Solving ImageNet: a Unified Scheme for Training any Backbone to Top Results

Tal Ridnik, Hussam Lawen, Emanuel Ben-Baruch, Asaf Noy
DAMO Academy, Alibaba Group
tal.ridnik@alibaba-inc.com

Abstract

ImageNet serves as the primary dataset for evaluating the quality of computer-vision models. The common practice today is training each architecture with a tailor-made scheme, designed and tuned by an expert. In this paper, we present a unified scheme for training any backbone on ImageNet. The scheme, named USI (Unified Scheme for ImageNet), is based on knowledge distillation and modern tricks. It requires no adjustments or hyper-parameters tuning between different models, and is efficient in terms of training times. We test USI on a wide variety of architectures, including CNNs, Transformers, Mobile-oriented and MLP-only. On all models tested, USI outperforms previous state-of-the-art results. Hence, we are able to transform training on ImageNet from an expert-oriented task to an automatic seamless routine. Since USI accepts any backbone and trains it to top results, it also enables to perform methodical comparisons, and identify the most efficient backbones along the speed-accuracy Pareto curve.

Implementation is available at: https://github.com/Alibaba-MIIL/Solving_ImageNet

1. Introduction

ImageNet (1K) dataset, introduced for the ILSVRC2012 visual recognition challenge [31], has been at the center of modern advances in deep learning [21, 14, 32]. It serves as a main dataset for pretraining computer-vision models [34, 22, 17], and measuring the accuracy of models on ImageNet was found to be a good proxy to actual performance on various downstream tasks [20, 29, 42].

However, training on ImageNet remains an ongoing challenge. Since the seminal work of AlexNet [21], new training tricks, regularizations and enhancements to improve results have been continuously suggested: One-cycle learning rate scheduling [33]; Stronger augmentations based on AutoAugment [5] and RandAugment [6]; Scaling learning rate with batch size [43]; Exponential-moving average (EMA) of model weights [19]; Improved weights initializations [13, 15]; Image-based regularizations such as Cutout [7], Cutmix [46] and Mixup [48]; Architecture regularizations like drop-path [4] and drop-block [9]; Label-smoothing [27]; Different train-test resolutions [39]; More training epochs [42]; Progressive image resizing during training [35]; True weight decay [36]; Dedicated optimizer for large batch size [44], and more.

Almost any new architecture proposed is accompanied by a dedicated training scheme (e.g. [25, 38, 29, 35, 15]). These schemes can significantly differ, and a tailored scheme for one model often underperforms when used for other models. For example, when a dedicated scheme for ResNet50 model [42] was used for training EfficieneNetV2 model, it yielded 3.3% lower accuracy than a tailor-made scheme [35].

Broadly speaking, deep learning backbones for computer vision can be divided into four categories: ResNet-like, Mobile-oriented, Transformers, and MLP-only. ResNet model [14] and its variants (TResNet [30], SEResNet [18], ResNet-D [15] to name a few) usually work well over a wide variety of training schemes [29]. A top-performance training scheme for ResNet models was suggested in [42], and became the standard for this type of models. Mobile-oriented models are architectures that heavily rely on depth-wise convolutions, and efficient CPU-oriented design [32, 17, 34]. Their dedicated training schemes usually consist of RMSProp optimizer, waterfall learning rate scheduling and EMA. Due to lack of inductive bias, Transformer-based [8, 24, 11] and MLP-only [36, 37] models for vision are harder to train, and less stable [29, 23]. A dedicated training scheme for these models was proposed in [38], which includes longer training (1000 epochs), strong cutmix-mixup and drop-path regularizations, large weight-decay and repeated augmentations [1].

Knowledge Distillation (KD), originally proposed in [16], uses a teacher model to guide the target network (often referred to as the student model) along the training. The student receives supervision from both the ground-truth label and the teacher’s prediction for each image. KL-divergence measures the extra loss between the teacher the and student. [38] proposed a dedicated KD scheme for training Transformers-based models on ImageNet, that relies on a
special distillation token, hard-label thresholding and long training. [3] used KD from super-network to train subnetworks during neural architecture search process. [22] showed marginal improvement for ResNet50 model when using KD. [40] demonstrated that KD suppresses noise from data augmentations, and enables using stronger augmentations. [47] suggested a variant of KD by cropping the spatial prediction layer of the teacher.

However, KD is not a common practice for ImageNet training. Most training schemes proposed throughout the years have not utilized KD, and it is not an integral part of the popular repositories for ImageNet training, such as [41]. For obtaining top results, a more frequent option is pretraining a model on the larger ImageNet-21K dataset [29], and fine-tuning it on ImageNet-1K [24, 25, 35, 37, 30]. This alternative, of course, requires longer training and larger computational budget. It is a common practice to separate between results obtained from using only ImageNet-1K images, to results obtained using extra-data, such as ImageNet-21K pretraining.

In this paper, we introduce a unified training scheme for ImageNet, called USI (Unified Scheme for ImageNet). USI can train any backbone to state-of-the-art results, without any hyper-parameter tuning or tailor-made tricks per model. An illustration of USI training scheme appears in Figure 1. The scheme is based on the observation that vanilla KD, which imposes an additional KL-divergence loss between the teacher and student predictions, works very well on any backbone. The reason for the effectiveness of KD is the introduction of additional information, that does not exist in the original ground-truth labels. The teacher’s predictions per image account for correlations and similarities between classes, they handle better pictures with several objects, and even compensate for ground-truth mistakes. KD also handle better augmentations, and removes the need for label smoothing. All these factors lead to a more robust and effective optimization process, that requires fewer training tricks and regularizations.

We thoroughly test USI on a wide variety of modern deep learning models, including ResNet-like, Mobile-oriented, Transformer-based and MLP models. On all model tested, USI outperforms previously reported state-of-the-art results, that were obtained with a dedicated scheme per model. USI is also efficient, and requires only 300 epochs of training.

Since the proposed scheme consistently leads to top results, it also enables a fair comparison of speed-accuracy trade-offs. We benchmark various models on GPU and
CPU, and identify leading models that provide the best speed-accuracy trade-off along the Pareto curve.

The paper’s contributions can be summarized as follow:

- We introduce a unified, efficient training scheme for ImageNet dataset, USI, that does not require hyper-parameter tuning. Exactly the same recipe is applied to any backbone. Hence, ImageNet training is transformed from an expert-oriented task into an automatic seamless procedure.
- We test USI on various deep learning models, including ResNet-like, Mobile-oriented, Transformer-based and MLP-only models. We show it consistently and reliably achieves state-of-the-art results, compared to tailor-made schemes per model.
- We use USI to perform a methodological speed-accuracy comparison of modern deep learning models, and identify efficient backbones along the Pareto curve.

2. Method

In this section, we will first review how to apply knowledge distillation (KD) for classification. Then we will discuss why we need KD in ImageNet training, and finally present USI, our KD-based training scheme for ImageNet.

2.1. KD for Classification

For any input image, a classification network outputs a logit vector \( \mathbf{z} = \{z_i\}_{i=1}^K \), where \( K \) is the number of classes. The softened prediction vector is denoted by \( \mathbf{p}(\tau) = \{p_i(\tau)\}_{i=1}^K \), where each element \( p_i(\tau) \) is given by applying the softmax activation function, with a temperature-scaling parameter \( \tau \):

\[
p_i(\tau) = \frac{\exp(z_i/\tau)}{\sum_{j=1}^K \exp(z_j/\tau)}.
\]

Let us define the softened prediction vectors of the student and teacher models as \( \mathbf{p}^s(\tau) \) and \( \mathbf{p}^t(\tau) \), respectively. The objective function used for training the student model is a combination of the Cross-Entropy (CE) loss between the student’s prediction and the ground-truth vector \( \mathbf{y} \), and the Kullback-Leibler (KL) divergence between the student and the teacher predictions,

\[
L = L_{CE}(\mathbf{p}^s(1), \mathbf{y}) + \alpha_{kd} L_{KL}(\mathbf{p}^s(\tau), \mathbf{p}^t(\tau)),
\]

where \( \alpha_{kd} \) is a hyper-parameter for adjusting the relative importance of the KD loss. The CE loss is given by,

\[
L_{CE}(\mathbf{p}^s(1), \mathbf{y}) = -\sum_j y_j \log p_j^s(1),
\]

and the KL divergence loss is given by,

\[
L_{KL}(\mathbf{p}^s(\tau), \mathbf{p}^t(\tau)) = \tau^2 \sum_j p_j^s(\tau) \log \frac{p_j^s(\tau)}{p_j^t(\tau)}.
\]

2.2. Why Do We Need KD in ImageNet Training?

ImageNet serves as the primary dataset for pretraining and evaluating computer-vision models. Unlike other classification datasets, on ImageNet we are training models from scratch, and not doing transfer learning. Training from scratch is, in general, harder, and requires higher learning rates, stronger regularizations, and more training epochs. Hence, the optimization process on ImageNet is more sensitive to different hyper-parameters, and the architecture used.

To gain more insight and motivation into the impact of KD, we present in Figure 2 some typical examples for the predictions of the teacher model, compared to ImageNet ground-truth labels.

- Picture (a) contains big salient nails. That is the ground-truth, and that’s also the teacher leading prediction (99.9%). Notice that the teacher’s 2nd and 3rd top predictions are related to nails (screw and hammer), but with negligible probability.
- Picture (b) contains an airliner. That is the top prediction of the teacher (83.6%). However, the teacher also predicts wing with a non-negligible probability (11.3%). That is not a mistake - an airliner has wings. The teacher here mitigates the case where the ground-truth labels are not mutually-exclusive, and provides more accurate information about the content of the image.
- Picture (c) contains a hen (female chicken). However, the hen is not very big and salient. The teacher’s predictions reflects that, by identifying an hen with lower probability (55.5%). The teacher also gives non-negligible probability to cock (male chicken) label - 8.9%. This is a mistake by the teacher, but a logical one - hen and cock are quite similar.
- In picture (d) the teacher disagrees with the ground-truth. The ground-truth is ice-lolly, while the teacher top prediction is English setter (a type of dog). The teacher is correct - the dog is more salient in the picture.

We see from the above examples that the teacher’s predictions contain more information than the plain (single-label) ground-truth. The rich predictions provided by the teacher account for correlations and similarities between classes. They handle better pictures with several objects, and even compensate for ground-truth mistakes. KD predictions also handles better strong augmentations, since they represent the correct content of the augmented image. They also removes the need for label smoothing, since the teacher inherently outputs soft predictions.

Due to these factors, training with a teacher provides better supervision, leading to a more effective and robust optimization process, compared to training with hard-labels only.
2.3. The Proposed Training Scheme

Our proposed training scheme for ImageNet, USI, is based on utilizing KD. When training on ImageNet with KD, we observe that the training process is far more robust to hyper-parameter selection, and requires fewer training tricks and regularizations. In addition, the need for dedicated tricks per backbone is eliminated - a single unified scheme can train any backbone to top results. An illustration of USI scheme appears in Figure 1. In Table 1 we present the full training configuration.

| Procedure               | Value             |
|-------------------------|-------------------|
| Train resolution        | 224               |
| Test resolution         | 224               |
| Epochs                  | 300               |
| Optimizer               | AdamW             |
| Weight decay            | 2e-2              |
| Learning rate           | 2e-3              |
| LR decay                | One-cycle policy  |
| Mixup alpha             | 0.8               |
| Cutmix alpha            | 1.0               |
| Augmentations           | Rand-augment (7/0.5) |
| Test crop ratio         | 0.95              |
| Repeated Augs           | 3                 |
| Base loss               | Cross entropy     |
| KD loss                 | KL-divergence     |
| KD temperature          | 1                 |
| $\alpha_{kd}$           | 5                 |
| Teacher                 | TResNet-L         |
| Batch size              | 512 to 3456       |

Table 1: USI training configuration. With USI, exactly the same training recipe is applied to any backbone, and no hyper-parameter tuning is needed. Some observations and insights into the proposed scheme:

**Batch size selection** The maximal batch size allowed by Different backbones varies significantly (see Table 10 in the appendix). Hence, using a fixed batch size for all backbones is not always possible. It is beneficial to choose a batch size as large as possible, since it enables fully utilizing the GPU cores, reducing communication overheads, and increasing training speed. Previous schemes suggested that larger batches require larger learning rates or a dedicated optimizer [43, 10].

USI, which is KD-based training scheme with AdamW optimizer, is more robust to batch size and learning rate tuning. We will show in Section 3.2 that with the same learning rate, USI consistently provides top results for a wide range of batch sizes. Hence, in Table 1 we state a range of batch sizes, instead of a fixed one. Any value along this range can be chosen. We recommend using 0.8 to 0.9 of the maximal possible batch size possible, for optimizing training speeds.

**Which teacher to choose** Our primary requirement is to choose a teacher who outperforms the student, a common requirement in KD [16]. Given that constraint, we suggest selecting a teacher model with good speed-accuracy trade-off (see Figure 5). We will show in Section 3.3 that our scheme is robust to teacher and student types. Teachers with similar accuracy train students to similar accuracy, regardless of their type (CNNs or Transformers).

**KD impact on training speed** Adding KD supervision incurs additional overhead, and reduces training speed. However, the additional overhead is usually small. While the student network needs to do forward pass, store intermediate maps, do backward pass and update weights, the teacher network only needs forward passes. In addition,
since the teacher model is fixed, we can apply various optimizations to it, like batch-norm fusion, channels-last and jit [30]. We found that the relative overhead of KD decreases as we increase the batch size, which is another reason to prefer large batch sizes. For TResNet-L [30] teacher model (83.9% accuracy), the additional overhead from KD reduces the training speed by 10%-20%.

3. Results

3.1. Comparison to Previous Schemes

In Table 2 we present the ImageNet top-1 accuracy obtained for various deep learning architectures, when trained with our proposed scheme, USI. We compare USI to previous state-of-the-art results, obtained with a tailor-made scheme per architecture. We see from Table 2 that on all architecture tested (CNN, Transformer, Mobile-oriented, MLP-only), USI reaches results better than previously reported top results:

- For CNN architectures, USI significantly outperforms previous results. This applies also to ResNet50 model, where we compare USI to a recently proposed dedicated scheme [42], and a KD-based scheme [47].
- For Transformer architectures, on two prominent models, ViT-S and LeViT-384, USI reaches better results compared to DeiT scheme [38], that also utilized KD. Notice that DeiT used a tailored KD training recipe for Transformers, which includes longer training (1000 epochs), an auxiliary KD head from special distillation token, and modifications to the KD algorithm (hard-thresholding the teacher predictions). In contrast, USI uses vanilla KD, less than a third of the epochs, and no architecture-tailored modifications. With equal number of epochs, the gap between USI and DeiT is even bigger (see Section 3.4).
- For Mobile-oriented and MLP-based architectures, USI shows significant improvement compared to previously reported results.

To conclude, Table 2 presents results for a wide variety of modern deep learning models. For each model, we compare results from our proposed scheme, USI, to top results from the literature, obtained with tailor-made schemes per model. On all models tested, without any hyper-parameter tuning, USI achieves state-of-the-art results. We believe that this is a fair comparison, that demonstrates that USI enables to transform high-quality training on ImageNet into an automatic routine, that requires no dedicated expertise and cumbersome tuning process.

3.2. Robustness to Batch-size

As discussed in Section 2.3, larger batch size leads to faster training speed. In Table 3 we test the robustness of USI, with fixed learning rate, to different batch sizes. For the tests we used TResNet-M model, which enables large maximal batch size due to usage of inplace-activated batch-norm instead of regular batch-norm [30] Table 3 demonstrates that over a large range of batch sizes, 512-3456, the accuracy remains almost the same. This indicates that USI operates well with a fixed learning rate.

For our runs, we used an 8xV100 Nvidia machine, TResNet-M student, and TResNet-L teacher. In terms of training speed, with a batch size of 512 (64 per GPU) we reached a training speed of 1100 img/sec, while with a batch size of 3456 (432 per GPU) we reached 4300 img/sec.
3.3. Robustness to Teacher Type

The results in Table 2 were obtained with TResNet-L teacher. We chose this model as a teacher since it provides high accuracy, and a good speed-accuracy trade-off on GPU (see Figure 5). In Table 4 we test if different student models benefit from different teacher models. Since TResNet-L is a CNN, we compared it to a Transformer-based teacher, Volo-d1 [45], which has similar top-1 accuracy (83.9% for TResNet-L, 84.1% for Volo-d1).

| Student | Student Type | Teacher Type | Top1 Acc. [%] |
|---------|--------------|--------------|---------------|
| ResNet50 | CNN          | TResNet-L    | 81.0          |
|         |              | Volo-d1      | 80.9          |
| LeViT384 | Transformer  | TResNet-L    | 82.7          |
|         |              | Volo-d1      | 82.7          |

Table 4: Testing different students with different teachers.

We see from Table 4 that both CNN and Transformer students work well with CNN and Transformer teachers. This implies we have flexibility in choosing the teacher type.

3.4. Number of Training Epochs

USI default configuration is KD training, for 300 epochs. However, for reaching the maximal possible accuracy, 300 epochs is not enough, and longer training would further improve the accuracy. This phenomenon, where in KD the student model benefits from very long training, is called patient teacher [2]. In Table 5 we present the accuracies obtained for various training lengths. As can be seen, the accuracy continues to improve as we increase training epoch from 300 to 600 and to 1000.

Our default training configuration was chosen to be 300 epochs since this value provides a good compromise - training times are reasonable (1-3 days on 8xV100 GPU, depending on the model), while we consistently achieve good results, as can be seen in Figure 1 (c). However, if training times are not a limitation, we recommend increasing the number of training epochs.

3.5. Speed-Accuracy Measurements

When using a tailor-made training scheme per backbone, that depends on hyper-parameter tuning, computing power and other factors, it is challenging to reliably compare different models. With USI, that consistently provides top results for any backbone, we can do a methodological, reproducible and reliable comparison of speed-accuracy trade-off on ImageNet. In Figure 3 and Figure 4 we compare various modern architectures, on GPU and CPU inference.

**Implementation details**  
On GPU, The throughput was tested with TensorRT inference engine, FP16, and batch size of 256. On CPU, The throughput was tested using Intel’s OpenVINO Inference Engine, FP16, a batch size of 1 and 16 streams (equivalent to the number of CPU cores). All measurements were done after models were optimized to inference by batch-norm fusion. This significantly accelerates models that utilize batch-norm, like ResNet50, TResNet and LeViT. Note that LeViT-768* model is not a part of the original paper [11], but a model defined by us, to test LeViT design on higher accuracies regime.

**GPU inference analysis**  
On GPU, for low-to-medium accuracies, the most efficient models are LeViT-256 and LeViT-384. For higher accuracies (> 83.5%), TResNet-L and LeViT-768* models provides the best trade-off among the models tested. Note that besides LeViT, other transformer models, such as Swin, TnT and ViT, provide inferior speed-accuracy trade-off compared to modern CNNs. Mobile-oriented models also do not excel on GPU inference, compared to top CNNs. Also note that several modern architectures, titled ”Small” (ConvNext-S, Swin-S, TnT-S), are in fact quite resource-intensive - their inference speed is approximately three times slower compared to a plain ResNet50 model.

**CPU inference analysis**  
On CPU, Mobile oriented models (OFA, MobileNet, EfficientNet) provide the best speed-
accuracy trade-off. LeViT models, who excelled on GPU inference, are not as efficient for CPU inference.

### 3.6. Additional Ablations

In this section we will present additional ablations and tests, to further validate our USI training configuration.

#### 3.6.1 KD teacher relative weight

In Table 6 we test the impact of the relative weight between the KD loss and and supervision loss ($\alpha_{kd}$ in Eq. 2).

As can be seen, without KD ($\alpha_{kd} = 0$), our training scheme performs poorly - 6.5% less than accuracy obtained with the default value, $\alpha_{kd} = 5$. If the KD relative weight is too low ($\alpha_{kd} = 1$), there is also a decline in scores.

| KD relative weight, $\alpha_{kd}$ | Top1 Acc. [%] |
|-----------------------------------|---------------|
| 0 (no KD loss)                    | 76.2          |
| 1                                 | 80.8          |
| 5                                 | 82.7          |
| 10                                | 82.6          |
| 20                                | 82.7          |
| $\infty$ (no CE loss)             | 82.7          |

Table 6: Accuracy for different KD relative weights. Model tested - LeViT-384

For $\alpha_{kd} \geq 5$ we achieve top results. Interestingly, results remain the same even when training without the original hard-label supervision, and relying only on the teacher.
This further demonstrates the effectiveness of KD in ImageNet training.

3.6.2 KD Temperature

In Table 7 we investigate the impact of KD Temperature ($\tau$ in Eq. 2) on the accuracy.

| KD Temperature, $\tau$ | Top1 Acc. [%] |
|------------------------|--------------|
| 0.1                    | 79.3         |
| 1                      | 82.7         |
| 2                      | 82.7         |
| 5                      | 81.7         |
| 10                     | 81.4         |

Table 7: Accuracy for different KD temperatures. Model tested - LeViT-384

Table 7 shows that there is no benefit from using temperature in our KD loss. Both $\tau < 1$ (sharpening the teacher predictions) and $\tau > 1$ (softening the teacher predictions) reduce the accuracy. Utilizing vanilla softmax probabilities leads to the best results.

3.6.3 Mixup-Cutmix vs. Cutout

Cutout, Mixup and Cutmix are important augmentations, that significantly improved ImageNet Scores [30]. While Cutout only augments the input image, Cutmix and Mixup also alter the labels. Cutout is more prevalent when training CNNs and Mobile-oriented models [17, 15], while a combination of Mixup and Cutmix, as proposed in [41], is popular for training Transformer-based models [11, 38]. In Table 8 we compare using Cutout to Mixup-Cutmix in our unified scheme.

| Augmentation Type     | Top1 Acc. [%] |
|-----------------------|--------------|
| None                  | 82.0         |
| Cutout                | 82.4         |
| Mixup-Cutmix          | 82.7         |

Table 8: Accuracy for different augmentations. Model tested - LeViT-384

As can be seen, applying each augmentation is beneficial, but Mixup-Cutmix augmentation contributes more to improving the accuracy.

3.6.4 Architecture-based regularizations

It is common to apply architecture-based regularizations, such as drop-path [4] and drop-block [9], mainly when training Transformer-based models [8, 38]. These regularizations are not always applicable to other types of architectures, and their implementations sometimes differ between different models. Hence we preferred to avoid using them in our unified scheme.

In Table 9 we test whether adding drop-path to our scheme, when training a Transformer-based model, would improve results.

| Drop-path | Top1 Acc. [%] |
|-----------|--------------|
| 0         | 82.7         |
| 0.1       | 82.6         |
| 0.2       | 82.5         |

Table 9: Accuracy for different values of drop-path regularization. Model tested - LeViT-384

As can be seen, there is no gain from adding drop-path regularizations to USI scheme.

3.6.5 Repository

Due to implementation details and other factors, training schemes on a specific repository sometimes under-perform when used by a different repository. We developed USI on an inner private repository. To increase our confidence in its validity, we re-implemented it on a publicly available repository - timm [41]. We were able to reproduce on timm all the results obtained on our private repo. In 1 we will share our timm-based implementation.

4. Discussion and Conclusions

In this paper, we introduced a unified scheme for ImageNet training, called USI. USI, which utilizes KD and modern training tricks, requires no hyper-parameters tuning between different models, and enables to train any backbone to top results. Hence, it transforms training on ImageNet from an expert-oriented task to an automatic procedure. With USI, we are also able to perform a methodical speed-accuracy comparison, and reliably identify efficient computer-vision backbones.

Application to other classification datasets For ImageNet, we are training a model from scratch. This implies using high learning rates, strong regularization, and more epochs. Hence, our ImageNet-dedicated USI scheme is not directly applicable to other classification datasets, which usually use transfer learning. However, KD remains a highly effective technique also for the transfer learning case. It not only contributes to improving scores, but also leads to a more robust training procedure, which is less sensitive to hyper-parameter tuning. We believe that various AutoML schemes would benefit from KD usage, and plan to demonstrate this in future work.

1https://github.com/Alibaba-MIIL/Solving ImageNet
References

[1] Maxim Berman, Hervé Jégou, Andrea Vedaldi, Iasonas Kokkinos, and Matthijs Douze. Multigrain: a unified image embedding for classes and instances. arXiv preprint arXiv:1902.05509, 2019.

[2] Lucas Beyer, Xiaohua Zhai, Amélie Royer, Larisa Markeeva, Rohan Anil, and Alexander Kolesnikov. Knowledge distillation: A good teacher is patient and consistent. arXiv preprint arXiv:2106.05237, 2021.

[3] Han Cai, Chuang Gan, Tianzhe Wang, Zhekai Zhang, and Song Han. For all of us: Train one network and specialize it for efficient deployment. In International Conference on Learning Representations, 2020.

[4] Shaofeng Cai, Yao Shu, Gang Chen, Beng Chin Ooi, Wei Wang, and Meihui Zhang. Effective and efficient dropout for deep convolutional neural networks. arXiv preprint arXiv:1904.03392, 2019.

[5] Ekin D Cubuk, Barret Zoph, Dandelion Mane, Vijay Vasudevan, and Quoc V Le. Autoaugment: Learning augmentation strategies from data. In Proceedings of the IEEE conference on computer vision and pattern recognition, pages 113–123, 2019.

[6] Ekin D Cubuk, Barret Zoph, Jonathon Shlens, and Quoc V Le. Rand augmentation: Practical automated data augmentation with a reduced search space. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops, pages 702–703, 2020.

[7] Terrance DeVries and Graham W Taylor. Improved regularization of convolutional neural networks with cutout. arXiv preprint arXiv:1708.04552, 2017.

[8] Alexey Dosovitskiy, Lucas Beyer, Alexander Kolesnikov, Dirk Weissenborn, Xiaohua Zhai, Thomas Unterthiner, Mostafa Dehghani, Matthias Minderer, Georg Heigold, Sylvain Gelly, et al. An image is worth 16x16 words: Transformers for image recognition at scale. arXiv preprint arXiv:2010.11929, 2020.

[9] Golnaz Ghiasi, Tsung-Yi Lin, and Quoc V Le. Dropblock: A regularization method for convolutional networks. Advances in neural information processing systems, 31, 2018.

[10] Akhilesh Gotmare, Nitish Shirish Keskar, Caiming Xiong, and Matthijs Douze. Transformers for image recognition at scale. arXiv preprint arXiv:2011.13243, 2018.

[11] Benjamin Graham, Alaeldin El-Nouby, Hugo Touvron, Pierre Stock, Armand Joulin, Hervé Jégou, and Matthijs Douze. Levit: A vision transformer in convnet’s clothing for faster inference. In Proceedings of the IEEE/CVF International Conference on Computer Vision, pages 12259–12269, 2021.

[12] Kai Han, An Xiao, Enhua Wu, Jianyuan Guo, Chunjing Xu, and Yunhe Wang. Transformer in transformer. Advances in Neural Information Processing Systems, 34, 2021.

[13] Boris Hanin and David Rolnick. How to start training: The effect of initialization and architecture. Advances in Neural Information Processing Systems, 31, 2018.

[14] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Deep residual learning for image recognition. In Proceedings of the IEEE conference on computer vision and pattern recognition, pages 770–778, 2016.

[15] Tong He, Zhi Zhang, Hang Zhang, Zhongyue Zhang,Junyuan Xie, and Mu Li. Bag of tricks for image classification with convolutional neural networks. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pages 558–567, 2019.

[16] Geoffrey Hinton, Oriol Vinyals, Jeff Dean, et al. Distilling the knowledge in a neural network. arXiv preprint arXiv:1503.02531, 2(7), 2015.

[17] Andrew Howard, Mark Sandler, Grace Chu, Liang-Chieh Chen, Bo Chen, Mingxing Tan, Weijun Wang, Yukun Zhu, Ruoming Pang, Vijay Vasudevan, et al. Searching for m Mobilenet-v3. In Proceedings of the IEEE/CVF International Conference on Computer Vision, pages 1314–1324, 2019.

[18] Jie Hu, Li Shen, and Gang Sun. Squeeze-and-excitation networks. In Proceedings of the IEEE conference on computer vision and pattern recognition, pages 7132–7141, 2018.

[19] Pavel Izmailov, Dmitrii Podoprikhin, Timur Garipov, Dmitry Vetrov, and Andrew Gordon Wilson. Averaging weights leads to wider optima and better generalization. arXiv preprint arXiv:1803.05407, 2018.

[20] Simon Kornblith, Jonathon Shlens, and Quoc V Le. Do better imagenet models transfer better? In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pages 2661–2671, 2019.

[21] Alex Krizhevsky, Ilya Sutskever, and Geoffrey E Hinton. Imagenet classification with deep convolutional neural networks. Advances in neural information processing systems, 25:1097–1105, 2012.

[22] Jungkyu Lee, Taeryun Won, Tae Kwan Lee, Hyemin Lee, Geonmo Gu, and Kiho Hong. Compounding the performance improvements of assembled techniques in a convolutional neural network. arXiv preprint arXiv:2001.06268, 2020.

[23] Liyuan Liu, Xiaodong Liu, Jianfeng Gao, Weizhu Chen, and Jiawei Han. Understanding the difficulty of training transformers. arXiv preprint arXiv:2004.08249, 2020.

[24] Ze Liu, Yutong Lin, Yue Cao, Han Hu, Yixuan Wei, Zheng Zhang, Stephen Lin, and Baining Guo. Swin transformer: Hierarchical vision transformer using shifted windows. In Proceedings of the IEEE/CVF International Conference on Computer Vision, pages 10012–10022, 2021.

[25] Zhuang Liu, Hanzi Mao, Chao-Yuan Wu, Christoph Feichtenhofer, Trevor Darrell, and Saining Xie. A convnet for the 2020s. arXiv preprint arXiv:2201.03545, 2022.

[26] Ilya Loshchilov and Frank Hutter. Decoupled weight decay regularization. arXiv preprint arXiv:1711.05101, 2017.

[27] Rafael Müller, Simon Kornblith, and Geoffrey E Hinton. When does label smoothing help? Advances in neural information processing systems, 32, 2019.

[28] Ilija Radosavovic, Raj Prateek Kosaraju, Ross Girshick, Kaiming He, and Piotr Dollár. Designing network design spaces. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pages 10428–10436, 2020.
[29] Tal Ridnik, Emanuel Ben-Baruch, Asaf Noy, and Lihi Zelnik-Manor. Imagenet-21k pretraining for the masses. *arXiv preprint arXiv:2104.10972*, 2021. 1, 2

[30] Tal Ridnik, Hussam Lawen, Asaf Noy, Emanuel Ben Baruch, Gilad Sharir, and Itamar Friedman. Tresnet: High performance gpu-dedicated architecture. In *Proceedings of the IEEE/CVF Winter Conference on Applications of Computer Vision*, pages 1400–1409, 2021. 1, 2, 5, 8

[31] Olga Russakovsky, Jia Deng, Hao Su, Jonathan Krause, Sanjeev Satheesh, Sean Ma, Zhiheng Huang, Andrej Karpathy, Aditya Khosla, Michael Bernstein, Alexander C. Berg, and Li Fei-Fei. ImageNet Large Scale Visual Recognition Challenge. *International Journal of Computer Vision (IJCV)*, 115(3):211–252, 2015. 1

[32] Mark Sandler, Andrew Howard, Menglong Zhu, Andrey Zhmoginov, and Liang-Chieh Chen. Mobilenetv2: Inverted residuals and linear bottlenecks. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 4510–4520, 2018. 1

[33] Leslie N Smith and Nicholay Topin. Super-convergence: Very fast training of neural networks using large learning rates. In *Artificial intelligence and machine learning for multi-domain operations applications*, volume 11006, page 1100612. International Society for Optics and Photonics, 2019. 1

[34] Mingxing Tan and Quoc Le. Efficientnet: Rethinking model scaling for convolutional neural networks. In *International conference on machine learning*, pages 6105–6114. PMLR, 2019. 1, 5

[35] Mingxing Tan and Quoc Le. Efficientnetv2: Smaller models and faster training. In *International Conference on Machine Learning*, pages 10096–10106. PMLR, 2021. 1, 5

[36] Ilya O Tolstikhin, Neil Houlsby, Alexander Kolesnikov, Lucas Beyer, Xiaohua Zhai, Thomas Unterthiner, Jessica Yung, Andreas Steiner, Daniel Keysers, Jakob Uszkoreit, et al. Mlp-mixer: An all-mlp architecture for vision. *Advances in Neural Information Processing Systems*, 34, 2021. 1, 5

[37] Hugo Touvron, Piotr Bojanowski, Mathilde Caron, Matthieu Cord, Alaeddin El-Nouby, Edouard Grave, Gautier Izacard, Armand Joulin, Gabriel Synnaeve, Jakob Verbeek, et al. Resmlp: Feedforward networks for image classification with data-efficient training. *arXiv preprint arXiv:2105.03404*, 2021. 1, 2, 5

[38] Hugo Touvron, Matthieu Cord, Matthijs Douze, Francisco Massa, Alexandre Sablayrolles, and Hervé Jéou. Training data-efficient image transformers & distillation through attention. In *International Conference on Machine Learning*, pages 10347–10357. PMLR, 2021. 1, 5, 8

[39] Hugo Touvron, Andrea Vedaldi, Matthijs Douze, and Hervé Jéou. Fixing the train-test resolution discrepancy. *Advances in neural information processing systems*, 32, 2019. 1

[40] Longhai Wei, An Xiao, Lingxi Xie, Xiaopeng Zhang, Xin Chen, and Qi Tian. Circumventing outliers of autoaugment with knowledge distillation. In *European Conference on Computer Vision*, pages 608–625. Springer, 2020. 2

[41] Ross Wightman. Pytorch image models. *https://github.com/rwightman/pytorch-image-models*, 2019. 2, 8

[42] Ross Wightman, Hugo Touvron, and Hervé Jéou. Resnet strikes back: An improved training procedure in timm. *arXiv preprint arXiv:2110.00476*, 2021. 1, 5

[43] Yang You, Igor Gitman, and Boris Ginsburg. Scaling sgd batch size to 32k for imagenet training. *arXiv preprint arXiv:1708.03888*, 6(12):6, 2017. 1, 4

[44] Yang You, Jing Li, Sashank Reddi, Jonathan Hseu, Sanjiv Kumar, Srinadh Bhojanapalli, Xiaodan Song, James Demmel, Kurt Keutzer, and Cho-Jui Hsieh. Large batch optimization for deep learning: Training bert in 76 minutes. *arXiv preprint arXiv:1904.00962*, 2019. 1

[45] Li Yuan, Qibin Hou, Zihang Jiang, Jiashi Feng, and Shuicheng Yan. Volo: Vision outlooker for visual recognition. *arXiv preprint arXiv:2106.13112*, 2021. 6

[46] Sangdoo Yun, Dongyoon Han, Seong Joon Oh, Sanghyuk Chun, Junsk Choe, and Youngjoon Yoo. Cutmix: Regularization strategy to train strong classifiers with localizable features. In *Proceedings of the IEEE/CVF international conference on computer vision*, pages 6023–6032, 2019. 1

[47] Sangdoo Yun, Seong Joon Oh, Byeongho Heo, Dongyoon Han, Junsk Choe, and Sanghyuk Chun. Re-labeling imagenet: from single to multi-labels, from global to localized labels, 2021. 2, 5

[48] Hongyi Zhang, Moustapha Cisse, Yann N Dauphin, and David Lopez-Paz. mixup: Beyond empirical risk minimization. *arXiv preprint arXiv:1710.09412*, 2017. 1
Figure 5: Speed-Accuracy comparison on an Nvidia V100 GPU, with PyTorch inference engine.

Appendices

A. Model Details

In Table 10 we provide full details for various models. Measurements were done using PyTorch engine.

| Model name   | Top-1 Accuracy [%] | Maximal Inference Speed [img/sec] | Maximal Training Speed [img/sec] | Maximal Batch Size |
|--------------|--------------------|-----------------------------------|----------------------------------|--------------------|
| MobileNetV3  | 77.3               | 6359                              | 1316                             | 480                |
| ResMLP-S12   | 78.8               | 4909                              | 1474                             | 440                |
| EfficientNet-B0 | 79.3           | 5112                              | 1047                             | 316                |
| OFA-595m     | 80.6               | 3919                              | 601                              | 292                |
| ResNet50     | 81.0               | 2819                              | 785                              | 316                |
| ViT-S        | 81.8               | 2432                              | 724                              | 244                |
| Mixer-B      | 82.0               | 1388                              | 457                              | 168                |
| EfficientNet-B3 | 82.1            | 2604                              | 511                              | 168                |
| TResNet-M    | 82.4               | 2917                              | 720                              | 504                |
| TrnT-S       | 82.6               | 782                               | 152                              | 146                |
| LeViT-384    | 82.7               | 5175                              | 1400                             | 448                |
| LeViT-768    | 84.2               | 2116                              | 594                              | 196                |
| RegNetY-32   | 82.8               | 2013                              | 546                              | 260                |
| TResNet-L    | 83.9               | 1563                              | 340                              | 228                |
| Swin-S       | 84.0               | 858                               | 223                              | 112                |
| ConvNext-S   | 84.0               | 1172                              | 350                              | 128                |

Table 10: Full model details. All measurements were done on Nvidia V100 GPU, with 16GB. Train and test resolution - 224.

B. GPU Inference using PyTorch inference engine

In Figure 5 we compare GPU speed-accuracy trade off of different models with a PyTorch inference engine.