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DEEP NEURAL FRAMEWORK FOR IMAGE INPAINTING AND INTERPOLATION

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ABSTRACT
Picture inpainting and addition are basic errands in computer vision, empowering the reclamation of lost or undermined locales in pictures and the era of smooth moves between outlines in video arrangements. This extend proposes a profound neural system that leverages progressed convolutional neural systems (CNNs) and generative ill-disposed systems (GANs) to realize high-quality picture recreation. The demonstrate coordinating consideration components and multi-scale include extraction to upgrade relevant understanding, guaranteeing consistent and outwardly coherent comes about. Moreover, a versatile misfortune work is consolidated to adjust basic consistency and surface authenticity. The system is prepared on different datasets to generalize over diverse picture spaces. Test comes about illustrate the adequacy of the proposed strategy in reestablishing lost pixels, remaking complex designs, and producing reasonable introductions. This work contributes to progressions in robotized picture preparing, with applications in therapeutic imaging, computerized reclamation, and video outline era.

1. INTRODUCTION

In later a long time, profound learning has revolutionized picture preparing, empowering shrewdly frameworks to reestablish and improve pictures with surprising exactness. Picture inpainting and addition are two basic assignments that bargain with remaking lost or harmed districts and producing smooth moves between picture outlines. Conventional approaches frequently battle with complex surfaces and huge lost zones, but profound neural systems (DNNs) have illustrated noteworthy progressions in taking care of such challenges. This venture centers on creating a Profound Neural System that leverages state-of-the-art designs, such as convolutional neural systems (CNNs) and generative ill-disposed systems (GANs), to attain high-fidelity picture rebuilding and introduction.

The proposed system points to coordinated progressed profound learning procedures to upgrade the precision and authenticity of reproduced pictures. By utilizing profound generative models, consideration instruments, and ill-disposed preparing, the framework can gather lost subtle elements whereas keeping up basic coherence and surface consistency. The inpainting module will be planned to reestablish blocked districts in pictures, whereas the introduction component will produce smooth moves between outlines in recordings or consecutive information. The execution will be optimized for tall execution utilizing large-scale datasets, guaranteeing vigorous generalization over different picture sorts. This venture has critical applications in different spaces, counting restorative imaging, film reclamation, and computer vision. The capacity to precisely reproduce lost parts of an picture or insert outlines can improve visual quality in advanced substance creation, legal examinations, and independent frameworks. By creating a Profound Neural System for Picture Inpainting and Insertion, this investigate points to thrust the boundaries of picture reproduction and contribute to the progression of AI-driven visual handling.

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2. IMAGE INPAINTING

For the modifying of misplaced districts in an picture, the comes approximately in a few cases are not one of a kind, especially for gigantic misplaced zones. Hence, there fundamentally exists two lines of examine inside the composing: (1) deterministic picture inpainting and (2) stochastic picture inpainting. Given a undermined picture, deterministic picture inpainting procedures because it were abdicate an inpainted result though stochastic picture inpainting methodologies can abdicate diverse conceivable comes approximately with a unpredictable assessing handle. Motivated by multi-modal learning, a couple of investigators have as of late centered on text-guided picture inpainting by giving additional information with substance prompts.

2.1 Deterministic Image Inpainting

From a high-level viewpoint, deterministic picture inpainting regularly takes after three primary approaches:
single-shot, two-stage, and dynamic systems. Within the single-shot strategy, a generator arrange forms the undermined picture in one step, specifically creating the inpainted result. The two-stage approach, on the other hand, includes two generators—one produces a harsh assess, whereas the moment refines it for made strides precision. In the mean time, the dynamic system takes an iterative approach, utilizing one or more generators to steadily reproduce the lost locales, especially along the picture boundaries.

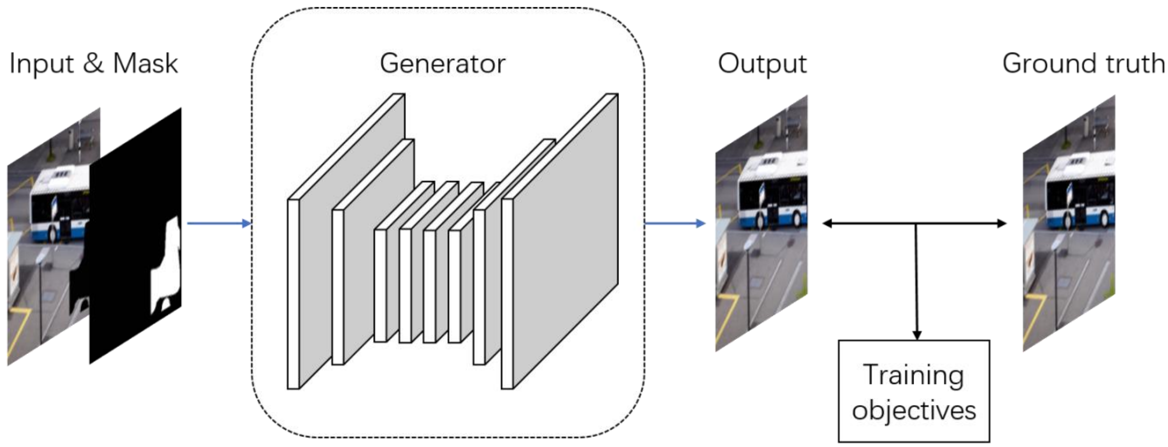

Figure 3: Representative pipeline of the single-shot inpainting framework.

2.2 Single-shot framework

Numerous existing inpainting strategies receive a single-shot system, as appeared in Fig. 3. It basically learns a mapping from a undermined picture to a total picture. The system as a rule comprises of generators and comparing preparing objectives.Generators. To make strides the inpainting capacity of the generator, there exist a few lines of inquire about: mask-aware plan, consideration instrument, multi-scale conglomeration, change space, encoder-decoder association, and profound earlier guidance.The lost districts (demonstrated with a double cover) have diverse shapes and convolutional operations covering with these lost districts may be the source of visual artifacts. Hence, a few analysts proposed mask-aware arrangements for classical convolutional operation and normalization. Motivated by the characteristic spatially changing property of picture inpainting, Ren et al. (2015) designed a Shepard addition layer where the highlight outline and cover both conduct the same convolution operation. Its yield is the division of highlight convolution and cover convolution comes about. Cover convolution can at the same time overhaul the cover. To way better handle different sporadic gaps and advance the gap amid veil updating, Liu et al. (2018) proposed a mask-guided convolution operation, i.e., fractional convolution, which recognizes between the substantial locale and gap in a convolutional window. Xie et al. (2019) proposed trainable bidirectional consideration maps to amplify the fractional convolution (Liu et al., 2018), which can adaptively learn the include re-normalization and mask-updating. Diverse from the highlight normalization considered by past methods, Yu et al. (2020) focused on the cruel and change shift-related normalization and presented a spatial region-wise normalization into the inpainting network. Wang et al. (2020c) designed a visual

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consistency organize for daze picture inpainting. They to begin with anticipated the harmed districts yielding a veil, and after that connected

2.1.2 Two-stage framework

Due to the computational overhead and the need of supervision for the relevant consideration in (Yu et al., 2018), Zeng et al. (2021b) removed this consideration square and learned its patch-borrowing behavior with a so-called relevant remaking misfortune. Based on the understanding that recuperating diverse sorts of lost zones require a diverse scope of neighboring areas, Quan et al. (2022) designed a neighborhood and worldwide refinement organize with little and huge open areas, which can be specifically connected to the conclusion of existing systems to encourage improve their inpainting capability. Kim et al. (2022) developed a coarse-super-resolution-refine pipeline, where they include a super-resolution organize to reproduce better points of interest after the coarse organize and present a dynamic learning component to repair bigger holes.Some works embrace a coarse-to-fine system to get high-resolution inpainting. Yang et al. (2017) designed a two-stage inpainting system comprising of a substance organize and a surface organize. The previous predicts the all encompassing substance within the moo determination (128×128) and the last mentioned iteratively optimizes the surface points of interest of lost locales from moo to tall determination (512×512). Song et al.

2.1.3 Progressive frameworks

Zhang et al. (2018a) formulated picture inpainting as a consecutive issue, where the lost locales are filled in four inpainting stages. They outlined an LSTM (long short-term memory) (Hochreiter and Schmidhuber, 1997)-based system to string these four inpainting stages together. In any case, this strategy cannot handle sporadic gaps common in real-world applications. Guo et al. (2019) devised a remaining engineering to dynamically upgrade sporadic covers and presented a full-resolution arrange to encourage include integration and surface remaking. Motivated by structure-guided inpainting methods (Nazeri et al., 2019; Xiong et al., 2019), Li et al. (2019c) proposed a dynamic reproduction with a visual structure arrange to consolidate structure data into the visual highlights step by step, which can produce a more organized picture. Dynamic inpainting strategies have the potential to fill in expansive gaps, be that as it may, it is still troublesome due to the need of limitations on the gap center. To handle this drawback, Li et al. (2020c) designed a repeat highlight thinking arrange with steady consideration and weighted include combination. This arrange repetitively gathers and assembles the gap boundaries of the highlight outline so as to dynamically reinforce the imperatives for evaluating inside contents. Zeng et al. (2020b) proposed an iterative inpainting strategy with certainty criticism for high-resolution pictures. SRInpaintor (Li et al., 2022a) combined super-resolution and the transformer in a dynamic pipeline. It reasons almost the worldwide structure in moo determination, and continuously refines the surface points of interest in tall determination.

2.4 Inpainting Mask

Sporadic masks. Letter masks ((Bertalmio et al., 2000; Bian et al., 2022)) and object-shaped masks ((Criminisi et al., 2004; Yi et al., 2020)) are especially planned for particular assignments, for case, caption evacuation and protest removal. Liu et al. (2018) introduced free-form covers, where the previous collected irregular streaks and self-assertive gaps from the comes about of the occlusion/dis-occlusion veil estimation strategy. The sporadic covers shared by (Liu et al., 2018) are exceptionally common within the existing inpainting methods. Suvorov et al. (2022) further part free-form veils into narrow masks, large wide veils, and large box veils, where two sorts of huge veils are produced by means of an forceful cover strategy examining polygonal chains with a tall irregular width and rectangles of irregular viewpoint proportions, individually.

3. VIDEO INPAINTING

3.1 Method

Not at all like pictures, recordings have an extra worldly measurement which gives additional data approximately objects or camera development. This data makes a difference systems to get an improved understanding of the setting of the video. Subsequently, the video inpainting assignment points to guarantee both spatial consistency and worldly coherence. Existing profound learning-based video inpainting strategies can be generally partitioned into four categories:

3D CNN-based approaches, shift-based approaches, flow-guided approaches, and attention-based approaches. We allude the perusers to more routine strategies in (Ilan and Shamir, 2015).

3.1.1 3D CNN-based Approaches

To bargain with the transient measurement, analysts proposed 3D CNN-based approaches, which regularly combine transient reclamation and picture inpainting. Wang et al. (2019a) proposed a two-stage pipeline to together gather worldly structure and spatial surface points of interest. The primary sub-network forms the low-resolution recordings with a 3D CNN, and the

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moment sub-network completes the original-resolution video outlines with an amplified 2D inpainting network (Iizuka et al., 2017). Motivated by the gated convolution in picture inpainting (Yu et al., 2019), Chang et al. (2019a) proposed a 3D gated convolution and a transient SN-PatchGAN for free-form video inpainting. They moreover coordinates the perceptual loss (Johnson et al., 2016) and fashion loss (Gatys et al., 2016) into the preparing objective. Hu et al.

3.1.2 Shift-based Approaches

Considering the tall computational fetched of 3D convolution, Lin et al. (2019) proposed a nonexclusive worldly move module (TSM) to capture worldly connections with tall effectiveness. This procedure is expanded for video inpainting. Chang et al. (2019b) developed a learnable gated TSM, which combines a TSM with learnable moving parts and gated convolution (Yu et al., 2019). They moreover prepared the 2D convolution layers in SN-PatchGAN (Yu et al., 2019) with gated TSM. In any case, TSM regularly leads to foggy substance due to misaligned highlights. To unravel this, Zou et al. (2021) proposed a spatially-aligned TSM (TSAM), adjusting highlights to the current outline after moving highlights. The arrangement handle is based on evaluated stream with a legitimacy mask. Ouyang et al. (2021) applied an inside learning technique for video inpainting, which certainly learns the data move from substantial locales to obscure parts in a single video test. They moreover outlined the slope regularization term and the anti-ambiguity misfortune term for worldly consistency reproduction and reasonable detail generation. Ke et al.

3.1.3 Flow-guided Approaches

Optical stream may be a common instrument to model the transient data in recordings, which is additionally connected to solve video inpainting. Based on the completed stream, the lost pixels within the current outline can be filled by proliferating pixels from neighboring frames. Kim et al. (2019b) modeled the video inpainting errand as a multi-to-single outline inpainting issue and proposed a 3D-2D encoder-decoder organize VINet. This organize incorporates a few stream and veil sub-networks in a dynamic way. They too presented the stream and twist misfortune to advance uphold transient
consistency. Chang et al. (2019c) proposed a three-stage video inpainting system comprising of a distorting organize, an inpainting arrange, and a refinement organize. Within the twisting organize, bilinear introduction is utilized to recoup foundation stream without learning. Then the refinement arrange chosen the leading candidate from two outlines completed by twisting and inpainting organize to produce the ultimate output. Zhang et al. (2019a) applied inside learning to induce both outlines and stream from input irregular clamor and utilized stream era misfortune to improve transient coherence. Xu et al. (2019) proposed a flow-guided completion system comprising of three steps. It to begin with fills the fragmented optical stream with stacked CNN systems, at that point engenders pixels from known districts to gaps with inpainted stream direction, and at last completes concealed districts with an image inpainting network (Yu et al., 2019). To decrease the over-smoothing within the boundary locales amid stream completion, they utilized difficult stream case mining to encourage the arrange to create sharp edges. To unravel the same problem, Gao et al. (2020) explicitly completed movement edges and utilized them to direct stream completion. In expansion, they presented a non-local stream association to empower substance proliferation from removed outlines.

3.1.4 Attention-based Approaches

The consideration instrument is regularly connected to show the relevant data and broaden the spatial-temporal window. Oh et al. (2019) recurrently calculated the consideration scores between the target and reference outlines, and dynamically filled gaps of the target outline from the boundary. Lee et al. (2019) firstly adjusted outlines by an relative change, and after that replicated pixels based on the similitude between the target outline and adjusted reference frames. Woo et al. (2020) proposed a coarse-to-fine framework for video inpainting. The primary arrange generally recoups the target gaps based on the computed homography between the target and reference outlines, and the moment arrange refines the filled substance with non-local consideration. They moreover presented an optical stream estimator to upgrade worldly consistency. Considering the movement of the frontal area objects is assorted, the choice of reference outlines gets to be more vital. Whereas other strategies take neighboring outlines or outlines in a particular remove as reference frames, Li et al. (2020a) dynamically overhauled long-term reference outlines after accumulating short-term adjusted highlights.

4. RESULTS AND DISCUSSION

Whereas the proposed system accomplishes state-of-the-art execution in both picture inpainting and insertion, there's room for enhancement. The demonstrate can be assist improved by coordination dissemination models and versatile misfortune capacities to make strides surface authenticity and auxiliary judgment. Furthermore, fine-tuning with domain-specific datasets (e.g., therapeutic imaging or chronicled picture rebuilding) can make strides vigor in specialized applications.

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Lessening computational complexity and optimizing preparing proficiency through lightweight designs or information refining can too make the demonstrate more down to earth for real-time applications

4.1 Performance of Machine Learning Models

To this end, we organize the important and prevalent technical aspects for the network design, as shown in Table 1.

Table 1. The summary of important techniques for deep learning-based image inpainting

Aspects	Blocks	Core idea
mask-aware convolution	Shepard interpolation (Ren et al., 2015)	translation variant interpolation
	partial convolution (Liu et al., 2018)	convolution on valid regions
	gated convolution (Yu et al., 2019)	adaptive gating
	priority-guided partial convolution (Wang et al., 2021c)	structure and texture priority
Attention	contextual attention (Yu et al., 2018)	background patches with high
		similarity to the coarse prediction
	coherent semantic attention (Liu et al., 2019)	correlation between patches within the hole
	multi-scale attention module (Wang et al., 2019b)	attention with two patch sizes
	multi-scale attention uint (Qin et al., 2021)	attention with four different dilation rates
Normalization	region normalization (Yu et al., 2020)	spatial and region-wise
	probabilistic context normalization (Wang et al., 2020c)	transfer mean and variance
	regional composite normalization (Wang et al., 2021a)	batch, instance, and layer normalization
	point-wise normalization (Zhu et al., 2021)	mask-ware batch normalization
	frequency region attentive normalization (Zhu et al., 2021)	align low- and high-frequency features
Discriminator	global discriminator (Pathak et al., 2016)	entire image
	local discriminator (Iizuka et al., 2017)	corrupted region
	patch-based discriminator (PatchDis) (Yu et al., 2019)	eense local patches
	conditional multi-scale discriminator (Li et al., 2020b)	PatchDis with two different scales
	soft mask-guided PatchDis (Zeng et al., 2022)	central parts of the missing regions

Taking after the fundamental thought of conventional inpainting strategies, a few works have been proposed to abuse dynamic inpainting with profound models. As appeared in Fig. 5, the progressive strategies iteratively fill within the gaps from the boundary to the center of the gaps, and the lost zone slowly gets to be littler until it disappears. Zhang et al. (2018a) formulated picture inpainting as a successive issue, where the lost districts are filled in four inpainting stages. They outlined an LSTM (long short-term memory) (Hochreiter and Schmidhuber, 1997)-based system to string these four inpainting stages together. Be that as it may, this strategy cannot handle unpredictable gaps common in real-world applications. Guo et al. (2019) devised a leftover design to continuously overhaul unpredictable covers and presented a full-resolution arrange to encourage highlight integration and surface reproduction. Motivated by structure-guided inpainting methods (Nazeri et al., 2019; Xiong et al., 2019), Li et al. (2019c) proposed a dynamic remaking with a visual structure arrange to consolidate structure data into the visual highlights step by step, which can produce a more organized picture. Dynamic inpainting strategies have the potential to fill in expansive gaps, in any case, it is still troublesome due to the need of limitations on the gap center. To handle this drawback, Li et al. (2020c) designed a repeat highlight thinking arrange with reliable consideration and weighted highlight combination. This arrange recurrently infers and assembles the gap boundaries of the highlight outline so as to dynamically fortify the limitations for assessing inner contents. Zeng et al. (2020b) proposed an iterative inpainting strategy with confidence criticism for high-resolution picture

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Table 2. Quantitative comparison of several representative image inpainting methods on CelebA-HQ and Places2. ‡ Higher is better. † Lower is better. From M1 to M6, the mask ratios are 1%-10%, 10%-20%, 20%-30%, 30%-40%, 40%-50%, and 50%-60%, respectively. Because of the heavy inference time, we do not show the results of RePaint for M1, M2, M4, and M6.

	Dataset	**CelebA-HQ**						**Places2**					
	Mask	M1	M2	M3	M4	M5	M6	M1	M2	M3	M4	M5	M6
ℓ1(%) †	RFR	1.59	2.47	3.58	4.90	6.44	9.47	0.83	2.20	3.93	5.83	7.96	11.37
	MADF	0.47	1.30	2.40	3.72	5.26	8.43	0.80	2.18	3.96	5.91	8.10	11.68
	DSI	0.60	1.65	3.08	4.80	6.83	11.11	0.88	2.42	4.48	6.75	9.32	13.82
	CR-Fill	0.79	2.15	3.95	6.01	8.33	13.18	0.78	2.17	4.02	6.11	8.46	12.43
	CoModGAN	0.48	1.38	2.66	4.28	6.20	10.53	0.72	2.05	3.83	5.89	8.27	12.58
	LGNet	0.46	1.28	2.38	3.72	5.27	8.38	0.68	1.89	3.51	5.33	7.41	10.86
	MAT	0.83	1.74	3.00	4.52	6.30	9.98	1.07	2.53	4.48	6.69	9.20	13.70
	RePaint	-	-	3.37	-	7.47	-	-	-	4.96	-	10.01	15.27
PSNR ‡	RFR	36.39	31.87	29.07	26.87	25.09	22.51	35.74	30.24	27.24	25.13	23.48	21.33
	MADF	39.68	33.77	30.42	27.95	25.99	23.07	36.17	30.37	27.17	25.00	23.31	21.10
	DSI	37.68	31.74	28.39	25.88	23.91	20.87	35.40	29.47	26.15	23.91	22.19	19.75
	CR-Fill	35.67	29.87	26.60	24.29	22.53	19.70	36.35	30.32	26.96	24.63	22.85	20.50
	CoModGAN	39.56	33.15	29.41	26.62	24.49	21.16	37.00	30.82	27.35	24.92	23.05	20.43
	LGNet	40.04	33.99	30.54	27.99	26.01	23.12	37.62	31.61	28.18	25.84	24.05	21.69
	MAT	38.44	32.62	29.21	26.70	24.72	21.78	35.66	29.76	26.41	24.09	22.30	19.81
	RePaint	-	-	28.38	-	23.16	-	-	-	26.04	-	21.72	18.99
SSIM ‡	RFR	0.991	0.976	0.957	0.932	0.902	0.834	0.983	0.952	0.911	0.862	0.805	0.699
	MADF	0.995	0.984	0.967	0.945	0.917	0.848	0.984	0.953	0.910	0.859	0.800	0.690
	DSI	0.992	0.976	0.951	0.918	0.877	0.778	0.982	0.945	0.892	0.832	0.763	0.636
	CR-Fill	0.988	0.965	0.931	0.890	0.842	0.729	0.985	0.954	0.909	0.855	0.794	0.675
	CoModGAN	0.994	0.981	0.960	0.929	0.891	0.792	0.987	0.957	0.914	0.860	0.796	0.671
	LGNet	0.995	0.985	0.968	0.945	0.917	0.849	0.988	0.963	0.925	0.878	0.823	0.714
	MAT	0.993	0.980	0.959	0.931	0.897	0.814	0.983	0.948	0.898	0.839	0.772	0.645
	RePaint	-	-	0.952	-	0.867	-	-	-	0.892	-	0.750	0.606
MS-SSIM ‡	RFR	0.992	0.976	0.956	0.933	0.900	0.830	0.986	0.960	0.924	0.880	0.828	0.731
	MADF	0.994	0.983	0.966	0.942	0.913	0.846	0.987	0.961	0.923	0.877	0.824	0.722
	DSI	0.992	0.976	0.952	0.919	0.878	0.784	0.984	0.952	0.905	0.850	0.785	0.664
	CR-Fill	0.987	0.963	0.928	0.887	0.839	0.732	0.987	0.960	0.920	0.872	0.814	0.704
	CoModGAN	0.994	0.980	0.958	0.926	0.888	0.793	0.988	0.961	0.921	0.870	0.810	0.692
	LGNet	0.995	0.984	0.968	0.945	0.917	0.851	0.990	0.968	0.935	0.894	0.844	0.744
	MAT	0.994	0.980	0.960	0.932	0.898	0.818	0.986	0.957	0.913	0.859	0.796	0.676
	RePaint	-	-	0.953	-	0.870	-	-	-	0.903	-	0.771	0.633
FID †	RFR	0.86	1.68	2.67	3.77	5.21	7.60	2.62	5.99	9.47	12.90	16.62	22.13
	MADF	**0.52**	**1.55**	**3.28**	**5.43**	**8.35**	**13.54**	**2.15**	**5.58**	**9.20**	**13.08**	**17.36**	**24.42**
	DSI	0.59	1.58	3.01	4.50	6.51	9.76	2.51	6.52	11.35	15.99	21.75	29.38
	CR-Fill	1.06	2.86	5.26	7.79	11.23	19.52	2.37	6.24	10.54	15.17	20.36	26.43
	CoModGAN	0.44	1.25	2.45	3.65	5.03	6.89	2.11	5.63	9.58	13.65	17.68	22.58
	LGNet	0.39	1.06	2.08	3.16	4.61	7.07	1.97	5.25	8.90	13.02	17.60	25.99
	MAT	0.41	1.13	2.05	2.96	4.05	5.43	2.13	5.47	9.26	13.00	16.62	21.88
	RePaint	-	-	2.14	-	4.24	-	-	-	8.85	-	15.90	21.58

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LPIPS †	RFR	0.015	0.028	0.042	0.060	0.081	0.118	0.021	0.047	0.074	0.106	0.142	0.201
	MADF	0.009	0.025	0.048	0.077	0.109	0.168	0.014	0.038	0.068	0.102	0.141	0.209
	DSI	0.010	0.026	0.048	0.074	0.104	0.160	0.018	0.047	0.085	0.125	0.169	0.242
	CR-Fill	0.017	0.043	0.074	0.107	0.143	0.212	0.016	0.042	0.076	0.114	0.156	0.226
	CoModGAN	0.008	0.022	0.041	0.065	0.092	0.143	0.016	0.044	0.080	0.121	0.164	0.236
	LGNet	0.006	0.017	0.031	0.048	0.069	0.108	0.014	0.035	0.064	0.096	0.132	0.198
	MAT	0.007	0.019	0.035	0.054	0.077	0.120	0.014	0.040	0.073	0.111	0.152	0.224
	RePaint	-	-	0.038	-	0.093	-	-	-	0.077	-	0.167	0.259

CONCLUSION

the predominance of visual information counting pictures and video advances the improvement of related preparing technologies eg picture and video inpainting due to their viable applications in numerous areas these procedures have pulled in awesome consideration from both the mechanical and inquire about communities over the past decade we displayed a survey of profound learning-based strategies for picture and video inpainting particularly we layout distinctive angles of the inquire about counting a scientific categorization of existing strategies preparing goals benchmark datasets assessment conventions execution assessment and real-world applications future inquire about bearings are moreover examined

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