Table 1. Summary of several results for lesion detection/segmentation on IDRiD dataset

Reference	Backbone	Loss	PR/%	SE/%	SP/%	ACC/%	AUPR/%	AUC/%	F1/%
Hemorrhage detection/segmentation									
Guo et al. (2019)	FCN	Top-k loss, Bin loss	-	-	-	-	-	**67.34**	-
Yan et al. (2019a)	U-Net	weighted CE	-	-	-	-	**70.3**	-	-
Microaneurysms detection/segmentation									
Sarhan et al. (2019)(geometric)	FCN	Dice loss, CE and Triplet loss	**61.128**	28.07	-	-	41.96	-	**38.4877**
Guo et al. (2019)	FCN	Top-k loss, Bin loss	-	-	-	-	-	46.27	-
Yan et al. (2019a)	U-Net	weighted CE	-	-	-	-	52.5	-	-
Xue et al. (2019)	Mask-RCNN	log loss, regression loss, CE loss	-	**76.4**	**99.8**	**99.7**	-	-	-
Xia et al. (Knowledge-Based Systems 2021)	CNN	BCE	-	-	-	-	**77.9**	**99.5**	-
Hard exudate detection/segmentation									
Guo et al. (2020a)	HED	Top-k loss, Bin loss	-	95.74	-	-	-	**98.71**	**95.57**
Guo et al. (2019)	FCN	Top-k loss, Bin loss	-	-	-	-	-	79.45	-
Yan et al. (2019a)	U-Net	weighted CE	-	-	-	-	**88.9**	-	-
Xue et al. (2019)	Mask-RCNN	log loss, regression loss, CE loss	-	77.9	**99.6**	**99.2**	-	-	-
Huang et al. (Neurocomputing 2021)	CNN	CE loss	-	**98.40**	90.67	98.19	-	96.74	-
Soft exudate detection/segmentation									
Guo et al. (2019)	FCN	Top-k loss, Bin loss	-	-	-	-	-	**71.13**	-
Yan et al. (2019a)	U-Net	weighted CE	-	-	-	-	**67.9**	-	-
Joint detection/segmentation									
Wang et al. (ISBI 2021)	U-Net	BCE,MSE	**64.93 ±1.27**	**48.54 ±3.94**	**99.88 ±0.02**	**98.33 ±0.33**	-	-	-

Table 2. Summary of several results for lesion detection/segmentation on E-ophtha dataset

Reference	Task	Backbone	Loss	PR/%	SE/%	SP/%	ACC/%	AUPR/%	AUC/%	F1/%
Carson et al. (2018)	MA classification	CNN	-	-	-	-	-	**86**	**94**	-
Guo et al. (2019)	MA segmentation	FCN	Top-k loss, Bin loss	-	-	-	-	-	16.87	-
Xue et al. (2019)	MA segmentation	Mask-RCNN	log loss, regression loss and CE loss	-	**67.2**	**99.8**	**99.7**	-	-	-
Xia et al. (Knowledge-Based Systems 2021)	MA segmentation	CNN	BCE	-	-	-	-	**61.5**	**99.8**	-
Carson et al. (2018)	Exudates classification	CNN	-	-	-	-	-	**64**	**95**	-
Guo et al. (2020a)	EX detection	HED	Top-k loss, Bin loss	-	86.44	-	-	-	91.84	**87.01**
Guo et al. (2019)	EX segmentation	FCN	Top-k loss, Bin loss	-	-	-	-	-	41.71	-
Xue et al. (2019)	EX segmentation	Mask-RCNN	log loss, regression loss and CE loss	-	84.6	**98.8**	**98.4**	-	-	-
Huang et al. (Neurocomputing 2021)	EX segmentation	CNN	CE loss	-	**98.33**	91.17	97.65	-	**97.03**	-
Playout et al. (2019)	Bright Lesion segmentation	U-Net	loss based on Cohen's coefficient	**78.50**	**80.02**	**99.88**	**99.77**	-	-	**79.25**
Playout et al. (2019)	Red Lesion segmentation	U-Net	loss based on Cohen's coefficient	**75.26**	**75.62**	**99.99**	**99.88**	-	-	**75.44**

Table 3. Summary of several results for lesion detection/segmentation on DiaretDB1 dataset

Reference	Task	Backbone	Loss	PR/%	SE/%	SP/%	ACC/%	AUC/%	F1/%
Dai et al. (2018)	MA detection	CNN	-	**99.7**	**87.8**	-	**96.1**	**93.4**	-
Adem (2018)	Exudate detection	CNN	-	-	**99.2**	**97.97**	-	-	-
Playout et al. (2018)	Bright lesion segmentation	U-Net	loss based on Cohen's coefficient	-	75.35	99.86	-	-	-
Playout et al. (2019)	Bright lesion segmentation	U-Net	loss based on Cohen's coefficient	**81.70**	**88.29**	**99.93**	**99.89**	-	**84.87**
Playout et	Red lesion	U-Net	loss based on	-	66.91	99.82	-	-	-

al. (2018)	segmentation		Cohen’s coefficient						
Playout et al. (2019)	Red lesion segmentation	U-Net	loss based on Cohen’s coefficient	**78.96**	**85.18**	**99.89**	**99.83**	-	**81.95**

Table 4. Summary of several results for lesion detection/segmentation on other datasets

Reference	Task	Dataset	Backbone	Loss	SE/%	SP/%	AUC/%	mAP/%
van Grinsven et al. (2016)	HE detection	Kaggle	CNN	CE	**83.7**	**85.1**	**89.4**	-
van Grinsven et al. (2016)	HE detection	Messidor	CNN	CE	**91.9**	**91.4**	**97.2**	-
Huang et al. (2020)	HE segmentation	private	CNN	MSE, IoU, GIoU	-	-	-	**52.20**
Yan et al. (2018a)	Drusen segmentation	STARE, DRIVE	Encoder-decoder Network	-	**92.02**	**97.30**	-	-
Adem (2018)	Exudate detection	DiaretDB0	CNN	-	**100**	**98.41**	-	-
Adem (2018)	Exudate detection	DrimDB	CNN	-	**100**	**98.44**	-	-
Tan et al. (2017)	EX detection	CLEOPATRA	CNN	log-likelihood function	**87.58**	**98.73**	-	-
Tan et al. (2017)	HE detection	CLEOPATRA	CNN	log-likelihood function	**62.57**	**98.93**	-	-
Tan et al. (2017)	MA detection	CLEOPATRA	CNN	log-likelihood function	**46.06**	**97.99**	-	-
Guo et al. (2019)	EX segmentation	DDR	FCN	Top-k loss, Bin loss	-	-	**55.46**	-
Guo et al. (2019)	SE segmentation	DDR	FCN	Top-k loss, Bin loss	-	-	**26.48**	-
Guo et al. (2019)	HE segmentation	DDR	FCN	Top-k loss, Bin loss	-	-	**35.86**	-
Guo et al. (2019)	MA segmentation	DDR	FCN	Top-k loss, Bin loss	-	-	**10.52**	-
Xia et al. (Knowledge-Based Systems 2021)	MA segmentation	RC-RGB-MA	CNN	BCE	-	-	**99.9**	-

Table 5. Summary of several results for vessel segmentation on DRIVE dataset

Reference	Backbone	Loss	SE/%	SP/%	ACC/%	AUC/%	F1/%
Khalaf et al. (2016)	CNN	-	83.97	95.62	94.56	-	-
Liskowski and Krawiec (2016)	CNN	CE	**91.60**	92.41	92.30	97.38	-

Yu et al. (2020)	CNN	-	76.43	98.03	95.24	97.23	-
Fu et al. (2016)	FCN	CBCE	76.03	-	95.23	-	-
Dasgupta and Singh (2017)	FCN	CE	76.91	98.01	95.33	97.44	-
Feng et al. (2017)	FCN	CBCE	78.11	98.39	95.60	97.92	-
Oliveira et al. (2018)	FCN	categorical CE	80.39	98.04	95.76	98.21	-
Zhang and Chung (2018)	U-Net	CE	87.23	96.18	95.04	97.99	-
He et al. (2018)	U-Net	Focal loss	77.61	97.92	95.19	-	81.29
Yan et al. (2018b)	U-Net	Proposed segment-level loss	76.53	98.18	95.42	97.52	-
Yan et al. (2019b)	U-Net	CE	76.31	98.20	95.38	97.50	-
Wu et al. (2018)	U-Net	CE	78.44	98.19	95.67	98.07	-
Wu et al. (2020)	U-Net	CE	79.96	98.13	95.82	98.30	-
Wang et al. (2020)	U-Net	CE	78.49	98.13	95.67	97.88	82.41
Hu et al. (2018)	FCN	improved CE	77.72	97.93	95.33	97.59	-
Wu et al. (2019)	U-Net	CE	80.38	98.02	95.78	98.21	-
Soomro et al. (2019)	SegNet	CBCE	87	98.5	95.6	98.6	-
Zhang et al. (2019a)	U-Net	-	81.00	98.48	96.92	98.56	-
Wang et al. (2019a)	U-Net	CE and Jaccard loss	79.40	98.16	95.67	97.72	82.70
Ma et al. (2019)	U-Net	CE	79.16	98.11	95.70	98.10	-
Zhao et al. (2020a)	Dense U-Net	global pixel loss, local matting loss	83.29	97.67	-	-	82.29
Mishra et al. (2020)	U-Net	CE	89.16	96.01	95.40	97.24	-
Feng et al. (2020)	FCN	MSE	76.25	98.09	95.28	96.78	-
Cherukuri et al. (2020)	Residual FCN	MSE	84.25	98.49	97.23	98.70	-
Kromm and Rohr (2020)	CapsNet	margin loss	76.51	98.18	95.47	97.50	-
Liu et al. (2019a)	No-reference net	MSE	80.72	97.80	95.59	97.79	82.25
Wang et al. (MICCAI2020)	U-Net		81.07	98.45	96.81	98.17	-
Xu et al.(MICCAI2020)	U-Net	CE	91.2	94.7	-	98.1	-
Zhang et al. (MICCAI2020)	U-Net	-	82.15	98.45	97.01	98.67	82.67
Kamran et al. (MICCAI 2021)	GAN	Proposed loss	79.27	**99.69**	**97.90**	98.87	**86.90**
Zhou et al. (MICCAI 2021)	U-Net	CE	83.80	98.34	97.05	98.86	-

Mishra et al.(ISBI2021)	Encoder-decoder	Proposed	90.14	96.50	95.84	98.33	-
Wang et al.(ISBI2021)	U-Net	BCE	83.05	-	96.47	98.65	-
Wu et al. (MIA2021)	U-shape FCN	Dice loss	82.89±0.11	98.38±0.29	96.97±0.05	98.37±0.06	-
Li et al. (JBHI 2021)	U-Net	CE	81.45	98.83	97.69	**98.95**	-
Wang et al. (JBHI 2021)	U-Net	CE	80.71	97.82	95.65	98.01	82.51
Xu et al. (JBHI 2021)	Encoder-decoder	class-balanced CE	83.39	97.50	95.71	98.21	83.19
Zhao et al. (Pattern Recognition 2021)	Nested U-Net	CE	80.60	98.55	97.09	98.78	-
Chala et al. (Expert Systems with Applications 2021)	Encoder decoder	Dice loss	82.14	98.59	97.16	-	83.21
Yang et al. (Neurocomputing 2021)	Encoder decoder	Focal loss	83.53	97.51	95.79	-	82.97
Zhou et al. (Neurocomputing 2021)	Encoder decoder, GAN	Proposed	82.94	98.12	95.63	98.30	83.45

Table 6. Summary of several results for vessel segmentation on STARE dataset

Reference	Backbone	Loss	SE/%	SP/%	ACC/%	AUC/%	F1/%
Liskowski and Krawiec (2016)	CNN	CE	**93.07**	93.04	93.09	98.20	-
Yu et al. (2020)	CNN	-	78.37	98.22	96.13	97.87	-
Fu et al. (2016)	FCN	CBCE	74.12	-	95.85	-	-
Oliveira et al. (2018)	FCN	categorical CE	83.15	98.58	96.94	99.05	-
Zhang and Chung (2018)	U-Net	CE	76.73	99.01	97.12	98.82	-
He et al. (2018)	U-Net	Focal loss	81.20	98.95	97.04	-	85.53
Yan et al. (2018b)	U-Net	Proposed segment-level loss	75.81	98.46	96.12	98.01	-
Yan et al. (2019b)	U-Net	CE	77.35	98.57	96.38	98.33	-
Wu et al. (2020)	U-Net	CE	79.63	98.63	96.72	98.75	-
Wang et al. (2020)	U-Net	CE	90.24	**99.34**	**98.49**	**99.60**	**91.84**
Hu et al. (2018)	FCN	improved CE	75.43	98.14	96.32	97.51	-
Feng et al. (2020)	FCN	MSE	77.09	98.48	96.33	97	-
Soomro et al. (2019)	SegNet	CBCE	84.8	98.6	96.8	98.8	-
Cherukuri et al. (2020)	Residual FCN	MSE	86.64	98.95	98.03	99.35	-
Zhao et al. (2020a)	Dense U-Net	global pixel loss, local matting loss	84.33	98.57	-	-	83.51

Mishra et al. (2020)	U-Net	CE	87.71	96.34	95.71	97.42	-
Liu et al. (2019a)	No-reference net	MSE	77.71	98.43	96.23	97.93	80.36
Xu et al. (MICCAI 2020)	U-Net	CE	92.8	95.4	-	98.6	-
Kamran et al. (MICCAI 2021)	GAN	Proposed loss	83.56	98.64	97.54	98.87	83.23
Mishra et al. (ISBI2021)	Encoder-decoder	Proposed	89.11	97.23	96.66	98.59	-
Wu et al. (MIA2021)	U-shape FCN	Dice loss	82.07±0.66	98.39±0.68	97.36±0.28	98.77±0.06	-
Li et al. (JBHI 2021)	U-Net	CE	85.05	98.89	97.79	99.24	-
Wang et al. (JBHI 2021)	U-Net	CE	84.32	98.45	97.02	98.25	85.16
Xu et al. (JBHI 2021)	Encoder-decoder	class-balanced CE	84.63	98.02	96.64	98.81	83.84
Zhao et al. (Pattern Recognition 2021)	Nested U-Net	CE	85.11	99.00	97.94	99.44	-
Chala et al. (Expert Systems with Applications 2021)	Encoder decoder	Dice loss	80.96	98.41	96.53	-	82.61
Yang et al. (Neurocomputing 2021)	Encoder decoder	Focal loss	79.46	98.21	96.26	-	81.55
Zhou et al. (Neurocomputing 2021)	Encoder decoder, GAN	Proposed	88.12	97.81	96.71	98.63	-

Table 7. Summary of several results for vessel segmentation on CHASE DB1 dataset

Reference	Backbone	Loss	SE/%	SP/%	ACC/%	AUC/%	F1/%
Fu et al. (2016)	FCN	CBCE	71.30	-	94.89	-	-
Oliveira et al. (2018)	FCN	categorical CE	77.79	98.64	96.53	98.55	-
Zhang and Chung (2018)	U-Net	CE	76.70	**99.09**	97.70	99.00	-
Yan et al. (2018b)	U-Net	Proposed segment-level loss	76.33	98.09	96.10	97.81	-
Yan et al. (2019b)	U-Net	CE	76.41	98.06	96.07	97.76	-
Wu et al. (2018)	U-Net	CE	75.38	98.47	96.37	98.25	-
Wu et al. (2020)	U-Net	CE	80.03	98.80	96.88	98.94	-
Wang et al. (2020)	U-Net	CE	79.48	98.42	96.48	98.47	82.20
Wu et al. (2019)	U-Net	CE	81.32	98.14	96.61	98.60	-
Soomro et al. (2019)	SegNet	CBCE	88.6	98.2	97.6	98.5	-
Zhang et al. (2019a)	U-Net	-	81.86	98.48	97.43	98.63	-
Cherukuri et al. (2020)	Residual FCN	MSE	80.17	99.08	97.88	98.64	-
Wang et al. (2019a)	U-Net	CE and Jaccard loss	80.74	98.21	96.61	98.12	80.37

Mishra et al. (2020)	U-Net	CE	88.05	96.51	96.01	97.63	-
Liu et al. (2019a)	No-reference net	MSE	87.69	98.43	97.42	99.05	85.98
Wang et al. (MICCAI 2020)	U-Net	-	80.69	98.36	97.26	98.33	-
Xu et al. (MICCAI2020)	U-Net	CE	92.3	95.4	-	98.5	-
Kamran et al. (MICCAI 2021)	GAN	Proposed loss	81.99	98.06	96.97	99.14	**89.57**
Zhou et al. (MICCAI 2021)	U-Net	CE	86.90	98.43	97.71	**99.20**	-
Mishra et al. (ISBI 2021)	Encoder-decoder	Proposed	**89.07**	97.78	97.18	98.63	-
Wang et al.(ISBI2021)	U-Net	BCE	86.78	-	97.06	98.96	-
Wu et al. (MIA2021)	U-shape FCN	Dice loss	83.65 ±0.69	98.39 ±0.47	97.44 ±0.10	98.67 ±0.05	-
Li et al. (JBHI 2021)	U-Net	CE	83.34	98.62	**98.03**	99.12	-
Wang et al. (JBHI 2021)	U-Net	CE	84.27	98.36	97.06	98.24	81.05
Xu et al. (JBHI 2021)	Encoder-decoder	class-balanced CE	85.08	97.80	96.51	98.73	82.70
Yang et al. (Neurocomputing 2021)	Encoder decoder	Focal loss	81.76	97.76	96.32	-	79.97
Zhou et al. (Neurocomputing 2021)	Encoder decoder, GAN	Proposed	84.35	97.82	96.30	98.72	82.18

Table 8. Summary of several results for vessel segmentation on HRF dataset

Reference	Backbone	Loss	SE/%	SP/%	ACC/%	AUC/%	F1/%
Soomro et al. (2019)	SegNet	CBCE	82.9	96.1	96.2	**98.5**	-
Zhao et al. (2020a)	Dense U-Net	global pixel loss, local matting loss	78.09	98.18	-	-	78.13
Wu et al. (MIA2021)	U-shape FCN	Dice loss	81.14 ±0.22	**98.23 ±0.40**	**96.87 ±0.17**	98.42 ±0.05	-
Zhao et al. (Pattern Recognition 2021)	Nested U-Net	CE	**85.54**	97.41	96.48	98.24	-
Zhou et al. (Neurocomputing 2021)	Encoder decoder, GAN	Proposed	83.10	97.30	95.59	96.93	**82.11**

Table 9. Summary of several results for OD/OC segmentation on Drishiti-GS dataset

Reference	Backbone	Loss	OD		OC		δ
			Dice/%	IoU/%	Dice/%	IoU/%	
Edupuganti et al. (2018)	FCN	weighted CE	-	69.58	-	81.22	-

Mohan et al. (2018)	FCN	bootstrapped CE and Dice loss	96.4	-	-	-	-
Mohan et al. (2019)	FCN	bootstrapped CE and Dice loss	97.13	-	-	-	-
Liu et al. (2019e)	FCN	spatial-aware error function	**98**	-	89	-	-
Shankaranarayana et al.(2019)	Encoder-decoder net	multi-class CE	96.3	-	84.8	-	0.1045
Shah et al. (2019) (PSBN)	U-Net	logarithmic dice loss	95	91	88	**80**	-
Shah et al. (2019)(WRoIM)	U-Net	logarithmic dice loss	96	**93**	89	**80**	-
Wang et al. (2019c)	Deeplab, GAN	dice coefficient loss, smoothness loss and adversarial loss	97.4	-	**90.1**	-	**0.048**
Wang et al. (2019b)	DeeplabV3+, GAN	CE, MSE, Adversarial loss	96.1	-	86.2	-	-
Chen et al. (MICCAI 2021)	Encoder-decoder	CE	96.39 ± 1.33	-	83.53 ± 17.80	-	-
Zhang et al. (Knowledge-based systems 2021)	U-Net	CE	-	-	-	-	-

Table 10. Summary of several results for OD/OC segmentation on ORIGA dataset

Reference	Backbone	Loss	OD		OC		Rim		δ
			A/%	E	A/%	E	A/%	E	
Liu et al. (2019e)	FCN	spatial-aware error function	-	0.059	-	**0.208**	-	**0.215**	-
Fu et al. (2018a)	U-Net	proposed multi-label loss	98.3	0.071	93.0	0.230	94.1	0.233	0.071
Shankaranarayana et al.(2019)	Encoder-decoder net	multi-class CE	97.4	**0.051**	92.8	0.212	-	-	0.067
Yin et al. (2019)	RPN	Multi-label CE	98.6	0.066	**94.2**	**0.208**	**94.9**	0.224	**0.065**
Jiang et al. (2020)	atrous CNN and RPN	Smooth L1 loss and BCE	-	0.063	-	0.209	-	-	0.068
Wang et al. (Pattern Recognition 2021)	Encoder-decoder	Dice loss	**99.38 ±1.31**	-	-	-	-	-	-

Table 11. Summary of several results for OD/OC segmentation on RIM-ONE-r3 dataset

Reference	Backbone	Loss	OD				OC				δ
			A/%	E	Dice/%	IoU/%	A/%	E	Dice/%	IoU/%	
Shankaranarayanaet al. (2019)	Encoder-decoder net	multi-class CE	**97.5**	**0.058**	**97.0**	-	**92.0**	**0.284**	**87.6**	-	0.066
Shah et al. (2019)(PSBN)	U-Net	logarithmic dice loss	-	-	91	84	-	-	75	60	-

Shah et al. (2019)(WRoIM)	U-Net	logarithmic dice loss			94	**90**	-	-	82	**71**	-
Wang et al.(2019c)	Deeplab, GAN	dice coefficient loss, smoothness loss, adversarial loss	-	-	96.8	-	-	-	85.6	-	**0.049**
Wang et al. (2019b)	DeeplabV3 +, GAN	CE, MSE, Adversarial loss	-	-	89.8	-	-	-	81.0	-	-
Chen et al. (MICCAI 2021)	Encoder-decoder	CE	-	-	90.13 ± 3.06	-	-	-	79.78 ± 11.05	-	-
Li et al. (MICCAI 2021)	Transformer	Proposed domain adversarial loss	-	-	91.3	-	-	-	76.3	-	-
Zhang et al. (Knowledge-based systems 2021)	U-Net	CE	-	-	-	-	-	-	-	-	-

Table 12. Summary of several results for OD/OC segmentation on REFUGE dataset

Reference	Backbone	Loss	OD			OC			Rim		δ
			A/%	E	Dice/%	A/%	E	Dice/%	A/%	E	
Wang et al. (2019f)	RPN	Weighted CE, regression loss	-	-	95.3	-	-	87.2	-	-	0.047
Yin et al. (2019)	RPN	Multi-label CE	**97.9**	**0.088**	-	**98.0**	**0.223**	-	**93.6**	**0.204**	0.048
Wang et al. (2019c)	Deeplab, GAN	dice coefficient loss, smoothness loss and adversarial loss	-	-	**96.02**	-	-	**88.26**	-	-	**0.0450**
Liu et al. (2019d)	GAN	dice segmentation loss, adversarial loss and MSE loss	-	-	94.16	-	-	86.27	-	-	0.0481
Wang et al. (Pattern Recognition 2021)	Encoder-decoder	Dice loss	0.9627 ±0.0246	-	-	-	-	-	-	-	-
Zhang et al. (Knowledge- based systems 2021)	U-Net	CE	-	-	-	-	-	-	-	-	-

Table 13. Summary of several results for OD/OC segmentation on other datasets

Reference	Dataset	Backbone	Loss	OD		OC		δ
				E	Dice/%	E	Dice/%	
Mohan et al. (2018)	DrionsDB	FCN	bootstrapped CE, Dice loss	-	95.5	-	-	-
Mohan et al. (2019)	DrionsDB	FCN	bootstrapped CE, Dice loss	-	**96.6**	-	-	-
Mohan et al. (2018)	MESSIDOR	FCN	bootstrapped CE,	-	95.7	-	-	-

Mohan et al. (2019)	MESSIDOR	FCN	Dice loss bootstrapped CE, Dice loss	-	96.8	-	-	-
Fu et al. (Pattern Recognition 2021)	MESSIDOR	U-Net	Balanced CE	-	-	-	-	-
Wang et al. (Pattern Recognition 2021)	MESSIDOR	Encoder-decoder	Dice loss	-	**98.70 ±1.23**	-	-	-
Escorcia-Gutierrez et al. (Knowledge-based systems 2021)	MESSIDOR	CNN	-	-	-	-	-	-
Jiang et al. (2020)	SCES	atrous CNN, RPN	Smooth L1 loss, BCE	**0.063**	-	**0.209**	-	**0.068**
Sedai et al. (2017a)	EyePACS	VAE	negative KL-divergence, BCE	-	-	-	-	**0.80**

Table 14. Summary of several results for DR diagnosis/grading

Reference	Dataset	Category	Backbone	Loss	SE/%	SP/%	AUC/%	Kappa/%
David et al. (2016)	Messidor-2	4	CNN	-	**96.8**	**87.0**	**98.0**	-
Gulshan et al. (2016)	Messidor-2	2	Inception-v3	-	87.0	**98.5**	**99.0**	-
Gargeya and Leng(2017)	Messidor-2	2	CNN	2-class categorical CE	**93**	87	94	-
Wang et al. (2017)	Messidor	5	CNN	-	-	-	95.7	-
Lin et al. (2018)	Messidor	5	CNN	-	-	-	**96.8**	-
He et al. (TMI 2021)	Messidor	4	CNN	CE	-	-	-	**87.23**
Martinez-Murcia et al. (Neurocomputing 2021)	Messidor	2	CNN	-	**98.3**	**94.5**	-	-
Gargeya and Leng(2017)	E-Ophtha	2	CNN	2-class categorical CE	**90**	**94**	**95**	-
Quellec et al. (2017)	E-Ophtha	2	CNN	-	-	-	94.9	-
Gulshan et al. (2016)	EyePACS	2	Inception-v3	-	90.3	**98.1**	**99.1**	-
Gargeya and Leng(2017)	EyePACS	2	CNN	2-class categorical CE	**94**	98	97	-
Yang et al. (2017)	EyePACS	4	CNN	-	-	-	**95.90**	-
Quellec et al. (2017)	EyePACS	2	CNN	-	-	-	95.5	-
Galdran et al. (MICCAI 2020)	EyePACS	5	CNN	proposed	-	-	-	78.71 ± 0.28
Liu et al.(MICCAI2020)	EyePACS	-	CNN+GCN	-	-	-	-	72.7
Huang et al. (MICCAI 2021)	EyePACS	5	CNN	defined contrastive loss	-	-	-	83.22
Galdran et al. (MICCAI 2021)	EyePACS	5	CNN	CE	-	-	-	80.78
Wang et al. (AAAI2021)	EyePACS	5	CNN, encoder-decoder	proposed	-	-	-	83.7

He et al. (TMI 2021)	EyePACS	5	CNN	CE	-	-	-	86.78
Sun et al. (CVPR2021)	EyePACS	5	Transformer	proposed	-	-	-	**88.4**
Gondal et al. (2017)	DiaretDB1	2	CNN	-	**93.6**	**97.6**	**95.4**	-
Wang et al. (AAAI2021)	DDR	5	CNN, encoder-decoder	proposed	-	-	-	77.8
He et al. (TMI 2021)	DDR	5	CNN	CE	-	-	-	**78.63**
Foo et al. (2020)	SiDRP14-15	5(No DR here)	U-Net, VGG16	binary CE	-	-	**78.56**	-
Foo et al. (2020)	IDRiD	5(No DR here)	U-Net, VGG16	binary CE	-	-	**99.00**	-
Lin et al. (2018)	private	5	CNN	-	-	-	-	**87.5**
Krause et al. (2017)	private	5 (moderate or worse DR here)	Inception-v4	-	**97.1**	**92.3**	**98.6**	**84**
Li et al. (2018b)	private	2	Inception-v3	-	**92.5**	**98.5**	**95.5**	-
Zhang et al. (2019b)	private	2	CNN	CE	**97.5**	**97.7**	**97.7**	-
Zhang et al. (2019b)	private	4	CNN	CE	**98.1**	**98.9**	-	-
Gulshan et al. (2019)	hospital in Sankara	2	CNN	-	**92.1**	**95.2**	**98.0**	-
Gulshan et al. (2019)	hospitals in Aravind	2	CNN	-	**88.9**	**92.2**	**96.3**	-
Liu et al.(MICCAI2020)	APTOS2019	-	CNN+GCN	-	-	-	-	91.2
Xing et al.(MICCAI2021)	APTOS2019	5	Teacher-student net	Proposed loss	-	-	-	-
Yu et al. (MICCAI 2021)	APTOS2019	5	Transformer	CE	-	-	**97.9**	**92.0**
Bi et al. (MICCAI 2021)	APTOS2019	5	CNN	-	**99.46**	-	-	-
Marrakchi et al. (MICCAI 2021)	APTOS2019	5	CNN	CE	-	-	-	-
Yu et al. (MICCAI 2021)	RFMiD2020	2	Transformer	CE	**93.7**	-	**95.9**	-
Luo et al. (Pattern Recognition 2021)	private	5	CNN	-	-	-	-	-

Table 15. Summary of several results for glaucoma diagnosis/grading

Reference	Dataset	Backbone	Loss	SE/%	SP/%	ACC/%	BACC/%	AUC/%
Li et al. (2019a)/Li et al. (2020b)	RIM-ONE	CNN	K-L divergence function and CE	84.8	85.5	85.2	-	91.6
dos Santos Ferreira et al. (2018)	RIM-ONE, DRISHTI-GS	U-Net, CNN	-	**100**	**100**	**100**	-	**100**
Carvalho et al. (Neurocomputing 2021)	RIM-ONE, DRISHTI-GS	CNN,3DCNN	CE	**100**	93.02	96.40	-	96.5

Zhao et al. (ECCV 2020)	RIM-ONE	CNN, teacher-student	proposed	91.6	97.9	95.1	-	97.6
Zhao et al. (2019d)	ORIGA	CNN	contrastive loss and hinge loss	-	--	-	-	**92**
Liao et al. (2020)	ORIGA	CNN	-	-	-	--	-	88
Li et al. (2019a)	LAG	CNN	K-L divergence function and CE	95.4	95.2	95.3	-	97.5
Li et al. (2020b)	LAG	CNN	K-L divergence function and CE	95.4	**96.7**	96.2	-	98.3
Wu et al. (MICCAI 2020)	LAG	CNN, teacher-student	BCE	**98.72**	94.75	96.04	-	**99.51**
Zhao et al. (ECCV 2020)	LAG	CNN, teacher-student	proposed	97.21	97.07	97.12	-	99.31
Tian et al. (MICCAI 2021)	LAG	CNN (self-supervised way)	Proposed CCD loss	-	-	-	-	87.4
Bi et al. (MICCAI 2021)	LAG	CNN	-	97.08	-	**97.74**	-	-
Pal et al. (2018)	DRIONS-DB	Encoder-decoder network	Reconstruction loss and CE	-	-	-	-	**92.3**
Fu et al. (2018b)	SCES	U-Net, ResNet50	Dice coefficient loss and CE	**84.78**	**83.80**	-	**84.29**	**91.83**
Fu et al. (2018b)	SINDI	U-Net, ResNet50	Dice coefficient loss and CE	**78.76**	**71.15**	-	**74.95**	**81.73**
Raghavendra et al.(2018)	Private	CNN	-	**98.00**	**98.30**	**98.13**	-	-
Li et al. (2018a)	Private	Inception-v3	-	**95.6**	**92.0**	-	-	**98.6**
Phene et al. (2019)	Private	Inception-v3	-	-	-	-	-	**94.5**
Chai et al. (2018)	Private	FCN, CNN, Faster-RCNN	CE	**92.33**	**90.90**	**91.51**	-	-
Liu et al. (2019c)	Private FIGD	ResNet	CE	**96.2**	**97.7**	-	-	**99.6**
Wu et al. (MICCAI2020)	RIGA	Teacher-student net	BCE	**96.03**	**91.42**	**93.29**	-	**98.29**
Yu et al. (MICCAI2020)	DRISHTI	CNN	CE, KL loss	**91.43**	**74.19**	**86.14**	-	**89.63**
Li et al. (MICCAI2020)	SIGF	CNN+LSTM	-	**85.7**	**80.6**	**80.7**	-	**87.0**
Gunasinghe et al. (ISBI 2021)	REFUGE2	CNN+classifier	-	-	-	-	-	**97.85**
Jun et al. (Expert Systems with Applications 2021)	private	CNN	categorical cross-entropy loss with accuracy	**95.12**	**93.33**	**92.96**	-	-

Table 16. Summary of several results for AMD diagnosis/grading

Reference	Dataset	Backbone	Loss	Category	SE/%	SP/%	ACC/%	AUC/%	Kappa/%
Burlina et al. (2016)	AREDS	CNN with SVM	-	2(1vs.3,4)	**93.4**	**95.6**	**95.0**	-	-
Burlina et al. (2017)	AREDS	CNN with	-	2	-	-	88.4~91.6	**94~96**	-

Horta et al. (2017)	AREDS	SVM CNN with RF	-	2	66.34	88.95	79.04	84.76	-
Govindaiah et al. (2018)	AREDS	CNN	-	2	-	-	92.5	-	-
Govindaiah et al. (2018)	AREDS	CNN	-	-	-	-	**83**	-	-
Burlina et al. (2018)	AREDS	ResNet50	Regression loss	4	-	-	**75.7**	-	-
Peng et al. (2018)	AREDS	Inception-v3	-	6	**59.0**	**93.0**	**67.1**	-	**55.8**
Burlina et al. (2018)	AREDS	ResNet50	Regression loss	9	-	-	**59.1**	-	-
Grassmann et al. (2018)	AREDS, KORA	CNN	weighted k metric	13	-	-	**63.3**	-	-
Tan et al. (2018)	Collected	CNN	-	2	**96.43**	**93.75**	**95.45**	-	-
Bi et al. (MICCAI 2021)	private	CNN	-	-	**98.09**	-	**98.20**	-	-
Li et al. (TMI 2021)	Ichallenge-AMD	CNN (self-supervised)	proposed	2	**78.11**	-	**87.85**	**78.11**	-
Hervella et al. (Expert Systems with Applications 2021)	ADAM	CNN (self-supervised)	BCE	2	-	-	-	**89.57 ± 3.22**	-

Table 17. Summary of several results for other tasks

Reference	Task	Dataset	Backbone	Loss	SE/%	SP/%	ACC/%	AUC/%	F1/%	Dice/%
Sedai et al. (ISBI 2017)	Fovea seg	EyePACS	VGG16	CE						**81 ± 5**
Xie et al. (TMI 2021)	Fovea Localisation	PALM, Messidor	CNN	weighted sum of the Euclidean distance	-	-	-	-	-	-
Raj et al. (ISBI 2020)	A/V classification	HRF	ResNet50	CE	**90.7**	**91.5**	**91.5**	**96.5**		
Raj et al. (ISBI2020)	A/V classification	IOSTAR	ResNet50	CE	**92.5**	**93.2**	**93.2**	**97.5**		
Raj et al. (ISBI2020)	A/V classification	LES-AV	ResNet50	CE	**94.4**	**94.6**	**94.6**	**98**		
Galdran et al. (ISBI 2019)	A/V classification	LES-AV	U-Net	-	88	85	86	94	**86**	
Zhou et al. (MICCAI 2021)	A/V classification	LES-AV	Encoder-decoder GAN	adversarial loss, BCE, MSE	62.94 ±0.93	-	-	81.03 ±0.04	66.69 ±0.47	-
Raj et al. (ISBI2020)	A/V classification	DRIVE-AV	ResNet50	CE	**93.7**	**94.3**	**94.3**	**98**		

Galdran et al. (ISBI 2019)	A/V classification	DRIVE-AV	U-Net	-	89	90	89	95	**88**	
Zhou et al. (MICCAI 2021)	A/V classification	DRIVE-AV	Encoder-decoder GAN	adversarial loss, BCE, MSE	69.87 ±0.11	-	-	84.13 ±0.05	70.03 ±0.03	-
Galdran et al. (ISBI 2019)	A/V classification	INSPIRE	U-Net	-	**89**	**90**	**89**	**89**	**86**	
Zhou et al. (MICCAI 2021)	A/V classification	HRF-AV	Encoder-decoder GAN	adversarial loss, BCE, MSE	67.68 ±1.57	-	-	83.44 ±0.75	71.7 ±0.44	-
Mo et al. (Neurocomputing 2018)	DME recognition	HEI-MED	Residual net	CE				**97.09**		
Mo et al. (Neurocomputing 2018)	DME recognition	e-ophtha EX	Residual net	CE				**96.47**		
He et al. (MICCAI2019)	DME grading	IDRiD	VGG-16 XGBoost	-	**95.53**	**93.84**	**94.17**	**96.37**		
He et al. (MICCAI 2019)	DME grading	Messidor	VGG-16 XGBoost	-	**97.12**	**95.91**	**96.33**	**98.24**		
Cheng et al. (MICCAI 2021)	Image enhancement	Eye-Q	Encoder-decoder GAN	proposed	-	-	-	-	-	-
Cheng et al. (ISBI 2021)	Image enhancement	Eye-Q	Encoder-decoder GAN	proposed	-	-	-	-	-	-
Shen et al. (TMI 2021)	Image enhancement	Eye-Q	Encoder-decoder	proposed	-	-	-	-	-	-
Ilanchezian et al. (MICCAI 2021)	Gender Classification	UK Biobank	CNN	-	-	-	**85.26**	**93**	-	-
Li et al. (ISBI2021)	Image restoration	Collected	GAN	proposed	-	-	-	-	-	-
Li et al. (TMI 2021)	Pathological Myopia classification	Ichallenge-PM	CNN (self-supervised)	proposed	**99.12**	-	**99.19**	**99.12**	**99.18**	-
Hervella et al. (Expert Systems with Applications 2021)	Pathological Myopia classification	PALM	CNN (self-supervised)	BCE	-	-	-	**99.48 ± 0.58**	-	-