Image quality enhancement using CLAHlet RetiGaussian filter for maize leaf images

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Abstract: In this world of digitization, most of the data is in the form of images acquired using camera. Image enhancement plays a vital role in the quality improvement of digital images. In this work, a combined approach based on the contrast limited adaptive histogram equalization (CLAHE) and Retinex algorithm is proposed. It is a wavelet based Retinex algorithm with adaptive histogram equalization and gaussian filter. Firstly, the image is enhanced using CLAHE. Then the image is decomposed using Daubechies wavelet followed by the Retinex algorithm, which uses low frequency components to enhance the image. Lastly, a gaussian filter is used to smoothen the image. The dataset of maize leaf disease is used for the analysis of quality enhancement and denoising. It is clear from the results that the proposed method improves the quality by reducing the noise of the maize leaf images. Theses refined images can be used for maize leaves disease detection and classification system to achieve high accuracy.

Keywords: image quality enhancement, denoising, wavelet, histogram, retinex, maize leaf disease

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1 Introduction

The goal of the image enhancement is to improve the quality of the image and prepare the image so that it can be used for specific application (Qi et al., 2021). Generally speaking, the fundamental idea behind image enhancement is to change informational content of an image to make it more suitable for a certain purpose. Denoising is done to remove different types of noises from the image which may be present due to internal and external conditions of the sensors. The primary principles of conventional image enhancement techniques are frequency domain and spatial domain processing which also help in the removal of noise (Yang et al., 2021). The traditional modified histogram tec and the enhanced unsharp mask methods (Edla et al., 2022), are two examples of spatial image enhancement that directly process the pixels in the picture. The Fourier Transform (FT), Discrete Cosine Transforms (DCT), and Discrete Wavelet Transform (DWT) areexamples of mathematical operations that can be used to convert an image to the frequency domain (Li et al., 2021).

After processing the image using the special characteristics of the frequency domain, the image is then returned to its original image space. The Contrast Limited Adaptive Histogram Equalization (CLAHE) approach boosts the efficiency of image processing techniques in low-contrast and low-resolution settings (S.K, 2019). Numerous unique techniques, like the Retinex model (Kong et al., 2021), fuzzy theory (Toğaçar et al., 2021), neural network (Alenezi and Ganesan, 2021), etc., have evolved as a

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result of the quick growth of image-enhancing technology. Several techniques like histogram equalization (Dharejo et al., 2020) and deep learning techniques are the prominent ones (Li et al., 2021). Each technique for improving images has benefits and drawbacks of its own.The simplicity of comprehension, lack of complexity, and real-time execution are the key benefits of spatial domain image enhancement. The spatial domain image enhancement approach does have certain drawbacks, such asthe insufficiency of the robustness and imperceptibility criteria (Alshoura et al., 2021).

It is challenging to provide a technique that provides a good enhancement for every image. The non-university of the image-enhancing method, the selection of the assessment index, the impact of noise, the selection of the ideal parameters, etc., are the primary causes of this (Qi et al., 2021). In this paper, a new CLAHLET Retigaussian filter is proposed that utilizes multiple image enhancement methods, especially for maize leaf disease detection system. The next section of this paper deliberates maize leaf diseases, then the literature study demonstrates the previous approaches developed for plant disease detection system also including maize leaf disease detection systems. Furthermore, details of the proposed filter are illustrated with experimentation and results are analysed based on different performance metrics. A comparative analysis is also done with the recent approaches to authenticate the efficiency of the proposed approach.

2 Materials and methods

2.1 Maize leaf diseases

The growth of human civilization has been significantly influenced by agriculture. Since maize is a very important food grain worldwide, output losses brought on by diseases have a big effect on the world economy. The third-largest crop in India is maize. The grains of maize are rich in dietary fibre, proteins, vitamins, and minerals including magnesium, potassium, zinc, copper, iron, and selenium (Gupta and Mishra, 2021). It is frequently present in glucose, cornflakes, popcorn, and starch. Chickens are fed maize to boost the production of chicken products. Its dried stalks can be used as a source of household energy as well as animal Plant diseases significantly reduce crop yield, which has a detrimental effect on the economy of the country. There is a terrible food crisis happening all across the world. As a result, malnutrition and hunger are more common, especially in developing countries like India.

The product loss brought on by the sicknesses makes it impossible for the agricultural community to provide the crop's expanding demand. Plant infections are inevitable since there are plants everywhere. Early diagnosis of these disorders is crucial in the agriculture sector (Raja and Rajendran, 2022). The scientific study of plant illnesses brought on by infections and other environmental factors is known as plant pathology. Plants with diseases develop colored stripes or dots on their leaves. The form, color, and size of the visual symptoms on the leaves will continue to change as the sickness worsens. Plants get ill due to pest infestations, shifting weather patterns, soil composition, and other causes. Each year, diseases result in the loss of more than 20% of the maize harvest (Waldamichael et al., 2022). Early sickness detection and prompt access to proper treatment can prevent crop loss.

There are three important yield-restricting diseases wreaking havoc on Indian maize crops: northern corn leaf blight, grey leaf spot, and common rust (Shenbagam and Sanjana, 2022). Early detection of these disorders can increase crop quality and yield. Early indications of maize disease appear on numerous parts of the plant, primarily on the leaves. Plant illnesses may be identified early on by looking at the leaves of the plant, and when a disease is found early on, fewer pesticides are required to treat it, which is safe for the human health, environment and productivity enhancement. Currently, the majority of plant disease detection relies on visual evaluation, where a breeder or researcher visually inspects each plant and grades it for disease severity (Ouhami et al., 2021). However, there are certain drawbacks to this approach. Early disease detection and diagnosis are of primary interest to geneticists and plant breeders. Disease diagnosis requires routine inspection of cornfields by experts and pathologists, but this is seldom possible owing to a lack of specialists. Occasionally, even seasoned farmers may have trouble diagnosing diseases. Due to the complexity and vast variety of cultivated plants, even experienced farmers and plant pathologists occasionally make errors in their disease diagnoses (Sudar et al., 2022). This results in inadequate diagnosis and treatments, which leads to crop loss. An automated plant disease detection system would be very helpful to farmers. Nearly a hundred fungi can cause infections in maize. On the other hand, pathogens are influenced by a wide range of factors, including moisture, temperature, the quality of the soil, the seed, and so on (Wason et al., 2021). The three most common diseases affecting maize crops are shown in Figure 1.

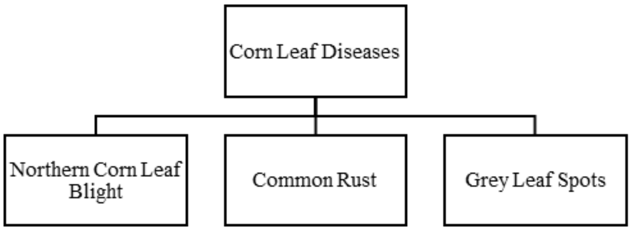


Figure 1 Common maize leaf diseases

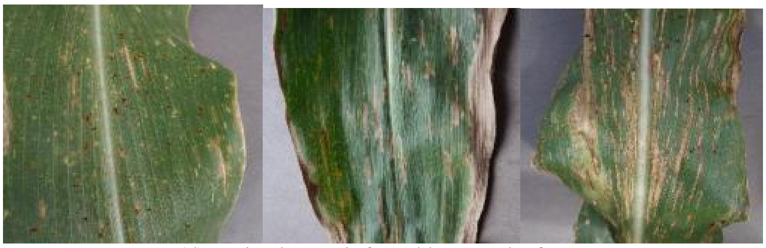
The Exserohilum turcicum, a fungus, is the culprit for the Northern corn leaf blight diseases of maize plant. The diseased plant's leaves develop large grey or greenish elliptical or cigar-shaped spots. The length of these specks, which can be anywhere between an inch and over six inches, is parallel to the leaf veins. The photosynthetic area of the leaf shrinks as the illness advances, limiting grain output. Even the leaf veins are powerless to stop the disease's progress, which affects every part of the leaf. Warm temperature and high relative humidity favour the disease's growth. These conditions support the development and germination of fungal spores. Lesions start to show up on the leaf within seven to ten days after the infection (Kumar et al., 2022). Himachal Pradesh, Andhra Pradesh, Bihar, Karnataka, Punjab, and Maharashtra are among the Indian states where this illness is prevalent. The fungus Puccinia sorghi is responsible for the Common rust disease.

The most dangerous fungal foliar disease of maize in the world is this one. Common rust causes patches to appear on the leaves of maize plants that resemble rust on metal objects. According to some reports, typical rust infections can reduce the yield of maize grains by up to 40% on average (Utpal et al., 2015; Sibiya and Sumbwanyambe, 2021). The Cercospora zeae-maydis fungus is what causes grey leaf spot. This is one of the world's most harmful and yield-restricting illnesses (Dhami et al., 2015). The lesions develop from mid to late summer due to favourable circumstances including high relative humidity, warm temperatures, and little tilling. Early rain facilitates the spread of infection on the leaf surface. The healthy leaves, on the other hand, are flawless and have a smooth texture. These leaves look to be brilliant greenish-white and completely dried (Ward et al., 1999). Figure 2 shows some of the sample images for healthy, and unhealthy leaves of maize.

(a) Healthy leaves

(b) Maize leaves infected by northern corn leaf blight

(c) Maize leaves infected by common rust



(d) Maize leaves infected by grey leaf spot

Figure 2 Healthy and unhealthy maize leaves images

2.2 Related work

The main focus of this paper is to improve the quality of the image samples of maize leaf, so that the detection of disease gets easy and appropriate. In this section, the existing approaches that are used in the field of plant disease detection, including maize leaf disease detection, are discussed.

The image acquisition phase in a system for recognizing maize illnesses is frequently impacted by the outside environment, making it less ideal for extracting and identifying corn diseases. Therefore, to identify the corn illnesses, the image must first be denoised to emphasize the affected region. Colored images were first processed as greyscale images to increase identification speed. The example of the Northern corn leaf blight picture was used in this study to demonstrate the pre-treatment impact. The image may be automatically enhanced and its quality is improved using histogram equalization approach. The distribution of the picture pixels is more uniform after the equalization transform, and the contrast is improved. The neighbourhood average approach was used to denoise the noise in this improved picture (Zhu et al., 2012). The other image enhancement method using image resizing, filtering, color space conversion, and histogram equalization was discussed by Ngugi et al. (2021). Moreover, resizing and data augmentation was according to Bhagwat and Dandawate (2021) and Qian et al. (2022).

Nowadays, deep learning-based methods are in a trend and most disease detection system use deep learning technology. Similarly, Fraiwan et al. (2022) designed a deep learning-based corn leaf disease detection and classification system. Authors designed a CNN to classify the corn leaf images into four categories i.e. cercospora leaf spot, common rust, northern leaf blight and healthy leaves. Another deep learning-based disease identification system was designed for apple fruit diseases, and in that, data augmentation as pre-processing method was used (Wang et al., 2021). Some Geometric and intensity transformation-based image enhancement was also proposed with a deep learning-based plant disease detection system where tomato plants were examined (Fuentes et al., 2021). The Convolutional Neural Network (CNN) was also proposed for the detection of diseases in multiple crops where instead of Red Green Blue (RGB), LAB model was used and data augmentation was performed (Singh et al., 2022).

Table 1 Existing pre-processing methods in Plant leaf disease detection systems

Reference	Year	Crop	Pre-Processing
S.K	2019	Corn	CLAHE
Sibiya and Sumbwanyambe	2021	corn	RGB to Gray scale
Zhu et al.	2012	corn	Converted to grey scale, grey scale transformation, histogram equalization, average filter
Qian et al.	2022	Maize leaf	Data Augmentation
Fraiwan et al.	2022	corn	Normalization, and data augmentation
Wang et al.	2021	Apple	Data Augmentation
Fuentes et al.	2021	tomato	Geometric and Intensity Transformations
Singh et al.	2022	Corn and other crops	RGB to grey and RGB to LAB
Vallabhajosyula et al.	2021	Multiple crops	Image enhancement, color space transformation, resizing, and noise removal
Lilhore et al.	2022	Cassava leaf	CLAHE method
Bao et al.	2021	Wheat	Single-scale Retinex algorithm
Anjna et al.	2020	Multiple crops	Histogram Equalization
Chen et al.	2020	tomato	Binary Wavelet Decomposition, Retinex algorithm, Gauss convolution filter, Binary wavelet image reconstruction
Khan et al.	2020	Cucumber leaf	Local contrast enhancement, top-hat andhessian-based filtering, image sharpening and 3D median filtering, and HSV color space transformation
Ashwinkumar et al.	2022	tomato	Bilateral Filter
Zhang et al.	2018	Corn	Data augmentation, resize
Zhang et al.	2021	Maize leaf	Grey scale, Erosion and dilation
Hu et al.	2020	Corn	Data augmentation

Different pre-processing methods like, color space transformation, resizing, and noise removal were used along with the transfer learning-based disease detection system and were tested on multiple crops dataset (Vallabhajosyula et al., 2021). CLAHE method was proposed by Lilhore et al. (2022) for casava leaf image enhancement and by using an improved CNN, authors detected and classified the disease. Furthermore, a single-scale Retinex algorithm was proposed for image enhancement with lightweight CNN for wheat ear disease identification (Bao et al., 2021). In addition to this, histogram equalization for multiple crops (Anjna et al., 2020).

Wavelet based Retinex algorithm applied for tomato (Chen et al., 2020), and improved top-hat hessian-based filtering method for cucumber leaf image enhancement were earlier opted by the researchers who focus on plant disease detection system (Khan et al., 2020). Comparison of various Image Filtering methods is given (Mahakale and Thakur, 2013). Different noises can affect the image in different ways. Noises are introduced in images while capturing the image, during transmission etc. In this paper authors discuss Gaussian noise, Salt and Pepper Noise and speckle noise. Various methods used to remove these noises are also given in the paper. Fan et al. (2019) summarize some important research in the field of image denoising. They formulate the image denoising problem, and then several image denoising techniques along with their characteristics are discussed. It is concluded that different types of noise require different denoising methods. The analysis of noise can be useful in developing novel denoising schemes.

Table 1 provides an overview of the existing pre-processing techniques that were used earlier in different plant disease detection systems including corn or maize leaf diseases. These techniques provide an effective result in the current detection systems, but improvement is still required to enhance the performance of the systems. By taking advantage of these different methods, in this work, an enhanced CLAHlet RetiGaussian filter is proposed. The details of these filters are given in the next section of the paper.

2.3 Proposed method for image enhancement

Image quality enhancement has an inevitable role in the improvement of the performance of disease detection and classification systems, because images with high quality can help to provide an efficient result.

Fig.3 presents detailed process and highlights different methods used in the proposed technique. It is a combination of CLAHE, wavelet, Retinex, and gaussian filter. Here wavelet decomposition is specifically performed to divide low and high-frequency pixels. This is done because Retinex can enhance low intensity pixels to keep high frequency intensities as it is. This avoids image quality from being deteriorated. Here, the process starts with the CLAHE method where RGB images are converted into LAB model and followed by adaptive histogram equalization. Then Daubechies wavelet is used to decompose the image. Further, the Retinex algorithm processes only low-frequency pixels and then a gaussian filter is applied on both low and high-frequency pixels. Finally, reconstruction is performed to generate an enhanced image. The image of maize leaf diseases is denoised in this work using the suggested way to make the image characteristics more noticeable. The detailed process and explanation of the methods are as given below:

Contrast Limited Adaptive Histogram Equalization ***(CLAHE):*** CLAHE is used to equalize images. It is a variation of Adaptive Histogram Equalization (AHE) that addresses the issue of contrast over-amplification. Instead of processing the full image, CLAHE works with discrete sections of image, called tiles (Lilhore et al., 2022). CLAHE approach boosts the efficiency of image processing techniques in low-contrast and low-resolution settings. The RGB to LAB conversion converts the original color picture. This technique is used in the LAB color spaces in the next stage to create better photographs. The photos that have been enhanced in LAB are then transferred to RGB color space.

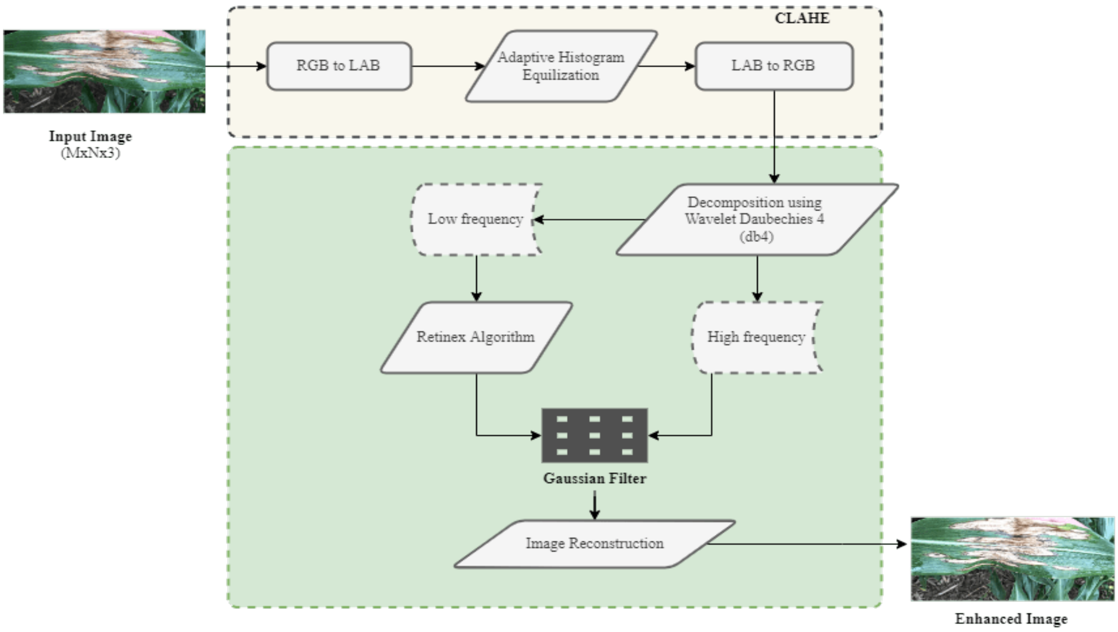


Figure 3 Proposed method for image enhancement (CLAHlet RetiGaussian Filter)

Decomposition using Wavelet**:** To begin, db4 (Daubechies 4) is used to deconstruct the original images into their high-frequency and low-frequency components. The relevant enhancement algorithm then processes the high- and low-frequency components. Here image *I (m, n)* is decomposed into three high-frequency components and one low-frequency component. To maximise the detail components representing various types of information, it is required to choose a suitable enhancement function (Liu et al. 2014). In the equation given below *h (m, n)* contains high frequency components and *l (m, n)* are low frequency components.

$$I(m,n)=\begin{cases}h(m,n)\\ l(m,n)\end{cases} \quad (1)$$

Retinex Algorithm: This method is used here for the low frequency components to enhance the image (Chen et al., 2020). According to the Retinex hypothesis, the interplay between the illumination picture and the reflected image produces the final image information that is experienced by the human visual system.

$$l(m,n)=L(m,n)\times R(m,n) \quad (2)$$

The low-frequency information of the original maize leaf image, l (m, n), which contains the substance of the item. The L (m, n) is the illumination image, which may explain the light intensity and other information around the image, whereas R (m, n) is the reflection image. Reflectance provides the most high-frequency precise picture information, whereas illumination is a type of low-frequency, slowly changing image information. The Retinex theory attempts to solve this problem by first estimating the light and then calculating the reflectance by division. Firstly, picture is converted into the logarithmic domain as given below:

$$\log l=\log R+\log L \quad (3)$$

By taking the logarithm of the image and subtracting the logarithm of the illumination, one may obtain the logarithm of the reflectance.

$$\log R=\log l-\log L \quad (4)$$

The reflectance may then be calculated as given in Equation (5).

$$R=\exp(\log l-\log L) \quad (5)$$

Since the illumination is a low-frequency component relative to the reflectance, the Retinex Algorithm utilises a low-pass filter to estimate the illumination.

$$r(m,n)=\ln l(m,n)-\ln[F(m,n)*l(m,n)] \quad (6)$$

The Gauss filter function is denoted by F (m, n) in this equation. The formula r (m, n) in the low-frequency improves the image of maize leaves.

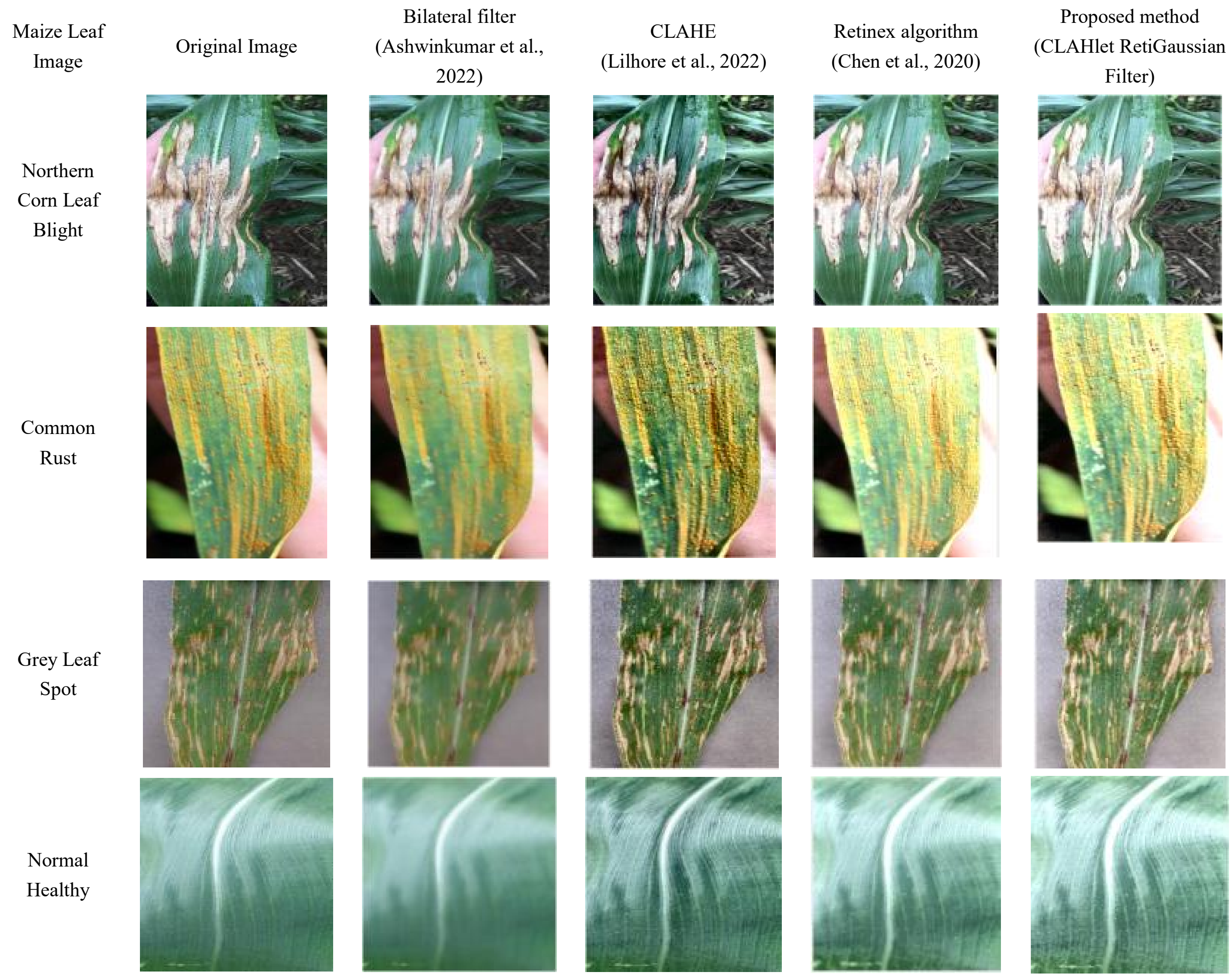
Gaussian Filter: Finally, Gaussian filter is used to enhance both low and high frequency components. A 2-D convolution operator called Gaussian smoothing operator is used to 'blur' pictures and eliminate noise and detail (Wang et al., 2014).

Wavelet Reconstruction: Wavelet reconstruction is used to create fully improved images after denoising enhancement to combine high-frequency and low-frequency images.

3 Results and discussion

In this section, results of the proposed method are presented and analysed qualitatively and quantitatively. The Kaggle–Plant Village dataset is used to evaluate the performance of the proposed method. The Kaggle–Plant Village data set has four kinds of classes and has a total of 4188 images of the corn crops. It has 574 images for grey leaf spot dataset, 1306 images for common rust corn leaf disease, 1146 images for northern corn leaf blight disease, and a dataset of healthy corn leaves contains 1162 images. For the analysis of the proposed method 100 images from each class, i.e. northern corn leaf blight, common rust, grey leaf spot and healthy image dataset are selected. These images contain only one leaf in the frame.

The proposed method is designed to improve the quality of maize leaf images to detect the four categories of leaves. Moreover, the performance of the proposed method is compared with recently developed techniques namely, bilateral filter (Ashwinkumar et al., 2022, CLAHE (Lilhore et al., 2022), and improved retinex algorithm (Chen et al., 2020), used in plant disease detection. The qualitative and quantitative analysis of the proposed method and its comparison with different methods is given in Fig. 4.



(a) northern corn leaf blight, (b) common rust, (c) grey leaf spot and (d) normal healthy images

Figure 4 Output images of Bilateral filter, CLAHE, improved Retinex algorithm and proposed method of maize images

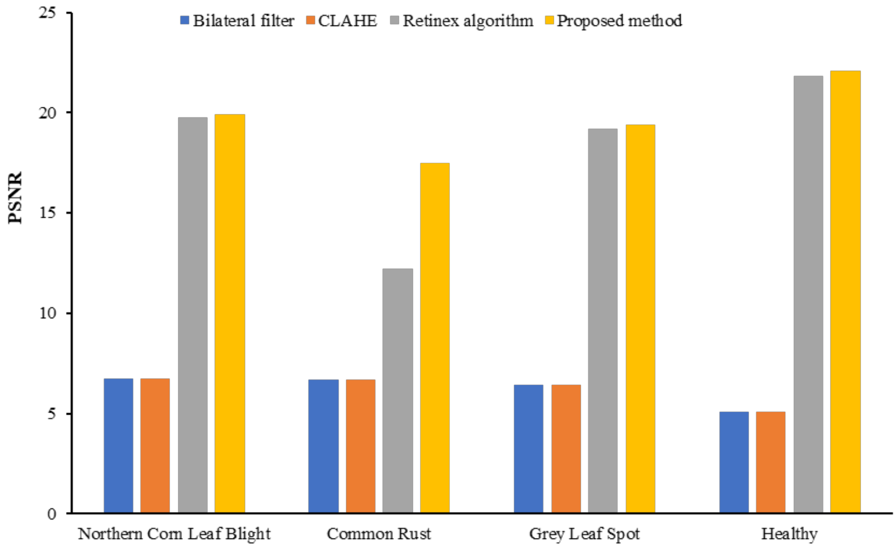
This figure displays the output images for each class of the maize leaf data including healthy and unhealthy samples and compared with bilateral filter (Ashwinkumar et al., 2022), CLAHE (Lilhore et al., 2022), and improved retinex algorithm (Chen et al., 2020). Furthermore, the performance of the proposed filter is analysed using quantitative measure, which includes, Peak Signal to Noise Ratio (PSNR), Mean Square Error (MSE), Structure Similarity (SSIM), Signal to Noise Ratio (SNR), Average Difference (AD), Structural Content (SC), Mean Difference (MD), Laplacian Mean Square Error (LMSE), and Normalized Absolute Error (NAE).

Table 2 Performance Metrics used to analyse the performance of proposed method

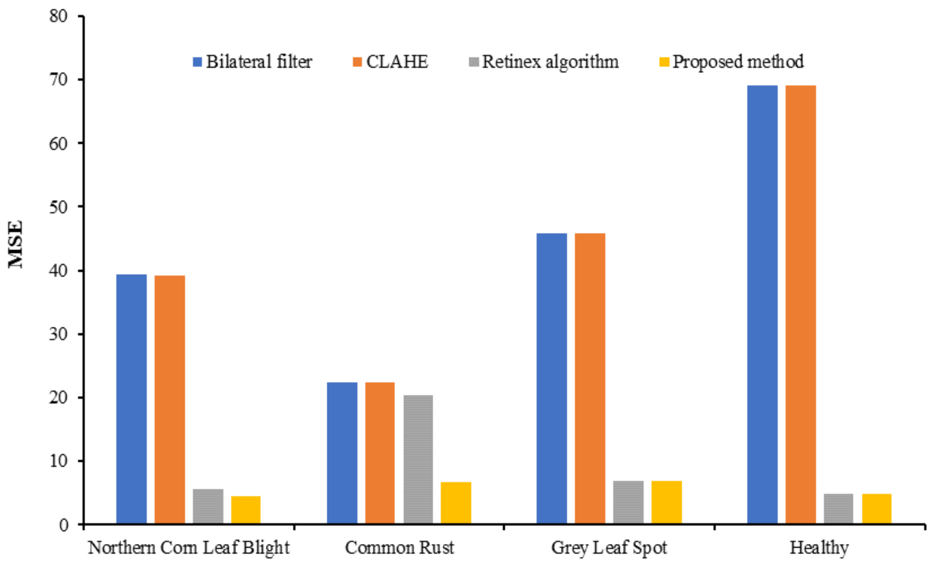
Sr. No.	Parameter Name	Parameter Formula	Remarks
1	PSNR	$PSNR = 10\log\frac{255^2}{MSE}$	Higher the PSNR, lesser the noise.
2	MSE	$MSE = \frac{1}{MN}\sum_{m=1}^{M}\sum_{n=1}^{N} x(m,n)$	Lesser the value of MSE, better the performance of the algorithm.
3	SSIM	$SSIM = f(l(x(m,n)), c(x(m,n)), s(x(m,n)))$ Where, luminance (l), contrast (c) and structural correlation (s)	The SSIM index value varies between 0 and 1. The value close to 1 shows the highest correspondence with the original images and vice-versa.
4	SNR	$SNR = 10\log[\frac{vax(x(m,n))}{mean(x(m,n) - \hat{x}(m,n))}]$	Signal to Noise ratio, higher the SNR, lesser the noise, better the reconstruction
5	AD	$AD = \frac{1}{M*N}(x(m,n) - \hat{x}(m,n))$	As small as possible, the ideal value is 0.

Sr. No.	Parameter Name	Parameter Formula	Remarks
6	SC	$SC = \frac{\sum_{m=1}^{M}\sum_{n=1}^{N} x(m,n)^2}{\sum_{m=1}^{M}\sum_{n=1}^{N} \hat{x}(m,n)^2}$	It is the ratio of sums of the squares of the original and recovered image pixel values.
7	MD	$MD = Max(\lvert x(m,n) - \hat{x}(m,n)\rvert)$	As small as possible
8	LMSE	$LMSE = \frac{\sum_{m=1}^{M}\sum_{n=1}^{N}[L(x(m,n)) - L(\hat{x}(m,n))]^2}{\sum_{m=1}^{M}\sum_{n=1}^{N}[L(x(m,n))]^2}$	As small as possible
9	NAE	$NAE = \frac{\sum_{m=1}^{M}\sum_{n=1}^{N}[\lvert x(m,n)\rvert - \hat{x}(m,n)]^2}{\sum_{m=1}^{M}\sum_{n=1}^{N}\lvert x(m,n)\rvert}$	As small as possible, the ideal value is 0.

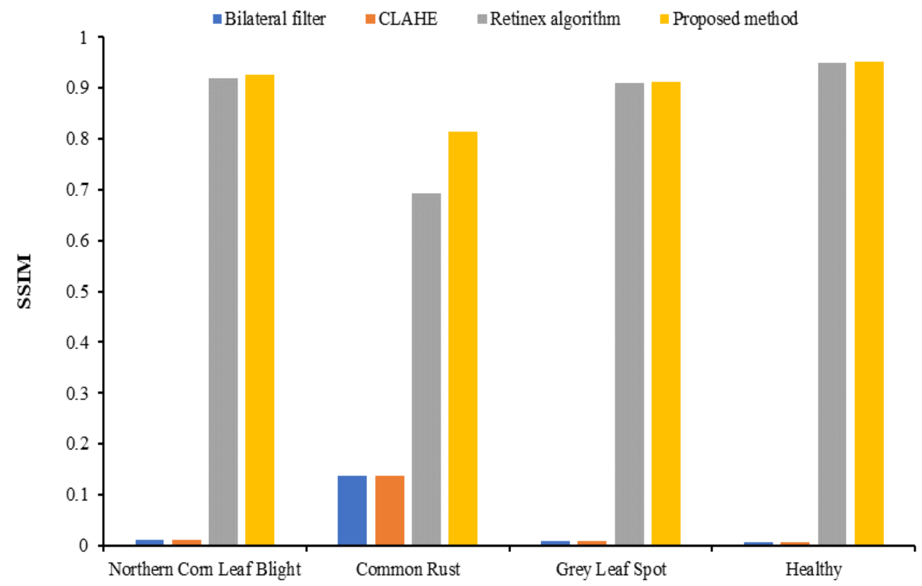
Table 2 demonstrates the formulas for each performance metric, considered in this work to measure the image enhancement quality. It also provides description of the formulas. In the remarks column, it is clearly mentioned which performance metric should be high or low to define effective performance. The testing of maize leaf images is done by taking a set of 400 images and using four different methods including the proposed method. So, the average computed performance for the same is shown in Fig. 5.



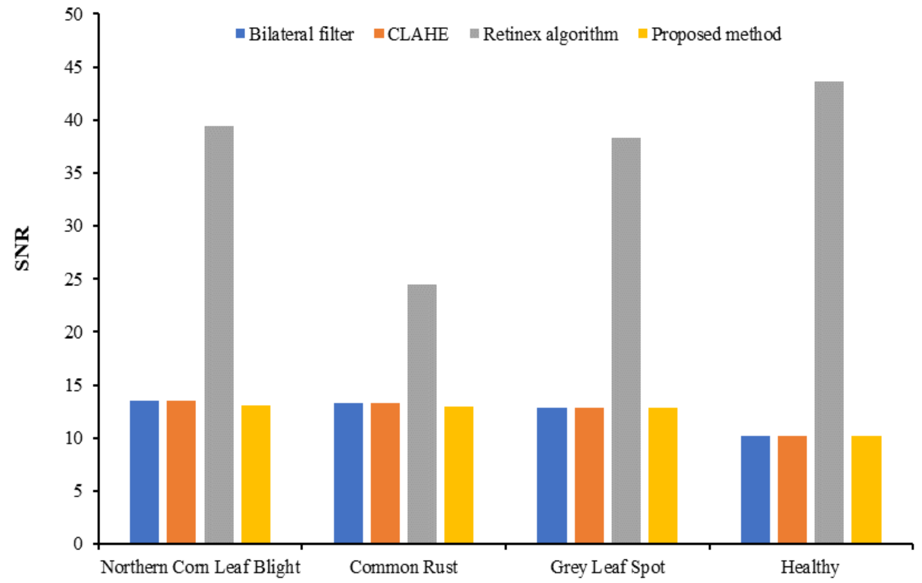
5(a) PSNR



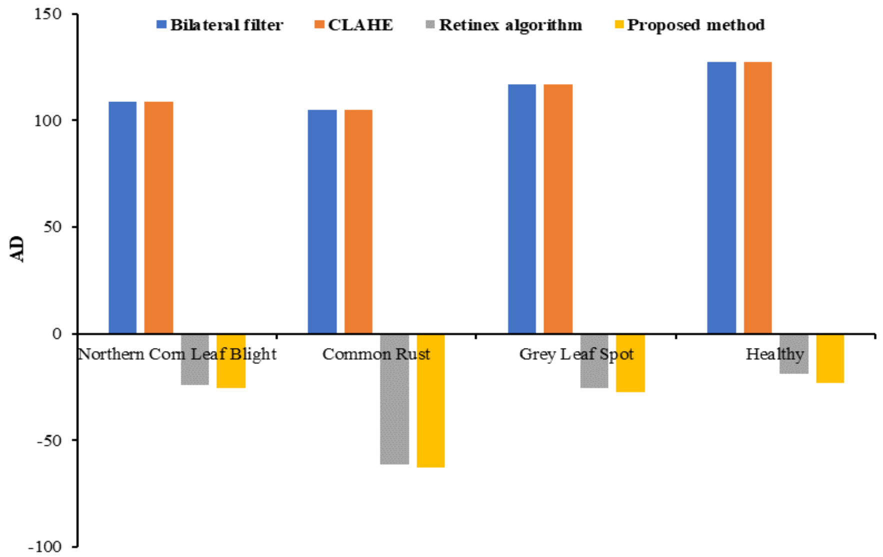
5(b) MSE



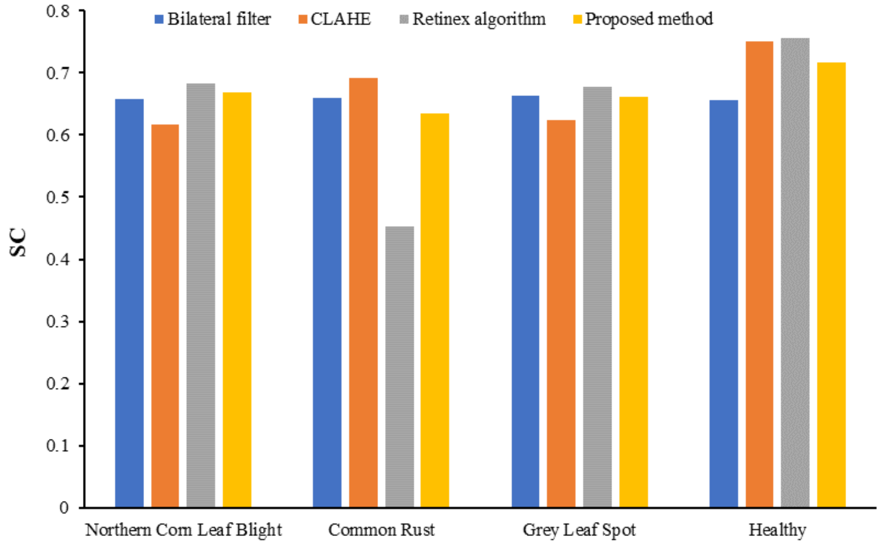
5(c) SSIM



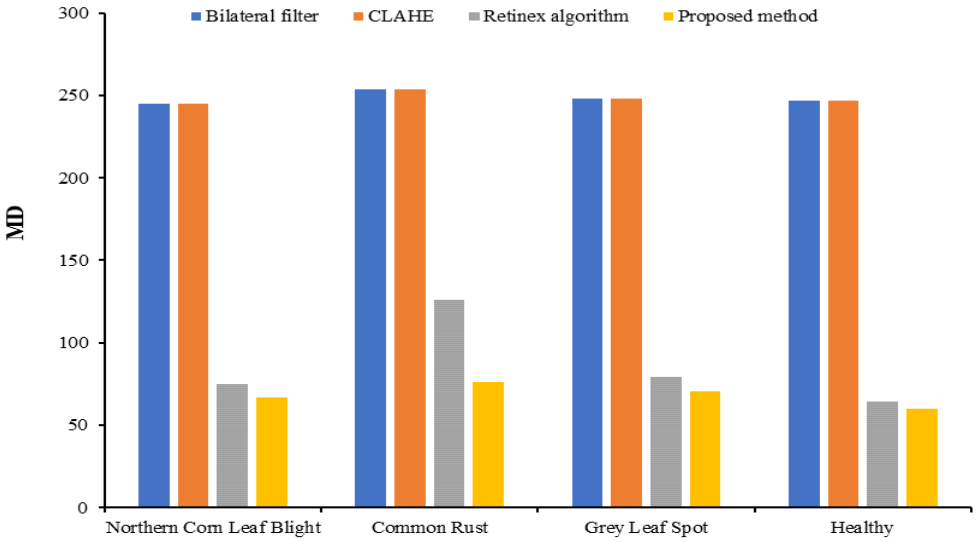
5(d) SNR



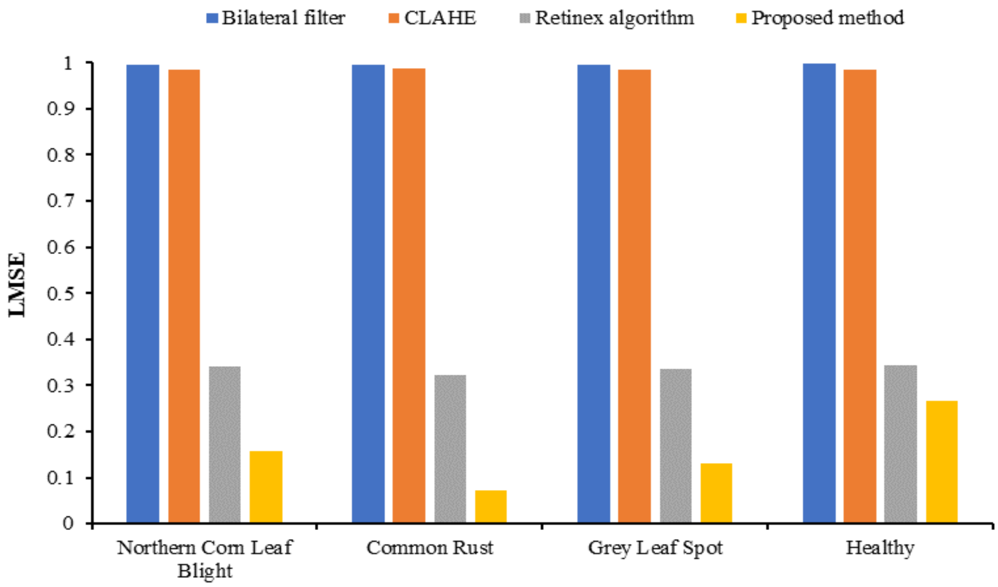
5(e) AD



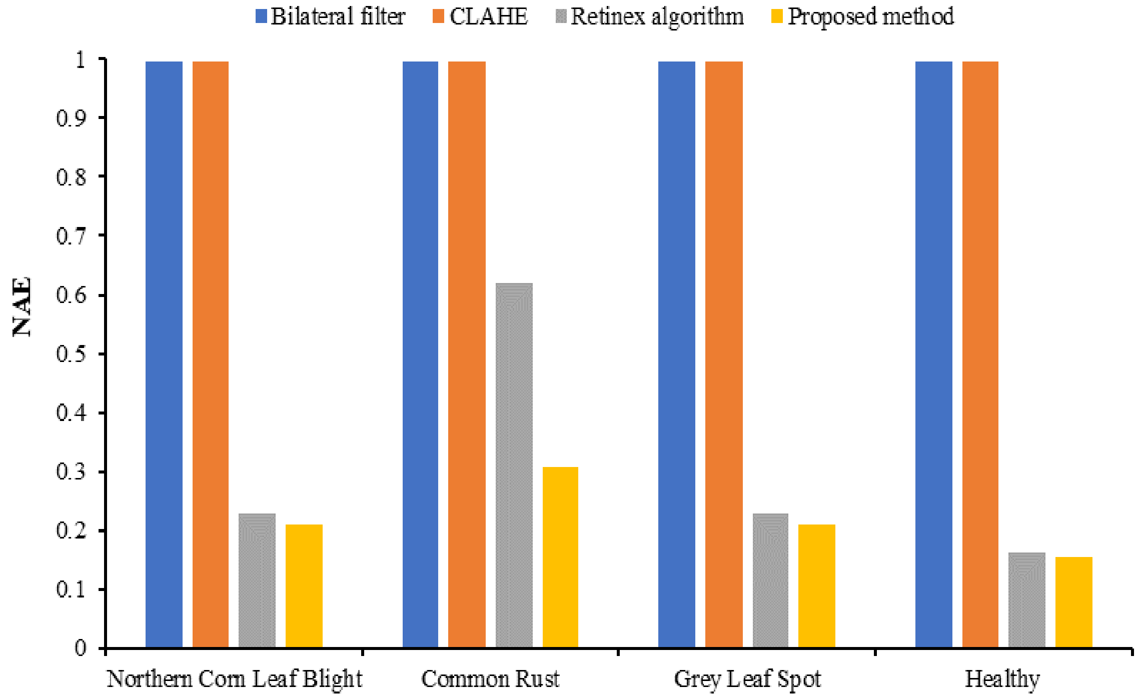
5(f) SC



5(g) MD



5(h) LMSE



5(i) NAE

Figure 5 Comparison of performance analysis of the proposed method with Bilateral filter, CLAHE, improved Retinex algorithm for northern corn leaf blight, common rust, grey leaf spot and healthy leaves images of maize plant

The performance of the proposed method is computed on the basis of different performance metrics and then it is compared with bilateral filter (Ashwinkumar et al., 2022), CLAHE (Lilhore et al., 2022), and improved retinex algorithm (Chen et al., 2020). It is clearly shown in Fig 5, that the performance of the proposed method for each class of images is better than all the existing methods for each metric. Moreover, the average performance is also computed and is as shown in Table 3.

Table 3 Average Performance of bilateral filter, CLAHE, retinex algorithm and proposed method

	PSNR	MSE	SSIM	SNR	AD	SC	MD	LMSE	NAE
Bilateral filter	6.240991	44.11539	0.040666	12.48198	114.542	0.65891	248.4083	0.996694	0.996085
CLAHE	6.240517	44.12394	0.040819	12.48103	114.5591	0.6706	248.2982	0.985981	0.996199
Retinex algorithm	18.2343	9.430372	0.867249	36.4686	-32.4849	0.642064	86.06	0.334897	0.309668
Proposed method	19.71611	5.665535	0.900643	12.25722	-34.6188	0.670136	68.35	0.156898	0.220646

In the Table 3, the average values for each metric are computed and the best performance value is highlighted among all other values. It is clear from the above results for most of the metrics; proposed method achieved better performance as compared to the other methods. Moreover, the experimentation is also done to analyse whether the proposed method works for different type of noises or not. The Gaussian noise, salt and pepper noise, and Poisson noise are added to the maize leaf images and then by applying proposed method, these noises are removed. Table 4 shows both qualitative and quantitative results of proposed method by applying on noisy maize leaf images. In this table, results of denoised image are compared with noisy image and also with original image. All the results show that when image is compared with noisy image, all the parameters are improved and, when image is compared with original image, the value of parameters represent that original and denoised image are not much different.

Table 4 Comparison of image enhancement results of proposed method with original image and noisy image

Maize Leaf Image	Noise	Noisy Image	Denoised Image using Proposed method	Performance Measure (Denoised image is compared with noisy image)	Performance Measure (Denoised noise is compared with original image)
Northern Corn Leaf Blight	Gaussian Noise			PSNR:19.5 MSE: 0.4964 SSIM: 0.9037 SNR: 39.052 AD:-23.7 SC:0.7294 MD:67 LMSE:0.0485 NAE:0.2312	PSNR: 16.9 MSE:0.7075 SSIM:0.2792 SNR:33.805 AD:-23.8 SC:0.7069 MD:174 LMSE:47.3415 NAE:0.2842
	Salt and Pepper Noise			PSNR:19.2 MSE:0.4931 SSIM:0.8677 SNR:38.4612 AD:-24.4 SC:0.7284 MD:70 LMSE:0.0347 NAE:0.2354	PSNR:15.9 MSE:0.7942 SSIM:0.6292 SNR31.9140 AD:-25.7 SC:0.6875 MD:255 LMSE:68.7809 NAE:0.2884
	Poisson Noise			PSNR:18.6 MSE:0.5703 SSIM:0.8997 SNR:38.7416 AD:-24.2 SC:0.7155 MD:65 LMSE:0.1832 NAE:0.2367	PSNR:15.7 MSE:0.8804 SSIM:0.6238 SNR:37.7214 AD:-24.1 SC:0.7131 MD:99 LMSE:7.1664 NAE:0.2416
Common Rust	Gaussian Noise			PSNR: 18.4 MSE:2.8788 SSIM:0.8808 SNR:36.7585 AD:-24.5 SC:0.7686 MD:73 LMSE:0.1123 NAE:0.1606	PSNR: 16.4 MSE: 4.3454 SSIM:0.3654 SNR:32.8314 AD:-24.3 SC:0.7636 MD:148 LMSE:14.0545 NAE:0.1867
	Salt and Pepper Noise			PSNR:18.79 MSE:2.7195 SSIM:0.8822 SNR:37.5910 AD:-23.3 SC:0.7810 MD:73 LMSE:0.0369 NAE:0.1536	PSNR:15.79 MSE:5.2947 SSIM: 0.6638 SNR:31.5821 AD:-22.1 SC:0.7740 MD:255 LMSE:25.5132 NAE:0.1864
	Poisson Noise			PSNR:16.8 MSE:3.4933 SSIM:0.8615 SNR:33.6202 AD:-29.9 SC:0.7236 MD:77 LMSE:0.2394 NAE:0.1962	PSNR:16.5 MSE:3.5223 SSIM:0.6666 SNR:33.1018 AD:-29.5 SC:0.7256 MD:100 LMSE:3.1605 NAE:0.1945

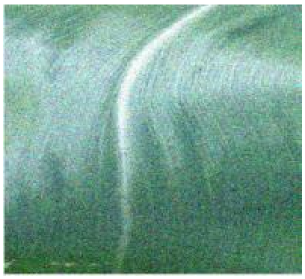
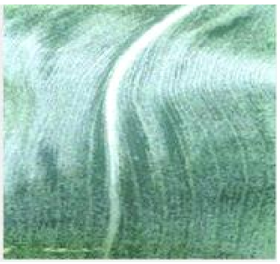
Maize Leaf Image	Noise	Noisy Image	Denoised Image using Proposed method	Performance Measure (Denoised image is compared with noisy image)	Performance Measure (Denoised noise is compared with original image)
Grey Leaf Spot	Gaussian Noise			PSNR:18.09 MSE:7.6273 SSIM:0.9408 SNR:36.1876 AD:-28.3 SC:0.6509 MD:66 LMSE:0.0202 NAE:0.2430	PSNR:15.7 MSE:10.05 SSIM: 0.3527 SNR:31.5282 AD:-28.3 SC:0.6224 MD:141 LMSE:6.1848 NAE:00.2921
	Salt and Pepper Noise			PSNR:17.46 MSE:8.8439 SSIM:0.8869 SNR:34.9215 AD:-30.2 SC:0.6425 MD:78 LMSE:0.0583 NAE:0.2585	PSNR:15.36 MSE:11.3375 SSIM:0.6573 SNR:30.7233 AD:-30.8 SC:0.6038 MD:223 LMSE:6.1435 NAE:0.3033
	Poisson Noise			PSNR:17.0 MSE:9.4985 SSIM:0.9146 SNR:34.0064 AD:-32.3 SC:0.6070 MD:77 LMSE:0.0518 NAE:0.2774	PSNR:16.59 MSE:9.8601 SSIM:0.6576 SNR:33.1998 AD:-32.2 SC:0.6026 MD:103 LMSE:1.1963 NAE:0.2823
Healthy leaves	Gaussian Noise			PSNR:29.29 MSE:5.3348 SSIM: 0.9374 SNR:40.5992 AD:-21.9 SC:0.7312 MD:60 LMSE:0.0252 NAE:0.1927	PSNR:17.09 MSE:8.4481 SSIM: 0.2440 SNR:34.1962 AD:-21.8 SC:0.7021 MD:130 LMSE:67.37 NAE:0.2541
	Salt and Pepper Noise			PSNR:19.04 MSE:4.9936 SSIM:0.8705 SNR:38.0843 AD:-25.3 SC:0.7042 MD:75 LMSE:0.0411 NAE:0.2208	PSNR:16.12 MSE:8.0861 SSIM:0.6148 SNR:32.2464 AD:-26.07 SC:0.6637 MD:213 LMSE:75.5842 NAE:0.2674
	Poisson Noise			PSNR:18.6183 MSE:5.7599 SSIM:0.8897 SNR:37.2366 AD:-27.26 SC:0.6719 MD:71 LMSE:0.0997 NAE:0.2390	PSNR:17.9664 MSE:6.3467 SSIM:0.5262 SNR:35.9329 AD:-27.29 SC:0.6667 MD:95 LMSE:12.4312 NAE:0.2458

Table 4 presents the results for both healthy and unhealthy maize leaves with three different types of noises. Table 4 shows the images of maize leaves infected with northern corn leaf blight and by adding gaussian noise, salt and pepper noise, and Poisson noise and their results after enhancement. Table 4 shows the images of maize leaves infected with common rust and by adding Gaussian noise, salt and pepper noise, and Poison noise and their results after enhancement. Table 4 shows the images of maize leaves infected with grey leaf disease and by adding Gaussian noise, salt and pepper noise, and Poisson noise and their results after enhancement. Table 4shows the images of healthy maize leaves infected by adding Gaussian noise, salt and pepper noise, and Poisson noise and their results after enhancement. The quantitative results in terms of PSNR, MSE, SSIM, SNR, AD, SC, MD, LMSE, and NAE are computed by comparing the denoised image with the noisy image and the original image. From the above results, it is clear that the proposed method is best for Poisson noise as compared to other noises but it is also effective for Gaussian noise as well as salt and pepper noise. These results define that the proposed CLAHlet RetiGaussian filter removes the unwanted external inferences or noises added to the images and enhance the quality of the image.

4 Conclusion

In this paper, an image enhancement method named as CLAHlet RetiGaussian filter, which is a combination of CLAHE, wavelet, retinex, and gaussian filter, is proposed. The focus of the proposed work is to enhance the quality of the maize leaves. The dataset of northern corn leaf blight, common rust, grey spot leaf, and healthy images has been utilized and testing is done with 100 images of each class. The performance of the proposed method is compared with bilateral filter, CLAHE, and improved retinex algorithm, used in plant leaf disease detection system. The quantitative results use nine different metrics for performance analysis and are compared with the existing methods. The results show the effectiveness of the proposed method and it is shown that PSNR and SSIM are high among all. MSE, SNR, AS, MD, LMSE and NAE are low. Only SC is not the highest with the proposed method. Also, three different noises, Gaussian, salt and pepper, and Poisson noise are added to the sample and then it is removed using the proposed method. The comparison with noisy image shows the quality improvement of an image from noisy image. However, the comparison with original image demonstrates the enhancement quality as well. The qualitative and quantitative results for denoising presented the efficiency of the proposed method. Hence, it reveals the effectiveness of the proposed method to be used in various applications. The images enhanced, using the proposed method, can be used for maize leaf diseases detection and classification system.

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