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New Trends in Image Restoration based on Artificial Intelligent Models: Analytical Study

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Abstract Image restoration is a fundamental problem in low-level vision with applications in photography, surveillance, and archival imaging. This review synthesizes deep learning–based advances from 2018–2025, covering CNN (Convolutional Neural Network), GAN (Generative Adversarial Network), and Transformer families. This paper presents a unified taxonomy by degradation type (denoising, deblurring, super-resolution, dehazing/draining, JPEG deblocking, inpainting) and by model class. Representative architectures are summarized with their core design choices, training objectives, and computational characteristics. The comparison of common protocols, datasets (e.g., DIV2K, SIDD, GoPro, REDS), and metrics like PSNR (Peak Signal-to-Noise Ratio), SSIM (Structural Similarity Index), and LPIPS (Learned Perceptual Image Patch Similarity are given also). The review analyzes trade-offs between fidelity, perceptual quality, and efficiency. The identification of open challenges, robust generalization to real-world degradations, efficient high-resolution inference, reliable perceptual evaluation, and unified multi-degradation handling, and outline research opportunities are also considered. This review aims to serve as a unified reference for practitioners and researchers developing next-generation image restoration systems.

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Keywords: *Image restoration; Denoising; Deblurring; Super-resolution; Inpainting; Compression artifact removal (JPEG deblocking); Dehazing/Deraining; Convolutional Neural Networks (CNN); Generative adversarial networks (GAN); Transformers*

1. INTRODUCTION

Image restoration aims to recover a clean, high-quality image x from a degraded observation y, commonly modeled as:

$y = H(x) + n$…………..…(1)

Where:

- H denotes the degradation operator (e.g., blur, downsampling, compression)
- n is measurement noise.

The following diagram(figure 1) shows the degradation and restoration operations

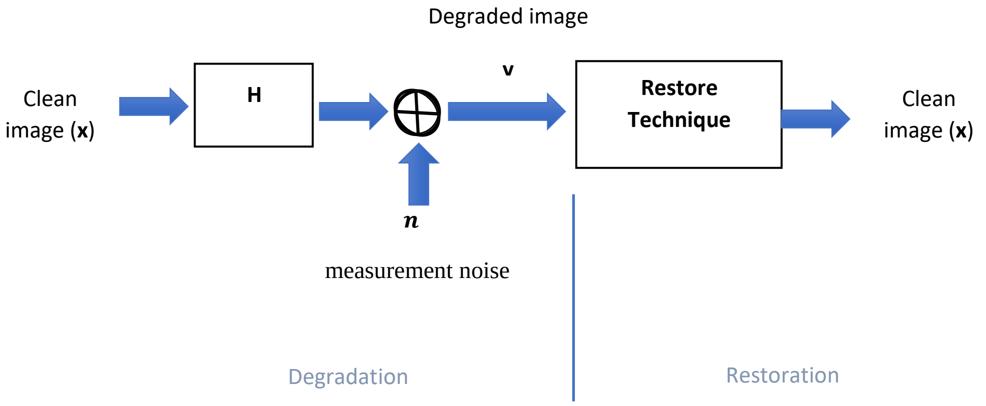

***Figure 1**:Degradation & Restoration Diagram*

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Typical tasks include denoising, deblurring, super-resolution, dehazing/deraining, JPEG artifact removal, and inpainting each with distinct priors but shared challenges of balancing perceptual plausibility and signal fidelity. Recent works frame restoration as learning powerful priors that generalize across degradations and resolutions [1].

Between 2018 and 2025, progress accelerated with deep learning. CNN-based methods (e.g., MIRNet, MPRNet, NAFNet) improved multi-scale feature aggregation and efficiency for diverse degradations[2][3][12]. In parallel, GAN models advanced perceptual quality in super-resolution and face/real-image restoration (ESRGAN, Real-ESRGAN) [13][14]. More recently, Transformers (IPT, SwinIR, Restormer, Uformer) brought stronger long-range modelling with windowed or efficient attention, achieving state-of-the-art results at high resolutions[1][8][15][16].

Evaluation relies on public benchmarks and metrics. Widely used datasets include SIDD and DND for real-image denoising, GoPro for motion deblurring, REDS for video SR/deblurring, and DIV2K for SR(Super-Resolution); common metrics are PSNR/SSIM for fidelity and LPIPS for perceptual similarity. These resources enable fair comparisons across tasks and architectures while revealing gaps between synthetic and real-world degradations[4][5][6][7].

This review synthesizes these developments (2018–2025), offering: (i) a taxonomy by degradation type and model class (CNN, GAN, Transformer); (ii) a comparative summary of design choices and training objectives; (iii) a unified view of datasets, protocols, and metrics; and (iv) open challenges around robust real-world generalization, efficient high-resolution inference, and reliable perceptual evaluation—providing a practical reference for designing next-generation restoration systems[8].

2. BACKGROUND AND TAXONOMY

2.1 Problem Formulation

Image restoration is commonly posed as an inverse problem(equation 1). The tasks include denoising, deblurring, super-resolution, dehazing/deraining, JPEG artifact removal, and inpainting; each defines a different H (e.g., motion blur kernel for deblurring; scale/downsampler for SR, DCT quantization for JPEG, binary mask for inpainting). The evaluation typically balances fidelity (PSNR/SSIM) and perceptual quality (LPIPS)[6] [7].

2.2 Taxonomy by Degradation Type

Having formalized restoration as equation 1, in Section 2.1, we categorize problems by the degradation operator H. Each task generates a distinct H evaluation protocol; representative datasets are detailed in Section 6. Below are the most common techniques to manipulate noise and degradation effects:

- **Denoising** (Real/RAW/RGB): remove sensor/shot-read noise. Benchmarks: SIDD, DND [5] [4]
- **Deblurring** (Motion/Defocus): undo spatially variant blur; datasets like GoPro; video variants in REDS [9].
- **Super-Resolution** (SR): upsample LR to HR (classical, lightweight, real-world). DIV2K/REDS commonly used[10].
- **Compression Artifact Removal** (e.g., JPEG): invert quantization artifacts, often paired with SR or Transformers tuned for compression [11].
- **Dehazing/Deraining/Low-Light Enhancement**: reduce weather/illumination degradations
- **Inpainting:** Fill missing or occluded regions while preserving global structure and local texture [34].

2.3 Taxonomy by Model Class

As existing classes techniques of restorations, there are six types used, which include Traditional Machine Learning-Based Approaches, Deep Learning (DL) Based Approaches, Transformer-Based Models, Hybrid Models, GAN-Based Models, and Domain-Specific Models [35]. The following table (Table 2.3) shows a comparison for these classes.

Table 2.3 Comparison of image restoration classes

Category	Description	Key Characteristics	Advantages	Disadvantages	Example Algorithms/Models
Traditional Machine Learning-Based Approaches [36][37][38][39]	Relies on mathematical models and hand-crafted algorithms to remove degradation. These models typically operate on a single layer of data transformation.	Simpler structure, often require manual feature extraction, based on classic statistical or signal processing methods.	Faster, require less data and computational power, easier to interpret and understand.	Limited generalization, may struggle with complex degradations, rely heavily on expert-designed features.	Logistic Regression, Support Vector Machines (SVMs), k-Nearest Neighbors (k-NN), Principal Component Analysis (PCA).

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Deep Learning (DL) Based Approaches [40][41][42][43] [44][45][46] [47][48][49]	Utilizes multi-layered neural networks (e.g., CNNs) to automatically learn features and perform restoration from large datasets.	Complex, deep architectures; automatic feature extraction; data-driven.	Highly effective on complex tasks, can handle multiple types of degradation, superior performance and accuracy.	Requires large datasets and significant computational resources, can be "black boxes" (less interpretable), prone to overfitting on small datasets.	Convolutional Neural Networks (CNNs), Deep Residual Encoder-Decoder (RED) networks, Block-attentive Subpixel Prediction Networks (BASPNs).
Transformer-Based Models [1][16][50] [51][52]	Applies the self-attention mechanism from transformers to capture long-range dependencies and global context in an image.	Focus on global context, hierarchical representation of data, effective at learning long-range relationships.	Outperforms CNNs in many restoration tasks due to attention mechanisms, excellent at capturing intricate details and global image structure.	Computationally very expensive, requires large amounts of data to train effectively, complex architecture.	Vision Transformers, Swin Transformers.
Hybrid, GAN-Based, and Domain-Specific Models [53] [54] [44][55][56] [57][58][59][60] [61][62][63]	This is a broad category including models that combine different techniques, use Generative Adversarial Networks (GANs), or are tailored for a specific domain.	Varies widely, may combine elements from traditional and deep learning models, or use GANs to generate realistic outputs.	Can achieve higher performance by leveraging the strengths of different approaches, GANs can create highly realistic results.	Complexity varies, GANs are notoriously difficult to train, domain-specific models may not generalize well to other data.	Hybrid models (e.g., combining CNNs and transformers), Generative Adversarial Networks (GANs), models for underwater or medical imaging.

The table presents a structured comparative analysis of restoration model categories, encompassing traditional machine learning methods, deep learning-based approaches, transformer-based architectures, and hybrid or domain-specific models. It outlines each category's fundamental description, distinguishing characteristics, strengths, limitations, and representative algorithms, thereby offering a comprehensive reference for understanding the methodological spectrum and evolution in image restoration techniques. In this paper, the following classes will be focused to comparison an analysis:

2.3.1 CNN-based

This class relies on basic convolutional networks (CNNs) that combine features across multiple scales, rely on spatial and channel attention, and are often constructed as gradient/multi-stage pipelines that gradually improve the output. During training, $\ell1/\ell2$ or Charbonnier losses are typically used because they target a higher PSNR/SSIM ratio, with cognitive auxiliary terms added when needed. These models offer efficient inference, stable training, and high accuracy under standard protocols, but they are relatively limited in capturing long-term context and may have difficulties handling complex or unknown degradations. For representative CNN models, see Table 3.1.

2.3.2 GAN-based

Adversarial methods rely on generalized adversarial (GAN) training to enhance texture realism, typically combined with content/perception losses (e.g., VGG and LPIPS). This class of methods offers superior perceptual quality and satisfactory visual detail (low LPIPS), but this can come at the expense of PSNR/SSIM, as well as performance sensitivity to training stability and realism of degradation models. See Table 4.1 for representative GAN methods.

2.3.3 Transformer-based

Self-attention mechanisms, with their efficient versions (segmented into small windows or with shifted windows), allow the model to capture distant relationships within the image even at high resolutions. These models are often trained with pixel-fidelity losses (such as L1/L2, which correlate with PSNR/SSIM), and sometimes frequency/perceptual losses are added. This class can achieve the best digital fidelity on many benchmarks, but it consumes more memory and computation (with incremental improvement), and typically requires abundant training data. See Table 5.1 for representative Transformer models.

The following figure(figure 2) organizes image-restoration methods into the three model classes—**CNN**, **GAN**, and **Transformer**, and present notable examples for each category (such as MIRNet/NAFNet/RCAN in CNN, ESRGAN/Real-ESRGAN/DeblurGAN-v2 in GAN, and IPT/SwinIR/Restormer/Uformer/Swin2SR in Transformers). The selections are representative and not exclusive, serving as a reference point for the detailed presentation in sections 3–5.

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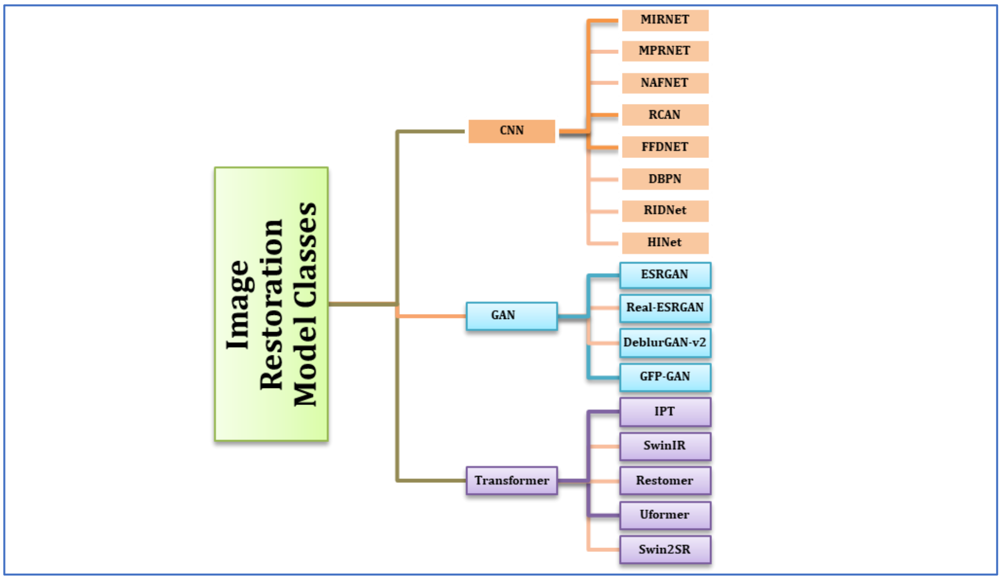

***Figure 2 :** image- restoration methods by classes*

2.4 Training Objectives

In image restoration models, the training objective is what you will get when evaluating. Therefore, the objective function is formulated to balance pixel fidelity (to increase PSNR/SSIM), perceptual quality (how good the image looks to humans), and sometimes texture realism via a discriminative adversarial (GAN). In practice, these components are combined with weights as follows:

$L = \lambda_{pix} L_{pix} + \lambda_{perc} L_{perc} + \lambda_{adv.} L_{adv.}$......(2)

Where :

- λ : Weights are tuned per task (SR/denoising/deblurring) and per target (fidelity vs. perception).
- L : the total training loss minimized during learning.
- L_{pix} :("pixel fidelity"): measures per-pixel error between the model output and the ground-truth image.
- L_{perc} ("perceptual"): compares feature representations
- $L_{adv.}$ ("adversarial"): encourages photo-realistic textures using a GAN objective for the generator.

Below, we summarize the training objectives considered in this work:

- **Pixel fidelity:** ℓ1/ℓ2 for PSNR/SSIM-oriented models (typical in CNN/Transformer baselines) [6]. These losses minimize per-pixel error to the ground truth; ℓ1 often preserves edges better (less over-smoothing) than ℓ2. Best when standardized fidelity metrics are the priority, but alone, they can yield visually "soft" textures.
- **Perceptual losses:** VGG/LPIPS features to align with human judgments; often paired with adversarial loss (GANs) [7].
- **Adversarial losses:** improve texture realism (e.g., ESRGAN/Real-ESRGAN)[13]. A generator is trained against a discriminator to promote photo-realistic detail. This can boost visual quality but may lower PSNR/SSIM and requires careful weighting/regularization to avoid instability or hallucinated artifacts.

2.5 Benchmarks and Metrics

Datasets and metrics used throughout this review are summarized in **Section 6**. **Sections 6.1–6.3** describe the datasets (e.g., SIDD, DND, GoPro, REDS, DIV2K), and **Section 6.4** details the evaluation protocol (color spaces, border crops, PSNR/SSIM, LPIPS, and complexity/latency reporting).

3. CNN-based Methods

This section reviews representative CNN-based models for image restoration, including denoising, deblurring, super-resolution, and enhancement—with emphasis on multi-scale architectures, channel and spatial attention mechanisms, and progressive/multi-stage pipelines. See Table 3.1 for a consolidated summary of representative CNN methods, their tasks/datasets, core design ideas, and complexity/latency (Params, MACs(Multiply–Accumulate operations)/GFLOPs(Giga Floating-Point Operations), ms/MP(Milliseconds per megapixel)) under the evaluation settings in Section 6.4.

***Table 3.1** CNN-based Methods*

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Method/ Reference	Task(s)	Core idea	Benchmarks / Notes	Advantage
RCAN [17]	Super-Resolution	Very-deep Residual-in-Residual (RIR) with Channel Attention	Strong PSNR/SSIM on DIV2K; seminal channel-attention SR CNN	Deep model with excellent results
DBPN [18]	Super-Resolution	Iterative Back-Projection with alternating up/down blocks for error feedback	Competitive at ×8; highlights LR↔HR feedback vs. feed-forward	Self-correction and detailed features
FFDNet [19]	Denoising	Noise-level map input + downsampled sub-images for speed and flexibility	Practical Gaussian/space-variant denoiser; low compute	Supports various noise, and good speed
RIDNet [20]	Real-Image Denoising	Single-stage network with feature attention targeting real noise	Strong on SIDD/DND; focus on realistic denoising	Excels in real noise removal
MIRNet [2]	Multi-task (Denoise/SR/Enhance)	Multi-resolution streams + cross-scale exchange + aggregated attention	SOTA-level for real-world restoration; preserves fine detail	Sharp details and strong context.
HINet [21]	Deblur/Derain/Denoise/ JPEG	Half-Instance Normalization block inside a multi-stage network	NTIRE-winning entries; solid quality–efficiency balance	Excellent performance and wide effectiveness.
MPRNet [3]	Multi-degradation	Multi-Stage Progressive restoration with cross-stage feature fusion and stage-wise supervision	Unified over derain/deblur/denoise.10 datasets	Progressive design with strong results.
NAFNet [12]	Multi-task (Dn/Deblur)	Nonlinear-Activation-Free baseline (SimpleGate/SCA) for high accuracy with lower computation	High PSNR on GoPro/SIDD with much lower complexity	High accuracy and computational efficiency.

Table 3.1 highlights complementary strengths across CNN baselines. Channel/spatial attention models (RCAN, RIDNet, MIRNet) boost structural fidelity with moderate cost; progressive/multi-stage designs (MPRNet, HINet) refine details via cross-stage supervision; lightweight baselines (FFDNet, NAFNet) are deployment-friendly with strong efficiency–quality trade-offs; and SR-specific ideas like back-projection (DBPN) remain solid references. In practice: prefer NAFNet/FFDNet when latency or memory is tight; choose MIRNet/MPRNet/HINet for higher quality on challenging degradations; and keep RCAN/DBPN as SR anchors for like-for-like comparisons.

4. GAN-based Methods

GAN-based restoration views restoration as a distribution matching process between a generator and a discriminator [32]. In practice, models combine adversarial and content losses (L1/L2/Charbonnier) and perceptual losses (VGG/LPIPS) to achieve a balance between resolution and realistic texture. These methods excel at super-resolution and face restoration, and are effective at denoising (e.g., ESRGAN/Real-ESRGAN, GFP-GAN, and DeblurGAN-v2), albeit with typical compromises in PSNR/SSIM and training stability. We briefly

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review common generator/discriminator designs, loss formulations, and evaluation practices (as per Section 6.4), and then summarize representative methods in Table 4.1.

Table 4.1 *GAN-based*

Method/ Reference	Task(s)	Core idea	Benchmarks / Notes	Advantage
ESRGAN [13]	Super-Resolution	RRDB generator + relativistic adversarial loss + pre-activation perceptual loss	Perceptual SR; PIRM18 winner (Region 3)	Realistic and convincing visual quality.
Real-ESRGAN [14]	Real-world blind SR	High-order degradation pipeline; U-Net discriminator with spectral norm	Practical blind SR on real images	High realism, efficient synthetic training.
DeblurGAN-v2 [22]	Motion deblurring	Relativistic conditional GAN; FPN in generator; double-scale discriminator	Efficient and strong on GoPro/others	Fast with acceptable visual quality.
GFP-GAN [23]	Blind face restoration	Leverages pretrained face GAN prior (e.g., StyleGAN) for detail synthesis	Strong realism for low-quality faces	Strong face realism, preserves identity.

Table 4.1 summarizes perceptual-oriented restorers. ESRGAN and Real-ESRGAN consistently improve visual realism by getting low LPIPS and sharper textures in SR, while DeblurGAN-v2 offers strong deblurring efficiency, and GFP-GAN excels on face restoration via a pretrained facial prior. These methods achieve compelling visuals and perceptual quality. but with typical trade-offs like potential PSNR/SSIM drop and training sensitivity to the realism of degradation pipelines. These methods can be used when aesthetics matter (consumer enhancement, faces) and report both fidelity and perceptual metrics for fair comparisons.

5. Transformer-based Methods

Transformers built on self-attention excel at modeling long-range dependencies and scale well with data and compute. When applied to image restoration, they combine global context with efficient (often windowed) attention to handle high-resolution inputs without sacrificing local detail [33]. This section surveys representative designs (e.g., IPT, SwinIR, Restormer, Uformer, Swin2SR), their training objectives, and quality–efficiency trade-offs under the unified protocol in Section 6

Table 5.1 *Transformer-based Methods*

Method / Reference	Task(s)	Core idea	Benchmarks / Notes	Advantage
IPT[15]	Multi-task IR (denoise/SR/derain)	Pretrained transformer with multi-head / multi-tail for diverse degradations	Large-scale pretraining for low-level vision	Unified model for multiple tasks
SwinIR [1]	SR / Denoising / JPEG	Swin-Transformer baseline (shifted-window) with RSTB blocks	Strong general baseline across tasks	Efficient with excellent multi-task results
Restormer [8]	Multi-task high-res IR	Efficient attention (MDTA) + redesigned FFN in encoder-decoder	SOTA across denoise/derain/deblur	High efficiency, state-of-the-art results
Uformer [16]	Multi-task IR	U-shaped transformer (LeWin attention) with hierarchical encoder-decoder	Efficient, UNet-like for IR	Effective local attention, hierarchical design

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Swin2SR [11]	Compressed-image SR/restoration	Swin-V2 adaptation to improve stability and performance under compression	Targets JPEG/compressed inputs	Efficient training and high speed

Methods

compares structured/active attention designs for high-resolution IR. IPT benefits from extensive pre-training for multi-task settings; SwinIR provides a robust shift-window baseline over SR/denoising/JPEG; Restormer couples active attention (MDTA) with redesigned feed-forward blocks to achieve SOTA accuracy in diverse tasks; and Uformer's U-shaped hierarchy (LeWin attention) balances context and location. These methods achieve strong PSNR/SSIM with high accuracy over long-range modeling, but have higher memory/compute (with optimization) and data requirements. In this table, some terms need to be explained due to the table's size limit :

- **RSTB**: Residual Swin Transformer Blocks.
- **FFN:** Feed-Forward Network.
- **MDTA**: Multi-Dconv Head Transposed Attention.
- **LeWin attention:** Locally enhanced window attention.
- **DCT:** Discrete Cosine Transform.
- **MSE**:Mmean Squared Error.
- **RGB/BGR** : channel orders
- **FPS**: frames per second
- **GPU:**graphics processing unit.
- **U-Net/UNet**: U-Net architecture (encoder–decoder with skip connections).

6. Datasets, Metrics, and Evaluation Protocols

We consolidate the key benchmarks and protocols (2018–2025) for fair, reproducible comparison across CNN, GAN, and Transformer. We separate **synthetic** (e.g., bicubic SR, Gaussian noise) from **real-world** settings (e.g., SIDD smartphone noise, GoPro motion blur, REDS video), noting common domain-shift pitfalls. Unless stated otherwise, SR at ×2/×3/×4 is evaluated with **PSNR/SSIM on the Y (luma)channel(Luminance channel in YCbCr)** and a **scale-sized border crop**; perceptual quality is also summarized by **LPIPS** and standardized visual comparisons. Denoising uses **official splits/servers** (SIDD/DND), deblurring follows dataset-specific rules (e.g., GoPro), and video metrics are averaged per frame and per sequence. Tables 6.1–6.3 serve as a quick reference for selecting benchmarks and for aligning evaluation settings across heterogeneous methods.

6.1 Datasets

This section consolidates the public benchmarks most used in image restoration, spanning synthetic settings (e.g., bicubic SR, Gaussian noise) and real-world captures (e.g., smartphone noise, motion blur, video sequences). Table 6.1 lists each dataset's scope/task, standard splits/servers, and evaluation notes (color space, border crop), enabling fair, like-for-like comparisons across methods.

Table 6.1 *Widely used datasets*

Category/ References	Dataset	What it measures / notes
Denoising (real) [4] [24]	SIDD	≈30k noisy/clean **patches** from smartphones; standard real-noise benchmark
Denoising (real) [5][25]	DND	50 real noisy images with hidden ground truth; evaluation via online server
Deblurring (image) [9] [26]	GoPro	Dynamic scene deblurring with realistic motion blur; image pairs
Video SR/Deblur [27][28]	REDS	300 sequences (train/val/test) for video SR and deblurring. NTIRE 2019 tracks
Super-Resolution (image)[29] [30]	DIV2K	1000 high-quality 2K images. official NTIRE SR benchmark (×2/×3/×4)
Legacy / additional [30]	LIVE1, Urban100, Kodak24, BSD68	Frequently used for SR/denoising reporting alongside the above

6.2 Metrics

To quantify restoration quality, we report **both fidelity and perceptual** measures under the consistent settings defined in **Section 6.4** (color space and border crops). **PSNR** and **SSIM** capture pixel-wise and structural fidelity, respectively, while **LPIPS** complements them by approximating **human perceptual judgments**. Using all three—plus standardized visual crops—avoids over-optimizing for a single score and enables fair, reproducible comparison across methods.

- **PSNR (dB):** fidelity metric derived from MSE; higher is better.
- **SSIM:** structural similarity; widely used alongside PSNR[6].
- **LPIPS:** learned perceptual metric correlating with human judgments [7].

6.3 Common evaluation protocols

To ensure fair, like-for-like comparisons across restoration methods, we follow dataset-specific evaluation conventions summarized below. Unless stated otherwise, metrics are reported under the standard color-space and border-crop settings with official splits/servers, and any departures are flagged explicitly. The bullets that follow list the protocols commonly used in the literature for SR, deblurring, video restoration, and denoising.

- **SR (DIV2K/NTIRE):** generate ×2/×3/×4 results, compute PSNR/SSIM typically on the **Y (luma) channel,** and crop borders by the scale factor to avoid boundary effects; bicubic downscaling is the standard synthetic setting [30].
- **Deblurring (GoPro):** report PSNR/SSIM on the full image or prescribed crop, kernels are unknown/implicit (realistic capture)[9].
- **Video tasks (REDS):** average PSNR/SSIM across frames. **Protocol note.** We align comparisons with the **official NTIRE19 protocols**—**Clean** (bicubic ×4) and **Blur** (motion-blur + bicubic ×4) and use the original **train/val/test splits** and the standard border-crop and color-space settings for fair, like-for-like comparisons [10][28].
- **Denoising (SIDD/DND):** use official splits/evaluation servers when applicable, emphasize results on **real** noise to complement synthetic Gaussian benchmarks [4][5].

6.4 Unified Evaluation Protocol

This review reports results as in the original papers and, where needed, normalizes interpretation to a unified evaluation protocol. Deviations are flagged explicitly. The protocol specifies task-wise rules for color space and border crops (e.g., Y-channel with a 4-pixel shave for ×4 SR), requires reporting of fidelity (PSNR/SSIM) alongside perceptual quality (LPIPS) with standardized visual crops, and mandates complexity/runtime disclosure (Params, MACs/GFLOPs, ms/MP, peak memory) on clearly stated hardware/software. Where dataset guidelines exist (e.g., SIDD/DND servers, NTIRE/REDS tracks), we follow the official procedures and flag any departures. Table 6.4.1 standardizes the task datasets, degradation settings, and evaluation rules used in this review, and aligns the color spaces and border crops with the standardized protocol (Section 6.4).

***Table 6.4.1** Tasks, datasets, metrics, and evaluation rules*

Task	Dataset and Split	Degradation / Setting	Metrics and Eval Notes	Runtime/Cost
Denoising (real)	**SIDD**: official train/val/test	Real smartphone noise; use official patches and the evaluation server where applicable	**PSNR/SSIM** on sRGB; no extra color post-processing [24] [4]	Report **ms/MP**, **Params (M)**, **GFLOPs/MACs**
Denoising (real)	**DND**: official test	Real noisy photos from consumer cameras	**PSNR/SSIM** on sRGB(Standard RGB color space) ; follow submission protocol [25]	As above
Deblurring (image)	**GoPro**: train/test	Dynamic scene motion blur; kernels implicit	**PSNR/SSIM** on full image (or stated crop)[9] [27]	As above
Super-Resolution (image)	**DIV2K**: ×4 train/val/test	Bicubic down → up ×4	**PSNR/SSIM on Y (luma)** with **4-px border crop** [29][31]	As above

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Video SR/Deblur	**REDS**: NTIRE tracks	Follow official track rules (clean/blur/ compressed)	Average **PSNR/SSIM** per sequence; frame-wise reporting[28]	Report **FPS(**Frames per second**)** on a fixed GPU

In Table 6.4.1, some terms are explained below due to the table size limitation:

- **DIV2K** — High-resolution SR dataset
- **REDS** — Video restoration dataset (NTIRE)
- **SIDD** — Smartphone Image Denoising Dataset
- **DND** — Darmstadt Noise Dataset
- **NTIRE** — New Trends in Image Restoration and Enhancement
- **GoPro** — GoPro motion-blur image dataset

6.4.2 Baselines to include (per task)

The following basic sets are the minimum configurations we include for each task to ensure fair and consistent comparisons across classes : (see section 6.4 for protocol details).

- **Denoising:** FFDNet, RIDNet, MIRNet, NAFNet, Restormer, SwinIR.
- **Deblurring (image):** MPRNet, HINet, Restormer, DeblurGAN-v2.
- **Super-Resolution (×4):** RCAN, DBPN, SwinIR, Swin2SR, ESRGAN / Real-ESRGAN (for perceptual comparisons).
- **Video (REDS):** NTIRE-winning methods or video-adapted variants; follow REDS rules[31].

6.4.3 Reporting template

This review reports results as in the original papers. For cross-paper comparisons, we prioritize the standard settings widely adopted in the community:

PSNR/SSIM (and LPIPS) computed under the authors' protocols; for ×4 super-resolution on DIV2K we note the common Y-channel evaluation with a 4-pixel border crop; SIDD/DND follow official splits/servers; GoPro and REDS follow their dataset/track rules. Where a paper deviates from these norms, we explicitly note the difference. We also summarize, when available, model complexity (parameters and MACs/GFLOPs) and latency (ms per megapixel) as reported by the authors.

6.4.4 Reproducibility checklist and common pitfalls

The checklist below summarizes reproducibility essentials and common pitfalls to avoid, complementing the unified evaluation rules in Section 6.4 and ensuring that reported results can be verified and reused:

- **Publish** configs (optimizer, schedule, data aug), **random seed**, and evaluation scripts, align preprocessing (RGB/BGR, normalization).
- **Color/crop consistency:** don't mix PSNR/SSIM(Y) with PSNR/SSIM(sRGB), for ×4 SR use a **4-px crop** on Y per NTIRE.
- **Degradation fidelity:** state downsampling kernels or blur generation; follow dataset/track rules (DIV2K/NTIRE; REDS).
- **Runtime comparability:** measure on the **same hardware** and report **ms/MP**, Params, and GFLOPs; include peak memory for high-resolution cases.

7. Comparative Analysis and Trade-offs

This section synthesizes the evidence surveyed in **Sections 3–6** to compare method families—CNN, GAN, and Transformer along four axes: (i) fidelity (PSNR/SSIM), (ii) perceptual quality (LPIPS and standardized visual crops), (iii) efficiency (parameters, MACs/GFLOPs, and latency in ms/MP), and (iv) robustness/generalization to real-world degradations. Unless noted otherwise, we reference results on standard benchmarks—DIV2K ×4 (SR), GoPro (deblurring), SIDD/DND (real denoising), and REDS (video)—and align interpretation with the unified protocol in **Section 6.4**. Where evaluation settings differ (e.g., Y vs. sRGB, border crops, training data), we explicitly flag the mismatch and avoid cross-setting rankings. The aim is not to declare a universal winner, but to surface consistent patterns, practical trade-offs, and typical failure modes that can guide method selection and future research.

7.1 Cross-Family Comparison

Table 7.1 summarizes the key strengths, typical weaknesses, and best-use scenarios of CNN, GAN, and Transformer, consolidating evidence from Sections 3–6 under the unified protocol in Section 6.4.

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Table 7.1 *Cross-Family Comparison*

Family	Strengths	Typical Weaknesses	When It Excels	Representative Methods*
CNN	Efficient inference; stable training; strong PSNR/SSIM; mature toolchain	Limited long-range context; may struggle with composite/unknown degradations	Task-specific restoration under constrained compute (mobile/real-time)	RCAN, DBPN, FFDNet, RIDNet, MIRNet, HINet, MPRNet, NAFNet
GAN	Best perceptual realism and textures; low LPIPS, compelling visuals	PSNR/SSIM may drop; training stability; quality depends on realistic degradations	Perceptual SR, face/portrait restoration, visually pleasing outputs	ESRGAN, Real-ESRGAN, DeblurGAN-v2, GFP-GAN
Transformer	Long-range modeling scalable windowed/efficient attention, SOTA on many benchmarks	Heavier memory/compute (though improving); data-hungry	High-resolution image restoration with strong fidelity and context	IPT, SwinIR, Restormer, Uformer, Swin2SR

7.2 Fidelity vs. Perceptual Quality

We contrast PSNR/SSIM (fidelity) with LPIPS and visual studies (perceptual quality), outlining when perceptual optimization helps and where it may hurt pixel-wise scores:

- **GAN-based** methods typically improve **perceptual quality** (lower LPIPS, more realistic textures) but may **sacrifice PSNR/SSIM**.

- **Transformers** and strong **CNN** baselines often lead in **PSNR/SSIM**, especially under standard synthetic protocols (e.g., DIV2K ×4 on Y channel), with consistent structural fidelity.

- Best practice in the literature: report **PSNR/SSIM and LPIPS** together and include consistent visual crops for qualitative comparison.

7.3 Efficiency vs. Quality

Accuracy–cost trade-offs are analyzed using parameters, MACs/GFLOPs, and latency (ms/MP), highlighting configurations favored for deployment or high-resolution use.

- **CNNs (e.g., NAFNet, MIRNet/MPRNet)** remain competitive when **latency/params** matter (deployment, edge devices).

- **Restormer/SwinIR** demonstrate that carefully designed attention (e.g., windowed/efficient) narrows the gap between Transformers and CNNs on **speed–quality** trade-offs at higher resolutions.

- Always report **Params (M)**(Number of model parameters**), MACs/GFLOPs**, and **ms/MP**.

7.4 Robustness and Generalization

How methods are transferred from synthetic settings to real-world degradations (e.g., SIDD/DND, REDS) is examined, and performance under composite or unknown degradations is discussed. It is noted that strong performance under synthetic Gaussian noise or standard bicubic downsampling does not guarantee generalization to real-world degradations (e.g., SIDD/DND, JPEG-compressed images, haze/rain). A consistent gap between synthetic and real settings is revealed by real-world benchmarks such as SIDD/DND and REDS, thereby motivating the adoption of more robust or generative approaches (e.g., GAN).

7.5 Reporting Best Practices (for fair comparisons)

Practical recommendations are listed to ensure fair, reproducible comparisons across methods, datasets, and evaluation settings:

- Fix the evaluation color space and crop (e.g., Y-channel + 4-px crop for ×4 SR).

- Use official splits/servers (SIDD/DND) and follow the degradation definitions in GoPro/REDS.

- Report Params, MACs/GFLOPs, ms/MP latency, and peak memory; specify hardware and software versions.

- Include standardized visual crops (3–5 per task) alongside the numeric tables.

8. Open Challenges and Future Directions

Building on the evidence synthesized in Sections 3–7 and the unified evaluation protocol in Section 6.4, this section distills the most persistent gaps and actionable research opportunities

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in image restoration. We highlight issues of real-world generalization, composite/unknown degradations, perceptual evaluation beyond PSNR/SSIM, efficiency at high resolutions, data/pretraining realism, and the need for robust protocols, reproducibility, and responsible practice, framing concrete directions for the next wave of work.

- **Real-world generalization and domain shift**

Models that excel in synthetic settings (e.g., Gaussian noise, bicubic downsampling) often underperform when faced with real-world smartphone/camera noise, compression distortions, weather effects, or mixed degradations. Bridging this gap requires wider training distributions, more robust degradation modeling, and periodic evaluation on realistic benchmarks (e.g., SIDD, DND, GoPro, and REDS).

- **Composite or unknown degradations**

Images in the wild rarely suffer from a single, clean corruption; they frequently exhibit multiple interacting degradations (e.g., low-light, noise, blur, and compression). A useful path is to combine reliable degradation detection/routing with joint modeling—avoiding long, brittle cascades. Mixture-of-experts, degradation-aware feature conditioning, and simple uncertainty estimates can improve robustness without overcomplicating pipelines.

- **Perceptual evaluation beyond PSNR/SSIM**

PSNR/SSIM correlate imperfectly with human perception; robust evaluation should combine them with LPIPS and standardized visual crops (see Metrics in Section 6.2 and reporting practices in Section 6.4.3). GAN-based perceptual methods (e.g., ESRGAN/Real-ESRGAN) are summarized in Table 4.1.

- **Efficiency at high resolution (4K–8K)**

Memory and latency remain the bottlenecks, especially for attention-heavy backbones. Practical workarounds include windowed/efficient attention, tiled inference with overlap, and lightweight residual blocks. Always report Params, MACs/GFLOPs, ms/MP, peak memory, and the exact hardware/software stack.

- **Data, pretraining, and synthetic realism**

Large-scale pretraining helps, but only when the synthetic "degradation engine" reflects real capture conditions. Document training data clearly, stress-test on real benchmarks, and share recipes for generating degradations so others can reproduce and critique them.

- **Reproducibility and transparency**

Release checkpoints, evaluation scripts, and configs alongside the paper. Include seeds, pre/post-processing, and exact dataset versions. Clear artifacts make results verifiable, lower the barrier to reuse, and generally increase downstream impact.

As future work the use transformations like Fortier, Wavelet, Multiwavelet and Hybrid will improve the quality of obtained images from restoration [64 - 78]. As well us the optimization should improve the over all performance and hence the quality of the produced images from thr restoration process [79 – 85].

9. Conclusion

Taken together, the evidence points to a simple lesson: the right model depends on the job. If you need high fidelity with low latency—on mobile or in real-time—compact CNNs and efficient Transformers are the safest bet. When what matters most is how the image *looks* to people, GANs usually deliver more convincing textures and detail, even if PSNR/SSIM go down.

Equally important is how we compare methods. Once color space, border crops, and TTA(Test-Time Augmentation) are aligned, many headline gaps shrink and rankings often change. Fair, like-for-like evaluation should be the default. We also see a persistent synthetic–real gap: results that shine under bicubic or Gaussian settings don't automatically carry over to real noise, blur, compression, or mixed degradations. Finally, there's a genuine perception–fidelity trade-off—optimizing for LPIPS and visual quality can hurt PSNR/SSIM—so both perspectives should be reported to make results meaningful.

Cost is part of the claim. Parameters, MACs/GFLOPs, latency in ms per megapixel, and peak memory determine whether a method is practical. Efficient attention has narrowed—but not erased—the gap with lightweight CNNs, so complexity and runtime still need to be measured and disclosed alongside accuracy. And to turn progress into impact, transparency matters: releasing configurations, code, evaluation scripts, and exact hardware/software details makes results easier to verify and reuse, and helps the community build on them in real settings.

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