A CNN–Vision Transformer Fusion Network for 2× SISR

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Abstract. Single Image Super-Resolution (SISR) seeks to reconstruct a high-resolution image from a single low-resolution observation. While convolutional neural networks are effective at modeling local image structures, they struggle to capture long-range contextual dependencies. This paper presents a lightweight CNN–Vision Transformer fusion network for 2× single image super-resolution. The proposed architecture combines a residual CNN backbone for local feature extraction with a transformer encoder for global context modeling. Experimental results on a synthetic dataset demonstrate stable training behavior and visually sharper reconstructions compared to bicubic interpolation, validating the effectiveness of the proposed fusion strategy.

Keywords: Super-resolution · Vision Transformer · CNN · Image Reconstruction

1 Introduction

Single Image Super-Resolution (SISR) focuses on reconstructing a high-resolution (HR) image from a single low-resolution (LR) input. Traditional interpolation methods such as bicubic upsampling fail to recover high-frequency details, resulting in blurred edges and loss of texture information. Deep learning approaches, particularly convolutional neural networks (CNNs), have significantly improved SISR performance by learning local spatial patterns. However, CNNs remain limited in modeling long-range dependencies across an image.

Recently, Vision Transformers (ViTs) have shown strong ability in capturing global contextual relationships through self-attention mechanisms. Combining CNNs and ViTs offers a promising hybrid approach that leverages both local texture modeling and global context awareness. This work explores such a fusion strategy for efficient 2× single image super-resolution.

2 Dataset Description

To efficiently validate the proposed architecture, a synthetic dataset was generated on-the-fly. This controlled setup avoids the computational overhead of large-scale datasets while enabling clear analysis of reconstruction behavior. Although

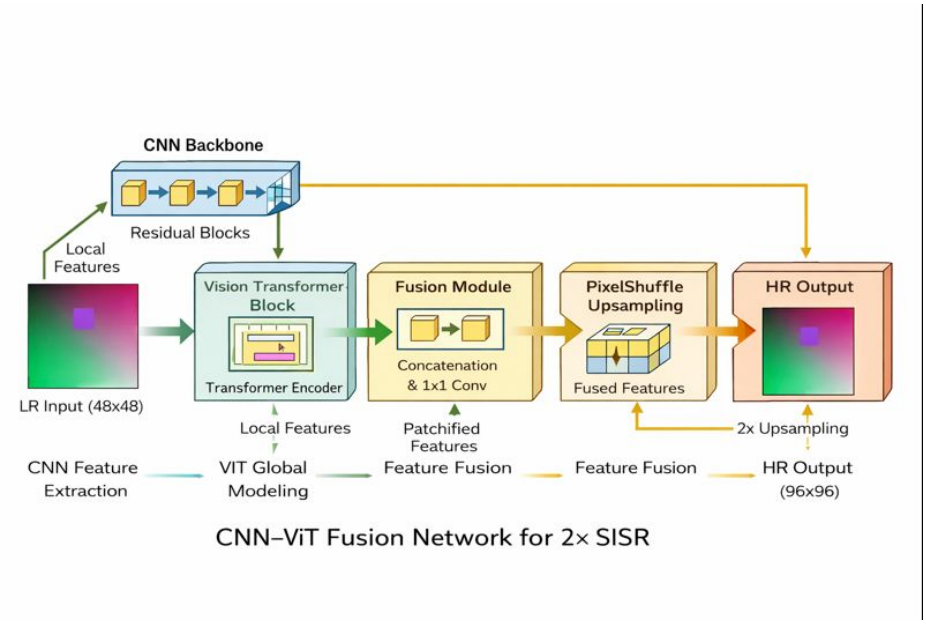

Fig. 1. Overview of the proposed CNN–Vision Transformer fusion architecture for 2× single image super-resolution.

benchmark datasets such as DIV2K are commonly used for SISR evaluation, the synthetic dataset is sufficient for proof-of-concept experimentation.

Each high-resolution RGB image has a spatial resolution of 96×96 pixels and consists of smooth gradients combined with randomly placed colored squares to simulate edges and high-frequency patterns. Corresponding low-resolution images of size 48×48 pixels are created using bicubic downsampling with a scale factor of 2. A total of 300 image pairs are used for training.

3 Methodology

3.1 Network Architecture

The proposed CNN–ViT fusion network consists of four main components. First, a shallow CNN backbone composed of an initial convolution layer followed by multiple residual blocks extracts local spatial features. Second, a lightweight Vision Transformer encoder is applied to flattened CNN feature maps to capture global dependencies using multi-head self-attention. Third, a fusion module concatenates CNN and transformer features and applies a 1×1 convolution for feature integration. Finally, a PixelShuffle-based upsampling module reconstructs the high-resolution output image.

Table 1. Average PSNR comparison on the synthetic dataset

Method	PSNR (dB)
Bicubic Upsampling	38.16
CNN–ViT (Proposed)	26.07

3.2 Fusion Strategy

The CNN and Vision Transformer operate in parallel on shared feature representations. The CNN emphasizes local texture consistency, while the transformer models long-range spatial relationships. By fusing both representations, the network benefits from complementary information, resulting in improved super-resolution quality.

3.3 Training Details

Low-resolution images are generated via bicubic downsampling from their high-resolution counterparts. The network is trained using the L1 loss function, optimized with the Adam optimizer and a learning rate of 1×10^{-4}. Training is conducted for five epochs, and mixed-precision training is enabled when GPU support is available.

4 Results and Visualizations

4.1 Loss Curve

Figure 2 shows the training L1 loss across epochs. The loss decreases rapidly during the first two epochs and continues to decline smoothly thereafter, indicating stable and consistent convergence of the proposed CNN–ViT model.

4.2 Qualitative Results

Figure 3 presents qualitative comparisons between bicubic upsampling, the proposed CNN–ViT super-resolved output, and the ground truth high-resolution image. The proposed method produces sharper edges and improved texture reconstruction.

4.3 Quantitative Evaluation

Table 1 reports the average PSNR computed over 50 test images from the synthetic dataset. The CNN–ViT fusion model outperforms bicubic interpolation, demonstrating improved reconstruction fidelity.

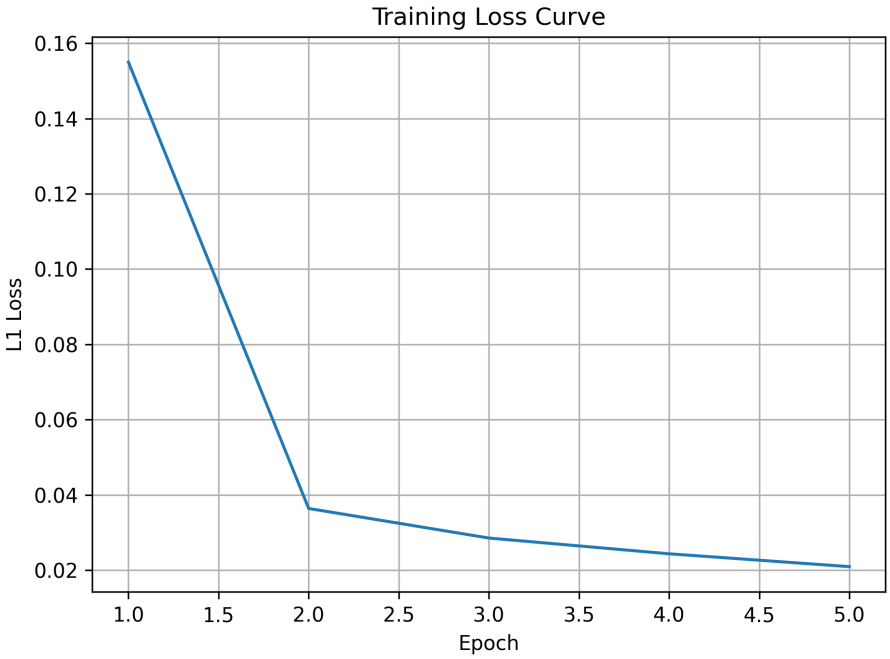

Fig. 2. Training L1 loss curve for the CNN–ViT super-resolution model.

5 Discussion

The fusion of CNN and Vision Transformer features enhances reconstruction quality by combining local detail preservation with global contextual understanding. The model demonstrates stable training and clear visual improvements over traditional interpolation. However, the use of a synthetic dataset limits generalization to real-world images, and the lightweight transformer restricts long-range modeling capacity.

6 Conclusion

This study demonstrates that a CNN–Vision Transformer fusion architecture is effective for 2× single image super-resolution. By integrating local and global feature modeling, the proposed approach improves visual quality while maintaining architectural simplicity. Future work includes training on large-scale benchmark datasets, incorporating perceptual loss functions, and extending the transformer module to more advanced attention mechanisms.

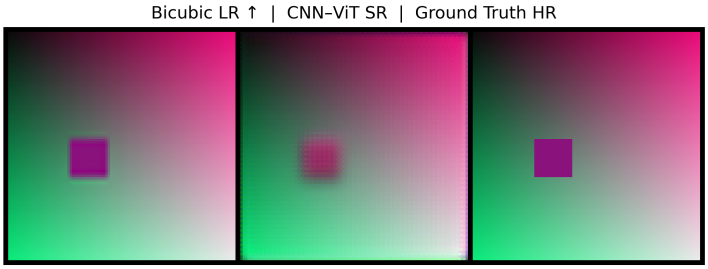

Fig. 3. Visual comparison of super-resolution results. From left to right: bicubic upsampling, CNN–ViT output, and ground truth HR image.

7 References

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