AI-Based Longitudinal Prediction of Vitreomacular Traction Progression Using 3D Macular Cube OCT

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Purpose

To evaluate the ability of deep learning to predict vitreomacular traction (VMT) progression from longitudinal 3D macular cube OCT imaging.

Methods

We retrospectively identified patients with VMT at Columbia University Irving Medical Center between 2015 and 2025. Clinical characteristics and serial macular cube OCT volumes were collected. Raw 6x6 mm OCT macular cubes (512x128 scans) were used without manual segmentation. Eyes were categorised based on final OCT outcome: (1) spontaneous release, (2) stable VMT, or (3) macular hole. Multiple deep learning approaches, including recurrent temporal models, were trained on OCT sequences to predict outcomes. 3D macular cube OCT visualisations were generated using gradient weighted class activation maps (3D GradCAMs).

Results

A total of 283 eyes from 225 patients were analysed (mean age 72 ± 9 years; 62% female, 64% pseudophakic; 14% bilateral VMT). Among these, 87 eyes (31%) released spontaneously, 189 (67%) remained stable, and 7 (2%) developed a macular hole. The best-performing model, consisted of a hybrid backbone (ResNet-3D) with a temporal head (GRU trained on 3 sequential OCT volumes within 2 years of the final exam, predicted spontaneous release vs stable VMT with AUROC of 0.787 and F1 score of 0.726. Macular hole prediction ability was limited due to low incidence. 3D GradCAMs consistently highlighted the posterior hyaloid and vitreoretinal interface as areas of primary interest. Additionally, peripheral vitreous attachments at the optic nerve and far macula were also frequently highlighted.

Conclusions

Deep learning applied to real-world OCT volumes can predict spontaneous VMT release with clinically meaningful performance. Such tools may help refine follow-up intervals and reduce unnecessary surgery or pharmacologic intervention. Prospective validation and integration of multimodal data may further improve prognostic accuracy, while explainability analysis of 3D macular cube reconstructions may uncover previously unknown or underestimated anatomical predictors of progression.

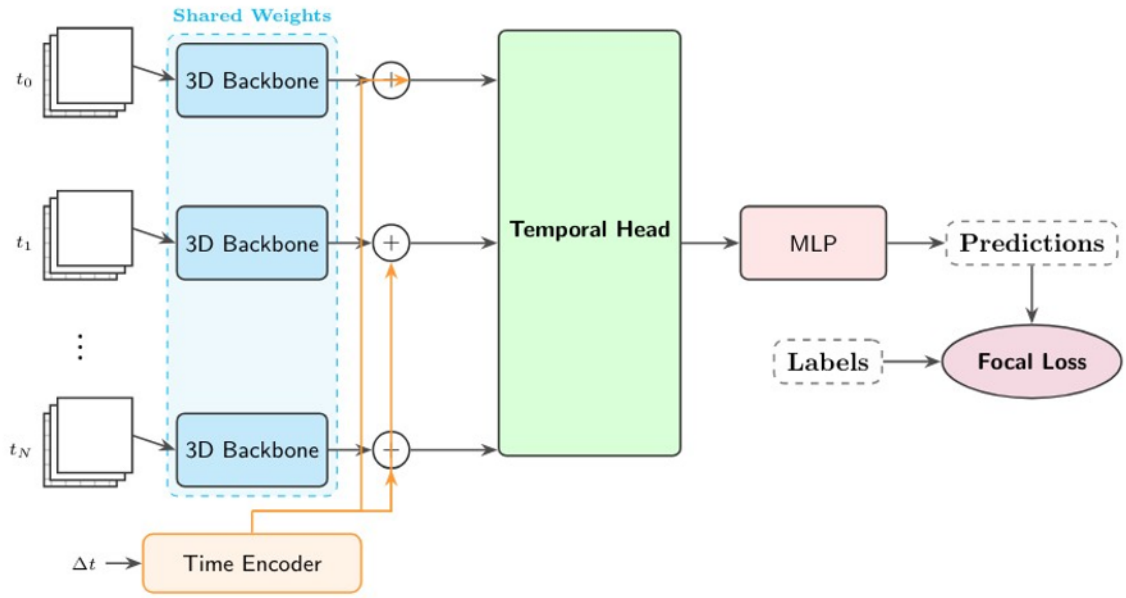

Figure 1. Model architecture. The figure visually represents the underlying structure and data flow used by the deep learning system.

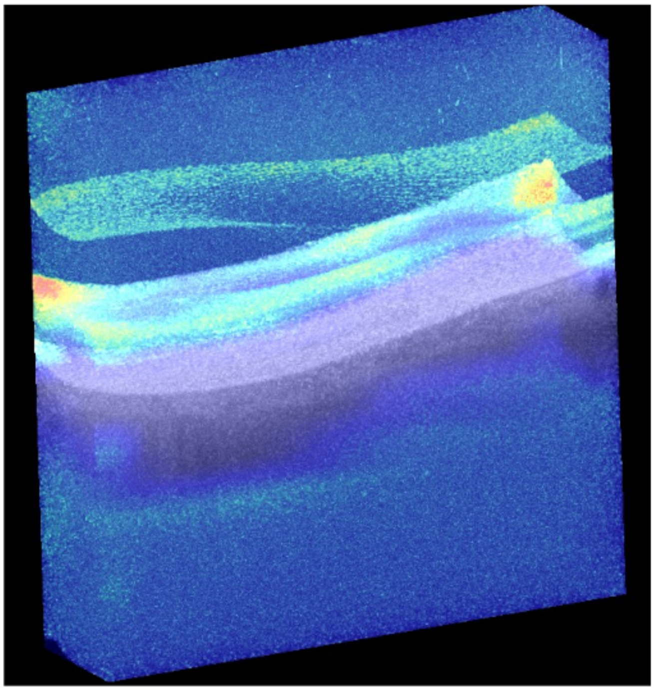

Figure 2. 3D macular cube OCT visualisation example. The reconstructed 3-dimensional macular cube includes 3D GradCAM highlighting the model's areas of interest.