EfficientNetV2: Smaller Models and Faster Training

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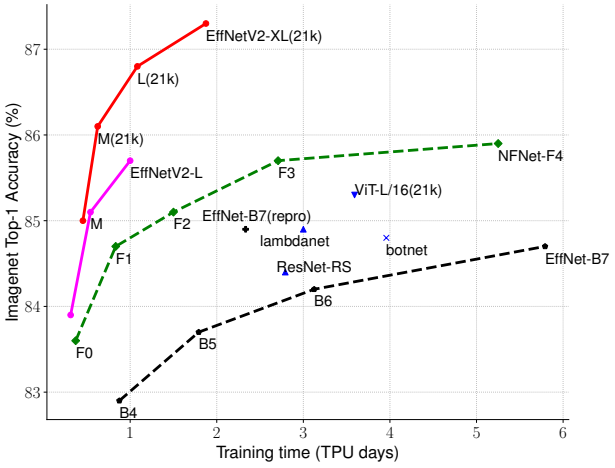
Abstract

This paper introduces EfficientNetV2, a new family of convolutional networks that have faster training speed and better parameter efficiency than previous models. To develop this family of models, we use a combination of training-aware neural architecture search and scaling, to jointly optimize training speed and parameter efficiency. The models were searched from the search space enriched with new ops such as Fused-MBConv. Our experiments show that EfficientNetV2 models train much faster than state-of-the-art models while being up to 6.8x smaller.

Our training can be further sped up by progressively increasing the image size during training, but it often causes a drop in accuracy. To compensate for this accuracy drop, we propose an improved method of progressive learning, which adaptively adjusts regularization (e.g., dropout and data augmentation) along with image size.

With progressive learning, our EfficientNetV2 significantly outperforms previous models on ImageNet and CIFAR/Cars/Flowers datasets. By pretraining on the same ImageNet21k, our EfficientNetV2 achieves 87.3% top-1 accuracy on ImageNet ILSVRC2012, outperforming the recent ViT by 2.0% accuracy while training 5x-11x faster using the same computing resources. Code will be available at https://github.com/google/automl/efficientnetv2.



(a) Training efficiency.

	EfficientNet (2019)	ResNet-RS (2021)	DeiT/ViT (2021)	EfficientNetV2 (ours)
Top-1 Acc.	84.3%	84.0%	83.1%	83.9%
Parameters	43M	164M	86M	24M

(b) Parameter efficiency.

Figure 1. **ImageNet ILSVRC2012 top-1 Accuracy vs. Training Time and Parameters** – Models tagged with `21k` are pretrained on ImageNet21k, and others are directly trained on ImageNet ILSVRC2012. Training time is measured with 32 TPU cores. All EfficientNetV2 models are trained with progressive learning. Our EfficientNetV2 trains 5x - 11x faster than others, while using up to 6.8x fewer parameters. Details are in Table 7 and Figure 5.

1. Introduction

Training efficiency is important to deep learning as the sizes of models and training data are increasingly larger. For example, GPT-3 (Brown et al., 2020), with an unprecedented model and training data sizes, demonstrates the remarkable capability in few shot learning, but it requires weeks of training with thousands of GPUs, making it difficult to retrain or improve.

Training efficiency has gained significant interests recently. For instance, NFNets (Brock et al., 2021) aim to improve training efficiency by removing the expensive batch normalization; ResNet-RS (Bello et al., 2021) improves training efficiency by optimizing scaling hyperparameters; Lambda Networks (Bello, 2021) and BotNet (Srinivas et al., 2021) improve training speed by using attention layers in ConvNets; Vision Transformers (Dosovitskiy et al., 2021) improves training efficiency on large-scale datasets by using Transformer blocks. However, these methods often come with expensive overhead on parameter size, as shown in Figure 1(b).

In this paper, we use an combination of training-aware neural architecture search (NAS) and scaling to improve both training speed and parameter efficiency. Given the parame-

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ter efficiency of EfficientNets (Tan & Le, 2019a), we start by systematically studying the training bottlenecks in EfficientNets. Our study shows in EfficientNets: (1) training with very large image sizes is slow; (2) depthwise convolutions are slow in early layers. (3) equally scaling up every stage is sub-optimal. Based on these observations, we design a search space enriched with additional ops such as Fused-MBConv, and apply training-aware NAS and scaling to jointly optimize model accuracy, training speed, and parameter size. Our found networks, named *EfficientNetV2*, train up to 4x faster than prior models (Figure 3), while being up to 6.8x smaller in parameter size.

Joint optimization

Our training can be further sped up by progressively increasing image size during training. Many previous works, such as progressive resizing (Howard, 2018), FixRes (Touvron et al., 2019), and Mix&Match (Hoffer et al., 2019), have used smaller image sizes in training; however, they usually keep the same regularization for all image sizes, causing a drop in accuracy. We argue that keeping the same regularization for different image sizes is not ideal: for the same network, small image size leads to small network capacity and thus requires weak regularization; vice versa, large image size requires stronger regularization to combat overfitting (see Section 4.1). Based on this insight, we propose an improved method of *progressive learning*: in the early training epochs, we train the network with small image size and weak regularization (e.g., dropout and data augmentation), then we gradually increase image size and add stronger regularization. Built upon progressive resizing (Howard, 2018), but by dynamically adjusting regularization, our approach can speed up the training without causing accuracy drop.

Diff between normal progressive learning and current approach

With the improved progressive learning, our EfficientNetV2 achieves strong results on ImageNet, CIFAR-10, CIFAR-100, Cars, and Flowers dataset. On ImageNet, we achieve 85.7% top-1 accuracy while training 3x - 9x faster and being up to 6.8x smaller than previous models (Figure 1). Our EfficientNetV2 and progressive learning also make it easier to train models on larger datasets. For example, ImageNet21k (Russakovsky et al., 2015) is about 10x larger than ImageNet ILSVRC2012, but our EfficientNetV2 can finish the training within two days using moderate computing resources of 32 TPUv3 cores. By pretraining on the public ImageNet21k [2], our EfficientNetV2 achieves 87.3% top-1 accuracy on ImageNet ILSVRC2012, outperforming the recent ViT-L/16 by 2.0% accuracy while training 5x-11x faster (Figure 1).

Our contributions are threefold:

- We introduce EfficientNetV2, a new family of smaller and faster models. Found by our training-aware NAS and scaling, EfficientNetV2 outperform previous models in both training speed and parameter efficiency.
- We propose an improved method of progressive learning, which adaptively adjusts regularization along with image size. We show that it speeds up training, and simultaneously improves accuracy.
- We demonstrate up to 11x faster training speed and up to 6.8x better parameter efficiency on ImageNet, CIFAR, Cars, and Flowers dataset, than prior art.

[2] We do not compare results on non-public JFT or Instagram .

2. Related work

Training and Parameter efficiency: Many works, such as DenseNet (Huang et al., 2017) and EfficientNet (Tan & Le, 2019a), focus on parameter efficiency, aiming to achieve better accuracy with less parameters. More recent works aim to improve training or inference speed instead of parameter efficiency. For example, RegNet (Radosavovic et al., 2020), ResNeSt (Zhang et al., 2020), TResNet (Ridnik et al., 2020), and EfficientNet-X (Li et al., 2021) focus on GPU and/or TPU inference speed; Lambda Networks (Bello, 2021), NFNets (Brock et al., 2021), BoTNets (Srinivas et al., 2021), ResNet-RS (Bello et al., 2021) focus on TPU training speed. However, their training speed often comes with the cost of more parameters. This paper aims to significantly improve both training and parameter efficiency than prior art.

Progressive Training: Previous works have proposed different kinds of progressive training, which dynamically change the training settings or networks, for GANs (Karras et al., 2018), transfer learning (Karras et al., 2018), adversarial learning (Yu et al., 2019), and language models (Press et al., 2021). Progressive resizing (Howard, 2018) is mostly related to our approach, which aims to improve training speed. However, it usually comes with the cost of accuracy drop. For example, Fastai team use progressive resizing in the DAWNBench competition for fast training, but it has to increase the final image size with higher inference cost to meet the accuracy constraint (Howard, 2018). Another closely related work is Mix&Match (Hoffer et al., 2019), which randomly sample different image size for each batch. Both progressive resizing and Mix&Match use the same regularization for all image sizes, causing a drop in accuracy. In this paper, our main difference is to adaptively adjust regularization as well so that we can improve both training speed and accuracy. Our approach is also partially inspired by curriculum learning (Bengio et al., 2009), which schedules training examples from easy to hard. Our approach also gradually increases learning difficulty by adding more regularization, but we don't selectively pick training examples.

Neural Architecture Search (NAS): By automating the network design process, NAS has been used to optimize the network architecture for image classification (Zoph et al., 2018), object detection (Chen et al., 2019; Tan et al., 2020), segmentation (Liu et al., 2019), hyperparameters (Dong

et al., 2020), and other applications (Elsken et al., 2019). Previous NAS works mostly focus on improving FLOPs efficiency (Tan & Le, 2019b;a) or inference efficiency (Tan et al., 2019; Cai et al., 2019; Wu et al., 2019; Li et al., 2021). Unlike prior works, this paper uses NAS to optimize training and parameter efficiency.

3. EfficientNetV2 Architecture Design

In this section, we study the training bottlenecks of EfficientNet (Tan & Le, 2019a), and introduce our training-aware NAS and scaling, as well as EfficientNetV2 models.

3.1. Review of EfficientNet

EfficientNet (Tan & Le, 2019a) is a family of models that are optimized for FLOPs and parameter efficiency. It leverages NAS to search for the baseline EfficientNet-B0 model that has better trade-off on accuracy and FLOPs. The baseline model is then scaled up with a simple compound scaling strategy to obtain a family of models B1-B7. While many recent works have claimed large gains on training or inference speed, they are often much worse than EfficientNet in terms of parameters and FLOPs efficiency (Table 1). In this paper, we aim to improve the training speed while maintaining the parameter efficiency.

Table 1. EfficientNets have good parameter and FLOPs efficiency.

	Top-1 Acc.	Params	FLOPs
EfficientNet-B6 (Tan & Le, 2019a)	84.3%	**43M**	**19B**
ResNet-RS-420 (Bello et al., 2021)	84.4%	192M	128B
NFNet-F1 (Brock et al., 2021)	84.7%	133M	36B

3.2. Understanding Training Efficiency

We study the training bottlenecks of EfficientNet (Tan & Le, 2019a), henceforth is also called EfficientNetV1, and a few simple techniques to improve training speed.

Training with very large image sizes is slow: As pointed out by previous works (Radosavovic et al., 2020), EfficientNet's large image size results in significant memory usage. Since the total memory on GPU/TPU is fixed, we have to train these models with smaller batch size, which drastically slows down the training. A simple improvement is to apply FixRes (Touvron et al., 2019), by using a smaller image size for training than for inference. As shown in Table 2, smaller image size leads to less computations and enables large batch size, and thus improves training speed by up to 2.2x. Notably, as pointed out in (Touvron et al., 2020; Brock et al., 2021), using smaller image size for training also leads to slightly better accuracy. But unlike (Touvron et al., 2019), we do not finetune any layers after training.

In Section 4, we will explore a more advanced training approach, by progressively adjusting image size and regularization during training.

Table 2. EfficientNet-B6 accuracy and training throughput for different batch sizes and image size.

	Top-1 Acc.	TPUv3 imgs/sec/core batch=32	TPUv3 imgs/sec/core batch=128	V100 imgs/sec/gpu batch=12	V100 imgs/sec/gpu batch=24
train size=512	84.3%	42	OOM	29	OOM
train size=380	84.6%	76	93	37	52

Depthwise convolutions are slow in early layers: Another training bottleneck of EfficientNet comes from the extensive depthwise convolutions (Sifre, 2014). Depthwise convolutions have fewer parameters and FLOPs than regular convolutions, but they often cannot fully utilize modern accelerators. Recently, Fused-MBConv is proposed in (Gupta & Tan, 2019) and later used in (Gupta & Akin, 2020; Xiong et al., 2020; Li et al., 2021) to better utilize mobile or server accelerators. It replaces the depthwise conv3x3 and expansion conv1x1 in MBConv (Sandler et al., 2018; Tan & Le, 2019a) with a single regular conv3x3, as shown in Figure 2. To systematically compares these two building blocks, we gradually replace the original MBConv in EfficientNet-B4 with Fused-MBConv (Table 3). When applied in early stage 1-3, Fused-MBConv can improve training speed with a small overhead on parameters and FLOPs, but if we replace all blocks with Fused-MBConv (stage 1-7), then it significantly increases parameters and FLOPs while also slowing down the training. Finding the right combination of these two building blocks, MBConv and Fused-MBConv, is non-trivial, which motivates us to leverage neural architecture search to automatically search for the best combination.

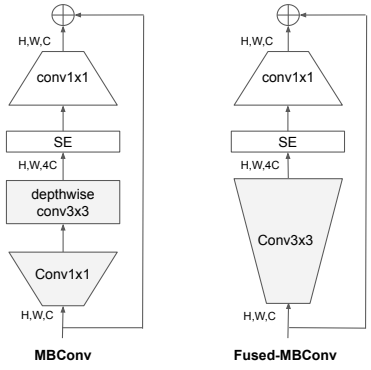


Figure 2. Structure of MBConv and Fused-MBConv.

Table 3. Replacing MBConv with Fused-MBConv. `No fused` denotes all stages use MBConv, `Fused stage1-3` denotes replacing MBConv with Fused-MBConv in stage {2, 3, 4}.

	Params (M)	FLOPs (B)	Top-1 Acc.	TPU imgs/sec/core	V100 imgs/sec/gpu
No fused	19.3	4.5	82.8%	262	155
Fused stage1-3	20.0	7.5	83.1%	362	216
Fused stage1-5	43.4	21.3	83.1%	327	223
Fused stage1-7	132.0	34.4	81.7%	254	206

Equally scaling up every stage is sub-optimal: EfficientNet equally scales up all stages using a simple compound scaling rule. For example, when depth coefficient is 2, then all stages in the networks would double the number of layers. However, these stages are not equally contributed to the training speed and parameter efficiency. In this paper, we will use a non-uniform scaling strategy to gradually add more layers to later stages. In addition, EfficientNets aggressively scale up image size, leading to large memory consumption and slow training. To address this issue, we slightly modify the scaling rule and restrict the maximum image size to a smaller value.

3.3. Training-Aware NAS and Scaling

To this end, we have learned multiple design choices for improving training speed. To search for the best combinations of those choices, we now propose a training-aware NAS.

NAS Search: Our training-aware NAS framework is largely based on previous NAS works (Tan et al., 2019; Tan & Le, 2019a), but aims to jointly optimize accuracy, parameter efficiency, and training efficiency on modern accelerators. Specifically, we use EfficientNet as our backbone. Our search space is a stage-based factorized space similar to (Tan et al., 2019), which consists of the design choices for convolutional operation types {MBConv, Fused-MBConv}, number of layers, kernel size {3x3, 5x5}, expansion ratio {1, 4, 6}. On the other hand, we reduce the search space size by (1) removing unnecessary search options such as pooling skip ops, since they are never used in the original EfficientNets; (2) reusing the same channel sizes from the backbone as they are already searched in (Tan & Le, 2019a). Since the search space is smaller, we can simply apply random search on much larger networks that have comparable size as EfficientNet-B4. Specifically, we sample up to 1000 models and train each model about 10 epochs with reduced image size for training. Our search reward combines the model accuracy A, the normalized training step time S, and the parameter size P, using a simple weighted product $A \cdot S^w \cdot P^v$, where w = -0.07 and v = -0.05 are the hyper-parameters that are empirically determined to balance the trade-offs similar to (Tan et al., 2019).

EfficientNetV2 Architecture: Table 4 shows the architecture for our searched model EfficientNetV2-S. Compared to the EfficientNet backbone, our searched EfficientNetV2 has several major distinctions: (1) The first difference is EfficientNetV2 extensively uses both MBConv (Sandler et al., 2018; Tan & Le, 2019a) and the newly added fused-MBConv (Gupta & Tan, 2019) in the early layers. (2) Secondly, EfficientNetV2 prefers smaller expansion ratio for MBConv since smaller expansion ratios tend to have less memory access overhead. (3) Thirdly, EfficientNetV2 prefers smaller 3x3 kernel sizes, but it adds more layers to compensate the reduced receptive field resulted from the smaller kernel size. (4) Lastly, EfficientNetV2 completely removes the last stride-1 stage in the original EfficientNet, perhaps due to its large parameter size and memory access overhead.

Table 4. EfficientNetV2-S architecture – MBConv and Fused-MBConv blocks are described in Figure 2.

Stage	Operator	Stride	#Channels	#Layers
0	Conv3x3	2	24	1
1	Fused-MBConv1, k3x3	1	24	2
2	Fused-MBConv4, k3x3	2	48	4
3	Fused-MBConv4, k3x3	2	64	4
4	MBConv4, k3x3, SE0.25	2	128	6
5	MBConv6, k3x3, SE0.25	1	160	9
6	MBConv6, k3x3, SE0.25	2	272	15
7	Conv1x1 & Pooling & FC	-	1792	1

EfficientNetV2 Scaling: We scale up EfficientNetV2-S to obtain EfficientNetV2-M/L using similar compound scaling as (Tan & Le, 2019a), with a few additional optimizations: (1) we restrict the maximum inference image size to 480, as very large images often lead to expensive memory and training speed overhead; (2) as a heuristic, we also gradually add more layers to later stages (e.g., stage 5 and 6 in Table 4) in order to increase the network capacity without adding much runtime overhead.

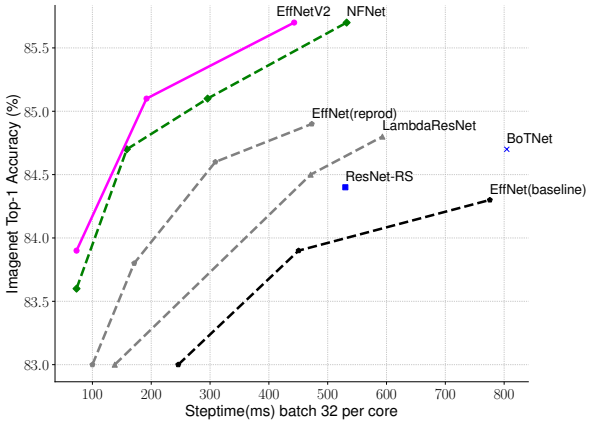


Figure 3. ImageNet accuracy and training step time on TPUv3 – Lower step time is better; all models are trained with fixed image size without progressive learning.

Training Speed Comparison: Figure 3 compares the training step time for our new EfficientNetV2, where all models are trained with fixed image size without progressive learning. For EfficientNet (Tan & Le, 2019a), we show two curves: one is trained with the original inference size, and the other is trained with about 30% smaller image size, same as NFNet (Touvron et al., 2019; Brock et al., 2021). All models are trained with 350 epochs, except NFNets are trained with 360 epochs, so all models have a similar number of training steps. Interestingly, we observe that when trained properly, EfficientNets still achieve pretty strong

performance trade-off. More importantly, with our training-aware NAS and scaling, our proposed EfficientNetV2 model train much faster than the other recent models. These results also align with our inference results as shown in Table 7 and Figure 5.

4. Progressive Learning

4.1. Motivation

As discussed in Section 3, image size plays an important role in training efficiency. In addition to FixRes (Touvron et al., 2019), many other works dynamically change image sizes during training (Howard, 2018; Hoffer et al., 2019), but they often cause a drop in accuracy.

We hypothesize the accuracy drop comes from the unbalanced regularization: when training with different image sizes, we should also adjust the regularization strength accordingly (instead of using a fixed regularization as in previous works). In fact, it is common that large models require stronger regularization to combat overfitting: for example, EfficientNet-B7 uses larger dropout and stronger data augmentation than the B0. In this paper, we argue that even for the same network, smaller image size leads to smaller network capacity and thus needs weaker regularization; vice versa, larger image size leads to more computations with larger capacity, and thus more vulnerable to overfitting.

To validate our hypothesis, we train a model, sampled from our search space, with different image sizes and data augmentations (Table 5). When image size is small, it has the best accuracy with weak augmentation; but for larger images, it performs better with stronger augmentation. This insight motivates us to adaptively adjust regularization along with image size during training, leading to our improved method of progressive learning.

Table 5. ImageNet top-1 accuracy. We use RandAug (Cubuk et al., 2020), and report mean and stdev for 3 runs.

	Size=128	Size=192	Size=300
RandAug magnitude=5	**78.3** ±**0.16**	81.2 ±0.06	82.5 ±0.05
RandAug magnitude=10	78.0 ±0.08	**81.6** ±**0.08**	82.7 ±0.08
RandAug magnitude=15	77.7 ±0.15	81.5 ±0.05	**83.2** ±**0.09**

4.2. Progressive Learning with adaptive Regularization

Figure 4 illustrates the training process of our improved progressive learning: in the early training epochs, we train the network with smaller images and weak regularization, such that the network can learn simple representations easily and fast. Then, we gradually increase image size but also making learning more difficult by adding stronger regularization. Our approach is built upon (Howard, 2018) that progressively changes image size, but here we adaptively adjust regularization as well.

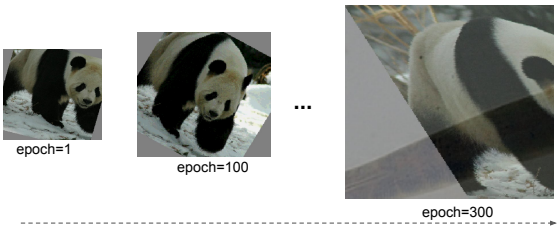


Figure 4. Training process in our improved progressive learning – It starts with small image size and weak regularization (epoch=1), and then gradually increase the learning difficulty with larger image sizes and stronger regularization: larger dropout rate, RandAugment magnitude, and mixup ratio (e.g., epoch=300).

Formally, suppose the whole training has N total steps, the target image size is S_e, with a list of regularization magnitude $\Phi_e = \{\phi_e^k\}$, where k represents a type of regularization such as dropout rate or mixup rate value. We divide the training into M stages: for each stage $1 \le i \le M$, the model is trained with image size S_i and regularization magnitude $\Phi_i = \{\phi_i^k\}$. The last stage M would use the targeted image size S_e and regularization Φ_e. For simplicity, we heuristically pick the initial image size S_0 and regularization Φ_0, and then use a linear interpolation to determine the value for each stage. Algorithm 1 summarizes the procedure. At the beginning of each stage, the network will inherit all weights from the previous stage. Unlike transformers, whose weights (e.g., position embedding) may depend on input length, ConvNet weights are independent to image sizes and thus can be inherited easily.

Algorithm 1 Progressive learning with adaptive regularization.

Input: Initial image size S_0 and regularization $\{\phi_0^k\}$.
Input: Final image size S_e and regularization $\{\phi_e^k\}$.
Input: Number of total training steps N and stages M.
for $i = 0$ **to** $M-1$ **do**
  Image size: $S_i \leftarrow S_0 + (S_e - S_0) \cdot \frac{i}{M-1}$
  Regularization: $R_i \leftarrow \{\phi_i^k = \phi_0^k + (\phi_e^k - \phi_0^k) \cdot \frac{i}{M-1}\}$
  Train the model for $\frac{N}{M}$ steps with S_i and R_i.
end for

Our improved progressive learning is generally compatible to existing regularization. For simplicity, this paper mainly studies the following three types of regularization:

- **Dropout** (Srivastava et al., 2014): a network-level regularization, which reduces co-adaptation by randomly dropping channels. We will adjust the dropout rate γ.
- **RandAugment** (Cubuk et al., 2020): a per-image data augmentation, with adjustable magnitude ϵ.
- **Mixup** (Zhang et al., 2018): a cross-image data augmentation. Given two images with labels (x_i, y_i) and (x_j, y_j), it combines them with mixup ratio λ: $\tilde{x_i} = \lambda x_j + (1-\lambda)x_i$ and $\tilde{y_i} = \lambda y_j + (1-\lambda)y_i$. We would adjust mixup ratio λ during training.

5. Main Results

This section presents our experimental setups, the main results on ImageNet, and the transfer learning results on CIFAR-10, CIFAR-100, Cars, and Flowers.

5.1. ImageNet ILSVRC2012

Setup: ImageNet ILSVRC2012 (Russakovsky et al., 2015) contains about 1.28M training images and 50,000 validation images with 1000 classes. During architecture search or hyperparameter tuning, we reserve 25,000 images (about 2%) from the training set as `minival` for accuracy evaluation. We also use `minival` to perform early stopping. Our ImageNet training settings largely follow EfficientNets (Tan & Le, 2019a): RMSProp optimizer with decay 0.9 and momentum 0.9; batch norm momentum 0.99; weight decay 1e-5. Each model is trained for 350 epochs with total batch size 4096. Learning rate is first warmed up from 0 to 0.256, and then decayed by 0.97 every 2.4 epochs. We use exponential moving average with 0.9999 decay rate, RandAugment (Cubuk et al., 2020), Mixup (Zhang et al., 2018), Dropout (Srivastava et al., 2014), and stochastic depth (Huang et al., 2016) with 0.8 survival probability.

Table 6. Progressive training settings for EfficientNetV2.

	S		M		L	
	min	max	min	max	min	max
Image Size	128	300	128	380	128	380
RandAugment	5	15	5	20	5	25
Mixup alpha	0	0	0	0.2	0	0.4
Dropout rate	0.1	0.3	0.1	0.4	0.1	0.5

For progressive learning, we divide the training process into four stages with about 87 epochs per stage: the early stage uses a small image size with weak regularization, while the later stages use larger image sizes with stronger regularization, as described in Algorithm 1. Table 6 shows the minimum (for the first stage) and maximum (for the last stage) values of image size and regularization. For simplicity, all models use the same minimum values of size and regularization, but they adopt different maximum values, as larger models generally require more regularization to combat overfitting. Following (Touvron et al., 2020), our maximum image size for training is about 20% smaller than inference, but we don't finetune any layers after training.

Results: As shown in Table 7, our EfficientNetV2 models are significantly faster and achieves better accuracy and parameter efficiency than previous ConvNets and Transformers on ImageNet. In particular, our EfficientNetV2-M achieves comparable accuracy to EfficientNet-B7 while training 11x faster using the same computing resources. Our EfficientNetV2 models also significantly outperform all recent RegNet and ResNeSt, in both accuracy and inference speed. Figure 1 further visualizes the comparison on training speed and parameter efficiency. Notably, this speedup is a combination of progressive training and better networks, and we will study the individual impact for each of them in our ablation studies.

Recently, Vision Transformers have demonstrated impressive results on ImageNet accuracy and training speed. However, here we show that properly designed ConvNets with improved training method can still largely outperform vision transformers in both accuracy and training efficiency. In particular, our EfficientNetV2-L achieves 85.7% top-1 accuracy, surpassing ViT-L/16(21k), a much larger transformer model pretrained on a larger ImageNet21k dataset. Here, ViTs are not well tuned on ImageNet ILSVRC2012; DeiTs use the same architectures as ViTs, but achieve better results by adding more regularization.

Although our EfficientNetV2 models are optimized for training, they also perform well for inference, because training speed often correlates with inference speed. Figure 5 visualizes the model size, FLOPs, and inference latency based on Table 7. Since latency often depends on hardware and software, here we use the same PyTorch Image Models codebase (Wightman, 2021) and run all models on the same machine using the batch size 16. In general, our models have slightly better parameters/FLOPs efficiency than EfficientNets, but our inference latency is up to 3x faster than EfficientNets. Compared to the recent ResNeSt that are specially optimized for GPUs, our EfficientNetV2-M achieves 0.6% better accuracy with 2.8x faster inference speed.

5.2. ImageNet21k

Setup: ImageNet21k (Russakovsky et al., 2015) contains about 13M training images with 21,841 classes. The original ImageNet21k doesn't have train/eval split, so we reserve randomly picked 100,000 images as validation set and use the remaining as training set. We largely reuse the same training settings as ImageNet ILSVRC2012 with a few changes: (1) we change the training epochs to 60 or 30 to reduce training time, and use cosine learning rate decay that can adapt to different steps without extra tuning; (2) since each image has multiple labels, we normalize the labels to have sum of 1 before computing softmax loss. After pretrained on ImageNet21k, each model is finetuned on ILSVRC2012 for 15 epochs using cosine learning rate decay.

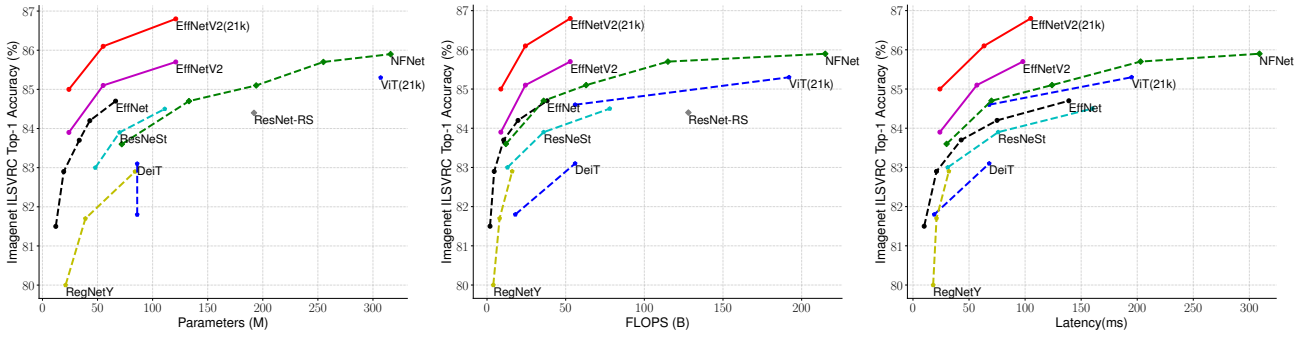
Results: Table 7 shows the performance comparison, where models tagged with `21k` are pretrained on ImageNet21k and finetuned on ImageNet ILSVRC2012. Compared to the recent ViT-L/16(21k), our EfficientNetV2-L(21k) improves the top-1 accuracy by 1.5% (85.3% vs. 86.8%), using 2.5x fewer parameters and 3.6x fewer FLOPs, while running 6x - 7x faster in training and inference.

We would like to highlight a few interesting observations:

Table 7. **EfficientNetV2 Performance Results on ImageNet** (Russakovsky et al., 2015) – `Infer-time` is measured on V100 GPU FP16 with batch size 16 using the same codebase (Wightman, 2021); `Train-time` is the total training time normalized for 32 TPU cores. Models marked with 21k are pretrained on ImageNet21k with 13M images, and others are directly trained on ImageNet ILSVRC2012 with 1.28M images from scratch. All EfficientNetV2 models are trained with our improved method of progressive learning.

	Model	Top-1 Acc.	Params	FLOPs	Infer-time(ms)	Train-time (hours)
ConvNets & Hybrid	EfficientNet-B3 (Tan & Le, 2019a)	81.5%	12M	1.9B	19	10
	EfficientNet-B4 (Tan & Le, 2019a)	82.9%	19M	4.2B	30	21
	EfficientNet-B5 (Tan & Le, 2019a)	83.7%	30M	10B	60	43
	EfficientNet-B6 (Tan & Le, 2019a)	84.3%	43M	19B	97	75
	EfficientNet-B7 (Tan & Le, 2019a)	84.7%	66M	38B	170	139
	RegNetY-8GF (Radosavovic et al., 2020)	81.7%	39M	8B	21	-
	RegNetY-16GF (Radosavovic et al., 2020)	82.9%	84M	16B	32	-
	ResNeSt-101 (Zhang et al., 2020)	83.0%	48M	13B	31	-
	ResNeSt-200 (Zhang et al., 2020)	83.9%	70M	36B	76	-
	ResNeSt-269 (Zhang et al., 2020)	84.5%	111M	78B	160	-
	TResNet-L (Ridnik et al., 2020)	83.8%	56M	-	45	-
	TResNet-XL (Ridnik et al., 2020)	84.3%	78M	-	66	-
	EfficientNet-X (Li et al., 2021)	84.7%	73M	91B	-	-
	NFNet-F0 (Brock et al., 2021)	83.6%	72M	12B	30	8.9
	NFNet-F1 (Brock et al., 2021)	84.7%	133M	36B	70	20
	NFNet-F2 (Brock et al., 2021)	85.1%	194M	63B	124	36
	NFNet-F3 (Brock et al., 2021)	85.7%	255M	115B	203	65
	NFNet-F4 (Brock et al., 2021)	85.9%	316M	215B	309	126
	ResNet-RS (Bello et al., 2021)	84.4%	192M	128B	-	61
	LambdaResNet-420-hybrid (Bello, 2021)	84.9%	125M	-	-	67
	BotNet-T7-hybrid (Srinivas et al., 2021)	84.7%	75M	46B	-	95
	BiT-M-R152x2 (21k) (Kolesnikov et al., 2020)	85.2%	236M	135B	500	-
Vision Transformers	ViT-B/32 (Dosovitskiy et al., 2021)	73.4%	88M	13B	13	-
	ViT-B/16 (Dosovitskiy et al., 2021)	74.9%	87M	56B	68	-
	DeiT-B (ViT+reg) (Touvron et al., 2021)	81.8%	86M	18B	19	-
	DeiT-B-384 (ViT+reg) (Touvron et al., 2021)	83.1%	86M	56B	68	-
	T2T-ViT-19 (Yuan et al., 2021)	81.4%	39M	8.4B	-	-
	T2T-ViT-24 (Yuan et al., 2021)	82.2%	64M	13B	-	-
	ViT-B/16 (21k) (Dosovitskiy et al., 2021)	84.6%	87M	56B	68	-
	ViT-L/16 (21k) (Dosovitskiy et al., 2021)	85.3%	304M	192B	195	172
ConvNets (ours)	**EfficientNetV2-S**	83.9%	24M	8.8B	24	7.1
	EfficientNetV2-M	85.1%	55M	24B	57	13
	EfficientNetV2-L	85.7%	121M	53B	98	24
	EfficientNetV2-S (21k)	85.0%	24M	8.8B	24	9.0
	EfficientNetV2-M (21k)	86.1%	55M	24B	57	15
	EfficientNetV2-L (21k)	86.8%	121M	53B	98	26

We do not include models pretrained on non-public Instagram/JFT images, or models with extra distillation or ensemble.



(a) Parameters (b) FLOPs (c) GPU V100 Latency (batch 16)

Figure 5. **Model Size, FLOPs, and Inference Latency** – Latency is measured with batch size 16 on V100 GPU. `21k` denotes pretrained on ImageNet21k images, others are just trained on ImageNet ILSVRC2012. Our EfficientNetV2 has slightly better parameter efficiency with EfficientNet, but runs 3x faster for inference.

Table 8. **Transfer Learning Performance Comparison** – All models are pretrained on ImageNet ILSVRC2012 and finetuned on downstream datasets. Transfer learning accuracy is averaged over five runs.

	Model	Params	ImageNet Acc.	CIFAR-10	CIFAR-100	Flowers	Cars
ConvNets	GPipe (Huang et al., 2019)	556M	84.4	99.0	91.3	98.8	94.7
	EfficientNet-B7 (Tan & Le, 2019a)	66M	84.7	98.9	91.7	98.8	94.7
Vision Transformers	ViT-B/32 (Dosovitskiy et al., 2021)	88M	73.4	97.8	86.3	85.4	-
	ViT-B/16 (Dosovitskiy et al., 2021)	87M	74.9	98.1	87.1	89.5	-
	ViT-L/32 (Dosovitskiy et al., 2021)	306M	71.2	97.9	87.1	86.4	-
	ViT-L/16 (Dosovitskiy et al., 2021)	306M	76.5	97.9	86.4	89.7	-
	DeiT-B (ViT+regularization) (Touvron et al., 2021)	86M	81.8	99.1	90.8	98.4	92.1
	DeiT-B-384 (ViT+regularization) (Touvron et al., 2021)	86M	83.1	99.1	90.8	98.5	93.3
ConvNets (ours)	EfficientNetV2-S	24M	83.2	98.7±0.04	91.5±0.11	97.9±0.13	93.8±0.11
	EfficientNetV2-M	55M	85.1	99.0±0.08	92.2±0.08	98.5±0.08	94.6±0.10
	EfficientNetV2-L	121M	85.7	**99.1**±0.03	**92.3**±0.13	**98.8**±0.05	**95.1**±0.10

- *Scaling up data size is more effective than simply scaling up model size in high-accuracy regime*: when the top-1 accuracy is beyond 85%, it is very difficult to further improve it by simply increasing model size due to the severe overfitting. However, the extra ImageNet21K pretraining can significantly improve accuracy. The effectiveness of large datasets is also observed in previous works (Mahajan et al., 2018; Xie et al., 2020; Dosovitskiy et al., 2021).
- *Pretraining on ImageNet21k could be quite efficient.* Although ImageNet21k has 10x more data, our training approach enables us to finish the pretraining of EfficientNetV2 within two days using 32 TPU cores (instead of weeks for ViT (Dosovitskiy et al., 2021)). This is more effective than training larger models on ImageNet. We suggest future research on large-scale models use the public ImageNet21k as a default dataset.

5.3. Transfer Learning Datasets

Setup: We evaluate our models on four transfer learning datasets: CIFAR-10, CIFAR-100, Flowers and Cars. Table 9 includes the statistics of these datasets.

Table 9. Transfer learning datasets.

	Train images	Eval images	Classes
CIFAR-10 (Krizhevsky & Hinton, 2009)	50,000	10,000	10
CIFAR-100 (Krizhevsky & Hinton, 2009)	50,000	10,000	100
Flowers (Nilsback & Zisserman, 2008)	2,040	6,149	102
Cars (Krause et al., 2013)	8,144	8,041	196

For this experiment, we use the checkpoints trained on ImageNet ILSVRC2012. For fair comparison, no ImageNet21k images are used here. Our finetuning settings are mostly the same as ImageNet training with a few modifications similar to (Dosovitskiy et al., 2021; Touvron et al., 2021): We use smaller batch size 512, smaller initial learning rate 0.001 with cosine decay. For all datasets, we train each model for fixed 10,000 steps. Since each model is finetuned with very few steps, we disable weight decay and use a simple cutout data augmentation.

Results: Table 8 compares the transfer learning performance. In general, our models outperform previous ConvNets and Vision Transformers for all these datasets, sometimes by a non-trivial margin: for example, on CIFAR-100, EfficientNetV2-L achieves 0.6% better accuracy than prior GPipe/EfficientNets and 1.5% better accuracy than prior ViT/DeiT models. These results suggest that our models also generalize well beyond ImageNet.

6. Ablation Studies

6.1. Comparison to EfficientNet

In this section, we will compare our EfficientNetV2 (V2 for short) with EfficientNets (Tan & Le, 2019a) (V1 for short) under the same training and inference settings.

Performance with the same training: Table 10 shows the performance comparison using the same progressive learning settings. As we apply the same progressive learning to EfficientNet, its training speed (reduced from 139h to 54h) and accuracy (improved from 84.7% to 85.0%) are better than the original paper (Tan & Le, 2019a). However, as shown in Table 10, our EfficientNetV2 models still outperform EfficientNets by a large margin: EfficientNetV2-M reduces parameters by 17% and FLOPs by 37%, while running 4.1x faster in training and 3.1x faster in inference than EfficientNet-B7. Since we are using the same training settings here, we attribute the gains to the EfficientNetV2 architecture.

Table 10. Comparison with the same training settings – Our new EfficientNetV2-M runs faster with less parameters.

	Acc. (%)	Params (M)	FLOPs (B)	TrainTime (h)	InferTime (ms)
V1-B7	85.0	66	38	54	170
V2-M (ours)	85.1	55 (-17%)	24 (-37%)	13 (-76%)	57 (-66%)

Scaling Down: Previous sections mostly focus on large-scale models. Here we compare smaller models by scaling down our EfficientNetV2-S using similar compound scaling

coefficients as EfficientNet. For easy comparison, all models are trained without progressive learning. Compared to these small-size EfficientNets (V1), our new EfficientNetV2 models are generally faster while maintaining comparable parameter efficiency.

Table 11. Scaling down model size – We measure the inference throughput on V100 FP16 GPU with batch size 128.

	Top-1 Acc.	Parameters	Throughput (imgs/sec)
V1-B1	79.0%	7.8M	2675
V2-7M	78.7%	7.4M	(2.1x) 5739
V1-B2	79.8%	9.1M	2003
V2-8M	79.8%	8.1M	(2.0x) 3983
V1-B4	82.9%	19M	628
V2-14M	82.1%	14M	(2.7x) 1693
V1-B5	83.7%	30M	291
V2-S	83.6%	24M	(3.1x) 901

6.2. Progressive Learning for Different Networks

We ablate the performance of our progressive learning for different networks. Table 12 shows the performance comparison between our progressive training and the baseline training, using the same ResNet and EfficientNet models. Here, the baseline ResNets have higher accuracy than the original paper (He et al., 2016) because they are trained with our improved training settings (see Section 5) using more epochs and better optimizers. We also increase the image size from 224 to 380 for ResNets to further increase the network capacity and accuracy.

Table 12. Progressive learning for ResNets and EfficientNets – (224) and (380) denote the targeted inference image size. Our progressive training improves both the accuracy and training time for all different networks.

	Baseline		Progressive	
	Acc.(%)	TrainTime	Acc.(%)	TrainTime
ResNet50 (224)	78.1	4.9h	78.4	3.5h (-29%)
ResNet50 (380)	80.0	14.3h	80.3	5.8h (-59%)
ResNet152 (380)	82.4	15.5h	82.9	7.2h (-54%)
EfficientNet-B4	82.9	20.8h	83.1	9.4h (-55%)
EfficientNet-B5	83.7	42.9h	84.0	15.2h (-65%)

Baseline vs progressive learning

As shown in Table 12, our progressive learning generally reduces the training time and meanwhile improves the accuracy for all different networks. Not surprisingly, when the default image size is very small, such as ResNet50(224) with 224x224 size, the training speedup is limited (1.4x speedup); however, when the default image size is larger and the model is more complex, our approach achieves larger gains on accuracy and training efficiency: for ResNet152(380), our approach improves speed up the training by 2.1x with slightly better accuracy; for EfficientNet-B4, our approach improves speed up the training by 2.2x.

6.3. Importance of Adaptive Regularization

A key insight from our training approach is the adaptive regularization, which dynamically adjusts regularization according to image size. This paper chooses a simple progressive approach for its simplicity, but it is also a general method that can be combined with other approaches as well.

Table 13 studies our adaptive regularization on two training settings: one is to progressively increase image size from small to large (Howard, 2018), and the other is to randomly sample a different image size for each batch as proposed in Mix&Match (Hoffer et al., 2019). Because TPU needs to recompile the graph for each new size, here we randomly sample a image size every eight epochs instead of every batch. Compared to the vanilla approaches of progressive or random resizing that use the same regularization for all image sizes, our adaptive regularization improves the accuracy by 0.7%. Figure 6 further compares the training curve for the progressive approach. Our adaptive regularization uses much smaller regularization for small images at the early training epochs, allowing models to converge faster and achieve better final accuracy.

Table 13. Adaptive regularization – We compare ImageNet top-1 accuracy based on the average of three runs.

	Vanilla	+our adaptive reg
Progressive resize (Howard, 2018)	84.3±0.14	85.1±0.07 (+0.8)
Random resize (Hoffer et al., 2019)	83.5±0.11	84.2±0.10 (+0.7)

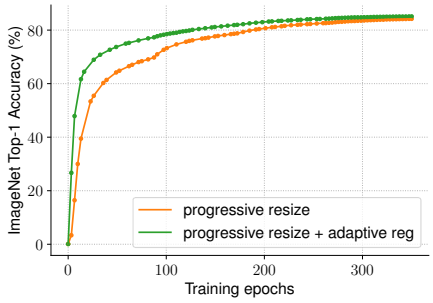


Figure 6. **Training curve comparison** – Our adaptive regularization converges faster and achieves better final accuracy.

7. Conclusion

This paper presents EfficientNetV2, a new family of smaller and faster neural networks for image recognition. Optimized with training-aware NAS and model scaling, our EfficientNetV2 significantly outperforms previous models, while being much faster and more efficient in parameters. To further speed up the training, we propose an improved method of progressive learning, that jointly increases image size and regularization during training. Extensive experiments show our EfficientNetV2 achieves strong results on ImageNet, and CIFAR/Flowers/Cars. Compared to EfficientNet and more recent works, our EfficientNetV2 trains up to 11x faster while being up to 6.8x smaller.

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Appendix

A1. Source Images

Figure 7 provides the original Panda and Snoek images used for mixup in Figure 4. These two images are first augmented with RandAug and then combined with Mixup to generate the final image in Figure 4.

Figure 7. Source files for the mixup of Panda and Snoek.

A2. Design Choices for Progressive Learning

As shown in Algorithm 1, we need to empirically determine the number of training stages M and the starting image size S_0. Table 14 shows the training time and ImageNet top-1 accuracy for different design choices of M and S_0. Overall, the learning is pretty robust to different design choices: for all 4/8/16 training stages with 128/256 initial image sizes, their accuracies are comparable. However, those different choices would lead to different training cost: larger initial image size would increase the training time as larger images require more computations; more training stages will also slightly increase the training time, as we need to recompile the model graph for each stage in our current TensorFlow framework (Abadi et al., 2016). In this paper, we use stages $M = 4$ and initial image size $S_0 = 128$ in default for all our experiments.

Table 14. Training stage and initial image size choices – Large initial image sizes or more training stages would increase the training time but doesn't improve accuracy. Overall, our improved method of progressive learning is robust to different choices.

Initial Size (S_0)	#Stages (M)	TrainTime	Acc.(%)
128x128	4	6.2h	83.24
	8	6.3h	83.11
	16	7.0h	83.20
256x256	4	8.1h	83.15
	8	8.5h	83.07
	16	9.4h	83.23

A3. Latency Measurements

Properly comparing the runtime latency is non-trivial, as latency often depends on the underlining hardware, software, and implementations. We observe that even for the same model, there are often large discrepancy between different papers. Here, we have tried out best to measure the inference latency for all models using the same Pytorch Image Models codebase (Wightman, 2021), and the same hardware/software on the same machine. Despite that, we would like to point out that the latency numbers may still vary for different hardware/software/implementations.

Table 15. Throughtput (imgs/sec/gpu) comparison (higher is better). All models have similar ImageNet top-1 accuracy.

	batch=1	batch=4	batch=16	batch=64	batch=256
EfficientNetV2-M	23	91	281	350	352
EfficientNet-B7	24	80	94	108	OOM
NFNet-F2	16	62	129	189	190

Batch size is another often overlooked factor. We observe that different models can have different behavior when batch size changes. Table 15 shows a few model examples: compared to NFNet and EfficientNetV2-M, the latency for EfficientNet-B7 becomes significantly worse for large batch size. We suspect this is because EfficientNet-B7 uses much larger image size, leading to expensive memory access overhead. This paper follows previous works (Zhang et al., 2020) and uses batch size 16 in default unless explicitly specified.

Summary

Page 1

- Proposes EfficientNetv2, the next generation of EfficientNets, much smaller in size and much faster to train
- Training efficient is as important as inference time. Why? If training a model, to check if it works for a specific task, takes days/weeks to run, the number of experiments that you can perform with such models shrinks because every experiment is gonna cost you time and $$. This paper tries to build models which are only smaller but also faster to train.
- Use training-aware neural architecture search along with other things like progressive resizing of images and adaptive regularization to achieve SOTA

Page 2

- Training bottlenecks in EfficientNets: 1) Large image size, 2) Some early DWConv layers, 3) uniform scaling of all dimensions (not image dimensions)
- Based on these observations, tries to jointly optimise model accuracy, training speed, and parameter size
- Progressive resizing helps but applying same amount of regularisation at different stages can lead to drop in accuracy. Hence adaptive regularisation is needed
- The hypothesis is that it is much easier to overfit on larger images as compared to smaller ones. Hence large images -> more regularisation needed
- Adaptive regularisation not only helps in speed up training but also improves final accuracy

Page 3

- Training with large image size is slow
    - Bigger images -> More memory required, more computations, lower batch size, hence slow training.
    - One way to overcome the above limitation is to use smaller image size for training compared to inference as done in FixRes. Smaller image size also improves overall accuracy.
- DWConv is slow in early layers
    - DWConv are highly efficient in terms of FLOPS/parameters but they can't utilise the modern accelerators properly
    - One of the ways to tackle is to replace the depthwise 3x3 and the expansion 1x1 with a normal 3x3 conv, though this will increase FLOPS/Paramus
    - One interesting thing that the authors noted is that when they replace all the MBConv blocks with Fused-MBConv blocks, it actually performs worse compared to when fusing is done only in early stage layers, and as expected the training became a lot slower in this case.
    - Finding the right combination of MBConv and Fused-MBConv is one of the tasks best suited for NAS
- Uniform scaling is sub-optimal
    - Scaling every dimension of a network as done in EfficientNets v1 isn't optimal. For example, doubling the number of layers at every stage leads to poor training and parameter efficiency
    - Non-uniform scaling is the key to address this issue and NAS is used again to find the best scaling Params

Page 4

- NAS search
    - EfficientNet as the backbone
    - Search for combination of MBConv, Fused-MBConv, kernel size (3x3, 5x5), expansion ratio of (1, 4, 6)
    - Reduce the search space by removing unnecessary ops like pooling
    - Reuse the channels size from the backbone as they are already searched in
    - Search reward = A x S^w x P^v, where A is Accuracy, S is training time step, and P is parameter size
- EfficientNetV2 architecture
    - Uses both MBConv and Fused-MBConv layers, especially in the early stages
    - Prefers a smaller expansion ratio for MBCOnv as it tends to have much smaller memory overhead
    - Uses small filters but with more layers to compensate for the effective receptive field (this is already known without NAS)

Page 5

- Image size is an important factor when it comes to performance both in terms of training time and accuracy
- Dynamically changing image size at different stages of training has already been proven to be effective
- Though the current approaches use same regularisation at all stages which is suboptimal as large image size leads to more overfitting, hence requires much stronger regularisation
- To address the above issue, the authors propose adapative regularisation. Gradually increase the image size but increase regularisation as well
- Divide the total training steps N into M stages, each stage using an increased image size from the previous stage and much stronger regularisation
- Three types of regularisation were applied: Dropout, RandAugment, and Mixup
- To apply mixup, the images are first,y augmented and then the mixup strategy is applied

Page 6, 7,8

- Consists of training results for different datasets
- The training settings and comparisons are very well laid out. Please read the sections and focus only on the annotations to save time