MoCoViT: Mobile Convolutional Vision Transformer

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Abstract. Recently, Transformer networks have achieved impressive results on a variety of vision tasks. However, most of them are computationally expensive and not suitable for real-world mobile applications. In this work, we present Mobile Convolutional Vision Transformer (MoCoViT), which improves in performance and efficiency by introducing transformer into mobile convolutional networks to leverage the benefits of both architectures. Different from recent works on vision transformer, the mobile transformer block in MoCoViT is carefully designed for mobile devices and is very lightweight, accomplished through two primary modifications: the Mobile Self-Attention (MoSA) module and the Mobile Feed Forward Network (MoFFN). MoSA simplifies the calculation of the attention map through Branch Sharing scheme while MoFFN serves as a mobile version of MLP in the transformer, further reducing the computation by a large margin. Comprehensive experiments verify that our proposed MoCoViT family outperform state-of-the-art portable CNNs and transformer neural architectures on various vision tasks. On ImageNet classification, it achieves 74.5% top-1 accuracy at 147M FLOPs, gaining 1.2% over MobileNetV3 with less computations. And on the COCO object detection task, MoCoViT outperforms GhostNet by 2.1 AP in RetinaNet framework.

Keywords: Vision Transformer, mobile transformer block, Mobile Self-Attention, Mobile Feed Forward Network, Lightweight Networks

1 Introduction

Vision transformer (ViT) \cite{12,35} achieves significant performance boost over CNNs on various tasks, e.g., image classification \cite{11}, object detection \cite{24}, and semantic segmentation \cite{24}. However, these performance improvement usually come at high computational cost. For example, DeiT requires more than 10G Mult-Adds in order to perform an image classification task. Such extremely high computational resources requirements is beyond the capabilities of many mobile devices, e.g., smart phone and self-driving cars. To relieve such problem, Swin \cite{25} limits the attention region of each token from full-attention to local attention where the input is split into sub-windows and the self-attention is only performed.
within each window. Twins [7] proposes spatially separable self-attention where locally-grouped self-attention and global sub-sampled attention are applied in two successive blocks. Unfortunately, the complexity is still too heavy to deploy on mobile devices.

On the contrast, in the past few years, much progress has been achieved in designing efficient convolutional neural networks (CNN) for mobile vision tasks. For instance, MobileNets [20, 30, 19] utilized the depthwise and pointwise convolutions to approximate the vanilla convolutional layer and achieved comparable performance. ShuffleNet [43, 27] further proposed a channel shuffle operation to enhance the performance of compact models. GhostNet [15] designed a Ghost module to generate rich features maps from cheap operations.

In this work, we seek to design a lightweight transformer for mobile devices and achieve a good trade-off between complexity and performance. Some researchers [14, 38, 28, 5] have made a first attempt to develop lightweight transformers by combining the strength of CNNs and transformers. In [28], MobileNetV2 block and transformer block are combined in series and a MobileVit block is developed to learn global representations. But MobileVit is still relatively heavy compared to Mobile CNNs. Mobile-Former is presented in [5], which is a parallel design of MobileNet and Transformer with a two-way bridge in between to communication. Different from previous works, we propose an extremely efficient Mobile Transformer Block (MTB). This block is carefully designed for mobile vision tasks, and consisted of two key components, Mobile Self-Attention (MoSA) and Mobile Feed Forward Network (MoFFN). In MoSA, in the computation of query, key and value, linear layers are replaced by lightweight Ghost module. Besides, Branch Sharing scheme is utilized to reuse weights during the computation. Thus MoSA is much more efficient than the vanilla self-attention. Regarding to Multi Layer Perception (MLP), its complexity can not be ignored in the transformer block. MoFFN is produced to relieve this issue. The up-projection and down-projection linear layer in MLP are substituted with efficient Ghost module as well to form MoFFN. Equipped with the proposed MTB, we present our Mobile Convolutional Vision Transformer (MoCoViT), a new architecture for mobile application, where CNN block and MTB block are combined in series. To achieve the best trade-off between complexity and performance, CNN blocks are placed in the early stages while MTB blocks are only used in the last stage.

To demonstrate the effectiveness of MoCoViT, we conduct a series of experiments on various vision tasks, e.g., ImageNet-1K classification [11], and objection detection and instance segmentation on COCO [24]. Extensive experimental results show that MoCoViT outperforms other state-of-the-art lightweight CNN networks and lightweight transformers, such as MobileNetV3, GhostNet, and Mobile-Former. As shown in Fig. [1] MoCoViT obtains the best result when FLOPs ranges from 40M to 300M. Specifically, MoCoViT achieves 74.5% top-1 accuracy on ImageNet-1K with 147M FLOPs, which is 1.2% higher than MobileNetV3, 0.6% higher than GhostNet. In a nutshell, the contributions of our work can be summarized as follows:
1. We propose an extremely lightweight transformer block for mobile devices. Inside the block, Mobile Self-Attention and Mobile Feed Forward Network are carefully designed, aiming to achieve the best trade-off between complexity and performance.

2. We present MoCoViT, an efficient architecture that combines the strength of CNN and Transformer, and achieves SOTA performance on various vision tasks.

![Fig. 1: Comparison among MoCoViT and efficient CNNs, in terms of accuracy-flop trade-off. The comparison is performed on ImageNet classification. MoCoViT consistently outperforms the SOTA efficient CNNs.](image)

2 Related Work

**Light-weight Convolutional Neural Networks (CNNs):** MobileNet\(^{30}\) proposes an efficient way to model local filter processing by using depthwise and pointwise convolution in an inverted bottleneck structure.\(^{27}\) proposes ShuffleNet that uses group convolution and channel shuffle to simplify pointwise convolution. Other efficient operators include butterfly transform\(^{29}\), cheap linear transformations in GhostNet\(^{15}\), and using cheap additions to trade massive multiplications in AdderNet\(^{2}\). MixConv\(^{34}\) explores mixing up multiple kernel sizes, and Sandglass\(^{44}\) flips the structure of inverted residual block. EfficientNet\(^{33}\) and TinyNet\(^{16}\) study the compound scaling of depth, width and resolution.
Vision Transformers (ViT): ViT[12] applied standard transformer encoders to build a convolution-free image classifier by decomposing the image into a sequence of non-overlapping patches directly. Although it harvested promising results, a gap still existed between data-hungry transformers and top-performing CNNs [33] when only training on the midsize ImageNet from scratch. In order to bridge this gap, DeiT[35] proposes a token-based distillation procedure and a data efficient training strategy to optimize the Transformer effectively. Later, the follow-ups improved different aspects of the ViT, making them more suitable for vision tasks. Cvt[38], CeiT[40] incorporated the convolution designs into the self-attention or the FFN to enhance the locality. CPVT[8] utilized the implicit position representation ability of convolutions (with zero padding) to encode the conditional position for the inputs with arbitrary size. Then, hierarchical pyramid structures[25][36] were performed by progressively shrinking the number of tokens and replacing the class token with the average pooling. Thus, the Transformer, supported by multi-level features [22], can handle object detection and image segmentation tasks conveniently.

Recent works [10] show that combining convolution and transformer achieves improvement in prediction accuracy as well as training stability. BoTNet[31] shows significant improvement in instance segmentation and object detection by just replacing the spatial convolutions with global self-attention in the final three bottleneck blocks of a ResNet[18]. ConViT[13] improves ViT with soft convolutional inductive biases by introducing a gated positional self-attention (GPSA). Cvt[38] introduces depthwise/pointwise convolution before each multi-head attention. LeViT[14] and ViTC[39] use convolutional stem (stacking 33 convolutions) to replace the patchify stem. LeViT and ViTC show clear improvement at the low FLOP regime. In this paper, we follow this idea of combining a CNN network and a transformer network to incorporate our proposed Mobile Self-Attention into a lightweight CNN network, outperforming other efficient CNN and ViT variants in low FLOPs states.

3 Methodology: MoCoViT

In this section, we first introduce the Mobile Self-Attention (MoSA) mechanism designed for lightweight networks, which can greatly reduce the computational overhead compared to the vanilla self-attention mechanism. Then we introduce how to use a more efficient operation to build Mobile Feed Forward Network (MoFFN), which replaces traditional MLP layers. Using our proposed MoSA and MoFFN, we are able to produce an efficient Mobile Transformer Block (MTB). Finally, we introduce how to use MTB to build our proposed Mobile Convolutional Vision Transformer (MoCoViT), which is an efficient lightweight network leveraging the benefits of convolutional neural network and vision transformer.

3.1 Mobile Self-Attention (MoSA)

The vanilla transformer architecture consists of alternating layers of multi-head self-attention (MHSA) and MLP layer. LayerNorm (LN) is applied before every
block, and residual connections after every block. The self-attention mechanism, as the core part of the visual transformer network, has demonstrated its effectiveness in a variety of visual tasks. The vanilla self-attention can be calculated as

$$\text{Self-Attention}(Q, K, V) = \text{Softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V$$  \hspace{1cm} (1)$$

where $Q, K, V \in \mathbb{R}^{N \times C}$ are the query, key and value matrices, $d_k$ is the query/key channel dimension, $N$ is the number of tokens, $C$ is the channel dimension of tokens. However, in the lightweight models with limited capacity, self-attention is less cost-effective than convolutional layer. The computational complexity of self-attention is quadratic with the spatial resolution. And three linear layers of the same level are introduced to compute a linear combination result of $V$. 

Fig. 2: The overall framework of proposed approach. **Left**: ViT model. **Right**: Our proposed MoCoViT. Mobile Transformer Block consists of our proposed Mobile Self-Attention and Mobile Feed Forward Network. The branch sharing mechanism in Mobile Self-Attention avoids computing $Q$ and $K$, and computes the attention map by reusing $V$. Ghost module is used to replace Linear layer, and LayerNorm is removed for efficiency.
To alleviate this issue, we introduce MoSA, an attention mechanism designed for the lightweight transformer structure. It mainly simplifies vanilla self-attention from two perspectives.

Firstly, in terms of fine-grained operation, we replace the linear layers in vanilla self-attention with more efficient Ghost modules, which is a commonly used structure in the lightweight networks and can be seen as an efficient variant of convolution operations to generate relatively similar feature pairs in a low-cost way. Figure 2 shows the structure of the Ghost module. Ghost module adopts ordinary convolution to first generate a few intrinsic feature maps, and then utilizes cheap linear operations to augment the features and increase the channels. In practice, cheap linear operations are usually implemented as depthwise convolutions for better performance-speed trade-off.

Secondly, from a macro perspective, we propose Branch Sharing mechanism to reuse the weights in $Q, K, V$ computation. As shown in Figure 2, $f^q, f^k, f^v$, are the projection for $Q, K, V$ respectively with the same input features. In our branch sharing mechanism, we directly reuse feature $V$ into $Q$ and $K$. This method is mainly based on one of our insights: $Q$ and $K$ only participate in the calculation of the attention map, while the final result of the self-attention mechanism is the linear combination of each token in $V$. Compared with $Q$ and $K$, $V$ needs to retain more semantic information to ensure the representation ability of the final weighted sum result. Therefore, the result of the self-attention mechanism is strongly correlated with $V$, but weakly correlated with $Q$ and $K$. So, for mobile networks of small capacity, we can simplify the computation of $Q$ and $K$ to achieve a better performance-overhead balance.

The branch sharing mechanism can be denoted as:

\[
\begin{align*}
  f^v &= f^k = f^q \\
  V &= f^v(X) \\
  K &= f^k(X) = \text{Identity}(V^T) \\
  Q &= f^q(X) = \text{Identity}(V)
\end{align*}
\]

(2)

where $f^v, f^k$ and $f^q$ are the projections to compute $Q, K, V$ respectively. To further improve the performance, we also introduce a depthwise convolutional layer as a refiner to further enhance this transformer block. The calculation of MoSA can be written as:

\[
\text{MoSA}(V) = \text{Softmax}\left(\frac{VV^T}{\sqrt{d_v}}\right)V + \text{Depthwise}(V)
\]

(3)

The computation complexity of our proposed Mobile Self-Attention is:

\[
\Omega(\text{MoSA}) = HWC^2 + 2(HW)^2C
\]

(4)

where $N = H \times W$ is the spatial dimension and $C$ is the channel dimension. To quantitatively demonstrate the overhead reduction, we compare the FLOPs and parameters of vanilla self-attention and MoSA at various resolutions. Compared
to vanilla self-attention, the FLOPs of MoSA is $3.6 \times$ less as shown in Figure 3, and the parameters is $2.4 \times$ less.

![Fig. 3: Comparison of FLOPs at various resolutions between Vanilla Self-Attention and MoSA.](image1)

![Fig. 4: Comparison of FLOPs at various resolutions between Vanilla MLP and MoFFN.](image2)

### 3.2 Mobile Feed Forward Network (MoFFN)

In vanilla ViT transformer block, the MLP layer consists of a up-projection fully connected (FC) layer and a down-projection FC layer and LayerNorm is applied before the MLP part. In order to deploy on mobile devices, we replace the FC layer in vanilla MLP with a more efficient Ghost module. As shown in Figure 2, we use batch normalization inside MoFFN, which can be merged at deployment time. In addition, instead of using the GeLU activation function which is not deployment-friendly on the mobile side, we adopt the ReLU activation function widely used in the lightweight models. And the Squeeze and Excite (SE) module [21] is also applied after the up-projection Ghost module.

In addition to be computationally efficient, MoFFN has a larger receptive field than vanilla MLP. In the original ViT architecture, the MLP focus on extracting the channel dimension information of a single token via linear layer, while the information interaction in the spatial dimension is mainly carried out in the self-attention part. In other words, the MLP in vanilla ViT has no spatial awareness and therefore needs to be used after self-attention. Our MoFFN addresses this drawback in vanilla MLP. We first extract the channel dimension features of each token through a pointwise convolution in Ghost Module, and then we use a depthwise convolution with a kernel of size $3 \times 3$ to extract the features in the spatial dimension. Finally, we concatenate the outputs of pointwise convolution and depthwise convolution.

We quantitatively analyze the computational overhead reduction brought by MoFFN at various resolutions. And the results are shown in Figure 4. We can see that the FLOPs of MoFFN is about $1.9 \times$ less than vanilla MLP.
Table 1: Comparison of FLOPs and parameters at various resolutions between Vanilla Transformer Block and Mobile Transformer Block (MTB).

| Resolution  | In/Out Channel | Mid Channel | Vanilla Transformer Block | MTB             |
|-------------|----------------|-------------|--------------------------|-----------------|
| [112, 112]  | 160/160        | 960         | 5140M                    | 2361.6M (2.2x↓) |
| [56, 56]    | 160/160        | 960         | 1285M                    | 590.1M (2.2x↓)  |
| [28, 28]    | 160/160        | 960         | 321.2M                   | 147.9M (2.2x↓)  |
| [14, 14]    | 160/160        | 960         | 80.3M                    | 37.3M (2.2x↓)   |
| [7, 7]      | 160/160        | 960         | 20.1M                    | 9.6M (2.1x↓)    |

3.3 Enhancing Lightweight Networks with Mobile Self-Attention and Mobile Feed Forward Network.

In this section, we first introduce the Mobile Transformer Block (MTB), which consists of our proposed MoSA and MoFFN. Then we introduce how we use mobile transformer blocks to build an efficient MoCoViT.

**Mobile Transformer Block (MTB).** Taking the advantages of MoSA and MoFFN, we introduce the Mobile Transformer Block specially designed for lightweight deep models. As shown in Figure 2, the vanilla transformer block consists of alternating layers of multi-head self-attention (MHSA) and MLP layers. LayerNorm (LN) and residual connections is applied before and after every block, respectively. In MTB, we keep the residual connection after each block, but replace vanilla self-attention and vanilla MLP with our proposed MoSA and MoFFN. In addition, we remove the inefficient LayerNorm before the attention and MLP part and replace it with batch normalization (BN) inside Ghost module. BN is a mobile-friendly normalization operation as it can be merged with convolutional layers at the deployment time.

Benefiting from the lightweight design of MoSA and MoFFN, our MTB has less computational overhead than vanilla transformer blocks. As shown in Table 1, FLOPs of MTB is about 2.2× less than vanilla transformer block.

**Building efficient networks with Mobile Transformer Block.** In this part, we introduce how to use MTB to build our proposed lightweight network MoCoViT that combines convolutional networks and transformer networks.

As shown in Figure 2, our MoCoViT adopts feature pyramid structure, where the resolution of feature maps decreases with network depth while the channel number increases. We divide the whole architecture into 4 stages and we only use MTB in the deepest stage. This is mainly based on two considerations: First, the computational complexity of self-attention is quadratic with the spatial resolution. In the shallow stages, features have high spatial resolution, which leads to large computational overhead and memory consumption. Second, in the early stages of lightweight networks, building a global representation is a relatively difficult task due to the limited representation capability of the network. The advantage of transformer blocks is to extract global information, while CNNs...
are good at extracting local information. Therefore, in the shallow layers of the network, using CNN block helps to improve the efficiency of feature extraction.

Table 2: Architecture of our MoCoViT. G-bneck denotes Ghost bottleneck. MTB denotes our mobile transformer block. Exp means expansion size. Out denotes the output channel of a block. Stride denotes the stride of the first block in a stage.

| Input shape | Operator | Exp | Out | Stride |
|-------------|----------|-----|-----|--------|
| 224^2 × 3   | Conv2d 3 × 3 | -   | 16  | 2      |
| 112^2 × 16  | G-bneck 16  | 16  | 16  | 1      |
| 112^2 × 16  | G-bneck 48  | 48  | 24  | 2      |
| 56^2 × 24   | G-bneck 72  | 72  | 24  | 1      |
| 56^2 × 24   | G-bneck 72  | 72  | 40  | 2      |
| 28^2 × 40   | G-bneck 120 | 120 | 40  | 1      |
| 28^2 × 40   | G-bneck 240 | 240 | 80  | 2      |
| 14^2 × 80   | G-bneck 200 | 200 | 80  | 1      |
| 14^2 × 80   | G-bneck 184 | 184 | 80  | 1      |
| 14^2 × 80   | G-bneck 184 | 184 | 80  | 1      |
| 14^2 × 112  | G-bneck 480 | 480 | 112 | 1      |
| 14^2 × 112  | G-bneck 672 | 672 | 112 | 1      |
| 14^2 × 112  | G-bneck 672 | 672 | 160 | 2      |
| 7^2 × 160   | MTB 960    | 960 | 160 | 1      |
| 7^2 × 160   | MTB 960    | 960 | 160 | 1      |
| 7^2 × 160   | MTB 960    | 960 | 160 | 1      |
| 7^2 × 160   | MTB 960    | 960 | 160 | 1      |
| 7^2 × 160   | Conv2d1 × 1| -   | 960 | 1      |
| 7^2 × 960   | Avg-Pool  - | -   | -   | -      |
| 1^2 × 960   | Conv2d1 × 1| -   | 1280| 1      |
| 1^2 × 1280  | FC 1000    | -   | 1000| -      |

The structural details of our MoCoViT are shown in Table 2. We use Ghost bottleneck in the early stages, which is widely used in mobile devices (e.g. smart phones and self-driving cars). All the Ghost bottlenecks are applied with stride=1 except that the last one in each stage with stride=2. Our proposed MTB is used in the final stage. At last a global average pooling and a convolutional layer are utilized to transform the feature maps to a 1280-dimensional feature vector for final classification.

To further improve the performance, we introduce the dynamic ReLU activation function to build the MoCoViT-D model. The overall framework of the network is the same as MoCoViT. But we replace the ReLU activation function with the dynamic ReLU function.
functions with dynamic ReLU both in the transformer block and CNN block. We train MoCoViT-D using a different strategy from that of MoCoViT and achieve higher accuracy on the ImageNet-1K dataset. Details will be introduced in the next section.

4 Experiments

In the following parts, we compare the proposed model with other previous state-of-the-arts on ImageNet-1K and COCO. Next, we conduct ablation studies to verify the effectiveness of each key component.

4.1 Classification on ImageNet-1K

To verify the superiority of the proposed MoCoViT, we conduct experiments on ImageNet classification task. We follow most of the settings used in GhostNet, except that the initial learning rate is set to 0.5 while batch size is 1,024. All the results are reported with single crop accuracy on ImageNet validation set. Several SOTA mobile network architectures are selected as competitors, including GhostNet series, MobileNet series, ShuffleNet series, and etc. All the networks are trained on 8 Tesla V100 GPUs.

And for a fair comparison, we use two different training settings for MoCoViT and MoCoViT-D.

Basic Training Setup. For MoCoViT we use the basic setting without training tricks. Specifically, all models are trained for 360 epochs with the input size of 224 × 224. We use the SGD optimizer with weight decay of $4 \times 10^{-5}$. The batch size and initial learning rate are set to 1024 and 0.5, and the cosine learning rate scheduler with 5 epochs linear warm-up is used. Extra data augmentations such as Mixup and autoaugment are not used.

Advanced Training Setup. For the MoCoViT-D family with dynamic ReLU, we adopt a more advanced training strategy with longer training process and stronger data augmentation. All models are trained from scratch using SGD optimizer for 450 epochs. Data augmentation includes autoaugment, Mixup, and Cutmix. Input image size is still 224 × 224 and the weight decay is set to $8 \times 10^{-5}$. The cosine learning rate scheduler with 5 epochs linear warm-up is used, while batch size and initial learning rate are set to 1024 and 0.5.

Comparison with State-of-the-art Mobile Models. In Table we compare our MoCoViT Transformer with state-of-the-art CNN and Transformer architectures. These models are divided into two groups. In the first group, we compare MoCoViT with CNN models without dynamic ReLU, and their training settings are basically the same as the basic training setup. In the second
group we compare MoCoViT with mobile transformer network. Our advanced training setup is similar to the training strategy adopted by Mobile-Former[5].

For the SOTA mobile CNNs, we present three models MoCoViT 0.5×, MoCoViT 1.0× and MoCoViT 1.3× according to GhostNet[15]. As shown in the first group in Table 3, it can reach significantly higher accuracy with lower FLOPs compared to manually designed CNNs. In particular, MoCoViT 0.5× achieves 67.6% with 44M FLOPs, which surpasses MobileNetV2(0.35X) top-1 accuracy by 7.3% while much faster (from 59M FLOPs to 44M FLOPs). Compared with MobileNetV3 Large 0.75×, ours MoCoViT 1.0× improves the accuracy by 1.2% but still less complexity (from 155M FLOPs to 147M FLOPs).

For the SOTA mobile transformers, we present four models MoCoViT-D 0.3×, MoCoViT-D 0.5×, MoCoViT-D 1.0× and MoCoViT-D 1.2×. Compared to SOTA manually designed mobile Transformers, as shown in the second group in Table 3, it can reach significantly higher accuracy with lower FLOPs. In particular, the top-1 accuracy of MoCoViT-D 0.3× is 64.3%, which is 0.3% higher than its counterpart Mobile-Former-26M. MoCoViT-D 0.5× achieves 68.9% top-1 accuracy, which is 0.2% higher than Mobile-Former-52M with lower FLOPs. MoCoViT-D 1.0× achieves 75.5% top-1 accuracy, 0.3% higher than Mobile-Former-151M with similar FLOPs.

4.2 COCO Object Detection and Instance Segmentation

In order to further evaluate the generalization ability of MoCoViT, we conduct object detection experiments on the COCO2017 dataset[24]. We use the train-val35k split as training data and report the results in mean Average Precision (mAP) on minival split, following[7].

**Training Setup.** We verify the model effectiveness on RetinaNet[23], Mask R-CNN[17] detection frameworks using the MMDetection[3] and MoCoViT acts as a drop-in replacement for the backbone feature extractor. All models utilize the same settings as [7]: AdamW[26] optimizer, 1× (12epoch) schedule with a global batch-size of 16 on 8 GPUs. The input images are resized to a short side of 800 and a long side not exceeding 1333. And the FLOPs are calculated using 224 × 224 images as common practice.

**Comparison with State-of-the-art Mobile Models.** As shown in Table 4, for object detection with RetinaNet, MoCoViT surpass MobileNetV3[19] by 4.2% mAP and surpass GhostNet by 2.1% mAP with similar computational cost. As stated in Table 5, for object detection with the Mask R-CNN framework, MoCoViT brings similar improvements over MobileNetV3 and GhostNet. Compared with GhostNet, MoCoViT obtains 2.2% higher mAP, which also surpasses MobileNetV3 by 1.0% mAP. For instance segmentation with Mask R-CNN framework, the mAP of of MoCoViT is 28.9, which is 1.9% higher than GhostNet.
Table 3: Comparison with the state-of-the-arts on ImageNet under mobile setting.

| Model                  | Params | FLOPs | Top-1 Acc (%) |
|------------------------|--------|-------|---------------|
| ShuffleNetV1 0.5×      | 1.0M   | 40M   | 58.8          |
| MobileNetV2 0.35×      | 1.7M   | 59M   | 60.3          |
| ShuffleNetV2 0.5×      | 1.4M   | 41M   | 61.1          |
| MobileNetV3 Small 0.75×| 2.4M   | 44M   | 65.4          |
| GhostNet 0.5×          | 2.6M   | 42M   | 66.2          |
| **MoCoViT 0.5×**       | 2.6M   | 44M   | **67.6**      |
| MobileNetV1 0.5×       | 1.3M   | 150M  | 63.3          |
| MobileNetV2 0.6×       | 2.2M   | 141M  | 66.7          |
| ShuffleNetV1 1.0× (g=3)| 1.9M   | 138M  | 67.8          |
| ShuffleNetV2 1.0×      | 2.3M   | 146M  | 69.4          |
| MobileNetV3 Large 0.75×| 4.0M   | 155M  | 73.3          |
| GhostNet 1.0×          | 5.2M   | 141M  | 73.9          |
| **MoCoViT 1.0×**       | 5.3M   | 147M  | **74.5**      |
| MobileNetV2 1.0×       | 3.5M   | 300M  | 71.8          |
| ShuffleNetV2 1.5×      | 3.5M   | 299M  | 72.6          |
| FE-Net 1.0×            | 3.7M   | 301M  | 72.9          |
| FBNet-B 37             | 4.5M   | 295M  | 74.1          |
| ProxylessNAS 1         | 4.1M   | 320M  | 74.6          |
| MnasNet-A1 32          | 3.9M   | 312M  | 75.2          |
| MobileNetV3 Large 1.0× | 5.4M   | 219M  | 75.2          |
| GhostNet 1.3×          | 7.3M   | 226M  | 75.7          |
| **MoCoViT 1.3×**       | 7.6M   | 237M  | **76.1**      |
| Mobile-Former-26M 5    | 3.2M   | 26M   | 64.0          |
| **MoCoViT-D 0.3×**     | 4.4M   | 24M   | **64.3**      |
| Mobile-Former-52M 5    | 3.5M   | 52M   | 68.7          |
| **MoCoViT-D 0.5×**     | 5.8M   | 47M   | **68.9**      |
| Mobile-Former-151M 5   | 7.6M   | 151M  | 75.2          |
| **MoCoViT-D 1.0×**     | 12.1M  | 154M  | **75.5**      |
| MobileViT-XXS 28       | 1.3M   | 450M  | 69.0          |
| MobileViT-XS 28        | 2.4M   | 950M  | 74.8          |
| Mobile-Former-214M 5   | 9.4M   | 214M  | 76.7          |
| **MoCoViT-D 1.2×**     | 15.6M  | 215M  | **77.0**      |

Table 4: Results on COCO2017 object detection using the RetinaNet framework.

| Model       | Backbone FLOPs | RetinaNet |
|-------------|----------------|-----------|
|             |                | AP | AP$_{50}$ | AP$_{75}$ | AP$_S$ | AP$_M$ | AP$_L$ |
| MobileNetV3 | 147M           | 26.1| 42.2 | 27.1 | 14.6 | 29.6 | 34.8 |
| GhostNet    | 148M           | 28.2| 45.3 | 29.5 | 15.1 | 29.3 | 39.5 |
| **MoCoViT** | 154M           | **30.3**| **48.5**| **31.3**| **16.9**| **32.3**| **41.3**|
Table 5: Results on COCO object detection and instance segmentation using the Mask R-CNN framework. The superscript $b$ refers to detection results, and $m$ refers to instance segmentation results.

| Model       | Backbone | FLOPs | Mask R-CNN | AP$^b_{50}$ | AP$^b_{75}$ | AP$^m_S$ | AP$^m_M$ | AP$^m_L$ | AP$^m_{50}$ | AP$^m_{75}$ | AP$^m_S$ | AP$^m_M$ | AP$^m_L$ |
|-------------|----------|-------|------------|-------------|-------------|---------|---------|---------|-------------|-------------|---------|---------|---------|
| MobileNetV3 | 190      | 147   | 29.6       | 49.3        | 31.2        | 16.6    | 32.0    | 38.7    | 28.3        | 46.8        | 29.5    | 14.7    | 30.7    | 38.2    |
| GhostNet    | 15       | 148   | 28.4       | 47.1        | 30.0        | 14.6    | 29.6    | 37.8    | 27.0        | 44.7        | 28.4    | 12.6    | 28.6    | 36.9    |
| MoCoViT     | 154      | 154   | 30.6       | 50.0        | 32.6        | 17.4    | 33.0    | 40.6    | 28.9        | 47.4        | 30.3    | 15.5    | 31.2    | 39.6    |

4.3 Ablation Study

To understand our MoCoViT better, we ablate each critical design by evaluating their performance on ImageNet-1K classification.

Impact of MTB at different stages. We compare the accuracy of using Mobile Transformer Block at different stages, and the results are shown in Table 6. It is worth mentioning that when mobile self-attention is used in the shallow layers, the memory footprint of the model increases significantly, and the training batch size is therefore reduced.

Table 6: Comparison of results of different positions of self-attention on MoCoViT 1.0×. All models are trained under basic training setup for 180 epoch. Stage 1 results is not shown because the training time is too long to be acceptable.

| Position | Feature Size | Batch Size per GPU | Params | FLOPs  | Top-1 Acc (%) |
|----------|--------------|-------------------|--------|--------|---------------|
| Stage 1  | 112×112      | 4                 | 5.2M   | 149M   |               |
| Stage 2  | 56×56        | 32                | 5.2M   | 145M   | 73.5          |
| Stage 3  | 28×28        | 128               | 5.2M   | 144M   | 73.5          |
| Stage 4  | 14×14        | 128               | 5.2M   | 149M   | 73.8          |
| Stage 5  | 7×7          | 128               | 5.3M   | 147M   | **74.1**      |

Impact of MoSA and MoFFN. Our MoCoViT contains two important designs: MoSA and MoFFN. To demonstrate their importance, we train GhostNet 0.5× for 180 epochs under basic training setup as a baseline. We then compare different types of self-attention mechanisms to evaluate the performance gains. The result is shown in Table 7.

Impact of Normalization. Furthermore, we compare the performance of batch normalization(BN) and layer normalization(LN) in different positions. As stated
in Table 8, putting BN after the convolution operation of the self-attention and MLP modules leads to higher accuracy, and it is also beneficial for merging BN and convolution layers at deployment time for further speed up.

Table 7: Comparison of results of different self-attention mechanism. All models are trained under basic training setup for 180 epochs.

| Model            | Vanilla MLP | MoFFN | Vanilla SA | MoSA | Param(M) | FLOPs(M) | Top-1 Acc(%) |
|------------------|-------------|-------|------------|------|----------|----------|--------------|
| GhostNet 0.5×    | -           | -     | -          | -    | 2.6      | 42.6     | 64.9         |
| MoCoViT 0.5×     | √           |       | √          | -    | 2.7      | 47.7     | 65.0         |
|                  | √           |       | √          | √    | 2.6      | 44.0     | 65.4         |

Table 8: Comparison of results of Normalization placed in different positions.

| Model        | LN ahead | BN ahead | BN inside |
|--------------|----------|----------|-----------|
| MoCoViT 0.5× | 66.0     | 65.6     | 66.7      |
| MoCoViT 1.0× | 73.7     | 73.3     | 74.1      |

5 Conclusion

In this paper, we design a novel efficient Mobile Transformer Block (MTB). The block consists of two important modules: Mobile Self-Attention (MoSA) and Mobile Feed Forward Network (MoFFN). MoSA simplifies the calculation of the attention map through the Branch Sharing mechanism, avoiding computing Q and K in self-attention, and computes the attention map by reusing V. The FLOPs of MoSA is 3.6× less than vanilla self-attention. In addition, the proposed MoFFN can also greatly reduce the computation of vanilla MLP and can be seen as its mobile version. Different from vanilla, MoFFN has the perception ability of spatial dimension. It has a larger receptive field than vanilla MLP. In addition to extracting features of token channel dimension, it can also perform feature fusion in spatial dimension.

Equipped with MTB, we build the lightweight transformer network MoCoViT and MoCoViT-D that combines convolutional networks and transformer networks. Extensive experiments demonstrate that the introduced MoCoViT family outperform state-of-the-art portable lightweight CNNs and transformers on various vision tasks while maintaining computational efficiency.
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