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Towards label-free 3D segmentation of optical coherence tomography images of the optic nerve head using deep learning: supplement

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Supplement 1

Overall Schematic



Overall Schematic

Fig. S1 : The overall schematic of the study is shown. Broadly, we developed two DL networks: the (1) enhancer network to enhance the OCT image quality from multiple devices; and (2) the ONH-Net to segment the individual ONH tissues from 3D OCT volumes.



Enhancer network – architecture

Fig. S2 : The enhancer network architecture is shown. Briefly, the network consisted of a downsampling tower to extract the contextual features (i.e., spatial arrangement of tissues) and an upsampling tower to extract the local features (i.e., tissue texture). The skip connections between the downsampling and upsampling towers helped to jointly learn the local and contextual information. Multiscale hierarchical feature extraction blocks (in pink) helped the network to obtain sharper tissue boundaries.

3D segmentation – network description

Segmentation CNN

Each of the three segmentation CNNs (Fig. 2, A) comprised of four micro-U-Nets (Fig. 2, B; μ -U-Nets), and a latent space (Fig.2, C).

In every segmentation CNN, each of the four μ -U-Nets repeatedly extracted the local (i.e., tissue texture), contextual (i.e., spatial arrangement of tissues), and depth-wise spatial (i.e., tissue morphology in 3D) information at multiple scales, with an aim to maximize the network's understanding of the ONH morphology with limited training data.

The segmentation CNNs and the μ -U-Nets followed the same style of design that was based on the U-Net architecture [58].

They consisted of an encoder segment that extracted contextual features (i.e. spatial arrangement of tissues), and a decoder segment that extracted the local information (i.e. tissue texture). The encoder segment sequentially downsampled the feature maps using the 3D maxpooling layers (stride=2,2,2), while the decoder segment sequentially upsampled using the 3D transposed convolutional layers (stride=2,2,2; filter size: 3x3x3; no of filters: 48).

The latent space, implemented using residual blocks similar to our earlier study [39], transferred the extracted features from the encoder to the decoder segment. The use of residual learning improved the flow of gradient information through the network.

Skip connections [40] between the encoder and decoder segments helped the DL network to jointly learn the contextual and local information, and the relationships between them.

Also, as implemented in our earlier study [39], we used multi-scale hierarchical feature extraction to improve the delineation of tissue boundaries. The feature maps obtained from multi-scale hierarchical feature extraction were then added with the output of the decoder segment.

The three segmentation CNNs deferred from each other only in the design of the 'feature extraction' (FE) units (Fig. 2, D; Types 1-3) that were used in the μ -U-Nets.

The μ -U-Net used the FE units to extract the local, contextual, and depth-wise spatial information. Even among expert observers, there exists a good amount of intra- and interobserver variability in the delineations of ambiguous region such as the choroid-scleral interface and the posterior LC boundaries. To simulate a similar effect, we designed three types of FE units. Type 1 and Type 2 FE units (**Fig.2, D; Types 1-2**) differed from each other only by an additional elu activation [95] layer at the input to simulate the intra-observer variability (same learning approach, subtle variability due to additional activation). Type 3 FE unit however had a different design style, simulating the effect of inter-observer variabilities (greater variability due to different learning approaches) when compared to Type 1 or Type 2 FE units. The ensemble learning approach was then used to synergize the multiple equally plausible predictions in an attempt to reduce the error.

In both the Type 1 and Type 2 FE units, the input was passed through three parallel pathways: (1) the identity pathway; (2) the planar pathway; and (3) the volumetric pathway. The identity pathway implemented using a 1x1x1 3D convolutional layer allowed the unimpeded flow of gradient information throughout the network. In the planar pathway, the information from any two dimensions was extracted by the network at once (filter size: 3x3x1 [height x width]; 3x1x3 [height x depth]; 1x3x3 [width x depth]; 48 filters each). The volumetric pathway exploited the depth-wise spatially related and continuous information from all three dimensions at once (i.e., tissue morphology) using three 3D convolutional layers (filter size: 3x3x3; no of filters: 48). Finally, the feature maps from all the three pathways were added, batch normalized [96], and elu activated [95].

In the Type 3 FE (**Fig. 2, D**) unit, the input was elu activated and passed on to three sets of simple residual blocks with 48, 96, and 144 filters, respectively. In each residual block, one 3D convolutional layer (filter size: 3x3x3) extracted the features, while a 1x1x1 3D

convolution layer was used as the identity connection [42]. The feature maps were then added, elu activated, and passed on to the next block. Finally, the feature maps were batch normalized and elu activated.

For all three segmentation CNNs, the pre-final output feature maps (decoder output + multi-scale hierarchical feature extraction) were passed through a 3D convolutional layer (filter size: 1x1x1; no of filters: 8 [number of classes; 6 tissues + noise + vitreous humor]) and softmax activated to obtain the tissue-wise probability for each pixel. For each pixel, the tissue class of the highest probability was then assigned. Each segmentation CNN was trained separately end-to-end with stochastic gradient descent (SGD; learning rate: 0.01; Nesterov momentum: 0.05 [80]) optimizer, and the Jaccard distance [26] as the loss function.

Ensembler

The ensembler (**Fig. 2, E**) was implemented using three sets of 3D convolutional layers (specifications for each set; filter size [no of filters]: 3x3x3 [48]; 3x3x3 [96]; 3x3x3 [192]). A dropout [79] of 50% was used between each set to reduce overfitting and improve the generalizability of the DL network. The feature maps were then passed through two dense layers of 64 and 8 units (number of classes) respectively, that were separated by a dropout layer (50%). Finally, a softmax activation was applied to obtain the pixel-wise predictions.

Effect of Image Enhancement – ONH-Net Trained on Spectralis Volumes



Fig. S3: The segmentation performance (in 3D) on three healthy (1-3) and three glaucoma (4-6) subjects is shown. The ONH-Net was trained on volumes from Spectralis, and tested on Spectralis (1, 4), Cirrus (2, 5), and RTVue (3, 6) devices respectively. The 1,st 2,nd and 3rd columns represent the baseline, DL enhanced, and the corresponding manual segmentations for the chosen volumes. The 4th and 5th columns represent the DL segmentations when the ONH-Net was trained with and without image enhancement respective.

3D segmentation clinical reliability – automated parameter extraction

Upon obtaining the DL segmentations, two clinically relevant structural parameters that are crucial for the diagnosis of glaucoma: the (1) peripapillary RNFL thickness (p-RNFLT); and the (2) peripapillary GCC thickness (p-GCCT) were automatically extracted as in our earlier works [26, 39].

For each volume in the testing dataset, a circular scan of diameter 3.4mm centered around the ONH [97] was obtained. The p-RNFL thickness (global) was computed as the distance between the inner limiting membrane and the posterior RNFL boundary (mean of 360° measure). The p-GCT (global) was computed as the distance between the posterior RNFL boundary and the inner plexiform layer boundary (mean of 360° measure).

The intraclass correlation coefficients (ICCs) were obtained to compare the measurements computed from the DL and their corresponding manual segmentations for all cases.

When trained and tested (same device) on the 'baseline' OCT volumes, the ICCs were always greater than 0.99 for both the p-RNFLT and the p-GCCT. However, when tested on the other two devices, since that the ONH-Net was unable to segment even a single tissue reliably, we did not extract the p-RNFLT and the g-GCCT for these cases.

When repeated the same with the 'DL-enhanced' volumes, irrespective of the device used for training, the ICCs were always greater than 0.98 for all cases, indicating excellent reliability.

We observed through our experiments that, irrespective of the device used for training, when tested on OCT volumes from a given device, the mean error (mean \pm SD) in the measurement of the p-RNFLT was always less than $4.98 \pm 1.3 \mu m$, while for p-GCT, it was always less than $6.01 \pm 0.9 \mu m$. Although the preliminary results of device-independency seem encouraging, further validation and understanding is required by comparing clinically relevant measurements across DL models to truly assess its clinical value.

Benchmarking of the ONH-Net against 3D DRUNET

To better highlight the significance of the proposed 3D segmentation approach, the performance of the ONH-Net was compared against the 3D variant of our earlier DRUNET architecture [26] that offered an excellent performance in the segmentation of the individual ONH tissues (2D). We trained and tested (with DL enhanced images) the 3D variant of DRUNET by replacing the 2D layers (convolutional and pooling) with their 3D equivalent. Overall, for all cases, we observed that, the ONH-Net performed significantly superior than the 3D DRUNET. The performance (quantitative) comparison can be found in **Table S14**.

Table S1. The quantitative segmentation performance (DC: Dice coefficient; Sn: sensitivity; Sp: specificity) of ONH-Net with (w) and without (w/o) the use of image enhancement for glaucoma subjects. ONH-Net was trained on Spectralis, and tested on Spectralis, Cirrus, RTVue devices. The metrics for each tissue that were significantly higher (p<0.05) when image enhancement was used are underlined and in bold.

			Eff	ect of Image Enl	hancement - Spe	ectralis Trained	Framework (Gl	aucoma Subject	s)		
Testing		RNFL	. 1	G	cc	Other Ret	inal Layers	R	PE	Cho	roid
Device		0/M	M	0/M	M	0/M	M	0/M	M	0/M	м
;	DC	0.943 ± 0.02	0.933 ± 0.017	0.873 ± 0.019	0.931 ± 0.032	0.932 ± 0.021	0.951 ± 0.031	0.921 ± 0.005	0.931 ± 0.026	0.941 ± 0.016	0.934 ± 0.012
Spectralis	Sn	0.928 ± 0.011	0.964 ± 0.028	0.921 ± 0.048	0.933 ± 0.002	0.955 ± 0.041	0.972 ± 0.005	0.927 ± 0.025	0.955 ± 0.001	0.933 ± 0.036	0.942 ± 0.001
	$\mathbf{S}\mathbf{p}$	0.987 ± 0.001	0.996 ± 0.002	0.979 ± 0.006	0.985 ± 0.007	0.968 ± 0.008	0.984 ± 0.000	0.976 ± 0.002	0.981 ± 0.005	0.973 ± 0.002	0.988 ± 0.009
i	DC	0.500 ± 0.049	0.913 ± 0.033	0.332 ± 0.052	0.901 ± 0.037	0.617 ± 0.040	0.918 ± 0.031	0.562 ± 0.020	0.918 ± 0.019	0.477 ± 0.055	0.902 ± 0.033
Cirrus	Sn	0.701 ± 0.035	0.955 ± 0.024	0.560 ± 0.031	0.909 ± 0.014	0.720 ± 0.012	0.901 ± 0.018	0.711 ± 0.035	0.925 ± 0.016	0.710 ± 0.025	0.913 ± 0.041
	$\mathbf{S}\mathbf{p}$	0.803 ± 0.021	0.972 ± 0.000	0.723 ± 0.014	0.963 ± 0.028	0.865 ± 0.012	0.975 ± 0.006	0.813 ± 0.016	0.966 ± 0.018	0.832 ± 0.035	0.985 ± 0.009
	DC	0.364 ± 0.004	0.922 ± 0.010	0.266 ± 0.019	0.873 ± 0.031	0.308 ± 0.025	0.912 ± 0.002	0.311 ± 0.036	0.954 ± 0.031	0.302 ± 0.041	0.955 ± 0.001
RTVue	Sn	0.531 ± 0.013	0.914 ± 0.022	0.489 ± 0.034	0.959 ± 0.021	0.434 ± 0.015	0.928 ± 0.022	0.535 ± 0.026	0.962 ± 0.025	0.546 ± 0.047	0.942 ± 0.025
	$\mathbf{S}\mathbf{p}$	0.622 ± 0.009	$0.981{\pm}0.008$	0.536 ± 0.008	0.972 ± 0.004	0.577 ± 0.016	0.983 ± 0.005	0.706 ± 0.011	0.968 ± 0.012	0.762 ± 0.025	0.957 ± 0.015

Table S2. The quantitative segmentation performance (**DC: Dice coefficient; Sn: sensitivity; Sp: specificity**) of ONH-Net with (w) and without (w/o) the use of image enhancement for healthy subjects. ONH-Net was trained on Spectralis, and tested on Spectralis, Cirrus, RTVue devices. The metrics for each tissue that were significantly higher (p<0.05) when image enhancement was used are underlined and in bold.

			E	ffect of Image E	nhancement - Sl	pectralis Traine	d Framework (F	lealthy Subjects)			
Testing		RNFL		00	C	Other Ret	inal Layers	RI	PE	Cho	broid
Device		0/M	M								
	DC	0.959 ± 0.001	0.965 ± 0.004	0.913 ± 0.023	0.952 ± 0.002	0.892 ± 0.013	0.911 ± 0.023	0.871 ± 0.002	0.925 ± 0.023	0.863 ± 0.032	0.918 ± 0.013
Spectralis	\mathbf{Sn}	0.964 ± 0.002	0.956 ± 0.002	0.879 ± 0.012	0.959 ± 0.001	0.879 ± 0.025	0.922 ± 0.018	0.885 ± 0.024	0.921 ± 0.031	0.907 ± 0.013	0.900 ± 0.034
	$\mathbf{S}\mathbf{p}$	0.976 ± 0.005	0.989 ± 0.000	0.984 ± 0.004	0.988 ± 0.001	0.982 ± 0.000	0.985 ± 0.001	0.974 ± 0.021	0.984 ± 0.011	0.956 ± 0.021	0.988 ± 0.001
	DC	0.490 ± 0.042	0.965 ± 0.011	0.335 ± 0.014	0.873 ± 0.032	0.599 ± 0.012	0.904 ± 0.031	0.501 ± 0.011	0.894 ± 0.021	0.464 ± 0.025	0.873 ± 0.041
Cirrus	Sn	0.713 ± 0.022	0.944 ± 0.021	0.585 ± 0.025	0.887 ± 0.012	0.716 ± 0.015	0.973 ± 0.015	0.655 ± 0.025	0.915 ± 0.002	0.664 ± 0.016	0.879 ± 0.004
	$\mathbf{S}\mathbf{p}$	0.759 ± 0.041	0.935 ± 0.018	0.681 ± 0.021	0.966 ± 0.001	0.757 ± 0.031	0.954 ± 0.005	0.781 ± 0.026	0.982 ± 0.003	0.762 ± 0.027	0.997 ± 0.001
	DC	0.282 ± 0.012	0.923 ± 0.004	0.296 ± 0.051	0.923 ± 0.021	0.268 ± 0.027	0.885 ± 0.025	0.363 ± 0.031	0.873 ± 0.013	0.412 ± 0.021	0.913 ± 0.024
RTVue	Sn	0.503 ± 0.025	0.958 ± 0.007	0.441 ± 0.021	0.903 ± 0.049	0.498 ± 0.022	0.898 ± 0.007	0.515 ± 0.002	0.858 ± 0.026	0.488 ± 0.008	0.895 ± 0.018
	Sp	0.734 ± 0.023	0.986 ± 0.003	0.508 ± 0.025	0.988 ± 0.004	0.619 ± 0.052	0.977 ± 0.001	0.755 ± 0.025	0.984 ± 0.004	0.658 ± 0.024	0.983 ± 0.004

Table S3. The quantitative segmentation performance (**DC: Dice coefficient; Sn: sensitivity; Sp: specificity**) of the ONH-Net with (w) and without (w/o) the use of image enhancement for glaucoma subjects. The ONH-Net was trained on Cirrus, and tested on Spectralis, Cirrus, RTVue devices. The metrics for each tissue that were significantly higher (p<0.05) when image enhancement was used are underlined and in bold.

			Effe	ct of Image Enh	iancement - Ch	rrus i raineu ri	allework (GIa	ucoma subjects	(
Testing		RNFL		0C	C	Other Reti	nal Layers	RP	E	Ch	oroid
Device		0/M	w								
	DC	0.774 ± 0.032	0.951 ± 0.002	0.732 ± 0.026	0.964 ± 0.005	0.722 ± 0.042	0.941 ± 0.011	0.568 ± 0.003	0.912 ± 0.004	0.555 ± 0.034	0.941 ± 0.023
Spectralis	Sn	0.789 ± 0.02	0.952 ± 0.011	0.821 ± 0.033	0.955 ± 0.011	0.841 ± 0.023	0.964 ± 0.003	0.799 ± 0.025	0.952 ± 0.028	0.732 ± 0.051	0.941 ± 0.011
<u> </u>	Sp	0.812±0.016	0.993 ± 0.005	0.811 ± 0.027	0.997 ± 0.002	0.863 ± 0.021	0.996 ± 0.000	0.811 ± 0.012	0.985 ± 0.005	0.821 ± 0.021	0.991 ± 0.004
	DC	0.923 ± 0.003	0.941 ± 0.021	0.862 ± 0.011	0.900 ± 0.014	0.922 ± 0.029	0.931 ± 0.021	0.852 ± 0.016	$0.901{\pm}0.005$	0.905 ± 0.003	0.931 ± 0.025
Cirrus	Sn	0.954 ± 0.027	0.966 ± 0.021	0.905 ± 0.026	0.932 ± 0.011	0.901 ± 0.015	0.930 ± 0.015	0.921 ± 0.021	0.939 ± 0.021	0.932 ± 0.011	0.945 ± 0.011
<u> </u>	Sp	0.981 ± 0.005	0.994 ± 0.002	0.994 ± 0.001	0.998 ± 0.001	0.997 ± 0.002	0.978 ± 0.004	0.995 ± 0.003	0.978 ± 0.003	0.981 ± 0.004	0.986 ± 0.003
	DC	0.632 ± 0.041	0.921 ± 0.027	0.581 ± 0.024	0.921 ± 0.021	0.566 ± 0.008	0.932 ± 0.021	0.622 ± 0.002	0.925 ± 0.031	0.521 ± 0.021	0.913 ± 0.012
RTVue	Sn	0.644 ± 0.037	0.923 ± 0.021	0.721 ± 0.031	0.927 ± 0.031	0.679 ± 0.021	0.936 ± 0.008	0.761 ± 0.024	0.935 ± 0.003	0.755 ± 0.027	0.931 ± 0.017
	Sp	0.721 ± 0.026	0.990 ± 0.001	0.718 ± 0.027	$0.991{\pm}0.004$	0.751 ± 0.012	0.981 ± 0.002	0.744 ± 0.041	0.995 ± 0.000	0.821 ± 0.031	0.983 ± 0.004

Table S4. The quantitative segmentation performance (DC: Dice coefficient; Sn: sensitivity; Sp: specificity) of the ONH-Net with (w) and without (w/o) the use of image enhancement for healthy subjects. The ONH-Net was trained on Cirrus, and tested on Spectralis, Cirrus, RTV ue devices. The metrics for each tissue that were significantly higher (p<0.05) when image enhancement was used are underlined and in bold.

			EIII EIII	ect of Image Ef	nancement -	Irrus I rained I	r ramework (He	aitny subjects)			
Testing		RNFL		60	C	Other Reti	nal Layers	RI	E	Ch	oroid
Device		0/M	w	0/M	w	0/M	W	0/M	W	0/M	M
	DC	0.714 ± 0.025	0.941 ± 0.005	0.656 ± 0.025	0.906 ± 0.024	0.676 ± 0.022	0.905 ± 0.011	0.646 ± 0.024	0.912 ± 0.004	0.529 ± 0.031	0.933 ± 0.022
Spectralis	\mathbf{Sn}	0.693 ± 0.032	0.923 ± 0.035	0.759 ± 0.031	0.913 ± 0.036	0.787 ± 0.016	0.934 ± 0.021	0.701 ± 0.004	0.912 ± 0.024	0.814 ± 0.025	0.939 ± 0.018
	$\mathbf{S}\mathbf{p}$	0.758 ± 0.018	$0.981{\pm}0.003$	0.723 ± 0.029	0.987 ± 0.000	0.853 ± 0.025	0.972 ± 0.021	0.791 ± 0.026	0.986 ± 0.011	0.883 ± 0.009	0.993 ± 0.036
	DC	0.901 ± 0.022	0.939 ± 0.012	0.818 ± 0.018	0.884 ± 0.022	0.876 ± 0.035	0.907 ± 0.028	0.874 ± 0.031	0.915 ± 0.024	0.889 ± 0.012	0.907 ± 0.005
Cirrus	Sn	0.918 ± 0.005	0.952 ± 0.006	0.883 ± 0.024	0.924 ± 0.029	0.879 ± 0.011	0.920 ± 0.016	0.913 ± 0.038	0.927 ± 0.021	$0.894{\pm}0.018$	0.931 ± 0.028
	$\mathbf{S}\mathbf{p}$	0.971 ± 0.021	0.992 ± 0.001	0.974 ± 0.025	0.993 ± 0.001	0.985 ± 0.028	0.992 ± 0.003	0.987 ± 0.002	0.984 ± 0.009	0.978 ± 0.011	0.991 ± 0.000
	DC	0.654 ± 0.031	$0.930{\pm}0.018$	0.501 ± 0.41	0.903 ± 0.025	0.51 ± 0.041	0.902 ± 0.025	0.668 ± 0.039	0.910 ± 0.023	0.465 ± 0.024	0.907 ± 0.028
RTVue	Sn	0.642 ± 0.029	0.899 ± 0.031	0.563 ± 0.039	0.893 ± 0.003	0.641 ± 0.024	0.926 ± 0.005	0.689 ± 0.026	0.915 ± 0.024	0.775 ± 0.019	0.921 ± 0.011
	Sp	0.679 ± 0.031	0.968 ± 0.020	0.618 ± 0.024	0.991 ± 0.005	0.665 ± 0.022	0.985 ± 0.016	0.818 ± 0.013	0.988 ± 0.003	0.791 ± 0.031	0.991 ± 0.004

Table S5. The quantitative segmentation performance (**DC: Dice coefficient; Sn: sensitivity; Sp: specificity**) of the ONH-Net with (**w**) and without (**w**/**o**) the use of image enhancement for glaucoma subjects. The ONH-Net was trained on RTVue, and tested on Spectralis, Cirrus, RTVue devices. The metrics for each tissue that were significantly higher (p<0.05) when image enhancement was used are underlined and in bold.

			LITE	t of Image Enn	ancement - K I	v ue 1 ramed F	ramework (Gla	ucoma Subject	s)		
Testing		RNFL		GG	CC	Other Reti	nal Layers	RF	E	Che	roid
Device		0/M	w	0/M	M	0/M	w	0/M	w	0/M	M
	DC	0.747 ± 0.022	0.931 ± 0.013	0.663 ± 0.040	0.932 ± 0.015	0.647 ± 0.029	0.921 ± 0.025	0.632 ± 0.039	0.925 ± 0.025	0.577 ± 0.058	0.925 ± 0.022
Spectralis	Sn	0.697 ± 0.004	0.924 ± 0.010	0.692 ± 0.035	0.922 ± 0.028	0.723 ± 0.045	0.934 ± 0.035	0.653 ± 0.026	0.947 ± 0.001	0.711 ± 0.050	0.924 ± 0.029
	Sp	0.822±0.027	0.982 ± 0.003	0.723 ± 0.012	0.996 ± 0.000	0.716 ± 0.010	0.992 ± 0.001	0.752 ± 0.020	0.998 ± 0.002	0.741 ± 0.004	0.989 ± 0.006
	DC	0.689 ± 0.031	0.923 ± 0.009	0.699 ± 0.041	0.925 ± 0.020	0.611 ± 0.035	0.917 ± 0.031	0.612 ± 0.045	0.931 ± 0.019	0.512 ± 0.021	0.918 ± 0.031
Cirrus	Sn	0.731 ± 0.028	$0.944{\pm}0.012$	0.713 ± 0.033	0.933 ± 0.018	0.751 ± 0.030	0.932 ± 0.029	0.788 ± 0.039	0.911 ± 0.023	0.672 ± 0.041	0.915 ± 0.028
	Sp	0.762 ± 0.021	0.988 ± 0.017	0.758 ± 0.010	0.996 ± 0.000	0.712 ± 0.009	0.991 ± 0.005	0.812 ± 0.005	0.988 ± 0.006	0.734 ± 0.005	0.990 ± 0.002
	DC	0.951 ± 0.005	0.946 ± 0.018	0.902 ± 0.022	0.921 ± 0.020	0.901 ± 0.019	0.941 ± 0.005	0.822 ± 0.035	0.927 ± 0.020	0.934 ± 0.020	0.932 ± 0.025
RTVue	Sn	0.926 ± 0.011	$0.941{\pm}0.003$	0.921 ± 0.020	0.930 ± 0.011	0.909 ± 0.020	0.906 ± 0.008	0.919 ± 0.008	0.940 ± 0.023	0.911 ± 0.031	0.942 ± 0.008
	Sp	0.960 ± 0.018	0.991 ± 0.001	0.981 ± 0.008	0.994 ± 0.005	0.977 ± 0.005	0.993 ± 0.000	0.992 ± 0.003	0.997 ± 0.000	0.991 ± 0.001	0.994 ± 0.001
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Table S6. The quantitative segmentation performance (**DC: Dice coefficient; Sn: sensitivity; Sp: specificity**) of the ONH-Net with (w) and without (w/o) the use of image enhancement for healthy subjects. The ONH-Net was trained on RTVue, and tested on Spectralis, Cirrus, RTVue devices. The metrics for each tissue that were significantly higher (p<0.05) when image enhancement was used are underlined and in bold.

			Eff	ect of Image En	hancement - R	TVue Trained	Framework (He	salthy Subjects			
Testing		RNFL		GC	CC	Other Reti	nal Layers	RF	E	Chc	roid
Device		0/M	W	0/M	W	0/M	w	0/M	w	0/M	W
	DC	0.697 ± 0.024	0.940 ± 0.004	0.649 ± 0.032	0.912 ± 0.028	0.687 ± 0.030	0.918 ± 0.026	0.620 ± 0.039	0.915 ± 0.020	0.565 ± 0.058	0.915 ± 0.021
Spectralis	Sn	0.737 ± 0.016	0.938 ± 0.005	0.672 ± 0.033	0.915 ± 0.028	0.760 ± 0.040	0.921 ± 0.031	0.620 ± 0.038	0.917 ± 0.036	0.710 ± 0.044	0.922 ± 0.033
	Sp	0.782 ± 0.007	0.992 ± 0.005	0.722 ± 0.005	0.994 ± 0.001	0.709 ± 0.005	0.990 ± 0.001	0.706 ± 0.004	0.996 ± 0.003	0.732 ± 0.005	0.985 ± 0.006
	DC	0.715 ± 0.021	0.931 ± 0.021	0.699 ± 0.040	0.939 ± 0.024	0.600 ± 0.035	0.907 ± 0.031	0.595 ± 0.045	0.909 ± 0.029	0.499 ± 0.054	0.911 ± 0.027
Cirrus	\mathbf{Sn}	0.713 ± 0.041	$0.934{\pm}0.018$	0.720 ± 0.032	0.916 ± 0.028	0.744 ± 0.035	0.922 ± 0.030	0.765 ± 0.041	0.901 ± 0.025	0.667 ± 0.043	0.905 ± 0.025
	Sp	0.748 ± 0.003	0.992 ± 0.004	0.790 ± 0.008	0.993 ± 0.004	0.690 ± 0.008	0.990 ± 0.001	0.799 ± 0.007	0.984 ± 0.008	0.750 ± 0.005	0.993 ± 0.002
	DC	0.933 ± 0.006	0.936 ± 0.026	0.906 ± 0.029	0.911 ± 0.017	0.895 ± 0.021	0.932 ± 0.010	0.881 ± 0.035	0.917 ± 0.018	0.925 ± 0.020	0.928 ± 0.022
RTVue	Sn	0.938 ± 0.021	0.933 ± 0.009	0.898 ± 0.035	0.928 ± 0.019	0.915 ± 0.020	0.901 ± 0.019	0.899 ± 0.026	0.929 ± 0.024	0.890 ± 0.031	0.924 ± 0.020
	$\mathbf{S}\mathbf{p}$	0.996 ± 0.003	0.978 ± 0.016	0.988 ± 0.004	0.991 ± 0.003	0.985 ± 0.001	0.995 ± 0.001	0.990 ± 0.004	0.995 ± 0.003	0.989 ± 0.002	0.991 ± 0.006

			Training Device	
Tissue (Spectralis	s Volumes;	Spectralis	Cirrus	RTVue
Glaucoma Su	bjects)			
PNFI	DC	0.933±0.017	0.951±0.002	0.931±0.013
KNFL	Sn	0.964±0.028	0.952±0.011	0.924±0.010
	Sp	0.996±0.002	0.993±0.005	0.982±0.003
GCC	DC	0.931±0.032	0.964±0.005	0.932±0.015
dee	Sn	0.933±0.002	0.955±0.011	0.922±0.028
	Sp	0.985±0.007	0.997 ± 0.002	0.996±0.000
Other Retinal	DC	0.951±0.031	0.941±0.011	0.921±0.025
Layers	Sn	0.972±0.005	0.964 ± 0.003	0.934±0.035
	Sp	0.984±0.000	0.996±0.000	0.992±0.001
RPE	DC	0.931±0.026	0.912±0.004	0.925±0.025
KI L	Sn	0.955±0.001	0.952 ± 0.028	0.947±0.001
	Sp	0.981±0.005	0.985±0.005	0.998±0.002
Choroid	DC	0.934±0.012	0.941±0.023	0.925±0.022
Chorolu	Sn	0.942 ± 0.001	0.941±0.011	0.924 ± 0.029
	Sp	0.988 ± 0.009	0.991±0.004	0.989 ± 0.006

Table S7. The device independent segmentation performance (DC: Dice coefficient; Sn: sensitivity; Sp: specificity) of the ONH-Net (using DL-enhanced dataset) for glaucoma subjects. The volumes from Spectralis device were tested on three segmentation models (Spectralis, Cirrus, and RTVue trained).

Table S8. The device independent segmentation performance (**DC: Dice coefficient; Sn: sensitivity; Sp: specificity**) of the ONH-Net (using DL-enhanced dataset) for healthy subjects. The volumes from Spectralis device were tested on three segmentation models (Spectralis, Cirrus, and RTVue trained).

			Training Device	
Tissue (Spectrali	s Volumes;	Spectralis	Cirrus	RTVue
Healthy Sur	jects)			
RNFL	DC	0.965±0.004	0.941±0.005	0.940 ± 0.004
RUL	Sn	0.956±0.002	0.923±0.035	0.938±0.005
	Sp	0.989 ± 0.000	0.981±0.003	0.992±0.005
	DC	0.952±0.002	0.906±0.024	0.912±0.028
GUU	Sn	0.959±0.001	0.913±0.036	0.915±0.028
	Sp	0.988±0.001	0.987±0.000	0.994±0.001
Other Detinal	DC	0.911±0.023	0.905±0.011	0.918±0.026
Layers	Sn	0.922±0.018	0.934±0.021	0.921±0.031
	Sp	0.985±0.001	0.972±0.021	0.990±0.001
DDF	DC	0.925±0.023	0.912±0.004	0.915±0.020
KI E	Sn	0.921±0.031	0.912±0.024	0.917±0.036
	Sp	0.984±0.011	0.986±0.011	0.996±0.003
Charaid	DC	0.918±0.013	0.933±0.022	0.915±0.021
Chorola	Sn	0.900±0.034	0.939±0.018	0.922 ± 0.033
	Sp	0.988±0.001	0.993±0.036	0.985 ± 0.006

			Training Device	
Tissue (Cirrus Glaucoma Su	Volumes; 1bjects)	Spectralis	Cirrus	RTVue
DNEI	DC	0.913±0.033	0.941±0.021	0.923±0.009
KINFL	Sn	0.955±0.024	0.966±0.021	0.944±0.012
	Sp	0.972 ± 0.000	0.994±0.002	0.988±0.017
CCC	DC	0.901±0.037	0.900±0.014	0.925±0.020
ucc	Sn	0.909±0.014	0.932±0.011	0.933±0.018
	Sp	0.963±0.028	0.998±0.001	0.996±0.000
Other Potinel	DC	0.918±0.031	0.931±0.021	0.917±0.031
Layers	Sn	0.901±0.018	0.930±0.015	0.932±0.029
	Sp	0.975±0.006	0.978±0.004	0.991±0.005
PPF	DC	0.918±0.019	0.901±0.005	0.931±0.019
KI E	Sn	0.925±0.016	0.939±0.021	0.911±0.023
	Sp	0.966±0.018	0.978±0.003	0.988 ± 0.006
	DC	0.902±0.033	0.931±0.025	0.918±0.031
Choroid	Sn	0.913±0.041	0.945±0.011	0.915±0.028
	Sp	0.985 ± 0.009	0.986 ± 0.003	0.990 ± 0.002

Table S9. The device independent segmentation performance (DC: Dice coefficient; Sn: sensitivity; Sp: specificity) of the ONH-Net (using DL-enhanced dataset) for glaucoma subjects. The volumes from Cirrus device were tested on three segmentation models (Spectralis, Cirrus, and RTVue trained).

Table S10. The device independent segmentation performance (DC: Dice coefficient; Sn: sensitivity; Sp: specificity) of the ONH-Net (using DL-enhanced dataset) for healthy subjects. The volumes from Cirrus device were tested on three segmentation models (Spectralis, Cirrus, and RTVue trained).

			Training Device	
Tissue (Cirrus Healthy Sub	Volumes; ojects)	Spectralis	Cirrus	RTVue
DNEI	DĆ	0.965±0.011	0.939±0.012	0.931±0.021
KINFL	Sn	0.944±0.021	0.952±0.006	0.934±0.018
	Sp	0.935±0.018	0.992±0.001	0.992±0.004
CCC	DC	0.873±0.032	0.884±0.022	0.939±0.024
GCC	Sn	0.887±0.012	0.924±0.029	0.916±0.028
	Sp	0.966±0.001	0.993±0.001	0.993±0.004
Other Defined	DC	0.904±0.031	0.907±0.028	0.907±0.031
Layers	Sn	0.973±0.015	0.920±0.016	0.922±0.030
	Sp	0.954±0.005	0.992±0.003	0.990±0.001
DDE	DC	0.894±0.021	0.915±0.024	0.909±0.029
KPE	Sn	0.915±0.002	0.927±0.021	0.901±0.025
	Sp	0.982±0.003	0.984±0.009	0.984±0.008
	DC	0.873±0.041	0.907±0.005	0.911±0.027
Choroid	Sn	0.879 ± 0.004	0.931±0.028	0.905 ± 0.025
	Sp	$0.997 {\pm} 0.001$	0.991±0.000	0.993 ± 0.002

Table S11. The device independent segmentation performance (DC: Dice coefficient; Sn: sensitivity; Sp: specificity) of the ONH-Net (using DL-enhanced dataset) for glaucoma subjects. The volumes from RTVue device were tested on three segmentation models (Spectralis, Cirrus, and RTVue trained).

			Training Device	
Tissue (RTVue Glaucoma Su	Volumes; bjects)	Spectralis	Cirrus	RTVue
DNEI	DC	0.922±0.010	0.921±0.027	0.946±0.018
KINFL	Sn	0.914±0.022	0.923±0.021	0.941±0.003
	Sp	0.981±0.008	0.990±0.001	0.991±0.001
CCC	DC	0.873±0.031	0.921±0.021	0.921±0.020
GCC	Sn	0.959±0.021	0.927±0.031	0.930±0.011
	Sp	0.972±0.004	0.991±0.004	0.994±0.005
Other Ratinal	DC	0.912±0.002	0.932±0.021	0.941±0.005
Layers	Sn	0.928±0.022	0.936±0.008	0.906±0.008
	Sp	0.983±0.005	0.981±0.002	0.993±0.000
PDF	DC	0.954±0.031	0.925±0.031	0.927±0.020
KI E	Sn	0.962±0.025	0.935±0.003	0.940±0.023
	Sp	0.968±0.012	0.995±0.000	0.997±0.000
	DC	0.955±0.001	0.913±0.012	0.932±0.025
Choroid	Sn	0.942±0.025	0.931±0.017	0.942 ± 0.008
	Sp	0.957±0.015	0.983 ± 0.004	0.994±0.001

Table S12. The device independent segmentation performance (DC: Dice coefficient; Sn: sensitivity; Sp: specificity) of the ONH-Net (using DL-enhanced dataset) for healthy subjects. The volumes from RTVue device were tested on three segmentation models (Spectralis, Cirrus, and RTVue trained).

			Training Device	
Tissue (RTVue	Volumes;	Spectralis	Cirrus	RTVue
Healthy Sub	jects)			
DNFI	DC	0.923±0.004	0.930±0.018	0.936±0.026
KNFL	Sn	0.958±0.007	0.899±0.031	0.933±0.009
	Sp	0.986±0.003	0.968±0.020	0.978±0.016
CCC	DC	0.923±0.021	0.903±0.025	0.911±0.017
GCC	Sn	0.903±0.049	0.893±0.003	0.928±0.019
	Sp	0.988 ± 0.004	0.991±0.005	0.991±0.003
Other Potinal	DC	0.885±0.025	0.902±0.025	0.932±0.010
Layers	Sn	0.898 ± 0.007	0.926±0.005	0.901±0.019
	Sp	0.977±0.001	0.985±0.016	0.995±0.001
RPF	DC	0.873±0.013	0.910±0.023	0.917±0.018
KI E	Sn	0.858±0.026	0.915±0.024	0.929±0.024
	Sp	$0.984{\pm}0.004$	0.988±0.003	0.995±0.003
	DC	0.913±0.024	0.907±0.028	0.928 ± 0.022
Choroid	Sn	$0.895 {\pm} 0.018$	0.921±0.011	0.924 ± 0.020
	Sp	0.983 ± 0.004	0.991±0.004	0.991 ± 0.006

			Comparis	on Between Digital	y Enhanced and I	DL Enhanced Segn	nentations - Spectr	alis Trained Fran	nework		
Testing		RNI	FL)	CC	Other Re	tinal Layers	F.	RPE	Ch	oroid
Device		Digital	DL	Digital	DL	Digital	DL	Digital	DL	Digital	DL
	DC	0.901 ± 0.020	0.954 ± 0.017	0.891 ± 0.012	0.931 ± 0.020	0.903 ± 0.018	0.936 ± 0.010	0.883 ± 0.041	0.918 ± 0.014	0.901 ± 0.022	0.926 ± 0.031
Spectralis	Sn	0.956 ± 0.019	0.960 ± 0.026	0.911 ± 0.008	0.946 ± 0.019	0.931 ± 0.021	0.947 ± 0.010	0.915 ± 0.020	0.938 ± 0.022	0.921 ± 0.020	0.931 ± 0.038
_	Sp	0.989 ± 0.001	0.993 ± 0.001	0.990 ± 0.007	0.996 ± 0.003	0.978 ± 0.001	0.995 ± 0.001	0.975 ± 0.010	0.994 ± 0.002	0.979 ± 0.001	0.996 ± 0.002
	DC	0.802 ± 0.048	0.943 ± 0.027	0.781 ± 0.044	0.919 ± 0.032	0.858 ± 0.024	0.918 ± 0.031	0.741 ± 0.021	0.918 ± 0.019	0.820 ± 0.039	0.902 ± 0.033
Cirrus	Sn	0.880 ± 0.018	0.955 ± 0.024	0.854 ± 0.024	0.899 ± 0.024	0.890 ± 0.010	0.937 ± 0.020	0.830 ± 0.048	0.920 ± 0.023	0.901 ± 0.001	0.896 ± 0.043
	$\mathbf{S}\mathbf{p}$	0.942 ± 0.011	0.988 ± 0.000	0.955 ± 0.019	0.983 ± 0.004	0.948 ± 0.011	0.992 ± 0.004	0.921 ± 0.020	0.991 ± 0.001	0.950 ± 0.019	0.991 ± 0.004
	DC	0.778 ± 0.039	0.951 ± 0.031	0.721 ± 0.056	0.898 ± 0.030	0.801 ± 0.038	0.896 ± 0.041	0.691 ± 0.056	0.912 ± 0.029	0.783 ± 0.042	0.934 ± 0.028
RTVue	Sn	0.858 ± 0.023	0.936 ± 0.032	0.860 ± 0.044	0.931 ± 0.038	0.901 ± 0.031	0.913 ± 0.038	0.780 ± 0.051	0.910 ± 0.031	0.872 ± 0.033	0.901 ± 0.028
	Sp	0.902 ± 0.020	0.996 ± 0.003	0.910 ± 0.013	0.992 ± 0.006	0.930 ± 0.009	0.994 ± 0.005	0.840 ± 0.039	0.994 ± 0.003	0.903 ± 0.026	0.994 ± 0.005
			Compar	ison Between Digits	ully Enhanced and	d DL Enhanced Seg	mentations - Cirri	is Trained Frame	swork		
Testing		RNI	FL		CC	Other Re	tinal Layers	4	RPE	Ch	oroid
Device		Digital	DL	Digital	DL	Digital	DL	Digital	DL	Digital	DL
	DC	0.689 ± 0.033	0.966 ± 0.027	0.654 ± 0.045	0.935 ± 0.020	0.760 ± 0.039	0.923 ± 0.023	0.701 ± 0.038	0.932 ± 0.018	0.662 ± 0.041	0.937 ± 0.029
Spectralis	Sn	0.734 ± 0.037	0.946 ± 0.031	0.790 ± 0.022	0.934 ± 0.021	0.834 ± 0.033	0.949 ± 0.027	0.770 ± 0.044	0.932 ± 0.032	0.760 ± 0.037	0.940 ± 0.034
	$\mathbf{S}\mathbf{p}$	0.801 ± 0.004	0.987 ± 0.000	0.767 ± 0.036	0.992 ± 0.002	0.878 ± 0.003	0.994 ± 0.002	0.811 ± 0.003	0.995 ± 0.003	0.829 ± 0.020	0.995 ± 0.002
	DC	0.924 ± 0.019	0.965 ± 0.022	0.880 ± 0.034	0.920 ± 0.027	0.891 ± 0.018	0.932 ± 0.026	0.848 ± 0.041	0.913 ± 0.020	0.871 ± 0.024	0.924 ± 0.025
Cirrus	Sn	0.966 ± 0.031	0.974 ± 0.030	0.899 ± 0.028	0.918 ± 0.026	0.920 ± 0.020	0.922 ± 0.021	0.907 ± 0.026	0.933 ± 0.015	0.913 ± 0.033	0.923 ± 0.028
_	Sp	0.969 ± 0.002	0.988 ± 0.001	0.984 ± 0.002	0.994 ± 0.002	0.991 ± 0.004	0.995 ± 0.001	0.991 ± 0.002	0.996 ± 0.002	0.989 ± 0.001	0.993 ± 0.005
	DC	0.761 ± 0.049	0.936 ± 0.035	0.701 ± 0.025	0.896 ± 0.029	0.794 ± 0.059	0.917 ± 0.028	0.699 ± 0.045	0.905 ± 0.030	0.712 ± 0.054	0.910 ± 0.031
RTVue	Sn	0.801 ± 0.028	0.925 ± 0.033	0.820 ± 0.039	0.920 ± 0.031	0.860 ± 0.048	0.928 ± 0.022	0.760 ± 0.038	0.925 ± 0.027	0.765 ± 0.055	0.926 ± 0.034
	Sp	0.867 ± 0.010	0.980 ± 0.003	0.880 ± 0.018	0.986 ± 0.004	0.908 ± 0.010	0.988 ± 0.003	0.831 ± 0.020	0.990 ± 0.004	0.816 ± 0.010	0.990 ± 0.005
			Compari	ison Between Digita	Ily Enhanced and	1 DL Enhanced Seg	mentations - RTV	ue Trained Frame	ework		
Testing		RNI	FL)	CC	Other Re	tinal Layers	F	RPE	Ch	oroid
Device		Digital	DL	Digital	DL	Digital	DL	Digital	DL	Digital	DL
-	DC	0.701 ± 0.028	0.966 ± 0.029	0.646 ± 0.032	0.912 ± 0.028	0.721 ± 0.043	0.918 ± 0.026	0.667 ± 0.033	0.915 ± 0.020	0.701 ± 0.036	0.915 ± 0.021
Spectralis	Sn	0.768 ± 0.017	0.951 ± 0.035	0.766 ± 0.039	0.915 ± 0.028	0.831 ± 0.036	0.931 ± 0.031	0.730 ± 0.028	0.917 ± 0.036	0.770 ± 0.044	0.922 ± 0.033
	Sp	0.830 ± 0.018	0.986 ± 0.003	0.804 ± 0.012	0.994 ± 0.003	0.870 ± 0.016	0.996 ± 0.001	0.808 ± 0.010	0.996 ± 0.003	0.822 ± 0.025	0.985 ± 0.006
_	DC	0.728 ± 0.026	0.942 ± 0.024	0.662 ± 0.041	0.939 ± 0.024	0.701 ± 0.033	0.907 ± 0.031	0.630 ± 0.042	0.909 ± 0.029	0.711 ± 0.036	0.911 ± 0.027
Cirrus	Sn	0.770 ± 0.033	0.954 ± 0.033	0.720 ± 0.038	0.916 ± 0.028	0.784 ± 0.029	0.922 ± 0.030	0.705 ± 0.034	0.901 ± 0.035	0.778 ± 0.026	0.905 ± 0.025
	Sp	0.822 ± 0.021	0.995 ± 0.002	0.799 ± 0.020	0.993 ± 0.004	0.848 ± 0.020	0.994 ± 0.002	0.769 ± 0.010	0.984 ± 0.008	0.799 ± 0.018	0.993 ± 0.002
_	DC	0.902 ± 0.028	0.951 ± 0.028	0.900 ± 0.019	0.911 ± 0.017	0.915 ± 0.021	0.925 ± 0.008	0.878 ± 0.025	0.917 ± 0.018	0.919 ± 0.020	0.931 ± 0.022
RTVue	Sn	0.920 ± 0.020	0.947 ± 0.010	0.918 ± 0.025	0.928 ± 0.019	0.922 ± 0.020	0.931 ± 0.019	0.901 ± 0.026	0.929 ± 0.024	0.921 ± 0.030	0.924 ± 0.020
_	Sn	0 980+0 009	0 997+0.001	0 987+0 005	0 991+0 003	0 965+0 001	0 995+0.001	0 990+0 004	0 995+0 003	0 989+0 002	0.991 ± 0.006

Table S13: The quantitative segmentation performance (DC: Dice coefficient; Sn: sensitivity; Sp: specificity) of ONH-Net when trained and tested on the digitally enhanced (Digital) and the DL enhanced

				Performance Con	nparison Between L	DRUNET and ONH-F	Vet - Spectralis Tra	ned Framework			
Testing		RNFI	L)	GCC	Other Re	tinal Layers	I	RPE	CF	ioroid
Device		DRUNET	ONH-Net	DRUNET	ONH-Net	DRUNET	ONH-Net	DRUNET	ONH-Net	DRUNET	ONH-Net
	DC	0.845 ± 0.018	0.954 ± 0.017	0.820 ± 0.015	0.931 ± 0.020	0.860 ± 0.011	0.936 ± 0.010	0.790 ± 0.041	0.918 ± 0.014	0.868 ± 0.012	0.926 ± 0.031
Spectralis	Sn	0.923 ± 0.016	0.960 ± 0.026	0.920 ± 0.008	0.946 ± 0.019	0.941 ± 0.021	0.947 ± 0.010	0.915 ± 0.020	0.938 ± 0.022	0.921 ± 0.020	0.931 ± 0.038
	$\mathbf{S}\mathbf{p}$	0.978 ± 0.004	0.993 ± 0.001	0.969 ± 0.011	0.996 ± 0.003	0.981 ± 0.001	0.995 ± 0.001	0.956 ± 0.009	0.994 ± 0.002	0.983 ± 0.001	0.996 ± 0.002
	DC	0.748 ± 0.024	0.943 ± 0.027	0.702 ± 0.014	0.919 ± 0.032	0.763 ± 0.033	0.918 ± 0.031	0.699 ± 0.022	0.918 ± 0.019	0.734 ± 0.032	0.902 ± 0.033
Cirrus	Sn	0.852 ± 0.021	0.955 ± 0.024	0.824 ± 0.024	0.899 ± 0.024	0.870 ± 0.012	0.937 ± 0.020	0.801 ± 0.032	0.920 ± 0.023	0.846 ± 0.020	0.896 ± 0.043
	$\mathbf{S}\mathbf{p}$	0.899 ± 0.014	0.988 ± 0.000	0.867 ± 0.019	0.983 ± 0.004	$0.901{\pm}0.010$	0.992 ± 0.004	0.813 ± 0.022	0.991 ± 0.001	0.899 ± 0.021	0.991 ± 0.004
	DC	0.721 ± 0.023	0.951 ± 0.031	0.701 ± 0.036	0.898 ± 0.030	0.753 ± 0.030	0.896 ± 0.041	0.676 ± 0.048	0.912 ± 0.029	0.756 ± 0.038	0.934 ± 0.028
RTVue	Sn	0.832 ± 0.023	0.936 ± 0.032	0.810 ± 0.031	0.931 ± 0.038	0.867 ± 0.028	0.913 ± 0.038	0.750 ± 0.041	0.910 ± 0.031	0.851 ± 0.030	0.901 ± 0.028
	Sp	0.870 ± 0.020	0.996 ± 0.003	0.850 ± 0.020	<u>0.992±0.006</u>	0.899 ± 0.012	0.994 ± 0.005	0.811 ± 0.021	0.994 ± 0.003	0.880 ± 0.022	<u>0.994± 0.005</u>
				Performance Co	omparison Between	DRUNET and ONH	-Net - Cirrus Train	ed Framework			
Testing		RNFI	L		GCC	Other Re	tinal Layers	ł	RPE	C	ioroid
Device		DRUNET	ONH-Net	DRUNET	ONH-Net	Digitally En	DL En	DRUNET	ONH-Net	DRUNET	ONH-Net
	DC	0.701 ± 0.023	0.966 ± 0.027	0.661 ± 0.032	0.935 ± 0.020	0.743 ± 0.039	0.923 ± 0.023	0.676 ± 0.028	0.932 ± 0.018	0.712 ± 0.036	0.937 ± 0.029
Spectralis	Sn	0.791 ± 0.026	0.946 ± 0.031	0.743 ± 0.021	0.934 ± 0.021	0.823 ± 0.030	0.949 ± 0.027	0.750 ± 0.024	0.932 ± 0.032	0.789 ± 0.031	0.940 ± 0.034
	$\mathbf{S}\mathbf{p}$	0.810 ± 0.021	0.987 ± 0.000	0.801 ± 0.026	0.992 ± 0.002	0.889 ± 0.012	0.994 ± 0.002	0.791 ± 0.013	0.995 ± 0.003	0.803 ± 0.021	0.995 ± 0.002
	DC	0.856 ± 0.016	0.965 ± 0.022	0.803 ± 0.042	0.920 ± 0.027	0.889 ± 0.021	0.932 ± 0.026	0.800 ± 0.032	0.913 ± 0.020	0.876 ± 0.014	0.924 ± 0.025
Cirrus	Sn	0.920 ± 0.024	0.974 ± 0.030	0.887 ± 0.025	0.918 ± 0.026	0.920 ± 0.020	0.922 ± 0.021	0.880 ± 0.022	0.933 ± 0.015	0.922 ± 0.030	0.923 ± 0.028
	$\mathbf{S}\mathbf{p}$	0.956 ± 0.010	0.988 ± 0.001	0.941 ± 0.012	0.994 ± 0.002	0.967 ± 0.009	0.995 ± 0.001	0.942 ± 0.014	0.996 ± 0.002	0.978 ± 0.021	0.993 ± 0.005
	DC	0.743 ± 0.038	0.936 ± 0.035	0.699 ± 0.022	0.896 ± 0.029	0.767 ± 0.045	0.917 ± 0.028	0.702 ± 0.042	0.905 ± 0.030	0.756 ± 0.045	0.910 ± 0.031
RTVue	Sn	0.834 ± 0.011	0.925 ± 0.033	0.760 ± 0.032	0.920 ± 0.031	0.856 ± 0.032	0.928 ± 0.022	0.789 ± 0.034	0.925 ± 0.027	0.823 ± 0.050	0.926 ± 0.034
	Sp	0.889 ± 0.009	0.980 ± 0.003	0.834 ± 0.017	0.986 ± 0.004	0.881 ± 0.009	0.988 ± 0.003	0.821 ± 0.022	0.990 ± 0.004	0.856 ± 0.013	<u>0.990±0.005</u>
				Performance Co	mparison Between	DRUNET and ONH	-Net - RTVue Trair	ed Framework			
Testing		RNFI	L		GCC	Other Re	tinal Layers	ł	RPE	C	oroid
Device		DRUNET	ONH-Net	DRUNET	ONH-Net	DRUNET	ONH-Net	DRUNET	ONH-Net	DRUNET	ONH-Net
	DC	0.711 ± 0.023	0.966 ± 0.029	0.700 ± 0.034	0.912 ± 0.028	0.733 ± 0.021	0.918 ± 0.026	0.676 ± 0.020	0.915 ± 0.020	0.733 ± 0.022	0.915 ± 0.021
Spectralis	Sn	0.801 ± 0.012	0.951 ± 0.035	0.778 ± 0.031	0.915 ± 0.028	0.846 ± 0.020	0.931 ± 0.031	0.765 ± 0.022	0.917 ± 0.036	0.820 ± 0.037	0.922 ± 0.033
	$\mathbf{S}\mathbf{p}$	0.823 ± 0.014	0.986 ± 0.003	0.802 ± 0.022	0.994 ± 0.003	0.851 ± 0.010	0.996 ± 0.001	0.787 ± 0.010	0.996 ± 0.003	0.855 ± 0.030	0.985 ± 0.006
i	DC	0.699 ± 0.021	0.942 ± 0.024	0.689 ± 0.032	0.939 ± 0.024	0.711 ± 0.032	0.907 ± 0.031	0.661 ± 0.052	0.909 ± 0.029	0.710 ± 0.030	0.911 ± 0.027
Cirrus	Sn	0.750 ± 0.032	0.954 ± 0.033	0.750 ± 0.025	0.916 ± 0.028	0.794 ± 0.022	0.922 ± 0.030	0.755 ± 0.041	0.901 ± 0.035	0.788 ± 0.022	0.905 ± 0.025
	$\mathbf{S}\mathbf{p}$	0.792 ± 0.040	0.995 ± 0.002	0.769 ± 0.025	0.993 ± 0.004	0.800 ± 0.014	0.994 ± 0.002	0.770 ± 0.021	0.984 ± 0.008	0.801 ± 0.008	0.993 ± 0.002
	DC	0.780 ± 0.012	0.951 ± 0.028	0.732 ± 0.034	0.911 ± 0.017	0.790 ± 0.023	0.925 ± 0.008	0.765 ± 0.024	0.917 ± 0.018	0.775 ± 0.026	0.931 ± 0.022
RTVue	Sn	0.856 ± 0.011	0.947 ± 0.010	0.812 ± 0.023	0.928 ± 0.019	0.856 ± 0.024	0.931 ± 0.019	0.845 ± 0.015	0.929 ± 0.024	0.867 ± 0.042	0.924 ± 0.020
	Sp	0.880 ± 0.009	0.997 ± 0.001	0.833 ± 0.010	0.991 ± 0.003	0.899 ± 0.008	0.995 ± 0.001	0.867 ± 0.008	0.995 ± 0.003	0.899 ± 0.032	0.991 ± 0.006

Table S14: The quantitative segmentation performance (DC: Dice coefficient; Sn: sensitivity; Sp: specificity) comparison between the 3D DRUNET and the ONH-Net when trained and tested on the DL enhanced OCT volumes. The metrics for each tissue that were significantly higher (p<0.05) are underlined and in bold.