EfficientViT: Enhanced Linear Attention for High-Resolution Low-Computation Visual Recognition

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Abstract

Vision Transformer (ViT) has achieved remarkable performance in many vision tasks. However, ViT is inferior to convolutional neural networks (CNNs) when targeting high-resolution mobile vision applications. The key computational bottleneck of ViT is the softmax attention module which has quadratic computational complexity with the input resolution. It is essential to reduce the cost of ViT to deploy it on edge devices. Existing methods (e.g., Swin, PVT) restrict the softmax attention within local windows or reduce the resolution of key/value tensors to reduce the cost, which sacrifices ViT’s core advantages on global feature extractions. In this work, we present EfficientViT, an efficient ViT architecture for high-resolution low-computation visual recognition. Instead of restricting the softmax attention, we propose to replace softmax attention with linear attention while enhancing its local feature extraction ability with depthwise convolution. EfficientViT maintains global and local feature extraction capability while enjoying linear computational complexity. Extensive experiments on COCO object detection and Cityscapes semantic segmentation demonstrate the effectiveness of our method. On the COCO dataset, EfficientViT achieves 42.6 AP with 4.4G MACs, surpassing EfficientDet-D1 by 2.4 AP while having 27.9% fewer MACs. On Cityscapes, EfficientViT reaches 78.7 mIoU with 19.1G MACs, outperforming SegFormer by 2.5 mIoU while requiring less than 1/3 the computational cost. On Qualcomm Snapdragon 855 CPU, EfficientViT is \(3 \times\) faster than EfficientNet while achieving higher ImageNet accuracy.

1 Introduction

Vision Transformer (ViT) [1] has recently demonstrated great success in various computer vision tasks and received considerable attention [1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17]. Compared to convolutional neural networks (CNNs), ViT enjoys a stronger ability to capture global information and long-range interactions, showing superior accuracy to CNNs, especially when scaling up the training data size and model size [1, 6].

Despite the great success of ViT in the low-resolution & high-computation region, ViT is still inferior to CNNs for high-resolution & low-computation scenarios. For instance, Figure 1 (left) compares current CNN-based and ViT-based one-stage detectors on the COCO dataset [18]. There is more than an order of magnitude efficiency gap between ViT-based detectors (160G MACs) and CNN-based detectors (6G MACs). This hinders deploying ViT on real-time high-resolution vision applications on edge devices.

The root computational bottleneck of ViT is the softmax attention module, whose computational cost grows quadratically with the input resolution. For example, as shown in Figure 1 (middle), the computational cost of ViT-Small [19] quickly becomes significantly larger than ResNet-152's computational cost as the input resolution increases.

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We introduce the first ViT-based real-time object detector to close the gap. On COCO, EfficientViT achieves 3.8 higher AP than EfficientDet while having lower MACs. Compared with YoloX, EfficientViT saves 67.2% computational cost while providing higher AP. Middle: The computational cost of ViT grows quadratically as the input resolution increases, making it unable to handle high-resolution vision applications efficiently. Right: High resolution is important for image segmentation.

A straightforward approach to address this issue is to reduce the input resolution. However, high-resolution visual recognition is essential in many real-world computer vision applications such as autonomous driving, medical image processing, etc. Small objects and fine details in the images will vanish when reducing the input resolutions, causing dramatic performance loss in object detection [20] and semantic segmentation [21]. Figure 1 (right) shows the performance of MobileNetV2 [22] under different input resolutions and width multipliers on the Cityscapes dataset [23]. For instance, decreasing the input resolution from 1024x2048 to 512x1024 hurts the performance by 12% (8.5 mIoU) on Cityscapes. Only scaling up the model size without scaling up the resolution cannot close the performance gap.

Apart from reducing the resolution, another representative approach is to restrict the softmax attention by limiting its scope within fixed-size local windows [4,24] or reducing the dimension of key/value tensors [5,9]. However, it hurts ViT’s non-local attention capability and reduces the global receptive field (the most crucial merit of ViT), making ViT less distinguishable from large-kernel CNNs [25,26,27].

This paper introduces EfficientViT, an efficient ViT architecture to address these challenges. We find that it is not necessary to stick to softmax attention. Instead, we propose to substitute softmax attention with linear attention [28]. The key benefit of linear attention is that it maintains the full $N^2$ attention map like softmax attention. Meanwhile, it leverages the associative property of matrix multiplication to avoid explicitly computing the full attention map while preserving the same functionality (Section 3.1). As such, it maintains the global feature extraction capacity of softmax attention with only linear computational complexity. Another key merit of linear attention is that it avoids softmax, making it much more efficient on mobile (Figure 2 left).

However, directly applying linear attention has drawbacks. Previous studies [29,30,31,32,33,34] suggest that there is a significant performance gap between linear attention and softmax attention (Figure 5 middle). Delving into the detailed formulations of linear attention and softmax attention (Section 3.1), one key difference is that linear attention lacks the non-linear attention score normalization scheme. It makes linear attention unable to effectively concentrate its attention distribution on high attention scores produced by local patterns (Figure 2 middle, Figure 6), thereby weakening its local feature extraction capacity. We argue this is the main limitation of linear attention, making its performances inferior to softmax attention. We propose a simple yet effective solution to address this limitation while maintaining linear attention’s advantages in low complexity and low hardware latency. Specifically, we propose to enhance linear attention by inserting an extra depthwise convolution in each FFN layer (Figure 2 right). As such, we do not need to rely on linear attention for local feature extraction, avoiding its weakness in capturing local features and taking advantage of its strength in capturing global features.
We extensively evaluated the effectiveness of EfficientViT on various vision tasks under low computation budget, including COCO [18] object detection, Cityscapes [23] semantic segmentation and ImageNet [35] classification. We would like to highlight the efficient backbone design, so we didn’t include any add-on techniques that are orthogonal (e.g., knowledge distillation [36], neural architecture search [37]). Still, EfficientViT provides 2.4 higher AP than EfficientDet-D1 [38] on COCO val2017 while saving 27.9% computational cost. On Cityscapes, EfficientViT provides 2.5 higher mIoU than SegFormer [9] while reducing the computational cost by 69.6%. On ImageNet, EfficientViT achieves 79.7% top1 accuracy with 584M MACs, outperforming EfficientNet-B1 [39]’s accuracy while saving 16.6% computational cost.

Unlike existing mobile ViT models [40,41,42] that target reducing the parameter size or MACs, we target latency reduction on mobile devices. Our model does not involve complicated dependency [40] or hardware inefficient operations [41,42]. Thus, our computational cost reduction can easily translate to latency reduction on mobile devices. On Qualcomm Snapdragon 855 CPU, EfficientViT runs 3× faster than EfficientNet while providing higher ImageNet accuracy. Our code and pre-trained models will be released to the public upon publication. We hope our study can facilitate the development of ViT for mobile vision. We summarize our contributions below:

- We are the first to investigate high-resolution low-computation visual recognition using ViT architecture. We perform an in-depth analysis on the bottlenecks of ViT and show that linear attention is a strong alternative to softmax attention and is more hardware-friendly. It alerts us to rethink the necessity of softmax attention in ViT.
- We propose enhanced linear attention to address linear attention’s limitation of local feature extraction. Our enhanced linear attention shows strong capacity in visual feature extraction while maintaining low complexity and high hardware efficiency (Figure 5 left).
- We build EfficientViT based on our enhanced linear attention. On three representative vision tasks (COCO object detection, Cityscapes semantic segmentation, ImageNet classification), EfficientViT provides significant improvements over state-of-the-art methods (e.g., EfficientDet, SegFormer, EfficientNet) without add-on techniques (e.g., neural architecture search and knowledge distillation). To the best of our knowledge, EfficientViT is the first ViT-based model that outperforms state-of-the-art CNN-based models in mobile object detection.

2 Related Work

Vision Transformer. Inspired by the great success of Transformer in natural language processing (NLP), Vision Transformer recently gained lots of interest and has been applied to various computer vision tasks, including image classification [1, 3, 4, 43], object detection [2, 7, 44], semantic segmentation [5, 8, 9, 45], pose estimation [10], etc. Unlike CNNs, ViT relies on the softmax attention module that directly models the interaction between each pair of tokens in the feature map to aggregate spatial information. Therefore, ViT can better capture long-range interaction and global information than CNNs. However, this does not come for free. ViT has a higher computational complexity with the input resolution than CNNs (Figure 1 middle), making it computationally prohibitive to use ViT in high-resolution vision applications.

One representative approach for tackling this challenge is restricting softmax attention within fixed-size (e.g., 7x7) local windows [4,24], reducing the computational complexity from quadratic to linear. Another representative approach [5, 9] is to decrease the resolution of the key/value tensors, which reduces the cost by a fixed factor. Apart from these two representative approaches, [46] employs structured sparse softmax attention, and [47] approximates the softmax attention by factorizing it into two functions to reduce the cost. While these models can handle high-resolution images, they sacrifice ViT’s core advantages on global feature extractions. In addition, they still rely on softmax in the attention modules, making them unsuitable for mobile vision (Figure 2 left, Figure 5). Our extensive experiments on object detection (Table 1), semantic segmentation (Table 2), and image classification (Table 3) demonstrate that our models are more effective for high-resolution low-computation visual recognition than these models.

Efficient Vision Transformer. Improving the efficiency of ViT is essential for deploying ViT on resource-constrained edge platforms, such as mobile phones, IoT devices, etc. While ViT provides impressive performances in the high-computation region, it is usually inferior to previous efficient
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3 Method

In this section, we first review linear attention [28] in NLP and discuss its merits and drawbacks. Next, we introduce a simple yet effective solution to overcome the limitations of linear attention. Finally, we present the detailed architecture of EfficientViT.

3.1 Review of Linear Attention in NLP

Given input \( x \in \mathbb{R}^{N \times f} \), the generalized form of softmax attention can be written as:

\[
O_i = \sum_{j=1}^{N} \frac{\text{Sim}(Q_i, K_j)}{\sum_{j=1}^{N} \text{Sim}(Q_i, K_j)} V_j, \quad \text{where } Q = xW_Q, K = xW_K, V = xW_V.\]

(1)

\( W_Q/W_K/W_V \in \mathbb{R}^{f \times d} \) is the learnable projection matrix. \( O_i \) represents the \( i \)-th row of matrix \( O \). \( \text{Sim}(\cdot, \cdot) \) is the similarity function. When using \( \text{Sim}(Q, K) = \exp(\frac{QK^T}{\sqrt{d}}) \), Eq. (1) becomes the softmax attention [1].

While softmax attention has been highly successful in vision [1] and NLP [50, 51], it is not the only choice. For example, linear attention [28] proposes the following similarity function:

\[
\text{Sim}(Q, K) = \phi(Q)\phi(K)^T,
\]

(2)

where \( \phi(\cdot) \) is the kernel function. In this work, we choose ReLU as the kernel function as it is friendly for hardware. With \( \text{Sim}(Q, K) = \phi(Q)\phi(K)^T \), Eq. (1) can be rewritten as:

\[
O_i = \sum_{j=1}^{N} \frac{\phi(Q_i)\phi(K_j)^T}{\sum_{j=1}^{N} \phi(Q_i)\phi(K_j)^T} V_j = \frac{\sum_{j=1}^{N} (\phi(Q_i)\phi(K_j)^T)V_j}{\phi(Q_i)\sum_{j=1}^{N} \phi(K_j)^T}. \]

(3)
We introduce a simple and effective solution to address this limitation. Our idea is to enhance linear weakening its local feature extraction capacity. According to Eq. (4), we only need to compute $(\sum_{j=1}^{N} \phi(K_j)T V_j) \in \mathbb{R}^{d \times 1}$ once, then can reuse them for each query, thereby only requires $O(N)$ computational cost and $O(N)$ memory.

In addition to linear complexity, another key merit of linear attention is that it does not involve softmax in the attention modules. Softmax is highly inefficient on hardware. Avoiding it can significantly reduce the latency. For example, Figure 2 (left) shows the latency comparison between softmax attention and linear attention. With similar MACs, linear attention is significantly faster than softmax attention on mobile.

### 3.2 EfficientViT

#### 3.2.1 Enhancing Linear Attention with Depthwise Convolution

Although linear attention is superior to softmax attention in terms of computational complexity and hardware latency, linear attention has limitations. Previous studies [29, 30, 31, 32] suggest that there is usually a significant performance gap between linear attention and softmax attention in NLP. For vision tasks, previous work [33, 34] also suggests that linear attention is inferior to softmax attention. In our experiments, we also have similar observations (Figure 5 middle).

We challenge this assumption and argue that the inferior performances of linear attention are mainly due to the loss of local feature extraction capacity. Without the non-linear score normalization used in softmax attention, it is difficult for linear attention to concentrate its attention distribution like softmax attention [32, 52, 53, 54]. Figure 2 (middle) provides an example of this difference. Given the same raw attention score, using softmax is better at concentrating than without softmax. Therefore, linear attention cannot effectively focus on high attention scores produced by local patterns (Figure 6), weakening its local feature extraction capacity.

We introduce a simple and effective solution to address this limitation. Our idea is to enhance linear attention with convolution, which is highly effective in local feature extraction. In this way, we do not need to rely on linear attention for capturing local features, and it can focus on global feature extraction. Specifically, to keep linear attention’s efficiency and simplicity, we propose to insert a depthwise convolution [35] in each FFN layer (Figure 2 right), which incurs little computational overhead while greatly improving linear attention’s local feature extraction capacity (Table 1, 2, 3).

### 3.2.2 Building Block

Figure 2 (right) demonstrates the detailed architecture of the enhanced linear attention, which consists of a linear attention layer and an FFN layer. A depthwise convolution is inserted into the middle of FFN as discussed in Section 3.2.1.
We refer to this model as EfficientViT-Base in the following section. To highlight the efficient backbone itself, we keep the hyper-parameters simple using the same expand stem, stage 1, and stage 2) and using layer normalization \[60\] for later stages (stage 3 and stage 4). For normalization, we follow the design of \[6\], using batch normalization \[59\] for early stages (input convolution layers, following Fast-SCNN \[21\]. For classification, we feed P4 to the lightweight head, segmentation, we fuse P2 and P4. The fused feature is fed to a lightweight head comprising several and P4 denote the outputs of stages 2, 3, and 4, forming a pyramid of feature maps. We feed P2, P3, and P4 to the detection head following the common practice. We use YoloX \[58\] for detection. For segmentation, we fuse P2 and P4. The fused feature is fed to a lightweight head comprising several convolution layers, following Fast-SCNN \[21\]. For classification, we feed P4 to the lightweight head, same as MobileNetV3 \[48\].

3.2.3 Macro Architecture

Figure 3 illustrates the macro architecture of EfficientViT. It consists of the input stem and 4 stages. Recent studies \[6, 56, 57\] suggest that using convolution in early stages is better for ViT. We follow this design and start using the enhanced linear attention in stage 3.

To highlight the efficient backbone itself, we keep the hyper-parameters simple using the same expand ratio \(e\) for MBConv \[22\] and FFN \((e = 4)\), the same kernel size \(k\) for all depthwise convolution \((k = 5\) except the input stem\), and the same activation function (hard swish \[48\]) for all layers. P2, P3, and P4 denote the outputs of stages 2, 3, and 4, forming a pyramid of feature maps. We feed P2, P3, and P4 to the detection head following the common practice. We use YoloX \[58\] for detection. For segmentation, we fuse P2 and P4. The fused feature is fed to a lightweight head comprising several convolution layers, following Fast-SCNN \[21\]. For classification, we feed P4 to the lightweight head, same as MobileNetV3 \[48\].

4 Experiments

4.1 Setups

Datasets. We evaluated EfficientViT on three representative vision datasets, including COCO object detection \[18\], Cityscapes semantic segmentation \[23\], and ImageNet classification \[35\].

Model Architecture. We build our model to have around 400M MACs under a 224x224 input resolution. The macro architecture is illustrated in Figure 3. The detailed configuration is:

- \(C0=16, C1=24, C2=48, C3=96, C4=192;\) \(L1=2, L2=3, L3=5, L4=2\)

In linear attention, the key/value dimension is 16, while the number of heads is 12/24 in stage 3/4. For normalization, we follow the design of \[6\], using batch normalization \[59\] for early stages (input stem, stage 1, and stage 2) and using layer normalization \[60\] for later stages (stage 3 and stage 4). We refer to this model as EfficientViT-Base in the following section.
Table 1: EfficientViT outperforms state-of-the-art one-stage detectors on COCO (val2017). ‘r608’ denotes the input resolution is 608x608. † denotes the best result we find for CNN-based mobile object detection, which is achieved with a bunch of additional techniques (e.g., neural architecture search, ghost module, CSP, Cycle-EMA, etc.). Compared with this strong baseline (PP-PicoDet-L [61]), EfficientViT provides 1.7 higher AP with slightly lower MACs.

| Models                  | Params  | MACs  | AP  | AP50 | AP75 |
|-------------------------|---------|-------|-----|------|------|
| CNN-based               |         |       |     |      |      |
| MobileDet-DSP [62]      | 9.2M    | 3.2G  | 29.1| -    | -    |
| RetinaNet+ResNet50 [63] | 34M     | 97G   | 39.2| -    | -    |
| EfficientDet-D0 [38]    | 3.9M    | 2.5G  | 34.3| -    | -    |
| EfficientDet-D1 [38]    | 6.6M    | 6.1G  | 40.2| -    | -    |
| YOLOv4-Tiny [64]        | 6.1M    | 3.5G  | 21.7| 40.2 | -    |
| YOLOX-Tiny [58]         | 5.1M    | 3.2G  | 32.8| -    | -    |
| YOLOv5s                 | 7.2M    | 8.3G  | 37.2| 56.0 | -    |
| YOLOX-s [58]            | 9.0M    | 13.4G | 40.5| -    | -    |
| PP-PicoDet-L† [61]      | 3.3M    | 4.5G  | 40.9| 57.6 | -    |
| ViT-based               |         |       |     |      |      |
| RetinaNet+PVT-Tiny [5]  | 23.0M   | 221G  | 36.7| 56.9 | 38.9 |
| RetinaNet+ConT-M [65]   | 27.0M   | 217G  | 37.9| 58.1 | 40.2 |
| RetinaNet+MobileFormer [40] | 17.9M | 168G  | 38.0| 58.3 | 40.3 |
| ViT-based               |         |       |     |      |      |
| EfficientViT-Det-r416 (ours) | 10.6M  | 2.1G  | 38.1| 55.6 | 40.3 |
| EfficientViT-Det-r512 (ours) | 10.6M  | 3.2G  | 40.7| 58.6 | 43.6 |
| EfficientViT-Det-r608 (ours) | 10.6M  | 4.4G  | 42.6| 60.5 | 45.3 |

Training Details. We use AdamW [66] for training our models. For simplicity, we do not use add-on techniques that are orthogonal to backbone design, such as knowledge distillation [36], neural architecture search [37], etc.

For COCO object detection [18], we train models for 300 epochs with a batch size of 192. We use weights pretrained on ImageNet [35] for initializing the backbone while the detection head is initialized randomly. For data augmentation, we use the setting suggested in [67], including color jitter, random expansion, random crop, and random horizontal flip. We also adopt detection mixup [67] to prevent overfitting.

For Cityscapes semantic segmentation [23], we train models for 485 epochs with a batch size of 16. Same as detection, we use weights pretrained on ImageNet for initializing the backbone while randomly initializing the head. Data augmentation includes random scaling with a ratio of 0.5-2.0, random horizontal flip, and random crop.

For ImageNet classification, we train models for 450 epochs with a batch size of 2048. We use RandAugment [68], Mixup [69], Cutmix [70], StochasticDepth [71] to avoid overfitting. We also use label smoothing with a factor of 0.1.

4.2 COCO Object Detection

Table 1 and Figure 4 (left) report the comparison between EfficientViT and state-of-the-art one-stage object detectors. Compared to previous ViT-based object detectors, EfficientViT provides noticeable improvements in both performance and efficiency. Specifically, EfficientViT requires 38.2× fewer MACs than MobileFormer [40] and provides 4.6 higher AP.

Compared with state-of-the-art CNN-based object detectors (e.g., YoloX [58], EfficientDet [38], PP-PicoDet-L [61]), EfficientViT also provides significant improvements. Specifically, EfficientViT-Det-r608 provides 1.7 AP improvement over PP-PicoDet-L and requires slightly fewer MACs. EfficientViT-Det-r416 provides 3.8 AP improvement over EfficientDet-D0 while reducing the computational cost by 1.2×. In addition, EfficientDet and PP-PicoDet-L are optimized with extra techniques (e.g., neural architecture search, compound scaling, etc.) that are orthogonal to backbone design. In contrast, EfficientViT does not leverage these techniques, thus still has a large room for further improvement.
Table 2: Results on Cityscapes semantic segmentation. ‘r2048’ denotes the input resolution is 1024x2048. Unlike SegFormer [9] that runs inference on 1024x1024 sliding windows, we directly run inference on high-resolution images (1024x2048), thanks to the high efficiency. This brings significant performance improvements. With 19.1G MACs, EfficientViT provides 78.7 mIoU, surpassing SegFormer by 2.5 mIoU while requiring 3.3× fewer MACs.

| Models                | Backbone | Params | MACs  | mIoU  |
|-----------------------|----------|--------|-------|-------|
| CNN-based             |          |        |       |       |
| FCN [72]              | MobileNetV2 | 9.8M   | 158.6G| 61.5  |
| Fast-SCNN [21]        | -        | 1.1M   | 69.8G | 68.0  |
| PSPNet [73]           | MobileNetV2 | 13.7M  | 211.7G| 70.2  |
| DeepLabV3+ [74]       | MobileNetV2 | 15.4M  | 277.7G| 75.2  |
| ViT-based             |          |        |       |       |
| SegFormer [9]         | MiT-B0   | 3.8M   | 62.8G | 76.2  |
| NASViT [42]           | -        | -      | -     | 76.1  |
| ViT-based             |          |        |       |       |
| EfficientViT-Seg-r1408 (ours) | EfficientViT-Base     | 6.5M   | 9.1G  | 76.1  |
| EfficientViT-Seg-r1536 (ours) | EfficientViT-Base     | 6.5M   | 10.8G | 77.0  |
| EfficientViT-Seg-r2048 (ours) | EfficientViT-Base     | 6.5M   | 19.1G | 78.7  |

Figure 5: **Left:** Accuracy and latency trade-off on Qualcomm Snapdragon 855. EfficientViT is 3× faster than EfficientNet with higher accuracy. **Middle:** Comparison between softmax attention and linear attention on ImageNet. We observe a significant accuracy gap between softmax attention and linear attention under the same computation. However, the linear attention’s accuracy is significantly improved after enhancing the models with depthwise convolution. In contrast, the accuracy of softmax attention does not change a lot. Under the same MAC constraint, the enhanced linear attention provides 0.3% higher accuracy than the enhanced softmax attention. **Right:** The enhanced linear attention is more hardware-efficient and the latency grows slower with the resolution compared with the enhanced softmax attention.

### 4.3 Cityscapes Semantic Segmentation

Table 2 provides the comparison between EfficientViT and state-of-the-art segmentation models on Cityscapes. Thanks to the high efficiency, EfficientViT can directly run inference on high-resolution images (1024x2048) instead of using 1024x1024 sliding windows as done in SegFormer [9]. This brings significant performance improvements. Specifically, EfficientViT provides 2.5 higher mIoU and reduces the computational cost by 3.3× compared with SegFormer. We also scale down the input resolution of EfficientViT to get multiple models under different MACs constraints. The trade-off curve is illustrated in Figure 4 (middle). Compared with SegFormer, EfficientViT requires 6.9× fewer MACs to achieve a similar mIoU.

### 4.4 ImageNet Classification

Table 3 and Figure 4 (right) demonstrate the comparison between EfficientViT and state-of-the-art classification models on ImageNet. NASViT [42] and LeViT [56] are not included in Table 3 as they are trained with knowledge distillation [36] and a very long training schedule (e.g., 1000 epochs).

Thanks to the strong visual feature extraction capacity, EfficientViT provides highly competitive performances, though it is not specifically designed for image classification. We highlight that EfficientViT is fast and practical on mobile device (Figure 5 left). Compared with EfficientNet [39],
Table 3: Results on ImageNet classification. ‘r224’ denotes the input resolution is 224x224. ‘w1.2’ denotes the width multiplier [22] is 1.2. † denotes the result is from [40]. While EfficientViT is not specifically designed for image classification, it still provides highly competitive performances on ImageNet. With 584M MACs, EfficientViT achieves 79.7% ImageNet top1 accuracy, outperforming EfficientNet-B1 by 0.6% while saving the computational cost by 1.2×. It demonstrates the strong capacity of EfficientViT in visual feature learning.

| Models                               | Params | MACs  | Accuracy |
|--------------------------------------|--------|-------|----------|
|                                      |        |       | Top1 (%) | Top5 (%) |
| CNN-based                            |        |       |          |          |
| MobileNetV2 [22]                     | 3.4M   | 300M  | 72.0     | -        |
| ShuffleNetV2 1.5x [75]               | -      | 299M  | 72.6     | -        |
| FBNet-B [76]                         | 4.5M   | 295M  | 74.1     | -        |
| ProxylessNAS-Mobile [77]             | 4.1M   | 320M  | 74.6     | 92.2     |
| MnasNet-A1 [78]                      | 3.9M   | 312M  | 75.2     | 92.5     |
| MobileNetV3-Large 1.25x [48]        | 7.5M   | 356M  | 76.6     | -        |
| EfficientNet-B0 [39]                 | 5.3M   | 390M  | 77.1     | 93.3     |
| EfficientNetV2-B0 [79]               | 7.4M   | 700M  | 78.7     | -        |
| EfficientNet-B1 [39]                 | 7.8M   | 700M  | 79.1     | 94.4     |
| ViT-based                            |        |       |          |          |
| T2T-ViT-7 [80]                       | 4.3M   | 1.2G  | 71.7     | -        |
| QuadTree-B-b0 [34]                   | 3.5M   | 0.7G  | 72.0     | -        |
| ConViT-Tiny [81]                     | 6.0M   | 1.0G  | 73.1     | -        |
| PVT-Tiny [5]                         | 13.2M  | 1.9G  | 75.1     | -        |
| CetT-T [82]                          | 6.4M   | 1.2G  | 76.4     | 93.4     |
| ViL-Tiny-RPB [46]                    | 6.7M   | 1.3G  | 76.7     |          |
| Swin-1G [41]‡                        | 7.3M   | 1.0G  | 77.3     | -        |
| HVT-S-1 [83]                         | 22.1M  | 2.4G  | 78.0     | 93.8     |
| PVT-XS [84]                          | 10.6M  | 1.4G  | 78.1     | -        |
| CoaT Tiny [47]                       | 5.5M   | 4.4G  | 78.3     |          |
| HRFormer-T [10]                      | 8.0M   | 1.8G  | 78.5     |          |
| MobileViT-XS [41]                    | 2.3M   | 700M  | 74.8     | -        |
| MobileFormer w/o DY-ReLU [40]        | 10.1M  | 290M  | 76.8     | 93.2     |
| ViT-based                            |        |       |          |          |
| EfficientViT-Base-r192 (ours)        | 7.9M   | 304M  | 77.7     | 93.6     |
| EfficientViT-Base-r224 (ours)        | 7.9M   | 406M  | 78.6     | 94.2     |
| EfficientViT-Base-r224-w1.2 (ours)   | 10.9M  | 584M  | 79.7     | 94.8     |

EfficientViT is 3× faster with higher ImageNet accuracy. Compared to MobileNetV3, EfficientViT provides 1.1% higher accuracy improvement while maintaining a similar latency. The latency is measured on Qualcomm Snapdragon 855 CPU with Tensorflow-Lite, batch size 1.

Compared with MobileFormer [40], EfficientViT provides 0.9% higher ImageNet top1 accuracy with slightly higher MACs. Remarkably, EfficientViT does not involve a complicated two-branch design like MobileFormer, making EfficientViT more friendly for deployment on mobile. Compared with MobileNetV3-Large [48], EfficientViT provides 1.1% higher ImageNet top1 accuracy while requiring fewer MACs. Compared with EfficientNet-B1 [39], EfficientViT achieves 0.6% higher ImageNet top1 accuracy and reduces the computational cost by 1.2×.

4.5 Analysis and Discussion

Visualization. In Figure 6, we visualize the attention maps of softmax attention and linear attention on ImageNet. The input resolution is 224x224. Without the non-linear attention normalization scheme, linear attention cannot produce concentrated attention distributions like softmax attention. Linear attention is weaker than softmax attention in capturing local details.

Ablation Study. We study the effectiveness of our enhanced linear attention module in Figure 5 (middle). We train models for 180 epochs with random initialization on ImageNet. We build softmax attention models by replacing linear attention with softmax attention in EfficientViT-Base, while the other modules remain unchanged. We reduce the key/value dimension of softmax attention to 8, as suggested in [42]. We also adjust the number of heads to ensure softmax attention has similar MACs.
Figure 6: Visualizations of the attention maps that show the limitation of linear attention. With non-linear attention normalization, softmax attention can produce sharp attention distributions, as shown in the middle row. In contrast, linear attention’s distributions are relatively smooth, making linear attention weaker at capturing local details and causing significant accuracy loss. We addressed this limitation by enhancing linear attention with depthwise convolution and effectively improved the accuracy (Figure 5 middle).

5 Conclusion

We proposed EfficientViT for high-resolution low-computation visual recognition. Our study suggests that linear attention is a strong alternative to softmax attention for hardware-friendly visual recognition. However, directly applying linear attention cannot capture local information. Without sacrificing its merits, enhancing it with depthwise convolution can effectively address this limitation. Extensive experiments on three representative vision tasks (COCO, Cityscapes, ImageNet) demonstrate the effectiveness of EfficientViT, significantly outperforming state-of-the-art models.

Limitations, Future Work, and Social Impact. Though our proposed EfficientViT provides strong performances for high-resolution low-computation vision, it is not studied whether our study is still effective in the high-computation scenarios. Future work will scale up EfficientViT to study this question. Regarding negative societal impacts, our study involves GPU resources for training the models, which will result in CO2 emissions.

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