SEAFORMER: SQUEEZE-ENHANCED AXIAL TRANSFORMER FOR MOBILE SEMANTIC SEGMENTATION

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ABSTRACT

Since the introduction of Vision Transformers, the landscape of many computer vision tasks (*e.g.*, semantic segmentation), which has been overwhelmingly dominated by CNNs, recently has significantly revolutionized. However, the computational cost and memory requirement render these methods unsuitable on the mobile device, especially for the high-resolution per-pixel semantic segmentation task. In this paper, we introduce a new method *squeeze-enhanced Axial Transformer* (***SeaFormer***) for mobile semantic segmentation. Specifically, we design a generic attention block characterized by the formulation of squeeze Axial and detail enhancement. It can be further used to create a family of backbone architectures with superior cost-effectiveness. Coupled with a light segmentation head, we achieve the best trade-off between segmentation accuracy and latency on the ARM-based mobile devices on the ADE20K and Cityscapes datasets. Critically, we beat both the mobile-friendly rivals and Transformer-based counterparts with better performance and lower latency without bells and whistles. Beyond semantic segmentation, we further apply the proposed SeaFormer architecture to image classification problem, demonstrating the potentials of serving as a versatile mobile-friendly backbone. Our anonymous repository is at `https://anonymous.4open.science/r/SeaFormer_anonymous-5C8C`.

1 INTRODUCTION

As a fundamental problem in computer vision, semantic segmentation aims to assign a semantic class label to each pixel in an image. Conventional methods rely on stacking local convolution kernel Long et al. (2015) to perceive the long-range structure information of the image.

Since the introduction of Vision Transformers Dosovitskiy et al. (2021), the landscape of semantic segmentation has significantly revolutionized. Transformer-based approaches Zheng et al. (2021); Xie et al. (2021) have remarkably demonstrated the capability of global context modeling. However, the computational cost and memory requirement of Transformer render these methods unsuitable on mobile devices, especially for high-resolution imagery inputs.

Following the conventional wisdom of efficient operation, local/window-based attention Luong et al. (2015); Liu et al. (2021); Huang et al. (2021a); Yuan et al. (2021), efficient attention Shen et al. (2021); Xu et al. (2021), Axial attention Huang et al. (2019b); Ho et al. (2019); Wang et al. (2020a) and some other lightweight attention mechanisms Liu et al. (2018); Cao et al. (2019); Woo et al. (2018); Wang et al. (2020b); Choromanski et al. (2021); Chen et al. (2017); Mehta & Rastegari (2022a) are introduced.

However, these advances are still insufficient to satisfy the design requirements and constraints for mobile devices due to the high latency on the high-resolution inputs (see Figure 1). Recently there is a surge of interest in building a Transformer-based mobile semantic segmentation.

In order to reduce the computation cost at high resolution, TopFormer Zhang et al. (2022b) dedicates to applying the global self-attention at a 1/64 scale of the original input, which definitely harms the segmentation performance.

To solve the dilemma of high-resolution computation for pixel-wise segmentation task and low latency requirement on the mobile device in a performance harmless way, we propose a family

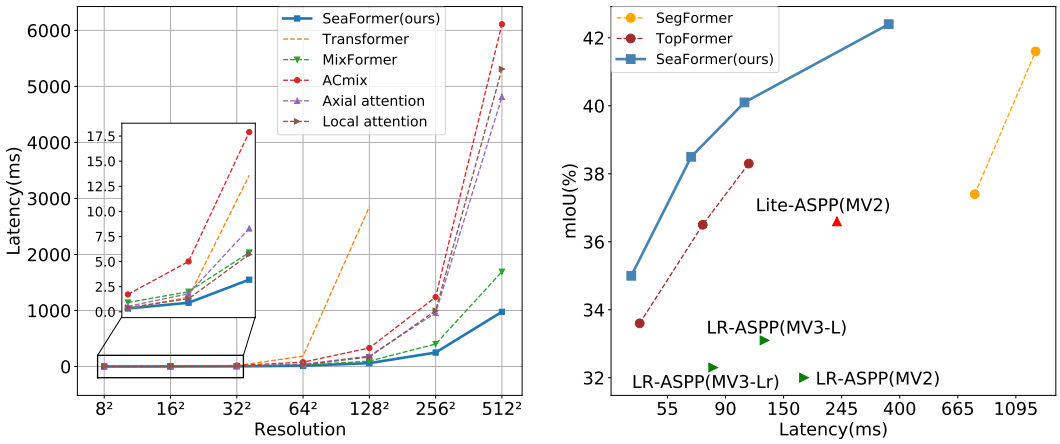

Figure 1: ***Left***: Latency comparison with Transformer Vaswani et al. (2017), MixFormer Chen et al. (2022a), ACmix Pan et al. (2022b), Axial attention Ho et al. (2019) and local attention Luong et al. (2015). It is measured with a single module of channel dimension 64 on a Qualcomm Snapdragon 865 processor. ***Right***: The mIoU versus latency on the ADE20K *val* set. MV2 means MobileNetV2 Sandler et al. (2018). MV3-L means MobileNetV3-Large Howard et al. (2019). MV3-Lr denotes MobileNetV3-Large-reduce Howard et al. (2019). The latency is measured on a single Qualcomm Snapdragon 865, and only an ARM CPU core is used for speed testing. No other means of acceleration, e.g., GPU or quantification, is used. For figure *Right*, the input size is 512×512. SeaFormer achieves superior trade-off between mIoU and latency.

of mobile-friendly Transformer-based semantic segmentation model, dubbed as *squeeze-enhanced Axial Transformer* (SeaFormer), which reduces the computational complexity of axial attention from $\mathcal{O}((H+W)HW)$ to $\mathcal{O}(HW)$, to achieve superior accuracy-efficiency trade-off on mobile devices and fill the vacancy of mobile-friendly efficient Transformer.

The core building block *squeeze-enhanced Axial attention* (SEA attention) seeks to squeeze (pool) the input feature maps along the horizontal/vertical axis into a compact column/row and computes self-attention. We concatenate query, keys and values to compensate the detail information sacrificed during squeeze and then feed it into a depth-wise convolution layer to enhance local details.

Coupled with a light segmentation head, our design (see Figure 2) with the proposed SeaFormer layer in the small-scale feature is capable of conducting high-resolution image semantic segmentation with low latency on the mobile device. As shown in Figure 1, the proposed SeaFormer outperforms other efficient neural networks on the ADE20K dataset with lower latency. In particular, SeaFormer-Base is superior to the lightweight CNN counterpart MobileNetV3 (41.0 *vs.*33.1 mIoU) with lower latency (106ms *vs.*126ms) on an ARM-based mobile device.

We make the following **contributions**: **(i)** We introduce a novel *squeeze-enhanced Axial Transformer* (SeaFormer) framework for mobile semantic segmentation; **(ii)** Critically, we design a generic attention block characterized by the formulation of squeeze Axial and detail enhancement; It can be used to create a family of backbone architectures with superior cost-effectiveness; **(iii)** We show top performance on the ADE20K and Cityscapes datasets, beating both the mobile-friendly rival and Transformer-based segmentation model with clear margins; **(iv)** Beyond semantic segmentation, we further apply the proposed SeaFormer architecture to the image classification problem, demonstrating the potential of serving as a versatile mobile-friendly backbone.

2 Related work

Combination of Transformers and convolution Convolution is relatively efficient but not suitable to capture long-range dependencies and vision Transformer has the powerful capability with a global receptive field but lacks efficiency due to the computation of self-attention. In order to make full use of both of their advantages, MobileViT Mehta & Rastegari (2022a), TopFormer Zhang et al. (2022b), LVT Yang et al. (2022), Mobile-Former Chen et al. (2022b), EdgeViTs Pan et al. (2022a), MobileViTv2 Mehta & Rastegari (2022b), EdgeFormer Zhang et al. (2022a) and EfficientFormer Li et al. (2022) are constructed as efficient ViTs by combining convolution with Transformers. Mobile-

ViT, Mobile-Former, TopFormer and EfficientFormer, they are restricted by Transformer blocks and have to trade off between efficiency and performance in model design. As for LVT, MobileViTv2 and EdgeViTs, they keep the model size small at the cost of relatively high computation, which also means high latency.

Axial attention and variants Axial attention Huang et al. (2019b); Ho et al. (2019); Wang et al. (2020a) is designed to reduce the computational complexity of original global self-attention Vaswani et al. (2017). It computes self-attention over a single axis at a time and stacks a horizontal and a vertical axial attention module to obtain the global receptive field. Strip pooling Hou et al. (2020) and Coordinate attention Hou et al. (2021) uses a band shape pooling window to pool along either the horizontal or the vertical dimension to gather long-range context. Kronecker Attention Networks Gao et al. (2020) uses the juxtaposition of horizontal and lateral average matrices to average the input matrices and performs attention operation after that. These methods and other similar implementations provide performance gains partly at considerably low computational cost compared with Axial attention. However, they ignore the lack of local details brought by the pooling/average operation.

Mobile semantic segmentation The mainstream of efficient segmentation methods are based on lightweight CNNs. DFANet Li et al. (2019) adopts a lightweight backbone to reduce computation cost and adds a feature aggregation module to refine high-level and low-level features. ICNet Zhao et al. (2018) designs an image cascade network to speed up the algorithm, while BiSeNet Yu et al. (2018; 2021) proposes two-stream paths for low-level details and high-level context information, separately. Fast-SCNN Poudel et al. (2019) shares the computational cost of the multi-branch network to yield a run-time fast segmentation CNN. TopFormer Zhang et al. (2022b) presents a new architecture with a combination of CNNs and ViT and achieves a good trade-off between accuracy and computational cost for mobile semantic segmentation. However, it is still restricted by the heavy computation load of global self-attention.

3 METHOD

3.1 OVERALL ARCHITECTURE

Inspired by the two-branch architectures Yu et al. (2021); Poudel et al. (2019); Hong et al. (2021); Huang et al. (2021b); Chen et al. (2022b), we design a **s**queeze-**e**nhanced **A**xial Trans**former** (**SeaFormer**) framework. As is shown in Figure 2, SeaFormer consists of these parts: *shared STEM*, *context branch*, *spatial branch*, *fusion block* and *light segmentation head*. For a fair comparison, we follow TopFormer Zhang et al. (2022b) to design the STEM. It consists of one regular convolution with stride of 2 followed by four MobileNet blocks where stride of the first and third block is 2. The context branch and the spatial branch share the produced feature map, which allows us to build a fast semantic segmentation model.

Context branch The context branch is designed to capture context-rich information from the feature map $\mathbf{x}_s$. As illustrated in the red branch of Figure 2, the context branch is divided into three stages. To obtain larger receptive field, we stack SeaFormer layers after applying a MobileNet block to down-sampling and expanding feature dimension. Compared with the standard convolution as the down-sampling module, MobileNet block increases the representation capacity of the model while maintaining a lower amount of computation and latency. For variants except SeaFormer-Large, SeaFormer layers are applied in the last two stages for superior trade-off between accuracy and efficiency. For SeaFormer-Large, we insert SeaFormer layers in each stage of context branch. To achieve a good trade-off between segmentation accuracy and inference speed, we design a squeeze-enhanced Axial attention block (SEA attention) illustrated in the next subsection.

Spatial branch The spatial branch is designed to obtain spatial information in high resolution. Identical to the context branch, the spatial branch reuses feature maps $\mathbf{x}_s$. However, the feature from the early convolution layers contains rich spatial details but lacks high-level semantic information. Consequently, we design a fusion block to fuse the features in the context branch into the spatial branch, bringing high-level semantic information into the low-level spatial information.

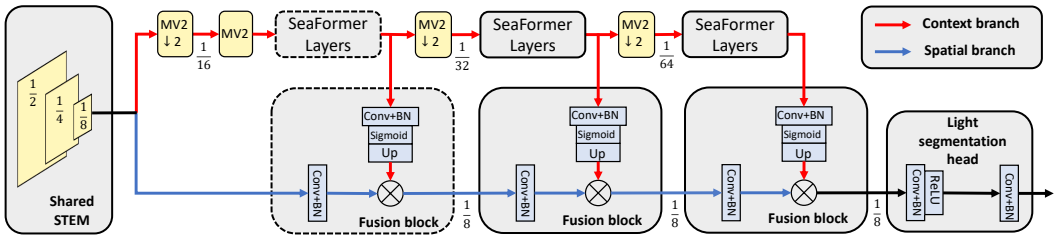

Figure 2: The overall architecture of Seaformer. It contains shared STEM, context branch (**red**), spatial brach (**blue**), fusion block and light segmentation head. `MV2` block means MobileNetV2 block and `MV2` $\downarrow 2$ means MobileNetV2 block with downsampling. SeaFormer layers and fusion blocks with dash box only exist in SeaFormer-L. The symbol $\bigotimes$ indicates an element-wise multiplication.

Fusion block As depicted in Figure 2, high resolution feature maps in the spatial branch are followed by a 1×1 convolution and a batch normalization layer to produce a feature to fuse. Low resolution feature maps in the context branch are fed into a 1×1 convolution layer, a batch normalization layer, a sigmoid layer and up-sampled to high resolution to produce semantics weights by bilinear interpolation. Then, the semantics weights from context branch are element-wisely multiplied to the high resolution feature from spatial branch. The fusion block enables low-level spatial features to obtain high-level semantic information.

Light segmentation head The feature after the last fusion block is fed into the proposed segmentation head directly, as demonstrated in Figure 2. For fast inference purpose, our light segmentation head consists of two convolution layers, which are followed by a batch normalization layer separately and the feature from the first batch normalization layer is fed into an activation layer.

3.2 Squeeze-enhanced Axial attention

The global attention can be expressed as

$$\mathbf{y}_o = \sum_{p \in \mathcal{G}(o)} \text{softmax}_p \left(\mathbf{q}_o^\top \mathbf{k}_p \right) \mathbf{v}_p \tag{1}$$

where $\mathbf{x} \in \mathbb{R}^{H \times W \times C}$. $\mathbf{q}, \mathbf{k}, \mathbf{v}$ are linear projection of $\mathbf{x}$, *i.e.*$\mathbf{q} = \mathbf{W}_q \mathbf{x}, \mathbf{k} = \mathbf{W}_k \mathbf{x}, \mathbf{v} = \mathbf{W}_v \mathbf{x}$, where $\mathbf{W}_q, \mathbf{W}_k \in \mathbb{R}^{C_{qk} \times C}, \mathbf{W}_v \in \mathbb{R}^{C_v \times C}$ are learnable weights. $\mathcal{G}(o)$ means all positions on the feature map of location $o = (i, j)$. When traditional attention module is applied on a feature map of $H \times W \times C$, the time complexity can be $\mathcal{O}(H^2 W^2 (C_{qk} + C_v))$, leading to low efficiency and high latency.

$$\mathbf{y}_o = \sum_{p \in \mathcal{N}_{m \times m}(o)} \text{softmax}_p \left(\mathbf{q}_o^\top \mathbf{k}_p \right) \mathbf{v}_p \tag{2}$$

$$\mathbf{y}_o = \sum_{p \in \mathcal{N}_{1 \times W}(o)} \text{softmax}_p \left(\mathbf{q}_o^\top \mathbf{k}_p \right) \mathbf{v}_p + \sum_{p \in \mathcal{N}_{H \times 1}(o)} \text{softmax}_p \left(\mathbf{q}_o^\top \mathbf{k}_p \right) \mathbf{v}_p \tag{3}$$

To improve the efficiency, there are some works Liu et al. (2021); Huang et al. (2019b); Ho et al. (2019) computing self-attention within the local region. We show two most representative efficient Transformer in Equation 2, 3. Equation 2 is represented by window-based attention Luong et al. (2015) successfully reducing the time complexity to $\mathcal{O}(m^2 HW(C_{qk} + C_v)) = \mathcal{O}(HW)$, where $\mathcal{N}_{m \times m}(o)$ means the neighbour $m \times m$ positions of o, but loosing global receptiveness. The Equation 3 is represented by Axial attention Ho et al. (2019), which only reduces the time complexity to $\mathcal{O}((H + W)HW(C_{qk} + C_v)) = \mathcal{O}((HW)^{1.5})$, where $\mathcal{N}_{H \times 1}(o)$ means all the positions of the column of o; $\mathcal{N}_{1 \times W}(o)$ means all the positions of the row of o.

According to their drawbacks, we propose the mobile-friendly squeeze-enhanced Axial attention, with a succinct squeeze Axial attention for global semantics extraction and an efficient convolution-based detail enhancement kernel for local details supplement.

$$\mathbf{q}_{(h)} = \frac{1}{W} \left(\mathbf{q}^{\rightarrow (C_{qk}, H, W)} \mathbb{1}_W \right)^{\rightarrow (H, C_{qk})}, \quad \mathbf{q}_{(v)} = \frac{1}{H} \left(\mathbf{q}^{\rightarrow (C_{qk}, W, H)} \mathbb{1}_H \right)^{\rightarrow (W, C_{qk})} \tag{4}$$

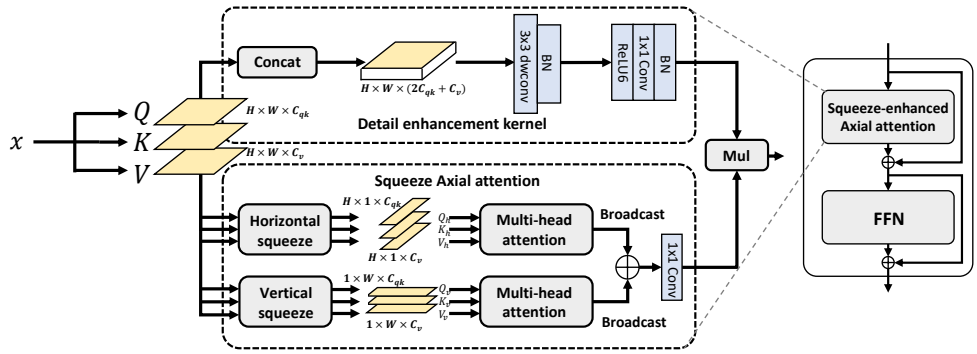

Figure 3: ***Right***: the schematic illustration of the proposed squeeze-enhanced Axial Transformer layer including a squeeze-enhanced Axial attention and a Feed-Forward Network (FFN). ***Left*** is the squeeze-enhanced Axial Transformer layer, including detail enhancement kernel and squeeze Axial attention. The symbol $\bigoplus$ indicates an element-wise addition operation. Mul means multiplication.

Squeeze Axial attention To achieve a more efficient computation and aggregate global information at the same time, we resort to a more radical strategy. In the same way, $\mathbf{q}, \mathbf{k}, \mathbf{v}$ are first get from $\mathbf{x}$ with $\mathbf{W}_q^{(s)}, \mathbf{W}_k^{(s)} \in \mathbb{R}^{C_{qk} \times C}, \mathbf{W}_v^{(s)} \in \mathbb{R}^{C_v \times C}$. According to Equation 4, we first implement *horizontal squeeze* by taking average of query feature map on the horizontal direction. In the same way, the right shows the *vertical squeeze* on the vertical direction. $\mathbf{z}^{\rightarrow(\cdot)}$ means permuting the dimension of tensor $\mathbf{z}$ as given, and $\mathbb{1}_m \in \mathbb{R}^m$ is a vector with all the elements equal to 1. The squeeze operation on $\mathbf{q}$ also repeats on $\mathbf{k}$ and $\mathbf{v}$, so we finally get $\mathbf{q}_{(h)}, \mathbf{k}_{(h)}, \mathbf{v}_{(h)} \in \mathbb{R}^{H \times C_{qk}}$, $\mathbf{q}_{(v)}, \mathbf{k}_{(v)}, \mathbf{v}_{(v)} \in \mathbb{R}^{W \times C_{qk}}$. The squeeze operation reserves the global information to a single axis, thus greatly alleviating the following global semantic extraction showing by Equation 5.

$$\mathbf{y}_{(i,j)} = \sum_{p=1}^{H} \text{softmax}_p \left(\mathbf{q}_{(h)i}^{\top} \mathbf{k}_{(h)p} \right) \mathbf{v}_{(h)p} + \sum_{p=1}^{W} \text{softmax}_p \left(\mathbf{q}_{(v)j}^{\top} \mathbf{k}_{(v)p} \right) \mathbf{v}_{(v)p} \tag{5}$$

Each position of feature map propagates information only on two squeezed axial features. Although it shows no distinct computation reduction comparing to Equation 3, repeat of Equation 5 can be simply implemented by the most efficient `broadcast` operation. The detail is shown in Figure 3. Time complexity for squeezing $\mathbf{q}, \mathbf{k}, \mathbf{v}$ is $\mathcal{O}((H+W)(2C_{qk}+C_v))$ and the attention operation takes $\mathcal{O}((H^2+W^2)(C_{qk}+C_v))$ time. Thus, our squeeze Axial attention successfully reduces time complexity to $\mathcal{O}(HW)$.

Squeeze Axial position embedding Equation 4 are, however, not positional-aware, including no positional information of feature map. Hence, we propose squeeze Axial position embedding to squeeze Axial attention. For squeeze Axial attention, we render both $\mathbf{q}_{(h)}$ and $\mathbf{k}_{(h)}$ to be aware of their position in squeezed axial feature by introducing positional embedding $\mathbf{r}_{(h)}^q, \mathbf{r}_{(h)}^k \in \mathbb{R}^{H \times C_{qk}}$, which are linearly interpolated from learnable parameters $\mathbf{B}_{(h)}^q, \mathbf{B}_{(h)}^k \in \mathbb{R}^{L \times C_{qk}}$. L is a constant. In the same way, $\mathbf{r}_{(v)}^q, \mathbf{r}_{(v)}^k \in \mathbb{R}^{W \times C_{qk}}$ are applied to $\mathbf{q}_{(v)}, \mathbf{k}_{(v)}$. Thus, the positional-aware squeeze Axial attention can be expressed as Equation 6.

$$\begin{aligned} \mathbf{y}_{(i,j)} = & \sum_{p=1}^{H} \text{softmax}_p \left((\mathbf{q}_{(h)i} + \mathbf{r}_{(h)i}^q)^{\top} (\mathbf{k}_{(h)p} + \mathbf{r}_{(h)p}^k) \right) \mathbf{v}_{(h)p} \\ & + \sum_{p=1}^{W} \text{softmax}_p \left((\mathbf{q}_{(v)j} + \mathbf{r}_{(v)i}^q)^{\top} (\mathbf{k}_{(v)p} + \mathbf{r}_{(v)p}^k) \right) \mathbf{v}_{(v)p} \end{aligned} \tag{6}$$

Detail enhancement kernel The squeeze operation, though extracting global semantic information efficiently, sacrifices the local details. Hence an auxiliary convolution-based kernel is applied to enhance the spatial details. As is shown in the upper path of Figure 3, $\mathbf{q}, \mathbf{k}, \mathbf{v}$ are first get from $\mathbf{x}$ with another $\mathbf{W}_q^{(e)}, \mathbf{W}_k^{(e)} \in \mathbb{R}^{C_{qk} \times C}, \mathbf{W}_v^{(e)} \in \mathbb{R}^{C_v \times C}$ and are concatenated on the channel dimension and then passed to a block made up of 3×3 depth-wise convolution and batch normalization.

Backbone	Decoder	Params	FLOPs	mIoU	Latency
MobileNetV2	LR-ASPP	2.2M	2.8G	32.0	177ms
MobileNetV3-Large-reduce	LR-ASPP	1.6M	1.3G	32.3	81ms
MobileNetV3-Large	LR-ASPP	3.2M	2.0G	33.1	126ms
HRNet-W18-Small	HRNet-W18-Small	4.0M	10.2G	33.4	639ms
TopFormer-T	Simple Head	1.4M	0.6G	33.6	43ms
TopFormer-T*	Simple Head	1.4M	0.6G	34.6	43ms
SeaFormer-T	Light Head	1.7M	0.6G	**35.0**	**40ms**
SeaFormer-T*	Light Head	1.7M	0.6G	**35.8$\pm$0.35**	**40ms**
ConvMLP-S	Semantic FPN	12.8M	33.8G	35.8	777ms
EfficientNet	DeepLabV3+	17.1M	26.9G	36.2	970ms
MobileNetV2	Lite-ASPP	2.9M	4.4G	36.6	235ms
TopFormer-S	Simple Head	3.1M	1.2G	36.5	74ms
TopFormer-S*	Simple Head	3.1M	1.2G	37.0	74ms
SeaFormer-S	Light Head	4.0M	1.1G	**38.1**	**67ms**
SeaFormer-S*	Light Head	4.0M	1.1G	**39.4$\pm$0.25**	**67ms**
MiT-B0	SegFormer	3.8M	8.4G	37.4	770ms
ResNet18	Lite-ASPP	12.5M	19.2G	37.5	648ms
ShuffleNetV2-1.5x	DeepLabV3+	16.9M	15.3G	37.6	960ms
MobileNetV2	DeepLabV3+	15.4M	25.8G	38.1	1035ms
TopFormer-B	Simple Head	5.1M	1.8G	38.3	110ms
TopFormer-B*	Simple Head	5.1M	1.8G	39.2	110ms
SeaFormer-B	Light Head	8.6M	1.8G	**40.2**	**106ms**
SeaFormer-B*	Light Head	8.6M	1.8G	**41.0$\pm$0.45**	**106ms**
MiT-B1	SegFormer	13.7M	15.9G	41.6	1300ms
SeaFormer-L	Light Head	14.0M	6.5G	**42.7**	**367ms**
SeaFormer-L*	Light Head	14.0M	6.5G	**43.7$\pm$0.36**	**367ms**

Table 1: Results of semantic segmentation on ADE20K *val* set, * indicates training batch size is 32. The latency is measured on a single Qualcomm Snapdragon 865 with input size 512×512, and only an ARM CPU core is used for speed testing. References: MobileNetV2 Sandler et al. (2018), MobileNetV3 Howard et al. (2019), HRNet Yuan et al. (2020), TopFormer Zhang et al. (2022b), ConvMLP Li et al. (2021), Semantic FPN Kirillov et al. (2019), EfficientNet Tan & Le (2019), DeepLabV3+ and Lite-ASPP Chen et al. (2018a), SegFormer Xie et al. (2021), ResNet He et al. (2016), ShuffleNetV2-1.5x Ma et al. (2018).

By using a 3×3 convolution, auxiliary local details can be aggregated from $\mathbf{q}, \mathbf{k}, \mathbf{v}$. And then a linear projection with activation function and batch normalization are used to squeeze $(2C_{qk} + C_v)$ dimension to C and generate detail enhancement weights. Finally, the enhancement feature will be fused with the feature given by squeeze Axial attention. Different enhancement mode including element-wise addition and multiplication will be compared in experiment section. Time complexity for the 3×3 depth-wise convolution is $\mathcal{O}(3^2HW(2C_{qk} + C_v))$ and the time complexity for the 1×1 convolution is $\mathcal{O}(HWC(2C_{qk} + C_v))$. Time for the other operations like activation can be omitted.

Complexity analysis In our application, we set $C_{qk} = 0.5C_v$ to further reduce computation cost. The total time complexity of squeeze-enhanced Axial attention is

$$\begin{aligned}&\mathcal{O}((H^2 + W^2)(C_{qk} + C_v) + \mathcal{O}((H + W)(2C_{qk} + C_v)) + \mathcal{O}((HWC + 9HW)(2C_{qk} + C_v))\\&= \mathcal{O}((1.5H^2 + 1.5W^2 + 2HWC + 18HW + 2H + 2W)C_v) = \mathcal{O}(HW),\end{aligned} \tag{7}$$

if we assume $H = W$ and take channel as constant. SEA attention is linear to the feature map size theoretically. Moreover, SEA Attention only includes mobile-friendly operation like convolution, pooling, matrix multiplication and so on.

Architecture and Variants We introduce four variants, SeaFormer-Tiny, Small, Base and Large (T, S, B and L). More configuration details are listed in the supplementary material.

4 EXPERIMENTS

We evaluate our method on semantic segmentation and image classification tasks. First, we describe implementation details and compare results with state of the art. We then conduct a series of ablation studies to validate the design of SeaFormer. Each proposed component and important hyper-parameters are examined thoroughly.

Method	Backbone	FLOPs	mIoU(val)	mIoU(test)	Latency
FCN	MobileNetV2	317G	61.5	-	24190ms
PSPNet	MobileNetV2	423G	70.2	-	31440ms
SegFormer(h)	MiT-B0	17.7G	71.9	-	1586ms
SegFormer(f)	MiT-B0	125.5G	76.2	-	11030ms
L-ASPP	MobileNetV2	12.6G	72.7	-	887ms
LR-ASPP	MobileNetV3-L	9.7G	72.4	72.6	660ms
LR-ASPP	MobileNetV3-S	2.9G	68.4	69.4	211ms
Simple Head(h)	TopFormer-B	2.7G	70.7	-	173ms
Simple Head(f)	TopFormer-B	11.2G	75.0	75.0	749ms
Light Head(h)	**Sea-Former-S**	2.0G	70.7	71.0	129ms
Light Head(f)	**Sea-Former-S**	8.0G	76.1	75.9	518ms
Light Head(h)	**Sea-Former-B**	3.4G	72.2	72.5	205ms
Light Head(f)	**Sea-Former-B**	13.7G	77.7	77.5	821ms

Table 2: Results on Cityscapes *val* set. The results on *test* set of some methods are not presented due to the fact that they are not reported in their original papers.

4.1 Experimental setup

4.1.1 Dataset

We perform segmentation experiments over ADE20K Zhou et al. (2017), CityScapes Cordts et al. (2016). The mean of intersection over union (mIoU) is set as the evaluation metric. We convert full-precision models to TNN Contributors (2019) and measure latency on an ARM-based device with a single Qualcomm Snapdragon 865 processor.

ADE20K ADE20K dataset covers 150 categories, containing 25K images that are split into 20K/2K/3K for *Train*, *val* and *test*.

CityScapes CityScapes is a driving dataset for semantic segmentation. It consists of 5000 fine annotated high-resolution images with 19 categories.

4.1.2 Implementation details

We set ImageNet-1K Deng et al. (2009) pretrained network as the backbone, and training details of ImageNet-1K are illustrated in the last subsection. For semantic segmentation, the standard BatchNorm Ioffe & Szegedy (2015) layer is replaced by synchronized BatchNorm.

Training Our implementation is based on public codebase `mmsegmentation` Contributors (2020). We follow the batch size, training iteration scheduler and data augmentation strategy of TopFormer Zhang et al. (2022b) for a fair comparison. The initial learning rate is 0.0005 and the weight decay is 0.01. A "poly" learning rate scheduled with factor 1.0 is adopted. During inference, we set the same resize and crop rules as TopFormer to ensure fairness. The comparison of Cityscapes contains full-resolution and half-resolution. For the full-resolution version, the training images are randomly scaled and then cropped to the fixed size of 1024×1024. For the half-resolution version, the training images are resized to 1024×512 and randomly scaling, the crop size is 1024×512.

4.2 Comparison with state of the art

ADE20K Table 1 shows the results of SeaFormer and previous efficient backbones on ADE20K *val* set. The comparison covers Params, FLOPs, Latency and mIoU. As shown in Table 1, SeaFormer outperforms these efficient approaches with comparable or less FLOPs and lower latency. Compared with specially designed mobile backbone, TopFormer, which sets global self-attention as its semantics extractor, SeaFormer achieves higher segmentation accuracy with lower latency. And the performance of SeaFormer-B surpasses MobileNetV3 by a large margin of +7.9% mIoU with lower latency (-16%). The results demonstrate that our SeaFormer layers improve the representation capability significantly.

Enhance kernel	Attn branch	Enhance input	Enhance mode	Params	FLOPs	Latency	Top1	mIoU
✔		-	-	1.3M	0.58G	38ms	65.9	32.5
	✔	-	-	1.4M	0.57G	38ms	66.3	33.5
✔	✔	conv(x)	Mul	1.6M	0.60G	40ms	67.2	34.9
✔	✔	upconv(x)	Mul	1.8M	0.62G	41ms	68.1	35.9
✔	✔	concat[qkv]	Mul	1.7M	0.60G	40ms	67.9	35.8
✔	✔	concat[qkv]	Add	1.7M	0.60G	40ms	67.3	35.4

Table 3: Ablation studies on components in SEA attention on ImageNet-1K and ADE20K datasets. Enhancement input means the input of detail enhancement kernel. conv(x) means x followed by a point-wise conv. upconv(x) is the same as conv(x) except different channels as upconv(x) is from C_{in} to $C_q + C_k + C_v$ and conv(x) is from C_{in} to C_{in}. concat[qkv] indicates concat of Q,K, V.

Cityscapes From the table 2, it can be seen that SeaFormer-S achieves comparable or better results than TopFormer-B with less computation cost and latency, which proves that SeaFormer could also achieve a good trade-off between performance and latency in high-resolution scenario.

4.3 Ablation studies

In this section, we ablate different self-attention implementations and some important design elements in the proposed model, including our squeeze-enhanced Axial attention module (SEA attention) and fusion block on ADE20K dataset.

The influence of components in SEA attention We conduct experiments with several configurations, including detail enhancement kernel only, squeeze Axial attention only, and the fusion of both. As is shown in Table 3, only detail enhancement or squeeze Axial attention achieves a relatively poor performance, and enhancing squeeze Axial attention with detail enhancement kernel brings a performance boost with a gain of 2.3% mIoU on ADE20K. The results indicate that enhancing global semantic features from squeeze Axial attention with local details from convolution optimizes the feature extraction capability of Transformer block. For enhancement input, there is an apparent performance gap between upconv(x) and conv(x). And we conclude that increasing the channels will boost performance significantly. Comparing concat[qkv] and upconv(x), which also correspond to w/ or w/o convolution weight sharing between detail enhancement kernel and squeeze Axial attention, we can find that sharing weights makes our model improve inference efficiency with minimal performance loss (35.8 *vs.*35.9). As for enhancement modes, multiplying features from squeeze Axial attention and detail enhancement kernel outperforms add enhancement by +0.4% mIoU.

Comparison with different self-attention modules In order to eliminate the impact of our architecture and demonstrate the effectiveness and generalization ability of SEA attention, we ran experiments on Swin Transformer Liu et al. (2021) by replacing window attention in Swin Transformer with different attention blocks. We set the same training protocol, hyper-parameters, and model architecture configurations as Swin for a fair comparison. When replacing window attention with CCAttention (CCNet) or DoubleAttention (A2-Nets), they have much lower FLOPs than SeaFormer and other attention blocks. Considering that we may not be able to draw conclusions rigorously, we doubled the number of their Transformer blocks (including MLP). As ACmix has the same architecture configuration as Swin, we borrow the results from the original paper. From Table 4, it can be seen that SeaFormer outperforms other attention mechanisms with lower FLOPs and latency.

Model	Params(B)	FLOPs(B)	mIoU	Latency
Swin	27.5M	25.6G	44.5	3182ms
CCNet	41.6M	37.4G	43.1	3460ms
ISSA	31.8M	33.3G	37.4	2991ms
A2-Nets	37.2M	31.1G	28.9	2502ms
Axial	36.2M	32.5G	45.3	3121ms
Local	27.5M	25.1G	34.2	3059ms
MixFormer	27.5M	24.9G	45.5	2817ms
ACmix	27.9M	26.6G	45.3	3712ms
Global	27.5M	0.144T	OOM	14642ms
SeaFormer	34.0M	**24.9G**	**46.5**	**2278ms**

Table 4: Results on ADE20K *val* set based on Swin Transformer architecture. (B) denotes backbone. OOM means CUDA out of memory. References: ISSA Huang et al. (2019a), A2-Nets Chen et al. (2018b)

M	Params	FLOPs	Latency	mIoU
64,96	8.5M	1.7G	102ms	40.3
128,160	8.6M	1.8G	106ms	41.0
192,256	8.7M	2.0G	121ms	41.2

Posbias	Params	FLOPs	Latency	mIoU
✘	1.65M	0.60G	40ms	35.6
✔	1.67M	0.60G	40ms	35.8

Table 5: Ablation studies on embedding dimensions and position bias.M = [128, 160] is an optimal embedding dimension in fusion blocks.

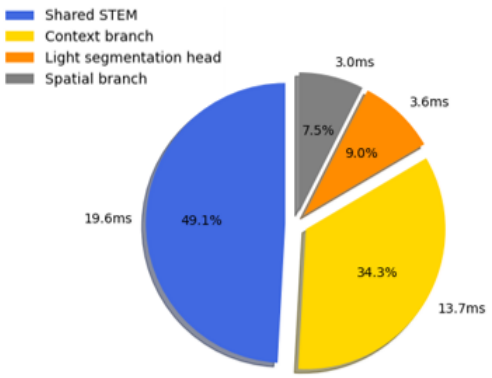

Figure 4: The inference latency of components.

The influence of the width in fusion block To study the influence of the width in fusion block, we perform experiments with different embedding dimensions in fusion blocks on SeaFormer-Base, M denotes the channels that spatial branch and context branch features mapping to in two fusion blocks. Results are shown in Table 5.

4.4 Image classification

We conduct experiments on ImageNet-1K Deng et al. (2009), which contains 1.28M training images and 50K validation images from 1,000 classes. We employ an AdamW Kingma & Ba (2014) optimizer for 600 epochs using a cosine decay learning rate scheduler. A batch size of 1024, an initial learning rate of 0.064, and a weight decay of 2e-5 are used. The results are illustrated in Table 6. Compared with other efficient approaches, SeaFormer achieves a relatively better trade-off between latency and accuracy.

Method	P	F	Top1	L
MobileNetV3-Small	2.9M	0.1G	67.4	**5ms**
SeaFormer-T	1.8M	0.1G	**67.9**	7ms
MobileViT-XXS	1.3M	0.4G	69.0	24ms
MobileViTv2-0.50	1.4M	0.5G	70.2	32ms
MobileOne-S0*	2.1M	0.3G	71.4	14ms
MobileNetV2	3.4M	0.3G	72.0	17ms
Mobile-Former96	4.8M	0.1G	72.8	31ms
SeaFormer-S	4.1M	0.2G	**73.3**	**12ms**
EdgeViT-XXS	4.1M	0.6G	74.4	71ms
LVT	5.5M	0.9G	74.8	97ms
MobileViT-XS	2.3M	0.9G	74.8	54ms
MobileNetV3-Large	5.4M	0.2G	75.2	**16ms**
Mobile-Former151	7.7M	0.2G	75.2	42ms
MobileViTv2-0.75	2.9M	1.0G	75.6	68ms
MobileOne-S1*	4.8M	0.8G	75.9	40ms
SeaFormer-B	8.7M	0.3G	**76.0**	20ms
MobileOne-S2*	7.8M	1.3G	77.4	63ms
EdgeViT-XS	6.8M	1.1G	77.5	124ms
MobileViTv2-1.00	4.9M	1.8G	78.1	115ms
MobileOne-S3*	10.1M	1.9G	78.1	91ms
MobileViT-S	5.6M	1.8G	78.4	88ms
EfficientNet-B1	7.8M	0.7G	79.1	61ms
EfficientFormer-L1	12.3M	1.3G	79.2	94ms
Mobile-Former508	14.8M	0.5G	79.3	102ms
MobileOne-S4*	14.8M	3.0G	79.4	143ms
SeaFormer-L	14.0M	1.2G	**79.9**	**61**ms

Table 6: Image classification results on ImageNet-1K *val* set. The FLOPs and latency are measured with input size 256×256 for MobileViT and MobileViTv2 according to its original implementation and 224×224 for other models. `P`, `F` and `L` mean `Parameters`, `FLOPs` and `latency`. * indicates re-parameterized variants Vasu et al. (2022). The latency is measured on a single Qualcomm Snapdragon 865, and only an ARM CPU core is used for speed testing. No other means of acceleration, e.g., GPU or quantification, is used.

4.5 Latency statistics

We make the statistics of the latency of the proposed SeaFormer-Tiny, as shown in Figure 4, the shared STEM takes up about half of the latency of the whole network (49%). The latency of the context branch is about a third of the total latency (34%), whilst the actual latency of the spatial branch is relatively low (8%) due to sharing early convolution layers with the context branch. Our light segmentation head (8%) also contributes to the success of building a light model.

5 Conclusion

In this paper, we propose *squeeze-enhanced Axial Transformer* (***SeaFormer***) for mobile semantic segmentation, filling the vacancy of mobile-friendly efficient Transformer. Moreover, we create a family of backbone architectures of SeaFormer and achieve cost-effectiveness. The superior performance on the ADE20K and Cityscapes, and the lowest latency demonstrate its effectiveness on the ARM-based mobile device. Beyond semantic segmentation, we further apply the proposed SeaFormer architecture to image classification problem, demonstrating the potential of serving as a versatile mobile-friendly backbone.

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