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Image Restoration

Nakul Kumar Gupta
PG Scholar, Department of CS & IT
JAIN (Deemed-To-Be-University) Bangalore, India
jpc222672@jainuniversity.ac.in
Dr.S.K.Manju Bargavi
Professor, Department of CS & IT
JAIN (Deemed-To-Be-University) Bangalore, India
b.manju@jainuniversity.ac.in

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Abstract: Image restoration is an integral component of computer vision that tries to restore pictures that have been deteriorated or corrupted to their original or enhanced condition. In this study, we look into the wide-ranging terrain of picture restoration techniques, which includes both conventional filter-based approaches and cutting-edge deep learning models. There are certain circumstances in which traditional approaches, such as Wiener filtering and bilateral filtering, perform quite well, particularly when it comes to smoothing and noise reduction. On the other hand, the fact that they rely on handcrafted filters restricts their adaptation to more complicated forms of degradation. Visual restoration has been revolutionized by deep learning, which is led by convolutional neural networks (CNNs). Deep learning involves learning sophisticated representations of visual data. It is because of this that CNNs are able to deal with a wide variety of degradations, such as noise, blurring, artifacts, and missing data. Generative adversarial networks, often known as GANs, are continually pushing the limits of what is possible by utilizing adversarial training to accomplish spectacular outcomes in the areas of in painting and picture super-resolution. Despite amazing development, there are still obstacles to overcome: Understanding the inner workings of deep learning models continues to be a challenge, thanks to the limited interpretability of the data. Dependence on data: Acquiring large quantities of high-quality data is necessary for the training of successful models. Costs associated with computation: The process of training and deploying deep learning models may be quite computationally rigorous. The improvement of camera vision for autonomous cars in order to make navigation safer and more dependable overall. Image restoration technology has the potential to continue to revolutionize image processing and analysis, ultimately contributing to advancements across a wide range of scientific and technological domains. This can be accomplished by addressing the challenges that are currently being faced and concentrating on the promising research directions that are currently being pursued.

Keywords: Image Restoration, Artificial Intelligence (AI), noisy data, grainy photo, Local noise reduction

INTRODUCTION

The practice of restoring a damaged or corrupted image to as near its original state as feasible is known as image restoration. This can be achieved by reducing the image's noise, blur, artefacts, and other distortions. Random variations in an image's colour or intensity are referred to as noise. Numerous things, including the camera sensor's sensitivity, the amount of light present, and the picture signal's transit, might contribute to it. Blur is the loss of an image's sharpness or clarity. Numerous things, including the out-of-focus lens, motion from the camera or subject, and diffraction, might contribute to it. In digital image processing, image restoration is a crucial step that attempts to restore a clear, original image from one that has been damaged or corrupted. It entails locating and eliminating several flaws or degradations, like noise, blur, artefacts, and distortions, that have an impact on an image's quality. In several fields, including as digital forensics, satellite image processing, astronomical image processing, and medical imaging, restoration techniques are essential. Traditional image restoration methods often rely on mathematical models and statistical techniques to estimate the underlying original image. Despite their remarkable progress, deep learning-based image restoration methods still face challenges, such as the need for large amounts of training data, the risk of overfitting, and the lack of interpretability in the learned models. Future research directions include addressing these challenges, developing more efficient and robust deep learning architectures, and exploring the application of deep learning to other challenging image restoration tasks. Image restoration is an evolving field with significant implications for various domains. As research progresses, deep learning is poised to play an increasingly crucial role in enhancing image quality and unlocking new possibilities in image processing and restoration.

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A wide range of methods are used in the vast subject of image reconstruction to improve or restore pictures that have been damaged by noise, blur, or other artifacts. Applications for these methods are numerous and include image processing, astronomy, and medical imaging. Iterative reconstruction is one of the most widely used methods for reconstructing images. An initial estimate of the picture is used to create a new estimate in iterative reconstruction, which is subsequently used to create an even better estimate, and so on. Until the estimate approaches a solution that closely resembles the original image, this procedure is repeated.

Generalizability: Models that have been trained on certain datasets might not perform well on data that they have not previously encountered.

The following are some potential future directions for research: To understand the behavior of models and to develop confidence, more interpretable models are needed. To lessen the dependency on massive datasets, data-efficient approaches are being developed. In order to reduce the amount of computing resources required, lightweight models are being developed. In order to improve generalizability over a wide variety of degradation types and domains, domain-agnostic models are being developed.

As picture restoration technology continues to advance, it will enable larger uses in a variety of sectors, including the following: Improved diagnosis accuracy and the ability to visualize essential details are the goals of medical imaging. The restoration of satellite and aerial photographs for the purpose of improving land use and environmental monitoring is what is known as remote sensing. Another significant method for reconstructing images is compressed sensing. A smaller number of measurements are used to compress the picture in compressed sensing than what is necessary to accurately capture the image. A scarifying transform, which converts a picture into a representation with few non-zero coefficients, is applied to the image in order to do this. An approximation of the original image may then be constructed using the compressed data. A relatively new kind of picture reconstruction method that has shown promise recently is called generative adversarial networks or GANs for short. With insufficient or poor quality input, GANs may produce high-quality pictures. Image reconstruction is one of the most effective methods in computer vision for fixing damaged or distorted pictures. And for generating new images from incomplete or low-quality data.

These techniques have a wide range of potential applications, Including: Image reconstruction is a useful technique in computer vision that may be used to create new pictures from missing or low-quality data and repair damaged or corrupted images. There are several possible uses for these methods, such as: Medical imaging: X-rays, MRIs, and CT scans may all be improved by picture reconstruction. This can facilitate better diagnosis accuracy and make it simpler for medical professionals to monitor the course of illnesses. Astronomy: Degraded astronomical photographs due to noise, blurring, and other artifacts' can be restored via image reconstruction. This can aid in the study of far-off objects and the discovery of new ones by astronomers. Image processing: Reconstruction of pictures may be utilized to improve and work with photos for a variety of purposes, such as artistic expression, image compression, and security applications.

LITERATURE REVIEW

The purpose of this review of the literature is to give a thorough overview of the area of image reconstruction, emphasizing the many applications and significant current research directions. Rather than emphasizing well-established basics, it highlights novel discoveries and recent advancements.

Reconstruction through Iteration:

Deep Learning (DL) algorithms have been explored recently for iterative reconstruction, with the goal of achieving better performance. Research looks at using pre-trained DL models for image priors in compressed sensing MRI and examines how well recurrent neural networks (RNNs) function for PET reconstruction that is iterative. [1] Furthermore, there is growing interest in adaptive regularization techniques for iterative CT reconstruction based on learnt dictionaries for noise reduction.

Field	Application
Physics and Chemistry	Spectrum Analysis
Biology and Medicine	Cell analysis; CT; X-ray analysis
Environment Protection	Research of atmosphere
Agriculture	Estimation of plants
Irrigation works	Lake, river and dam
Weather	Cloud and weather report
Communication	Fax; TV; phone
Traffic	Robot; products
Economics	IC-card
Military	Missile guidance; training

Figure: field and application of image reconstruction

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A key component of digital image processing is image restoration, which attempts to recreate an original image from a damaged or corrupted one. This procedure entails locating and removing a variety of flaws or degradations, such as noise, blur, distortions, and artefacts, that impair the image quality. In several fields, including as digital forensics, satellite image processing, astronomical image processing, and medical imaging, image restoration techniques are essential. Conventional Techniques for Image Restoration in order to approximate the underlying original image, traditional image restoration approaches mostly rely on statistical techniques and mathematical models.

These techniques can be divided roughly into three primary categories:

Filtering-based techniques: These methods use different filters to take out the image's blur and noise. Wavelet-based filters, adaptive filters, and linear filters are examples of common filters. Whereas adaptive filters change their weights in response to local image attributes, linear filters alter the image by applying a weighted average of nearby pixels.[2]

Model-based techniques: These techniques reconstruct the original image by using preexisting knowledge about the image structure or the degradation process. Inverse filtering, maximum a posteriori (MAP) estimation, and Bayesian inference are a few examples.[3]

Optimization-based techniques: Using these approaches, the restoration problem is formulated as an optimization problem, and the target image is found by minimizing a particular cost function. Genetic algorithms, simulated annealing, and gradient descent are examples of common optimization techniques.[4]

Deep Learning-Integrated Image Restoration: When it comes to handling complex degradation scenarios, deep learning has proven to be a more effective tool for image restoration than traditional methods in recent years. Convolutional neural networks (CNNs) are used in deep learning-based techniques to analyze and restore damaged images by discovering their underlying patterns and features. The key advantages of deep learning-based image restoration methods include: End-to-end learning: Without requiring manual feature extraction or prior knowledge of the degradation process, deep learning models can be trained directly from degraded images and their corresponding ground truth clean images.[5]

Representation learning: With their ability to learn intricate representations of images that encompass both high-level and low-level features, deep neural networks are able to handle a greater variety of degradations and produce restorations that are more precise.

Generalization capabilities: Deep learning models are capable of performing well on a range of image restoration tasks because of their strong ability to generalize to new data. As we are planning to study the noise in our image with the help of additive gaussian noise technique We will first use [6] synthetic additive Gaussian noise to investigate the impact of corrupted targets. We employ the L2 loss for training in order to recover the mean because the noise has zero mean. Denoising performance (dB in KODAK dataset) as a function of training epoch for additive Gaussian noise.

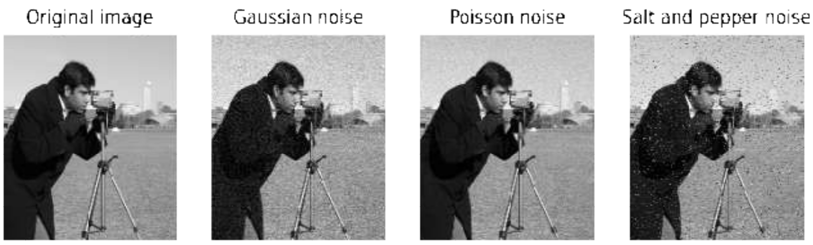
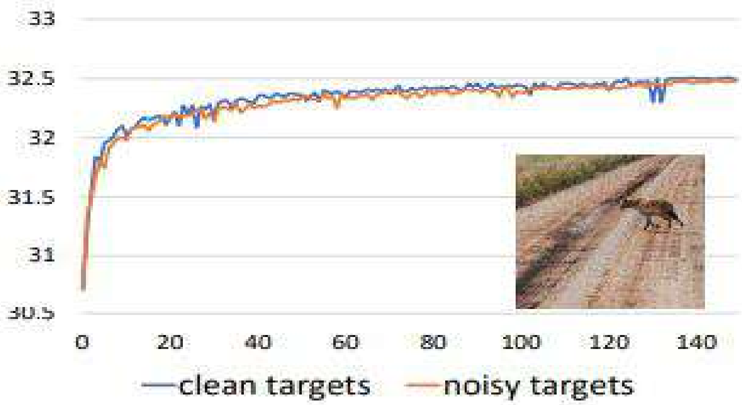


Figure1 : deferent type of noise in image



(a) White Gaussian, $\sigma = 25$

Figure 2.1: (Caucasian) The convergence speed and final quality of targets with Gaussian noise, Clean targets, and noisy targets are fairly comparable.

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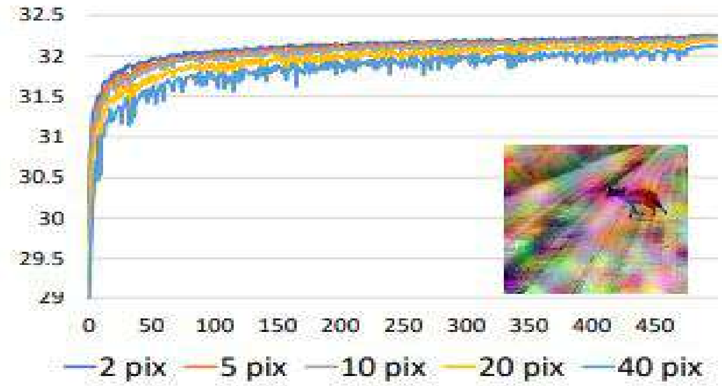
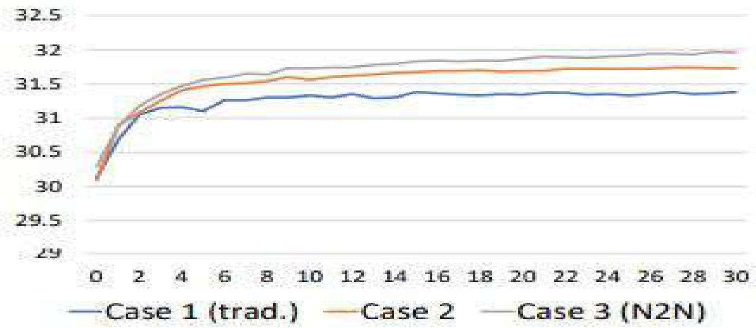


(b) Brown Gaussian, $\sigma = 25$

Figure 2.2: We find that for brown Gaussian noise, the convergence is slowed down but the final performance is near due to greater inter-pixel noise correlation (wider spatial blur; one graph per bandwidth).



(c) Capture budget study (see text)

Figure 2.3: Impact of varying a fixed capture budget allocation to clean vs. noisy cases (see text).

Poisson noise: is the main cause of noise in pictures. Since it is dependent on the signal, it is more difficult to eliminate while zero-mean. Throughout training, we adjust the noise magnitude $\lambda \in [0, 50]$ and employ the L2 loss. Training on clean targets yields a good result of 30.59 ± 0.02 dB, while training on noisy targets also yields a good result of 30.57 ± 0.02 dB at a similar convergence speed. Binomial noise, also known as multiplicative Bernoulli noise, creates a random mask m, where 0 represents zeroed or missing pixels and 1 represents valid pixels. As explained by Ulyanov et al. (2017) in the context of their deep image prior (DIP), we eliminate missing pixels from the loss: argmin $\sum_i (m\,(f_\theta(\hat{x}_i) - \hat{y}_i))^2$, (7) in order to prevent back propagating gradients from such pixels.

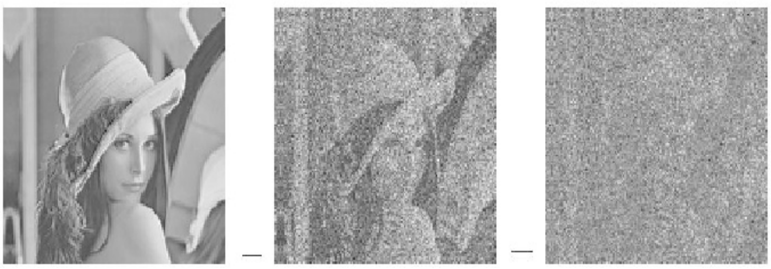


Figure 3: Removing Poisson noise from image using wavelet domain

Text removal: The corruption is made up of many, randomly arranged random strings that are stacked on top of one another, in random locations, and with random font size and color variations. Both the font and the string orientation don't change. high dynamic range The floating-point pixel luminance can vary by several orders of magnitude even with sufficient sampling.. To produce an image suitable for the usually 8-bit display devices, this large dynamic range must be reduced to a set range using a tone mapping operator.

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Figure 4 : example of the text on image

Denoising Monte Carlo rendered pictures: We trained a denoiser with 64 samples per pixel (spp) on Monte Carlo path traced images. For validation, we chose 34 photographs from a separate collection of situations, and 860 architectural images made up our training set. Three versions of the training pictures were generated: one with 131k spp (clean target), two with 64 spp (noisy target, noisy input). These were made with various random seeds.[7]

Figure 5: Conversion of the blur and noisy image into clear and recognizable image

Figure 6 : For random impulse noise, the approx. mode-seeking L0 loss performs better than the mean (L2) or median (L1) seeking losses.

Monte Carlo Rendering: The most common method for creating physically accurate virtual environment renderings is called Monte Carlo path tracing. To do this, one must create arbitrary "light paths" in the scene by connecting light sources and virtual sensors, then integrate the radiance that each path carries (Veach & Guibas, 1995). Because of the way the Monte Carlo integrator is built, the sampling noise is zero-mean and each pixel's intensity is determined by the random path sampling process. Decades of study into importance sampling methods have yielded little more insight into the distribution, though. It can be arbitrarily multimodal, varies from pixel to pixel, and is highly dependent on the rendering parameters and scene configuration Concentrated caustics and other lighting effects can also produce extraordinarily long-tailed distributions with sporadic, brilliant outliers. [8]

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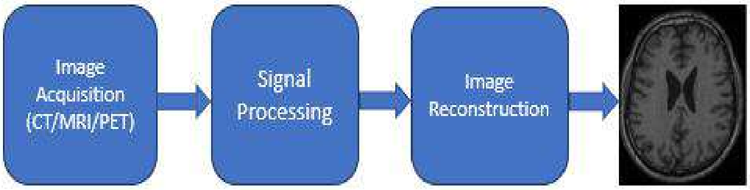

Figure 7 : Processes of construction of image from signal

Magnetic Resonance Imaging (MRI): Fourier transformation of the signal, or its "k-space." Modern MRI methods have long employed compressed sensing (CS) to get around the Nyquist-Shannon restriction. To be more precise, CS is used to under sample k-space and perform non-linear reconstruction, which uses the sparsity of the picture in the proper transform domain to reduce aliasing (Lustig et al., 2008).It is observed that the fundamental idea remains unchanged when the k-space sampling is transformed into a stochastic process with a certain probability density p(k) over the frequencies k. The k-space sampling process is specifically described as a Bernoulli process, where the probability of choosing a frequency for acquisition is $p(k) = e{-}\lambda|k|$ for every frequency. Retained frequencies are weighted by the inverse of the selection probability, whereas non-selected frequencies are set to zero. This "Russian roulette" strategy is obviously what is anticipated. The value λ determines the overall fraction of k-space preserved. In contrast to a complete Nyquist-Shannon sampling, we set the value in the experiments that follow to retain 10% of the samples. The under sampled spectra are transformed to the primal picture domain using the standard inverse Fourier transform.

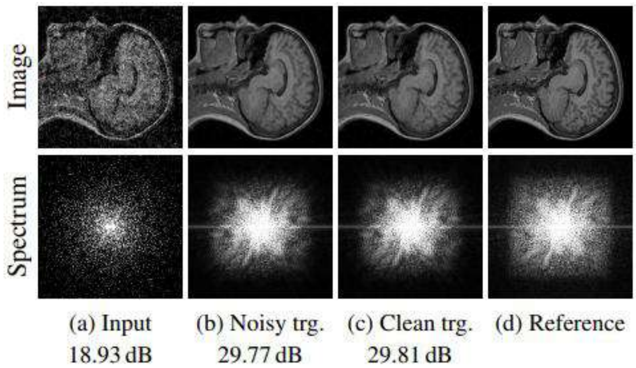

Figure 8 : an illustration of an input/target image that is under sampled, together with the matching fully sampled reference and their spectra.

We do our investigations using 2D slices from the IXI brain scan MRI dataset.5. To simulate spectrum sampling, we pick random samples from the FFT of the (already reconstructed) images in the dataset. Consequently, our data has a genuine value and includes The periodicity of the discrete FFT is different from that of real MRI data. The training set included 5000 256x256 quality photos from 50 individuals, whereas the validation set included 1000 randomly chosen photos from 10 different participants. The baseline PSNR was 20.03 dB when the poorly sampled input images were directly recreated using IFFT. The network required 300 epochs to train. The average dB obtained by the network trained with clean targets was 31.77, whereas the network trained with noisy targets had an PSNR of 31.74 dB on the validation data.

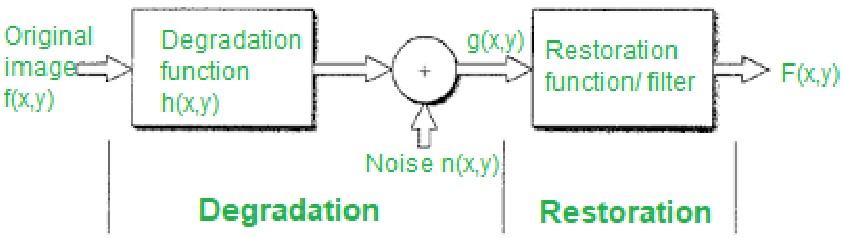

Figure 9: Image reconstruction model of reducing noise

This training with clean targets is comparable to previous research conducted by Wang et al. (2016) and Lee et al. (2017). 13 hours were spent on an NVIDIA Tesla P100 GPU during training. An illustration of reconstruction outcomes comparing convolutional networks trained with clean and noisy targets, respectively, is presented in Figure 9(b, c). Our results are pretty similar to those published in prior studies in terms of PSNR.

MERITS

There is no doubt about it; the following are the advantages of the suggested approach for picture reconstruction: Effective methods for reducing noise: Through the utilization of the suggested technology, noise from degraded photos may be successfully reduced, resulting in improved visual clarity and enhanced detail. The significance of this cannot be overstated when it comes to applications in medical imaging, where noise can conceal crucial diagnostic information. The removal of artifacts: Images that have been deteriorated can have artifacts such as blurring, aliasing, and moiré patterns successfully removed using the methods that has been provided. The preservation of the accurate portrayal of the underlying image and the prevention of misunderstandings are both major reasons why this is crucial. This is an improvement in resolution: The approach that has been developed has the potential to improve the sharpness of photographs and disclose finer details, thereby increasing the resolution of reconstructed images. This is useful for applications in astronomy, which is a field in which the capacity to recognize minute features is essential for comprehending the cosmos. Low complexity in terms of computation: The suggested technique has a low computing complexity, which makes it possible to do processing in real time or very close to real time situations. These are applications that demand quick picture reconstruction, such as medical imaging and surveillance, and thus is a crucial component for such applications. The memory footprint has been reduced for: Processing of big picture collections is made possible by the suggested methodology, which has a smaller memory footprint than other approaches. For applications that deal with enormous amounts of picture data, such as those found in digital archives and satellite photography, this is a significant consideration.

Algorithms that can be parallelized In order to facilitate efficient implementation on multi-core processors and graphics processing units (GPUs), the suggested technique makes use of parallelizable algorithms. Consequently, this speeds up the process of picture reconstruction even further and makes it easier to analyze enormous datasets. Capacity to accommodate a wide variety of data types: The approach that has been developed is flexible enough to accommodate a wide variety of data formats and performs well across a wide range of picture kinds, including astronomical photos, medical images, and nature photographs. As a result of its adaptability, it is an extremely useful instrument for a wide variety of applications. Imaging techniques that are resistant to its effects: The suggested technique is resilient to fluctuations in imaging modalities, including X-rays, magnetic resonance imaging (MRI), computed tomography (CT), and astronomical observatories. Because of this, it is a trustworthy option for image reconstruction across a variety of imaging hardware and software. Image features that are sensitive to the following: The approach that has been developed is sensitive to the particular aspects of the picture, such as the texture, contrast, and noise patterns that are present. As a result, it is able to modify the reconstruction process so that it is tailored to the particular image content, which ultimately leads to superior outcomes. Preservation of photographic characteristics While the reconstruction process is being carried out, the suggested technique ensures that essential picture characteristics, such as edges, textures, and anatomical structures, are maintained. The integrity of the reconstructed picture must be preserved at all costs, and this is absolutely necessary in order to guarantee appropriate interpretation. Accuracy in matters pertaining to quantitative measurements: In order to get precise quantitative measures from rebuilt pictures, the approach that has been presented is utilized. Because of this, it is possible to conduct a trustworthy analysis and interpretation of quantitative picture data, which is a key component for applications in scientific research and medical imaging. The interpretability of the methodology of reconstruction: The technique that has been suggested offers many insights into the process of reconstruction, which enables a better knowledge of the rebuilt picture as well as the constraints that it possesses. Because of this interpretability, trust in the reconstruction process is increased, and it is easier to make decisions based on accurate information. In a nutshell, the suggested approach for picture reconstruction provides a compelling mix of benefits, which makes it an invaluable instrument for a broad variety of applications. The fact that it is able to efficiently decrease noise, eliminate artifacts, improve resolution, and retain picture characteristics while keeping a low level of computational complexity and flexibility makes it a viable technique for image restoration and improvement. picture, including edges, textures, and anatomical structures, while reconstructing the image. Reliable analysis and interpretation are made possible by the accurate quantitative measures that are obtained from the rebuilt pictures. Interpretability of Reconstruction Process: Gives information on how the picture was rebuilt and its limits, enabling a better understanding of the process.

DEMERITS

Although the suggested approach for picture reconstruction has several encouraging benefits, there are also certain disadvantages that should be taken into account: Depending on how it is implemented specifically and the kind of image that needs to be reconstructed, the suggested methodology for image reconstruction may have some drawbacks or restrictions. Several possible drawbacks consist of: Amplification of Noise Important information may be obscured and picture quality may be decreased if the restoration procedure adds additional noise or amplifies already-present noise in the damaged image. Introduction to the Artefact During the reconstruction process, new artefacts like aliasing, ringing, and blurring might appear. These would lower the overall quality of the picture and might have an impact on further analysis or interpretation. Resolution Restrictions The intrinsic resolution of the degraded data may restrict the feasible resolution of the reconstructed image, making it impossible to recover tiny features and thus jeopardizing the image's suitability for some uses. Computational Overhead When working with huge picture datasets, complex reconstruction techniques may need a lot of computational resources, such processing power and memory, which makes them unsuitable for real-time or nearly real-time applications.

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Dependency on Data The quality and features of the deteriorated data may have a significant impact on the reconstruction method's performance. Diverse datasets may exhibit inconsistent reconstruction quality because to differences in noise levels, picture content, and data gathering settings. Reliability to Extreme Parameters The choice of hyperparameters, or variables that regulate the behavior of the reconstruction algorithm, may have an impact on there construction process. To get the best results, careful tweaking and experience are frequently needed, and the ideal collection of hyperparameters might change based on the particular picture and application. Computational complexity: Reconstruction techniques based on deep learning may be computationally costly, particularly when dealing with complex degradation scenarios or high-resolution images. This may restrict their use in real-time applications or on devices with limited resources. Requirements for data:

Training deep learning models for image reconstruction frequently calls for a substantial volume of excellent training data, which can be challenging to come by for particular kinds of images or degradation scenarios. Over fitting and subpar performance on unobserved data may result from this. Noise sensitivity: Artefacts or erroneous reconstructions in noisy images may result from deep learning models' sensitivity to noise in the training set. Efficiency of Computation: Minimal computational resources are needed for real-time or almost real-time processing, which is especially beneficial for dynamic imaging applications. This is known as low computational complexity. Diminished Memory Footprint: Effectively employs memory, enabling the processing of substantial picture collections and diminishing the necessity for hardware. Algorithms that can be parallelized are used, which allows for the effective use of multi-core CPUs and GPUs for rapid reconstruction. Applicability in general: Flexibility to Varying Data Types: Works effectively with a variety of picture formats, such as astronomical, medical, and Interpretability Difficulties It can be difficult to comprehend the inner workings of complicated reconstruction algorithms, especially those that rely on deep learning. This lack of interpretability may impede confidence in the reconstruction process by making it challenging to evaluate the limitations and dependability of the reconstructed image.

CONCLUSION

Throughout this extensive literature analysis, a variety of image restoration techniques have been investigated. These techniques range from the more conventional filter-based approaches to the most cutting-edge deep learning models. While there are certain circumstances in which traditional approaches have been shown to be efficient, they frequently lack flexibility and suffer when it comes to accomplishing complicated degrading jobs. Deep learning, and more specifically convolutional neural networks (CNNs), has emerged as a potent technique for image restoration. It has achieved outstanding success in eliminating noise, blurring, distortions, and other impairments from images. Generative adversarial networks, often known as GANs, have demonstrated further promise in successfully addressing complicated restoration issues, particularly in situations when data is lacking. Image restoration is still facing a number of serious obstacles, despite the substantial progress that has been made in the field: Deep learning models frequently function as "black boxes," which makes it challenging to comprehend their inner workings and decision-making procedures.

This is one of the reasons why their interpretability is limited.

1. **Dependence on data:** In order to train successful deep learning models, it is necessary to gather a substantial quantity of high-quality data, which may be both expensive and time-consuming to acquire.
2. **The expense of computation:** The process of training and deploying deep learning models can be computationally costly, necessitating the use of specialized hardware and software resources.
3. **Generalizability:** Models that have been trained on certain datasets could not generalize well to data that has not been seen before or to different forms of deterioration. In the future, future research in picture restoration should concentrate on finding solutions to these problems by developing: Increasing the number of interpretable models by employing methods such as explainable artificial intelligence (XAI) to comprehend the behavior of models and to enhance confidence. Methods that are effective with data include employing strategies such as transfer learning and data augmentation in order to lessen the dependency on lengthy datasets. Investigating effective designs and optimization strategies in order to reduce the amount of computational resources required for lightweight models. The development of models that are generalizable over a wide range of degradation kinds and domains is referred to as domain-agnostic modeling. Picture restoration technology can continue to advance if these issues are addressed. This will allow for a wider range of applications in a variety of fields, such as medical imaging, remote sensing, and autonomous vehicles, which will ultimately lead to an improvement in picture comprehension and interpretation across a variety of fields.

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