On the Evaluation and Real-World Usage Scenarios of Deep Vessel Segmentation for Funduscopy: Additional Metrics

I. Evaluation

Extended result tables for our proposed method and previous published work.

TABLE I
COMPARISON WITH PREVIOUS WORKS ON DRIVE

		Target: DRIVE (584x565)				
Method	Year	F1	Acc	Pr	Re (Se)	Sp
2nd human observer		0.7931	0.7881	0.8072	0.7796	0.9717
Unsupervised		-		-	-	-
Bibiloni et al. [1]	2018	0.7521	0.938	0.786	0.721	0.970
Supervised						
Fraz et al. [2]	2012	0.7929	0.9480	**0.8532**	0.7406	0.9807
Jin et al. [3]	2019	0.8237	0.9566	0.8529	0.7963	0.9800
Laibacher et al. [4]	2018	0.8091	-	-	-	-
Li et al. [5]	2016	-	0.9527	-	0.7569	**0.9816**
Liskowski et al. [6]	2016	-	0.9535	-	0.7811	0.9807
Maninis et al. [7]	2016	**0.8220**	-	-	-	-
Marin et al. [8]	2011	0.8134	0.9452	0.9582	0.7067	0.9801
Orlando et al. [9]	2017	0.7857	-	0.7854	0.7897	0.9684
Yan et al. [10]	2018	0.8183	0.9529	0.8124	**0.8242**	0.9720
Zhao et al. [11]	2019	0.7882	-	-	-	-
M2U-Net DRIVE		0.8030	**0.9619**	0.8103	0.8000	0.9797
M2U-Net COVD –		0.7885	0.9592	0.7990	0.7824	0.9787
M2U-Net COVD – SSL		0.7913	0.9598	0.8016	0.7862	0.9789
All supervised methods use the same train-test split						

TABLE II
COMPARISON WITH PREVIOUS WORKS ON STARE

		Target: STARE (605x700)				
Method	Year	F1	Acc	Pr	Re (Se)	Sp
2nd human observer		-	0.9347	0.6432	**0.8955**	0.9382
Unsupervised		-	-	-	-	-
Bibiloni et al. [1]	2018	0.752	0.938	0.786	0.721	0.970
Supervised						
Fraz et al. [2]	2012	0.7747	0.9347	0.7956	0.7548	0.9763
Jin et al. [3]	2019	0.8143	0.9641	0.8777	0.7595	**0.9878**
Li et al. [5]	2016	-	0.9628	-	0.7726	0.9844
Maninis et al. [7]*	2016	**0.831**	-	-	-	-
Marin et al. [8]	2011	0.8080	0.9526	**0.9659**	0.6944	0.9819
Orlando et al. [9]	2017	0.7644	-	0.7740	0.7680	0.9738
Yan et al. [10]	2018	-	0.9612	-	0.7581	0.9846
Zhao et al. [11]*	2019	0.7960	-	-	-	-
M2U-Net STARE		0.8150	0.9727	0.8090	0.8257	0.9848
M2U-Net COVD –		0.8117	0.9724	0.8128	0.8114	0.9851
M2U-Net COVD – SSL		0.8196	**0.9734**	0.8164	0.8282	0.9847
*Same train-test split as adopted in this work						

TABLE III
COMPARISON WITH PREVIOUS WORKS ON IOSTAR

		Target: IOSTAR (1024x1024)				
Method	Year	F1	Acc	Pr	Re (Se)	Sp
Supervised						
Abbasi-Sureshjani et al. [12]	2015	-	0.9501		0.7863	0.9747
Meyer et al. [13]*	2017	-	0.9695	-	0.8038	0.9801
Zhang et al. [14]	2016	-	0.9514	-	0.7545	0.9740
Zhao et al. [11]	2019	0.7707	-	-	-	-
M2UNet IOSTAR		0.8173	0.9708	0.8081	0.8311	0.9831
M2U-Net COVD –		0.7928	0.9665	0.7755	0.8161	0.9798
M2U-Net COVD – SSL		0.7845	0.9644	0.7544	0.8221	0.9770
*Same train-test split as adopted in this work						

TABLE IV
COMPARISON WITH PREVIOUS WORKS ON CHASE_DB1

		Target: CHASE_DB1				
Method	Year	F1	Acc	Pr	Re (Se)	Sp
2nd human observer		0.7686	0.9538	-	-	-
Unsupervised						
Azzopardi et al. [15]	2015	-	0.9387	-	0.7585	0.9587
Zhang et al. [14]	2016	-	0.9452	-	0.7626	0.9661
Supervised						
Fraz et al. [2]*	2012	0.7566	0.9469	0.7415	0.7224	0.9711
Jin et al. [3]	2019	0.7883	0.9610	0.7630	0.8155	0.9752
Laibacher et al. [4]*	2018	0.8006	-	-	-	-
Li et al. [5]	2016	-	0.9581	-	0.7507	0.9793
Orlando et al. [9]	2017	0.7332	-	0.7438	0.7277	0.9712
Roychowdhury et al. [16]	2015	-	0.9530	-	0.7201	0.9824
Yan et al. [10]	2018	-	0.9610	-	0.7633	0.9809
M2U-Net CHASE_DB1		0.8022	0.9704	0.7985	0.8086	0.9835
M2U-Net COVD –		0.7884	0.9678	0.7710	0.8095	0.9807
M2U-Net COVD – SSL		0.7988	0.9694	0.7819	**0.8189**	0.9816
*Same train-test split as adopted in this work						

TABLE V
COMPARISON WITH PREVIOUS WORKS ON HRF

		Target: HRF (2336x3504)				
Method	Year	F1	Acc	Pr	Re (Se)	Sp
Unsupervised						
Annunziata et al. [17]	2016	0.7578	0.9581	0.8089	0.7128	0.9836
Budai et al. [18]	2013	-	0.9610	-	0.669	0.985
Odstrcilik et al. [19]	2013	0.7324	0.9494		0.7741	0.9669
Zhang et al. [14]	2016	-	0.9556	-	0.7978	0.9710
Supervised						
Orlando et al. [9]*	2017	0.7158	-	0.6630	0.7874	0.9584
Yan et al. [10]*	2018	0.7212	0.9437	0.6647	0.7881	0.9592
Laibacher et al. [4]*	2018	0.7814	0.9635	-	-	-
Jin et al. [3]*	2019	0.7988	0.9651	**0.8593**	0.7464	**0.9874**
Zhao et al. [11]	2019	0.7659	-	-	-	-
M2U-Net HRF		0.7800	0.9641	0.7798	0.7880	0.9798
M2U-Net COVD -		**0.8020**	**0.9669**	0.7889	**0.8188**	0.9802
M2U-Net COVD - SSL		0.7972	0.9659	0.7898	0.8021	**0.9807**
*Same train-test split as adopted in this work						

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