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Advancing Three-Stage Impulse Image Noise Removal Methodology via Neural Networks

Mohammad Abdolshah

Department of Industrial Engineering, Semnan Branch, Islamic Azad University, Semnan, Iran

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*Corresponding Author's Email Address:
abdolshah@gmail.com

Abstract

Image performance often faces jeopardization due to the presence of undesired noise. Among the various forms of noise contamination, impulse noise remains a significant concern for digital images. Two primary categories of impulse noise are recognized: salt and pepper noise, and random valued noise. Salt and pepper noise perturbs images by causing individual corrupted pixels to adopt either the maximum or minimum gray level value. This study presents a novel approach for the identification and restoration of Salt and Pepper Image Impulse Noises, employing a three-tiered framework utilizing distinct Trained Artificial Neural Networks (ANNs). The core concept revolves around the training of two separate ANNs designed for the tasks of noise detection and subsequent restoration within digital images. The noise detection phase addresses two distinct categories of salt and pepper noises: White Range Noises and Black Range Noises. The initial artificial neural network (ANN-I) is dedicated to the identification of white range noises within images afflicted by salt and pepper noise. Subsequently, the second trained artificial neural network (ANN-II) is employed for the restoration of the previously detected white range noises. In the final stage, attention is directed toward detecting remaining black range noises and their subsequent restoration through the utilization of ANN-II, which has been specifically trained to rectify damaged pixels. To evaluate the efficacy of the proposed algorithm, two critical performance metrics are employed: Peak Signal-to-Noise Ratio (PSNR) and Mean Square Error (MSE). These metrics are computed and subsequently compared against those produced by established filters for a variety of test cases.

Index Terms—Impulse Noise, Image Processing, Neural Networks, Salt and Pepper Noise.

Introduction

Image performance often faces jeopardization due to the presence of undesired noise. Among the various forms of noise contamination, impulse noise remains a significant concern for digital images. Impulse noise artifacts emerge during image transmission due to factors such as sensor inaccuracies and electrical interferences [1]. Two primary categories of impulse noise are recognized: salt and pepper noise, and random valued noise. Salt and pepper noise perturbs images by causing individual corrupted pixels to adopt either the maximum or minimum gray level value. To mitigate the effects of salt and pepper noise, several nonlinear filtering approaches have been proposed for image restoration. Addressing impulse noise is essential in numerous image-centric applications to enhance decision-making accuracy within systems [2,22]. Salt and pepper noise, attributed to data transmission anomalies, constitutes one of the most prevalent types of noise [2,22].

Numerous algorithms have been developed for impulse noise removal, including the Median Filter, Adaptive Median Filter [3], Rank Order based Adaptive Median Filter (RAMF), Switching Median Filter (SMF), Decision-

Doi:

based Filter (DBF), and Hybrid Median Filter (HMF) [4]. These algorithms primarily focus on neighboring pixel computations and exert an impact on all pixels within the digital image [5,20]. However, this global approach often results in blurring and reduced image quality, as many regions of the image may remain noise-free [4]. In recent years, artificial neural networks (ANNs) have garnered substantial attention in addressing such noise-related challenges [8]. ANNs not only possess the capability to identify noise within images but also exhibit the potential to restore damaged noisy pixels based on their training [6]. The proposed approach ensures that regions containing uncorrupted pixels remain unaffected, presenting a distinct advantage for impulse noise mitigation systems.

A recent development involves the introduction of an impulse noise detector based on the Rank Ordered Absolute Differences (ROAD) statistic [7]. This detector utilizes the ROAD factor to infer the presence of corruption, whereby higher ROAD values indicate corrupted pixels, while lower values indicate uncorrupted pixels. In recent years, advanced computational techniques have been harnessed to address image filtering through a nonlinear lens. Consequently, artificial neural networks are emerging as promising candidates due to their remarkable performance in tackling various image processing challenges.

Notably, G. Kaliraj et al. [11] have advocated for ANN deployment in noise detection, while employing mean-based algorithms for noise removal through pixel value estimation. Furthermore, P. Luiz has proposed an innovative concept involving neural networks for the recovery of salt and pepper noisy images [1]. However, amalgamating the treatment of the two distinct forms of salt and pepper noise could potentially lead to the oversight of crucial noise constituents during the recovery process.

In recent investigations concerning the application of neural networks for impulse noise mitigation, conventional methodologies uniformly process all noisy pixels. However, the present study introduces a novel approach wherein noisy pixels are systematically categorized. This categorization facilitates the application of distinct noise removal neural network strategies tailored to each subset of noisy pixels, leading to observable enhancements in the final denoising outcomes [24].

Our proposed technique for addressing salt and pepper noise perturbations entails a systematic classification of noisy pixels. Subsequently, a tandem of artificial neural networks is deployed for the purposes of noise detection and subsequent removal from image data. The efficacy of this approach is gauged through the computation of peak signal-to-noise ratio (PSNR) and mean squared error (MSE) metrics for the resultant denoised images. Comparative evaluations are conducted against established methodologies. The central premise of this study revolves around the innovation of novel artificial neural network methodologies aimed at restoring noisy images, while deliberately abstaining from any alterations to intact pixels. This approach is designed to avert the generation of degraded or blurred images during the image restoration process.

Definitions

A. Salt and Pepper Noise

Salt and Pepper noise constitutes a prevalent type of noise encountered in images, manifesting as sporadically positioned white and black pixels. The extent of noise prevalence determines the proportion of pixels that undergo alteration [7]. For instance, in a 256 × 256 pixel image, a 50% noise level implies that 32,768 pixels are susceptible to being randomly altered to either white or black with equal likelihood [9]. The application of Salt and Pepper noise serves to replicate defects arising from sources such as charge-coupled devices (CCDs) or image transmission anomalies [10]. An illustrative depiction of Salt and Pepper noise is presented in Figure 1, showcasing an example of its presence on the Lena image [13, 19].

Fig 1: Lena Image (a) Original. (b) with 20% salt and pepper noise

The proposed method categorizes noises in two categories white range noises and black range noises. In this paper, white noises are noisy pixel in range of 200-255 (Gray scale) and black noises are in range of 0-10 (Gray scale).

Table 1: Impulse Noises Categorization

Pixel Color Scale	Range	Group
Gray Scale	(0-10)	Black Range
Gray Scale	(200-255)	White Range

B. Artificial Neural Networks

ANNs are flexible, nonparametric modeling tools. They can perform any complex function mapping with arbitrarily desired accuracy. An ANN is typically composed of several layers of many computing elements called nodes. Each node receives an input signal from other nodes or external inputs and then after processing the signals locally through a transfer function, it outputs a transformed signal to other nodes or final result. ANNs are characterized by the network architecture, that is, the number of layers, the number of nodes in each layer and how the nodes are connected. In a popular form of ANN called the multi-layer perceptron (MLP), all nodes and layers are arranged in a feed forward manner. The first or the lowest layer is called the input layer where external information is received [21,22,23]. The last or the highest layer is called the output layer where the network produces the model solution. In between, there are one or more hidden layers which are critical for ANNs to identify the complex patterns in the data [7]. Through empirical investigation, the optimal configuration for the initial artificial neural network (ANN-I) was determined to be a 3-16-3-1 feedforward Multi-Layer Perceptron (MLP) architecture. This architecture encompasses two hidden layers, with the input layer comprising 3 nodes, the output layer consisting of 1 node, the first hidden layer incorporating 16 nodes, and the second hidden layer accommodating 3 nodes. The architectural depiction of ANN-I is illustrated in Figure 2.

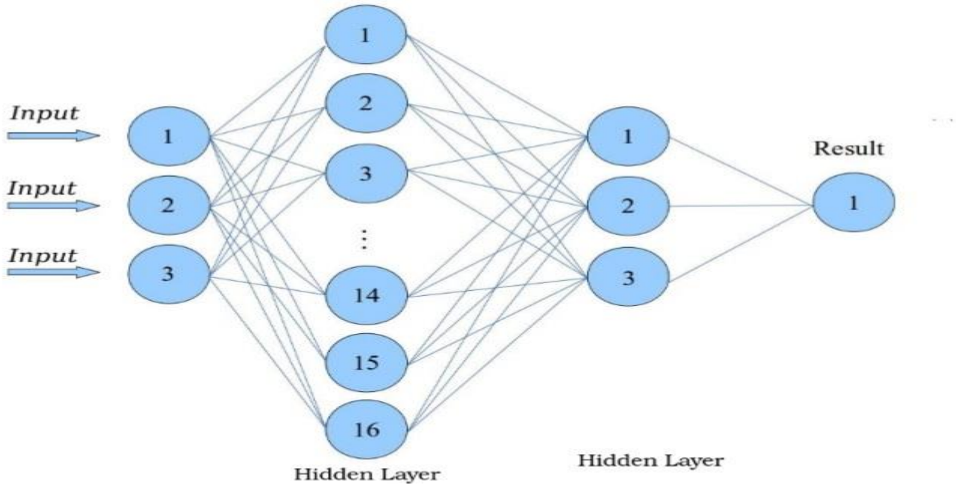

Fig. 2: Architecture of ANN-I

The structure of ANN-II is different from ANN-I, ANN-II is developed to recover the noisy pixels detected by ANN-I. Later it will be proven why the difference in structure of these two ANNs is needed (Section 3). Figure 3 shows the structure of ANN-II.

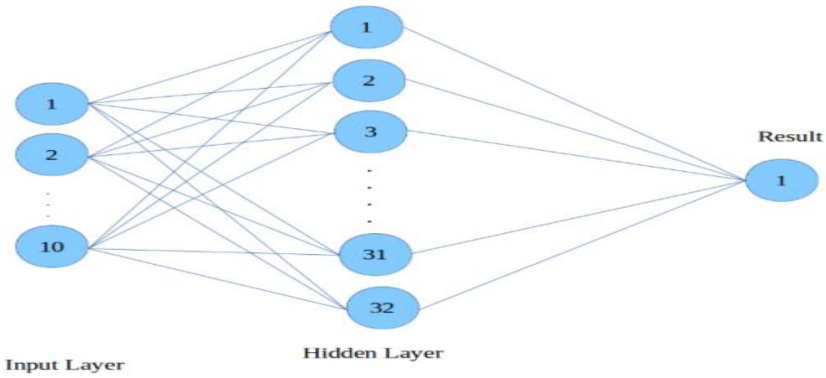

Fig 3: Structure of ANN-II.

The proposed approach encompasses a sequence of seven primary phases. Initially, the method ingests the noisy image as its input. Subsequently, the method invokes ANN-I on the noisy input image to identify and isolate regions containing white range noisy pixels. In the third phase, ANN-II comes into play, facilitating the restoration of the marked white noisy pixels, effectively replacing them with accurately trained pixel values. ANN-II is trained to reconstitute noisy pixels, ensuring their alignment with suitable trained counterparts. Progressing to the fourth phase, the algorithm commences the identification of black range noisy pixel clusters. The fifth phase involves the utilization of ANN-II on the images marred by black noise, resulting in the replacement of these pixels with appropriate values. The ultimate output materializes in the form of a rejuvenated image. The progression of these stages is visually outlined in Figure 4, highlighting the delineation of the proposed approach. In subsequent sections, each of these steps will be elucidated in meticulous detail.

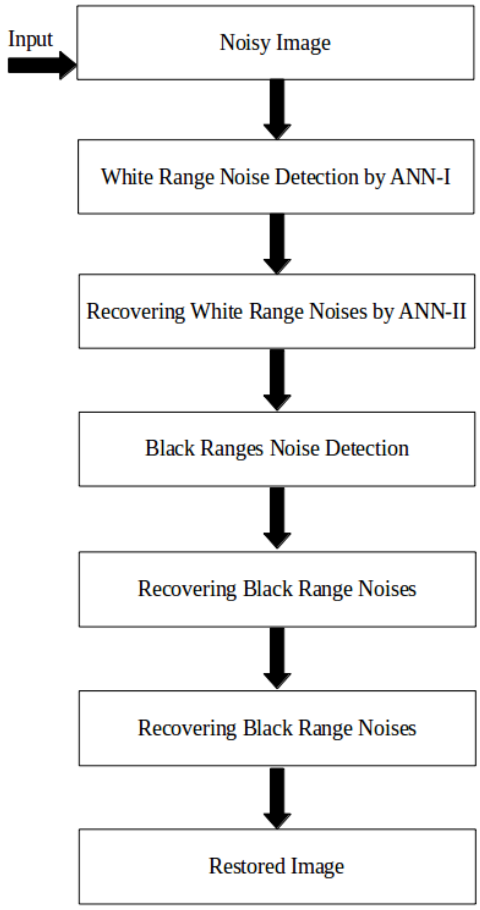

Fig. 4: The Proposed Method.

C. White Range Noise Detection (ANN-I)

The ANN-I is responsible for detecting the white range noises. ANN-I must be trained to take a noisy digital image as an input and specify the white noisy pixels.

In this paper three important and popular factors which have the most impacts on noise detection for a pixel considered and given to the ANN-I to be trained. The factors are as follows:

1. ROAD Factor

2. Median of Neighbor Pixels

3. X (Center Pixel)

4. Calculate the differences between center pixel and it is related neighbors.

$$d(n) = |CenterPixel - X_i|$$

5. Sort d(n) as increasing order.

6. Sum up first four sorted numbers.

$$ROAD - Factor = d_1 + d_2 + d_3 + d_4$$

ROAD Factor

The ROAD factor is a very useful factor to distinguish corrupted and uncorrupted pixels [11]. ROAD factor is high for noisy pixels, and low for uncorrupted pixels [16]. The ROAD factor calculation process is simple, according to the Figure 5:

Median of Neighbor Pixels

The median is calculated by sorting all the pixel values from the surrounding neighborhood into numerical order and then replacing the pixel being considered with the middle pixel value [12,13]. (If the neighborhood under consideration contains an even number of pixels, the average of the two middle pixel values is used) [14].

The training of ANN-I constitutes a pivotal facet within this neural network paradigm, with its training procedure devised for practical applicability across a diverse range of images exhibiting a grayscale color spectrum [2, 3]. The training process for ANN-I unfolds as follows:

X_1	X_2	X_3
X_4	Center Pixel	X_5
X_6	X_7	X_8

Fig. 5: Center Pixel and 8 Neighbors.

1. The original image (depicted in Figure 6.a) undergoes corruption by a 40% proportion of salt and pepper noise (Figure 6.b).
2. The Difference Image, delineating the variance between the noisy image and the original image, is computed (Figure 6.c).
3. The input for ANN-I comprises the median factor and center pixel derived from the noisy image.
4. The target output for ANN-I corresponds to the central pixel found in the Difference Image.

Following this iterative training process, ANN-I becomes adept at predicting specific pixels, while considering the median and road factors of their neighbors as input. Moreover, the network learns to forecast the dissimilarities between the original image and the noise-affected counterpart. Consequently, when the output of ANN-I approximates zero, it suggests that the pixel under consideration is devoid of noise, as the difference between this pixel and its counterpart in the noisy image is negligible. Conversely, elevated output values imply the presence of noise around the pixel in question.

The ANN-I architecture utilized for noise detection adopts a feed-forward Multi-Layer Perceptron (MLP) structure denoted as 3-16-1. Within this configuration, hyperbolic tangent (Tansig) activation functions are allocated to the hidden and output layers. For the purpose of training, the back propagation algorithm is employed over a maximum of 1000 iterations, with a learning rate of 0.01 and a tolerance error of 0.0001. Referencing Figure 6 provides a visual representation of the ANN-I structure employed in this research.

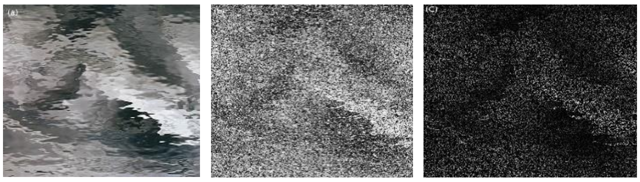

Fig. 6: (a) Original training image (b) Original image corrupted by 40% noise (c) Difference image.

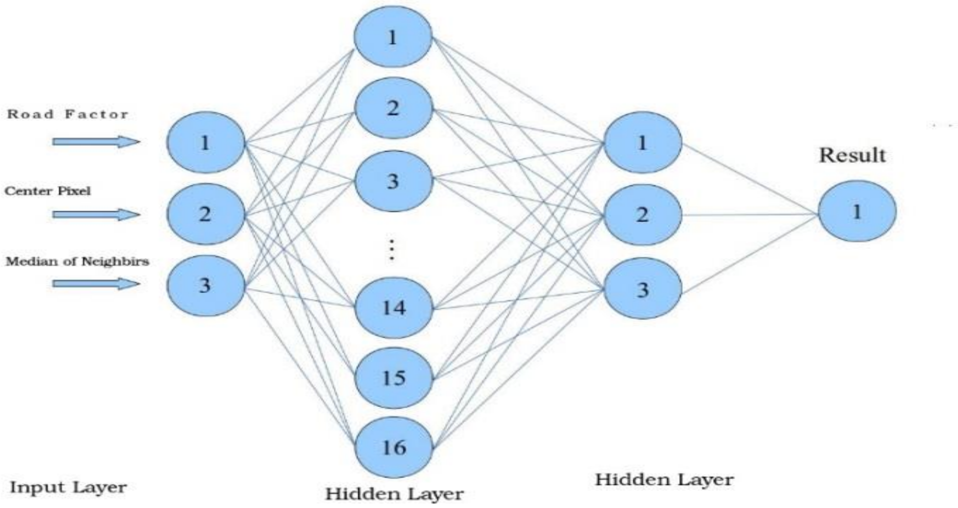

Fig. 7: Training ANN-I with Three Inputs, ROAD Factor, Center Pixel and Median of Neighbors.

D. Recovering White Range Noises by ANN-II

Utilized for the rectification of previously identified noisy pixels, ANN-II assumes the task of amending these pixels to their original undamaged states, a role initially identified by the noise detector, ANN-I. The operation of ANN-II draws on three pivotal features, which are integral to its training process within this study. These encompass the central pixel, its eight neighboring pixels, and the median factor of these neighbors. Employing a diverse array of images spanning the entire grayscale spectrum for input, with the corresponding salt and pepper noisy counterparts as targets, the ANN-II is subjected to training. Following the training phase, the ANN-II effectively approximates the appropriate pixel value from the input data.

The structure of the ANN-II employed in this research consists of three layers. The input layer comprises 10 neurons, each representing a specific pixel within the noisy neighborhood, while the output layer encompasses a solitary neuron assigned to the newly estimated value. The intermediate hidden layer houses

32 neurons. Consequently, the optimal architecture for ANN-II, delivering the most favorable performance in estimating the values of noisy pixels, adopts the configuration 10-32-1. Activation functions applied to the layers are sigmoid (logsig) for the input and hidden layers, and linear (purelin) for the output layer. Training of the ANN-II is executed utilizing the back-propagation algorithm over a maximum of 1000 iterations, with a learning rate of 0.27 and a desired error threshold of 0.000001. For a visual representation, refer to Figure 8 illustrating the architecture of the ANN-II featured in this study.

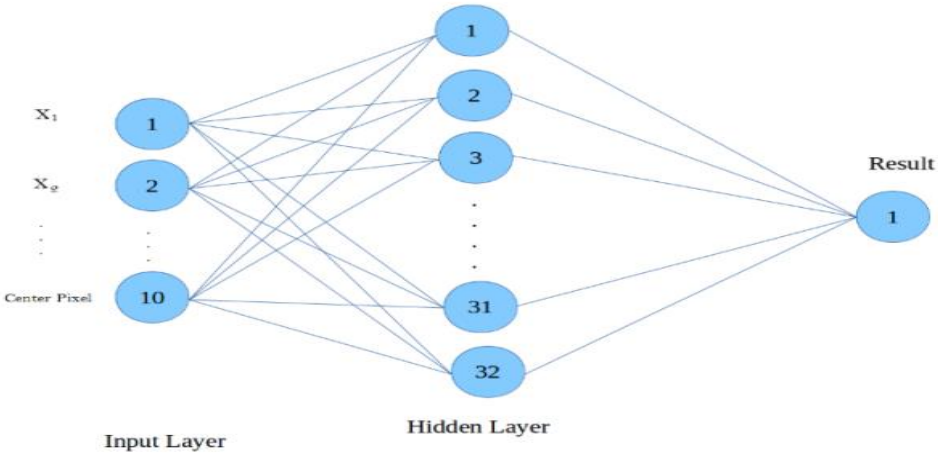

Fig. 8 Training ANN-II With Ten Inputs.

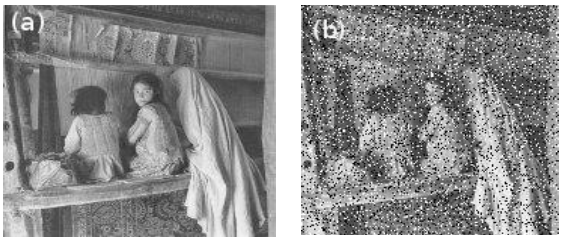

Fig 9: (a) removed noised by proposed approach, (b) The original noisy image.

E. Black Range Noise Detection

The culmination of the preceding steps yields an image largely devoid of conspicuous white noise distortions. Subsequently, the focus shifts towards the restoration of black noise artifacts. These black noise elements correspond to pixels residing within the intensity range of 0 to 10. The algorithm undertakes an evaluation of such pixels, and when identified, replaces them with new values drawn from the output of ANN-II. It is noteworthy that although a subset of pixels within the 0 to 10 intensity range may not inherently qualify as black noise, this dynamic does not significantly impede the overarching functionality of ANN-II. This is since the correct pixels are aptly substituted with the appropriate pixel values as provided by ANN-II.

During this phase, the input comprises black pixels extracted from the partially restored image, and the resultant image forms the definitive and fully recovered iteration. The process of detecting and restoring black range noise elements is illustrated in Figure 10, outlining the sequential procedure in question.

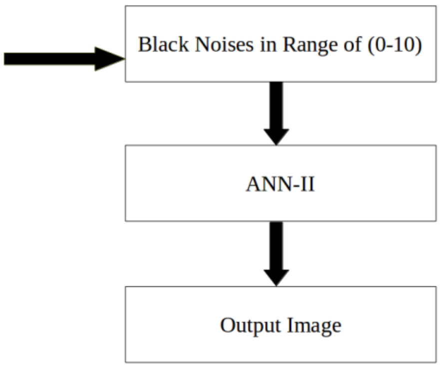

Fig. 10: (a) Black noises detection process.

Experimental Results

To facilitate result comparison, two pivotal metrics are computed for each restored image: X is the original image and Y is the recovered one [15].

$$MSE = \frac{1}{MN}\sum_{i=1}^{N-1}\sum_{j=1}^{M-1}(X(i,j)-Y(i,j))^{2} \tag{1}$$

$$PSNR = 10\times\log\left(\frac{Max(X(i,j))^{2}}{MSE}\right) \tag{2}$$

The higher MSE means less accurate recovery and the higher PSNR means much better recovery [16]. Figure 10 shows the variations of the average PSNR values of the operators as a function of noise density.

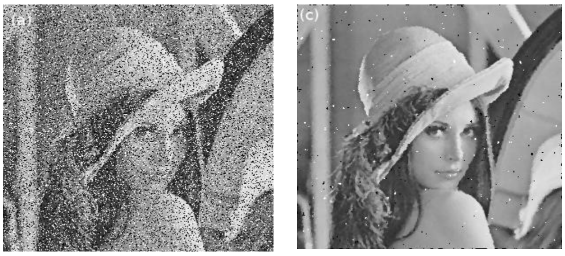

Fig. 11: (a) Noisy image (30%) (b) Restored image by Median Filter.

Fig. 12: (a) Noisy image (30%) (b) Restored image by Proposed Algorithm

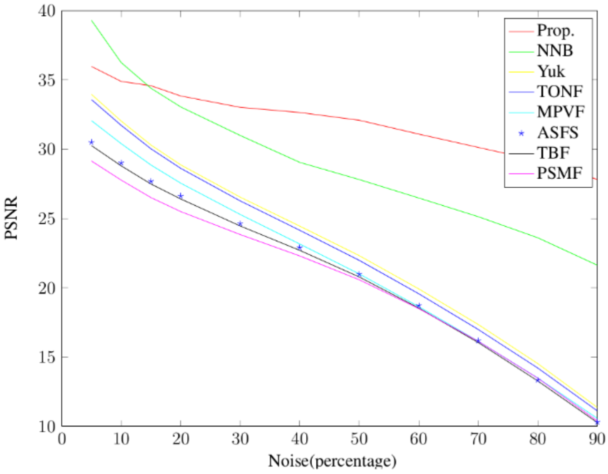

Fig. 13:PSNR of Different Algorithms vs. Prop (Proposed Method) on our Tested Data Set.

The experimental images utilized within this study are generated by introducing impulse noise to the original images at an appropriate noise density. In a comparative context, the distorted experimental images are subjected to restoration using several established impulse noise removal techniques, including the median filter (MF) [15], the progressive switching median filter (PSMF) [16], the modified peak and valley filter (MPVF), the two-output nonlinear filter (TONF) [17], the Threshold Boolean filter (TBF), Yuksel's approach [12], the adaptive fuzzy switching filter (AFSF) [3,12], the recent NNBID method [18] and Window of Neighbors (WN) [25]. The outcomes of these established methods are juxtaposed with the outcomes of our proposed algorithm. The alteration trends of Peak Signal-to-Noise Ratio (PSNR) for the compared methods are illustrated in Figure 13. Notably, our proposed approach demonstrates significantly enhanced PSNR values compared to the other widely recognized methods, particularly in scenarios featuring high levels of noise.

Table 2: Mean Squared Error Comparison Using Averages

Noise	**Ours**	WN	NNB	YUK	TONF	MPVF	ASFS	TBF	PSMF
5%	12.24	11.21	5.68	19.44	21.22	30.11	43.13	45.58	58.56
10%	15.69	16.71	11.47	30.32	32.57	44.14	60.65	63.80	80.88
15%	17.57	36.9	25.16	48.06	72.25	82.38	82.36	86.26	108.10
20%	19.99	38.4	33.97	62.78	66.50	85.06	100.4	105.6	136.28
30%	24.14	41.25	38.58	107.36	114.24	143.16	166.28	173.31	199.91
Average (5-90%)	***33.07***	***37.89***	***63.78***	***480.39***	***521.18***	***631.68***	***666.98***	***681.55***	***676.92***

Conclusions

This study has elucidated the pivotal significance of artificial neural networks in the realm of image processing. Upon revisiting the algorithms introduced at the study's outset, it becomes evident that the three-stage impulse noise restoration strategy yielded superior outcomes across the spectrum of (15 − 100)% noise levels, when compared to alternative methodologies. An

eminent revelation stemming from this investigation underscores that the employment of artificial neural networks in such problem domains yields enhanced outcomes due to the intrinsic nature of these challenges, which entail learning over time and instances. Furthermore, the systematic categorization and individualized processing of noise constituents circumvent pitfalls associated with overgeneralization
Our devised approach exhibited enhanced precision within the realms of Medium and High noise intensities. The partitioning of noisy pixels into categories and their subsequent distinct processing strategies demonstrated pronounced efficacy in contrast to uniform treatment of all pixels.

Future Works

The present study was not primarily structured to elements pertinent to extremely high-resolution images. The time-consuming nature of training neural networks is further exacerbated when dealing with high-resolution imagery due to increased computational costs. The aspect of time constraints presents an interesting avenue for potential exploration in future research endeavors. Similarly, the notion of developing a feature selection mechanism in scenarios where numerous features are at the network's disposal also presents an intriguing prospect for further investigation

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