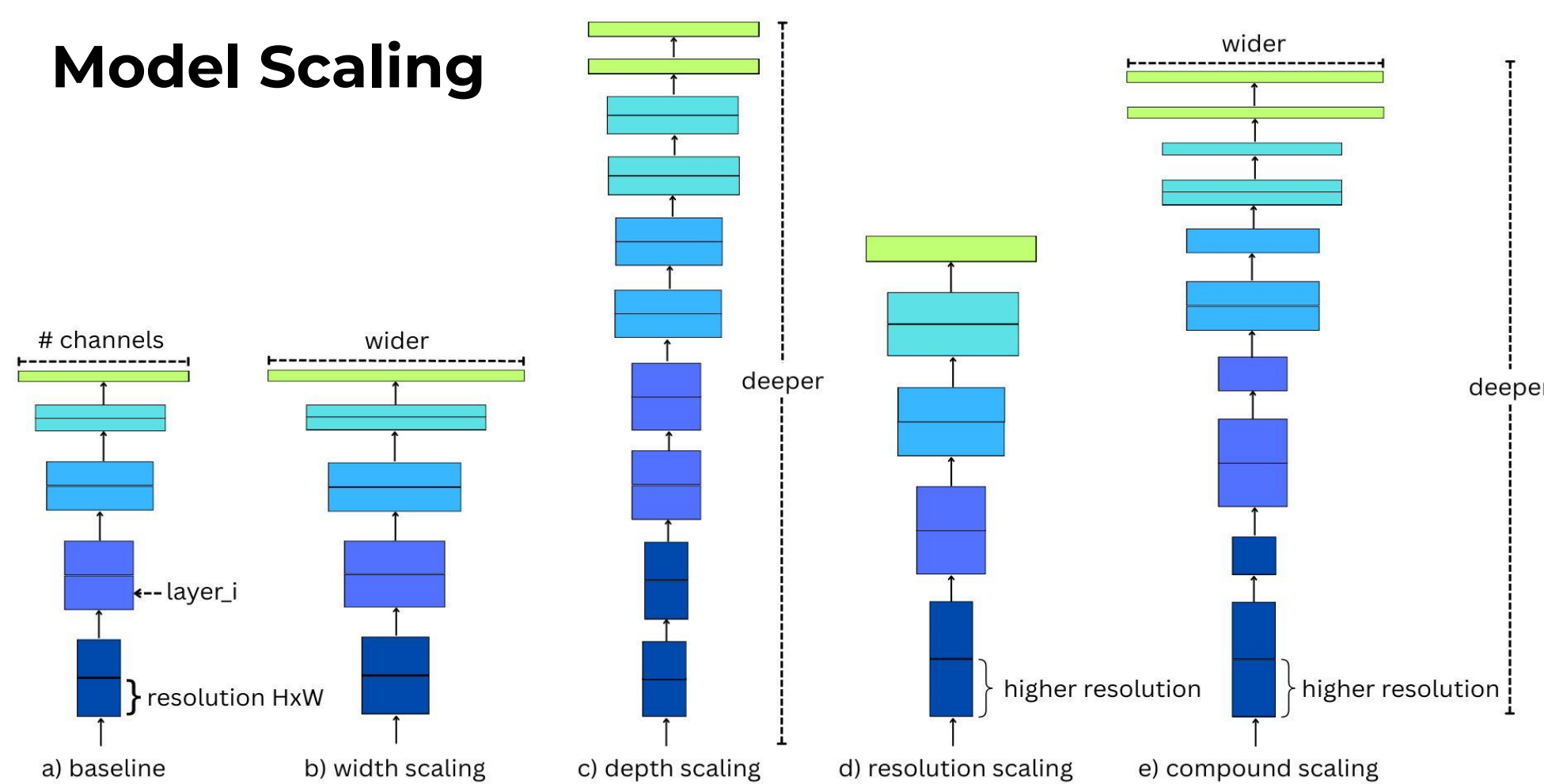


## Problem

- **Single-dimension scaling is inefficient:** Scaling depth, width, or input resolution alone yields diminishing accuracy gains as you make models larger.
- **No principled way to balance all three dimensions:** Manually tuning combinations of layers, channels, and image size is tedious and sub-optimal.
- **Huge search space for ConvNet design:** Exploring every mix of depth/width/resolution for a given compute budget is prohibitively expensive.

## Model Scaling



## Paper's Solution

- **Introduce a new baseline (EfficientNet-B0):** Used neural-architecture search to find an efficient MobileNet-style backbone with MBConv+SE blocks.
- **Compound scaling rule:** Uniformly scale depth, width, and resolution by:

$$d = \alpha^\phi, w = \beta^\phi, r = \gamma^\phi$$

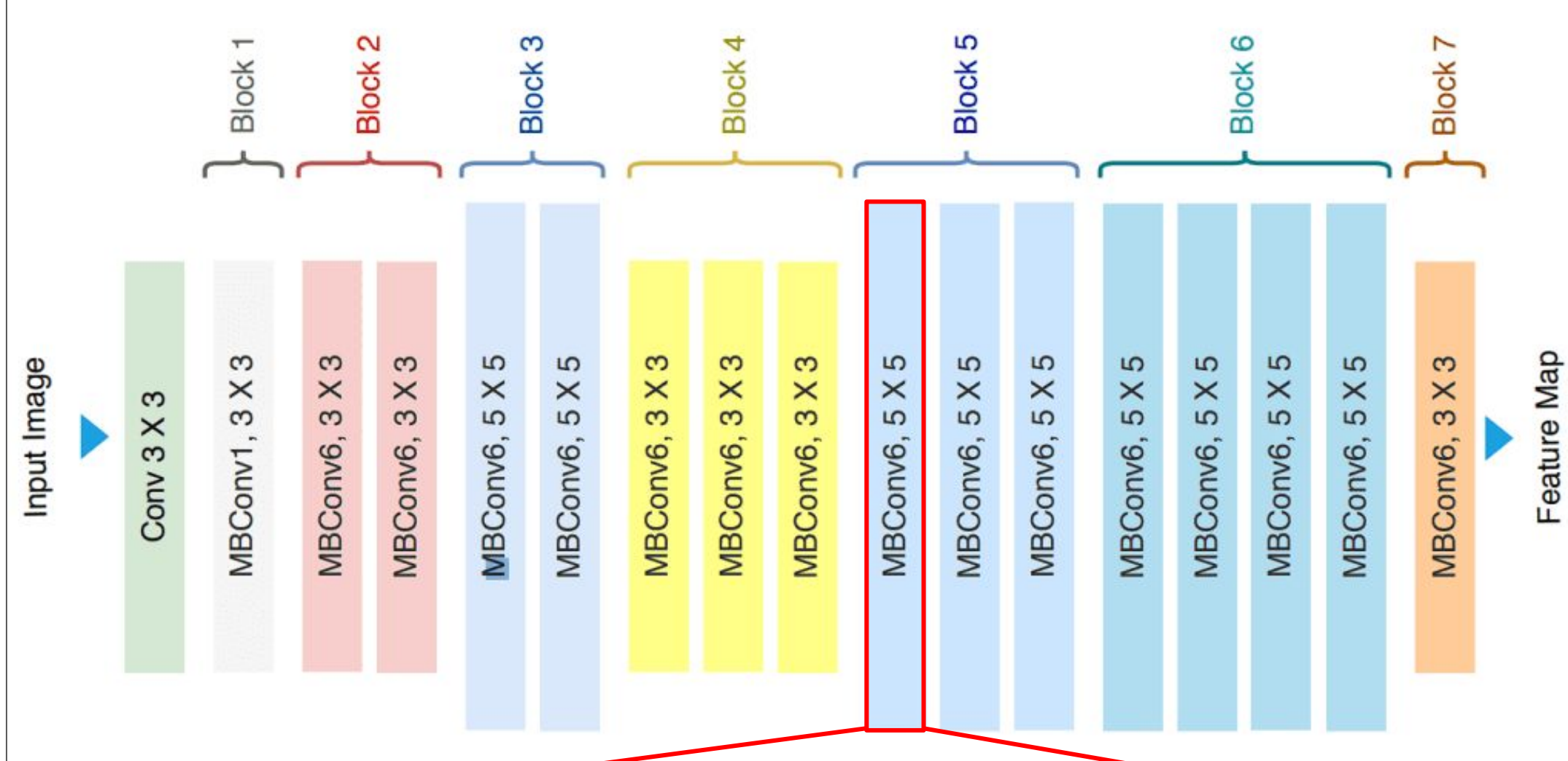
with coefficients  $\alpha = 1.2$ ,  $\beta = 1.1$ ,  $\gamma = 1.15$  chosen via a small grid search.

- **Generate a model family (B0–B7):** Vary the compound coefficient  $\phi$  to smoothly trade off compute vs. accuracy.
- **Dramatic efficiency gains:** Achieve up to 8× fewer parameters and 6× faster inference for the same (or better) ImageNet accuracy!

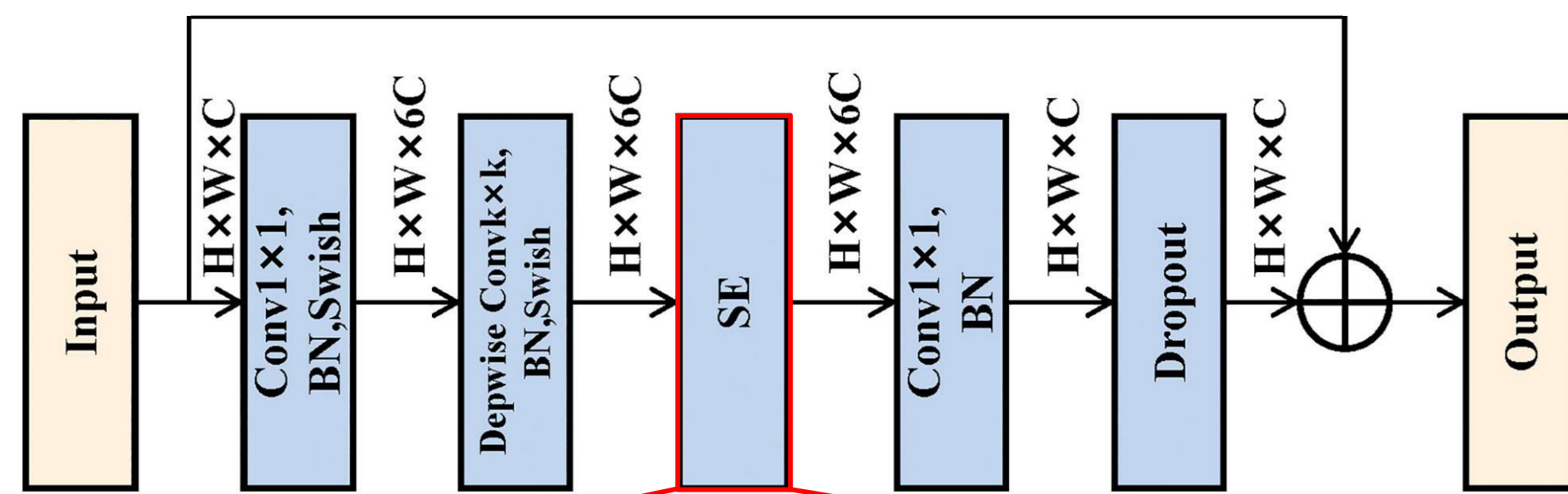
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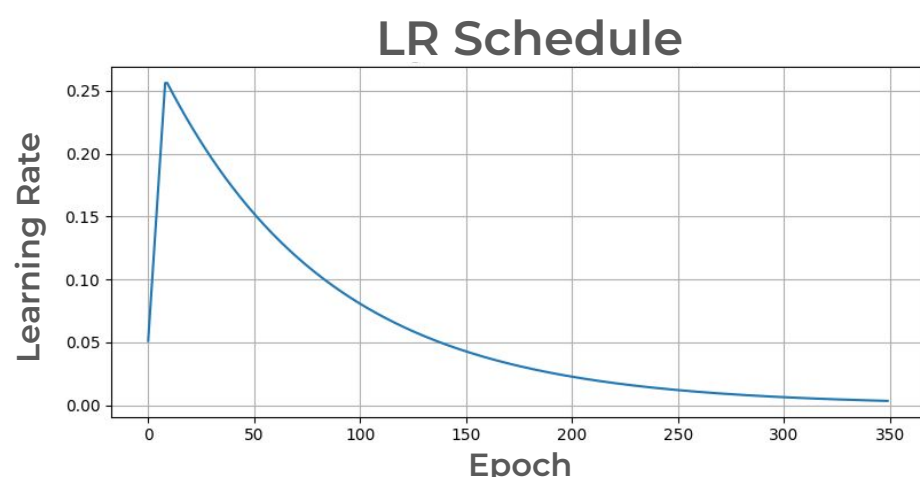
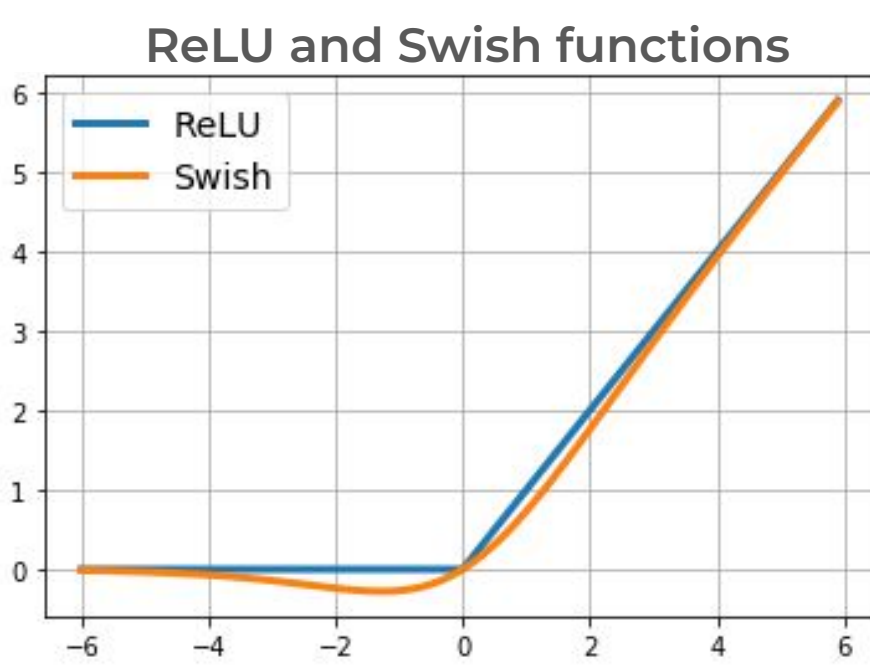
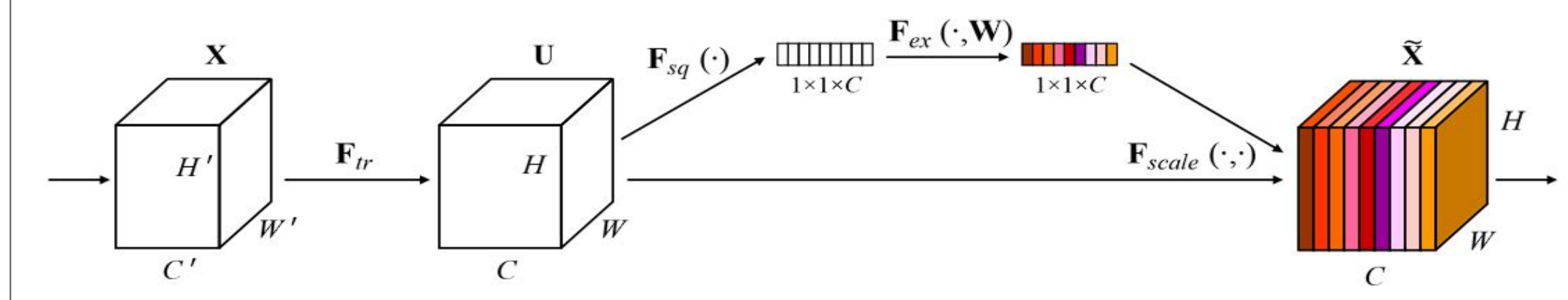
## EfficientNet-B0 Model Architecture



## Main Building Block of EfficientNet: Mobile Inverted Bottleneck (MBConv)



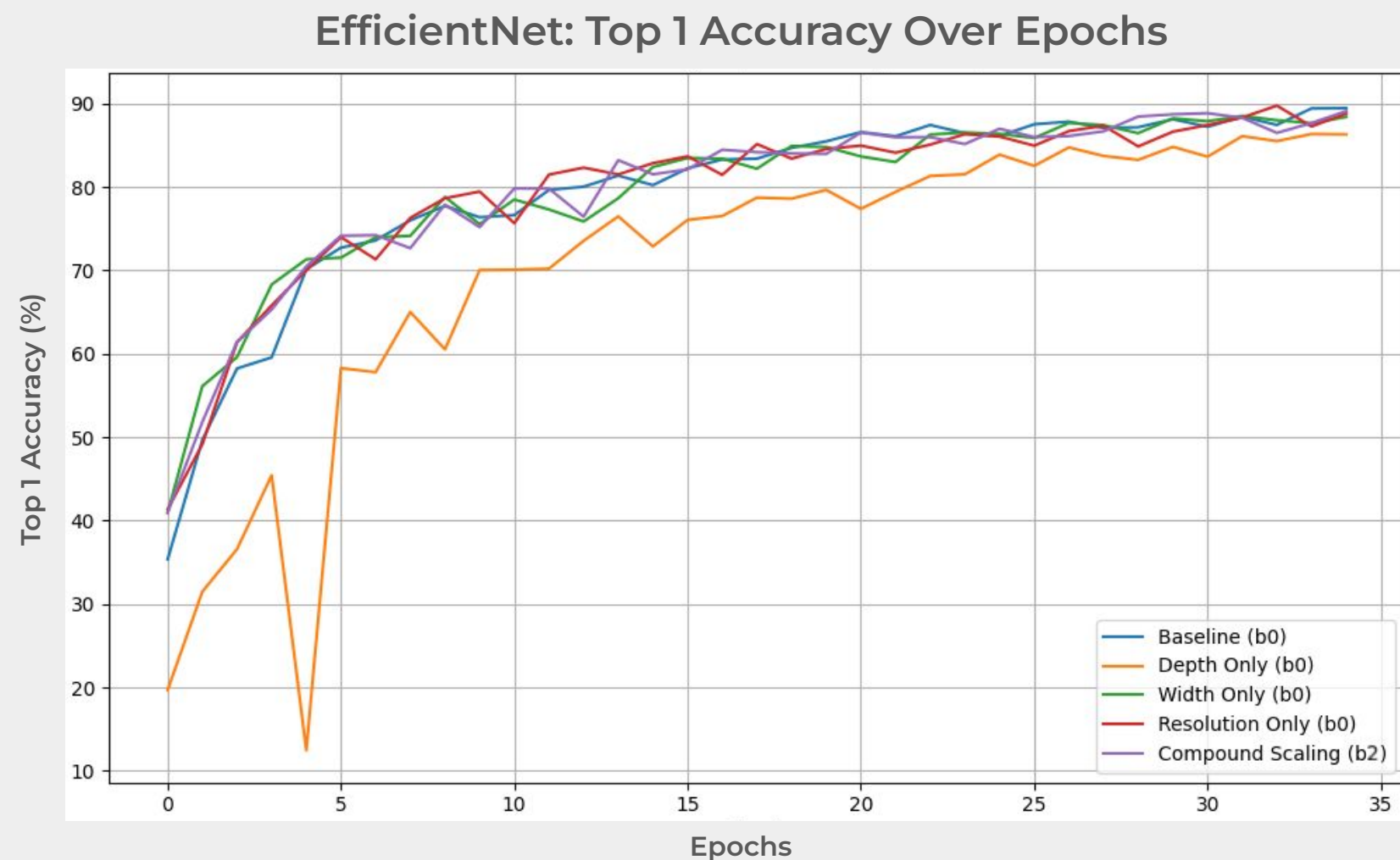
## Squeeze-and-Excitation



## Our Methodology

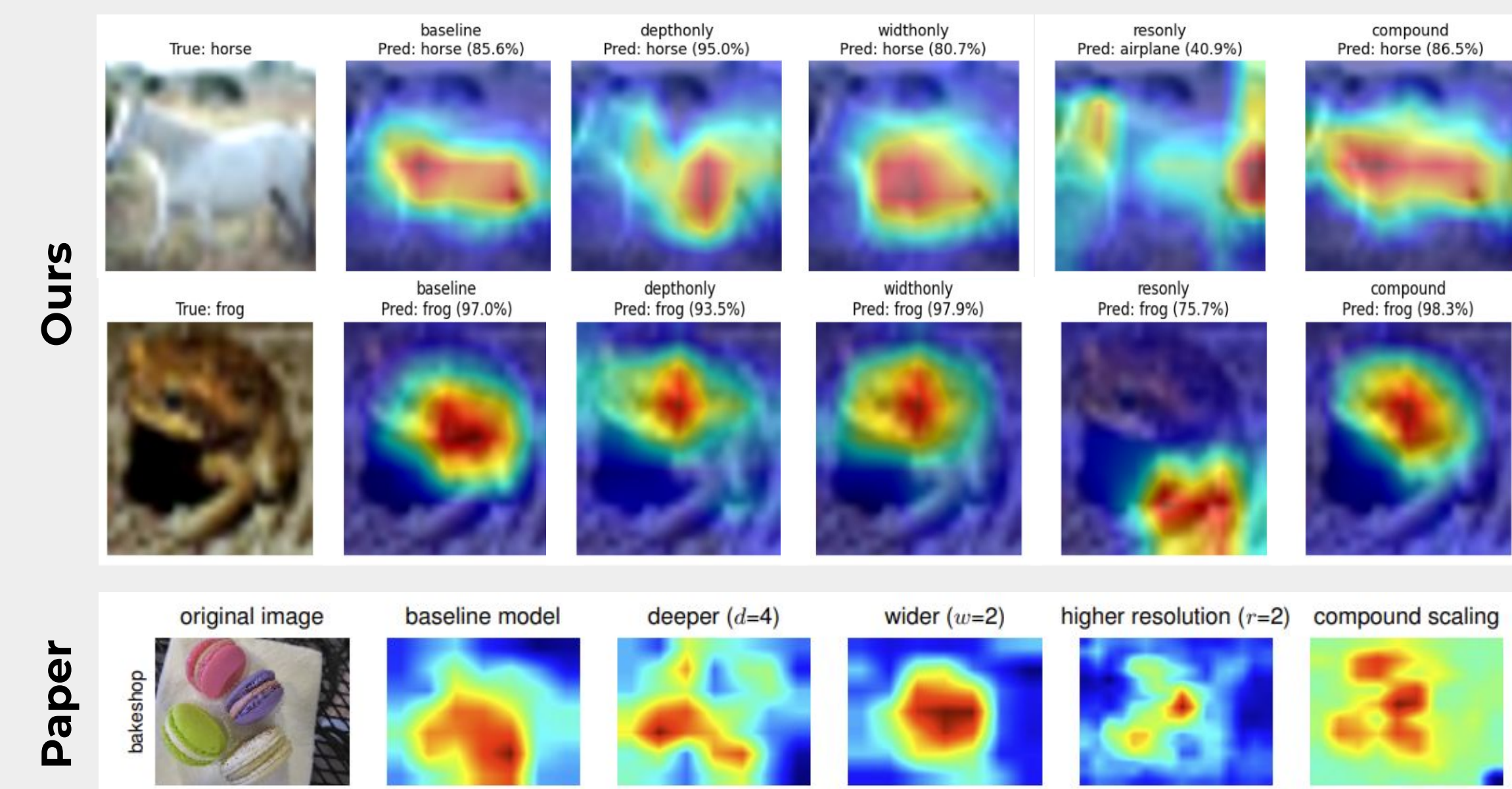
- **Dataset:** CIFAR-10 (60K images, 10 classes).
- **Models:** B0 (baseline), depth-only, width-only, resolution-only, B2 (compound).
- **Optimizer:** *RMSProp* (momentum = 0.9,  $\alpha = 0.9$ ,  $\epsilon = 0.1$ ) with *linear* → *exponential learning rate decay*.
- **Training:** 35 epochs (vs. 350 in paper).

## Results



Over 35 epochs, one compound step (B0 → B2) gave **negligible improvement** over single dimension scaling; larger steps (more compounding) hit **OOM beyond B2**.

## Class Activation Maps



Model	Our FLOPS	Our Top 1 Acc	Paper FLOPS	Paper Top 1
Baseline B0 model	0.82B	89.45%	0.4B	77.3%
Scale by depth (B0)	3.35B	86.31%	1.8B	79.0%
Scale by width (B0)	3.02B	88.40%	1.8B	78.9%
Scale by resolution (B0)	3.27B	88.80%	1.9B	79.1%
<b>Compound scale (B2)</b>	<b>1.82B</b>	<b>85.21%</b>	<b>1.8B</b>	<b>81.1%</b>

Table 1. Scaling effect on FLOPS and Top-1 Accuracy

## Conclusion/Future Work:

- **Conclusion:** Our findings did not directly align with the paper's key insight. Compound scaling did not seem to deliver noticeable gains than scaling any single dimension alone.
- **Future Work:**
  - Extend experiments across the full EfficientNet family (B0–B7)
  - Match the original training schedule (350 epochs) for fair comparison
  - Scale up to and evaluate on the full ImageNet dataset instead of just CIFAR-10