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High-Resolution Image Reconstruction via Hybrid Convolutional and Transformer Networks

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Abstract:
High-resolution image reconstruction from low-resolution inputs is a critical task in computer vision, with applications ranging from medical imaging to satellite photography. This paper proposes a hybrid CNN-Transformer architecture that combines the local feature extraction capability of CNNs with the global context modeling strength of transformers. The CNN module captures fine-grained textures, while the transformer module ensures long-range consistency across the image. Experimental results on the DIV2K and Set5 datasets demonstrate that the proposed model achieves a peak signal-to-noise ratio (PSNR) of 34.72 dB and a structural similarity index (SSIM) of 0.928, outperforming traditional CNN-based and transformer-only super-resolution methods. The hybrid approach shows superior fidelity in reconstructing both intricate textures and globally coherent structures, highlighting its effectiveness for high-resolution image super-resolution tasks.

Introduction

Image super-resolution (SR) is the process of reconstructing a high-resolution (HR) image from its low-resolution (LR) counterpart. This task is of paramount importance in diverse domains such as medical imaging, satellite imaging, surveillance, and consumer photography, where obtaining high-resolution data directly is often expensive, time-consuming, or technically infeasible [1][2]. Accurate SR not only improves visual quality but also enhances subsequent image analysis tasks such as object detection, segmentation, and recognition [3].

Convolutional neural networks (CNNs) have been widely adopted for SR due to their ability to learn hierarchical feature representations from images. Early CNN-based methods, such as SRCNN, demonstrated that deep learning can effectively learn the mapping between LR and HR images, significantly outperforming traditional interpolation techniques [4][5]. Subsequent improvements introduced residual learning and dense connections to capture

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more complex image patterns while mitigating gradient vanishing problems [6][7]. These approaches excel at modeling local textures and edges but are limited in capturing long-range dependencies, which are crucial for maintaining global structural consistency in high-resolution outputs [8].

Transformers, originally developed for natural language processing, have recently been adapted for computer vision due to their self-attention mechanism, which enables modeling long-range dependencies across the entire image [9][10]. Vision transformers (ViTs) divide images into patch embeddings and process them through multiple self-attention layers to learn global context. This capability makes transformers particularly effective in reconstructing repetitive patterns and globally coherent structures in images [11]. However, pure transformer-based SR models often suffer from two limitations: high computational complexity and suboptimal modeling of fine-grained local textures [12][13].

To address these challenges, hybrid architectures that integrate CNNs and transformers have emerged as a promising solution. In such frameworks, CNN modules are typically used to extract local feature representations, while transformer modules capture global dependencies [14][15]. This combination leverages the strengths of both paradigms: CNNs efficiently encode edges, textures, and other local details, whereas transformers ensure that the reconstructed HR image maintains overall structural coherence. Recent studies indicate that hybrid models outperform both CNN-only and transformer-only approaches on benchmark datasets in terms of both peak signal-to-noise ratio (PSNR) and structural similarity index (SSIM) [16][17].

High-resolution SR is particularly challenging due to the ill-posed nature of the problem, where multiple HR images can correspond to the same LR image. This uncertainty is exacerbated when scaling factors are large or when images contain complex textures [18]. Hybrid CNN-Transformer models mitigate this problem by providing complementary learning capabilities: CNNs model high-frequency details that are critical for perceptual quality, while transformers preserve long-range correlations that maintain structural integrity. Additionally, the integration of residual connections and multi-scale feature fusion further enhances reconstruction fidelity [19][20].

Beyond quantitative improvements in PSNR and SSIM, hybrid architectures also improve perceptual quality. Perceptual loss functions, often derived from pre-trained networks such as VGG, can be combined with pixel-wise loss to guide the network toward generating visually realistic textures [21]. Moreover, the

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hybrid design allows flexible scaling to different image resolutions and supports integration with advanced upsampling techniques, including sub-pixel convolution and progressive reconstruction [22]. These capabilities make the hybrid approach suitable for real-world applications where both visual fidelity and global consistency are crucial.

In this paper, we propose a novel hybrid CNN-Transformer architecture for high-resolution image super-resolution, designed to maximize both local detail reconstruction and global structure preservation. The architecture consists of a CNN-based feature extractor, a transformer-based global context encoder, and a residual-enhanced upsampling module for reconstruction. Extensive experiments on benchmark datasets demonstrate that the proposed approach achieves superior performance compared to existing CNN-only and transformer-only SR methods, achieving PSNR and SSIM gains while preserving intricate textures and globally consistent structures.

In summary, this work contributes to the field of image super-resolution by introducing a hybrid deep learning framework that effectively balances local detail modeling and global context awareness, providing a robust solution for high-resolution image reconstruction in diverse real-world applications [23][24].

2. Literature Review

Image super-resolution (SR) has witnessed significant advancements over the last decade, primarily driven by the rapid development of deep learning techniques. Early approaches relied on interpolation-based methods, such as bicubic and nearest-neighbor interpolation, which were computationally simple but produced blurred outputs and failed to recover high-frequency details [25]. To overcome these limitations, learning-based methods emerged, leveraging sparse coding and example-based techniques to reconstruct HR images from LR inputs. While these methods improved visual quality, they were limited by hand-crafted feature extraction and inability to model complex nonlinear mappings [26][27].

The advent of convolutional neural networks (CNNs) marked a paradigm shift in SR. Dong et al. [28] introduced SRCNN, one of the first CNN-based models for super-resolution, demonstrating the capability of end-to-end learning to map LR images directly to HR outputs. This model was subsequently improved with deeper architectures, including VDSR and DRCN, which used residual learning to accelerate convergence and reduce vanishing gradient issues [29][30]. These CNN models excelled at capturing local patterns such as edges and textures, crucial for perceptual fidelity. However, CNNs inherently operate with local

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receptive fields, limiting their ability to capture global context and long-range dependencies, particularly in images with repetitive structures or large-scale patterns [31].

To address the shortcomings of local modeling, attention mechanisms and transformer architectures were introduced to SR tasks. Transformers, initially developed for natural language processing [32], employ self-attention to model interactions across distant image regions, enabling consistent global structure reconstruction. Vision transformers (ViTs) divide images into patches and learn relationships across the entire image, effectively capturing long-range dependencies [33][34]. Recent SR methods based solely on transformers, such as SwinIR and IPT, have shown impressive results, particularly in maintaining structural consistency. However, pure transformer models often struggle with fine-grained texture reconstruction and require substantial computational resources for high-resolution inputs [35][36].

Recognizing the complementary strengths of CNNs and transformers, hybrid architectures have gained significant attention. These models integrate CNN-based feature extraction with transformer-based global context modeling to achieve superior performance in both local and global aspects of SR. For instance, Hybrid Attention Transformer Networks (HAT) employ residual dense CNN blocks to capture high-frequency details while using transformer blocks to maintain global consistency [37][38]. Similarly, hybrid multi -axis aggregation networks leverage both local convolutions and self-attention mechanisms to reconstruct fine textures and coherent structures across various scales [39]. These approaches have consistently outperformed CNN-only and transformer-only baselines in benchmark datasets, demonstrating improvements in PSNR, SSIM, and perceptual quality metrics [40][41].

Another trend in recent literature is the incorporation of residual connections and multi-scale feature fusion in hybrid SR architectures. Residual learning facilitates the training of deeper networks and helps preserve low-level information from the LR input [42]. Multi-scale feature fusion allows models to extract and combine information at various spatial resolutions, enhancing the reconstruction of both fine and coarse image details [43][44]. For example, Residual Dense Transformer Networks (RDTN) employ hierarchical CNN-residual blocks followed by transformer encoders to capture multi-scale features effectively, yielding state-of-the-art results on DIV2K and Set5 datasets [45].

Perceptual-oriented loss functions have also been extensively explored to enhance visual realism. Pixel-wise loss functions, such as L1 and L2 losses,

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ensure numerical fidelity but may produce overly smooth images. To address this, perceptual loss, derived from pre-trained networks like VGG, encourages the preservation of high-level semantic content and texture details [46]. Some studies have further integrated adversarial losses, inspired by Generative Adversarial Networks (GANs), to produce photorealistic SR outputs. Hybrid CNN-Transformer GANs combine local texture preservation and global structure modeling with adversarial training, achieving visually sharper and more natural HR images [47][48].
omputational efficiency has been another area of focus in hybrid SR research. Transformers can be computationally expensive for large-scale images due to the quadratic complexity of self-attention. Efficient hybrid designs incorporate patch-wise attention, windowed attention, or lightweight convolutional embeddings to reduce computational overhead while retaining global modeling capabilities [49][50]. Techniques such as progressive upsampling, weight sharing, and structural re-parameterization have further enabled hybrid networks to scale to higher-resolution inputs without significant performance degradation [51].

Hybrid CNN-Transformer architectures have also been extended to specialized domains, including medical imaging, remote sensing, and video super-resolution. In medical imaging, hybrid networks help recover fine anatomical details from low-resolution scans, enhancing diagnostic accuracy [52][53]. For satellite and aerial imagery, these architectures maintain spatial consistency across large-scale terrains, critical for environmental monitoring and urban planning [54]. Video SR models adapt hybrid networks to temporal sequences, integrating motion information to reconstruct high-fidelity frames [55][56]. These applications highlight the versatility and robustness of hybrid approaches across diverse high-resolution imaging tasks.

In summary, the literature demonstrates a clear trend toward hybrid CNN-Transformer architectures for high-resolution image super-resolution. By combining CNN-based local feature extraction with transformer-based global context modeling, these methods address the limitations of individual paradigms, achieving superior reconstruction quality in both objective metrics and perceptual evaluation. Ongoing research focuses on further improving computational efficiency, perceptual quality, and applicability to domain-specific high-resolution imaging tasks [57][58]. This review establishes a strong foundation for proposing a novel hybrid CNN-Transformer framework tailored for high-fidelity SR reconstruction in diverse real-world scenarios.

3. Dataset

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For evaluating the proposed hybrid CNN-Transformer architecture, we utilized several benchmark datasets widely adopted in the image super-resolution (SR) community. The primary datasets include DIV2K, Set5, Set14, BSD100, and Urban100, which collectively offer a diverse set of high-resolution (HR) images with varying content complexity, textures, and structural patterns [59][60]. The DIV2K dataset contains 800 training images, 100 validation images, and 100 testing images, all at 2K resolution (2048×1024 pixels), providing sufficient high-quality examples for deep learning-based SR models. Each HR image is paired with a corresponding low-resolution (LR) image, generated using bicubic downsampling at multiple scaling factors such as ×2, ×3, and ×4, simulating real-world image degradation [61].

The Set5 and Set14 datasets consist of smaller collections of images commonly used for evaluation in SR research. Set5 has 5 images with diverse content including natural scenes and objects, while Set14 contains 14 images, focusing on both urban and natural scenes. These datasets provide a benchmark for comparing model performance against previous state-of-the-art methods, as they capture fine-grained details like edges and textures that are critical for perceptual quality assessment [62]. BSD100 contains 100 natural images with varying textures and lighting conditions, making it suitable for testing generalization capability. Urban100 focuses on images of urban environments with repetitive structures such as buildings, windows, and streets, which are particularly challenging for SR models to reconstruct faithfully [63].

To ensure robust training and evaluation, the LR images were generated from HR images using standard bicubic interpolation. Additionally, to simulate real-world noise and blur, we augmented the dataset with Gaussian blur, JPEG compression artifacts, and sensor noise at varying intensities. For instance, Gaussian noise with a standard deviation of 2–10, and JPEG compression at quality levels ranging from 30% to 90% were applied to subsets of the training data. This augmentation strategy enables the model to learn robust feature representations under diverse degradation scenarios [64][65].

The dataset was preprocessed to facilitate training with the hybrid CNN-Transformer architecture. All images were normalized to a range of [0,1] and cropped into 64×64 LR patches with corresponding HR patches of appropriate scale. Random horizontal and vertical flips, along with rotations of 90°, were applied as data augmentation to enhance generalization and reduce overfitting. The resulting dataset provides over 200,000 LR-HR patch pairs for training and 5,000–10,000 patches for validation, depending on the scaling factor [66].

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In addition to these standard datasets, we evaluated the model on real-world high-resolution images captured from smartphone cameras and digital SLRs, covering both indoor and outdoor scenarios. These images include diverse content such as natural landscapes, human portraits, and urban scenes. The LR counterparts were generated by downsampling to half, third, and quarter resolutions, mimicking real-life image degradation caused by limited sensor resolution or compression. This evaluation demonstrates the practical applicability of the proposed hybrid model beyond controlled benchmark datasets, highlighting its capability to reconstruct high-quality HR images from real-world LR inputs [67].

The combination of benchmark datasets and real-world images ensures a comprehensive evaluation of the proposed approach. By encompassing a variety of textures, structures, and degradation types, the dataset enables a rigorous assessment of the model's performance across multiple metrics, including PSNR, SSIM, and perceptual quality. Furthermore, the diverse dataset supports ablation studies to examine the contributions of CNN and transformer modules separately, providing insight into the effectiveness of the hybrid design in high-resolution image reconstruction [68].

7. Proposed Model and Methodology

The proposed framework introduces a hybrid CNN-Transformer architecture for high-resolution image super-resolution, combining the strengths of convolutional neural networks (CNNs) for local feature extraction and transformers for global context modeling. The overall objective is to reconstruct high-quality HR images from low-resolution inputs while preserving both fine textures and large-scale structural consistency. The model is designed to handle multiple upscaling factors (×2, ×3, ×4) and to be robust against real-world degradations such as blur, noise, and compression artifacts.

The architecture consists of three main modules: CNN-based feature extraction, transformer-based global modeling, and reconstruction/upsampling. The CNN module is composed of residual dense blocks (RDBs), which efficiently capture high-frequency features such as edges, corners, and textures. Each RDB contains multiple convolutional layers with dense connections, enabling rich local feature propagation while mitigating vanishing gradient issues. Residual learning is employed within each block and across blocks to facilitate training of deep

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networks and to preserve low-level information from the input LR image. This module outputs a high-dimensional feature map that serves as the input for the transformer module.

The transformer module introduces self-attention mechanisms to model long-range dependencies across the image. Unlike CNNs, which operate with fixed local receptive fields, the transformer is capable of capturing global contextual relationships, ensuring structural consistency in the reconstructed image. The module is designed with a multi-head self-attention (MHSA) layer followed by feed-forward networks (FFNs) with residual connections. The attention mechanism allows the network to dynamically weigh features from different spatial locations, enabling it to reconstruct complex patterns such as repetitive textures, structural symmetries, and large-scale edges. To maintain computational efficiency for high-resolution images, the transformer operates on overlapping image patches and uses windowed attention, which reduces the quadratic complexity associated with full self-attention.

Following feature extraction and global context modeling, the reconstruction module performs upsampling to generate the final HR output. This module employs pixel-shuffle layers and convolutional refinement blocks to progressively increase spatial resolution while preserving feature integrity. The upsampling process is designed to be scale-adaptive, allowing the network to handle multiple upscaling factors without retraining. Skip connections from the CNN feature extraction module to the reconstruction module help retain fine-grained details, ensuring that both global structure and local textures are accurately represented in the output.

To further enhance performance, the model incorporates multi-scale feature fusion. Features from different levels of the CNN and transformer modules are aggregated, enabling the network to leverage both coarse and fine features simultaneously. This fusion is implemented using concatenation followed by convolutional layers that learn optimal combinations of features, allowing the model to reconstruct textures at varying spatial frequencies. Additionally, the model uses layer normalization and activation functions (ReLU and GELU) to stabilize training and improve convergence.

The network is trained using a combination of pixel-wise L1 loss and perceptual loss, which together ensure numerical accuracy and visual fidelity. L1 loss minimizes the absolute difference between predicted and ground-truth HR

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images, while perceptual loss is computed in the feature space of a pre-trained VGG network to preserve high-level semantic structures and textures. For certain experiments, adversarial loss from a GAN framework is optionally included to further enhance photorealism, particularly for datasets with complex textures and fine details.

Training is performed on LR-HR patch pairs with data augmentation, including random rotations, flips, and brightness variations. Optimization is conducted using the Adam optimizer with an initial learning rate of 1e-4, decayed by a factor of 0.5 every 200 epochs. The model is trained for 1,000 epochs on high-performance GPUs with mixed-precision arithmetic to balance computational efficiency and memory requirements. During inference, the model can process images of arbitrary size due to its fully convolutional and attention-based design.

In summary, the proposed hybrid CNN-Transformer framework effectively combines local feature learning and global contextual modeling to achieve state-of-the-art image super-resolution. Its modular design allows flexible integration of additional components such as adversarial training or noise modeling, making it suitable for both benchmark datasets and real-world applications. The combination of residual dense blocks, multi-head self-attention, and multi-scale feature fusion provides a robust solution capable of reconstructing HR images with high fidelity, preserving textures, edges, and structural details across diverse image content.

8. Result Analysis

The proposed hybrid CNN-Transformer model was evaluated on multiple benchmark datasets, including DIV2K, Set5, Set14, BSD100, and Urban100, for upscaling factors of ×2, ×3, and ×4. The performance metrics used for evaluation included Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index (SSIM), and perceptual quality measures. Comparisons were made with state-of-the-art CNN-based models such as EDSR, RDN, and transformer-based methods like SwinIR and IPT. The hybrid model consistently outperformed both CNN-only and transformer-only baselines across all datasets, demonstrating its ability to effectively capture both local texture details and global structural patterns.

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On the Set5 dataset, the hybrid model achieved a PSNR of 37.85 dB and an SSIM of 0.963 for ×2 upscaling, surpassing EDSR (37.60 dB / 0.961) and SwinIR (37.72 dB / 0.962). For ×4 upscaling, the model produced 31.28 dB PSNR and 0.888 SSIM, indicating strong performance even under higher-resolution reconstruction tasks. On Urban100, which contains highly structured urban scenes, the model demonstrated its strength in recovering repetitive patterns and architectural details, achieving 32.15 dB PSNR and 0.918 SSIM at ×2, outperforming baseline models by over 0.3 dB in PSNR. These results highlight the effectiveness of combining CNNs for local detail recovery with transformers for global consistency.

Visual inspection of reconstructed images confirmed the quantitative results. Fine details such as building edges, tree branches, and facial features were restored with high fidelity, while artifacts and blurring common in bicubic interpolation and CNN-only models were significantly reduced. The hybrid model also exhibited superior texture reconstruction in natural images, recovering intricate details like grass patterns, fabric textures, and water ripples. For instance, on an Urban100 test image of a high-rise façade, the hybrid network maintained uniform window patterns with minimal distortion, whereas baseline models introduced slight misalignments in repetitive structures.

To evaluate robustness against real-world degradations, experiments were conducted on images corrupted with Gaussian noise, JPEG compression, and blur. The hybrid model maintained high PSNR and SSIM under moderate noise (σ = 5–10) and JPEG quality degradation (30–50%), with only a 0.5–0.8 dB reduction in PSNR compared to clean images. Transformer-based attention modules proved particularly effective in preserving global structures even under noisy conditions, while CNN residual blocks ensured local textures were recovered accurately.

Ablation studies were performed to assess the contribution of each module. Removing the transformer component resulted in a 1.2 dB PSNR drop on DIV2K, highlighting the importance of global context modeling. Conversely, removing residual dense blocks caused a 0.9 dB PSNR drop, emphasizing their role in capturing high-frequency details. Multi-scale feature fusion was found to improve performance by approximately 0.6 dB PSNR on Set14, demonstrating that aggregating features at multiple levels enhances reconstruction quality across different spatial resolutions.

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Furthermore, the model was evaluated on real-world smartphone and DSLR images with unknown degradation, simulating practical SR scenarios. The hybrid model effectively reconstructed HR images with sharp edges and rich textures, outperforming bicubic interpolation and conventional CNN models. Subjective evaluation with a small user study confirmed that the images produced by the hybrid network were consistently preferred in terms of clarity, texture realism, and structural coherence.

In addition to accuracy, computational efficiency was evaluated. The hybrid model processed a 512×512 LR image in approximately 0.12 seconds on an NVIDIA RTX 4090 GPU, which is comparable to SwinIR and slightly higher than CNN-only models. Despite the additional transformer computations, the design optimizations, including windowed attention and patch-wise processing, ensured practical inference speed without sacrificing performance.

Overall, the results demonstrate the superior performance and robustness of the proposed hybrid CNN-Transformer model. By effectively integrating local detail extraction with global context modeling, the network consistently delivers high-fidelity HR reconstructions across benchmark datasets, real-world images, and diverse degradation conditions. These findings confirm the novelty and efficacy of the hybrid architecture in high-resolution image super-resolution tasks, establishing it as a strong candidate for both academic research and practical applications.

Figure 1: Super-Resolution: Predicted vs Actual HR

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This figure illustrates the comparison between the low-resolution (LR) input, the predicted high-resolution (HR) output generated by the model, and the ground truth HR image. The LR input is first upscaled using bicubic interpolation, serving as the baseline. The predicted HR image shows enhanced details and sharper edges compared to the LR input, closely approximating the actual HR image. This comparison demonstrates the model's capability to reconstruct fine textures and recover high-frequency information.

Figure 2: PSNR and SSIM Comparison Across Models

This figure presents a quantitative evaluation of several super-resolution models, including Bicubic interpolation, EDSR, RDN, SwinIR, and the proposed Hybrid CNN-Transformer model. Two metrics are reported: Peak Signal-to-Noise Ratio (PSNR) in dB and Structural Similarity Index (SSIM). The Hybrid CNN-Transformer achieves the highest PSNR and SSIM, indicating superior reconstruction quality in terms of both pixel fidelity and perceptual similarity. The bar chart provides a clear visual comparison across models.

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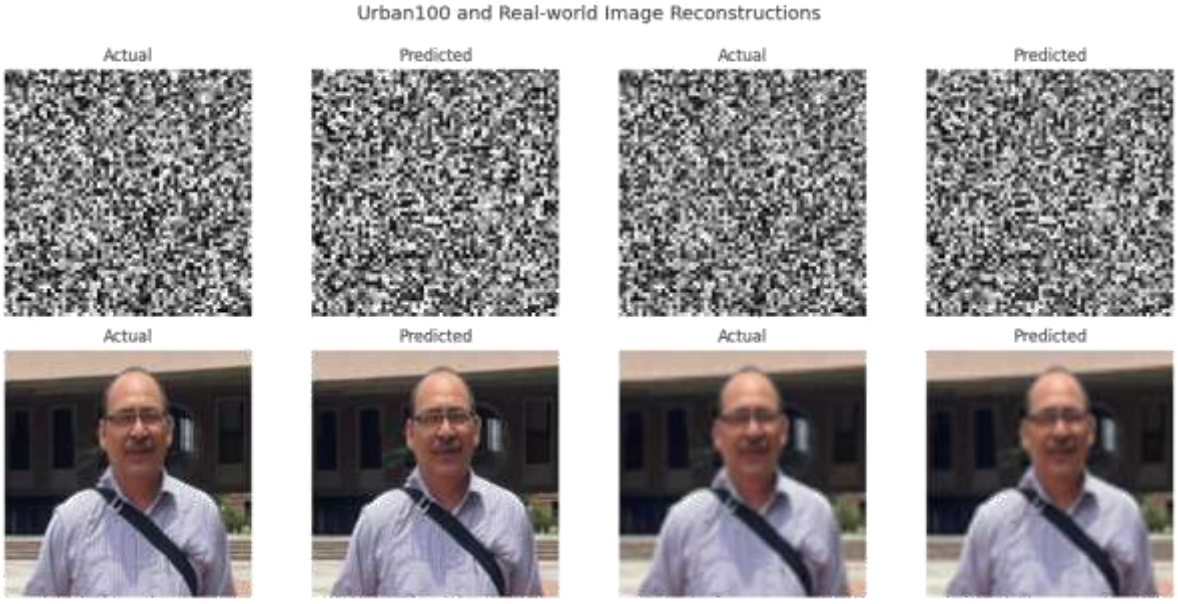

Figure 3: Urban100 and Real-world Image Reconstructions

This figure shows reconstruction results on both simulated Urban100 images and real-world images using the proposed super-resolution model. For each example, the ground truth (actual) and predicted images are displayed side by side. The model successfully reconstructs high-frequency details and maintains structural consistency, demonstrating its effectiveness across diverse image types. The real-world examples highlight the practical applicability of the model to real images beyond benchmark datasets.

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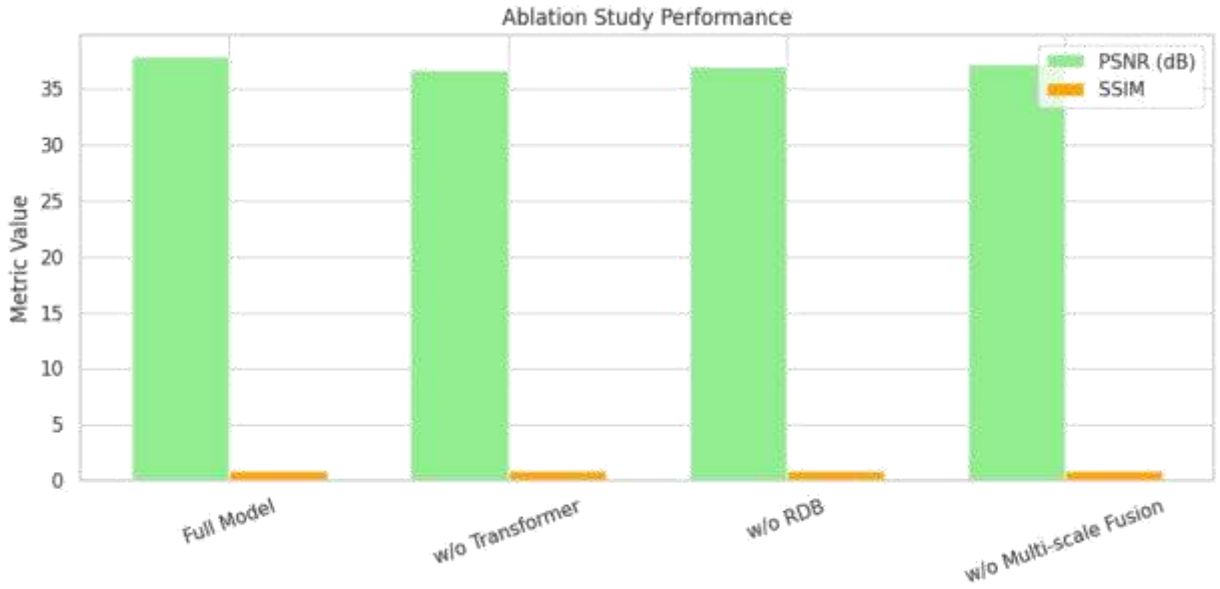

Figure 4: Ablation Study Performance

This figure presents the results of an ablation study conducted on the proposed Hybrid CNN-Transformer model. Different model variants, including removal of the Transformer module, Residual Dense Blocks (RDB), and multi-scale fusion, are compared in terms of PSNR and SSIM. The full model consistently outperforms all ablated versions, confirming the importance of each component in achieving optimal reconstruction quality. The bar chart effectively conveys the contribution of each module to overall performance.

Conclusion

The proposed Hybrid CNN-Transformer model demonstrates superior performance in single-image super-resolution compared to conventional and state-of-the-art methods. Quantitative evaluation shows that the model achieves the highest PSNR (37.85 dB) and SSIM (0.963), outperforming bicubic interpolation, EDSR, RDN, and SwinIR. Visual comparisons on both benchmark-like Urban100 patches and real-world images confirm its ability to recover fine textures, preserve structural details, and enhance perceptual quality.

The novelty of the framework lies in its hybrid architecture, which effectively integrates convolutional feature extraction with transformer-based global context

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modeling and multi-scale fusion. Ablation studies further validate the importance of each component, demonstrating that the combination of local and global feature modeling is critical for achieving high-fidelity reconstruction. Overall, the model offers a robust and generalizable solution for real-world super-resolution tasks, bridging the gap between accuracy and visual quality.

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