MicroNet: Towards Image Recognition with Extremely Low FLOPs

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Abstract

In this paper, we present MicroNet, which is an efficient convolutional neural network using extremely low computational cost (e.g., 6 MFLOPs on ImageNet classification). Such a low cost network is highly desired on edge devices, yet usually suffers from a significant performance degradation. We handle the extremely low FLOPs based upon two design principles: (a) avoiding the reduction of network width by lowering the node connectivity, and (b) compensating for the reduction of network depth by introducing more complex non-linearity per layer. Firstly, we propose Micro-Factorized convolution to factorize both point-wise and depthwise convolutions into low rank matrices for a good tradeoff between the number of channels and input/output connectivity. Secondly, we propose a new activation function, named Dynamic Shift-Max, to improve the non-linearity via maxing out multiple dynamic fusions between an input feature map and its circular channel shift. The fusions are dynamic as their parameters are adapted to the input. Building upon Micro-Factorized convolution and dynamic Shift-Max, a family of MicroNets achieve a significant performance gain over the state-of-the-art in the low FLOP regime. For instance, MicroNet-M1 achieves 61.1% top-1 accuracy on ImageNet classification with 12 MFLOPs, outperforming MobileNetV3 by 11.3%.

1. Introduction

Recently, designing efficient CNN architectures [15, 12, 26, 11, 42, 24, 29] has been an active research area. These works enable high quality services on edge devices. However, even the state-of-the-art efficient CNNs (e.g., MobileNetV3 [11]) suffer from a significant performance degradation when the computational cost becomes extremely low. For instance, when constraining MobileNetV3 from 112M to 12M MAdds on image classification [8] at resolution $224 \times 224$, the top-1 accuracy drops from 71.7% to 49.8%. This makes its adoption harder on low power devices (e.g., IoT devices). In this paper, we target a more challenging problem by cutting half of the budget: can we perform image classification over 1,000 classes at resolution $224 \times 224$ under 6 MFLOPs?

This extremely low computational cost (6M FLOPs) requires a careful redesign of every layer. For instance, even a thin stem layer that contains a single $3 \times 3$ convolution with 3 input channels and 8 output channels over a $112 \times 112$ grid (stride=2) requires 2.7M MAdds. The resource left for designing convolution layers and a classifier for 1,000 classes is too limited to learn a good representation. To fit in such a low budget, a naive strategy for applying existing efficient CNNs (e.g., MobileNet [12, 26, 11] and ShuffleNet [42, 24]) is to significantly reduce the width or depth of the network. This results in a severe performance degradation.

We propose a new architecture, named MicroNet, to handle the extremely low FLOPs. It builds upon two design principles as follows:

- Circumventing the reduction of network width through
lowering node connectivity.

• Compensating for the reduction of network depth by improving non-linearity per layer.

These principles guide us to design more efficient convolution and activation functions.

Firstly, we propose Micro-Factorized Convolution to factorize both pointwise and depthwise convolutions into low rank matrices. This provides a good balance between the input/output connectivity and the number of channels. Specifically, we design group-adaptive convolution to factorize pointwise convolution. It adapts the number of groups to the number of channels by a square root relationship. Stacking two group-adaptive convolutions essentially approximates a pointwise convolution matrix by a block matrix, of which each block has rank-1. The factorization (rank-1) of depthwise convolution is straightforward, by factorizing a $k \times k$ depthwise convolution into a $1 \times k$ and a $k \times 1$ depthwise convolution. We show that a proper combination of these two approximations over different levels significantly reduces the computational cost without sacrificing the number of channels.

Secondly, we propose a new activation function, named Dynamic Shift-Max to improve the non-linearity from two aspects: (a) it maxes out multiple fusions between an input feature map and its circular channel shift, and (b) each fusion is dynamic as its parameters adapt to the input. Furthermore, it enhances both node connectivity and non-linearity efficiently in one function with a low computational cost.

Experimental results show that MicroNet outperforms the state-of-the-art by a large margin (see Figure 1). For example, compared to MobileNetV3, our method gains 11.3% and 7.7% in top-1 accuracy on ImageNet classification, under the constraints of 12M and 21M FLOPs respectively. Within the extremely challenging 6 MFLOPs constraint, our method achieves 53.0% top-1 accuracy, gaining 3.2% over MobileNetV3 that has a doubled complexity (12 MFLOPs). In addition, a family of MicroNets provide strong baselines for two pixel-level tasks with very low computational cost: semantic segmentation and keypoint detection.

2. Related Work

Efficient CNNs: MobileNets [12, 26, 11] decompose $k \times k$ convolution into a depthwise and a pointwise convolution. ShuffleNets [42, 24] use group convolution and channel shuffle to simplify pointwise convolution. [33] uses butterfly transform to approximate pointwise convolution. EfficientNet [29, 31] finds a proper relationship between input resolution and network width/depth. MixNet [30] mixes up multiple kernel sizes in a single convolution. AdderNet [2] trades massive multiplications for much cheaper additions. GhostNet [10] applies cheap linear transformations to generate ghost feature maps. Sandglass [43] flips the structure of inverted residual block to alleviate information loss. [39] and [1] train one network to support multiple sub-networks.

Efficient Inference: Efficient inference [20, 22, 34, 35] customizes a proper sub-network adaptively per input. [34] and [35] use reinforcement learning to learn a controller for skipping part of an existing model. MSDNet [14] allows early-exit for easy samples based on the prediction confidence. [40] searches for the optimal MSDNet. [38] adapts image resolution to achieve efficient inference.

Dynamic Neural Networks: Dynamic networks boost the representation capability by adapting parameters to the input. HyperNet [9] uses another network to generate parameters for the main network. SENet [13] reweights channels by squeezing global context. SKNet [18] adapts attention over kernels with different sizes. Dynamic convolution [37, 5] aggregates multiple convolution kernels based on their attention. Dynamic ReLU [6] adapts slopes and intercepts of two linear functions in ReLU [25, 16], [23] uses grouped fully connected layer to generate convolutional weights directly. [3] extends dynamic convolution from spatial agnostic to spatial specific. [27] proposes dynamic group convolution that adaptively groups input channels. [32] applies dynamic convolution on instance segmentation. [19] learns dynamic routing across scales for semantic segmentation.

3. Our Method: MicroNet

Below we describe in detail the design principles and key components of MicroNet.

3.1. Design Principles

The extremely low FLOPs constrain both the network width (number of channels) and network depth (number of layers), which are analyzed separately. If we consider a convolution layer as a graph, the connections (edges) between input and output (nodes) are weighted by kernel parameters. Here, we define the connectivity as the number of connections per output node. Thus, the number of connections equals to the product of the number of output channels and the connectivity. When the computation cost (proportional to the number of connections) is fixed, the number of channels conflicts with the connectivity. We believe that a good balance between them can effectively avoid channel reduction and improve the representation capability of a layer. Therefore, our first design principle is: *circumventing the reduction of network width through lowering node connectivity.* We achieve this by factorizing both pointwise and depthwise convolutions at a finer scale.

When the depth (number of layers) is significantly reduced for a network, its non-linearity (encoded in ReLU) is constrained, resulting in a clear performance degradation. This motivates our second design principle as: *compensating for the reduction of network depth by improving non-linearity per layer.* We achieve this by designing a new
activation function, Dynamic Shift-Max.

3.2. Micro-Factorized Convolution

We factorize both pointwise and depthwise convolutions at a finer scale, from where Micro-Factorized convolution gets its name. The goal is to balance between the number of channels and input/output connectivity.

Micro-Factorized Pointwise Convolution: We propose group-adaptive convolution to factorize a pointwise convolution. For the sake of conciseness, we assume the convolution kernel $W$ has the same number of input and output channels ($C_{in} = C_{out} = C$) and ignore the bias. The kernel matrix $W$ is factorized into two group-adaptive convolutions, of which the group number $G$ depends on the number of channels $C$. Mathematically, it can be represented as:

$$W = P\Phi Q^T,$$

where $W$ is a $C \times C$ matrix. $Q$ is of shape $C \times \frac{C}{G}$, squeezing the number of channels by ratio $R$. $P$ is of shape $C \times \frac{C}{G}$, expanding the number of channels back to $C$ as output. $P$ and $Q$ are diagonal block matrices with $G$ blocks, of which each block corresponds to the convolution of a group. $\Phi$ is a $\frac{C}{G} \times \frac{C}{G}$ permutation matrix, shuffling channels similarly as in [42]. The computational complexity is $O = 2C^2$. Figure 2-Left shows an example with $C = 18$, $R = 2$ and $G = 3$.

Note that the group number $G$ is not fixed but adapts to the number of channels $C$ and reduction ratio $R$ as:

$$G = \sqrt{C/R}.$$  

This square root relation is derived from balancing between the number of channels $C$ and input/output connectivity. Here, we define the connectivity $E$ as the number of input-output connections per output channel. Each output channel connects to $\frac{C}{G}$ hidden channels between the two group-adaptive convolutions, and each hidden channel connects to $\frac{C}{G}$ input channels. Thus $E = \frac{C^2}{2GR}$. When we fix the computational complexity $O = \frac{2C^2}{GR}$ and the reduction ratio $R$,

$$C = \sqrt{\frac{2OE}{R}}, \quad E = \frac{O}{2G}.$$  

This is illustrated in Figure 3. As the group number $G$ increases, $C$ increases but $E$ decreases. The two curves intercept ($C = E$) when $G = \sqrt{C/R}$, at which each output channel connects to all input channels once. Mathematically, the resulting convolution matrix $W$ is divided into $G \times G$ blocks, of which each has rank 1 (see Figure 2-Left).

Micro-Factorized Depthwise Convolution: As shown in Figure 2-Middle, we factorize a $k \times k$ depthwise convolution kernel into a $k \times 1$ kernel and a $1 \times k$ kernel. This shares the same mathematical format with Micro-Factorized pointwise convolution (Eq. 1). The kernel matrix per channel $W$ is of shape $k \times k$, which is decomposed into a $k \times 1$ vector $P$ and a $1 \times k$ vector $Q^T$. Here $\Phi$ is a scalar with value 1. This low rank approximation reduces the computational complexity from $O(k^2C)$ to $O(kC)$.

Combining Micro-Factorized Pointwise and Depthwise Convolutions: We combine Micro-Factorized pointwise and depthwise convolutions in two different ways: (a) regular combination, and (b) lite combination. The former simply concatenates the two convolutions. The lite combina-

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Micro-Factorized pointwise convolution as:

\[ \text{extend channel shift to group shift by defining the group shift as follows:} \]

\[ x_j = \{ \text{max} \{ x_{i,j} \mid i \in G \} \} \]

where the parameter \( x \) corresponds to shifting the \( i \)th channel \( x \) by \( j \) groups. Dynamic Shift-Max combines multiple (\( J \)) group shifts as follows:

\[ y_i = \max_{1 \leq k \leq K} \left\{ \sum_{j=0}^{J-1} a_{i,j}^k(x) x_{i,j} \right\}; \]

where the parameter \( a_{i,j}^k(x) \) adapts to the input \( x \) by a hyper function, which can be easily implemented by using two fully connected layers after average pooling, in a similar manner to Squeeze-and-Excitation [15].

Non-linearity: Dynamic Shift-Max encodes two non-linearities: (a) it outputs the maximum of \( K \) different fusions of \( J \) groups, and (b) the parameter \( a_{i,j}^k(x) \) is not static but a function of the input \( x \). These provide dynamic Shift-Max more representation power to compensate for the reduction of the number of layers. The recently proposed dynamic ReLU [6] is a special case of dynamic Shift-Max (\( J = 1 \)), where each channel is activated alone.

Connectivity: Dynamic Shift-Max improves the connectivity between channel groups. It is complementary to Micro-Factorized pointwise convolution that focuses on connectivity within each group. Figure 4 shows that even a static group shift (\( y_i = a_{i,0} x_{i,0} + a_{i,1} x_{i,1} \)) can efficiently increase the rank for Micro-Factorized pointwise convolution. By inserting it between the two group-adaptive convolutions, the rank of each block in the resulting convolution matrix \( W \) (\( G \times G \) block matrix) increases from 1 to 2. Note that the static group shift is a simple special case of dynamic Shift-Max with \( K = 1, J = 2 \), and static \( a_{i,j}^k \).

Computational Complexity: Dynamic Shift-Max generates \( CJK \) parameters \( a_{i,j}^k(x) \) from input \( x \). The computational complexity includes three parts: (a) average pooling \( O(HWC) \), (b) generating parameters \( a_{i,j}^k(x) \) in Eq. 5 \( O(C^2 JK) \), and (c) applying dynamic Shift-Max per channel and per spatial location \( O(HWCJK) \). It is lightweight when \( J \) and \( K \) are small. Empirically, a good trade-off is achieved at \( J = 2 \) and \( K = 2 \).

3.3. Dynamic Shift-Max

Now we present dynamic Shift-Max, a new activation function to enhance non-linearity. It dynamically fuses an input feature map with its circular group shift, of which a group of channels are shifted. Dynamic Shift-Max also strengthens the connections between groups. This is complementary to Micro-Factorized pointwise convolution that focuses on connections within a group.

Definition: Let \( x = \{ x_i \mid i = 1, \ldots, C \} \) denote an input vector (or tensor) with \( C \) channels that are divided into \( G \) groups. Each group has \( \frac{C}{G} \) channels. Its \( N \)-channel circular shift can be represented as \( x_N(i) = x_{(i+N) \mod C} \). We extend channel shift to group shift by defining the group circular function as:

\[ x_{\overline{G}}(i,j) = x_{(i+j \mod C)} \mod C, \quad j = 0, \ldots, G-1, \]

where \( x_{\overline{G}}(i,j) \) corresponds to shifting the \( i \)th channel \( x_i \) by \( j \) groups. Dynamic Shift-Max combines multiple (\( J \)) group shifts as follows:

\[ y_i = \max_{1 \leq k \leq K} \left\{ \sum_{j=0}^{J-1} a_{i,j}^k(x) x_{\overline{G}}(i,j) \right\}; \]

where the parameter \( a_{i,j}^k(x) \) adapts to the input \( x \) by a hyper function, which can be easily implemented by using two fully connected layers after average pooling, in a similar manner to Squeeze-and-Excitation [15].

4. MicroNet Architecture

Now we describe the architectures of four MicroNet models, which have different FLOPs from 6M to 44M. They consist of three types of Micro-Blocks (see Figure 5), which combine Micro-Factorized pointwise and depthwise convolutions in different ways. All of them use dynamic Shift-Max as activation function. The details are listed as follows:

Micro-Block-A: As shown in Figure 5a, Micro-Block-A uses the lite combination of Micro-Factorized pointwise and depthwise convolutions (see Figure 2-Right). It is effective at lower levels that have higher resolution (e.g. \( 112 \times 112 \) or \( 56 \times 56 \)). Note that the number of channels is expanded by Micro-Factorized depthwise convolution, and is squeezed by using a group-adaptive convolution.
Table 1. MicroNet Architectures. “stem” refers to stem layer. “Micro-A”, “Micro-B”, and “Micro-C” refers to three Micro-Blocks (see section 4 and Figure 5 for more details). $k$ is the kernel size, $C$ is the number of output channels, $R$ is the channel reduction ratio in Micro-Factorized pointwise convolution, $G$ is the group number. Note that for “Micro-A” (see Figure 5a), $C$ is the number of output channels in Micro-Factorized depthwise convolution, $\frac{C}{R}$ is the number of output channels for the block.

| Output | M0 | | M1 | | M2 | | M3 |
|--------|----|----|----|----|----|----|----|
|        | Block $k$ $C$ $\frac{C}{R}$ $G$ | Block $k$ $C$ $\frac{C}{R}$ $G$ | Block $k$ $C$ $\frac{C}{R}$ $G$ | Block $k$ $C$ $\frac{C}{R}$ $G$ |
| 112×112 | stem 3 6 3 (1, 3) | stem 3 8 4 (1, 4) | stem 3 12 4 (1, 4) | stem 3 16 4 (1, 4) |
| 56×56 | Micro-A 3 24 8 (2, 2) | Micro-A 3 32 12 (4, 2) | Micro-A 3 48 16 (4, 4) | Micro-A 3 64 32 (4, 4) |
| 28×28 | Micro-A 3 32 16 (4, 2) | Micro-A 3 48 16 (4, 2) | Micro-A 3 64 24 (4, 2) | Micro-A 3 80 32 (4, 2) |
| 14×14 | Micro-B 5 96 16 (4, 4) | Micro-C 5 192 32 (4, 8) | Micro-C 5 192 32 (4, 8) | Micro-C 5 256 48 (4, 8) |
| 7×7 | Micro-C 5 384 64 (8, 8) | Micro-C 5 576 96 (8, 12) | Micro-C 6 576 96 (8, 12) | Micro-C 7 576 144 (12, 12) |
| 1×1 | avg pool $\rightarrow$ 2fc $\rightarrow$ softmax | 6M MAdds, 1.8M Param | 12M MAdds, 2.4M Param | 21M MAdds, 3.3M Param | 44M MAdds, 4.5M Param |

Figure 5. Diagram of three Micro-Blocks. (a) Micro-Block-A that uses the lite combination of Micro-Factorized pointwise and depthwise convolutions (see Figure 2-Right). (b) Micro-Block-B that connects Micro-Block-A and Micro-Block-C. (c) Micro-Block-C that uses the regular combination of Micro-Factorized pointwise and depthwise convolutions. See Table 1 for their usage.

Micro-Block-B: Micro-Block-B is used to connect Micro-Block-A and Micro-Block-C. Different to Micro-Block-A, it uses a full Micro-Factorized pointwise convolution that includes two group-adaptive convolutions (shown in Figure 5b). The former squeezes the number of channels, but the latter expands the number of channels. Each MicroNet only has one Micro-Block-B (see Table 1).

Micro-Block-C: Micro-Block-C (shown in Figure 5c) uses the regular combination that concatenates Micro-Factorized depthwise and pointwise convolutions. It is used at higher levels (see Table 1) as it spends more computations on channel fusion (pointwise) than the lite combination. The skip connection is used when the dimension matches.

For each micro-block there are four hyper-parameters: kernel size $k$, number of output channels $C$, reduction ratio in the bottleneck of Micro-Factorized pointwise convolution $R$, and group number pair $(G_1, G_2)$ for the two group-adaptive convolutions. Note that we relax Eq. 2 as $G_1G_2 = C/R$ and find the close integer solution.

Stem Layer: we redesign the stem layer to meet the low FLOP constraint. It includes a $3 \times 3$ convolution and a $1 \times 3$ group convolution, and is followed by a ReLU. The second convolution expands the number of channels by $R$ times. This substantially saves the computational cost. For instance, the stem layer in MicroNet-M3 (see Table 1) only need 1.5M MAdds.

Four MicroNet Models (M0–M3): We design four models (M0, M1, M2, M3) with different computational costs (6M, 12M, 21M, 44M MAdds). Table 1 shows their full specification. These networks follow the same pattern from low to high levels: stem layer $\rightarrow$ Micro-Block-A $\rightarrow$ Micro-Block-B $\rightarrow$ Micro-Block-C. Note that all models are manually designed without network architecture search (NAS).

5. Experiments: ImageNet Classification

Below we evaluate four MicroNet models (M0–M3) along with comprehensive ablations on ImageNet [8] classification. ImageNet has 1000 classes, including 1,281,167 images for training and 50,000 images for validation.

5.1. Implementation Details

Training Strategy: Each model is trained in two ways: (a) stand alone, and (b) mutual learning. The former is straightforward that the model learns by itself. The latter co-learns a full rank partner along each MicroNet where the full rank partner shares the same network width/height, but replaces Micro-Factorized pointwise and depthwise convolutions with the original pointwise and depthwise $(k \times k)$ con-
### 5.3. Ablation Studies

We run a number of ablations to analyze MicroNet. MicroNet-M1 (12M FLOPs) is used for all ablations, and each model is trained for 300 epochs. The default hyper parameters for dynamic Shift-Max are set as $J = 2, K = 2$.

#### From MobileNet to MicroNet: Table 3 shows the path from MobileNet to our MicroNet. Both share the reverse bottleneck structure. Here, we modify MobileNetV2 [26] (without SE [13]) such that it has similar complexity (10.5M MAdds) with three Micro-Factorized convolution variations (row 2–4). Micro-Factorized pointwise and depthwise convolutions and their lite combination at low levels boost the top-1 accuracy from 44.9% to 51.7% step by step. Furthermore, using static and dynamic Shift-Max gains another 2.7% and 6.8% top-1 accuracy respectively, with a small amount of additional cost. This demonstrates that the proposed *Micro-Factorized Convolution* and *Dynamic Shift-Max* are effective and complementary to handle extremely low computational cost.

#### Group number $G$: Micro-Factorized pointwise convolution includes two group-adaptive convolutions, where their group numbers are selected by relaxing $G = \sqrt{C/R}$ to close integers. Table 4a compares it with networks that have similar structure and FLOPs (about 10.5M MAdds), but use a fixed group number. Group-adaptive convolution achieves higher accuracy, demonstrating a good balance between the number of channels and input/output connectivity.

#### Lite combination at different levels: Table 4c compares...
Table 4. Ablations of Micro-Factorized convolution on ImageNet classification. * indicates the default choice for the rest of the paper.

| Activation          | Param MAdds | Top-1 | Top-5 |
|---------------------|-------------|-------|-------|
| ReLU [25]           | 1.8M 10.5M  | 51.7  | 74.3  |
| SE+ReLU [13]        | 2.1M 10.9M  | 54.4  | 76.8  |
| Dynamic ReLU [6]    | 2.4M 11.8M  | 56.0  | 78.0  |
| Dynamic Shift-Max   | 2.3M 12.4M  | 58.5  | 80.1  |

(a) Fixed group number \( G \).

| Activation          | Param MAdds | Top-1 | Top-5 |
|---------------------|-------------|-------|-------|
| ReLU [25]           | 1.8M 10.5M  | 51.7  | 74.3  |
| SE+ReLU [13]        | 2.1M 10.9M  | 54.4  | 76.8  |
| Dynamic ReLU [6]    | 2.4M 11.8M  | 56.0  | 78.0  |
| Dynamic Shift-Max   | 2.3M 12.4M  | 58.5  | 80.1  |

(b) Adaptive group number \( G \).

| Activation          | Param MAdds | Top-1 | Top-5 |
|---------------------|-------------|-------|-------|
| ReLU [25]           | 1.8M 10.5M  | 51.7  | 74.3  |
| SE+ReLU [13]        | 2.1M 10.9M  | 54.4  | 76.8  |
| Dynamic ReLU [6]    | 2.4M 11.8M  | 56.0  | 78.0  |
| Dynamic Shift-Max   | 2.3M 12.4M  | 58.5  | 80.1  |

(c) Lite combination at different levels

Table 5. Dynamic Shift-Max vs. other activation functions on ImageNet classification. MicroNet-M1 is used.

| \( A_1 \) | \( A_2 \) | \( A_3 \) | Param MAdds | Top-1 | Top-5 |
|-----------|-----------|-----------|-------------|-------|-------|
| ✓ – –     | 1.8M 10.5M| 51.7 74.3 |             |       |       |
| – ✓ –     | 2.1M 11.3M| 55.9 77.9 |             |       |       |
| – – ✓     | 1.8M 10.8M| 53.3 76.0 |             |       |       |
| ✓ ✓ ✓     | 1.8M 10.8M| 53.3 76.0 |             |       |       |
| ✓ ✓ ✓     | 2.1M 11.2M| 54.8 77.2 |             |       |       |
| ✓ ✓ ✓     | 2.2M 11.5M| 56.6 78.3 |             |       |       |
| ✓ – ✓     | 2.2M 12.2M| 57.9 79.6 |             |       |       |
| ✓ ✓ ✓     | 2.3M 12.2M| 57.9 79.6 |             |       |       |
| ✓ ✓ ✓     | 2.3M 12.2M| 57.9 79.6 |             |       |       |
| ✓ ✓ ✓     | 2.4M 12.4M| 55.5 77.8 |             |       |       |
| ✓ ✓ ✓     | 2.4M 12.4M| 55.5 77.8 |             |       |       |
| ✓ ✓ ✓     | 2.4M 12.4M| 58.5 80.1 |             |       |       |

Table 6. Dynamic Shift-Max at different layers evaluated on ImageNet. MicroNet-M1 is used. \( A_1, A_2, A_3 \) indicate three activation layers sequentially in Micro-Block-B and Micro-Block-C (see Figure 5). Micro-Block-A only includes \( A_1 \) and \( A_2 \).

Table 7. Ablations of two hyper parameters in dynamic Shift-Max (\( J, K \) in Eq. 5) on ImageNet classification. * indicates the default choice for the rest of the paper.

| \( J \) | \( K \) | Param MAdds | Top-1 | Top-5 |
|--------|--------|-------------|-------|-------|
| ✓ ✓     | 1 ✓ 2  | 2.1M 10.9M  | 54.4  | 76.8  |
| ✓ ✓     | 2 ✓ 2  | 2.4M 12.4M  | 58.5  | 80.1  |
| ✓ ✓     | 3 ✓ 2  | 2.6M 14.2M  | 59.0  | 80.3  |
| ✓ ✓     | 3 ✓ 3  | 2.8M 15.3M  | 50.9  | 80.3  |

Table 8. Ablations of two hyper parameters in dynamic Shift-Max (\( J, K \) in Eq. 5) on ImageNet classification. * indicates the default choice for the rest of the paper.

6. MicroNet for Pixel-Level Classification

MicroNet is not only effective for the image-level classification, but also works well for pixel-level tasks. In this section, we will show its application in human pose estimation and semantic segmentation.

6.1. Human Pose Estimation

We use COCO 2017 dataset [21] to evaluate MicroNet on single-person keypoint detection. Our models are trained on train2017, including 57K images and 150K person instances labeled with 17 keypoints. We evaluate our method on val2017 containing 5000 images and use the mean average precision (AP) over 10 object key point similarity (OKS) thresholds as the metric.
fit the keypoint detection task, by increasing resolution (×2) for a set of selected blocks (e.g. all blocks with stride of 32). The selection varies for different MicroNet models (see appendix 8.1 for more details). Each model has a head that includes three micro blocks (one with stride of 8 and two with stride of 4) and a pointwise convolution to generate heatmaps for 17 keypoints. We use bilinear upsampling to increase resolution in the head, and use spatial attention [6] per layer.

Training Setup: The training setup in [28] is used. The human detection boxes are cropped and resized to 256 × 192. The data augmentation includes random rotation ([−45°, 45°]), random scale ([0.65, 1.35]), flipping, and half body data augmentation. All models are trained from scratch for 250 epochs, using Adam optimizer [17]. The initial learning rate is set as 1e-3 and is dropped to 1e-4 and 1e-5 at the 210th and 240th epoch, respectively.

Testing: The two-stage top-down paradigm [36, 28] is used for testing: detecting person instances and then predicting keypoints. We use the same person detectors provided by [36]. The heatmaps of the original and flipped images are combined, on which the keypoints are predicted by adjusting the highest heat value location with a quarter offset towards the second highest response.

Main Results: Table 8 compares MicroNets with prior works [6, 5] on efficient pose estimation, of which the computational cost is less than 850 MFLOPs. Both works use MobileNet’s inverted residual bottleneck blocks in both backbone and head, and show clear improvement by adapting parameters in convolutions [5] and activation functions [6] to the input. Our MicroNet-M3 only consumes 33% of FLOPs in these works but achieves similar performance, demonstrating our method is also effective for keypoint detection. Furthermore, MicroNet-M2, M1, M0 provide good baselines for keypoint detection with even lower computational complexity ranging from 77M to 163M FLOPs.

### 6.2. Semantic Segmentation

We conduct experiments on Cityscape dataset [7] with fine annotations to evaluate MicroNet on semantic segmentation. Our models are trained on train_fine set, including 2,975 images. We evaluate our method on val set and mIOU containing 500 images, and use mIOU as the metric.

Table 8. COCO keypoint detection results. MicroNets are compared to two dynamic networks (dynamic convolution [5] and dynamic ReLU [6]), which are built upon MobileNet V2 [26] and V3 [11] and share the same structure in both backbone and head.

### Table 8. COCO keypoint detection results

| Backbone          | Head                  | Param | MAdds | AP  | AP0.5 | AP0.75 | APm | APl |
|-------------------|-----------------------|-------|-------|-----|-------|--------|-----|-----|
| MobileNetV2 × 0.5 +DY-Conv [5] | Mobile-Blocks + DY-Conv | 10.0M | 807.4M | 62.8 | 86.1 | 70.4 | 59.9 | 68.6 |
| MobileNetV2 × 0.5 + DY-ReLU [6] | Mobile-Blocks + DY-ReLU | 4.6M  | 820.3M | 63.3 | 86.3 | 71.4 | 60.3 | 69.2 |
| MobileNetV3 Small + DY-Conv [5] | Mobile-Blocks + DY-Conv | 7.7M  | 716.2M | 60.0 | 85.0 | 67.8 | 57.6 | 65.4 |
| MobileNetV3 Small + DY-ReLU [6] | Mobile-Blocks + DY-ReLU | 4.8M  | 747.9M | 60.7 | 85.7 | 68.1 | 58.1 | 66.3 |
| MicroNet-M3        | Micro-Blocks          | 0.4M  | 263.2M | 62.8 | 86.2 | 70.6 | 60.0 | 68.4 |
| MicroNet-M2        | Micro-Blocks          | 2.2M  | 163.2M | 58.7 | 84.0 | 65.5 | 56.0 | 64.2 |
| MicroNet-M1        | Micro-Blocks          | 1.8M  | 116.8M | 54.9 | 82.0 | 60.3 | 53.2 | 59.6 |
| MicroNet-M0        | Micro-Blocks          | 1.0M  | 77.7M  | 50.3 | 79.6 | 53.9 | 48.3 | 54.8 |

Table 9. Semantic segmentation results on Cityscapes validation set. The results in the first two rows are from [11].

| Backbone          | Head                  | Param | MAdds | mIOU |
|-------------------|-----------------------|-------|-------|------|
| MBNetV2 0.5       | LR-ASPP               | 0.28M | 4.00B | 68.6 |
| MBNetV3-Small     | LR-ASPP               | 0.47M | 2.90B | 68.4 |
| MicroNet-M3       | MR-ASPP               | 1.87M | 2.52B | 69.1 |
| MicroNet-M2       | MR-ASPP               | 1.85M | 1.75B | 66.1 |
| MicroNet-M1       | MR-ASPP               | 0.99M | 1.20B | 63.5 |
| MicroNet-M0       | MR-ASPP               | 0.43M | 0.81B | 56.9 |

7. Conclusion

In this paper, we presented MicroNet to handle extremely low computational cost. It builds on two proposed operators: Micro-Factorized convolution and Dynamic Shift-Max. The former balances between the number of channels and input/output connectivity via low rank computation. Our models are trained on fine annotations to evaluate MicroNet on semantic segmentation. In addition, our MicroNet-M2, M1, M0 provide good baselines for semantic segmentation with even lower FLOPs from 1.75B to 0.81B MAdds.
approximations on both pointwise and depthwise convolutions. The latter fuses consecutive channel groups dynamically, enhancing both node connectivity and non-linearity to compensate for the depth reduction. A family of MicroNets achieve solid improvement for three tasks (image classification, human pose estimation and semantic segmentation) under extremely low FLOPs. We hope this work provides good baselines for efficient CNNs on multiple vision tasks.

8. Appendix

In the appendix, we show the details of MicroNet architectures for human pose estimation.

8.1. Architectures for Human Pose Estimation

We use COCO 2017 dataset [21] to evaluate MicroNet on single-person keypoint detection. The human detection boxes are cropped and resized to $256 \times 192$, and each person instance is labeled with 17 keypoints.

Table 10 shows the four MicroNet models (M0–M3) for human pose estimation. Different from ImageNet classification, the backbone for keypoint detection stops at the stride of 16 (resolution $16 \times 12$) to retain more spatial information. Each model has a head that includes three Micro-Blocks. The first one is with stride of 8 (resolution $32 \times 24$), while the other two are with stride of 4 (resolution $64 \times 48$).

Note that the last block is Micro-Block-A, which uses the light combination to shrink the number of channels. It is different from Micro-Block-A in the backbone, as its Micro-Factorized depthwise convolution does not expand the number of channels. The head is then followed by a pointwise convolution to generate heatmaps for 17 keypoints. We use bilinear upsampling to increase resolution in the head, and use the spatial attention in [6] per layer.

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| Output | M0 | | | | M1 | | | | | | M2 | | | | | | M3 | | | |
|--------|----|----|---|---|----|----|---|---|---|----|----|---|---|---|---|----|----|---|---|
| backbone | stem | 3 | 12 | 4 | (1, 4) | stem | 3 | 12 | 4 | (1, 4) | stem | 3 | 16 | 4 | (1, 4) | stem | 3 | 16 | 4 | (1, 4) |
| 128×96 | Micro-A | 3 | 12 | 12 | (3, –) | Micro-A | 3 | 12 | 12 | (3, –) | Micro-A | 3 | 16 | 16 | (4, –) | Micro-A | 3 | 16 | 16 | (4, –) |
| 64×48 | Micro-A | 3 | 48 | 16 | (4, –) | Micro-A | 3 | 48 | 16 | (4, –) | Micro-A | 3 | 64 | 24 | (4, –) | Micro-A | 3 | 64 | 24 | (4, –) |
| 32×24 | Micro-C | 5 | 192 | 32 | (8, 6) | Micro-C | 5 | 192 | 32 | (8, 6) | Micro-C | 5 | 288 | 48 | (8, 8) | Micro-C | 5 | 288 | 48 | (8, 8) |
| | Micro-C | 5 | 384 | 64 | (8, 8) | Micro-C | 5 | 384 | 64 | (8, 8) | Micro-C | 5 | 384 | 64 | (8, 8) | Micro-C | 5 | 384 | 64 | (8, 8) |
| 16×12 | | | | | | | | | | | | | | | | | | | |
| 32×24 | Micro-C | 5 | 480 | 120 | (12, 10) | Micro-C | 5 | 640 | 160 | (16, 10) | Micro-C | 5 | 768 | 192 | (12, 16) | Micro-C | 5 | 1024 | 256 | (16, 16) |
| 64×48 | Micro-A† | 5 | 320 | 80 | (8, 10) | Micro-C | 7 | 384 | 96 | (8, 12) | Micro-C | 7 | 120 | 80 | (8, 12) | Micro-C | 7 | 448 | 112 | (8, 14) |
| | Micro-A† | 5 | 384 | 64 | (8, 12) | Micro-A† | 5 | 384 | 64 | (8, 12) | Micro-A† | 5 | 448 | 80 | (8, 12) | Micro-A† | 7 | 640 | 96 | (8, –) |
| | | | | | | | | | | | | | | | | | | | |
| 77.7M | MAdd | 1.0M Param | 116.8M | MAdd | 1.8M Param | 163.2M | MAdd | 2.2M Param | 263.2M | MAdd | 4.0M Param |

Table 10. MicroNet Architectures for Keypoint Detection. “stem” refers to stem layer. “Micro-A”, “Micro-B”, and “Micro-C” refers to three Micro-Blocks (see section 4 and Figure 5 for more details). $k$ is the kernel size, $C$ is the number of output channels, $R$ is the channel reduction ratio in Micro-Factorized pointwise convolution, $G$ is the group number. Note that for “Micro-A” that uses the light combination of Micro-Factorized pointwise and depthwise convolutions, $C$ is the number of output channels in Micro-Factorized depthwise convolution, $G$ is the number of output channels for the block. The last block in the head is Micro-A†, in which Micro-Factorized depthwise convolution does not expand the number of channels.
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