Study of Recent Image Restoration Techniques: A Comprehensive Survey

Article *in* Jordanian Journal of Computers and Information Technology · January 2025

DOI: 10.5455/jjcit.71-1735034495

Nikita Singhal
Army Institute of Technology

Jordanian Journal of Computers and Information Technology (JJCIT), Vol. 11, No. 02, June 2025.

STUDY OF RECENT IMAGE RESTORATION TECHNIQUES: A COMPREHENSIVE SURVEY

Nikita Singhal, Anup Kadam, Pravesh Kumar, Hritik Singh, Aaryan Thakur and Pranay

(Received: 24-Dec.-2024, Revised: 22-Feb.-2025, Accepted: 26-Mar.-2025)

ABSTRACT

The rapid advancements in digital imaging technologies, including image restoration (IR), have created a growing demand for effective image-restoration techniques. Various kinds of degradation, including noise, blur and low resolution, should be handled with these techniques. Restoration is important in many applications, including medical imaging, surveillance, photography and remote sensing, where image quality will be critical to the correctness of analysis and decision. This article provides an all-inclusive review of state-of-the-art (SOTA) methods in image restoration, covering traditional methods as well as modern techniques like deep learning (DL) and transformer-based models. Traditional image-restoration techniques include deblurring, denoising and super-resolution based on mathematical models and handcrafted algorithms. These methods were indeed effective for certain types of noise or blur, but generalized poorly to various real-world scenarios. Recent advances in machine learning (ML), especially DL using convolutional neural networks (CNNs), have made data-driven approaches that learn directly from large datasets much more effective. Recently, transformer-based models, such as Vision Transformers and Swin Transformers, have shown the ability to capture global dependencies in images, leading to superior performance on complex restoration tasks. It is also to mention the challenge of generalization across the type of degradation, say mixed noise or blur, and across different datasets. The proposed survey indicates the limitations of existing approaches, including computational cost and generalization challenges and offers insights into possible directions for future research. Considering these challenges and achievements, this article attempts to provide helpful guidance on methods for future research on restoring images.

KEYWORDS

Image restoration, Deep learning, Transformer-based architectures, Noise reduction, Cross-domain models.

1. INTRODUCTION

Image restoration, which aims to preserve high-quality images from deteriorating or damaged ones, has gained increased attention in modern multimedia-driven society due to the growing usage of digital photos. Degradations such as noise and blur can significantly affect image quality, affecting everything from everyday photography to medical imaging. Because it preserves details and improves visual clarity—two things that are often required for jobs involving image analysis, image restoration is therefore an important field of research in computer vision and image processing. The challenge of addressing various forms of degeneration has led academics to explore innovative methods for accurate and efficient image restoration.

Traditional approaches to image deblurring, denoising and super-resolution focused on specially designed algorithms that introduced regularization and filtering techniques to attempt to make use of mathematical models in recovering lost information. Such approaches proved to be very effective for some classes of noise or blur, but fared rather poorly at generalizing to other classes of degradation and sometimes produced sub-optimal results when applied directly to real-world problems. Thus, the entire domain has undergone major changes with recent developments in the fields of ML and DL, where a model becomes capable of learning from data rather than from rules.

The recent resurgence of interest in image restoration is due to architectures that have been designed primarily within the context of natural-language processing, particularly those built on the Transformer model. Here, among heroes, Swin Transformers and Vision Transformers, or ViTs, have proven to capture long-range dependencies and accurately model global interactions within images and return much detail lost in more traditional approaches for restoring images. So, mainly, wide pre-training on megascale data provides those Transformer-based models with a rather strong sense of

N. Singhal, A Kadam, P. Kumar, H. Singh,A. Thakur and Pranay are with Department of Computer Engineering, Army Institute of Technology, Pune, India. Emails: [ngupta, akadam, praveshkumar_21195, hritiksingh_21186, aaryanthakur_21161, pranay_21211] @aitpune.edu.in

both global and local features. So, this kind of model proves to be extremely efficient in many restoration tasks, from video- and image-compression enhancement to the repair of damaged medical images. For this reason, Swin Transformers and ViTs are now the main representatives of modern image restoration. It is here that success lies-largest capacity for recovering the finest detail and significantly raising the quality of degraded images.

In recent years, multiple ML techniques are implemented to solve complicated tasks in image restoration and related problems. Those methods consist mainly of traditional machine learning, deep learning-based methods and more advanced models that include Transformers and GAN-based approaches. Each technique presents advantages and limitations and offers a specific solution for challenges. Table 1 summarizes these diverse methodologies, highlighting some important studies related to each approach. This general summary serves as a foundation for the development of techniques in machine learning and offers some insight into just how each approach uniquely contributes to image restoration. Notably, traditional methods continue to dominate baseline comparisons, but DL, Transformer and diffusion-based models are beginning to take the field, because they pose SOTA performance on complex restoration tasks.

Table 1. Summary of machine-learning approaches and related studies.

Machine-learning Approach	**Related Studies**
Traditional Machine-learning Approaches	[1],[2],[3],[4]
DL-based Approaches	[5],[6],[7],[8],[9],[10],[11],[12],[13],[14]
Transformer-based Models	[15],[16],[17],[18],[19]
Multitask and Meta-learning Approaches	[20],[21]
GAN-based Approaches	[22],[23]
Diffusion-based Models	[11],[24],[25],[26],[27],[28],[29]
Hybrid Models	[9],[30]
Domain-specific Approaches	[31],[32],[33],[34],[35],[36],[37],[38]

Despite the remarkable progress made so far, the research in image restoration remains a burdensome task with several difficulties. Those include a significant reduction in the computational cost of restoring methods for real-time applications, handling multiple degradations together and boosting the generality of models across different domains. Lack of high-quality annotated datasets for specific domains, such as medical images and setting up cross-domain restoration models are vital today. This work considers the techniques developed for image restoration, focusing on deep-learning strategies, traditional methods and more recent transformer-based models. At the same time, we pass through the main datasets that are generally utilized alongside performance indicators and challenges that characterize the state of image restoration research today and point out possible lines for further research.

1.1 Comprehensive Comparison between Existing Survey Papers

In the field of image restoration, numerous survey articles have been published, each providing unique insights into various algorithms, methodologies and applications. However, these surveys differ in focus, evaluation criteria and comprehensiveness. Table 2 provides a comparative summary of prominent survey articles, which outline their respective strengths and limitations. This comparison enables a clearer understanding of the existing literature, helping to identify common approaches, as well as gaps in coverage that may benefit from further research. By examining the merits and demerits, this review aims to position our study in the context of existing work and to highlight areas where our approach may offer additional insights.

Table 2. Comparison of paper with existing surveys.

Review Paper	**Objective**	**Merits**	**Demerits**
[39], 2021	To explore the application of DL methods in SAR image restoration.	Offers a detailed analysis of SAR-specific restoration challenges with deep learning.	Limited to SAR images, not generalizable to other image modalities.

Jordanian Journal of Computers and Information Technology (JJCIT), Vol. 11, No. 02, June 2025.

Continuation of Table 2

Review Paper	Objective	Merits	Demerits
[40], 2021	To review GAN-based methods for image reconstruction in medical imaging.	Explores the successful use of GANs in improving medical-imaging quality and accuracy.	Primarily focuses on medical imaging, limiting its applicability to other fields.
[41], 2022	To explore DL and smart technologies for image super-resolution.	Provides a critical analysis of recent advancements in super-resolution techniques.	Focuses primarily on super-resolution, lacks coverage of other restoration techniques.
[42], 2022	To review DL approaches for demoiring screen-shot images.	Focuses on a niche issue in image restoration, providing specialized solutions.	Limited to demoiring applications, lacks broader applicability to other restoration tasks.
[43], 2022	To review various image-restoration methods for different image types.	Provides a broad review of restoration methods across diverse image types and applications.	Lacks depth in any specific domain due to its broad scope.
[44], 2023	Surveys diffusion models for image restoration and enhancement, analyzing their advantages, challenges and recent improvements.	Provides a structured taxonomy of diffusion models and their applications in denoising, super- resolution and deblurring.	Diffusion models often require high computational resources, which is not thoroughly discussed in terms of practical deployment.
[45], 2023	To review various IR methods designed to handle salt and pepper noise.	Provides an extensive survey of both linear and non-linear filtering techniques to restore ground- truth images.	Primarily focuses on salt and pepper noise, limiting its generalizability to other types of image degradation.
[46], 2023	To compare GAN-based approaches for image deblurring.	Offers a comparative analysis of multiple GAN- based methods for deblurring.	Limited to GAN-based approaches, excluding other potential techniques.
[47], 2023	To review DL-based techniques for image restoration in real-world settings.	Provides a comprehensive analysis of different DL techniques for image	Does not focus on specific restoration domains, making it broad in scope.
[48], 2023	To review underwater image-restoration techniques.	Addresses specific challenges of underwater imaging and offers solutions for image	Limited to underwater optical imaging, lacks generalization to other image types.
[49], 2023	To review quality assessment algorithms for realistic blurred images.	Provides insights into quality assessment for blurred images using a comprehensive database.	Limited to quality assessment, lacking exploration of actual image restoration techniques.
[50], 2025	To analyze and compare machine learning-based techniques for improving image quality.	Offers a broad comparison of machine-learning models, highlighting their strengths and applications in image enhancement.	Lacks in-depth discussion on DL-based approaches, focusing more on traditional ML techniques.
[51], 2024	To develop and analyze a GAN-based image-restoration algorithm for engineering applications.	Highlights the potential of GANs in reconstructing and restoring images with high precision in engineering contexts.	Focuses on engineering applications, with limited exploration of general-purpose image-restoration techniques.
[52], 2024	To analyze deep-learning techniques applied to image denoising.	Provides an in-depth review of SOTA methods in denoising using deep learning.	Primarily focuses on denoising, with limited exploration of other restoration tasks.
[53], 2024	To report on the NTIRE 2024 challenge focused on bracketing image restoration.	Highlights the latest advancements from the NTIRE challenge with benchmark results.	Results are constrained to the challenge datasets, limiting real-world applicability.
Proposed Survey	To offer an overview of image restoration methods with a focus on recent advancements.	Provides a comprehensive analysis of image restoration techniques, including GAN, hybrid, DL and transformer-based methods, …etc. Additionally, it presents key metrics such as inference time, PSNR and SSIM, enabling detailed evaluation of each method's efficacy.	

1.2 Performance Comparison of Image-restoration and denoising Techniques

Table 3 presents a comparative evaluation of the effectiveness of various denoising and IR methods. DnCNN easily handles both known and unknown noise levels while achieving good PSNR in a range of denoising applications. As noise-reduction settings are changed, the efficacy of Wiener filtering improves, offering a balanced approach to both noise reduction and feature retention. An extremely useful technique for minimizing noise and preserving significant image edges is total variation regularization. QTP loss improves perceptual quality by addressing problems, such as inadequate augmentation and misleading color. The Three-stage CNN exhibits remarkable performance in color-image restoration, especially in denoising and demosaicking. Finally, VCRNet is a strong candidate for real-world settings, since it effectively resolves no-reference image-quality assessment (NR-IQA) tasks, retrieving images even in the absence of reference data. Depending on the particular needs of image-restoration activities, these approaches provide a variety of possibilities.

Table 3. Performance comparison of image-restoration and denoising techniques.

Model/Technique	**Accuracy/Performance**
Deep Neural Networks (DnCNNs)	High PSNR results across various tasks; specific improvements noted in denoising.
Wiener Filtering	Performance improves with better noise reduction; often provides a good balance.
Total Variation Regularization	Effective in reducing noise while preserving image edges.
Quality-Task-Perception (QTP) Loss	Enhanced perceptual quality for images during restoration.
Three-stage CNN	Effectively restores color images with high performance in various tasks.
Visual Compensation Network (VCRNet)	Efficiently handles NR-IQA tasks, showing significant promise in restoring images.

2. LITERATURE SURVEY

This section explores the various algorithms used in Image Restoration. Figure 1 depicts a taxonomy of image restoration that divides the methods into several categories of model-based approaches. The systematic classification above indicates an overview of methods proposed to address various problems associated with image restoration, from diffusion-based models, GANs, transformer-based models, deep-learning techniques, hybrid approaches, multi-task/meta-learning approaches, to conventional machine learning-based models. Each category has several methods proposed to address a specific type of vision impairment.

2.1 Traditional Machine Learning-based Approaches

Traditional machine-learning techniques have played a very crucial role in image restoration. They were applied to various restoration tasks under conditions, like diffraction effects and limited visibility. The techniques use mathematical models and feature-driven approaches to solve the problem of image degradation, where the model's understanding of local image properties and image production is essential. Although these approaches were significant advances in particular domains, they were also inherently limited as techniques based on rigid priors and handcrafted features. These models were much less flexible than the subsequently developed DL-based techniques, because they frequently required intense fine-tuning to work generically over many applications. However, they formed a strong basis for adaptive previous use and image formation that went into the formulation of modern image-restoration frameworks. A comparison of various traditional image-restoration methods, highlighting their key characteristics and performance, is presented in Table 4.

Generalized Image Formation Model (GIFM) is a framework in computer vision and image processing that describes the process of capturing and reconstructing images. It generalizes the traditional image-formation models, thus enabling a broader range of applications and accommodating various imaging modalities. Liang et al. [1] objective was to rebuild images shot in low-visibility conditions using the GIFM. Using a machine learning-based approach, this tactic integrated domain information relevant to creating images in challenging conditions, such as fog and dim illumination. The recommended method worked well on datasets with poor visibility, successfully enhancing image clarity. However, its applicability to a greater range of vision problems was restricted by its inability to adapt to significant variations in lighting conditions.

Jordanian Journal of Computers and Information Technology (JJCIT), Vol. 11, No. 02, June 2025.

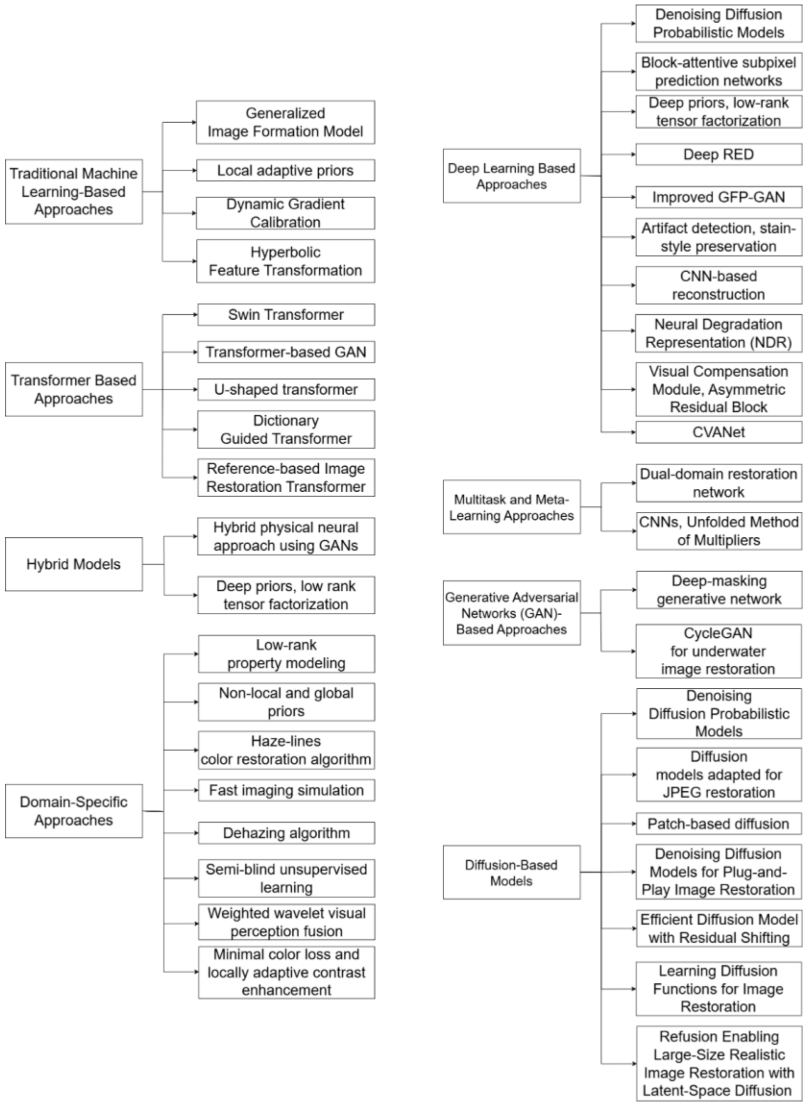

Figure 1. Taxonomy diagram for image restoration.

Local Adaptive Prior-based Image Restoration (LAPIR) is a technique in image processing that deals with the process of recovering or enhancing images by using prior knowledge about the content of the image, particularly in areas degraded or noisy. Jiang et al. [2] introduced a LAPIR technique specifically tailored for space diffraction imaging systems. Using priors that adapt to the specifics of the diffraction process, the technique effectively reduced noise and enhanced the restoration of features in diffraction-distorted images. This technique, which focused on the distinctive properties of space diffraction, significantly improved image quality and was particularly helpful in fields where effects of diffraction are frequent, such as astronomy and remote sensing. The algorithm fared better than traditional methods in a number of instances when it came to recovering structural information. Its use in fixing other image issues, such as motion blur or general low-light photography, was constrained by its difficulty in generalizing beyond its original application due to its uniqueness to spatial diffraction.

Yang et al. [3] formalized a generic Image Restoration framework for Visual Recognition (IRVR) designed to facilitate holistic semantic recovery across various high-level tasks in image restoration. To improve generalization, they maximized semantic recovery during the training of IR models and used image regression as an additional regularization term. For compatibility with any potentially unseen recognition models, they adjusted the gradient of the primary objective with the regularization gradient. The IRVR was recognition-agnostic and integrated as a plug-and-play module into existing IR techniques without adding computational cost at inference time. Through extensive experiments, Yang et al. [3] demonstrated IRVR’s effectiveness and its strong generalization across different downstream high-level tasks. This precise recovery of intrinsic semantic details proved critical for advanced machine analysis, ensuring integrity and authenticity in multi-media content.

Recent breakthroughs in the restoration of aged photos have improved greatly by generative networks, while the restoration quality still remains heavily affected by the latent space properties, which captures the necessary semantic information essential for successful recovery. To resolve this problem, Chen et al. [4] developed a new generative network that uses hyperbolic embeddings to regenerate old photos affected by multiple degradations. For further improving hierarchical representational capability, the intermediate hyperbolic features were processed with channel mixing and group convolutions. Furthermore, an attention-based aggregation mechanism in hyperbolic space was employed; this enabled the latent vectors to capture important semantic factors that contribute to higher-quality restoration. A diversity loss function was also defined for steering each latent vector toward the disentangling of semantically different aspects. Extensive experiments showed that this method outperforms existing restoration techniques with visually pleasing results even for complex degradations.

Table 4. Comparison of traditional image-restoration methods.

Study	Methods/ Algorithms Used	Dataset Used	Accuracy/ Performance	Limitations
[1], 2022	Generalized Image Formation Model	Poor-visibility datasets	PSNR: 17.198, SSIM: 0.565, CIEDE: 14.402	Struggles with extreme lighting variations
[2], 2023	Local Adaptive Priors	Space-diffraction datasets	SSIM: 0.8503, VIF: 0.6425, SNR: 22.9858	Limited generalization to other imaging systems
[3], 2024	Dynamic Gradient Calibration, Intrinsic Semantic Consistency Constraint, Ground-truth Augmentation Strategy	CUB DATASET	PSNR: 29.94, SSIM: 0.8892	Limited testing on real-time applications, requires more exploration for model robustness in dynamic conditions
[4], 2024	Hyperbolic Feature Transformation, Group-wise Feature Aggregation	TJU-OPR, FFHQ [54]	PSNR: 23.64, SSIM: 0.8206, LPIPS: 0.25, FID: 13.175	Sensitive to latent space selection, which affects stability in complex images; computational complexity due to hyperbolic transformations, challenging for large-scale or real- time applications

2.2 Deep Learning-based Approaches

Deep-learning methods have revolutionized photo restoration by utilizing the capacity of neural networks to automatically recognize complex relationships and patterns in images. DL models can extract hierarchical representations from unprocessed image data, allowing for more complex and efficient restoration solutions than traditional machine-learning models that depend on manually created features. Deep learning is particularly well-suited to image-restoration applications, because CNNs efficiently maintain spatial information throughout feature-extraction layers. Table 5 presents a comparison of DL-based IR methods, outlining their key features and effectiveness. These techniques have greatly improved image restoration by removing the need for manually constructed features and allowing models to learn directly from data. Despite challenges with computational resources and data requirements, deep learning-based methods continue to advance, adopting innovations that increase their accuracy and adaptability across a variety of image-restoration applications. The generalized deep-learning architecture, depicted in Figure 2, highlights the key components and workflow of a typical neural-network model.

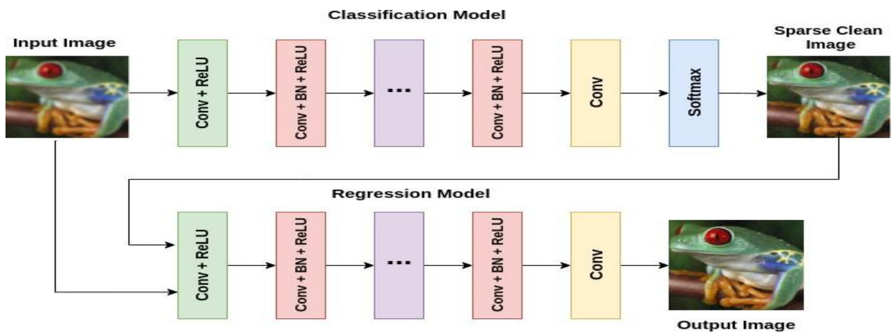

Figure 2. Overview of a generalized deep-learning framework.

Block-attentive subpixel-prediction networks (BASPNs) represent a neural-network architecture used for high-resolution image generation tasks and also in terms of performance, a high level of improvement for the case of sub-pixel image prediction. This network architecture is applied in the related applications, such as: image super-resolution, enhancement, or video-frame prediction. In place of full-resolution images, this paper introduced a novel family of networks known as Subpixel Prediction Networks (SPNs), which predict reshaped and spatially down-sampled block-wise tensors. This novel method significantly increased network speed by reducing the impact of spatial downsampling on restoration performance. Kim et al. [5] included a unique Subpixel Block Attention module which reduced discontinuities between blocks by recalibration of block-wise characteristics in order to further improve performance. Experimental results showed that these networks successfully matched computational efficiency and restoration quality in three important image restoration tasks: image augmentation, color-image denoising and image-compression artifact removal. This study demonstrated how SPNs can improve image-restoration procedures' speed and effectiveness.

Deep Residual Encoder-Decoder (RED) is a neural-network architecture for IR tasks, particularly deblurring, inpainting and denoising. It combines the deep-learning approach with the residual-learning technique to boost performance in recovering images from distorted or low-quality inputs. The Deep Unfolding Network (DUN) developed an effective framework for image restoration by combining a regularization module with a data-fitting module. In classic DUN models, which often used a DCNN for regularization, data fitting was done prior to regularization at each stage. The regularization module was positioned before the data-fitting module in the enhanced DUN that the authors of this study deployed. The Regularization by Denoising (RED) method served as the foundation for this regularization model, which included a recently developed DCNN. For the data-fitting part, Kong et al. [6] employed a closed- form method based on the Faster Fourier Transform (FFT). Among the many advantages of the proposed DRED-DUN model were its capacity to integrate the interpretability of RED with the adaptability of discovered image-adaptive regularization; its full end-to-end trainability, which allowed for cooperative regularization-network optimization with extra parameters; and its superior performance compared to both model-based and learning-based methods, as evidenced by higher PSNR values and better visual quality. Notably, this approach performed better than cut CNN-based Reconstruction, which refers to the use of CNNs for the task of reconstructing images or signals from incomplete or degraded data. Perdios et al. [7] allowed full-view frame capture at rates more than 1 kHz, ultrafast ultrasound (US) which has greatly improved biomedical imaging and paved the way for novel methods, such as shear-wave elastography. However, diffraction artifacts from sidelobes and grating lobes provide difficulties. Frame rates are decreased by the need for several acquisitions for sufficient image quality in traditional methods. A two-step image-reconstruction technique based on CNNs was developed for real-time imaging in order to address this issue. This method uses a residual CNN trained to eliminate diffraction artifacts to perform a high-quality restoration after beginning with a poor-quality estimation from a back-projection-based operation. The mean signed logarithmic absolute error was established as the training loss function to address the high dynamic range of radio frequency US images. Tests using a linear transducer array showed that this technique could achieve a dynamic range of more than 60 dB and rebuild images taken from single plane-wave acquisitions with quality on par with the best artificial aperture imaging.

Based on the free-energy principle, no-reference image-quality assessment techniques have attracted much attention and applied GANs recently. As a result, they achieve more accuracy in quality prediction than the former methods. However, most of the GAN-based methods can barely recover very poor-quality images, resulting in the broken relationship of distorted images and restored images between their quality reconstruction. To solve this problem, Pan et al. [8] proposed a VCRNet based on the non-adversarial model for better compensation of heavily distorted images. The innovations in this model would be a visual compensation module, an optimized asymmetric residual block and a mixed loss function based on error maps. All these further enhance the restoration capacity of the visual restoration network (VRN) by better handling the visual restorations. VCRNet further enhances the ability to accurately estimate the qualities of severely degraded images with multi-level restoration features coming from the VRN. Performing SOTA in all seven widely used IQA databases demonstrates the effectiveness of the proposed VCRNet for image-quality assessment.

These are concepts that have been used for various applications in machine learning, image processing and computer vision, including representation learning, denoising and image reconstruction. Deep priors are neural networks that serve as implicit priors in generative modeling. Low-rank tensor factorization is a mathematical method to decompose an array (tensor) that exists in multi-dimensional form into the sum of lower-dimensional tensors. This is very important to handle high-dimensional data by retaining significant structures and patterns. Zhang et al. [9] looked at the difficulties related to processing mixed noise pollution in hyperspectral images (HSIs). Although a number of approaches have been put out to address this problem, they typically fall into one of the following categories: model-driven or data-driven. Model-driven approaches were frequently criticized for being sensitive to changes in parameters and having high processing costs due to iterative optimization. However, data-driven techniques often performed poorly due to overfitting. This study suggested a unique approach to HSI restoration that blends low- rank tensor factorization (DP-LRTF) with deep denoising priors to get beyond these restrictions. Tucker tensor factorization was used to enforce global spectral low-rank requirements and two deep denoising priors were used to improve the spectral orthogonal basis and spatial reduced factor. This combined strategy effectively used the low-rank structure of HSIs and the powerful feature-extraction capabilities of deep learning. Experimental evaluations demonstrated that DP-LRTF significantly exceeded both model- driven and data-driven methods in terms of blended noise reduction and execution efficiency in a range of simulated and real-world scenarios.

Table 5. Comparison of deep learning image restoration methods.

Study	Methods/ Algorithms Used	Dataset Used	Accuracy/ Performance	Limitations
[5], 2021	Block-attentive sub-pixel prediction networks	Div2k dataset [56]	PSNR: 33.89, SSIM: 0.934, LPIPS: 0.0990	Risk of overfitting
[6], 2021	Deep RED (Regularization by Denoising)	Multiple benchmark datasets	PSNR: 35.98	Limited to certain types of degradations
[7], 2021	CNN-based reconstruction	Ultrasound imaging datasets	PSNR:14.23, SSIM: 0.31	Limited to specific ultrasound configurations
[8], 2022	Visual Compensation Module, Asymmetric Residual Block, Error Map-based Mixed Loss Function	Seven representative IQA databases	SROCC: 0.973, PLCC: 0.974	May face challenges in cases of extreme degradation
[9], 2023	Deep priors, low-rank tensor factorization	Hyperspectral datasets	PSNR: 32.943, SSIM: 0.9704	Computational complexity
[10], 2023	Artifact detection, stain-style preservation	Histology datasets	PSNR: 26.37, SSIM: 0.9359, SRE: 56.31	Limited generalizability
[14], 2024	A DL-based super-resolution method that utilizes feature, channel and pixel attention mechanisms to enhance image details.	DIV2K [57], Set 5, Set 14, BSD100, Urban100	PSNR: 38.19, SSIM: 0.9613	Computationally more expensive and the robustness of the complex network remains a challenge
[11], 2024	Denoising Diffusion Probabilistic Models	CelebA-HQ [55] and FFHQ [54]	PSNR: 33.2055, SSIM: 0.8662, LPIPS: 0.0966	Slow Convergence
[12], 2024	Improved GFP-GAN	Miner face dataset	PSNR:26.1061, SSIM:0.7236, LPIPS: 0.3827, FID: 46.51	Specific to miner face images
[13], 2024	Neural Degradation Representation (NDR), Degradation Query and Injection Modules, Bidirectional Optimization Strategy	BSD68, UR-BAN100	PSNR: 26.02, SSIM: 0.8657	Potential complexity in handling highly heterogeneous degradations

Artifact detection and Stain-style preservation are two closely associated ideas found in the broad category of image processing and computer vision, often utilized specifically within medical imaging and digital art, as well as within the area of image restoration. Artifact detection consists of detecting distortions or errors within an image not existing in the scene under photo. Ke et al. [10] addressed these artifacts through manual quality control, where the level of automation in image analysis is significantly reduced. By detecting and fixing artifacts, a systematic pre-processing technique was proposed to bridge this gap and lessen its impact on subsequent AI diagnostic tasks. At first, the AR-Classifier artefact-detection network distinguished between normal tissues and common artifacts, such as out-of-focus regions, spots, marking dye, tattoo pigment and tissue folds. It also categorized artifact fixes based on how restorable they were. Then, in an effort to preserve tissue architecture and stain styles, the AR-CycleGAN artifact restoration network performed de-artifact processing. A standard for performance evaluation was built using both publicly available datasets of breast and colorectal cancer and clinically gathered whole slide images. The functional structures of the suggested method were rigorously evaluated across multiple metrics in a variety of tasks, including artifact restoration and classification, as well as downstream diagnostic tasks, like tumor classification and cell segmentation.

DCNNs demonstrated remarkable capabilities in feature extraction and detail reconstruction for single-image super-resolution (SISR). However, previous DCNN-based approaches often failed to fully leverage the complementary strengths among feature maps, channels and pixels, which limited their ability to capture rich image details. To address these challenges, Zhang et al. [14] introduced a Cascaded Visual Attention Network (CVANet). This network was designed to mimic the human visual-attention mechanism to enhance detail reconstruction. The proposed approach incorporated three key modules: a Feature Attention Module (FAM) for feature-level attention learning, a Channel Attention Module (CAM) to strengthen feature maps through channel-level attention and a Pixel Attention Module (PAM) that adaptively selected representative features from previous layers to generate a high-resolution output. By effectively exploring feature-representation capabilities and human visual-perception properties, CVANet significantly improved image resolution. Experimental evaluations on four benchmark datasets demonstrated that CVANet outperformed SOTA methods in terms of subjective visual perception, PSNR and SSIM.

Denoising Diffusion Probabilistic Models (DDPMs) is a class of generative models that have gained acceptance for their ability to provide high-quality images and successfully perform various tasks in the field of computer vision, especially in image generation and in painting as well as denoising. Pang et al. [11] examined a facial image-restoration technique that made use of a pre-trained unconditional DDPM model in order to offer more flexible restoration procedures. The overall quality of the restored photos was found to suffer from low iterations throughout the resampling process. The study suggested an optimization technique for the inversion process that combined continuous sampling and sample scheduling in order to lessen this problem and improve image quality. The suggested strategy outperformed current techniques in facial image restoration, according to extensive testing utilizing the CelebA-HQ [55] and FFHQ datasets [54]. In terms of LPIPS and PSNR measures, the outcomes showed an excellent performance. Additionally, face-recognition accuracy improved by 15.7% when photos were restored using random masks and by a significant 26% when images were restored using central masks.

Improved GFP-GAN is an advanced model of the original GFP-GAN model, designed with the intention of high-quality facial image generation and restoration. GFP-GAN pays special attention to generating more realistic human faces while also preserving details and improving quality. A New Blind Restoration Approach for Miner Face Images Utilizes an Enhanced GFP-GAN Model. The challenges presented by miner face images, which are crucial for information exchange and for the digital transformation and astute management of mining firms, were addressed. To solve the issues of complex degradation variables including noise, blurring and low resolution, Zhang et al. [12] proposed a blind-restoration model built on an improved GFP-GAN. This concept attempted to achieve a balance between integrity and authenticity throughout the repair process. The authors successfully removed the complex degeneration from the miner face photos by first integrating a UNet++ network, using the pre- trained StyleGAN2 network as a source of previous knowledge. To improve the use of previous features from the pre-training network, they also added a channel-attention technique to the channel-split spatial feature-transform layer. This method allowed the miner face photographs to more accurately and authentically portray their end result. According to experimental data, the suggested approach significantly outperformed competing model methods in terms of reconstructing miner face photos.

At present, the conventional techniques used in the restoration of images are adequate for only one type of degradation in the image. However, in real-time applications, the nature of degradation varies and is mostly unknown. This mismatch may lead to a considerable drop in the performance of the model under consideration. With the motivation to overcome the mentioned problem, Yao et al. [13] came up with the all-in-one image-restoration network for managing multiple degradation types inside a single framework. The core of this approach is a neural degradation representation (NDR), which captures the unique characteristics of different degradation types. The NDR acts like a neural dictionary, which can adaptively decompose various degradations into fundamental components and allows the network to generalize across multiple degradation types. The authors introduced a degradation-query module and a degradation-injection module to utilize the NDR in order to approximate and inject the specific degradation patterns according to the learned representation, thus allowing the network to handle diverse degradations in a unified way. Moreover, it makes use of two-way optimization strategy: It actually degrades and reconstructs in the process, one after another, in order to enhance the degradation representation.

2.3 Transformer-based Models

Recently, transformer-based models have emerged as highly successful image-restoration techniques by leveraging the ability to detect local and global dependencies in image data. First developed for applications in natural-language processing, transformers established the self-attention mechanism that enables them to look at data in their entirety by evaluating the significance of different input elements. Since transformers can understand more complex patterns in images, as well as contextual links across the entire image, they tend to perform well in restoring images compared to traditional CNNs that basically rely on localized features. Even though the transformer-based models for image restoration are still nascent, there is definitely a lot of room to improve, because they can fit well and also capture high-order correlations in images. Such transformers are bound to be part of future SOTA image-restoration systems, not to mention the critical components of the systems, since efficiency gains and architectural advances are ongoing. Figure 3 illustrates the structure of a Transformer-based model, which processes information by focusing on different parts of the input data. This approach allowed the model to understand relationships between elements efficiently.

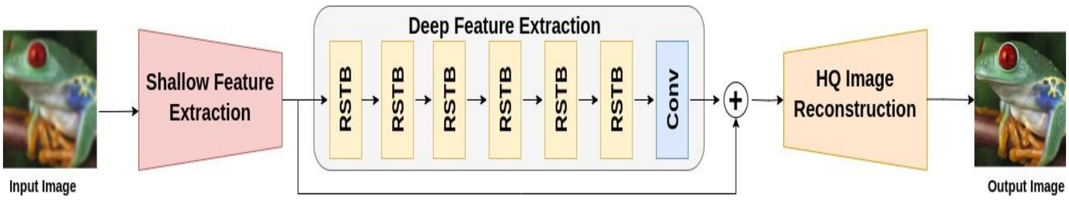

Figure 3. Overview of a generalized transformer-based model.

SwinIR includes three main parts, which are shallow feature extraction, deep-feature extraction and high-quality image reconstruction. Deep Feature Extraction combines several residual Swin Transformer blocks, having several layers of Swin Transformers combined with residual connections. Liang et al. [15] tested the model on three sample tasks: image super-resolution (including classical, lightweight and real-world scenarios), image denoising (including both grayscale and color images) and JPEG compression artifact removal. Experimental results demonstrate that SwinIR outperforms SOTA approaches in performance by 0.14 to 0.45 dB, while also achieving a decrease of up to 67% in the total number of parameters.

RFormer (Reconstruction Transformer) combines reconstruction tasks with transformer architectures for applications in image processing and computer vision. This method leverages the transformers' ability to capture long-range dependencies and learn complex data patterns in applications, such as image inpainting, noise removal and super-resolution. Deng et al. [16] presented this approach coupled with a new dataset, Real Fundus, consisting of 120 pairs of low and high-quality fundus images; this dataset focuses on addressing the difficulties of reconstructing clinical fundus images. Their contribution introduced a Transformer-based Generative Adversarial Network (GAN), which addresses real-world degradation in clinical fundus images. At the heart of this architecture is the Window-based Self-attention Block, which captures the long-range dependencies and the non-local self-similarity in an efficient manner. Furthermore, a Transformer-based discriminator was used to further improve the visual quality of reconstructed images. Experiments on the RF dataset showed that

RFormer performed substantially better than the SOTA methods.

Wang et al. [17] developed the Uformer, a Transformer-based architecture for image restoration which balances efficiency with effectiveness using Transformer blocks in forming a hierarchical encoder-decoder network. There are two novel designs, one is the locally-enhanced window Transformer block and the other one is a learnable multi-scale restoration modulator. LeWin Transformer block employs non-overlapping window-based self-attention to efficiently capture the local context without consuming considerable computation for high-resolution feature maps. Meanwhile, the multi-scale restoration modulator is, in fact, a kind of multi-scale spatial bias that refines features from the decoder's layers while enhancing detail restoration without computational overhead or significant increases in parameters. These improvements can help Uformer model essential dependencies for image restoration at different levels; namely, local and global. Thorough testing has been conducted on various tasks of restoration and as a result, Uformer has shown comparable or sometimes superior performance to SOTA methods while maintaining architectural simplicity.

The Under-Display Camera (UDC) allows users to realize an all-screen experience based on the placement of a camera below the display panel, but this setup heavily degrades the image quality due to the unique properties which affect the display, so restoration is really challenging. Although multiple solutions have been proposed toward dealing with the UDC image-restoration issue, there are yet no specific methods and databases used for restoring UDC face images, which happen to be a basic problem when taking into consideration UDC applications. In response to the same, Tan et al. [18] designed a two-stage network and named it UDC Degradation Model Network (UDC-DMNet). This simulates the color filtering effect, brightness attenuation and diffraction effects seen when using UDC imaging as it synthesizes UDC images. The authors developed dedicated UDC face training and testing datasets named FFHQ and CelebA- Test in aid of UDC face restoration by making use of UDC-DMNet in combination with good-quality face images; namely, from FFHQ [54] and CelebA-Test. They introduced a new kind of dictionary-guided transformer network known as DGFormer that comes up with facial component dictionary, with image characteristic accounting for the particular features of UDC image and can hence blindly recover a face related specifically to a UDC scenario. Experimental results show that the proposed DGFormer and UDC-DMNet have the SOTA performance in UDC image restoration.

Zhang et al. [19] introduced a multi-stage image-restoration (IR) approach for progressively restoring images with multiple degradations by transferring similar edges and textures from a reference image, referred to as the Reference-based Image Restoration Transformer (Ref-IRT). The proposed method operates in three stages. In the first stage, a cascaded U-Transformer network performs the preliminary recovery of the degraded image. This network comprises two U-Transformer architectures connected by feature-fusion layers at both encoder and decoder levels, enabling each U-Transformer to predict the residual image step-by-step, progressing from simple to complex and from coarse to fine toward complete recovery. The second and third stages aim to enhance the restoration quality by transferring textures from a reference image to the partially restored target image. To achieve accurate content and texture matching between the reference and target images, the authors propose a quality-degradation-restoration method. A texture-transfer and reconstruction network then maps these transferred features to generate the final high-quality output. By progressively refining degraded inputs, the method enhances restoration quality, particularly in cases involving severe distortions. This approach demonstrates effectiveness in handling complex degradations by incorporating contextual information from high-quality references. Experiments conducted on three benchmark datasets confirm the superior performance of Ref-IRT in comparison to other cutting-edge techniques for multi-degraded image restoration.

Table 6 provides a comparison of transformer-based models, highlighting their architectures and performance in image restoration.

2.4 Multi-task and Meta-learning Approaches

Recent image-restoration techniques have become popular due to multi-tasking and meta-learning techniques, because they offer solutions that can work based on shared data-related activities or quickly adapt novel restoration settings. They overcome the pitfalls with single-task models, which struggle most of the time not to generalize across other degradations and various context-specific types of images by allowing the model to learn common representations of improvements in performance in various tasks. All things considered, the multi-task and meta-learning techniques have enlarged the scope of image restoration in that they provide tools for not only improving the performance on known tasks, but also allowing models to be well equipped in coping with new and challenging degradation conditions. Further development is expected to advance resilient and flexible models in image restoration that could solve a range of dynamic problems of image deterioration. A detailed comparison of multi-task and meta-learning approaches, showcasing their key strategies and performance in image restoration, is provided in Table 7.

Table 6. Comparison of transformer-based models.

Study	Methods/ Algorithms Used	Dataset Used	Accuracy/ Performance	Limitations
[15], 2021	Swin Transformer for image restoration	Classic5 [58], LIVE1 [59], Flickr2K	PSNR: 34.52, SSIM: 0.908	High resource consumption
[16], 2022	Transformer-based GAN	Fundus clinical dataset	PSNR: 28.38, SSIM: 0.873	Specific to fundus images
[17], 2022	U-shaped transformer, Window-based Self-attention, hierarchical encoder-decoder structure, skip connections	SIDD (Smartphone Image Denoising Dataset) [60], GoPro Dataset, DIV2K Dataset [56]	PSNR: 26.28 ,	High computational cost due to transformer-based architecture
[18], 2023	DGFormer, UDC-DMNet	FFHQ-P/T, CelebA-Test-P/T	PSNR: 38.35, SSIM: 0.9678, LPIPS: 0.0720	Limited to UDC-specific scenarios
[19], 2024	Reference-based Image Restoration Transformer (Ref- IRT), Cascaded U-Transformer Network, Texture Transfer and Reconstruction Network	CUFED5, WR_SR, XRIR	PSNR: 28.893, SSIM: 0.905, LPIPS: 0.421	Requires reference image for optimal restoration

Table 7. Comparison of multi-task and Meta-learning approaches.

Study	Methods/ Algorithms Used	Dataset Used	Accuracy/ Performance	Limitations
[20], 2022	Dual-domain restoration network	CT and low-dose imaging datasets	PSNR: 42.03, SSIM: 0.966, RMSE: 20.18	Specific to CT and low-dose images
[21], 2022	CNNs, Unfolded of Multi-method pliers	Multispectral datasets are used	PSNR: 36.47, SSIM: 0.9873	Increased complexity and computation limited

DuDoUFNet is a specialized DL model that is set to solve the challenges of image restoration by progressively reconstructing images in a dual-domain framework. It is a dual domain under-to-fully complete progressive restoration network which was created in this work with the goal of combining low-dose computed tomography (LDCT) with metal artifact removal (MAR). Due to the increasing use of low-dose computed tomography (LDCT) to reduce radiation exposure in patients, image quality is frequently compromised by noise, particularly in cases where patients have metallic implants. This can lead to extra streak artifacts and increased noise, which can impair medical diagnoses and related applications. The main emphasis of previous studies was either full-dose CT MAR or denoising LDCT images without considering the effect of metallic implants. Reconstructions from MARLD may not be as good as they may be if conventional MAR or LDCT methods are used. Zhou et al. [20] used a two-stage progressive restoration network to effectively restore from the sinogram to the image domain while drastically lowering noise and artifacts.

Marivani et al. [21] examined MIR and fusion by framing the problem as a linked convolutional sparse coding challenge, employing the Method of Multipliers (MM) for resolution. The MM-based strategy drove the building of a CNN encoder, relying on the concepts of deep unfolding. Marivani et al. [21] suggested two multimodal models that combined the specified encoder, followed by a customized decoder that transformed the learned representations into the appropriate output. Unlike most current deep learning techniques, which often featured several encoding branches blended by concatenation or linear combination, this technique offered a more efficient and systematic approach for fusing input at various stages of the network. This method resulted in representations that permitted accurate image

Jordanian Journal of Computers and Information Technology (JJCIT), Vol. 11, No. 02, June 2025.

reconstruction. Marivani et al. [21] evaluated the models on three image-restoration domains and two image-fusion domains. Those quantitative and qualitative comparisons with other SOTA analytical and deep-learning techniques further emphasized that the proposed framework outperforms.

2.5 Generative Adversarial Network (GAN)-based Approaches

GAN is a strong image-restoration technology that emerges from a novel framework, which is capable of generating realistic images from the damaged input. They are composed of two neural networks, the discriminator and the generator. GANs have been trained against each other. The goal of the generator is to generate high-quality restored images. The discriminator judges the realism of the generated images by distinguishing between made and genuine outputs. The adversarial structure of GANs makes them particularly effective in restoration tasks that preserve the texture and details of the original image. The generator has to produce images that look more realistic. GAN-based approaches focus on the generation of images that should have realistic textures and structural features and hence these are useful for applications where perceptual quality is the requirement. They are very effective whenever the classical models fail, as for example, in extreme noise reduction or super-resolution at very high levels, they have the capacity to learn complex distributions. Figure 4 illustrates the structure of a GAN, which consists of two components—a generator and a discriminator. The generator creates data samples, while the discriminator evaluates their authenticity, enabling the model to generate high-quality outputs through an adversarial training process.

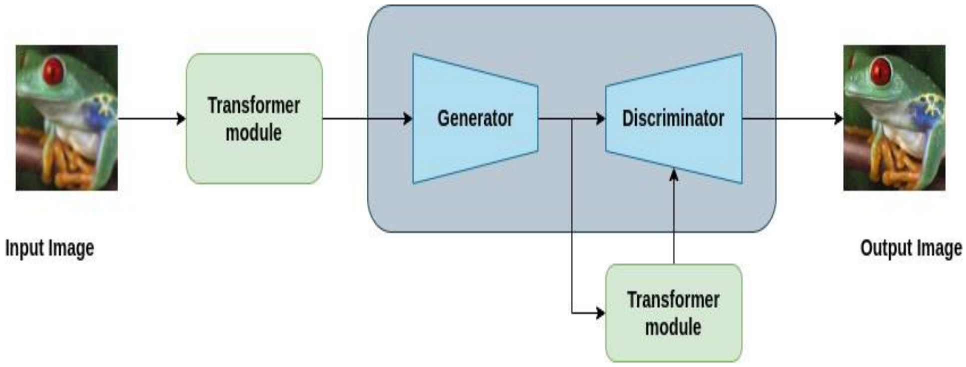

Figure 4. Generalized representation of a GAN architecture.

Deep-Masking Generative Network (DMGN) is specifically a deep-learning model set up for numerous image-generation and restoration applications, typically where selective masking of various parts of the images under consideration is involved. It is a unified technique for recovering backgrounds from images that have been superimposed. Feng et al. [22] unified framework for background restoration from overlain images that successfully handles different kinds of noise—the DMGN—was presented. The generative technique used by the DMGN is coarse-to-fine. It starts by producing a noise image and a coarse background image simultaneously. The background image is then improved in quality by using the noise image for refinement. The unique Residual Deep-Masking Cell, which enhances the extraction of pertinent information while reducing noise using a learnt gating mask that regulates information flow, lies at the heart of the DMGN. The DMGN gradually produces noisy images and high-quality background images by repeatedly applying this cell. To help with backdrop refining, a two-pronged approach is also used to take use of the created noise image as contrasted signals. Extensive tests on three challenges (image dehazing, image reflection removal and rain streak removal) showed that the DMGN consistently beats the SOTA techniques customized for each particular job.

UW-CycleGAN refers to the advanced version of the CycleGAN model which has been designed specifically with unsupervised image-to-image translation tasks in the forefront. It uses transformations involving wavelets to refine traditional CycleGAN architectures on their performance. Yan et al. [23] suggested Model-driven and cycle-consistent generative adversarial network (CycleGAN) which is inspired by the underwater image-creation model. Targeting the transmission map, scene depth, attenuation coefficient and background light directly was the goal of the model. Extensive trials proved that this technique produced recovered photographs with improved color saturation and brightness, surpassing other approaches for restoring underwater images in both quantitative and qualitative aspects. The efficiency of the CycleGAN in enhancing detection accuracy was further shown by research on underwater item detection.

Table 8 presents an overview of GAN-based approaches, emphasizing their methodologies and effectiveness in image restoration.

Table 8. Comparison of GAN-based approaches.

Study	Methods/ Algorithms Used	Dataset Used	Accuracy/ Performance	Limitations
[22], 2021	Deep-masking generative network	PLNet [61]	PSNR:23.05, SSIM:0.823	Struggles with complex occlusions
[23], 2023	CycleGAN for underwater image restoration	NYU-V2 dataset [62]	PSNR: 21.14, SSIM: 0.83 , UIQM: 2.24, CCF: 50.10	Struggles with complex underwater conditions

2.6 Diffusion-based Models

Diffusion-based models have been the latest advancement in image restoration. Image models can enhance damaged images with probabilistic-modeling simulation of physical-diffusion processes iteratively. Such models work to revert a noisy image to its original state through progressive and reversible procedures that borrow inspirations from concepts, such as image denoising and noise diffusion. Unlike the rest of the restoration algorithms that predict restored results almost instantaneously, diffusion models learn complicated noise patterns and gradually eliminate them to produce images with a very fine degree of control over the restoration process. This is novel in the context of diffusion-based models and with it, the future prospects are promising in image restoration. As the techniques for more efficient computations and faster sampling continue to advance, it can be anticipated that diffusion-based models will increasingly be integrated into flexible frameworks of high-fidelity image restoration toward wide applications requiring high quality and flexibility over many types of degradations. Figure 5 depictes the framework of a diffusion model, where data is gradually transformed into noise in a forward process and then reconstructed in the reverse process.

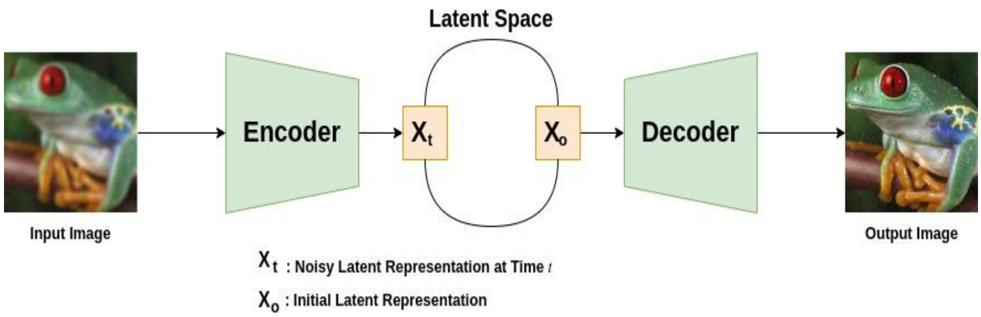

Figure 5. Architecture of a diffusion-based generative model.

Plug-and-Play IR covered a well-established and flexible way to solve inverse problems by making use of pre-trained denoisers as implicit image priors. Most current methods were discriminative Gaussian denoisers. However, there was no research on diffusion models as generative denoiser priors. Although some research incorporated diffusion models into image restoration, they had either sub-optimal performance or needed an extreme number of Neural Function Evaluations (NFEs) during inference. To overcome such limitations, Zhu et al. [24] introduced DiffPIR that combined the plug-and-play scheme with the diffusion sampling. In contrast to traditional plug-and-play IR schemes relying on Gaussian denoisers, DiffPIR utilized the generation ability of diffusion models to produce better image restoration. The scheme was tested on three prominent IR tasks; i.e., super-resolution, deblurring and inpainting. Experimental performance on the FFHQ and ImageNet benchmarks confirmed that DiffPIR achieved SOTA reconstruction accuracy as well as visual quality and, at the same time, kept an inference process within 100 NFEs.

Luo et al. [27] aimed to enhance the usability of diffusion models in IR by optimizing important factors, like network architecture, noise intensity, denoising steps, training image size and optimization methods. Luo et al. [27] introduced Refusion, a U-Net-based latent diffusion model, that performed diffusion in a low-resolution latent space with high-resolution details left for decoding. In contrast to other latent diffusion models that employed VAE-GAN for compression, their model was more stable and produced very precise reconstructions without adversarial training. Such improvement enabled the model to efficiently handle various image-restoration tasks like real-world shadow removal, high-resolution non-homogeneous dehazing, stereo super-resolution and bokeh-effect conversion. Refusion was shown to handle large-scale images (e.g. 6000×4000×3 in high-resolution dehazing) without sacrificing robust performance on various restoration tasks. Notably, it achieved the best perceptual performance in the NTIRE 2023 Image Shadow Removal Challenge.

Ortega et al. [28] analyzed the role of anisotropic-diffusion models in image restoration and emphasized the role of the diffusion function, where, traditionally, this diffusion function was fixed as part of the classical approach. The idea is introduced on learning this function dynamically using either a Fields of Experts (FoE) or a U-Net, demonstrating that their approach outperformed conventional and SOTA models with some numerical experiments. Ortega et al. [28] Perona-Malik model combined with machine-learning techniques was leveraged to directly learn an optimized diffusion function from data. By combining classical approaches with data-driven methods, a balance between interpretability in a mathematical sense and improved restoration was achieved. By demonstrating generalization to a host of image-restoration tasks, this approach offered the possibility of offering a more stable and effective replacement for purely deep learning-based models, such as blind denoising.

Although diffusion-based IR techniques have shown impressive results, their poor inference speeds—which required hundreds or even thousands of sample steps—hampered their applicability. Current acceleration methods tried to expedite this process, but they frequently resulted in performance issues and very blurry restored photos. In order to overcome this restriction, Yue et al. [29] put out an effective IR diffusion model that greatly decreased the number of necessary diffusion steps without sacrificing image quality. By doing away with the requirement for post-acceleration during inference, their method prevented performance deterioration. By modifying their residuals, they specifically created a Markov chain to ease the transitions between high- and low-quality images, significantly increasing transition efficiency. Furthermore, in order to regulate the noise strength and the varying speed during the diffusion process, they created a noise schedule. According to experimental assessments, the suggested method only required four sample steps and performed better than or on par with SOTA methods in four important IR tasks: image high resolution, inpainting, blind facial restoration and deblurring.

In order to increase versatility in face-image restoration, Pang et al. [11] created a method using DDPM and made use of an unbiased DDPM model that had already been trained. Pang et al. [11] found that the quality of the recovered photos suffered when there were not as many iterations in the resampling procedure. An optimization strategy for the inversion process was put out to address this problem and produce better restoration quality by combining sample scheduling with progressive sampling. Numerous tests with the CelebA-HQ[55] and FFHQ datasets[54] showed that their approach outperformed other methods in face-image restoration. It performed outstandingly in terms of LPIPS and PSNR measurements, specifically. Additionally, the restoration method increased the accuracy of detection of faces by 15.7% for facial photos with random masks and by 26% for images with central masks.

Welker et al. [25] tackled the problem of blind JPEG restoration at high compression levels by leveraging the high-fidelity generating capabilities of diffusion models. S. Welker et al. [25] named their approach DriftRec and suggested a change to the forward stochastic differential equation in diffusion models. DriftRec successfully avoided the blurriness typical in other approaches and substantially better restored the distribution of clean images, as evidenced by a comparative study against an L2 regression baseline using the same network design and cutting-edge JPEG restoration techniques. This method’s applicability to different restoration jobs is increased, because it merely needed a dataset of clean/corrupted image pairings and did not require any prior knowledge of the corruption process. DriftRec took use of the closeness of both clean and damaged image distributions, which are far closer to one another than they are to the usual Gaussian prior utilized in diffusion models, in contrast to other conditional and unconditional diffusion models. Because of this, even in the absence of additional improvements, it only required small amounts of extra noise and fewer sample steps. Despite not being trained on instances of this nature, the study demonstrated that DriftRec extended well to difficult circumstances, including unaligned double JPEG compression and blind restoration of JPEGs received from the internet.

PD-CR is patch-based diffusion with constrained refinement that uses the diffusion processes to improve images through refinement of local patches. The method introduced by Cho et al. [26] improved the noise estimates that were produced by patch-based diffusion models so that the restored image, with maintained brightness of the damaged input image, could be given. In the proposed method, patch- based diffusion models were applied to efficiently address high-resolution photos with minimal memory usage. The experimental results indicated that the proposed method was superior to existing leading-edge approaches in various image-restoration tasks, which included image denoising and raindrop removal.

Table 9 presents a comparison of diffusion-based models, outlining their methodologies, datasets, accuracy and key limitations in image restoration.

Table 9. Comparison of diffusion-based models.

Study	Methods/ Algorithms Used	Dataset Used	Accuracy/ Performance	Limitations
[24], 2023	Denoising Diffusion Models for Plug-and-Play Image Restoration	FFHQ[54], ImageNet	PSNR: 31.01, LPIPS: 0.152	High computational cost and slow inference due to iterative denoising steps
[27], 2023	Enabling Large-Size Realistic Image Restoration with Latent-Space Diffusion Models	Flickr1024	PSNR: 21.88, SSIM: 0.6977, LPIPS: 0.121	Limited generalization to diverse degradations and training stability challenges.
[28], 2024	Learning Diffusion Functions for Image Restoration	BSD500 [63]	PSNR: 29.5, SSIM: 0.83, LPIPS :0.15	High computational cost
[29], 2024	Efficient Diffusion Model for Image Restoration by Residual Shifting	RealSR-V3, Re- alSet80	PSNR: 25.02, SSIM: 0.6833, LPIPS: 0.2076	Limited generalization to unseen noise types
[11], 2024	Denoising Diffusion Probabilistic Models	CelebA-HQ [55] and FFHQ [54]	PSNR: 33.2055, SSIM: 0.8662, LPIPS: 0.0966	Slow convergence
[25], 2024	Diffusion models adapted for JPEG restoration	JPEG image datasets	PSNR: 25.78, SSIM: 0.73, FID: 29.7	Limited to JPEG artifacts
[26], 2024	Patch-based diffusion	SIDD [60] and Raindrop dataset [64]	PSNR: 38.21, SSIM: 0.901, LPIPS: 0.134, NIQE: 13.72	Edge artifacts

2.7 Hybrid Models

Hybrid models in image restoration exploited the advantages of multiple methods, including generative models, deep learning and traditional machine learning for added performance and adaptability. Hybrid models can be constructed by combining the global contextual understanding of transformers, localizing the feature-extraction capacities of CNNs to specific interest regions and the qualities of image-creation realism as provided by diffusion models or GANs. This synergy allows for stronger image restoration solutions that can handle a variety of degradation types and challenging restoration tasks. Future research on hybrid models is likely to focus on more effective structures that balance performance with complexity. Innovations, such as attention processing, adaptive feature extraction and knowledge distillation, may enhance the effectiveness of hybrid methods even further. Hybrid models are expected to be pivotal for optimal performance in many image-restoration tasks as the current developments progress. Table 10 compares various hybrid approaches, highlighting their combined methodologies, performance across datasets, accuracy and associated limitations in image restoration.

Hybrid Unfolding Reconstruction (HybrUR) is a deep-learning model aimed towards image-reconstruction tasks in MRI and other imaging modalities. It combines elements of traditional image-reconstruction techniques and modern deep-learning methods with the goal of improving image-restoration quality and efficiency. Yan et al. [30] provided an unsupervised framework for underwater photo restoration using unpaired underwater and airborne photos, based on data and physics. To improve image quality and perform effective colour correction, an explicit degeneration model of underwater photos was developed using well-established optical-physics concepts. The loss of underwater vision was modelled using neural networks and a generator based on the Jaffe-McGlamery degeneration theory was created. The scene depth and degeneration factors for backscattering estimate were additionally physically restricted in order to solve the vanishing-gradient problem during hybrid physical-neural model training. The experimental results demonstrated that the proposed method successfully restored high-quality unmanaged underwater photographs without supervision. On many benchmarks, their technique outperformed several cutting- edge supervised and unsupervised algorithms, indicating that it will perform well in real-world situations.

Table 10. Comparison of Hybrid approaches.

Study	**Methods/ Algorithms Used**	**Dataset Used**	**Accuracy/ Performance**	**Limitations**
[30], 2023	Hybrid physical- neural approach using GANs	RUIE[65]	UICM: 5.142, UCIQE: 0.495	Struggles with edge retention
[9], 2023	Deep priors, low- rank tensor factorization	Hyperspectral datasets	PSNR: 32.943, SSIM: 0.9704	Computational complexity

Combined Deep Priors with Low-rank Tensor Factorization for Hyperspectral Image (HSI) Restoration is a novel approach designed to improve the quality of HSIs, which often suffer from noise, distortions and incomplete data. This method integrates deep-learning techniques with low-rank tensor factorization to effectively restore and reconstruct HSIs while preserving essential details and spectral information.

The global spectral low-rank criterion was represented by Tucker-tensor factorization in the proposed technique. Two deep denoising priors were then used to optimize the spectral orthogonal basis and the spatial reduction factor. With this combined approach, Zhang et al. [9] were able to benefit from the low-rank characteristics of HSIs and the potent feature-extraction capabilities of deep learning for HSI restoration. The DP-LRTF outperformed both model-driven and data-driven approaches in terms of execution efficiency and mixed-noise removal from HSIs in a number of simulated and real-world studies.

2.8 Domain-specific Approaches (Underwater, Hyperspectral, Remote Sensing, Medical Imaging, …etc.)

In image restoration, domain-specific approaches focus on adapting methods and algorithms to better adapt to the specific challenges each particular application domain has, such as medical imaging, remote sensing, underwater imaging and hyperspectral imaging. These domains often display characteristic degradation types and quality of restoration requirements that necessetate highly specialized procedures that capitalize upon the features of the domains and the type of images. Table 11 summarizes domain-specific approaches, focusing on their tailored methodologies, performance on specialized datasets and key limitations in image restoration.

Chang et al [31] explored the low-rank features across spatial, spectral and non-local self-similarity modes in hyperspectral images (HSIs), showing that the internal low-rank correlations within every mode affect restoration results to different extents. Their results identified the potential of spectral, along with non-local induced low-rank features toward HSI modeling, therefore resulting in the development of an optimal low-rank tensor (OLRT) model for improved HSI recovery. This work also investigated the existence of low-rank properties in both the image and sparse error parts, such as stripe noise in HSIs. Taking advantage of low-rank tensor priors for sparse errors and HSIs, OLRT developed into OLRT-robust principal-component analysis. The earlier methods were not versatile; they were often designed for specific HSI tasks, whereas the ideal low-rank prior was highly versatile across different HSI restoration applications. Thorough assessments on different benchmarks indicated that the proposed approaches significantly outperformed the SOTA methods.

The iterative model Non-local meets Global provides an all-inclusive approach for hyperspectral image (HSI) restoration, which is based on both non-local and global information for better quality. He et al. [32] proposed that the spectral sub-spaces of each full-band patch group align with the global spectral low-rank sub-space, which covers the whole HSI. This observation led to the development of a unified model for HSI restoration that integrates both spectral and spatial elements. The approach uses non-local spatial denoising and low-rank orthogonal basis exploration to streamline computational demands. The restoration process begins with updating the latent input image by resolving a fidelity term, followed by implementing an efficient alternating minimization method with adaptive-rank selection. It learns an orthogonal basis in the low-dimensional space and decreases the image representation. Re-iteration of non-local low-rank denoising refines restoration further. The experiments conducted on both the simulated as well as the real-world dataset show that the proposed approach achieves superior performance compared to any existing SOTA HSI restoration techniques.

The low contrast and color distortion in underwater photographs brought on by wavelength-dependent light attenuation were the subjects of this investigation. Color restoration is more difficult with underwater images than with terrestrial ones due to the different attenuation across wavelengths that depends on the water body and the three-dimensional structure of the scene. Berman et al. [33] proposed the method, which considered multiple spectral profiles of different types of water and reduced the problem to single-image dehazing by computing two global parameters: the attenuation ratios of the blue-red and blue-green channels. Because the type of water was unknown, a variety of characteristics from an existing library of water types were evaluated. The color distribution was utilized to automatically identify the optimal solution. The collection includes 57 underwater photographs taken in various locations; stereo photography was used to determine the 3D structure and color charts were applied to the scenes for ground truth.

Zhang et al. [37] addressed the problems of limited visibility and color aberrations in underwater photographs brought on by light scattering and absorption that varies with wavelength. Zhang et al. [37] developed MLLE, an effective and reliable technique for enhancing underwater images, to get around these problems. Using a maximum attenuation map-guided fusion technique and a minimum color-loss concept, they first locally altered an image’s color and features. In order to adaptively improve the image contrast, the mean and variance of local image blocks were then calculated using integral and squared integral maps. Furthermore, a color-balance technique was presented to rectify color discrepancies between CIELAB color space channels a and b. The improved photos had more contrast, vibrant colors and better detail retention. Three datasets for underwater-picture enhancement were used in extensive studies, which showed that MLLE performed better than the SOTA techniques. A single CPU could handle 1024 x 1024 × 3 photos in a single second, demonstrating the method’s computational efficiency. Further tests showed that the MLLE-realized improvement greatly enhanced saliency detection, keypoint recognition and underwater-picture segmentation.

Zhang et al. [38] focused on how light scattering and absorption degraded underwater image quality, making them less useful for analysis and applications. Zhang et al. [38] developed Weighted Wavelet Visual Perception Fusion (WWPF), an underwater image-augmentation technique, to address these problems. To fix color aberrations in underwater photos, they first used a color-correction technique guided by an attenuation map. To enhance the overall contrast, they then used a maximum information entropy optimized global contrast-augmentation approach. At the same time, localized details were enhanced using a quick integration optimized local contrast-enhancement technique. A WWPF technique was presented in order to integrate the advantages of both local and global contrast-enhanced images. High-quality underwater photos were created by fusing low-frequency and high-frequency components at various scales. Comprehensive tests on three benchmark datasets showed that WWPF performed better than current SOTA techniques in both qualitative and quantitative assessments.

Li et al. [34] proposed a fast simulation approach for image acquisition with the remote sensing TDI camera, employing image resampling to simulate degraded image qualities with high accuracy. This process considered various degradation factors, enabling the creation of a rather large dataset suitable for most modern supervised learning-based approaches to image restoration. Moreover, the work presented a new network architecture, containing a row-attention block and a row-encoder block, especially tailored to tackle row-variant blur and restore degraded images efficiently. The method was tested through real-world images and simulated degraded datasets with good experimental performances. In contrast to previously blind image-restoration techniques, the technique here showed superior results without resorting to multi-spectral bands or high-frequency sensor data.

Jordanian Journal of Computers and Information Technology (JJCIT), Vol. 11, No. 02, June 2025.

Table 11. Domain-specific approaches.

Study	Methods/ Algorithms Used	Dataset Used	Accuracy/ Performance	Limitations
[31], 2020	Low-rank property modeling	Hyperspectral datasets	PSNR: 57.02, SSIM: 0.9985, SAM: 0.0216	Computationally intensive
[32], 2020	Non-local and global priors	CAVE dataset	PSNR: 3.03, SSIM: 0.9807	Computational complexity
[33], 2020	Haze-lines, color restoration algorithm	New quantitative underwater dataset	PCC: 0.85	Limited to specific underwater conditions
[37], 2022	Minimal Color Loss and Locally Adaptive Contrast Enhancement (adaptive enhancement of contrast and color preservation)	UCCS, UIQS, UIEB	PCQI: 1.136, UIQM: 5.293, CCF: 46.872	Cannot handle the underwater images acquired in low light conditions well
[38], 2023	Weighted Wavelet Visual Perception Fusion (WWPF) using wavelet transform for multi-scale frequency decomposition and contrast enhancement	UCCS, UIQS, UIEB	UCIQE: 0.617, AG: 10.818, CCF: 40.851	Cannot suppress image noise well
[34], 2023	Fast imaging simulation, image resampling	Remote sensing datasets	PSNR: 30.970, SSIM: 0.882	Trade-off between Speed and Accuracy
[35], 2023	Dehazing algorithm	Outdoor/remote sensing datasets	PSNR: 27.08, SSIM : 0.94, PI: 2.24	Limited to specific atmospheric conditions
[36], 2024	Semiblind unsupervised learning for co-phase errors	Optical synthetic aperture imaging datasets	PSNR: 25.72, SSIM: 0.758	Dependence on Phase Initialization

An efficient image-dehazing method that works with both outdoor and remote-sensing photos is presented by Li et al. [35]. The plan combined the benefits of image enhancement and repair methods. To increase transmittance and fix errors in transmittance estimations reported in previous methods, the researchers employed Gaussian-weighted image fusion. After dehazing, color distortion was also corrected using an unsharp mask technique. The approach suggested by Li et al. [35] outperformed current dehazing techniques in the effective removal of haze from images, according to experimental results on both synthetic and real-world datasets. The solution outperformed other approaches with a PSNR of 27.08 and SSIM of 0.94 when applied to the RICE dataset.

Zhong et al. [36] introduced RPIR, a semi-blind, unsupervised learning technique for image restoration in OSAI systems with co-phase faults. Based on the traditional maximum a posteriori (MAP) model, RPIR used a multi-scale neural network that required no prior training. This network gathered input blur kernel flaws for use as residual priors in the MAP model. To solve the data and earlier terms, they employed alternating minimization. RPIR reduced erroneous blur kernels in OSAI systems due to co-phase error variations. The results indicated that RPIR considerably enhanced image resolution and clarity in treating co-phase faults in OSAI systems, exceeding other unsupervised deep-learning techniques and standard deconvolution methods.

Machine-learning models are frequently tailored to meet the unique requirements of specific domains, such as underwater imaging, hyperspectral analysis, remote sensing and medical imaging. While general- purpose architectures, such as CNNs, transformers, GANs and diffusion models, are frequently used in a variety of applications, applying them directly to domain-specific tasks may not necessarily produce the best results. These tasks frequently necessitate specialized architectures, task-specific loss functions and domain-aware pre-processing approaches to improve model performance. For example, underwater-image restoration requires models capable of correcting color aberrations and scattering effects, which are specific to aquatic environments. Likewise, medical-imaging models need to consider low contrast and anatomical features, necessitating domain-specific training procedures and domain-aware regularization methods. In remote sensing and hyperspectral imaging, models must maintain spectral fidelity and handle high-dimensional data efficiently. By adding such domain-specific adaptations, machine-learning models can perform much better than their general-purpose equivalents.

2.9 Comprehensive Image-restoration and Denoising Datasets

In recent years, a wide variety of datasets have been developed to benchmark the performance of image-restoration and denoising algorithms. These datasets vary in content, type of degradation and complexity, providing diverse scenarios for evaluating model effectiveness. Table 12 summarizes key datasets frequently used in image-restoration and denoising research, highlighting characteristics, such as dataset size, types of degradation (e.g. noise, blur, low resolution) and typical applications. This compilation serves as a foundation for comparing algorithm performance across different degradation scenarios and understanding the suitability of specific datasets for various restoration tasks.

Table 12. Comprehensive image-restoration and denoising datasets.

Name of Dataset	Year	Brief Description
BSD500 [63]	2012	Part of the Berkeley Segmentation Dataset, containing 500 images used for enoising and segmentation.
URBAN100	2015	Contains 100 high-resolution images of urban scenes, featuring buildings, streets and architectural structures. It is widely used in image super-resolution and restoration tasks to evaluate model performance on complex textures and fine details.
GoPro [66]	2017	Contains paired blurred and sharp images from GoPro cameras, used for motion-deblurring research.
DIV2K [57]	2017	High-quality dataset with 1,000 images for super-resolution and general image restoration, with multiple degradation levels.
SIDD [60]	2018	A dataset consisting of more than 30,000 noisy images under different lighting conditions, along with ground-truth images.
Color BSD68 [67]	2018	Part of Berkeley Segmentation Dataset and Benchmark, it contains 68 images for measuring image-denoising algorithms' performance.
PIRM [68]	2018	Comprises 200 diverse images divided for validation and testing, used for perceptual image-restoration tasks.
HAC [69]	2019	Contains 316K pairs show casing various weather conditions for testing restoration under adverse circumstances.
FFHQ [70]	2019	Contains 70000 high-quality face dataset from NVIDIA, used for inpainting and denoising, with diverse ages, ethnicities and lighting conditions.
SCISR [71]	2019	Synthetic and camera-based image super-resolution dataset, used for super-resolution in low-quality smartphone-captured images. Contains 50000+ images.
Hide [72]	2019	It consists of 8,422 blurry images and with them their corresponding image pairs with 65,784 densely annotated FG human bounding boxes.
Raindrop [73]	2020	A dataset containing 1,119 pairs of images, where one is degraded by raindrops and the other is clean.
UHDS [74]	2022	A dataset of 29,500 rain and rain-free image pairs covering various natural rain scenarios.
Sentinel-2 Satellite Images [75]	2022	Includes 3,740 pairs of overlapping image crops with cross-band and cross-detector parallax effects for analysis.
TinyPerson [76]	2022	A dataset focusing on tiny objects with 72,651 annotated images, collected from high-resolution videos.
LSDIR [77]	2023	A large-scale dataset containing 84,991 training images, 1,000 validation images and 1,000 test images.
HQ-50K [78]	2023	Introduces 50,000 high-quality images with rich textures for image-restoration applications.

3. EVALUATION METRICS USED FOR IMAGE RESTORATION

Various evaluation metrics have been utilized in the literature survey to effectively evaluate performance and compare different image restoration algorithms. They are essential to objectively quantify how good image quality is after restoration, thus allowing researchers to compare different approaches in different degradation conditions. Table 13 provides a detailed summary of widely used evaluation metrics, highlighting their specific purposes and the aspects of image quality they focus on.

4. RESULTS AND DISCUSSION

The evaluation of multiple image-restoration models was conducted on a high-performance hardware configuration comprising a Tesla T4 GPU equipped with 15,360 MB of VRAM, supported by NVIDIA-SMI 535.104.05, Driver Version 535.104.05 and CUDA Version 12.2. The hardware operated under optimal conditions, maintaining a stable temperature of 54°C. The models were

Jordanian Journal of Computers and Information Technology (JJCIT), Vol. 11, No. 02, June 2025.

evaluated using the SIDD (Smartphone Image Denoising Dataset) and DND (Darmstadt Noise Dataset), a benchmark dataset widely utilized for assessing image-restoration techniques. This experimental setup facilitated precise benchmarking of inference times and PSNR values, which are pivotal metrics for assessing the performance of pre-trained models in image-restoration tasks. The results, summarized in Table 14, provide a comprehensive comparison of the evaluated models.

Table 13. Summary of evaluation metrics for image restoration.

Evaluation Metric	Description
Peak Signal to Noise Ratio (PSNR)	Calculates the ratio between maximum signal power and noise power.
Structural Similarity Index Measure (SSIM)	Evaluates similarity between two images based on brightness, contrast and structure. Values closer to 1 indicate higher similarity.
Perception-based Contrast Quality Index (PCQI)	Measures image quality by evaluating contrast and structural fidelity, considering human visual perception.
Underwater Image Quality Measure (UIQM)	A composite metric used to assess underwater image quality based on colorfulness (UICM), sharpness (UISM) and contrast (UIConM). Higher UIQM values indicate better visual quality.
Color Contrast Factor (CCF)	Quantifies color contrast in images by analyzing pixel-intensity differences across different channels. Higher values indicate more vibrant and enhanced images.
Fréchet Inception Distance (FID)	It quantifies the disparity in feature distributions between real and generated images using deep-learning features, where lower FID scores signify improved visual quality.
Average Gradient (AG)	Evaluates image sharpness by calculating the mean gradient magnitude across the image.
Natural Image Quality Evaluator (NIQE)	A no-reference image-quality assessment metric that compares statistical deviations from natural image characteristics. Lower NIQE scores indicate better image quality.
Signal-to-Reconstruction Error (SRE)	Measures the ratio of signal strength to reconstruction error, assessing restoration accuracy. Higher SRE values indicate better restoration performance.
Mean Absolute Error (MAE)	Computes the average of absolute differences between original and restored images. Lower MAE indicates higher restoration accuracy.
Normalized Root Mean Squared Error (NRMSE)	Provides a normalized measure of deviation between restored and original images, making it suitable for comparing images with different brightness levels.
Feature Similarity Index Measure (FSIM)	Assesses similarity by focusing on high-frequency components, capturing perceptual differences aligned with human vision.
Visual Information Fidelity (VIF)	Measures the amount of visual information preserved in the restored image compared to the original, reflecting human visual perception.
LPIPS	Uses deep neural-network features to evaluate perceptual similarity, emphasizing visual quality as perceived by humans.
Diversity Index for Image Denoising	Analyzes the variability between multiple denoising outputs for the same noisy input, useful for exploring alternative restoration methods.
Perceptual Loss Metric	Leverages features from pretrained models to assess perceptual quality, optimizing image restoration for human-like perception rather than pixel-level accuracy.
No-reference Evaluation Metric	Evaluates image quality without needing the original image, using methods like NIQE and BRISQUE to assess naturalness and perceptual features important to human observers.

Transformer models showed high restoration performance, with Restormer realizing a PSNR of 39.12 and an SSIM of 0.913 at an inference rate of 0.7581 images per second, while MIRNet realized a PSNR of 38.86 and an SSIM of 0.940 but at a much slower processing rate. SwinIR kept a balance between accuracy and efficiency with a PSNR of 36.30 and an inference rate of 1.12 images per second.

CNN-based models, including SRCNN, MPRNet and NAFNet, demonstrated mixed compromises between accuracy and speed. MPRNet had a comparable inference rate of 2.18 images per second with a PSNR of 33.86. In the same way, NAFNet had a PSNR of 32.93 along with an SSIM of 0.867, proving its stability. From models of denoising, DDNM recorded a PSNR of 24.32 and an SSIM of 0.794, while in this class, CycleISP led others with a PSNR of 39.43 and an SSIM of 0.955. Other models of denoising, including CBDNet, RidNet and DREAMNet, also performed robustly in removing noise, with RidNet recording a PSNR of 38.26 and an SSIM of 0.945.

Table 14. Comparison of various models based on inference time, PSNR and SSIM for both SIDD and DND datasets.

Model	**Inference Time**	**SIDD Dataset**		**DND Dataset**	
		PSNR	**SSIM**	**PSNR**	**SSIM**
Restormer	0.7581	39.12	0.913	36.41	0.926
SRCNN	0.075	34.80	0.7184	32.75	0.862
MIRNet	0.033	36.30	0.950	38.86	0.940
DDNM	0.153	22.07	0.832	24.32	0.794
CWR	0.0315	27.85	0.817	26.76	0.851
SwinIR	1.120	36.30	0.847	34.52	0.896
MPRNet	2.180	33.86	0.844	34.56	0.817
NAFNET	0.7382	32.93	0.867	30.09	0.865
HINET	0.8737	29.97	0.906	30.65	0.894
GFPGAN	1.063	26.01	0.763	26.42	0.713
ESRGAN	0.790	27.24	0.791	26.30	0.711
DnCNN	0.058	21.96	0.571	31.74	0.780
CycleISP	0.132	36.81	0.930	39.43	0.955
CBDNet	0.15	30.44	0.795	36.12	0.920
RidNEt	0.3921	36.01	0.903	38.26	0.945
DREAMNET	0.417	35.72	0.916	38.23	0.940

Super-resolution and enhancement frameworks, such as GFPGAN and ESRGAN, weighed perceptual quality against efficiency, with GFPGAN delivering a PSNR of 26.42 at a rate of 1.063 images per second. ESRGAN, however, had a PSNR of 27.24, making it suitable for perceptual restoration. The Contrastive Underwater Restoration (CWR) framework, developed specifically for underwater image restoration, posted a PSNR of 27.85 and an SSIM of 0.817, making it more domain-specific to restoration.

The SSID and DND dataset served as a critical benchmark, offering realistic noisy images captured from smartphones, which posed a challenging yet relevant scenario for image restoration models. These findings underline the diverse trade-offs between speed and accuracy among contemporary image restoration techniques. The summarized results provide valuable insights for guiding future advancements in the development of image restoration methodologies.

In general, the research points to significant trade-offs between restoration performance and computational cost, with transformer-based models producing high image quality at the expense of processing speed, while CNN-based methods keep accuracy and real-time feasibility in balance. Denoising methods, especially CycleISP and RidNet, exhibited robust noise reduction performance and super-resolution models such as ESRGAN improved image perceptual quality well. The results indicate that hybrid methods combining transformers, CNNs and self-supervised learning would potentially further enhance image restoration performance under various imaging conditions.

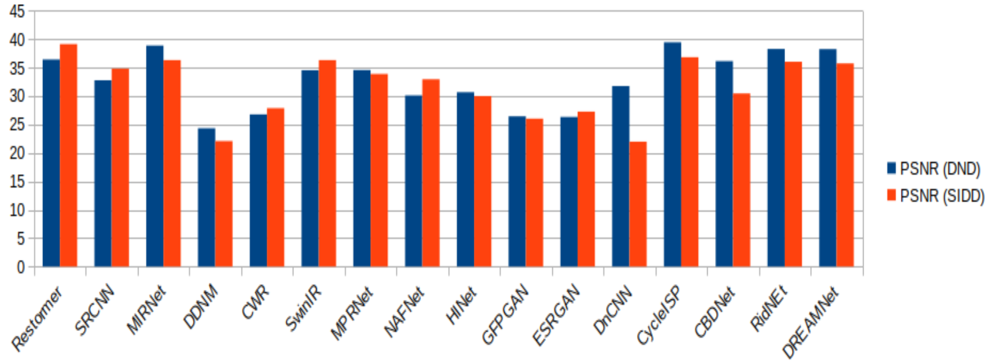

Figure 6. A comparison of PSNR values across various models on the SIDD and DND datasets.

To offer a thorough comparison, the PSNR and SSIM values of several image-restoration techniques, assessed on the SIDD and DND datasets, were shown in Figure 6 and Figure 7. These bar graphs illustrated how performance varied among several methods, emphasizing variances in restoration quality. In addition to providing insights on general-performance trends in picture restoration, the visual representation highlighted how different approaches maintained structural features and perceived quality.

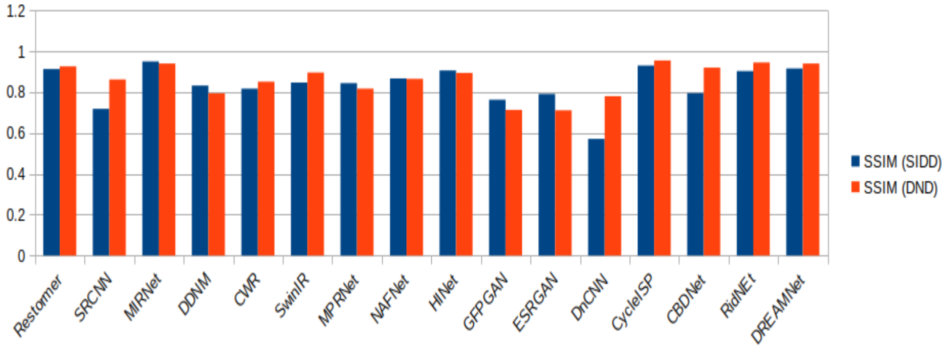

Figure 7. A comparison of SSIM values across various models on the SIDD and DND datasets.

5. Open Challenges for Future Research

Despite substantial advancements in image-restoration techniques, several open challenges remain that warrant further investigation. One significant area requiring attention is the treatment of multiple and complex types of degradation commonly encountered in real-world situations. These include combinations of blur, noise and compression artifacts, where existing models, often calibrated for a single type of degradation, frequently underperform in multi-faceted scenarios. Therefore, there is a critical need for methods that can adaptively address a range of real-world degradation levels, ensuring that restoration techniques are robust against diverse degradation types.

Another pressing challenge is achieving an optimal balance between model complexity and processing speed. Many advanced restoration techniques demand substantial computational resources, which limits their scalability and practicality in real-time applications, particularly on mobile devices. Future research should focus on developing lightweight, yet effective, models that facilitate image restoration across a broader spectrum of applications, particularly in resource-constrained environments where efficient processing is essential. Maintaining the fidelity of natural textures and minute details in restored images presents an ongoing challenge. Restoration techniques that excessively enhance sharpness or contrast can distort the original essence of the scene, leading to unrealistic outcomes. It is imperative that successful restoration processes not only enhance visual appeal, but also faithfully represent the scene as it was originally depicted, preserving the integrity of visual information.

Lastly, the lack of effective domain adaptation poses a significant limitation to the applicability of image-restoration models. General-purpose restoration frameworks often fail to capture features unique to specific application domains, such as medical imaging, underwater photography and remote sensing. To enhance the impact and functionality of IR techniques, the development of adaptable or domain-specific methodologies is essential, as these can effectively address the unique requirements of diverse contexts. In summary, addressing these challenges will not only improve existing image-restoration techniques, but also expand their applicability across various fields, paving the way for innovative solutions in an increasingly visual-centric world.

6. Conclusion

A comprehensive analysis of the existing literature reveals both the advantages and limitations of current approaches, as well as outlining prospective directions for future research. In light of recent advancements in deep learning, traditional machine-learning and innovative architectures, such as Transformers and GANs, significant progress has been made in enhancing image restoration across various applications, including mobile photography, remote sensing and medical imaging. These methodologies have consistently demonstrated improvements in the clarity, quality and utility of degraded images. Nevertheless, several challenges persist that warrant further investigation. These challenges encompass the effective management of complex mixed degradation types, achieving a balance between computational efficiency and restoration quality and ensuring adaptability across diverse imaging scenarios.

Future-research endeavors are anticipated to concentrate on the development of more flexible and efficient models capable of addressing a wide spectrum of degradation scenarios while remaining suitable for real-time applications, particularly on resource-constrained devices. Furthermore, advancing hybrid models alongside domain-specific strategies will be essential in propelling research initiatives forward. Addressing these unresolved issues and enhancing image quality and accessibility will amplify the impact of image-restoration technologies in an increasingly visual-centric society.

REFERENCES

[1] Z. Liang et al., "GIFM: An Image Restoration Method with Generalized Image Formation Model for Poor Visible Conditions," IEEE Trans. on Geoscience and Remote Sensing, vol. 60, pp. 1–16, 2022.
[2] S. Jiang et al., "Local Adaptive Prior-based Image Restoration Method for Space Diffraction Imaging Systems," IEEE Transactions on Geoscience and Remote Sensing, vol. 61, pp. 1–10, 2023.
[3] Z. Yang, J. Huang, M. Zhou, N. Zheng and F. Zhao, "IRVR: A General Image Restoration Framework for Visual Recognition," IEEE Transactions on Multimedia, vol. 26, pp. 7012-7026, 2024.
[4] R. Chen, T. Guo, Y. Mu and L. Shen, "Learning Compact Hyperbolic Representations of Latent Space for Old Photo Restoration," IEEE Transactions on Image Processing, vol. 33, pp. 3578–3589, 2024.
[5] T. Kim, C. Shin, S. Lee and S. Lee, "Block-attentive Subpixel Prediction Networks for Computationally Efficient Image Restoration," IEEE Access, vol. 9, pp. 90881–90895, 2021.
[6] S. Kong, W. Wang, X. Feng and X. Jia, "Deep RED Unfolding Network for Image Restoration," IEEE Transactions on Image Processing, vol. 31, pp. 852–867, 2021.
[7] D. Perdios et al., "CNN-based Image Reconstruction Method for Ultrafast Ultrasound Imaging," IEEE Transactions on Ultrasonics, Ferroelectrics and Frequency Control, vol. 69, no. 4, pp. 1154–1168, 2021.
[8] Z. Pan et al., "VCRNet: Visual Compensation Restoration Network for No-reference Image Quality Assessment," IEEE Transactions on Image Processing, vol. 31, pp. 1613–1627, 2022.
[9] Q. Zhang et al., "Combined Deep Priors with Low-rank Tensor Factorization for Hyperspectral Image Restoration," IEEE Geoscience and Remote Sensing Letters, vol. 20, pp. 1–5, 2023.
[10] J. Ke et al., "Artifact Detection and Restoration in Histology Images with Stain-style and Structural Preservation," IEEE Transactions on Medical Imaging, vol. 42, no. 12, pp. 3487–3500, 2023.
[11] Y. Pang, J. Mao, L. He, H. Lin and Z. Qiang, "An Improved Face Image Restoration Method Based on Denoising Diffusion Probabilistic Models," IEEE Access, vol. 12, pp. 3581-3596, 2024.
[12] X. Zhang and J. Feng, "A Novel Blind Restoration Method for Miner Face Images Based on Improved GFP-GAN Model," IEEE Access, vol. 12, pp. 104676–104687, 2024.
[13] M. Yao, R. Xu, Y. Guan, J. Huang and Z. Xiong, "Neural Degradation Representation Learning for All-in-one Image Restoration," IEEE Transactions on Image Processing, vol. 33, pp. 5408–5423, 2024.
[14] W. Zhang, W. Zhao, J. Li, P. Zhuang, H. Sun, Y. Xu and C. Li, "Cvanet: Cascaded Visual Attention Network for Single Image Super-resolution," Neural Networks, vol. 170, pp. 622–634, 2024.
[15] J. Liang et al., "SwinIR: Image Restoration Using Swin Transformer," Proc. of the IEEE/CVF Int. Conf. on Computer Vision, pp. 1833–1844, Montreal, Canada, 2021.
[16] Z. Deng et al., "RFormer: Transformer-based Generative Adversarial Network for Real Fundus Image Restoration on a New Clinical Benchmark," IEEE Journal of Biomedical and Health Informatics, vol. 26, no. 9, pp. 4645–4655, 2022.
[17] Z. Wang et al., "Uformer: A General U-shaped Transformer for Image Restoration," Proc. of the IEEE/CVF Conf. on Computer Vision and Pattern Recog., pp. 17683–17693, New Orleans, USA, 2022.
[18] J. Tan et al., "Blind Face Restoration for Under-display Camera *via* Dictionary Guided Transformer," IEEE Transactions on Circuits and Systems for Video Technology, vol. 34, no. 6, pp. 4914–4927, 2023.
[19] Y. Zhang, Q. Yang, D. M. Chandler and X. Mou, "Reference-based Multi-stage Progressive Restoration for Multi-degraded Images," IEEE Transactions on Image Processing, vol. 33, pp. 4982–4997, 2024.
[20] B. Zhou et al., "DuDoUFNet: Dual-domain Under-to-fully-complete Progressive Restoration Network for Simultaneous Metal Artifact Reduction and Low-dosect Reconstruction," IEEE Transactions on Medical Imaging, vol. 41, no. 12, pp. 3587–3599, 2022.
[21] I. Marivani et al., "Designing CNNS for Multimodal Image Restoration and Fusion *via* Unfolding the Method of Multipliers," IEEE (TCSVT) Journal, vol. 32, no. 9, pp. 5830–5845, 2022.
[22] X. Feng et al., "Deep-masking Generative Network: A Unified Framework for Background Restoration from Superimposed Images," IEEE Transactions on Image Processing, vol. 30, pp. 4867–4882, 2021.
[23] H. Yan et al., "UW-CycleGAN: Model-driven CycleGAN for Underwater Image Restoration," IEEE Transactions on Geoscience and Remote Sensing, vol. 61, DOI: 10.1109/TGRS.2023.3315772, 2023.
[24] Y. Zhu et al., "Denoising Diffusion Models for Plug-and-play Image Restoration," Proc. of the IEEE/CVF Conf. on Computer Vision and Pattern Recogn., pp. 1219–1229, Vancouver, Canada, 2023.

[25] S. Welker, H. N. Chapman and T. Gerkmann, "DriftRec: Adapting Diffusion Models to Blind JPEG Restoration," IEEE Transactions on Image Processing, vol. 33, pp. 2795-2807, 2024.
[26] H. Cho, H.-K. Shin et al., "PD-CR: Patch-based Diffusion Using Constrained Refinement for Image Restoration," IEEE Signal Processing Letters, vol. 31, pp. 949–953, 2024.
[27] Z. Luo et al., "Refusion: Enabling Large-size Realistic Image Restoration with Latent-space Diffusion Models," Proc. of the IEEE/CVF Conf. on Computer Vision and Pattern Recognition, pp. 1680–1691, Vancouver, Canada, 2023.
[28] J. V. Ortega, M. Haas and A. Effland, "Learning Diffusion Functions for Image Restoration," Proc. of the 2024 IEEE Int. Symposium on Biomedical Imaging (ISBI), Athens, Greece, 2024.
[29] Z. Yue, J. Wang and C. C. Loy, "Efficient Diffusion Model for Image Restoration by Residual Shifting," arXiv preprint, arXiv: 2403.07319, 2024.
[30] S. Yan et al., "HybrUR: A Hybrid Physical-neural Solution for Unsupervised Underwater Image Restoration," IEEE Trans. on Image Processing, vol. 32, pp. 5004–5016, 2023.
[31] Y. Chang et al., "Hyperspectral Image Restoration: Where Does the Low-rank Property Exist?" IEEE Trans. on Geoscience and Remote Sensing, vol. 59, no. 8, pp. 6869–6884, 2020.
[32] W. He et al., "Non-local Meets Global: An Iterative Paradigm for Hyperspectral Image Restoration," IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 44, no. 4, pp. 2089–2107, 2020.
[33] D. Berman, D. Levy, S. Avidan and T. Treibitz, "Underwater Single Image Color Restoration Using Haze-lines and a New Quantitative Dataset," IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 43, no. 8, pp. 2822–2837, 2020.
[34] M. Li et al., "Imaging Simulation and Learning-based Image Restoration for Remote Sensing Time Delay and Integration Cameras," IEEE Transactions on Geoscience and Remote Sensing, vol. 61, 2023.
[35] C. Li et al., "Efficient Dehazing Method for Outdoor and Remote Sensing Images," IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, vol. 16, pp. 4516–4528, 2023.
[36] S. Zhong et al., "RPIR: A Semi-blind Unsupervised Learning Image Restoration Method for Optical Synthetic Aperture Imaging Systems with Co-phase Errors," IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, vol. 17, pp. 15344-15358 2024.
[37] W. Zhang et al., "Underwater Image Enhancement *via* Minimal Color Loss and Locally Adaptive Contrast Enhancement," IEEE Transactions on Image Processing, vol. 31, pp. 3997–4010, 2022.
[38] W. Zhang et al., "Underwater Image Enhancement *via* Weighted Wavelet Visual Perception Fusion," IEEE Transactions on Circuits and Systems for Video Technology, vol. 34, no. 4, pp. 2469–2483, 2023.
[39] L. Denis et al., "A Review of Deep-learning Techniques for SAR Image Restoration," Proc. of the 2021 IEEE Int. Geoscience and Remote Sensing Symposium GARSS, pp. 411–414, 2021.
[40] R. Kumar et al., "A Review on Generative Adversarial Networks Used for Image Reconstruction in Medical Imaging," Proc. of the 2021 9th Int. Conf. on Reliability, Infocom Technologies and Optimization (Trends and Future Directions) (ICRITO), pp. 1–5, Noida, India, 2021.
[41] W.-C. Sui, X. Cheng and H. A. Chan, "Critical Review on Deep Learning and Smart Technologies for Image Super-resolution," Proc. of the IEEE TENCON 2022-2022 IEEE Region 10 Conf. (TENCON), pp. 1–8, Hong Kong, Hong Kong, 2022.
[42] S. Hou, Y. Wang, K. Li, Y. Zhao, B. Lu and L. Fan, "Deep Learning for Screen-shot Image Demoiréing: A Survey," IEEE Access, vol. 10, pp. 108453–108468, 2022.
[43] M. Pandey, G. Rawat and P. Kanti, "Image Restoration Application and Methods for Different Images: A Review," Proc. of the 2022 IEEE Int. Conf. on Advances in Computing, Communication and Materials (ICACCM), pp. 1–4, Dehradun, India, 2022.
[44] X. Li, Y. Ren, X. Jin, C. Lan, X. Wang, W. Zeng, X. Wang and Z. Chen, "Diffusion Models for Image Restoration and Enhancement: A Comprehensive Survey," arXiv preprint, arXiv:2308.09388, 2023.
[45] G. P. Kumar et al., "A Comprehensive Review on Image Restoration Methods Due to Salt and Pepper Noise," Proc. of the 2023 2nd IEEE Int. Conf. on Automation, Computing and Renewable Systems (ICACRS), pp. 562– 567, Pudukkottai, India, 2023.
[46] Q. Feng et al., "GAN-based Image Deblurring: A Comparison," Proc. of the 2023 IEEE 2nd Int. Conf. on Electrical Engineering, Big Data and Algorithms (EEBDA), pp. 318–324, 2023.
[47] L. Zhai, Y. Wang, S. Cui and Y. Zhou, "A Comprehensive Review of Deep Learning-based Real-world Image Restoration," IEEE Access, vol. 11, pp. 21049–21067, 2023.
[48] N. Deluxni et al., "A Scrutiny on Image Enhancement and Restoration Techniques for Underwater Optical Imaging Applications," IEEE Access, DOI:10.1109/ACCESS.2023.3322153, 2023.
[49] S. Yu et al., "Review of Quality Assessment Algorithms on the Realistic Blurred Image Database (BID2011)," Proc. of the 2023 8th IEEE Int. Conf. on Signal and Image Process., pp. 450–454, 2023.
[50] K. Rajput et al., "An Enhanced Analysis of Machine Learning Techniques for Image Restoration and Enhancement," Proc. of the 2024 15th IEEE Int. Conf. on Computing Communication and Networking Technologies (ICCCNT), pp. 1–6, 2024.
[51] T. Manjunath et al., "Development of an Image Restoration Algorithm Utilizing Generative Adversarial Networks (GAN's) for Enhanced Performance in Engineering Applications: A Comprehensive

Approach to Improving Image Quality and Clarity through Advanced Machine Learning Techniques," Proc. of the 2024 IEEE Int. Conf. on Innovation and Novelty in Eng. and Tech., vol. 1, pp. 1–6, 2024.
[52] R. S. Jebur et al., "A Comprehensive Review of Image Denoising in Deep Learning," Multimedia Tools and Applications, vol. 83, no. 20, pp. 58181–58199, 2024.
[53] Z. Zhang et al., "NTIRE 2024 Challenge on Bracketing Image Restoration and Enhancement: Datasets, Methods and Results," Proc. of the IEEE/CVF Conf. on Computer Vision and Pattern Recognition, pp. 6153–6166, Seattle, USA, 2024.
[54] T. Karras et al., "A Style-based Generator Architecture for Generative Adversarial Networks," Proc. of the IEEE/CVF Conf. on Computer Vision and Pattern Recognition, pp. 4401–4410, 2019.
[55] Z. Liu, P. Luo, X. Wang and X. Tang, "Deep Learning Face Attributes in the Wild," Proc. of the IEEE International Conference on Computer Vision, pp. 3730–3738, 2015.
[56] R. Timofte et al., "NTIRE 2017 Challenge on Single Image Super-resolution: Methods and Results," Proc. of the Conf. on Comp. Vision and Pattern Recog. Workshops, pp.114–125, Honolulu, USA, 2017.
[57] E. Agustsson and R. Timofte, "NTIRE 2017 Challenge on Single Image Super-resolution: Dataset and Study," Proc. of the IEEE Conf. on Computer Vision and Pattern Recognition (CVPR) Workshops, Honolulu, USA, July 2017.
[58] A. Foi et al., "Pointwise Shape-adaptive DCT for High-quality Denoising and Deblocking of Grayscale and Color Images," IEEE Transactions on Image Processing, vol. 16, no. 5, pp. 1395–1411, 2007.
[59] H. Sheikh, "Live Image Quality Assessment Database Release 2," [Online], Available: http://live.ece.utexas.edu/research/quality, 2005.
[60] A. Abdelhamed et al., "A High-quality Denoising Dataset for Smartphone Cameras," Proc. of the IEEE Conf. on Computer Vision and Pattern Recognition, pp. 1692– 1700, Salt Lake City, USA, 2018.
[61] X. Zhang et al., "Single Image Reflection Separation with Perceptual Losses," Proc. of the IEEE Conf. on Computer Vision and Pattern Recognition, pp. 4786–4794, Salt Lake City, USA, 2018.
[62] N. Silberman et al., "Indoor Segmentation and Support Inference from RGBD Images," Proc. of the Computer Vision–ECCV 2012: 12th European Conf. on Computer Vision, Part V12, pp. 746–760, Florence, Italy, 2012.
[63] D. Martin, C. Fowlkes, D. Tal and J. Malik, "A Database of Human Segmented Natural Images and Its Application to Evaluating Segmentation Algorithms and Measuring Ecological Statistics," Proc. of the 8th Int. Conf. Computer Vision, vol. 2, pp. 416–423, Vancouver, Canada, July 2001.
[64] R. Qian, R. T. Tan, W. Yang, J. Su and J. Liu, "Attentive Generative Adversarial Network for Raindrop Removal from a Single Image," Proc. of the IEEE Conf. on Computer Vision and Pattern Recognition, pp. 2482–2491, Salt Lake City, USA, 2018.
[65] C. Li, J. Guo and C. Guo, "Emerging from Water: Underwater Image Color Correction Based on Weakly Supervised Color Transfer," IEEE Signal Processing Letters, vol. 25, no. 3, pp. 323–327, 2018.
[66] S. Nah, T. H. Kim and K. M. Lee, "Deep Multi-scale Convolutional Neural Network for Dynamic Scene Deblurring," Proc. of the 2017 IEEE Conf. on Computer Vision and Pattern Recognition (CVPR), pp. 257-265, July 2017.
[67] B. A. Research, "BSD68: Part of Berkeley Segmentation Dataset and Benchmark," [Online], Available: https://www2.eecs.berkeley.edu/Research/Projects/CS/vision/bsds/, 2018.
[68] A. Blau, K. Michaeli, et al., "The PIRM Challenge on Perceptual Image Enhancement on Smartphones," Proc. of the European Conf. Computer Vision Workshops, pp. 391–411, 2018.
[69] J. Zhang et al., "HAC Dataset: Benchmarking Adverse Condition Image Restoration," [Online], Available: https://github.com/jzbjyb/HAC-dataset, 2019.
[70] T. Karras et al., "FFHQ: Flickr-faces-HQ Dataset," [Online], Available: https://github.com/NVlabs/ffhq-dataset, 2019.
[71] H. Yue et al., "SCISR: Synthetic and Camera-based Image Super-resolution Dataset," [Online], Available: https://github.com/SCISR/dataset, 2019.
[72] S. Shen et al., "Hide: Human-aware Image Deblurring Dataset," [Online], Available: https://github.com/joeylitalien/hide-dataset, 2019.
[73] W. Qian et al., "Raindrop Dataset: Image Pairs with Raindrop Artifacts," [Online], Available: https://github.com/riddhishb/raindrop-removal, 2020.
[74] J. Wei et al., "UHDS: Ultra High-definition Synthetic Dataset for Rainy Image Restoration," [Online], Available: https://github.com/uhds/uhds-dataset, 2022.
[75] C. Program, "Sentinel-2 Satellite Images Dataset," [Online], Available: https://scihub.copernicus.eu/, 2022.
[76] Y. Yu et al., "TinyPerson Dataset for Tiny Object Detection," [Online], Available: http://github.com/TinyPerson/dataset, 2022.
[77] Z. Liu et al., "LSDIR: Large-scale Dataset for Image Restoration," [Online], Available: https://github.com/LSDIR/dataset, 2023
[78] N. Corporation, "HQ-50K: High-quality Dataset for Image Restoration," [Online], Available: https://github.com/NVIDIA/ HQ-50K, 2023.

Jordanian Journal of Computers and Information Technology (JJCIT), Vol. 11, No. 02, June 2025.

ملخص البحث:

خلقــت التّطــورات السّــريعة فــي تقنيــات التّصــوير الرّقمــي –بمــا فيهــا اســتعادة الصّــور- طلبــاً متزايــداً علــى تقنيــاتٍ فعّالــةٍ فــي مجــال اســتعادة الصّــور. ويتعــيّن علــى تلــك التّقنيــات معالجــة عــددٍ مــن العيــوب، مثــل التّشــويش والغَبــاش وانخفــاض دقّــة الصّــور. ويُــذكر أنّ اســتعادة الصّــور تعــدّ مــن الأمــور المهمّــة فــي العديــد مــن التّطبيقــات، مثــل التّصــوير الطّبّــي والتّصــوير المســاحِي والاستشــعار عــن بُعــد، حيــث تُعــدّ جــودة الصّــورة أمــراً حاســماً لصّحة التّحليل والقرار.

هــذه الورقــة تقــدّم مراجعــةً تنطــوي علــى مســحٍ شــاملٍ لطُــرق اســتعادة الصّــور الّتــي تناولتهــا أدبيــات الموضــوع، بمــا فيهــا الطّــرق التّقليديّــة والتّقنيــات الحديثــة القائمــة علــى نمــاذج الــتّعلُّم العميــق والنّمــاذج المســتندة الــى المحــوّلات. وتعــالج تقنيــات اســتعادة الصّــور التقليديــة عــدداً مــن عيــوب الصّــور؛ فتعمــل علــى إزالــة التّشــويش والغَبــاش وزيــادة تحليــل الصُّــور بنــاءً علــى نمــاذج رياضــية وخوارزميــات خاصّــة. وعلــى الــرّغم مــن نجاعــة تلــك التّقنيــات فــي إزالــة بعــض عُيــوب الصّــور المســتعادة، فإنهــا لــم تكــنْ كــذلك فــي بعــض سيناريوهات العالم الحقيقي.

وقــد نجحــت التّطــوّرات الحديثــة فــي مجــال تعلُّــم الآلــة بشــكلٍ عــامّ والــتّعلُّم العميــق بشــكلٍ خــاصّ باســتخدام الشّــبكات العصــبية الالتفافيــة فــي إنجــاز طــرقٍ مدفوعــةٍ بالبيانــات يُمكنهــا الــتّعلّم مباشــرةً مــن مجموعــات البيانــات الضّــخمة وتتّســم بــالكثير مــن الفعاليــة لــدى مقارنتهــا بــالطّرق التّقليديــة. وحــديثاً، فقــد أظهــرت النّمــاذج القائمــة علــى المحــوّلات القــدرة علــى التقــاط الاعتمــادات الكامنــة فــي الصّــور، مؤدّيــةً إلــى تفــوّقٍ واضــح لتلــك النّمــاذج فــي عــددٍ مــن المهــامّ المعقّــدة المرتبطــة بإزالــة عُيــوب الصّــور المســتعادة. وقــد تبــين أنّ تلــك النّماذج كانت ناجعةً في معالجة مدىً واسع من مجموعات البيانات ذات العلاقة.

يتنــاول المســح الشّــامل الّــذي تقدّمــه هــذه الورقــة التّحــدّيات الّتــي ينطــوي عليهــا موضــوع اســتعادة الصّــور، إضــافةً إلــى كيفيــة معالجتهــا، ومنهــا تحــدّي التكلفــة الحوســبية وتحــدّي التّعمــيم، ويفــتح آفاقــاً جديــدة لبحــوث مســتقبلية فــي مجــال معالجــة عيــوب الصّــور المستعادة.