

# Effect of Stage Training for Long-Tailed Multi-Label Image Classification

## **OVERVIEW**

### Focus:

Multi-stage training approach for image classification in the ICCV CVAMD 2023 Shared Task CXR-LT: Multi-Label Long-Tailed Classification on Chest X-Rays. **Stage Training:** 

Adjusting input image size and batch size at each training stage. First stage: Smaller image size, larger batch size. <u>Second stage</u>: Increased image size, reduced batch size.

## MODELS

Model	Stage	Pre-Weight	Image size	Batch size	Max LR	OS-threshold	Val mAP	Dev mAP
model0	1st	ImageNet	224x224	256	0.001	N/A	0.282	0.298
model1	1st	ImageNet	224x224	128	0.001	N/A	0.268	0.256
model2	2nd	model0	320x320	128	0.001	N/A	0.300	0.302
model3	2nd	model0	320x320	128	0.001	0.10	0.303	0.304
model4	2nd	model1	320x320	128	0.001	0.10	0.297	0.298
model5	2nd	model0	320x320	128	0.001	0.15	0.299	N/A
model6	2nd	model0	384x384	80	0.001	0.10	0.301	0.306
model7	3rd	model3	512x512	48	0.001	0.10	0.305	0.304

All models used EfficientNetV2-S as the backbone [1]. The training stages are indicated by the "Stage" column. Pre-trained weights for stage 1 models come from ImageNet [2], while stage 2 used either model0 or model1. The "OS-threshold" column shows the threshold for oversampling, with "N/A" meaning no oversampling. "Val mAP" and "Dev mAP" represent the mean average precision (mAP) on validation and development data, respectively. Four models in bold were used in the ensemble.



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The graph displays loss function curves for training and validation, with a separate mAP curve for validation data. The first stage, up to the 30th epoch, used two settings: "image 224x224, batch 256" and "image 320x320, batch 128". The second stage, up to the 60th epoch, standardized both experiments to "image 320x320, batch 128".

At the start of stage2, the optimizer and scheduler were reset, therefore both loss and mAP showed a temporary deterioration. Under both settings, the final loss and mAP were almost equal.

### RESULT

Label	1st stage	2nd stage	Oversampling	Postprocess	Ensemble
Support Devices	0.870 / 0.865	0.887 / 0.884	0.885 / 0.881	0.888 / 0.885	0.897 / 0.894
Lung Opacity	0.580/0.561	0.593 / 0.571	0.588 / 0.569	0.600 / 0.581	0.611 / 0.590
ardiomegaly	0.646 / 0.647	0.646 / 0.648	0.644 / 0.646	0.663 / 0.665	0.669 / 0.668
leural Effusion	0.802/0.810	0.808 / 0.817	0.805 / 0.816	0.807 / 0.816	0.812 / 0.822
telectasis	0.569/0.575	0.579 / 0.583	0.578/0.583	0.593 / 0.596	0.600 / 0.602
neumonia	0.288 / 0.281	0.296 / 0.289	0.290/0.286	0.283 / 0.286	0.301 / 0.292
o Finding	0.459 / 0.462	0.461 / 0.467	<b>0.464</b> / 0.464	0.460 / 0.464	0.470 / 0.471
dema	0.525 / 0.521	0.536 / 0.532	0.533 / <b>0.533</b>	0.545 / 0.543	0.551 / 0.551
nlarged Cardiomediastinum	0.166 / 0.171	0.168 / 0.177	0.166 / 0.176	0.168 / <b>0.181</b>	0.171 / 0.183
onsolidation	0.210/0.203	0.210 / 0.206	0.205 / 0.202	0.212 / 0.216	0.216 / 0.225
neumothorax	0.350/0.367	0.399 / 0.418	0.393/0.416	0.407 / 0.431	0.421 / 0.451
acture	0.102/0.107	0.123 / 0.120	0.124 / 0.120	0.146 / 0.133	0.186 / 0.171
filtration	0.061 / 0.053	0.064 / 0.056	0.063 / 0.055	0.064 / 0.055	0.064 / 0.056
odule	0.098 / 0.093	0.113 / 0.105	0.111/0.103	0.117 / 0.112	0.153 / 0.137
ass	0.164/0.152	0.166 / 0.168	0.163 / 0.165	0.185 / 0.175	0.198 / 0.187
alcification of the Aorta	0.081/0.075	0.110 / 0.103	0.109 / 0.098	0.141 / 0.112	0.156 / 0.130
nphysema	0.268 / 0.149	0.263 / 0.155	<b>0.278</b> / 0.146	<b>0.284</b> / 0.146	0.279 / 0.161
ernia	0.478 / 0.457	0.506 / 0.487	<b>0.513</b> / 0.481	<b>0.491</b> / 0.481	0.531 / 0.499
leural Thickening	0.063 / 0.063	0.078 / 0.073	0.069 / 0.078	0.094 / 0.105	0.114 / 0.119
ortuous Aorta	0.059/0.052	0.064 / 0.055	0.065 / 0.055	0.069 / 0.058	0.066 / 0.063
ang Lesion	0.055 / 0.029	0.068 / 0.030	0.062 / 0.028	0.055 / 0.028	0.064 / 0.031
ibcutaneous Emphysema	0.338/0.457	0.427 / 0.488	0.416/0.457	<b>0.450</b> / 0.471	0.465 / 0.507
brosis	0.087 / 0.105	0.117 / 0.108	0.114 / <b>0.110</b>	0.117/0.106	0.148 / 0.116
eural Other	0.017 / 0.024	0.022 / 0.036	<b>0.037</b> / 0.026	0.028 / 0.032	0.050 / 0.059
eumomediastinum	0.075/0.223	0.075 / 0.266	0.139 / 0.296	0.152 / 0.319	0.149 / 0.326
leumoperitoneum	0.020/0.076	0.085 / 0.175	0.123 / 0.195	0.129 / 0.206	0.134 / 0.262
Iean	0.286/0.291	0.302 / 0.308	0.305 / 0.307	0.313/0.315	0.326 / 0.330



### Conclusion

We utilized stage training, dividing the learning process into multi-stages. By using a smaller image size and a larger batch size in the first stage, we were able to optimize the learning efficiency. In the second stage, we achieved performance equivalent to training with a larger image size from the start. This method has been confirmed to be effective for nearly all labels within long-tailed data.

[1] Mingxing Tan and Quoc V. Le. "EfficientNetV2: Smaller Models and Faster Training." arXiv preprint arXiv:2104.00298 (2021). [2] Jia Deng, Wei Dong, Richard Socher, Li-Jia Li, Kai Li, and Li Fei-Fei. Imagenet: A large-scale hierarchical image database. In 2009 IEEE Conference on Computer Vision and Pattern Recognition, pages 248–2.

The table shows the AP for each el and the mAP (Development / data). The AP that achieved the t performance up to that point is nlighted in bold. The second ge training improved the APs of ost all labels. The postcessing used the view position in same study and unifies the diction of PA or AP images. The t-processing and ensemble eraging multi predictions) prove the APs remarkably.

Flowchart of training and prediction. A total of three stage trainings were conducted to create the models. The four models circled in gray were used for the final prediction. To obtain the final prediction, the predictions of the models were averaged and post-

