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Noise Removal From Images Using Adaptive Neuro/Network-Fuzzy Interface Systems

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Abstract. Any Information signal is best desirable without any external noise/ disturbances. Noise in any signal is the undesirable quantity present which deteriorates the signal's quality, thus compromising the information. Any signal, be it an image signal (2-D) or else a video signal (3-D) in the field of communication, if not always but most number of times prone to noise. In this paper, we would be dealing with removing types of noise on an image, using various filter techniques such as vector median filter, vector directional filter. Using the image processing tools in MATLAB, we could achieve this quite effortlessly. Looking at the prior approaches and keeping those factors in understanding, this paper would intend to path a more thoughtful way to bifurcate the image from its noise using the techniques of the neural networks. With thorough scrutiny and understanding of filters, this paper ensemble the performance of filters, through which we would be applying the most suitable filter out of the lot with the neural networks.

1. Introduction

Having information about something stands out to be the most potent weapon in today's digital world, especially if the information is a picture, a picture representing the position of the Mars Lander, or a picture that would describe the functioning of human organs. Though sometimes this information can be uncertain, unclear, it serves the purpose, i.e., it helps us to obtain knowledge over something most of the time. From the communications engineering perspective, this information can sometimes be degraded by external factors from source to destination. This degradation is primarily caused by the addition of noise in the path of communication. This noise with the image pixels randomly variates the pixel value, thus compromising the picture quality and presenting the end-user with a piece of undesirable information.In regular day-to-day communication, it is okay to have such noise, and most of the time, it is manageable. However, in particular areas, such as getting information from medical reports/x-rays, understanding satellite images in remote sensing, and military applications, the margin of error is too less. Hence there is an utmost necessity, and it is vital to remove or at least reduce the noise from these images.

For this reason, numerous approaches have been introduced in the field of image processing and are applied by previous researchers. Those approaches were indeed served the purpose of removing noise. Noise reduction filters such as Mean Filter, Median Filter, Weiner Filter could remove various types of noise. By measuring the mean-square error (MSE), we could understand the quality levels of noisy images and denoised images. To further simplify human involvement and remove noise, a more innovative method came into existence. Artificial intelligence has a significant contribution to this development. The concept of deep learning and transfer learning has brought in the idea of neural networks. These neural networks work on the training data, learn with experience, and remove noise in the image. Now, this has further improved the efficiency of the whole noise removal process.

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Understanding the Previous Studies

Carefully looking at the previous approaches made by engineers across the world, such as [7, 20, 21, 9], these methods neatly applied the present concepts very much and served the purpose quite efficiently. The work proposed in [7,9] precisely describes the study about using the basic filters to remove the noise from the color and grayscale images, respectively. These papers neatly illustrate the effects of various types and densities of noise on clear images and reproduce the denoised images. Wang Jianwei's work enhanced on the values of mean square error as the qualifying factor to measure the accuracy of the output images.

Moving onto the proposed models in [21,20] demonstrated the concepts of utilizing the neural networks, the convolution neural networks with the gaussian and salt and pepper noises with both the color and grayscale images and sophisticatedly elucidated the benefits of the neural networks over the conventional methods.

The Approach of our Method

Our readings of these works motivated us to work on filling in those gaps that the above left vacant and tried to prepare a model that could prove more robust than the former. The previously made research works in[2,8] emphasized developing models that could tackle only a limited range of noises, and the comparison criterion between the mentioned spatial filtering techniques could be a better one. The later works made an extensive research using the deep convolution networks and have shown more promising results in obtaining a high-quality denoised image and developed a solid model to tackle the Gaussian and salt & pepper noises. [22,23].

After a thorough investigation and research, we tried to develop a much more sophisticated model dealing with various kinds of noise through this paper to overcome the constraints of the previous works. In this paper, we have considered the concept of the Adaptive Neuro – Fuzzy Interface Systems. The model which we proposed in this paper would take the image data from the user, the network learns about the noise, and based on its learning experience it works decisively to remove noise, i.e., it learns about the noise pixels and removes only pixels that are affected by noise. We could efficiently produce denoised images using the Adaptive Neuro-Fuzzy Interface Systems, adding to that we have considered the PSNR as the degree of measure of the asses the level of signal quality, which helps the audience to understand better about the process outcome.

The contributions of this literature are summarized as follows:

1) We intend to find the most suitable spatial filter to remove various types of noise from the color images.
2) Then, we implement the idea of neural networks in the form of the Adaptive Neuro-Fuzzy Interface systems to the suitable spatial filter as a proposal to smartly eliminate the noise from the images. As we have mentioned earlier, this model predicts the locations of noise in the image pixels and selectively removes the noise.
3) We can extend our work to various types and densities of noise that usually affect and destroy the image quality.

This paper reflects our study on implementing the most suitable and more innovative way to eliminate or at least reduce distinctive noises using image processing tools.

The remainder of the paper is developed as follows: Section 2 presents preliminaries of each of the filters used as part of the related work and further illustrates the proposed model. Section 3 offers the comparison between those filter's performance and then extends it to presenting conclusive evidence on choosing the most suited filter for general image denoising. In Section 4, we would discuss the proposed ANFIS model for image denoising and experiment on the model extensively.

The Experimental observations of the proposed model are presented in Section 5, and with Section 6, we present the conclusion of the work.

2. Preliminaries of The Work

This section would elucidate our paper's workflow in a gradual manner and describe the preliminaries about the image filtering techniques and their mathematical models. The theory is elucidated based on our readings from the book Digital Image Processing Using MATLAB®, [Rafael C. Gonzalez et all.][12] and our understandings of the previous works, as cited accordingly.

Image Filtering Models

Any image going through a channel or a medium is prone to disturbance. As discussed earlier in the paper, this disturbance can significantly impact the information present in the image, which makes the image corrupted, such as variating the levels of contrast, displacing the values of pixels, which must be corrected in the early stages of image processing. In this section, we would go through the standard filtering methods used as part of our work.

1) **Vector Median Filter** : The Vector median filter is a non-linear image filtering technique [1] known in monochrome image processing. As the name suggests, it selects the pixels with median intensity from among the pixels in the given neighbourhood & has that valuable property in removing noise without blurring the edges. The VMF can be understood simply as a median filter to the vector-valued signals and images. The color images are processed using this filtering technique, so the image pixels are treated as vector quantities rather than separate components. In this paper, we have defined the color image is defined as a two-dimensional matrix of size N1 × N2 consisting of pixels xi = (xi1,xi2,xi3), indexed by i, which gives the pixel location on the image domain. Components xik, for i =1, 2....N, N = N1 ·N2 and k =1, 2, 3 denote the color channel values quantified into the integer domain. The most critical part of this approach is to calculate the pixel distances. Each time for mask/kernel chosen, applying the distances between each pixel in the mask and its neighbours are computed. [2] For each pixel in the chosen neighbourhood, the following sum is computed:

$$s_i = \sum_{j=1}^{n} \left\| x_i - x_j \right\| \text{ where i=1,2…N} \tag{2.1}$$

Where, x_i is the i^{th} pixel in the neighbourhood, and N = 9 for a 3 x 3 neighbourhood. The minimum value of s yielded is selected as the vector median of the neighbourhood and used as the corresponding pixel position in the filtered images.

Where $\left\| x_i - x_j \right\|$ the Pythagorean distance between the two pixels thus

$$\|x\_i - x\_j\| = \sqrt{\llbracket(r\rrbracket_i - r_j)^2 + (g_i - g_j)^2 \quad + (b_i - b_j)^2} \;) \tag{2.2}$$

where *ri* is the red component of pixel *xi*, *gi* is the green component of pixel *xi*, *bi* is the blue component of pixel *xi*. Thus, S is the sum of distances in RGB space from the pixel to all other pixels in the neighbourhood. We may readily visualize the selection of the pixel with minimum S as finding the pixel nearest the 'centre' of the pixels within the neighbourhood viewed as a cluster in RGB space.

2) **Gaussian Filter** : The Gaussian filter performs a vital role in filtering different kinds of signals. In image processing and graphics software, this is often referred to as Gaussian Smoothing, or Gaussian Blur is typically used to reduce noise. The filter is also used in computer vision algorithms to enhance image standards. The Gaussian filter is a 2-D convolution operator used to `blur' images and remove detail and noise. It is similar to any other filter in this text. However, it uses a different kernel describing the shape of a Gaussian (`bell-shaped') projection.

   The notion of Gaussian smoothing is to use the Gaussian distribution as its point-spread function, and this smoothing is achieved by convolution. Once a proper kernel has been estimated, then the Gaussian smoothing can be performed using standard convolution methods. This filter can complete the convolution sensibly quickly since the equation for the 2-D isotropic Gaussian represented above is separable into x and y components. The Kernel acts as a smoothing mask and acts on each pixel, convolves, and normalizes the value.[3] The value of smoothing mask can be defined according to the gaussian distribution function, for instance if we consider a 3x3 kernel, and defining the center element (x,y) of the kernel, and the mask ranging from (-1,-1) to (1,1). So, the value of each pixel in smoothing mask can be defined by the Gaussian Function

$$\mathrm{G}(x, y) = 1/2\pi\sigma^2 * e^{-}(x^2 + y^2)/2 \tag{2.3}$$

   In theory, the Gaussian distribution is non-zero throughout, which would demand an infinitely large convolution kernel. Nevertheless, in practice, it is effectively zero more than about three standard deviations from the mean. So, the Gaussian kernel can be truncated at this point.

3) **Rank Filter** : Rank filters are non-linear filters that identify in time or spatial domain the signal of p^{th} rank among all elements of an n-dimensional signal vector. These filters remove noise from color images and provide fine detail preservation & remove noise. The filter in this work replaces the element in the image pixels with the $order^{th}$ element in the sorted set of neighbors specified by the non-zero elements in the domain. Rank filters operating on images assign the p^{th} value of the gray levels from the window consisting of M pixels arranged according to their value to the center point of the window. The Maximum and Minimum, and Median filters are the extended cases of the rank filter. These filters usually work well for various noise types, with less blurring than linear filters of similar size. The Odd sized neighborhoods and efficient sorts yield a computationally efficient implementation.

4) **Wiener Filter**: The Wiener filter works on the technique of deconvolution. In the Wiener filter, the noisy image is further degraded or somewhat blurred by using a point spread function, and this is typically referred to as the degradation function or a low pass filter. Now, once this low pass filter output is taken as input, it is possible to recover the image with inverse filtering (or) generalized inverse filtering. The Wiener filtering technique provides a decent result in terms of removing noise. To elucidate, it decreases the overall mean square error in this process of deconvolution and inverse filtering. The Wiener filtering is a linear evaluation of the original image. However, the filter is susceptible to noise, but it removes the additive noise and inverts the blur simultaneously.

   The orthogonality principle suggests that the Wiener filter in the Fourier domain can be represented as follows:

$$W(f1, f2) = \frac{H'(f1,f2) S_{xx}(f1,f2)}{|H(f1,f2)|^2 S_{xx}(f1,f2) + S_{yy}(f1,f2)} \tag{2.4}$$

where $S_{xx}(f1,f2)$, $S_{yy}(f1,f2)$ are respectively power spectra of the original image and the additive noise, and H(f1,f2) is the blurring filter. It is easy to grasp that the Wiener filter has two different parts, an inverse filtering part and a noise smoothing part. The Wiener filter simultaneously performs the deconvolution by inverse filtering (high pass filtering) and removes the noise with a compression operation (low pass filtering).

5) **Guided Filter**: The Guided Filter is considered a better option than the bilateral filters in color image processing and noise removal. It is based on the local linear model and spatial domain enhancement techniques. The guided filter computes the filtering output by considering the content of a guidance image, which can be either a clear input image or any other image. The stated filtering method is considered the most durable [4,5] edge-preserving filter and a smoothing operator. The filter finds the statistics of a region in the corresponding spatial neighbourhood in the guidance image while calculating the value of the o/p pixels. If the guidance image is the same as the input image, the output retains the structure of the input image and preserves the edges as the critical parts of the image. The Guided filter output is more structured and comparatively less smoothened This filter can transfer the structures of the guidance image to the filtering output, enabling new filtering applications like de-hazing and guided feathering. Moreover, the guided filter naturally has a fast and non-approximate linear time algorithm, regardless of the kernel size and the intensity range.

6) **Mean Filter**: It is the simplest of all the filters, concept-wise and implementation-wise, to remove noise and restore the original image. These filters were one of the most used models in removing the noise. The mean filter is often a simple and easy filtering method used for smoothing the image to reduce the intensity variation of one pixel to the pixel next to it, decreasing the noise and improving the quality of the picture. This filter uses a mask over every pixel of the image. Every component of the pixel that comes in the same mask is averaged together to form a single pixel. This approach eliminates the abnormalities in the pixels, reducing the uncorrelation between the surroundings. The mean filter does not preserve the edges properly. The concept of mean filtering is to displace each pixel value in an image with the mean (`average') value of its neighbours, including itself. This filter has the impact of eliminating pixel values that are unrepresentative of their surroundings. Mean filtering usually is considered as a convolution filter. Like other convolutions, it is based around a kernel, representing the shape and size of the neighbourhood to be sampled when calculating the mean. Often a 3×3 square kernel is used.

Fuzzy Interface System

The Fuzzy interface system is the most integral part of the proposed model, and we would be dealing with it in much detail in section 4. At this stage of the paper, let us presently get a brief idea about fuzzy logic and its principles.

Fuzzy applies to things that are not clear or are uncertain. Any event, process, or function that is changing cannot always be defined as true or false. The fuzzy logic deals with imprecise data and has to choose based upon the learning experience and makes decision-based upon the over-simplification of the Boolean algebra, i.e., true/false or 1/0. This fuzzy logic further rather represents this as a multivalued logic; in a logic system, multivalued logic is a propositional calculus in which there are more than two truth values.[6]

We need to define such actions in a Fuzzy manner. The fuzzy logic is pretty much based on replicating the human-decision making principles in neural networks. The fuzzy logic deals with imprecise data and has to choose based upon the learning.

An adaptive neuro-fuzzy inference system (ANFIS) is a variety of artificial neural networks based on the Takagi–Sugeno fuzzy inference system. An adaptive neuro-fuzzy inference system (ANFIS) is a category of artificial neural networks based on the Takagi–Sugeno fuzzy inference system. It is a well-known computing framework based on the fuzzy set theory, fuzzy if-then rules, and fuzzy reasoning These are pretty much powerful tools and kind of time-savers when working with an artificial neural network, having both the benefits of neural networks and fuzzy rules in a given system, and further in this paper, we would explain how to cash on these features and advantages of fuzzy set theory/ fuzzy logic.

Image Noise

Noise in an image is a familiar concept discussed everywhere, and we shall not dive deep into it in this paper. Many previous works have mainly focused on describing the various types of noise in very much detail and at elementary level. [24, 25] These elaboratively mentioned the noises considered in this paper, and additionally, the work in [8] also illustrated shot noise.
Now that this section has briefly elucidated the crucial concepts that are part of this model, we then further look into the performance of each filter and produce the conclusive results in the next section.

3. Experimental Results-I

Experimental Setting

Here, we would be analysing the filters based upon their image processing methods and then comparing their final results. For these filter models in the paper, we have considered a dataset of 10 color images of size 256x256 i.e., 8-bit images for our comparison. These are randomly chosen color images for the experiment purpose. The images chosen in this paper are the standard open-source test images available in the Google images.

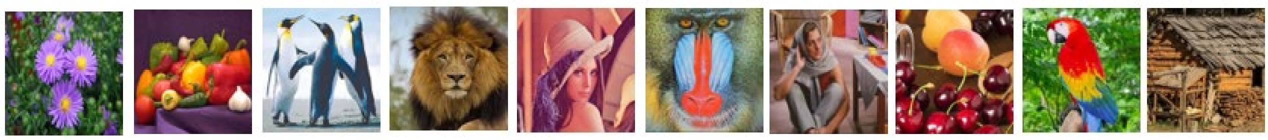


Figure 1(a). The dataset of images used for the model

We then test each of the filters with the different noises and at different densities and let them do their job. After extensive observations of the outputs of each of the filters, we would then apply the concept of Peak-Signal-to-Noise-Ratio to mathematically assess the quality of the output image concerning the original image from the dataset. Further in the section, we have capitulated the results into a tabular form.

The below flowchart, Fig.1(b) depicts the pictorial representation of the algorithm and the workflow of the experiment. As stated above, the algorithm proceeds accordingly as represented in the flowchart diagram.

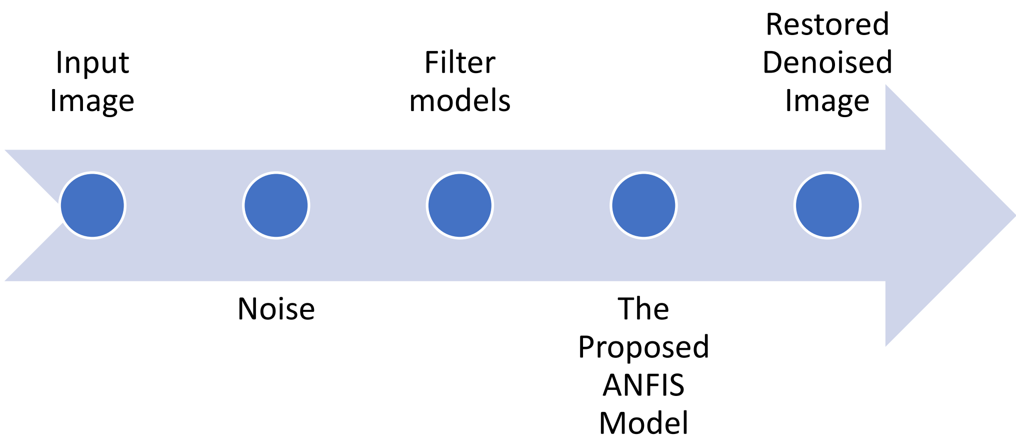


Figure 1. (b) Flowchart representing the algorithm of the experiment.

The Comparison Criteria

We compared the outputs of the filtering method with different kinds of noises. To Further assess the efficiency of the filtering method, we have considered the PSNR as our criteria. The tabular form represents the PSNR values of all the filters for the dataset images. For the practical sense, we went with PSNR over MSE, as in the works [7,8].
The PSNR provides a much more consistent value for multiple experiments, whereas there is a marginal change in the value of MSE.

Quantitative and Qualitative Evaluation

The average PSNR results of different methods against different noises are shown in Table1. As one can see, despite the Vector Median Filter (VMF) almost outperformed other filtering techniques by a comfortable margin on average, it falls marginally short of the Guided filter by 0.20 dB. We can duly note the few instances where some filters performed better than any other filter. for example, for an unknown Poisson noise, the Guided-Filter did better than any different filter, giving PSNR around 33.6 dB, and another such instance when the wiener filter had an unusual spike in the PSNR for the Poisson noise, when compared to other noises. We can see, the best values of the PSNR are highlighted in bold.

Table1.The psnr(db) results of different methods on dataset of images.

Noise Type	Salt & Pepper, Density=0.20									
	Flower	Pepper	Penguin	Lion	Lena	Baboon	Barbara	Cherry	Parrot	House	Average
VMF	34.202	33.505	32.081	31.323	32.384	28.937	31.904	32.83	30.649	28.822	**31.6637**
Gaussian	19.33	21.207	17.15	21.284	20.316	18.725	21.667	19.245	19.31	16.103	19.4337
Rank	24.197	28.999	22.555	27.65	25.869	20.163	24.768	26.48	25.032	17.831	24.3544
Guided	22.227	22.683	21.893	23.217	23.858	23.196	24.134	21.984	22.236	22.069	22.7497
Wiener	19.206	19.755	18.038	20.09	20.182	19.189	20.284	18.95	19.011	16.731	19.1436
Mean	19.273	19.513	17.941	19.667	19.856	19.075	20.101	18.96	19.115	17.408	19.0909

Noise Type	Gaussian Noise, Variance =0.03										
	Flower	Pepper	Penguin	Lion	Lena	Baboon	Barbara	Cherry	Parrot	House	Average
VMF	25.211	25.074	25.54	25.121	25.098	25.34	25.159	25.111	25.15	25.587	25.2391
Gaussian	20.755	23.91	18.867	23.498	21.706	19.991	21.739	21.254	20.842	16.595	20.9157
Rank	21.753	23.847	21.302	23.287	22.732	20.035	22.135	23.074	22.17	17.382	21.7717
Guided	27.532	28.291	29.247	27.855	28.851	27.093	28.257	28.09	27.205	27.184	**26.9605**
Wiener	23.743	26.376	24.504	25.547	25.214	22.167	24.628	25.278	23.294	19.051	23.9802
Mean	24.806	26.033	23.206	25.054	24.884	22.238	24.58	25.295	24.546	19.987	24.0629

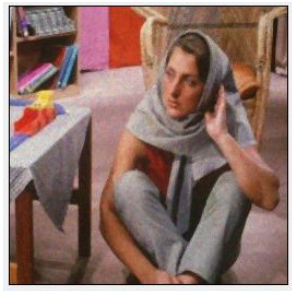
Noise Type	Speckle Noise, Variance=0.04										
	Flower	Pepper	Penguin	Lion	Lena	Baboon	Barbara	Cherry	Parrot	House	Average
VMF	27.999	28.536	26.692	27.411	26.466	26.522	26.992	28.354	27.536	27.593	27.4101
Gaussian	21.041	24.644	18.37	24.084	21.891	20.16	22.148	21.518	21.282	16.778	21.1916
Rank	24.288	28.014	22.043	25.873	24.334	21.168	24.189	25.965	24.63	18.473	23.8977
Guided	30.135	31.198	27.183	32.091	31.021	28.902	32.644	31.105	30.925	31.35	**30.6554**
Wiener	24.425	27.232	22.812	25.968	25.575	22.383	25.586	26.077	24.984	19.518	24.456
Mean	24.793	26.039	23.176	25.1	24.862	22.21	24.622	25.302	24.542	20.001	24.0647

Noise Type	Poisson Noise										
	Flower	Pepper	Penguin	Lion	Lena	Baboon	Barbara	Cherry	Parrot	House	Average
VMF	32.768	31.723	29.205	29.963	29.593	27.967	29.819	31.433	30.071	28.58	**30.1122**
Gaussian	21.229	25.071	19.011	24.261	22.148	20.289	22.224	21.882	21.412	16.804	21.4331
Rank	25.05	30.221	23.807	28.174	26.823	21.845	25.699	27.793	25.983	18.477	25.3872
Guided	32.39	35.577	34.074	33.606	34.515	30.612	34.508	35.436	32.858	33.173	33.6749
Wiener	26.122	31.657	26.798	28.881	28.772	23.54	27.844	29.852	26.859	19.97	27.0295
Mean	28.18	31.904	24.396	28.828	27.805	23.575	27.565	29.481	27.964	20.943	27.0641

Noise Type	Gaussian Noise, Variance=0.05										
	Flower	Pepper	Penguin	Lion	Lena	Baboon	Barbara	Cherry	Parrot	House	Average
VMF	24.674	24.523	24.985	24.580	24.571	24.834	24.618	24.546	24.610	25.136	24.7077
Gaussian	20.095	22.667	18.616	22.390	20.959	19.487	20.927	20.583	20.180	16.323	20.2227
Rank	20.436	21.819	20.231	21.503	21.048	19.020	20.634	21.418	20.707	16.722	20.3538
Guided	24.766	25.230	26.506	24.932	25.434	24.591	25.179	25.206	24.640	24.610	**25.1094**
Wiener	22.442	24.230	23.417	23.721	23.527	21.236	23.082	23.571	22.577	18.535	22.6338
Mean	23.214	24.051	22.389	23.373	23.299	21.268	23.014	23.580	22.998	19.387	22.6573

Fig. 2, represents the denoised images of the Vector Median Filter for all the noises considered, we can see the filter removes noise in each case and preserves the structure and colours of the original image.

(a) (b) (c) (d)



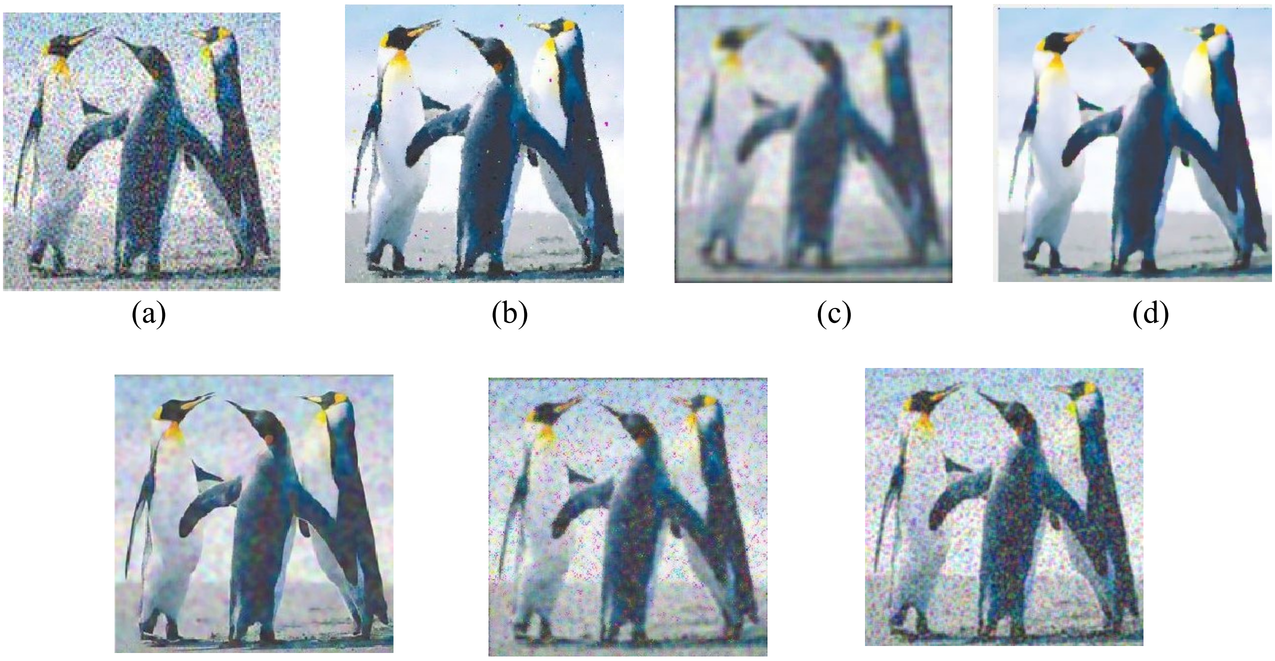
(e)

Figure 2. Represent the result of the Vector Median Filter for the considered noises: a) Salt & pepper Noise; b) Gaussian Noise (0.03); c) Speckle Noise (0.04); d) Gaussian Noise (0.05); e) Poisson Noise

We can observe the VMF and the Gaussian filter almost battle each other for each noise type, and maintain a consistent range of PSNR levels. The Gaussian filter and the Wiener filter underperformed for most noises, and the Gaussian filter barely crossed 19dB on average. Fig. 3,contains the visual representation of all the filtering methods against the salt & pepper noise. If we look closely, the Gaussian typically blurs the image and produces over-smooth edges and textures. However, there is no proper definition. Rank-Order filter completely removes the noise and slightly blurs the image. The Rank filter does well by preserving the structure. However, it does not preserve the edges of the image, as in the guided filter. The Wiener filter and mean filter produce almost a similar kind of output; they both leave the translucent freckles of noise on the image resulting in a pretty poor picture. The Vector median filter and the guided filter return better images than the other filtering techniques.

Fig. 4, represents the denoised images of the Guided Filter for all the noises considered. The filter consistently delivers the output precisely, but then it relatively smoothens or blurs the image in the due process, only preserving the edges.
Fig. 5, provides a visual comparison of the VMF & the Guided-Filter denoised output for a known salt & pepper noise. Now, keeping them side by side gives us a clear-cut idea about both the filters. We have considered the salt & pepper noise as a qualifying factor. It is the most common noise, and at the same time, it is tough to get removed when present in high densities. The VMF, on the one hand, performs quite well, it removes most of the noise present in the image, and at the same time, preserves the structure of the image while keeping the colours unchanged. There is still some tiny amount of noise left in the image, which can be removed by further processing of the image.

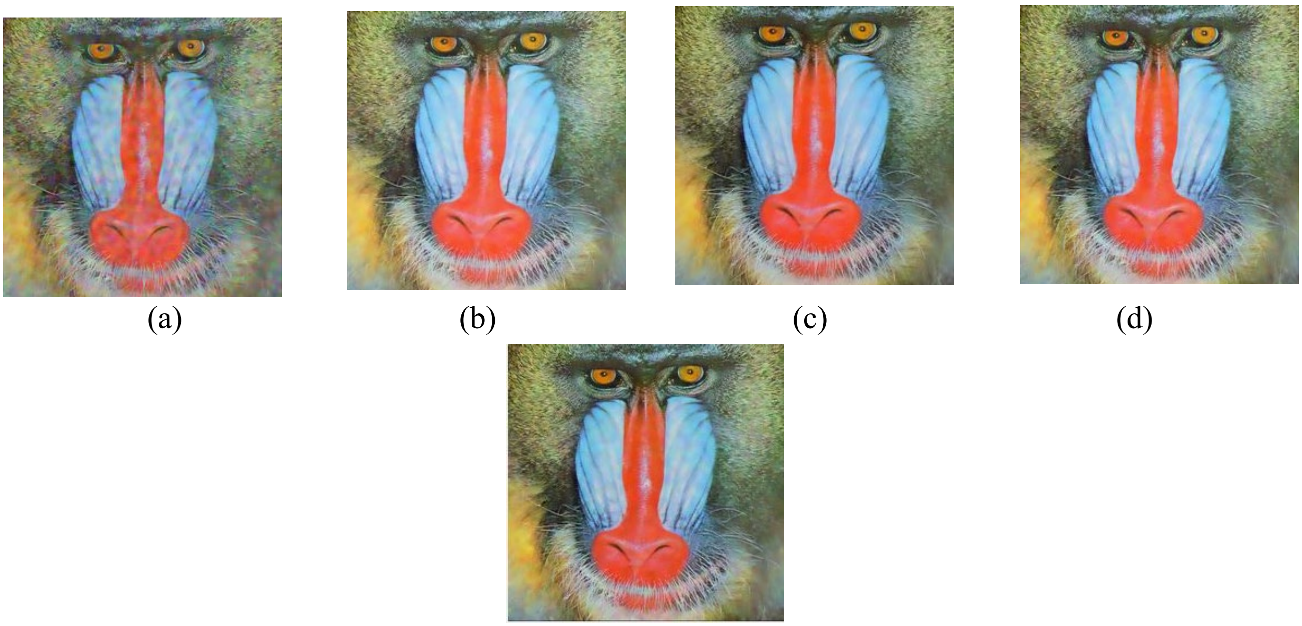
On the other hand, the Guided-Filter eliminates the noise from the pixels. Still, in due process filtering the image, it slightly changes the image structure, i.e., it leaves behind a translucent film of noise over the final image, which gives us a blurry impression of the image. Nevertheless, it preserves the edges and presents them sharper than the rest of the parts of the image. With a bit of improvement in the PSNR, the guided filter eventually fails to reach the level of fidelity of VMF. This demonstrated the dominance of VMF over the other filters, and especially over the guided filter, and gave us the motivation to go further using the VMF.



(a) (b) (c) (d)

(e) (f) (g)

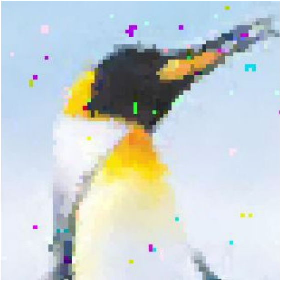
Figure 3. Visual Representation of all the filters against salt & pepper noise, of 20% density: a) Noisy Image, 11.494 dB; b) VMF, 32.081 dB; c) Gaussian, 17.15 dB; d) Rank, 22.55dB; e) Guided, 21.893 dB; f) Wiener, 18.038 dB; g) Mean, 17.941 dB



(a) (b) (c) (d)

(e)

Figure 4. Represent the result of the Gaussian for the considered noises: a) Salt & Pepper; b) Gaussian, (0.03); c) Speckle Noise, (0.04); d) Poisson Noise; e) Gaussian, (0.05)



(a)

(b)

Figure 5. Visual Comparison of details in the magnified result between the VMF and the Guided Filter: a) Vector Median Filter; b) Gaussian Filter

4. Proposed Denoising ANFIS Model

In this section of the paper, we would talk and present our proposed model, discuss the skeleton of the model, mention the essentials of the model, and illustrate its algorithm. The Modular Predictive algorithm ANFIS has been used for our model. ANFIS applies two techniques in the updating features. For premise characteristics that define membership functions, ANFIS employs gradient descent for fine-tuning purposes. For sequential parameters that define the coefficients of each yield equations, ANFIS uses the least-squares method. For consequent parameters that define the coefficients of each output equations, ANFIS uses the least-squares method. This approach is called the hybrid learning method since it combines gradient descent and the least-squares methods. This model dramatically combines the advantages of both the concepts of fuzzy rules and neural networks, thus building a robust model for our work.
Now that we have obtained insight into the fuzzy logic in section 2, we shall proceed onto its interface system and learn about its architecture in detail. Then we gradually get into the ANFIS Architecture, provide a precise outline needed for the proposed model, and then get into the actual working of the model.

Fuzzy Interface Systems

The fuzzy interface system is the crucial part of the fuzzy logic system, and it is entirely based on decision-making based on the input data. It uses its set of If-else rules, OR-AND rules, before arriving at a decision. A *fuzzy inference system* is a method that renders the values in the input vectors and, based on user-defined rules, assigns values to the output vector.
The editors and viewers are utilized to edit and inspect the membership functions and rules for the fuzzy inference system [6].
The two primary components of fuzzy systems are fuzzy sets and operations on fuzzy sets. Fuzzy logic defines rules based on combinations of fuzzy sets by these operations. [11]

1) **Fuzzy Sets** : The fuzzy sets are the generalization of the traditional sets. These sets are dependent on the membership function of that set. The Fuzzy set provides a framework for incorporating human knowledge to solve problems whose formation is based on vague concepts. The overall concept of fuzzy sets was introduced by L.A. Zadeh (Zadeh[1965]).
Variating from the crisp sets, based on the concept 'belongs to,' [12] , the fuzzy sets are more continuous and can have infinite elements. The degree of membership is the key here, as crisp sets always associate with either belongs or does not belong to a set, while with fuzzy sets, we say that the element can either have a full membership, partial membership, and zero degree of membership.
Hence, a fuzzy set, A, is an ordered pair comprising values of z, and a membership function that designates a grade of membership in A to each z. That is,

$$A = \{z, \mu_A(z) | z \in Z\} \tag{4.1}$$

Where z is the value of generic element in Z; $\mu_A(z)$ is the membership function
Although the fuzzy logic and probability operate over the same interval, i.e.[0,1], there is a significant distinction between the two. While probability speaks for a chance of occurring a random event, fuzzy logic deals with the degree of the randomness in the event.
The Comparison between the fuzzy logic and probability is accurately stated in [12]

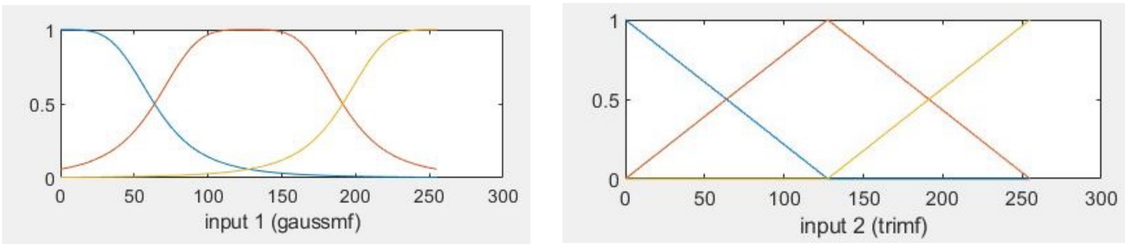


Figure 6. Visual representation of the membership functions used in the model: a) The Gaussian Bell Membership Function; b) Triangular Membership Function

2) **Membership Functions**: The member function is solely a curvature that defines how each point from the input set is mapped to a membership value between 0 and 1. These member functions come in many shapes. The gaussian member function(gaussmf) or a bell-shaped member function(gbellmf), and a triangular member function(trimf) are a few of the most common examples. These member functions take the vaguely represented fuzzy logic, and based upon the degree of the membership, these functions validate the preliminary data and arrive at a particular conclusion. In this paper we have used the gbellmf, and trimf. Fig 6, displays the membership functions used in this model.

3) **If-Then Rules**: The if-then rules are used to formulate the conditional statements that hold the fuzzy logic. These rules are purely constructed according to the application, and these rules vary with need. These rules incorporate the total of our understanding of the problem. These rules validate the model and present an accurate result.
The rule-based techniques, for example, have the general form:

If condition X1, **and** condition X2, **and** ... , **then** action Y

Proposed ANFIS Model

So far, we have understood that the fuzzy logic takes the imprecision and uncertainty of the system that is being modeled into account, while the neural network gives it single adaptability. Now, using this hybrid method, at first, an initial fuzzy model and its input variables are desired with the help of the rules extracted from the input-output data of the system that is being modeled. Next, the neural network is used to fine-tune the rules of the initial fuzzy model to produce the final ANFIS model of the system.

1) **ANFIS Architecture** : ANFIS's network constitutes two parts like fuzzy systems. The first part is the predecessor part, and the second part is the judgment part, which is connected by rules in network form. If ANFIS in network structure is shown, that is demonstrated in five layers, and it can be described as a multi-layered neural network. The network layers are described in the works [6,13,14] we would not discuss them in this paper. Instead, we talk about the working of the proposed ANFIS Model.

In layman's understanding, the ANFIS structure contains an input layer and membership function layer, a decision-making layer based on the fuzzy rules, a normalization layer, and an output layer. For example, an Adaptive Neuro-Fuzzy Inference System (ANFIS) proposed by Robert Jang, mentioned in [14], is a five-layer feed-forward neural network, which includes a fuzzification layer, rule layer, normalization layer, defuzzification layer, and a single summation neuron. An ANFIS uses a hybrid learning algorithm that combines the least-squares estimator and the gradient descent method.

2) **Setting Up the Woking Model:** After a thorough experimental procedure carried out in section 3, it gave us a shred of clear evidence on utilizing the features of VMF over any of the discussed filters. Though the guided filter is also a notable alternative option, since the fidelity of the VMF is unmatched, we shall now apply the VMF, in combination with the ANFIS. Once the filter was chosen, we then set up the training images, and again we have chosen five standard 256 * 256 color images, that is, 8-bit images for our model. Yet again, we have considered the five noise models as the parameters to test the model.
   a. **Working Algorithm**: The foremost critical thing to keep in mind is that when using fuzzy sets for spatial filtering, the basic approach is to define fuzzy neighbourhood properties that capture the essence of what the filters are deemed to identify. For example, we can develop a fuzzy boundary detection algorithm based on the following fuzzy statement: '**If** a pixel belongs to a uniform region, **then** make it white; **else** make it black,' stated in [13]. Accordingly, we have built a fuzzy algorithm based on the selective approach of our filtering technique. The selective application of the VMF to only those neighbourhoods containing 'noisy pixels' allows these pixels to be omitted from the calculation of the vector median. The advantage is obvious: impulsive noise, for example, will be removed by a vector median filter, replacing the noisy pixel with one of its neighbours, thus preserving the local color properties; whereas median filtering of the RGB image components separately may replace, say, the noisy red component of a pixel with one of its neighbours, leaving the noise-free green and blue components unaltered, achieving only a change of color of the noise-corrupted pixel rather than its removal. So, what we initially were to let the model understand the difference between clear image, noisy image, and noise pixels without the images. We have generated random 8-pixel data, applied the noise, and subtracted the noisy image from the original image to get the data about the noisy pixels. The fuzzy systems learn about these pixels such that it targets only the noisy affected areas and passes the command to the filter to remove the noise only in those areas. The algorithm can be represented as a statement as follows:

'**If** the pixel value in the given neighbourhood is close to 0, **then** it is replaced by a new pixel, **else** the original pixel is preserved by the system'

   b. **Run Time:** We have defined the membership functions that declare the degree of membership on the training data. The training data is simply the randomly generated 8-bit pixel image as mentioned above. The whole training procedure is completed using the Fuzzy tool box. Observe the Fig 7.d, as to how the random pixels are generated.

Now that the algorithm and the membership functions are defined, we can further apply the model to cater to our need, that is, to remove the noise smartly. As the algorithm suggests, the proposed ANFIS model, after understanding the noise pixels, looks out for the locations of the noisy pixels and identifies them in the given image. Now once they are identified, they are interchanged with the pixels from the actual image and present the denoised image as the final result. All the experiments are carried out in the MATLAB (R2015b) environment and MATLAB (R2021a - Trail version) running on a PC with CPU Intel(R) Core(TM) i5-8300H CPU @ 2.30GHz and an Nvidia GEFORCE GTX 1050 GPU. It takes 15-20 minutes on a single GPU.

Section 5 contains the tabular and visual representations of this experimental procedure.

5. Experimental Results-II

Now that we have learned about the various filtering techniques and applying them to the fuzzy interfaces system and generated our model, it is finally time to observe and introspect the output result. In the ultimate section of our paper, i.e., Section 5, we showcase the final results and come to terms with a conclusion of our work.

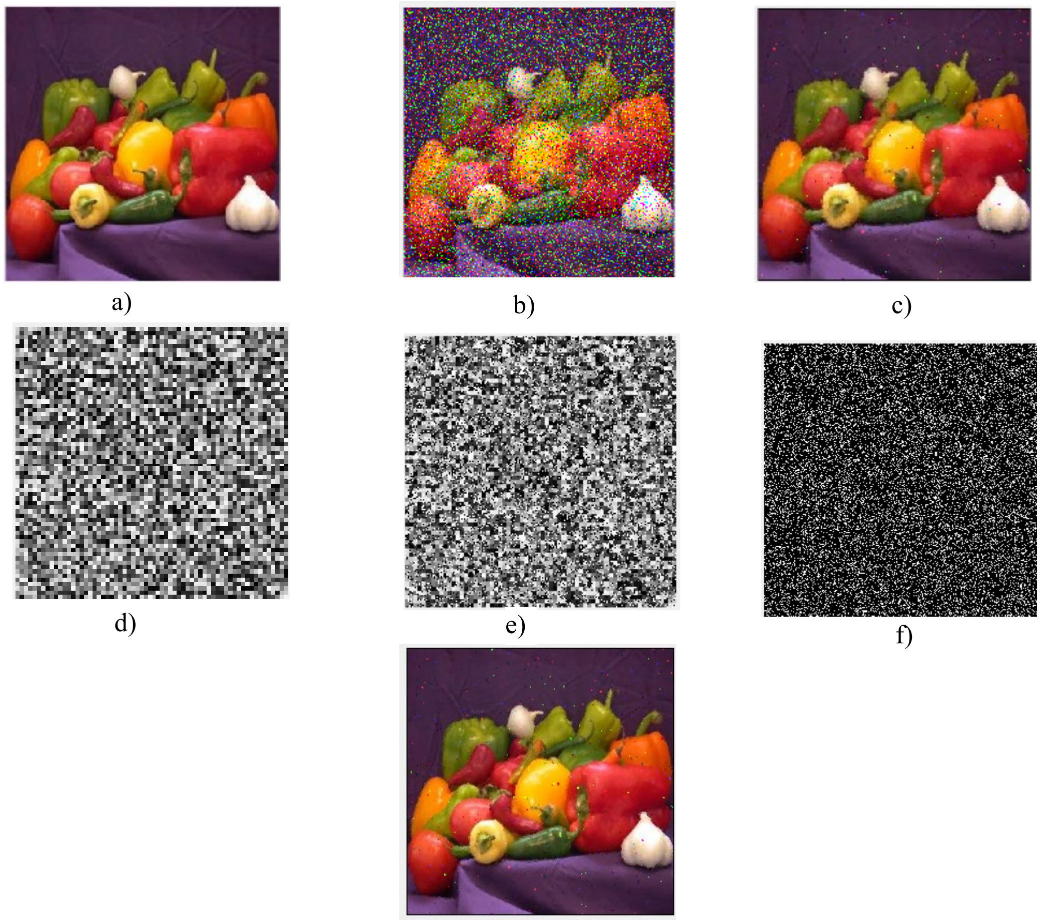
Quantitative and Qualitative Evaluation

The average PSNR results of different noises considered with the proposed ANFIS model are tabulated in Table 2. We can see the model performs quite consistently with each type of noise. The Maximum PSNR is highlighted in bold. We can see the model performed quite efficiently with all the noises, but its performance stands out with the salt & pepper noise. The PSNR is also slightly improved compared to the application of VMF (from Table 1) alone without the Fuzzy systems, and this is not just in the case of VMF, but also with the Speckle Noise.

Table 2. The psnr(db) results of the proposed model against the different noises on 5 randomly chosen widely used images.

Noise Type	The Proposed Model					
	Pepper	Penguins	Lena	Baboon	Barbara	Average
Salt & Pepper Noise (0.20)	35.248	34.3133	34.4155	32.056	34.885	**34.185**
Gaussian Noise (0.03)	25.068	25.529	25.066	25.346	25.142	25.230
Gaussian Noise(0.05)	24.516	24.987	24.563	24.834	24.618	24.7036
Speckle Noise(0.04)	28.292	27.638	27.472	27.537	27.102	**27.6082**
Poisson Noise	31.78	29.308	29.655	27.947	29.836	29.7052

Fig 7 represents the model response of one of the standard images against the salt & pepper noise. Once again, we can see the structure of the image is reproduced as it is, and the edges are preserved. Though there is a subtle difference between PSNR and the Clarity of the image compared to the result of Fig 2, the local color properties in the neighbourhood are preserved. Fig 8, represents the visual comparison between the conventional VMF and the proposed ANFIS model against the standard peppers image. The proposed model provides a better result compared to the VMF. The details and texture are much more precise, and also the structure outline is intac, and edges of the peppers look are much more faithfully preserved in the proposed model.



a) b) c) d) e) f) g)

Figure 7.Result of the proposed model of a standard test image against the salt & pepper noise:a) Original Image; b) Noisy Image; c) VMF output; d) Random Pixels; e) Pixels with Noise; f) Noisy Pixels; g) Proposed model output.

a) **b)**

Figure 8. Comparison of results between the standard a) VMF and b) The proposed model

Challenges and Future Prospects

In this section, we review our model and mention the shortcomings and future prospects of the work.

We have produced a sophisticated model and promising results; However, we still feel there is room for improvement that can be achieved with future studies.

A few more filters, such as Non-Local Algorithmic Filter, Anisotropic Filter, can be considered to denoise an image [16,19] However, we have limited our approach as we already included six different filters. When we observe Table 1, the guided filter's PSNR values were almost equally consistent with the Vector Median filter. Image processing techniques can further reduce the Blurriness in the result of the guided filter, which then can be applied to our model.

The shortcoming or a challenge of our model that needs to be addressed is that, when we observe Table 2, the model did an excellent work against the salt & pepper noise and the speckle noise and did a decent job against Poisson noise. However, it was just par in performing against the Gaussian noise.
Several models are proposed already using the convolution neural networks, which did pretty well against the additive white gaussian noise (AWGN) that can be applied in fusion with the filter.[15]
One more significant thing we can work our model with and test its effectiveness is exposure to random noise. This random noise can be a known random noise, which the user can generate, or an unknown random noise. We indeed like to work upon the concept of random noise and test our model. [26]

6. Conclusions

In this paperwork, an adaptive neuro-fuzzy interface system model was proposed for image denoising, where the model learns about the locations of the noise pixels in an image and applies the fuzzy logic and if-then rules. The model follows a human-like decisive approach in identifying the noise-affected locations and removing noise, thus conserving the structure of the unaffected image pixels. Initially, we compared all the filters basis on their degree of retaining the originality of the image, preserving the structure and local colours of the neighbourhood, and the PSNR values. Although the guided filter provided marginally better PSNR consistently for all the noises than the vector median filter, the reason for selecting the latter over the former as the guided filter despite providing the better PSNR, the guided filter partially blurs the image and only preserves the edges. Now, this factor might be crucial in certain areas. Hence, we have chosen the vector median filter, which provided a comparatively better definition in the image after processing.The Vector Median filter thus considered for this model where we felt there is a need of maximum faithfulness in the output.
As mentioned in the section 1, our method overcomes the shortcomings of the existing methods, such as limited range of noises, and the comparison criteria between the filters, thus providing a better edge to our method. What makes it effective is the fusion of Adaptive Neuro-Fuzzy Interface Systems and VMF model, which indeed proved very powerful and robust to remove the noise in the given image smartly, and it is safe to say that we finally developed a sophisticated model that dealt precisely with various noises and produced a satisfactory output.
Comprehensive experimental outcomes demonstrated that the proposed method produces a favourable image denoising performance quantitatively and qualitatively and has good run time by GPU implementation.

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