A Clinical-oriented Lightweight Network for High-resolution Medical Image Enhancement (Supplemental Material)

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Table 1. The ablation study of the enhancement loss $\mathcal{L}_{En} = \mathcal{L}_1 + \mathcal{L}_{SSIM} + \mathcal{L}_{HF}$ on the Real Fundus dataset. The $\mathcal{L}_1$ loss serves as the fundamental pixel-level loss, the $\mathcal{L}_{SSIM}$ loss captures the human visual perception of image quality, and the $\mathcal{L}_{HF}$ loss extracts high-frequency information. It can be observed that all three losses contribute to the enhancement results.

$\mathcal{L}_1$	$\mathcal{L}_{SSIM}$	$\mathcal{L}_{HF}$	PSNR	SSIM
✓			25.94	0.870
✓	✓		26.30	0.877
✓		✓	29.74	0.934
✓	✓	✓	**30.41**	**0.942**

Table 2. The ablation study of the semantic guidance loss type on the Real Fundus dataset. The results indicate that employing knowledge distillation with KL divergence loss leads to improved feature alignment and superior performance.

Loss Function	PSNR	SSIM
$\mathcal{L}_1$ Loss	29.37	0.933
CMD Loss	29.10	0.927
KL divergence loss	**30.41**	**0.942**

† Yaqi Wang, Leqi Chen and Qingshan Hou contribute equally to this work.

Table 3. Implementation Details.

Parameter	**Value**
Optimizer	Adam
GPU	NVIDIA Quadro RTX 6000
Learning Rate	1e-3
Learning Rate Update Schedule	Cosine Annealing
Batch Size	32
Total Epochs	2500
High-resolution Image Size	1280×1280
Low-resolution Image Size	256×256