The capacity of transfer learning to reshape the landscape of myopic practice

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Introduction

Myopia is highly prevalent among Asian children and adolescents, with over 600 million individuals affected in China, signifying a 'myopia boom'.[1,2] Moreover, 21.9% of these individuals exhibit high myopia (HM).[3] High myopia can gradually progress to posterior staphyloma and maculopathy, leading to the diagnosis of pathological myopia, a leading cause of blindness in young people.[4,5]

Artificial intelligence (AI), particularly deep learning (DL), which is widely applied in image classification, has attracted global interest in recent years.[6] Given its capacity to analyse massive amounts of data, DL may offer a solution to the growing myopia burden.[6] However, training DL models from scratch requires substantial computing and memory resources, as well as vast volumes of labelled datasets.[7] For specific myopia cases, large annotated datasets are not always available.[7] Furthermore, the creation of such datasets is both time-consuming and costly.[7]

Transfer learning (TL) has been introduced as an alternative method for training DL models.[7] In DL, a model's knowledge is typically stored in its trained weights.[7] These weights, established after extensive training on a comprehensive dataset, assist in recognising data patterns relevant to the target problem.[7] Transfer learning is a fine-tuning approach in which the weights of a pre-trained model for an upstream AI task are transferred to another AI model to achieve optimal performance on a similar downstream task using a smaller, task-specific dataset.[7] This method enables a new model to reuse knowledge previously learned from a different task (source domain) to improve its performance in the new target task.[8] Because the model already possesses some knowledge related to the new task, it can learn more efficiently from a smaller dataset and fewer training epochs.[7] Therefore, TL is considered a promising approach for overcoming dataset size limitations in the myopia field, while also improving AI training time and performance.[9] By reviewing how TL has been implemented in myopic AI (online supplementary Table),[15-20] we aim to highlight how TL has reshaped the landscape of myopic practice, as well as the continuing challenges it faces.

Current challenges associated with myopic practice and conventional deep learning developed for myopia

At present, substantial challenges in the myopic field persist regarding diagnostic and predictive medicine.[10] First, there is a considerable screening burden for myopia.[10] Myopia, particularly vision-threatening complications such as macular hole and choroidal neovascularisation (CNV), is preventable but not curable; mass screening with regular follow-up remains the most effective strategy.[10] However, the insufficient number of ophthalmologists makes large-scale population screening and monitoring coverage unfeasible.[10] Second, it is difficult to accurately predict the risk of myopia progression.[10] The absence of a reliable risk prediction model for HM and pathological myopia, coupled with individual variability in progression, makes timely and customised intervention challenging.[10] Finally, ophthalmologists still lack a comprehensive understanding of myopia pathophysiology.[10] Many factors that influence myopia, including genetics, environment, and lifestyle, are difficult to assess with precision.[10] Morphological changes in myopic eyes also remain poorly defined.[10]

Although conventional DL models built on single-field fundus photographs (FPs) may assist with FP-based screening, prognostication, and exploration of myopia pathogenesis, these models have substantial limitations. They often fail to detect peripheral retinal lesions, such as lattice degeneration and retinal breaks, due to the restricted field of view within FPs (50°).[11] Additionally, they struggle to identify posterior staphylomas, a hallmark of pathological myopia, when solely relying on two-dimensional FPs.[11] The limited resolution and poor contrast between retinal tissues and the underlying choroid also hinder AI-based analysis of myopic foveoschisis on FPs.[11] Artificial intelligence models developed using ultra-widefield (UWF) retinal imaging and optical coherence tomography (OCT) may provide greater accuracy in detecting and characterising morphological changes associated with myopia.[11] This enhanced accuracy arises because UWF images capture a broader retinal field (200°), while OCT images deliver excellent depth resolution for the visualisation of myopic lesions, such as myopic traction maculopathy and posterior staphylomas.[11,12]

However, UWF and OCT images present comparable challenges when utilised for DL applications. Ground truth–labelled UWF images remain scarce in the myopic field because manually annotating the morphological features of myopia is more difficult in high-resolution UWF images than in simple FPs.[13] The available labelled UWF images are often insufficient for conventional DL, which requires large datasets for training.[13] Similarly, a substantial volume of annotated OCT images for myopia is not readily available, given that OCT image annotation is tedious, costly, and time-consuming; it also requires specialised expertise.[14] The limited availability of large datasets of UWF and OCT images for myopia has hampered the development of DL models for screening, prediction, and pathological examination. Transfer learning has addressed this challenge by enabling AI model training using small numbers of UWF and OCT images, while allowing the resulting models to achieve high accuracy in myopia-related tasks.

Transfer learning for myopic screening

Transfer learning has been instrumental in the development of robust screening tools for myopic maculopathy and vision-threatening conditions such as macular holes, despite the limited number of annotated OCT images available. He et al[15] employed a cross-domain TL strategy to create a myopic maculopathy screening tool. They utilised the model parameters and weights obtained by a deep residual network extensively trained on the large ImageNet dataset (millions of images), then fine-tuned the network using a limited set of OCT images during retraining.[15] The TL model ultimately achieved a high area under the receiver operating characteristic curve of 0.986, an accuracy of 96.04%, and a quadratic-weighted kappa of 0.940 in diagnosing various myopic maculopathies.[15] Notably, the TL model outperformed a bespoke DL model created using the same limited set of OCT training images.[15] In another study, Li et al[16] employed TL to develop a screening tool for vision-threatening conditions (retinoschisis, macular hole, retinal detachment, and CNV) in patients with HM. Despite the limited number of OCT images available, the TL-retrained model achieved high area under the receiver operating characteristic curve values for all four conditions (0.961 to 0.999) by leveraging the weights generated during pretraining on the robust ImageNet dataset.[16] The model demonstrated high specificities (>90%) and sensitivities comparable to or exceeding those of retina specialists.[16] The high levels of screening accuracy and sensitivity attained through TL highlight its potential to support large-scale, standardised screening and monitoring of myopic patients at the community level, thereby facilitating early detection of fundus changes and enabling timely intervention before irreversible vision loss (online supplementary Table).

Transfer learning for myopic prognostication and refractive error prediction

Transfer learning has also substantially contributed to myopic prognostication and refractive error prediction. Oh et al[17] applied TL to develop an AI-based axial length prediction model using restricted UWF images of myopes. By utilising the robustly trained weights obtained during ImageNet pretraining, the model predicted axial length with a low mean absolute error of 0.744 mm and an R^2 value of 0.815.[17] The UWF image model also achieved a higher R^2 value than two earlier FP-based axial length prediction models (R^2=0.59 and 0.67, respectively).[17] Transfer learning has thus improved the accuracy of axial length estimation beyond that of current predictive DL algorithms, with potential to enhance prognosis and progression forecasts for myopic patients, particularly in paediatric and adolescent populations. Meanwhile, Jain et al[18] employed TL to predict uncorrected refractive error, primarily varying levels of myopia, based on a limited set of OCT images from an ethnically distinct Indian cohort. Transfer learning enabled the model to achieve strong predictive performance in this data-constrained population by domain adaptation and fine-tuning, using the weights of the ResNet50 architecture pretrained on a large Korean OCT dataset.[18] Despite the small Indian dataset (60 eyes), the model estimated spherical equivalent and keratometry values with a mean absolute error as low as 1.58 dioptres. These findings demonstrate the ability of TL to accurately predict varying degrees of myopia in patients, as well as its potential to increase the applicability of myopic models across diverse populations (online supplementary Table).

Transfer learning for myopic pathogenesis investigation

Finally, TL has substantially advanced ophthalmologists' understanding of the pathogenesis and morphological changes associated with myopia. Mao et al[19] employed TL to investigate the morphological characteristics of retinal vessels on UWF photographs of high myopes. Despite the limited number of UWF images available (50 images), the TL-retrained model achieved a segmentation accuracy of 98.24% for retinal vessels by leveraging robust feature extraction for blood vessels and the blood vessel segmentation ability developed during pretraining on a larger regular FP dataset (380 FPs).[19] This TL model has aided ophthalmologists in gaining deeper insight into the progressive pathophysiology of HM and the vascular changes that accompany disease progression.[19] The study also reported that increased vessel density and reduced vascular branching are risk factors for CNV in patients with HM.[19] This finding enables the identification of high myopes at risk of CNV, allowing them to be closely monitored for timely intervention; thus, it redefines the current approach to predictive and personalised treatment in myopia. In another study, Chen et al[20] applied TL to evaluate the association between choroidal thickness and myopia progression. Using pretrained weights from the large-scale Common Objects in Context database, the mask region–based convolutional neural network model achieved excellent performance in choroidal segmentation and quantification on a limited set of OCT images, with errors of 6.72 ± 2.12 μm and 13.75 ± 7.57 μm for choroidal inner and outer boundary segmentation, respectively.[20] Transfer learning may thus be particularly valuable in examining more complex morphological alterations, such as those occurring in the choroidal regions, during myopia progression (online supplementary Table).

Transfer learning's benefits, challenges, and future directions

Transfer learning has demonstrated strong potential in providing highly precise screening, risk prediction, and pathophysiological studies of myopia by enabling AI to perform accurate, fine-grained analysis of myopic lesions through advanced imaging modalities such as OCT and UWF. Transfer learning eliminates the need for large volumes of annotated training OCT and UWF images. Additionally, it shortens training time and lowers computing requirements, substantially decreasing backpropagation calculations by reusing components of an already trained model (eg, model weights and parameters). Furthermore, TL has been shown to enhance DL model accuracy because pretrained networks have reliably learned to recognise a broad range of patterns and features from large, diverse image sets (eg, ImageNet). When applied to limited sets of UWF and OCT images, this prior knowledge improves accuracy and reduces model overfitting, which is otherwise likely due to the small size and specificity of these datasets.

Nonetheless, the implementation of TL for myopic tasks presents several challenges. Although the large ImageNet dataset has been valuable for deriving robust model parameters and weights, concerns remain regarding whether the more complex anatomical structures in ophthalmic imaging are adequately represented in ImageNet's natural images, given the distinctive differences between medical and natural image domains. ImageNet-pretrained networks may not consistently transfer optimally to real-world myopic tasks. Moreover, TL has been described as advantageous in elevating the performance of myopic AI, but many studies have not provided baseline ML models for comparison to clearly demonstrate its performance-enhancing benefits.[17-20] Finally, similar to conventional DL, TL decision-making remains difficult to interpret, leading to concerns about transparency and ethical aspects, including the risk of sensitive information leakage from source domains in fine-tuned TL models.

In the future, performing systematic transferability assessments between source and target domains, improving TL benchmarking against baseline DL models or ophthalmologists, and incorporating interpretability solutions (eg, saliency maps) along with data privacy–preserving approaches (eg, federated learning) may help ensure the development and deployment of effective and safe TL models for myopic tasks.

Author contributions

All authors contributed to the concept or design, acquisition of data, analysis or interpretation of data, drafting of the manuscript, and critical revision of the manuscript for important intellectual content. All authors had full access to the data, contributed to the study, approved the final version for publication, and take responsibility for its accuracy and integrity.

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All authors have disclosed no conflicts of interest.

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Supplementary material

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