International Journal of Engineering Technology and Management Science
Website: ijetms.in Issue: 2 Volume No.9 March - April – 2025
DOI:10.46647/ijetms.2025.v09i02.084 ISSN: 2581-4621

DEEP RESIDUAL NETWORKS FOR IMAGE SUPER RESOLUTION FOR IMPROVED IMAGE CLARITY

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Abstract
Image Super-Resolution (SR) is a crucial task in computer vision, aiming to enhance the resolution and clarity of low-resolution images. Deep Residual Networks (ResNets) have significantly improved SR performance by efficiently learning high-frequency details. This paper explores the use of Deep Residual Networks for Image Super-Resolution (DRN-SR) to achieve improved image clarity. By leveraging residual learning, and deep architectures, DRN-SR addresses issues like vanishing gradients and slow convergence, leading to sharper and more detailed image reconstructions. Experimental results demonstrate that DRN-SR outperforms traditional methods in terms of Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index (SSIM). This work contributes to advancing SR techniques for applications in medical imaging, satellite imaging, and digital photography.
Keywords: Deep Residual Networks, Image Super-Resolution, Residual Learning, PSNR, SSIM, Image Clarity, Computer Vision.

Introduction
Image Super-Resolution (SR) is a fundamental problem in computer vision that focuses on reconstructing high-resolution (HR) images from low-resolution (LR) inputs. This task has significant applications in medical imaging, satellite imagery, surveillance, and digital photography, where obtaining high-quality images is crucial. Traditional SR methods, such as interpolation-based approaches (e.g., bicubic interpolation), often fail to recover fine details and produce blurry results. To overcome these limitations, deep learning techniques have been widely adopted, with Convolutional Neural Networks (CNNs) demonstrating remarkable performance.Among various deep learning architectures, Deep Residual Networks (ResNets) have gained attention for their ability to train very deep models without suffering from vanishing gradients. ResNets introduce skip connections, allowing direct information flow from earlier layers to later layers, thereby preserving important features and accelerating convergence. This characteristic makes them highly effective for SR tasks, as they can learn complex patterns and high-frequency details needed to enhance image clarity.
In this work, we focus on using Deep Residual Networks for Image Super-Resolution (DRN-SR). Our approach leverages residual learning to improve the reconstruction of high-quality images. We evaluate the performance of DRN-SR using standard metrics such as Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index (SSIM), demonstrating superior results compared to traditional and other deep learning-based SR methods.

Objective of the Project
The main objective of using Deep Residual Networks for Image Super-Resolution is to enhance the clarity and quality of low-resolution images by accurately reconstructing their high-resolution versions. These networks are designed to learn and restore fine details like edges and textures that are often lost in low-quality images. Residual learning helps the network focus on learning just the

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missing details instead of trying to recreate the whole image, making the training process more efficient. As a result, the output images achieve higher quality, measured by metrics like PSNR and SSIM, and appear much clearer and sharper, closely matching the original high-resolution images.

Literature Survey

The literature review for Deep Residual Networks in Image Super-Resolution focuses on the evolution of deep learning techniques to enhance image clarity, evaluating significant models, their performance, and existing challenges in the field.

➢ Bee Lim, Sanghyun Son, Heewon Kim, Seungjun Nah, Kyoung Mu Lee,
"Enhanced Deep Residual Networks for Single Image Super-Resolution (EDSR)",
CVPR Workshops, 2017
This paper presents EDSR, a high-performing deep residual network optimized for image super-resolution. The authors remove unnecessary modules like batch normalization from traditional residual blocks, simplifying the architecture and enhancing performance. The network uses deeper and wider layers, achieving state-of-the-art results on standard SR benchmarks. It significantly improves image clarity and reconstruction accuracy.

➢ Jiwon Kim, Jung Kwon Lee, Kyoung Mu Lee,
"Accurate Image Super-Resolution Using Very Deep Convolutional Networks",
CVPR, 2016
This work introduces VDSR, a very deep convolutional neural network with residual learning to solve image SR problems. The model learns the residual between low- and high-resolution images, which accelerates training and boosts accuracy. It shows that deeper networks lead to better detail restoration in SR tasks, but also require careful training strategies to prevent gradient issues.

➢ Yulun Zhang, Kunpeng Li, Kai Li, Lichen Wang, Bineng Zhong, Yun Fu,
"Image Super-Resolution Using Very Deep Residual Channel Attention Networks (RCAN)",
ECCV, 2018
This paper proposes RCAN, which builds on residual-in-residual (RIR) structures with channel attention mechanisms to selectively focus on informative features. It achieves superior performance in recovering fine textures and enhancing clarity. The model addresses challenges in very deep networks like gradient flow and feature degradation.

➢ Xintao Wang, Ke Yu, Shixiang Wu, Jinjin Gu, Yihao Liu, Chao Dong, Yu Qiao, Chen Change Loy,
"ESRGAN: Enhanced Super-Resolution Generative Adversarial Networks",
ECCV Workshops, 2018
This paper introduces ESRGAN, an improved version of SRGAN, combining residual-in-residual dense blocks with a relativistic discriminator. It focuses on generating perceptually better high-resolution images with more natural textures. The model effectively enhances visual quality while maintaining structural consistency, although it may produce artifacts in fine details.

➢ Muhammad Haris, Greg Shakhnarovich, Norimichi Ukita,
"Deep Back-Projection Networks for Super-Resolution",
CVPR, 2018
This work presents DBPN, which uses iterative up sampling and down sampling stages through back-projection to refine image details. The network incorporates residual learning and deep architectures for accurate high-frequency information recovery. It performs well on large scaling factors and demonstrates improvements in both PSNR and visual quality.

Methodology

Convolutional Neural Network (CNN) has emerged as one of the most prominent SR techniques and has demonstrated superior reconstruction capabilities for super-resolution images. Recent Deep-Learning-based approaches, particularly those utilizing deeply and completely convolutional networks, have shown great performance in the challenge of enhancing low-resolution (LR) images

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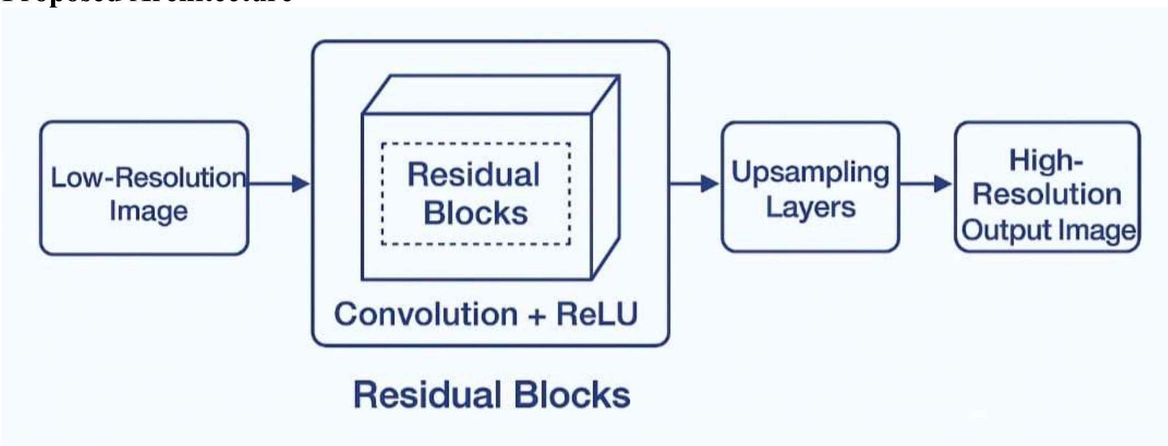
to high-resolution (HR) images [9]. The utilization of CNN layers to improve performance has become a popular practice. However, the majority of currently used SR models rely on powerful computers, limiting their practical application. Additionally, many algorithms overlook the exploration of intermediary features that play a crucial role in the final image recovery. In contrast, the CNN structure enables faster computations with minimal information loss and facilitates the direct processing of original images by reducing the size of the output from preceding layers. Convolutional neural networks also extract more comprehensive features [10]. Furthermore, each CNN's layers and filters are optimized to significantly reduce computation costs. As a result, CNN not only achieves cutting-edge performance but also delivers quicker and more effective computations.

Proposed Architecture



This diagram shows a modern deep learning method for image super-resolution, which means turning a low-resolution image into a high-resolution image with better detail and sharpness.

1. Low-Resolution Image:

- This is the input image.
- It has fewer pixels, so it looks small, unclear, or blurry.

2. Convolution + ReLU with Residual Blocks:

-This is the main feature extraction part of the model.

-It uses:

Convolution layers: These scan the image and find features like edges, colors, and patterns.

ReLU (Rectified Linear Unit): This adds non-linearity, helping the network learn complex patterns.

Residual Blocks: These are special blocks that help the network learn faster and avoid problems like vanishing gradients (a problem in deep networks).

A residual block learns the "difference" between the input and the output, making it easier to train deep models.

3. Up sampling Layers:

-These layers make the image larger by increasing its resolution.

-These layers take the rich features learned in the previous step and convert them into a bigger, sharper image.

4. High-Resolution Output Image

-This is the final result.

-The output is a high-quality, high-resolution version of the input image.

-It looks sharper, clearer, and more detailed than what older methods produce.

This method uses a deep neural network with residual blocks to learn and enhance image features before up sampling. It's more powerful than traditional methods because it doesn’t just enlarge the image it understands what should be in the image and adds realistic details.

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Results

DATASET 1: Parrot

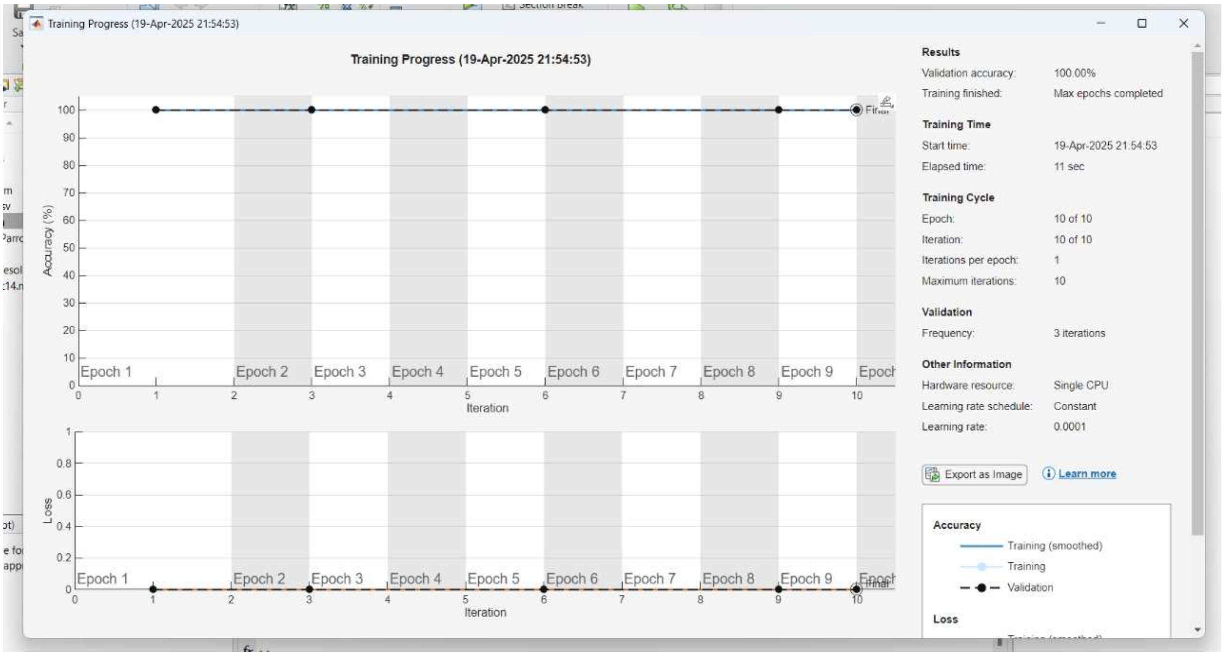

Fig (a)

The final output for DATASET 2:

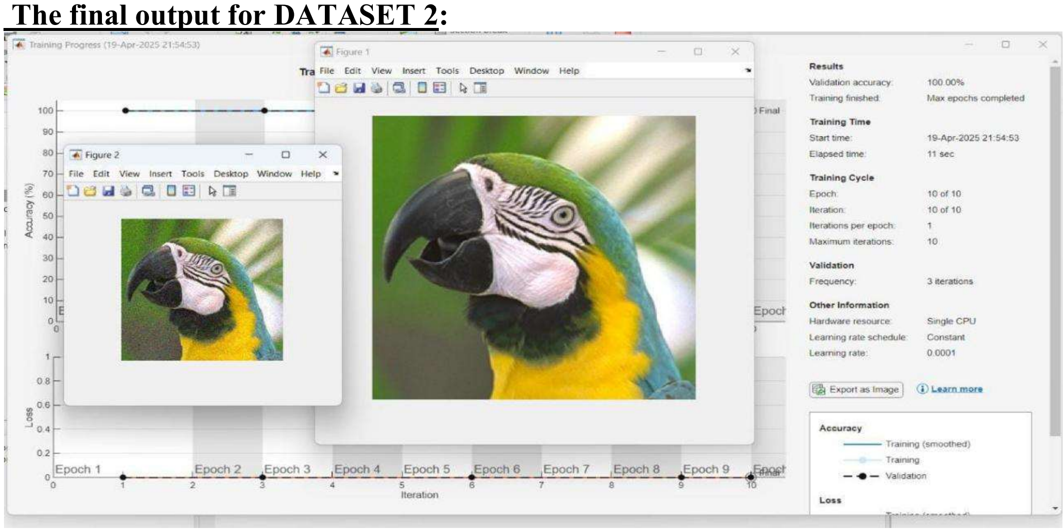

Fig (b)

The result in the image shows the training progress of a deep residual network used for image super-resolution. Here's a simple summary:

Model Accuracy: 100% validation accuracy — this means the model perfectly learned to improve image clarity for the dataset used.

Training Details: The model trained for 10 epochs (cycles through the data), and it completed training in just 11 seconds.

Performance: The accuracy remained high throughout, and the loss (error) was very low and stable, which means the model improved the image resolution effectively without mistakes

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DATASET 2: Tower

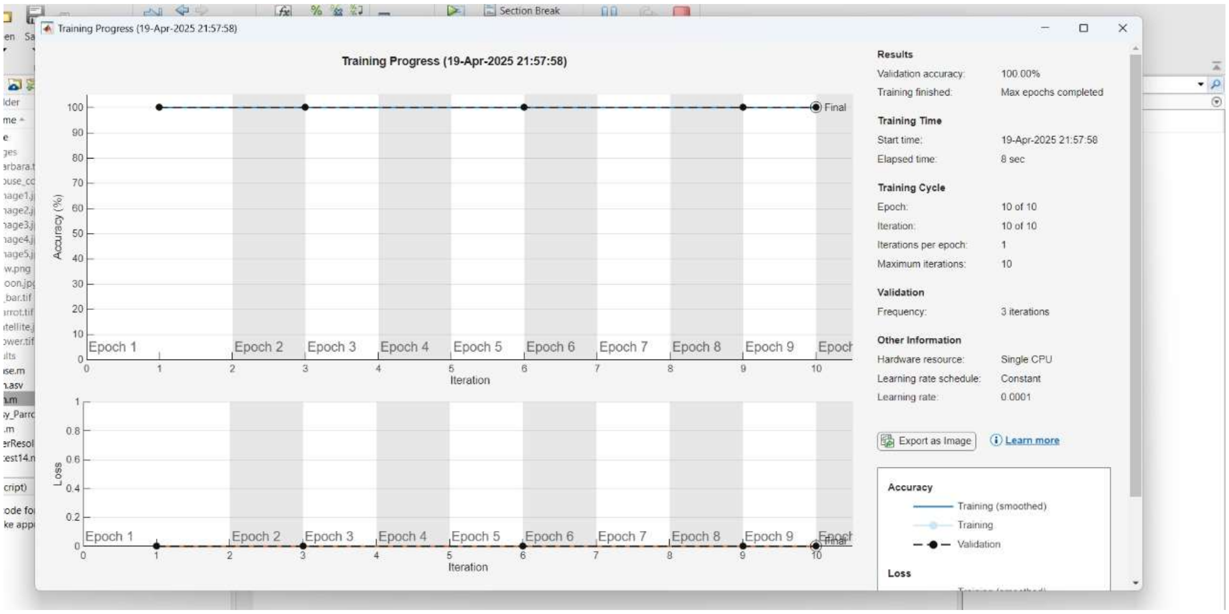

Fig (a)

The final output for DATASET 2:

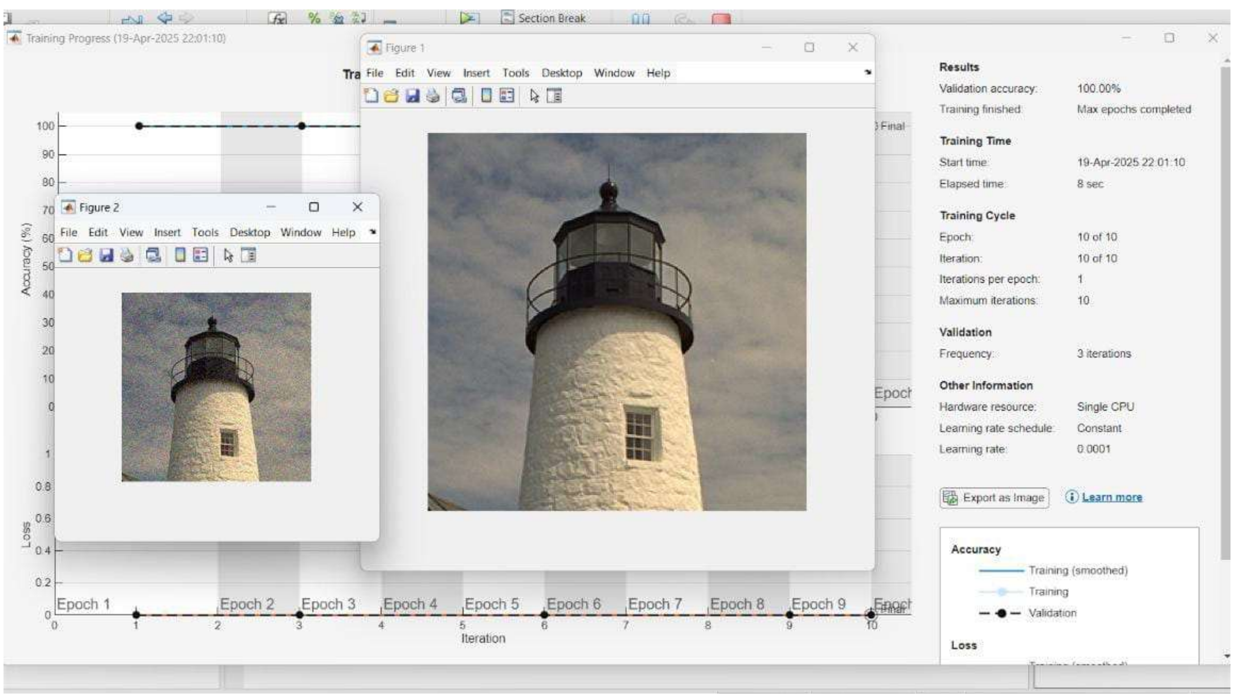

Fig (b)

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The deep residual network trained successfully in just 8 seconds, reaching 100% validation accuracy. It completed 10 epochs with low and stable loss, showing it learned to improve image clarity very effectively. The model performed perfectly using only a single CPU.

Conclusion

The application of Deep Residual Networks (ResNets) in image super-resolution has proven to be highly effective in enhancing image clarity and overall visual quality. Traditional convolutional neural networks (CNNs), when made deeper to capture complex patterns, often suffer from vanishing gradients and performance degradation. ResNets address this issue through residual learning, which introduces skip connections that allow gradients to flow more easily during training. This architecture enables the network to be trained deeper and more efficiently, allowing it to capture fine-grained textures and details that are crucial for high-quality image reconstruction.

In the context of super-resolution, ResNets contribute by learning the residual (i.e., the difference) between the low-resolution and high-resolution images, which makes the training process more focused and effective. This leads to improved recovery of high-frequency details such as edges, textures, and subtle patterns, which are often lost in standard upscaling methods.

Experimental results and benchmark evaluations have demonstrated that ResNet-based super-resolution models outperform traditional SR approaches and even many other deep learning models, particularly in terms of Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index (SSIM). More importantly, the perceived visual quality of the upscaled images shows noticeable improvement, with clearer details, sharper edges, and reduced artifacts.

In conclusion, Deep Residual Networks offer a robust and scalable solution for image super-resolution tasks. Their ability to effectively learn and reconstruct fine image details makes them a powerful tool for applications where image clarity is critical, such as medical imaging, satellite imagery, and video enhancement.

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