EfficientNet

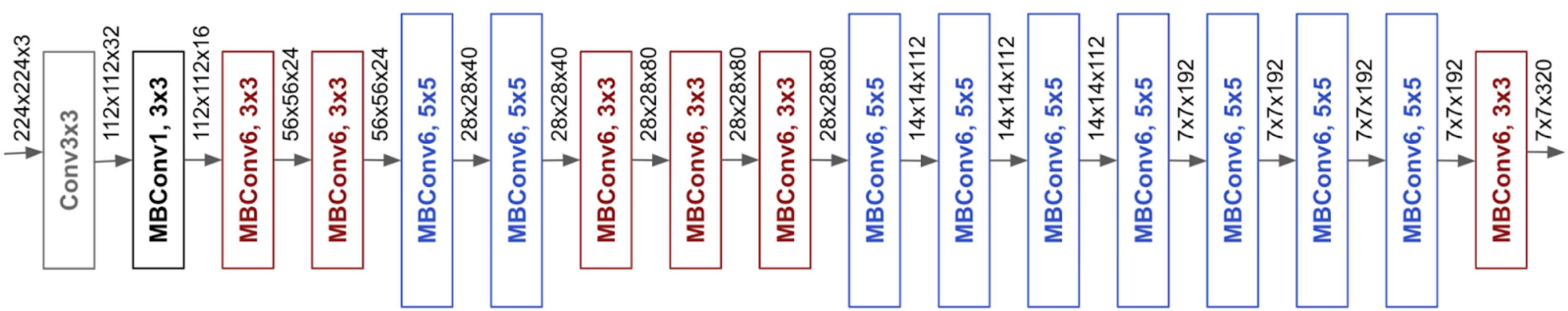
M. Tan et al, EfficientNet: Rethinking Model Scaling for Convolutional Neural Networks, arXiv 2019

Scale Up

Recent Trends of CNNs

Repeating Base Blocks

Stage i	Operator $\hat{\mathcal{F}}_i$	Resolution $\hat{H}_i \times \hat{W}_i$	#Channels $\hat{C}_i$	#Layers $\hat{L}_i$
1	Conv3x3	224×224	32	1
2	MBConv1, k3x3	112×112	16	1
3	MBConv6, k3x3	112×112	24	2
4	MBConv6, k5x5	56×56	40	2
5	MBConv6, k3x3	28×28	80	3
6	MBConv6, k5x5	28×28	112	3
7	MBConv6, k5x5	14×14	192	4
8	MBConv6, k3x3	7×7	320	1
9	Conv1x1 & Pooling & FC	7×7	1280	1



Scale Up

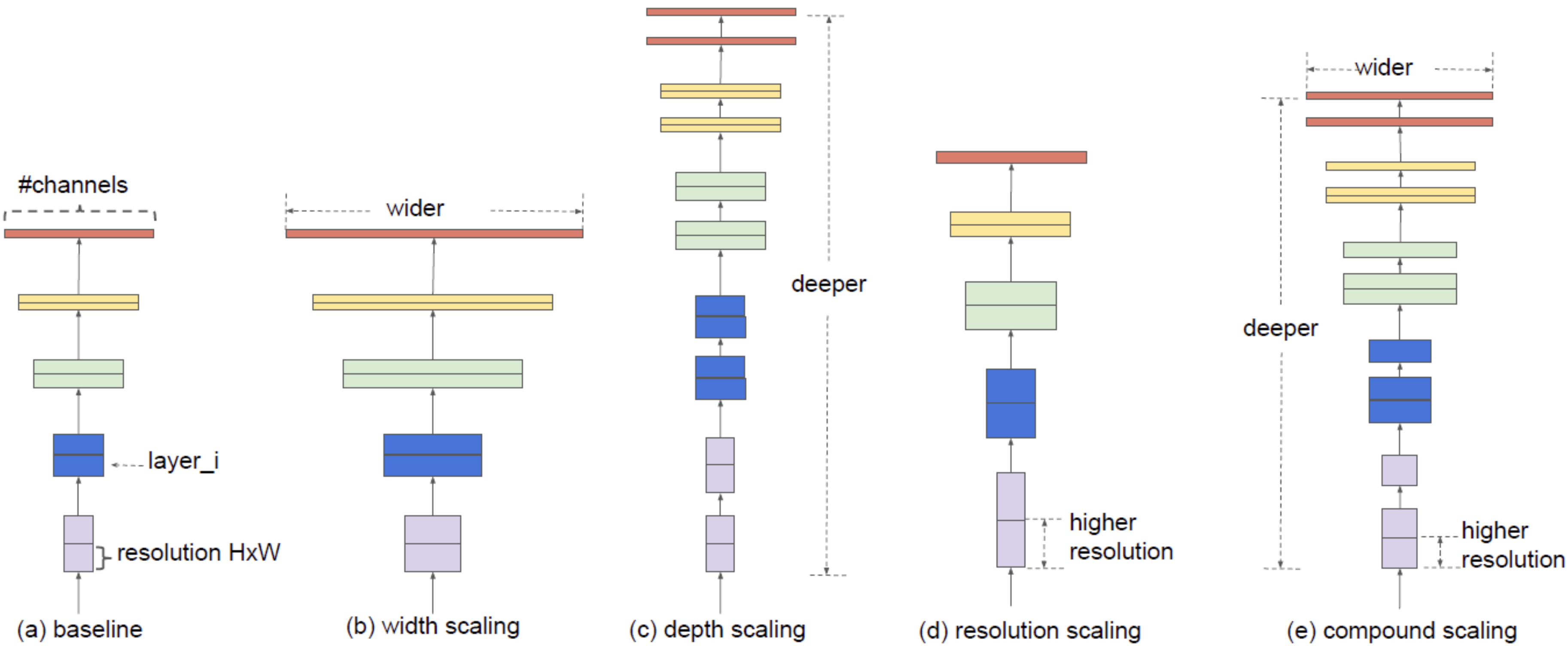
- **Scaling up ConvNets is widely used to achieve better accuracy.**
  - **ResNet can be scaled from ResNet 18 to ResNet 200 by using more layers.**
  - **GPipe achived 84.3% ImageNet top 1 accuracy by scaling up a baseline model 4 times larger.**
- **What to Scale Up**
  - **# of Layers: Depth**
  - **# of Channels: Width**
  - **Size of Input Images: Resolution**

Scale Up

- **What to Scale Up**
  - **# of Layers: Depth**
  - **# of Channels: Width**
  - **Size of Input Images: Resolution**
- **Why to Scale Up**
  - **If a network has more layers**
    - We can capture richer and more complex features
  - **If a network has more channels**
    - We can have various patterns
  - **If an input image is bigger**
    - We can use fine-grained patterns
    - Early networks used 224x224, but these days use 299x299, 331x331 or 480x480 (Gpipe)

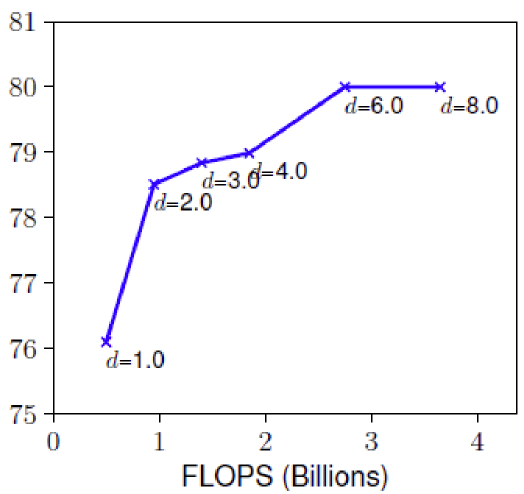
Scale Up

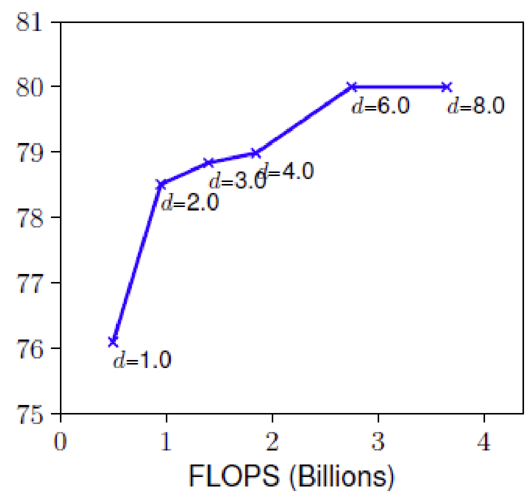
- **Width, Depth, Resolution Scaling**

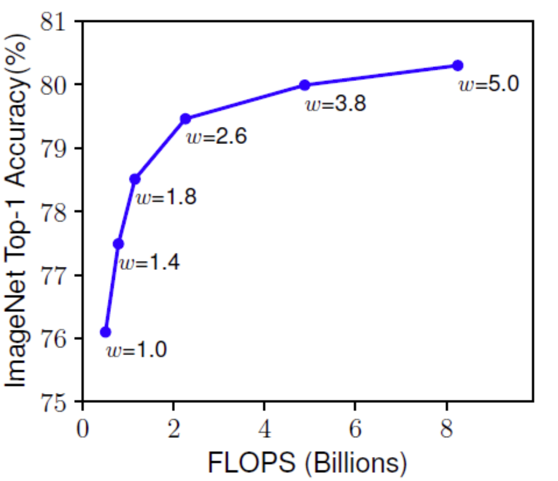


Difficulties

- **Saturation**
  - **ResNet 1000 has similar accuracy as ResNet 101 even though it has much more layers.**
  - **Hard to capture good features if networks are shallow even though it is wider**







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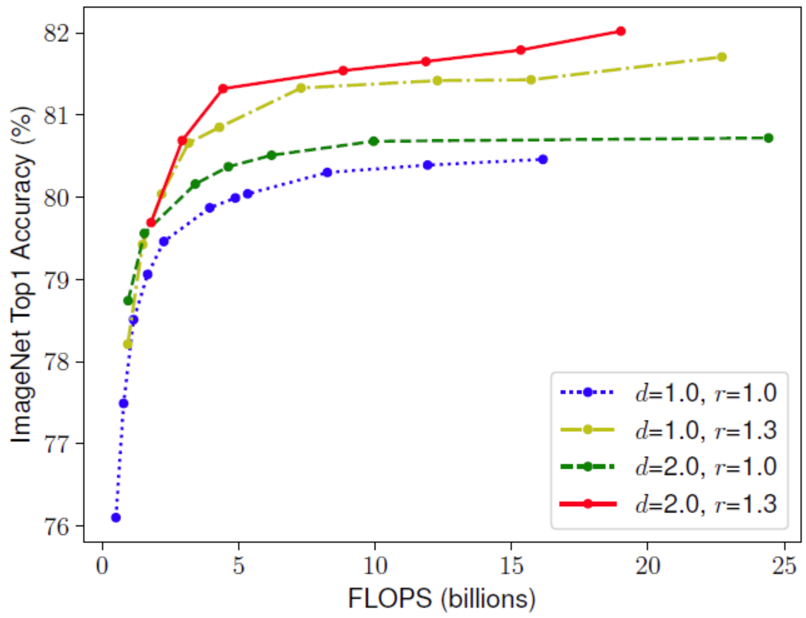
Difficulties

- **It is critical to balance width, depth and resolution**
  - **Scaling width w without changing depth (d=1.0) and resolution (r=1.0) results in quick saturation**
  - **With deeper (d=2.0) and higher resolution (r=2.0), width scaling achieves much better accuracy under the same FLOPS cost.**



Idea for Best Compound Scaling

1. **Find out a good baseline model**
2. **Find out the golden ratio of width, depth and resolution for scaling**
3. **Scaling up each dimension of the baseline model keeping the golden ratio of width, depth and resolution**

Formulation

- **Recap: CNN**

$$\mathcal{N} = \bigodot_{i=1\ldots s} \mathcal{F}_i^{L_i}\left(X_{\langle H_i, W_i, C_i \rangle}\right)$$

s: stage,
F_i: operation of stage i,
L_i: repetition of F_i,
$X_{<H_i, W_i, C_i>}$: input

Example

Stage i	Operator $\hat{\mathcal{F}}_i$	Resolution $\hat{H}_i \times \hat{W}_i$	#Channels $\hat{C}_i$	#Layers $\hat{L}_i$
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7	MBConv6, k5x5	14×14	192	4
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Formulation

- **Compound Scaling**

$$\max_{d,w,r} \quad Accuracy\big(\mathcal{N}(d,w,r)\big)$$

$$s.t. \quad \mathcal{N}(d,w,r) = \bigodot_{i=1\ldots s} \hat{\mathcal{F}}_i^{d\cdot\hat{L}_i}\big(X_{\langle r\cdot\hat{H}_i, r\cdot\hat{W}_i, w\cdot\hat{C}_i\rangle}\big)$$

$$\text{Memory}(\mathcal{N}) \leq \text{target\_memory}$$

$$\text{FLOPS}(\mathcal{N}) \leq \text{target\_flops}$$

s: stage
F_i: operation of stage i,
L_i: repetition of F_i,
$X_{<H_i,W_i,C_i>}$: input

d: scale facor of depth
w: scale facor of width
r: scale facor of resolution

- **Assumption**
  - All stages and layers share the scaling factors to reduce the search space

Formulation

- **FLOPS of a CNN is proportional to d, w^2 , r^2**
  - **Doubling depth doubles FLOPS**
  - **Doubling width or resolution increases FLOPS by four times**

- **So, following constraints are added to searching for *d*, *w* and *r***

$$
\begin{aligned}
\text{depth: } & d = \alpha^{\phi} \\
\text{width: } & w = \beta^{\phi} \\
\text{resolution: } & r = \gamma^{\phi} \\
\text{s.t. } & \alpha \cdot \beta^2 \cdot \gamma^2 \approx 2 \\
& \alpha \geq 1, \beta \geq 1, \gamma \geq 1
\end{aligned}
$$

ϕ is a user specific parameter

Searching for Baseline Model

- **By MNasNet**
  - **a multi objective neural architecture search that optimizes both accuracy and FLOPS**
  - **Optimization Goal :**

$$ACC(m) \times [FLOPS(m)/T]^w$$

- **The found baseline model will be scaled up for better accuracy with less resources.**

Searching for Baseline Model

- **Found Baseline Model**

Stage i	Operator $\hat{\mathcal{F}}_i$	Resolution $\hat{H}_i \times \hat{W}_i$	#Channels $\hat{C}_i$	#Layers $\hat{L}_i$
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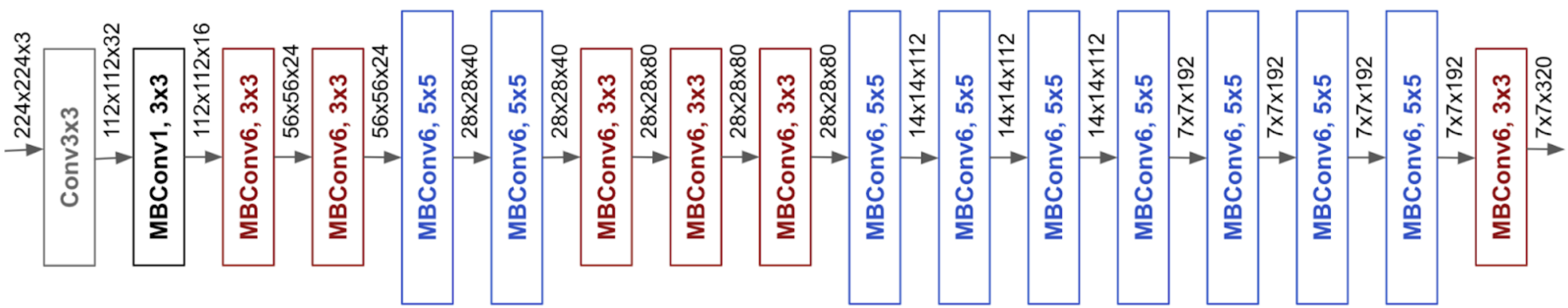


Golden Ratio and Model Scaling

- **Golden Ratio of α, β, γ by grid search**
  - **Assuming twice more resources available, i.e., $\phi = 1$**
  - **The best values are α =1.2, β=1.1, γ=1.15**

- **Scaling the Baseline Model**
  - **Choosing ϕ considering available resources**
  - **Scale the base model by $w = \alpha^{\phi}$, $d = \beta^{\phi}, r = \gamma^{\phi}$**

  - **They chose 7 different values for ϕ, i.e., generated 7 different networks by scaling.**

Performance

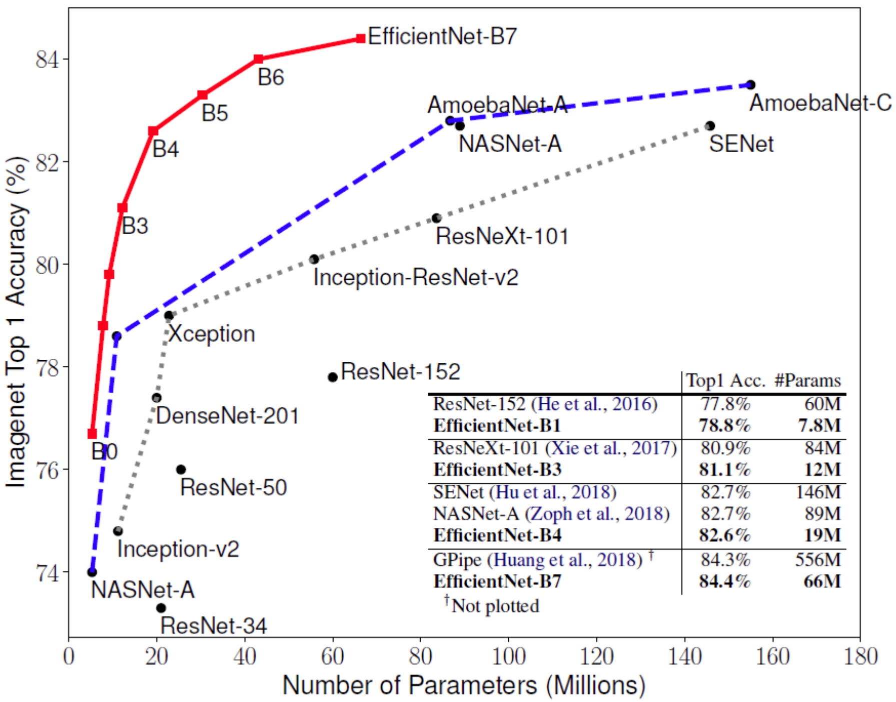
ImageNet Classification

Model	Top-1 Acc.	Top-5 Acc.	#Params	Ratio-to-EfficientNet	#FLOPS	Ratio-to-EfficientNet
EfficientNet-B0	**76.3%**	**93.2%**	**5.3M**	**1x**	**0.39B**	**1x**
ResNet-50 (He et al., 2016)	76.0%	93.0%	26M	4.9x	4.1B	11x
DenseNet-169 (Huang et al., 2017)	76.2%	93.2%	14M	2.6x	3.5B	8.9x
EfficientNet-B1	**78.8%**	**94.4%**	**7.8M**	**1x**	**0.70B**	**1x**
ResNet-152 (He et al., 2016)	77.8%	93.8%	60M	7.6x	11B	16x
DenseNet-264 (Huang et al., 2017)	77.9%	93.9%	34M	4.3x	6.0B	8.6x
Inception-v3 (Szegedy et al., 2016)	78.8%	94.4%	24M	3.0x	5.7B	8.1x
Xception (Chollet, 2017)	79.0%	94.5%	23M	3.0x	8.4B	12x
EfficientNet-B2	**79.8%**	**94.9%**	**9.2M**	**1x**	**1.0B**	**1x**
Inception-v4 (Szegedy et al., 2017)	80.0%	95.0%	48M	5.2x	13B	13x
Inception-resnet-v2 (Szegedy et al., 2017)	80.1%	95.1%	56M	6.1x	13B	13x
EfficientNet-B3	**81.1%**	**95.5%**	**12M**	**1x**	**1.8B**	**1x**
ResNeXt-101 (Xie et al., 2017)	80.9%	95.6%	84M	7.0x	32B	18x
PolyNet (Zhang et al., 2017)	81.3%	95.8%	92M	7.7x	35B	19x
EfficientNet-B4	**82.6%**	**96.3%**	**19M**	**1x**	**4.2B**	**1x**
SENet (Hu et al., 2018)	82.7%	96.2%	146M	7.7x	42B	10x
NASNet-A (Zoph et al., 2018)	82.7%	96.2%	89M	4.7x	24B	5.7x
AmoebaNet-A (Real et al., 2019)	82.8%	96.1%	87M	4.6x	23B	5.5x
PNASNet (Liu et al., 2018)	82.9%	96.2%	86M	4.5x	23B	6.0x
EfficientNet-B5	**83.3%**	**96.7%**	**30M**	**1x**	**9.9B**	**1x**
AmoebaNet-C (Cubuk et al., 2019)	83.5%	96.5%	155M	5.2x	41B	4.1x
EfficientNet-B6	**84.0%**	**96.9%**	**43M**	**1x**	**19B**	**1x**
EfficientNet-B7	**84.4%**	**97.1%**	**66M**	**1x**	**37B**	**1x**
GPipe (Huang et al., 2018)	84.3%	97.0%	557M	8.4x	-	-

We omit ensemble and multi-crop models (Hu et al., 2018), or models pretrained on 3.5B Instagram images (Mahajan et al., 2018).

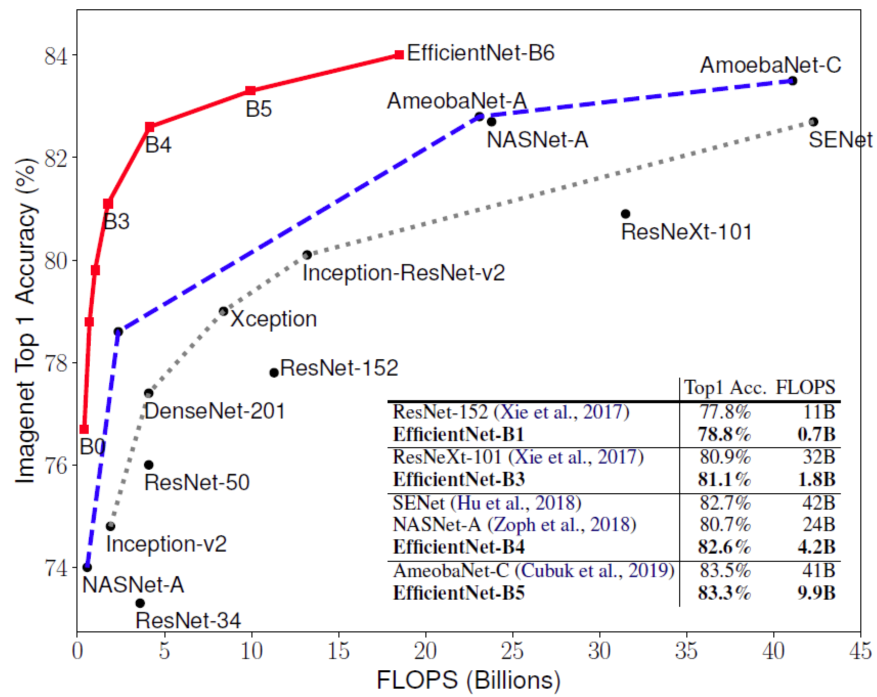
Performance

ImageNet Classification



	Top1 Acc.	#Params
ResNet-152 (He et al., 2016)	77.8%	60M
EfficientNet-B1	**78.8%**	**7.8M**
ResNeXt-101 (Xie et al., 2017)	80.9%	84M
EfficientNet-B3	**81.1%**	**12M**
SENet (Hu et al., 2018)	82.7%	146M
NASNet-A (Zoph et al., 2018)	82.7%	89M
EfficientNet-B4	**82.6%**	**19M**
GPipe (Huang et al., 2018) †	84.3%	556M
EfficientNet-B7	**84.4%**	**66M**

†Not plotted



	Top1 Acc.	FLOPS
ResNet-152 (Xie et al., 2017)	77.8%	11B
EfficientNet-B1	**78.8%**	**0.7B**
ResNeXt-101 (Xie et al., 2017)	80.9%	32B
EfficientNet-B3	**81.1%**	**1.8B**
SENet (Hu et al., 2018)	82.7%	42B
NASNet-A (Zoph et al., 2018)	80.7%	24B
EfficientNet-B4	**82.6%**	**4.2B**
AmeobaNet-C (Cubuk et al., 2019)	83.5%	41B
EfficientNet-B5	**83.3%**	**9.9B**

Performance

ImageNet Classification

Table 4. **Inference Latency Comparison** – Latency is measured with batch size 1 on a single core of Intel Xeon CPU E5-2690.

	Acc. @ Latency		Acc. @ Latency
ResNet-152	77.8% @ 0.554s	GPipe	84.3% @ 19.0s
EfficientNet-B1	78.8% @ 0.098s	EfficientNet-B7	84.4% @ 3.1s
Speedup	**5.7x**	**Speedup**	**6.1x**

Performance

Scaling Comparison

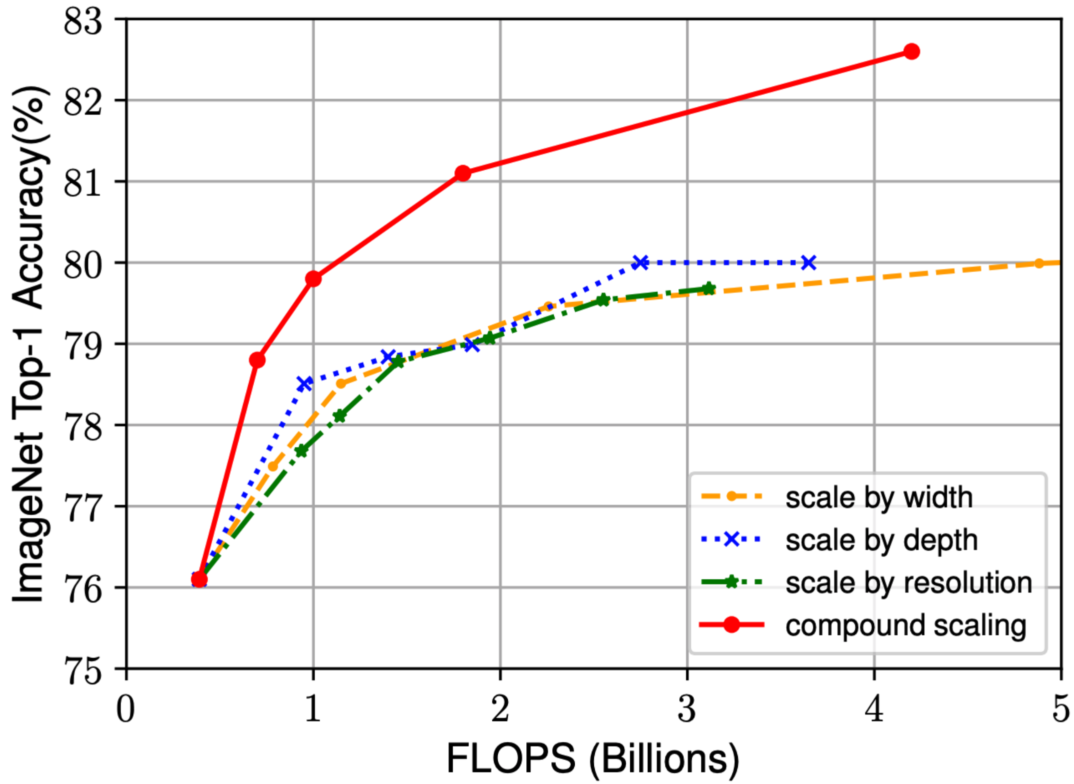


Figure 8. **Scaling Up EfficientNet-B0 with Different Methods.**

Performance

Scaling Comparison

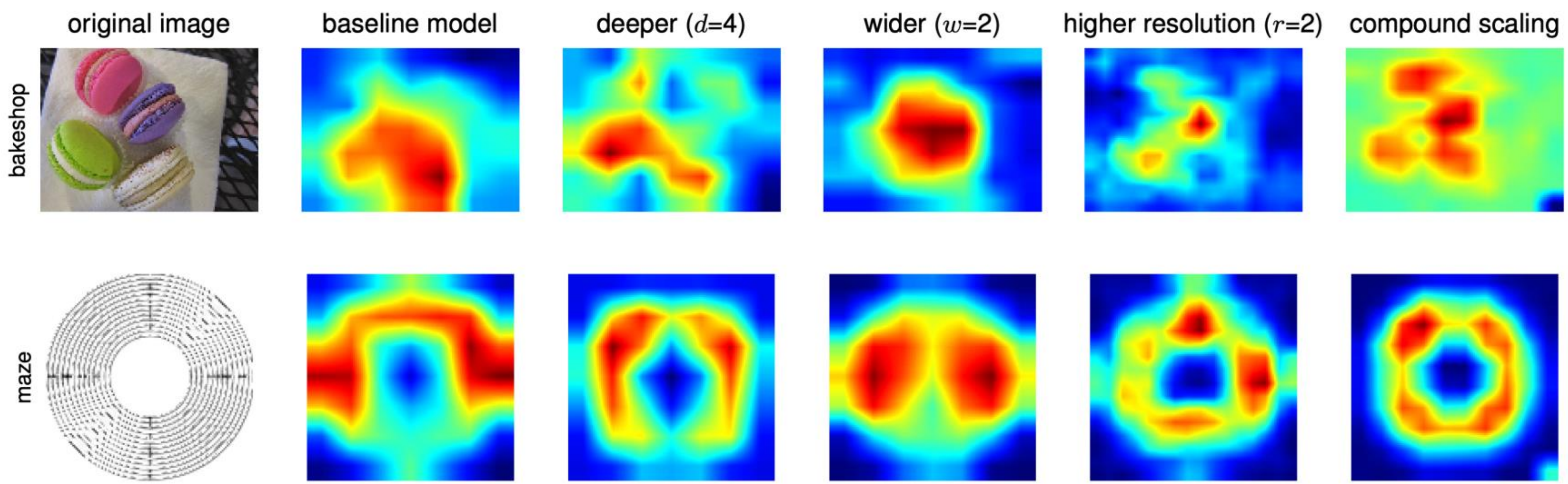


Figure 7. **Class Activation Map (CAM) (Zhou et al., 2016) for Different Models in Table 7 -** Our compound scaling method allows the scaled model (last column) to focus on more relevant regions with more object details. Model details are in Table 7.

Baseline: MobileNet and RestNet

- **They have applied the same approach to scale MobileNet and ResNet**

Model	FLOPS	Top-1 Acc.
Baseline MobileNetV1 (Howard et al., 2017)	0.6B	70.6%
Scale MobileNetV1 by width (w=2)	2.2B	74.2%
Scale MobileNetV1 by resolution (r=2)	2.2B	72.7%
compound scale (d=1.4, w=1.2, r=1.3)	**2.3B**	**75.6%**
Baseline MobileNetV2 (Sandler et al., 2018)	0.3B	72.0%
Scale MobileNetV2 by depth (d=4)	1.2B	76.8%
Scale MobileNetV2 by width (w=2)	1.1B	76.4%
Scale MobileNetV2 by resolution (r=2)	1.2B	74.8%
MobileNetV2 compound scale	**1.3B**	**77.4%**
Baseline ResNet-50 (He et al., 2016)	4.1B	76.0%
Scale ResNet-50 by depth (d=4)	16.2B	78.1%
Scale ResNet-50 by width (w=2)	14.7B	77.7%
Scale ResNet-50 by resolution (r=2)	16.4B	77.5%
ResNet-50 compound scale	**16.7B**	**78.8%**

Question and Answer