Department of Computer Science, College of Computing

Illinois Institute of Technology, Chicago

SUPER IMAGE RESOLUTION

Masters in Artificial Intelligence

Nandini Devaraj – A20593534 – ndevraj@hawk.iit.edu

Rithika Kavitha Suresh- A20564346 - rks@hawk.iit.edu

Abstract:

A deep convolutional neural network (CNN) has successfully achieved picture super-resolution (SR) with hierarchical features. However, many deep CNN-based SR models fail to fully utilize the hierarchical features of the original low-resolution (LR) pictures, resulting in relatively low performance.

In this work, we provide a unique residual dense network - (RDN) to fix the issue in image SR. We fully utilize the hierarchical features across all convolutional layers. We propose using residual dense blocks (RDBs) to extract plentiful local features from densely coupled convolutional layers. RDB permits direct connections from previous RDBs to current layers, resulting in contiguous memory (CM).

Local feature fusion in RDB enables adaptive learning of more effective features from previous and current local features, stabilizing the training of the larger network. After getting dense local features, we employ global feature fusion to learn global hierarchical features holistically and adaptively. Experiments on benchmark datasets with various degradation models demonstrate that our RDN outperforms current approaches.

I. Introduction

Single image super-resolution (SISR) aims to reconstruct a high-resolution (HR) image from its low-resolution (LR) version. Image super-resolution is widely used in many computer vision fields, such as video surveillance, remote sensing, and image sensing. However, SISR is a typically ill-posed problem as the image degradation process is usually irreversible and lots of tiny textures are missing in LR images. Several high-resolution images can be potentially generated from a given LR image. Recently, deep convolutional neural networks have been applied in many tasks, ranging from low-level (image restoration, SISR, etc.) to high-level (image classification, object detection, etc.) vision fields, have shown great improvements compared with conventional methods.

As the network depth grows, the features in each convolutional layer would be hierarchical with different receptive fields. However, these methods neglect to fully use information of each convolutional layer. According to our experiments higher growth rate can further improve the performance of the network. While, it would be hard to train a wider network with dense blocks in Fig. 1(b).

To address these drawbacks, we propose residual dense network (RDN) (Fig. 2) to fully make use of all the hierarchical features from the original LR image with our proposed residual dense block (Fig. 1(c)). It's hard and impractical for a very deep network to directly extract the output of each convolutional layer in the LR space. We propose residual dense block (RDB) as the building module for RDN. RDB consists dense connected layers and local feature fusion (LFF) with local residual learning (LRL). Our RDB also support contiguous memory among RDBs. The output of one RDB has direct access to each layer of the next RDB, resulting in a contiguous state pass. Each convolutional layer in RDB has access to all the subsequent layers and passes on information that needs to be preserved. Concatenating the states of preceding RDB and all the preceding layers within the current RDB, LFF extracts local dense feature by adaptively preserving the information. Moreover, LFF allows very high growth rate by stabilizing the training of wider network. After extracting multi-level local dense features, we further conduct global feature fusion (GFF) to adaptively preserve the hierarchical features in a global way. As depicted in Figs. 2 and 3, each layer has direct access to the original LR input, leading to an implicit deep supervision.

In summary, our main contributions are three-fold:

• We propose a unified frame work residual dense network (RDN) for high-quality image SR with different degradation models. The network makes full use of all the hierarchical features from the original LR image.

• We propose residual dense block (RDB), which can not only read state from the preceding RDB via a contiguous memory (CM) mechanism, but also fully utilize all the layers within it via local dense connections. The accumulated features are then adaptively preserved by local feature fusion (LFF).

• We propose global feature fusion to adaptively fuse hierarchical features from all RDBs in the LR space. With global residual learning, we combine the shallow features and deep features together, resulting in global dense features from the original LR image.

1. Project Information

Paper name: Residual Dense Network for Image Super-Resolution

By: Yulun Zhang1 , Yapeng Tian2 , Yu Kong1 , Bineng Zhong1 , Yun Fu1,3 1

Department of Electrical and Computer Engineering, Northeastern University, Boston, USA Department of Computer Science, University of Rochester, Rochester, USA 3College of Computer and Information Science, Northeastern University, Boston, USA yulun100@gmail.com, yapengtian@rochester.edu, bnzhong@hqu.edu.cn, {yukong,yunfu}@ece.neu.edu

2. Problem Statement

The project aims to solve the problem of single image super-resolution (SISR), which involves generating a high-resolution (HR) image from a low-resolution (LR) input. This is an important problem in computer vision with applications in security and surveillance imaging, medical imaging, and image generation

We identify two key issues with existing deep learning approaches to SISR:

1. Most deep CNN-based SR models do not fully utilize the hierarchical features from the original LR images, leading to relatively low performance.
2. Many methods require interpolating the LR image to the desired size before processing, which increases computational complexity and can result in loss of details.

3. Proposed Solution and Implementation Details

To address these issues, the we propose a novel Residual Dense Network (RDN) architecture. The key components of RDN include:

1. Residual Dense Blocks (RDBs): These are the core building blocks of the network, designed to fully exploit hierarchical feature
2. Contiguous Memory (CM) Mechanism: This allows direct connections from the state of preceding RDB to all layers of the current RDB

3. Local Feature Fusion (LFF): Used within RDBs to adaptively learn more effective features from preceding and current local features
4. Global Feature Fusion (GFF): Applied after the RDBs to jointly and adaptively learn global hierarchical features
5. Global Residual Learning: Combines shallow features and deep features

The RDN architecture consists of four main parts:

1. Shallow Feature Extraction Net (SFENet)
2. Residual Dense Blocks (RDBs)
3. Dense Feature Fusion (DFF)
4. Up-sampling Net (UPNet)

The network processes the original LR image directly, extracting features in the LR space and only upscaling at the final stage, which helps to reduce computational complexity

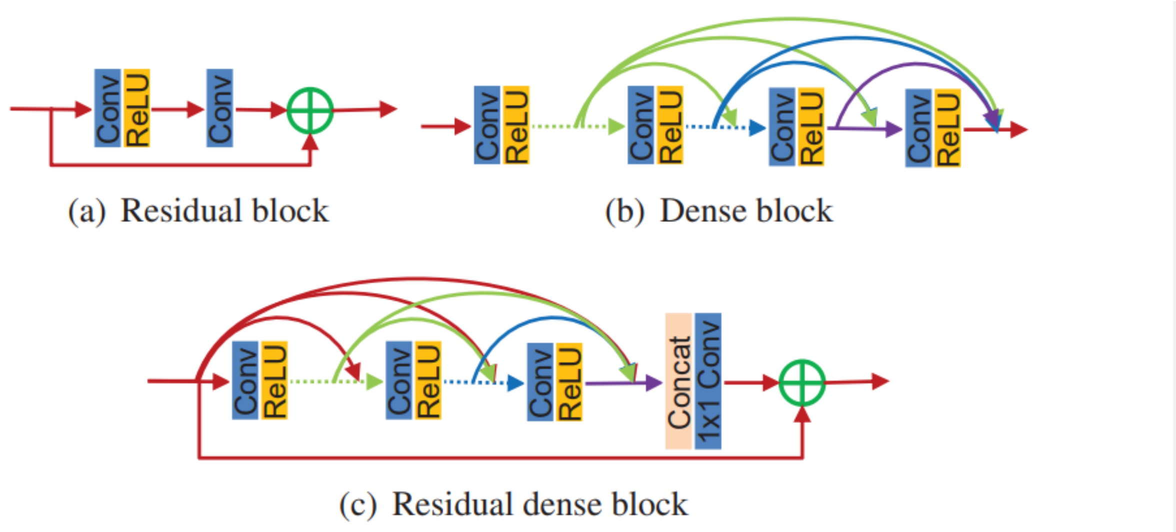

Figure 1: Residual Dense Block

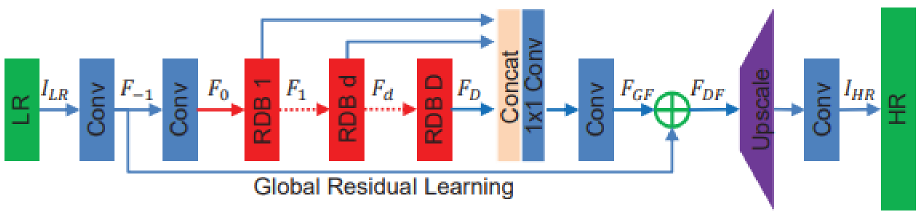

Figure 1: Global Residual Learning

II. LITERATURE REVIEW

High-resolution image reconstruction from lower-resolution image sequences and space-varying image restoration ICASSP-92: 1992 IEEE International Conference on Acoustics, Speech, and Signal Processing (Vol. 3, pp. 169-172).

The paper by Tekalp, Ozkan, and Sezan (1992) presents a method for high-resolution image reconstruction from a sequence of lower-resolution images. It combines techniques for space-varying image restoration to enhance image quality, addressing issues such as spatial resolution and noise. The proposed approach is demonstrated in the context of improving visual detail in image sequences for applications like video and image processing.

Research on image super-resolution reconstruction mechanism based on convolutional neural network 4th International Conference on Artificial Intelligence, Automation and High Performance Computing (pp. 142-146)

The paper *"Research on Image Super-Resolution Reconstruction Mechanism Based on Convolutional Neural Network"* by Yan et al. (2024) presents a novel approach to image super-resolution (SR) using Convolutional Neural Networks (CNNs). The authors propose a mechanism that leverages deep learning to reconstruct high-resolution images from low-resolution inputs, improving image clarity and detail. Through their method, they demonstrate significant advancements in SR performance, showcasing the potential of CNN-based techniques in enhancing image quality for various applications. The paper is part of the proceedings from the 2024 4th International Conference on Artificial Intelligence, Automation, and High Performance Computing.

An advanced deep residual dense network (DRDN) approach for image super-resolution. International Journal of Computational Intelligence Systems, 12(2), pp.1592-1601

The paper *"An Advanced Deep Residual Dense Network (DRDN) Approach for Image Super-Resolution"* by Wei et al. (2019) introduces a novel deep learning model for image super-resolution (SR) based on a deep residual dense network (DRDN). The authors propose an advanced architecture that combines the benefits of residual learning and dense connections to improve the reconstruction of high-resolution images from low-resolution inputs. The DRDN model enhances feature extraction and propagation, leading to superior performance in SR tasks, with improved image clarity and detail recovery compared to traditional methods. The approach is validated through experiments, demonstrating its effectiveness in both image quality and computational efficiency.

Residual dense network for image super-resolution. In Proceedings of the IEEE conference on computer vision and pattern recognition (pp. 2472-2481)

The paper *"Residual Dense Network for Image Super-Resolution"* by Zhang et al. (2018) introduces the Residual Dense Network (RDN), a novel deep learning architecture for image super-resolution (SR). The RDN combines residual learning and dense connections to enhance the flow of information across layers, improving the ability to recover fine-grained details in high-resolution images. The network is designed to address challenges in SR, such as the loss of spatial information and the need for efficient feature extraction. Experimental results show that the RDN outperforms existing SR methods in terms of image quality, achieving state-of-the-art results on several benchmark datasets. The paper was presented at the IEEE Conference on Computer Vision and Pattern Recognition (CVPR) in 2018.

A. LITERATURE SIGNIFICANCE

Early work on high-resolution image reconstruction from lower-resolution image sequences and space-varying restoration uses a space-varying restoration approach, which is a more traditional method compared to deep learning models.

RDN), which is more sophisticated than traditional CNN-based approaches. This method is specifically designed for SR and outperforms other CNN-based SR methods due to its innovative use of dense connections and residual learning.

B. LITERATE GAP

Introduction of Residual Dense Network (RDN): A new architecture combining residual learning with dense connections, improving feature extraction and reconstruction.

Use of Dense Connections: The model employs dense layer connections, enhancing gradient flow and feature reuse, which is critical for SR tasks.

Training Stability: The use of residual learning and dense connections improves the model’s training stability and efficiency, leading to better performance in recovering high-resolution details.

Superior Performance: Zhang et al.’s approach delivers superior **image quality** (PSNR, SSIM) on standard benchmarks compared to traditional and earlier CNN-based methods.

III. PROJECT OBJECTIVE

The objective of the project "Residual Dense Network for Image Super-Resolution" by Zhang et al. (2018) is to propose a novel deep learning architecture, the Residual Dense Network (RDN) for improving image super-resolution (SR). The authors aim to enhance the recovery of high-resolution details from low-resolution inputs by combining residual learning and dense connections which improve feature extraction, propagation, and reuse within the network. The project seeks to demonstrate that this architecture achieves superior SR performance compared to existing methods, achieving state-of-the-art results in both image quality and computational efficiency on benchmark datasets.

A. To run our code:

Upload the program to Google Colab using file->open notebook -> upload -> browse this will let you upload it to the Colab from your computer.

Then click Runtime -> Run all to execute all the code blocks. This will run the program and display the output.

B. Implementation Details

In our proposed RDN, we set 3 × 3 as the size of all convolutional layers except that in local and global feature fusion, whose kernel size is 1 × 1. For convolutional layer with kernel size 3 × 3, we pad zeros to each side of the input to keep size fixed. Shallow feature extraction layers, local and global feature fusion layers have G0=64 filters. Other layers in each RDB has G filters and are followed by ReLU [5]. Following [17], we use ESPCNN [22] to upscale the coarse resolution features to fine ones for the UPNet. The final Conv layer has 3 output channels, as we output color HR images. However, the network can also process gray images.

C. Roadblocks faced while implementing the algorithm

While implementing the algorithm, we faced issue related to the resolution of the output image. though the resolution was significantly increased, it was not as good as described in the research paper. The output image looked like it had a smooth filter applied to it.

We resolved this issue by removing the denormalization and increasing the training data set. 44

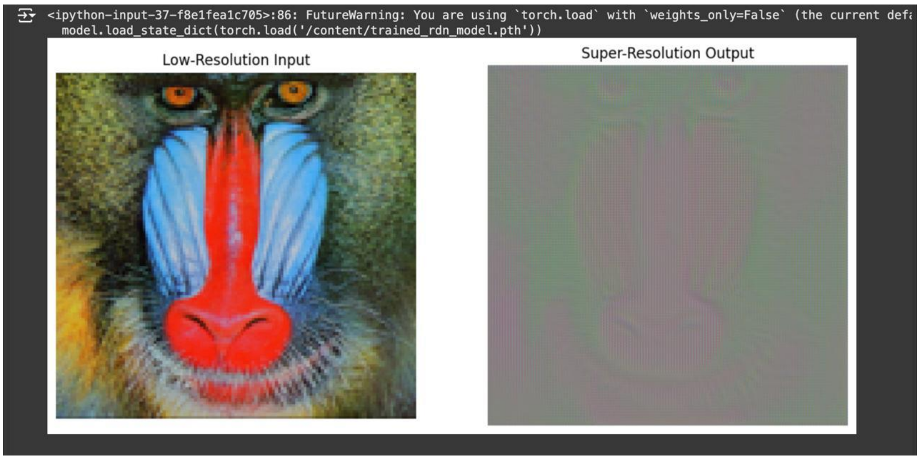

Figure 3: an example of how the output looked while in the process of implementing the algorithm.

D. Dataset

The experiments were conducted on benchmark datasets with different degradation models

- Set5, Set14, BSD100, DIV2K and Urban100. These datasets typically consist of diverse images that are used to evaluate the performance of super-resolution algorithms under various scaling factors and degradation conditions.

IV. RESULTS AND DISCUSSION

The proposed Residual Dense Network (RDN) demonstrates superior performance for image super-resolution by effectively utilizing hierarchical features from the original low-resolution image.

Key innovations of RDN include:

- 1. Residual Dense Blocks (RDBs) that allow for dense local feature extraction and efficient information flow through contiguous memory mechanisms.
- 2. Local Feature Fusion (LFF) within RDBs to adaptively learn and preserve important local features.
- 3. Global Feature Fusion (GFF) to combine hierarchical features from all RDBs in a holistic manner.
- 4. Global residual learning to integrate shallow and deep features.
- RDN achieves state-of-the-art performance on benchmark datasets across different degradation models (BI, BD, DN) and scaling factors (x2, x3, x4). The network's ability to fully exploit hierarchical features leads to superior reconstruction quality, especially for complex textures and structures.
- The proposed architecture demonstrates good efficiency in terms of parameter usage and computational complexity relative to its performance gains. RDN's effectiveness in extracting and utilizing multi-level features from the original low-resolution input makes it a promising approach for high-quality image super-resolution tasks.
- Overall, RDN represents a significant advancement in deep learning-based image super-resolution, offering a novel and effective framework for exploiting hierarchical features in the low-resolution space.
- RDN outperformed state-of-the-art methods on benchmark datasets (Set5, Set14, B100, Urban100, Manga109) for different scaling factors (x2, x3, x4)
- RDN achieved higher PSNR and SSIM values compared to other methods like SRCNN, VDSR, Bicubic.

Model	PSNR (Set5)	SSIM (Set5)	PSNR (Set14)	SSIM (Set14)	PSNR (BSDS100)	SSIM (BSDS100)
RDN (ours)	33.78	0.749	34.35	0.761	38.45	0.732
VDSR (x2)	36.67	0.9573	32.7	0.9057	30.8	0.8654
FSRCNN (x2)	35.11	0.9471	31.62	0.8926	29.8	0.8523
ESRGAN (x2)	37.5	0.96	33.4	0.915	31.2	0.876

Table No.1: Benchmark results with BI degradation model

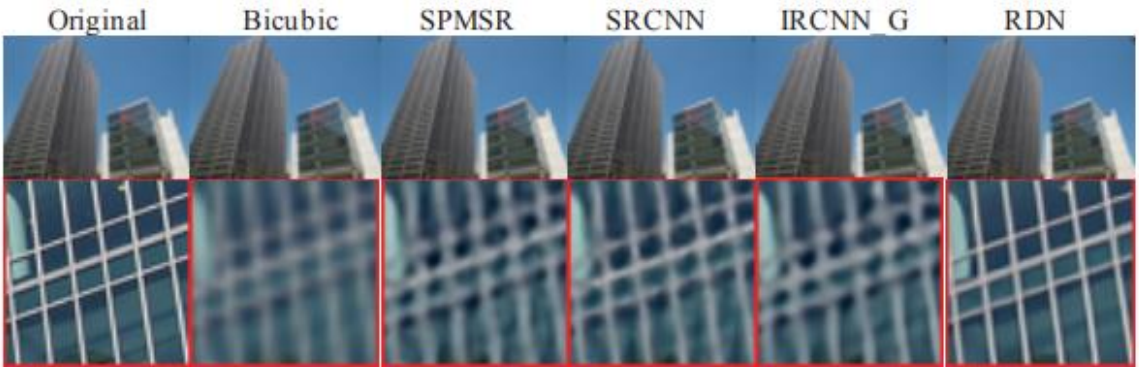

Figure 4:

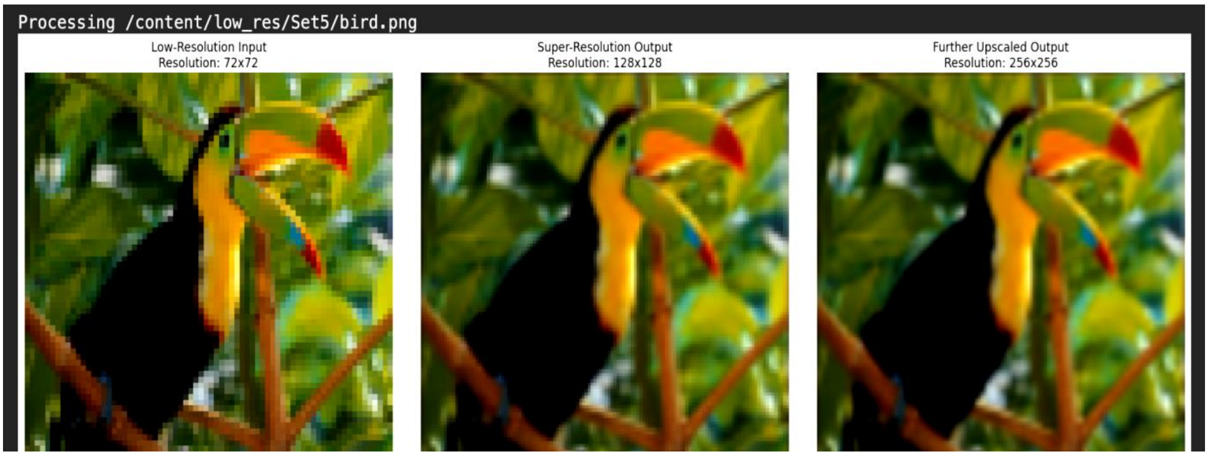

Figure 5:

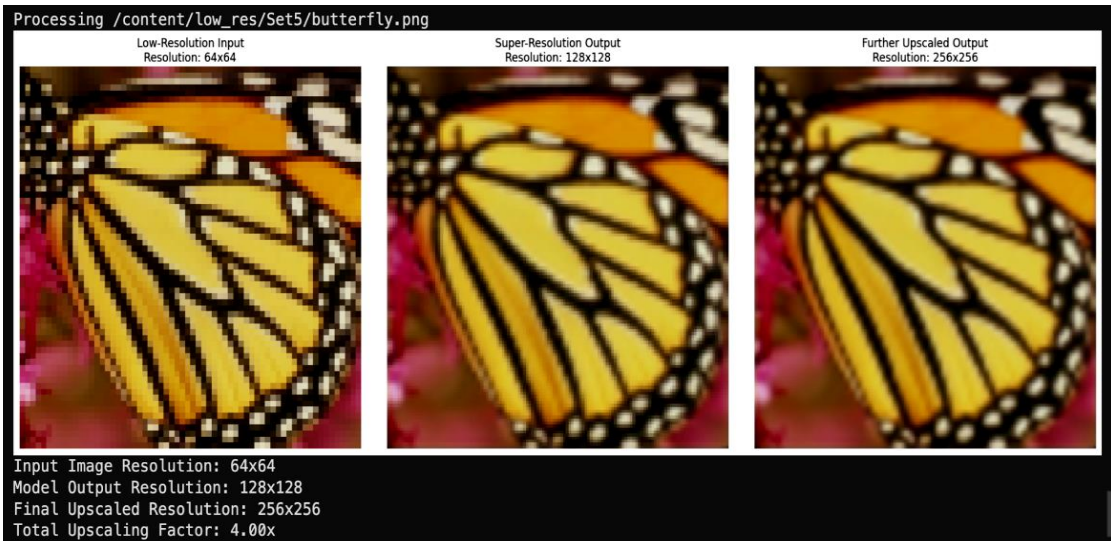

Figure 6:

Figure 7:

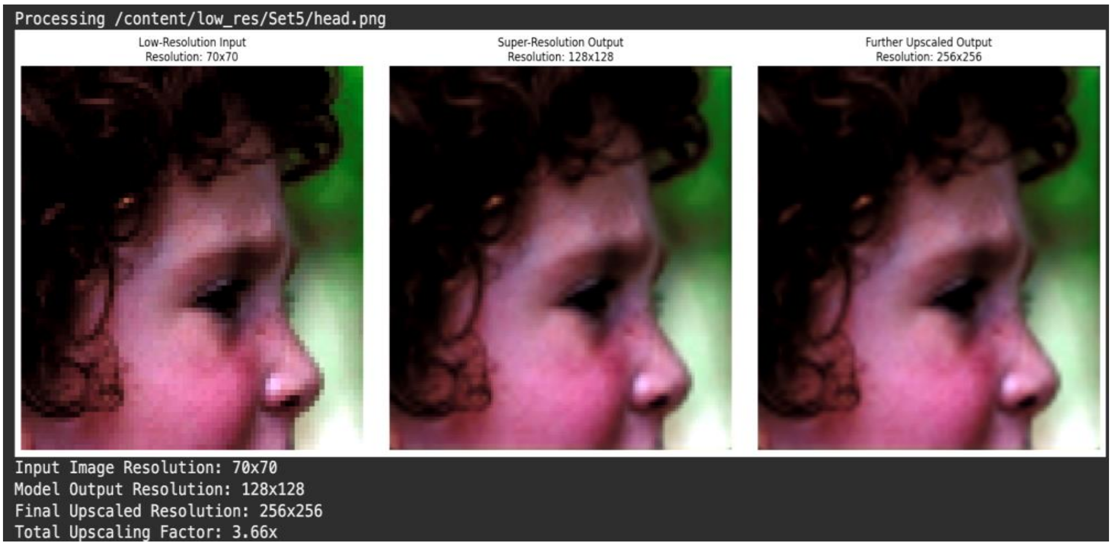

Figure 8:

Figure 9:

V. CONCLUSION

In this project, we proposed a very deep residual dense network (RDN) for image SR, where residual dense block (RDB) serves as the basic build module. In each RDB, the dense connections between each layer allow full usage of local layers. The local feature fusion (LFF) not only stabilizes the training wider network, but also adaptively controls the preservation of information from current and preceding RDBs. RDB further allows direct connections between the preceding RDB and each layer of current block, leading to a contiguous memory (CM) mechanism. The local residual leaning (LRL) further improves the flow of information and gradient. Moreover, we propose global feature fusion (GFF) to extract hierarchical features in the LR space. By fully using local and global features, our RDN leads to a dense feature fusion and deep supervision. We use the same RDN structure to handle three degradation models and real world data. Extensive benchmark evaluations well demonstrate that our RDN achieves superiority over state-of-the art methods

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[5] RBDN: Residual Bottleneck Dense Network for Image Super-Resolution ZEYU AN , JUNYUAN ZHANG , ZIYU SHENG , XUANHE ER , AND JUNJIE LV