Supplementary Material
MCUNetV2: Memory-Efficient Patch-based Inference for Tiny Deep Learning

Contents

35th Conference on Neural Information Processing Systems (NeurIPS 2021).

A Flow Chart of Contributions

We provide a flow chart to summarize our contributions in Figure S1.

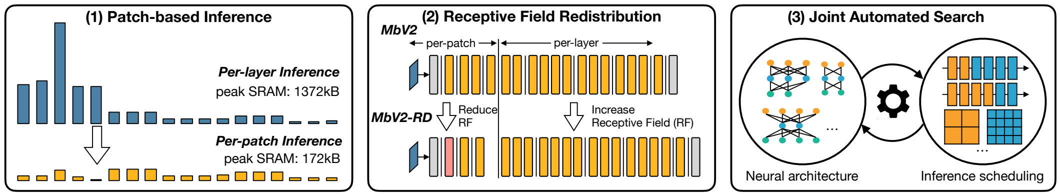


Figure S1. Contributions of MCUNetV2: (1) Analyze and find the imbalanced memory distribution; propose a patch-based inference scheduling to reduce the peak memory significantly; (2) Propose redistributing receptive fields to reduce the overhead from overlapping patches; (3) Jointly optimize the neural architecture and inference scheduling in the same loop.

B Experimental Details

Search space. We used a MnasNet-alike search space [12, 9, 1] for neural architecture search. The search space consists with the following knobs:

- Kernel size for each separable convolution block $k_{[\,]}$, choosing from $\{3, 5, 7\}$.
- Expansion ratio for each inverted residual block $e_{[\,]}$, choosing from $\{3, 4, 6\}$.
- Number of blocks for each stage $d_{[\,]}$, choosing from $\{2, 3, 4\}$.
- Width multiplier for each block $w_{[\,]}$, choosing from $\{0.5, 0.75, 1.0\}$.
- Input image resolution r, choosing from $\{96, 128, 160, 192, 224, 256\}$.

For the inference scheduling, apart from the optimization knobs inherited from TinyEngine [9], we also include the following knobs:

- Number of patches to split the input image p, choosing from $\{1, 2, 3, 4\}$ according to the input image resolution. The image will be split into $p \times p$ patches.
- Number of layers to run patch-based inference $n, n < N$, where N is the total number of layers. The rest of the network will be run with per-layer inference.

Training. We follow the training protocol in [9] for super network training. The training dataset is randomly split into a sub-training set and validation set. The validation set size is 10,000 for ImageNet [3] and 5,000 for other datasets. We first train the largest network in the search space on the sub-training set using SGD with batch size 1024, initial learning rate 0.2, weight decay 4e-5, and a cosine learning rate decay. The training epochs is 150 for ImageNet [3] and 30 for VWW [2]. Afterward, we sort the channels according to their importance (we used L-1 norm for importance estimation [5]). Then we initialize the super network with the weights and then perform super network training using the same hyper-parameters for twice the epochs. For each iteration, 4 random architectures are sampled, and the gradients are averaged to train the network.

After getting the sub-network architecture from the evolutionary search, we fine-tuned the networks using 1/10 of the initial learning rate for 10 epochs.

Validation. To prevent over-fitting the real validation set, we evaluate the performance of each sub-network on the split validation set. The weights are taken from the super network using indexing. We re-calibrate the batch normalization statistics using 20 batches of data with a batch size 64.

Evolutionary search. We used evolutionary search to find the best sub-network architecture under certain constraints. We use a population size of 100. We randomly sample 100 sub-networks satisfying the constraints to form the first generation of population. For each iteration, we only keep the top-20 candidates with the highest accuracy. Then we perform crossover to generate 50 new candidates and mutation to generate another 50, forming a new generation. The mutation rate is 0.1. We repeat the process for 30 iterations and choose the sub-network with the highest accuracy on the split validation set.

Quantization. We perform int8 quantization following the format in [8]. To reduce the accuracy loss from quantization, we perform quantization-aware training for 10 epochs.

C Memory Distributions of Efficient Models

We further provide the memory distributions of three efficient models: MnasNet [12], FBNet [14], and MCUNet-320kB [9] in Figure S2. All the models have a highly imbalanced memory distribution, even for MCUNet, which is specialized for memory-constrained settings. The results demonstrate the generality of the imbalanced memory distribution phenomenon. Enabling patch-based inference can cut the peak memory usage of the models by 3.5-6.1×.

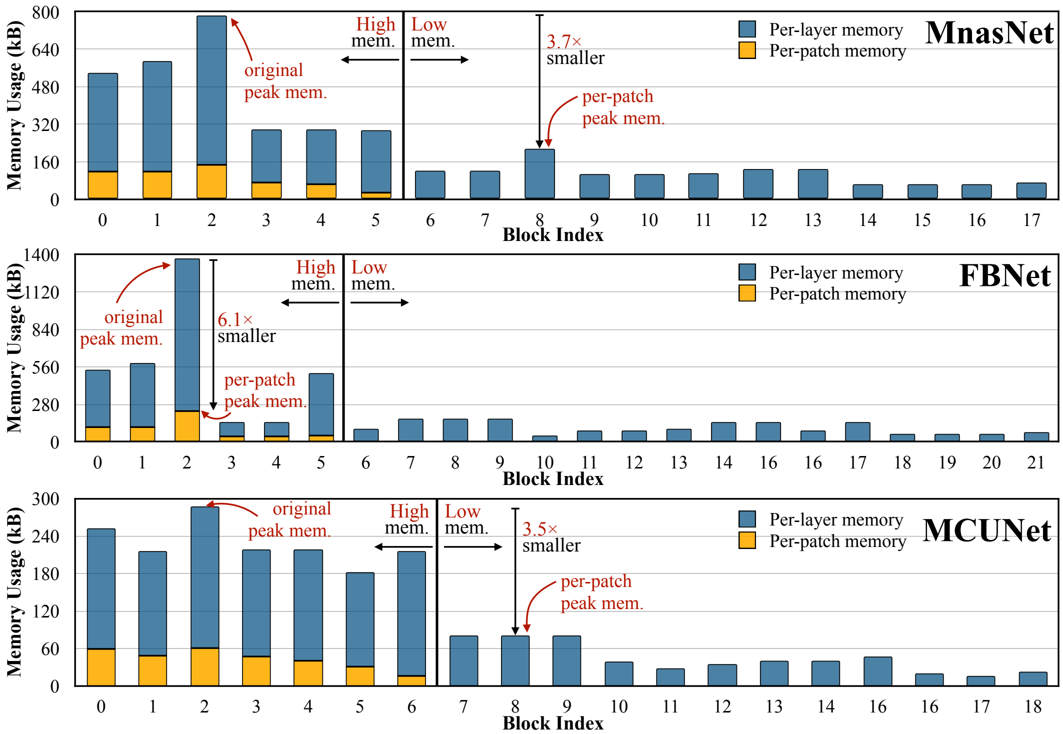


Figure S2. Memory distribution of MnasNet [12], FBNet [14], and MCUNet-320kB [9]. All the models have an imbalanced memory distribution. Enabling patch-based inference can reduce the peak memory by $3.5 - 6.1\times$.

D Ablation Study on Neural Architecture Search

Adding width multiplier w and input resolution r in the search space can greatly improve neural architecture search under tiny deep learning settings, because a flexible r and w allows us to globally *scale* the neural network to fit a tight resource budget. This is also mentioned as "search space optimization" in [9], where the authors proposed a two-step method that first chooses the optimal w and r, and then performs neural architecture search under the given w and r. Instead, we merge the two stages by directly adding r and w into the search space.

To show the advantage of our method, we conduct experiments on MobileNetV3 [6] space by extending it to support different r's and w's. We compared it with state-of-the-art methods under different computation budgets in Table S1. Our NAS method consistently outperforms existing techniques for tiny networks in terms of computation-accuracy trade-off. Existing techniques usually need a scaling method to scale down the searched network and fit different budgets. With the extended search space, all our models are derived from the *same* super network while obtaining the best accuracy. The accuracy improvement is more significant under a tiny computation setting ($\leq$25M). We also try supporting flexible w's per block, which improves the accuracy for smaller computation budgets. Therefore, we enable flexible w's by default in our experiments.

Table S1. Our NAS method outperforms existing state-of-the-art tiny networks in terms of computation-accuracy trade-off, especially under tiny computation settings (<50M). All our models are derived from *the same search space*, while obtaining the best accuracy at different budgets. For models with *, we re-measure the MACs and parameters using our profiler.

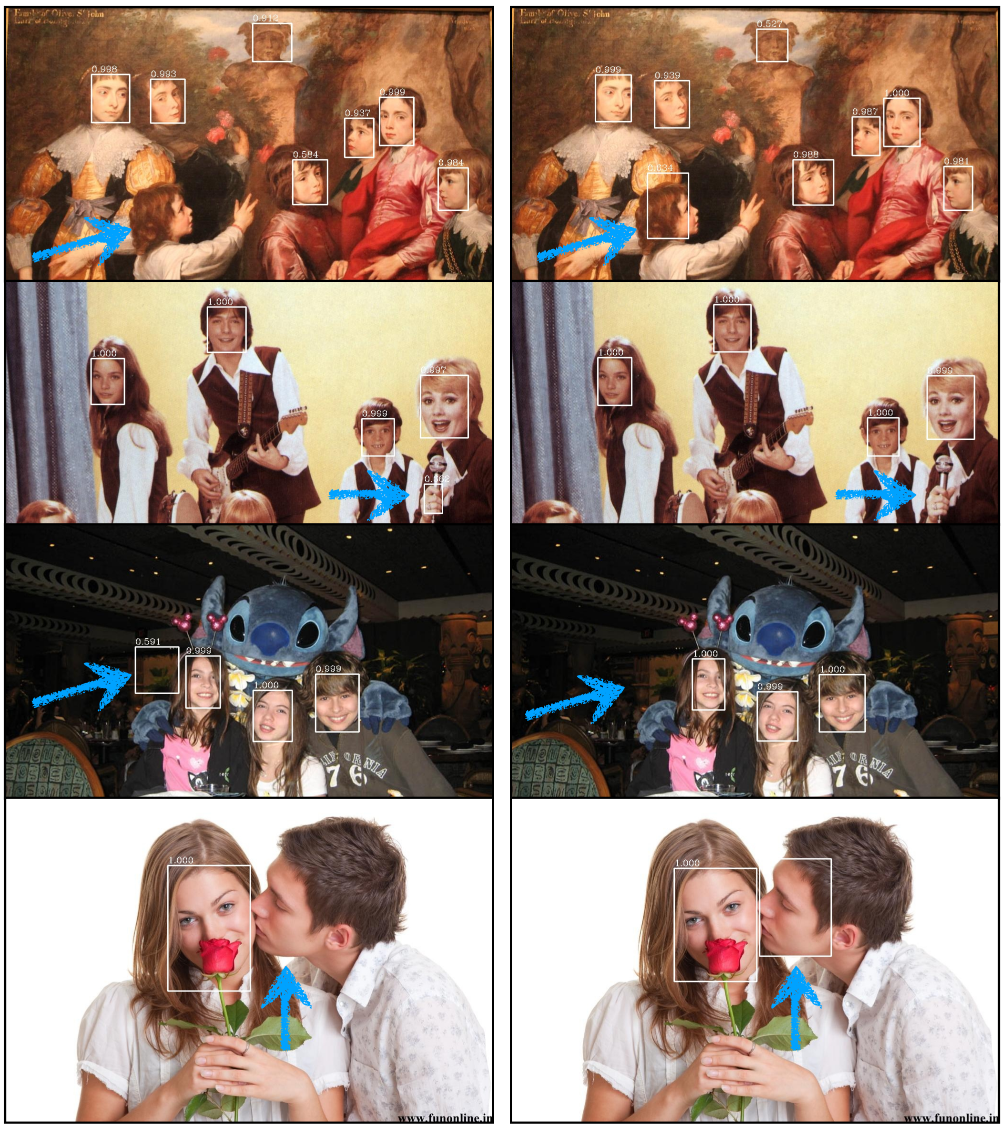
Budget	Model	Setting	MACs	Weights	Top-1	Top-5
100M MACs	MobileNetV1 0.5× (r=192) [7]	Manual+Scale	110M	1.3M	61.7%	83.6%
	MobileNetV2 0.75×(r=160) [11]	Manual+Scale	107M	2.6M	66.4%	87.3%
	MobileNetV3 Small 1.25× [6]	NAS+Scale	91M	3.6M	70.4%	-
	EfficientNet-B^{-2} [13, 4]	NAS+Scale	98M	3.0M	70.5%	89.5%
	TinyNet-C [4] *	NAS+Scale	103M	2.5M	71.2%	89.7%
	Ours (uniform w)	Joint Search	98M	4.2M	**72.3%**	**90.6%**
	Ours (flexible w)	Joint Search	99M	3.9M	**72.3%**	90.5%
50M MACs	MobileNetV2 0.35× [11]	Manual+Scale	59M	1.7M	60.3%	82.9%
	MnasNet-A1 0.35× [12]	NAS+Scale	63M	1.7M	64.1%	85.1%
	MnasNet-search1 [12]	NAS	65M	1.9M	64.9%	-
	EfficientNet-B^{-3} [13, 4]	NAS+Scale	51M	2.0M	65.0%	85.2%
	TinyNet-D [4] *	NAS+Scale	53M	2.3M	67.0%	87.1%
	MobileNetV3 Small 1.0× [6]	NAS	56M	2.5M	67.4%	-
	Ours (uniform w)	Joint Search	50M	2.8M	67.9%	87.7%
	Ours (flexible w)	Joint Search	50M	3.5M	**68.8%**	**88.2%**
25M MACs	MobileNetV2 0.35× (r=160) [11]	Manual+Scale	30M	1.7M	55.7%	79.1%
	MnasNet-A1 0.57× (r=128) [12]	NAS+Scale	22M	1.7M	54.8%	78.1%
	EfficientNet-B^{-4} [13, 4]	NAS+Scale	24M	1.3M	56.7%	79.8%
	MobileNetV3 Small 0.5× [6]	NAS+Scale	23M	1.6M	58.0%	-
	TinyNet-E [4] *	NAS+Scale	25M	2.0M	59.9%	81.1%
	Ours (uniform w)	Joint Search	25M	2.6M	63.2%	84.7%
	Ours (flexble w)	Joint Search	25M	3.2M	**63.9%**	**84.9%**

E Qualitative Results of Face Detection

We provide the face detection results on WIDER FACE validation set with RNNPool-Face-Quant [10] and MCUNetV2-S. The quantitative results are shown in Table S2, where we follow [10] to calculate the peak memory. Our model has better mAP at 1.3× smaller peak memory. The qualitative results are shown in Figure S3. Our model is more robust to poses and background false positives.

Table S2. MCUNetV2-S outperforms RNNPool-Face-Quant [10] on WIDER FACE at 1.3× smaller peak memory.

Method	MACs ↓	Peak Memory ↓ (`int8`)	mAP ↑			mAP ($\leq$3 faces) ↑		
			Easy	Medium	Hard	Easy	Medium	Hard
RNNPool-Face-Quant [10]	0.12G	225kB (1.3×)	0.80	0.78	0.53	0.84	0.83	0.81
MCUNetV2-S	**0.11G**	**168kB** (1.0×)	**0.85**	**0.81**	**0.55**	**0.90**	**0.89**	**0.87**



(a) RNNPool-Face-Quant (b) MCUNetV2

Figure S3. Qualitative results of face detection with RNNPool-Face-Quant [10] and MCUNetV2-S on WIDER FACE [15] validation set. Check the blue arrows: our model is more robust to poses and background false positives. The predictions are filtered with confidence threshold 0.5.

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