SIPA: A Simple Framework for Efficient Networks

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Abstract

With the success of deep learning in various fields and the advent of numerous Internet of Things (IoT) devices, it is essential to lighten models suitable for low-power devices. In keeping with this trend, MicroNet Challenge, which is the challenge to build efficient models from the view of both storage and computation, was hosted at NeurIPS 2019. To develop efficient models through this challenge, we propose a framework, coined as SIPA, consisting of four stages: Searching, Improving, Pruning, and Accelerating. With the proposed framework, our team, OSI AI, compressed 334× the parameter storage and 357× the math operation compared to WideResNet-28-10 and took 4th place in the CIFAR-100 track at MicroNet Challenge 2019 with the top 10% highly efficient computation. Our source code is available from https://github.com/Lee-Gihun/MicroNet_OSIAI.

Keywords: efficient neural network, compression, acceleration, MicroNet challenge

1. Introduction

With the ubiquity of not only mobile phones but also the Internet of Things (IoT) devices such as smartwatches, lightening deep neural networks has become unavoidable since the devices have limited resources. However, lightweight models with fewer neurons or shallower depth tend to have lower performance. Various model compression methods like neural architecture search, pruning, and quantization have been studied along each path to mitigate performance degradation. In line with this trend, MicroNet Challenge was hosted at NeurIPS 2019, and the goal of this challenge was to build an efficient model with respect to the number of parameters and the number of computations, while the performance has equal to or greater than the proposed threshold accuracy. The two criteria are used to grade the efficiency of models in this challenge1:

- **Parameter Storage**: the number of parameters of the model in inference time.
- **Math Operation**: the mean number of multiply-adds operations per example in inference time.

We participated in CIFAR-100 (Krizhevsky et al., 2009) track of which the threshold accuracy was 80%. For scoring, the two criteria are normalized relative to WideResNet-

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1. https://micronet-challenge.github.io/scoring_and_submission.html
28-10 (Zagoruyko and Komodakis, 2016), which stores 36.5M parameters and has 10.49B multiply-adds computations. The lower the score, the more efficient the model is.

In this paper, we propose a simple framework SIPA to build efficient networks. As the first step in this framework, we search a block-based baseline model suitable for a particular dataset, and improve the found baseline model by taking advantage of existing training methods, e.g., data augmentation, label smooth, and a learning rate scheduler. Next, we prune the improved model. Finally, we accelerate computation through sample-dependent adaptive paths, where the inference path varies according to the confidence of the decision. To this aim, we introduce a novel loss function, coined as softsmoothing loss, for preventing over-confidence. Through the proposed framework, our final model achieved the final score of 0.0058 and took 4th place in the challenge with the top 10% highly efficient computation. Our key contributions can be summarized as follows:

- We propose a simple 4-step framework for efficient networks: Searching, Improving, Pruning, and Accelerating. This simple framework gives an easy and general strategy for developing lightweight neural networks.
- We test various existing performance-efficient training methods and verify which techniques are compatible or not.
- We show that lightweight models can be more effectively compressed by analyzing the effects of pruning factors.
- We accelerate computation by making samples follow adaptive computational paths through which easy samples (i.e., highly confident samples) exit earlier. We provide a comprehensive study for a sample-dependent architecture design: exit position, exit module, and exit condition.

2. SIPA: Searching, Improving, Pruning, and Accelerating

For developing efficient networks, we establish a four-stage strategy depicted in Figure 1. This strategy is simple yet effective with generality. This section is described in the order of the framework: Searching (Section 2.1), Improving (Section 2.2), Pruning (Section 2.3), and Accelerating (Section 2.4).

![Figure 1: SIPA: A simple four-stage strategy for efficient networks.](image-url)
2.1. Searching

Searching is a step to find the baseline model structure through iterative validations, where the validation assesses each model by a fitness function based on performance and compactness, e.g., with positive constants $\alpha$ and $w$, (Dai et al., 2019) defines a fitness function of a vector of hyperparameters $x$ as follows: $R(x) = A(x) - [\alpha I(F(x, plat) - thres)]^w$, where $A(x)$, $I$, $F(x, plat)$, $plat$ and $thres$ are the accuracy, the unit step function, the latency of platform, target platform, and the resource constraint, respectively. However, searches often require a lot of computations since they are usually based on reinforcement learning (Zoph and Le, 2016). Therefore, it is important to restrict search spaces when sufficient resources are not allowed.

We use a popular block-based model as an initial model to reduce the search cost. With the block-based model, we search balanced coefficients of width, depth, and resolution using the compound scaling method proposed by Tan and Le (2019) to compensate any possible performance loss due to the reduced structure search space. In summary, we search in two steps.

- **Step 1 (Block arguments search):** Most of recent convolutional networks exploit block-based architectures, e.g., WideResNet (Zagoruyko and Komodakis, 2016), MobileNetV2 (Sandler et al., 2018), and EfficientNet (Tan and Le, 2019). These models are good initial models to reduce the search space greatly because the number and order of layers that compose a block are given. Therefore, we just need to search kernel size, stride, input channels, and output channels for each block.

- **Step 2 (Scaling coefficients search):** EfficientNet (Tan and Le, 2019) proposes the compound scaling rule, defined with a compound coefficient $\phi$ so that network width, depth, and resolution scale in a way: $\alpha^\phi$, $\beta^\phi$, and $\gamma^\phi$, respectively, with a constraint $\alpha \cdot \beta^2 \cdot \gamma^2 \approx 2$. Here, balancing among depth, width, and input resolution scaling coefficients (i.e., $\alpha$, $\beta$, and $\gamma$) is the key to improve performance under available resources. We thus search the three scaling coefficients.

Furthermore, Bayesian optimization (Shahriari et al., 2015) is incorporated for searching hyperparameters since the Bayesian method could reduce the search cost through inference with prior knowledge.

2.2. Improving

The baseline model obtained from the searching stage is expected to be at a desirable trade-off spot between model size and performance. In the improving stage, various methods are applied to improve the performance of the baseline model. These methods range from training settings (e.g., learning rate, batch size, and the number of epochs) to regularization or distillation. Any methods that can be applied to the training process are candidate methods. Through this stage, the model performance can be boosted without or with negligible additional parameters.

In this stage, we focus on how to obtain a desirable combination from a set of candidate techniques. It turns out that some methods are not compatible with others, and the effect of the method may vary on the efficient models that use much fewer parameters than general
architectures. However, the number of possible combinations grows exponentially as $O(2^n)$ with respect to $n$, the number of candidate methods. Therefore, it is computationally intractable to examine all the combinations. To cope with the difficulty of having a wide variety of combinations, we use a greedy-based approach. More precisely, a method is added and adopted only when it makes performance improvement. Although this cannot guarantee optimal combination, a useful sub-optimal combination is achievable. In this process, to determine the order of methods to be tested, we first divide the methods into four categories: general training settings, structural methods, loss-related methods, and others, and then sort the method group from the least sensitive to the most sensitive with respect to the change of settings. This tactic reduces the chance of a specific volatile method leads to rejecting potentially beneficial methods. Figure 2 illustrates the general procedure of the approach mentioned above.

**Figure 2: Procedure of improving stage.**

### 2.3. Pruning

Pruning is a popular compression method to remove unnecessary connections between neurons without significant performance degradation. However, most pruning methods have been tested on large networks (Liu et al., 2018; Li et al., 2016), and it is not clear whether the pruning algorithm still performs well with the efficient model obtained from the previous step. Recent lightweight networks such as MobileNetV2 or EfficientNet uses much less parameters, from which more performance degradation is expected with the same pruning ratio compared to the general networks. Considering the less over-parameterized setting, we analyze the pruning methods in four aspects.

#### A. Weight pruning vs. Filter pruning

Pruning methods are divided into weight pruning (LeCun et al., 1990) and filter pruning (Molchanov et al., 2016) according to pruning targets. Although filter pruning relieves the burden of using a library and hardware for the sparse matrix multiplications (Li et al., 2016), the way to prune the whole filters might not be good with the lightweight networks. For instance, in depthwise filters, which apply a single convolutional filter per input channel, the importance of a single filter significantly increases compared to the conventional convolution layer.

#### B. Global vs. Layer-wise

The necessity of parameters is decided by comparison either in a global or in a layer-wise perspective. From a global perspective, the pruning ratio of each layer is determined by the overall comparison between all parameters. On the other hand, from a layer-wise perspective, all layers have the same sparsity as a result of the magnitude comparison within each layer. However, when the importance of each layer is different, having the same sparsity over all layers can cause a performance degradation.
C. One-shot pruning vs. Iterative pruning  One-shot pruning eliminates the target percentage of parameters in one round, while iterative pruning eliminates them in multiple rounds. Iterative pruning is inclined to preserve a better performance with the same pruning ratio compared to the one-shot pruning but requires more computations to finish the pruning process in general.

D. Fine-tuning vs. Re-initialization  Retraining step is essential to ensure that the pruned model reproduces the performance of the original model. There are two approaches for retraining: fine-tuning and re-initialization. In fine-tuning, the pruned model continues to learn from the checkpoint weight of the trained model. On the other hand, re-initialization retrains from scratch with re-initialized weights. Since it trains from the initial weights, re-initialization requires much more retraining cost than fine-tuning. Moreover, re-initialization cannot achieve comparable accuracy with fine-tuning on a difficult dataset (Liu et al., 2018).

2.4. Accelerating

In this work, we introduce an exit model so that the neural network can predict easy samples earlier without changing the main network architecture. By using the sample-dependent adaptive paths, network inference time can be accelerated (Wang et al., 2018b; Zhang et al., 2019). A network model with a single early prediction path is illustrated in Figure 3. Every sample is predicted first at the early prediction path after block 2. If the prediction result is confident enough, the prediction is accepted as the output and the inference process quits. Otherwise, further computation is conducted at later blocks, and the main network predicts the output.

![Figure 3: An overview of early prediction.](image)

A. Exit Position  As the exit position is located earlier, more computational costs are saved but less likely to obtain confident predictions since the features are not organized enough to be classified. Note that if the prediction at an exit position is not accepted, we spend extra computational cost at the exit position to check the prediction and the confidence. It means that selecting many exit positions might not help to accelerate inference.

B. Exit Module  In the exit module, additional representation capacity is introduced to extract features because it is hard to predict directly from intermediate features, which
mainly trained for prediction from the main path. The more capacity is added to the exit module, the better the performance of early prediction. However, the costs of the early prediction also increase with the bigger exit module.

C. Exit Condition Exit condition has to define how to measure the confidence and how to set the accept threshold. Here, we use the maximum value of softmax output as the confidence of prediction, but other confidence measures can be adopted as well. The threshold setting controls the trade-off between the model accuracy and the computational cost. We very carefully tune the threshold to optimize the competition score.

To have a better confidence measure at the exit module, we propose a novel loss function, referred to as softsmoothing loss. The loss function for the early prediction path $L_{ep}$ is defined as follows:

$$L_{ep} = (1 + \text{Confidence}(\hat{y})) \cdot H(\hat{y}, y)$$

where $H(\hat{y}, y)$ is cross-entropy loss between prediction probability $\hat{y}$ and target probability $y$. By giving more weights to samples with larger confidence in training batch, early prediction becomes more stable in the larger confidence region in the test time.

3. Experiments

Our experiments through SIPA are detailed in this section. Table 1 shows the accuracy and scores of our model, which are normalized relative to WideResNet-28-10 (36.5M parameters and 10.49B FLOPS) and applied fake quantization. Here, $n$ and $s$ indicate the counted numbers and the normalized scores, respectively.

| Stage       | Accuracy | Parameters($n$) | FLOPS($n$) | Parameters($s$) | FLOPS($s$) | Total       |
|-------------|----------|-----------------|-----------|-----------------|-----------|-------------|
| Searching   | 73.47%   | 0.238M          | 0.089B    | 0.006534        | 0.008447  | 0.014981    |
| Improving   | 80.47%   | 0.238M          | 0.089B    | 0.006534        | 0.008447  | 0.014981    |
| Pruning     | 80.05%   | 0.103M          | 0.034B    | 0.002833        | 0.003267  | 0.006100    |
| Accelerating| 80.04%   | 0.109M          | 0.029B    | 0.002995        | 0.002803  | 0.005798    |

3.1. Searching

Taking into account the challenge period and the computing power we have (three RTX Titan V GPU devices), we start with EfficientNet (Tan and Le, 2019), which is the most lightweight model among the top-level accuracy models, as an initial block-based model. The block of EfficientNet depicted in Figure 6b (Appendix A.1) consists of a bottleneck residual block of MobileNetV2 (Sandler et al., 2018) and a squeeze-and-excitation block of SENet (Hu et al., 2018). Two sets of hyperparameters mentioned in Section 2.1 (i.e., block arguments and scaling coefficients) are searched through HyperOpt (Bergstra et al., 2013), which is a tool for Bayesian hyperparameter optimization, and a little manual tuning. The baseline model is given in Figure 6a (Appendix A.1).

2. The details of scoring can be found at https://github.com/Lee-Gihun/MicroNet_OSI-AI.
3.2. Improving

Our approach for the improving stage is outlined in Figure 4. The amount of improvement is estimated by comparing the average performance difference between groups with and without each method. Indeed, this stage increases the accuracy of our model significantly. The detailed descriptions of each method and how it applies to, including the method that does not work with our approach, is explained in Appendix A.2.

![Figure 4: Order of applied improving methods in our approach.](image)

3.3. Pruning

With our efficient network and limited computation resources, it is better to iteratively prune the smallest individual parameters from the global perspective and fine-tune from the checkpoint of the trained model. Furthermore, we propose a layer-wise normalization technique to balance the norm values of each layer and to prevent imbalanced pruning between layers. Because the lightweight model shows a more sensitive response to the change of pruning ratio, it is better to keep or decrease the pruning ratio per round for accuracy maintenance. Results of model accuracy, according to pruning ratio, are detailed in Figure 7 (Appendix A.3).

3.4. Accelerating

Since our network is extremely small, selecting more than one path results in a bad trade-off between computational cost and accuracy. We search multiple positions using our simple exit module design depicted in Figure 8 (Appendix A.4). The detailed result of early prediction performance for exit positions is reported in Appendix A.4. The parameters of the main network are frozen during early prediction path training to avoid hurting the main network performance. After training, a confidence threshold is decided using the validation set.

4. Discussion

Rethinking Efficient Networks We have several interesting observations that could give useful insights for designing efficient networks. In the searching stage, the expansion ratio, which controls how much the input channels are expanded, is the most sensible factor among block arguments. Moreover, increasing input resolution via nearest neighbor interpolation, where an upscaled point uses the same intensity of its nearest neighbor, improves performance considerably. The observations suggest that the performance bottleneck of efficient networks is on preserving the information of the previous step, and expanding the
information to a high-dimensional space is prone to maintain essential information. We also observe that the pruned model sometimes shows better performance than before. This phenomenon implies that the unnecessary parameters of the network are more related to the noise in the inference of the model rather than the essential information to be exploited in inference.

**Network Quantization**  It is found that quantizing the network parameters to 16-bit does not hurt performance at any stage with proper fine-tuning. We use 16-bit training from the beginning and there is only negligible performance degrade. Although more recent quantization methods with 8-bit (Wang et al., 2018a) or 4-bit (Banner et al., 2019) are not tested in this paper, we recommend applying from the beginning with any quantization methods for the stability of training.

**Distribution Stabilization**  Although strong data augmentation methods show impressive performance improvements, we also observe that too strong augmentations, e.g., (Zhang et al., 2017; Yun et al., 2019; Cubuk et al., 2019), sometimes induce the model to learn with samples that are unlikely to be in the real world. To fix this problem, we suggest an additional fine-tuning step stabilize learned distribution. By training a few epochs with augmented samples, which are *more likely in real-world*, the learned distribution can be shifted close to the test time distribution. Figure 5 shows an overview of how our proposed stabilization step works. We find that training a few epochs with a small learning rate can stabilize the learned distribution, without hurting generalization ability.

![Figure 5: An overview of learning stabilization.](image)

**5. Conclusion**

There is a growing interest in building efficient network models to reduce computational and storage costs. In this work, we introduce a simple yet effective framework to build an efficient network. This paper describes key components to build our model, which was submitted to NeurIPS 2019 MicroNet challenge and took 4th place. The framework consists of four stages: searching, improving, pruning, and accelerating. This framework is not limited to a specific model but can be applied to any models with general convolutional network architectures. We find that several improvement techniques are incompatible and even hurt performance in a lightweight network. While many pruning methods have been claimed to attain a 90-95% pruning ratio in large models, pruning for the already small model is another story. We use iterative pruning and layer normalization to preserve model performance for the pruning process. In the accelerating step, a simple extension module enables the early prediction for easy samples without changing the main architecture. We hope that our framework can enlarge the deployment of efficient network models.
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Appendix A. Details of the experiment results

Appendix section A contains details of the experimental results in the order of our framework. The found baseline model and EfficientNet block are described in Appendix A.1, the improving techniques that tested in our improving stage is explained in Appendix A.2. Appendix A.3 shows the varying performance of the model by iterative pruning. Finally, the early prediction results and effect of softsmoothing loss is described in Appendix A.4.

A.1. Searching

Through searching, block arguments of EfficientNet and three scaling coefficients, $\alpha = 1$, $\beta = 0.9$, and $\gamma = 1.4$, are searched. Figure 6a describes our baseline model and Figure 6b describes an EfficientNet block.

![Main Network](image)

(a) Main network

![EfficientNet block](image)

(b) EfficientNet block ($k, s, e, i, o, se$)

Figure 6: Architecture overview.
A.2. Improving

**AutoAugment** searches dataset-specific augmentation policy based on a method using HyperOpt on the augmentation space proposed in (Cubuk et al., 2019). We search 25 sub-policies for the CIFAR-100 dataset.

**Cosine annealing scheduler** adjusts the learning rate as a cosine function (Loshchilov and Hutter, 2016). The learning rate $\eta_t$ is defined as $\eta_t = \eta_{\text{min}} + \frac{1}{2}(\eta_{\text{max}} - \eta_{\text{min}})(1 + \cos\left(\frac{T_{\text{cur}}}{T_{\text{max}} \pi}\right))$, where $\eta_{\text{min}}$ and $\eta_{\text{max}}$ are minimum and maximum learning rate. $T_{\text{cur}}$ is the number of epochs elapsed, and $T_{\text{max}}$ is the maximum number of epochs. Although the original method includes restarting and warm-up, we can not see the performance difference in our work and just apply as a monotonically decreasing learning rate scheduler.

**Increasing initial learning rate** is known to help the model learned by the SGD algorithm converge to flat minima, which tends to show better generalization (Bjorck et al., 2018). We use an initial learning rate of 0.13, which is larger than 0.1 in standard settings.

**No bias decay & No Batch Normalization (BN) decay** help generalization, which is not using weight decay to the bias parameters and batch normalization parameters, respectively. Because these parameters are little portion, compare to the whole parameters, decaying these parameters does not have a significant effect on regularization. Rather, it results in under-fitting problem (He et al., 2019). In our case, only not applying weight decay to bias works, while the other does not.

**Ghost batch normalization** calculates BN statistics ($\beta$ and $\gamma$) from small virtual batch splits (Hoffer et al., 2017). This has a similar effect of training with small batch size while maintaining the training speed of when using a large batch size. We split batch size 128 into 4 virtual batches with size 32.

**Mix-up training** uses training samples that consist of a convex combination of two different classes, where the combining coefficient is sampled from beta distribution (Zhang et al., 2017). This results in the model can learn more smooth distribution and relieves over-fitting because there is a scarce chance to generate the same sample.

**Label smoothing** softens target distribution by giving $1-\epsilon$ to the correct class and disperses $\epsilon$ to the other classes (Szegedy et al., 2016). Although the exact behavior of this method is not discovered, it still is a widely used method. We used $\epsilon$ as 0.3.

**Activation function** adds non-linearity to models. We examine several activation functions such as CeLU, ReLU, Swish, and leaky-ReLU and find Swish activation generalizes well with a relatively less computational cost. Swish activation function (Ramachandran et al., 2017) is $f(x) = x \cdot \text{sigmoid}(\beta x)$ where $\beta$ is a hyperparameter and we use $\beta$ as 1.

**No validation data** is not splitting dataset for validation. After optimizing all the hyperparameters using the validation dataset, we use both the training dataset and the validation dataset for the final training.

**Others** There are some techniques that we test but do not improve performance in our cases, such as refurbishing mis-labeled data in CIFAR-100 (Song et al., 2019) and symmetric padding (Wu et al., 2019).
A.3. Pruning

Figure 7 describes our pruning results per round. The bold line indicates the round of iterative pruning, which is selected as the result of the pruning stage. We empirically observe that significant performance reduction begins when more than 50% of parameters are pruned. After reaching 50% sparsity, we control the pruning ratio per round.

| Round | Pruning Ratio per Round | Sparsity  | Accuracy  |
|-------|-------------------------|-----------|-----------|
| 0     | 0%                      | 0% (baseline) | 80.47%    |
| 1     | 10%                     | 10%       | 80.41%    |
| 2     | 10%                     | 20%       | 80.30%    |
| 3     | 10%                     | 30%       | 80.31%    |
| 4     | 10%                     | 40%       | 80.02%    |
| 5     | 10%                     | 50%       | 80.08%    |
| 6     | 2.5%                    | 52.5%     | 80.11%    |
| 7     | 2.5%                    | 55%       | 80.09%    |
| 8     | 2.5%                    | 57.5%     | 80.21%    |
| 9     | 2.5%                    | 60%       | 80.36%    |
| 10    | 2%                      | 62%       | 79.89%    |
| 11    | 2%                      | 64%       | 80.05%    |
| 12    | 2%                      | 66%       | 79.57%    |
| 13    | 2%                      | 68%       | 79.21%    |
| 14    | 2%                      | 70%       | 79.19%    |

Figure 7: Results of iterative pruning.

A.4. Accelerating

Table 2 shows the results according to the exit position. The Path FLOPs and Added Params show the cost ratio of early prediction path to the main path when exit from the corresponding Exit Position. Exit Ratio and Total Acc is tested with a fixed candidate confidence threshold (0.85, 0.88, 0.92). Exit position 4 with confidence threshold 0.85 is selected as the result of the accelerating stage. By further pruning and stabilizing for the early prediction path, we acquire our final model with 80.04% accuracy. From these results, the overall structure of our model with an early prediction path is illustrated in Figure 8. Besides, Figure 9 shows the effect of softsmoothing loss on a risk-coverage curve (Geifman and El-Yaniv, 2017). Softsmoothing loss(sm) shows low risk in high coverage region compare to cross-entropy loss(ce).
Table 2: Early prediction results for different exit positions.

| Exit Position | Path Acc | Path FLOPS | Added Params | Threshold | Exit Ratio | Total Acc |
|---------------|----------|------------|--------------|-----------|------------|-----------|
| Block 2       | 55.81%   | 21.19%     | 9.53%        | 0.85      | 20.43%     | 79.94%    |
|               | 58.66%   | 29.58%     | 9.53%        | 0.88      | 22.92%     | 80.26%    |
|               | 64.62%   | 38.91%     | 10.10%       | 0.92      | 20.24%     | 80.35%    |
| Block 3       | 55.81%   | 21.19%     | 9.53%        | 0.85      | 22.92%     | 80.26%    |
|               | 58.66%   | 29.58%     | 9.53%        | 0.88      | 20.24%     | 80.35%    |
|               | 64.62%   | 38.91%     | 10.10%       | 0.92      | 18.33%     | 80.38%    |
| Block 4       | 64.62%   | 38.91%     | 10.10%       | 0.85      | 36.31%     | 79.94%    |
|               | 69.85%   | 52.72%     | 11.23%       | 0.88      | 33.27%     | 80.11%    |
|               | 69.85%   | 52.72%     | 11.23%       | 0.92      | 31.11%     | 80.19%    |

Figure 8: Main network & exit module.

Figure 9: Effect of softsmoothing loss.