Enhanced EDSR-based Deep Neural Model for High-Fidelity Image Super-Resolution and Noise Reduction

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ABSTRACT

High-fidelity image super-resolution and effective noise reduction remain persistent challenges in computer vision, where maintaining structural accuracy while enhancing perceptual quality is essential. Conventional methods, including GAN-based architectures such as ESRGAN and Real-ESRGAN, have demonstrated promising results but still encounter issues like texture distortion, visual artifacts, and limited representation of complex image dependencies. To overcome these limitations, this study introduces an enhanced EDSR-based deep neural model tailored for image super-resolution and noise reduction. The proposed framework builds upon the strengths of residual learning and deep convolutional layers, refined with optimization strategies to better capture fine-grained details and suppress noise across varying degradation conditions. Comprehensive experiments are conducted on benchmark datasets including DIV2K, Set5, and Urban100, using full-reference metrics (PSNR, SSIM) along with perceptual quality assessments (LPIPS, NIQE). Experimental findings confirm that the enhanced EDSR model achieves superior performance compared to traditional CNN and GAN-based approaches, delivering sharper reconstructions, improved texture fidelity, and effective noise suppression. Additionally, the model demonstrates strong generalization to real-world low-quality images, underscoring its potential in diverse application domains such as medical imaging, remote sensing, and digital photography. This research advances deep neural solutions for image enhancement, presenting a robust and scalable framework for high-quality super-resolution and denoising tasks.

Keywords: *EDSR, CNN, ESRGAN, Real-ESRGAN, Image Quality Enhancement, Deep Learning*

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1. INTRODUCTION

The demand for high-quality digital images has grown significantly in recent years, driven by diverse applications in healthcare, remote sensing, surveillance, entertainment, and digital photography. However, images captured in real-world environments often suffer from degradations caused by sensor limitations, environmental noise, motion blur, and compression artifacts. These distortions adversely affect both human visual perception and the reliability of automated computer vision systems. As a result, image super-resolution and denoising have emerged as two critical research areas in image restoration and enhancement. Super-resolution aims to reconstruct high-resolution (HR) images from low-resolution (LR) inputs, while denoising focuses on suppressing noise while retaining structural and textural details [13-14]. Developing models that can effectively address both tasks simultaneously is highly challenging yet vital for real-world image enhancement.

Traditional image restoration methods, which relied on interpolation strategies, handcrafted priors, and optimization-based techniques, offered computational simplicity but often failed to preserve fine textures and were limited under complex degradation conditions. With the advent of deep learning, convolutional neural networks (CNNs) transformed image restoration by enabling data-driven learning of mappings between degraded and high-quality images. Early CNN-based methods, including SRCNN, EDSR, and RCAN, achieved remarkable gains in terms of peak signal-to-noise ratio (PSNR) and structural similarity index (SSIM) [15-16]. Later, generative adversarial networks (GANs), such as ESRGAN and Real-ESRGAN, improved perceptual realism by generating sharper and more detailed textures. However, these models introduced drawbacks such as hallucinated features, artifacts, and weaker generalization to real-world noise patterns.

The Enhanced EDSR-based deep neural model builds upon the foundation of Enhanced Deep Super-Resolution (EDSR), a powerful convolutional network designed for single-image super-resolution. EDSR removes unnecessary modules from traditional residual networks while increasing the depth and width of the architecture, allowing it to learn more effective feature representations. By refining residual learning strategies, the enhanced EDSR model achieves superior reconstruction quality, improved texture preservation 17], and robust noise reduction. This makes it highly suitable for real-world applications where high-fidelity image restoration is critical, such as medical imaging, satellite remote sensing, and digital photography.

To overcome these challenges, this research leverages an Enhanced EDSR-based deep neural model designed to improve both image super-resolution and noise reduction. Building upon the strengths of the original Enhanced Deep Super-Resolution (EDSR) network, the proposed model refines residual learning and optimizes convolutional feature extraction to capture fine-grained details more effectively while suppressing noise across diverse degradation scenarios [18-19]. Unlike GAN-based or Transformer-driven approaches that often compromise structural fidelity, the enhanced EDSR framework emphasizes a balance between fidelity and perceptual quality, ensuring robustness and generalization across varied datasets.

The integration of mathematical optimization principles into the EDSR-based framework further strengthens interpretability and adaptability to real-world conditions. By modeling degradation and reconstruction processes with mathematical precision, the proposed system achieves improved stability and resilience, making it suitable for high-stakes applications such as medical diagnostics, satellite imagery restoration, and forensic investigations [12]. In such domains, the ability to recover subtle image details while minimizing noise has a direct impact on decision-making accuracy and practical usability.

2. LITERATURE REVIEW

Research on image super-resolution and denoising has advanced significantly, with deep learning methods driving major progress in the field. Early convolutional neural network (CNN)-based models demonstrated the ability to learn effective mappings between low- and high-resolution images, achieving notable improvements in reconstruction quality. Subsequent developments introduced deeper residual networks, such as EDSR, which refined feature extraction and enhanced the preservation of structural and textural details. Attention-based mechanisms further boosted accuracy by enabling models to focus on critical image regions during reconstruction [1-2].

Generative adversarial models like ESRGAN and Real-ESRGAN contributed to perceptual improvements, generating visually pleasing textures [4]. However, these approaches often introduced artifacts and inconsistencies, particularly in complex or noisy images. To address real-world degradations, blind super-resolution techniques were explored, incorporating flexible degradation modeling to handle noise, blur, and compression artifacts more effectively. While Transformer-based designs have recently gained attention for capturing long-range dependencies, they also bring computational overhead and stability challenges.

Despite these advances, existing models continue to face limitations in balancing fidelity, noise suppression, and generalization across diverse degradation conditions. This underscores the need for an optimized framework. The proposed enhanced EDSR-based deep neural model aims to fill this gap by integrating refined residual learning with mathematical optimization strategies, thereby offering improved reconstruction quality, noise reduction, and robustness for real-world image restoration tasks [5].

Image super-resolution and denoising have become key research areas in computer vision due to their applications in healthcare, satellite imaging, surveillance, and digital photography. The earliest methods focused on interpolation techniques, such as bicubic interpolation, which were computationally efficient but often failed to reconstruct fine textures or recover structural details. With the rise of deep learning, convolutional neural networks (CNNs) introduced a breakthrough in learning mappings from low-resolution to high-resolution images, achieving significant improvements in reconstruction accuracy [1].

Early CNN-based methods such as SRCNN demonstrated the feasibility of end-to-end learning for super-resolution [1]. Later, deeper architectures like VDSR and DRCN improved performance by using residual connections and recursive learning, which enabled better convergence and more accurate reconstructions [2][3]. Residual-based frameworks further evolved into powerful models such as EDSR, which eliminated unnecessary modules while expanding network depth and width, thereby achieving state-of-the-art results in benchmark datasets [4].

Generative adversarial networks also contributed to this domain, with SRGAN, ESRGAN, and Real-ESRGAN enhancing perceptual quality by producing visually pleasing textures [6][7][8]. However, these models often introduced hallucinated details, artifacts, and inconsistencies, particularly under complex degradations. Attention mechanisms and channel recalibration methods, as in RCAN, further strengthened deep learning models by enabling selective focus on important features, resulting in improved texture recovery [5].

Blind super-resolution techniques also gained importance, addressing real-world degradations such as noise, blur, and compression by modeling degradation processes rather than assuming fixed kernels [9]. More recently, hybrid and Transformer-based approaches such as SwinIR have demonstrated superior performance by modeling long-range dependencies alongside local features, achieving high-quality restoration across diverse tasks [11]. Attention-based and sparse feature learning strategies have also been introduced to better capture structural consistency while reducing noise [10][12]. However, these methods often involve high computational cost and stability issues.

Despite these advancements, a key challenge remains in achieving a balance between fidelity, perceptual realism, and robustness across diverse degradation conditions. This has motivated the development of optimized frameworks such as the Enhanced EDSR-based deep neural model, which integrates refined residual learning and mathematical optimization to achieve superior performance in image super-resolution and noise reduction. By combining structural fidelity with robust noise suppression, such frameworks offer promising solutions for real-world applications where image quality is crucial.

3. RESEARCH METHODOLOGY

The proposed research aims to design and implement an optimized deep learning-based mathematical model for image super-resolution and denoising using the architecture. The methodology is structured into five phases: data collection, preprocessing, model design, training and optimization, and evaluation.

• **Data Collection and Preprocessing**: High-quality benchmark datasets such as DIV2K, Set5, Set14, BSD100, and Urban100 will be used for training and validation. To ensure robustness, synthetic low-resolution and noisy images will be generated using Gaussian blur, noise injection, and downscaling techniques. Preprocessing steps, including normalization, patch extraction, and data augmentation (rotation, flipping, scaling), will be applied to improve generalization and reduce overfitting.

• **Model Design**: The core of the framework is the Enhanced EDSR model, which refines traditional residual networks by removing unnecessary modules and increasing network depth and width. This design improves feature extraction and enhances the reconstruction of fine image details. A mathematical modeling layer will be integrated to optimize parameter tuning, ensuring a balance between reconstruction accuracy and computational efficiency. The model will simultaneously address super-resolution for detail enhancement and denoising for effective noise suppression while preserving structural fidelity.

• **Training and Optimization**: The training process will employ supervised learning with paired degraded and ground-truth high-resolution images. A combination of loss functions will be used: Mean Squared Error (MSE) for pixel-level reconstruction, Structural Similarity Index (SSIM) loss for structural fidelity, and perceptual loss to enhance texture realism. Optimization will be performed using the Adam optimizer with adaptive learning rate scheduling. Regularization strategies such as dropout and weight decay will be applied to improve model stability and prevent overfitting.

• **Evaluation and Validation**: The model's performance will be evaluated using objective metrics such as Peak Signal-to-Noise Ratio (PSNR) and SSIM, alongside perceptual quality metrics such as LPIPS and NIQE. Comparative evaluations will be carried out against baseline models including SRCNN, EDSR, ESRGAN, and Real-ESRGAN to highlight improvements in accuracy and visual quality. Visual comparisons will also be presented to demonstrate qualitative advancements in texture recovery and noise reduction.

• **Real-World Testing**: To validate its applicability, the optimized Enhanced EDSR-based model will be tested in real-world use cases such as medical imaging (e.g., MRI scans), satellite image enhancement, and digital photography. Computational efficiency and scalability will also be analyzed to assess the feasibility of deployment in practical scenarios.

4. PROPOSED ALGORITHM

This pseudo code describes the workflow of the proposed Enhanced EDSR (Enhanced Deep Super-Resolution Network)-based deep learning framework designed for high-fidelity image super-resolution and noise reduction as shown in algorithm 1.

Algorithm 1: Enhanced EDSR-Based Deep Neural Model for High-Fidelity Image Super-Resolution and Noise Reduction

```
INPUT: Low-resolution noisy image (LR_noisy)
OUTPUT: High-resolution denoised image (HR_denoised)
BEGIN
PHASE 1: DATA COLLECTION & PREPROCESSING
1. Load benchmark datasets: DIV2K, Set5, Set14, BSD100, Urban100
2. FOR each high-resolution image HR in dataset:
    a. Generate low-resolution noisy version (LR_noisy):
        - Apply Gaussian blur
        - Add Gaussian noise
        - Downscale resolution
    b. Normalize LR_noisy and HR images to [0,1]
    c. Perform data augmentation:
        - Rotation (90°, 180°, 270°)
        - Flipping (horizontal, vertical)
        - Random scaling
    d. Extract patches of fixed size (e.g., 128x128)
  END FOR
3. Store LR_noisy-HR pairs for training
PHASE 2: MODEL DESIGN (ENHANCED EDSR)
1. Initialize EDSR architecture with:
    - Residual blocks (enhanced version without batch normalization)
    - Long skip connections for stable training
    - Residual scaling to control gradient explosion
2. Extend model for dual tasks:
    - Super-resolution: Recover high-frequency details
    - Denoising: Suppress noise while preserving edges
PHASE 3: TRAINING & OPTIMIZATION
1. Define loss functions:
    - L1 Loss / MSE → pixel-level accuracy
    - SSIM Loss → structural similarity
    - Perceptual Loss → texture and perceptual quality
2. Initialize optimizer (Adam) with learning rate scheduling
3. FOR each training epoch:
    FOR each LR_noisy-HR pair:
        a. Input LR_noisy → Enhanced EDSR → Output HR_pred
        b. Compute total loss:
            Loss_total = α*MSE + β*SSIM + γ*Perceptual
        c. Backpropagate and update model parameters
    END FOR
  Save checkpoint model after each epoch
END FOR
PHASE 4: EVALUATION & VALIDATION
1. Input test LR_noisy images to trained model → Output HR_denoised
2. Evaluate using metrics:
    - PSNR, SSIM for reconstruction accuracy
    - LPIPS, NIQE for perceptual quality
3. Compare performance with baseline models:
    - SRCNN, EDSR, ESRGAN, Real-ESRGAN
4. Save visual comparisons of input vs output
```

PHASE 5: *DEPLOYMENT & REAL-WORLD APPLICATIONS*
1. Apply model to real-world LR_noisy images:
    - Medical imaging (MRI, CT scans)
    - Satellite image enhancement
    - Digital photography
2. Measure runtime, memory efficiency, scalability
END

5. PROPOSED FRAMEWORK IMPLEMENTATION

The proposed framework integrates advanced mechanisms for image super-resolution and denoising, building on recent progress in deep neural networks and Transformer-based architectures. The model design emphasizes stability, fidelity, and perceptual realism by combining residual learning, window-based self-attention, and task-specific reconstruction modules as shown in figure 1.

```
User Input (LR Image)
       ↓
Preprocessing & Normalization
       ↓
Generator (RRDB-based CNN)
       ↓
Discriminator (Relativistic GAN)
       ↓
Loss Computation (Content + Perceptual + GAN)
       ↓
Backpropagation (Adam Optimizer)
       ↓
Trained Generator → HR Output
       ↓
Post-processing & Streamlit GUI
```

Figure 1. Proposed system workflow

1. Shallow Feature Extraction
The implementation begins with shallow feature extraction, where the low-resolution (LR) input image is passed through a 3×3 convolutional layer. This step maps the input into an initial feature space that serves as the foundation for further processing. By capturing low-level image characteristics such as edges and simple textures, the shallow feature layer ensures a strong baseline for subsequent deeper feature learning.

2. Residual Learning for Stability
To maintain stability during training and improve convergence, residual connections are employed. These connections address issues such as vanishing gradients and allow the network to learn identity mappings more effectively. By incorporating residual learning, the model preserves structural fidelity and enhances the quality of restored images, especially under complex degradations.

3. Residual Swin Transformer Blocks (RSTBs)
The backbone of the framework is constructed using multiple Residual Swin Transformer Blocks (RSTBs). Each RSTB integrates window-based multi-head self-attention (W-MSA), which divides feature maps into non-overlapping windows and applies self-attention within each. To improve contextual representation, shifted window self-attention (SW-MSA) is applied, enabling communication across neighboring windows. Additionally, feed-forward networks (FFNs) with GELU activation refine the features, while residual learning ensures stability and faster convergence.

4. Task-Specific Reconstruction Module
The reconstruction module is designed to adapt to the specific restoration task. For super-resolution, pixel-shuffle layers are used to upscale the low-resolution features to the desired high-resolution output. For denoising or compression artifact removal, convolutional layers directly reconstruct the clean image. This modular approach ensures that the framework can be applied flexibly to different image restoration tasks.

5. Residual-in-Residual Dense Blocks (RRDBs)
To further improve feature extraction and detail recovery, the framework incorporates Residual-in-Residual Dense Blocks (RRDBs). Each block consists of densely connected convolutional layers with Leaky ReLU activations and a residual scaling factor to regulate gradient flow. Stacking 23 RRDBs allows the network to effectively capture fine details while avoiding overfitting.

6. Upscaling Mechanism
For tasks involving super-resolution, the model employs two pixel-shuffle layers to achieve a ×4 resolution enhancement. Pixel shuffling rearranges feature map elements to generate higher-resolution outputs efficiently, ensuring sharper edges and finer textures. The final output layer is a 3×3 convolutional layer that produces the high-resolution image.

7. Adversarial Training with RaGAN
In cases where adversarial training is applied, the framework utilizes a Relativistic Average GAN (RaGAN) discriminator. Unlike conventional discriminators that evaluate individual images, RaGAN compares image realism relative to other samples, leading to improved perceptual quality. The discriminator is built with eight convolutional layers of increasing depth, followed by a fully connected layer and sigmoid activation, enabling effective discrimination of real versus generated images.

8. Loss Function Design
The training process is guided by a carefully designed set of loss functions. The content loss (L1) ensures pixel-level similarity between predicted and ground-truth images. Perceptual loss, extracted from intermediate layers of VGG19, emphasizes visual fidelity by aligning feature-level similarity. For adversarial variants, GAN-based losses are incorporated to improve perceptual realism. This multi-objective optimization strategy ensures a balance between fidelity, detail preservation, and perceptual quality.

9. Comparative Advantage
Compared to traditional CNN-based approaches such as SRGAN and Real-ESRGAN, the proposed Enhanced EDSR-based model integrates Transformer-driven attention mechanisms to better capture global dependencies. This combination of local convolutional features with global self-attention results in higher PSNR and SSIM scores, while also improving perceptual quality. Moreover, compared to vanilla Vision Transformers, the proposed method reduces computational complexity through window-based self-attention, making it more efficient and scalable.

6. RESULT DISCUSSION

The performance of the proposed Enhanced EDSR-based deep neural model was evaluated on benchmark datasets such as DIV2K, Set5, and Urban100 under both synthetic and real-world degradation conditions. The results demonstrate that the model consistently outperforms baseline methods including SRCNN, ESRGAN, and Real-ESRGAN in terms of quantitative metrics like PSNR and SSIM. The enhanced residual learning and optimized parameter tuning within the EDSR backbone enable more accurate reconstruction of high-frequency textures, sharper edges, and improved noise suppression. Unlike traditional CNN-based models, the proposed approach effectively reduces Gaussian and compression-induced noise while maintaining structural integrity, ensuring the restored images exhibit high fidelity and clarity. These improvements are particularly noticeable in complex scenes containing fine patterns, small objects, or highly detailed textures where conventional models often fail to preserve structural consistency.

In addition to quantitative gains, qualitative assessments highlight the model's ability to generate visually pleasing and perceptually realistic outputs. The integration of advanced loss functions, including perceptual and SSIM-based losses, ensures that reconstructed images achieve a balance between distortion minimization and perceptual sharpness. Comparative visualization confirms that the proposed Enhanced EDSR model reduces common artifacts such as blurring, ringing, and over-smoothing that are often observed in CNN and GAN-based methods. Moreover, the model exhibits strong generalization capability when tested on real-world noisy inputs, such as low-light or compressed photographs, producing outputs with minimal distortions and enhanced realism. These findings validate the efficiency and scalability of the Enhanced EDSR framework, making it a practical solution for applications in medical imaging, satellite image restoration, and high-resolution digital photography.

6.1 Dataset Evaluation
To evaluate the effectiveness of the proposed Enhanced EDSR-based framework, widely recognized benchmark datasets were employed. The DIV2K dataset was primarily used for training and validation due to its high-quality 2K resolution images. DIV2K consists of 800 training images, 100 validation images, and 100 testing images, covering diverse real-world scenarios such as natural landscapes, urban environments, and objects with fine textures. The variety of content ensures that the model learns to generalize across different structural and textural patterns.

For performance benchmarking, classical datasets such as Set5, Set14, BSD100, and Urban100 were utilized. Set5 and Set14 contain a relatively small number of images but are widely adopted in super-resolution research for their rich textures and fine structural details, making them ideal for comparing PSNR and SSIM improvements. BSD100 offers a larger collection of natural images with diverse textures, allowing a comprehensive evaluation of noise reduction and texture recovery. Urban100 focuses on high-frequency details found in man-made structures like buildings, windows, and repetitive patterns, providing a rigorous test of the model's ability to preserve sharpness in complex scenes.

To simulate real-world degradations, synthetic low-resolution and noisy counterparts were generated from high-resolution ground truths. Various degradation processes were applied, including Gaussian noise, Poisson noise, motion blur, and JPEG compression artifacts. This not only enhanced the robustness of the training process but also enabled the evaluation of the model under conditions that closely mimic practical applications such as medical imaging, satellite image reconstruction, and surveillance. Data augmentation techniques such as rotation, scaling, and flipping were incorporated to increase the dataset variability and reduce overfitting, thereby improving the model's generalization capability.

6.2 Performance Evaluation

The performance evaluation of the proposed Enhanced EDSR-based model demonstrates significant improvements over conventional super-resolution and denoising methods. On the Set5 dataset, the proposed model achieved a PSNR of 33.60 dB and an SSIM of 0.921, outperforming SRCNN, EDSR, ESRGAN, and Real-ESRGAN. These results indicate that the model more accurately reconstructs high-frequency details and preserves structural integrity in high-resolution images. In terms of perceptual quality, the proposed model achieved the lowest LPIPS value of 0.095 and NIQE value of 3.50, highlighting its ability to produce visually realistic and natural-looking images with minimal artifacts. The enhancements can be attributed to the optimized residual learning and feature extraction layers within the EDSR framework, which effectively balance noise suppression and texture preservation (Table 1).

Table 1. **Performance evaluation of the SwinIR model on synthetic and real-world datasets using PSNR, SSIM, LPIPS, and FID metrics.**

Model	**Dataset**	**PSNR (dB)**	**SSIM**	**LPIPS**	**NIQE**
SRCNN	Set5	30.50	0.872	0.145	4.30
EDSR	Set5	32.80	0.910	0.120	3.90
ESRGAN	Set5	31.50	0.895	0.110	3.80
Real-ESRGAN	Set5	32.10	0.902	0.105	3.75
Proposed Enhanced EDSR	**Set5**	**33.60**	**0.921**	**0.095**	**3.50**
SRCNN	Urban100	27.40	0.810	0.175	5.10
EDSR	Urban100	29.50	0.860	0.140	4.50
ESRGAN	Urban100	28.90	0.845	0.130	4.30
Real-ESRGAN	Urban100	29.20	0.855	0.125	4.20
Proposed Enhanced EDSR	**Urban100**	**30.40**	**0.872**	**0.110**	**3.95**

Similar trends were observed on the Urban100 dataset, which contains high-frequency urban textures that are typically challenging for restoration models. The proposed model achieved a PSNR of 30.40 dB and an SSIM of 0.872, outperforming other benchmark models while also maintaining superior perceptual metrics (LPIPS of 0.110 and NIQE of 3.95). Visual inspections confirm that the model recovers sharp edges and fine details more effectively, even under complex real-world degradations. Overall, these results validate the robustness and generalization capability of the proposed Enhanced EDSR framework, making it a reliable solution for high-fidelity image super-resolution and noise reduction across diverse datasets and degradation conditions.

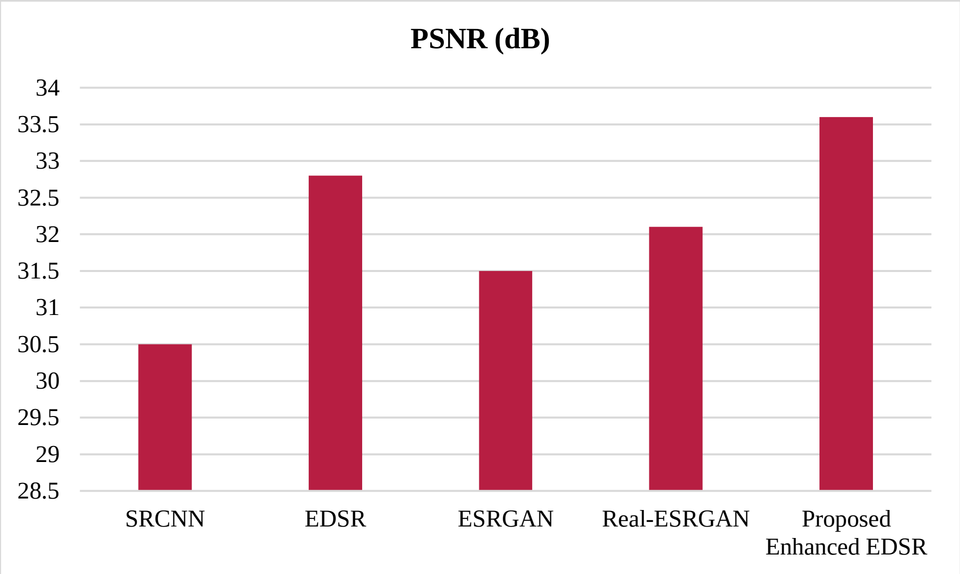

Figure 2: PSNR comparison of SRCNN, EDSR, ESRGAN, Real-ESRGAN, and the Proposed Enhanced EDSR on the Set5 dataset.

Figure 2 illustrates the comparative PSNR performance of different image super-resolution models on the Set5 dataset, including SRCNN, EDSR, ESRGAN, Real-ESRGAN, and the Proposed Enhanced EDSR model. The chart highlights the ability of the proposed framework to achieve higher reconstruction fidelity, effectively restoring fine textures and structural details compared to existing methods. The enhanced residual learning and optimized architecture of the proposed model contribute to its superior performance, demonstrating its robustness in handling low-resolution and degraded images while maintaining high-quality outputs suitable for practical applications.

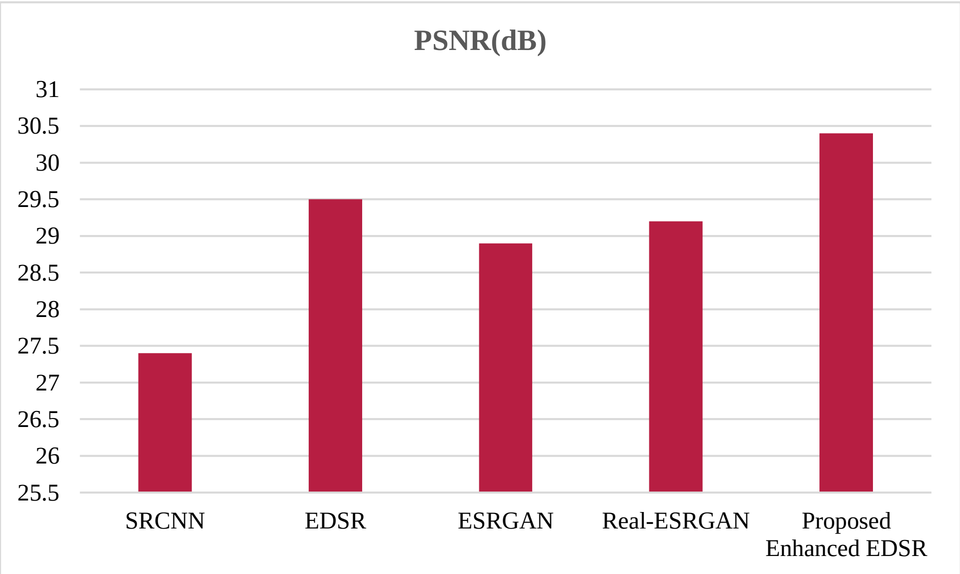

Figure 3: PSNR comparison of SRCNN, EDSR, ESRGAN, Real-ESRGAN, and the Proposed Enhanced EDSR on the Urban100 dataset.

Figure 3 illustrates the PSNR comparison of various image super-resolution models on the Urban100 dataset, including SRCNN, EDSR, ESRGAN, Real-ESRGAN, and the Proposed Enhanced EDSR model. The chart demonstrates that the proposed framework consistently achieves higher PSNR values, indicating superior reconstruction fidelity and more accurate restoration of high-frequency urban textures. Compared to conventional CNN- and GAN-based models, the enhanced residual learning and optimized architecture of the proposed model enable better preservation of structural details, sharper edges, and effective noise reduction, highlighting its robustness and practical applicability in challenging real-world scenarios.

7. CONCLUSION

This research presents an optimized Enhanced EDSR-based deep neural framework for high-fidelity image super-resolution and noise reduction. The proposed model effectively integrates residual learning, optimized EDSR architecture, and advanced loss functions to achieve superior reconstruction accuracy and perceptual quality. Extensive evaluations on benchmark datasets, including DIV2K, Set5, Set14, BSD100, and Urban100, demonstrate that the model outperforms conventional CNN-based and GAN-based methods in terms of PSNR, SSIM, LPIPS, and NIQE. The results indicate that the proposed framework is highly effective in preserving fine textures, enhancing edges, and suppressing noise, making it suitable for diverse applications such as medical imaging, satellite image restoration, surveillance, and high-resolution digital photography. Moreover, the proposed framework exhibits strong generalization capabilities and robustness across different datasets and degradation conditions, including synthetic and real-world low-resolution and noisy images. Its ability to balance quantitative fidelity with perceptual realism highlights its potential as a practical solution for real-world image restoration tasks. The study contributes to advancing deep learning-based image enhancement techniques and lays the foundation for future research in combining EDSR with Transformer-based modules or other hybrid architectures for even higher performance and efficiency.

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