MEDICAL UNIVERSITY OF VIENNA

OPTIMA Ophthalmic Image Analysis

Contact:
simon.schuerer-waldheim@meduniwien.ac.at
https://optima.meduniwien.ac.at/

2392 - A0284

Selecting a well-performing approach for automated SDD quantification

Simon Schürer-Waldheim[1]*, José Morano[1], Guilherme Aresta[1], Klaudia Birner[1], Gregor S. Reiter[1], Ursula Schmidt-Erfurth[1], Hrvoje Bogunović[1]

[1]Laboratory for Ophthalmic Image Analysis, Department of Ophthalmology and Optometry, Medical University of Vienna, Vienna, Austria

* simon.schuerer-waldheim@meduniwien.ac.at

Introduction

- **SDD** are an important **risk factor** for **faster disease progression** in **AMD**.[1,2]
- **Manually** annotating SDD is extremely **time consuming**
- Aim: **automated detection** and **quantification** of **SDD** in OCT (Choice of algorithm important)

Methods

- **Data:**
  - **1358** manual graded **B-scans** (Spectralis)
  - **14 OCT volumes** from 14 subjects.
  - Only SDD of **stage 2** and **stage 3**
- **Algorithms:**
  - **Mask R-CNN**[3] -> 2D instance segmentation
  - **Swin UNETR**[4] -> 3D segmentation
- **Evaluation:**
  - **Dice metric** assessing similarity
  - **Spearman's rank correlation coefficients (ρ)** for **SDD volume** and the **number of SDD** correlations.

Results

- **Dice** values on the test set:
  - **Mask R-CNN: 0.579**
  - **Swin UNETR: 0.326**
- **Mask R-CNN** vs. human grading:
  - **SDD volume** -> **good** correlation
  - **Number of SDD -> good** correlation
- **Swin UNETR** vs. human grading:
  - **SDD volume** -> **moderate** correlation
  - **Number of SDD** -> **poor** correlation

	Dice	ρ volume	ρ number SDD
Mask R-CNN	**0.579** (± 0.071)	**0.82** (p=0.0003)	**0.76** (p=0.0016)
Swin UNETR	**0.326** (± 0.035)	**0.70** (p=0.0052)	**0.48** (p=0.0814)

Conclusion

- **Mask R-CNN model was shown successful** in detecting and segmenting SDD in OCT, reaching **good correlations with human gradings**
- Outperforming another state-of-the-art deep learning approach (Swin UNETR) by a big margin.

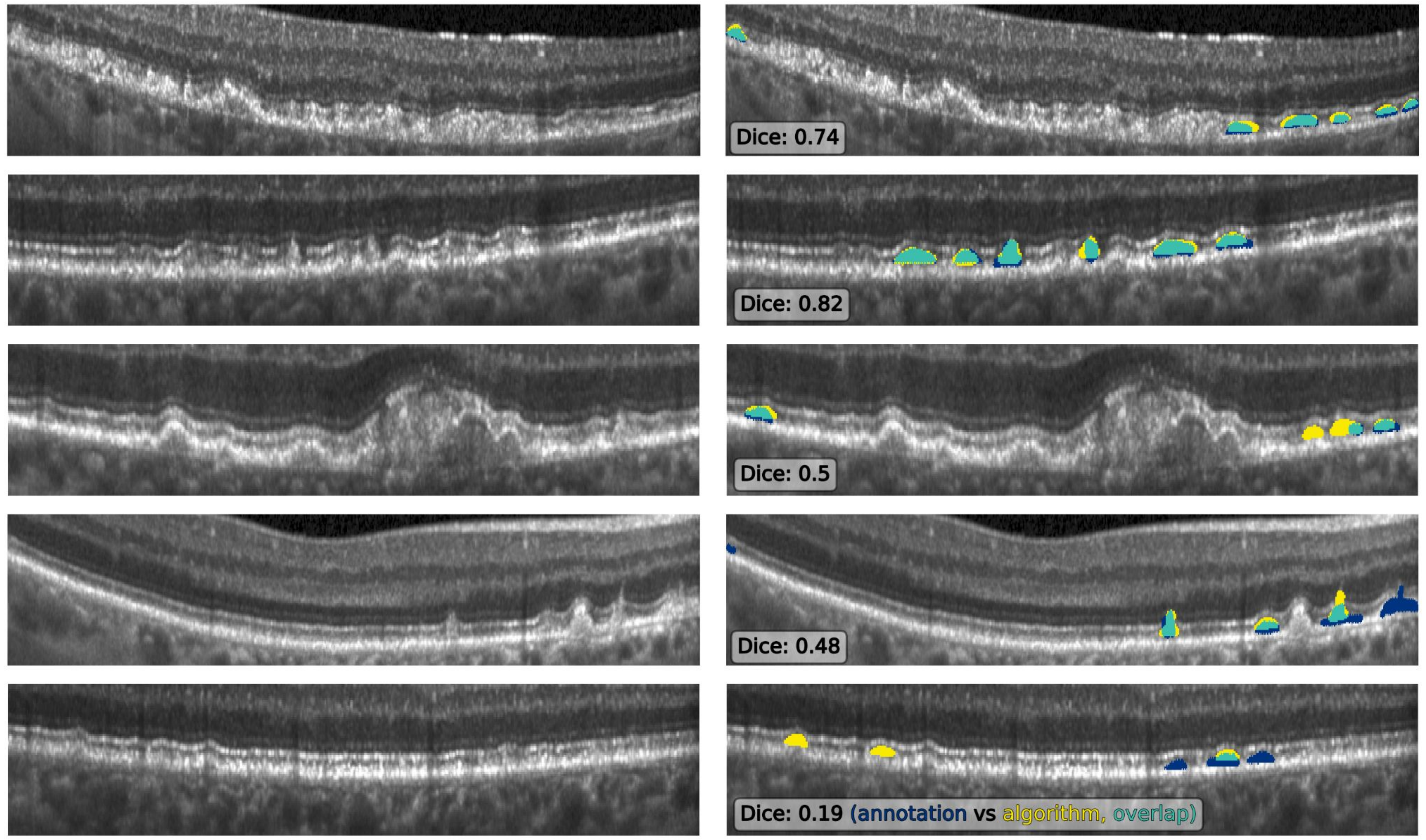

Figure 1: Examples of the segmentation results of the selected deep learning approach (Mask R-CNN) compared to the expert manual annotations.

References

1. Wightman, A. J., & Guymer, R. H. (2019). Reticular pseudodrusen: current understanding. *Clinical and Experimental Optometry*, *102*(5), 455-462.
2. Marsiglia, M., Boddu, S., Bearelly, S., Xu, L., Breaux, B. E., Freund, K. B., ... & Smith, R. T. (2013). Association between geographic atrophy progression and reticular pseudodrusen in eyes with dry age-related macular degeneration. *Investigative ophthalmology & visual science*, *54*(12), 7362-7369.
3. He, K., Gkioxari, G., Dollár, P., & Girshick, R. (2017). Mask r-cnn. In *Proceedings of the IEEE international conference on computer vision* (pp. 2961-2969).
4. Hatamizadeh, A., Nath, V., Tang, Y., Yang, D., Roth, H. R., & Xu, D. (2021, September). Swin unetr: Swin transformers for semantic segmentation of brain tumors in mri images. In *International MICCAI Brainlesion Workshop* (pp. 272-284). Cham: Springer International Publishing.

Financial Disclosures: None