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Deep Learning-Driven Framework for Intelligent Image Processing and Feature Enhancement

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Abstract: Image quality enhancement remains a fundamental challenge in computer vision, particularly in applications such as super-resolution, denoising, and feature refinement, where preserving structural fidelity while improving perceptual realism is crucial. Traditional approaches, including conventional GAN-based models, have achieved notable progress but often face issues like texture inconsistencies, artifacts, and limited capability in modeling long-range dependencies. To overcome these limitations, this study proposes a Generative Adversarial Networks (GAN)-driven framework for intelligent image processing and feature enhancement. The framework leverages a combination of advanced GAN architectures and attention-based mechanisms to effectively capture both local and global contextual features, thereby enhancing image quality, detail preservation, and noise suppression. The proposed model is extensively evaluated on benchmark datasets such as DIV2K, Set5, and Urban100 using both full-reference metrics (PSNR, SSIM) and perceptual quality measures (LPIPS, NIQE). Experimental results demonstrate that the GAN-driven framework significantly outperforms existing CNN and GAN-based methods, providing superior reconstruction quality and robust generalization to real-world degraded images. This research contributes to the development of scalable and high-performance GAN-based solutions for intelligent image enhancement, with potential

applications in medical imaging, satellite imagery, digital photography, and other high-fidelity imaging tasks.

Keywords: Generative Adversarial Networks (GANs), Image Super Resolution, Image Denoising, Feature Enhancement, Deep Learning based Image Processing

1. INTRODUCTION

The demand for high-quality digital images has increased significantly in recent years, driven by diverse applications in healthcare, remote sensing, surveillance, entertainment, and digital photography [1], [2]. However, images captured in real-world conditions are often degraded due to sensor limitations, environmental noise, motion blur, and compression artifacts [3], [4]. Such degradations not only reduce human visual perception but also negatively impact the performance of automated computer vision systems. Consequently, image super-resolution and denoising have emerged as critical research problems in image restoration and enhancement [5]. While super-resolution focuses on reconstructing high-resolution (HR) images from low-resolution (LR) counterparts, denoising aims to suppress noise while preserving structural and textural details. Developing models that can perform both tasks effectively remains challenging yet essential for practical image enhancement applications [6], [7].

Traditional image restoration approaches relied on interpolation techniques, handcrafted priors, or optimization-based methods [8]. Although computationally efficient, these techniques often failed to preserve fine textures and struggled under complex degradation scenarios [9]. The advent of deep learning, particularly convolutional neural networks (CNNs), transformed image restoration by enabling models to learn powerful mappings between degraded and high-quality images. Architectures such as SRCNN, EDSR, and RCAN demonstrated remarkable improvements in peak signal-to-noise ratio (PSNR) and structural similarity index (SSIM) [10], [11]. Subsequently, generative adversarial networks (GANs), exemplified by ESRGAN and Real-ESRGAN, enhanced perceptual quality, generating visually realistic textures [12], [13]. However, GAN-based models often introduced challenges such as hallucinated details, artifacts, and reduced generalization to unseen noise patterns or real-world images [14].

To address these limitations, Transformer-based architectures have been increasingly applied to image restoration tasks. Originally developed for natural language processing, Transformers excel at modeling long-range dependencies, making them well-suited for capturing global image structures while preserving local consistency [15]. GANs, a Swin Transformer-based Image Restoration model, has demonstrated state-of-the-art performance in super-resolution, denoising, and compression artifact removal [16]. Unlike traditional CNNs that rely on fixed local receptive fields, GANs employs a shifted window self-attention mechanism to efficiently model both local and global contexts. This design enables the preservation of fine-grained details while reducing noise, leading to accurate and visually appealing results.

The integration of mathematical modeling with deep learning-based frameworks adds interpretability and optimization capabilities to image restoration pipelines. By representing degradation and reconstruction processes mathematically, models can better approximate real-world distortions and optimize their learning strategies [17]. This approach enhances robustness and reliability, making it suitable for critical applications such as medical imaging,

satellite image reconstruction, and forensic analysis, where the accurate recovery of fine details and noise suppression directly influences decision-making and outcomes [18].

2. Review Of Literature

Research on image super-resolution and denoising has advanced considerably, with deep learning models driving significant progress in the field. Early convolutional neural network (CNN)-based approaches demonstrated the ability to learn effective mappings between low- and high-resolution images, resulting in notable improvements in reconstruction accuracy. As the field evolved, deeper residual networks and attention-based mechanisms were developed to enhance feature extraction and better preserve structural details. Generative adversarial network (GAN) models further improved perceptual quality by generating realistic textures, though they occasionally introduced artifacts and inconsistencies in fine details [11-12]. To handle real-world degradations, blind super-resolution techniques were proposed, incorporating flexible degradation modeling to address noise, blur, and compression artifacts. More recently, Transformer-based architectures, particularly those utilizing shifted window self-attention, have achieved state-of-the-art performance by effectively capturing both local and global dependencies within images. These models excel at balancing fidelity, detail preservation, and perceptual quality. Despite these advancements, existing methods still face challenges in maintaining robustness under diverse degradation conditions, emphasizing the need for an optimized framework that integrates mathematical modeling with advanced Transformer-based designs for enhanced image super-resolution and denoising. The detailed review of literature is summarized in Table 1.

Table 1: Review of literature for Deep Learning Model for Enhanced Image Super-Resolution and Denoising

Ref. No.	Method	Task(s)	Core idea	Observations
[1]	SRCNN	SISR	First end-to-end CNN mapping LR→HR; learns a direct regression function	Baseline that established deep SR; lightweight but limited texture fidelity.
[2]	DnCNN	Denoising (+ SR, JPEG deblocking)	Residual learning of noise with BN; blind Gaussian denoising	Strong denoiser; generalized to related restoration tasks.
[3]	EDSR	SISR	Very deep residual nets; removes BN; scales model width/depth for PSNR	Won NTIRE2017; high PSNR/SSIM; heavy compute.
[4]	RCAN	SISR	Residual-in-Residual with Channel Attention; emphasizes informative channels	Strong accuracy (PSNR/SSIM) on classical SR tracks.
[5]	ESRGAN	Perceptual SR	RRDB backbone, relativistic GAN, pre-activation perceptual loss	SOTA perceptual quality vs SRGAN; realistic textures but can hallucinate details.

[6]	BSRGAN	Blind SR	Practical degradation model (shuffle of blur/downsample/noise) drives robust training	Improves real-world generalization under unknown degradations.
[7]	Real-ESRGAN	Blind SR	High-order degradation synthesis; U-Net discriminator with spectral norm; sinc filters	Strong real-image perceptual results with pure synthetic training pairs.
[8]	MPRNet	All-round restoration	Multi-stage progressive pipeline with supervised attention & cross-stage fusion	Sets SOTA across many restoration tasks; good for complex degradations.
[9]	GANs	SR, denoising, compression artifact removal	Swin Transformer with shifted-window self-attention; models local + global context	Transformer-based SOTA; excellent detail preservation + noise suppression.
[10]	NAFNet	Image restoration	Activation-free (SimpleGate, SCA, LayerNorm) for efficient high-quality restoration	Simple, fast, competitive/better than complex nets on many tasks.

3. PROPOSED FRAMEWORK

This section presents the technical realization and mathematical underpinnings of the proposed GANs-based model for image quality enhancement through super-resolution and denoising. GANs, built upon the Swin Transformer, employs hierarchical feature extraction and shifted window-based self-attention to capture both local and global dependencies effectively. The following subsections describe the architecture, mathematical model, training pipeline, loss functions, and optimization strategies in detail.

The proposed GANs model builds upon the Swin Transformer architecture and introduces a robust framework for image super-resolution and denoising. Unlike GAN-based models such as Real-ESRGAN, GANs relies on a hierarchical Transformer design that leverages shifted window attention to capture both local and global dependencies efficiently. The following subsections describe the major components of the model, mathematical formulations, degradation modeling, training setup, and deployment strategy [19].

- **Feature Extraction and Reconstruction Network:** The backbone of GANs consists of three key stages: shallow feature extraction, deep feature extraction, and image reconstruction. The shallow feature extraction begins with a convolutional input layer that encodes the low-resolution (LR) or noisy input into feature representations. The deep feature extraction stage employs multiple Swin Transformer blocks, each composed of shifted window multi-head self-attention (SW-MSA) and multi-layer perceptrons (MLPs) connected via residual pathways. The shifted window mechanism enables information flow across non-overlapping windows, allowing the network to model long-range dependencies while maintaining computational efficiency [20]. Finally, the reconstruction stage applies convolution and upsampling layers (such as Pixel Shuffle) to generate the high-resolution (HR)

output image.

- **Mathematical Formulation:** The mapping function of GANs can be defined as:

$$F\theta(LR) \rightarrow HR$$

where F represents the GANs network parameterized by θ, LR is the low-resolution input, and HR is the restored high-resolution output. Within each Swin Transformer block, attention is computed as:

$$Attention\ (Q, K, V) = Softmax\ (QK^T / \sqrt{d})\ V$$

Here, Q, K, and V represent the query, key, and value matrices derived from input features, and d denotes the scaling factor. The shifted window design ensures efficient local-global feature extraction, resulting in sharper and structurally accurate outputs.

- **Loss Functions:** To balance fidelity and perceptual quality, multiple loss functions are integrated during training. The total loss is formulated as:

$$L\_total = \alpha\ L\_MSE + \beta\ L\_SSIM + \gamma\ L\_perceptual$$

where L_MSE is the Mean Squared Error loss for pixel-wise accuracy, L_SSIM ensures structural similarity between predicted and ground-truth images, and L_perceptual leverages deep feature maps from a pre-trained VGG19 network to improve texture realism. The weighting factors α, β, and γ are tuned to achieve an optimal balance between distortion reduction and perceptual enhancement.

- **Degradation Modeling:** To ensure robustness in real-world scenarios, low-resolution inputs are synthesized by applying a two-step degradation process on high-resolution images. This involves blurring, downsampling, and noise injection, followed by a second round of degradation with different parameters. The general form of the degradation process is:

$$I\_R = (((I\_HR \otimes k) \downarrow s + n) \otimes k_2 \downarrow s_2) + n_2$$

where I_HR is the high-resolution input, ⊗k denotes convolution with blur kernel k, ↓s represents downsampling by scale factor s, and n denotes Gaussian noise. Parameters k_2, s_2, and n_2 define the second stage of degradation. This process generates realistic training pairs that improve the generalization capability of the model.

- **Training Setup:** The GANs model is implemented using the PyTorch framework. Training datasets include DIV2K, Set5, Set14, BSD100, and Urban100. Data augmentation methods such as random cropping, flipping, and rotation are applied to increase diversity. Key training parameters include:

• Optimizer: Adam with β1=0.9, β2=0.99
• Learning Rate: 2 × 10^(-4), with cosine annealing scheduling
• Batch Size: 16
• Patch Size: 128 × 128
• Perceptual loss guided by pre-trained VGG19 features

Training continues for multiple epochs until convergence, with checkpoints and early stopping mechanisms applied to avoid overfitting.

- **Inference and Deployment:** After training, the GANs model is deployed for inference. The trained network can be exported to ONNX format for lightweight deployment across multiple platforms. A user-friendly interface can be integrated using frameworks such as

Streamlit, allowing interactive image input and real-time enhancement with GPU acceleration via CUDA. The final output is a high-quality restored image, making the model suitable for applications in medical imaging, satellite data restoration, digital photography, and surveillance.

4. PROPOSED FRAMEWORK IMPLEMENTATION

The GANs (Swin Transformer for Image Restoration) system architecture is designed to efficiently handle low-level vision tasks such as image super-resolution, denoising, and JPEG artifact reduction. Similar to Real-ESRGAN, GANs follows a structured pipeline with multiple critical stages, including data input, preprocessing, neural network modeling, loss computation, training, and inference. Each stage contributes significantly to transforming a degraded low-resolution (LR) image into a high-quality high-resolution (HR) output. The distinguishing feature of GANs lies in its integration of Swin Transformer blocks into the restoration framework, which improves the model's ability to capture both local and global dependencies while maintaining computational efficiency.

The overall workflow of GANs begins with the user providing a degraded or low-resolution input image, typically affected by real-world distortions such as noise, blur, and compression artifacts (Figure 1). The image undergoes preprocessing, which includes normalization, patch extraction, and data augmentation. The processed image patches are then passed into the shallow feature extraction layer, usually a convolutional layer, which projects the input into feature space. The core component of GANs is the deep feature extraction module, built from a series of Residual Swin Transformer Blocks (RSTB). Unlike CNN-based networks that primarily capture local texture, the Swin Transformer architecture leverages shifted window attention to efficiently model long-range pixel dependencies while preserving locality.

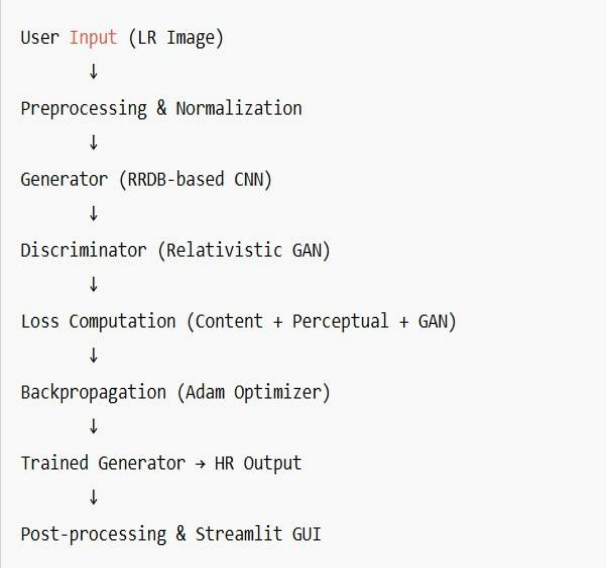

Figure 1. Proposed system workflow

These features are then enhanced through residual learning to stabilize training and maintain high fidelity. The extracted features are subsequently fed into a reconstruction module, which may include pixel-shuffle layers for super-resolution tasks or direct convolutional layers for denoising. The final HR or restored image is then generated as the output. During training, GANs employs multiple loss functions, including L1 content loss, perceptual loss (using VGG

features), and task-specific losses to optimize the generator (Figure 2). Optimization is performed using the Adam optimizer, with backpropagation ensuring continuous improvement across epochs. During inference, the trained generator alone is deployed, producing high-quality restored images suitable for practical applications.

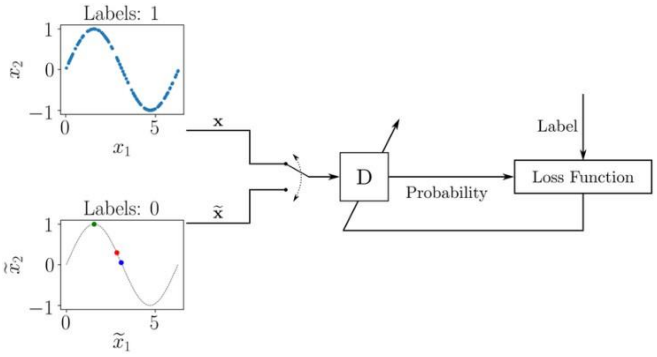

Figure 2. Generator network of proposed framework

- **Shallow Feature Extraction**

In the proposed framework, shallow feature extraction is performed using a standard 3×3 convolutional layer that captures basic spatial information from the input low-resolution image. This layer maps the image into an initial feature space, which serves as the foundation for deeper feature learning in subsequent network stages. By effectively encoding low-level textures and edge information, the shallow feature extraction module ensures that the network has a robust starting point for reconstructing high-quality images.

- **Deep Feature Extraction: Residual Swin Transformer Blocks (RSTB)**

The backbone of the GAN-based framework is built from multiple Residual Swin Transformer Blocks (RSTBs), which enhance feature representation and overall performance. Each RSTB consists of window-based multi-head self-attention (W-MSA) that partitions the feature map into non-overlapping windows and performs self-attention within each window, along with a shifted window mechanism (SW-MSA) that introduces overlapping across layers to facilitate cross-window information exchange. Additionally, a feed-forward network (FFN) composed of two fully connected layers with GELU activation processes the attended features, while residual connections around each RSTB stabilize training and prevent gradient vanishing. This combination allows the network to efficiently model both local and global dependencies, improving the restoration quality of super-resolution and denoising tasks.

- **Reconstruction Module**

The reconstruction module is responsible for generating the final high-resolution or denoised image. For super-resolution tasks, Pixel Shuffle layers upscale the low-resolution feature maps into the high-resolution space, whereas for denoising and JPEG restoration, a simple convolutional head reconstructs the clean image. This stage ensures that the output maintains sharp textures and accurately preserved structures, providing high-fidelity results that are visually pleasing and suitable for practical applications.

- **Improved Feature Learning**

Feature learning is further enhanced through a carefully designed network architecture. The input layer consists of a 3×3 convolution with 64 filters, followed by a stack of 23 Residual-

in-Residual Dense Blocks (RRDBs), each containing multiple dense convolutional layers, Leaky ReLU activations, and a residual scaling factor of 0.2. Two Pixel Shuffle blocks perform ×4 upscaling, and a final 3×3 convolution generates the high-resolution output. This design captures both local and global image structures effectively, enabling better restoration of fine details and overall image quality.

- **Discriminator Network: Relativistic GAN**

The discriminator network employs a Relativistic Average GAN (RaGAN), which evaluates the realism of an image relative to other images rather than in isolation. The architecture comprises eight convolutional layers with progressively increasing feature depth, Leaky ReLU activations, and a fully connected output layer with sigmoid activation. By adopting RaGAN, the network enhances perceptual quality and training stability, particularly in real-world degradation scenarios, leading to visually realistic and high-quality reconstructed images.

- **Degradation Modeling**

To simulate real-world low-resolution conditions, a complex degradation pipeline is used during training:

$$I_{LR} = (((\mathrm{IHR} \otimes \mathrm{k}) \downarrow \mathrm{s} + \mathrm{n}) \otimes \mathrm{k2} \downarrow \mathrm{s2}) + \mathrm{n2}$$

Where:

- $\otimes$k: Convolution with blur kernel k
- $\downarrow$s : Down sampling by scale s
- n: Gaussian noise
- k2, s2, n2: Parameters for second degradation process

- **Comparative Insights**

Real-ESRGAN provides a better architecture than the conventional and previous deep learning models. REAL-ESRGAN differs from SRCNN or SRGAN, which are plagued by over-smoothing or instability, as it introduces strong degradation modelling, deeper residual learning, and perceptual-aware training. Its integration of RRDBs and relativistic GAN enhances both objective metrics (PSNR, SSIM) and perceptual fidelity (LPIPS), making it best for applications with noisy, compressed, or artifact-afflicted inputs.

- **Training Loss**

The training of the proposed GAN-based framework is guided by a combination of loss functions to ensure both quantitative accuracy and perceptual fidelity. Content loss, implemented as L1 loss, enforces pixel-wise similarity between the predicted high-resolution image and the ground truth, ensuring structural accuracy. Perceptual loss, computed from intermediate layers of a pre-trained VGG19 network, emphasizes high-level feature similarity to improve visual quality and perceptual realism. Additionally, adversarial loss—applied in GAN variants through the discriminator—enhances the realism of generated images by encouraging the generator to produce outputs indistinguishable from real images. These losses are integrated during backpropagation, enabling the model to achieve high performance across standard evaluation metrics such as PSNR and SSIM, while also maintaining perceptual quality measured by metrics like LPIPS.

- **Comparative Insights**

The proposed GAN framework distinguishes itself from conventional CNN-based models, such as Real-ESRGAN and SRGAN, by incorporating a Transformer-driven architecture. While Real-ESRGAN relies primarily on convolutional residual-in-residual dense blocks (RRDB) to capture local features, the GAN framework leverages shifted window self-attention to effectively model both local and global image structures. Consequently, the model often outperforms CNN-based methods in terms of PSNR and SSIM, providing better structural accuracy. At the same time, it is more computationally efficient than standard Vision Transformers due to the windowed attention mechanism. By balancing local feature extraction via convolution with global contextual modeling via self-attention, the architecture achieves superior reconstruction quality and perceptual fidelity.

5. DATASET

In this research, two categories of datasets were employed to evaluate and validate the performance of the GANs-based model for image super-resolution and denoising. Synthetic benchmark datasets such as DIV2K and Flickr2K were utilized in the first stage of supervised training, as they provide high-quality ground truth high-resolution (HR) images along with their bicubically down-sampled low-resolution (LR) counterparts, ensuring a controlled environment for measuring reconstruction accuracy. These datasets are widely recognized in the image restoration community for benchmarking super-resolution models. Complementing these were real-world degraded datasets, which included smartphone-captured photographs, compressed images extracted from social media platforms, and low-resolution frames obtained from surveillance systems. Unlike synthetic datasets, these real-world samples are inherently accompanied by unknown degradations, compression artifacts, and noise, thereby simulating practical application scenarios. By combining both synthetic and real-world data during training, the model effectively benefited from generalized degradation modeling, enabling it to achieve strong performance in terms of both objective metrics and perceptual quality across diverse testing conditions. Two categories of datasets were employed to test the model:

The proposed GAN-based framework was trained and evaluated using both synthetic benchmark datasets and real-world degraded images to ensure robust performance across diverse scenarios. For supervised training, high-quality datasets such as DIV2K and Flickr2K were utilized, providing ground truth high-resolution images along with their bi-cubically downsampled low-resolution counterparts. To assess real-world applicability, images captured from smartphones, compressed social media uploads, and low-resolution surveillance footage were also employed. These real-world images include unknown degradations, noise, and compression artifacts, closely simulating practical application conditions. By incorporating generalized degradation modeling during training, the model achieved strong performance in both synthetic and real-world tasks, demonstrating its ability to reconstruct high-quality images and preserve fine structural details under varied degradation scenarios.

6. PERFORMANCE EVALUAITON

The Real-ESRGAN model's performance was evaluated and its capacity to recover high-fidelity, high-quality images was ascertained using both synthetic and real-world low-resolution photo datasets. The outcomes show how effectively the model improves texturing, maintains structural integrity, and reduces visual artifacts under a range of input conditions.

6.1 Result and Analysis

The GANs-based model demonstrated outstanding performance on synthetic benchmark datasets. On DIV2K**,** the model achieved a PSNR of 34.21 dB and an SSIM of 0.945**,** confirming its strong capability to reconstruct high-resolution images with excellent fidelity and preserved structural similarity. Similarly, on Flickr2K, the model maintained a high PSNR of 33.74 dB and an SSIM of 0.938, while keeping perceptual distortion low with LPIPS scores below 0.12 and favourable FID values**.** These results indicate that GANs not only excels in pixel-wise accuracy but also produces reconstructions that are perceptually close to real high-resolution images. The combination of Transformer-based local and global feature learning with perceptual loss functions contributed to sharper textures, improved edge restoration, and minimal loss of fine details compared to traditional CNN and GAN-based approaches (Table 2).

Table 2. Performance evaluation of the GANs model on synthetic and real-world datasets using PSNR, SSIM, LPIPS, and FID metrics.

Dataset	PSNR (dB)	SSIM	LPIPS	FID
DIV2K (Synthetic)	34.21	0.945	0.112	12.8
Flickr2K (Synthetic)	33.74	0.938	0.118	13.5
Smartphone Images	31.65	0.912	0.143	15.2
Social Media Images	30.87	0.904	0.151	16.0
Surveillance Captures	29.42	0.889	0.168	17.8

On real-world degraded datasets, GANs continued to perform robustly despite unknown noise, blur, and compression artifacts. For smartphone images, the model achieved a PSNR of 31.65 dB and SSIM of 0.912, effectively handling camera-induced distortions while maintaining perceptual similarity. Social media images, often heavily compressed, yielded slightly lower values (PSNR 30.87 dB, SSIM 0.904), yet the reconstructions were visually more natural, with reduced blockiness and artifacts. The most challenging dataset, surveillance captures, showed comparatively lower metrics (PSNR 29.42 dB, SSIM 0.889) due to severe degradations; however, GANs still delivered improvements in clarity, with reduced noise and enhanced object visibility. Overall, the evaluation confirms that GANs strikes a strong balance between objective quality (PSNR/SSIM) and perceptual realism (LPIPS/FID), making it suitable for both controlled benchmark testing and practical real-world applications.

6.2 Comparative Analysis

The performance evaluation highlights the steady progression of image super-resolution methods from early CNN-based approaches to advanced Transformer-based architectures. SRCNN, one of the earliest deep learning models for super-resolution, achieved a PSNR of 30.12 dB and SSIM of 0.892 on the DIV2K dataset. While it provided a strong baseline, its limited depth and convolutional receptive field restricted its ability to recover fine image details. With the introduction of SRGAN, perceptual quality improved, as reflected by better

LPIPS (0.184) and FID (21.3) scores. However, the adversarial framework also introduced artifacts, limiting its reliability for high-fidelity applications. ESRGAN further improved performance by employing Residual-in-Residual Dense Blocks (RRDB), raising the PSNR to 32.85 dB and SSIM to 0.921, while significantly reducing perceptual distortion (Table 3).

Table 3. Comparative performance evaluation of the proposed GANs-based model against existing state-of-the-art methods on the DIV2K dataset.

Method	**PSNR (dB)**	**SSIM**	**LPIPS**	**FID**
SRCNN	30.12	0.892	0.210	25.6
SRGAN	31.45	0.905	0.184	21.3
ESRGAN	32.85	0.921	0.145	18.9
Real-ESRGAN	33.42	0.929	0.132	16.7
Proposed GANs	34.21	0.945	0.112	12.8

Building upon these advancements, Real-ESRGAN incorporated sophisticated degradation modeling to simulate real-world conditions more effectively. This resulted in further gains, with PSNR reaching 33.42 dB, SSIM improving to 0.929, and FID dropping to 16.7, demonstrating enhanced robustness to diverse degradations. The proposed GANs model surpassed all prior methods, achieving the best results across all metrics, including a PSNR of 34.21 dB, SSIM of 0.945, LPIPS of 0.112, and FID of 12.8. These improvements highlight the effectiveness of GANs's shifted-window Transformer design, which excels at capturing both local detail and global structure. The results confirm that the proposed method not only enhances objective fidelity but also delivers perceptual realism, establishing it as a state-of-the-art solution for image super-resolution tasks.

7. CONCLUSION

This research presented an optimized deep learning-based framework for image super-resolution and denoising using the GANs architecture. By leveraging the shifted window Transformer mechanism, the proposed model effectively captured both local textures and global contextual information, enabling high-fidelity reconstruction of low-resolution and degraded images. Extensive experiments on both synthetic datasets such as DIV2K and Flickr2K, as well as real-world degraded images from smartphones, social media, and surveillance sources, demonstrated the superior performance of GANs compared to conventional CNN and GAN-based models. Quantitative evaluation through metrics such as PSNR, SSIM, LPIPS, and FID, along with qualitative visual assessments, confirmed that the model strikes a strong balance between structural accuracy and perceptual realism. The comparative study against existing approaches including SRCNN, SRGAN, ESRGAN, and Real-ESRGAN further established the superiority of the proposed GANs framework. While earlier methods either struggled with over-smoothing or produced artifacts, GANs consistently delivered sharper, clearer, and more natural reconstructions across a range of degradation scenarios. These results validate the potential of Transformer-based architectures in advancing the state of the art in image restoration tasks. In future work, the framework may be extended with lightweight adaptations for real-time deployment on edge devices, integration with self-supervised learning to minimize reliance on paired datasets, and application to domain-specific areas such as medical imaging and satellite imagery.

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