Automated identification of geographic atrophy eyes with and without subfoveal involvement using machine learning and real-world ophthalmic images in the IRIS® Registry

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Purpose

To develop a machine learning (ML)-aided pipeline to identify eyes with geographic atrophy (GA) that have subfoveal involvement and eyes without subfoveal involvement using real-world optical coherence tomography (OCT) images linked to the American Academy of Ophthalmology IRIS® Registry (Intelligent Research in Sight).

Methods

- The IRIS® Registry (Intelligent Research in Sight) is the nation's first electronic health record-based comprehensive eye disease and condition registry.
- An ML-aided pipeline was developed using a de-identified clinical-imaging dataset of patients with dry age-related macular degeneration (AMD) identified through ICD-9/10 codes from 2006 to 2022.
- Previously developed and presented ML models that identify eyes with GA secondary to AMD were used to identify eyes with GA.
- Only images centered on the fovea with gradable image quality (assessed by previously described ML models) were included in this study.
- From eyes with GA, a training and testing set were selected using patient-level stratified sampling (age, sex, and race) and labeled by two fellowship-trained retinal specialists. A three-round consensus workflow was implemented to ensure both graders agreed on all labels, with the center point of the fovea being involved as the definition of subfoveal involvement.
- A deep learning model was developed to classify GA with subfoveal involvement from GA without subfoveal involvement, trained on the training set with an 80:20 split between training and validation.

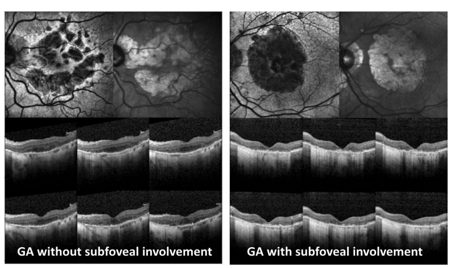

Figure 1.
Examples of labeled images in the training/testing set. Each label job must include FAF and IR images of the same patient visit, OCT images were also included when available.

Results

- In total, 265 OCT volumetric images from 256 eyes of 232 patients were labeled. A training set of 178 images, a validation set of 45 images and a testing set of 42 images were randomly split (stratified by subfoveal involvement status) where no patients were included in more than one set.
- A revised 3D ResNet50 model was developed and trained.
- The model achieved an accuracy of 0.88 , 0.82 and 0.86 for training, validation and testing, respectively.

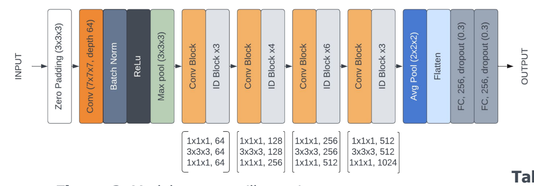

Figure 2. Model structure illustration.

	Precision	Recall	F-1 score
GA without subfoveal involvement	0.93	0.74	0.82
GA with subfoveal involvement	0.81	0.96	0.88

Table 1. Performance metrics breakdown of GA with and without subfoveal involvement

Figure 3. The confusion matrix of the testing set to show the true positives, true negatives, false positives and false negatives.

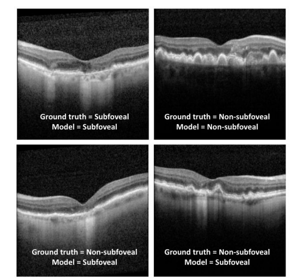

Figure 4. Examples of correct and incorrect predictions from the trained deep learning model.

Conclusions

The proposed pipeline demonstrated satisfactory performance identifying GA eyes with and without subfoveal involvement using images collected in real world practice. It could potentially be useful in screening patients for GA trials and identifying patients for future GA treatments.

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This study was funded by Verana Health and all authors are employees or consultants of Verana Health.