Mutual Learning for Long-Tailed Recognition Supplementary Material

Changhwa Park
42dot Inc.
changhwa.park@42dot.ai

Junho Yim*
AI Technology Division, LG Energy Solution
junho.yim@lgensol.com

Eunji Jun*
Institute of Advanced Technology Development, Hyundai Motor Group
ejjun@hyundai.com

A. More Implementation Details

We mainly follow the experimental settings of [2, 7]. Table A1 provides the detailed hyperparameter and training settings for all datasets used in our work.

Dataset	LR	BS	WD	Epochs	LRS
CIFAR100-LT	0.1	128	5e-4	200	multistep
ImageNet-LT	0.025	64	5e-4	180	cosine
iNaturalist 2018	0.1	256	1e-1	200	cosine

Table A1. More implementation details.

B. More results on ImageNet-LT and iNaturalist 2018

We provide more detailed results in Table A2 and A3. Ours (each expert) denotes the accuracy of PC softmax on each expert's output. We can observe that even the single expert network with the reduced dimension achieves state-of-the-art performance, outperforming other multi-expert based methods. This indicates the proposed framework's great use in enhancing representation quality.

*Work done at AIRS Company, Hyundai Motor Group

Method	ResNet-50				ResNeXt-50			
	Many	Med.	Few	All	Many	Med.	Few	All
Cross Entropy	**68.7**	41.8	10.3	47.9	68.9	43.2	12.6	49.0
PC Softmax	64.1	50.3	29.0	52.7	64.8	50.6	31.9	53.5
LADE [4]	-	-	-	-	65.1	48.9	33.4	53.0
MiSLAS [7]	61.7	51.3	35.8	52.7	-	-	-	-
SSD [5]	-	-	-	-	66.8	53.1	35.4	56.0
DIVE [3]	-	-	-	-	64.1	50.4	31.5	53.1
RIDE [6]	66.2	51.7	34.9	54.9	67.6	53.5	35.9	56.4
ACE [1]	-	-	-	54.7	-	-	-	56.6
Ours (each expert)	65.8	53.3	36.4	55.8	68.0	54.4	37.1	57.3
Ours	67.6	**55.3**	**38.2**	**57.7**	**70.2**	**56.7**	**39.1**	**59.5**

Table A2. Top-1 accuracy on ImageNet-LT with ResNet-50 and ResNeXt-50.

Method	Top-1 accuracy
Cross Entropy †	65.0
PC Softmax †	69.3
BBN [8]	69.6
LADE [4]	70.0
MiSLAS [7]	71.6
SSD [5]	71.5
DIVE [3]	71.7
ACE [1]	72.9
Ours (each expert)	73.0
Ours	**74.9**

Table A3. Top-1 accuracy on iNaturalist 2018. Rows with † denote results directly borrowed from [4].

References

[1] Jiarui Cai, Yizhou Wang, and Jenq-Neng Hwang. Ace: Ally complementary experts for solving long-tailed recognition in one-shot. In *Proceedings of the IEEE/CVF International Conference on Computer Vision (ICCV)*, pages 112–121, October 2021.

[2] Kaidi Cao, Colin Wei, Adrien Gaidon, Nikos Arechiga, and Tengyu Ma. Learning imbalanced datasets with label-distribution-aware margin loss. In H. Wallach, H. Larochelle, A. Beygelzimer, F. d'Alché-Buc, E. Fox, and R. Garnett, editors, *Advances in Neural Information Processing Systems*, volume 32. Curran Associates, Inc., 2019.

[3] Yin-Yin He, Jianxin Wu, and Xiu-Shen Wei. Distilling virtual examples for long-tailed recognition. In *Proceedings of the IEEE/CVF International Conference on Computer Vision (ICCV)*, pages 235–244, October 2021.

[4] Youngkyu Hong, Seungju Han, Kwanghee Choi, Seokjun Seo, Beomsu Kim, and Buru Chang. Disentangling label distribution for long-tailed visual recognition. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 6626–6636, 2021.

[5] Tianhao Li, Limin Wang, and Gangshan Wu. Self supervision to distillation for long-tailed visual recognition. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pages 630–639, 2021.

[6] Xudong Wang, Long Lian, Zhongqi Miao, Ziwei Liu, and Stella Yu. Long-tailed recognition by routing diverse distribution-aware experts. In *International Conference on Learning Representations*, 2021.

[7] Zhisheng Zhong, Jiequan Cui, Shu Liu, and Jiaya Jia. Improving calibration for long-tailed recognition. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 16489–16498, 2021.

[8] Boyan Zhou, Quan Cui, Xiu-Shen Wei, and Zhao-Min Chen. Bbn: Bilateral-branch network with cumulative learning for long-tailed visual recognition. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 9719–9728, 2020.