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. First, image is enhanced using CLAHE, image is decomposed using Daubechies wavelet and then followed by the Retinex algorithm, which used 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.

1. Introduction

The goal of image enhancement is to improve the quality of the image and prepare the image to be used for specific application [1]. Generally speaking, the fundamental idea behind image enhancement is to change informational content of an image to make it more suited for a certain purpose and denoising is to remove different types of noises from the image which may be because of any 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 [2]. The traditional modified histogram techniques [3], and the enhanced unsharp mask methods [4], 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) are examples of mathematical operations that can be used to convert an image to the frequency domain [5]. 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 [6]. Numerous unique techniques, like the Retinex model [7], fuzzy theory [8], neural network [9], etc., have evolved as a result of the quick growth of image-enhancing technology. Several techniques like histogram equalization [10], visual cortex neural network [11], and deep learning techniques [12] are the prominent ones. 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 as the insufficiency of the robustness and imperceptibility criteria [13]. 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 [14].

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. 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 disease 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 [15]. 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 feed. In addition, it gives the soil the minerals that other crops need to grow. It takes 90% fewer soil nutrients and water to grow than paddy and wheat. Maintaining the availability of maize is now more important than ever with the expanding population. It is essential to keep the plants healthy and free of various diseases to satisfy such a high demand [16]. 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 COVID-19 outbreak caused a decline in global trade, which has made the situation worse [17]. Therefore, many nations are placing a greater emphasis on raising the yield of commodities like maize, which may be used in a range of industries. As a result, it is necessary to take the necessary actions to improve the production. On the other side, product loss brought on by 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 [18]. 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 [19]. 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 [20]. 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 also increases productivity. 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 [21]. 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 [22]. 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 [23]. The three most common diseases affecting maize crops are shown in Fig. 1.

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 [24][25]. 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 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 [26][27]. The Cercospora zeae-maydis fungus is what causes Grey leaf spot. This is one of the world's most harmful and yield-restricting illnesses [28]. 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 [29]. Fig:2 shows some of the sample images for healthy, and unhealthy leaves of maize.

3. 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 will be 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 than ideal for extracting and identifying corn diseases. Therefore, to identify the corn illnesses, the image must first be denoised to emphasize the affected region [30]. The color 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 contrast in the grey scale picture of the corn disease is the distinction in brightness between light and dark. Images of corn diseases have tremendous contrast, and the items appear chiselled. Low-contrast photos, on the other hand, have indistinct object features. The entire image is too faint if the light is underexposed or imaged too darkly, and the opposite is true if the light is overexposed or imaged too brightly. Low visual contrast will be the outcome of all these factors. The term "grey extreme concentration" applies to this. Thus, an enhancement approach should be used to process the photos. The grey-scale transformation method is one of the primary techniques for improving grey-scale images. The image may be automatically enhanced and its quality improved using the 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.

The other image enhancement method using image resizing, filtering, color space conversion, and histogram equalization was discussed by Ngugi et al.[31]. Moreover, resizing [32] and data augmentation [33] approaches were also opted for image enhancement for maize leaves as well as for multiple crops. The other leaf disease detection system that detects diseases in sorghum leaf utilized basic image processing methods including, Edge detection, thresholding, and noise reduction[34].

Now a day's, deep learning-based methods are in a trend and most disease detection system use deep learning technology. Similarly, Fraiwan et al. [35] designed a deep learning-based corn leaf disease detection and classification system. They 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 they also used data augmentation as pre-processing method [36]. One more deep learning-based disease detection system that was designed for multiple crops disease detection utilized rescaling as its pre-processing method [37]. 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 [38]. 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 [39]. MobileNet based CNN was used for the classification and identification of tomato disease where a bilateral filter was used for image enhancement [35].

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 [40]. CLAHE method was proposed by Lilhore et al.[41] for casava leaf image enhancement and by using an improved CNN they detect and classify the disease. Furthermore, a single-scale Retinex algorithm was proposed for image enhancement with lightweight CNN for wheat ear disease identification [42]. In addition to this, histogram equalization for multiple crops [43], Wavelet based Retinex algorithm [44] for tomato, and improved top-hat hessian-based filtering method [45] for cucumber leaf image enhancement were earlier opted by the researchers who focuses on plant disease detection system. Comparison of various Image Filtering methods is given [46]. 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 & Pepper Noise and speckle noise. Various methods used to remove these noises are also given. Fan et al. [47] summarize some important research in the field of image denoising. they formulate the image denoising problem, and then several image denoising techniques alongwith their characteristics are discussed. It has been concluded that different types of noise require different denoising methods, the analysis of noise can be useful in developing novel denoising schemes.

The above 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 still, improvement is required to improve 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.

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

Reference	Year	Crop	Pre-Processing
[6]	2019	Corn	CLAHE
[27]	2021	corn	RGB to Gray scale
[30]	2012	corn	Converted to grey scale, grey scale transformation, histogram equalization, average filter
[33]	2022	Maize leaf	Data Augmentation
[34]	2021	Sorghum	Edge Detection, Thresholding, Noise reduction
[35]	2021	corn	Normalization, and data augmentation
[38]	2021	tomato	Geometric and Intensity Transformations
[36]	2021	Apple	Data Augmentation
[36]	2021	Multiple crops	Rescaling
[39]	2022	Corn and other crops	RGB to grey and RGB to LAB
[40]	2021	Multiple crops	Image enhancement, color space transformation, resizing, and noise removal
[41]	2022	Cassava leaf	CLAHE method
[42]	2021	Wheat	Single-scale Retinex algorithm
[43]	2020	Multiple crops	Histogram Equalization
[44]	2020	tomato	Binary Wavelet Decomposition, Retinex algorithm, Gauss convolution filter, Binary wavelet image reconstruction
[45]	2020	Cucumber leaf	Local contrast enhancement, top-hat &hessian-based filtering, image sharpening & 3D median filtering, and HSV color space transformation
[48]	2022	tomato	Bilateral Filter
[49]	2018	Corn	Data augmentation, resize
[50]	2021	Maize leaf	Grey scale, Erosion and dilation
[51]	2020	Corn	Data augmentation
[52]	2021	Corn	RGB to HSI

4. 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.

The above Fig. 3 presented the detailed process and highlighted the different methods used in the proposed method. It is a combination of CLAHE, wavelet, Retinex, and gaussian filter. Here wavelet decomposition is specifically performed to divide low and high-frequency pixels so that Retinex can enhance low intensity pixels to keep high frequency intensities as it is so that image quality doesn't get deteriorated. In this, 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:

CLAHE

It is Contrast Limited Adaptive Histogram Equalization which 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 [41]. The 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. The CLAHE 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.

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 [53]. In the equation given below *h (m, n)* contains high frequency components and *l (m, n)* are low frequency components.

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

1

Retinex Algorithm

This method is used here only the low frequency components to enhance the image[44]. 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.

$$l\left(m,n\right)=L\left(m,n\right)\times R(m,n)$$

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:

$$\log l=\log R+\log L$$

3

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

$$\log R=\log l-\log L$$

4

The reflectance may then be calculated as given in equation(v)

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

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.

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

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, the gaussian filter is used to enhance both low and high frequency components. A 2-D convolution operator called the Gaussian smoothing operator is used to 'blur' pictures and eliminate noise and detail [54].

Wavelet Reconstruction

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

5. Results And Discussion

In this section, the results of the proposed method are presented and analyzed in both qualitative and quantitative. 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 [48], CLAHE [41], and improved retinex algorithm [44], used in plant disease detection. The qualitative and quantitative analysis of the proposed method and its comparison with different methods is given below in Fig. 4.

This figure displays the output images for each class of the maize leaf data including healthy and unhealthy samples and compared with bilateral filter [48], CLAHE [41], and improved retinex algorithm [44]. Furthermore, the performance of the proposed filter is analyzed 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).

The Table 2 demonstrates the formulas for each performance metric considered in this work to measure the image enhancement quality and also provides its description. In the remark's column, it is clearly mentioned which performance metric should be high or which should be 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.

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

Sr. No.	**Parameter Name**	**Parameter Formula**	**Remarks**
1.	PSNR	$PSNR = 10log\frac{255^2}{MSE}$	Higher the PSNR, lesser the noise.
2.	MSE	$MSE = \frac{1}{MN}\sum_{m=1}^{M}\sum_{n=1}^{N}\left(x\left(m,n\right)-\widehat{x}(m,n)\right)^2$	Lesser the value of MSE, better the performance of the algorithm.
3.	SSIM	$SSIM = f(l\left(x\left(m,n\right)\right),c\left(x\left(m,n\right)\right),s\left(x\left(m,n\right)\right))$ 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	$SNR = 10\log\left[\frac{var(x(m,n))}{mean(x(m,n)-\widehat{x}(m,n))}\right]$	Signal to Noise ratio, higher the SNR, lesser the noise, better the reconstruction
5.	AD	$AD = \frac{1}{MN}\left(x\left(m,n\right)-\widehat{x}\left(m,n\right)\right)$	As small as possible, the ideal value is 0.
6.	SC	$SC = \frac{\sum_{m=1}^{M}\sum_{n=1}^{N}x(m,n)^2}{\sum_{m=1}^{M}\sum_{n=1}^{N}\widehat{x}(m,n)^2}$	It is the ratio of sums of the squares of the original and recovered image pixel values.
7.	MD	$MD = Max\left(\lvert x\left(m,n\right)-\widehat{x}(m,n)\rvert\right)$	As small as possible
8.	LMSE	$LMSE = \frac{\sum_{m=1}^{M}\sum_{n=1}^{N}\left[L(x(m,n))-L(\widehat{x}(m,n))\right]^2}{\sum_{m=1}^{M}\sum_{n=1}^{N}\left[L(x(m,n))\right]^2}$	As small as possible
9.	NAE	$NAE = \frac{\sum_{m=1}^{M}\sum_{n=1}^{N}\left[\lvert x(m,n)-\widehat{x}(m,n)\rvert\right]^2}{\sum_{m=1}^{M}\sum_{n=1}^{N}\lvert x(m,n)\rvert}$	As small as possible, the ideal value is 0.

The performance of the proposed method is computed on the basis of different performance metrics and compared with bilateral filter [48], CLAHE [41], and improved retinex algorithm [44],and it is clear from the above 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 given below.

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 above table, 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 analyze whether the proposed method works for different type of noises. 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. The following Table 4 deliberate 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 given above, presented the results for both healthy and unhealthy maize leaves with three different types of noises. 4(a) 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. 4(b) shows the images of maize leaves infected with common rust and by adding gaussian noise, salt and pepper noise, and poisson noise and their results after enhancement. 4(c) 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. 4(d) shows 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.

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 maize leaves. In this, 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 9 different metrics for performance analysis and are compared with the existing methods. The results show the effectiveness of the proposed method as PSNR is high among all, MSE is lesser, SSIM is also highest, SNR is low, AS is again low, MD is low, LMSE is low, and NAE is low as required. Only SC is not the highest with the proposed method. Also, three different type of 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 tells 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.

Declarations

Compliance with ethical standards

The research itself do not have participate have any involvement of any clinical trial/animal studies, not applicable here.

Competing interest

All the authors and co-authors counted here in this manuscript have no competing interest for this publication under “International journal of multimedia and information retrieval”.

Research data policy and data availability standards

Dataset used in this publication is freely available online at PlantVillage Dataset | Kaggle. 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.

Conflict of interest

The authors declare no conflict of interest.

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Table 4

Table 4 is available in Supplementary Files section.

Figures

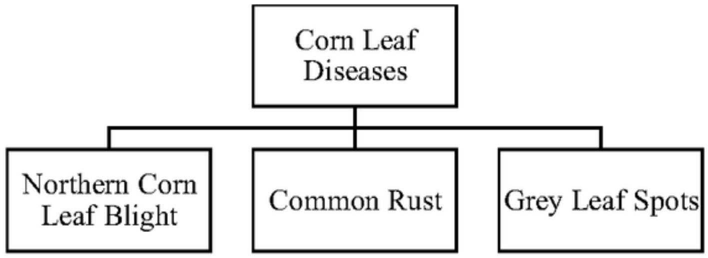

Fig1: Common Maize Leaf Diseases

Figure 1

See image above for figure legend

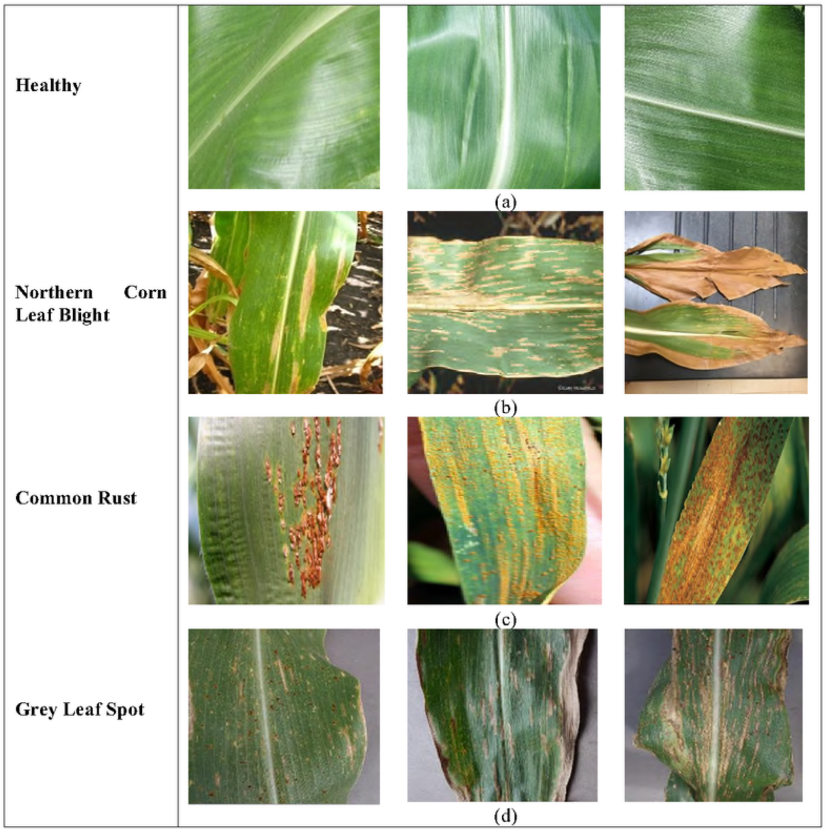

Fig 2: Healthy and unhealthy maize leaves images. (a) Healthy leaves. (b) Maize leaves infected by northern corn leaf blight. (c) Maize leaves infected by common rust. (d) Maize leaves infected by grey leaf spot.

Figure 2

See image above for figure legend

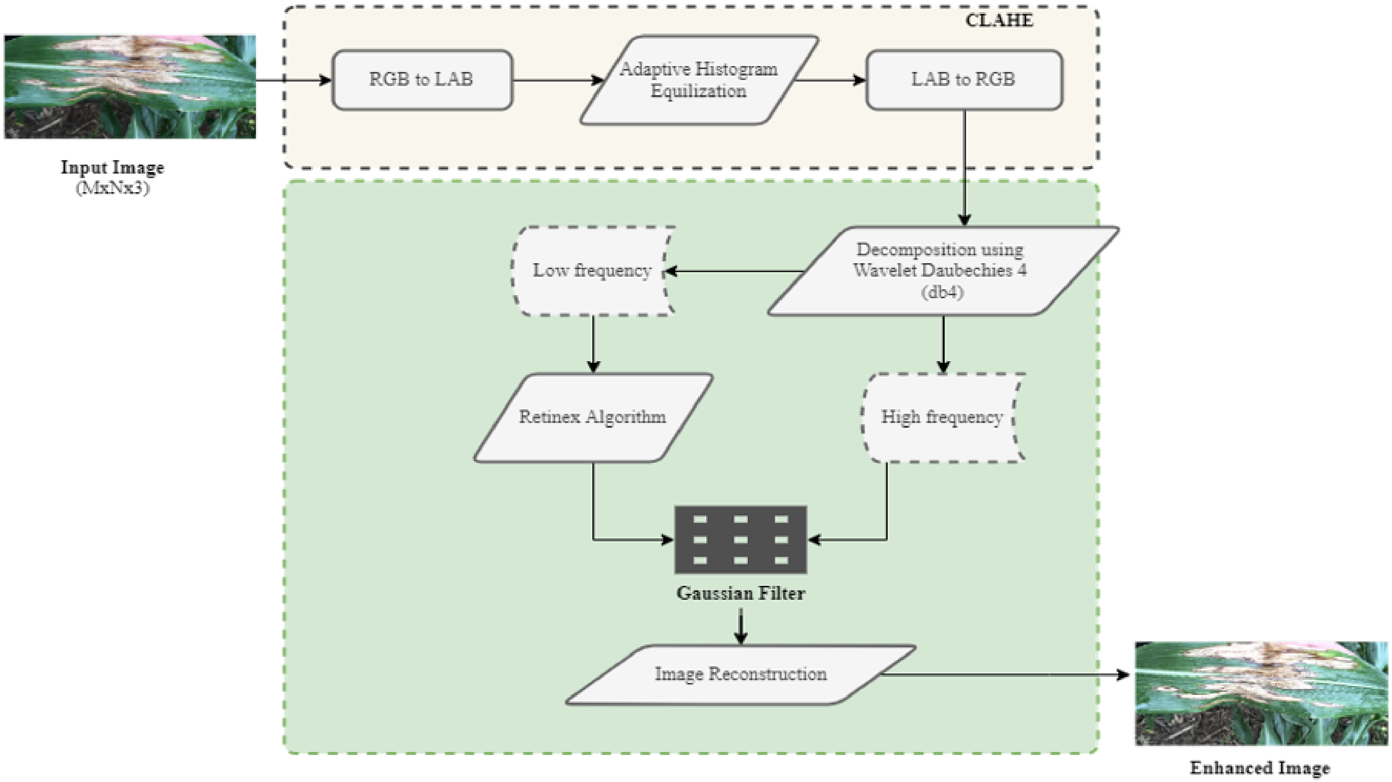

Figure 3

Proposed method for image enhancement (CLAHlet RetiGaussian Filter)

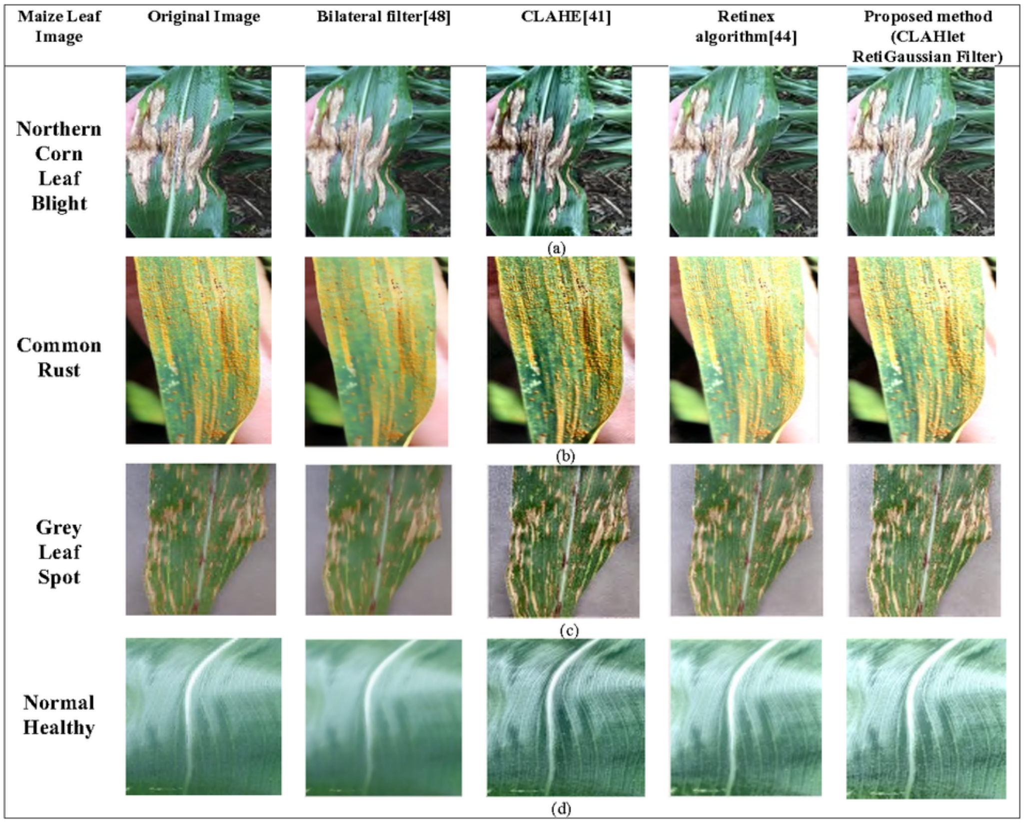

Fig 4: Output images of Bilateral filter, CLAHE, improved Retinex algorithm and proposed method of maize images: a) northern corn leaf blight, b) common rust, c) grey leaf spot and d) normal healthy images

Figure 4

See image above for figure legend

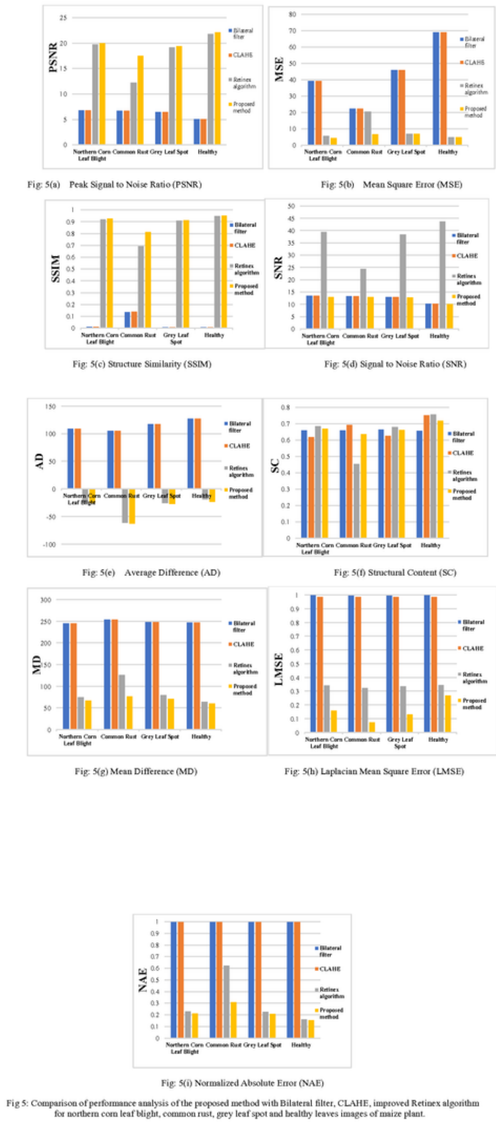

Figure 5

See image above for figure legend

Supplementary Files

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- Table4.docx