convolutional}\)
With a ResNet backbone, SAFR extract parts-based features for re-id on the same backbone. Local feature extraction. We propose a local attention modified local features with dedicated subnetworks to improve training, supervision is not necessary, reducing labeling load. Global attention increases activation block attention (DBAM) derived from CBAM [Woo et al., 2019] to a smaller spatial size as deeper bottlenecks. We apply dense attention to take advantage of larger spatial size compared to blocks. At the first ResNet bottleneck block, we use local attention from the first layer after global attention to ResNet bottleneck blocks. To obtain local features from global features, we use the output of the final conv layer passed through a global average pooling layer as re-id features. Since conv layers preserve image spatial attributes, they are more useful for feature interpretation [Basha et al., 2019]. Lack of dense layers allows our models to remain smaller and faster with respect to existing approaches. Using CNN features provides good results; our baseline, which adopts only these practices, remains competitive with current methods (see Figure 2).

**Local Features.** Part-based features have shown significant promise in improving re-id by helping re-id models focus on differences in relevant vehicle components such as emblem, headlights, or doors [He et al., ; Wang et al., ; Lou et al., 2019]. Many works on vehicle re-id use supervised local features with dedicated subnetworks to improve local feature extraction. We propose a local attention module for unsupervised local feature extraction; this allows us to extract parts-based features for re-id on the same backbone. With a ResNet backbone, SAFR passes the global features from the first layer after global attention to ResNet bottleneck blocks. At the first ResNet bottleneck block, we use local attention to take advantage of larger spatial size compared to smaller spatial size as deeper bottleneck layers. We apply dense block attention (DBAM) derived from CBAM [Woo et al., ] to obtain local features from global features. DBAM learns spatial attention for each kernel, instead of single spatial attention map for the entire layer. DBAM also uses no pooling layers because they cause loss of information between layers. Since relying on only local features can cause overfitting, we apply a channel mask to ensure both global ($F_G$) and local ($F_L$) features are passed to the remaining ResNet bottleneck layers:

$$F_{(L+G)} = M_C \odot F_L + (1 - M_C) \odot F_G$$  \hspace{1cm} (1)

where $M_C$ is a learned channel mask, $M_C \in \{0,1\}^K$ and $K$ is the number of channels for the layer where DBAM is applied. Since local attention learns part-based features through training, supervision is not necessary, reducing labeling load. We also do not need specialized part detection modules as in [Wang et al., ; He et al., ], reducing model size/cost.

**Impact of Attention.** Global attention increases activation density in the input conv layer. We demonstrate this in Figure 3, where we show feature activations with. We also examine the feature activation density with local attention, both global and local attention, and without any attention modules (our baseline model) in Figure 4. The baseline model without attention begins with low density activations in the input. This is useful for situations where classes are separable [Gale et al., 2019]. Since re-id contains high inter-class similarity, higher density of activations in the input is more useful to ensure fine-grained feature extraction for re-id. Adding global attention significantly increases input layer activation density, with increasing sparsity (low activation density) as depth increases. Though local attention also increases input activation density, a combination of global and local attention ensures high input activation density along with higher sparsity at increasing network depth better than just local or just global attention.

**4.2 Feature Interpretation**

Once we have extracted global and local features, we need to perform feature interpretation to project CNN features for triplet loss. Usually this is performed with dense layers for both representation learning and image classification tasks. We can improve our model speed by examining these approaches to build more effective designs that span cloud, mobile, and edge deployability as well as improve re-id.

Feature interpretation is usually performed with dense layers, but it can be performed by conv layers as well [Basha et al., 2019]. Approaches described in §3.2 use dense layers for interpretation, which increase the size of the models and computation time. In SAFR, we eliminate dense layers from the backbone; instead of using dense layer output as re-id features, we use the output of the final conv layer passed through a global average pooling layer as re-id features. Since conv layers preserve image spatial attributes, they are more useful for feature interpretation [Basha et al., 2019]. Lack of dense layers allows our models to remain smaller and faster with respect to existing approaches. Using CNN features provides good results; our baseline, which adopts only these practices, remains competitive with current methods (see Figure 2).

**Data and Training Augmentation.** Data augmentation has shown surprising promise in improving re-id performance. We use random erasing augmentation to improve local feature extraction. We also use the warm-up learning rate from [Luo et al., ] and linearly increase the learning rate at first.

**Multiple Losses.** Recent approaches in person re-id suggest using a combination of triplet and softmax loss. We extend this to use three losses: smoothed softmax loss, standard triplet loss, and center loss. The softmax loss helps in fine-grained feature extraction; we use smoothed softmax to reduce overfitting by decreasing classifier confidence, since the training and test set distributions are disjoint in vehicle re-id. The smoothed softmax reduces classifier confidence by smoothing the ground truth logits. We formulate the smoothed softmax loss with:

$$L_S = \sum q_i \log p_i, \text{ where } q_i = \mathbb{I}(y = i) - \epsilon \text{sgn}(\mathbb{I}(y = i) - 0.5)$$

to perform label smoothing; we let the smoothing parameter $\epsilon$ be $N^{-1}$.

The triplet loss $L_T$ ensures inter-class separability by enforcing the triplet constraint $d(a, p) + \alpha \leq d(a, n)$, where $a, p, n, d, \text{ and } \alpha$ are the anchor, positive, negative, l2 norm, and margin constraint. Finally, center loss improves intra-class compactness by storing each training identity’s centroid and minimizing distance to the centroid with:

$$L_C = 0.5 \sum_{i=1}^{m} \|x_i - c_{y_i}\|_2^2$$  \hspace{1cm} (2)

where $c$ is the centroid for image $x_i$ with identity $y_i$. During training, centroids are learned for training identities to maximize intra-class compactness with the l2 norm.
training identities are disjoint. We combine the three losses with: \( L_F = L_S + L_T + \lambda L_C \). We let \( \lambda = 0.0005 \) scale center loss to same magnitude as softmax/triplet losses.

**Normalization.** Batch normalization strategy is used in [Luo et al., ] to ensure the loss features are correctly projected between softmax and metric loss. Batch normalization is sensitive to the true batch size, which varies during re-id training because of the triplet loss. With hard example mining, the number of hard negatives changes in each batch as the model improves. We find that layer and group normalizations are better choices, because they perform normalization across the same channel without relying on batch size. Compared to group normalization, where contiguous groups of channels are given equal weight, layer normalization gives each channel equal contribution. So, we use layer normalization.

### 4.3 SAFR Model Design

**Baseline.** Our baseline is a ResNet-50 model. We remove all dense layers for feature extraction and use the last layer of convolutional features for re-id. We add a global average pooling layer to ensure consistent feature dimensions for varying image sizes. During training, we use softmax and triplet loss with hard mining, with layer norm\(^3\).

**SAFR-Large.** We use a ResNet-50 backbone with global and local attention modules to build SAFR-Large. Layer norm is used between triplet and softmax loss. We add center loss during training as well. The DBAM local attention module is used at all ResNet bottlenecks.

**SAFR-Medium.** SAFR-Medium is identical to SAFR-Large with two changes: the backbone is ResNet-34 & local attention is used at the first bottleneck.

**SAFR-Small.** We replace the ResNet-50 backbone with ResNet-18, with both attention modules. Local attention is applied to only the first ResNet bottleneck, since adding it to later layers decreased performance. We use center loss during training in addition to triplet and smoothed softmax loss.

**SAFR-Micro.** Since edge-applicable models require tiny memory footprint and low computation operations, we adopt the ShuffleNet-v2+ architecture\(^4\) derived from [Ma et al., 2018]. We make the following modifications to ShuffleNet-v2+: (i) we remove the last SE layer to ensure each channel has equal weight for feature interpretation, (ii) we remove the final dropout layer, since sparsity is enforced by global and local attention and dense layers are not used, and (iii) we add an additional Shuffle-Xception block after local attention module to improve local feature extraction. Local attention is applied to the first ShuffleNet block after input conv layer. We add center loss during training.

### 5 Results

#### 5.1 Experimental Design

**Training.** For each model, we use warmup learning: given base learning rate \( l_r \), we begin with \( 0.1 l_r \) at epoch 0 and increment linearly to \( l_r \) by epoch 10. During training, we use a batch size of 72 with 18 unique ids per batch and image size \( 350 \times 350 \)(SAFR-Micro uses 224 \( \times \) 224).

**Metrics.** For SAFR evaluation, we use the standard mAP and rank-1 metrics. Distances are measured pairwise between gallery and query image embeddings matrices. We adopt the evaluation methods described in [Liu et al., ]; Liu et al. uses explicit vehicle parts for re-id, it is more suited to VehicleID. Because [He et al., ] uses explicit vehicle parts for re-id, it is more suited to VehicleID. Because SAFR-Large uses unsupervised local feature extraction, it has more robust performance in multi-orientation settings of VeRi-776/Wild and VRIC.

![Figure 5: SAFR Components](image_url)

Each of our proposed modifications improves over the baseline (ResNet-50 only). Together, global and local attention with layer norm improve accuracy in re-id.

#### 5.2 SAFR Component Analysis

We examine impact of layer norm, batch norm, global attention, and local attention in Figure 5. Layer norm improves performance by ensuring losses are correctly back-propagated. Since triplet loss maximizes the inter-class L2 norm and softmax maximizes the inter-class cosine angle, we need to project the triplet loss around the unit hypersphere to ensure it can be added directly to the softmax loss [Luo et al., ]. Normalization performs this projection [Luo et al., ]; layer norm outperforms batch norm since it does not rely on batch size, which changes during training (see §4.2). Global and local attention also improve performance; with increased information density (Figure 4), SAFR models have improved feature extraction. Local attention improves feature richness by ensuring fine-grained, parts-based features are detected. Also, our local attention module automatically detects these part-based features; this increases robustness (mAP) by reducing overfitting to supervised parts-based features as in [Wang et al., ].

#### 5.3 SAFR Model Performance

**SAFR-Large.** We evaluate SAFR-Large on VeRi-776, VRIC, VeRi-Wild, and VehicleID, shown in Table 1. On VeRi-776, SAFR-Large achieves state-of-the-art results with mAP 81.34 and Rank-1 of 96.93. On VRIC, SAFR-Large can handle the multi-scale, multi-resolution vehicle images. On the more recent VeRi-Wild, SAFR-Large also achieves good results, with nearly 7% better Rank-1 accuracy. On VehicleID (high inter-class similarity), SAFR-Large is second to [He et al., ]; since [He et al., ] uses explicit vehicle parts for re-id, it is more suited to VehicleID. Because SAFR-Large uses unsupervised local feature extraction, it has more robust performance in multi-orientation settings of VeRi-776/Wild and VRIC.
Table 1: SAFR-Large performance comparison to current approaches across several datasets. We outperform most approaches; Part-Model achieves 4% higher Rank-1 on VehicleID but has lower Rank-1 and mAP in VeRi-776, indicating SAFR-Large is more robust.

| Approach                  | VeRi-776 | VRIC | VeRi-Wild | VehicleID |
|---------------------------|----------|------|-----------|-----------|
|                           | mAP      | Rank-1 | Rank-5 | mAP | Rank-1 | Rank-5 | mAP | Rank-1 | Rank-5 |
| MSVR [Kanacı et al.,]     | 49.3     | 88.6  | -     | 46.6 | 65.6  | -     | -   | -     | -     |
| OIFE [Wang et al.,]       | 51.4     | 68.3  | 89.7 | 24.6 | 51.0  | -     | -   | -     | -     |
| GSTRE [Bai et al., 2018]  | 59.5     | 96.2  | 99.0 | -   | -     | -     | 31.4 | 60.5  | 80.1  |
| MSL [Alfaşy et al., 2019] | 61.1     | 90.0  | 96.0 | -   | -     | 46.3  | 86.0 | 95.1  | -     |
| VAMI [Zhou and Shao, ]    | 61.3     | 85.9  | 91.8 | -   | -     | -     | -   | -     | -     |
| Parts-Model [He et al.,]  | 70.3     | 92.2  | 97.9 | -   | -     | -     | -   | -     | -     |
| **SAFR-Large**            | **81.3** | **96.9** | **99.1** | **79.1** | **94.7** | **77.9** | **92.1** | **97.4** | **75.4** |

Table 2: SAFR and related work on VeRi-776. $GF = GFLOPS$

| Approach                  | mAP    | R-1 | Params | GF  |
|---------------------------|--------|-----|--------|-----|
| OIFE [Wang et al.,]       | 51.42  | 68.30 | 350M   | 20  |
| P-LSTM [Shen et al.,]     | 58.27  | 83.49 | 190M   | 20  |
| GSTRE [Bai et al., 2018]  | 59.47  | 96.24 | 138M   | 15  |
| VAMI [Zhou and Shao, ]    | 61.32  | 85.92 | 300M   | 13  |
| RAM [Liu et al., 2018]    | 61.50  | 88.60 | 164M   | 11  |
| MTML [Kanacı et al.,]     | 64.60  | 92.00 | 110M   | 16  |
| Baseline                  | 74.14  | 88.14 | 26M    | 4   |
| SAFR-Large                | 81.34  | 96.93 | 30M    | 4.5 |
| SAFR-Medium               | 79.34  | 93.34 | 21M    | 3.8 |
| SAFR-Small                | 77.14  | 93.14 | 12M    | 1.8 |
| SAFR-Micro                | 75.80  | 92.61 | 1.5M   | 0.13|

**SAFR Variations.** We compare our four models plus baseline to current approaches on VeRi-776 in Table 2 and Figure 6. The baseline performs well because we remove dense layers to improve feature interpretation and use softmax plus triplet loss with layer norm during training. SAFR-Large further improves performance with global and local attention modules to increase information density and improve local feature extraction, respectively. Reducing the size of the backbone in SAFR-Medium trades 2.5% drop in mAP and 2.7% in Rank-1 accuracy to deliver 30% decreased model size and 18% speedup. SAFR-Small has similar accuracy tradeoffs for 60% compression and 150% speedup. For SAFR-Micro, where we use a modified ShuffleNet-v2+ backbone, we see a significant efficiency improvement. SAFR-Micro comes in at 6MB model size and 130M FLOPS, a 95% decrease in size and 33x increase in speed compared to SAFR-Large at a cost of 6.8% decrease in mAP and 4.5% decrease in Rank-1. These sizes are comparable to edge models in object detection and classification [Zhang et al., 2018; Ma et al., 2018]. More importantly, SAFR allows the same model design at each level of compute from cloud to edge, allowing easier maintainability.

5.4 Conclusion

In this paper we have presented SAFR - a small-and-fast re-id model that achieves state-of-the-art results on several vehicle re-id datasets under a variety of adversarial conditions. We present three variations of SAFR: (i) SAFR-Large is designed for traditional offline vehicle re-id and delivers the best results while still being 4x faster than related work; (ii) SAFR-Small is designed for mobile devices with lower memory+compute constraints and trades a 5.2% drop in accuracy compared for over 150% increase in speed; and (iii) SAFR-Micro is designed for edge devices and offers over 95% model compression (1.5M parameters) and 3362% speedup (130M FLOPS) with 6.8% decrease in accuracy compared to SAFR-Large.

We have described SAFR, a small, accurate, and fast vehicle re-id model design approach that achieves state-of-the-art accuracy results on several standard vehicle re-id datasets under a variety of conditions. As concrete illustration, four variants of SAFR models are evaluated: SAFR-Large achieves mAP 81.34 on VeRi-776, while still being 4x faster than state-of-the-art; SAFR-Medium and SAFR-Small are designed for mobile devices achieve accuracy within 2-5% of SAFR-Large, at 30-60% memory size and 1.5x faster; at the smallest size, SAFR-Micro offers over 95% model compression (1.5M parameters) and 33x speedup (130M FLOPS), achieving accuracy within 6.8% of SAFR-Large.
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