Towards Efficient and Data Agnostic Image Classification Training Pipeline for Embedded Systems

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Abstract. Nowadays deep learning-based methods have achieved a remarkable progress at the image classification task among a wide range of commonly used datasets (ImageNet, CIFAR, SVHN, Caltech 101, SUN397, etc.). SOTA performance on each of the mentioned datasets is obtained by careful tuning of the model architecture and training tricks according to the properties of the target data. Although this approach allows setting academic records, it is unrealistic that an average data scientist would have enough resources to build a sophisticated training pipeline for every image classification task he meets in practice. This work is focusing on reviewing the latest augmentation and regularization methods for the image classification and exploring ways to automatically choose some of the most important hyperparameters: total number of epochs, initial learning rate value and it's schedule. Having a training procedure equipped with a lightweight modern CNN architecture (like MobileNetV3 or EfficientNet), sufficient level of regularization and adaptive to data learning rate schedule, we can achieve a reasonable performance on a variety of downstream image classification tasks without manual tuning of parameters to each particular task. Resulting models are computationally efficient and can be deployed to CPU using the OpenVINO[™] toolkit. Source code is available as a part of the OpenVINOTM Training Extensions¹.

Keywords: Image classification \cdot deep learning \cdot lightweight models

1 Introduction

Throughout the past decade deep learning-based image classification methods have made a great progress increasing their performance by 45% [40] from the AlexNet [20] level on well-known ImageNet benchmark [7]. Although SOTA results are obtained by a fine-grained adaptation of all the training pipeline components to the target task, in practice a data engineer could not have enough resources to do it. Typically to solve an image classification task we need to make the following decisions:

- Choose a model architecture;

¹ https://github.com/openvinotoolkit/training_extensions

- Build data augmentation pipeline;
- Choose optimization method and it's parameters (learning rate schedule, length of the training);
- Apply some extra regularization methods in case of overfitting;
- Apply additional techniques to handle hard classes imbalance or high level of label noise if needed.

Wrong decisions on each step can hurt the resulting classification model performance or bring misalignments with the requirements to computational complexity, for instance. At the same time, techniques and models which are successful on one dataset may not be beneficial on others, i.e. they are not dataset-agnostic. From the practical perspective, although reaching the ultimate performance is very demanding task, one can still think about some fail-safe training configuration that would allow obtaining moderate results on a wide range of middle-sized image classification datasets with minimum effort to further tuning. In this work we aim to propose such a configuration for a couple of modern computationally effective architectures: EfficientNet-B0 [34] and MobileNetV3 [14] family. To reach the goal we added the adaptability to the optimization process of scheduling the weights, designed a robust initial learning rate estimation heuristic and curated a set of regularization techniques that suit well to the considered model architectures.

In brief, the key contributions of this paper can be summarized as follows:

- Designed an optimization controlling policy that includes an optimal initial learning rate estimator and a modified version of the ReduceLROnPlateau [2] scheduler equipped with an early stopping procedure;
- Proposed a way of applying Deep Mutual Learning [44] to reduce overconfidence of model predictions;
- For each of the considered models curated a suitable bundle of data augmentation and regularization methods and validated it on various middle-sized downstream image classification datasets.

2 Related Work

Optimal learning rate estimation and scheduling. The problem of initial learning rate setting can be seen as a general hyperparameter optimization and, thus, a variety of general methods can be directly applied [3, 21]. From the other side, several simple heuristics were designed to directly tackle it [1, 24]. The last approach is more lightweight because it doesn't imply dependencies on any hyperparameters estimation frameworks, but at the same time, it is not very reliable since assumptions that these algorithms are based on, could not strictly hold in a wide range of real-world tasks. Considering a fine-grained grid search as the most robust method, we believe that a combination of a hyperparameters tuning framework and properly designed trials execution process will be a good trade-off between robustness and accuracy. When the initial learning rate is chosen, the schedule and stopping criteria define the final result of the training. Typically researchers set reasonable amount of training epochs in advance,

especially if they focus on a single dataset, but to save computational resources and avoid overfitting it is beneficial to stop training early [31,42]. Early stopping can break logic of popular schedulers like cosine or 1cycle [33], especially if too large number of total epochs was set initially, so in this work we use drops to decrease learning rate in combination with initial linear warm-up.

Data augmentation. Recently a wide range of effective data augmentation methods has been proposed [11,25]. Augmix [13] allows combining several simple augmentations (like random crop, color perturbation, rotation, flip) into a pipeline with adjustable applying policy. That allows to use Augmix as a replacement for classic sequential pipeline of transformations. In case of high capacity models, additional mixing-sample augmentations like fmix [11] can be applied on the top of Augmix output to further diversify the input data.

Regularization. To achieve higher classification accuracy, a training pipeline should keep a balance between fitting ability and regularization. We have tested a lot of approaches acting on different directions: continuous dropout [32], mutual learning [44], label smoothing and confidence penalty [29], no bias decay [12], and found a suitable combination for each of considered architecture type. Complexity of data augmentation, batch size and learning rate values can also be viewed as regularization factors. Taking this into account, transferring regularization parameters between different datasets and architectures should be done with care.

Optimization. Currently even SOTA approaches in classification still use SGD [30,39] for finetuning on small target datasets, while use stronger adaptive optimizers [23,38] for initial pre-training with huge amount of samples. We are aiming to finetune already pre-trained models and choose the SGD-based Sharpness-Aware Minimizer (SAM) [10] as a default optimizer. SAM, like SGD, preserves the mentioned fitting-regularization tradeoff, it's authors claim that SAM also provides robustness to label noise. This property is useful if we aim to build a reliable training pipeline.

3 Method

In this section, we describe the overall training pipeline from models architectures to training tricks.

3.1 Models

We chose MobileNetV3 [14] and EfficientNet [34] as base architectures for performing image classification. Namely, we conducted all the experiments on MobileNetV3 small 1x, large 0.75x, large 1x and EfficientNet-B0. The chosen models form a strong performance accuracy trade-off in the range from 0.06 to 0.4 GFLOPs, which is enough in most of edge-oriented applications.

3.2 Training tricks

Data Augmentation. Properly chosen data augmentation pipeline can boost classification accuracy on a variety of downstream tasks. At the same time, optimal augmentations are different for different datasets. Thus, any hand-crafted pipeline would be suboptimal and considering this, our goal is to to find a pipeline that maintains fitting-regularization tradeoff for MobileNetV3 and EfficientNet. After conducting experiments with modern techniques [11, 13, 37, 43], we found AugMix [13] with a pre-trained on ImageNet policy is the most beneficial for our setup. When we add MixUp [43], CutMix [37] or FMix [11] to the pipeline we observe a performance drop compared to pure AugMix. This indicates that AugMix provides a better fitting-regularization tradeoff for the chosen lightweight models, while MixUp-like augmentations are too hard for them.

Optimization. Conventionally, SGD with momentum is widely used for fine-tuning in downstream classification tasks [30,39]. An extension to SGD, Sharpness Aware Minimization (SAM) [10], allows to achieve higher results in the fine-tuning than SGD, while requiring two forward-backward passes of the model per training iteration. We operate with lightweight models, so additional cost of SAM is not critical. We also tried AdamW [16], but it performed slightly worse than SGD.

Additionally, we employ no bias decay (turning off weight decay for biases in all layers) [12] for better generalization.

Optimal Learning Rate Estimation. Since SGD performance on a given dataset is highly correlated with the initial learning rate magnitude, we have to incorporate estimation of this parameter into our training pipeline. Straightforward approach is to use grid or random search within a given range, but we were focusing on less time consuming methods. Fast-ai's heuristic [15] can generate learning rate proposal after performing several training iterations, but in our experiments it tends to output too high values which destroy ImageNet initialization even if warmup strategy is applied. To overcome this problem, we propose to finetune the model with a pre-defined small learning rate for one epoch on the target data and then run the original fast-ai algorithm. In this case the model would react to fast increase of the learning rate more smoothly and the algorithm will select a value which is quite close to one located with the grid search (see Figure 1). Fast-ai's heuristic with pre-training is almost as lightweight as the original one: for instance if the training is scheduled for 100 epochs, one extra epoch for finetuning will introduce only 1% of additional overhead.

For fine-grained learning rate selections we use Tree-structured Parzen Estimator (TPE) from the Optuna [3] framework. We set optimization criterion as top-1 accuracy on the validation subset after training on the target data for several epochs. We use median trial pruning criterion which breaks a trial if the best intermediate result is worse than the median of intermediate results of the previous trials at the same step. Pruning heuristic also could be used for grid search, but TPE also generates locations of the next trials based on previous trials locations instead of random choice or using a grid, which allows us to set

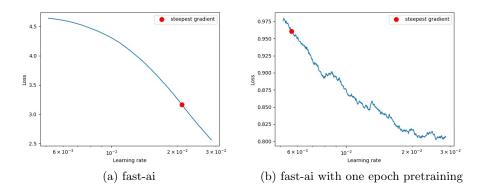


Fig. 1: Without pretraining the estimated learning rate is too large (≈ 0.02). Whereas with one epoch pretraining the estimated learning rate is more suitable for the CIFAR-100 dataset (≈ 0.0056).

a lower total trails limit compared to the grid search. We set TPE as a default initial learning estimator in our pipeline, though fast-ai with pre-training could be used in case of limited resources.

Learning Rate Scheduling and Early Stopping. Complexity of the input dataset can drastically vary and thus the number of epochs that are sufficient for training also varies. For efficient training we have to adapt to different data. To achieve this, we need a flexible learning rate schedule and reliable early stopping criterion. Popular SOTA schedulers like cosine [22] and 1cycle [33] require a pre-defined number of epochs and the shape of the produced learning rate curve depends on it. If we, for an instance, predefine 200 training epochs and early stopping criterion returns a stop flag on the 20th epoch, the training will be stopped at an unstable state of the model, because convergence hasn't been reached yet. If we take into account this drawback and prohibit early stopping criterion returning a stop flag till the half of the training pass, this will cause too long training, but the model will converge.

To overcome these problems we propose to use a modified version of ReduceLROnPlateau [2] scheduler denoted hereafter as ReduceLROnPlateauV2. In ReduceLROnPlateauV2 we force learning rate decay if 75% of the maximum training length had been reached, but learning rate drop have not been performed yet. This helps model to converge when average training loss, which we use as a criterion for learning rate drop, is unstable. Also we incorporated early stopping into ReduceLROnPlateauV2: if the learning rate was decayed to a predefined minimal value and the best top-1 score on validation subset hadn't been improving for a predefined number of epochs, we stop the training.

Additionally we use 5 epoch linear learning rate warmup and, following no bias decay practice, we increase learning rate for biases by a factor of 2.

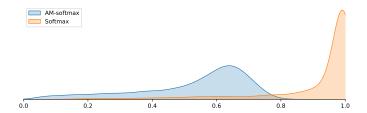


Fig. 2: Distributions of the most probable class confidence produced by the fast model on validation data. If slow student is trained with AM-Softmax, fast student does not tend to return overconfident predictions. Experiment is conducted with a pair of MobileNetV3 small models on Cars Dataset [18] containing 196 classes.

Mutual Learning. To further boost the performance of classification models we tried to apply deep mutual learning (DML) [44]. This technique implies mutual learning of a collection of simple student models. As a result, performance of each student individually is supposed to be increased. We directly apply this technique to pairs of identical models and didn't obtain substantial accuracy gain. This framework could also be used in a different manner: if one of the students has a stronger regularization and trains slower than the others, it may prevent others from overfitting and softly transfer properties of it's regularized distribution to faster students. We applied the second setup to pairs of models with the same architecture, but different loss functions. Fast student is trained with the cross-entropy loss while slow one is trained with the AM-Softmax [8] loss with scale s = 1 and margin m = 0. Such settings of the angular loss make output distribution of the slower model less confident and it also pushes the faster model to output a smoother distribution while strong discriminative properties formed by AM-Softmax are transferred to the faster model as well. In the described scheme the overall training losses are defined as follows:

$$L_{fast}(x) = L_{CE}(p_1(x), y) + D_{KL}(p_2(x)||p_1(x))$$

$$L_{slow}(x) = L_{AMS}(p_2(x), y) + D_{KL}(p_1(x)||p_2(x))$$

where (x, y) is a training sample and it's label, $D_{KL}(p||q)$ is Kullback Leibler divergence between discrete distributions p and q, $p_1(x)$ – distribution estimated by the fast model on the sample x, $p_2(x)$ – distribution estimated by the slow model on the sample x. Results of applying this approach are demonstrated on the Figure 2.

Drawback of the DML is significant increase of the training time and memory footprint. Taking this into account, we decide to include this technique only to the training strategy for MobileNetV3 family, besides for EfficientNet-B0 it is not so beneficial. Instead, we train EfficientNet-B0 with AM-Softmax directly. In that case $s = \max(\sqrt{2} \cdot \log(C-1), 3)$ (where C is the number of classes) and margin m = 0.35.

4 Experiments

This section describes the evaluation process, metrics, datasets and reports the evaluation results. For a given model family we use the same training techniques and parameters across all the considered datasets; this allows us to validate how well the proposed training pipeline can work on variable data.

4.1 Datasets

To validate the proposed approach we choose 11 widespread classification datasets, that are listed in Table 1.

Table 1: Image classification datasets which were used for training.								
Dataset	Number of classes Number of Images							
		Train	Validation					
Oxford-IIIT Pets [28]	37	3680	3369					
Describable Textures (DTD)* [6]	47	4826	814					
Oxford 102 Flowers* [27]	102	6614	1575					
Caltech 101* [9]	101	6941	1736					
Cars Dataset [18]	196	8144	8041					

500

100

10

47386

50000

60000

2443

10000

10000

 SVHN [26]
 10
 73257
 26032

 Food-101 [5]
 101
 75750
 25250

 SUN397* [36]
 397
 92440
 16314

* for experiments on these datasets we do custom random splits.

4.2 Evaluation protocol

Birdsnap* [4]

CIFAR-100 [19]

Fashion-MNIST [35]

To evaluate image classification models besides commonly used top-k accuracy metric, we also calculate mean average precision (mAP) in the same sense as it is considered in person re-identification field [45]. We would denote a set of C classes as a gallery and each of N samples in the evaluation set as a query. Then, in terms of the retrieval task, we have to rank the gallery by similarity with the query, compute the average precision of this query, and then collect the mAP. In terms of the classification task, the similarity is the predicted probability of a class, and, thus, computing average precision is straightforward:

$$mAP = \frac{\sum_{q=1}^{Q} AP(q)}{Q} = \frac{\sum_{i=1}^{N} AP(i)}{N} = \frac{1}{N} \sum_{i=1}^{N} \frac{1}{K_i},$$

where K_i is the index of the probability of ground truth class in the sorted set of predicted class probabilities for a sample. AP(i) varies from 1 (if the

model prediction is always correct) to $\frac{1}{C}$ (if the model always assigns the lowest probability to the true class). mAP can be viewed as an aggregation of all C possible top-k scores and reveals the ranking ability of the evaluated classification models.

After single dataset evaluation metrics are defined, we also have to define a way to compare different strategies for a given model taking into account results on a set of datasets. In this work, we will follow [41] and consider metrics averaging across datasets as a measure of the quality of a training strategy for a given model. This approach doesn't imply any weighting procedure, so each dataset equally contributes to the final metric.

4.3 Results

We trained all the models starting from the ImageNet-pretrained weights. We consider the following training setup as a baseline: training length is 200 epochs; learning rate is annealed to zero with cosine schedule; optimization is performed with SGD with momentum; training images are augmented with random flip, random color jittering, random crop and random rotation; dropout with p=0.2 is applied to the classifier layer; learning rate is set as an average of optimal learning rates obtained by grid search over all the 11 considered datasets for each model individually.

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Model	AVG top-1, %	AVG $top-5$, %	AVG mAP	AVG epochs
MobileNetV3-small baseline	82.24	95.29	82.35	200
Our MobileNetV3-small	85.00	96.15	88.01	86
MobileNetV3-large-0.75x baseline	85.28	96.30	87.03	200
Our MobileNetV3-large- $0.75x$	87.60	96.97	91.14	83
MobileNetV3-large baseline	85.79	96.47	87.99	200
Our MobileNetV3-large	88.26	97.34	91.79	81
EfficientNet-B0 baseline	86.47	96.77	89.27	200
Our EfficientNet-B0	89.13	97.79	92.75	82

For our adaptive pipeline we set the maximum training length to 200 epochs, maximum amount of trials in TPE to 15 (each trial takes 6 epochs or less); learning rate search range for EfficientNet-B0 is [0.001-0.01], while for MobileNetV3 the range is [0.005-0.03]; Augmix with a pre-trained on ImageNet policy, random flip, random crop and random rotation are employed for data augmentation; early stopping and learning rate decay patiences are equal to 5 epochs; ρ in SAM is 0.05. Weight decay is always set to $5 \cdot 10^{-4}$. Input resolution for all versions of the considered models is 224×224 , no test time augmentation is applied.

The final results are presented for all our models in the Table 2. Our adaptive training strategy clearly outperforms baseline by 2-3% AVG top-1 and 3-5%

AVG mAP. Also it reduces average number of epochs required for training more than twice: from 200 to 86 or less.

Top-1 scores by datasets are presented in the Table 3 as well as comparison with other solutions. Our MobileNetV3-small with adaptive training outperforms both our baseline and one of the best publicly available repositories with advanced training tricks for MobileNetV3-small (it includes label smoothing [29], Mixup [43], no bias decay [12], EMA decay and learning rate warmup). At the same time, two non-adaptive strategies for MobileNetV3-small perform on par. EfficientNet-B0 with adaptive strategy demonstrates results similar to ResNet-50 from VTAB [41], which is trained with heavyweight search over hyperparameters (learning rate, schedule, optimizers, batch size, train preprocessing functions, evaluation pre-processing, and weight decay). The results of heavyweight SOTA models are also presented in the Table 3 for the reference.

Table 3: Detailed comparison with other methods. Top-1 metric is presented.

Model	CIFAR-100*	DTD^*	Food-101*	SUN397	$^*\mathrm{NHN}^*$	Birdsnap	Caltech101	Cars*	Fashion-MNIST*	Flowers*	Pets*
Our MNV3-small baseline	79.57	68.58	74.71	57.38	96.02	77.12	90.41	87.24	95.13	93.89	84.65
Our MNV3-small	83.49	72.45	79.59	62.83	97.29	79.04	92.94	91.33	95.74	94.86	85.55
MNV3-small ⁺	82.43	68.13	69.45	61.13	96.49	78.75	91.74	86.66	95.48	92.81	85.41
MNV3-large-0.75x baseline	81.05	72.28	80.97	61.97	96.13	81.39	92.87	91.18	95.02	95.36	89.86
Our MNV3-large- $0.75x$	85.36	74.50	85.53	67.02	97.54	83.21	95.23	93.75	95.83	96.22	90.51
Our MNV3-large baseline	81.70	73.53	81.57	62.65	96.18	82.21	93.46	91.29	95.31	95.69	90.13
Our MNV3-large	86.24	76.49	85.77	67.96	97.57	84.1	95.42	93.76	96.17	96.63	91.21
Our EffNet-B0 baseline	84.84	74.81	83.75	64.43	96.88	80.03	94.54	90.46	95.80	95.26	91.74
Our EffNet-B0	86.52	77.18	86.06	72.10	97.82	83.33	95.63	93.77	96.28	97.10	92.00
VTAB ResNet-50 [41]	84.00	76.8	-	-	97.40	-	-	-	-	97.40	92.6
Inception v4 [17]	87.5	78.1	90.00	-	-	-	-	93.30	-	98.50	94.50
EffNet-B7+SAM [10]	92.56	-	92.98	-	-	-	-	94.82	-	99.37	96.03
		78.1			-		-		-		

^{*} for these datasets we do splits as defined by the authors, for others we use custom splits

4.4 Ablation study

We conduct an ablation study by removing each single component of our training pipeline, while others are enabled (see Table 4). For experiments we use all the data except the SUN397 for MobilenetV3 and subset of 6 datasets for EfficientNet-B0 (CIFAR-100, DTD, Flowers, Cars, Pets, Caltech101). Each of

⁺Implementation is taken from https://github.com/ShowLo/MobileNetV3, learning rate is set the same as for our baseline.

the training tricks has roughly equal gain (< 2% top-1), excepting AM-Softmax related ones that add 2-3% of mAP to the result.

Table 4: Impact of each training trick to MobileNetV3-large and EfficientNet-B0 results.

Configuration	MobileNe	tV3-large	Efficien	Net-B0	
	AVG top-1	AVG mAP	AVG top-1	AVG mAP	
Final solution	90.63	94.17	90.63	94.14	
w/o SAM	89.74	93.34	90.44	94.14	
w/o Mutual Learning	89.58	90.71	-	-	
w/o AugMix	90.14	93.75	90.41	93.88	
w/o NBD	90.16	93.49	90.43	94.14	
w/o AM-Softmax	-	-	90.51	92.14	
w/o adaptive learning rate strategy	89.97	93.38	90.16	93.83	

5 Conclusion

In this work, we presented adaptive training strategies for several lightweight image classification models that can perform better on a wide range of downstream datasets in finetuning from ImageNet scenario than conventional training pipelines if there are no resources available for heavyweight models and extensive hyperparameters optimization. These strategies are featured with optimal learning rate estimation and early stopping criterion, allowing them to adapt to the input datasets to some extent. The ability to adapt is shown by conducting experiments on 11 diverse image classification datasets.

References

- fast.ai: Learning rate finder, https://fastai1.fast.ai/callbacks.lr_finder. html#Learning-Rate-Finder
- pytorch: Reducelronplateau scheduler, https://pytorch.org/docs/stable/ generated/torch.optim.lr_scheduler.ReduceLROnPlateau.html#torch. optim.lr_scheduler.ReduceLROnPlateau
- 3. Akiba, T., Sano, S., Yanase, T., Ohta, T., Koyama, M.: Optuna: A next-generation hyperparameter optimization framework. In: Proceedings of the 25rd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining (2019)
- Berg, T., Liu, J., Lee, S.W., Alexander, M.L., Jacobs, D.W., Belhumeur, P.N.: Birdsnap: Large-scale fine-grained visual categorization of birds. In: 2014 IEEE Conference on Computer Vision and Pattern Recognition. pp. 2019–2026 (2014). https://doi.org/10.1109/CVPR.2014.259
- 5. Bossard, L., Guillaumin, M., Van Gool, L.: Food-101 mining discriminative components with random forests. In: European Conference on Computer Vision (2014)

- Cimpoi, M., Maji, S., Kokkinos, I., Mohamed, S., , Vedaldi, A.: Describing textures in the wild. In: Proceedings of the IEEE Conf. on Computer Vision and Pattern Recognition (CVPR) (2014)
- Deng, J., Dong, W., Socher, R., Li, L.J., Li, K., Fei-Fei, L.: ImageNet: A Large-Scale Hierarchical Image Database. In: CVPR09 (2009)
- 8. Deng, J., Guo, J., Zafeiriou, S.: Arcface: Additive angular margin loss for deep face recognition. ArXiv (2018)
- 9. Fei-Fei, L., Fergus, R., Perona, P.: Learning generative visual models from few training examples: An incremental bayesian approach tested on 101 object categories. 2004 Conference on Computer Vision and Pattern Recognition Workshop pp. 178–178 (2004)
- Foret, P., Kleiner, A., Mobahi, H., Neyshabur, B.: Sharpness-aware minimization for efficiently improving generalization. ArXiv abs/2010.01412 (2020)
- 11. Harris, E., Marcu, A., Painter, M., Niranjan, M., Prügel-Bennett, A., Hare, J.S.: Fmix: Enhancing mixed sample data augmentation. arXiv: Learning (2020)
- 12. He, T., Zhang, Z., Zhang, H., Zhang, Z., Xie, J., Li, M.: Bag of tricks for image classification with convolutional neural networks. In: 2019 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR). pp. 558–567 (2019)
- Hendrycks, D., Mu, N., Cubuk, E.D., Zoph, B., Gilmer, J., Lakshminarayanan, B.: AugMix: A simple data processing method to improve robustness and uncertainty. Proceedings of the International Conference on Learning Representations (ICLR) (2020)
- Howard, A.G., Sandler, M., Chu, G., Chen, L.C., Chen, B., Tan, M., Wang, W., Zhu, Y., Pang, R., Vasudevan, V., Le, Q.V., Adam, H.: Searching for mobilenetv3.
 2019 IEEE/CVF International Conference on Computer Vision (ICCV) pp. 1314– 1324 (2019)
- 15. Jeremy Howard, S.G.: Deep Learning for Coders with fastai and PyTorch. O'Reilly Media, Inc. (2020)
- Kingma, D.P., Ba, J.: Adam: A method for stochastic optimization. CoRR abs/1412.6980 (2015)
- 17. Kornblith, S., Shlens, J., Le, Q.V.: Do better imagenet models transfer better? 2019 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR) pp. 2656–2666 (2019)
- 18. Krause, J., Stark, M., Deng, J., Fei-Fei, L.: 3d object representations for fine-grained categorization. In: 4th International IEEE Workshop on 3D Representation and Recognition (3dRR-13). Sydney, Australia (2013)
- 19. Krizhevsky, A.: Learning multiple layers of features from tiny images (2009)
- 20. Krizhevsky, A., Sutskever, I., Hinton, G.E.: Imagenet classification with deep convolutional neural networks. In: Pereira, F., Burges, C.J.C., Bottou, L., Weinberger, K.Q. (eds.) Advances in Neural Information Processing Systems 25, pp. 1097-1105. Curran Associates, Inc. (2012), http://papers.nips.cc/paper/4824-imagenet-classification-with-deep-convolutional-neural-networks.pdf
- Liaw, R., Liang, E., Nishihara, R., Moritz, P., Gonzalez, J.E., Stoica, I.: Tune: A research platform for distributed model selection and training. arXiv preprint arXiv:1807.05118 (2018)
- Loshchilov, I., Hutter, F.: Sgdr: Stochastic gradient descent with warm restarts. arXiv: Learning (2017)
- 23. Loshchilov, I., Hutter, F.: Decoupled weight decay regularization. In: ICLR (2019)
- 24. Mukherjee, K., Khare, A., Verma, A.: A simple dynamic learning rate tuning algorithm for automated training of dnns. ArXiv abs/1910.11605 (2019)

- Naveed, H.: Survey: Image mixing and deleting for data augmentation. ArXiv abs/2106.07085 (2021)
- 26. Netzer, Y., Wang, T., Coates, A., Bissacco, A., Wu, B., Ng, A.: Reading digits in natural images with unsupervised feature learning (2011)
- 27. Nilsback, M.E., Zisserman, A.: Automated flower classification over a large number of classes. In: Indian Conference on Computer Vision, Graphics and Image Processing (Dec 2008)
- 28. Parkhi, O.M., Vedaldi, A., Zisserman, A., Jawahar, C.V.: Cats and dogs. In: IEEE Conference on Computer Vision and Pattern Recognition (2012)
- Pereyra, G., Tucker, G., Chorowski, J., Kaiser, L., Hinton, G.E.: Regularizing neural networks by penalizing confident output distributions. ArXiv abs/1701.06548 (2017)
- Pham, H.H., Xie, Q., Dai, Z., Le, Q.V.: Meta pseudo labels. ArXiv abs/2003.10580 (2020)
- 31. Prechelt, L.: Early stopping but when? (03 2000)
- 32. Shen, X., Tian, X., Liu, T., Xu, F., Tao, D.: Continuous dropout. IEEE Transactions on Neural Networks and Learning Systems 29, 3926–3937 (2018)
- 33. Smith, L.N., Topin, N.: Super-convergence: very fast training of neural networks using large learning rates. In: Defense + Commercial Sensing (2019)
- 34. Tan, M., Le, Q.V.: Efficientnet: Rethinking model scaling for convolutional neural networks. ArXiv abs/1905.11946 (2019)
- 35. Xiao, H., Rasul, K., Vollgraf, R.: Fashion-mnist: a novel image dataset for benchmarking machine learning algorithms (2017)
- 36. xiong Xiao, J., Hays, J., Ehinger, K.A., Oliva, A., Torralba, A.: Sun database: Large-scale scene recognition from abbey to zoo. 2010 IEEE Computer Society Conference on Computer Vision and Pattern Recognition pp. 3485–3492 (2010)
- 37. Yun, S., Han, D., Oh, S.J., Chun, S., Choe, J., Yoo, Y.: Cutmix: Regularization strategy to train strong classifiers with localizable features. 2019 IEEE/CVF International Conference on Computer Vision (ICCV) pp. 6022–6031 (2019)
- 38. Zeiler, M.D.: Adadelta: An adaptive learning rate method. ArXiv abs/1212.5701 (2012)
- 39. Zhai, X., Kolesnikov, A., Houlsby, N., Beyer, L.: Scaling vision transformers. ArXiv abs/2106.04560 (2021)
- 40. Zhai, X., Kolesnikov, A., Houlsby, N., Beyer, L.: Scaling vision transformers (2021)
- 41. Zhai, X., Puigcerver, J., Kolesnikov, A., Ruyssen, P., Riquelme, C., Lucic, M., Djolonga, J., Pinto, A.S., Neumann, M., Dosovitskiy, A., Beyer, L., Bachem, O., Tschannen, M., Michalski, M., Bousquet, O., Gelly, S., Houlsby, N.: The visual task adaptation benchmark. ArXiv abs/1910.04867 (2019)
- 42. Zhang, C., Bengio, S., Hardt, M., Recht, B., Vinyals, O.: Understanding deep learning requires rethinking generalization. ArXiv abs/1611.03530 (2017)
- 43. Zhang, H., Cissé, M., Dauphin, Y., Lopez-Paz, D.: mixup: Beyond empirical risk minimization. ArXiv abs/1710.09412 (2018)
- 44. Zhang, Y., Xiang, T., Hospedales, T.M., Lu, H.: Deep mutual learning. 2018 IEEE/CVF Conference on Computer Vision and Pattern Recognition pp. 4320–4328 (2018)
- 45. Zheng, L., Shen, L., Tian, L., Wang, S., Wang, J., Tian, Q.: Scalable person reidentification: A benchmark. 2015 IEEE International Conference on Computer Vision (ICCV) pp. 1116–1124 (2015)

Supplementary Material

1.1 Classification Tasks

We provide a brief description of each task:

- Caltech101. The task consists in classifying pictures of objects (101 classes plus a background clutter class), including animals, airplanes, chairs, or scissors. The image size varies, but it typically ranges from 200-300 pixels per edge.
- Oxford-IIIT Pets. The task consists in classifying pictures of cat and dog breeds (37 classes with around 200 images each), including Persian cat, Chihuahua dog, English Setter dog, or Bengal cat. Images dimensions are typically 200 pixels or larger.
- Describable Textures (DTD). The task consists in classifying images of textural patterns (47 classes, with 120 training images each). Some of the textures are banded, bubbly, meshed, lined, or porous. The image size ranges between 300x300 and 640x640 pixels.
- Oxford 102 Flowers. The task consists in classifying images of flowers present in the UK (102 classes, with between 40 and 248 training images per class). Azalea, Californian Poppy, Sunflower, or Petunia are some examples. Each image dimension has at least 500 pixels.
- SUN397. The Sun397 task is a scenery benchmark with 397 classes and, at least, 100 images per class. Classes have a hierarchy structure, and include cathedral, staircase, shelter, river, or archipelago. The images are (colour) 200x200 pixels or larger.
- SVHN. This task consists in classifying images of Google's street-view house numbers (10 classes, with more than 1000 training images each). The image size is 32x32 pixels.
- Cars Dataset. The task consists in classifying images of the cars, where each class has been split roughly in a 50-50 split. Classes are typically at the level of Make, Model, Year, e.g. 2012 Tesla Model S or 2012 BMW M3 coupe.
- Birdsnap. The task of the fine-grained visual categorization of birds. There are 500 species of North American birds represented, labeled by species.
 There are between 69 and 100 images per species.
- CIFAR-100. The task consists in classifying natural images (100 classes, with 500 training images each). Some examples include apples, bottles, dinosaurs, and bicycles. The image size is 32x32.
- Fashion-MNIST. Fashion-MNIST is a dataset of Zalando's article images.
 Each example is a 28x28 grayscale image, associated with a label from 10 classes.
- Food-101. The data set of 101 food categories. For each class, 250 manually reviewed test images are provided as well as 750 training images. On purpose, the training images were not cleaned, and thus still contain some amount of noise. This comes mostly in the form of intense colors and sometimes wrong labels. All images have a maximum side length of 512 pixels.

1.2 Performance Evaluation on CPU

We evaluate the performance of our models in the OpenVINO $^{\text{TM}}$ 2021.3 Toolkit. Results are presented in the Table 5. Models provide a performance-accuracy trade-off in 0.4 GFLOPs budget.

Table 5: Performance on the Intel®Xeon[™]Gold 6230 2.1GHz CPU in Open-VINO[™]2021.3 Toolkit. Batch size is set to 1, input resolution is 224×224 , inference precision is FP32.

Model	GFLOPs	Parameters, M	FPS	Latency, ms
MobileNetV3-small-1x	0.06	1.61	467.9	2.05
MobileNetV3-large-0.75x	0.15	2.83	365.22	2.65
MobileNetV3-large- $1x$	0.22	4.31	336.09	2.89
EfficientNet-B0	0.4	4.11	322.75	3.01

1.3 Extended Ablation Study

For the extended ablation study we use all the data except the SUN397 for MobileNetV3 and subset of 6 datasets for EfficientNet-B0 (CIFAR-100, DTD, Flowers, Cars, Pets, Caltech101) if nothing else is said.

Table 6: Augmentation influence for the MobileNetV3-large.

Augmentation	AVG metric		
	top-1	mAP	
Basic augmentations	88.89	90.33	
FMix	89.00	91.17	
AugMix	89.37	90.53	
CutMix	89.35	91.50	
MixUp	88.11	90.41	
AugMix + CutMix	89.15	90.98	
AugMix + MixUp	88.31	90.36	
AugMix + Fmix	89.15	90.86	

Data augmentations. The Table 6 and Table 7 show the results of applying augmentations for MobileNetV3-Large and EffficientNet-B0. As basic augmentations, we adopt random flip, rotate, scale, and color jitter. AugMix reaches the highest AVG top-1 score, while it's combination with other *mix augmentations slightly degrades the quality.

Table 7: Augmentation influence for the EfficientNet-B0.

Table 8: Results of training EfficientNet-B0 and MobileNetV3-large with SAM.

	AVG metrics				
	top-1	mAP	top-1	mAP	
$\overline{MNV3}$ -large $1x + SGD$					
MNV3-large $1x + SAM$					
		91.78			
EffNet-B0 + SAM	90.37	92.20	86.76	89.69	

Optimization. Table 8 shows the results of adopting SAM as optimizer for EfficientNet-B0 and MobileNetV3-Large. We set hyperparameter $\rho = 0.05$ for all our models as it was proposed in [10].

From Table 4 the overall NBD influence on the algorithm could be seen. As it was mentioned in Section 3.2, in case of NBD we scale the learning rate for biases by a factor of 2 and use warmup for 5 epochs. In Table 9 the impact of these settings could be seen.

Table 9: Results of applying NBD to MobileNetV3-small with different settings.

Optimization method	AVG metrics			
	top-1	mAP		
Raw NBD	86.85	90.01		
NBD + 2*lr	86.89	90.15		
$\begin{array}{l} {\rm Raw\ NBD} \\ {\rm NBD} + 2^*{\rm lr} \\ {\rm NBD} + 2^*{\rm lr} + {\rm warmup} \end{array}$	87.15	90.15		

Learning Rate Scheduling and Early Stopping. To validate our ReduceLROn-PlateauV2 scheduler we compare it against cosine schedule for 200 epochs. For all the cases learning rate was fixed to 0.013, SGD was set as an optimizer. In this experiment we use all of the 11 datasets for MobileNetV3 and the subset of 7 datasets (CIFAR-100, FOOD101, DTD, Flowers, Cars, Pets, Caltech101) for EfficientNet-B0. ReduceLROnPlateauV2 strategy clearly outperforms cosine schedule (see Table 10), while maintaining 2x and less training length on all the considered datasets. Thus, applying adaptive training controlling allows us to mitigate computational overhead introduced by SAM or mutual learning techniques.

EffNet-B0 + ReduceLROnPlateauV2

EffNet-B0 + Cosine

Table 10. Results of applying a				
Loss	AVG r	netrics	AVG # of epochs	Max # of epochs
	top-1	mAP		
MNV3-large + Cosine	86.01	88.05	200	200
MNV3-large + ReduceLROnPlateauV2	86.89	88.46	81	107

88.39 | 91.35

88.67 | 91.35

200

82

200

95

Table 10: Results of applying adaptive training controlling policy.

Optimal Learning Rate Estimation. For each of the considered model families we conduct extensive experiments to find the optimal learning rate on each dataset. We set the searching space to [0.001, 0.1] and use grid search with a uniform grid of 10 points. A trial in each grid point takes 9 epochs.

We found that in average EfficientNet-B0 requires an order of magnitude lower learning rate than MobileNetV3 (see Figure 3). According to our experiments, the most optimal search range for EfficientNet is [0.001, 0.01] with the average 0.003, while for MobileNetV3 the range is [0.005, 0.03] with the average 0.013. We use this information to limit boundaries for learning rate search algorithms. This helps to save time for learning rate estimation.

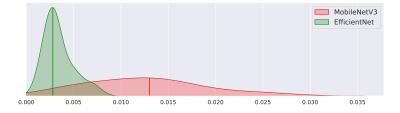


Fig. 3: Distribution of optimal learning rates on the considered set of 11 classification tasks.

For TPE we use discrete searching space with a step size 0.001. We use 6 epochs per trial and restrict the number of trials to 15. Trials are conducted on all the training data. This number of trials lets the algorithm to find a good value for learning rate in a reasonable amount of time. In the Table 11 we provide the results of all three methods for MobileNetV3-large.

Table 11: Learning rate estimation based on different algorithms.

LB finder method AVG ton-1 AVG mAP AVG time to estimate ln min

LK illider method	AvG top-1	AVG MAF	AvG time to estimate if, inin
Fast-ai	88.27	90.37	2
Grid search	88.44	90.78	36
TPE	91.19	88.91	32

Mutual Learning. We studied the impact of different DML settings to Mobilenet V3-large (see Table 12). Although after applying AM-Softmax to the slow student, classification accuracy increases by a small margin, mAP increases significantly. This indicates that the proposed setup of mutual learning indeed generates a model with more discriminative features and a greater ranking ability.

Table 12: Mutual learning with AM-Softmax validation results.

Model				Cars dataset	
		top-1	mAP	top-1	mAP
MNV3	ML + Softmax	89.03	90.59	90.92	91.64
MNV3	$ML + AM-Softmax, s = max(\sqrt{2} \cdot log(C-1), 3)$	89.082	92.24	91.35	93.98
MNV3	ML + AM-Softmax, $s = 1$	89.18	92.42	91.96	94.23