Supplementary Material: Occluded Face In-painting Using Generative Adversarial Networks — A Review*

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1 Research questions

The review attempts to answer the following research questions (RQ):

(RQ1) What are the state-of-the-art models used as baseline?
(RQ2) What are the datasets used in face inpainting?
(RQ3) What are the occlusions used during training?
(RQ4) What are the evaluation metrics?
(RQ5) What are the model performance?
(RQ6) What are the computational costs?

2 Research procedure

This review focuses the research on peer-reviewed online publishers' databases, recognized by the scientific community for their high standard of quality. Some leading publishers of scientific publications include Springer, ACM, IEEE, Elsevier, Taylor & Francis, Inderscience, Emerald, World Scientific and Wiley. The research was carried out on the Scopus[1] portal, which indexes the publications of these publishers and provides an integrated search engine with advanced options for searching, filtering and linking to articles.

Chart 1 describes the canonical form of the search string applied to the title, abstract, and keywords of articles.

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[1] http://www.scopus.com

Table 1: Canonical search string.

TITLE-ABS-KEY ((gan OR generative) AND (inpaint* OR *occlu*) AND (face OR facial)) AND (LIMIT-TO (SRCTYPE , “p”) OR LIMIT-TO (SRCTYPE , “j”)) AND (LIMIT-TO (PUBSTAGE , “final”)) AND (EXCLUDE (DOCTYPE , “cr”) OR EXCLUDE (DOCTYPE , “re”)) AND (LIMIT-TO (LANGUAGE , “English”)) AND (LIMIT-TO (PUBYEAR , 2021) OR LIMIT-TO (PUBYEAR , 2020) OR LIMIT-TO (PUBYEAR , 2019) OR LIMIT-TO (PUBYEAR , 2018) OR LIMIT-TO (PUBYEAR , 2017))

Search date: 18/Nov/2021.
Years: from 2017 to 2021.
Document types: Article and conference paper.
Publication stage: Final.
Source type: Conference Proceeding and Journal.
Language: English, Portuguese and Spanish.

3 Inclusion and exclusion criteria

The literature review applied inclusion (IC) and exclusion (EC) criteria to select the articles to be read. Only articles that met at least one IC and are not rejected by any EC were selected.

Inclusion criteria (IC):

(IC1) The article proposes a new generative architecture, loss, or dataset for facial inpainting.
(IC2) The article proposes a new generative architecture, loss, or dataset for face painting.

Exclusion criteria (EC):

(EC1) Duplicate articles.
(EC2) Non-peer-reviewed articles, such as white papers, reports, book chapters, etc.
(EC3) Articles that were not written entirely in English, Portuguese, or Spanish.
(EC4) Articles not related to generative adversarial networks, computer vision, facial occlusion or face painting.
(EC5) Non-primary studies, such as reviews and meta-analyses.
(EC6) Studies published before 2017.

Scopus filters EC2, EC3, EC5 and EC6 after executing the search string.

4 Exported format

The fields exported in BibTeX format are in chart 2.

Table 2: Fields exported from Scopus search.

Author(s) – Document title – Year – Source title – volume, issue, pages – Source & document type – DOI – Publisher – Editor(s) – Language of original document – Abstract – Author keywords

5 Data extraction

After applying the inclusion and exclusion criteria, each remaining article was read in full and the information necessary to answer the research questions was extracted. The data extracted from each study were:

(RQ1) Baseline models.
(RQ2) Datasets used for model training.
(RQ3) Occlusion objects and datasets.
(RQ4) Performance evaluation metrics.
(RQ5) Model performance.
(RQ6) Computational costs.

6 Results

The search on Scopus returned 127 articles, 67 of which were rejected for one or more exclusion criteria and the others were read in full. This section summarizes the information collected from the research papers.

6.1 (RQ1) What are the state-of-the-art models used as baseline?

Table 3 lists the frequency the baseline models are used in other studies.

Table 3: Frequency of baseline models used in other studies.

Baseline	Number of studies	Baseline reference
DeepFillv1	24	[84]
Global&Local	21	[25]
ContextEncoder	18	[54]
PartialConv	11	[39]
GFC	10	[35]

continue

continuation

Table 3: Frequency of baseline models used in other studies.

Baseline	Number of studies	Baseline reference
PatchMatch	8	[4]
SIIGM	7	[80]
Not available	7	-
EdgeConnect	7	[52]
deepfillv2	7	[83]
GMCNN	4	[68]
DCGAN	4	[60]
PICNet	3	[98]
CycleGAN	3	[99]
WGAN	2	[3]
TP-GAN	2	[23]
PEN-Net	2	[87]
MstNet	2	[92]
FCSW	2	[37]
EdgeCon2	2	[51]
DR-GAN	2	[62]
DFNet	2	[22]
CSA	2	[41]
Vid2Vid	1	[67]
UFID	1	[74]
SRN	1	[69]
SRGAN	1	[31]
SRC	1	[55]
SPN	1	[56]
SIMPCL	1	[79]
Shift-Net	1	[75]
SF	1	[61]
Self-regularization	1	[76]
RN	1	[86]
RGANFC	1	[66]
RegionFilling	1	[12]
OA-GAN	1	[14]
MVP+LDA	1	[103]
MSNPS	1	[77]
MLGN	1	[42]
Light-CNN	1	[71]
IdPrev	1	[96]
ICNN	1	[2]
GANimation	1	[57]
FRRN	1	[19]

continue

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Table 3: Frequency of baseline models used in other studies.

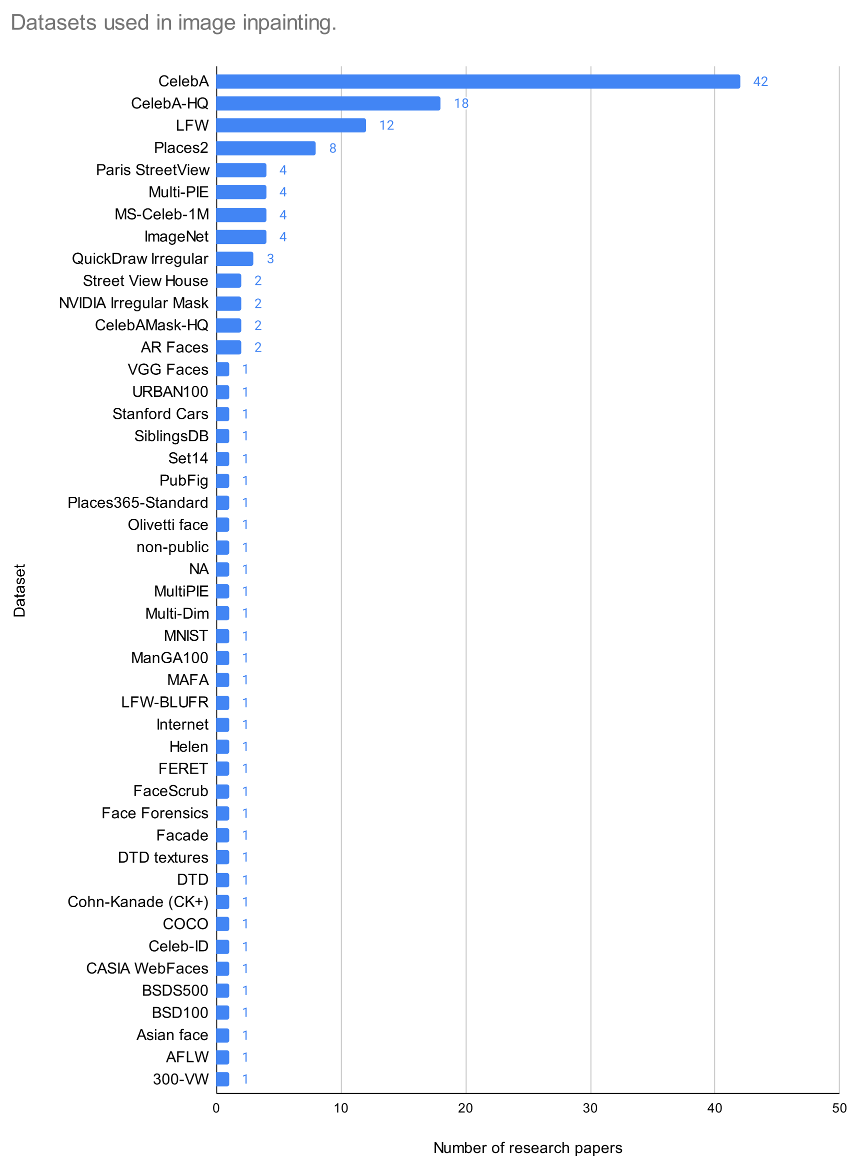
Baseline	Number of studies	Baseline reference
FIP+LDA	1	[102]
FF-GAN	1	[82]
Eyes2Face	1	[10]
DR-GANAM	1	[63]
DMFN	1	[24]
DeMeshNet	1	[93]
DEGNet	1	[95]
CPF	1	[81]
CL	1	[73]
CDCGAN	1	[18]
CA	1	[32]
BicycleGAN	1	[100]

6.2 (RQ2) What are the datasets used in face inpainting?

He *et al.* use a private dataset (“non-public”), Niu *et al.* don’t disclose the dataset used in the research, and Cai *et al.* use images from the internet [21,53,5].

Figure 1 shows the frequency the datasets are used in research. The face datasets CelebA, CelebA-HQ and LFW are the most frequent datasets. QuickDraw Irregular Mask and NVIDIA Irregular Mask are datasets of binary masks used to create a synthetic occlusion dataset. In addition to face inpainting, some research use non-face datasets such as number, places, facades, or objects. A research may use more than one dataset.

Fig. 1: Datasets used in the research of face inpainting. The top 3 are face datasets. QuickDraw Irregular Mask and NVIDIA Irregular Mask are datasets of binary masks used to create a synthetic occlusion dataset. “NA” means “not available”, “non-public” is a private dataset, and “internet” means images collected from the internet. A research may use more than one dataset.

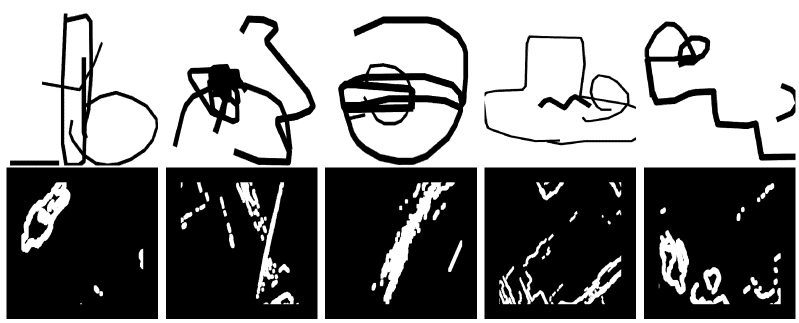


6.3 (RQ3) What are the occlusions used during training?

Model training requires a ground-truth occlusion-free face image to compare with the inpainted one. Since it's not possible to take pictures of the same individual with and without occlusions simultaneously, researchers create synthetic datasets. In general, the image of an object, binary mask or geometric shape with random normal noise or blank pixels is placed over the face image to create a synthetic occluded face dataset.

A simple method to create occluded images is placing objects over the face. Common objects are sunglasses, facial and eye masks, microphone, glasses, and hands. A binary mask is a matrix or a one-channel image whose pixel values are either 0 or 1. There's no hard convention on which value indicates the occluded and non-occluded regions, so the values may differ among models. The occlusion area may have any shape and size, such as square, circle, or irregular random format [38]. Yang *et al.* proposed an algorithm to create random rectangular and random shape masks [78]; whereas some studies use public available binary mask datasets [48,28,29]. The Quick Draw irregular mask dataset contains 50k training and 10k testing binary masks of size 512×512 pixels, and the test set in NVIDIA irregular mask dataset contains 12,000 binary masks with hole-to-image area ratios ranging from 0% to 60% and mask size 512×512 pixels. Figure 2 shows examples of binary masks in Quick Draw [26] and NVIDIA [40] irregular mask datasets.

Fig. 2: Binary masks datasets used to create synthetic occluded faces. The masks are placed over the entire image using equation 1. First rows: Quick Draw [26]. Second row: NVIDIA [40] irregular binary mask dataset.



The binary mask is used with an occluded-face or an occlusion-free image. In the first approach, the binary mask indicates the hidden parts in the occluded-face image, and both mask and input image are the inputs of the network's generator. In the second approach, the binary mask is combined with an occlusion-free image to create the masked image, which is the single input of the generator. The mask and image combination is a matrix multiplication given by equation 1.

$$I_{masked} = I \otimes \mathbf{M} \tag{1}$$

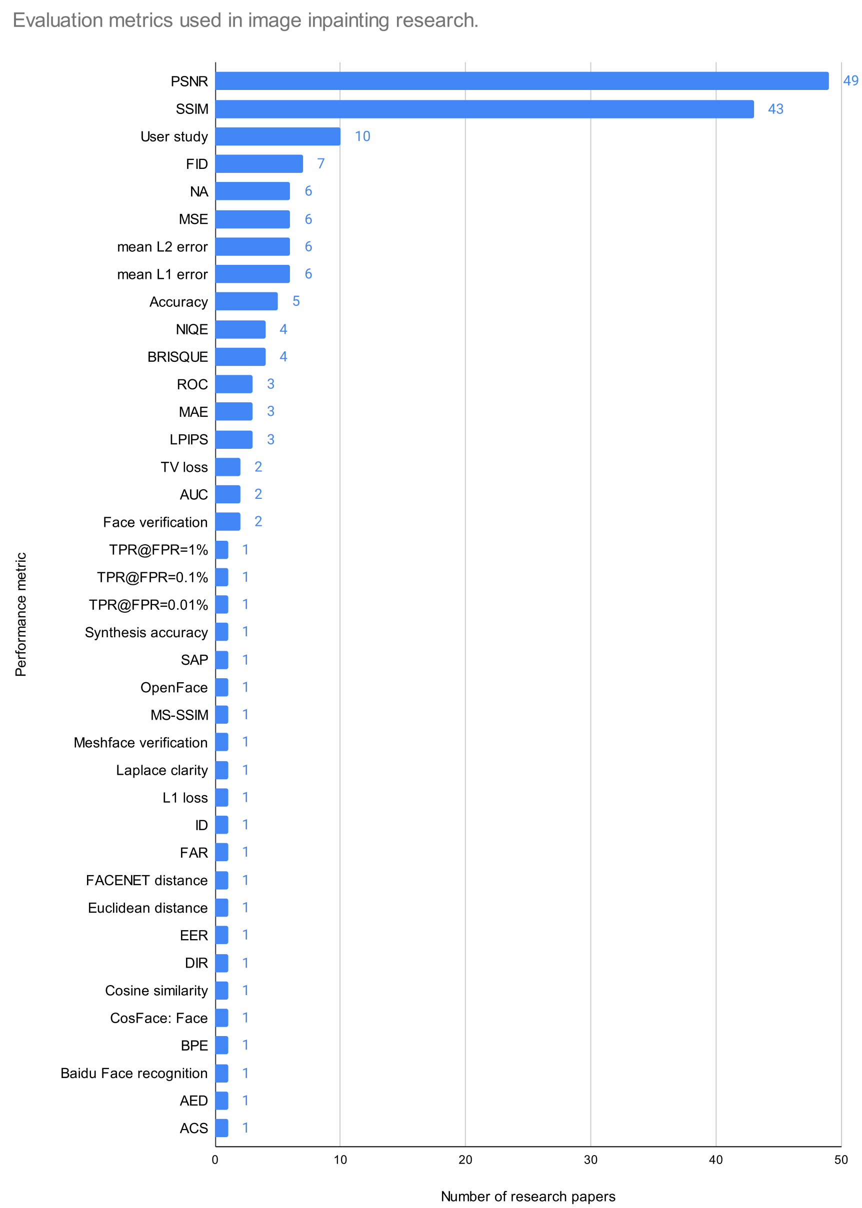
where I_{masked} is the masked image, I is the original image, $\mathbf{M}$ is the binary mask and $\otimes$ is the Hadamard product. The inverse of the mask is simply $\mathbf{1} - \mathbf{M}$, where $\mathbf{1}$ is a matrix of elements 1 with the same height and width as $\mathbf{M}$

Other less common synthetic occlusions are homocentric squares pattern masks [16], mesh-like occlusions with random position, width, and transparency [36], circles around eyes, nose, and mouth [72], and irregular convex fiducial masks formed by connecting the contouring landmarks of the corresponding facial fiducial points [33].

6.4 (RQ4) What are the evaluation metrics?

Forty-nine research report PSNR and forty-three research report SSIM, the two most frequent quantitative metrics. User study is the third most frequent metric used in 10 studies. The chart in figure 3 shows the frequency of evaluation metrics found in the literature.

Fig. 3: Evaluation metrics used in the research of face inpainting. PSNR and SSIM are pixel-level quantitative metric. User study is a qualitative metric. “NA” means “not available”. The others are quantitative metrics.



6.5 (RQ5) What are the models performance?

Tables 4 to 19 show the model performance with the evaluation metrics reported in respective study.

Table 4: Model performance by PSNR and SSIM.

Reference	Dataset	Occlusion %	PSNR	SSIM
[68]	CelebA-HQ 2k	-	25.7	0.955
[1]	CelebA	-	23.5	-
[46]	CelebA	-	20.4	0.832
[70]	CelebA	-	27.0	0.900
[58]	CelebA	20%	20.1	0.953
[58]	CelebA	40%	20.0	0.909
[58]	CelebA	60%	19.9	0.889
[58]	CelebA	80%	19.7	0.846
[96]	MS-celeb-1M	-	24.9	0.870
[6]	CelebA	O1	20.7	0.793
[6]	CelebA	O2	20.6	0.795
[6]	CelebA	O3	19.3	0.745
[6]	CelebA	O4	20.3	0.764
[6]	CelebA	O5	20.0	0.767
[6]	CelebA	O6	20.5	0.816
[6]	CelebA	average	20.2	0.780
[30]	CelebA	various	29.9	0.937
[50]	CelebA train /LFW test	center	35.6	-
[50]	CelebA train /LFW test	left	32.3	-
[50]	CelebA train /LFW test	mask	29.3	-
[50]	CelebA train /LFW test	random	37.1	-
[50]	CelebA train /LFW test	grid	30.2	-
[49]	-	25%	21.5	0.665
[36]	AR	-	23.9	0.917
[36]	MultiPIE	-	28.2	0.918
[36]	FERET	-	28.2	0.931
[36]	LFW	-	23.2	0.869
[91]	CelebA	25%	19.3	0.913
[91]	CelebA	50%	18.9	0.836
[7]	CelebA	-	20.7	0.842
[17]	CelebA	14%	31.6	0.960
[14]	-	-	22.4	0.754
[14]	-	-	22.4	0.752
[38]	Places365-Standard	25%	24.1	0.851
[38]	CelebA-HQ	25%	27.1	0.905
[97]	CelebA	20%	22.2	0.861
[5]	-	-	22.6	0.787

continue

continuation

Table 4: Model performance by PSNR and SSIM.

Reference	Dataset	Occlusion %	PSNR	SSIM
[20]	CelebA	-	24.2	0.832
[101]	CelebA	-	21.1	0.737
[88]	LFW	-	32.3	0.847
[64]	CelebA	-	26.8	0.874
[11]	Set1-CelebA	-	21.1	0.794
[11]	Set2-CelebA	-	20.4	0.870
[11]	Set1-LFW	-	22.0	0.834
[11]	Set2-LFW	-	19.8	0.871

Table 5: Model performance by PSNR, SSIM, NIQE and BRISQUE.

Reference	Dataset	Occlusion	PSNR	SSIM	NIQE	BRISQUE
[13]	-	Mask	28.7	0.908	0.908	40.883
[13]	-	Hands	26.9	0.882	4.443	24.206
[13]	-	Sunglass	28.9	0.914	4.458	38.111
[13]	-	Mic	31.3	0.944	4.105	34.038
[47]	-	medical mask or microphone	24.5	0.813	4.464	34.175
[27]	-	-	32.8	0.981	4.499	42.504
[30]	CelebA	-	-	-	3.548	29.970

Table 6: Model performance by PSNR, SSIM and MSE

Reference	Dataset	Occlusion	PSNR	SSIM	MSE
[16]	CelebA	-	31.6	0.950	51.89
[16]	Multi-PIE	-	31.4	0.940	53.74
[16]	Places2	-	28.5	0.920	120.72
[89]	CelebA	25%	27.4	0.900	128.34
[85]	-	rectangular mask	32.4	0.973	0.044
[85]	-	random mask	30.3	0.930	0.097
[27]	-	-	32.8	0.981	34.145

Table 7: Model performance by PSNR, SSIM and Identity Distance.

Reference	Dataset	Occlusion	PSNR	SSIM	Identity Distance
[59]	CelebA	Center - 25%	28.6	0.920	0.65
[59]	CelebA	Center - 50%	24.3	0.810	0.93
[59]	CelebA	Vertical - 50%	19.5	0.760	0.26
[59]	CelebA	Horizontal - 50%	19.8	0.960	0.48

Table 8: Model performance by PSNR, SSIM, FID and MAE.

Reference	Dataset	Occlusion	PSNR	SSIM	FID	MAE
[28]	CelebA-HQ	QuickDraw (1%∼60%)	40.4	0.940	3.09	31.91
[28]	Paris Street View	QuickDraw (1%∼60%)	39.6	0.910	17.64	33.81
[28]	Places2	QuickDraw (1%∼60%)	39.7	0.930	4.47	27.77
[44]	CelebA-HQ	10%∼20%	30.3	0.943	18.66	-
[44]	CelebA-HQ	20%∼30%	27.7	0.906	32.72	-
[44]	CelebA-HQ	30%∼40%	26.0	0.887	45.59	-
[44]	CelebA-HQ	40%∼50%	24.3	0.830	65.29	-
[44]	Façade	10%∼20%	28.0	0.928	10.22	-
[44]	Façade	20%∼30%	25.3	0.872	20.62	-
[44]	Façade	30%∼40%	24.3	0.832	21.83	-
[44]	Façade	40%∼50%	23.1	0.795	25.9	-
[44]	Places2	10%∼20%	27.6	0.918	14.05	-
[44]	Places2	20%∼30%	25.0	0.856	14.18	-
[44]	Places2	30%∼40%	23.1	0.807	25.95	-
[44]	Places2	40%∼50%	28.8	0.761	35.56	-
[44]	ImageNet	10%∼20%	28.1	0.910	15.02	-
[44]	ImageNet	20%∼30%	25.9	0.859	23.78	-
[44]	ImageNet	30%∼40%	23.9	0.812	35.22	-
[44]	ImageNet	40%∼50%	22.7	0.765	45.1	-
[48]	Places2/CelebA	QuickDraw 10-20%	27.7	0.900	-	1.65
[48]	Places2/CelebA	QuickDraw 20-30%	25.7	0.881	-	2.83
[48]	Places2/CelebA	QuickDraw 30-40%	23.5	0.810	-	3.69
[48]	Places2/CelebA	QuickDraw 40-50%	22.0	0.740	-	5.00
[48]	Places2/CelebA	Fixed (25%)	22.1	0.841	-	3.76
[78]	Paris Street View	Center mask	27.5	0.930	-	0.28

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Table 8: Model performance by PSNR, SSIM, FID and MAE.

Reference	Dataset	Occlusion	PSNR	SSIM	FID	MAE
[78]	Paris Street View	Random mask	25.4	0.920	153.28	0.71

Table 9: Model performance by PSNR, SSIM, MS-SSIM, TV and FID.

Reference	Dataset	PSNR	MS-SSIM	TV	FID
[72]	CelebA	28.6	0.982	12.8	36.2
[72]	300-VW	28.7	0.976	9.3	11.1

Table 10: Model performance by AED, ACS, SAP and FID

Reference	Dataset	AED	ACS	SAP	FID
[45]	LFW	0.8493	81.38%	94.19%	26.53
[45]	CelebA	0.7547	85.14%	98.04%	20.51

Table 11: Model performance by lowest score, highest score, average score and face recognition rate.

Reference	Dataset	Lowest score	Highest score	Average score	Face recognition rate
[45]	CelebA	65.32	98.73	94.21	96.10%

Table 12: Model performance by L1 loss, PSNR, SSIM and FID.

Reference	Dataset	Occlusion	L1 loss	PSNR	SSIM	FID
[9]	Places2	25%	0.034	23.0	0.791	23.4
[9]	CelebA-HQ	25%	0.024	25.7	0.900	8.3

Table 13: Model performance by AUC and ACC for face rotations at ±30º, ±60º and ±90º.

		±30○	±30○	±60○	±60○	±90○	±90○
Reference	Dataset	ACC	AUC	ACC	AUC	ACC	AUC
[33]	Multi-Dim	92.45	40.25	87.12	39.45	85.48	36.44

Table 14: Model performance by ACC and AUC.

Reference	Dataset	Occlusion	ACC(%)	AUC(%)
[15]	LFW	Key point region	87.78	93.88
[15]	LFW	Random block	89.58	94.75
[15]	LFW	Irregular block	86.66	92.89

Table 15: Model performance by PSNR, SSIM and Accuracy.

Reference	Dataset	PSNR	SSIM	Accuracy (%)
[90]	CelebA	34.3	0.894	94.42

Table 16: Model performance by PSNR, SSIM, LPIPS and FID.

Reference	Dataset	Occlusion	PSNR	SSIM	LPIPS	FID
[43]	CelebA	25%	27.5	0.933	0.045	3.21
[43]	CelebA-HQ	25%	27.2	0.920	0.042	7.14
[34]	CelebA-HQ	Irregular mask	26.6	0.942	0.076	-
[34]	CelebA-HQ	Center mask	25.3	0.953	0.056	-
[42]	CelebA	25%	28.0	0.930	0.056	-
[42]	CelebA-HQ	25%	26.3	0.900	0.047	-

Table 17: Model performance by rank-1, rank-5 and rank-10.

Reference	Dataset	Rank-1	Rank-5	Rank-10
[11]	Set2-CelebA	64,2 ± 4,7	76,3 ± 3,3	80,3 ± 2,4
[11]	Set2-LFW	68,6 ± 4,6	77,6 ± 3,4	80,1 ± 2,7

Table 18: Model performance by PSNR, SSIM, L1 and L2.

Reference	Dataset	PSNR	SSIM	L1	L2
[8]	CelebA	32.3	0.890	0.95	0.08
[29]	CelebA-HQ	29.9	0.940	66.09	81.03
[94]	CelebA	26.1	0.895	15.63	-
[94]	CelebA-HQ	26.2	0.890	6.74	-

Table 19: Model performance by L1 error and L2 error.

Reference	Occlusion	L1 error	L2 error
[83]	Rectangular mask	8.6%	2%
[83]	free-form mask	9.1%	1.6%

6.6 (RQ6) What are the computational costs?

Table 20 lists the inference time and number of parameters of models found in the literature, and table 21 shows the training time.

Table 20: Reported inference time per image on GPU and CPU.

Reference	GPU Model	Image size	GPU (ms)	CPU (s)	# of Params
[96]	NVIDIA GTX 1080	128×128	50		
[9]	NVIDIA TITAN X	256×256	28		
[65]	NVIDIA GTX 1080 Ti	256×256	13		
[68]	NVIDIA TITAN X	256×256	49		12.562M
[44]	NVIDIA TITAN XP	256×256	200	1.5	
[28]	NVIDIA GeForce GTX 1080 Ti	256×256	193		
[45]	NVIDIA GTX 1080 Ti	512×256	107		
[29]	NVIDIA Quadro P6000	512×512	193		
[83]	NVIDIA Tesla V100	512×512	210	1.9	41M
[84]	NVIDIA GTX 1080 Ti	512×512	200	1.5	2.9M
[68]	NVIDIA TITAN X	512×512	146		12.562M

Table 21: Training time of models reported in the literature.

Reference	Dataset	Image size	Batch size	Training time	Iterations	GPU
[72]	300-VW	-	12	8h	5 epochs	NVIDIA TITAN X

continue

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Table 21: Training time of models reported in the literature.

Reference	Dataset	Image size	Batch size	Training time	Iterations	GPU
[72]	Face Forensics	-	12	1.5h	5 epochs	NVIDIA TITAN X
[65]	Celeb-ID	256×256	12	3 days	-	NVIDIA GTX 1080 Ti
[72]	CelebA	128×128	16	15h	200k iterations	NVIDIA TITAN X
[16]	CelebA	128x128	-	3 days	50 epochs	NVIDIA TITAN X
[30]	CelebA	-	10	3 days	600 epochs	NVIDIA GeForce 1080 Ti
[42]	CelebA	256×256	10	3 days	40 epochs	-
[38]	CelebA-HQ	256×256	1	1.5 days	30 epochs	NVIDIA GTX 2070
[29]	CelebA-HQ	512×512	5	10 days	100 epochs	NVIDIA Quadro P6000
[28]	CelebA-HQ	256×256	5	7 days	100 epochs	NVIDIA GeForce GTX 1080 Ti
[78]	CelebA-HQ	256×256	16	1 day	40 epochs	NVIDIA RTX 5000 Max-Q
[42]	CelebA-HQ	256×256	10	3 days	80 epochs	-
[47]	CelebA Mask-HQ	256×256	12	3 days	600 epochs	NVIDIA GeForce 2080 Ti
[15]	Multi-PIE, LFW	128×128	4	6∼8 days	4∼5 epochs	NVIDIA 1080 Ti
[78]	Paris Street View	256×256	16	17h	52 epochs	NVIDIA RTX 5000 Max-Q
[38]	Place365-Standard	256×256	1	6h	30 epochs	NVIDIA GTX 2070
[84]	Places2	256x256	-	5 days	-	NVIDIA GTX 1080 Ti

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