Shradha Kumavat, 2026, 14:2
ISSN (Online): 2348-4098
ISSN (Print): 2395-4752

International Journal of Science, Engineering and Technology
An Open Access Journal

A Performance Assessment of Machine Learning-Based Techniques for Image Restoration

Shradha Kumavat [1], Kapil Shah[2]
[1]Research Scholar, [2]Assistant Professor
[1,2]Department of Computer Science and Engineering
[1,2,]Jawaharlal Institute of Technology, Borawan, India;

Abstract- Image restoration is a fundamental task in image processing with wide-ranging applications in modern life, including medical imaging, remote sensing, radar imaging, and digital preservation of historical and museum artifacts. The objective of image restoration is to recover a high-quality image from degraded observation by reducing the effects of noise and blur. Effective restoration depends on understanding the degradation process; therefore, identifying the type of noise and the blur model is essential. In practical scenarios, images are often degraded by atmospheric and environmental conditions and restoring them requires appropriate restoration techniques tailored to the distortion characteristics. This paper reviews and assesses contemporary machine learning-based image restoration methods. The proposed evaluation reports quantitative performance across four standard benchmark datasets Kodak24, CBSD68, Urban100, and LIVE—using PSNR (dB), MSE, and SSIM as primary quality metrics. The achieved PSNR scores are 27.24 dB, 29.38 dB, 30.04 dB, and 30.91 dB on Kodak24, CBSD68, Urban100, and LIVE, respectively. The corresponding MSE values are 367.56, 224.88, 193.10, and 158.02, while SSIM values are 0.8690, 0.9337, 0.9432, and 0.8008. These results demonstrate the effectiveness of the evaluated approach in improving image quality across diverse image restoration benchmarks.

Keywords: Image Restoration, Image Filtering, Noise Removal, Image Denoising, Fast Deep Neural Networks, Augmented Lagrangian Multipliers, Kodak24, CBSD68, Urban100, LIVE.

I. INTRODUCTION

Photos are an effective medium for communication because they preserve unique moments and allow people to relive meaningful memories over time [1]. Traditionally, however, the limited number of printed photographs people owned could only be protected by storing them in photo albums or placing them in frames. Over time, many old photographs become yellowed due to aging and oxidation processes, and they are also prone to physical damage through improper handling [2]. With recent advances in digital image processing, it is now possible to restore aged, yellowed, or damaged photographs and recover their visual quality, helping preserve valuable personal and cultural memories for future generations [3].

Deep learning is a major subfield of machine learning that enables systems to learn directly from data using artificial neural networks [4], [5]. In recent years, deep learning has become increasingly influential in computer vision because it provides powerful feature representations for image data [6]. Many researchers have explored deep learning-based approaches for image enhancement and restoration to improve the quality and structure of reconstructed images [7]. In particular, deep convolutional neural networks (CNNs) and generative adversarial networks (GANs) have shown strong performance in tasks such as feature extraction, image generation, and image restoration [8]. As a result, deep neural networks are now widely used for restoring degraded images, including the reconstruction of old and damaged photographs.

Neural networks form the foundation of most deep learning models, and their primary objective is to discover complex patterns and underlying structures that may not be easily captured using traditional techniques. Among the most widely used architectures, CNNs and GANs are prominent deep learning models for image restoration [9]. Consequently, researchers increasingly propose CNN- and GAN-based restoration frameworks to address various photo restoration challenges [10]. These methods typically leverage large-scale datasets to improve upon classical restoration approaches [11]. By learning richer image representations, deep models can better reconstruct fine details and structures, leading to substantial improvements in restoration quality [12].

This paper is organized as follows: Section II reviews related literature on image degradation and restoration methods; Section III presents the problem statement and proposed task; Section IV discusses the motivation, significance, and methodology of the study; and Section V concludes the paper and outlines future research directions.

II. LITERATURE WORK

According to the quality assessment index, it was discovered that recovering simply the conspicuous item enhanced picture quality much more than restoring only the background [12]. Only the most prominent component was brought back to its previous glory. Using a deep neural network called GAN, damaged photographs may be restored. Restoring broken visual sequences is the goal of the strategy that was proposed [13]. Experiments conducted in Italy using photos captured by Sentinel-2 of artificial clouds provided evidence that the method was successful [14]. This method removes JPEG artifacts and offers noise reduction and blind image super-resolution, all of which are considered to be state-of-the-art. It can be found at https://github.com/JWSoh/VDIR. Our information and code may be found in [15].

The cryo-TEM contrast, as well as the data processing, may be improved with the advised image restoration. The authors provide evidence that automated processing in the downstream stages improves performance [16]. In spite of the fact that the authorre experiment only used a limited number of different tactics, it nonetheless produced high-quality findings. The approach described in [17] could make such calculations go more quickly. The suggested method is based on the primary objectives of completeness and super-resolution, both of which are important aspects of picture restoration. Our approach is superior to the approaches that are currently considered the most sophisticated and is unaffected by image corruption [18]. At a minimum of five diverse undersea circumstances need to be studied and thoroughly researched in order to demonstrate the practicability of representative procedures. In conclusion, the author discusses unanswered issues as well as possible research topics [19]. There is a need for image sharpening. The use of aerial imagery allowed for the recovery of photographs. Both qualitatively and statistically, the recovered pictures are shown to be accurate [20].

This paper presents a hierarchical K-Means clustering approach for improving friend recommendation systems. The method aims to enhance the accuracy of suggesting friends to users by employing a hierarchical structure within the K-Means clustering algorithm [21]. This paper focuses on human face mask identification using deep learning techniques in conjunction with OpenCV. The study explores methods for detecting whether individuals are wearing masks using computer vision and deep learning algorithms [22]. The paper addresses cancer prediction using a combination of random forest and deep learning techniques. The authors propose a methodology to predict cancer occurrences using advanced machine learning methods [23]. This study presents an approach for activity detection and people counting using Mask R-CNN (Region Convolutional Neural Network) in combination with bidirectional ConvLSTM (Convolutional Long Short-Term Memory).

The focus is on tracking and analyzing human activities [24]. This chapter introduces an AIoT-based (Artificial Intelligence of Things) device designed for real-time object recognition. The system utilizes voice conversion to provide audio feedback, enhancing accessibility for object recognition [25]. The paper presents an ultra-area-efficient Arithmetic Logic Unit (ALU) design using Quantum-dot Cellular Automata (QCA) technology. The design incorporates a synchronized clock zone scheme to enhance efficiency [26].This technique offers state-of-the-art grayscale picture restoration capabilities and is thus at the forefront of technological advancement. Modifications need to be made to SBA. This module re-calibrates the blockwise features, which contributes to a reduction in discontinuities and an increase in performance. Experiments have shown that these networks trade off their ability to repair themselves for their calculating speed [27].

III. PROPOSED METHOD

Proposed algorithm

Input: Images.

Output: Result validation in terms of PSNR(dB), MSE, and SSIM.

Step 1: Defined SRCNN model.

Step 2: Set model type sequential().

Step 3: Set CNN layers and filter, filters=128, kernel sie =(9,9).

Step 4: Set Adam optimizer.

Step 5: Compiled model and get Los and MSE.

Proposed working flow

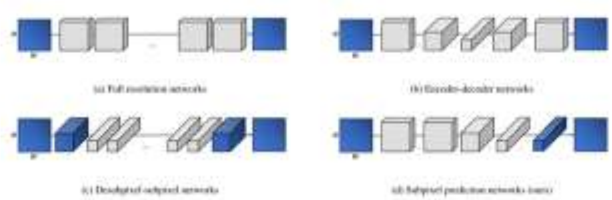

Figure 1. Blue layers are data-level representations without learnable parameters (e.g., reshaping).

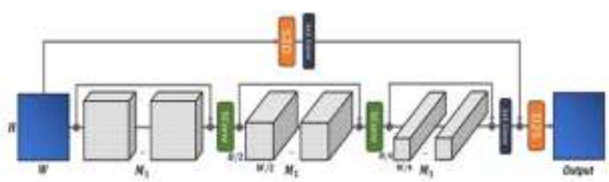

Figure 2. Subpixel Prediction Networks (SPNs) for each level, showing M1, M2, and M3 residual blocks. SConv means 2 downsampling convolutions. Space-to-depth (S2D) and depth-to-space (D2S).

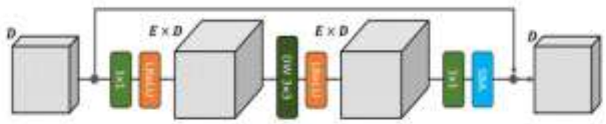

Figure 3. Residual block configuration. By using E. Leaky ReLU, Depthwise Convolution, and the Subpixel Block Attention Module, the intermediate layers are able to expand the D-dimensional input channel.

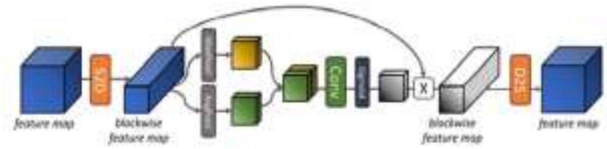

Figure 4. SBA module illustration. SBA is a block-based attention module for SPNs..

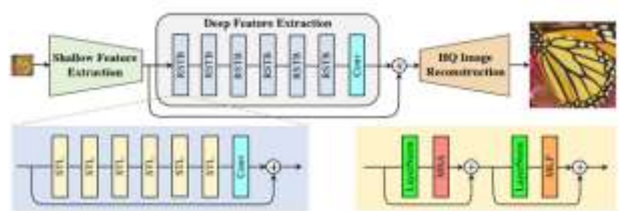

Figure 5: Proposed deep feature extraction

IV. IMPLEMENTATION AND RESULT

Hardware and software

Platform for hardware developed by Google Colab. Import sys, import Keras, import cv2, import NumPy, import matplotlib, import skimage; these are all Python libraries.

Dataset

The LIVE1 dataset [28] serves as a testing set for the networks to be evaluated. There are 29 photos in the LIVE1 collection, including 5 videos. Denoising testing datasets include the 24, 68, and 100-image Kodak24 [29], CBSD68 [30], and Urban100 [31] collections.

Parameters of results

In this paper, we have compared results in terms of PSNR(dB), MSE, and SSIM.

MSE (Mean Square Error) [32]

When evaluating image quality, the mean squared error (MSE) is what's expected. Since this is a complete reference measure, it makes sense to go towards values closer to zero.

This is really the second mistake, which makes the situation a lot more difficult. When determining the mean squared error, both the bias and the variance of the estimator are included in to the process. If the estimator is supposed to be objective, then the MSE is identical to the estimator's variance. In order to calculate the variance, square-root transformed copies of the original values are used. The idea of the Root-Mean-Square Error (RMSE), also known as the Root-Mean-Square Deviation (RMSD) and the standard deviation of the variance, is presented by the MSE for the first time.

A device known as an estimator may be used to calculate the unseen quantity in a picture. Squared errors (SE) and their variances (MSD) may be measured using mean squared error (MSE) and mean squared standard deviation (MSD), respectively (SD). When comparing an estimate to the actual outcome, the margin of error is the difference between the two. It depends on whether the squared error loss or the quadratic loss is expected to have a larger impact on the system's performance.

$$Mean\ Squared\ Error\ (\ MSE) between\ two\ images\ such\ as\ g(x,y) and\ \widehat{g}\ (\mathrm{x,y})$$

$$MSE = \frac{1}{MN}\sum_{n=0}^{M}.\sum_{m=0}^{N}.[\hat{g}(n,m) - g(n,m)]^2$$

Structure Similarity Index Method (SSIM) [33]

A technique for calculating the Structural Similarity Index based on Perception This approach addresses the problem of deteriorating visuals by concentrating on the way in which an individual's understanding of an image's structure changes with time. It works in conjunction with a number of other essential perceptual facts, such as the masking of brightness and contrast, amongst others. The phrase "structural information" refers to specifics of the connections between pixels that are either physically near to one another or significantly dependent on one another. The highly interdependent pixels in an image allude to additional, vital information about the objects observed. Due to luminescence masking, picture edges are often less distorted than the center. Contrast masking, on the other hand, makes a picture's texture less prone to distortions. SSIM employs an approximation technique to evaluate an image or video's reception. By using this strategy, we can evaluate how closely the restored images resemble the originals.

PSNR (Peak Signal to Noise Ratio) [34]

The PSNR is a metric for determining how much the noise power reduces the quality of a signal's representation in relation to the signal's own PSNR. In this case, the decibel level represents the degree to which two images differ from one another. Usually, the PSNR is stated as a logarithmic term in the decibel scale due to the huge dynamic range of the signals. This dynamic range is the total difference between the highest possible and lowest possible quality settings.

One of the standard measures that is used to evaluate how good the reconstruction of a lossy image compression codec is is the Peak signal-to-noise ratio. The signal is an indication of the data that was initially input, while the noise is an indication of any mistakes that may have been introduced as a consequence of the transformation. The PSNR is a parameter that provides a ballpark figure for how effectively a reconstruction will be perceived by a person, particularly in comparison to compression codecs.

PSNR is expressed as:

$$PSNR\ is\ expressed\ as:\quad PSNR = 10\ log_{10}\frac{(peakval^2)}{MSE}$$

Result

Table 1: Propose result in Kodak24, CBSD68, Urban 100, LIVE.

Dataset	Freq. Domain	PSNR(dB)	MSE	SSIM
Kodak24	Yes	27.24	367.56	0.869
CBSD68	Yes	29.38	224.88	0.9337
Urban 100	Yes	30.04	193.1	0.9432
LIVE1	Yes	30.91	158.02	0.8008

The table shows the result in Kodak24, CBSD68, Urban 100, LIVE dataset, terms of frequency, PSNR(dB), MSE, and SSIM. PSNR like 27.24,29.38,30.04,30.91. MSE like 367.56,224.88,193.1,158.02. and SSIM like 0.8690,0.9337,0.9432,0.8008.

Figure 6: Result of Kodak24 dataset.

Figure 7: Result of CBSD68 dataset.

Figure 8: Result of Urban 100 dataset.

Figure 9: Result of LIVE dataset.

VI. CONCLUSION

This study provides an in-depth examination as well as a comparison of a number of modern strategies for the improvement and maintenance of underwater images. In the past, one needed to take several images of the same subject while using various pieces of photographic equipment such as polarizers, sensors, and others in order to get a clear image. The development of computer vision techniques has resulted in the creation of optical models that are capable of generating images in environments with low levels of visibility, such as the open air and the depths of the ocean. These models may take a single photo that has an apparent degradation and create a result that is of a higher quality.

Instead of using more classic techniques such as histogram equalization and contrast stretching, the majority of image enhancement methods depend on an optical model of the original, low-quality picture as their foundation. The results of the suggested methodology are shown in terms of frequency, PSNR(dB), MSE, and SSIM in the LIVE dataset, Kodak24, CBSD68, and Urban 100. Similar PSNR values include 27.24, 29.38, 30.04, and 30.91. MSE values such as 367.56,224.88,193.1,158.02 and SSIM values such as 0.8690,0.9337,0.9432,0.8008. These values may be found in related datasets such as Kodak24, CBSD68, Urban 100, and LIVE.

REFERENCES

1. L. Qi et al., "Photoacoustic Tomography Image Restoration With Measured Spatially Variant Point Spread Functions," in IEEE Transactions on Medical Imaging, vol. 40, no. 9, pp. 2318-2328, Sept. 2021, doi: 10.1109/TMI.2021.3077022.
2. T. -O. Buchholz, M. Jordan, G. Pigino and F. Jug, "Cryo-CARE: Content-Aware Image Restoration for Cryo-Transmission Electron Microscopy Data," 2019 IEEE 16th International Symposium on Biomedical Imaging (ISBI 2019), 2019, pp. 502-506, doi: 10.1109/ISBI.2019.8759519.
3. R. Mishra, N. Mittal and S. K. Khatri, "Digital Image Restoration using Image Filtering Techniques," 2019 International Conference on Automation, Computational and Technology Management (ICACTM), 2019, pp. 268-272, doi: 10.1109/ICACTM.2019.8776813.
4. Q. He and C. Miao, "Lossless restoration of local blurred image based on deep residual network," 2021 International Conference on Intelligent Transportation, Big Data & Smart City (ICITBS), 2021, pp. 672-676, doi: 10.1109/ICITBS53129.2021.00170.
5. J. Qiu and K. Xie, "A GAN-based Motion Blurred Image Restoration Algorithm," 2019 IEEE 10th International Conference on Software Engineering and Service Science (ICSESS), 2019, pp. 211-215, doi: 10.1109/ICSESS47205.2019.9040717.
6. S. Bao, "An Improved Non-local Mean Filtering Algorithm Based on Medical Image Restoration," 2021 International Conference on Computer

Engineering and Artificial Intelligence (ICCEAI), 2021, pp. 43-47, doi: 10.1109/ICCEAI52939.2021.00008.

7. Y. Wang, W. Song, G. Fortino, L. -Z. Qi, W. Zhang and A. Liotta, "An Experimental-Based Review of Image Enhancement and Image Restoration Methods for Underwater Imaging," in IEEE Access, vol. 7, pp. 140233-140251, 2019, doi: 10.1109/ACCESS.2019.2932130.
8. K. Panfilova and S. Umnyashkin, "Correlation-based Quality Measure for Blind Deconvolution Restoration of Blurred Images based on Lucy-Richardson Method," 2019 IEEE Conference of Russian Young Researchers in Electrical and Electronic Engineering (EIConRus), 2019, pp. 2222-2225, doi: 10.1109/EIConRus.2019.8657324.
9. M. Goto and T. Goto, "Performance Improvement of Blind Image Restoration Using Ringing Removal Processing," 2019 IEEE 8th Global Conference on Consumer Electronics (GCCE), 2019, pp. 139-140, doi: 10.1109/GCCE46687.2019.9015431.
10. T. Ueda, K. Yamada and Y. Tanaka, "Underwater Image Synthesis from RGB-D Images and its Application to Deep Underwater Image Restoration," 2019 IEEE International Conference on Image Processing (ICIP), 2019, pp. 2115-2119, doi: 10.1109/ICIP.2019.8803195.
11. J. Lu, F. Yuan, W. Yang and E. Cheng, "An Imaging Information Estimation Network for Underwater Image Color Restoration," in IEEE Journal of Oceanic Engineering, vol. 46, no. 4, pp. 1228-1239, Oct. 2021, doi: 10.1109/JOE.2021.3077692.
12. W. Pan, H. Li, Y. Jia, X. Jia and H. Jiang, "Image Restoration and Evaluation Based on Saliency Detection," 2021 IEEE International Conference on Poauthorr Electronics, Computer Applications (ICPECA), 2021, pp. 770-772, doi: 10.1109/ICPECA51329.2021.9362586.
13. C. He and Z. Zhang, "Restoration of Underwater Distorted Image Sequence Based on Generative Adversarial Network," 2019 IEEE 8th Joint International Information Technology and Artificial Intelligence Conference (ITAIC), 2019, pp. 866-870, doi: 10.1109/ITAIC.2019.8785496.
14. M. Bertoluzza, C. Paris and L. Bruzzone, "A Fast Method for Cloud Removal and Image Restoration on Time Series of Multispectral Images," 2019 10th International Workshop on the Analysis of Multitemporal Remote Sensing Images (MultiTemp), 2019, pp. 1-4, doi: 10.1109/Multi-Temp.2019.8866920.
15. J. W. Soh and N. I. Cho, "Variational Deep Image Restoration," in IEEE Transactions on Image Processing, vol. 31, pp. 4363-4376, 2022, doi: 10.1109/TIP.2022.3183835.
16. T. -O. Buchholz, M. Jordan, G. Pigino and F. Jug, "Cryo-CARE: Content-Aware Image Restoration for Cryo-Transmission Electron Microscopy Data," 2019 IEEE 16th International Symposium on Biomedical Imaging (ISBI 2019), 2019, pp. 502-506, doi: 10.1109/ISBI.2019.8759519.
17. R. P. Kumar, S. C. Neela, S. Reddy Murikinati, M. Reddy Yachavarapu and A. Reddy Gayam, "Image Restoration by Inverse Filtering," 2022 6th International Conference on Computing Methodologies and Communication (ICCMC), 2022, pp. 1227-1231, doi: 10.1109/ICCMC53470.2022.9754161.
18. [18] M. Zhang and C. Desrosiers, "High-quality Image Restoration Using Low-Rank Patch Regularization and Global Structure Sparsity," in IEEE Transactions on Image Processing, vol. 28, no. 2, pp. 868-879, Feb. 2019, doi: 10.1109/TIP.2018.2874284.
19. M. Yang, J. Hu, C. Li, G. Rohde, Y. Du and K. Hu, "An In-Depth Survey of Underwater Image Enhancement and Restoration," in IEEE Access, vol. 7, pp. 123638-123657, 2019, doi: 10.1109/ACCESS.2019.2932611.
20. V. Prasad, P. S. S. Kumar and S. Bachu, "Multilevel Pipelined Processing for Aerial Image Restoration," 2019 International Conference on Emerging Trends in Science and Engineering (ICESE), 2019, pp. 1-5, doi: 10.1109/ICESE46178.2019.9194619.
21. A. Taiwade, N. Gupta, R. Tiwari, S. Kumar and U. Singh, "Hierarchical K-Means Clustering Method for Friend Recommendation System," 2022 International Conference on Inventive Computation Technologies (ICICT), 2022, pp. 89-95, doi: 10.1109/ICICT54344.2022.9850852.
22. R. Baghel, P. Pahadiya and U. Singh, "Human Face Mask Identification using Deep Learning with OpenCV Techniques," 2022 7th

International Conference on Communication and Electronics Systems (ICCES), 2022, pp. 1051-1057, doi: 10.1109/ICCES54183.2022.9835884.

23. M. Ranjan, A. Shukla, K. Soni, S. Varma, M. Kuliha and U. Singh, "Cancer Prediction Using Random Forest and Deep Learning Techniques," 2022 IEEE 11th International Conference on Communication Systems and Network Technologies (CSNT), 2022, pp. 227-231, doi: 10.1109/CSNT54456.2022.9787608.
24. Singh, Upendra, Gupta, Puja, and Shukla, Mukul. 'Activity Detection and Counting People Using Mask-RCNN with Bidirectional ConvLSTM'. 1 Jan. 2022 : 6505 – 6520.
25. Gupta, P., Shukla, M., Arya, N., Singh, U., Mishra, K. (2022). Let the Blind See: An AIIoT-Based Device for Real-Time Object Recognition with the Voice Conversion. In: Al-Turjman, F., Nayyar, A. (eds) Machine Learning for Critical Internet of Medical Things. Springer, Cham. https://doi.org/10.1007/978-3-030-80928-7_8
26. Patidar, M., Singh, U., Shukla, S.K. et al. An ultra-area-efficient ALU design in QCA technology using synchronized clock zone scheme. J Supercomput (2022). https://doi.org/10.1007/s11227-022-05012-2
27. T. Kim, C. Shin, S. Lee and S. Lee, "Block-Attentive Subpixel Prediction Networks for Computationally Efficient Image Restoration," in IEEE Access, vol. 9, pp. 90881-90895, 2021, doi: 10.1109/ACCESS.2021.3091975.
28. H. Sheikh. (2005). Live Image Quality Assessment Database Release 2. [Online]. Available: http://live.ece.utexas.edu/research/quality
29. R. Franzen. (1999). Kodak Image Dataset. [Online]. Available: http://r0k.us/graphics/kodak/
30. 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,'' in Proc. 8th IEEE Int. Conf. Comput. Vis. (ICCV), vol. 2, Jul. 2001, pp. 416–423.
31. J.-B. Huang, A. Singh, and N. Ahuja, ''Single image super-resolution from transformed self-exemplars,'' in Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR), Jun. 2015, pp. 5197–5206
32. Mean Squared Error. https://math.tutorvista.com/statistics/mean-squared-error.html
33. Li, C.F. and Bovik, A.C. (2009) Three-Component Weighted Structural Similarity Index. Image Quality and System Performance VI, SPIE Proc. 7242, San Jose, CA, 19 January 2009, 1-9.
34. Deshpande, R.G., Ragha, L.L. and Sharma, S.K. (2018) Video Quality Assessment through PSNR Estimation for Different Compression Standards. Indonesian Journal of Electrical Engineering and Computer Science, 11, 918-924.