

# MixFormer: Mixing Features across Windows and Dimensions

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## Abstract

While local-window self-attention performs notably in vision tasks, it suffers from limited receptive field and weak modeling capability issues. This is mainly because it performs self-attention within non-overlapped windows and shares weights on the channel dimension. We propose MixFormer to find a solution. First, we combine local-window self-attention with depth-wise convolution in a parallel design, modeling cross-window connections to enlarge the receptive fields. Second, we propose bi-directional interactions across branches to provide complementary clues in the channel and spatial dimensions. These two designs are integrated to achieve efficient feature mixing among windows and dimensions. Our MixFormer provides competitive results on image classification with EfficientNet and shows better results than RegNet and Swin Transformer. Performance in downstream tasks outperforms its alternatives by significant margins with less computational costs in 5 dense prediction tasks on MS COCO, ADE20k, and LVIS. Code is available at <https://github.com/PaddlePaddle/PaddleClas>.

## 1. Introduction

The success of Vision Transformer (ViT) [10, 36] in image classification [8] validates the potential to apply Transformer [38] to vision tasks. Challenges remain for downstream tasks, especially the inefficiency in high-resolution vision tasks and the ineffectiveness in capturing local relations. One possible solution is to use local-window self-attention. It performs self-attention within non-overlapped windows and shares weights on the channel dimension. Although this process improves efficiency, it poses the issues of limited receptive field and weak modeling capability.

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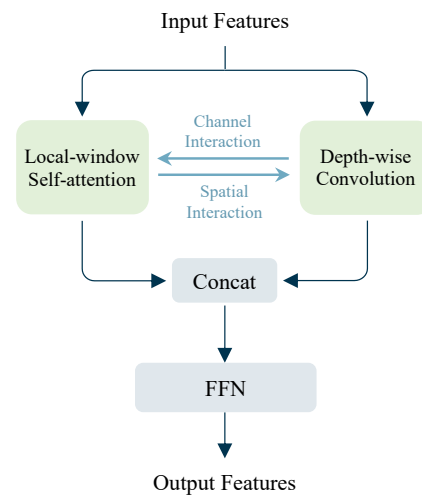


Figure 1. **The Mixing Block.** We combine local-window self-attention with depth-wise convolution in a parallel design. The captured relations within and across windows in parallel branches are concatenated and sent to the Feed-Forward Network (FFN) for output features. In the figure, the blue arrows marked with *Channel Interaction* and *Spatial Interaction* are the proposed bi-directional interactions, which provide complementary clues for better representation learning in both branches. Other details in the block, such as module design, normalization layers, and short-cuts, are omitted for a neat presentation.

A common approach to expand receptive field is to create cross-window connections. Windows are connected by shifting [30], expanding [37, 49], or shuffling [22] operations. Convolution layers are also employed as they capture natural local relations. Researches [22, 53] combine local-window self-attention with depth-wise convolution base on this and provide promising results. Still, the operations capture intra-window and cross-window relations in successive steps, leaving these two types of relations less interweaved. Besides, neglect of modeling weakness in these attempts hinders further advances in feature representation learning.

We propose Mixing Block to address both these issues (Figure 1). First, we combine local-window self-attention with depth-wise convolution, but in a parallel way. The parallel design enlarges the receptive fields by modeling intra-window and cross-window relations simultaneously. Second, we introduce bi-directional interactions across branches (illustrated as blue arrows in Figure 1). The interactions offset the limits caused by the weight sharing mechanism<sup>1</sup>, and enhance the modeling ability in channel and spatial dimensions by providing complementary clues for local-window self-attention and depth-wise convolution respectively. The above designs are integrated to achieve complementary feature mixing across windows and dimensions.

We present MixFormer to verify the block’s efficiency and effectiveness. A series of MixFormers with computational complexity ranging from 0.7G (B1) to 3.6G (B4) are built to perform distinguished in multiple vision tasks, including image classification, object detection, instance segmentation, semantic segmentation, etc. On ImageNet-1K [8], we achieve competitive results with EfficientNet [35], surpassing RegNet [32] and Swin Transformer [30] by a large margin. MixFormer markedly outperforms its alternatives in 5 dense prediction tasks with lower computational costs. With Mask R-CNN [16](1×) on MS COCO [29], MixFormer-B4 shows a boost of 2.9 box mAP and 2.1 mask mAP on Swin-T [30] while requiring less computational cost. Substituting the backbone in UperNet [46], MixFormer-B4 delivers a 2.2 mIoU gain over Swin-T [30] on ADE20k [55]. Plus, MixFormer is effective in keypoint detection [29] and long-tail instance segmentation [13]. In brief, our MixFormer achieves state-of-the-art performance on multiple vision tasks as an efficient general-purpose vision transformer.

## 2. Related Works

**Vision Transformers.** The success of the pioneering work, ViT [10, 36], shows great potentials to apply transformer to the computer vision community. After that, various methods [2, 14, 25, 36, 51, 56] are proposed to improve the performance of vision transformers, demonstrating competitive results on the image classification task. As the self-attention [38] is different from the convolution in nature: self-attention models long-range dependencies while convolution captures relations in local windows, there are also works aiming for integrating convolution and vision transformer. Works like PVT [41] and CvT [45] insert spatial reduction or convolution before global self-attention, yielding the merits of self-attention and convolution.

<sup>1</sup>Local-window self-attention shares weights on the channel dimension while depth-wise convolution shares weights on the spatial one [15]. From the weight sharing perspective, sharing weights results in limited modeling ability in the correspond dimension.

**Window-based Vision Transformers.** Although global Vision Transformer shows its success on image classification; challenges remain for downstream tasks. For high-resolution vision tasks, the computation cost of the Vision Transformer is quadratic to image size, making it unaffordable for real-world applications. Recently, researchers have proposed plenty of methods [6, 9, 30, 41, 45, 48] to make vision transformers become general-purpose backbones as ConvNets [17, 19, 47]. Among them, Window-based Vision Transformer [6, 22, 30] adopts the local window attention mechanism, making its computational complexity increase linearly to image size.

**Receptive Fields.** Receptive fields are important for the downstream vision tasks. However, Window-based Vision Transformer computes self-attention within non-overlapping local windows, which limits the receptive fields in local windows. To solve the problem, researchers propose to use shifting [30], expanding [37, 49], or shuffling [22] operations to connect nearby windows. There are also works [22, 53] using convolutions to enlarge the receptive fields efficiently. Convolution layers are used to create connections because they capture local relations in nature. We combine local-window self-attention and depth-wise convolution in our block design.

**Dynamic Mechanism.** Dynamic networks here [7, 21, 24, 28, 38, 44] refer to networks whose parts of weights or paths are data-dependent. Generally speaking, the dynamic network achieves higher performance than its static alternative as it is more flexible in modeling relations. In ConvNets, the dynamic mechanism is widely used to better extract customized features given different inputs. There are various types of dynamic networks that focus on the channel [21, 28] and the spatial dimension [7, 24, 44]. These works promote many tasks to new state-of-the-art. For Transformer [38], the self-attention module is a dynamic component, which generates attention maps based on the inputs. In this paper, we also adopt the dynamic mechanism in the network design, while our application is based on the finding that the two efficient components share their weights on different dimensions [15]. To construct a powerful block while maintaining efficiency, we introduce dynamic interactions across two branches, which are light-weighted and improve the modeling ability in both channel and spatial dimensions.

## 3. Method

### 3.1. The Mixing Block

Our Mixing Block (Figure 1) adds two key designs upon the standard window-based attention block: (1) adopt a parallel design to combine local-window self-attention and depth-wise convolution, (2) introduce bi-directional interactions across branches. They are proposed to address the

	Attention	W-Attention	Conv	DwConv
Sharing Weights	Channel Dim	Channel Dim	Spatial Dim	Spatial Dim
FLOPs	$2NCH^2W^2$	$2NCHWK^2$	$NC^2HWK^2$	$NCHWK^2$

Table 1. **Sharing Weights Dimensions and FLOPs.** We provide comparison among four operations: global self-attention(Attention), local window self-attention(W-Attention), convolution(Conv) and depth-wise convolution(DwConv). In the table, we provide the dimension of weight sharing for all components in the first row. Besides, the FLOPs is calculated with a  $N \times C \times H \times W$  input and a output with the same shape. The K in the table represents the window size in local-window self-attention or convolution. Note that the Attention operator adopts a window size of  $H \times W$  as it models global dependencies in the spatial dimension.

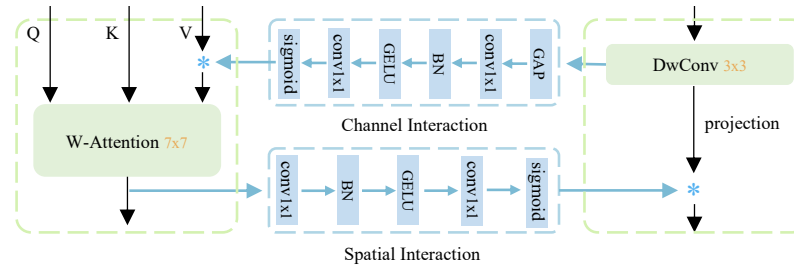


Figure 2. **Detailed design of the Bi-directional Interactions.** The channel/spatial interaction provides channel/spatial context extracted by depth-wise convolution/local-window self-attention to the other path.

limited receptive fields and weak modeling ability issues in local-window self-attention. We first present these two designs then integrate them to build the Mixing Block. Details are described next.

**The Parallel Design.** Although performing self-attention inside non-overlapped windows brings computational efficiency<sup>2</sup>, it results in a limited receptive field due to no cross-window connections being extracted. Several methods resort to shift [30], expand [37, 49], shuffle [22], or convolution [22, 53] to model connections across windows. Considering that convolution layers are designed to model local relations, we choose the efficient alternative (depth-wise convolution) as a promising way to connect windows.

Attention then moves to adopt a proper way to combine local-window self-attention and depth-wise convolution. Previous methods [22, 30, 37, 49, 53] fill the goal by stacking these two operators successively. However, capturing intra-window and cross-window relations in successive steps make these two types of relations less interweaved.

In this paper, we propose a parallel design that enlarges the receptive fields by simultaneously modeling intra-window and cross-window relations. As illustrated in Figure 1, local-window self-attention and depth-wise convolution lie in two parallel paths. In detail, they use different window sizes. A  $7 \times 7$  window is adopted in local-window self-attention, following previous works [20, 30, 37, 54]. While in depth-wise convolution, a smaller kernel size  $3 \times 3$  is applied considering the efficiency<sup>3</sup>. Moreover, as their

<sup>2</sup>It has linear computational complexity concerning image size, as shown in Table 1.

<sup>3</sup>The results in Table 8 show that  $3 \times 3$  is a good choice to achieve balance in accuracy and efficiency.

FLOPs are different, we adjust the number of channels according to the FLOPs proportion in Table 1. Then, their outputs are normalized by different normalization layers [1, 23] and merged by concatenation. The merged feature is sent to the successive Feed-Forward Network (FFN) to mix the learned relations across channels, generating the final output feature.

The parallel design benefits two-folds: First, combining local-window self-attention with depth-wise convolution across branches models connections across windows, addressing the limited receptive fields issue. Second, parallel design models intra-window and cross-window relations simultaneously, providing opportunities for feature interweaving across branches and achieving better feature representation learning.

**Bi-directional Interactions.** In general, sharing weights limits the modeling ability in the shared dimension. A common way to solve the dilemma is to generate data-dependent weights as done in dynamic networks [4, 21, 26, 44]. Local-window self-attention computes weights on the fly on the spatial dimension while sharing weights across channels, resulting in the weak modeling ability issue on the channel dimension. We focus on this issue in this subsection.

To enhance the modeling capacity of local-window self-attention on the channel dimension, we try to generate channel-wise dynamic weights [21]. Given that depth-wise convolution shares weights on the spatial dimension while focusing on the channel. It can provide complementary clues for local-window self-attention and vice versa. Thus, we propose *bi-directional interactions* (in Figure 1 and Figure 2) to enhance modeling ability in the channel and spatial dimension for local-window self-attention and depth-

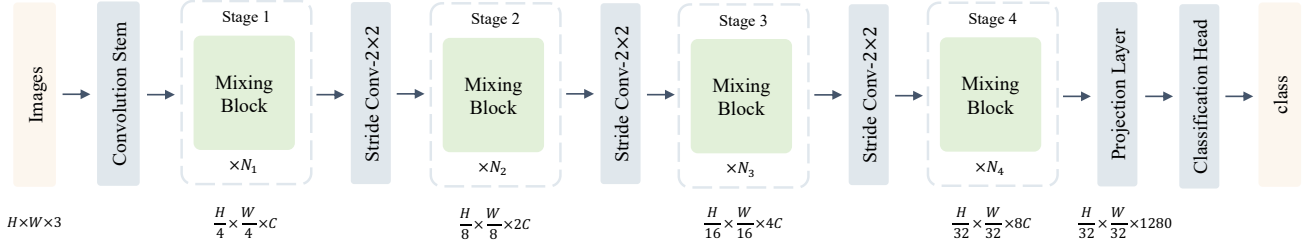


Figure 3. **Overall Architecture of MixFormer.** There are four parts in MixFormer: Convolution Stem, Stages, Projection Layer, and Classification Head. In Convolution Stem, we apply three successive convolutions to increase the channel from 3 to  $C$ . In Stages, we stack our Mixing Block in each stage and use stride convolution ( $stride = 2$ ) to downsample the feature map. For Projection Layer, we use a linear layer with activation to increase the channels to 1280. The Classification Head is for the classification task.

wise convolution respectively. The bi-directional interactions consist of *the channel and spatial interaction* among the parallel branches. The information in the depth-wise convolution branch flows to the other branch through the channel interaction, which strengthens the modeling ability in the channel dimension. Meanwhile, the spatial interaction enables spatial relations to flow from the local-window self-attention branch to the other. As a result, the proposed bi-directional interactions provide complementary clues for each other. Next, we present the designs of the channel and spatial interactions in detail.

*For the channel interaction*, we follow the design of the SE layer [21], as shown in Figure 2. The channel interaction contains one global average pooling layer, followed by two successive  $1 \times 1$  convolution layers with normalization (BN [23]) and activation (GELU [18]) between them. At last, we use sigmoid to generate attention in the channel dimension. Although our channel interaction shares the same design with the SE layer [21], they differ in two aspects: (1) The input of the attention module is different. The input of our channel interaction comes from another parallel branch, while the SE layer is performed in the same branch. (2) We only apply the channel interaction to the value in the local-window self-attention instead of applying it to the module’s output as the SE layer does.

*For the spatial interaction*, we also adopt a simple design, which consists of two  $1 \times 1$  convolution layers with followed BN [23] and GELU [18]. The detailed design is presented in Figure 2. These two layers reduce the number of channels to one. At last, a sigmoid layer is used to generate the spatial attention map. Same as we did in the channel interaction, the spatial attention is generated by another branch, where the local-window self-attention module is applied. It has a larger kernel size ( $7 \times 7$ ) than the depth-wise  $3 \times 3$  convolution and focuses on the spatial dimension, which provides strong spatial clues for the depth-wise convolution branch.

**The Mixing Block.** Thanks to the above two designs, we mitigate two core issues in local-window self-attention. We

integrate them to build a new transformer block, Mixing Block, upon the standard window attention block. As shown in Figure 1, the Mixing Block consists of two efficient operations in a parallel design, bi-directional interactions (Figure 2), and an FFN (Feed-Forward Networks) [38]. It can be formulated as follow:

$$\hat{X}^{l+1} = \text{MIX}(\text{LN}(X^l), \text{W-MSA}, \text{CONV}) + X^l, \quad (1)$$

$$X^{l+1} = \text{FFN}(\text{LN}(\hat{X}^{l+1})) + \hat{X}^{l+1} \quad (2)$$

Where MIX represents a function that achieves feature mixing between the W-MSA (Window-based Multi-Head Self-Attention) branch and the CONV (Depth-wise Convolution) branch. The MIX function first projects the input feature to parallel branches by two linear projection layers and two norm layers. Then it mixes the features by following the steps shown in Figure 1 and Figure 2. For FFN, we keep it simple and follow previous works [30,36], which is an MLP that consists of two linear layers with one GELU [18] between them. Moreover, we also try to add depth-wise convolution as done in PVTv2 [40] and HRFormer [53], which does not give many improvements over the MLP design (Table 9). Thus, to keep the block simple, we use MLP in FFN.

### 3.2. MixFormer

**Overall Architecture.** Based on the obtained block, we design an efficient and general-purpose vision transformer, MixFormer, with pyramid feature maps. There are four stages with downsampling rates of  $\{4, 8, 16, 32\}$  respectively. MixFormer is a hybrid vision transformer, which uses convolution layers in both stem layers and downsampling layers. Besides, we introduce a projection layer in the tail of the stages. The projection layer increases the feature’s channels to 1280 with a linear layer followed by an activation layer, aiming to preserve more details in the channel before the classification head. It gives a higher performance in classification, especially works well with smaller models. Same design can be found in previous efficient networks, such as MobileNets [19,33] and EfficientNets [35]. The sketch of our MixFormer is given in Figure 3.

Models	#Channels	#Blocks	#Heads
MixFormer-B1	$C = 32$	[1, 2, 6, 6]	[2, 4, 8, 16]
MixFormer-B2	$C = 32$	[2, 2, 8, 8]	[2, 4, 8, 16]
MixFormer-B3	$C = 48$	[2, 2, 8, 6]	[3, 6, 12, 24]
MixFormer-B4	$C = 64$	[2, 2, 8, 8]	[4, 8, 16, 32]

Table 2. **Architecture Variants.** Detailed configurations of architecture variants of MixFormer.

**Architecture Variants.** We stack the blocks in each stage manually and format several models in different sizes, whose computational complexities ranges from 0.7G (B1) to 3.6G (B4). The number of blocks in different stages is set by following a recipe: putting more blocks in the last two stages, which is roughly verified in Table 10. As shown in Table 2, we present the detailed settings of the models.

## 4. Experiments

We validate MixFormer on ImageNet-1K [8], MS COCO [29], and ADE20k [55]. We first present the accuracy on image classification. Then we do transfer learning to evaluate the models on three main tasks: object detection, instance segmentation, and semantic segmentation. Besides, ablations of different design modules in MixFormer and results with more vision tasks are provided.

### 4.1. Image Classification

**Setup.** We first verify our method by classification on ImageNet-1K [8]. To make a fair comparison with previous works [30, 36, 41], we train all models for 300 epochs with an image size of  $224 \times 224$  and report Top-1 validation accuracy. We apply an AdamW optimizer using a cosine decay schedule. By following the rule that smaller models need less regularization, we adjust the training settings gently when training models in different sizes. Details are in Appendix.

**Results.** Table 3 compares our MixFormer with efficient ConvNets [32, 35] and various Vision Transformers [22, 27, 30, 36, 41, 45, 49]. MixFormer performs on par with EfficientNet [35] and outperforms RegNet [32] by significant margins under various computational budgets (from B1 to B4). We note that it is *nontrivial* to achieve such results for vision transformer-based models, especially on small models (FLOPs  $< 1.0G$ ). Previous works such as DeiT [36] and PVT [41] show dramatic performance drops when reducing model complexities ( $-7.7\%$  from DeiT-S to DeiT-T and  $-4.7\%$  from PVT-S to PVT-T). Compared with Swin Transformer [30] and its variants [22, 27, 49], MixFormer shows better performance with less computational costs. In detail, MixFormer-B4 achieves 83.0% Top-1 accuracy with only 3.6G FLOPs. It outperforms Swin-T [30] by 1.7% while saving 20% computational costs and gives comparable results with Swin-S [30] but being  $2.4\times$  efficient.

Method	#Params	FLOPs	Top-1
ConvNets			
RegNetY-0.8G [32]	6M	0.8G	76.3
RegNetY-1.6G [32]	11M	1.6G	78.0
RegNetY-4G [32]	21M	4.0G	80.0
RegNetY-8G [32]	39M	8.0G	81.7
EffNet-B1 [35]	8M	0.7G	79.1
EffNet-B2 [35]	9M	1.0G	80.1
EffNet-B3 [35]	12M	1.8G	81.6
EffNet-B4 [35]	19M	4.2G	82.9
Vision Transformers			
DeiT-T [36]	6M	1.3G	72.2
DeiT-S [36]	22M	4.6G	79.9
DeiT-B [36]	87M	17.5G	81.8
PVT-T [41]	13M	1.8G	75.1
PVT-S [41]	25M	3.8G	79.8
PVT-M [41]	44M	6.7G	81.2
PVT-L [41]	61M	9.8G	81.7
CvT-13 [45]	20M	4.5G	81.6
CvT-21 [45]	32M	7.1G	82.5
TwinsP-S [6]	24M	3.8G	81.2
DS-Net-S [31]	23M	3.5G	82.3
Swin-T [30]	29M	4.5G	81.3
Swin-S [30]	50M	8.7G	83.0
Twins-S [6]	24M	2.9G	81.7
LG-T [27]	33M	4.8G	82.1
Focal-T [49]	29M	4.9G	82.2
Shuffle-T [22]	29M	4.6G	82.5
MixFormer-B1 (Ours)	8M	0.7G	78.9
MixFormer-B2 (Ours)	10M	0.9G	80.0
MixFormer-B3 (Ours)	17M	1.9G	81.7
MixFormer-B4 (Ours)	35M	3.6G	83.0

Table 3. **Classification accuracy on the ImageNet validation set.** Performances are measured with a single  $224 \times 224$  crop. “Params” refers to the number of parameters. “FLOPs” is calculated under the input scale of  $224 \times 224$ .

The competitive advantage of MixFormer maintains when it comes to LG-Transformer [27], Focal Transformer [49] and Shuffle Transformer [22]. Moreover, our MixFormer also scales well to smaller and larger models. More results are provided in Appendix.

### 4.2. Object Detection and Instance Segmentation

**Setup.** We validate the effectiveness of MixFormer on downstream tasks. We train Mask R-CNN [16] on the COCO2017 *train* split and evaluate the models on the *val* split. Two training schedules ( $1\times$  and  $3\times$ ) are adopted to show a consistent comparison with previous methods [17, 27, 30, 36, 49]. For the  $1\times$  schedule, we train for 12 epochs with a single size (resizing the shorter side to 800 while keeping its longer side no more than 1333) [16]. While in  $3\times$  schedule (36 epochs), we use multi-scale training by randomly resizing the shorter side to the range of [480, 800] (See Appendix for more details). Expect for Mask R-CNN [16], we also provide comparisons with pre-

Backbones	#Params	FLOPs	Mask R-CNN 1x schedule						Mask R-CNN 3x + MS schedule					
			$AP^b$	$AP_{50}^b$	$AP_{75}^b$	$AP^m$	$AP_{50}^m$	$AP_{75}^m$	$AP^b$	$AP_{50}^b$	$AP_{75}^b$	$AP^m$	$AP_{50}^m$	$AP_{75}^m$
ResNet18 [17]	31M	-	34.0	54.0	36.7	31.2	51.0	32.7	36.9	57.1	40.0	33.6	53.9	35.7
ResNet50 [17]	44M	260G	38.0	58.6	41.4	34.4	55.1	36.7	41.0	61.7	44.9	37.1	58.4	40.1
ResNet101 [17]	63M	336G	40.4	61.1	44.2	36.4	57.7	38.8	42.8	63.2	47.1	38.5	60.1	41.3
ResNeXt101-64x4d [47]	101M	493G	42.8	63.8	47.3	38.4	60.6	41.3	44.4	64.9	48.8	39.7	61.9	42.6
PVT-T [41]	33M	-	36.7	59.2	39.3	35.1	56.7	37.3	39.8	62.2	43.0	37.4	59.3	39.9
PVT-S [41]	44M	245G	40.4	62.9	43.8	37.8	60.1	40.3	43.0	65.3	46.9	39.9	62.5	42.8
PVT-M [41]	64M	302G	42.0	64.4	45.6	39.0	61.6	42.1	44.2	66.0	48.2	40.5	63.1	43.5
PVT-L [41]	81M	364G	42.9	65.0	46.6	39.5	61.9	42.5	44.5	66.0	48.3	40.7	63.4	43.7
TwinsP-S [6]	44M	245G	42.9	65.8	47.1	40.0	62.7	42.9	46.8	69.3	51.8	42.6	66.3	46.0
DS-Net-S [31]	43M	-	44.3	-	-	40.2	-	-	-	-	-	-	-	-
Swin-T [30]	48M	264G	42.2	64.6	46.2	39.1	61.6	42.0	46.0	68.2	50.2	41.6	65.1	44.8
Twins-S [6]	44M	228G	43.4	66.0	47.3	40.3	63.2	43.4	46.8	69.2	51.2	42.6	66.3	45.8
Focal-T [49]	49M	291G	-	-	-	-	-	-	47.2	69.4	51.9	42.7	66.5	45.9
Shuffle-T [22]	48M	268G	-	-	-	-	-	-	46.8	68.9	51.5	42.3	66.0	45.6
MixFormer-B1(Ours)	26M	183G	40.6	62.6	44.1	37.5	59.7	40.0	43.9	65.6	48.1	40.0	62.9	42.9
MixFormer-B2(Ours)	28M	187G	41.5	63.3	45.2	38.3	60.6	41.2	45.1	66.9	49.2	40.8	64.1	43.6
MixFormer-B3(Ours)	35M	207G	42.8	64.5	46.7	39.3	61.8	42.2	46.2	68.1	50.5	41.9	65.6	45.0
MixFormer-B4(Ours)	53M	243G	<b>45.1</b>	<b>67.1</b>	<b>49.2</b>	<b>41.2</b>	<b>64.3</b>	<b>44.1</b>	<b>47.6</b>	<b>69.5</b>	<b>52.2</b>	<b>43.0</b>	<b>66.7</b>	<b>46.4</b>

Table 4. **COCO detection and segmentation with the Mask R-CNN.** The performances are reported on the COCO *val* split under 1× and 3× schedules. The FLOPs (G) are measured at resolution 800 × 1280, and all models are pre-trained on the ImageNet-1K [8]. In the table, ‘-’ means that the result is not reported by the original paper.

Backbones	#Params	FLOPs	$AP^b$	$AP_{50}^b$	$AP_{75}^b$	$AP^m$	$AP_{50}^m$	$AP_{75}^m$
ResNet50 [17]	82M	739G	46.3	64.3	50.5	40.1	61.7	43.4
Swin-T [30]	86M	745G	50.5	69.3	54.9	43.7	66.6	47.1
Shuffle-T [22]	86M	746G	50.8	69.6	55.1	44.1	66.9	48.0
MixFormer-B4(Ours)	91M	721G	<b>51.6</b>	<b>70.5</b>	<b>56.1</b>	<b>44.9</b>	<b>67.9</b>	<b>48.7</b>

Table 5. **COCO detection and segmentation with the Cascade Mask R-CNN.** The performances are reported on the COCO *val* split under a 3× schedule. Results show consistent improvements of MixFormer over Swin Transformer.

Backbone	Method	#Params	FLOPs	mIoU <sub>ss</sub>	mIoU <sub>ms</sub>
ResNet-101 [17]	DANet [11]	69M	1119G	43.6	45.2
ResNet-101 [17]	DLab.v3+ [5]	63M	1021G	45.1	46.7
ResNet-101 [17]	ACNet [12]	-	-	45.9	-
ResNet-101 [17]	DNL [50]	69M	1249G	46.0	-
ResNet-101 [17]	OCRNet [52]	56M	923G	-	45.3
ResNet-101 [17]	UperNet [46]	86M	1029G	43.8	44.9
HRNet-w48 [39]	OCRNet [52]	71M	664G	-	45.7
DeiT-S [36] <sup>†</sup>	UperNet [46]	52M	1099G	44.0	-
TwinsP-S [6]	UperNet [46]	55M	919G	46.2	47.5
Swin-T [30]	UperNet [46]	60M	945G	44.5	45.8
Twins-S [6]	UperNet [46]	54M	901G	46.2	47.1
LG-T [27]	UperNet [46]	64M	957G	-	45.3
Focal-T [49]	UperNet [46]	62M	998G	45.8	47.0
Shuffle-T [22]	UperNet [46]	60M	949G	46.6	47.6
MixFormer-B1(Ours)	UperNet [46]	35M	854G	42.0	43.5
MixFormer-B2(Ours)	UperNet [46]	37M	859G	43.1	43.9
MixFormer-B3(Ours)	UperNet [46]	44M	880G	44.5	45.5
MixFormer-B4(Ours)	UperNet [46]	63M	918G	<b>46.8</b>	<b>48.0</b>

Table 6. **ADE20K semantic segmentation.** We report mIoU on the ADE20K [55] *val* split with single scale (ss) testing and multi-scale (ms) testing. A resolution 512 × 2048 is used to measure the FLOPs (G) in various models.

vious works based on a stronger model, Cascade Mask R-CNN [3, 16], where a 3× schedule is conducted.

**Comparison on Mask R-CNN.** Table 4 shows that MixFormer consistently outperforms other competitors [17, 27, 30, 41, 45, 49] under various model sizes with Mask R-CNN [16]. In particular, MixFormer-B4 achieves +2.9(+1.6) higher box mAP and +2.1(+1.4) higher mask mAP than the Swin-T [30] baseline with 1× (3×) schedule. Moreover, MixFormer keeps its efficiency in detection and instance segmentation, enabling higher performance with less computational costs than other networks [17, 30]. It is a surprise that our MixFormer-B1 (only with 0.7G) performs strongly with Mask R-CNN (1×), which exceeds ResNet-50 (with 4.1G) [17] by 2.3 box mAP and 2.9 mask mAP. The results suggest that implications for designing high-performance small models on detection are highlighted in MixFormer.

**Comparison on Cascade Mask R-CNN.** We also evaluate MixFormer with Cascade Mask R-CNN [3, 16], which is a stronger variant of Mask R-CNN [16]. MixFormer-B4 provides robust improvements over Swin-T [30] (Table 5) regardless of different detectors, as it shows similar gains (+1.1/1.2 box/mask mAP v.s. +1.6/1.4 box/mask mAP) with the ones on Mask R-CNN (3×) (Table 4).

### 4.3. Semantic Segmentation

**Setup.** Our experiments are conducted on ADE20K [55] using UperNet [46]. For training recipes, we mainly follow the settings in [30]. We report mIoU of our models in single scale testing (ss) and multi-scale testing (ms). Details are provided in Appendix.

**Results.** In Table 6, MixFormer-B4 consistently achieves better mIoU performance than previous networks. It seems

Parallel	Interactions		ImageNet		COCO		ADE20k
	Channel	Spatial	Top-1	Top-5	AP <sup>box</sup>	AP <sup>mask</sup>	mIoU
			77.4	93.8	38.2	35.7	38.9
✓			78.1	94.1	39.4	36.6	39.8
✓	✓		78.3	94.1	40.1	37.1	40.6
✓		✓	78.3	94.1	39.7	36.6	40.5
✓	✓	✓	<b>78.4</b>	<b>94.3</b>	<b>40.3</b>	<b>37.3</b>	<b>40.9</b>
	Δ		+1.0	+0.5	+2.1	+1.6	+2.0

Table 7. **Parallel Design with Bi-directional Interactions.** The baseline model in this table adopts a successive design and has no interactions in the block.

Window Sizes	ImageNet		COCO		ADE20k
	Top-1	Top-5	AP <sup>box</sup>	AP <sup>mask</sup>	mIoU
1 × 1	77.1	93.6	36.3	34.3	37.6
<b>3 × 3</b>	<b>78.4</b>	<b>94.3</b>	<b>40.3</b>	<b>37.3</b>	<b>40.9</b>
5 × 5	78.4	94.3	40.3	37.2	40.8

Table 8. **Window Sizes in DwConv.** We investigate various window sizes for DwConv. MixFormer uses the 3 × 3 window size for DwConv by default.

that the connections across windows and dimensions in the Mixing Block provide more benefits on semantic segmentation as the gains are larger than the ones on detection tasks (Table 4, Table 5) with the same backbones. In particular, MixFormer-B4 outperforms Swin-T [30] by 2.2 mIoU.

Moreover, other variants of MixFormer (from B1 to B3) also achieve higher performance while being more efficient than previous networks. Notably, MixFormer-B3 obtains 45.5 mIoU (comparable with Swin-T [30] but less FLOPs), which achieves on par results with OCRNet [52] with HRNet-W48 [39] (45.7 mIoU). Note that HRNet [39] is carefully designed to aggregate the features in different stages, while MixFormer simply constructs pyramid feature maps, indicating the strong potential for further improvements on dense prediction tasks.

#### 4.4. Ablation Study

**Setup.** We provide ablations with respect to our designs on MixFormer-B1. We report all variations of different designs on ImageNet-1K [8] classification, COCO [29] detection and segmentation, and ADE20K [55] semantic segmentation. To make quick evaluations, we only train MixFormer-B1 for 200 epochs on ImageNet-1K [8]. Then, the pre-trained models are adopted by Mask R-CNN [16] (1×) on MS COCO [29] and UperNet [46] (160k) on ADE20K [55]. Note that, the differences in pre-train models provide slightly different results with the ones in Table 4 and Table 6.

**Ablation: Parallel or Not.** Table 7 provides the comparison of the ways (successive design or parallel design) to combine local-window self-attention and depth-wise convolution. Our parallel design consistently outperforms the

Techniques	ImageNet		COCO		ADE20k
	Top-1	Top-5	AP <sup>box</sup>	AP <sup>mask</sup>	mIoU
MixFormer-B1( <b>Ours</b> )	78.4	94.3	40.3	37.3	40.9
+shifted windows	78.3	94.1	40.5	37.3	40.7
+DwConv in FFN	78.6	94.4	40.5	37.4	40.9

Table 9. **Other Techniques.** We combine two techniques with our MixFormer. When inserting DwConv in FFN, we only consider 3 × 3 DwConv.

#Blocks #Channels	FLOPs	ImageNet		COCO		ADE20k
		Top-1	Top-5	AP <sup>box</sup>	AP <sup>mask</sup>	mIoU
[2, 2, 8, 2] [32, 64, 160, 256]	0.9G	77.7	93.9	40.1	37.3	40.6
[2, 2, 6, 4] [32, 64, 128, 256]	0.9G	77.5	93.7	39.6	36.7	39.8
[1, 2, 6, 2] [32, 64, 160, 320]	0.8G	77.2	93.5	39.3	36.6	40.4
[1, 2, 6, 6] [32, 64, 128, 256]	<b>0.7G</b>	<b>78.4</b>	<b>94.3</b>	<b>40.3</b>	<b>37.3</b>	<b>40.9</b>

Table 10. **Number of Blocks in Stages.** In the table, the first two models and the last two models share similar computational complexities with each other.

successive design across various vision tasks, which verifies the hypothesis that the parallel design enables better feature representation learning in Section 1. The models below use parallel design by default.

**Ablation: Bi-directional Interactions.** Table 7 shows the results of the proposed interactions. According to the results, we see that both channel and spatial interactions outperform the model without interactions across all different vision tasks. Combining two interactions promotes better performance, resulting in consistent improvements by 0.3% Top-1 accuracy on ImageNet-1K, 0.9/0.7 box/mask mAP on COCO, and 1.1 mIoU on ADE20K. Given that we only use simple and light-weighted designs for bi-directional interactions, the gains are nontrivial, which indicates the effectiveness of providing complementary clues for local-window self-attention and depth-wise convolution.

**Ablation: Window Sizes in DwConv.** Table 8 shows that the performance will drop significantly on various vision tasks (−1.3 Top-1 accuracy on ImageNet-1K, −4.0/−3.0 box/mask mAP on COCO, and −3.3 mIoU on ADE20K) if we reduce the window size of the depth-wise convolution from 3 × 3 to 1 × 1. This phenomenon means that it’s necessary for depth-wise convolution to use a window size (at least 3 × 3) with the ability to connect across-window. Besides, when we increase the window size to 5 × 5, no clear further gains are observed. Thus, we use a window size of 3 × 3 regarding the efficiency.

**Ablation: Other Techniques.** We also investigate other designs in MixFormer, including applying shifted windows

Backbones	COCO keypoint detection		
	AP <sup>kp</sup>	AP <sub>50</sub> <sup>kp</sup>	AP <sub>75</sub> <sup>kp</sup>
ResNet50 [17]	71.8	94.9	49.2
Swin-T [30]	74.2	92.5	82.5
HRFormer-S [30]	74.5	92.3	82.1
MixFormer-B4(Ours)	<b>75.3</b> (+1.1)	<b>93.5</b> (+1.0)	<b>83.5</b> (+1.0)

Backbones	LVIS Instance Segmentation		
	AP <sup>mask</sup>	AP <sub>50</sub> <sup>mask</sup>	AP <sub>75</sub> <sup>mask</sup>
ResNet50 [17]	21.7	34.3	23.0
Swin-T [30]	27.6	43.0	29.3
MixFormer-B4(Ours)	<b>28.6</b> (+1.0)	<b>43.4</b> (+0.4)	<b>30.5</b> (+1.2)

Table 11. **More Downstream Tasks.** We compare our MixFormer with ResNet50 [17] and Swin Transformer [30] on keypoint detection and long-tail instance segmentation.

and inserting  $3 \times 3$  depth-wise convolution in FFN, which play significant roles in previous works [30, 53]. As presented in Table 9, shifted window fails to provide gains over MixFormer. We hypothesize that the depth-wise convolution builds connections among windows, removing the need for shift operation. Besides, although inserting  $3 \times 3$  depth-wise convolution in FFN can provide further gains, the room for improvements is limited with MixFormer. Thus, we use MLP in FFN by default.

**Ablation: Number of Blocks in Stages.** Previous works usually put more blocks in the third stage and greatly increase the number of blocks in that stage when scaling models [17, 30, 41]. We show an alternative way that can achieve the goal. We roughly conduct experiments on the way of stacking blocks. In Table 10, we achieve slightly higher performance on various vision tasks under less computational complexities by putting more blocks in both the last two stages. We follow this recipe to build our MixFormer.

#### 4.5. Generalization

**More Downstream Tasks.** In Table 11, we conduct experiments on two more downstream tasks: keypoint detection and long-tail instance segmentation. Detailed experimental settings are provided in Appendix.

*COCO keypoint Detection:* In Table 11, MixFormer-B4 outperforms baseline models [17, 30] by significant margins in all metrics. Moreover, MixFormer also shows clear advantages compared with HRFormer [53], which is specifically designed for dense prediction tasks.

*LVIS 1.0 Instance Segmentation:* This task has  $\sim 1000$  long-tailed distribution categories, which relies on the discriminative feature learned by the backbone. Results in Table 11 show that MixFormer outperforms the Swin-T [30] by 1.0 AP<sup>mask</sup>, which demonstrates the robustness of the learned representation in MixFormer.

*Summary:* Considering the promising results given by MixFormer in previous tasks: object detection, instance segmentation, and semantic segmentation, MixFormer can

Models	FLOPs	Top-1	Top-5
ResNet50 [36]	4.1G	78.4	-
ResNet50 [43]	4.1G	79.8	-
ResNet50*	4.1G	79.0	94.3
ResNet50 + Mixing Block	3.9G	<b>80.6</b> (+1.6)	<b>95.1</b> (+0.8)
MobileNetV2 [33]	0.3G	72.0	-
MobileNetV2*	0.3G	71.7	90.3
MobileNetV2+SE+Non-Local*	0.3G	72.5	91.0
MobileNetV2 + Mixing Block	0.3G	<b>73.6</b> (+1.9)	<b>91.6</b> (+1.3)

Table 12. **Apply Mixing Block to ConvNets on ImageNet-1K.** We introduce our Mixing Block to typical ConvNets, ResNet [17] and MobileNetV2 [33]. As different training recipes give variant accuracy [43], we also train ResNet50 [17] and MobileNetV2 [33] with the same setting as ours, denoted with \* in the Table.

serve as a general-purpose backbone and outperform its alternatives in 5 dense prediction tasks.

**Apply Mixing Block to ConvNets.** We apply our Mixing Block to typical ConvNets, ResNet50 [17] and MobileNetV2 [33]. Following [34], we replace all the blocks in the last stage with our Mixing Block in ConvNets. To make a fair comparison, we adjust the number of blocks to maintain the overall computational cost. Table 12 shows that the Mixing Block can provide gains on ConvNets [17, 33] as an alternative to ConvNet blocks. Specifically, Mixing Block brings 1.9% and 1.6% Top-1 accuracy on ImageNet-1K [8] over MobileNetV2 [33] and ResNet50 [17]. Moreover, we also provide the result of MobileNetV2 [33] with SE layer [21] and Non-Local [42] in Table 12. It gives inferior performance than our mixing block.

## 5. Conclusion

In this paper, we propose MixFormer as an efficient general-purpose vision transformer. Addressing issues in Window-based Vision Transformer, we seek to alleviate limited receptive fields and weak modeling capability on the channel dimension. Our MixFormer enlarges receptive fields efficiently without shifting or shuffling windows, thanks to a parallel design coupling local window and depth-wise convolution. The bi-directional interactions boost modeling ability in the channel and spatial dimension for local-window self-attention and depth-wise convolution, respectively. Extensive experiments show that MixFormer outperforms its alternatives on image classification and various downstream vision tasks. We expect the designs in MixFormer to serve as a base setup for designing efficient networks.

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