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Medicinal Plant Leaf Image Enhancement using Guided Filter and Adaptive Gamma Correction with Weighting Distribution

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Abstract:

Noise is a random variation of intensity or brightness or color information and is visible as part of grains in the image.Noise degrades the quality of the image. During image acquisition and transmission of digital images noise will be added to the image. Physical environmental conditions like intensity of light, humidity, Sensor heat, temperature, camera lens intrinsic parameters, camera characteristics, Dust particles in the scanner, etc., may affects the imaging sensors which may cause noise in the image. Transmission channel interference may introduce noise digitally, particularly the network with no error detection/correction.Image de-noising becomes one of the key factors in the applications images. In order to improve the features and the quality of medicinal plant leaf images for disease detection and analysis, this paper proposes the combination of Adaptive Gamma Correction with Weighting Distribution(AGCWD) technique for contrast enhancement and Guided filter for removal of noisein the image. Experimental results validate the performance of the proposed approach.The performance parameters like peak signal-to-noise ratio(PSNR), mean-square error (MSE), mean absolute error (MAE) and image enhancement factor (IEF) are evaluated between the proposed method and the bilateral filter, the proposed methodis showing good performance in terms of performance parameters evaluation.

Keywords: Adaptive Gamma Correction, Contrast, De-noising, Image acquisition, Guided filter, IEF, MAE, MSE, PSNR.

I. INTRODUCTION:

Digital images play an important role in applications of digital image processing[1] such as Medical field, Color processing, Image sharpening and restoration, pattern recognition, machine/robot processing, Microscopic Imaging, transmission and encoding, video processing and others. Noise [2][3]refers to the random variation in intensity or brightness or color informationof a pixel and is visible as part of grains in the image. Some additional information is added to the pixels of image and makes the noisy image.Due to noise some important details may be hidden, these details may be important in the further steps of processing like edge detection, segmentation, analysis etc. Noise not only degrades the quality of the image also degrades the ability of the human observation to some diagnosisobject. During image acquisition, coding and transmission of digital images noise will be added to the image. Physical environmental conditions like intensity of light, humidity, Sensor heat, temperature, camera lens intrinsic parameters, camera

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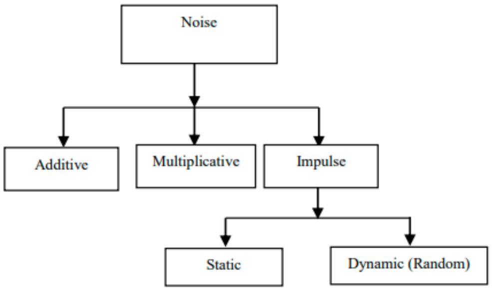
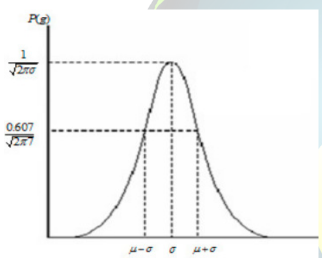


characteristics, Dust particles in the scanner, etc., may affects the imaging sensors, which may cause noise in the capturedimage. Furthermore, transmission errors and compression methods may introduce noise in the images. Thus, image de noising is one of the necessary and first stepto be followed before the images are considered for analysis.Removal of noise is a challenging task because it introduces additional issues in images related to artifacts



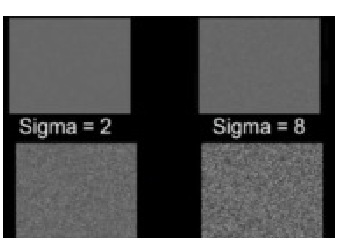
and blurring. Various de noising algorithms are available based on the type of noise model.

Noise[2] is classified as either multiplicative, additive or impulse. The impulse noise [4] modifies the pixel intensities randomly and it is classified into static and dynamic(random) noise.

Salt and pepper also known as impulse noise, Gaussian noise, uniform noise, Erlang(gamma) noise, exponential noise, speckle noise, etc are the various types of noises. Gaussian Noise is assumed to have additive noise in most of the natural images. Mostly speckle noise is observed in Radar images, ultra sound images and medical images.

Fig.1.Classification of Noise Models.

II. PROPOSED WORK



A. *Gaussian Noise:*

Gaussian noise[2], named after Carl Friedrich Gauss. It is a statistical noise, having a probability density function (PDF) equal to that of the normal distribution, which is also known as the Gaussian distribution. It is also called as electronic noise because it arises in amplifiers or detectors. Natural sources such as discrete nature of radiation of warm objects and thermal vibration of atoms causes Gaussian noise. Gaussian noise distributes the gray values (adds random values to each pixel) in digital images, so Gaussian noise model is designed and characterized by its PDF or normalizes histogram with respect to gray value. The probability density function P(g) of a Gaussian random variable g is given by:

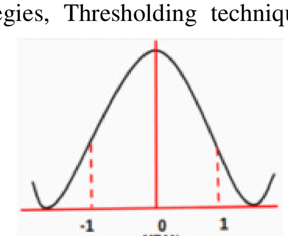
$$P(g) = \sqrt{\frac{1}{2\pi\sigma^2}}\, e^{-\frac{(g-\mu)^2}{2\sigma^2}} \tag{1}$$

Where g=gray value, σ=standard deviation and μ= mean.

Correct approximation of real world scenarios can be represented with Mathematical model of Gaussian noise. In this noise model, the mean value is zero, variance is 0.1 and 256 gray levels in terms of its PDF, which is shown in Fig. 2.

Fig.2. PDF of Gaussian noise

Normalized Gaussian noise curve is bell shaped due to its equal randomness. The PDF of Gaussian noise model shows that 70 to 90% of noisy pixel values of degraded image will lie in between μ-σ and μ+σ. It is almost similar to the shape of normalized histogram in spectral domain. [10] discussed that Biomedical and anatomical data are made simple to acquire because of progress accomplished in computerizing picture division. More research and work on it has improved more viability to the extent the subject is concerned. A few tech- niques are utilized for therapeutic picture division, for example, Clustering strategies, Thresholding technique, Classifier,



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Region Growing, Deformable Model, Markov Random Model and so forth. This work has for the most part centered consideration around Clustering techniques, particularly k-implies what's more, fluffy c-implies grouping calculations.

The Fig.3 shows bell shaped probability distribution function(PDF) with mean(U) 0 and standard deviation(sigma) 1.

Figure 3. Plot of Probability Distribution Function

Gaussian noise arises in digital images mainly from image acquisition process, sensor noise caused by poor illumination, high temperature, characteristics of the sensor, etc. and or electronic circuit noise during transmission. Gaussian noise is generated by adding Random Gaussian function to the image. Spatial filters can be used to smooth and reduce the Gaussian noise.

Effect of Standard Deviation(sigma) on Gaussian noise: In Gaussian noise model, noise magnitude is direct proportional to the sigma(Standard Deviation) value, so the magnitude of Gaussian noise depends the standard deviation value.

Fig.4. Effect of Sigma on Gaussian Noise

B. Guided filter:

Guided filter [5] is non-iterative edge preserving smoothing filter derived from a local linear model. It can filter out the noise while retaining sharp edges. Guided filter computes the output image with the content of a guidance image; the guidance image[7] can be the same input image or another different image. In case of guidance image and input image to be filtered are similar, the guidance image and input images have similar structures i.e edges in both images are same. Guided image filtering is one of the spatial domain enhancement technique in which the filtering output is locally a linear transform of the guidance image. While calculating the output pixel value, the corresponding spatial neighbourhood in the guidance image and region related statistics are to be considered. Two advantages of Guided filter over bilateral filter are, Guided filters does not use complicated mathematical calculations, which has simple linear complexity, whereas bilateral filters [8] have high computational complexity. Bilateral filters sometimes suffer from unwanted gradient reversal artifacts they may cause distortion in the image due to the mathematical model. Guided filter uses linear mathematical model, so the problem of gradient reversal does not occur and the output image must be consistent with the gradient direction of the guidance image. [6] discussed about the combination of Graph cut liver segmentation and Fuzzy with MPSO tumor segmentation algorithms. The system determines the elapsed time for the segmentation process. The accuracy of the proposed system is higher than the existing system. The algorithm has been successfully tested in multiple images where it has performed very well, resulting in good segmentation. It has taken high computation time for the graph cut processing algorithm. In future work, we can reduce the computation time and improves segmentation accuracy.

Pixels near the edges are better filtered by the guided filter than the bilateral filter. Beyond the smoothing, by using the guidance image the Guided filter makes the output filtering more structured and less smoothed than the original input image.

Guided Filter Algorithm[5]:

Assume filtering input image as I, guidance image as G, regularization as ε, and filtering output as Q.

1. Reading pixel values of image.
2. Pass them to 5x5 or 3x3 line buffers.
   Window can be chosen with any size. With large window size BRAM and slice register usage is increased.
3. Getting all window pixels.
4. Apply averaging filter (f_{mean}) on guidance and input image and also find correlation (corr) as shown below:
   $mean_G = f_{mean}(G)$
   $mean_I = f_{mean}(I)$
   $corr_G = f_{mean}(G .* G)$
   $corr_{GI} = f_{mean}(G .* I)$
5. Compute the covariance by using obtained mean and correlation values in the above step
   $cov_{GI} = corr_{GI} - mean_G .* mean_I$
6. Compute the variance
   $var_G = corr_G - mean_G .* mean_G$

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7. Compute the linear coefficients X& Y by using obtained covariance, variance, mean values.
   $X = cov_{GI} ./(var_G + \epsilon)$
   $Y = mean_I - X .* mean_G$
8. Compute the mean of linear coefficients X and Y
   $Mean_X = f_{mean}(X)$
   $Mean_Y = f_{mean}(Y)$
9. Calculate the filtered image by using the calculated mean values of linear coefficients X and Y
   $q = mean_X .* G + mean_Y$

C. Adaptive Gamma Correction with Weighting Distribution(AGCWD)

Adaptive Gamma Correction with Weighting Distribution [9] is an efficient method to enhance contrast in digital images by modifying the histograms in digital images. In any subjective evaluation of image quality of image processing applications, contrast plays a key role. Subjective quality is important for human interpretation. Contrast is nothing but the difference in luminance reflected from two adjacent surfaces. In simple terms contrast is the difference between the intensity of maximum pixel and intensity minimum pixel in an image. Contrast enhancement [9] plays a key role in applications of digital image processing, pattern recognition and computer vision.

Adaptive Gamma Correction with Weighting Distribution is an automatic transformation technique which increases the brightness of low intensity images with the gamma correction and probability distribution of luminance pixels.

The Adaptive Gamma Correction (AGC) is represented as shown below.

$$T(l) = l_{max}(l/l_{max})^{\gamma} = l_{max}(l/l_{max})^{1-cdf(l)} \qquad (2)$$

Adaptive Gamma Correction (AGC) method avoids the significant decrement of high intensity and can progressively increases the low intensity. The weighting distribution (WD) function is applied to slightly modify the statistical histogram and decrease the generation of opposing effects. The weighting distribution function is formulated as:

$$pdf_w(l) = pdf_{max}\left(\frac{pdf(l)-pdf_{min}}{pdf_{max}-pdf_{min}}\right)^{\alpha} \qquad (3)$$

Where α is the adjusted parameter, *pdf* max is the maximum *pdf* of the statistical histogram, and pdf_{min} is the minimum *pdf*. Based on equation (3), the modified *cdf* is approximated by

$$cdf_w(l) = \sum_{l=0}^{l_{max}} pdf_w / \sum pdf_w \qquad (4)$$

Where the sum of pdf_w is calculated as follows:

$$\sum pdf_w = \sum_{l=0}^{l_{max}} pdf_w(l) \qquad (5)$$

Finally, the gamma parameter based on *cdf*of Equation (2) is modified as follows.

$$\gamma = 1 - cdf_w(l) \qquad (6)$$

The proposed work enhances the features in leafs of medicinal plants using guided filtering along with Adaptive Gamma Correction with Weighting Distribution, and helps in next i.e,image analysis for clear identification and detection of diseases if any.

III. Experimental Results

This section summarizes the experimental results of proposed work for different leaf images with various noise variations, and also to prove that the proposed work outputsbest image quality compared with other image enhancement[11]algorithms like guided filter, bilateral filter etc., for those the metrics [12] under investigation are PSNR, MSE, MAE and IEF.

MSE: mean-square error (MSE)

MSE measures the cumulative squared error between the values of enhanced image and the original image. MSE should be lower, then lower the error. MSE is a quality measure of an estimator. MSE is given by the following formula

$$MSE = \frac{1}{R*S}\sum_{i=0,j=0}^{M-1,N-1}[P(x,y) - Q(x,y)]^2 \qquad (7)$$

Where R and S represents the width and height of the images, P(i,j) represents the pixel in the enhanced image, Q(i,j) represents the pixel in the original image. The

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x and y represents the rows and columns of enhanced and original images.

PSNR: peak signal-to-noise ratio (PSNR)

It is the ration between the peak value of a signal and power of corrputing noise that affects the quality of its representation. PSNR should be higher, then better the quality of the reconstructed image. PSNR is measured in decibels.

$$PSNR = 10 * \log_{10}(\frac{MAX_I^2}{MSE})$$
$$= 20 * \log_{10}(\frac{MAX_I}{\sqrt{MSE}})$$
$$= 20 * \log_{10}(MAX_I) - 10 * \log_{10}(MSE) \quad (8)$$

Here, MAX_I represents the maximum value of the pixel in the image. The PSNR is commonly used as measure of quality reconstruction of image.

MAE: Mean Absolute Error (MAE)

MAE is a measure of errors between the original image and the enhanced image. MAE is calculated as

$$MAE = \frac{\sum_{i=1}^{n}|y_i - x_i|}{n} = \frac{\sum_{i}^{n}|e_i|}{n} \quad (9)$$

MAE is an arithmetic average of the absolute errors$|e_i| = |y_i - x_i|$, where $y_i$is the prediction and x_i the true value. MAE should be lower.

IEF: Image Enhancement Factor (IEF)

The IEF for an image is calculated as

$$IEF = \frac{MSE(Original\ Image, Noise\ Image)}{MSE(Original\ Image, Restored\ Image)} \quad (10)$$

The proposed method is applied to denoise and enhance the leafs of medicinal platnts. The plant leaf images of Jatropha, Chinar and Pongamia tested for different mean values like, 0, 0.01 and 0.05 and variances in the range of 0.01 to 0.05 and for all the performance parameters PSNR, MSE, MAE and IEF are evaluated.The results for Jatropha image are shown in Tables 1,2 and 3 for means 0,0.01 and 0.05 respectively for variance range 0.01 to 0.05. The resulting images are shown in Figres 5 to 10. The comparative graphs are shown in Figures 23 to 34.

The results for Chinar image are shown in Tables 4,5 and 6 for means 0,0.01 and 0.05 respectively for variance range 0.01 to 0.05. The resulting images are shown in Figres 11 to 16.The results for Pongamia image are shown in Tables 7,8 and 9 for means 0,0.01 and 0.05 respectively for variance range 0.01 to 0.05. The resulting images are shown in Figres 17 to 22.

The proposed method of denoising and enhancement has shown good performance in removing noise and enhanment of features than the bilateral filter and guided filter. The decement in PSNR, increment in MSE, MAE and decrement in IEF shows that the proposed method is denoising and enhancing the features far betterfor a given mean and variance than the bilateral and guided filters.

Table 1. Comparison of parameters (PSNR,MSE,MAE, and IEF) for Jatropha Leaf image with mean μ=0

Variance (σ)	Guided filter				Bilateral filter				Proposed Method			
	PSNR	MSE	MAE	IEF	PSNR	MSE	MAE	IEF	PSNR	MSE	MAE	IEF
0.01	26.28	152.86	10.12	3.78	32.61	35.58	4.95	1.50	14.48	2317.06	41.00	0.20
0.02	26.47	146.26	10.02	2.37	35.50	18.30	3.43	1.17	15.32	1909.06	38.04	0.31
0.03	26.88	133.15	9.62	1.93	37.25	12.23	2.69	1.09	16.03	1619.43	35.34	0.38
0.04	27.28	121.53	9.23	1.72	38.40	9.39	2.26	1.05	16.63	1409.95	33.07	0.43
0.05	27.64	111.79	8.87	1.59	39.22	7.77	1.98	1.04	17.16	1248.12	31.10	0.47

Table 2. Comparison of parameters (PSNR,MSE,MAE, and IEF) for Jatropha Leaf image with mean μ=0.01

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Variance (σ)	Guided filter				Bilateral filter				Proposed Method			
	PSNR	MSE	MAE	IEF	PSNR	MSE	MAE	IEF	PSNR	MSE	MAE	IEF
0.01	26.28	153.06	10.11	3.6	32.67	35.17	4.92	1.49	14.48	2317.41	41.25	0.2
0.02	26.5	145.73	9.99	2.31	35.63	17.8	3.38	1.17	15.32	1908.32	38.26	0.31
0.03	26.92	132.2	9.58	1.9	37.41	11.8	2.64	1.09	16.04	1617.47	35.53	0.38
0.04	27.33	120.34	9.18	1.69	38.58	9.02	2.21	1.06	16.66	1402.27	33.17	0.43
0.05	27.7	110.53	8.82	1.57	39.41	7.45	1.93	1.04	17.21	1236.97	31.12	0.47

Table 3. Comparison of parameters (PSNR,MSE,MAE, and IEF) for Jatropha Leaf image with mean μ=0.05

Variance (σ)	Guided filter				Bilateral filter				Proposed Method			
	PSNR	MSE	MAE	IEF	PSNR	MSE	MAE	IEF	PSNR	MSE	MAE	IEF
0.01	26.27	153.41	10.07	2.34	32.81	34.08	4.82	1.34	14.55	2282.23	41.76	0.2
0.02	26.55	143.77	9.87	1.94	36.0	16.35	3.21	1.13	15.4	1874.84	38.71	0.3
0.03	27.03	128.71	9.41	1.7	37.94	10.45	2.45	1.07	16.14	1582.31	35.88	0.37
0.04	27.48	116.1	8.98	1.56	39.19	7.83	2.03	1.04	16.79	1362.15	33.35	0.43
0.05	27.88	105.97	8.61	1.47	40.09	6.38	1.76	1.03	17.35	1197.62	31.23	0.48

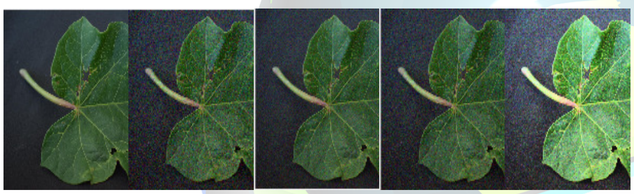

Fig.5. Jatropha Leaf a) Original image b) Gaussian noise image mean μ=0, variance σ=0.01 c) Guided filtered d) Bilateral filtered e) Smoothed and enhanced image with proposed method.

Fig.6. Jatropha Leaf a) Original image b) Gaussian noise image mean μ=0, variance σ=0.03 c) Guided filtered d) Bilateral filtered e) Smoothed and enhanced image with proposed method.

Fig.7. Jatropha Leaf a) Original image b) Gaussian noise image mean μ=0.01, variance σ=0.01 c) Guided filtered d) Bilateral filtered e) Smoothed and enhanced image with proposed method.

Fig.8. Jatropha Leaf a) Original image b) Gaussian noise image mean μ=0.01, variance σ=0.03 c) Guided filtered d) Bilateral filtered e) Smoothed and enhanced image with proposed method.

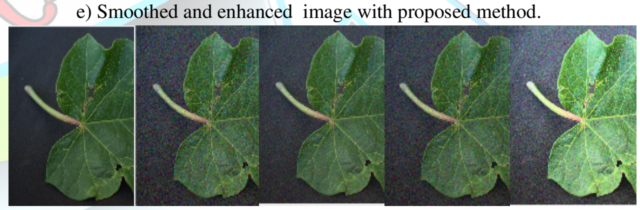

Fig.9. Jatropha Leaf a) Original image b) Gaussian noise image mean μ=0.05, variance σ=0.01 c) Guided filtered d) Bilateral filtered e) Smoothed and enhanced image with proposed method.

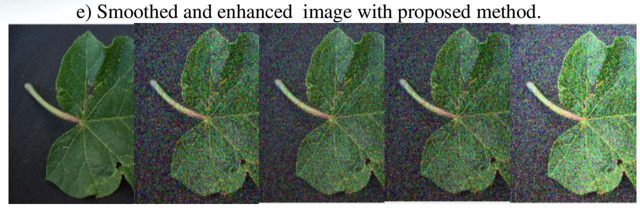

Fig.10. Jatropha Leaf a) Original image b) Gaussian noise image mean μ=0.05, variance σ=0.03 c) Guided filtered d) Bilateral filtered e) Smoothed and enhanced image with proposed method.

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Table 4. Comparison of parameters (PSNR,MSE,MAE, and IEF) for Chinar leaf image with mean μ=0

Variance (σ)	Guided filter				Bilateral filter				Proposed Method			
	PSNR	MSE	MAE	IEF	PSNR	MSE	MAE	IEF	PSNR	MSE	MAE	IEF
0.01	26.3	152.53	10.15	3.91	32.47	36.86	5.06	1.54	14.47	2322.42	40.33	0.2
0.02	26.43	147.83	10.12	2.45	35.17	19.78	3.59	1.19	15.29	1923.38	37.44	0.3
0.03	26.8	135.83	9.75	1.98	36.82	13.52	2.85	1.1	15.99	1638.87	34.96	0.36
0.04	27.17	124.7	9.37	1.75	37.91	10.51	2.42	1.07	16.59	1424.8	32.74	0.41
0.05	27.52	115.17	9.02	1.62	38.7	8.77	2.12	1.05	17.1	1266.68	30.89	0.45

Table 5. Comparison of parameters (PSNR,MSE,MAE, and IEF) for Chinar leaf image with mean μ=0.01

Variance (σ)	Guided filter				Bilateral filter				Proposed Method			
	PSNR	MSE	MAE	IEF	PSNR	MSE	MAE	IEF	PSNR	MSE	MAE	IEF
0.01	26.29	152.93	10.15	3.68	32.53	36.28	5.01	1.51	14.46	2325.85	40.62	0.19
0.02	26.45	147.32	10.09	2.36	35.32	19.12	3.52	1.18	15.26	1934.75	37.84	0.29
0.03	26.83	134.8	9.71	1.93	37	12.96	2.78	1.1	15.98	1642	35.23	0.36
0.04	27.22	123.4	9.32	1.72	38.12	10.03	2.35	1.06	16.58	1428.87	33.01	0.41
0.05	27.57	113.79	8.96	1.59	38.91	8.35	2.06	1.04	17.13	1259.88	30.99	0.45

Table 6. Comparison of parameters (PSNR,MSE,MAE, and IEF) for Chinar leaf image with mean μ=0.05

Variance (σ)	Guided filter				Bilateral filter				Proposed Method			
	PSNR	MSE	MAE	IEF	PSNR	MSE	MAE	IEF	PSNR	MSE	MAE	IEF
0.01	26.27	153.66	10.11	2.35	32.73	34.64	4.87	1.35	14.47	2323.51	41.59	0.19
0.02	26.51	145.16	9.95	1.95	35.8	17.09	3.3	1.14	15.27	1931	38.75	0.29
0.03	26.96	130.88	9.52	1.71	37.65	11.18	2.55	1.07	16.02	1627.11	35.91	0.36
0.04	27.39	118.68	9.11	1.57	38.84	8.49	2.13	1.05	16.65	1407.48	33.5	0.41
0.05	27.77	108.73	8.74	1.48	39.68	7	1.86	1.03	17.19	1241.59	31.44	0.46

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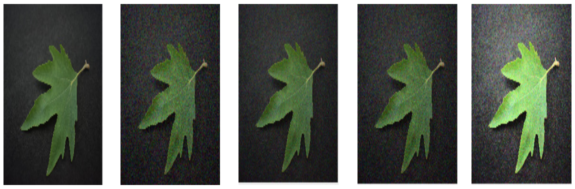

Fig.11. Chinar leaf a) Original image b) Gaussian noise image mean μ=0, variance σ=0.01 c) Guided filtered d) Bilateral filtered e) Smoothed and enhanced image with proposed method.

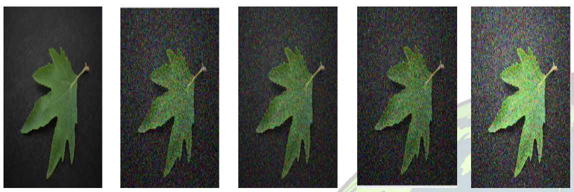

Figure 12 Chinar leaf a) Original image b) Gaussian noise image mean μ=0, variance σ=0.03 c) Guided filtered d) Bilateral filtered e) Smoothed and enhanced image with proposed method.

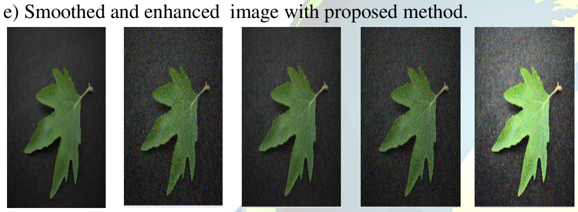

Figure 13 Chinar leaf a) Original image b) Gaussian noise image mean μ=0.01, variance σ=0.01 c) Guided filtered d) Bilateral filtered e) Smoothed and enhanced image with proposed method.

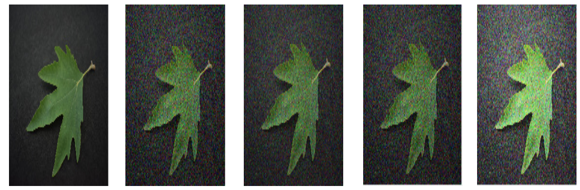

Figure 14 Chinar leaf a) Original image b) Gaussian noise image mean μ=0.01, variance σ=0.03 c) Guided filtered d) Bilateral filtered e) Smoothed and enhanced image with proposed method.

Figure 15 Chinar leaf a) Original image b) Gaussian noise image mean μ=0.05, variance σ=0.01 c) Guided filtered d) Bilateral filtered e) Smoothed and enhanced image with proposed method.

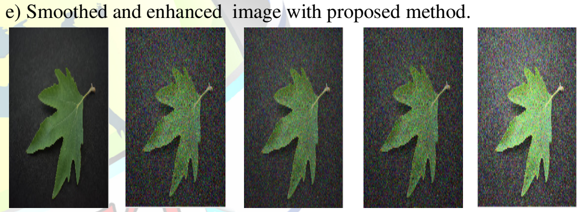

Figure 16 Chinar leaf a) Original image b) Gaussian noise image mean μ=0.05, variance σ=0.03 c) Guided filtered d) Bilateral filtered e) Smoothed and enhanced image with proposed method.

Table 7. Comparison of parameters (PSNR,MSE,MAE, and IEF) for Pongamia leaf image with mean μ=0

Variance (σ)	Guided filter				Bilateral filter				Proposed Method			
	PSNR	MSE	MAE	IEF	PSNR	MSE	MAE	IEF	PSNR	MSE	MAE	IEF
0.01	26.3	152.51	10.17	3.94	32.43	37.14	5.08	1.55	14.07	2545.24	41.89	0.18
0.02	26.42	148.43	10.15	2.47	35.09	20.15	3.63	1.2	15	2058.25	38.65	0.27
0.03	26.77	136.84	9.8	2	36.71	13.86	2.9	1.11	15.79	1715.81	35.7	0.34
0.04	27.13	125.92	9.43	1.77	37.8	10.8	2.46	1.07	16.42	1482.52	33.32	0.39
0.05	27.47	116.48	9.08	1.63	38.58	9.02	2.17	1.05	16.96	1308.01	31.31	0.43

Table 8. Comparison of parameters (PSNR,MSE,MAE, and IEF) for Pongamia Leaf image with mean μ=0.01

Variance (σ)	Guided filter				Bilateral filter				Proposed Method			
	PSNR	MSE	MAE	IEF	PSNR	MSE	MAE	IEF	PSNR	MSE	MAE	IEF
0.01	26.29	152.95	10.16	3.7	32.51	36.51	5.03	1.52	14.04	2567.77	42.45	0.17

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0.02	26.43	147.88	10.12	2.38	35.24	19.44	3.56	1.19	14.97	2070.69	39.06	0.27
0.03	26.8	135.76	9.76	1.95	36.91	13.25	2.83	1.1	15.76	1724.27	36.02	0.33
0.04	27.18	124.58	9.37	1.73	38	10.3	2.4	1.06	16.42	1483.94	33.53	0.39
0.05	27.52	115.04	9.02	1.6	38.79	8.59	2.11	1.05	16.97	1305.58	31.47	0.43

Table 9. Comparison of parameters (PSNR,MSE,MAE, and IEF) for Pongamia Leaf image with mean μ=0.05

Variance (σ)	Guided filter				Bilateral filter				Proposed Method			
	PSNR	MSE	MAE	IEF	PSNR	MSE	MAE	IEF	PSNR	MSE	MAE	IEF
0.01	26.26	153.76	10.12	2.34	32.72	34.75	4.88	1.35	14.01	2584.44	43.61	0.17
0.02	26.5	145.61	9.98	1.95	35.76	17.26	3.32	1.14	14.96	2077.32	40.12	0.27
0.03	26.94	131.65	9.56	1.72	37.58	11.36	2.58	1.08	15.77	1722.14	36.89	0.34
0.04	27.35	119.61	9.15	1.58	38.75	8.67	2.16	1.05	16.46	1469.35	34.15	0.39
0.05	27.73	109.69	8.79	1.48	39.59	7.15	1.89	1.03	17.04	1284.33	31.91	0.44

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Figure 17 Pongamia leaf a) Original image b) Gaussian noise image mean μ=0.01, variance σ=0.01 c) Guided filtered d) Bilateral filtered e) Smoothed and enhanced image with proposed method.

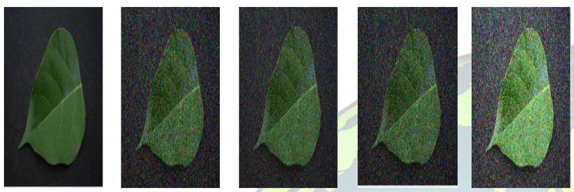

Figure 18 Pongamia leaf a) Original image b) Gaussian noise image mean μ=0.01, variance σ=0.03 c) Guided filtered d) Bilateral filtered e) Smoothed and enhanced image with proposed method.

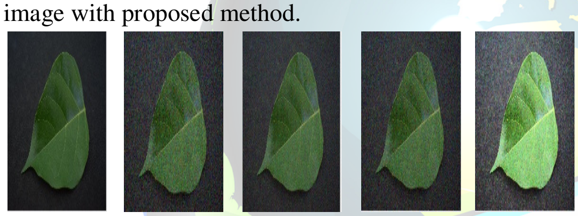

Figure 19 Pongamia leaf a) Original image b) Gaussian noise image mean μ=0.05, variance σ=0.01 c) Guided filtered d) Bilateral filtered e) Smoothed and enhanced image with proposed method.

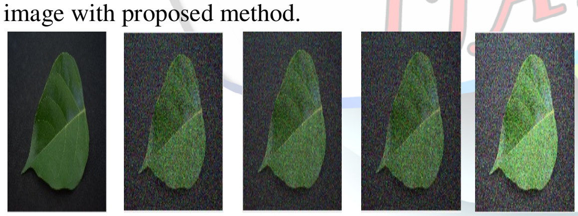

Figure 20 Pongamia leaf a) Original image b) Gaussian noise image mean μ=0.05, variance σ=0.03 c) Guided filtered d) Bilateral filtered e) Smoothed and enhanced image with proposed method.

IV. Conclusion

For obtaining accurate results in identification and detection of deseases in leafs of medicinal plants there is a need to undergo preprocessing the images before analysis, the tasks related todenoising, smoothening and enhancement are taken place in preprocessing. This paper presents an image enhancement method using a combination of guided filter along with adaptive gamma correction with weighting distribution. It is found that, this method is denoising the image without deteriorating the quality of the image. An additional advantage is that, it may reduce artifactsin the image,wich are occurred duing the acquition process. Most important thing is that, edge-preserving denoising approach is combined with the contrast enhancement. Important details in the image are preserved and plays a key role in the image analysis for identification and detection deseases.Experimental results shows that the proposed method outperforms the other denoising methods, preserving the edges and other important detail, and better objective performance. Future work will be related to enhanmentof images, suffering from blurring,uneven illumination and backgrounds.

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