HONG KONG MEDICAL JOURNAL 香港醫學雜誌

Supplementary material

Supplement to: CYT Wong, LJ Chen, HHW Lau. The capacity of transfer learning to reshape the landscape of myopic practice. Hong Kong Med J 2025;Epub 8 Oct 2025. https://doi.org/10.12809/hkmj2411559.

Supplementary Table. Transfer learning for myopic tasks

Study	Myopic task	Source (pretrained) dataset	Network architecture	Target (retraining) dataset	Important findings	Issues solved with TL	Benefits of the TL model in myopic practice
He et al[1]	Screening for various myopic maculopathy conditions (eg, macular schisis, MH, RD, and CNV)	ImageNet (millions of natural images)	ResNet18	3400 macular OCT images	The TL model showed robust screening performance with an AUC of 0.986, an accuracy of 96.04%, and a quadratic-weighted kappa of 0.940	Limited annotated OCT training images available; improved convergence speed and training accuracy of DL network	Promotes use of automated screening systems for myopic maculopathy in myopic patients, facilitating broader clinical management coverage
Li et al[2]	Screening for four vision-threatening conditions (retinoschisis, MH, RD, and CNV) in patients with HM	ImageNet	InceptionResNetV2	5505 macular OCT images	The TL model achieved high AUC values for the four conditions (0.961-0.999) The model attained sensitivities equal to or greater than those of retina specialists, as well as high specificities (>90%)	Limited annotated OCT training images available	Facilitates OCT-based screening of vision-threatening conditions in myopia, enabling timely intervention

Oh et al[3]	Prediction of axial length on UWF retinal images	ImageNet	EfficientNet	8657 UWF images	The TL model predicted axial lengths in the test dataset with a mean absolute error of 0.744 mm and an R^2 value of 0.815	Limited annotated UWF images	Facilitates prediction of axial length changes in myopic patients and supports investigation of individualised risk profiles in axial length elongation
Jain et al[4]	Prediction of refractive error, particularly degrees of myopia, in a data-constrained population group (Indian cohort)	ImageNet and large-scale Korean image set	ResNet50	Indian OCT image set (60 eyes)	The TL model predicted spherical equivalent and mean keratometry values with a low mean absolute error of 1.58 dioptres	Limited annotated image set (Indian cohort)	Facilitates development of a refractive error prediction tool that can be generalised across diverse patient populations
Mao et al[5]	Investigation of retinal vascular morphological features in patients with HM of varying severity	Publicly available fundus image set	Reinforced U-Net	50 manually labelled UWF images	The TL model achieved an accuracy of 98.24%, a sensitivity of 71.42%, and a specificity of 99.37% in retinal vessel	Limited UWF images	Enhances understanding of the correlation between retinal vascular morphology and the pathological process of myopia

					segmentation		
Chen et al[6]	Investigation of the correlation between choroidal thickness and myopia progression	Common Objects in Context database	Mask region–based convolutional neural network	123 OCT images	The TL model achieved excellent performance in choroidal segmentation and quantification on limited OCT images, with errors of 6.72 ± 2.12 µm and 13.75 ± 7.57 µm for choroidal inner and outer boundary segmentation, respectively	Limited OCT images	Supports investigation of more intricate morphological changes (eg, choroidal alterations) in myopia progression

Abbreviations: AUC = area under the receiver operating characteristic curve; CNV = choroidal neovascularisation; DL = deep learning; HM = high myopia; MH = macular hole; OCT = optical coherence tomography; RD = retinal detachment; TL = transfer learning; UWF = ultra-widefield

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