Exploiting data characteristics to improve automated optic nerve head segmentation and localization in OCT en face images

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PURPOSE

- Most frequently, machine learning (ML) engineering focuses on improvements based on model architecture, optimization or learning strategies.
- In contrast, we tune the underlying data by using domain knowledge and exploiting data characteristics to improve optic nerve head (ONH) segmentation and localization.

METHODS

- We exploit the evidence-based area of possible ONH locations by cropping the input images from 256×256 pixels to the central 96×256 pixels region and feed those images to a standard U-Net.

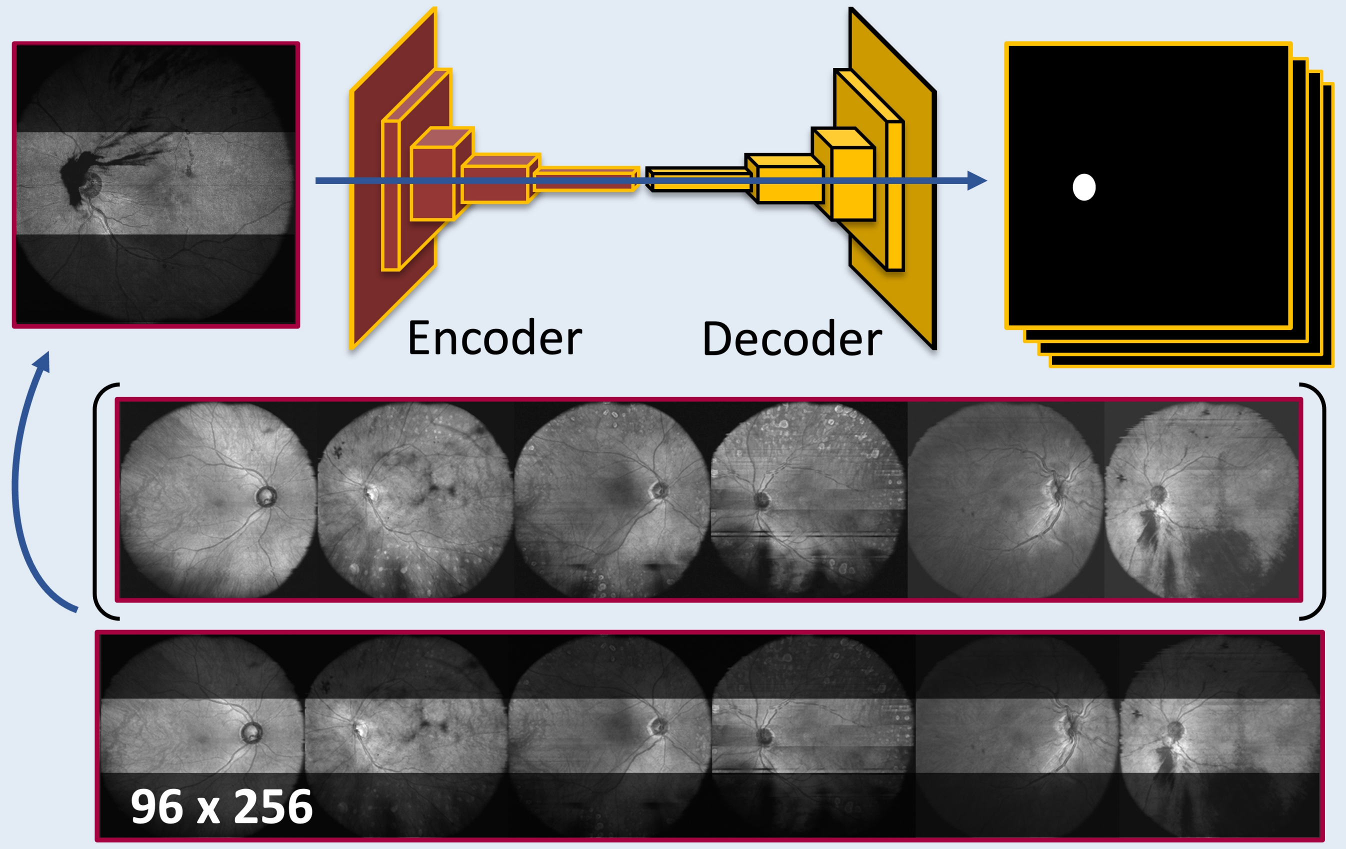

Figure 1. Data-centric deep learning approach

- To evaluate the general contribution of the data-centric approach to an improved performance, model training is repeated with the binary cross entropy loss and the Tversky loss.
- The Dice's coefficient (DC) and the Euclidean distance (ED) are calculated to evaluate the ONH segmentation performance and the localization performance of the model, respectively.

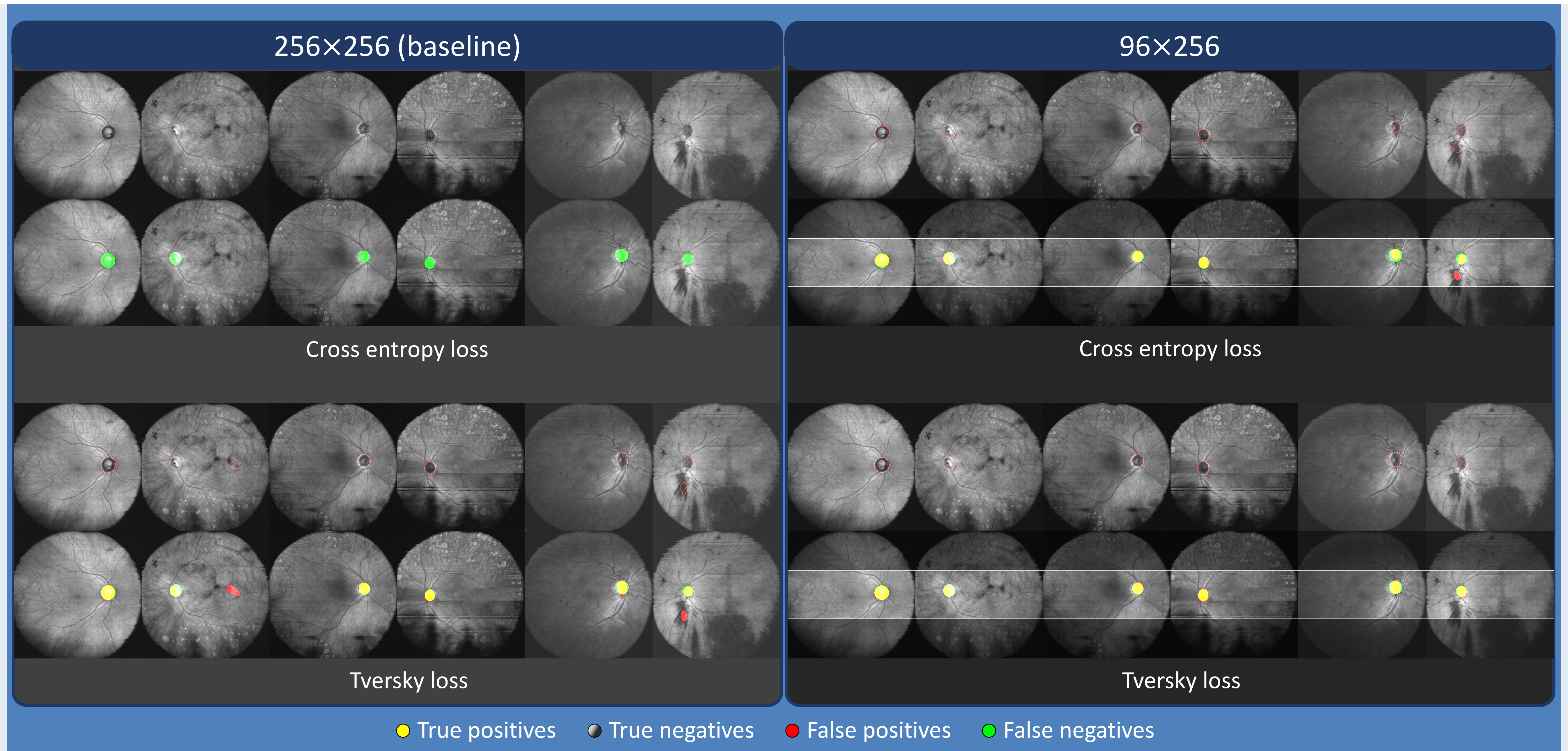

Figure 2. Qualitative ONH segmentation results on test set samples for a U-Net trained on the non-cropped 256×256 images or on images cropped to the central 96×256 pixels region using the cross entropy loss or the Tversky loss function.

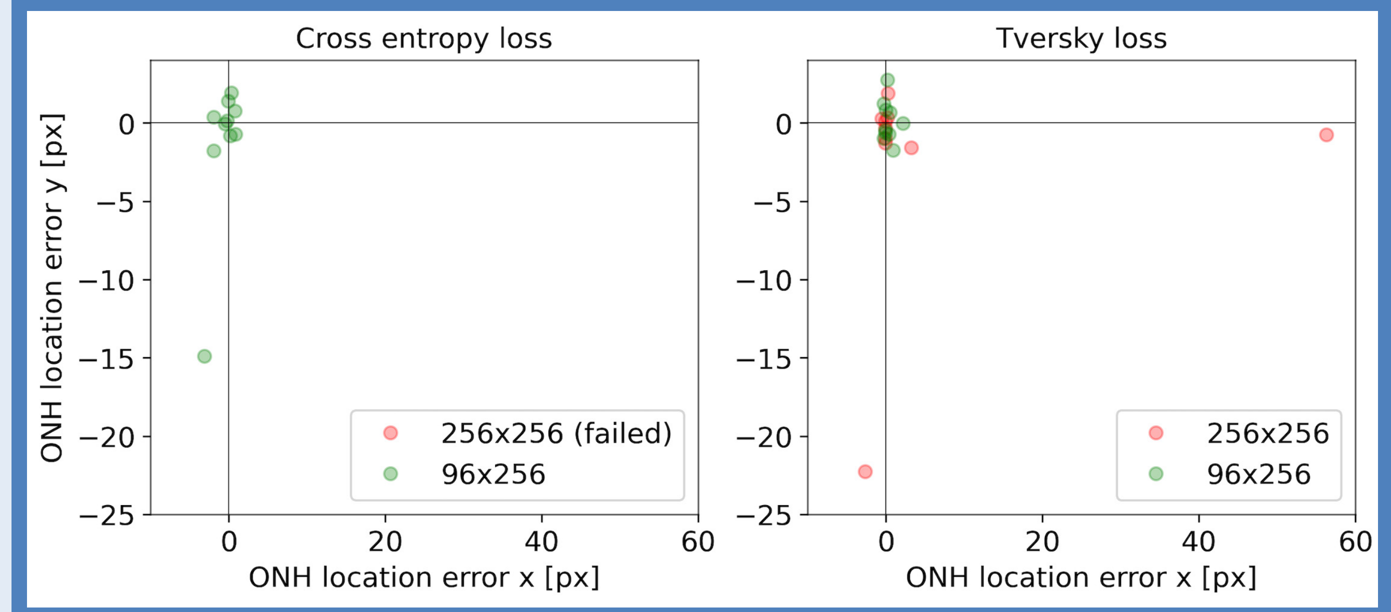

Figure 3. Spatial distribution of ONH location errors in x- and y-direction based on automated ONH segmentations on test set samples from a U-Net trained on the non-cropped 256×256 images or on images cropped to the central 96×256 pixels region using the cross entropy loss or the Tversky loss function.

Table 1. Quantitative evaluation results for a U-Net trained on non-cropped 256×256 images or on images cropped to the central 96×256 pixels region using the cross entropy loss (CL) or the Tversky loss (TL) function.

Image input	Loss function	Average precision	Dice's coefficient	Euclidean distance
256×256	CL	0.0073	0.0	-
96×256	CL	0.9447	0.8615	2.70
256×256	TL	0.8291	0.8521	8.79
96×256	TL	0.8705	0.9154	1.27

Disclosures: ThS (C), MN (C), KH (C), AS (E), AP (F), WD (C,F), RL (C,F), TiS (E) – Carl Zeiss Meditec, Inc.; HS, USE – None

RESULTS

- The model was trained on 100, validated on 10 and tested on 10 en face projections from volumetric 60 degree widefield swept-source optical coherence tomography (SS-OCT) scans acquired with a 1.7 MHz prototype OCT device.
- For both loss functions, compared to training on non-cropped data, with the data-centric approach, mean DC increased and the mean ED decreased. Corresponding quantitative evaluation results are shown in Table 1.

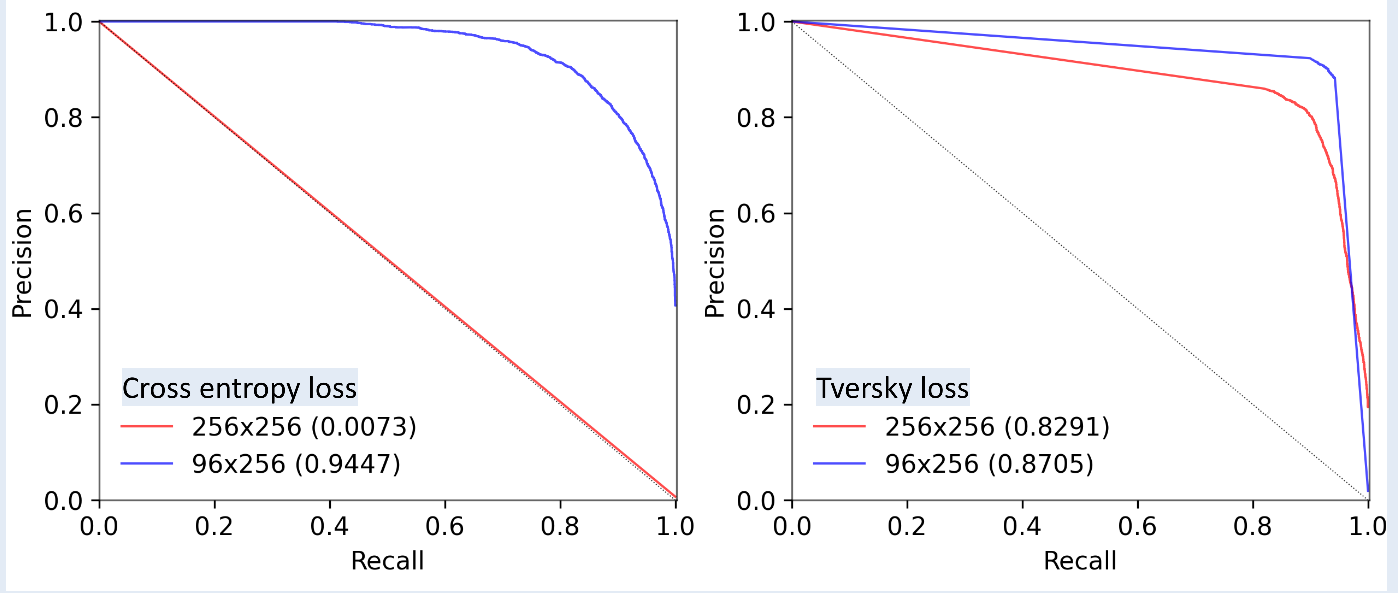

Figure 4. Precision-recall curves for models with 256×256 pixel inputs or with 96×256 pixel inputs. Corresponding average precision values are given in parenthesis.

CONCLUSIONS

- Results demonstrate that the spatial restriction of the input images improves ONH segmentation and localization and is independent of the utilized loss functions.
- The results suggest that focusing not only on model architecture and optimization strategies but also on data engineering can improve the overall ML model performance in any medical imaging domain.

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