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An efficient enhanced medicinal leaf image production using Adaptive Gamma Correction Weighting Distribution (AGCWD) algorithm with guided filter

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***Abstract*---**The quality of an image is always degraded by the random variation called noise which is included in the contrast, intensity and other properties like brightness. Noise is added with an image during the digital image transmission. The image sensors are always affected by the normal physical environment factors like temperature, scanner dust particles and the parametric characteristics of the lens and the camera. Noise removal is important in the image transmission because any interference in the transmission channel can include noise into it. A medicinal plant leaf needs to be disease free for a harmless medicine production. It becomes a necessity for a method to produce a more contrast enhanced image with the efficient noise removal mechanism. The paper proposes a combinational approach of an Adaptive Gamma Correction Weighting Distribution (AGCWD) which mainly serves to enhance the contrast of the image and the Noise removal mechanism which is performed by a guided filter. The proposed method evaluated various performance metrics like Mean square error (MSE), Image enhancement factor (IEF), Peak Signal to noise Ratio (PSNR) And Mean Absolute Error (MAE). The evaluation of the proposed system gave more better performance results than while using the existent Bilateral filter.

***Keywords*---**AGCWD, efficient enhanced medicinal, Weighting.

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Introduction

Digital images play an important role in applications of digital image processing such as medical field, Color processing, Image sharpening and restoration, pattern recognition, machine/robot processing, Microscopic Imaging, transmission and encoding, video processing and others [1]. Noise is classified as either multiplicative, additive or impulse. Noise [2][3] refers to the random variation in intensity or brightness or color information of 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. The impulse noise modifies the pixel intensities randomly and it is classified into static and dynamic(random) noise [4] [5]. 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 thequality of the image also degrades the ability of the human observation to some diagnosis

object. 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 characteristics, Dust particles in the scanner, etc., may affects the imaging sensors, which may cause noise in the captured image. Furthermore, transmission errors and compression methods may introduce noise in the images. Thus, image de noising is one of the necessary and first step to 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 [6][7]. Various de noising algorithms are available based on the type of noise model.

The leaves can be classified by a common feature that helps biologists identify different leafs based on their shape, texture, and colour. The physical appearance of plants can change depending on their surroundings. The goal of image pre-processing methods is to improve some image features that are important for further processing, such as edge detection or object recognition [8][9]. Plant identification is said to require extensive knowledge and complex terminology; even professional botanists must spend a significant amount of time in the field to master plant identification [10][11]. Image enhancement and segmentation performance metrics are also used to evaluate the proposed method's efficacy [12]. Digital image processing aids in manipulating digital images in order to analyse and extract useful information from them [12][13]. One of the issues concerning herbal medicine plants is their application and utilisation. Though many are aware of the existence of various herbal medicine plants and their familiar applications, many are still unable to identify which of these herbal medicine plants are these herbal medicine plants from the vast diversity of plants in the environment; thus, as their noted and approved applications by health professionals. Furthermore, researchers in botany, medicine, chemical structure analysis, and other plant-related fields face the challenge of putting in significant effort to identify plants. 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 [14][15]. Mostly speckle noiseis observed in Radar images, ultra sound images and medical images.

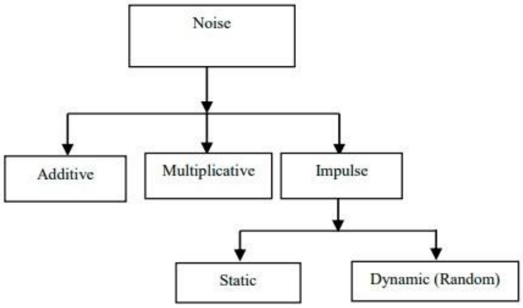

Figure 1. Classification of Noise models.

The following section will discuss the literature review.

II Literature Review

Kan, H.X., et.al., [16] have suggested classification of medicinal plant leaf image based on multi-feature extraction. To address the limitations of the manual classification method in identifying medicinal plants, this paper proposes an automatic classification method based on leaf images of medicinal plants. Our method will first preprocess medicinal plant leaf images, then compute the ten shape features (SF) and five texture characteristics (TF), and finally classify the medicinal plant leaves using a support vector machine (SVM) classifier.

Guo, X., et.al., [17] have proposed lime: low-light image enhancement via illumination map estimation. This paper proposed a simple yet effective low-light image enhancement (LIME) method in this paper. More specifically, the illumination of each pixel is first estimated individually by determining the maximum value in the R, G, and B channels. Experiments on a variety of difficult low-light images are presented to demonstrate the efficacy of our LIME. He, K., et.al., [18] have examined Guided Image Filtering. This paper proposed a new explicitimage filter called guided filter. The guided filter, like the popular bilateral filter, can be used as an edge-preserving smoothing operator. Beyond smoothing, the guided filter is a more general concept. Besides that, regardless of kernel size or intensity range, the guided filter has a fast and non-approximate linear time algorithm.

M. M. Ibrahim and Q. Liu, [19] have developed optimized color-guided filter for depth image denoising. This paper proposed a new framework for reducing texture coping and enhancing depth discontinuities, particularly in noisy environments. The depth driven color flattening model and the patch synthesis-based Markov random field model make up this framework. In this paper, the blurry effect is mitigated using a Markov random field and an optimization technique.

Zhang, M. and Gunturk, B.K., [20] have suggested multiresolution bilateral filtering for image denoising. An empirical study of the best bilateral filter parameter selection in image denoising applications is the first contribution. The second contribution is a multiresolution bilateral filter, which applies bilateral filtering to the approximation (low-frequency) sub bands of a signal that has been decomposed using a wavelet filter bank.

Huang, S.C., et.al., [21] have proposed efficient contrast enhancement using adaptive gamma correction with weighting distribution. This paper proposes an effective method for enhancing contrast in digital images by modifying histograms. This paper shows an automatic transformation technique that uses gamma correction and probability distribution of luminance pixels to improve the brightness of dimmed images. To reduce computational complexity, the proposed image enhancement method uses temporal information about the differences between each frame to enhance video.

Liu, J., et.al., [22] have recommended an efficient contrast enhancement method for remote sensing images. This paper presents a novel self-adaptive histogram compacting transform- based contrast enhancement method for remote sensing images that satisfy the requirements of automation, robustness, and efficiency in applications. To capture more details during grey extending with the linear stretch, a local remapping algorithm is proposed. Finally, to improve contrast in both bright and dark areas, a dual-gamma transform is proposed.

III Proposed work

3.1 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:

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

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

Correct approximation of real world scenarios can be represented with Mathematical modelof 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. 1.2.

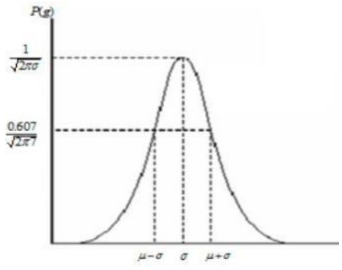

Figure 2. PDF of Gaussian noise

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 spectraldomain.

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

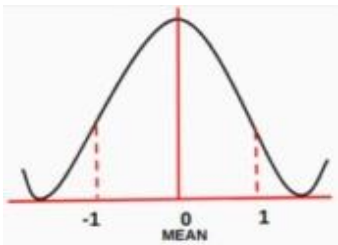

Figure 3. Plot of Probability Distribution Function

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 Gaussiannoise.

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.

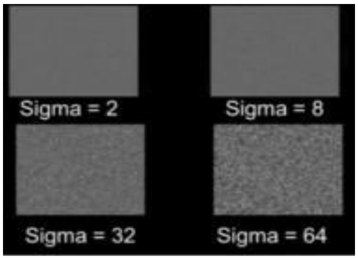

Figure 4. Effect of Sigma on Gaussian Noise

3.2 Guided filter:

Guided filter [5][6] 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.

Guided Filter Algorithm [5]:

Assume filtering input image as I, guidance image as G, regularization as , 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:

   $mean_G = f_{mean}(G)$

   $meanI = fmean(I)$

   $corr_G = f_{mean}(G .* G)$

   $corr_{GI} = f_{mean}(G .* I)$

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 $var_G = corr_G - mean_G .* mean_G$
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

   $q = mean_X .* G + mean_Y$

3.3 AGCWD with Firefly Optimization algorithm

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 [10] 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.

(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:

(3)

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

(4)

Where the sum of pdf_w is calculated as follows:

(5)

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

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

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.

IV 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 outputs best 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

(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 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.

(8)

Here, MAX_I represents the maximum value of the pixel in the image. The PSNR is commonlyused 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 iscalculated as

(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

(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 better for 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	Guided filter				Bilateral filter				Proposed Method			
(σ)	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

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			
	PSN	MSE	MA	IEF	PSN	MSE	MA	IEF	PSN	MSE	MA	IEF

	R		E		R		E		R		E	
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

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

Figure 6. Jatropha Leaf a) Original image b) Gaussian noise image mean μ=0, variance σ=0.03 c) Guided filtered d) Bilateral filtered 5) Smoothed and enhanced image withproposed method.

Figure 7. Jatropha Leaf a) Original image b) Gaussian noise image mean μ=0.01, variance σ=0.01 c) Guided filtered d) Bilateral filtered 5) Smoothed and enhanced image withproposed method.

Figure 8. Jatropha Leaf a) Original image b) Gaussian noise image mean μ=0.01, variance σ=0.03 c) Guided filtered d) Bilateral filtered 5) Smoothed and enhanced image withproposed method.

Figure 9. Jatropha Leaf a) Original image b) Gaussian noise image mean μ=0.05, variance σ=0.01 c) Guided filtered d) Bilateral filtered 5) Smoothed and enhanced image withproposed method.

Figure 10. Jatropha Leaf a) Original image b) Gaussian noise image mean μ=0.05, variance σ=0.03 c) Guided filtered d) Bilateral filtered 5) Smoothed and enhanced image with proposed method.

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	153.6	10.1	2.3	32.73	34.6	4.87	1.3	14.47	2323.5	41.5	0.1
		6	1	5		4		5		1	9	9
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

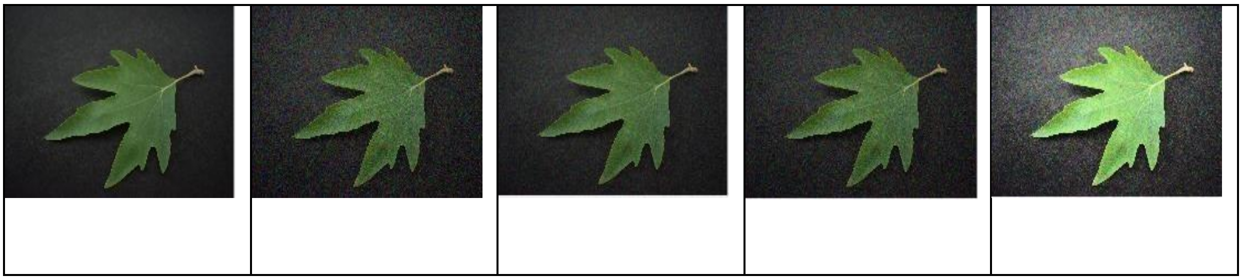

Figure 11. Chinar leaf a) Original image b) Gaussian noise image mean μ=0, variance σ=0.01
c) Guided filtered d) Bilateral filtered 5) Smoothed and enhanced imag
e with proposedmethod.

Figure 12. Chinar leaf a) Original image b) Gaussian noise image mean μ=0, variance σ=0.03
c) Guided filtered d) Bilateral filtered 5) Smoothed and enhanced imag
e with proposedmethod.

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 5) Smoothed and enhanced image withproposed 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 5) Smoothed and enhanced image withproposed 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 5) Smoothed and enhanced image withproposed 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 5) Smoothed and enhanced image withproposed method.

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

Variance	Guided filter				Bilateral filter				Proposed Method			
(σ)	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	Guided filter				Bilateral filter				Proposed Method			
(σ)	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
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	Guided filter				Bilateral filter				Proposed Method			
(σ)	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

Figure 17. Pongamia leaf a) Original image b) Gaussian noise image mean μ=0, variance σ=0.01 c) Guided filtered d) Bilateral filtered 5) Smoothed and enhanced image withproposed method.

Figure 18. Pongamia leaf a) Original image b) Gaussian noise image mean μ=0, variance σ=0.03 c) Guided filtered d) Bilateral filtered 5) Smoothed and enhanced image withproposed method.

Figure 19. Pongamia leaf a) Original image b) Gaussian noise image mean μ=0.01, variance σ=0.01 c) Guided filtered d) Bilateral filtered 5) Smoothed and enhanced image withproposed method.

Figure 20. Pongamia leaf a) Original image b) Gaussian noise image mean μ=0.01, variance σ=0.03 c) Guided filtered d) Bilateral filtered 5) Smoothed and enhanced image withproposed method.

Figure 21. Pongamia leaf a) Original image b) Gaussian noise image mean μ=0.05, variance σ=0.01 c) Guided filtered d) Bilateral filtered 5) Smoothed and enhanced image withproposed method.

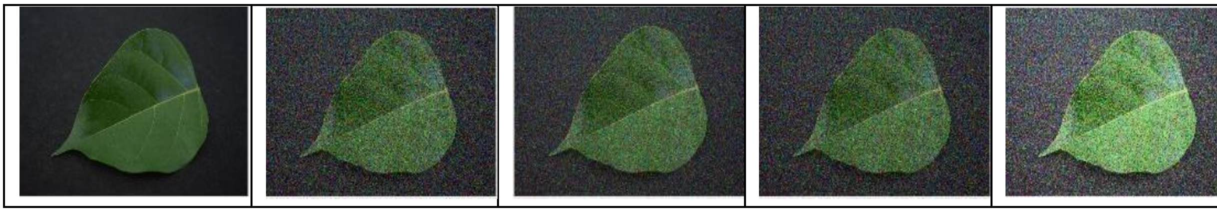

Figure 22. Pongamia leaf a) Original image b) Gaussian noise image mean μ=0.05, variance σ=0.03 c) Guided filtered d) Bilateral filtered 5) Smoothed and enhanced image withproposed method.

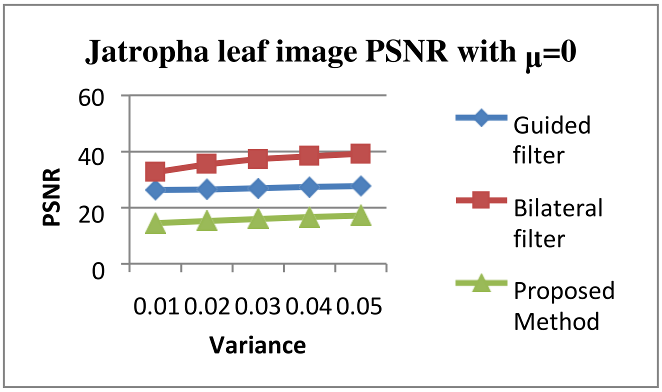

Figure 23. Graph of PSNR for Jatropha leaf image with mean=0.

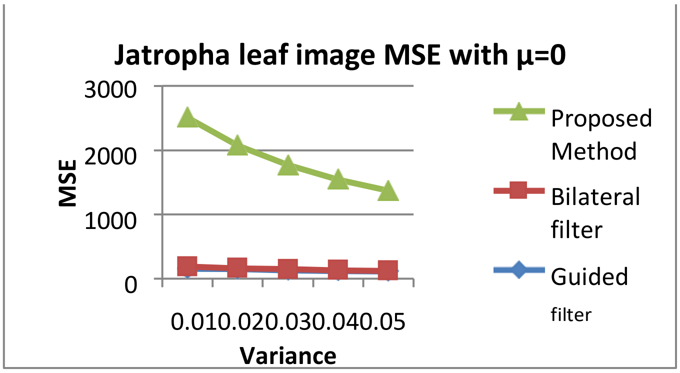

Figure 24. Graph of MSE for Jatropha leaf image with mean=0.

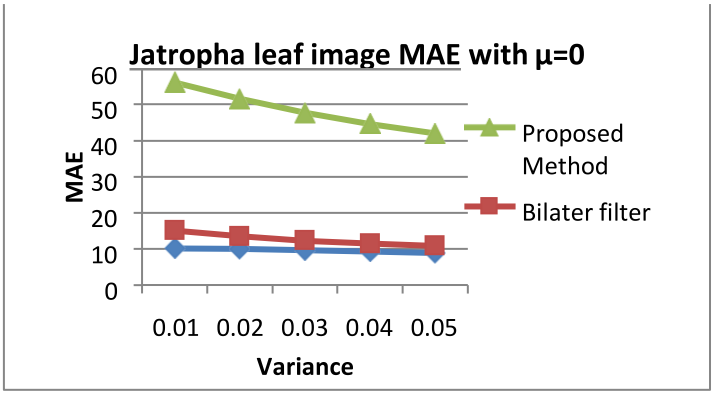

Figure 25. Graph of MAE for Jatropha leaf image with mean=0.

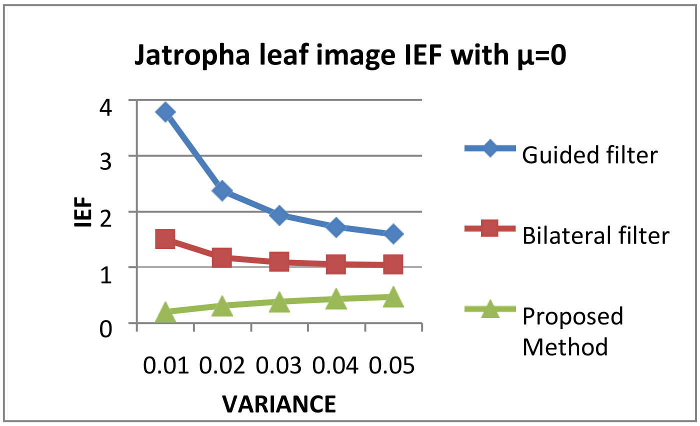

Figure 26. Graph of IEF for Jatropha leaf image with mean=0.

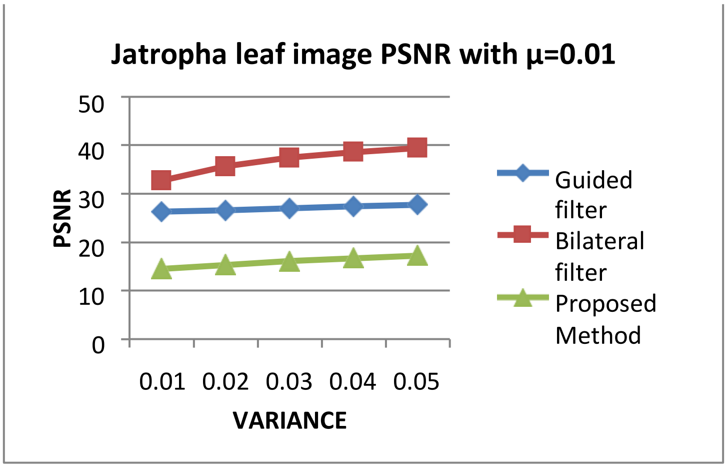

Figure 27. Graph of PSNR for Jatropha leaf image with mean=0.01

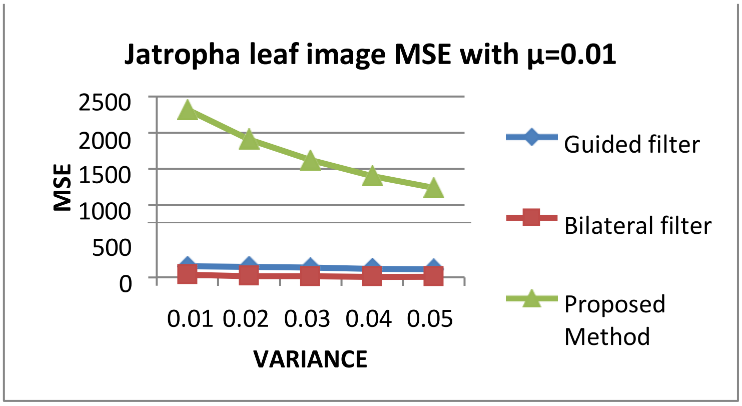

Figure 28. Graph of MSE for Jatropha leaf image with mean=0.01

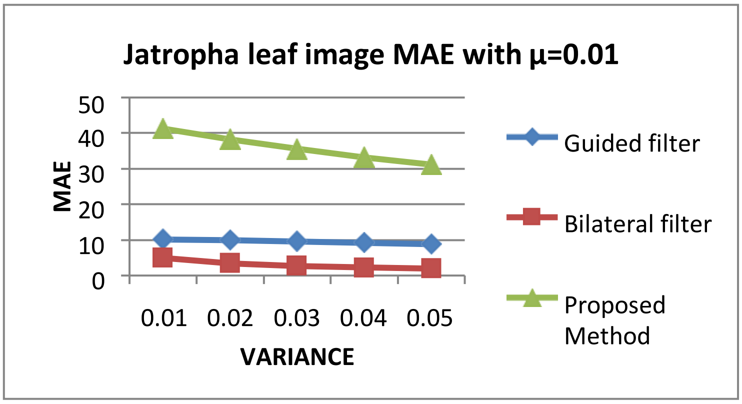

Figure 29. Graph of MAE for Jatropha leaf image with mean=0.01

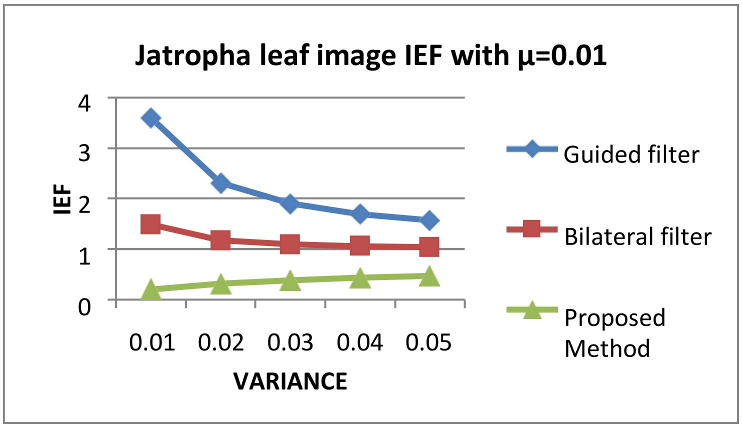

Figure 30. Graph of IEF for Jatropha leaf image with mean=0.01

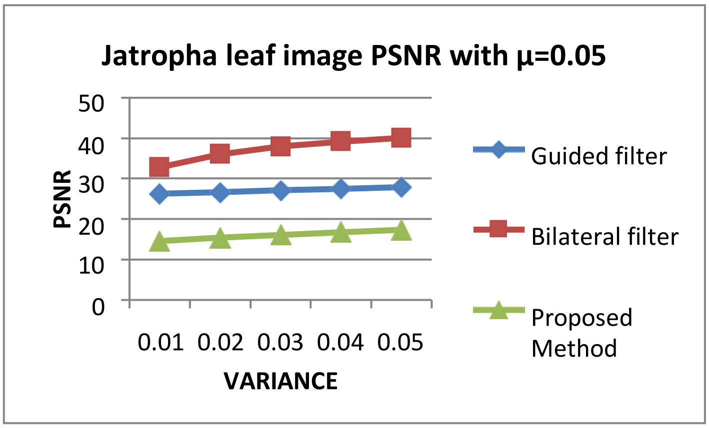

Figure 31. Graph of PSNR for Jatropha leaf image with mean=0.05

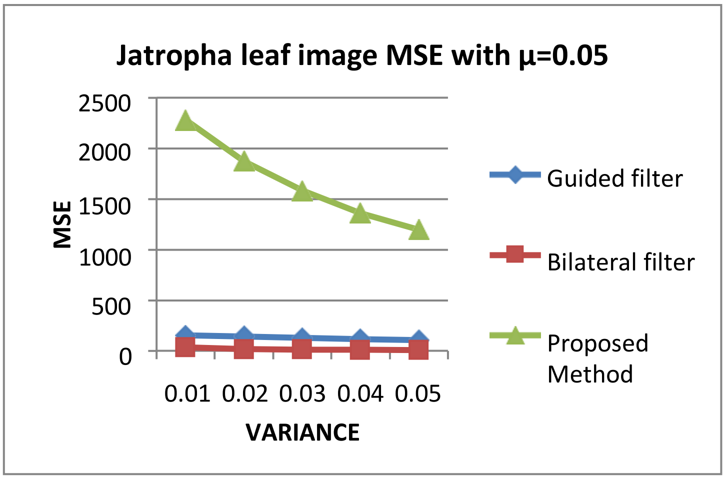

Figure 32. Graph of MSE for Jatropha leaf image with mean=0.05

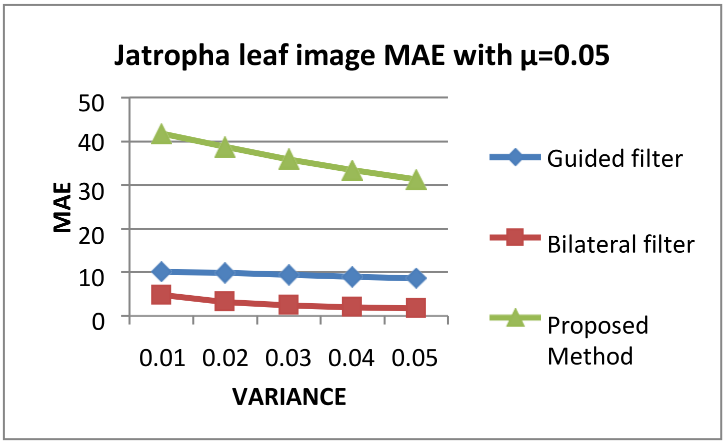

Figure 33. Graph of MAE for Jatropha leaf image with mean=0.05

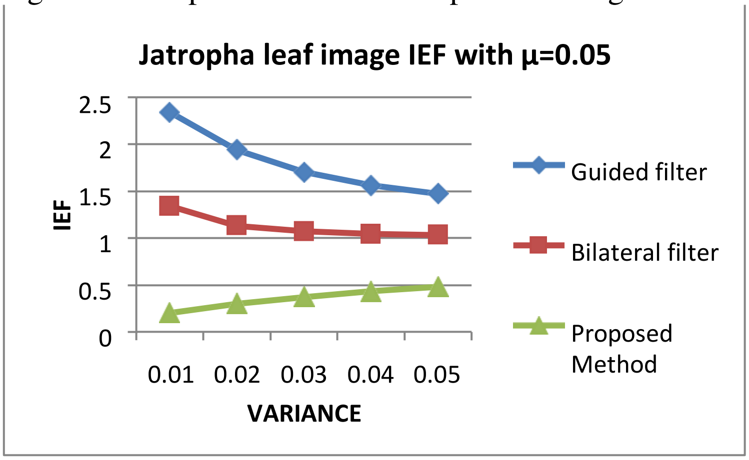

Figure 34. Graph of IEF for Jatropha leaf image with mean=0.05

Conclusion

The image preprocessing methods like image enhancement, smoothening of image and denoising is very much needed before the analysis process of the accuracy in the disease identification and prediction in a medicinal plant leaf. An adaptive gamma correction with weighting distribution algorithm used along with a guided filter is presented in this paper. The quality is not deteriorated and the noise is also removed. In the process of image acquisition there is a reduction in the production of the artifacts in the image which is an added benefit to this method. The contrast enhancement along with the edge preserving denoising helps to preserve the fine details of the image for the disease identification and prediction. The proposed method produced better results compared to the other methods of denoising proving it to have a better performance. The enhancement of blurring images and backgrounds with uneven brightness can be considered as the future work for this implementation.

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