AN OUTSTRETCHED EXPLORATION ON IMPULSE NOISE REDUCTION FOR TARNISHED IMAGES

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Abstract
Image de-noising is one of the most fundamental difficulties in image processing and computer vision, with the goal of estimating the original image by suppressing noise from a noise-contaminated version of the image. The need for more accurate pictures is steadily increasing, with the growth in the amount of digital images created every day. Many approaches for removing salt and pepper noise from various image types have been reported in the literature. This paper explores many de-noising techniques and investigates on noise reduction by considering the de-noising field's essential properties. This survey considers fifty papers in order to blow light on many de-noising techniques which helps young researchers to broaden up their knowledge. Since, for the vast majority of image processing applications, image de-noising is the principal task.
KEY WORD: Salt and Pepper noise, Image de-noising, Impulse noise reduction, Image enhancement, Noise removal

I. INTRODUCTION

The elimination of impulsive noise while maintaining the integrity of an image is a critical issue in image processing. Images degraded by noise leads to deteriorated visual image quality. Removal of randomly occurring impulses without disrupting edges, corners and other sharp structures is a basic signal processing requirement. Several ways for reducing noise have already been proposed by researchers. Each method has its own set of benefits and drawbacks. While considering medical images, noise in the acquisition or transmission is very common. The noise signal can be easily misinterpreted and results a considerable reduction in the fusion effect. To overcome this scenario a variation model for diagnostic medical image fusion and denoising has been developed [1]. De-noising is a technique for reducing image noise while retaining desirable details utilizing prior knowledge of the images [2]. De-noising images with Gaussian and Poisson noise has garnered a great deal of interest in the image processing field [3]. Discriminative learning-based de-noising methods have gotten a lot of attention and have been explored extensively due to their strong de-noising performance and much lower inference time compared to model-based de-noising approaches [4]. Filtering images from many channels is difficult both in terms of efficiency and efficacy. A simple transform-threshold-inverse strategic approach could generate hypercompetitive results by training a good global patch basis and a local principal component analysis transform in the grouping dimension [5]. The preponderance of contemporary image de-noising techniques is intended to enhance de-noising quality. Thus in terms of the amount of parameters and computational complexity, the framework can be extended to numerous existing approaches to enable them attain more competitive de-noising performance [6]. This paper provides a summary and/or a synthesis of the findings of selected research contributions being published by other researchers.

II A COMPENDIUM OF IMAGE DENOISING METHODS

This study considers fifty papers from different years starting from 1996 to 2021. Also by considering each technique in these papers, they have been categorized and fall in to groups like Deep learning and Neural network, Mean based filter, Median based filter, Fuzzy logic and Miscellaneous. Based on the noise ratio considered and also its PSNR values, the efficient and favorable noise reduction technique is identified.

A) Deep learning and Neural Network

H. Kong et al. [7] use a Neural Network Adaptive Filter (NNAF) for the removal of impetuous noise in digital images. The NNAF filter is used to eliminate the impulses, and pixel classification is utilized to detect the noisy pixels. It shows better performance than the traditional median type filters. But the shortcoming of this filter is its computational complexity due to its large dynamic window size.

Zhe Zhou [26] presents an Adaptive Detail-Preserving Filter (ADPF) based on the Cloud Model (CM) to remove impulse noise. An uncertainty-based detector is used in this filter to identify the pixels that have been distorted by impulse noise. The stumbling block of this method is that the edges may get a blur if the image has a high noise level and also it can detect only the fixed-valued impulse noise.

Fariborz Taherkhani et al. [37] provide a Radial Basis Functions (RBFs) interpolation-based approach for estimating the intensities of damaged pixels from their neighbors. The advantage of using this algorithm is that it restores images with higher visual quality, smoother edges, and better texture detail. The demerit of using this algorithm is that it fails to address Gaussian and Speckle noises.

Minghui Zhang et al. [38] put forth a data-driven algorithm for impulse noise removal via Iterative Scheme-Inspired Network (ISIN). The suggested network will not only change the focus from online optimization to an upfront offline training phase, but it will also be applied to all new data using the learnt parameters.

Lianghai Jin et.al [42] present an image recovery method based on deep convolutional neural network for impulse noise removal. In this de-noising framework, there are two deep CNNs: a classifier network and a regression network. The merit of this method is the better de-noising performance. But the pitfall is that the running time of this method is very high, also it has a higher computational complexity

Guanyu Li et al. [45] provide an approach for investigating the Densely Connected Network for Impulse Noise Removal (DNINR), a method for learning pixel-distribution properties from noisy images that use CNN. The goodness of this method is that it shows better performance on edge preservation and noise suppression. The pitfall of this method is that this scheme loses its glory when applied to other non-Gaussian noises like Poisson noise and Rician noise.

Chun Li et al. [56] divulge an impulse noise removal model (INRM) algorithm based on logarithmic image prior for medical image. Herein used the split Bregman iterative method to solve the objective function. The input used in this model are natural images and CT and MRI images. The goodness of this algorithm is that it is better than some existing classic algorithms for impulse signal removal. The downfall of this algorithm is that it fails to address the inverse problem such as image patching problems, image segmentation problems, image blending to noise.

XuYan et al. [58] developed Unsupervised Image De-noising algorithm based on Generative Adversarial Networks (UIDGAN). The model employs perceptual loss and cycle-consistency loss to ensure consistency of content information which is considered it to be its shinning side. The drawback of this method is that it considers many parameters which in turn increases its complexity and processing time.

B) Fuzzy logic

Stefan Schulte et al. [15] present an impulse noise reduction method called a Novel Fuzzy Impulse Noise Detection Method (NFIND) for color images. Color information is considered in this paper in order to design an improved impulse noise detection algorithm that filters just the corrupted pixels while maintaining color and edge sharpness. The pitfall of this method is that it fails to reduce α-stable (a mixture of Gaussian and impulse noise) efficiently. The use of an additive noise reduction method is not adequately examined in this method.

Kenny Kal Vin Toh et al. [22] develop a filter called, the Cluster-based Adaptive Fuzzy Switching Median (CAFSM) which consists of a detail-preserving noise filter and a cascading, easy-to-implement impulse detector. The advantages of the proposed CAFSM filter are its capability in handling realistic impulse noise model for real-world applications and the relatively fast runtime. The pitfall of this framework is that it loses its efficiency while using it for high-resolution images and huge noise level.

Sana Sadeghi et al. [25] present a method for impulse noise reduction from images using fuzzy cellular automata. The merit of this method is the Simplicity, robustness, parallel manner and distribution ability for noise enhancement using fuzzy cellular automata. The limitation of this approach is that the accuracy in detecting noisy pixel is less when testing with images with a high noise level.

U. Sahin et al. [30] put forth an image de-noising algorithm to restore digital images corrupted by impulse noise. It is based on two-dimensional cellular automata (CA) with the help of fuzzy logic theory. The approach describes a local fuzzy transition rule that assigns the next state value as a central pixel value and assigns a membership value to the corrupted pixel neighborhood. This filter has the benefit of being consistent and stable across a wide range of noise levels. The demerit of this filter is that it loses its efficiency while filtering high-resolution images.

Yi Wang et al. [33] present an adaptive fuzzy switching weighted mean filter to remove salt-and-pepper (SAP) noise. Noise detection and noise elimination are the two stages of the de-noising process. The first step is to provide a more precise mathematical expression for SAP noise. Second, in order to detect SAP noise, an enhanced maximum Absolute Luminance Difference (ALD) approach is devised.

Vikas Singh et al. [35] put forth an adaptive Type-2 fuzzy filter for removing salt and pepper noise from the images. The benefit of employing this technique is that the filter keeps important visual data even when there is a lot of noise. The stumbling block of using this technique is that the computational time increases drastically for the images which have a high noise level.

C) Mean based filter

Wei-Yu Han et al. [8] use the Minimum-Maximum Exclusive Mean (MMEM) filter, to remove impulse noise from highly corrupted images. This technique is preferable since it removes high impulse noises while simultaneously preserving image information. The pitfall of this filter is that it loses its efficiency when it is applied for other types of images other than grey images.

B. Smolka et al. [11] divulge a method, where a new class of filters for noise attenuation is introduced. It is considered to be the modified and improved version of Vector Median Filter (VMF) and its relationship with commonly used filtering techniques is also investigated. The root of the mean squared error (RMSE), peak signal to noise ratio (PSNR) and normalized mean square error (NMSE) were used for the comparisons The goodness of this method is that it has a low computational complexity. The flaw of this method is that it works efficiently only for a particular application, and less reliable. Also, the degradation of image quality is possible.

X.M. Zhang et al. [18] propose the Adaptive Switching Mean (ASM) filter to remove impulse noise. The filter uses conditional morphological noise detection to identify the corrupted pixels, and then uses the adaptive mean filter to eliminate the identified impulses. In terms of noise reduction and detail retention, this ASM filter surpasses many switching-based filters. The stumbling block of this filter is that, it is incompatible with high-resolution images.

Samsad Beagum Sheik Fareed et al. [36] present a mean filter for effectively removing salt and pepper noise from images with greater noise densities. In this method, the filter works under two stages like Impulse Detection and Restoration (IDR). The first stage finds the noisy pixels, whereas the second stage recovers the noisy pixels that have been identified. The advantage of employing this filter is that it consumes less time to compute than other adaptive filters. The disadvantage of this filter is its computational complexity

Qianqian Liu et al. [47] put forth a nonlinear Spline Adaptive Filter based on the Robust Geman-McClure estimator (SAF-RGM).Herein used the steady-state excess mean-square-error (EMSE) ζ to measure the performance of an adaptive filter. Also cost function based on Geman-McClure is used in this approach. The merit of using this filter is that it has a better stable performance against impulsive noise. The drawbacks of using this technique are that it has high time consumption and high computational complexity

Mustapha Bouhrara et al. [48] develop an efficient method for noise estimation and reduction in multispectral MR images. This filter is a multispectral extension of the nonlocal maximum likelihood filter (NLML) combining both spatial and spectral information. The goodness of this filter is that the Numerical and experimental analysis indicated the better performance for estimation of noise SD (Standard Deviation). The performance is limited in spatially heterogeneous regions, such as edges and small structures, where patch redundancy is relatively poor which mitigates its efficiency.

D) Median based filter

Zhou Wang et al. [9] use a Progressive Switching Median (PSM) filter to remove the impulsive noise and also retaining the integrity of the images. The merits of this method are that better results are obtained while using PSM filters. The stumbling block of this method is that it works only for grayscale images; hence it can't support other types of images. Also this filter holds high computational complexity.

F.J. Gallegos-Funes et al. [10] introduces The Median M-type K-nearest neighbour (MM-KNN) filter to remove the salt and pepper noise from highly corrupted images. The robust point of the pixels within the filtering frame is estimated by the filters.

Xiaoyin Xu et al. [12] present an adaptive two-pass rank order filter (ATPMF) which undergoes two-pass filtering operations to remove salt and pepper noise in highly corrupted images. The merit of this method is that the adaptive process detects irregularities in the spatial distribution of the estimated impulse noise at the same time the false alarm was also corrected efficiently. The main demerit is a high time consumption since the filtration method is done twice in this method.

Zhonghua Ma et al. [13] use a neighborhood evaluated adaptive vector filter (NEAVF) which utilizes a novel neighborhood evaluation process to improve the performance of noise detection and detail preservation. The main detriment of this method is the usage of a highly sophisticated filter that considers color images as an only input and loses its credibility while considering grayscale images.

K. S. Srinivasan et al. [16] propose a filter which uses a decision-based algorithm and non-linear signal processing technique (NLSP) for restoring heavily distorted images due to impulse noise by removing only corrupted pixel by the median value, or by it neighboring pixel value. The benefit of this filter is that, it prevents image blurring for large window sizes. This filter also performs consistently and reliably over a wide range of noise levels. This loses its efficiency while using switching window technique which heads to low performance

Zhengya Xu et al. [20] present a geometric features-based filtering technique called as the Adaptive Geometric Features Based Filtering Technique (AGFF) along with its restoration technique which is based on the modified median for the removal of impulse noise in corrupted color images. The goodness of this technique is that it provides a very reliable impulse noise type and ratio discrimination method. The pitfall of this technique is that it is not integrated with other benchmark techniques to suppress a mixed Gaussian and impulse noise contamination for color images which results in low performance.

Smaïl Akkoul et al. [21] propose an Adaptive Switching Median (ASWM) filter for removing impulse noise from distorted images. The benefit of ASWM is that no a priori Threshold is to be given as in the case of a classical SWM (Switching Median Filter) filter. Instead, using weighted statistics, the threshold is calculated locally from image pixel intensity values in a sliding window. The advantage of this filter is that, the psycho visual results are of high quality. The downside of this filter is that it has a fixed window size, which implies it cannot use the switching window technique.

Wei Wang et al. [24] present the framework of switching median filtering for removing impulse noise from corrupted images. In this method, the noisy pixels are distinguished by Local Outlier Factor incorporating with Boundary Discriminative Noise Detection (LOFBDND) algorithm. The advantage of this framework is that here the noise detection algorithm minimizes the miss detection rate and false detection rate. The drawback of this framework is that it will not support the huge noise level.

Iyad F. Jafar et al. [27] put forward a method with efficient Improvements on the Boundary Discriminative Noise Detection (BDND) Filtering Algorithm which is a popular switching median filter for the removal of high-density impulse noise. This filter is tweaked by removing the restriction on expanding the filtering window and incorporates the spatial information of the pixels in the filtering process.

Osama S. Faragallah et al. [32] describe an optimal method for suppressing salt-and-pepper (S&P) noise under the Adaptive Switching Weighted Median Filter (ASWMF) paradigm. The ASWMF includes noise detection and noise removal stages. The goodness of this technique is that it provides good performance for a wide set of images. The stumbling block of this method is that this method cannot be supportive of the huge noise level.

Jiayi Chen et al. [40] put forth an Adaptive Sequentially Weighted Median Filter (ASWMF) for images corrupted by impulse noise. The benefit of implementing this ASWMF is that it outperforms state-of-the-art filters when there is impulse noise. Furthermore, the computation time is really short. The stumbling block of this filter is that it is hard to be applied for real-time de-noising.

C. Jaspin Jeba Sheela et al. [44] present an Adaptive Switching Modified Decision Based Un-symmetric Trimmed Median Filter (ASMDBUTMF) for noise reduction in grayscale MR

Images which are affected by salt and pepper noise. The good point of this technique is that it can be used as a preprocessing method for scanning machines for better robustness against the noisy environment. The drawback of this method is that it cannot work efficiently for other types of images except MRI.
Golam Muktadir Mukti et al. [57] present a MatLab-based Noise Removal Technique (MNRT) for removing salt and pepper noise from brain MR image. The goodness of this technique is that this weighted median filter provides high quality images by removing salt and pepper noises. The drawback of this technique is that it loses its efficiency while working with the kernel size above three.

E) Miscellaneous

Igor Aizenberg et al. [14] put forth the impulse-detecting Boolean functions for detection and elimination of impulsive noises. This can be achieved by using single-pass filtering. The smoothing of edges and destruction of details are prevented, which can be considered as the merit of this method. The pitfall of this method is that the priority given for edge preservation. Hence, the textures are not preserved
Wenbin Luo et al. [17] present an algorithm called Impulse Noise Removal Algorithm (INRA) which can remove impulse noise from corrupted images while preserving image details. Impulse noise detection and impulse noise cancellation are the two steps followed in this algorithm. The goodness of this algorithm is the efficiency, and it requires no previous training. The demerit of this algorithm is that, it fails to support gray-scale images of high noise level.
Y. Shih et al. [19] present a convection diffusion equation for processing image de-noising, edge preservation and compression. In this method a PDE (Partial Differential Equations) based image restoration method called Convection diffusion equation is used for image de-noising. The implementation gains its merit by removing noise without using the nonlinear smoothing kernel which needs extra cost in solving the heat equation. The demerit of this method is that due to the implementation of highly sophisticated method the time consumption and computational complexity is very high.
S. Huang et al. [23] present an image restoration method (IRM) for removing salt-and-pepper noise. This method concentrates on the removal of salt-and-pepper noise, where the noisy pixels can take only the maximum and minimum values in the dynamic range. The goodness of this method is that it simplifies noisy pixels detection. The demerit of this method is that there is a possibility that some noise-free pixels may also be considered as noisy pixels.
Zayed M. Ramadan [28] presents a method for Impulse Noise Elimination and Edge Preservation (INEEP). In this paper, two impulsive noise models are applied to multiple images with various features, and a wide range of noise densities is explored. The benefit of this method is that it surpasses existing state-of-the-art methods in the literature of the image restoration field. The pitfall of this method is that there is a possibility of blurring of images because of high smoothing operation.
Umesh Ghanekar et al. [29] introduce an Impulse Detection Scheme (IDS) that detects all kinds of fixed-valued impulse noise and distinguishes between noisy and noise-free pixels of equal intensity levels. The difficulty of differentiating noisy pixels from noise-free pixels when their intensity levels are identical is addressed in this study in two steps by detecting fixed-valued impulse noise.
Ruixuang Wang et al. [31] provide a single-patch technique for detecting and removing nonpoint wise Random-Valued Impulse Noise within a generalized joint low-rank and sparse matrix recovery framework. The merit of this method is that it shows better performance on non-point wise RVIN. The method's limitations include that, while most image patches are low-rank after being properly orientated, there are a few patches that do not meet the low-rank assumption.
Qing-Qiang Chen et al. [34] illustrate an effective and adaptive algorithm called Noise Removal Algorithm (NRA) for removing pepper and salt noise. The algorithm contains noise-pixel-detection and noise-filtering processes. The advantage of this method is that it performs better in term of the PSNR (Peak Signal to Noise Ratio). The drawback of this approach is that it only supports grayscale images; thus, it cannot handle any other type of image, resulting in poor performance.
Ganzhao Yuan et al. [39] put forth a model in the field of regularization-based image processing. A new sparse optimization method, called `l0TV-PADMM, solves the (Total Variation) TV-based restoration problem with `l0-norm data fidelity. The benefit of utilizing this approach is that image de-noising and de-blurring difficulties in the presence of impulsive noise are better addressed. The stumbling block of this technique is that this technique cannot support efficiently high-resolution images.
Sonali et al. [41] present a noise removal and contrast enhancement algorithm for fundus image. Integration of filters and Contrast Limited Adaptive Histogram Equalization (CLAHE) technique is applied for solving the issues of de-noising and enhancement of color fundus images. The benefits of utilizing this technique include the removal of noise and the enhancement of contrast in fundus images. The demerit of this technique is that it works only for the Medical domain and restricted to fundus images
Xiaoqin Zhang et al. [43] put forth an Exemplar-based image de-noising algorithm (EIDA) which has shown better potential for image restoration. The goodness of using this algorithm is that it shows better potential for image restoration. The pitfall of this algorithm is that it is not dealt with multiple datasets. Also, it cannot work efficiently for other types of images.
Qi Wang et al. [46] describe a Fractional Differential Gradient (FDG) approach for detecting noise locations in images, as well as an enhanced image de-noising algorithm based on fractional integration. The merit of using this model is that it can remove the noise and preserves the details of image edges in a better manner. The demerit of this model is that it shows less performance with other types of images.
Lina Jia et al. [49] develop an image de-noising algorithm, which is based on discriminative weighted nuclear norm minimization (DWNNM) in order to improve LDCT (Low-dose computed tomography) image. This method shows better performance in noise and artifacts removal, and also in details and structure preservation. The pitfall of this algorithm is that the parameter is selected in a rough manner hence the de-noised images fail to achieve a better accuracy.

III PERLUSTRATION AND DISCUSSION

Table 1: Analysis on de-noising algorithm and its Expansion

METHOD	PUBLICATION & YEAR	AUTHOR NAME	DE-NOISING TECHNIQUES
NNAF[7]	ELSEVIER,1996	H. KONG et al.	Neural Network Adaptive Filter
MMEM[8]	IEEE,1997	Wei-Yu Han et al.	Minimum-Maximum Exclusive Mean
PSM[9]	IEEE, 1999	Zhou Wang et al.	Progressive Switching Median
MM-KNN[10]	IEEE, 2002	F.J. Gallegos-Funes et al.	M-type K-nearest neighbor
Modified VMF[11]	ELSEVIER,2003	B. Smolka et al.	Modified vector median filter
ATPMF[12]	IEEE,2004	Xiaoyin Xu et al.	Adaptive Two-Pass Rank Order Filter
NEAVF[13]	ELSEVIER,2005	Zhonghua Ma et al.	Neighborhood Evaluated Adaptive Vector Filter
TBF[14]	IEEE,2006	Igor Aizenberg et al.	Threshold Boolean Filtering
NFIND[15]	IEEE,2007	Stefan Schulte et al.	Novel Fuzzy Impulse Noise Detection Method
NLSP[16]	IEEE,2007	K. S. Srinivasan et al.	Non-Linear signal processing technique
INRA[17]	ELSEVIER,2007	Wenbin Luo et al.	Impulse Noise Removal Algorithm
ASM[18]	IEEE,2008	X.M. Zhang et al.	Adaptive Switching Mean
PDE[19]	ELSEVIER,2009	Y. Shih et al.	Partial Differential Equations
AGFF[20]	IEEE,2009	Zhengya Xu et al.	Adaptive Geometric Features Based Filtering Technique
ASWM[21]	IEEE,2010	Smaïl Akkoul et al.	Adaptive Switching Median
CAFSM[22]	IEEE,2010	Kenny Kal Vin Toh et al.	Cluster-based Adaptive Fuzzy Switching Median
IRM[23]	IEEE,2010	S. Huang et al.	Image Restoration Method
LOFBDND[24]	IEEE,2011	Wei Wang et al	Local Outlier Factor incorporating with Boundary Discriminative Noise Detection Algorithm
FCA[25]	ELSEVIER,2012	Sana Sadeghi et al.	Fuzzy Cellular Automata
ADPF[26]	IEEE,2012	Zhe Zhou	Adaptive Detail-Preserving Filter
BDND[27]	IEEE,2013	Iyad F. Jafar et al.	Boundary Discriminative Noise Detection
INEEP[28]	IEEE,2014	Zayed M. Ramadan	Impulse Noise Elimination And Edge Preservation
IDS[29]	ELSEVIER,2014	Umesh Ghanekar et al.	Impulse Detection Scheme
CA[30]	ELSEVIER,2014	U. Sahin et al.	Cellular Automata
RVIN[31]	IEEE,2015	Ruixuang Wang et al.	Random-Valued Impulse Noise
ASWMF[32]	ELSEVIER,2016	Osama S. Faragallah et al.	Adaptive Switching Weighted Median Filter
ALD[33]	IEEE,2016	Yi Wang et al.	Absolute Luminance Difference Method
NRA[34]	IET,2017	Qing-Qiang Chen et al.	Noise Removal Algorithm
MF[35]	IEEE,2018	Vikas Singh et al.	Membership Function
IDR[36]	IET,2018	Samsad Beagum Sheik Fareed et al.	Impulse Detection and Restoration
RBF[37]	IET,2017	Fariborz Taherkhani et al.	Radial Basis Functions
ISIN[38]	SPRINGER,2018	Minghui Zhang et al.	Iterative Scheme-Inspired Network
$l0TV$-PADMM[39]	IEEE,2018	Ganzhao Yuan et al.	Total Variation Proximal Alternating Direction Method Of Multipliers
ASWMF[40]	IEEE,2019	Jiayi Chen et al.	Adaptive Sequentially Weighted Median Filter

CLAHE[41]	ELSEVIER,2019	Sonali et al.	Contrast Limited Adaptive Histogram Equalization
CNN[42]	ELSEVIER,2019	Lianghai Jin et.al	Deep Convolutional Neural Network
EIDA[43]	IEEE,2020	Xiaoqin Zhang et al.	Exemplar-Based Image De-Noising Algorithm
ASMDBUTMF[44]	SPRINGER,2020	C. Jaspin Jeba Sheela et al.	Adaptive Switching Modified Decision Based Un-symmetric Trimmed Median Filter
DNINR[45]	SPRINGER,2020	Guanyu Li et al.	Densely Connected Network for Impulse Noise Removal
FDG[46]	ELSEVIER,2020	Qi Wang et al.	Fractional Differential Gradient
SAF-RGM[47]	IEEE,2020	Qianqian Liu et al.	Spline Adaptive Filter based on the Robust Geman-McClure estimator
NLML[48]	IEEE,2017	Mustapha Bouhrara et al.	Non Local Maximum Likelihood filter
DWNNM[49]	IEEE,2018	Lina Jia et al.	Discriminative Weighted Nuclear Norm Minimization
RNRM[50]	IEEE,2019	Hongli Lv et al.	Rician Noise Reduction Method
IMF[51]	IEEE,2019	Ugur Erkan et al.	Iterative Mean Filter
QWT[52]	IEEE,2020	Rashid Ali et al.	Quaternion Wavelet Transform
GAN[53]	IEEE,2021	Miao Tian et al.	Generative Adversarial Networks
Unsupervised NLF[54]	IEEE,2021	Swati Rai et al.	Unsupervised Noise Learning Framework
DOF[55]	IEEE,2021	Huaian Chen et al.	Demand-Oriented Framework
INRM[56]	SPRINGER,2021	Chun Li et al.	Impulse noise removal model algorithm
MNRT[57]	IJRES,2022	Golam Muktadir Mukti et al	Weighted median filter
UIDGAN [58]	JTPES, 2024	XuYan et al.	De-noising algorithm based on Generative Adversarial Networks

Table 1 represents the analysis on de-noising techniques that is been used since the previous fifteen years. The total number of papers considered for this study is fifty. The table also holds the information regarding the author, the journal on which it gets published and also the published year. Also the de-noising techniques used in the previous fifteen years has been segregated and classified in to five groups' namely Deep learning and neural network, Fuzzy logic, Mean based filter, Median based filter and Miscellaneous, and each technique falls on to any appropriate group. Techniques like NNAF[7], ADPF[26], RBF[37], ISIN[38], DNINR[42], INRM[56] falls into Deep learning and Neural network group, NFIND[15], CAFSM[22], FCA[25], IDR[30], SAP[33], MF[35] falls into Fuzzy logic, NMEM[8], VMF[11], ASM[18], IDR[36], SAF-RGM[47], NLML[48] techniques uses Mean based filter, PSM[9], MM-KNN[10], ATPMF[12], NEAVF[13], NLSP[16], AGFF[20], ASWM[21], LOFBDND[24], BDND[27], ASWMF[32], ASMDBUTMF[44] techniques uses Median based filter, Rest of the other techniques like IDBF[14], INRA[17], PDE[19], IRM[23], INEEP[28], IDS[29], RVIN[31], CA[34], l0TV-PADMM[39], CLAHE[41], EIDA[43], FDG[46], DWNNM[49] falls into Miscellaneous type.

Table 2: Analysis on merits, demerits and MSE

S. NO	METHODOLOGY	MERITS	DEMERITS	NOISE RATIO; PSNR
1.	PSM[9]	Works effectively on highly corrupted images	Consumes large computational time	NOT MENTIONED
2.	MM-KNN[10]	Better quality of image processing, both in the visual and the analytical sense	Fails to support high-resolution images	15% ; 25.29
3.	Modified VMF[11]	Low computational complexity	Less reliable and degradation of image quality is possible	11.5% ; 38.074
4.	ATPMF[12]	Irregularities in the spatial distribution of the estimated impulse noise are detected	higher structural complexity	30% ; 37.522
5.	NEAVF[13]	Better accuracy in noise detection	Loses its credibility while considering grayscale images	20% ; 31.30

6.	TBF[14]	Smoothing of edges and destruction of details are prevented	Textures are not preserved	30% ; 28.61
7.	NFIND[15]	Does not introduce blurring artifacts	Fails to reduce α-stable efficiently	40% ; 35.87
8.	NLSP[16]	Better performance across a wide range of noise densities	Fails to support the switching window technique	60% ; 36.32
9.	INRA[17]	Requires no previous training	Fails to remove noises of highly corrupted gray-scale images	20% ; 37.36
10.	ASM[18]	Better performance in terms of noise suppression and details preservation	Not competitive to industrial standard	50% ; 33.76
11.	PDE[19]	Removes noise without using the nonlinear smoothing kernel which needs extra cost in solving the heat equation	Large time consumption and computational complexity	5% ; 27.077
12.	AGFF[20]	Provides a very reliable impulse noise type and ratio discrimination method	Not integrated with other benchmark techniques to suppress a mixed Gaussian and impulse noise contamination	20% ; 27.659
13.	ASWM[21]	The psycho visual results are of high quality	Cannot support the switching window technique which leads to low performance	30% ; 32.91
14.	CAFSM[22]	Capable in handling realistic impulse noise model for real-world applications	Fails to support high-resolution images and huge noise level	50% ; 27.45
15.	IRM[23]	Simplifies noisy pixels detection	There is a possibility that some noise-free pixels can be misinterpreted as a noisy one	NOT MENTIONED
16.	LOFBDND[24]	Minimizes the miss detection rate and false detection rate	High computational complexity	40% ; 33.95
17.	FCA[25]	Simplicity, robustness, parallel manner and distribution ability	Eliminating noise from color images is not supported	60% ; 27.8
18.	ADPF[26]	Better Detection accuracy	Edges may get blur if the image has a high noise level	60% ; 25.53
19.	BDND[27]	noisy pixels are identified ideally by the detection step	Large window size increases large computational complexity	60% ; 34.45
20.	INEEP[28]	The preservation of images with fine details and edges are maintained	Texture areas are affected due to blur, because of high smoothing operation	60% ; 30.86
21.	IDS[29]	Better performance for different types of fixed valued impulse noise	since it supports two steps of activity the time complexity increases	60% ; 31.8
22.	CA[30]	It is consistent and stable across a wide range of noise densities	It does not support the switching window technique.	60% ; 30.5
23.	RVIN[31]	Better performance on nonpoint wise Random-Valued Impulse Noise	There is a trade-off between removing RVIN and preserving fine texture details	20% ; 30.58
24.	ASWMF[32]	Better performance for a wide set of images	It cannot support images with high noise level	40% ; 33.76
25.	ALD[33]	It can suppress the noise even at high noise ratios, and performs well in maintaining edges	Texture areas can be affected due to blur	50% ; 29.1793

26.	NRA[34]	Better in term of the PSNR	The accuracy is checked only by using a limited quantity of test images	60% ; 32.89
27.	MF[35]	Filter preserves meaningful image details even at a high noise level	Validated only for grayscale images	50% ; 34.88
28.	IDR[36]	Restoring image details are maintained	Larger the window size, the computational complexity also increases	60% ; 32.25
29.	RBF[37]	Tuning parameters by trial and error to achieve the best result is avoided	Fails to address Gaussian and Speckle noises	60% ; 31.23
30.	ISIN[38]	Better ability to decrease the noise quickly with the simple iterative scheme	Network is not dealt with multiple datasets.	30% ; 27.93
31.	*l0TV*-PADMM[39]	Image de-noising and de-blurring in the presence of impulse noise are addressed in a better manner	Not been developed in C++ hence it provides less speed	50% ; 22.4
32.	ASWMF[40]	Computational time is considerably low	It is hard to be applied for real-time de-noising	50% ; 34.4
33.	CLAHE[41]	Removes noise and enhances contrast in fundus images	It works only for the Medical domain and restricted to fundus images	0.2; 35.171
34.	CNN[42]	Better de-noising performance	Running time of this method is very high	20% ; 33.94
35.	EIDA[43]	Better potential for image restoration	It cannot work efficiently for other types of images	20% ; 35.072
36.	ASMDBUTMF[44]	It can be used as a preprocessing method for scanning machines for better robustness	It lacks in providing the solution for the removal of random noises	50% ; 33.867
37.	DNINR[45]	Better performance on edge preservation and noise suppression	It loses its efficiency when applied to other non-Gaussian noises like Poisson noise and Rician noise	50% ; 31.08
38.	FDG[46]	Remove the noise and preserves the details of image edges in a better manner	This model is evaluated only by the minimum quantity of test images	60% ; 34.02
39.	SAF-RGM[47]	Better stable performance against impulsive noise	high time consumption and high computational complexity	NOT MENTIONED
40.	NLML[48]	Better performance for estimation of noise SD	Performance is limited in spatially heterogeneous regions	NOT MENTIONED
41.	DWNNM[49]	Better performance in noise and artifacts removal	Parameter is selected in a rough manner hence the de-noised images fail to achieve a better accuracy	50% ; 25.1314
42.	RNRM[50]	Better performance in terms of objective metrics and visual inspection	larger computational time which in term increases the complexity	15% ; 30.69
43.	IMF[51]	Works better than the methods using dynamic adaptive windows	Fails to remove the random-valued impulse noise	60% ; 32.49
44.	QWT[52]	The de-noised images have the finest visual quality	It is not been tested with different types of filters and mixed noises	75% ; 34.28
45.	GAN[53]	Better in terms of de-noising level, SSIM (structural similarity index)	Not tested upon the real hospital environment	10% ; 34.62

46.	Unsupervised NLF[54]	Does not require the clean (de-noised) images for training the model	Fails to address any degradation in the multimodal images along with the noise	15% ; 35.185
47.	DOF[55]	Better performance in terms of the number of parameters and the de-noising quality	The network needs to be retrained when faced with different demands	15% ; 30.69
48.	INRM[56]	Better than existing classic algorithms for impulse signal removal	Fails to address the inverse problem such as image patching problems, image segmentation problems, image blending to noise	40%; 41.21
49.	MNRT[57]	It provides high quality images by removing salt and pepper noises	It loses its efficiency while working with the kernel size above three	75%; 58.93
50.	UIDGAN[50]	The consistency of content information is maintained	It considers many parameters which in turn increases its complexity	60%; 45.27

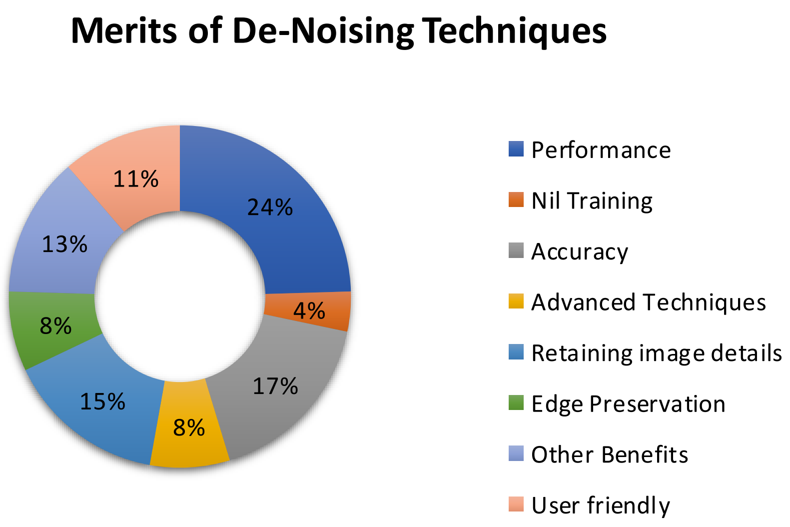

Fig. 1: Merits of De-Noising techniques.

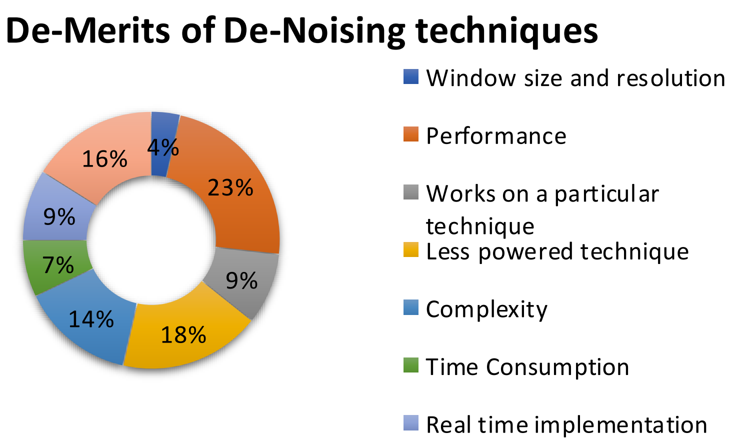

Fig. 2: De-Merits of De-noising techniques.

Table 2 and Fig (1) & (2) describes the Merit and the short coming of the de-noising technique that is been considered in our study. The merits of the implemented noise reduction techniques include performance [10], [16], [18], [31], [32], [42], [47], [48], [49], [50], [55], [56], nil training [54], [17], accuracy [13], [53], [41], [34], [20], [21], [24], [26], advanced techniques [51], [39], [22], [9], retaining image details [7], [14], [18], [35], [36], [43], [46], edge preservation [14], [28], [33], [45], and a user-friendly approach [11], [23], [25], [37], [38], [40]. Some of the short comings of these techniques were the window size and resolution [27],[36], performance [11],[14], [15],[20], [26],[28], [31],[33],[44], [48],[52], works on a particular technique [16],[30],[45],[51],[56], less power techniques [20],[21], [25],[34], [37],[38], [39],[46], [49],[52], complexity [6],[7], [19],[24], [27],[29], [36],[47], time consumption [9],[42], [47],[50], real time implementation [18],[40],[50],[53],[55], works on a particular type of images [8],[10], [13],[17], [32],[35], [41],[43], [48]. This table also has the details of noise ratio considered and also the achieved psnr value.

Fig 3 gives a detailed chart on the various noise reduction techniques that is been used on various corrupted noise level and the PSNR value obtained for each techniques.

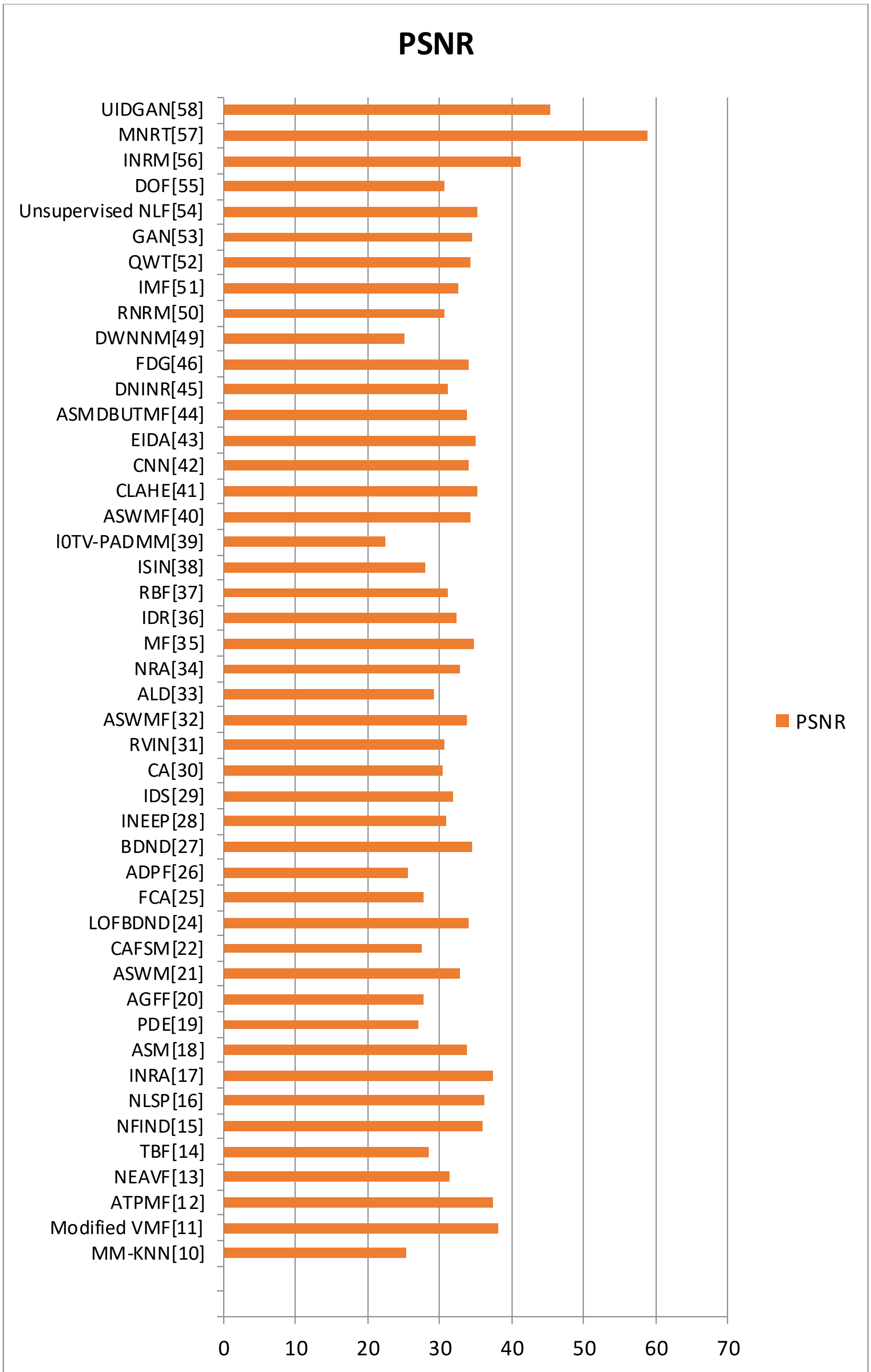

Fig. 3: Implemented noise reduction technique and the PSNR value obtained.

Table 3: Methodoloy and Types of Dataset

S. NO	METHODOLOGY	TYPES OF IMAGES	IMAGE SIZE	CORRUPTED NOISE PERCENTAGE
1.	PSM[9]	1.Corrupted Pepper 2.Bridge	512 X 512	5% to 70%
2.	MM-KNN[10]	1.Lenna	256 X 256	15%

3.	Modified VMF[11]	1.Lenna 2.Peppers 3. Gold hill etc…	500 X 500 500 X 500 500 X 500	11.5%
4.	ATPMF[12]	1.Lenna 2.Boat	625 X 625	20% to 35%
5.	NEAVF[13]	1.Lenna 2.Parrot	256 X 256	0.5% to 20%
6.	TBF[14]	1.Girl	256 X 256	1% to 30%
7.	NFIND[15]	1.Lenna 2.Baboon 3. Parrot 4. Boat	256 X 256 256 X 256 175 X 150 300 X 300	5% to 40%
8.	NLSP[16]	1. Lenna 2. Girl	256 X 256	10% to 90%
9.	INRA[17]	1.Lenna 2. Bridge 3. Gold hill Etc …	512 X 512	20 %
10.	ASM[18]	1.Pepper 2.Bridge	512 X 512	10 % to 70%
11.	PDE[19]	1.License plate Image 2.Spade-Heart-Diamond-Club Image 3.Elaine	198 X 85 257 X 257 257 X 257	5% to 20%
12.	AGFF[20]	1.Boat 2.Zoomed portion of a Parrot Etc…	512 X 512 1986 X 1986	5% to 50%
13.	ASWM[21]	1. Lenna 2. Boat 3. Pepper etc…	Not Mentioned	10 % to 60%
14.	CAFSM[22]	100 Grayscale test images	512 X 512	5% to 50%
15.	IRM[23]	Grey-scale Lena image	512 X 512	10% to 90%
16.	LOFBDND[24]	1.Lenna 2. Gold hill 3. Boat 4. Bridge	512 X 512	10% to 90%
17.	FCA[25]	1.Lenna 2.Peppers 3.Baboon	Not Mentioned	10% to 80%
18.	ADPF[26]	1. Lenna 2. Corrupted Bridge 3. Peppers 4. Baboon	512 X 512	10% to 90%
19.	BDND[27]	1. Camera man 2. Peppers 3. Boat etc…	Not Mentioned	10% to 90%
20.	INEEP[28]	1. Bridge 2. Mammogram 3. Compound Eye of Fly.	Not Mentioned	4% to 60%
21.	IDS[29]	1. Lenna 2. Peppers 3. Baboon	512 X 512	10% to 60%
22.	CA[30]	1. Lenna 2. Bridge	256 X 256 512 X 512	10% to 70%
23.	RVIN[31]	1.Baboon 2. Finger 3. Bridge etc…	300 X 300	10% to 20%

24.	ASWMF[32]	Gray Scale Images	256 X 256	20% to 90%
25.	ALD[33]	1. Hill 2. Lenna etc…	512 X 512	90%
26.	NRA[34]	1. Lenna 2. Baboon	512 X 512	10% to 90%
27.	MF[35]	1. Lenna 2. Corrupted Bridge 3. Peppers 4. Baboon etc…	512 X 512	20% to 99%
28.	IDR[36]	Standard Grey-Scale Images	Not Mentioned	40% to 90%
29.	RBF[37]	8-bit standard grey-scale images	512 X 512	10% to 95%
30.	ISIN[38]	Images from Berkeley Segmentation Dataset	Not Mentioned	20% to 40%
31.	*l0TV*-PADMM[39]	Gray scale and colored images of a Camera Man, Lenna etc…	512 X 512	10 % to 90%
32.	ASWMF[40]	BSD68 DATASET Containing Medical Images	Not Mentioned	10 % to 90%
33.	CLAHE[41]	Red, Blue and Green Channel of Fundus Images	605 X 700	Up to 20%
34.	CNN[42]	400 Images from Berkeley segmentation dataset	180 X 180	5% to 60%
35.	EIDA[43]	1. Monarch 2. Barbara 3. Monarch etc…	256 X 256	10% to 30%
36.	ASMDBUTMF[44]	Medical Databases namely cancer Imaging Archive (TCIA) and real time database from Kerala Institute of Medical Science (KIMS)	Not Mentioned	Up to 99%
37.	DNINR[45]	1.Foreman 2. Bottom 3. Pentagon 4. Pepper etc…	256 X 256	30% to 80%
38.	FDG[46]	Lenna images	Not Mentioned	Up to 50%
39.	SAF-RGM[47]	Gaussian signal and colored signal	Nil	Not Mentioned
40.	NLML[48]	T2-weighted (T2W) images of human brain	200 X 180	Not Mentioned
41.	DWNNM[49]	Low Dose CT Images	Nil	Up to 80%
42.	RNRM[50]	3D MR data	181 × 217 × 181	1% to 15%
43.	IMF[51]	Peppers Image	512 X 512	Up to 90%
44.	QWT[52]	1.Lenna 2.Corrupted 3.Bridge 4. Peppers etc…	256 X 256 512 X 512 1024X 1024	15% to 75%
45.	GAN[53]	Synthetic Data obtained from Brain Web dataset	181 X 217 X 181	1% to 10%
46.	Unsupervised NLF[54]	MRI, CT, and LDCT images	64 X 64 512 X 512	5% to 15%
47.	DOF[55]	Berkeley segmentation dataset (BSD500)	256 X 256 512 X 512	15% to 70%
48.	INRM[56]	Natural images, CT images and MRI images.	NIL	Up to 40%
49.	MNRT[57]	MRI images	256X256	Up to 75%
50.	UIDGAN[58]	A Self-Guided Deep Learning Technique for MRI Image Noise Reduction", JTPES	NIL	Up to 60%

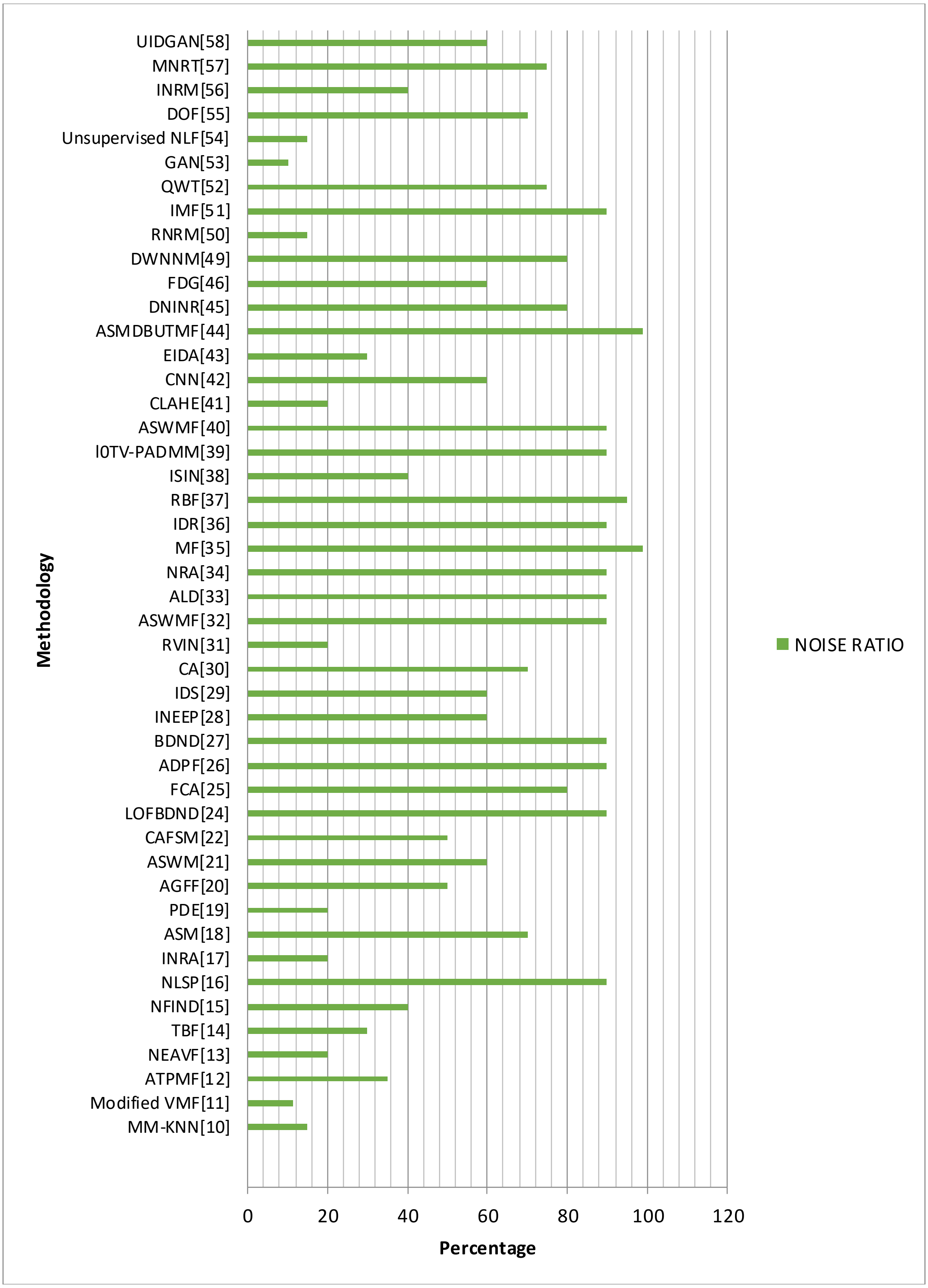

Fig 4: Implemented Methodology Vs Percentage of noise ratio

Fig 4 represented the pictorial representation of various methodologies that is been used on various corrupted noise level since the past few years.

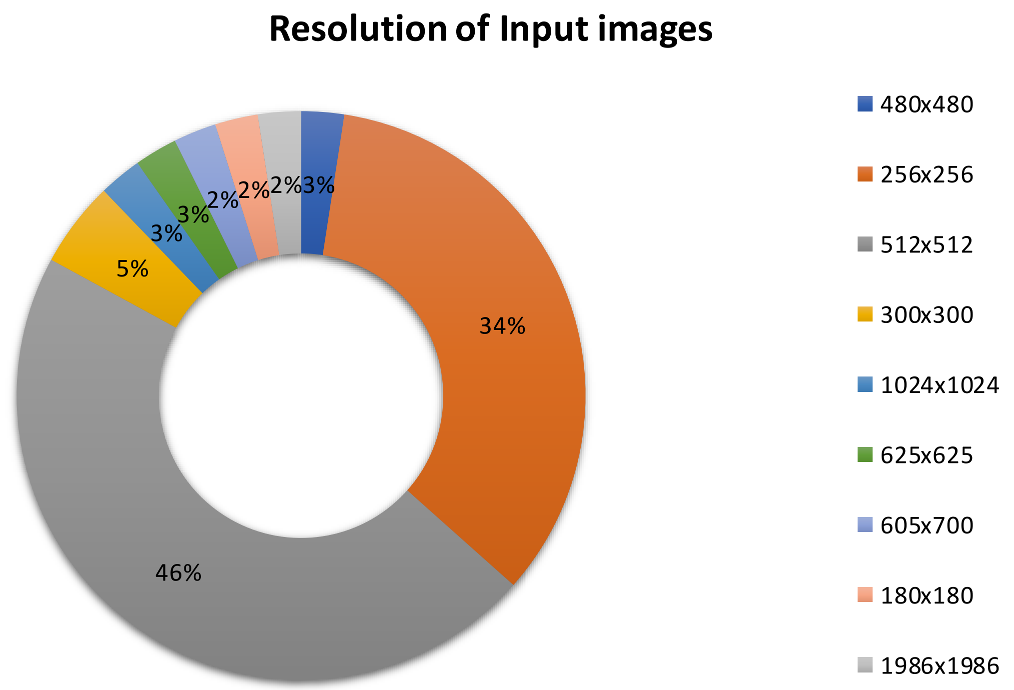

Fig. 5: Chart on the various resolutions of input images that is been used on various denoising techniques.

Table 3 and Fig (5) describes the various de-noising techniques that is been used on different noise level. It also holds the information about the types of data sets that is been used as an input and the resolution of the various types of input images. It also describes the details of the Noise ratio percentage. From this chart it is clear that most of the noise reduction techniques have considered 512 x 512 resolution as its maximum inputs. Apart from input images of different resolution certain techniques also considered databases like Medical Databases namely cancer Imaging Archive (TCIA) and real time database from Kerala Institute of Medical Science (KIMS), BSD68 DATASET Containing Medical Images, Images from Berkeley segmentation dataset, Synthetic Data obtained from Brain Web dataset.

Table 4: Performance Evaluation

S.No	METHODOLOGY	PERFORMANCE
1.	PSM[9]	Medium
2.	MM-KNN[10]	Medium
3.	Modified VMF[11]	Fair
4.	ATPMF[12]	Fair
5.	NEAVF[13]	Medium
6.	TBF[14]	Fair
7.	NFIND[15]	Fair
8.	NLSP[16]	Fair
9.	INRA[17]	High
10.	ASM[18]	High
11.	PDE[19]	High
12.	AGFF[20]	High
13.	ASWM[21]	High
14.	CAFSM[22]	High
15.	IRM[23]	High
16.	LOFBDND[24]	High
17.	FCA[25]	Medium
18.	ADPF[26]	High
19.	BDND[27]	High
20.	INEEP[28]	Very High
21.	IDS[29]	Very High
22.	CA[30]	Very High
23.	RVIN[31]	Very High
24.	ASWMF[32]	Very High
25.	ALD[33]	Medium
26.	NRA[34]	Very High
27.	MF[35]	Very High
28.	IDR[36]	Very High
29.	RBF[37]	Excellent
30.	ISIN[38]	High
31.	*l0TV*-PADMM[39]	Very High
32.	ASWMF[40]	Very High
33.	CLAHE[41]	Very High
34.	CNN[42]	Very High
35.	EIDA[43]	Excellent
36.	ASMDBUTMF[44]	Excellent
37.	DNINR[45]	Excellent
38.	FDG[46]	Excellent
39.	SAF-RGM[47]	High
40.	NLML[48]	Excellent
41.	DWNNM[49]	Excellent
42.	RNRM[50]	Excellent
43.	IMF[51]	Excellent

44.	QWT[52]	Excellent
45.	GAN[53]	Very High
46.	Unsupervised NLF[54]	Excellent
47.	DOF[55]	Excellent
48.	INRM[56]	Excellent
49.	MNRT[57]	Excellent
50.	UIDGAN[58]	Excellent

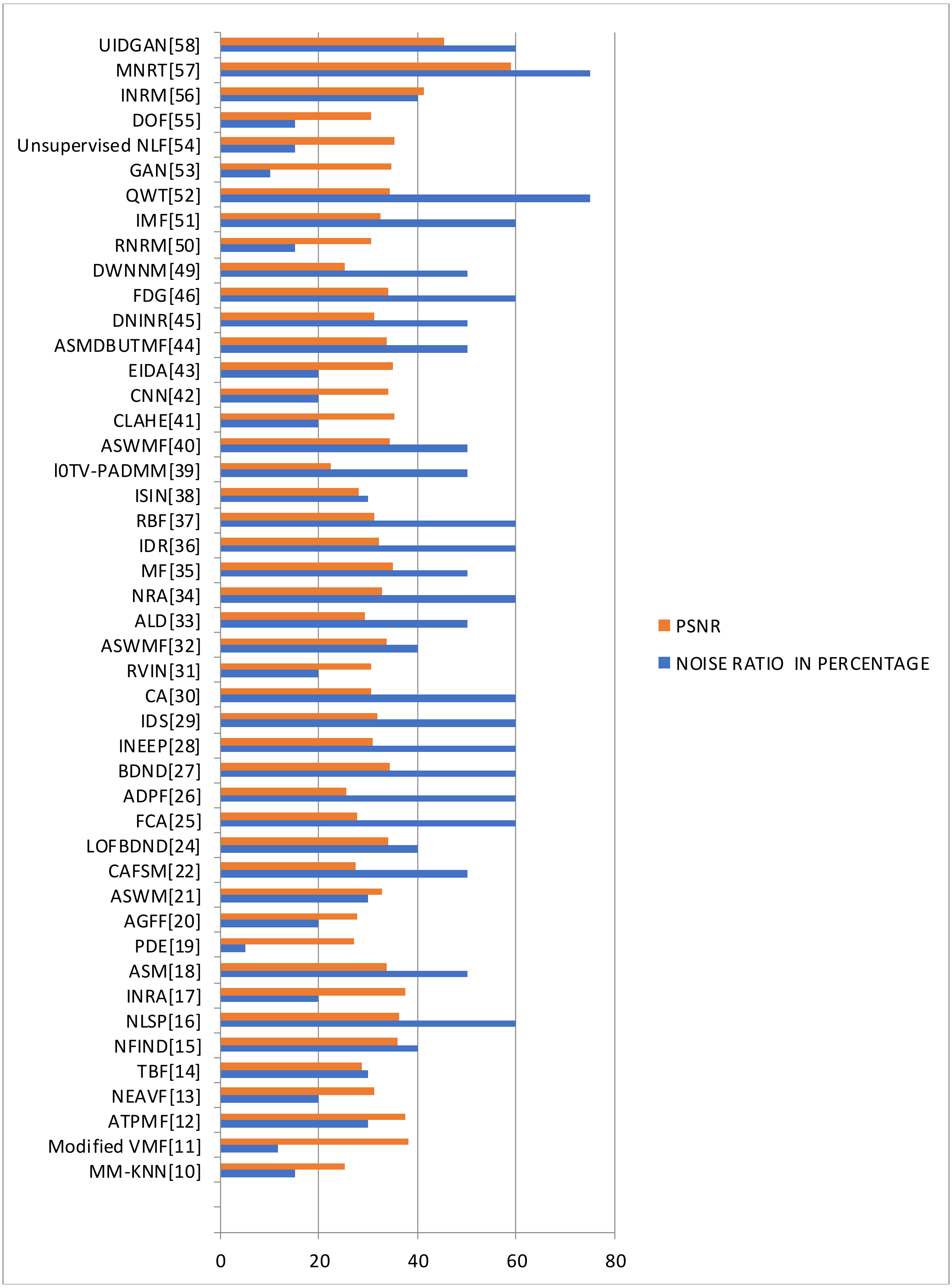

Fig. 6: PSNR Vs. Percentage of noise ratio.

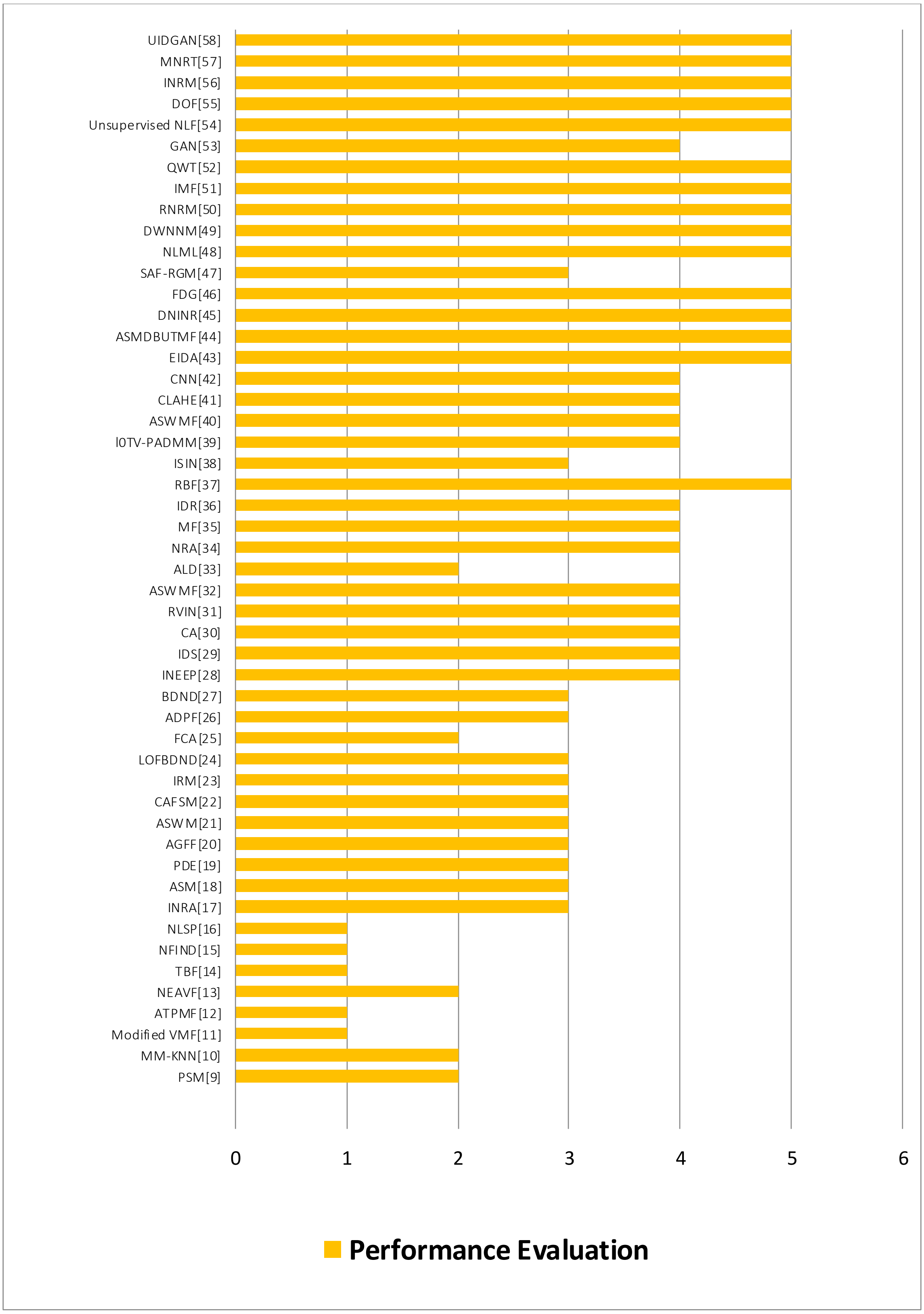

Fig. 7: Performance Evaluation of various noise reduction techniques on various corrupted noise level which is based on its corresponding PSNR values.

Table 4 describes the various noise detection and reduction techniques. It also carries the information of its performance evaluation. Herein Fig (6) exhibits the pictorial representation of PSNR values on various noise ratio used in various techniques and Fig (7) displays the performance evaluation of each techniques by considering PSNR in to account. From the table 4 and Fig (7) it is clear that the recent techniques like Demand-Oriented Framework (DOF) [55] and Impulse noise removal model algorithm (INRM) [56] performs better. The weighted median filter technique (MNRT) [57] outperforms all other filters and methods and has high PSNR value than the state of the art method.

IV CONCLUSION

Image de-noising research continues to be in great demand as the complexity and requirements of the process have escalated. This study pours light on the virtues and downsides of multiple image de-noising algorithms that have been developed in the past few years. The advent of techniques has recently supplanted the old local de-noising model, resulting in a new theoretical branch and substantial breakthroughs in image de-noising approaches, such as sparse representation, low-rank, and CNN (more precisely, deep learning) based methods. The purpose of this study is to provide an overview of the different de-noising methods. Also this study categorizes each methodology in to five groups. Hence INRM [56] from Deep learning and Neural network, NFIND [15] from Fuzzy logic, VMF [11] from Mean based filter, ATPMF [12] from Median based filter and INRA [17] are considered to be the favorable method holding high PSNR value. On considering the entire techniques in our study recent techniques like Demand-Oriented Framework (DOF) [55] and Impulse noise removal model algorithm (INRM) [56] performs second best. The weighted median filter technique (MNRT) [57] performs the best and gives high PSNR value. Because different types of noise necessitate different de-noising approaches, noise analysis can aid in the development of novel de-noising schemes.

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