EFFICIENT CNN ARCHITECTURE DESIGN GUIDED BY VISUALIZATION

Liangqi Zhang, Haibo Shen, Yihao Luo, Xiang Cao, Leixilan Pan, Tianjiang Wang*, Qi Feng

School of Computer Science and Technology, Huazhong University of Science and Technology, China
{zhangliangqi, shenhaibo, luoyihao, caoxiang112, d202081082, tjwang, fengqi}@hust.edu.cn

ABSTRACT
Modern efficient Convolutional Neural Networks(CNNs) always use Depthwise Separable Convolutions(DSCs) and Neural Architecture Search(NAS) to reduce the number of parameters and the computational complexity. But some inherent characteristics of networks are overlooked. Inspired by visualizing feature maps and N×N(N>1) convolution kernels, several guidelines are introduced in this paper to further improve parameter efficiency and inference speed. Based on these guidelines, our parameter-efficient CNN architecture, called VGNetG, achieves better accuracy and lower latency than previous networks with about 30%~50% parameters reduction. Our VGNetG-1.0MP achieves 67.7% top-1 accuracy with 0.997M parameters on ImageNet dataset.

Furthermore, we demonstrate that edge detectors can replace learnable depthwise convolution layers to mix features by replacing the N×N kernels with fixed edge detection kernels. And our VGNetF-1.5MP archives 64.4%(-3.2%) top-1 accuracy and 66.2%(-1.4%) top-1 accuracy with additional Gaussian kernels.

Index Terms — Visualization, Efficient, Edge detection, Gaussian blur

1. INTRODUCTION
Recently, Convolutional Neural Networks(CNNs) have made great progress in computer vision. Since AlexNet [1], CNN-based methods focus on designing wider or deeper network architectures for the accuracy gains, including VGGNets [2], ResNets [3], and DenseNets [4]. However, the computational and storage capacity is always limited. The most prominent approaches to reduce the parameters and computational complexity are based on Depthwise Separable Convolutions [5] and Neural Architecture Search, such as MobileNets [6,7], ShuffleNets [8,9], and EfficientNets [10]. Although these approaches have been greatly successful, they also overlook many inherent characteristics of convolutional neural networks.

Visualization is a powerful tool to study neural networks. Visualization of features in a fully trained model [11,12] makes us to see the process of extracting features. Feature Visualization by Optimization [13,14] explains what a network is looking for. Attribution [15–17] explains what part of an example is responsible for the network activating in a particular way. Visualization can reveal many inherent characteristics of neural networks.

In this paper, we study the characteristics of networks by visualizing the N×N kernels, the distribution of kernels, and feature maps. As shown in Figure 1, the N×N convolution kernels show distinctly different patterns and distributions at different stages of MobileNetV2 [7].

Our VGNetGs guided by these visualizations achieve better accuracy and lower latency than previous models with about 30%~50% parameters reduction. Specifically, Our VGNetG-1.0MP archives 67.7% top-1 accuracy with 0.997M parameters without strong regularization methods. Furthermore, we demonstrate that edge detectors can replace learnable depthwise convolutions for mixing features between different spatial locations.

2. RELATED WORK

DSCs-based Architectures Depthwise Separable Convolutions was introduced in [5] and subsequently used in efficient convolutional neural networks [6,10]. DSCs factorize a standard convolution into a light weight depthwise convolution for spatial filtering and a 1×1 convolution called a heavier pointwise convolution for feature generation. Typical 3×3
depthwise separable convolutions use between 8 to 9 times less computation than standard convolutions at only a small reduction in accuracy. MobileNetV1 \[6\] employs DSCs to substantially improve computational efficiency. MobileNetV2 \[7\] introduced the Inverted residual block, which takes as an input a low-dimensional compressed representation which is first expanded to high dimension and filtered with a lightweight depthwise convolution. Features are subsequently projected back to a low-dimensional representation with a linear convolution. ShuffleNetV1 \[8\], V2 \[9\] utilizes group convolution and channel shuffle operations to further reduce the complexity. MobileNetV3 \[18\], RegNets \[19\] and EfficientNets \[10\] built upon the InvertedResidualBlock structure by introducing lightweight attention modules \[20\] based on squeeze and excitation into the bottleneck structure.

Nyquist-Shannon Sampling Theorem and Shift-Invariant As reported in \[21\], the convolutional architecture does not give invariance since architecture ignores the classical sampling theorem, as small input shifts or translations can cause drastic changes in the output. Even though blurring before subsampling is sufficient for avoiding aliasing in linear systems, the presence of nonlinearity may introduce aliasing even in the presence of blur before subsampling. \[22\] integrates extra classic anti-aliasing to improve shift equivariance of deep networks.

Feature Visualization and Attribution Visualization is a powerful tool to study neural networks. Visualization of features in a fully trained model \[11,12\] makes us see the process of extracting features. Activation Maximization \[11,13\], Class Maximization \[14\] explains what a network is looking for. Saliency Maps \[15\], Guided Backpropagation \[16\], Grad-CAM \[17\] explains what part of an example is responsible for the network activating in a particular way. Network visualization also could give us many intuitive inspirations to design new architectures.

3. CHARACTERISTICS OF CNNS AND GUIDELINES

In this section, we study three typical networks constructed by (i) standard convolutions such as ResNet-RS, (ii) group convolutions such as RegNet, (iii) depthwise separable convolutions such as MobileNets, ShuffleNetV2 and EfficientNets. These visualizations demonstrate that M × N × N kernels have distinctly different patterns and distributions at different stages of networks. What follows are the characteristics of CNNs and guidelines:

3.1. CNNs can learn to satisfy the sampling theorem

The previous works \[21,22\] always thought that convolutional neural networks ignore the classical sampling theorem, but we found that convolutional neural networks can satisfy the sampling theorem to some extent by learning low-pass filters, especially the DSCs-based networks such as MobileNetV1 and EfficientNets, as shown in Figure 2.

Standard convolutions/Group convolutions As shown in Figure 3a and 3b, there are one or more salient N × N kernels like blur kernels in the whole M × N × N kernels, and this
phenomenon also means the parameters of these layers are redundant. Note that the salient kernels do not necessarily seem like Gaussian kernels.

**Depthwise separable convolutions** The kernels of strided-DSCs are usually similar to Gaussian kernels, including but not limited to MobileNetV1, MobileNetV2, MobileNetV3, ShuffleNetV2, ReXNet, EfficientNets. In addition, the distributions of strided-DSC kernels are not Gaussian distributions but Gaussian mixture distributions.

**Kernels of last convolution layers** Modern CNNs always use global pooling layers before the classifier to reduce the dimension. Therefore, similar phenomenon is also shown on the last depthwise convolution layers, as shown in Figure 4.

These visualizations indicate that we should choose depthwise convolutions rather than standard convolutions and group convolutions in the downsampling layers and last layers. And further, we could use fixed Gaussian kernels in the downsampling layers.

**3.2. Reuse feature maps between adjacent layers**

**Identity Kernel and Similar Features Maps** As shown in Figure 3, many depthwise convolution kernels only have a large value at the center like identity kernel in the middle part of networks. And convolutions with identity kernels lead to feature maps duplication and computational redundancy since the inputs are just passed to the next layer. On the other hand, Figure 6 shows that many feature maps are similar (duplicated) between adjacent layers.

As a result, we could replace partial convolutions with identity mapping. Otherwise, depthwise convolutions are slow in early layers since they often cannot fully utilize modern accelerators reported in [9]. So this method can improve both the parameter efficiency and inference time.

**3.3. Edge detectors as learnable depthwise convolutions**

Edge features contain important information about the images. As shown in Figure 5, a large part of kernels approximate to edge detection kernels, like the Sobel filter kernels and the Laplacian filter kernels. And the proportion of such kernels decreases in the later layers while the proportion of kernels that like blur kernels increases.

Therefore, maybe the edge detectors could replace the depthwise convolutions in the DSCs-based networks to mix features between different spatial locations. We will demonstrate that by replacing learnable kernels with edge detection kernels.
5. EXPERIMENTS

In this section, we present our experimental setups, the main results on ImageNet (the results on CIFAR-100 can be found in Appendix B).

5.1. ImageNet Classification

The ImageNet ILSVRC2012 dataset contains about 1.28M training images and 50,000 validation images with 1000 classes. We emphasize that VGNetG models are trained with no regularization except weight decay and label smoothing, while most networks use various enhancements, such as deep supervision, Cutout, DropPath, AutoAugment, RandAugment, and so on.

**Training setup** Our ImageNet training settings follow: SGD optimizer with momentum 0.9; mini-batch size of 512; weight decay 1e-4; initial learning rate 0.2 with 5 warmup epochs; batch normalization with momentum 0.9; cosine learning rate decay for 300 epochs; label smoothing 0.1; the biases and $\alpha$ and $\beta$ in BN layers are left unregularized. Finally, all training is done on resolution 224.

**Results** Table 5 shows the performance comparison on ImageNet, our VGNetGs achieves better accuracy and parameter efficiency than the MobileNet series and ShuffleNetV2 with more than 30% parameters reduction and lower inference latency. In particular, our VGNetG-1.0MP achieves 67.7% top-1 accuracy with less than 1M parameters and 69.2% top-1 accuracy with 1.14M parameters.

4. NETWORK ARCHITECTURE

Following these guidelines, we design our parameter-efficient architecture and study the function of depthwise convolutions. Note that only pointwise convolutions are followed by ReLU and batchnorm for better accuracy and inference speed.

**DownsamplingBlock** The *DownsamplingBlock* halves the resolution and expands the number of channels. As shown in Figure 8a, only the expanded channels are generated by the pointwise convolutions for reusing the features. The kernels of depthwise convolutions could be randomly initialized or use fixed Gaussian kernels.

**HalfIdentityBlock** As shown in Figure 8b, we replace half depthwise convolutions with identity mapping and reduce half pointwise convolutions while keeping the width of the block. Note that the right half channels of the input become the left half channels of the output for better feature reusing.

**VGNet Architecture** Using the DownsamplingBlock and HalfIdentityBlock, we build our VGNetGs limited by the number of parameters. The overall VGNetG-1.0MP architecture is listed in Table 1.

| Variant | DownsamplingBlock | HalfIdentityBlock |
|---------|-------------------|-------------------|
| VGNetC  | random & learnable| random & learnable|
| VGNetG  | GKs               | GKs               |
| VGNetF  | EKs & GKs         |                   |

Table 2: Variants of VGNet. *EKs* denotes edge detection kernels; *GKs* denotes Gaussian kernels. EKs and GKs are shown in Figure 7.

4.1. Ablation study

In this section, we conduct ablation experiments to gain a better understanding of the impact of the depthwise convolutions. The ablation experiments are performed on the ImageNet and CIFAR100 (see Appendix B).

**Kernels of downsampling layers** As shown in Table 4, The VGNetG-1.5MP which used the Gaussian blur kernels in the downsampling layers achieves 68.0% top-1 accuracy, outperforming the VGNetC-1.5MP by 0.4% accuracy.

**Kernels of depthwise convolutions** As shown in Table 4, the VGNetF4, only used 2 Sobel kernels and 2 Laplacian filter kernels instead of all the depthwise convolution kernels, has about 3% reduction in accuracy. The result indicates that CNNs can use edge detectors as learnable depthwise convolutions to mix features. As mentioned, the last few layers have more kernels like blur kernels. So the VGNetF2 which used additional Gaussian kernels achieves better accuracy than VGNetF4.

**Non-linearities and training epochs** Table 5 compares the performance of VGNetG-1.5MP according to the number of parameters.

| Input | Operator | Type | Stride | Channels | Layers |
|-------|----------|------|--------|----------|--------|
| 224   | Conv2d   | -    | 2      | 3        | 1      |
| 112   | DownsamplingBlock | blur | 2     | 28       | 1      |
| 56    | HalfIdentityBlock | -    | 1      | 56       | 3      |
| 56    | DownsamplingBlock | blur | 2     | 56       | 1      |
| 28    | HalfIdentityBlock | -    | 1      | 112      | 6      |
| 28    | DownsamplingBlock | blur | 2     | 112      | 1      |
| 14    | HalfIdentityBlock | -    | 1      | 224      | 12     |
| 14    | DownsamplingBlock | blur | 2     | 224      | 1      |
| 7     | HalfIdentityBlock | -    | 1      | 368      | 1      |
| 7     | SharedDWConv2d t=8 | -    | 1      | 368      | 1      |
| 7     | PointwiseBlock   | -    | 1      | 368      | 1      |
| 7     | AvgPool2d        | -    | -      | 368      | 1      |

Table 1: VGNetG-1.0MP Networks. *HalfIdentityBlock* and *DownsamplingBlock* are described in Figure 8. SharedDWConv2d just share the same depthwise convolution kernels for $t$ times.

Table 5 compares the performance of VGNetG-1.0MP according to the number of parameters of $N \times N$ kernels.
| Model                        | SE | Top-1 Acc. (%) | Top-5 Acc. (%) | Params (M) | Ratio-to VGNetG | GPU Speed (batches/sec.) | Infer-time (ms) |
|-----------------------------|----|----------------|----------------|-----------|-----------------|--------------------------|-----------------|
| MobileNet V2×0.5×0.5 [7]    | ✓  | 63.9           | 85.1           | 1.969     | 1.97×           | 209                      | 4.77            |
| MobileNet V3 Small† [18]    | ✓  | 67.4           | -              | 2.543     | 1.69×           | 196                      | 5.09            |
| VGNetG-1.0MP(ours)          | ✓  | 66.6           | 87.1           | 0.997     | 1.00×          | 228                      | 4.37            |
| VGNetG-1.0MP+SILU(ours)†     | ✓  | 67.7           | 87.9           | 0.997     | 1.00×          | 226                      | 4.41            |
| VGNetG-1.0MP+SE(ours)       | ✓  | 69.2           | 88.7           | 1.143     | 1.14×          | 107                      | 9.31            |
| MobileNet V2×0.75×0.75 [7]  | ✓  | 69.8           | 89.6           | 2.636     | 1.75×          | 194                      | 5.15            |
| ShuffleNet V2×1.0 [9]       | ✓  | 69.4           | 88.0           | 2.279     | 1.52×          | 162                      | 6.15            |
| VGNetG-1.5MP(ours)          | ✓  | 69.3           | 88.8           | 1.502     | 1.00×          | 222                      | 4.50            |
| VGNetG-1.5MP+SE(ours)       | ✓  | 71.3           | 90.1           | 1.702     | 1.13×          | 104                      | 9.55            |
| MobileNet V1×1.0 [6]        | ✓  | 70.6           | 88.2           | 4.232     | 2.11×          | 201                      | 4.97            |
| MobileNet V2×1.0 [7]        | ✓  | 72.0           | 91.0           | 3.505     | 1.75×          | 170                      | 5.87            |
| MobileNet V3 Large×0.75†    | ✓  | 73.3           | -              | 3.994     | 1.99×          | 166                      | 6.01            |
| VGNetG-2.0MP(ours)          | ✓  | 71.3           | 90.0           | 2.006     | 1.00×          | 224                      | 4.45            |
| VGNetG-2.0MP+SE(ours)       | ✓  | 73.5           | 91.4           | 2.345     | 1.17×          | 109                      | 9.14            |
| ShuffleNet V2×1.5 [9]       | ✓  | 72.6           | -              | 3.504     | 1.41×          | 157                      | 6.34            |
| GhostNet×1.0† [23]          | ✓  | 73.9           | 91.4           | 5.183     | 2.08×          | 114                      | 8.75            |
| RegNetX-400MF [19]          | ✓  | 72.7           | -              | 5.158     | 2.07×          | 109                      | 9.12            |
| RegNetY-400MF [19]          | ✓  | 74.1           | -              | 4.344     | 1.74×          | 94                       | 10.62           |
| VGNetG-2.5MP(ours)          | ✓  | 72.6           | 90.7           | 2.493     | 1.00×          | 200                      | 4.98            |
| VGNetG-2.5MP+SE(ours)       | ✓  | 74.2           | 91.8           | 2.922     | 1.17×          | 97                       | 10.31           |

Table 3: Performance Results on ImageNet. Our VGNetGs achieve better accuracy with about 30%~50% parameters reduction. GPU Speed and Infer-time are measured on RTX6000 GPU with batch size 16. Params is measured by facebookresearch/fvcore and the Params do not include the unlearnable parameters. The SEBlocks are used after every pointwise convolutions expect the last one. †: used SiLU(also known as the swish function) or HardSwish.

of training epochs and non-linearities. It can be seen that more epochs and the SiLU non-linearities show better performance.

| Model (1.5MP) | Downsampling Kernels | N×N Kernels | Last DSC kernels | Top-1 Acc. (%) |
|---------------|----------------------|-------------|------------------|----------------|
| VGNetC        | learnable            | learnable   | learnable        | 67.6           |
| VGNetG        | GKs                  | learnable   | learnable        | 68.0           |
| VGNetF1       | GKs                  | 6 EKs+2 GKs | learnable        | 66.8           |
| VGNetF2       | GKs                  | 6 EKs+2 GKs | 6 EKs+2 GKs      | 66.2           |
| VGNetF3       | GKs                  | 4 EKs       | learnable        | 66.1           |
| VGNetF4       | GKs                  | 4 EKs       | 4 EKs            | 64.4           |

Table 4: Ablation study for ImageNet classification. EK: Edge detection Kernel; GK: Gaussian Kernel.

| Model        | SiLU | Epochs | Top-1 Acc. (%) |
|--------------|------|--------|----------------|
| VGNetG-1.5MP | ✓    | 100    | 68.0           |
|              |      | 100    | 69.1           |
|              |      | 300    | 69.3           |

Table 5: Impact of non-linearities and training epochs.

6. DISCUSSION

We demonstrated that edge detectors can take the place of learnable depthwise convolution layers in CNNs. But how these edge features are used is still unclear.

Moreover, as shown in Figure 9, MobileNetV3 Small and Large have almost half zero N×N kernels in the front layers. Maybe we could reduce more parameters and computational complexity in the front layers.

7. CONCLUSION

In this paper, we designed parameter-efficient CNN architecture guided by visualizing the convolution kernels and feature maps. Based on these visualizations, we proposed VG Nets, a new family of smaller and faster neural networks for image recognition. Our VG Nets achieve better accuracy with about 30%~50% parameters reduction and lower inference latency than the previous networks. Finally, we demonstrated that fixed Gaussian kernels and edge detection kernels could replace the learnable depthwise convolution kernels.
8. REFERENCES

[1] Alex Krizhevsky, Ilya Sutskever, and Geoffrey E. Hinton, “ImageNet classification with deep convolutional neural networks,” in *Advances in Neural Information Processing Systems*, 2012, vol. 2, pp. 1097–1105.

[2] Karen Simonyan and Andrew Zisserman, “Very deep convolutional networks for large-scale image recognition,” 3rd International Conference on Learning Representations, *ICLR 2015 - Conference Track Proceedings*, pp. 1–14, 2015.

[3] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun, “Deep residual learning for image recognition,” in *Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, 2016, vol. 2016-Decem, pp. 770–778.

[4] Gao Huang, Zhuang Liu, Laurens Van Der Maaten, and Kilian Q. Weinberger, “Densely connected convolutional networks,” in *Proceedings - 30th IEEE Conference on Computer Vision and Pattern Recognition*, CVPR 2017, 2017, vol. 2017-Janua, pp. 2261–2269.

[5] Laurent Sifre, PhD thesis Rigid-Motion Scattering For Image Classification, 2014.

[6] Andrew G. Howard, Menglong Zhu, Bo Chen, Dmitry Kalenichenko, Weijun Wang, Tobias Weyand, Marco Andreetto, and Hartwig Adam, “MobileNets: Efficient Convolutional Neural Networks for Mobile Vision Applications,” 2017.

[7] Mark Sandler, Andrew Howard, Menglong Zhu, Andrey Zhmoginov, and Liang Chieh Chen, “MobileNetV2: Inverted Residuals and Linear Bottlenecks,” *Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, pp. 4510–4520, 2018.

[8] Xiangyu Zhang, Xinyu Zhou, Mengxiao Lin, and Jian Sun, “ShuffleNet: An Extremely Efficient Convolutional Neural Network for Mobile Devices,” *Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, pp. 6848–6856, 2018.

[9] Ningning Ma, Xiangyu Zhang, Hai Tao Zheng, and Jian Sun, “Shufflenet V2: Practical guidelines for efficient cnn architecture design,” *Lecture Notes in Computer Science* (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), vol. 11218 LNCS, pp. 122–138, 2018.

[10] Mingxing Tan and Quoc V. Le, “EfficientNet: Rethinking model scaling for convolutional neural networks,” 36th International Conference on Machine Learning, *ICML 2019*, vol. 2019-June, pp. 10691–10700, 2019.

[11] Dumitru Erhan, Yoshua Bengio, Aaron Courville, and Pascal Vincent, “Visualizing higher-layer features of a deep network,” *Bernoulli*, no. 1341, pp. 1–13, 2009.

[12] Matthew D. Zeiler and Rob Fergus, “Visualizing and understanding convolutional networks,” *Lecture Notes in Computer Science* (including subseries Lecture Notes in Artificial Intelligence), vol. 8689 LNCS, no. PART 1, pp. 818–833, 2014.

[13] Matthew D. Zeiler, Graham W. Taylor, and Rob Fergus, “Adaptive deconvolutional networks for mid and high level feature learning,” *Proceedings of the IEEE International Conference on Computer Vision*, pp. 2018–2025, 2011.

[14] Jason Yosinski, Jeff Clune, Anh Nguyen, Thomas Fuchs, and Hod Lipson, “Understanding Neural Networks Through Deep Visualization,” 2015.

[15] Karen Simonyan, Andrea Vedaldi, and Andrew Zisserman, “Deep inside convolutional networks: Visualising image classification models and saliency maps,” 2nd International Conference on Learning Representations, *ICLR 2014 - Workshop Track Proceedings*, pp. 1–8, 2014.

[16] Jost Tobias Springenberg, Alexey Dosovitskiy, Thomas Brox, and Martin Riedmiller, “Striving for simplicity: The all convolutional net,” 3rd International Conference on Learning Representations, *ICLR 2015 - Workshop Track Proceedings*, pp. 1–14, 2015.

[17] Ramprasaath R. Selvaraju, Michael Cogswell, Abhishek Das, Ramakrishna Vedantam, Devi Parikh, and Dhruv Batra, “Grad-CAM: Visual Explanations from Deep Networks via Gradient-Based Localization,” *International Journal of Computer Vision*, vol. 128, no. 2, pp. 336–359, 2020.

[18] Andrew Howard, Mark Sandler, Bo Chen, Weijun Wang, Liang Chieh Chen, Mingxing Tan, Grace Chu, Vijay Vasudevan, Yukun Zhu, Zhinong Pang, Quoc Le, and Hartwig Adam, “Searching for MobileNetV3,” *Proceedings of the IEEE International Conference on Computer Vision*, vol. 2019-Octob, pp. 1314–1324, 2019.

[19] Ilija Radosavovic, Raj Prateek Kosaraju, Ross Girshick, Kaiming He, and Pieter Dollar, “Designing network design spaces,” *Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, pp. 10425–10433, 2020.

[20] Jie Hu, Li Shen, Samuel Albanie, Gang Sun, and Enhua Wu, “Squeeze-and-Excitation Networks,” *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 42, no. 8, pp. 2011–2023, 2020.

[21] Aharon Azulay and Yair Weiss, “Why do deep convolutional networks generalize so poorly to small image transformations?,” *Journal of Machine Learning Research*, vol. 20, 2019.

[22] Richard Zhang, “Making convolutional networks shift-invariant again,” 2019, vol. 2019-June.

[23] Kai Han, Yunhe Wang, Qi Tian, Jianyuan Guo, Chunjing Xu, and Chang Xu, “GhostNet: More features from cheap operations,” *Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, pp. 1577–1586, 2020.