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Automated retinal fluid volume quantification: a nod to present and future applications of deep learning

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The chronicles of artificial intelligence (AI) in ophthalmology began circa 2017 in most clinician's minds, with multiple studies demonstrating comparable performance of deep-learning algorithms with human experts in diabetic retinopathy classification using fundus photographs.[1–3] The momentum around this work has driven important AI research in other ophthalmic diseases – notably glaucoma, age-related macular degeneration, and retinopathy of prematurity[4]– but diabetic retinopathy remains an archetypal training ground on which innovation in AI is studied. With a rising worldwide diabetic population threatening to overwhelm limited human screening resources, higher throughput DR screening has become an undisputed public health need. The routine acquisition of retinal imaging in the quotidian diagnosis and management of DR, in the context of recent advances in machine learning techniques and computer processing power to implement such techniques, positions DR screening perfectly for computer assisted image analysis and classification.

In this issue of *JAMA Ophthalmology*, You et al.[5] describe the performance of a novel deep-learning derived algorithm that quantifies fluid volume on Optovue optical coherence tomography (OCT) volumetric scans, and compares it to central subfield thickness (CST) on Spectralis OCT structural scans in determining the presence or absence of diabetic macular edema (DME). The diagnostic gold standard against which both methods are measured is the qualitative assessment of intraretinal and/or subretinal fluid presence by two independent retina specialists. For diagnosis of both DME and center-involving DME, a higher area under the receiver's operator characteristics curve (AUROC) was achieved with the deep-learning quantified fluid volume, suggesting that quantified fluid volume was a better model for identifying DME compared to CST. The study concludes that automated fluid volume quantification has promise for improving the accuracy of DME screening.

At a glance, the hypothesis that a direct measure of fluid (with total cyst volume) would be more specific for the diagnosis of DME than an indirect measure (the arithmetic mean of internal limiting membrane-to-retinal pigment epithelium segmentation within 1mm of the fovea) is self-evident. Central subfield thickness, albeit a commonly used surrogate for

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DME diagnosis in major clinical trials, as not been shown to have very good correlation with visual acuity or with change in visual acuity.[6] However, the technical challenge of accurate and efficient segmentation of intraretinal cysts to compute volume on OCT has historically been an impractical task. In recent years, convolutional neural networks (CNNs), the core architecture of deep learning models used for image classification tasks, have been applied to automated and semi-automated OCT segmentation with good diagnostic accuracy[5]. Even so, limitations related to OCT B-scan spacing, inconsistent image registration, and insufficient computing power have hindered 3-dimensional OCT analysis.[7]

The study by You et al[5] adopted the Retinal Fluid Segmentation Network, a CNN that included OCT angiography (OCTA) data in its training data set as a novel feature.[8] The intuition behind incorporating OCTA data was that it could add theoretical information to retinal fluid spaces that would correlate with areas of flow void. ReF-Net was developed and previously validated by the authors to segment retinal fluid volumetrically with good accuracy (F1 score of 0.892, equivalent to the Dice coefficient), and indeed demonstrated improved model accuracy compared to the same CNN trained on OCT data alone. However, that the training data set used 3×3-mm volumetric OCT and OCTA scans, whereas the study by You et al[5] applied the algorithm to 6 × 6-mm OCT volumetric scans alone. We might infer that transfer learning was applied to repurpose the Retinal Fluid Segmentation Network to the larger scan pattern, but details of the training, validation, and accuracy of the new algorithm are not presented. Other methodological limitations of the study are well addressed in the manuscript, and we particularly commend the authors for their thoughtful analysis of failure cases by both models, which provided a clinically relatable sanity check into the oft-criticized “black box” nature of deep learning algorithms.

The relevance of this study, in the context of the burgeoning interest in applications of artificial intelligence in ophthalmology, is readily apparent. However, if one of the attractive goals of AI is its potential to disburden healthcare systems of the vast financial and human resource strain ascribed to screening for disease, then this study topic is more germane for a future in which OCT and OCTA become economical enough for routine diabetic retinopathy screening. Until then, color fundus photography remains the most practical imaging data for deep learning algorithms to tackle in addressing the quandary of efficient screening. A more immediate application of fully automated volumetric retinal fluid quantification from OCT/OCTA scans as described might be its use as a biomarker to monitor disease progression and response to therapy for any exudative retinal disease. However, this study provides another step forward as the field of AI in ophthalmology continues to march towards the goal of practical implementation in clinical settings.

REFERENCES

1. Gulshan V, Peng L, Coram M, et al. Development and validation of a deep learning algorithm for detection of diabetic retinopathy in retinal fundus photographs. JAMA 2016;316:2402–10. [PubMed: 27898976]
2. Abràmoff MD, Lou Y, Erginay A, et al. Improved automated detection of diabetic retinopathy on a publicly available dataset through integration of deep learning. Invest Ophthalmol Vis Sci 2016;57:5200–6. [PubMed: 27701631]

3. Ting DS, Cheung CY, Lim G, et al. Development and validation of a deep learning system for diabetic retinopathy and related eye diseases using retinal images from multiethnic populations with diabetes. Jama. 2017 Dec 12;318(22):2211–23. [PubMed: 29234807]

4. Ting DS, Pasquale LR, Peng L, et al. Artificial intelligence and deep learning in ophthalmology. British Journal of Ophthalmology. 2019 Feb 1;103(2):167–75. [PubMed: 30361278]

5. You QS, Tsuboi K, Guo Y, et al. Comparison of central macular fluid volume with central subfield thickness in patients with diabetic macular edema using optical coherence tomography angiography. JAMA Ophthalmol. Published online May 13, 2021. doi:10.1001/jamaophthalmol.2021.1275

6. Bressler NM, Odia I, Maguire M, et al. ; DRCR Retina Network. Association between change in visual acuity and change in central subfield thickness during treatment of diabetic macular edema in participants randomized to aflibercept, bevacizumab, or ranibizumab: a post hoc analysis of the Protocol T randomized clinical trial. JAMA Ophthalmol. 2019;137(9):977–985. [PubMed: 31246237]

7. Yanagihara RT, Lee CS, Ting DS, et al. Methodological challenges of deep learning in optical coherence tomography for retinal diseases: a review. Translational Vision Science & Technology. 2020 Jan 28;9(2):11-.

8. Guo Y, Hormel TT, Xiong H, et al. Automated segmentation of retinal fluid volumes from structural and angiographic optical coherence tomography using deep learning. Translational vision science & technology. 2020 Jan 28;9(2):54-. [PubMed: 33110708]