DRCT: Saving Image Super-Resolution away from Information Bottleneck

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Abstract

In recent years, Vision Transformer-based applications to low-level vision tasks have achieved widespread success. Unlike CNN-based models, Transformers are more adept at capturing long-range dependencies, enabling the reconstruction of images utilizing information from non-local areas. In the domain of super-resolution, Swin-transformerbased approaches have become mainstream due to their capacity to capture global spatial information and their shifting-window attention mechanism that facilitates the interchange of information between different windows. Many researchers have enhanced image quality and network efficiency by expanding the receptive field or designing complex networks, yielding commendable results. However, we observed that spatial information tends to diminish during the forward propagation process due to increased depth, leading to a loss of spatial information and, consequently, limiting the model's potential. To address this, we propose the Dense-residual-connected Transformer (DRCT), aimed at mitigating the loss of spatial information through denseresidual connections between layers, thereby unleashing the model's potential and enhancing performance. Experiment results indicate that our approach is not only straightforward but also achieves remarkable efficiency, surpassing state-of-the-art methods and performing commendably at NTIRE2024.

1. Introduction

The task of Single Image Super-Resolution (SISR) is aimed at reconstructing a high-quality image from its low-resolution version. This quest for effective and skilled super-resolution algorithms has become a focal point of research within the field of computer vision, owing to its wide range of applications.

Following the foundational studies, CNN-based strategies [8, 10, 25, 31, 32, 56] have predominantly governed the super-resolution domain for an extended period. These strategies largely leverage techniques such as residual learning [19, 26, 38, 43, 53], or channel attention [46, 52] for de-

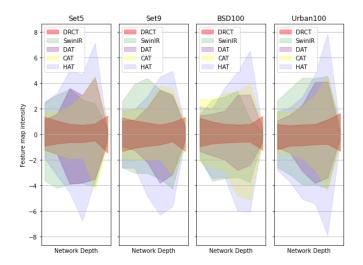


Figure 1. The feature map intensity on various benchmark datasets. We observed that feature map intensities decrease sharply at deeper network levels, indicating potential information loss. We propose DRCT, stabilizes this by enhancing receptive fields and adding dense-connections within residual blocks to mitigate information bottlenecks, thereby improving performance with a simpler model design.

veloping network architectures, significantly propelling the progress of super-resolution models forward.

CNN-based networks have achieved notable success in terms of performance. However, their inherent limitations stem from the parameter-dependent scaling of the receptive field and the local nature of convolutional interactions, which are independent of content. These characteristics limit CNNs' ability to effectively model long-range dependencies.

To overcome the limitations associated with CNN-based networks, researchers have introduced Transformer-based SISR networks that leverage the capability to model long-range dependencies, thereby enhancing SISR performance. Notable examples include IPT [3] and EDT [22], which utilize pre-training on the ImageNet [9] dataset to fully leverage Transformer capabilities for superior SISR results. SwinIR [24], inspired by the Swin-transformer [27] archi-

tecture, marks a significant advancement in SISR performance.

This approach significantly enhances capabilities beyond those of traditional CNN-based models across various benchmarks. Following SwinIR's success, several works [5, 7, 21, 24, 50, 51, 57, 58] have built upon its framework. These subsequent studies leverage Transformers to innovate diverse network architectures specifically for super-resolution tasks, showcasing the evolving landscape of SISR technology through the exploration of new architectural innovations and techniques.

While using HAT and SwinIR for inference across various datasets, we observed a common phenomenon: the intensity distribution of the feature maps undergoes more substantial changes as the network depth increases. This indicates the spatial information and attention intensity learned by the model. However, there's often a sharp decrease towards the end of the network, shrinking to a smaller range. This intriguing pattern suggests that such abrupt changes might be accompanied by a loss of information, indicating the presence of an information bottleneck.

Inspired by a series of works by Wang *et al.*, such as the YOLO-family [39, 42], CSPNet [40], and ELAN [41], we consider that network architectures based on SwinIR, despite significantly enlarging the receptive field through shift-window attention to address the issue of insufficient receptive fields in CNNs, are prone to gradient bottlenecks due to the loss of spatial information as network depth increases. This implicitly constrains the model's performance.

To address the issue of spatial information loss due to an increased number of network layers, we introduce the Dense-residual-connected Transformer (DRCT), designed to stabilize the forward-propagation process and prevent information bottlenecks. This is achieved by the proposed Swin-Dense-Residual-Connected Block (SDRCB), which incorporates Swin Transformer Layers and transition layers into each Residual Deep Feature Extraction group (RD-FEG). Consequently, this approach enhances the receptive field with fewer parameters and a simplified model structure, thereby resulting in improved performance.

2. Related works

2.1. Vision Transformer-based Super-resolution

IPT [3], a versatile model utilizing the Transformer encoder-decoder architecture, has shown efficacy in superresolution, along with denoising and deraining tasks. SwinIR [24], building on the Swin Transformer [27] encoder, employs self-attention within local windows during feature extraction, resulting in superior performance. UFormer [44] introduces an innovative local-enhancement window Transformer block, greatly reducing computational

demands for processing high-resolution features. Furthermore, it introduces a learnable multi-scale restoration modulator within the decoder to enhance the model's ability to detect both local and global patterns necessary for image restoration. ART [58] incorporates an attention retractable module to expand its receptive field, thereby enhancing SISR performance. CAT [6] leverages rectangle-window self-attention for feature aggregation, achieving a broader receptive field. It also integrates a locality complementary module to effectively merge global and local information, improving image restoration outcomes. HAT [5] integrates channel attention with window-based self-attention, leveraging both global information and precise local fitting abilities. Additionally, it introduces an overlapping crossattention module, specifically designed to improve the aggregation of information across different windows, thereby enhancing feature interaction and setting new benchmarks in the field.

2.2. Auxiliary Supervision and Feature Fusion

Auxiliary Supervision. Deep supervision is a commonly used auxiliary supervision method [20, 33] that involves training by adding prediction layers at the intermediate levels of the model [39–41]. This approach is particularly prevalent in architectures based on Transformers that incorporate multi-layer decoders. Another popular auxiliary supervision technique involves guiding the feature maps produced by the intermediate layers with relevant metadata to ensure they possess attributes beneficial to the target task [14, 15, 18, 43, 53]. Choosing the appropriate auxiliary supervision mechanism can accelerate the model's convergence speed, while also enhancing its robustness and performance.

Feature Fusion. Various studies have explored the integration of features across different dimensions in multiple visual tasks [26, 47] to enhance performance. In CNNs, attention mechanisms have been applied to both spatial and channel dimensions to improve feature representation; examples of which include RTCS [16] and SwinFusion [28]. In ViT [11], spatial self-attention is used to model the longrange dependencies between pixels. Additionally, some researchers have investigated the incorporation of channel attention within Transformers [4, 55] to effectively amalgamate spatial and channel information. This integration significantly enhances the modeling capabilities of Transformers.

3. Problem Statement

3.1. Information Bottleneck Principle

According to the information bottleneck principle [37], the given data X may cause information loss when going through consecutive layers. It may lead to gradient vanish

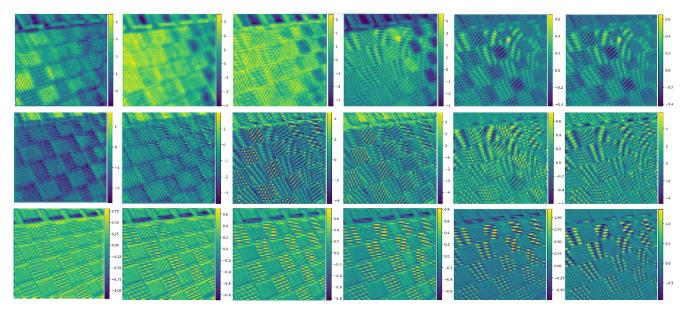


Figure 2. The feature map visualization displays, from top to bottom, SwinIR [24], HAT [5], and DRCT, with positions further to the right representing deeper layers within the network. For both SwinIR and HAT, the intensity of the feature maps is significant in the shallower layers but diminishes towards the network's end. We consider this phenomenon may imply the loss of spatial information, leading to the limitation and information bottleneck with SISR tasks.

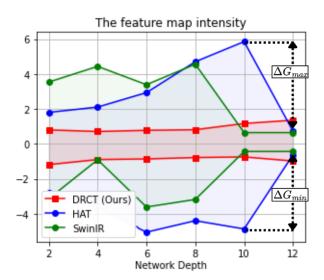


Figure 3. The G-index we propose is calculated by summing the absolute values of ΔG_{min} and ΔG_{max} , where ΔG represents the change in feature map intensity between two consecutive layers. This change is measured by the difference in intensity levels, capturing both the minimum and maximum shifts across layers.

when back-propagation for fitting network parameters and predicting Y, as shown in the equation below:

$$I(X,X) \ge I(Y,X) \ge I(Y,f_{\theta}(X)) \ge I(X,g_{\phi}(f_{\theta}(X))) \ge \dots \ge I(Y,\hat{Y})$$
(1)

where I indicates mutual information, f and g are transformation functions, and θ and ϕ are parameters of f and g,

respectively.

In deep neural networks, $f_{\theta}(\cdot)$ and $g_{\phi}(\cdot)$ respectively represent the two consecutive layers in neural network. From equation 1, we can predict that as the number of network layer becomes deeper, the original data will be more likely to be lost.

In term of SISR tasks, the general goal is to find the mapping function F to maximize the mutual information between HR and SR image.

$$F(I_{LR};\theta) = I_{SR}; \max_{\theta} I(I_{HR}; F(I_{LR}; \theta))$$
 (2)

3.2. Spatial Information Vanish in Super-resolution

Generally speaking, SISR methods [5–7, 21, 24, 50, 57, 58] can generally divided into three parts: (1) shallow feature extraction, (2) deep feature extraction, (3) image reconstruction.

In these methods, there is almost no difference between shallow feature extraction and image reconstruction. The former is composed of simple convolutional layers, while the latter consists of convolutional layers and upsampling layers. However, deep feature extraction differs significantly. Yet, their commonality lies in being composed of various residual blocks, which can be simply defined as:

$$X^{l+1} = X^l + f_{\theta}^{l+1}(X^l)$$
 (3)

where X indicates inputs, f is a consecutive layers for l'th residual group, and θ represents the parameters of f^l .

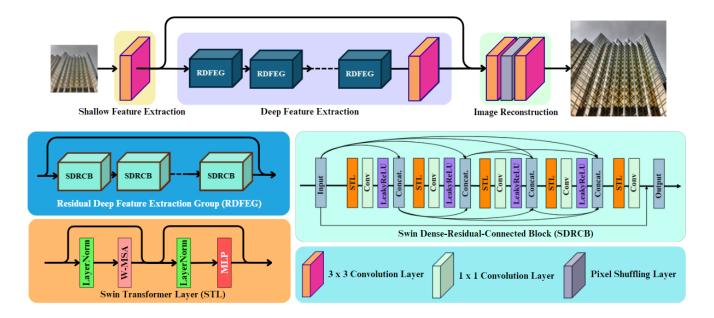


Figure 4. The overall architecture of the proposed DRCT and the structure of RDFEG and SDRCB.

Using residual learning allows the model to only update the differences between layers, rather than predicting the total output of a layer directly. This reduces the difficulty of model training and prevents gradient vanishing. However, according to our observations, while this design effectively transmits spatial information between different residual blocks, there may still be information loss.

Because the information within a residual block may not necessarily maintain spatial information, this ultimately leads to non-smoothness in terms of feature map intensity (refer to Fig. 2 and 3), causing an information bottleneck at the deepest layers during forward propagation. This makes it easy for spatial information to be lost as the gradient flow reaches the deeper layers of the network, resulting in reduced data efficiency or the need for more complex network designs to achieve better performance.

To better evaluate information loss, the G-index is defined by the sum of two components: the absolute change in the maximum intensities and the absolute change in the minimum intensities of the feature maps. It quantifies the absolute difference in both the highest and lowest feature map intensities between two consecutive layers.

$$GI = \sum_{l=1}^{L} (\|\Delta G_{min}^{l}\| + \|\Delta G_{max}^{l}\|)$$
 (4)

where L is the depth of network. G-index, encapsulating the total of these absolute changes, acts as a measure directly proportional to the information loss within the network. (refer to Figure 3.)

3.3. Dense-Residual Group Auxiliary Supervision

Motivated by RRDB [43], Wang *et al.* suggested that incorporating dense-residual connections can aggregate multilevel feature information and stabilize training through residual learning [25, 34]. Nonetheless, CNN-based approaches, which primarily focus on learning local information, often overlook the importance of capturing long-range dependencies. Recent studies on SwinIR-based methods have concentrated on enlarging the receptive field [5, 6, 58] or enhancing the network's capability to extract features [21, 44].

By adding dense connections within SwinIR-based blocks, we believe that it is possible to stabilize the gradient flow within each residual group during back-propagation, thereby addressing the issue of information bottlenecks and enhancing the receptive field. Consequently, this approach allows for achieving outstanding performance with simpler model architectures, or even by using shallower SISR networks.

4. Methodology

4.1. Network Architecture

As shown in Fig. 4, DRCT is composed of three distinct components: shallow feature extraction, deep feature extraction and image reconstruction module.

Shallow and deep feature extraction Given a low-resolution (LR) input $I_{LR} \in \mathbb{R}^{H \times W \times C_{in}}$ (H, W and C_{in} are the image height, width and input channel number, respectively), we use a 3×3 convolutional layer $\mathcal{C}_3(\cdot)$ [45] to

extract shallow feature $F_0 \in \mathbb{R}^{H \times W \times C}$ as

$$F_0 = \mathcal{C}_3(I_{LQ}),\tag{5}$$

Then, we extract deep feature which contains high-frequency spatial information $F_{DF} \in \mathbb{R}^{H \times W \times C}$ from F_0 and it can be defined as

$$F_{DF} = H_{DF}(F_0), (6)$$

where $H_{DF}(\cdot)$ is the deep feature extraction module and it contains K Residual deep feature extraction group (RD-FEG) and a convolutional layer \mathcal{C}_3 . More specifically, intermediate features F_1, F_2, \ldots, F_K and the output deep feature F_{DF} are extracted block by block as

$$F_i = RDFEG_i(F_{i-1}), \quad i = 1, 2, \dots, K,$$
 (7)

$$F_{DF} = \mathcal{C}_3(F_K),\tag{8}$$

Image reconstruction. We reconstruct the SR image $I_{SR} \in \mathbb{R}^{H \times W \times C_{in}}$ by aggregating shallow and deep features, it can be defined as:

$$I_{SR} = H_{REC}(F_0 + F_{DF}),$$
 (9)

where $H_{REC}(\cdot)$ is the function of the reconstruction module for fusing high-frequency deep feature F_{DF} and low-frequency feature F_0 together to obtain SR result.

4.2. Residual Deep Feature Extraction Group and Swin-Dense-Residual-Connected Block

In developing the RDFEG, we take cues from [16] and [43], employing a residual-dense block (RDB) as the foundational unit. The reuse of feature maps emerges as the enhanced receptive field in the RDB's feed-forward mechanism. The RDFEG contains a Swin-dense-residual-connected block (SDRCB) (refer to Figure 4), and the SDRCB can be defined as:

$$\begin{split} X_1 &= \operatorname{PE}\left(\mathcal{C}_\sigma\left(\operatorname{PUE}\left(\operatorname{STL}(X)\right)\right)\right) \\ X_2 &= \operatorname{PE}\left(\mathcal{C}_\sigma\left(\operatorname{PUE}\left(\operatorname{STL}\left(\operatorname{Cat.}(X,X_1),\right)\right)\right)\right) \\ X_3 &= \operatorname{PE}\left(\mathcal{C}_\sigma\left(\operatorname{PUE}\left(\operatorname{STL}\left(\operatorname{Cat.}(X,X_1,X_2)\right)\right)\right)\right) \\ X_4 &= \operatorname{PE}\left(\mathcal{C}_\sigma\left(\operatorname{PUE}\left(\operatorname{STL}\left(\operatorname{Cat.}(X,X_1,X_2,X_3)\right)\right)\right)\right) \\ X_5 &= \operatorname{PE}\left(\mathcal{C}_1\left(\operatorname{PUE}\left(\operatorname{STL}\left(\operatorname{Cat.}(X,X_1,X_2,X_3,X_4\right)\right)\right)\right) \end{split}$$

$$SDRCB(X) = \alpha \cdot X_5 + X \tag{10}$$

where $Cat.(\cdot)$ denotes the concatenation operator, which is designed to fuse multi-level feature. $STL(\cdot)$ represents the Swin-Transformer layer [24]. $PE(\cdot)$ and $PUE(\cdot)$ are the

patch embedding and patch unembedding operations [11], respectively. C_{σ} is the 1×1 convolutional layer with a LeakyReLU activate function for feature transition. The negative slope of LeakyReLU is set to 0.2. C_1 is the 1×1 convolutional layer. α is set to 0.2 for stabilizing the training process [43].

4.3. Same-task Progressive Training

In recent years, Progressive Training Strategy (PTS) [12, 54] have gained increased attention and can be seen as a method of fine-tuning. Compared to conventional training methods, PTS tends to converge model parameters to more desirable local-minima. Within the field of image processing, IPT [3] employs a variety of low-level tasks for pretraining, while EDT [22] utilizes different degradation levels within a single task. HAT [5] introduces the concept of same-task pre-training, where training on a larger and more diverse dataset like ImageNet [9] before fine-tuning on a specific dataset leads to improved super-resolution results. Lei et al. [49] proposed initially training a SISR network with L1-loss and then using L2-loss to eliminate artifacts, achieving better results on the PSNR metric. This concept has been widely adopted [58]. Our proposed Sametask Progressive Training (SPT), we first pre-trained DRCT on ImageNet to initialize model parameters and then finetuned on specific dataset with L1 loss as the optimization objective function,

$$Loss_1 = ||I_{HR} - I_{SR}||_1 \tag{11}$$

and finally use L2 loss to eliminate singular pixels and artifacts, therefore further archiving greater performance on PSNR metrics.

$$Loss_2 = ||I_{HR} - I_{SR}||_2 \tag{12}$$

5. Experiment Results

5.1. Dataset

Our DRCT model is trained on DF2K, a substantial aggregated dataset that includes DIV2K [1] and Flickr2K [36]. DIV2K provides 800 images for training, while Flickr2K contributes a larger set of 2650 images. For the training input, we generate low-resolution versions of these images by applying a bicubic downsampling method with scaling factors of 2, 3, and 4, respectively. To assess the effectiveness of our model, we conduct performance evaluations using well-known Image Super-Resolution benchmark datasets such as Set5 [2], Set14 [48], BSD100 [29], Urban100 [17], and Manga109 [30], which are standard in SISR tasks.

5.2. Implementation Details

The training process can be structured into three distinct phases, as ullustrated as Section 4-3. (1) pre-trained on Im-

Method	Scale	Training	Set5 [2] S		Set1	Set14 [48]		BSD100 [29]		Urban100 [17]		Manga109 [30]	
		Dataset	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM	
EDSR [25]	$\times 2$	DIV2K	38.11	0.9602	33.92	0.9195	32.32	0.9013	32.93	0.9351	39.10	0.9773	
RCAN [52]	$\times 2$	DIV2K	38.27	0.9614	34.12	0.9216	32.41	0.9027	33.34	0.9384	39.44	0.9786	
SAN [8]	$\times 2$	DIV2K	38.31	0.9620	34.07	0.9213	32.42	0.9028	33.10	0.9370	39.32	0.9792	
IGNN [56]	$\times 2$	DIV2K	38.24	0.9613	34.07	0.9217	32.41	0.9025	33.23	0.9383	39.35	0.9786	
HAN [32]	$\times 2$	DIV2K	38.27	0.9614	34.16	0.9217	32.41	0.9027	33.35	0.9385	39.46	0.9785	
NLSN [31]	×2	DIV2K	38.34	0.9618	34.08	0.9231	32.43	0.9027	33.42	0.9394	39.59	0.9789	
SwinIR [24]	×2	DF2K	38.42	0.9623	34.46	0.9250	32.53	0.9041	33.81	0.9427	39.92	0.9797	
CAT-A [6]	×2	DF2K	38.51	0.9626	34.78	0.9265	32.59	0.9047	34.26	0.9440	40.10	0.9805	
HAT [5]	×2	DF2K	38.63	0.9630	34.86	0.9274	32.62	0.9053	34.45	0.9466	40.26	0.9809	
DAT [7]	×2	DF2K	38.58	0.9629	34.81	0.9272	32.61	0.9051	34.37	0.9458	40.33	0.9807	
DRCT (Ours)	$\times 2$	DF2K	38.80	0.9646	35.02	0.9291	32.79	0.9071	34.58	0.9474	40.41	0.9816	
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EDT† [22]	$\times 2$	DF2K	38.63	0.9632	34.80	0.9273	32.62	0.9052	34.27	0.9456	40.37	0.9811	
HAT-L† [5]	$\times 2$	DF2K	38.91	0.9646	35.29	0.9293	32.74	0.9066	35.09	0.9505	41.01	0.9831	
DRCT-L‡ (Ours)	$\times 2$	DF2K	39.14	0.9658	35.36	0.9302	32.90	0.9078	35.17	0.9516	41.14	0.9842	
EDSR [25]	×3	DIV2K	34.65	0.9280	30.52	0.8462	29.25	0.8093	28.80	0.8653	34.17	0.9476	
RCAN [52]	$\times 3$	DIV2K DIV2K	34.74	0.9299	30.65	0.8482	29.32	0.8033	29.09	0.8702	34.44	0.9499	
SAN [8]	$\times 3$	DIV2K	34.75	0.9300	30.59	0.8476	29.33	0.8112	28.93	0.8671	34.30	0.9494	
IGNN [56]	$\times 3$	DIV2K DIV2K	34.72	0.9298	30.66	0.8484	29.31	0.8105	29.03	0.8696	34.39	0.9496	
HAN [32]	$\times 3$	DIV2K	34.75	0.9299	30.67	0.8483	29.32	0.8110	29.10	0.8705	34.48	0.9500	
NLSN [31]	$\times 3$	DIV2K	34.85	0.9306	30.70	0.8485	29.34	0.8117	29.25	0.8726	34.57	0.9508	
SwinIR [24]	$\times 3$	DF2K	34.97	0.9318	30.93	0.8534	29.46	0.8145	29.75	0.8826	35.12	0.9537	
CAT-A [6]	×3	DF2K	35.06	0.9326	31.04	0.8538	29.52	0.8160	30.12	0.8862	35.38	0.9546	
HAT [5]	×3	DF2K	35.07	0.9329	31.08	0.8555	29.54	0.8167	30.23	0.8896	35.53	0.9552	
DAT [7]	×3	DF2K	35.16	0.9331	31.11	0.8550	29.55	0.8169	30.18	0.8886	35.59	0.9554	
DRCT (Ours)	×3	DF2K	35.18	0.9338	31.24	0.8569	29.68	0.8182	30.34	0.8910	35.76	0.9575	
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EDT† [22]	$\times 3$	DF2K	35.13	0.9328	31.09	0.8553	29.53	0.8165	30.07	0.8863	35.47	0.9550	
HAT-L† [5]	$\times 3$	DF2K DF2K	35.13	0.9328	31.47	0.8584	29.63	0.8103	30.92	0.8981	36.02	0.9576	
DRCT-L‡ (Ours)	$\times 3$	DF2K DF2K	35.28 35.32	0.9348	31.54	0.8591	29.68	0.8191	31.14	0.8981	36.16	0.9570	
EDSR [25]	×4	DIV2K	32.46	0.8968	28.80	0.7876	27.71	0.7420	26.64	0.8033	31.02	0.9148	
RCAN [52]	$\times 4$	DIV2K DIV2K	32.40	0.9002	28.87	0.7889	27.71	0.7420	26.82	0.8033	31.02	0.9148	
SAN [8]	×4	DIV2K DIV2K	32.64	0.9002	28.92	0.7888	27.77	0.7436	26.79	0.8068	31.18	0.9173	
IGNN [56]	×4	DIV2K DIV2K	32.57	0.8998	28.85	0.7891	27.77	0.7434	26.84	0.8090	31.28	0.9182	
HAN [32]	×4	DIV2K DIV2K	32.64	0.9002	28.90	0.7890	27.80	0.7442	26.85	0.8094	31.42	0.9177	
NLSN [31]	×4	DIV2K DIV2K	32.59	0.9002	28.87	0.7891	27.78	0.7444	26.96	0.8109	31.42	0.9177	
SwinIR [24]	×4	DF2K	32.92	0.9044	29.09	0.7950	27.76	0.7489	27.45	0.8254	32.03	0.9260	
CAT-A [6]	×4	DF2K	33.08	0.9052	29.18	0.7960	27.99	0.7510	27.49	0.8339	32.39	0.9285	
HAT [5]	×4	DF2K	33.04	0.9056	29.23	0.7973	28.00	0.7517	27.97	0.8368	32.48	0.9292	
DAT [7]	×4	DF2K	33.08	0.9055	29.23	0.7973	28.00	0.7517	27.87	0.8343	32.51	0.9291	
DRCT (Ours)	×4	DF2K	33.11	0.9064	29.35	0.7984	28.18	0.7532	28.06	0.8378	32.59	0.9304	
DRC1 (Guis) = = = = = = = = = = = = = = = = = = =	= = = = = = = = = = = = = = = = = = =		32.64		29.01	======	27.82	+ = = = = :	27.26	= = = = =	=====	= = = = =	
EDT [22]	$\times 4$	ImageNet DF2K	32.82	0.9031	29.01	0.7939	27.82	0.7483	27.46	0.8246	32.05	0.9254	
HAT-L† [5]	$\times 4$	DF2K DF2K	33.30	0.9031	29.09	0.7939	28.09	0.7483	28.60	0.8498	33.09	0.9234	
DRCT-L‡ (Ours)	$\times 4$	DF2K DF2K	33.37	0.9083	29.47 29.54	0.8013	28.16	0.7577 0.7577	28.70	0.8498	33.14	0.9333 0.9347	
DRC1-L4 (Ours)	X4	DI'ZK	33.37	0.2020	47.34	0.0025	20.10	0.7577	40./U	0.0500	33.14	0.7347	

Table 1. Quantitative comparison with the several peer-methods on benchmark datasets. "†" indicates that methods adopt pre-training strategy [5] on ImageNet. "‡" represents that methods use same-task progressive-training strategy. The top three results are marked in **red**, **blue**, and **orange**, respectively.

ageNet [9], (2) optimize the model on the given dataset, (3) L2-loss for PSNR enhancement. Throughout the training process, we use the Adam optimizer with β_1 = 0.9, and β_2 = 0.999 and train for 800k iterations in each stage. The

learning rate is set to 2e-4, the multi-step learning scheduler is also used. The learning rate is halved at the 300k, 500k, 650k, 700k, 750k iterations respectively. Weight decay is not applied and the batch-size is set to 32. In the ar-

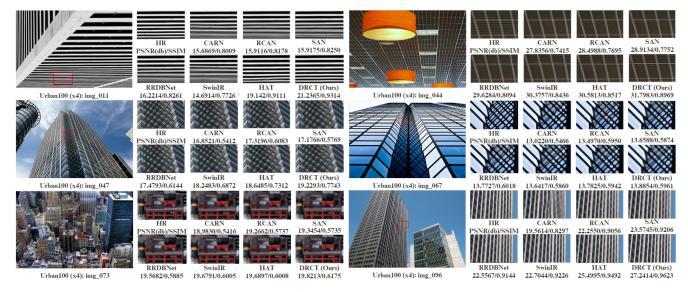


Figure 5. Visual comparison on \times 4 SISR. The patches for comparison are marked with red boxes in the original images. The higher the PSNR/SSIM metrics, the better the performance..

chitecture of DRCT, the configuration of depth and width is maintained identically to that of SwinIR. To elaborate, both the number of RDFEG and SDRCB units are established at 6, and the channel number of intermediate feature maps is designated as 180. The attention head number and window size are set to 6 and 16 for window-based multi head self-attention (W-MSA). In terms of data preparation, HR patches with dimensions of 256×256 pixels were extracted from the HR images. To improve the generalizability, we apply random horizontal flips and rotation augmentation.

5.3. Quantitative Results

For the evaluation, we use full RGB channels and ignore the $(2 \times \text{scale})$ pixels from the border. PSNR and SSIM metrics are used to evaluation criteria. Table 1 presents the quantitative comparison of our approach and the state-of-the-art methods, including EDSR [25], RCAN [52], SAN [8], IGN [56], HAN [32], NLSN [31], SwinIR [24], CAT-A [6], DAT [7], as well as approaches using ImageNet pretraining, such as IPT [3], EDT [22] and HAT [5]. We can see that our method outperforms the other methods significantly on all benchmark datasets. In addition, the DRCT-L can bring further improvement and greatly expands the performance upper-bound of this task. Even with fewer model parameters and computational requirements, DRCT is also significantly greater than the state-of-the-art methods.

5.4. Visual Comparison

The visual comparisons displayed in Figure 5. For the selected images from the Urban100 [17], DRCT is effective in restoring structures, whereas other methods suffer from notably blurry effects. The visual results demonstrate the

superiority of our approach.

Along with providing visualizations for the LAM [13], we compute the DI and GI. In scenarios where DRCT operates with fewer parameters (a topic for the next subsection), it achieves a higher DI. This outcome suggests that, after enhancing the receptive field through SDRCB, the model can leverage a greater amount of non-local information for SISR without the need for intricately designed W-MSA. Additionally, the GI of the proposed DRCT, being the lowest among the three, underscores its training process stability and its effectiveness in minimizing information loss.

There remains significant room for improvement in the way information loss is measured for SISR models. We conducted a detailed analysis of the G-index using 'image_092' from Urban100, as shown in Figure 6. DRCT managed to achieve a lower score on the GI, indicating that the changes in the network's feature maps are relatively stable. In contrast, The GI for HAT was significantly higher than the other two, which suggests that a lower GI value can effectively denote lesser information loss, whereas a higher GI might imply more drastic changes in feature maps. However, this doesn't necessarily correlate directly with the effectiveness of measuring information loss.

5.5. Model Complexity

To demonstrate the potential of our proposed method, we conducted further analysis on model complexity, with the results illustrated in Figure 7. From the figure, we can observe that the performance curves of the HAT and SwinIR models are approaching horizontal lines, suggesting that their model performance is nearing a bottleneck. Enhancing performance may require significantly more complex mod-

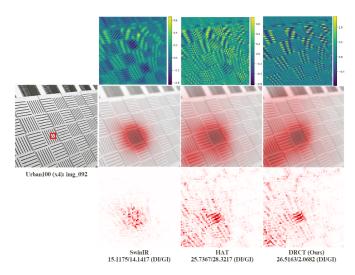


Figure 6. The LAM [13] visualization. DRCT improves performance by enhancing the receptive field to mitigate the issue of spatial information loss in deeper layers of the network. (zoom in to better see the color-bar of feature maps.)



Figure 7. The model complexity comparison between SwinIR, HAT, and proposed DRCT evaluated on Urban100 [17] dataset.

els or a greater number of parameters, potentially leading to prohibitive costs and practical implementation challenges. In contrast, our DRCT-L model outperforms HAT-L while saving 33% of model parameters. This indicates that stabilizing the training and inference processes within residual blocks through a dense-group is a viable strategy to prevent SISR models from encountering information bottlenecks.

5.6. NTIRE Image Super-Resolution (x4) Challenge

The dataset for the NTIRE 2024 Image Super-Resolution (x4) Challenge comprises three collections: DIV2K [1], Flickr2K [36], and LSDIR [23]. Specifically, the DIV2K dataset provides 800 pairs of high and low-resolution images for training. For validation, it offers 100 low-resolution

	Validation phase	Testing phase
PSNR	31.4852	31.7784
SSIM	0.8563	0.8655

Table 2. NTIRE 2024 Challenge Results with x4 SR in terms of PSNR and SSIM on validation phase and testing phase.

images for the purpose of creating super-resolution counterparts, with the high-resolution versions to be made available at the challenge's final stage. Additionally, the test dataset includes 100 varied images for generating their low-resolution equivalents. A self-ensemble strategy is used for testing-time augmentation (TTA) [35]. Our TTA methods include rotation, and horizontal and vertical flipping. We also conduct a model ensemble for fusing different reconstructed results by HAT [5] and the proposed DRCT. Our super-resolution (SR) model was entered into both the validation and testing phases of this Challenge, with the outcomes detailed in Table 2.

6. Conclusion

In this paper, we introduce the phenomenon of information bottlenecks observed in SISR models, where spatial information is lost as network depth increases during the forward-propagation process. This may lead to gradient vanishing and severe oscillations in the distribution of feature intensities, limiting the upper bound of model performance for the SISR task.

To address this issue, we present a novel Swintransformer-based model named the Dense-residual-connected Transformer (DRCT). The design philosophy behind DRCT centers on stabilizing the forward-propagation process and enhancing the receptive field by incorporating dense connections within residual blocks. This approach reduces the loss of spatial information, addressing the information bottleneck issues that SISR models may encounter in deeper network layers.

As a result, the model can better focus on global spatial information and surpass existing state-of-the-art methods without the need for designing complex window attention mechanisms or increasing model parameters.

The extensive experiments demonstrate that DRCT surpasses previous methods in image super-resolution, indicating its effectiveness and the benefits of the proposed approach.

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