Supplemental Materials

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Table 1. Ablation study of the number of negatives on EyeQ dataset. We investigate the effect of the number of hard negatives K_t on multi-level contrastive learning. Specifically, we adjust the number δ of negatives in the similarity matrix by setting δ to different values, which in turn dictates the number of hard negatives used for CL and self-paced learning. CoMCL obtains the best performance on EyeQ when δ is set to 4,000. The main reason lies in: a larger δ implies more negatives, which can improve the performance of CL, but also introduces a significant long-tail effect in self-paced learning. In contrast, a lower δ value is beneficial for self-paced learning but may degrade the effect of CL.

Methods	Accuracy	Kappa
δ=1,000	0.864	0.853
δ=2,000	0.873	0.863
δ=4,000	**0.884**	**0.872**
δ=8,000	0.875	0.866
δ=16,000	0.868	0.859