Making AI Transferable Across OCT Scanners from Different Vendors

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Purpose

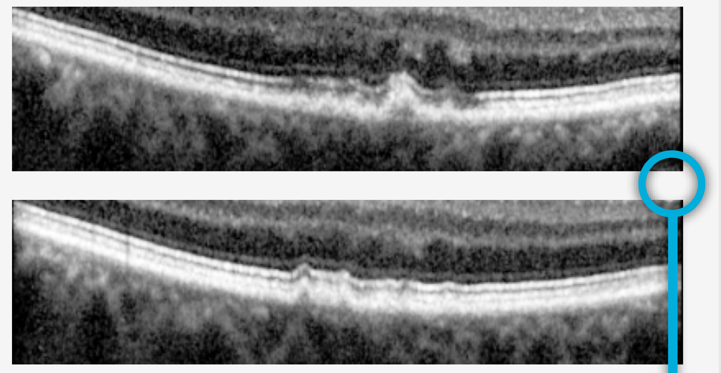
Deep neural networks (DNNs) for optical coherence tomography (OCT) classification have been proven to work well on images from scanners that were used during training. However, since the appearance of OCT scans can differ greatly between vendors, these DNNs often fail when they are applied to scans from different manufacturers. We propose a DNN architecture for age-related macular degeneration (AMD) grading that **maintains performance on OCTs from vendors not included during training**.

Methods

Heidelberg Spectralis

Dataset: EUGENDA
B-scan spacing: ~250 µm
Development: 2,598 OCTs
Internal testing: 680 OCTs

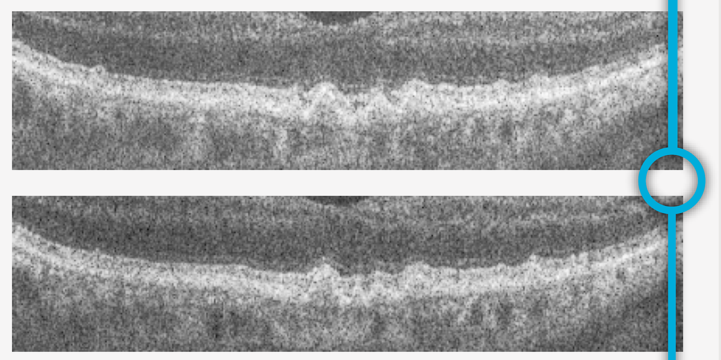
Crops of two adjacent B-scans



Topcon

Dataset: Rotterdam Study 1-6
B-scan spacing: ~50 µm
External testing: 339 OCTs

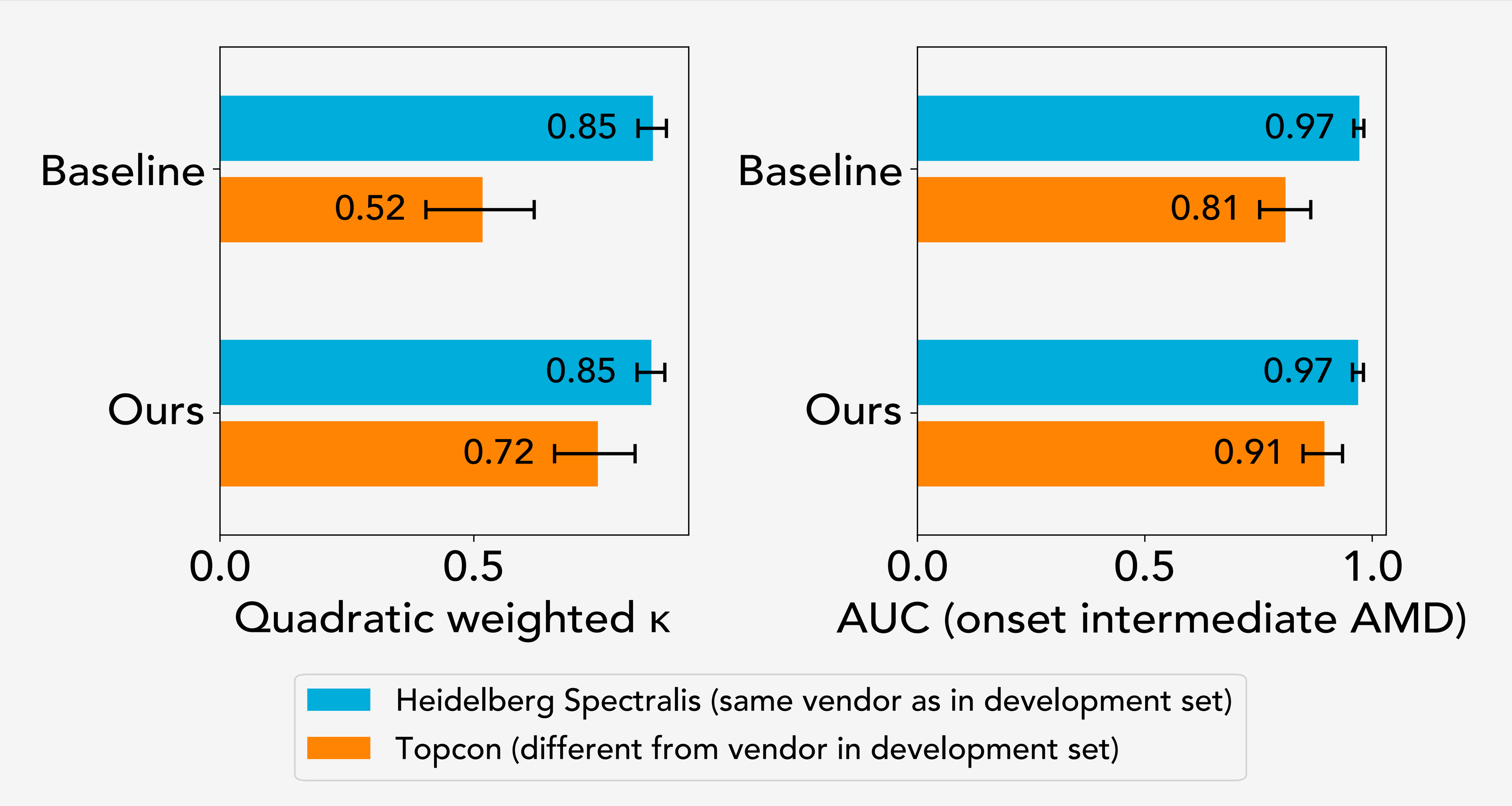
Crops of two adjacent B-scans



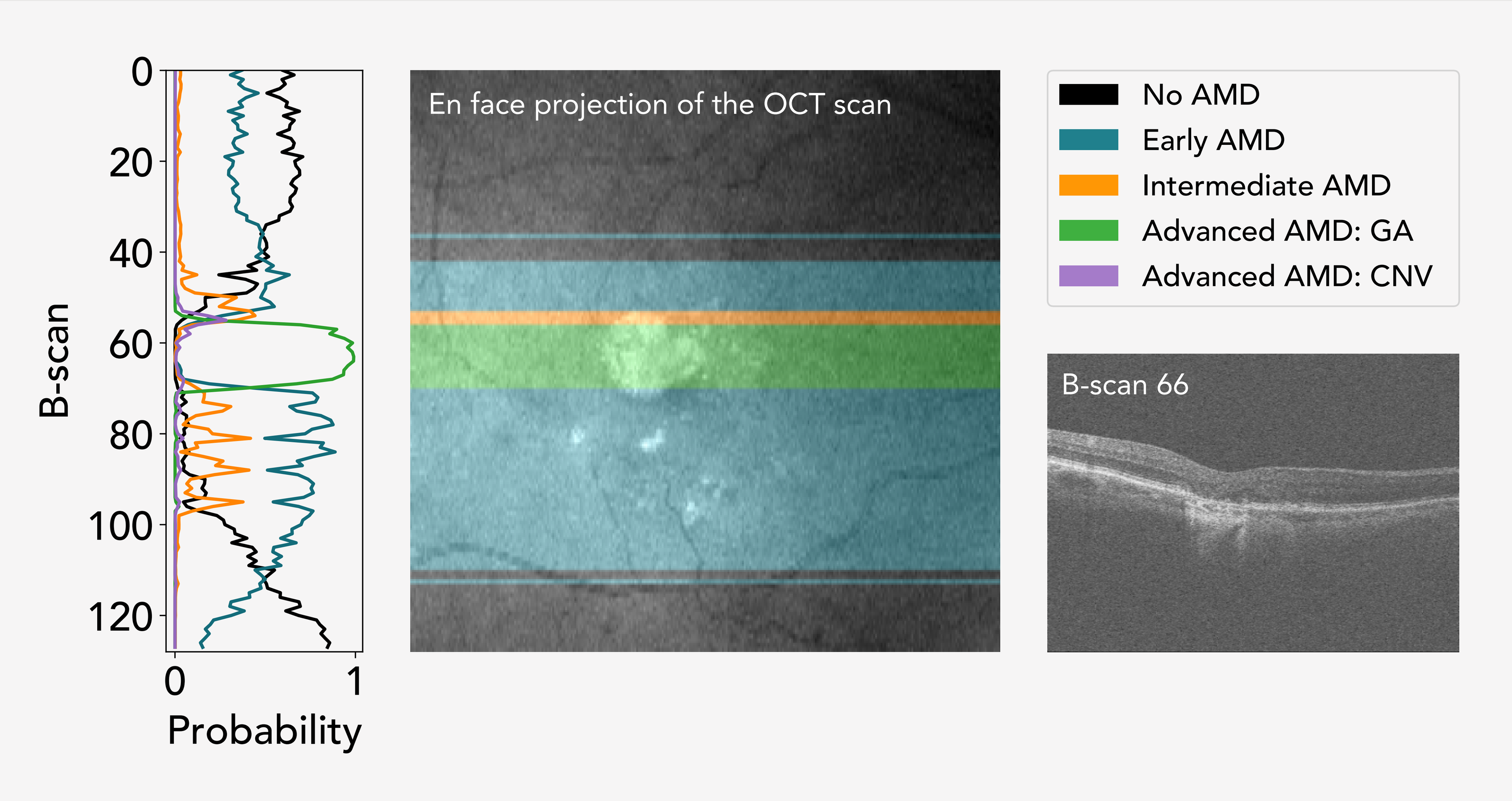
The large B-scan spacing in these Spectralis OCTs causes adjacent B-scans to differ much more in appearance than in Topcon OCTs. This would make 3D features learned on one dataset inappropriate for the other dataset.

Results

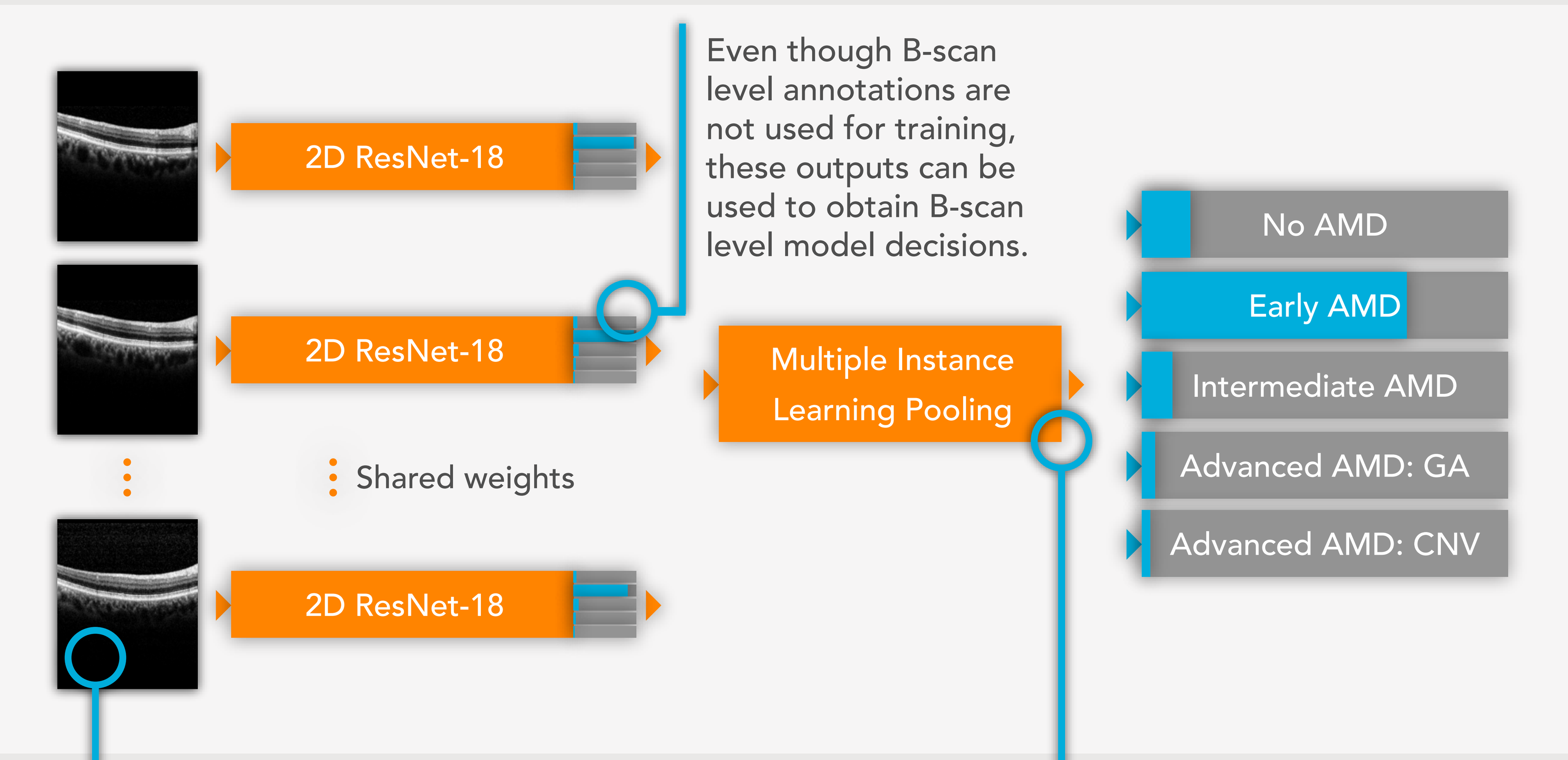
Classification performance The baseline is a 3D ResNet-18.



B-scan level output Example of an OCT with geographic atrophy (GA) from the RS1-6 dataset.



Model pipeline



Even though B-scan level annotations are not used for training, these outputs can be used to obtain B-scan level model decisions.

A 2D ResNet-18 considers each B-scan separately. This aspect of the approach makes it invariant to B-scan spacing, making our method more robust to the variability of scanning protocols across vendors.

This multiple instance learning pooling layer combines the intermediate outputs related to each B-scan and outputs a grade estimation for the full OCT volume.

Conclusions

We present a DNN for AMD classification on OCT scans that transfers well to scans from vendors that were not used for development. This **alleviates the need for retraining** on data from these scanner types, which is an expensive process in terms of data acquisition, model development, and human annotation time. Furthermore, this **increases the applicability of AI for OCT classification in broader scopes than the settings in which they were developed**.

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