# **RepViT: Revisiting Mobile CNN From ViT Perspective**

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## **Abstract**

Recently, lightweight Vision Transformers (ViTs) demonstrate superior performance and lower latency compared with lightweight Convolutional Neural Networks (CNNs) on resource-constrained mobile devices. This improvement is usually attributed to the multi-head self-attention module, which enables the model to learn global representations. However, the architectural disparities between lightweight ViTs and lightweight CNNs have not been adequately examined. In this study, we revisit the efficient design of lightweight CNNs and emphasize their potential for mobile devices. We incrementally enhance the mobilefriendliness of a standard lightweight CNN, specifically MobileNetV3, by integrating the efficient architectural choices of lightweight ViTs. This ends up with a new family of pure lightweight CNNs, namely RepViT. Extensive experiments show that RepViT outperforms existing state-of-theart lightweight ViTs and exhibits favorable latency in various vision tasks. On ImageNet, RepViT achieves over 80% top-1 accuracy with nearly 1ms latency on an iPhone 12, which is the first time for a lightweight model, to the best of our knowledge. Our largest model, RepViT-M3, obtains 81.4% accuracy with only 1.3ms latency. The code and trained models are available at https://github. com/jameslahm/RepViT.

# 1. Introduction

Research on lightweight models has been a focal point in computer vision tasks, driven by the objective of achieving superior model performance with reduced computational cost. This is particularly relevant for resource-limited mobile devices, enabling the deployment of visual models at the edge. In the past decade, researchers have mainly focused on the design of lightweight convolutional neural networks (CNNs), and have made significant progress. Many efficient design principles are proposed, including separable

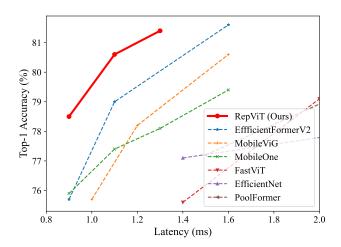


Figure 1. Comparison of latency and accuracy between RepViT (Ours) and other lightweight models. The top-1 accuracy is tested on ImageNet-1K and the latency is measured by iPhone 12 with iOS 16. RepViT achieves high performance with low latency across various model sizes.

convolutions [20], inverted residual bottleneck [43], channel shuffle [34, 63], and structural reparameterization [11], resulting in representative models like MobileNets [19, 20, 43], ShuffleNets [34, 63], and RepVGG [11].

In recent years, Vision Transformers (ViTs) [13] have emerged as a promising alternative to CNNs for learning visual representations. They show superior performance compared with CNNs on various computer vision tasks, such as image classification [31,52], semantic segmentation [4,56] and object detection [2,25]. However, the trend of increasing the number of parameters in ViTs to improve performance results in large model sizes and high latency [8,30], which makes them unsuitable for resource-constrained mobile devices [26,35]. Although reducing the model size of ViT models to match the constraints of mobile devices is possible, their performance is often suboptimal compared to lightweight CNNs [3]. Therefore, researchers have embarked on exploring the lightweight design of ViTs, aim-

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ing to achieve performance surpassing that of lightweight CNNs.

Many efficient design principles for ViTs have been proposed, greatly enhancing the computational efficiency of ViTs for mobile devices [3,24,35,38]. For example, some approaches propose innovative architectures that combine convolutional layers with ViTs, resulting in hybrid networks [3,35]. Additionally, new self-attention operations with linear complexity have been introduced to improve efficiency [36], and dimension-consistent design principles have been employed in [24, 26]. These studies demonstrate that lightweight ViTs [24, 36, 38] can achieve lower latency on mobile devices while outperforming lightweight CNNs [19, 43, 50] in terms of performance.

These lightweight ViTs exhibit certain structural similarities with previous lightweight CNNs. For instance, the convolutional module is used to construct some stages [26, 35, 36]. The depthwise and pointwise convolutions are employed to learn spatially local representations [35, 36, 38, 51]. Consequently, the reason why lightweight CNNs underperform lightweight ViTs is usually attributed to the multi-head self-attention module, which enables the model to learn global representations [24, 26, 35, 36, 38]. On the other hand, there are noteworthy differences in the block structure, macro, and micro architectural designs between lightweight ViTs and lightweight CNNs, which have yet to receive sufficient inquiry. This naturally raises a question: Can architectural choices of lightweight ViTs enhance lightweight CNNs' performance? In this work, we revisit the design of lightweight CNNs by incorporating the architectural choices of lightweight ViTs. Our research aims to narrow the divide between lightweight CNNs and lightweight ViTs, and highlight the potential of the former for employment on mobile devices compared to the latter.

To accomplish this objective, following [32], we begin with a standard lightweight CNN, i.e., MobileNetV3-L [19]. We gradually "modernize" its architecture by incorporating the efficient architectural designs of lightweight ViTs [24, 26, 29, 35]. Finally, we obtain a new family of lightweight CNNs, namely RepViT, for resourceconstrained mobile devices. RepViT has a MetaFormer [58] structure, but is composed entirely of convolutions. Surprisingly, as a pure lightweight CNN, RepViT shows superior performance and efficiency compared with existing state-of-the-art lightweight ViTs [24, 38] on various computer vision tasks, including imagenet classification on ImageNet [9], object detection and instance segmentation on COCO-2017 [27], and semantic segmentation on ADE20k [66]. Notably, RepViT reaches over 80% top-1 accuracy on ImageNet, with nearly 1ms latency on an iPhone 12, which is the first time for a lightweight model, to the best of our knowledge. We hope that RepViT can serve as a strong baseline and inspire further research into lightweight

models for edge deployments.

# 2. Related Work

In the past decade, Convolutional Neural Networks (CNNs) have emerged as the predominant approach for computer vision tasks due to their natural inductive biases of locality and translation equivalence. However, the extensive computation required by standard CNNs renders them unsuitable for deployment on resource-constrained mobile devices. To overcome this challenge, numerous techniques have been proposed to make CNNs more lightweight and mobile-friendly, including separable convolutions [20], inverted residual bottleneck [43], channel shuffle [34, 63], mixed depthwise convolution [47], network architecture search [45] and structural reparameterization [11], among others. These methods have paved the way for the development of widely used lightweight CNNs, such as MobileNets [19, 20, 43], ShuffleNets [34, 63], MixNet [47], MNASNet [45] and RepVGG [11].

Subsequently, the Vision Transformer (ViT) [13] was introduced, which adapts the transformer architecture to achieve state-of-the-art performance on large-scale image recognition tasks, surpassing that of CNNs [13, 48]. DeiT represents a further improvement in the ViT training recipe by leveraging distillation, thereby eliminating the need for large-scale datasets [48]. Building on the competitive performance of ViTs, subsequent works have sought to incorporate spatial inductive biases to enhance their stability and performance [7,16], design more efficient self-attention operations by regularizing the pattern of attention mechanisms [12,67], and adapt ViTs to a diverse range of computer vision tasks [14,62].

Although ViTs have shown superior performance over CNNs on various vision tasks, most of these models are heavy-weight, requiring substantial computation and memory footprint [31, 48, 52]. This makes them unsuitable for mobile devices with limited resources [35, 38]. Consequently, researchers have dedicated to exploring various techniques to make ViTs more lightweight and more friendly for mobile devices [26, 36, 49, 51]. For example, MobileViT [35] adopts a hybrid architecture, combining lightweight MobileNet blocks and MHSA MobileViT2 [36] further presents a separable self-attention methods to alleviate the quadratic computation complexity of MHSA. EfficientFormer [26] proposes a dimension-consistent design paradigm to enhance the latency-performance boundary of pure ViTs. Mobile-Former [3] introduces a parallel architecture which parallelizes MobileNet and transformer with a two-way bridge. These lightweight ViTs have demonstrated new state-ofthe-art performance in terms of accuracy and latency on mobile devices, outperforming the lightweight CNNs [43, 50].

The reason why lightweight ViTs outperform

lightweight CNNs is usually attributed to the multihead self-attention module with the capability of learning global representations. However, the notable architectural distinctions between lightweight CNNs and lightweight ViTs, such as their block structures, as well as macro and micro elements, have not been thoroughly investigated. As such, diverging from extant research, our primary goal is to revisit the design of lightweight CNNs by integrating the architectural choices of lightweight ViTs. We aim to bridge the gap between lightweight CNNs and lightweight ViTs, and emphasize their mobile-friendliness.

# 3. Methodology

In this section, we begin with a standard lightweight CNN, i.e., MobileNetV3-L, and then gradually modernize it from various granularities by incorporating the architectural designs of lightweight ViTs. We first introduce the metric to measure the latency on mobile devices, and then align the training recipe with existing lightweight ViTs in Section 3.1. Based on the consistent training setting, we explore the optimal block design in Section 3.2. We further optimize the performance of MobileNetV3-L on mobile devices from macro-architectural elements in Section 3.3, i.e., stem, downsample layers, classifier and overall stage ratio. We then tune the lightweight CNN through layer-wise micro designs in Section 3.4, involving kernel size selection and squeeze-and-excitation (SE) layer [21] optimal placement. Figure 2 shows the whole procedure and results we achieve in each step. Finally, we obtain a new family of pure lightweight CNNs designed for mobile devices in Section 3.5, namely RepViT, as shown in Figure 3. All models are trained and evaluated on ImageNet.

# 3.1. Preliminary

Latency metric. Previous researches [3,46] have focused on optimizing the inference speed of models through metrics such as floating point operations (FLOPs) or model sizes. However, these metrics do not always correlate well with real-world latency in mobile applications. To address this issue, we follow [24,26,35,50] and utilize the iPhone 12 as the test device and Core ML Tools [1] as the compiler. We measure the actual on-device latency for models as the benchmark metric. This approach provides a more accurate representation of the model's performance on real-world mobile devices. Besides, due to that the Hardswish nonlinearity used in MobileNetV3-L is not well supported by the compiler, we follow [26,50] to employ GeLU activations in the MobileNetV3-L model.

We measure the on-device latency of MobileNetV3-L to be 1.01ms.

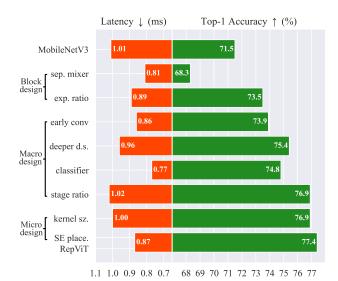


Figure 2. We modernize MobileNetV3-L from various granularities. We mainly consider the latency on mobile devices and the top-1 accuracy on ImageNet. Finally, we obtain a new family of pure lightweight CNNs, namely RepViT, which can achieve lower latency and higher performance.

Aligning training recipe. In the pytorch official published training recipe<sup>1</sup>, MobileNetV3-L is trained using RMSPropOptimizer with 0.9 momentum for 600 epochs, with auto-augmentation [5] and random erasing [65] data augmentation techniques, resulting in 74.0% top-1 accuracy. Recent lightweight ViTs [24, 26, 35, 38] generally adopt the training recipe from DeiT. Specifically, they use AdamW optimizer [33], warmup training with 5 epochs, and a cosine annealing learning rate schedule for 300 epochs, with a teacher of RegNetY-16GF [41] for distillation. They adopt Mixup [60], auto-augmentation [5], and random erasing [65] for data augmentation, and Label Smoothing [44] as the regularization scheme. Therefore, for a fair comparison, we first align the training recipe of MobileNetV3-L with other lightweight ViTs, with the exception of excluding distillation for now. Under 300 training epochs, MobileNetV3-L obtains 71.5% top-1 accuracy. Despite the observed decrease in accuracy, we adopt this training recipe to ensure fairness.

We will now use this training recipe by default.

## 3.2. Block design

**Separate token mixer and channel mixer.** The block structure of lightweight ViTs [24,26,36] incorporates an important design feature, namely the separate token mixer and channel mixer [59]. According to recent research [58], the effectiveness of ViTs primarily originates from their general token mixer and channel mixer architecture, namely

<sup>&</sup>lt;sup>1</sup>https://github.com/pytorch/vision/tree/main/references/classification

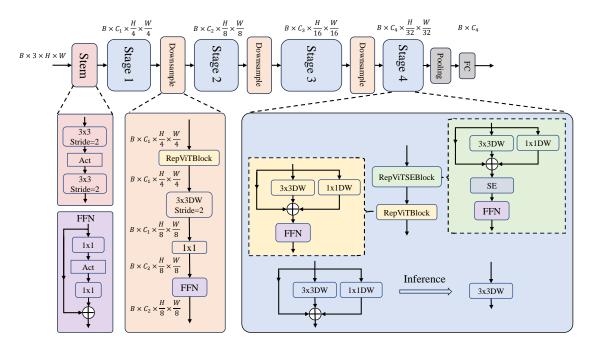


Figure 3. The overview of RepViT architecture. RepViT has four stages with  $\frac{H}{4} \times \frac{W}{4}$ ,  $\frac{H}{8} \times \frac{W}{8}$ ,  $\frac{H}{16} \times \frac{W}{16}$ ,  $\frac{H}{32} \times \frac{W}{32}$  resolutions respectively, where H and W denote the width and height of the input image.  $C_i$  represents the channel dimension of the i-th stage and B denotes the batch size.

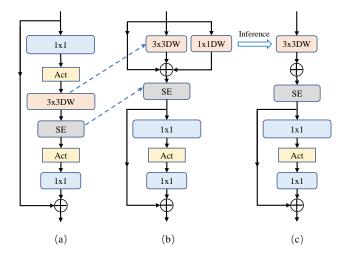


Figure 4. (a) represents a block of MobileNetV3 with an optional squeeze-and-excite layer. In (b), we employ structural reparameterization to separate the token mixer and channel mixer by relocating the depthwise convolution and squeeze-and-excite layer. (c) involves the consolidation of the multi-branch topology into a single branch during the inference stage.

MetaFormer architecture, rather than the specific token mixer with which they are equipped. In light of this finding, we aim to emulate existing lightweight ViTs by splitting the token mixer and channel mixer in MobileNetV3-L.

Specifically, as depicted in Figure 4.(a), the original Mo-

bileNetV3 block consists of a 1x1 expansion convolution, followed by a depthwise convolution and a 1x1 projection layer. The residual connection connects the input and output. Moreover, the squeeze and excitation modules may be optionally placed after the depthwise filters in the expansion. It is intuitive that the 1x1 expansion convolution and 1x1 projection layer enable interaction between channels, while the depthwise convolution facilitates the fusion of spatial information. The former and the latter correspond to the channel mixer and token mixer, respectively. The token mixer and channel mixer are now coupled together in the MobileNetV3 block. Therefore, as shown in Figure 4.(b), we move the depthwise convolution up to split them. Meanwhile, we employ structural reparameterization [11] to introduce a multi-branch topology for the depthwise filters at training time to improve performance. The squeeze and excitation module is also moved up to be placed after the depthwise filters, as it depends on spatial information interaction. Consequently, we successfully separate the token mixer and channel mixer in the MobileNetV3 block. Additionally, during inference, as illustrated in Figure 4.(c), the multi-branch topology of the token mixer is merged into a single depthwise convolution. We thus can eliminate the computational and memory costs associated with the skip connection, which is especially advantageous for mobile devices. We name such a block as RepViT block, which reduces the latency of MobileNetV3-L to 0.81ms, resulting in a temporary performance degradation to 68.3%.

We will now employ the RepViT block.

Reducing expansion ratio and increasing width. In ViTs, the channel mixer typically employs an expansion ratio of 4, meaning that the hidden dimension of the MLP block is four times wider the than input dimension in FFN. It thus consumes a significant portion of the computation resource, thereby contributing substantially to the overall inference time [64]. To alleviate this bottleneck, recent efficient and lightweight ViTs explore narrower FFN. For instance, LV-ViT [23] adopts a expansion ratio of 3 in FFN. LeViT [15] sets the expansion ratio to 2. Besides, based on the taylor structured pruning for ViTs [57], it shows that a significant amount of channel redundancy presents in FFN, providing experimental evidence for using a smaller expansion ratio.

In MobileNetV3-L, the expansion ratio ranges from 2.3 to 6, with a concentration of 6 in the last two stages that have a greater number of channels, which indicates a significant redundancy in the RepViT block. Therefore, we follow [23, 29] to set the expansion ratio to 2 in the channel mixer, to reduce the parameter redundancy and latency. This results in a latency reduction to 0.65ms for MobileNetV3-L. Moreover, with the smaller expansion ratio, we can increase the network width with minimal latency increase. Specifically, following [17, 32], we double the channels after each stage, ending up with 48, 96, 192, and 384 channels for each stage, respectively. This increases the top-1 accuracy to 73.5% with a latency of 0.89ms.

We will now employ the new expansion ratio and network width.

# 3.3. Macro design

In this part, we carry out optimizations with a specific focus on its macro-architecture for mobile devices, from the front to the back of the network.

Early convolutions for stem. ViTs typically use a patchify operation as the stem, dividing the input image into non-overlapping patches [13]. This simple stem corresponds to a non-overlapping convolution with a large kernel size (e.g. kernel size=16) and a large stride (e.g. stride = 16). Hierarchical ViTs [31, 52] adopt the same patchify operation, but with a smaller patch size of 4. However, recent work in [55] shows that the patchify operation results in ViTs' substandard optimizability and sensitivity to training recipes. To address these issues, they suggest using a small number of stacked stride-two 3\*3 convolutions as an alternative architectural choice for the stem, known as early convolutions. This approach is then widely adopted by lightweight ViTs [24,26,29]. In contrast, MobileNetV3-L leverages a more complex stem for a  $4 \times$  downsampling of the input image. As shown in Figure 5.(a), the stem

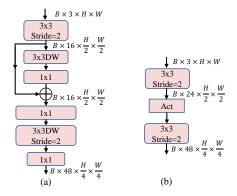


Figure 5. (a) is the original stem in MobileNetV3-L, with the nonlinearity omitted for simplicity. We use early convolutions as the stem in (b).

consists of a 3x3 convolution, a depthwise separable convolution, and an inverted bottleneck. However, a complex stem introduces significant latency bottlenecks on mobile devices, especially since it must process the input image at the highest resolution. As a trade-off, MobileNetV3-L reduces the initial number of filters to 16, which in turn limits the representation power of the stem. To address this issue, we replace the original stem with early convolutions, as shown in Figure 5.(b). Although the initial number of filters is increased to 24, the overall latency is reduced to 0.86ms. Meanwhile, this step brings the top-1 accuracy to 73.9%.

We will now use early convolutions as the stem.

Deeper downsampling layers. In ViTs, spatial downsampling is typically achieved by a separate patch merging layer. It corresponds to a convolution with a kernel size 4 and a stride of 2. As demonstrated in [32], a separate downsampling layer facilitates an increase in network depth and mitigates the information loss resulting from resolution reduction. For example, EfficientViT [29] adopts a sandwich layout to deepen the downsampling layer, achieving efficient subsampling. In contrast, MobileNetV3-L achieves downsampling by using the depthwise convolution with stride 2 in the inverted bottleneck block, as illustrated in Figure 6.(a). After applying the RepViT block design, the depthwise convolution with stride 2 reduces the spatial resolution, and two 1x1 convolutions increases the number of channels, as shown in Figure 6.(b). To achieve a separate and deeper downsampling layer, we first employ a single 1x1 convolution to modulate the channel dimensionality, which is positioned after the depthwise convolution, as shown in Figure 6.(c). As a result, the input and output of the two 1x1 convolution in Figure 6.(b) can be connected by a residual connection, forming a FFN. Additionally, we prepend a RepViT block to further deepen the downsam-

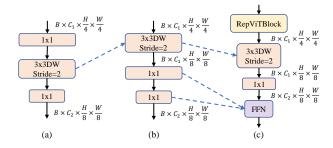


Figure 6. (a) is the original downsampling layer in the MobileNetV3-L block. It changes to (b) after adopting the RepViT block design. In (c), feature map resolution and channel dimensionality are modulated through the separate use of depthwise convolution and 1x1 convolution, respectively. The resulting downsampling layer is deepened through the incorporation of a RepViT block at the front and a FFN at the back, enhancing its overall architecture. The nonlinearity is omitted for simplicity

pling layer, to alleviate the information loss on the spatial dimension. This step brings the top-1 accuracy to 75.4% with a latency of 0.96ms.

We will now leverage the deeper downsampling layer.

Simple classifier. In lightweight ViTs [15, 26, 35], the classifier generally consists of a global average pooling layer followed by a linear layer. The classifier involves processing feature maps with the highest number of channels, and such a simple classifier is thus friendly to the latency, especially for mobile devices. In contrast, MobileNetV3-L adopts a more complex classifier, which employ one extra 1x1 convolution and one extra linear layer to expand the features to a higher-dimensional space to give the network a stronger fitting ability [6], as shown in Figure 7.(a). The incorporation of additional layers in the classifier of the original MobileNetV3-L is crucial for generating rich predictive features [19], particularly given the small output channel in the final stage. However, they in turn result in a latency bottleneck for mobile devices. Due to that the final stage now has more channels in Section 3.2, we thus replace it with a simple classifier, i.e., a global average pooling layer and a linear layer, as shown in Figure 7.(b). This step reduces the latency to 0.77ms with a top-1 accuracy of 74.8%.

We will now employ the simple classifier.

Overall stage ratio. Stage ratio represents the ratio of the number of blocks in different stages, thereby indicating the distribution of computation across the stages. Previous works [40, 41] have shown that the utilization of more blocks in the third stage confers a favorable balance between the accuracy and speed, which is generally adopted by lightweight ViTs. For example, EfficientFormer-L2 [26] employ a stage ratio of 1:1:3:1.5. Meanwhile,

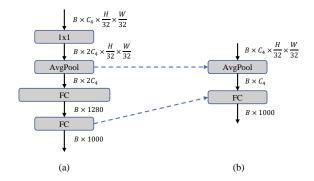


Figure 7. (a) is the original classifier in the MobileNetV3-L block. In (b), we adopt a global average pooling layer and a full connected linear as the classifier .The nonlinearity is omitted for simplicity

Conv2Former [18] shows that a more aggressive stage ratio and a deeper layout perform better for small models. They thus adopt the stage ratio of 1:1:4:1 and 1:1:8:1 for Conv2Former-T and Conv2Former-S, respectively. The original stage ratio of MobileNetV3-L is 1:2:5:2. Therefore, we follow [18] to employ a more optimal stage ratio of 1:1:7:1 for the network. We then increase the network depth to 2:2:14:2, achieving a deeper layout [18, 23]. This step increases the top-1 accuracy to 76.9% with a latency of 1.02ms.

We will use this stage ratio.

#### 3.4. Micro design

In this part, We optimize the network with a focus on its micro-architecture for mobile devices, including kernel size selection and squeeze-and-excitation (SE) layer optimal placement.

**Kernel size selection.** The performance and latency of CNNs are often impacted by the size of the convolution kernel. For example, to model long-range dependencies like MHSA, ConvNeXt [32] employs large kernelsized convolutions and demonstrates a significant performance gain. Similarly, RepLKNet [10] shows a powerful paradigm that utilizes super large convolution kernels in CNNs. However, large kernel-sized convolution is not friendly for mobile devices, due to its computation complexity and memory access costs. Additionally, compared to 3x3 convolutions, larger convolution kernels are typically not highly optimized by compilers and computing libraries [11]. MobileNetV3-L primarily utilizes 3x3 convolutions, with a small number of 5x5 convolutions employed in certain blocks. We thus replace them with 3x3 convolutions, resulting in a latency reduction to 1.00ms while maintaining top-1 accuracy at 76.9%.

We will now use 3\*3 convolutions.

Table 1. Classification performance on ImgeNet-1K. Following [26], latency is measured on iPhone 12 with models compiled by Core ML Tools. Similar to [15,29], throughput is tested on a Nvidia RTX3090 GPU with maximum power-of-two batchsize that fits in memory.

Model	Туре	Params (M)	GMACs	Latency ↓ (ms)	Throughput ↑ (im/s)	Epochs	Top-1(%)
MobileNetV2×1.0 [43]	CONV	3.5	0.3	0.9	6550	300	71.8
MobileViT-XS [35]	Hybrid	2.3	0.7	7.3	2303	300	74.8
EdgeViT-XXS [38]	Hybrid	4.1	0.6	2.4	3719	300	74.4
MobileOne-S1 [50]	CONV	4.8	0.8	0.9	4660	300	75.9
FastViT-T8 [49]	Hybrid	3.6	0.7	1.4	3810	300	75.6
MobileViG-Ti [37]	CNN-GNN	5.2	0.7	1.0	4337	300	75.7
EfficientFormerV2-S0 [24]	Hybrid	3.5	0.4	0.9	1274	300	75.7
RepViT-M1	CONV	5.1	0.8	0.9	4817	300	78.5
MobileNetV2×1.4 [43]	CONV	6.1	0.6	1.2	4369	300	74.7
EfficientNet-B0 [46]	CONV	5.3	0.4	1.4	4608	350	77.1
DeiT-T [48]	Attention	5.9	1.2	9.2	3470	300	74.5
EdgeViT-XS [38]	Hybrid	6.7	1.1	3.6	2773	300	77.5
MobileOne-S2 [50]	CONV	7.8	1.3	1.1	3642	300	77.4
FastViT-T12 [49]	Hybrid	6.8	1.4	2.0	2540	300	79.1
MobileViG-S [37]	CNN-GNN	7.2	1.0	1.2	2985	300	78.2
EfficientFormerV2-S1 [24]	Hybrid	6.1	0.7	1.1	1153	300	79.0
RepViT-M2	CONV	8.2	1.3	1.1	3604	300	80.6
EfficientNet-B3 [46]	CONV	12.0	1.8	5.3	1194	350	81.6
PoolFormer-s12 [58]	Pool	12.0	2.0	1.5	2860	300	77.2
DeiT-S [48]	Attention	22.5	4.5	11.8	1419	300	81.2
PVT-Small [52]	Attention	24.5	3.8	24.4	1165	300	79.8
LeViT-192 [15]	Hybrid	10.9	0.7	29.6	6289	1000	80.0
MobileFormer-508M [3]	Hybrid	14.0	0.5	6.6	2974	450	79.3
UniNet-B1 [28]	Hybrid	11.5	1.1	2.2	2175	300	80.8
EdgeViT-S [38]	Hybrid	11.1	1.9	4.6	1834	300	81.0
MobileOne-S3 [50]	CONV	10.1	1.9	1.3	2861	300	78.1
MobileOne-S4 [50]	CONV	14.8	3.0	1.6	1822	300	79.4
FastViT-S12 [49]	Hybrid	8.8	1.8	2.2	2271	300	79.8
MobileViG-M [37]	CNN-GNN	14.0	1.5	1.6	2491	300	80.6
EfficientFormer-L1 [26]	Hybrid	12.3	1.3	1.4	3360	300	79.2
EfficientFormerV2-S2 [24]	Hybrid	12.6	1.3	1.6	611	300	81.6
RepViT-M3	CONV	10.1	1.9	1.3	2495	300	81.4

Squeeze-and-excitation layer placement. One advantage of self-attention module compared to convolution is the ability to adapt weights according to input, known as the data-driven attribute [22, 54]. As a channel wise attention module, SE layers [21] can compensate for the limitation of convolutions in lacking data-driven attributes, bringing better performance [61]. MobileNetV3-L incorporates SE layers in certain blocks, with a primary focus on the latter two stages. However, as shown in [42], the stages with low-resolution maps get a smaller accuracy benefit from the global average pooling operation that SE provides, compared with stages with higher resolution maps. Meanwhile, along with performance gains, SE layers also introduce non-negligible computational costs. Therefore, we design a strategy to utilize SE layers in a cross-block manner for all stages, to maximizes the accuracy benefit with a minimal latency increment, as shown in Figure 3. This step brings the top-1 accuracy to 77.4% with a latency of 0.87ms.

We will now use this cross-block SE layer placement. This brings our final model, namely RepViT.

#### 3.5. Network architecture

Figure 3 shows the overall architecture of RepViT. Following [26, 35], we develope multiple RepViT variants, namely RepViT-M1/M2/M3. RepViT-M1 is the outcome of the "modernizing" process applied to MobileNetV3-L. The different variants are distinguished by the number of channels and the number of blocks within each stage. Appendix A provides the architecture details of RepViTs.

# 4. Experiments

We implement RepViT based on PyTorch [39] and Timm library [53]. Following [24,26,36,50], we export the model using Core ML Tools and measure its latency on iPhone 12 with iOS 16 by the Xcode performance tool. In addition, we provide throughput analysis on Nvidia RTX3090 GPU. We

Table 2. **Object detection & instance segmentation** results on MS COCO 2017 with the Mask RCNN framework. **Semantic segmentation** results on ADE20K by integrating models into Semantic FPN. Backbone latencies are measured with image crops of 512x512 on iPhone 12 by Core ML Tools.

Backbone	Latency (ms)	AP <sup>box</sup>	Dete AP <sub>50</sub>	ction & In	astance Segr AP <sup>mask</sup>	nentation AP <sub>50</sub> <sup>mask</sup>	$AP^{mask}_{75}$	Semantic mIoU
ResNet18 [17]	4.4	34.0	54.0	36.7	31.2	51.0	32.7	32.9
PoolFormer-S12 [58]	7.5	37.3	59.0	40.1	34.6	55.8	36.9	37.2
EfficientFormer-L1 [26]	5.4	37.9	60.3	41.0	35.4	57.3	37.3	38.9
RepViT-M2	4.9	39.8	61.9	43.5	37.2	58.8	40.1	40.6
ResNet50 [17]	9.8	38.0	58.6	41.4	34.4	55.1	36.7	36.7
PoolFormer-S24 [58]	12.3	40.1	62.2	43.4	37.0	59.1	39.6	40.3
PVT-Small [52]	53.7	40.4	62.9	43.8	37.8	60.1	40.3	39.8
EfficientFormer-L3 [26]	12.4	41.4	63.9	44.7	38.1	61.0	40.4	43.5
RepViT-M3	5.9	41.1	63.1	45.0	38.3	60.4	41.0	42.8

follow [29] to measure the throughput with the maximum power-of-two batchsize that fits in memory.

# 4.1. Image Classification

We conduct image classification experiments on ImageNet, using a standard image size of  $224 \times 224$  for both training and testing. All models are trained from scratch for 300 epochs using the same training recipe as [24,26,29,37], with an AdamW optimizer and a cosine learning rate scheduler. The initial learning rate is set to 10e-3, and the minimum learning rate is set to 10e-5. The total batch size is set to 2048, and the weight decay is set to 2.5x10e-2. The RegNetY-16GF model with a top-1 accuracy of 82.9% is employed as the teacher model for distillation. For data augmentation, we utilized Mixup, auto-augmentation, and random erasing.

As shown in Table 1, RepViT consistently achieves state-of-the-art performance across various model sizes. Compared with widely used lightweight CNNs, RepViT generally achieves a better trade-off between accuracy and latency. For example, RepViT-M1 outperforms MobileNetV2x1.0 with a 6.7% top-1 accuracy under the same latency. It also surpasses MobileOne-S1 with a 2.6% higher top-1 accuracy. In addition, for larger models, RepViT-M3 runs more 4× faster than EfficientNet-B3 with a comparable accuracy. Compared with conventional ViTs, RepViT demonstrates the significant advantage of lightweight CNNs in terms of latency. For example, compared with DeiT-S, RepViT-M3 achieves a higher accuracy (81.4% vs. 81.2%) with a  $9\times$  faster speed. Compared with lightweight ViTs, RepViT also shows favorable accuracy and latency. With a comparable or lower latency, RepViT-M1 and RepViT-M3 significantly outperforms EfficientFormerV2-S0 and EfficientFormer-L1 by 2.8% and 2.2% top-1 accuracy, respectively. These experimental results well demonstrate that pure lightweight CNNs can outperform existing state-of-the-art lightweight ViTs on mobile devices by incorporating the efficient architectural designs.

# 4.2. Object Detection and Instance Segmentation

We evaluate RepViT on object detection and instance segmentation tasks to verify its transfer ability. Following [24, 26, 37], we integrate RepViT as a backbone in the Mask-RCNN framework and conduct experiments on MS COCO 2017 dataset. We initialize the model with pretrained ImageNet-1k weights. We adopt AdamW optimizer with an initial learning rate of 2e-4 and train the model for 12 epochs with a standard resolution (1333×800). The backbone latency is measured with image crops of 512x512 on iPhone 12 with iOS 16.

As seen in Table 2, RepViT consistently outperforms CNN and ViT models in terms of latency,  $AP^{box}$  and  $AP^{mask}$ , under similar model size. Specifically, RepViT-M2 outperform EfficientFormer-L1 backbone by 1.9  $AP^{box}$  and 1.8  $AP^{mask}$ . For a larger model size, RepViT-M3 surpasses PoolFormer-S24 with 1.0  $AP^{box}$  and 1.3  $AP^{mask}$  with a more  $2\times$  faster speed. Compared with EfficientFormer-L3, it achieves comparable  $AP^{box}$  and  $AP^{mask}$  with a significant lower latency, highlighting the substantial advantage of lightweight CNNs in terms of latency for high-resolution vision tasks. These results well demonstrate the superiority of RepViT in transferring to downstream vision tasks.

## 4.3. Semantic Segmentation.

We conduct experiments on ADE20K to further verify the performance of RepViT on the semantic segmentation task. Following [24, 26], we integrate RepViT as a backbone in the Semantic FPN framework. We initialize the backbones with pretrained weights on ImageNet-1K. We train the models on ADE20K for 40K iterations with a batch size of 32. We adopt AdamW optimizer, and employ a poly learning rate schedule with power 0.9. The initial learning

rate is set to 2x10e-4. We employ the standard resolution  $(512\times512)$  for training and report the single scale testing results on the validation set.

As shown in Table 2, RepViT consistently show favorable mIoU-latency trade-off on two model sizes. For example, RepViT-M3 outperforms ResNet50 by 6.1 mIoU with a more 1.6× faster speed. RepViT-M2 achieves a 3.4 higher mIoU compared with PoolFormer-S12, along with a reduction in latency by one-third. In comparison to EfficientFormer-L1, RepViT-M2 and RepViT-M3 demonstrate a respective increase of 1.7 and 3.9 in mIoU while exhibiting comparable latency. These results show the efficacy of RepViT as a general vision backbone.

# 5. Conclusion

In this paper, we revisit the efficient design of lightweight CNNs by incorporating the architectural choices of lightweight ViTs. This ends up with RepViT, a new family of lightweight CNNs for resource-constrained mobile devices. RepViT outperforms existing state-of-the-art lightweight ViTs and CNNs on various vision tasks, showing favorable performance and latency. It highlights the potential of pure lightweight CNNs for mobile devices. We hope that RepViT can serve as a strong baseline and inspire further research into lightweight models.

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# A. Architecture of RepViTs

Table 3 provides the architecture details of RepViT variants.

Table 3. Architecture details of RepViT variants.

- G.	D 1.:	- C - C	RepViT			
Stage	Resolution	Config	M1	M2	M3	
stem	$\frac{H}{2} \times \frac{W}{2}$	channels	24	32	32	
	$\frac{H}{4} \times \frac{W}{4}$	channels	48	64	64	
1	$\frac{H}{4} \times \frac{W}{4}$	channels	48	64	64	
		blocks	2	2	4	
2	$\frac{H}{4} \times \frac{W}{4}$	channels	96	128	128	
		blocks	2	2	4	
3	$\frac{H}{4} \times \frac{W}{4}$	channels	192	256	256	
		blocks	14	12	18	
4	$\frac{H}{4} \times \frac{W}{4}$	channels	384	512	512	
		blocks	2	2	2	