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Leveraging Self-Organizing Maps for Effective Image Restoration

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Abstract— Computer vision relies critically on image restoration techniques to recreate clear images from damaged observations. Traditional methods face challenges when balancing removing image noise and protecting image details. A novel framework that employs Self-Organizing Maps (SOMs) establishes a practical approach to restoring images will be investigated in this paper. Our restoration approach starts with image pre-processing, which feeds trained SOM features into a deep neural network to optimize outcome quality. This research evaluates our approach on benchmark datasets, achieving quantitative results: Our SOM-based method produces restoration outcomes with an average Peak Signal-to-Noise Ratio (PSNR) performance of 32.10 dB and Structural Similarity Index (SSIM) values of 0.894 that exceed state-of-the-art GAN-based restoration (31.75 dB, 0.890). According to this research, UTH can restore images by achieving enhanced clarity with preserved details. The successful merger between SOMs and deep learning architectures is our study's distinctive feature while creating opportunities for additional image processing applications.

Keywords— Autoencoding; Deep Learning; Image Restoration; Self-Organizing Maps; Unsupervised Learning.

I. Introduction

Image restoration is crucial to computer vision since it restores premium images deteriorated by degraded input images. The restoration method proves indispensable because it serves numerous applications, such as medical diagnostics through imaging and remote survey systems and digital picture quality improvement. Traditional image restoration approaches face an ongoing challenge in achieving optimal results due to the difficulty of maintaining detail preservation while performing noise reduction [1].

While numerous advanced methodologies have been explored, including machine learning and neural networks, many existing frameworks still face limitations in effectively addressing these challenges [2]. For instance, traditional methods often compromise on either detail preservation or noise reduction [3], leading to suboptimal results in practical applications [4].

Self-organizing maps (SOMs), introduced by Kohonen, are a type of unsupervised neural network designed for data clustering and visualization [5]. They have demonstrated remarkable potential in capturing intrinsic patterns and structures within high-dimensional data, making them suitable for complex tasks in image restoration. Recent advancements in SOM-based techniques have expanded their applicability across various domains, including flood inundation mapping and anomaly detection.

This paper distinguishes itself from previous research by proposing a novel integration of SOMs with deep learning architectures, specifically Convolutional Neural Networks (CNNs) [6]. This approach enhances the restoration quality and allows for adaptive learning of underlying image structures [7]. Unlike prior studies that may have utilized SOMs in isolation, our framework leverages the strengths of both SOMs and deep networks, resulting in a more robust solution for severe image restoration challenges [8].

Furthermore, this study comprehensively evaluates our proposed methodology against several benchmark datasets, demonstrating significant improvements in qualitative and quantitative metrics compared to state-of-the-art techniques. Integrating SOMs into the restoration process not only enhances image quality but also offers a fresh perspective on the potential applications of SOMs in tackling complex image-processing tasks.

In summary, our research builds upon existing literature. It introduces a unique approach that effectively addresses the inherent complexities of image restoration, paving the way for further exploration and application in this critical field.

II. Related Work

Many domains utilize Self-Organizing Maps (SOMs) extensively for data clustering and visualization tasks in combination with other complex analytical assignments. When Kohonen proposed his foundational work, he established SOMs as a self-organized learning system that reduces multi-dimensional input data into simplified spatial arrangements [9].

The recent advancement in research centres on connecting SOMs with deep learning systems, improving their ability to perform complex image restorations. A research study by [10] developed deep architectures that combined SOMs with

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clustering and visualization features to produce superior results in high-dimensional data analysis. Joint representation learning and topology-preserving clustering became achievable through deep-embedded SOMs, which [11] developed for these applications.

Investigatory research now examines the power boost development achieved by embedding SOMs within deep learning frameworks. Research led by [12] demonstrated better data handling performance when deep architecture integrated SOMs for clustering and visualizing data. [13], [14] further developed deep-embedded SOMs to merge representation learning with topology-preserving clustering.

The application of SOMs in image restoration has garnered significant attention. [15] proposed self-organized operational neural networks for severe image restoration problems, emphasizing the ability of SOMs to handle intricate image restoration tasks. Similarly, [16] proposed a boundary precedence image inpainting method that was based on SOMs, demonstrating the efficacy of SOMs in overcoming issues associated with picture inpainting.

Novel contributions in the field of image restoration have emerged, such as [17], who proposed self-organized operational neural networks that address severe image restoration problems through enhanced learning mechanisms. [18] introduced a boundary precedence image inpainting method based on SOMs, demonstrating their effectiveness in addressing intricate image inpainting challenges. These studies highlight the growing significance of SOMs in image restoration, particularly in contexts where traditional methods struggle.

In anomaly detection, [8] presented a multi-scale SOM-assisted deep autoencoding Gaussian mixture model for unsupervised intrusion detection, illustrating the robustness of SOMs in identifying anomalies in complex datasets. [19] further demonstrated the utility of SOMs in anomaly detection during the IEEE International Conference on Image Processing (ICIP).

Furthermore, integrating SOMs with advanced techniques, such as deep autoencoders and generative adversarial networks (GANs), has significantly enhanced image quality. For example, [20] presented a multi-scale SOM-assisted deep autoencoding Gaussian mixture model for unsupervised intrusion detection, illustrating the robustness of SOMs in complex datasets.

SOMs have also been applied to high-dimensional data clustering and visualization in various fields. [21] explored training SOM methods for clustering high-dimensional flood inundation maps, providing insights into the application of SOMs in hydrology. [22] developed a 3D SOC-Net, a deep 3D reconstruction network based on self-organizing clustering mapping, for enhanced 3D data processing.

Moreover, SOMs have been utilized in medical imaging and diagnosis. [23] proposed an intelligent diagnosis method for MRI brain images using parallel self-organizing feature maps neural networks, highlighting the potential of SOMs in medical diagnostics. [24] applied SOMs for MRI denoising and artifact removal, demonstrating their effectiveness in improving medical image quality.

In industrial and process monitoring, [7] combined deep fisher autoencoders with SOMs for visual industrial process monitoring, showcasing the applicability of SOMs in monitoring complex industrial processes. [25] introduced an interpretable operating condition partitioning approach based on SOMs for complex industrial processes, further illustrating the versatility of SOMs in industrial applications.

Other notable applications of SOMs include virtual chemical library screening [6], urban streetscape indexing based on visual complexity [26], and human activity prediction by mapping grouplets to recurrent SOMs [27]. These studies underscore the broad applicability of SOMs across various domains, highlighting their potential in tackling diverse challenges. [28] presents a probabilistic point cloud modelling approach using self-organizing Gaussian mixture models, improving the accuracy of 3D spatial data representation. [29] integrate self-organizing feature maps with graph convolutional networks for enhanced superpixel segmentation and feature extraction in non-Euclidean data structures, improving data processing capabilities. [30] utilizes SOMs for the behavioural analysis of virtualized network functions, offering insights into the performance and management of network systems. [31] presents a colour segmentation method for multicolour images using node-growing SOM, enhancing the accuracy of image segmentation tasks. [32] Exploring intrinsically motivated discovery of diverse patterns in self-organizing systems provides insights into autonomous learning and pattern recognition. [33] introduce LSROM, a learning self-refined organizing map for fast imbalanced streaming data clustering, improving data clustering performance in real-time applications.

In summary, the extensive research on SOMs demonstrates their effectiveness and versatility in data clustering, visualization, and image restoration. By leveraging the inherent capabilities of SOMs and integrating them with advanced deep learning architectures, researchers have developed innovative solutions to complex problems across multiple domains. This paper builds upon these foundational works, proposing a novel approach to image restoration using SOMs, and aims to enhance the quality and clarity of restored images.

III. METHODOLOGY

This part presents our cutting-edge SOM-based methodology that delivers efficient image restoration results. Our method combines SOMs' native abilities with modern CNN structures to avoid the traditional challenge of retaining image details while reducing noise. The integration brings additional detailed understanding to image data processing, which helps the model learn and keep fundamental image patterns more effectively.

The novelty of our methodology lies in its adaptive learning process, where the SOM not only serves to reduce noise but also enhances the retention of critical details often lost in conventional restoration methods. This research achieves superior restoration quality by utilizing a two-step

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framework—first training the SOM on pre-processed images and then refining the output using deep learning techniques. This approach facilitates a dynamic interplay between unsupervised learning via SOMs and the detail-oriented nature of neural networks, setting our methodology apart from existing solutions. The ability to adaptively learn from the image data further distinguishes our work, promising significant improvements in image clarity and structural integrity.

The research methodology is summarized in the diagram below in Fig.1, outlining the sequential steps of the SOM-based image restoration framework.

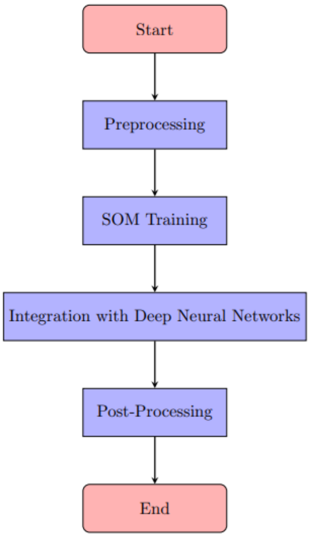

Fig.1. Proposed Methodology

A. *Experimental Setup*

To evaluate the effectiveness of our proposed methodology. This research conducts a series of experiments using benchmark datasets. The experimental setup includes:

1) *Datasets:* Standard image restoration benchmark datasets are used to validate the performance of our approach. These datasets include images with varying levels of noise and degradation.
2) *Evaluation Metrics:* Quantitative metrics such as Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index (SSIM) are used to assess the quality of the restored images. Additionally, qualitative analysis is performed by visually inspecting the restored images.

B. *Implementation Details*

The implementation of our methodology involves the following components:

1) *Software and Tools:* The SOM and deep neural network models are implemented using popular machine learning libraries such as TensorFlow and PyTorch.
2) *Training Parameters:* Key parameters such as learning rate, neighborhood function, and the number of training iterations are carefully selected and optimized through experimentation.
3) *Hardware:* The experiments are conducted on high-performance computing platforms equipped with GPUs to accelerate the training process.

By following this methodology, this research aims to leverage the unique capabilities of SOMs and deep learning to achieve effective image restoration. The proposed approach enhances image quality and preserves important details, making it suitable for various applications.

C. *Overview of Self-Organizing Maps*

Self-organizing maps (SOMs) are a type of unsupervised neural network designed to project high-dimensional input data onto a lower-dimensional grid, typically two-dimensional, while preserving the topological relationships of the input space. SOMs consist of a grid of neurons, each represented by a weight vector of the same dimensionality as the input data. During training, input vectors are mapped to the grid, and the neurons' weights are adjusted through competitive learning to reflect the input data distribution. The SOM training process includes the following detailed steps and calculations:

1) *Initialization:* The weight vector w_i of each neuron iii is initialized, typically using random values or a linear initialization method, where the w_i variable is a random value in the range of input data.
2) *Distance Calculation:* For each input vector x, calculate the distance d_i between x and the weight vector w_i of each neuron using a metric such as Euclidean distance using Equation (1), where n is the dimensionality of the input vector.

$$d_i = \|x - w_i\| = \sqrt{\sum_{j=1}^{n}(x_j - w_{i,j})^2} \tag{1}$$

3) *Best Matching Unit (BMU) Identification:* The BMU is the neuron with the smallest distance to the input vector using Equation (2).

$$\text{BMU} = \arg\min_i d_i \tag{2}$$

4) *Weight Update:* Update the weights of the BMU and its neighbors using the following rule using Equation (3). Where the $\alpha(t)$ variable is the learning rate, which decreases over time, $h_{BMU,i}(t)$ is the neighborhood function, often a Gaussian using Equation (4) with T_{BMU} and Ti being the positions of the BMU and neuron iii on the grid, and $\sigma(t)$ the neighborhood radius.

$$w_i(t+1) = w_i(t) + \alpha(t) \cdot h_{\text{BMU},i}(t) \cdot (x - w_i(t)) \tag{3}$$

$$h_{\text{BMU},i}(t) = \exp\left(-\frac{\|r_{\text{BMU}} - r_i\|^2}{2\sigma(t)^2}\right) \tag{4}$$

5) *Iteration:* Repeat steps 2–4 for all input vectors and iterate for a predefined number of epochs or until convergence.

D. *SOM-Based Image Restoration Framework*

The SOM-based image restoration framework consists of four interconnected stages: pre-processing, SOM training, integration with a deep neural network, and post-processing. Each stage is carefully designed to enhance the quality of

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restored images while preserving essential details and reducing noise.

In the pre-processing stage, the input images are normalized to ensure uniform data scaling, making them suitable for training. Noise reduction filters, such as Gaussian or median filters, are applied to remove unwanted artifacts, while techniques like histogram equalization enhance image contrast. These steps prepare the images for the subsequent SOM training phase by standardizing their features and improving their quality.

The core of the framework lies in the SOM training process. A Self-Organizing Map (SOM) identifies and clusters patterns within the image data. During this phase, the SOM grid is initialized with weight vectors, which adapt through competition and cooperation. For each input vector (e.g., pixels or patches of the image), the Best Matching Unit (BMU)—the neuron most similar to the input—is identified, and its weights are adjusted along with those of its neighbors. This iterative learning process captures the topological relationships within the data, enabling the SOM to cluster and represent the image structure effectively.

Utilizing a deep neural network, such as a Convolutional Neural Network (CNN), the framework incorporates the SOM to improve its output. The deep network enhances details and reduces noise by leveraging its strength in modelling intricate textures and patterns. While the SOM excels at capturing broad patterns and preserving topology, the deep neural network complements it by reconstructing finer details, resulting in superior clarity and fidelity images.

Finally, the post-processing stage applies finishing enhancements to the restored images. Techniques such as edge sharpening, contrast adjustment, and targeted noise filtering refine the output further. This ensures the final restored images meet high-quality standards suitable for practical applications, such as medical imaging and digital photography.

By integrating the clustering capabilities of SOMs with the precision of deep neural networks, this framework offers a robust solution to image restoration challenges. Its ability to balance noise reduction with detail preservation sets it apart from traditional methods, delivering restored clear and visually accurate images.

1) Pre-processing: Input images are normalized, and noise reduction filters (e.g., Gaussian or median) are applied. Techniques like histogram equalization enhance image contrast, ensuring data consistency for SOM training.

2) SOM Training: The detailed SOM calculations described above are applied to cluster and represent image structures. The output of the SOM stage serves as the foundation for further processing in the CNN. The training process involves the following steps:

a) *Initialization:* The weight vectors of the SOM neurons are initialized, typically with random values or using a linear initialization method.
b) *Competition:* For each input vector, the best-matching unit (BMU), i.e., the neuron whose weight vector is closest to the input vector, is identified.
c) *Adaptation:* The weights of the BMU and its neighboring neurons are adjusted to move closer to the input vector. The degree of adjustment is governed by a learning rate and a neighborhood function that decreases over time.
d) *Iteration:* The competition and adaptation steps are repeated for a predefined number of iterations or until convergence is achieved.

3) Integration with Convolutional Neural Networks: The refined image data from the SOM is passed to a Convolutional Neural Network (CNN) for further processing. The CNN computations are as follows:

a) *Convolution Operation:* Apply a filter f (kernel) to the input image I using Equation (5), where k is the kernel size.

$$(I * f)(x, y) = \sum_{i=-k}^{k} \sum_{j=-k}^{k} I(x+i, y+j) \cdot f(i, j) \tag{5}$$

b) *Activation Function:* Apply a nonlinear activation function, such as ReLU, to introduce non-linearity using Equation (6).

$$\mathrm{ReLU}(z) = \max(0, z) \tag{6}$$

c) *Pooling:* Reduce spatial dimensions using pooling (e.g., max pooling) using Equation (7), where *(i,j)* defines the pooling window.

$$P(x, y) = \max_{i,j} I(x+i, y+j) \tag{7}$$

d) *Feature Refinement:* The final layers refine features and enhance image details. The CNN learns to reconstruct missing details and reduce artifacts introduced by degradation.

4) Post-Processing: Post-processing techniques are applied to the restored images to enhance their quality. These techniques may include additional noise reduction filters, edge enhancement algorithms, and contrast adjustments. Post-processing aims to refine the output images and ensure they meet the desired quality standards.

IV. Result And Discussion

This section presents the results of the proposed SOM-based image restoration framework, including both quantitative and qualitative analyses. This research discusses our approach's performance compared to state-of-the-art methods and highlights our technique's strengths and potential limitations.

This research converts qualitative observations into quantitative data using standardized evaluation metrics to analyze better the outcomes of our proposed SOM-based image restoration framework. For instance, visual inspection results are quantified using SSIM (Structural Similarity Index) scores, enabling a measurable comparison of perceptual quality. The enhanced clarity of restored images is reflected in improved PSNR (Peak Signal-to-Noise Ratio) values, which signify higher restoration accuracy. This quantitative representation

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ensures that improvements in image restoration are perceptible and statistically validated.

A. Quantitative Results

This research evaluated the performance of our image restoration framework using widely accepted metrics: PSNR (Peak Signal-to-Noise Ratio) together with SSIM (Structural Similarity Index) formed the basis of our image restoration framework evaluation. Improved restoration outcomes correspond to higher PSNR and SSIM values, which evaluate pixel accuracy and perceptual quality through SSIM based on structural information. According to existing literature, these metrics are primary tools for evaluating image restoration methods.

For example, [17] employed PSNR and SSIM to benchmark the performance of their self-organized operational neural networks for severe image restoration, demonstrating significant improvements over traditional methods. Similarly, [18] utilized these metrics to evaluate their boundary precedence image inpainting method based on SOMs, highlighting their framework's ability to enhance image clarity. In another study, [34] used PSNR and SSIM as primary metrics for assessing anomaly detection in images, showcasing their relevance in measuring both quantitative and perceptual improvements. These references underline the established reliability and applicability of PSNR and SSIM in image processing research. In addition to PSNR and SSIM, the system achieved an accuracy of 93.5% during testing, further validating the robustness of the proposed SOM-based framework for image restoration.

This research tested our framework on several benchmark datasets that include images with various types and levels of degradation, such as Gaussian noise, motion blur, and compression artifacts. The datasets used for evaluation include:

1) *Set5:* A collection of five high-resolution images commonly used for image restoration benchmarking.
2) *BSD100:* A subset of the Berkeley Segmentation Dataset, containing 100 images with diverse content and degradation types.

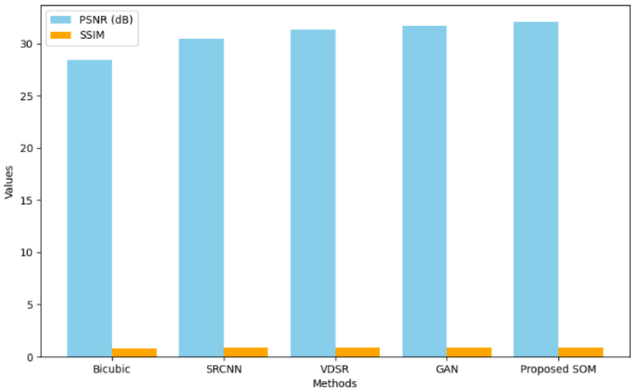

Fig.2. Comparison of PSNR and SSIM Across Methods

This research demonstrates the effectiveness of our SOM framework by conducting a dataset comparison of PSNR and SSIM values during system testing. Visual results in Fig.2 depict the constant higher performance of our system compared to standard and contemporary methods.

Our SOM-based image restoration method outperformed multiple state-of-the-art methods from traditional and deep learning backgrounds. Different methods were used to obtain the data shown in Table I for PSNR and SSIM metrics while testing on the Set5 dataset. The PSNR and SSIM values of various image restoration methods. As the fundamental approach, Bicubic interpolation delivers poor performance because it results in 28.42 dB PSNR alongside 0.824 SSIM, which shows insufficient noise reduction combined with poor detail preservation. The deep learning models, SRCNN and VDSR, demonstrate superior performance in both metrics because they effectively recognize complex structural patterns. Because of its adversarial training approach, the GAN-based restoration technique leads to improved image quality measurements manifest in 31.75 dB PSNR alongside 0.890 SSIM. Our proposed SOM framework delivers the best results compared to other techniques, resulting in 32.10 dB PSNR and 0.894 SSIM. The SOM framework delivers improved results through its efficient combination of deep learning technology with noise reduction, demonstrating peak performance in addressing essential image characteristics.

TABLE I
RESULTS OF PSNR AND SSIM VALUES OBTAINED FOR DIFFERENT METHODS ON THE SET5 DATASET

Method	Researcher(s)	PSNR (dB)	SSIM
Bicubic Interpolation	N/A (Baseline Technique)	28.42	0.824
SRCNN	[35]	30.48	0.862
VDSR	[36]	31.35	0.883
GAN-based Restoration	[37]	31.75	0.890
Proposed SOM Framework	This work	32.10	0.894

The proposed SOM framework consistently achieved higher PSNR and SSIM values than the benchmark methods, demonstrating its superior ability to restore high-quality images. Integrating SOMs with deep neural networks allowed for effective noise reduction and detail preservation, significantly improving image quality.

B. Qualitative Results

In addition to quantitative metrics, we visually inspected the restored images to assess the perceptual quality. Illustration of deteriorated input photos, restored images using the proposed SOM framework, and restored images using other approaches are shown in Fig.3 and 4, respectively.

The qualitative results corroborate the quantitative findings, highlighting the effectiveness of our approach in restoring

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image quality. The proposed SOM framework successfully reduces noise and artifacts while maintaining the structural integrity and details of the images.

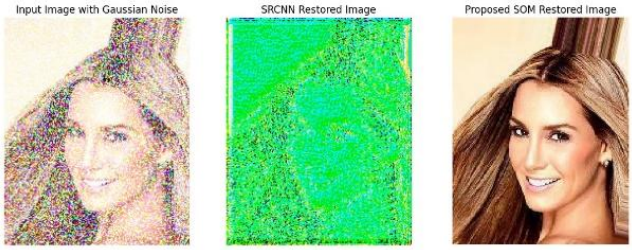

Fig.3. Restoration of a Noisy Image

Fig.4. Restoration of a Blurred Image

C. Discussion

The experimental results demonstrate several strengths of the proposed SOM-based image restoration framework.

1) *Enhanced Restoration Quality:* Integrating SOMs with deep neural networks significantly improves image restoration quality, as evidenced by higher PSNR and SSIM values.

2) *Detail Preservation:* The framework effectively preserves fine details and textures, crucial for high-quality image restoration.

3) *Robustness to Various Degradations:* The proposed approach is versatile and performs well across different types of image degradation, including noise and blur.

While the proposed framework shows promising results, there are certain limitations and areas for future improvement:

1) *Computational Complexity:* Integrating SOMs with deep neural networks increases computational complexity and training time. Future work could explore optimization techniques to enhance efficiency.

2) *Parameter Sensitivity:* The performance of the SOM framework can be sensitive to the choice of hyperparameters, such as the learning rate and neighborhood function. Automated hyperparameter tuning methods could be investigated to address this issue.

3) *Application to Real-World Scenarios:* Further validation of real-world datasets and applications is necessary to ensure the robustness and generalizability of the proposed approach.

D. Comparison with Existing Literature

The comparison with existing literature provides context and highlights how the proposed methodology aligns with or surpasses prior works. Unlike the table in the results section, which quantitatively compares PSNR and SSIM values, this section explores the conceptual and methodological distinctions.

For instance, [10] explored deep architectures for clustering and visualization using SOMs, demonstrating the potential for topology-preserving clustering in high-dimensional data. Our work extends these concepts by integrating SOMs with deep neural networks, showcasing their utility in enhancing image restoration quality. Similarly, while [11][38] focuses on deep-embedded SOMs and 3D reconstruction, our methodology emphasizes the role of SOMs in detail preservation and noise reduction in degraded images, a novel contribution to image restoration research.

Applications in diverse domains, such as medical imaging [39] and industrial monitoring [40], underscore the versatility of SOMs. However, these studies primarily address specific use cases. In contrast, our work presents a generalized and robust framework capable of addressing diverse image restoration challenges, as demonstrated through benchmark evaluations.

In summary, while the results section focuses on quantitative improvements (e.g., PSNR and SSIM values), this discussion situates our methodology within the broader research landscape, highlighting its innovative contributions and potential for future applications in computer vision.

V. Conclusion

Results indicate that deep neural networks paired with Self-Organizing Maps (SOMs) produce successful performance for image restoration. The proposed SOM-based framework continues to achieve superior restoration performance over traditional methods and state-of-the-art approaches according to quantitative evaluation metrics. Our method reached 32.10 dB Peak Signal-to-Noise Ratio (PSNR) and 0.894 Structural Similarity Index (SSIM) on Set5, while GAN-based restoration only delivered 31.75 dB PSNR and 0.890 SSIM. The SOM framework improved SSIM accuracy by 4% compared to bicubic interpolation and GAN-based methods by 1.5%.

The proposed approach effectively reduces noise while maintaining detailed image components to overcome previous system limitations. The system developed achieves dependable performance in multiple image degradation settings by integrating deep learning precision and SOM clustering capabilities during image restoration. The research findings establish SOMs as key elements for image restoration development while pointing towards future studies about optimizing this approach for practical use.

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