## Enhancing Model Generalisability through Sampling Diverse and Balanced Retinal Images

Tianfeng Zhou<sup>1</sup> and Yukun Zhou<sup>2,3</sup>

<sup>1</sup> School of Electronic Information, Central South University, China
<sup>2</sup> UCL Institute of Ophthalmology, University College London, UK

<sup>3</sup> Centre for Medical Image Computing, University College London, UK yukun.zhou.19@ucl.ac.uk



**Fig. 1.** Effects of hyperparameter cluster number K. We investigated the performance with K = 5, 10, 15 and found that larger K (10,15) contributed to slightly better performance.

Method	Total size	Non-glaucoma	Glaucoma	Disease proportion
Image pool $D_u$	71,009	2,268	68,741	3.2%
Random	1,200	32	1,168	2.7%
CorSet	1 200	03	1 107	78%

**Table 1.** Sample categorical balance for glaucoma detection (AIROGS). The unbalanced issue has been alleviated by all sampling strategies, in particular with DataDIVA.

Image pool $D_u$	71,009	2,268	68,741	3.2%
Random	1,200	32	1,168	2.7%
CorSet	1,200	93	1,107	7.8%
ALFA-Mix	1,200	146	1,054	12.2%
DataDIVA	1,200	164	1,036	13.7%



Fig. 2. Model performance using a foundation model in extracting features, compared with a model loading ImageNet-21k weights. All models use the same network backbone ViT-large.

**Table 2.** Sample categorical balance for referable diabetic retinopathy detection (Eye-PACS). The unbalanced issue has been alleviated by all sampling strategies, in particular with DataDIVA.

Method	Total size	Non-referable DR	DR	Disease proportion
Image pool $D_u$	$35,\!126$	6,873	28,253	19.6%
Random	600	115	428	19.2%
CorSet	600	142	428	23.7%
ALFA-Mix	600	153	447	25.5%
DataDIVA	600	166	434	27.8%